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Too Hot to Slow Down: Extreme Heat, Working Hours, and Constrained Adaptation in Punjab, Pakistan

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Abstract

Rising heat is usually expected to push workers out of employment. Punjab, Pakistan shows a different pattern. We combine three decades of satellite-derived wet bulb globe temperature (WBGT) with Pakistan Labour Force Survey microdata collapsed to a district-quarter panel covering 30 districts from 2001 to 2021 (2,269 cells), alongside roughly thirty interviews across five districts. We estimate how deviations of peak heat from each district's own seasonal norm affect labour outcomes. Anomalies in mean temperature have no detectable effect; anomalies in peak WBGT do. A 1 °C peak anomaly reduces average weekly hours by 0.33 (wild-cluster bootstrap $p = 0.003$), and by 1.21 hours in summer, close to 2.5 percent of mean hours, while raising underemployment. Employment and labour force participation do not contract. Women's participation rises with peak heat, at suggestively fewer hours and lower wages, and the hours loss concentrates in poorer districts. Interviews explain the pattern. Workers on daily wages and piece rates cannot afford to stop, so heat compresses labour time inside jobs while pushing additional household members, especially women, into distress participation. Employment-based indicators therefore understate the labour cost of warming in informal economies, and climate-responsive protection needs to reach the contracts that make exit impossible rather than relying on weather warnings alone.

Keywords Extreme heat · Labour supply · Wet bulb globe temperature · Informality · Gender · Pakistan

JEL Classification J22 · Q54 · O15 · J16

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Introduction

The summer of 2022 brought Jacobabad, a few hundred kilometres from our study area, to the edge of human heat tolerance, and Punjab's own peak wet bulb globe temperatures now regularly cross thresholds at which sustained physical work becomes physiologically difficult (Kjellstrom et al. 2016a; Vanos et al. 2023). For the province's workforce, most of whom work outdoors or in unventilated indoor settings and a large share of whom are informally employed, heat is no longer an occasional shock. It is a recurring feature of the working year that shapes when people work, how much they work, and what they earn. Yet empirical evidence from Pakistan on how heat translates into labour market outcomes remains thin, and the evidence that exists worldwide often relies on average temperatures and on employment counts, both of which, we will argue, miss most of the action.

This gap matters for how climate risk is measured and managed. If warming erodes earnings capacity without moving the indicators that governments and international agencies actually monitor, then the damage accumulates unrecorded, and the social protection built to respond to climatic shocks will be calibrated against the wrong signal. Punjab offers a useful setting for testing that possibility, because it combines severe and rising humid heat with a labour market in which a large share of workers are hired by the day, paid by the piece, or tied to employers through debt.

We ask two questions:

(1) Does extreme heat, measured as a deviation of peak WBGT from a district's own seasonal norm, reduce labour supply in Punjab, and through which margin does the adjustment run?

(2) How is that burden distributed across districts of differing wealth and between men and women, and what explains the pattern of adjustment we observe?

We combine two kinds of evidence. On the quantitative side, we build a district-quarter panel covering 30 districts of Punjab from 2001 to 2021, collapsing Pakistan Labour Force Survey (LFS) microdata to population-weighted cell means and matching each cell to daily satellite-derived temperature and humidity records spanning 1990 to 2021, from which we construct WBGT, the standard physiological heat stress measure. Identification comes from anomalies. We ask what happens to a district's labour outcomes when its peak WBGT in a given quarter deviates from that district's own long run average for that same quarter of the year. This within-district, within-season design

strips out everything permanent about a place and everything seasonal about its calendar, so the variation left over is plausibly random weather (Dell et al. 2014; Hsiang 2016). On the qualitative side, we conducted roughly thirty unstructured interviews with construction workers, brick kiln workers, agricultural and orchard workers, and home-based women workers across five districts spanning Punjab's climatic gradient, analysed thematically. The interviews are not decoration. They explain a set of quantitative results that a standard, frictionless labour supply model would struggle with.

Four findings organise the paper. First, average heat does nothing while extreme heat bites. Anomalies in mean WBGT leave weekly hours unchanged, but a 1 °C anomaly in peak WBGT reduces average weekly hours by 0.33 (wild-cluster bootstrap $p = 0.003$), and by 1.21 hours, roughly 2.5 percent of mean hours, when we restrict to summer quarters. We are deliberately clear about magnitude. The full sample effect is small, about 0.7 percent of mean hours, some twenty minutes per week per degree, and it is the seasonally concentrated summer response, landing on an already hot baseline, that is economically consequential. Days worked fall in parallel and underemployment rises. Second, the adjustment is almost entirely on the intensive margin. Employment and labour force participation do not contract under peak heat; if anything they expand. Workers do not leave their jobs when it gets hot. They lose hours inside jobs they cannot afford to leave. Third, the burden is regressive. Interacting peak heat with a pre-period wealth index concentrates the hours compression in poorer districts (wild $p = 0.043$). Fourth, the gender pattern is not the one usually told. Women's participation rises significantly with peak heat, while their hours and hourly wages decline only suggestively, a configuration consistent with distress or added-worker participation. Heat squeezes household income, and women enter paid work at the hottest times, on worse terms.

The interviews make sense of all four results. Daily wage and piece rate workers described working through dizziness, dehydration, and exhaustion because a missed day means a missed meal. Kiln workers bound by advance debt, known locally as *peshgi*, described being unable to rest at all. Heat strain here does not show up as absence, which surveys record, but as slowed pace, shortened days, and bodies pushed to their limits, which surveys mostly do not. Home-based women described reorganising the day around heat, shifting paid stitching into the night and absorbing exposure across both paid and unpaid labour. What looks in the data like resilience, meaning near-inelastic employment in poor districts, is on closer inspection the absence of any alternative.

The paper contributes three things. It provides, to our knowledge, the first district-level panel estimates of heat effects on labour outcomes for Pakistan, a country repeatedly ranked among the most heat exposed in projections (ILO 2019; Kjellstrom et al. 2016b) but rarely studied directly. It shows that the choice of heat measure is not a technicality. Mean-based measures, still common in this literature, would find no effect here, whereas peak WBGT anomalies reveal a robust one, consistent with binding stress at the hottest hours (Dasgupta et al. 2021; Vanos et al. 2023). And by pairing the panel with fieldwork it identifies the adjustment margin, compressed hours plus distress participation where exit is impossible, that explains why employment-based statistics understate the labour cost of warming in informal economies.

The rest of the paper proceeds as follows. The next section situates the study in the literature on heat, labour, and constrained adaptation. We then describe the data, the heat measures, the empirical specification and inference strategy, and the qualitative fieldwork. We present the quantitative results and then the qualitative findings, discuss their integration and policy implications, state the limitations, and conclude.

Heat, Labour Markets, and Constrained Adaptation

Two Channels: Fewer Hours, and Less Productive Hours

A substantial body of work documents that heat reduces labour through two channels that compound each other. Workers supply fewer hours, and each hour supplied is less productive. High frequency evidence from Delhi's informal settlements finds daily earnings of informal workers falling sharply with wet bulb temperature, through both missed work and reduced output, with heatwave episodes cutting net earnings dramatically (Das and Somanathan 2024). Meta-analytic and review evidence puts numbers on the physiological side. Workers labouring above WBGT thresholds of 22 to 25 °C show elevated core temperatures, dehydration, and measurable productivity losses, with chronic exposure linked to kidney disease (Flouris et al. 2018; Kjellstrom et al. 2016a). At the global scale, combined labour supply and productivity response functions imply that current climates already reduce effective labour in the tropics, with losses concentrated in outdoor, high exposure work (Dasgupta et al. 2021), and the ILO projects that heat stress will erase the equivalent of tens of millions of full time jobs by 2030, disproportionately in South Asia (ILO 2019; Kjellstrom et al. 2016b). Mortality adds a further margin. Across seven countries, premature deaths from non-optimal temperatures already impose a labour productivity burden that falls most heavily on socio-economically disadvantaged communities (Wen et al. 2024). Longitudinal evidence from

Australia shows that heat-induced work time losses are not recovered in subsequent weeks and extend beyond obviously outdoor sectors (Ireland et al. 2024), and field experimental evidence from Indonesia shows that removing natural shade measurably raises heat exposure and cuts output through more frequent breaks (Masuda et al. 2021).

A second strand traces heat through firms and economies. Hot days reduce firm level productivity, more so for smaller firms and with little adaptation at the extremes (Costa et al. 2024); heat shifts income from labour to capital as firms substitute toward machines (Lyu et al. 2024); and shocks propagate along supply chains to firms never directly exposed (Liu and Song 2026). Economy-wide models show sectorally concentrated losses in agriculture and construction spilling into aggregate output through input-output linkages (Kimmich et al. 2025), while structural reallocation out of climate-hit sectors is slowed by credit and mobility frictions (Albert et al. 2024). The distinction between short run weather responses and long run climate effects also matters. Panel estimates from year-to-year variation may differ from long run adjustment, with the hottest regions most exposed even after adaptation (Dong et al. 2025; Burke and Emerick 2016).

Who Bears the Loss, and Why Adaptation Fails

The strand closest to our setting concerns who bears these losses and why adaptation fails. Informal urban workers face heat on top of prior deprivations, including poor housing, absent occupational safety protection, and little social insurance, and cope through self-help measures of limited reach (Dodman et al. 2023). Surveys of construction workers in Nigeria document basic gaps, with most sites lacking even drinking water (Moda et al. 2024), and systematic reviews of the industry catalogue feasible protections such as rest scheduling, shade, and cooling gear that are rarely implemented in low income settings (Torbat Esfahani et al. 2024). Occupational health reviews emphasise that heat risk is mediated by payment structure, workload, job control, and sanitation access, so identical weather produces different labour outcomes in different institutional settings (Amoadu et al. 2023). Recent work shows West African farmers responding to extreme heat by reallocating inputs in ways contingent on the assets they hold (Tabe-Ojong and Lokossou 2026), a reminder that responses to heat are rational but resource constrained. Finally, the measurement literature argues that ambient temperature understates risk because humidity, radiation, and physiology jointly determine tolerable exposure, and that liveability thresholds relevant for work sit well below survivability thresholds (Vanos et al. 2023).

Read through the lens of a segmented, informal labour market, these literatures predict exactly the configuration we test for in Punjab. Where a large share of workers are hired daily, paid by the piece, or tied by debt, the extensive margin, meaning quitting or being laid off, is not a feasible response to a hot quarter, because forgoing a day's wage means forgoing a day's food. The margin that remains is the body and the clock: slower work, shorter days, more rest snatched where a supervisor permits it. The prediction, then, is of effects at the peak rather than the mean, adjustment through hours rather than employment where exit is unaffordable, and burdens concentrated on the poor and mediated by gendered constraints on which household members can be sent into paid work when income falls.

Gaps and Our Contribution

Three gaps follow from this review. Evidence for Pakistan is almost absent despite the country's exposure ranking. Most panel work relies on mean temperature measures that, as we show, would return a null result in this setting. And very little of the literature identifies the *margin* of adjustment in labour markets where exit is not an available response, which is precisely the margin that determines whether conventional statistics register the damage. We address all three by pairing a long district-quarter panel built on peak WBGT anomalies with fieldwork designed to recover the mechanism.

Data and Methods

Setting

Punjab is Pakistan's most populous province and spans a steep climatic gradient, from the relatively temperate north around Rawalpindi to a southern belt where peak summer WBGT approaches the limits of safe manual work. Its labour market is dominated by agriculture, construction, brick kilns, and informal services. In our panel the mean district-quarter cell has 78 percent of workers in outdoor-intensive occupations and roughly a third in informal enterprises. This is, in short, precisely the kind of segmented, informality-heavy labour market in which the extensive margin assumptions of frictionless models are least likely to hold.

Data and the Construction of Heat Measures

Labour outcomes come from the Pakistan Labour Force Survey, a nationally representative household survey fielded by the Pakistan Bureau of Statistics. We collapse individual microdata to district-quarter cells using the survey's sampling weights, following the standard practice of aggregating micro responses to the spatial level at which climate varies (Dell et al. 2014; Dasgupta et al. 2021). We hold district boundaries fixed at their late 1990s

definitions, yielding 30 consistent districts, because later administrative splits would otherwise mechanically break panel continuity.[1] The resulting panel contains 2,269 district-quarter cells over 2001 to 2021. Outcomes are mean weekly hours among the employed, days worked, the employment rate, the labour force participation rate, and the underemployment share, plus sex-specific versions of each and hourly wages by sex. All regressions are weighted by the cell's working age population, so estimates represent effects on the average worker rather than the average district, and cell-level sampling noise from smaller districts is appropriately down-weighted (Solon et al. 2015). Summary statistics are in Table 7 in Appendix A.

Climate data are satellite-derived daily temperature and humidity series extracted through Google Earth Engine for 1990 to 2021 and aggregated to district-quarters. From these we construct WBGT, which integrates temperature and humidity into the physiological heat stress index used in occupational standards. Humid heat, not dry bulb temperature, is what limits the body's ability to shed metabolic heat during work (Lemke and Kjellstrom 2012; Kjellstrom et al. 2016a).[2] We compute both the quarter's mean WBGT and its peak. The distinction is central to our design. Averages smooth over precisely the hours when heat stress binds. Physiological and empirical work argues that labour responses are driven by conditions at the hottest part of the day (Dasgupta et al. 2021; Vanos et al. 2023), and survivability-based thresholds can substantially understate risk when only means are observed (Vanos et al. 2023). We therefore treat peak WBGT as the preferred exposure measure and the mean as a deliberately included falsification contrast.

Measuring Heat Shocks: Anomalies, Not Levels

Our heat variable is the anomaly, meaning the deviation of a district-quarter's peak or mean WBGT from that district's long run average for the same calendar quarter, computed over the full 1990 to 2021 climate record. Three

[1] Holding boundaries fixed means that a small number of post-2000 districts are recombined with their parent districts. This is a conservative choice that trades spatial granularity for a balanced, comparable panel.

[2] We use the standard Lemke and Kjellstrom conversion of meteorological data to workplace WBGT (Lemke and Kjellstrom 2012). As with any WBGT constructed from ambient reanalysis-type inputs rather than on-site black globe measurements, our index approximates solar and wind contributions. We therefore treat it as a consistent relative measure of humid heat stress across district-quarters rather than as a clinical exposure reading.

considerations drive this choice. First, levels of heat are correlated with everything else that differs across Punjab's geography, including cropping systems, informality, and wealth, so cross-sectional level comparisons confound climate with place (Dell et al. 2014; Blanc and Schlenker 2017). Anomalies isolate weather, meaning transitory and plausibly exogenous deviations from expected conditions (Hsiang 2016). Second, agents optimise against the climate they expect. Responses to a hot quarter relative to a district's own norm identify the short run behavioural response that is our object of interest, whereas level variation partly reflects long run adaptation (Kolstad and Moore 2020; Burke and Emerick 2016). Third, anomaly measures make the identifying variation transparent. In our data the peak WBGT anomaly has a standard deviation of 0.84 °C with excursions beyond plus or minus 2 °C, which is ample variation once fixed effects are absorbed.

We enter the anomaly and its square. Temperature response functions are non-linear almost wherever they have been estimated flexibly (Schlenker and Roberts 2009; Burke et al. 2015), and imposing linearity risks averaging a steep extreme heat response with a flat moderate one. The quadratic is a parsimonious middle ground given 30 clusters. We probe it further by estimating summer-only samples, where anomalies land on an already hot baseline.

Empirical Specification

The baseline specification is

$$Y_{dqt} = \beta_1 A_{dqt} + \beta_2 A_{dqt}^2 + \mu_{dq} + \lambda_t + \varepsilon_{dqt}$$

{#eq:1}

where Y_{dqt} is a labour outcome in district d, calendar quarter q, year t; A_{dqt} is the peak WBGT anomaly; μ_{dq} are district-by-quarter fixed effects; and λ_t are year fixed effects. The district-by-quarter effects absorb each district's entire seasonal profile, including its cropping calendar, its Ramadan season composition, and its normal summer slowdown, so β_1 compares, say, Multan's second quarter in an unusually hot year to Multan's own average second quarter, never Multan to Rawalpindi. This is the within-unit weather design standard since Deschênes and Greenstone (2007) and reviewed in Dell et al. (2014) and Blanc and Schlenker (2017). The year effects sweep out national shocks such as the 2010 floods and the 2020 lockdown. We estimate Eq. (1) separately for hours, days, employment, participation, and underemployment, which decomposes the response into intensive and extensive margins in the spirit of Graff Zivin and Neidell (2014). Because anomalies are deviations from district-season means

by construction, coefficients read directly as the effect of a 1 °C hotter than normal quarter. We report the full sample estimate and a summer only estimate covering April to September, since a given anomaly on a 34 °C baseline is physiologically different from the same anomaly on a 22 °C baseline.

Inference and Diagnostics

Our panel has only 30 clusters, and cluster-robust variance estimators are known to over-reject in that range (Cameron et al. 2008; Bertrand et al. 2004). Every headline estimate therefore carries a wild-cluster bootstrap p value with Webb weights and 9,999 replications (Cameron et al. 2008; Webb 2023; Roodman et al. 2019). We treat the bootstrap p, not the analytic stars, as the arbiter of significance, following the practical guidance in MacKinnon et al. (2023). Diagnostics motivate two complements. A Wooldridge test rejects the null of no first order serial correlation ($p = 0.022$) (Drukker 2003; Wooldridge 2010), and although Pesaran's CD test does not indicate cross-sectional dependence ($p = 0.73$) (Pesaran 2015), weather is spatially correlated by nature, so we re-estimate the summer headline with Driscoll-Kraay standard errors, robust to both serial and spatial dependence (Driscoll and Kraay 1998). The effect survives ($p = 0.018$). Fisher-type ADF tests reject unit roots in all outcome and heat series (Choi 2001). Because we examine several outcomes, we report Romano-Wolf stepdown p values controlling the familywise error rate across the outcome set (Romano and Wolf 2005), and a leave-one-district-out jackknife confirms that no single district, including Lahore, drives the estimates. We regard this inferential caution as a substantive part of the contribution. With 30 clusters, honest small sample inference is what separates a credible claim from an artefact.

Gender, Heterogeneity, and Robustness

To estimate sex-specific responses we stack male and female cell panels and interact the heat terms with a female indicator,

$$Y_{sdqt} = \beta_1 A_{dqt} + \gamma_1 F_s \times A_{dqt} + \beta_2 A_{dqt}^2 + \gamma_2 F_s \times A_{dqt}^2 + \mu_{dqs} + \lambda_{ts} + \varepsilon_{sdqt}$$

{#eq:2}

with district-by-quarter-by-sex and year-by-sex fixed effects, so each sex has its own seasonal baseline and own national trend and γ_1 is identified purely from differential within-cell responses. Cells are weighted by the sex-specific working age population.

For distributional heterogeneity we construct a district wealth index from the first principal component of three pre-2000 baseline characteristics, namely urban share, mean years of education, and log male monthly wages, and classify districts below the median as poor. Using pre-period characteristics and the standard principal component asset index approach (Filmer and Pritchett 2001) guards against the index absorbing outcomes of heat exposure itself. Using south Punjab dummies instead would conflate poverty with climate. The interaction of the peak anomaly with the poor district indicator then tests whether hour losses concentrate where adaptive capacity is lowest.

A deliberate identification concern in Punjab is the harvest calendar. Summer quarters combine peak heat with wheat harvest completion, so a naive summer effect could reflect agricultural labour demand rather than heat. We address this three ways: controlling for the cell's agricultural employment share, interacting the anomaly with that share, and re-estimating on non-agricultural cells only. We then report a full robustness battery covering one-quarter-lagged heat, a one-quarter lead of heat, district-specific linear trends, region-by-year fixed effects, a first difference specification, and a control for recent in-migration. Importantly, we report the checks that weaken the result alongside those that do not. Transparency here is deliberate. The credibility of a small effect rests on showing the reader the whole distribution of specifications, not a curated subset.

Qualitative Fieldwork and Research Ethics

The quantitative design identifies how much labour adjusts. It cannot say why hours compress while employment holds, or what an hour lost to heat feels like from inside a piece rate contract. For that we conducted exploratory fieldwork across five districts chosen to span the province's climatic and occupational range: Rawalpindi and Lahore in the cooler, urbanised north, covering construction and home-based manufacturing; Multan and Bahawalpur in the southern heat belt, covering agriculture and brick kilns; and Sargodha in the centre, covering orchard farming and female agricultural labour. Approximately thirty respondents were interviewed across four occupational groups: construction workers, brick kiln workers, agricultural and orchard workers, and home-based women engaged in stitching and tailoring.

Interviews were unstructured and conversational, conducted in Urdu and Punjabi. Given the absence of prior ethnographic work on occupational heat stress among Punjab's informal workers, we prioritised depth over standardisation, letting respondents narrate their own working day in summer. An opening question about a typical

hot day was usually enough to elicit extended accounts of symptoms, rest, supervision, and income pressure. Access ran through personal networks rather than employers or labour contractors, a choice made to reduce the social desirability pressure that gatekeeper-mediated recruitment imposes on accounts of exhaustion and constrained autonomy. This purposive, network-based logic follows the case selection reasoning in Small (2009). Transcripts and field notes were analysed through inductive thematic analysis (Braun and Clarke 2006), involving repeated full readings, open coding generated from the data, then consolidation into themes brought into dialogue with the quantitative results. Integration follows a convergent mixed methods logic in which each data source is analysed on its own terms and the qualitative material is used to interpret mechanisms behind the panel estimates (Creswell and Plano Clark 2018).

The qualitative component was reviewed and approved by the Institutional Review Board of the Lahore University of Management Sciences, and was conducted in accordance with the principles of the Declaration of Helsinki. All participants were informed of the purpose of the research and of their right to decline or withdraw at any point, and provided verbal informed consent prior to interview. Verbal rather than written consent was approved by the Board given low literacy among respondents and the sensitivity of recording signatures. No personally identifying information was recorded, and all quotations are reported anonymously. The quantitative analysis uses de-identified secondary survey and satellite data and required no additional consent.

Results

Average Heat Does Nothing; Extreme Heat Compresses Hours

Table 1 presents the central contrast. Anomalies in mean WBGT have no detectable effect on weekly hours. The coefficient is 0.126 (wild bootstrap p = 0.335). The same specification with the peak anomaly yields -0.326 hours per 1 °C (SE 0.106, wild p = 0.003), about 0.7 percent of the 47.6 hour sample mean, a real but modest effect. Restricting to summer quarters, where the same anomaly lands on an already hot baseline, the coefficient rises to -1.206 (SE 0.293, wild p = 0.003), roughly 2.5 percent of mean hours per degree. This is the economically salient magnitude. The summer quadratic term is negative (-1.010, p = 0.054), so within summer the response is concave and losses accelerate as anomalies grow. The summer estimate is unchanged under Driscoll-Kraay standard errors robust to spatial and serial dependence (p = 0.018). Fig. 1 shows the relationship nonparametrically. A researcher

using quarterly mean temperature, still the modal choice in this literature, would have concluded from these data that heat does not affect labour in Punjab.

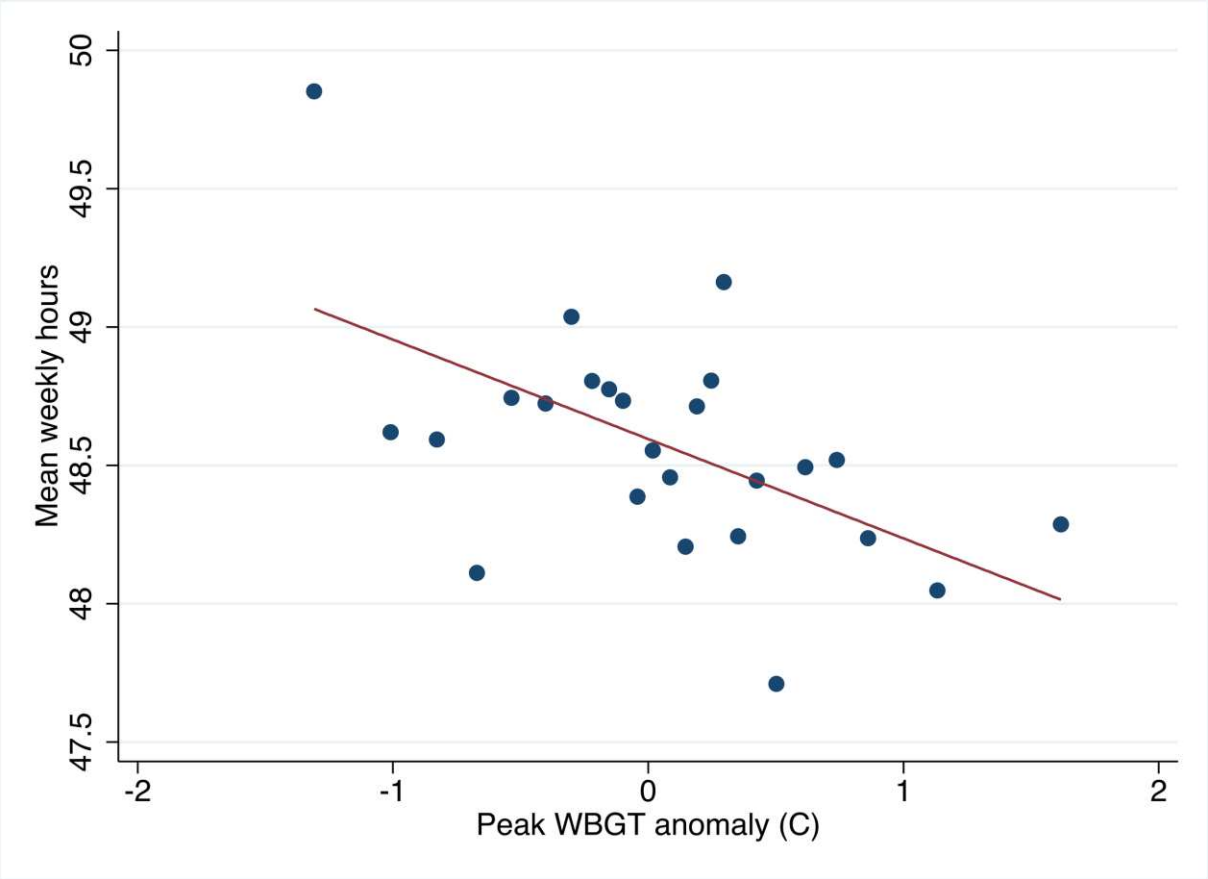


Fig. 1 Weekly hours and the peak WBGT anomaly, binned scatter with district and year effects removed

The Intensive Margin Absorbs the Shock

Table 2 decomposes the response. Hours and days worked fall together, at -0.326 and -0.041 per degree, both with wild p = 0.003, and the underemployment share rises by 0.55 percentage points per degree (wild p = 0.003), about 3.9 percent of its mean. Employment and participation, by contrast, do not contract. Both coefficients are positive and insignificant (wild p = 0.130 and 0.108). In summer the extensive margin in fact expands. The summer employment coefficient is 0.0251 (SE 0.0079), with a 95 percent confidence interval of 0.0096 to 0.0406, between 1.8 and 7.8 percent of the 0.524 mean employment rate, excluding any decline. Heat does not push workers out of employment in Punjab. It compresses work inside jobs while, if anything, drawing more people in.

Heat Pulls Women into Work, on Worse Terms

Table 3 reports the stacked gender model. The robust result is on participation. The female interaction is 0.0096 on employment and 0.0099 on labour force participation, with wild p = 0.004 for both, so a 1 °C peak anomaly raises women's employment and participation by roughly one percentage point relative to men's. The hours differential is negative but only suggestive (-0.255, wild p = 0.095). Fig. 2 shows the corresponding raw pattern. Hourly wages point the same direction. Under peak heat the female wage coefficient is -0.735 (p = 0.068) against an insignificant -0.306 for men (Table 8 in Appendix A). We read this as distress or added-worker participation. Hot quarters squeeze household earnings, and women enter paid work at precisely the times when its terms are worst. We are careful about weight here, since the hours and wage results clear only the ten percent bar, but the participation response is among the most robust estimates in the paper, and it is the one the interviews independently corroborate.

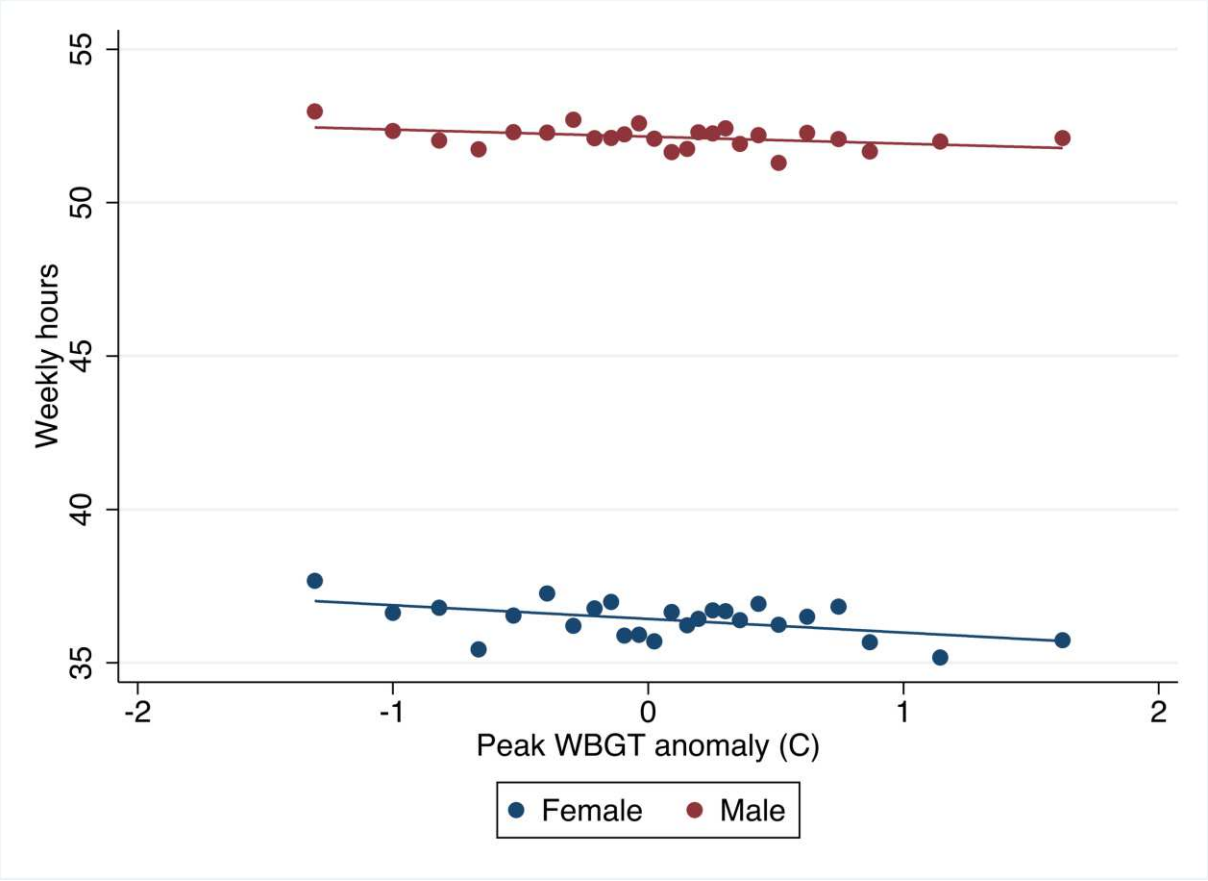


Fig. 2 Female and male weekly hours against the peak WBGT anomaly, binned scatter

The Compression Concentrates in Poor Districts

Interacting the peak anomaly with the pre-period poverty indicator (Table 4) shows that the hours effect is carried by poorer districts. The interaction is -0.413 (SE 0.189, wild $p = 0.043$), against a small and insignificant -0.184 in wealthier districts. The implied effect in a poor district is about -0.60 hours per degree, three times the richer district point estimate. Combined with the non-contracting extensive margin, the picture is of workers in low adaptive capacity districts absorbing heat almost entirely through lost hours within jobs they keep.

Robustness: What Survives, and What Only Partly Survives

We report the robustness battery in full, including the checks that weaken the effect, because an honest reading of a modest coefficient requires it. Table 5 collects the results. Three checks leave the effect essentially intact. Adding one-quarter-lagged heat, the contemporaneous term is -0.433 and the lag -0.264, both $p < 0.05$, consistent with multi-quarter heat episodes rather than a one-off. District-specific linear trends give -0.260 ($p < 0.05$) and region-by-year fixed effects give -0.258 ($p < 0.05$). Two checks retain the sign and marginal significance but attenuate the magnitude. First differencing consecutive quarters, which removes any persistent component of both heat and hours, gives -0.189 ($p < 0.10$), and adding a control for recent in-migration gives -0.205 ($p < 0.10$). We flag these two as weaker and do not lean on them.

A one-quarter lead of future heat enters negative and marginally significant (-0.176, SE 0.090, $p = 0.061$), which could in principle signal anticipation or a spurious correlation. It does not survive scrutiny as a threat. Because peak anomalies are serially correlated in these data, the lead partly re-measures the same multi-quarter episode. When the contemporaneous term, the lag, and the lead are entered together, the lead falls to -0.146 and loses significance ($p = 0.27$) while the lag remains at -0.250 ($p = 0.054$), the pattern expected from persistence rather than anticipation, and the first difference estimate, which nets out that persistence, remains negative and significant at ten percent. We report the lead rather than suppress it precisely so the reader can judge this.

The harvest calendar concern is answered directly (Table 6). Controlling for the agricultural employment share leaves the summer effect at -1.019 ($p < 0.01$). The heat-by-agricultural-share interaction is a flat and insignificant -0.02, and non-agricultural cells alone show -1.206 ($p < 0.01$), identical to the headline. The summer compression is heat, not the wheat harvest. Finally, a leave-one-district-out jackknife keeps the coefficient between -0.270, dropping Rahim Yar Khan, and -0.366, dropping Sialkot, and Romano-Wolf adjusted p values across the five

outcome family of hours, days, employment, participation, and underemployment are 0.018, 0.018, 0.014, 0.016, and 0.010, all significant after familywise correction.

Qualitative Findings

Three themes emerged from the interviews. Each speaks directly to a quantitative result the panel alone cannot explain.

Working Through the Body's Limits: Presenteeism Where Exit Is Unaffordable

Across all four occupational groups, respondents described heat first through the body, mentioning dizziness, muscular weakness, headaches, dehydration, and disrupted sleep, and only then, if at all, through the vocabulary of weather. What they almost never described was stopping. A construction worker in Lahore put the constraint plainly: 'We have to rethink taking a break. If we take a break there is no daily wage. Because of poverty, we have to work no matter the weather.' Another said: '*Hum bemar bhi hon tou kaam pe aana parta hai, nahi kiya tau ghar par aaj khaana nahi aye ga*' (even if we are ill we must come to work; if not, there is no food at home today). This is the mechanism behind Table 2. Daily wage and piece rate workers cannot convert heat strain into absence, so it surfaces instead as slowed pace, longer rests taken furtively, and days cut short, exactly the pattern of falling hours, falling days, rising underemployment, and unmoved employment that the panel records. Respondents also routinely reframed heat illness as ordinary tiredness or personal weakness rather than an occupational hazard, which implies that even our hours-based estimates understate the physiological cost. What surveys record as a worker present and employed is often a worker labouring at the edge of thermal tolerance.

The Unequal Right to Rest

Who gets to slow down was not an individual health decision but a feature of the labour contract. At brick kilns, families worked barefoot on open clay in the hottest weeks while handling bricks radiating kiln heat. One worker summarised the regime as '*Pani peene aur baithne ka waqt nahi milta*' (there is no time to drink water or sit down). Kiln households bound by *peshgi* advance debt described rest as economically impossible, since stopping work

slows piece rate output, which slows debt repayment, which deepens dependence.[3] Construction labourers under contractor supervision described delaying water and shade because interruption is visible and daily hiring is discretionary. Workers with more structured employment, by contrast, described being able to take leave on the worst days. This gradient in the right to rest is the qualitative face of Table 4. Hour losses concentrate in poor districts not because poor workers are more heat sensitive, but because the contractual forms that dominate there, namely daily wages, piece rates, and debt-tied labour, price rest at the cost of that day's food. What looks like inelastic labour supply in the richer districts' comparison is, on closer inspection, the absence of any margin on which to adjust except the body itself.

Gendered Thermal Reorganisation and Distress Participation

Women described heat exposure that began before sunrise with cooking and water work, ran through domestic labour in poorly ventilated brick homes, and continued into paid stitching and embroidery pushed late into the night once temperatures eased slightly. '*Aurat ghar ka kaam bhi karti hai aur bahar ka bhi, aram ka waqt nahi hota*' (a woman does the work of the home and outside it; there is no time to rest), as one home-based worker put it. Two features of these accounts map onto Table 3. First, when hot spells squeezed household earnings, through men's lost days or shrunken piece rate output, women reported taking on additional paid work, including stitching orders and field labour at harvest margins, precisely in the hottest periods. This is the distress participation channel behind the robust rise in female employment and participation. Second, the paid work available on those terms was flexible, home based, and poorly paid, consistent with the suggestive declines in women's hours and hourly wages. Unlike men, who described enduring heat collectively on sites, women absorbed it alone inside the household, where the strain stays invisible to labour statistics. Several noted that even at night their homes 'act like furnaces'. The gender result is therefore not that heat spares women. It is that heat pushes them into paid work while the total thermal burden, paid and unpaid combined, rises.

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[3] *Peshgi* is an advance payment from kiln owner or contractor to worker, repaid through labour. It is widely documented as a mechanism of debt bondage in South Asian brick production and functions here to remove the extensive margin almost entirely. # Tables

Discussion

Three results deserve emphasis, and each has a policy reading.

The first is that the choice of heat measure changes the answer. Mean WBGT anomalies leave hours untouched while peak anomalies compress them, which means that studies and monitoring systems built on average temperature will understate heat's labour cost in settings like Punjab. This is consistent with the physiological argument that binding stress occurs at the hottest hours (Dasgupta et al. 2021; Vanos et al. 2023) and with evidence that humidity-inclusive, peak-based exposure is the relevant object for outdoor work (Lemke and Kjellstrom 2012). For measurement and for early warning design, the implication is direct: track the peak, not the daily mean.

The second is that adjustment runs through hours, not employment. Workers do not exit, and if anything participation rises. The welfare loss therefore hides inside a labour market that looks, by the usual indicators, undisturbed, with participation and employment steady while hours and days quietly fall and underemployment climbs. Standard labour statistics, which foreground participation and employment counts, will register warming as roughly neutral for work even as it erodes earnings capacity. The interviews explain why exit is not an option. Daily wage and piece rate workers, and especially kiln households under *peshgi* debt, cannot convert heat strain into absence without forgoing that day's income. This echoes findings that informal workers absorb heat through their own constrained coping rather than institutional protection (Dodman et al. 2023; Das and Somanathan 2024) and that responses to heat are rational but bounded by the assets and contracts workers hold (Tabe-Ojong and Lokossou 2026; Amoadu et al. 2023).

The third is distributional. The compression concentrates in poorer districts and pushes women into paid work on worse terms, and these are not separate facts. The contractual forms that price rest most steeply, meaning daily hiring, piece rates, and debt-tied labour, dominate in the poorer, hotter, more informal districts, so the workers least able to reduce exposure bear the hour losses, while heat-driven earnings shortfalls draw additional household members, disproportionately women, into distress participation. Rising heat here widens existing gaps rather than affecting all workers alike.

Policy Implications

Taken together, these results point toward interventions matched to the constraint rather than to the weather alone. Three follow.

First, heat monitoring and early warning systems in settings like Punjab should be built on peak humid heat rather than daily or quarterly mean temperature, since the latter would have detected nothing here. Second, protections need to be enforceable at the worksite, covering rest scheduling, shade, and drinking water (Torbat Esfahani et al. 2024; Moda et al. 2024), because the binding constraint we observe is not worker ignorance of heat risk but the absence of any contractual right to act on it. Third, and most important for the design of climate-responsive social protection, transfers or insurance triggered by heat episodes need to make a lost hot day survivable at the household level. Because the adjustment margin is partly the reallocation of labour within families, with women drawn into paid work when men's earnings fall, the household rather than the individual worker is the appropriate unit for such instruments.

Because our estimates come from short run weather variation, they are responses under current adaptive capacity, not long run damages (Dell et al. 2014; Burke and Emerick 2016; Dong et al. 2025). The near-total reliance on the hours margin suggests those options are already thin.

Limitations

Several limitations bound what we can claim. On the quantitative side, the health and absence fields of the Labour Force Survey are almost entirely missing over 2001 to 2021, so we cannot estimate heat's direct effect on illness or injury and rely on the qualitative material for the physiological channel. The panel has only 30 clusters. We lean on wild-cluster bootstrap and Driscoll-Kraay inference throughout for this reason, but standard errors in this range remain demanding (Cameron et al. 2008; MacKinnon et al. 2023), and this is why we are explicit that the full sample hours effect is small and that the economically meaningful magnitude is the summer response. District-level wages in the LFS are noisy, so our reading that heat moves hours rather than wages, and the suggestive female wage decline, should be treated cautiously. The fixed effects design does not fully rule out that heat changes who is employed within a quarter, so the hours estimate may blend a labour supply response with modest compositional change, though the stability of the extensive margin limits how large that channel can be. Our WBGT is constructed from ambient satellite inputs rather than on-site measurement and is best read as a consistent relative index of humid heat. We interpret coefficients as within-district associations under current climate, not long run causal damages.

The fieldwork carries its own limits. Access ran through personal networks rather than random sampling, so the most isolated workers, including deeply indebted kiln households and women confined entirely to domestic

production, are likely under-represented. Accounts rest on self-report, with recall and social desirability pressures that may lead some men to describe heat illness as ordinary tiredness. Interviews covered a single season, so we cannot observe how coping shifts across the year, and translation across Urdu, Punjabi, and English may have flattened some nuance. We collected no direct physiological measurements, so the bodily strain arguments rest on testimony rather than clinical observation. Finally, we cannot fully separate heat from co-occurring stressors such as air pollution, undernutrition, and seasonal income shocks. The harvest decomposition addresses the most obvious confound, but not all of them.

Conclusions

In Punjab, extreme heat does not cost workers their jobs. It costs them hours inside jobs they cannot afford to leave. Average temperature reveals none of this, while peak WBGT anomalies show weekly hours and days falling and underemployment rising, modestly on average but sharply in summer, and most steeply in poorer districts, even as employment and participation hold or expand. Heat also pulls women into paid work at the hottest times, on suggestively fewer hours and lower wages, raising the household's total thermal burden rather than relieving it. The fieldwork ties these patterns together. Where labour is casual, piece rated, or debt bound, rest is priced at the cost of a meal, so heat surfaces as compressed and slowed work rather than as absence, precisely the margin conventional statistics miss.

The practical upshot is that employment-based indicators understate the labour cost of warming in informal economies, and that protecting workers will require measures matched to the contracts and constraints that make exit impossible, not weather warnings alone. As peak heat intensifies across South Asia, the workers with the least capacity to adapt will keep absorbing the most, one lost hour at a time.

Table 1 Weekly hours: average heat versus extreme heat

	(1) Mean	(2) Peak	(3) Peak, summer
WBGT anomaly	0.126	-0.326***	-1.206***
	(0.132)	(0.106)	(0.293)
Anomaly squared	-0.114	0.046	-1.010*

	(1) Mean	(2) Peak	(3) Peak, summer
	(0.172)	(0.113)	(0.503)
Wild-bootstrap *p*	0.335	0.003	0.003
Cells	2,269	2,269	1,125
R^2	0.466	0.468	0.481

Outcome is mean weekly hours. All columns include district by quarter and year fixed effects, weighted by working age population. Standard errors clustered on 30 districts in parentheses; wild-cluster bootstrap *p* (Webb weights, 9,999 replications) reported for the linear term

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 2 Margins of adjustment (peak WBGT anomaly)

	Hours	Days	Employment	LFP	Underemployment
Peak anomaly	-0.326***	-0.0407***	0.0030	0.0032	0.0055***
	(0.106)	(0.0133)	(0.0019)	(0.0020)	(0.0018)
Wild *p*	0.003	0.003	0.130	0.108	0.003
Cells	2,269	2,269	2,269	2,269	2,269

Each column is a separate estimate of Eq. (1); the quadratic term is included but not shown. Fixed effects, weights, and inference as in Table 1

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 3 Gendered responses to peak heat (stacked model)

	Hours	Employment	LFP
Peak anomaly	-0.194*	-0.0008	-0.0006
	(0.096)	(0.0014)	(0.0015)

	Hours	Employment	LFP
Female × anomaly	-0.255	0.0096***	0.0099***
	(0.152)	(0.0031)	(0.0031)
Wild *p* (interaction)	0.095	0.004	0.004
Cells	4,427	4,538	4,538

Eq. (2) with district by quarter by sex and year by sex fixed effects, weighted by sex-specific working age population; quadratic terms included but not shown. Inference as in Table 1

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 4 Peak heat and hours in poor versus non-poor districts

	Hours
Peak anomaly	-0.184
	(0.133)
Poor district × anomaly	-0.413**
	(0.189)
Wild *p* (interaction)	0.043
Cells	2,269

Poor districts are those below the median of the pre-2000 wealth index. Specification otherwise as in Table 1

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 5 Robustness of the peak heat effect on hours

	(1) Lag	(2) Trends	(3) Region × year	(4) First diff.	(5) Migration
Peak anomaly	-0.433***	-0.260**	-0.258**		-0.205*
	(0.120)	(0.0995)	(0.100)		(0.111)

	(1) Lag	(2) Trends	(3) Region × year	(4) First diff.	(5) Migration
Lagged anomaly	-0.264**				
	(0.0976)				
Δ Peak anomaly				-0.189*	
				(0.103)	
Recent migrant share					-0.861
					(6.070)
Cells	1,977	2,269	2,269	1,977	1,764

Outcome is weekly hours. Column (2) adds district-specific linear trends; column (3) adds region by year fixed effects; column (4) is estimated in first differences. Quadratic terms included but not shown. Fixed effects, weights, and clustering as in Table 1. A one-quarter lead of heat (not shown) enters at -0.176 ($p = 0.061$) on its own but at -0.146 ($p = 0.27$) once the contemporaneous term and the lag are included jointly

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Table 6 Harvest versus heat: the summer effect is heat

	(1) Agri. control	(2) × Agri. share	(3) Non-agri. cells
Peak anomaly	-1.019***	-1.196***	-1.206***
	(0.287)	(0.404)	(0.293)
Anomaly squared	-1.074**	-1.009*	-1.010*
	(0.470)	(0.501)	(0.503)
Agricultural share	-8.264***		
	(1.360)		
Anomaly × agri. share		-0.0245	
		(0.927)	

	(1) Agri. control	(2) × Agri. share	(3) Non-agri. cells
Cells	1,125	1,125	1,125

Summer quarters only. Outcome is weekly hours. Specification otherwise as in Table 1

* $p < 0.10$; ** $p < 0.05$; *** $p < 0.01$

Appendix A

Diagnostics referenced in the main text are as follows. The Wooldridge serial correlation test rejects the null ($p = 0.022$). The Pesaran CD test does not reject cross-sectional independence ($p = 0.73$). Fisher-type ADF tests reject unit roots in all outcome and heat series. Romano-Wolf adjusted p values across the five outcomes, using 500 resamples, are 0.018, 0.018, 0.014, 0.016, and 0.010. Jackknife coefficients dropping each district one at a time lie between -0.270, dropping Rahim Yar Khan, and -0.366, dropping Sialkot. Summary statistics are reported in Table 7 and the gendered hourly wage estimates in Table 8.

Table 7 Summary statistics, district-quarter cells

	Mean	SD	Min	Max
Weekly hours	47.61	5.12	31.99	72.22
Days worked	5.95	0.64	4.00	9.03
Employment rate	0.537	0.116	0.171	0.960
LFP rate	0.544	0.114	0.220	0.960
Underemployment share	0.143	0.114	0.000	0.625
WBGT, mean (°C)	20.12	5.86	8.53	28.88
WBGT, peak (°C)	29.16	4.51	16.48	36.06
Peak WBGT anomaly (°C)	0.00	0.84	-2.41	2.79
Peak WBGT ≥ 32 °C	0.411	0.492	0	1
Female weekly hours	36.02	7.03	1.00	83.62

	Mean	SD	Min	Max
Male weekly hours	51.18	4.73	32.92	72.96
Female hourly wage (Rs.)	13.04	30.11	0	425.78
Male hourly wage (Rs.)	15.96	25.21	0	213.18
Outdoor occupation share	0.776	0.127	0.235	1.000
Informal share	0.340	0.238	0.000	0.898
Agricultural share	0.457	0.200	0.000	1.000

N = 2,269 cells, of which 2,158 for female variables, across 30 districts, 2001 to 2021

Table 8 Hourly wages by sex under peak heat (suggestive)

	Female hourly wage	Male hourly wage
Peak anomaly	-0.735*	-0.306
	(0.387)	(0.349)
Anomaly squared	-0.0242	-0.217
	(0.185)	(0.197)
Cells	2,158	2,269

Specification as in Table 1

* $p < 0.10$

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Statements and Declarations

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Author Contributions. Both authors contributed to the study conception and design. Hasaan Haroon carried out the data curation, the construction of the district-quarter panel and heat measures, and the quantitative analysis. Hiba Ahmed carried out the qualitative fieldwork, including interviewing and thematic analysis. The first draft of the manuscript was written jointly by both authors, and both authors commented on and revised subsequent versions. Both authors read and approved the final manuscript.

Ethics Approval. The qualitative component of this study was reviewed and approved by the Institutional Review Board of the Lahore University of Management Sciences and was conducted in accordance with the principles of the Declaration of Helsinki. The quantitative analysis uses de-identified secondary survey and satellite data and required no additional ethical approval.

Consent to Participate. All interview participants were informed of the purpose of the research and of their right to decline or withdraw at any point, and provided verbal informed consent prior to interview. Verbal rather than written

consent was approved by the Institutional Review Board of Lahore University of Management Sciences (LUMS) given low literacy among respondents and the sensitivity of recording signatures.

Consent to Publish. No personally identifying information was recorded and all quotations are reported anonymously. Participants consented to the anonymous use of their accounts in published research.

Data Availability. The district-quarter analysis panel and the full replication code (Stata) that support the findings of this study are openly available in Figshare at https://doi.org/10.6084/m9.figshare.32969210 (Haroon and Ahmed 2026). Pakistan Labour Force Survey microdata are available from the Pakistan Bureau of Statistics at https://www.pbs.gov.pk/. The underlying daily temperature and humidity data are publicly accessible through Google Earth Engine at https://earthengine.google.com/. Qualitative interview transcripts are not publicly available because participants consented only to the anonymous reporting of quotations and because the small number of respondents in identifiable occupational settings makes full de-identification impracticable.

Use of Large Language Models. A generative AI tool was used in a limited technical and copy-editing capacity during manuscript preparation, no generative AI tool was used to design the study, to conduct the analysis, or to generate the scholarly content, interpretation, or argument of the manuscript. The authors reviewed and edited all output and take full responsibility for the content of this manuscript.