

Heat stress and labour share

Evidence from Indian manufacturing

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Abstract: Climate change poses significant challenges to labour markets in developing countries, where workers face high exposure to extreme heat and firms have limited adaptive capacity. This paper examines how heat stress affects the labour share—measured as labour compensation relative to firm sales—using a large panel of Indian manufacturing firms. Exploiting within-firm temperature variation over time, we find that heat stress significantly reduces the labour share, with results robust across alternative specifications. This decline is driven primarily by production adjustments, especially capital–labour substitution. We also present suggestive evidence that heat stress may strengthen firms' market power and interact with labour regulations in shaping firm responses. Combining our estimates with climate projections, future warming is likely to intensify labour share declines across regions. Our findings identify climate change as an important and underexplored driver of distributional change in developing economies.

Keywords: India, heat stress, labour share, manufacturing firms, temperature

JEL classification: D22, O14, Q54, Q56

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1 Introduction

The negative impacts of climate change on economies has emerged as one of the most pressing concerns around the globe. According to a recent report by the Intergovernmental Panel on Climate Change (IPCC), the rate of global warming is accelerating, with global surface temperatures already 1.1°C higher than pre-industrial levels (Intergovernmental Panel on Climate Change 2021). Such a warming trajectory is expected to intensify not only the frequency but also the severity of extreme weather events, creating profound challenges for economies and labour markets worldwide. Motivated by these concerns, a growing body of literature has examined the economic consequences of rising temperatures and extreme heat exposure. Existing studies document substantial impacts on economic growth (Burke et al. 2015; Kalkuhl and Wenz 2020), agricultural and industrial output (Colmer 2021; Mendelsohn et al. 1994; Schlenker et al. 2005; Somanathan et al. 2021), labour supply and productivity (Somanathan et al. 2021; Zivin et al. 2020), human health (Barreca et al. 2016; Patz et al. 2005), and emotional well-being (Rehdanz and Maddison 2005).

In this paper, we examine how heat stress affects the labour share in India's manufacturing sector, with labour share defined as the ratio of labour compensation to firm sales.¹ The decline in labour share is a well-documented phenomenon in both developed countries and low- and middle-income countries (LMICs) (Autor et al. 2020; Karabarbounis and Neiman 2014). While this trend poses challenges globally, it is particularly consequential in LMICs, where limited social safety nets and other structural features of labour markets can heighten worker vulnerability and shape firms' adjustment responses. These dynamics can intensify wage pressures, employment insecurity, and inequality, while also impeding the process of structural transformation. Existing research has primarily attributed the decline in labour share to globalization, technological change, shifts in industrial composition, and institutional reforms (for a review of this literature, see Grossman and Oberfield 2022). Yet, despite growing evidence on the economic impacts of climate change, the role of rising temperatures in driving labour share erosion remains underexplored.

Rising heat stress can affect the labour share through several distinct but interrelated pathways operating within firms. First, extreme heat reduces workers' productivity and effective labour supply while increasing health and safety risks, thereby raising the effective cost of labour (Park et al. 2021; Somanathan et al. 2021; Zivin et al. 2020). In settings where capital

¹ Our results remain robust to alternative specifications that use gross output or value added in the denominator. However, in the ASI data—as in many firm-level manufacturing datasets from developing countries—a consistent measure of gross value added is not directly reported by firms and must instead be constructed using information on output and inputs. These constructed value-added measures are particularly vulnerable to deflation issues and measurement error arising from the under-reporting of output and incomplete information on intermediate inputs. For these reasons, revenue-based measures are generally preferred.

and labour are technologically substitutable and the relative cost of capital has declined due to trade liberalization and capital market reforms (Karabarbounis and Neiman 2014; Mutreja et al. 2018), firms may respond to heat-induced efficiency losses by adopting more capital-intensive production techniques. When the elasticity of substitution between capital and labour is high—as documented for several manufacturing industries in India (Goldar et al. 2013; Gujarati 1966; Upender 2009)—such adjustments can lead to a decline in labour’s share of income even when firm identity remains fixed.

Beyond production choices, heat stress may also reshape the competitive environment faced by firms. By disproportionately constraining smaller, less productive, or more heat-exposed firms, rising temperatures can weaken competitive pressure within local markets, increasing concentration and strengthening the market power of incumbent firms (Autor et al. 2017, 2020; Ponticelli et al. 2023). Reduced competition can enable within-firm adjustments in pricing, output, and factor shares that further depress labour’s share. Finally, the impact of heat stress on labour share is mediated by labour market institutions. In the presence of rigid labour regulations that limit firms’ ability to adjust regular employment, such as firing restrictions under the IDA, firms may absorb heat-induced productivity shocks through alternative within-firm margins, including capital deepening and shifts towards more flexible forms of labour (Bertrand et al. 2025; Colmer 2021). Together, these channels underscore how climate stress can also operate as a force shaping market power, firms’ production decisions, and adjustment behaviour in ways that systematically disadvantage labour.

To proceed, we construct a long panel dataset from the Annual Survey of Industries (ASI) in India, employing a detailed matching methodology, and further link it with high-resolution climate data from the European Centre for Medium-Range Weather Forecasts (ECMWF). To our knowledge, this is the first paper to estimate the impact of heat stress on labour share in the Indian manufacturing sector using a comprehensive firm-level dataset. The analysis complements recent studies that examine the broader economic impacts of climate change in developing countries (Somanathan et al. 2021; Zivin et al. 2020), as well as work focusing on the relationship between automation and labour share dynamics (Acemoglu and Restrepo 2018; Karabarbounis and Neiman 2014).

Our main findings reveal that extreme heat significantly reduces the labour share in India’s manufacturing sector. Specifically, one additional day in a year with a maximum temperature recorded between 30°C and 33°C is associated with a 0.0071 percentage point (p.p.) decline in labour share, which is equivalent to nearly a 0.07 p.p. annual reduction for ten such hot days. The effect is slightly larger for days above 33°C, where each additional day decreases labour share by 0.0091 p.p. This corresponds to a 0.08% decline at the sample mean. Examining the underlying components of labour share, we find that these effects are driven by changes in both employment composition and wages within firms. In particular, heat stress re-

duces the employment and work days of female workers, while leaving male and contract employment largely unchanged. At the same time, the average wages of contract workers decline, whereas wages of permanent male workers increase. We also find that firm sales increase under heat stress, suggesting that the decline in labour share is not driven by a contraction in economic activity, but rather by within-firm adjustments in workforce composition, compensation, and revenue generation.

The findings are robust across a wide range of alternative specifications and checks. The estimates remain stable when we cluster standard errors at alternative levels, including firm, district–industry, and state levels. The results are also robust to controlling for state-specific time trends and industrial disputes and are not sensitive to alternative definitions of labour share, including measures based on gross output and value added. The findings remain qualitatively similar when restricting the sample to firms with at least ten employees. We further test our results to the alternative choice of reference temperature bins and a range of measures of extreme heat, including humidity-adjusted heat indices.

Examining potential channels, we provide suggestive evidence that the decline in labour share is driven primarily by production adjustments within firms, particularly capital–labour substitution. Consistent with this mechanism, we find that an increase in heat exposure relative to moderate temperatures increases the capital-to-labour ratio, automation-related capital stock (plant and machinery; computers and software), as well as investment in total fixed assets, and that the decline in labour share is more pronounced in industries with higher capital–labour substitutability. We also find evidence consistent with additional, complementary channels. Rising temperatures are associated with increased local market concentration, suggesting that heat stress alters the competitive environment in ways that may enable firms to adjust pricing, output, and factor use within the firm. Further, labour market institutions shape firms’ responses to heat-induced productivity shocks: in the presence of rigid labour regulations, firms rely more heavily on alternative adjustment margins such as employment composition of permanent and contract workers as well as capital deepening, amplifying the decline in labour share. Taken together, these results highlight capital–labour substitution as the primary adjustment margin, with changes in competitive conditions and institutional constraints further shaping firms’ responses to heat stress.

Further, we use climate model projections under alternative emissions scenarios to assess how continued warming may shape the future distribution of income between labour and capital. By combining estimated temperature–labour share relationships with downscaled climate projections, we provide a forward-looking assessment of how climate change may exacerbate existing declines in labour’s share, with substantial heterogeneity across regions. This exercise highlights the long-run distributional consequences of climate change and underscores the importance of incorporating labour market outcomes into climate impact assessments.

2 Literature

Our paper contributes to several strands of literature. First, we contribute to the literature on the long-run decline in labour share and its drivers. A growing macro- and microeconomic literature has documented falling labour shares across countries and industries (Autor et al. 2020; Karabarbounis and Neiman 2014). As noted previously, explanations that have been proposed include cheaper capital goods and capital deepening, globalization, market structure, and technology price shifts (Acemoglu and Restrepo 2018; Autor et al. 2020; Elsby et al. 2013; Leblebicioğlu and Weinberger 2021). Our paper highlights climate as an additional potentially important influence: heat stress, by raising effective labour costs, can accelerate capital deepening and automation, thereby contributing to labour share erosion at the firm level in manufacturing.

To our knowledge, there are only two studies that examine this link: Lyu et al. (2024) and Qiu and Yoshida (2024). Lyu et al. (2024) analyse Chinese manufacturing firms using the Annual Survey of Industrial Enterprises (ASIE), which primarily covers relatively large firms (with annual sales revenue exceeding RMB5 million or US\$726,069). They show that extreme heat reduces labour share mainly through capital–labour substitution. Qiu and Yoshida (2024), using US county-level labour shares, document that extreme temperatures reduce labour share and accelerate the adoption of industrial robots, an option more relevant for larger and more capital-intensive firms.

Our paper complements and extends this emerging literature along several dimensions. First, we provide evidence from India’s manufacturing sector, where both climatic conditions and institutional features differ markedly from those in China and the United States. In particular, higher baseline temperatures and humidity in many parts of India may amplify the productivity effects of heat stress, while the prevalence of contract labour and differences in the design and enforcement of labour regulations create distinct margins of adjustment for firms. In addition, unlike the ASIE, the ASI covers a broader set of firms, including smaller and less capital-intensive establishments.² This distinction is important in a developing-country context, where smaller firms face tighter financial constraints and may have limited capacity to adopt capital-intensive adaptation strategies, potentially altering both the magnitude of the effects and the mechanisms at play. Second, while existing work primarily emphasizes technological adjustment, we adopt a broader firm-level perspective and document multiple, complementary channels, including changes in local market concentration and the role of labour market regulation. Our findings suggest that the effects of heat on labour share operates also through these mechanisms.

² Indeed, our sample includes firms with annual sales revenue as low as INR36,000 in a year (approximately US\$385).

We also contribute to the literature on the economic effects of climate change. Our paper is most closely related to studies that investigate the impacts of climate change on firm dynamics, economic activity, and worker productivity (for a comprehensive review of early works, see Dell et al. 2014). At the macro level, cross-country evidence shows a nonlinear relationship between temperature and economic production, with hotter countries suffering disproportionately larger losses (Burke et al. 2015). At the micro level, daily temperature shocks have been linked to lower labour supply and productivity (Graff Zivin and Neidell 2014; Somanathan et al. 2021; Zhang et al. 2018), lower operating profits (Pankratz et al. 2023), reduced industrial output (Chen and Yang 2019; Somanathan et al. 2021), increased tax avoidance (Tang et al. 2023), and reallocation of labour across sectors (Colmer 2021). Our paper shifts the focus to the distributional consequences: we show that extreme heat erodes labour’s share of income by inducing capital–labour substitution and automation affecting worker welfare in an LMIC context.

Finally, we contribute to the labour regulation literature in India. Fallon and Lucas (1993) show the 1976 Industrial Disputes Act (IDA) amendment cut formal employment by 17.5%, while Dutta Roy (2004) notes significant adjustment costs, with the 1982 amendment having little impact. Strict labour laws, import competition, greater bargaining power of permanent workers, and open-ended efficiency wage contracts increase contract labour and informality: Chaurey (2015), Saha et al. (2013), Basu et al. (2021) Chakraborty et al. (2024), Bertrand et al. (2025), and Chiplunkar et al. (2024) document these effects. Evidence in the context of India also shows that pro-worker states experience lower output, employment, investment, and productivity (Besley and Burgess 2004), while similar dampening for trade and licensing reforms are documented by Hasan et al. (2007) and Aghion et al. (2008). Chakraborty et al. (2024) show that labour market regulation and its interaction with international trade determines the organization of production in manufacturing firms. Soundararajan (2019) finds that the effect of minimum wages on employment and wages significantly increases with an increase in enforcement. We extend this literature by examining how climate shocks interact with the regulations to shape labour share.

The rest of the paper unfolds as follows. Section 3 provides the background. Section 4 discusses the data and empirical method. Results are presented in Section 5. Section 6 explores the plausible mechanisms. The projected impacts on labour share under different warming scenarios are examined in Section 7. The last section concludes.

3 Background

3.1 Heat stress in LMICs

According to the IPCC (2021), rising global temperatures will increase the frequency, intensity, and duration of extreme heat events across all regions. LMICs are especially vulnerable to these hazards due to a combination of their geographic location, increasing exposure to heat, higher reliance on climate-sensitive sectors, limited access to adaptive technologies, and weaker institutional and infrastructural capacity. This makes LMIC economies more susceptible to broader economic disruption.

A significant portion of the workforce in LMICs is engaged in sectors such as agriculture, manufacturing, and construction, where work often takes place outdoors or in poorly climate-controlled environments. The International Labour Organization (2019) estimates that by 2030, global warming could result in a reduction of more than 2% of total working hours, with losses concentrated in LMICs due to their higher exposure to heat stress and the predominance of manual and routine labour tasks.

Heat stress reduces worker productivity, increases health risks, and drives absenteeism, contributing to the rising relative cost of labour (International Labour Organization 2019; Kjellstrom et al. 2009). Beyond these supply-side impacts, extreme heat can induce strategic firm-level responses. Firms may react to heat-induced productivity losses by increasing their reliance on automated production processes and substituting capital for labour—thereby reducing the labour share—or by investing in climate-control technologies. However, empirical evidence on firm-level responses remain limited in the context of LMICs, particularly on the extent to which such adaptation measures influence sectoral labour shares and inequality. To assess the broader economic implications of climate change, it is crucial to understand these mechanisms at the sector level.

3.2 Declining firm-level labour share

A significant decline in the labour share has been observed across advanced and developing economies over recent decades (Autor et al. 2020; Karabarbounis and Neiman 2014). In India, from 1980 to 2016 the aggregate economy-wide labour share declined from 54% to 49% (Basu and Veeramani 2021) and, more notably, within the organized manufacturing sector. A study utilizing data from the ASI reveals that the wage share in this sector declined from approximately 30% in 1980 to under 20% by 2021–22, while the profit share surged, especially post-2000, peaking at over 60% (Jha 2024). This trend reflects deep structural changes in production processes, driven by erosion of labour market institutions, technological progress, au-

tomation, globalization, and changes in relative factor prices.

The phenomenon is particularly concerning in the context of LMICs such as India, given the reliance of large segments of the population on wage employment in manufacturing and other sectors. Falling labour share implies not only growing inequality but also potential setbacks for inclusive growth and structural transformation. Unlike more advanced economies, many LMICs face weaker labour protections, larger informal sectors, and limited social safety nets, which make workers more vulnerable to adverse shifts in the labour–capital mix. In India, where the manufacturing sector remains crucial for employment generation and poverty reduction, the declining labour share could undermine economic development goals. As firms respond to changing economic and environmental conditions, structural shifts such as increased capital intensity or automation may lead to the marginalization of low-skilled workers, further exacerbating inequality.

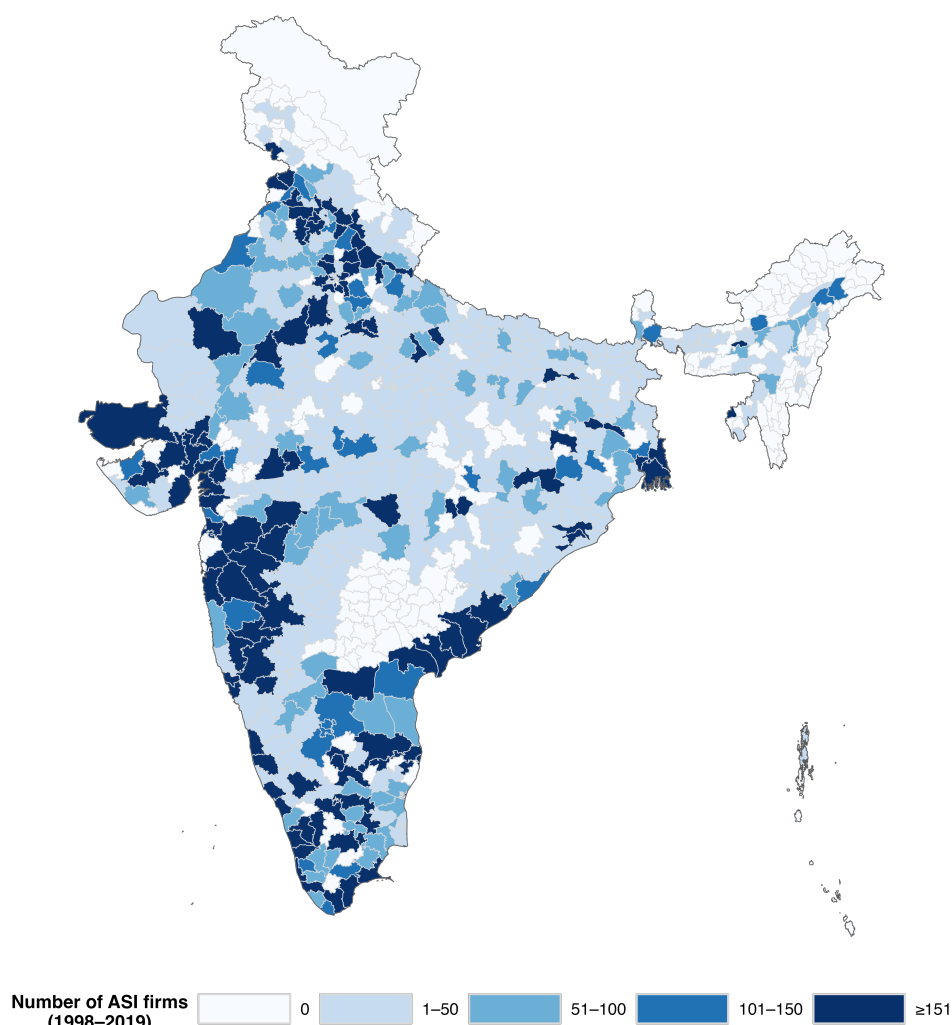
4 Data and empirics

4.1 Data sources

Annual Survey of Industries

We use ASI, a Government of India census of registered manufacturing firms, covering financial years between 1998–99 and 2019–20. The ASI provides information on all large firms (employing more than 100 workers) each year and about one-fifth of randomly selected small firms registered under the Indian Factories Act of 1948. Using a matching methodology similar to that of Allcott et al. (2016) and Somanathan et al. (2021), we generate a firm-level (unbalanced) panel with both firm and district identifiers for the entire sample period. This includes the firms that were in the same location during the sample period. The final dataset covers a total of 69,161 firms and 309,472 firm–year observations for the sample period. The distribution of ASI firms across districts is provided in Figure 1. The data classifies firms across manufacturing industries on the basis of National Industrial Codes (NIC) and provides statistics on production activities, inputs, fixed assets, working capital, debt, expenditures, output production, employment, and wages of workers. The data matching and cleaning process undertaken to generate the panel dataset is elaborated further in Appendix A.

Figure 1: District coverage of ASI firms in India (1998–2019)



Note: the figure provides the spatial coverage of total number of ASI firms surveyed between 1998 and 2019 at the district level. The map is generated in R, using a shapefile provided by Survey of India, Ministry of Science and Technology, India at http://onlinemaps.surveyofindia.gov.in/Digital_Product_Show.aspx.

Source: authors' compilation using Annual Survey of Industries (1998–2019), MOSPI.

The data has an exceptionally wide coverage and is comparable to industrial surveys in other developed countries, including the United States. However, the survey does not cover manufacturing industries that fall outside the purview of the Indian Factories Act.³ The exclusion of the informal manufacturing industry is a key limitation of our study. The employment growth in the informal tradable industry has been quite remarkable since the trade liberalization period of the early 1990s. As Ghani et al. (2015) document, informal tradable manufacturing accounted for 19% of employment in 1989 and grew to 39% by 2010. We acknowledge that by focusing solely on the formal sector we may overlook some key channels through which climate shocks

³ The ASI is a weighted sample, representative of manufacturing firms registered under the Factories Act. Smaller factories—those with fewer than ten workers (or fewer than 20 workers in factories without electricity)—are not required to register under the Act and are therefore excluded from the ASI.

affect firm-level labour share in a segment of the economy that is arguably more vulnerable due to weaker regulations, lower capital intensity, and limited adaptive capacity. As such, our findings may underestimate the full distributional impact of climate change on labour share in the broader manufacturing landscape and the impacts could be larger than for our ASI sample.

Weather data

We obtain high-resolution weather data for India from the ERA5-Land dataset, provided by the ECMWF and accessed through the Copernicus Climate Data Store (Buontempo et al. 2022). The dataset offers gridded climate variables with a horizontal resolution of $0.1^\circ \times 0.1^\circ$. Specifically, we utilize hourly temperature and dewpoint temperature data to construct a comprehensive set of heat exposure measures.⁴ In addition, monthly precipitation data is utilized to compute total annual precipitation.

The hourly weather data is aggregated to the annual level to match the frequency of our firm-level survey data. As the ASI dataset does not report precise geographic coordinates for individual firms, we spatially average the gridded weather data over the geographical boundaries of each district. These district-level averages are then assigned to firms based on their reported district of operation, ensuring consistent matching between weather data and firm location. The visual representation of average daily temperature ($^\circ\text{C}$) and total annual precipitation (millimetres) between 1998 and 2020 for India is provided in Figure 2.

Our main measure of heat exposure is the number of days in a year when the average daily temperature is recorded within a predefined bin. Contrary to the use of annual averages, this choice allows us to capture the temperature distribution within a year and avoids smoothing out extreme tails that can underestimate the impact of extreme heat. Using the temperature bins, we are able to capture the frequency and intensity of extreme heat exposure accurately, which is relevant in the estimation of economic responses to heat.

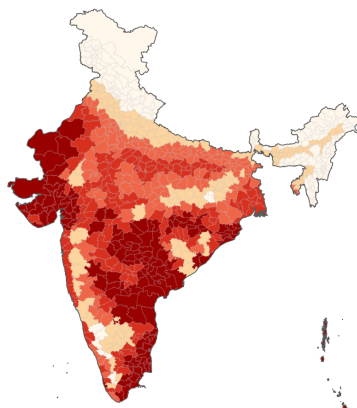
To further assess the robustness of our results, we construct alternative measures of extreme heat captured through daily maximum temperature bins, as well as a count of the number of days above predefined absolute temperature thresholds. In addition, to account for the combined effects of temperature and humidity, we construct the National Oceanic and Atmospheric Administration (NOAA) Heat Index and Wet-Bulb Globe Temperature (WBGT) using hourly temperature and relative humidity data. These measures provide complementary proxies of heat-related stress experienced by firms. We elaborate further on the construction of the Heat Index in Appendix B and WBGT in Appendix C. The distribution of days count across specified bins is visualized in Figures 3 and 4.

⁴ We follow Bolton (1980) to compute measures of atmospheric moisture—saturation vapour pressure and actual vapour pressure—and subsequently calculate relative humidity using the standard equation (CEOP 2013). This allows us to construct additional humidity-adjusted measures of heat exposure.

Figure 2: Spatial distribution of weather data in India (1993–2020)

A

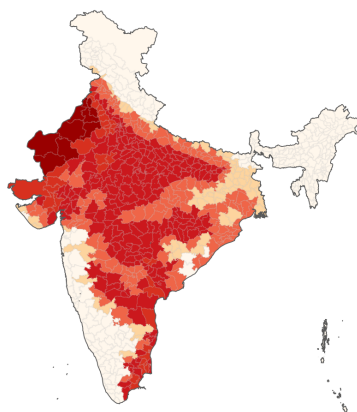
Average daily temperature (°C)



Temperature (°C) -10.3-23 23.1-24.7 24.8-25.4 25.5-26.3 26.4-28.2

B

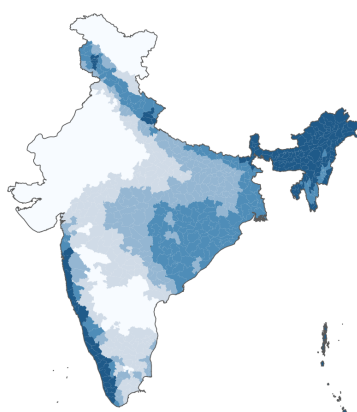
Number of days with daily average temperature > 32°C



Number of days <20 21-40 41-60 61-80 81-100 ≥100

C

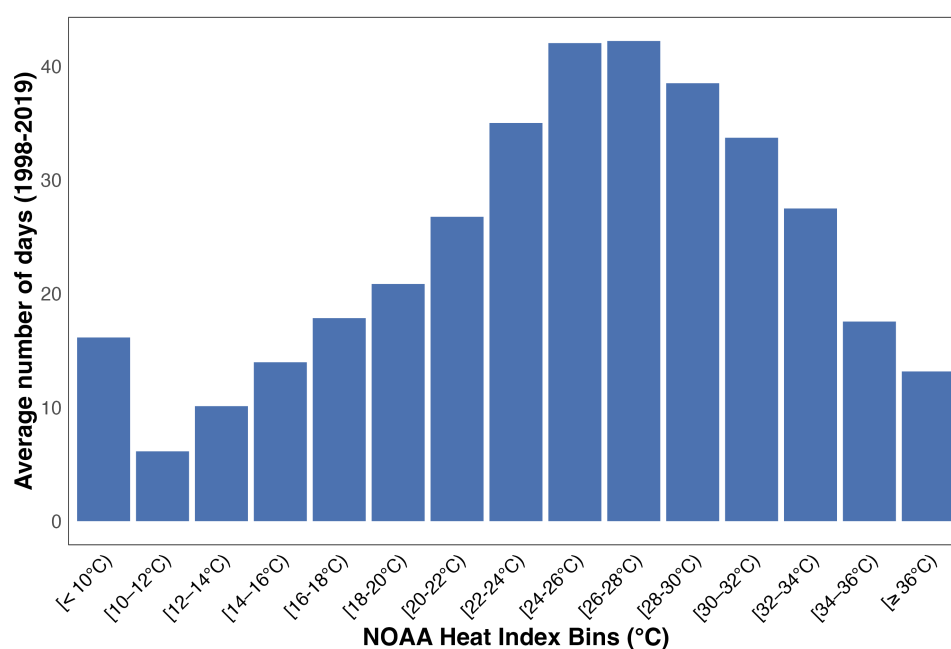
Total annual precipitation



Precipitation (mm) 189-819 820-1020 1021-1311 1312-1863 1864-6988

Note: the figure provides the spatial distribution at the district level (a) of average daily temperature (°C); (b) number of days with average daily temperature above 30°C; and (c) total annual precipitation (mm) between 1993 and 2020. The maps are generated in R, using a shapefile provided by Survey of India, Ministry of Science and Technology, India at http://onlinemaps.surveyofindia.gov.in/Digital_Product_Show.aspx.
Source: authors' compilation using ERA5-Land dataset (ECMWF).

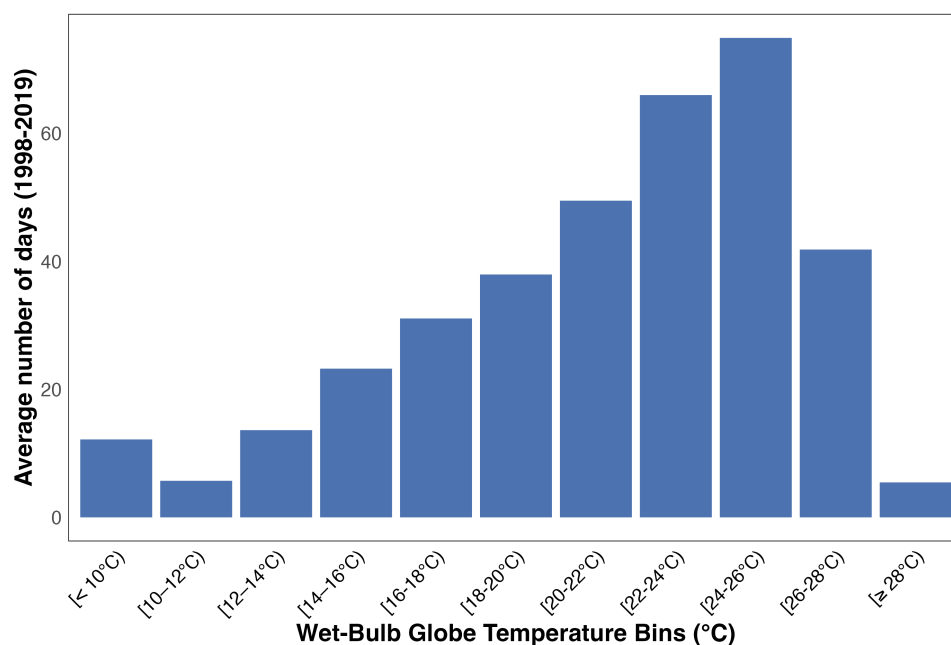
Figure 3: Distribution of the NOAA Heat Index across bins in India (1998–2020)



Note: the figure provides the distribution of days recording Heat Index (°C) in a specific bin between 1998 and 2020.

Source: authors' compilation using ERA5-Land dataset (ECMWF) and NOAA Heat Index formula.

Figure 4: Distribution of wet-bulb globe temperature across bins in India (1998–2020)



Note: the figure provides the distribution of days recording wet-bulb globe temperature (°C) in a specific bin between 1998 and 2020.

Source: authors' compilation using ERA5-Land dataset (ECMWF) and Lemke and Kjellstrom (2012) WBGT formula.

Labour regulations

We examine the role of labour regulation as a potential channel through which firms adjust to heat-induced productivity shocks. The institutional framework governing labour relations in India is anchored in the IDA of 1947, which outlines the legal processes for resolving industrial disputes and regulating employer–employee relations in the formal manufacturing sector. While originally enacted as a central law with uniform applicability, India’s federal structure allows states to amend its provisions, leading to substantial cross-state variation in labour regulations over time. The IDA governs several aspects of industrial relations, including strikes, layoffs, retrenchments, and plant closures.

Our analysis focuses on Chapter V(B) of the IDA, which imposes stricter regulations on industrial establishments above a size threshold. In particular, firms employing 100 or more regular workers (50 workers in the case of West Bengal) are required to obtain prior government approval before undertaking layoffs, retrenchments, or closures, and must comply with advance notice and severance requirements. We interpret this threshold as the point at which labour regulation becomes binding for firms. Importantly, these provisions do not apply to contract workers, creating incentives for firms to adjust their workforce composition by increasing reliance on temporary or contractual labour in order to circumvent regulatory constraints.

To operationalize this framework, we compile a novel dataset of state-level amendments to Chapter V(B) of the IDA over the period 1998–2020, capturing variation in the threshold for regulatory coverage across states and over time. Following Colmer (2021), we construct a firm-level indicator that takes the value 1 if a firm is subject to the provisions of Chapter V(B), and 0 otherwise. This measure captures applicable state-specific thresholds and firm-level exposure to labour regulation based on employment size. The indicator varies over time within firms due to changes in firm size as well as state-level amendments to the Act.

Summary statistics

Table 1 presents summary statistics for the key variables used in the analysis. The average labour share, measured as the ratio of total compensation to sales, is approximately 11.3%, indicating that labour accounts for a meaningful, though not dominant, share of firm revenue. There is considerable variation across firms, reflecting heterogeneity in production structures and workforce composition within the manufacturing sector.

In terms of firm characteristics, the average firm employs 178 workers, with substantial dispersion in firm size. Sales revenues vary widely across firms, with the average annual sales revenue at approximately INR500,000,000 (INR 50 crore). The capital-to-labour ratio and capital stock also exhibit significant heterogeneity, consistent with the coexistence of both labour-intensive and capital-intensive firms in the sample.

Turning to climate variables, firms are frequently exposed to high-temperature days, particularly in the upper-temperature bins (e.g. above 27°C), underscoring the relevance of heat stress in the Indian context. The average WBGT across firm locations is 22.2°C, corresponding to moderate heat stress conditions under which productivity losses may arise. Overall, the summary statistics highlight substantial variation in both firm characteristics and climate exposure, providing a suitable setting to examine the impact of temperature shocks on labour share.

Table 1: Summary statistics of variables of interest (1998-2019)

Variable	Obs.	Mean	Median	SD	Min.	Max.
A. Firm characteristics						
Age of the firm	309,472	19.4	15.0	15.7	0.0	116.0
Total labour compensation	309,472	24,731,992.0	3,387,159.5	58,397,670.9	22,032.0	1,534,965,424.0
Total employment	309,472	178.1	51.0	349.0	1.0	8,026.0
Capital	309,472	90,198,824.2	3,346,570.0	58,1146,264.1	1.0	52,545,285,432.0
GFCF	309,472	24,545,407.4	692,275.5	242,236,770.1	-14,777,429,937.0	50,619,494,608.0
Investment dummy (GFCF > 0)	309,472	0.8	1.0	0.4	0.0	1.0
Capital-to-labour ratio	309,472	11.0	11.2	2.1	0.0	18.8
Value added	309,472	13,7467,794.6	10,415,418.5	1,071,621,373.7	30.0	311,577,423,551.0
Sales	309,472	500,882,978.2	56,400,528.0	2,563,237,256.2	35,964.0	378,639,636,222.0
Wage per capita	309,472	93,082.4	62,455.1	108,380.1	196.7	10,359,296.3
Labour share (%)	309,472	11.3	7.5	12.2	0.0	100.0
B. Weather variables						
T ¹ : [<15°C)	309,472	16.2	0.0	29.3	0.0	366.0
T ² : [15–18°C)	309,472	14.9	2.0	18.5	0.0	159.0
T ³ : [18–21°C)	309,472	25.7	27.0	20.9	0.0	201.0
T ⁴ : [21–24°C)	309,472	65.4	48.0	52.1	0.0	272.0
T ⁵ : [24–27°C)	309,472	105.5	95.0	57.3	0.0	332.0
T ⁶ : [27–30°C)	309,472	88.3	87.0	39.9	0.0	213.0
T ⁷ : [30–33°C)	309,472	35.4	35.0	28.4	0.0	145.0
T ⁸ : [≥33°C)	309,472	13.9	3.0	18.6	0.0	118.0
Precipitation (mm)	309,472	1,266.4	1,037.9	1,126.6	2.2	8,626.2
WBGT (°C)	309,472	22.2	22.3	1.6	5.3	25.5
Heat index (°C)	309,472	26.3	26.3	2.4	1.0	31.7

Note: the table reports descriptive statistics for the main variables used in the analysis. The sample consists of 309,472 firm–year observations between financial year 1998–99 and 2019–20. Panel A provides a summary for firm-level characteristics. All monetary values are in Indian rupees (INR). Total labour compensation includes total wages and additional payments such as bonus, welfare expenses, and provident funds provided to workers. Capital denotes the opening balance of automation-related fixed assets such as plant and machinery and computers and software. Gross fixed capital formation (GFCF) is computed using the ASI definition and measures the net investment in fixed assets. The negative value of GFCF might be due to asset disposals or depreciation adjustments. The investment dummy equals 1 if GFCF is positive. Capital-to-labour ratio is defined as reported capital divided by total number of workers. Value added is gross output net of intermediate inputs and sales denote the gross revenues. Wage per capita is total wages divided by number of workers. Labour share is computed as the ratio of total compensation to sales (%). Panel B provides a summary for weather variables. T^j denote the number of days recording daily mean temperature (°C) in bin j and precipitation denotes total precipitation in a year in millimetres. The humidity-adjusted measures (Heat Index and WBGT) are measured in °C.

Source: authors' compilation.

4.2 Empirical strategy

The main estimating equation is given by:

$$LS_{idt} = \alpha + \sum_{j=1, j \neq 5}^8 \beta_j T_{dt}^j + \gamma W_{dt} + \theta Z_{idt} + \varphi_i + \eta_t + \varepsilon_{idt} \quad (1)$$

where i indexes firms, d districts, and t years. The dependent variable, LS_{idt} , is the firm-level labour share, defined as total compensation paid to workers as a proportion of the firm's sales revenue. Our primary variable of interest is extreme heat, captured using average daily temperature bins, T_{dt}^j . For each district–year, we aggregate average daily temperatures by counting the number of days falling within each non-overlapping temperature bin (T^j) over the course of a year. This step-function approach offers a quasi-nonparametric method of capturing potential nonlinear effects of temperature on outcomes, as employed in prior studies (Somanathan et al. 2021; Zhang et al. 2024).

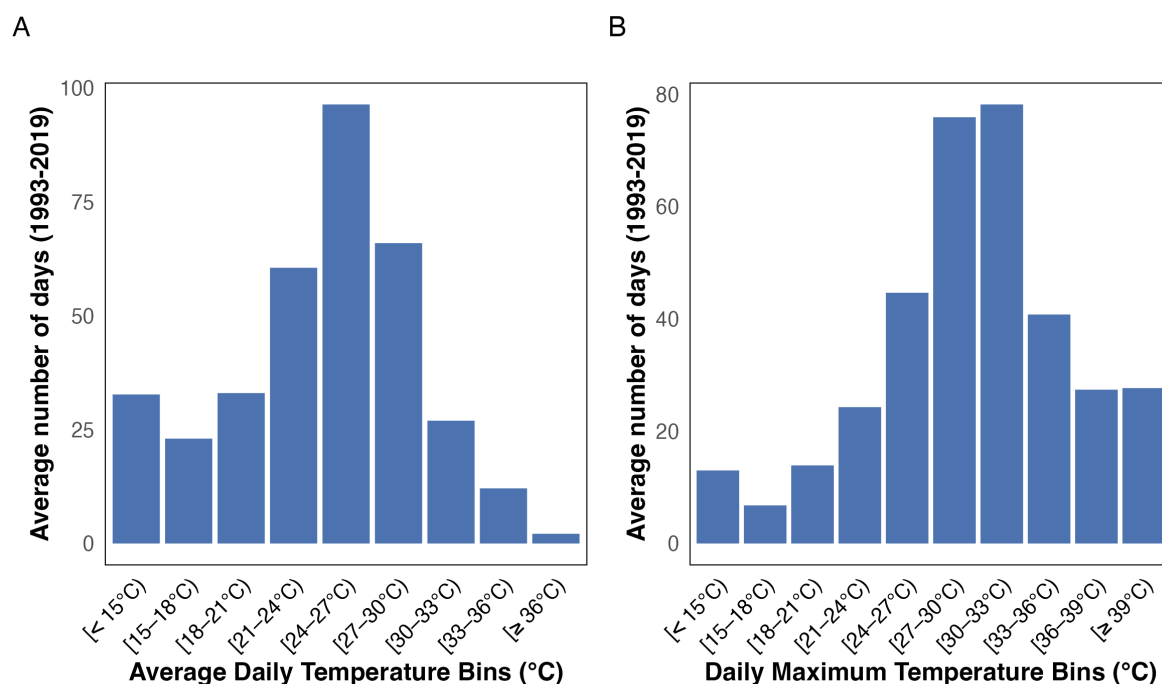
The temperature bins are defined as follows: $T^1 = [<15^\circ\text{C})$, $T^2 = [15^\circ\text{C}, 18^\circ\text{C})$, $T^3 = [18^\circ\text{C}, 21^\circ\text{C})$, $T^4 = [21^\circ\text{C}, 24^\circ\text{C})$, $T^5 = [24^\circ\text{C}, 27^\circ\text{C})$, $T^6 = [27^\circ\text{C}, 30^\circ\text{C})$, $T^7 = [30^\circ\text{C}, 33^\circ\text{C})$, and $T^8 = [\geq 33^\circ\text{C})$. The modal bin (T^5) serves as the reference category. The coefficients β_j thus capture the marginal effect of an additional day in a given temperature bin relative to the reference bin. The distribution of days count recording average daily temperature across the specified 3°C increment temperature bins is provided in Figure 5(a). For robustness, we also construct temperature bins using daily maximum temperature; the distribution is visualized in Figure 5(b).

We control for other weather variables (W_{dt}), namely linear and quadratic terms of annual precipitation, to isolate the effect of temperature from additional correlated shocks. Prior evidence suggests that heat coupled with changes in precipitation patterns can adversely affect labour supply and productivity Somanathan et al. (2021) and disrupt input supply chains and transport Chen et al. (2025). Firm-level controls (Z_{idt}) include observable characteristics such as firm age and size. φ_i denotes firm fixed effects, controlling for time-invariant firm characteristics, while η_t captures year fixed effects to account for common shocks over time. ε_{idt} is the idiosyncratic error term. Standard errors are clustered at the district level, which aligns with the spatial resolution of our climate variables.

The identification strategy leverages exogenous variations in annual temperature patterns across districts to estimate the effect of extreme heat on firm-level labour share. By including firm fixed effects, we exploit within-firm variation over time, identifying the impact of extreme heat from annual deviations in district-level temperature relative to the firm's average exposure over the sample period. This approach mitigates concerns about omitted variable bias arising from time-invariant unobserved heterogeneity across firms. We further address potential iden-

tification threats through a series of robustness checks, discussed in Section 5.3.

Figure 5: Distribution of average daily temperature and daily maximum temperature across bins in India (1993–2020)



Note: the figure provides the distribution of days recording average daily temperature (°C) in panel A and daily maximum temperature (°C) in panel B in a specific bin between 1993 and 2020.

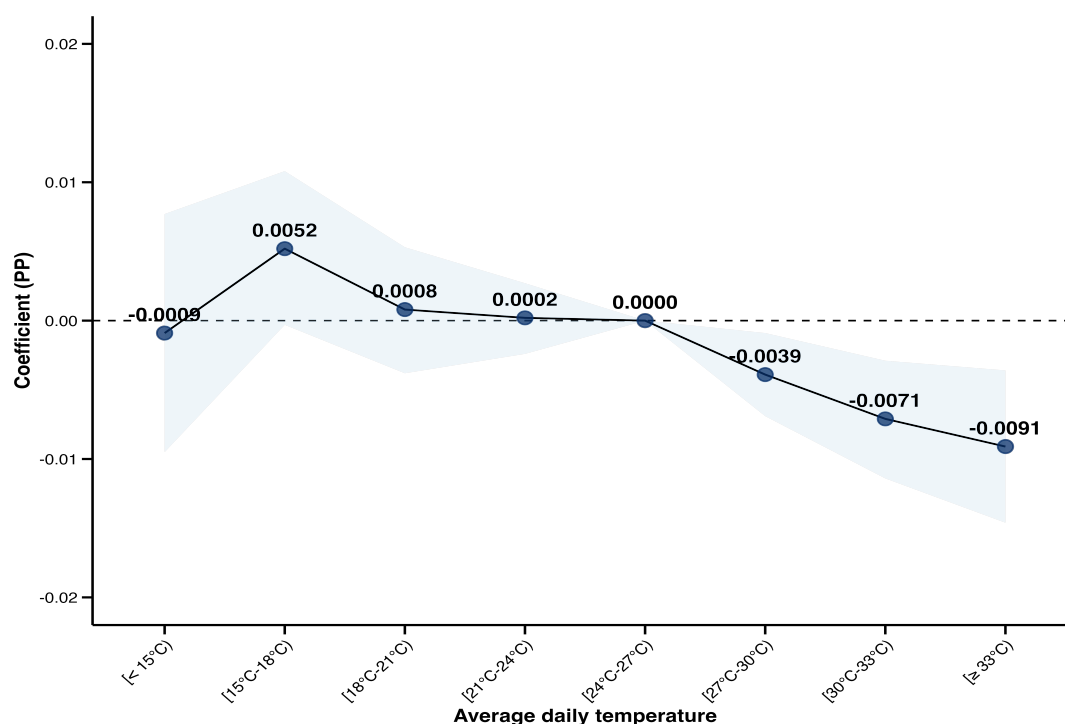
Source: authors' compilation using ERA5-Land dataset (ECMWF).

5 Results

5.1 Main findings

Figure 6 presents estimates of the impact of extreme heat on labour share (expressed as a percentage), based on the baseline regression model specified in Eq. (1). The dependent variable is labour share, defined as total compensation divided by sales and expressed in percentage points (i.e. labour share $\times$ 100). The specification includes firm and year fixed effects, with standard errors clustered at the district level.

Figure 6: Nonlinear impact of extreme heat on labour share



Note: the figure provides estimates for the nonlinear relationship between average daily temperature and labour share in reference to the modal temperature bin [24–27°C). The visualization of significant and negative effects is presented by solid blue bubbles. The light blue shaded area represents 95% confidence intervals. The specification includes firm and year fixed effects with precipitation, age of firm, and size classification of firm as per ASI as controls. The standard errors are clustered at the district level.

Source: authors' own estimation.

The results indicate a nonlinear and negative relationship between extreme heat and labour share. Specifically, one additional day in a year with average daily temperature between 30°C and 33°C is associated with a 0.0072 p.p. reduction in labour share, implying a modest decline of approximately 0.07 p.p. for 10 additional hot days. The effect becomes slightly more pronounced for very high temperatures: one additional day above 33°C corresponds to a 0.0091 p.p. reduction, equivalent to a 0.08% decrease relative to the sample mean labour share (11.3%). The negative and statistically significant coefficients suggest that higher temperatures are systematically associated with a lower labour share in the Indian manufacturing sector. These results point towards potentially important economic adjustments by firms under heat stress. These findings align with Lyu et al. (2024) and Qiu and Yoshida (2024), who document a similarly negative relationship between heat stress and labour share using data from China and the United States, respectively.

5.2 Additional results

We also decompose the effect of temperature on labour share into three key components: employment, wages, and sales. Employment is measured as the logarithm of the number of employees, while wages are measured as the logarithm of average wage per capita. To capture heterogeneous effects across worker categories, we separately examine employment (E) and average wages (W) for permanent female workers (E_{pf} , W_{pf}), permanent male workers (E_{pm} , W_{pm}), and contract workers (E_c , W_c). Additionally, we examine the impact of temperature on total work days, female work days, male work days, and contract work days.

The results, reported in Tables 2 and 3, indicate that heat stress alters the composition of employment within firms. While overall employment of male and contract workers remains largely unchanged, female employment and total female work days decline significantly. These declines may reflect several complementary mechanisms. For example, female workers may be disproportionately concentrated in tasks that are more sensitive to heat stress, leading firms to scale back such activities when temperatures rise, consistent with evidence that temperature shocks reduce firm-level productivity in heat-exposed activities (Graff Zivin and Neidell 2014; Somanathan et al. 2021).⁵ Further, heat stress may reduce female labour supply through increased health risks and household responsibilities, which disproportionately affect women in developing-country contexts (Dasgupta et al. 2021; Deschênes 2014). Finally, firms may respond to heat-induced cost pressures by prioritizing male workers while reducing employment among women.

⁵ To support this interpretation, we have undertaken a descriptive analysis using our ASI sample, and find that the industries undertaking tobacco manufacturing and manufacture of wearing apparel and leather products have the highest female employment shares. In addition, evidence provided by Somanathan et al. (2021) indicates that these sectors also experience a significant reduction in firm-level output production under high temperatures. While this evidence does not establish causality, it is consistent with the view that heat stress may disproportionately affect female employment through its impact on heat-sensitive production activities.

Table 2: Effect of extreme heat on components of labour share

Variables	log(E_f) (1)	log(E_m) (2)	log(E_c) (3)	log(W_f) (4)	log(W_m) (5)	log(W_c) (6)	log(sales) (7)
$T_{mean}[<15^{\circ}\text{C}]$	0.0027*** (0.0010)	0.0003 (0.0004)	0.0003 (0.0009)	-0.0011** (0.0004)	0.0001 (0.0003)	0.0003 (0.0005)	0.0004 (0.0004)
$T_{mean}[15-18^{\circ}\text{C}]$	0.0017*** (0.0006)	-0.0001 (0.0003)	0.0012** (0.0006)	-0.0004 (0.0004)	0.0000 (0.0002)	-0.0004 (0.0003)	-0.0001 (0.0003)
$T_{mean}[18-21^{\circ}\text{C}]$	0.0008* (0.0004)	0.0005** (0.0002)	-0.0004 (0.0005)	-0.0002 (0.0002)	-0.0001 (0.0001)	0.0001 (0.0002)	0.0001 (0.0002)
$T_{mean}[21-24^{\circ}\text{C}]$	0.0005* (0.0003)	-0.0001 (0.0002)	0.0006* (0.0003)	-0.0001 (0.0001)	0.0001 (0.0001)	0.0001 (0.0001)	0.0002 (0.0001)
$T_{mean}[27-30^{\circ}\text{C}]$	-0.0005* (0.0002)	0.0000 (0.0002)	0.0004 (0.0003)	0.0002 (0.0001)	0.0003*** (0.0001)	0.0000 (0.0001)	0.0002 (0.0001)
$T_{mean}[30-33^{\circ}\text{C}]$	-0.0009** (0.0004)	0.0000 (0.0002)	-0.0001 (0.0004)	0.0002 (0.0002)	0.0001 (0.0002)	-0.0002 (0.0002)	-0.0001 (0.0002)
$T_{mean}[\geq 33^{\circ}\text{C}]$	-0.0014** (0.0006)	0.0003 (0.0003)	0.0002 (0.0005)	0.0004 (0.0003)	0.0002 (0.0002)	-0.0005* (0.0003)	0.0007*** (0.0003)
Observations	91,424	290,745	104,856	91,424	290,745	104,856	309,472
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes	Yes

Note: the table provides estimates for various components of labour share. All columns provide an impact of one additional day recording average daily temperature in reference to the omitted bin $[24-27^{\circ}\text{C}]$. All models include firm and year fixed effects as well as total precipitation, age of firm, and firm size classification as per ASI as control variables. The robust standard errors, clustered at the district level, are reported in parentheses. Columns (1)–(3) provide estimates for employment of permanent female workers (Ef), permanent male workers (Em), and contract workers (Ec), respectively. Columns (4)–(6) provide estimates for the logarithm of average wage per capita for permanent female workers (Wf), permanent male workers (Wm), and contract workers (Wc). Column (7) provides estimates for the logarithm of sales. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Effect of extreme heat on labour work days

Variables	log(total work days) (1)	log(female work days) (2)	log(male work days) (3)	log(contract work days) (4)
$T_{mean}[\leq 15^{\circ}\text{C}]$	0.0004 (0.0004)	0.0027*** (0.0010)	0.0005 (0.0004)	0.0008 (0.0009)
$T_{mean}[15-18^{\circ}\text{C}]$	0.0004 (0.0003)	0.0021*** (0.0006)	0.0001 (0.0003)	0.0011* (0.0006)
$T_{mean}[18-21^{\circ}\text{C}]$	0.0002 (0.0002)	0.0009* (0.0005)	0.0005** (0.0002)	-0.0004 (0.0005)
$T_{mean}[21-24^{\circ}\text{C}]$	0.0001 (0.0001)	0.0006** (0.0003)	0.0000 (0.0002)	0.0006* (0.0003)
$T_{mean}[27-30^{\circ}\text{C}]$	0.0002 (0.0002)	-0.0005* (0.0003)	0.0000 (0.0002)	0.0003 (0.0003)
$T_{mean}[30-33^{\circ}\text{C}]$	0.0000 (0.0002)	-0.0009** (0.0004)	0.0001 (0.0002)	-0.0003 (0.0004)
$T_{mean}[\geq 33^{\circ}\text{C}]$	0.0002 (0.0003)	-0.0014** (0.0006)	0.0002 (0.0003)	-0.0001 (0.0005)
Observations	309,472	91,424	290,745	104,856
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Note: the table provides estimates for the total work days, aggregated across all the shifts worked in a year. All columns provide an impact of one additional day recording average daily temperature in reference to the omitted bin $[24-27^{\circ}\text{C}]$. All models include firm and year fixed effects as well as total precipitation, age of firm, and firm size classification as per ASI as control variables. The robust standard errors, clustered at the district level, are reported in parentheses. Column (1) provides estimates for the impact of extreme heat on total work days aggregated across all the shifts performed by all the workers employed in a firm in a year. Columns (2)–(4) provide estimates for the impact on work days of permanent female workers, permanent male workers, and contract workers, respectively. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

We also find evidence of an asymmetric impact of heat stress on wages. Specifically, the average wage of contract workers decreases, whereas the average wage of permanent male workers increases. This pattern is consistent with firms adjusting workforce composition in response to heat-induced labour cost pressures, potentially reflecting complementarities between permanent and contract workers as well as differences in bargaining power. It shows that firms tend to respond by shifting the burden of the adjustment towards the type of workers where labour market regulation allows for more flexibility or where there is lower bargaining power.

Finally, quite interestingly, we find a positive and significant effect on firm sales. This pattern suggests that firms are able to maintain—or even increase—revenue under heat stress. An explanation could be that heat stress might induce a series of adjustments at the firm level to maintain revenues, including an increase in automation or a shift away from labour-intensive activities. Another potential explanation is that heat stress might induce a change in the market structure, weakening competitive pressure within local markets and increasing the effective market power of incumbent firms. Taken together, these findings confirm that the decline in labour share is not driven by a contraction in economic activity per se, but rather by within-firm adjustments in average wages, production, and workforce composition.

5.3 Robustness checks

To assess the robustness of our findings, we conduct a range of robustness checks. The results of all the checks are presented in Appendix D.

Alternate level of clustering of standard errors

We assess the robustness of our inference to alternative clustering of standard errors. In our baseline specification, we cluster standard errors at the district level (reported in column (1) of Table D1), which accounts for spatial correlation in temperature shocks within districts. However, firms operating within the same industry or broader geographic units may also be exposed to common shocks, and failing to account for such correlation may lead to understated standard errors.

To address this concern, we re-estimate our baseline specification using alternative levels of clustering. Specifically, we cluster standard errors at the firm level, district–industry level (based on two-digit NIC codes), and state level. We also corrected the standard errors for spatial and serial correlation following Conley (2010). The Conley correction allows the covariance in regression residuals to decay with geographical distance and, therefore, accounts for potential spatial dependence in the standard errors arising from correlated climate shocks and potential spillover effects across neighbouring districts.

The results, reported in columns (2)–(5) of Table D1, show that the statistical significance of our estimates remains largely unchanged across these specifications. This indicates that our results are not sensitive to the choice of clustering and that our inference is robust to alternative assumptions regarding the correlation structure of the error terms.

Controlling for time trends

We next assess whether our results are driven by differential state-specific and sector-specific time trends. States in India may experience heterogeneous economic trajectories, policy changes, or structural transformation over time, which could be correlated with both temperature exposure and labour share. If such state-specific trends are not accounted for, our estimates may capture these underlying dynamics rather than the causal effect of heat stress. Similarly, it is important to ensure that the estimated impacts of heat exposure are not confounded by sector-specific trajectories, such as technological upgrading, regulatory regimes, changes in supply chains, trade, and shifts in consumer demand.

Therefore, we augment our baseline specification by including state-specific and sector-specific time trends. The results are reported in columns (1) and (2) of Table D2, respectively. We find that the effect of extreme heat on labour share remains statistically significant and economically meaningful after controlling for these trends. This suggests that our findings are not driven

by differential state-level or sector-level trends and reinforces the robustness of our baseline estimates.

Controlling for industrial disputes

We examine whether our results are sensitive to the inclusion of the measure of industrial disputes. Such disputes can lead to temporary disruptions in production and labour utilization, potentially affecting both firm output and labour compensation. In addition, extreme heat may increase the incidence of labour unrest by worsening working conditions in factories. Therefore, including a proxy of industrial disputes allows us to assess whether the effect of temperature on labour share operates partly through the time lost in industrial disputes. To the extent that industrial disputes are correlated with temperature, the specification controlling for industrial disputes should be interpreted as the effect of temperature, net of time lost in the disputes.

To compute a proxy for the industrial disputes, we compile state-level data on total minutes lost to industrial disputes, reported annually by the Labour Bureau, Government of India. We use the logarithm of total minutes lost and include this variable as an additional control in Eq. (1). The results, reported in column (3) of Table D2, show that the effect of extreme heat on labour share remains negative and statistically significant, with little change in magnitude. This suggests that our findings are not driven by concurrent labour disputes or disruptions in production due to industrial conflict.

Alternative measures of labour share

We further estimate the impacts of extreme heat on labour share, measured using alternative definitions of labour share. As discussed earlier, in LMICs, value-added and output-based measures of labour share may be subject to measurement error in firm-level manufacturing data due to the under-reporting of output, missing data on intermediate inputs, and deflation issues. While our baseline definition based on firm sales mitigates these concerns, it is nevertheless important to verify that our findings are not sensitive to the choice of the denominator.

To this end, we re-estimate our model using alternative measures of labour share defined as the ratio of total compensation to (a) gross output and (b) value added. The results, reported in columns (4) and (5) of Table D2, remain negative and statistically significant, with only modest changes in magnitude relative to the baseline estimates. This suggests that our findings are robust to alternative definitions of labour share, despite the potential measurement issues associated with these measures.

Restricting analysis to firms with at least ten employees

We next examine whether our results are driven by very small firms, which may be subject to greater measurement error in the reported financial and employment variables. In firm-level datasets, smaller establishments often exhibit noisier balance sheet reporting and greater

volatility, which may introduce bias in estimating labour share.

To address this concern, we restrict the sample to firms with at least ten employees. The resulting subsample comprises 274,208 observations. The results are reported in column (6) of Table D2. The coefficients remain negative and statistically significant, with slightly larger magnitudes compared to the baseline estimates. This suggests that our findings are not driven by small firms or reporting inconsistencies and, if anything, are stronger among relatively larger and more stable firms.

Alternative reference temperature bins

In specifications based on temperature bins, the estimated effects are interpreted relative to an omitted reference category, and the choice of this baseline can affect both the magnitude and interpretation of the coefficients. To ensure that our results are not driven by a particular choice of reference bin, we examine their sensitivity to alternative choices of reference temperature bins. Specifically, we re-estimate our model using two alternative reference categories, [21–24°C) and [27–30°C), instead of the baseline [24–27°C). The estimates, reported in columns (1) and (2) of Table D3, remain negative and statistically significant, with magnitudes comparable to the baseline estimates. This indicates that our findings are robust to reasonable variation in the choice of reference temperature bin.

Alternative measures of extreme heat

We also examine whether our results are sensitive to alternative measures of heat exposure. Since temperature can be captured using different metrics—such as average or maximum daily temperature—and different functional forms, we verify that our findings are not driven by a particular specification of extreme heat.

First, we redefine the 3°C temperature bins using daily maximum temperature to capture the effect of peak heat recorded during the day, with the modal bin [27–30°C) as the reference category. The results are reported in column (1) of Table D4 and remain negative and statistically significant, suggesting that our findings are robust to using maximum temperature instead of average temperature.

Second, we construct threshold-based measures of extreme heat. Specifically, we consider (1) the number of days with average daily temperature above 30°C, and (2) the number of days with daily maximum temperature above 30°C, 32°C, and 35°C. The results, reported in columns (2)–(5) of Table D4, remain negative and statistically significant across all specifications, although the magnitude varies with the choice of threshold.

Taken together, these results indicate that our findings are robust to alternative measures of heat exposure and are not driven by a particular choice of temperature metric or functional form.

Humidity-adjusted measures of extreme heat

We next examine the robustness of our results to alternative measures of heat stress that account for humidity. Since the physiological effects of heat depend not only on temperature but also on humidity, temperature-based measures alone may not fully capture the intensity of heat exposure. Ignoring humidity may therefore lead to measurement error in the estimation of heat stress.

To address this concern, we use two widely adopted humidity-adjusted measures of heat stress: the NOAA Heat Index and WBGT.⁶ The results are reported in Tables D5 and D6. We find that the coefficients remain negative and statistically significant across specifications, with magnitudes similar to those obtained using temperature-based measures. For instance, an additional day with the Heat Index above 36°C in reference to the omitted bin reduces labour share by 0.01%. Further, the threshold-based estimates show that an additional day with the Heat Index above 33°C reduces labour share by 0.0071%. Similarly, an additional day with the wet-bulb temperature above 28°C in reference to the omitted bin leads to a decline in labour share by 0.0172%.

Overall, these findings indicate that our results are robust to more comprehensive measures of heat stress that incorporate both temperature and humidity, reinforcing the interpretation that extreme heat adversely affects labour share.

6 Mechanisms

6.1 Capital-to-labour substitution

We investigate whether capital-to-labour substitution serves as a potential mechanism driving the decline in labour share under extreme heat. Evidence suggests that extreme heat has a negative effect on both labour supply and productivity (Somanathan et al. 2021; Zivin et al. 2020), and increases labour costs due to the physical risks associated with extreme heat (Park et al. 2021). In addition, Karabarounis and Neiman (2014) suggest that the liberalization of capital goods markets, reductions in tariffs, and increased inflows of foreign direct investment have collectively lowered the relative cost of capital in the manufacturing sector (Mutreja et al. 2018). Given the decrease in the relative price of capital to labour, it is plausible that firms

⁶ See Appendix B and C for details on construction of humidity-adjusted measures.

adopt more capital-intensive production methods in response to reduced workers' efficiency due to heat stress, thereby increasing the capital–labour ratio. This potentially provides an explanation for the decline in labour share provided that capital and labour are substitutable.

In the context of the Indian manufacturing sector, the literature provides a considerable variation in the elasticity of substitution between capital and labour. Prior evidence shows that, in several manufacturing industries, the elasticity deviates significantly from unity (Sankar 1970), while it is estimated to be below 1 in other industries (Gujarati 1966). In addition, Gujarati (1966) finds a positive rate of labour augmenting technological change in Indian manufacturing, indicating a systematic adoption towards labour-saving technological change and production techniques. Taken together, these findings support the assumption that Indian manufacturing firms may respond to extreme heat by reducing their reliance on labour, thus resulting in a decline in labour share.

To examine this mechanism, we first test whether extreme heat increases three different indicators of capital intensity, namely: log of the capital-to-labour ratio (defined as automation-related fixed assets, such as plant and machinery and computers and software, at the beginning of financial year t divided by the number of employees in firm i located in district d); log of capital stock; and GFCF.⁷ Table 4 presents the estimated results. We find that extreme heat leads to a significant increase in the capital-to-labour ratio, suggesting that firms respond to heat stress by increasing capital intensity relative to labour. We also find that extreme heat increases the firms' automation-related capital stock and the probability to invest (GFCF).

⁷ GFCF is constructed using the tabulation formula provided by ASI. Net fixed capital formation (NFCF) is calculated as the closing balance of fixed assets minus the opening balance of fixed assets, adjusted for revaluation. GFCF is then obtained as the sum of NFCF and depreciation. We further construct an indicator variable that takes the value 1 if firm-level GFCF is positive in a given financial year, and 0 otherwise. This approach is motivated by the presence of negative values of GFCF for some firms, making a binary measure of investment activity more appropriate for our analysis.

Table 4: Impact of extreme heat on capital-to-labour substitution

Variables	log(k/l) (1)	log(k) (2)	GFCF (3)
$T_{mean}[<15^{\circ}\text{C}]$	0.0000 (0.0006)	0.0001 (0.0006)	0.0002 (0.0002)
$T_{mean}[15-18^{\circ}\text{C}]$	-0.0002 (0.0004)	0.0000 (0.0004)	0.0000 (0.0002)
$T_{mean}[18-21^{\circ}\text{C}]$	0.0000 (0.0003)	0.0002 (0.0003)	0.0000 (0.0001)
$T_{mean}[21-24^{\circ}\text{C}]$	-0.0001 (0.0002)	0.0000 (0.0002)	0.0000 (0.0001)
$T_{mean}[27-30^{\circ}\text{C}]$	0.0003* (0.0002)	0.0005*** (0.0002)	-0.0001 (0.0001)
$T_{mean}[30-33^{\circ}\text{C}]$	0.0005* (0.0003)	0.0005* (0.0002)	0.0000 (0.0001)
$T_{mean}[\geq 33^{\circ}\text{C}]$	0.0006* (0.0004)	0.0009*** (0.0003)	0.0002** (0.0001)
Observations	309,472	309,472	309,472
Fixed Effects			
Firm fixed effects	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes

Note: the table provides estimates for the capital-to-labour substitution channel. All columns provide an impact of one additional day recording average daily temperature in reference to the omitted bin $[24-27^{\circ}\text{C}]$. All models include firm and year fixed effects as well as total precipitation, age of firm, and firm size classification as per ASI as control variables. The robust standard errors, clustered at the district level, are reported in parentheses. Column (1) provides estimates for the logarithm of capital-to-labour substitution, defined as the ratio of fixed assets (plant and machinery; computers and software) and total employment in a firm. Column (2) provides estimates for the logarithm of fixed assets (plant and machinery; computers and software), while column (3) provides estimates for the firm-level investment that takes value 1 if GFCF of a firm is positive in a given financial year. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

To better support our findings, we estimate the heterogeneous impact of extreme heat on the labour share across industries with different levels of capital-to-labour elasticity of substitution. For this, we first estimate the capital-labour substitution elasticity for firms in different industries (at the two-digit level) in India following the indirect approach by Bentolila and Saint-Paul (2003). The indirect inference approach proposes regressing labour share on the capital-labour ratio. The capital-labour substitution elasticity then depends on the sign of the coefficient of the capital-labour ratio, where a negative coefficient indicates an elasticity of substitution greater than 1 in absolute value and vice-versa. Specifically, we employ the following regression model:

$$LS_{ijt} = \alpha + \beta_j(K/L)_{ijt} + \eta_t + \varepsilon_{ijt} \quad (2)$$

where i indexes firms, j denotes the two-digit industry, and t denotes years. The dependent variable, LS_{ijt} , is the firm-level labour share in industry j , defined as total compensation paid to workers as a proportion of the firm's sales. Our primary variable of interest is the capital-labour ratio, where β_j captures the industry-specific relationship between labour share and capital intensity, such that $\beta_j < 0$ indicates a capital-to-labour elasticity of substitution > 1 and

vice-versa. Year fixed effects η_t absorb aggregate shocks common across industries.

The estimates, provided in Table D7, indicate that the capital–labour substitution elasticity exceeds unity across all manufacturing industries in India. We then merge back the estimated industrial-level coefficients to firm-level panel data and classify industries according to the degree of substitutability, defining a dummy variable that takes value 1 (high elasticity of substitution) if the estimated β_j is greater than its 50th percentile, and 0 otherwise.

Table 5: Effects of extreme heat on labour share, heterogeneity by elasticity of capital-to-labour substitution

Variables	(1)
$T_{mean}[\leq 15^\circ\text{C})$	0.0015 (0.0047)
$T_{mean}[15\text{--}18^\circ\text{C})$	0.0046 (0.0029)
$T_{mean}[18\text{--}21^\circ\text{C})$	0.0003 (0.0026)
$T_{mean}[21\text{--}24^\circ\text{C})$	0.0010 (0.0013)
$T_{mean}[27\text{--}30^\circ\text{C})$	−0.0043*** (0.0016)
$T_{mean}[30\text{--}33^\circ\text{C})$	−0.0074*** (0.0024)
$T_{mean}[\geq 33^\circ\text{C})$	−0.0057** (0.0029)
high eos	0.1698 (0.4808)
$T_{mean}[\leq 15^\circ\text{C}) \times \text{high eos}$	−0.0062 (0.0040)
$T_{mean}[15\text{--}18^\circ\text{C}) \times \text{high eos}$	0.0017 (0.0052)
$T_{mean}[18\text{--}21^\circ\text{C}) \times \text{high eos}$	0.0011 (0.0034)
$T_{mean}[21\text{--}24^\circ\text{C}) \times \text{high eos}$	−0.0021 (0.0019)
$T_{mean}[27\text{--}30^\circ\text{C}) \times \text{high eos}$	0.0010 (0.0025)
$T_{mean}[30\text{--}33^\circ\text{C}) \times \text{high eos}$	0.0005 (0.0036)
$T_{mean}[\geq 33^\circ\text{C}) \times \text{high eos}$	−0.0086** (0.0039)
Observations	309,472
Firm fixed effects	Yes
Year fixed effects	Yes

Note: the table provides estimates for the impact of extreme heat on labour share of firms with high and low capital-to-labour elasticity of substitution. Column (1) provides an impact of one additional day recording average daily temperature in reference to the omitted bin $[24\text{--}27^\circ\text{C})$. The model includes firm and year fixed effects as well as total precipitation, age of firm, and firm size classification as per ASI as control variables. The robust standard errors, clustered at the district level, are reported in parentheses. The temperature bins are interacted with a dummy variable for high elasticity of substitution that takes value 1 if the estimated elasticity of substitution at the two-digit industry level is greater than the industry median. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

Source: authors' compilation.

Finally, we examine the heterogeneous impacts of extreme heat on labour share across firms that operate in industries with high versus low capital-to-labour substitutability. The results are presented in Table 5 and show that extreme heat leads to a larger decline in labour share among firms with higher capital-to-labour substitution. The results are consistent with the literature Lyu et al. (2024) and point to the substitution mechanism through which firms adjust factor shares in response to heat-induced labour productivity losses. Specifically, we find that an additional day recording daily mean temperature above 33°C decreases labour share of firms with high substitution elasticity by 0.014%, but by 0.006% in firms with low substitution elasticity.

6.2 Market power and labour share

We next examine whether heat-induced changes in local product market structure may contribute to the decline in labour share. Extreme heat can affect firms asymmetrically, disproportionately increasing costs for smaller, less productive, or more heat-exposed firms. Such asymmetric impacts may weaken competitive pressure within local markets and increase the effective market power of incumbent firms. A growing literature links declining labour shares to rising market concentration and the increasing importance of firms with high markups and relatively low labour shares ('superstar firms') (Autor et al. 2017, 2020). In line with this perspective, recent evidence shows that higher temperatures can increase local market concentration in manufacturing industries (Ponticelli et al. 2023).

Changes in competitive conditions may, in turn, lead to within-firm adjustments in pricing, output, and factor shares. When competitive pressure weakens or market concentration increases, firms may increase markups and capture a larger share of economic rents, reducing the share of value added accruing to workers. In addition, firms expanding output in less competitive environments may spread fixed or overhead labour costs over larger production volumes, lowering labour's share of revenue even when employment changes little.

To examine this channel, we test whether extreme heat is associated with increased market concentration at the district $\times$ industry $\times$ year level, where districts represent economically meaningful product and labour markets in India. The results are reported in Table 6. We find that extreme heat significantly increases local market concentration represented by two standard measures of concentration: the Herfindahl–Hirschman Index (HHI) and the share of sales and employment accounted for by the largest firm (CR1). While these market-level estimates do not mechanically explain our firm-level coefficients, they provide *complementary evidence* that rising temperatures alter the competitive environment faced by firms, potentially amplifying within-firm adjustments that contribute to the observed decline in labour share.

Table 6: Effect of extreme heat on market concentration of sales and employment at district–industry–year level

Variables	HHI(sales) (1)	CR1(sales) (2)	HHI(employment) (3)	CR1(employment) (4)
$T_{mean}[\leq 15^{\circ}\text{C}]$	0.0005** (0.0002)	0.0446** (0.0194)	0.0004* (0.0002)	0.0356** (0.0174)
$T_{mean}[15\text{--}18^{\circ}\text{C}]$	0.0000 (0.0002)	0.0022 (0.0152)	0.0001 (0.0002)	0.0077 (0.0166)
$T_{mean}[18\text{--}21^{\circ}\text{C}]$	0.0003* (0.0002)	0.0215 (0.0149)	0.0003* (0.0002)	0.0243* (0.0147)
$T_{mean}[21\text{--}24^{\circ}\text{C}]$	-0.0001 (0.0001)	-0.0059 (0.0081)	-0.0001 (0.0001)	-0.0087 (0.0087)
$T_{mean}[27\text{--}30^{\circ}\text{C}]$	0.0004*** (0.0001)	0.0305*** (0.0075)	0.0005*** (0.0001)	0.0445*** (0.0083)
$T_{mean}[30\text{--}33^{\circ}\text{C}]$	0.0006*** (0.0001)	0.0459*** (0.0092)	0.0006*** (0.0001)	0.0504*** (0.0102)
$T_{mean}[\geq 33^{\circ}]$	0.0007*** (0.0001)	0.0553*** (0.0108)	0.0009*** (0.0001)	0.0697*** (0.0127)
Observations	60,211	60,211	60,211	60,211
District fixed effects	Yes	Yes	Yes	Yes
Two-digit industry fixed effects	Yes	Yes	Yes	Yes

Note: the table provides estimates for the market concentration channel. All columns provide an impact of one additional day recording average daily temperature in reference to the omitted bin $[24\text{--}27^{\circ}\text{C}]$. All models include district and industry (sector) fixed effects as well as total precipitation as a control variable. The robust standard errors, clustered at the district level, are reported in parentheses. The impact of heat on market concentration measured on the basis of sales is provided in columns (1) and (2), and on the basis of employment in columns (3) and (4). Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

It is important to note that a salient feature of the ASI is that it has a non-trivial share of single-firm markets at the district–industry–year level. Therefore, we retain markets with a single operating firm in our sample to avoid endogenous sample selection as well as preserve geographic coverage. Excluding them would remove relatively smaller and spatially isolated markets, potentially biasing inference. However, we do provide a supplementary analysis in Appendix D (see Table D8), where we restrict the sample to markets with at least two firms when constructing the measures of market concentration. We find that the coefficients remain positive but are significant only for the $[27\text{--}30^{\circ}\text{C}]$ temperature bin.

6.3 Labour regulations and firms' adjustment to heat stress

Extreme heat raises the effective cost of labour by reducing productivity and increasing real labour costs (Adhvaryu et al. 2020; Somanathan et al. 2021). When firms face firing restrictions, such shocks may lead them to rely more heavily on alternative adjustment margins, including capital deepening, increased reliance on contract labour, or changes in production processes, rather than reductions in regular employment. In this way, labour regulations may amplify the impact of heat stress on labour share even when firm identity remains fixed.

We focus on the IDA, a key labour regulation in India that has received considerable attention in recent research (Bertrand et al. 2025; Colmer 2021). Under Chapter VB of the IDA, manufacturing firms employing more than 100 regular workers are required to obtain government authorization before retrenching workers, and must comply with notice periods and severance pay requirements. These provisions introduce rigidity in firms' ability to adjust their regular workforce in response to shocks. Importantly, contract workers are exempt from these restrictions, allowing regulated firms to adjust labour inputs along alternative margins.

Following Colmer (2021), we construct a dataset of state-level amendments to Chapter VB of the IDA between 1998 and 2019 and classify firms as regulated or unregulated based on employment thresholds. We estimate specifications that interact temperature exposure with an indicator for IDA regulation, allowing the temperature–labour share relationship to differ depending on regulatory status. Specifically, our regression equation is given by:

$$Y_{idt} = \alpha + \sum_{j=1, j \neq 5}^8 \beta_j T_{dt}^j + \sum_{j=1, j \neq 5}^8 \delta_j T_{dt}^j \times R_{idt} + \lambda R_{idt} + \gamma W_{dt} + \theta Z_{idt} + \varphi_i + \eta_t + \varepsilon_{idt} \quad (3)$$

where Y_{idt} denotes the dependent variable of interest, β_j captures the impact of temperature on unregulated firms, and $\beta_j + \delta_j$ captures the impact of temperature on regulated firms.

The results reported in column (1) of Table 7 indicate that extreme heat leads to a significantly larger decline in labour share among regulated firms relative to unregulated firms. These findings suggest that labour market rigidity plays an important role in shaping how firms adjust to heat stress.

Table 7: Effect of extreme heat on labour share of regulated and unregulated firms

Variables	LS (1)	log(E_f) (2)	log(E_m) (3)	log(E_c) (4)
$T_{mean}[<15^{\circ}\text{C}]$	-0.0005 (0.0044)	0.0025*** (0.0009)	-0.0001 (0.0004)	0.0002 (0.0009)
$T_{mean}[15-18^{\circ}\text{C}]$	0.0025 (0.0030)	0.0023*** (0.0006)	-0.0001 (0.0003)	0.0011* (0.0006)
$T_{mean}[18-21^{\circ}\text{C}]$	0.0007 (0.0025)	0.0012** (0.0006)	0.0003 (0.0002)	-0.0005 (0.0005)
$T_{mean}[21-24^{\circ}\text{C}]$	0.0001 (0.0014)	0.0000 (0.0003)	-0.0002 (0.0002)	0.0005 (0.0003)
$T_{mean}[27-30^{\circ}\text{C}]$	-0.0047*** (0.0017)	-0.0009*** (0.0003)	-0.0002 (0.0002)	0.0004 (0.0003)
$T_{mean}[30-33^{\circ}\text{C}]$	-0.0067*** (0.0021)	-0.0007* (0.0004)	0.0000 (0.0002)	0.0000 (0.0004)
$T_{mean}[\geq 33^{\circ}\text{C}]$	-0.0079*** (0.0030)	-0.0021*** (0.0006)	-0.0001 (0.0003)	0.0002 (0.0005)
regulation	0.6059 (0.3976)	0.8241*** (0.0795)	0.9265*** (0.0544)	0.0351 (0.0880)
$T_{mean}[< 15^{\circ}\text{C}] \times \text{regulation}$	-0.0051 (0.0033)	0.0003 (0.0006)	0.0004 (0.0005)	0.0004 (0.0008)
$T_{mean}[15-18^{\circ}\text{C}] \times \text{regulation}$	0.0147*** (0.0047)	-0.0020** (0.0009)	0.0000 (0.0006)	0.0004 (0.0010)
$T_{mean}[18-21^{\circ}\text{C}] \times \text{regulation}$	-0.0001 (0.0046)	-0.0013 (0.0011)	0.0003 (0.0005)	0.0004 (0.0007)
$T_{mean}[21-24^{\circ}\text{C}] \times \text{regulation}$	-0.0002 (0.0021)	0.0006 (0.0005)	0.0003 (0.0003)	0.0003 (0.0003)
$T_{mean}[27-30^{\circ}\text{C}] \times \text{regulation}$	0.0030 (0.0023)	0.0009** (0.0005)	0.0005 (0.0003)	-0.0001 (0.0005)
$T_{mean}[30-33^{\circ}\text{C}] \times \text{regulation}$	-0.0024 (0.0032)	-0.0004 (0.0006)	-0.0001 (0.0004)	-0.0002 (0.0005)
$T_{mean}[\geq 33^{\circ}\text{C}] \times \text{regulation}$	-0.0081* (0.0046)	0.0012 (0.0009)	0.0015*** (0.0006)	0.0002 (0.0007)
Observations	309,472	91,424	290,745	104,856
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Note: the table provides estimates for the role of labour regulation in mediating the impact of extreme heat on labour share. All columns provide an impact of one additional day recording average daily temperature in reference to the omitted bin $[24-27^{\circ}\text{C}]$. The models includes firm and year fixed effects as well as total precipitation, age of firm, and firm size classification as per ASI as control variables. The robust standard errors, clustered at the district level, are reported in parentheses. The temperature bins are interacted with a dummy variable for regulation that takes the value 1 if the firm is regulated under the IDA (1948). Column (1) provides an impact of extreme heat on labour share, whereas columns (2)–(4) provide estimates for logarithm of regular female workers, regular male workers, and contract workers, respectively. * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Finally, we document heterogeneity in employment responses across worker types that is consistent with differential adjustment margins under labour regulation (columns (2)–(4) of Table 7). Heat stress reduces the employment of regular female workers in unregulated firms while having no significant effect in regulated firms. In contrast, regulated firms experience an increase in the employment of regular male workers in response to extreme heat, with no corresponding effect among unregulated firms. These patterns are consistent with firms reallocating labour inputs within the constraints imposed by regulation, in line with the findings of Colmer

(2021) and Bertrand et al. (2025).

7 Projected impacts on labour share under warming scenarios

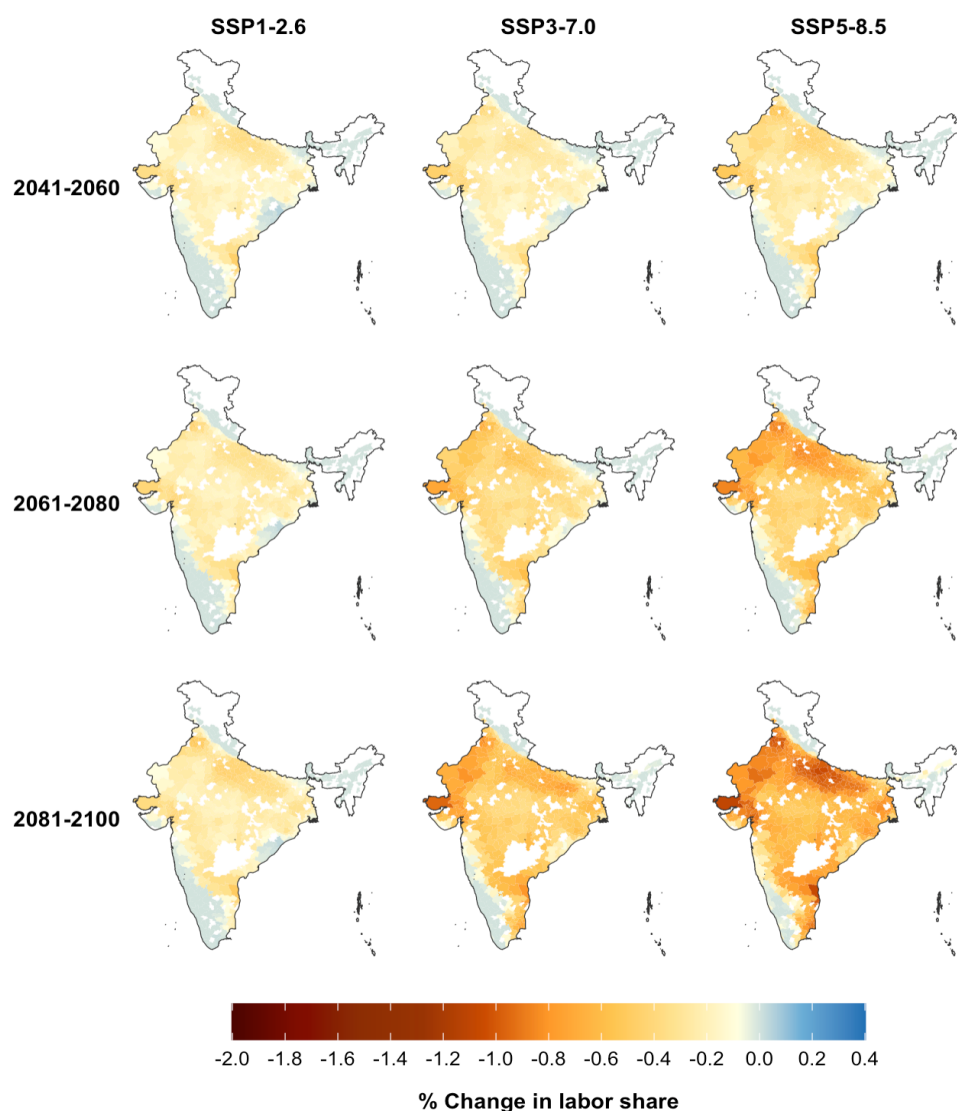
This section reports the projected percentage change in annual labour share under the following scenarios: (1) low emissions—SSP1-2.6, (2) medium emissions—SSP3-7.0, and (3) high emissions—SSP5-8.5. The bias-corrected statistically downscaled ($0.5^\circ \times 0.5^\circ$) climate-input datasets are obtained from ISIMIP3b for five global climate models (GCMs): GFDL-ESM4, IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL. We use the estimated historical labour share–temperature relationship from our baseline model in Eq. (1) and climate forecasts for the baseline (1995–2015), short run (2041–60), medium run (2061–80), and long run (2081–2100). To calculate the projected impacts, we first construct average daily temperature bins (3°C increment) for these years, following the method described above. Then, the difference in the historical estimates using the 1998–2019 data and the out-of-sample projected impacts provides the impacts of a warming climate on labour share.

The results of the assessment undertaken using climate projections from the global climate model (GFDL-ESM4) are summarized in Table 8 and visualized in Figure 7. We find that in comparison to the historical estimates (1998–2019), the labour share is expected to further decline in the largest two temperature bins ($30\text{--}33^\circ\text{C}$ and $\geq 33^\circ\text{C}$). The analysis shows that the labour share will decline between -0.15% and -0.19% under the low-emissions scenario (SSP1-2.6) and between -0.15% and -0.40% under the medium-emissions scenario (SSP3-7.0) for average daily temperature above 33°C . The labour share is likely to experience the largest decline under the high-emissions scenario (SSP8-5.8), between -0.21% and -0.57% . The projected impacts for the average daily temperature $< 15^\circ\text{C}$ show positive impacts on labour share, indicating that the labour share will increase for lower temperatures as compared to the baseline. Figure 7 provides the spatial distribution of the projected impacts of extreme heat on labour share, emphasizing the existence of heterogeneity across the districts in India. The projected impacts calculated using climate projections data from the remaining global climate models (IPSL-CM6A-LR, MPI-ESM1-2-HR, MRI-ESM2-0, and UKESM1-0-LL) are presented in Appendix D (Tables D9–D12 and Figures D1–D4).

Table 8: Projected impacts of climate change on labour share, using climate projections data from the global climate model GFDL-ESM4

Bin	SSP1-2.6			SSP3-7.0			SSP5-8.5		
	2041–060	2061–80	2081–2100	2041–60	2061–80	2081–2100	2041–60	2061–80	2081–2100
$T_{mean}[\leq 15^{\circ}\text{C})$	0.007	0.007	0.006	0.008	0.011	0.013	0.009	0.012	0.014
$T_{mean}[15\text{--}18^{\circ}\text{C})$	−0.003	−0.002	0.000	−0.009	−0.040	−0.054	−0.015	−0.045	−0.067
$T_{mean}[18\text{--}21^{\circ}\text{C})$	0.000	0.001	−0.001	−0.001	−0.002	−0.004	0.000	−0.004	−0.006
$T_{mean}[21\text{--}24^{\circ}\text{C})$	−0.003	−0.003	−0.003	−0.003	−0.003	−0.004	−0.003	−0.003	−0.004
$T_{mean}[27\text{--}30^{\circ}\text{C})$	−0.079	−0.095	−0.087	−0.097	−0.097	−0.065	−0.073	−0.059	−0.035
$T_{mean}[30\text{--}33^{\circ}\text{C})$	−0.161	−0.166	−0.183	−0.178	−0.289	−0.388	−0.197	−0.320	−0.395
$T_{mean}[\geq 33^{\circ}\text{C})$	−0.149	−0.170	−0.194	−0.150	−0.273	−0.403	−0.207	−0.409	−0.568

Figure 7: Projected change in labour share using climate projections data



Note: the figure plots projected change in labour share using climate projections data from the global climate model GFDL-ESM4 for the largest temperature bin $\geq 33^{\circ}\text{C}$. Reported are the projected analogues for the short run (2041–60), medium run (2061–80), and long run (2081–2100) under three warming scenarios: low emissions (SSP1-2.6), medium emissions (SSP3-7.0), and high emissions (SSP5-8.5). The maps are generated in R, using a shapefile provided by the Survey of India, Ministry of Science and Technology, India, at http://onlinemaps.surveyofindia.gov.in/Digital_Product_Show.aspx.

Source: authors' calculation using ISIMIP data and estimated change in labour share (%).

Note, the calculations provided in this section are built on the existing evidence on projected impacts (Dasgupta et al. 2021; Somanathan et al. 2021; Zhang et al. 2024, 2018) and are based on a few assumptions that are limiting in certain aspects. First, our analysis does not incorporate changes in firms' location decisions in response to climate change and assume that firms' locations remain constant throughout the assessment period. Second, we do not account for the role of potential adaptation strategies that might be implemented to mitigate the impacts of climate change. Finally, our calculations are based on 1998–2019 estimates under

an assumption that the relationship between labour share and temperature remains constant over time.

8 Conclusion

Climate change poses growing risks to the labour force, particularly in developing economies where workers are highly exposed to extreme heat. In this paper, using firm-level panel data combined with high-resolution weather data, we provide evidence that extreme heat significantly reduces the labour share in Indian manufacturing. We show that this decline reflects a combination of production adjustments towards capital, changes in competitive conditions that increase firms' market power, and the role of labour regulations in shaping firms' responses to heat-induced productivity shocks. Finally, our projections indicate that continued warming is likely to further depress labour share, with heterogeneous impacts across regions. Taken together, our findings highlight climate change as an important driver of distributional impacts in developing economies.

These findings carry important policy implications. As climate change intensifies, extreme heat is likely to become a persistent feature of the production environment, requiring both firms and workers to adapt. Our results suggest that firms respond to heat-induced productivity shocks not only through reduced labour demand, but through changes in production structure—particularly increased capital intensity and shifts towards more flexible forms of employment. In this context, policies that enhance workplace resilience—such as investments in cooling technologies and enforcement of occupational safety standards—can help mitigate productivity losses at the source. At the same time, the distributional consequences of firm-level adjustments call for complementary policies that protect vulnerable workers. Strengthening social protection, improving access to stable employment contracts, and addressing gender-specific constraints in labour markets will be critical to prevent further widening of inequality. Finally, the heterogeneous projected impacts indicate that labour policies should focus not only on adequate training of workers but also reduce frictions in reallocation of labour, allowing for inter- and intra-sectoral mobility of workers and enhancing their adaptability.

More broadly, our findings highlight the need to integrate climate risks into industrial and labour policy. Facilitating adaptation should not come at the cost of disproportionately shifting the burden onto labour. Designing policies that balance firms' need to adjust with protections for workers will be essential to sustain inclusive growth in increasingly warmer economies.

References

- Acemoglu, D., and Restrepo, P. (2018). 'The Race Between Man and Machine: Implications of Technology for Growth, Factor Shares, and Employment'. *American Economic Review*, 108(6): 1488–542. <https://doi.org/10.1257/aer.20160696>
- Adhvaryu, A., Kala, N., and Nyshadham, A. (2020). 'The Light and the Heat: Productivity Co-benefits of Energy-Saving Technology'. *Review of Economics and Statistics*, 102(4): 779–92. https://doi.org/10.1162/rest_a_00886
- Aghion, P., Burgess, R., Redding, S.J., and Zilibotti, F. (2008). 'The Unequal Effects of Liberalization: Evidence from Dismantling the License Raj in India'. *American Economic Review*, 98(4): 1397–412. <https://doi.org/10.1257/aer.98.4.1397>
- Allcott, H., Collard-Wexler, A., and O'Connell, S.D. (2016). 'How Do Electricity Shortages Affect Industry? Evidence from India'. *American Economic Review*, 106(3): 587–624. <https://doi.org/10.1257/aer.20140389>
- Anderson, G.B., Bell, M.L., and Peng, R.D. (2013). 'Methods to Calculate the Heat Index as an Exposure Metric in Environmental Health Research'. *Environmental Health Perspectives*, 121(10): 1111–19. <https://doi.org/10.1289/ehp.1206273>
- Autor, D., Dorn, D., Katz, L.F., Patterson, C., and Van Reenen, J. (2017). 'Concentrating on the Fall of the Labor Share'. *American Economic Review*, 107(5): 180–85. <https://doi.org/10.1257/aer.p20171102>
- Autor, D., Dorn, D., Katz, L.F., Patterson, C., and Van Reenen, J. (2020). 'The Fall of the Labor Share and the Rise of Superstar Firms'. *Quarterly Journal of Economics*, 135(2): 645–709. <https://doi.org/10.1093/qje/qjaa004>
- Barreca, A., Clay, K., Deschenes, O., Greenstone, M., and Shapiro, J.S. (2016). 'Adapting to Climate Change: The Remarkable Decline in the US Temperature–Mortality Relationship Over the Twentieth Century'. *Journal of Political Economy*, 124(1): 105–59. <https://doi.org/10.1086/684582>
- Basu, A., and Veeramani, C. (2021). *Labour Share in Indian Economy: An Exploratory Analysis of the Role of Trade, Technology and Structural Transformation*. Mumbai: Indira Gandhi Institute of Development Research.
- Basu, A.K., Chau, N.H., and Soundararajan, V. (2021). 'Contract Employment as a Worker Discipline Device'. *Journal of Development Economics*, 149: 102601. <https://doi.org/10.1016/j.jdeveco.2020.102601>
- Bentolila, S., and Saint-Paul, G. (2003). 'Explaining Movements in the Labor Share'. *The B.E. Journal of Macroeconomics*, 3(1): 1–33. <https://doi.org/10.2202/1534-6005.1103>
- Bertrand, M., Hsieh, C.-T., and Tsivanidis, N. (2025). 'Contract Labor and Establishment Growth in India'. *Econometrica*, 93(4): 1411–48. <https://doi.org/10.3982/ECTA20046>

- Besley, T., and Burgess, R. (2004). 'Can Labor Regulation Hinder Economic Performance? Evidence from India'. *Quarterly Journal of Economics*, 119(1): 91–134. <https://doi.org/10.1162/003355304772839533>
- Bolton, D. (1980). 'The Computation of Equivalent Potential Temperature'. *Monthly Weather Review*, 108(7): 1046–53. [https://doi.org/10.1175/1520-0493\(1980\)108<1046:TCOEPT>2.0.CO;2](https://doi.org/10.1175/1520-0493(1980)108<1046:TCOEPT>2.0.CO;2)
- Buontempo, C., Burgess, S.N., Dee, D., et al. (2022). 'The Copernicus Climate Change Service: Climate Science in Action'. *Bulletin of the American Meteorological Society*, 103(12): E2669–87. <https://doi.org/10.1175/BAMS-D-21-0315.1>
- Burke, M., Hsiang, S.M., and Miguel, E. (2015). 'Global Non-linear Effect of Temperature on Economic Production'. *Nature*, 527(7577): 235–39. <https://doi.org/10.1038/nature15725>
- CEOP (2013). 'CEOP Derived Parameter Equations'. Coordinated Energy and Water Cycle Observation Project. Available at: <https://www.cen.uni-hamburg.de/en/icdc/data/atmosphere/docs-atmo/ceop-derived-parameter-equations.pdf> (accessed 28 July 2026).
- Chakraborty, P., Singh, R., and Soundararajan, V. (2024). 'Import Competition, Formalization, and the Role of Contract Labor'. *The World Bank Economic Review*, 38(4): 741–71. <https://doi.org/10.1596/42355>
- Chaurey, R. (2015). 'Labor Regulations and Contract Labor Use: Evidence from Indian Firms'. *Journal of Development Economics*, 114: 224–32. <https://doi.org/10.1016/j.jdeveco.2014.12.008>
- Chen, X., and Yang, L. (2019). 'Temperature and Industrial Output: Firm-Level Evidence from China'. *Journal of Environmental Economics and Management*, 95: 257–74. <https://doi.org/10.1016/j.jeem.2017.07.009>
- Chen, X., Lin, Y., and Zhu, P. (2025). 'The Impact of Rainfall on Productivity: Implications for Chinese Manufacturing'. *Journal of Comparative Economics*, 53(2): 389–411. <https://doi.org/10.1016/j.jce.2025.03.005>
- Chiplunkar, G., Chaurey, R., and Soundararajan, V. (2024). 'Employment Protection Legislation and Informality: Theory and Evidence from India'. SSRN. Available at https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4204033 (accessed 28 July 2026).
- Colmer, J. (2021). 'Temperature, Labor Reallocation, and Industrial Production: Evidence from India'. *American Economic Journal: Applied Economics*, 13(4): 101–24. <https://doi.org/10.1257/app.20190249>
- Conley, T.G. (2010). 'Spatial Econometrics'. In Durlauf, S.N., and Blume, L.E. (eds), *Microeconometrics*. London: Palgrave Macmillan. https://doi.org/10.1057/9780230280816_33
- Dasgupta, S., van Maanen, N., Gosling, S., Piontek, F., Otto, C., and Schleussner, C.-F. (2021). 'Effects of Climate Change on Combined Labour Productivity and Supply: An Empirical, Multi-Model Study'. *The Lancet Planetary Health*, 5(7): e455–65. [https://doi.org/10.1016/S2542-5196\(21\)00170-4](https://doi.org/10.1016/S2542-5196(21)00170-4)

- Dell, M., Jones, B.F., and Olken, B.A. (2014). 'What Do We Learn from the Weather? The New Climate–Economy Literature'. *Journal of Economic Literature*, 52(3): 740–98. <https://doi.org/10.1257/jel.52.3.740>
- Deschênes, O. (2014). 'Temperature, Human Health, and Adaptation: A Review of the Empirical Literature'. *Energy Economics*, 46: 606–19. <https://doi.org/10.1016/j.eneco.2013.10.013>
- Dutta Roy, S. (2004). 'Employment Dynamics in Indian Industry: Adjustment Lags and the Impact of Job Security Regulations'. *Journal of Development Economics*, 73(1): 233–56. <https://doi.org/10.1016/j.jdeveco.2003.01.003>
- Elsby, M.W., Hobijn, B., and Şahin, A. (2013). 'The Decline of the US Labor Share'. *Brookings Papers on Economic Activity*, 2013(2): 1–63. <https://doi.org/10.1353/eca.2013.0016>
- Fallon, P.R., and Lucas, R.E. (1993). 'Job Security Regulations and the Dynamic Demand for Industrial Labor in India and Zimbabwe'. *Journal of Development Economics*, 40(2): 241–75. [https://doi.org/10.1016/0304-3878\(93\)90085-2](https://doi.org/10.1016/0304-3878(93)90085-2)
- Ghani, S.E., Kerr, W., and Segura, A. (2015). 'Informal Tradables and the Employment Growth of Indian Manufacturing'. World Bank Policy Research Working Paper 7206. Washington, DC: World Bank.
- Goldar, B., Pradhan, B.K., and Sharma, A.K. (2013). 'Elasticity of Substitution Between Capital and Labour Inputs in Manufacturing Industries of the Indian Economy'. *Journal of Industrial Statistics*, 2(2): 169–94.
- Graff Zivin, J., and Neidell, M. (2014). 'Temperature and the Allocation of Time: Implications for Climate Change'. *Journal of Labor Economics*, 32(1): 1–26. <https://doi.org/10.1086/671766>
- Grossman, G.M., and Oberfield, E. (2022). 'The Elusive Explanation for the Declining Labor Share'. *Annual Review of Economics*, 14(1): 93–124. <https://doi.org/10.1146/annurev-economics-080921-103046>
- Gujarati, D. (1966). 'A Test of ACMS Production Function: Indian Industries, 1958'. *Indian Journal of Industrial Relations*, 2(1): 95–97.
- Hasan, R., Mitra, D., and Ramaswamy, K.V. (2007). 'Trade Reforms, Labor Regulations, and Labor-Demand Elasticities: Empirical Evidence from India'. *The Review of Economics and Statistics*, 89(3): 466–81. <https://doi.org/10.1162/rest.89.3.466>
- Intergovernmental Panel on Climate Change (2021). *Climate Change 2021: The Physical Science Basis*. Cambridge: Cambridge University Press.
- International Labour Organization (2019). *Working on a Warmer Planet: The Impact of Heat Stress on Labour Productivity and Decent Work*. Geneva: International Labour Organization.
- Jha, R. (2024). 'Industry Dynamics and Income Distribution: An Exploratory Analysis of India's Manufacturing Sector'. SSRN. Available at: https://papers.ssrn.com/sol3/papers.cfm?abstract_id=4901332 (accessed 28 July 2026).

- Kalkuhl, M., and Wenz, L. (2020). 'The Impact of Climate Conditions on Economic Production: Evidence from a Global Panel of Regions'. *Journal of Environmental Economics and Management*, 103: 102360. <https://doi.org/10.1016/j.jeem.2020.102360>
- Karabarbounis, L., and Neiman, B. (2014). 'The Global Decline of the Labor Share'. *The Quarterly Journal of Economics*, 129(1): 61–103. <https://doi.org/10.1093/qje/qjt032>
- Kjellstrom, T., Kovats, R.S., Lloyd, S.J., Holt, T., and Tol, R.S. (2009). 'The Direct Impact of Climate Change on Regional Labor Productivity'. *Archives of Environmental & Occupational Health*, 64(4): 217–27. <https://doi.org/10.1080/19338240903352776>
- Leblebicioğlu, A., and Weinberger, A. (2021). 'Openness and Factor Shares: Is Globalization Always Bad for Labor?' *Journal of International Economics*, 128: 103406. <https://doi.org/10.1016/j.jinteco.2020.103406>
- Lemke, B., and Kjellstrom, T. (2012). 'Calculating Workplace WBGT from Meteorological Data: A Tool for Climate Change Assessment'. *Industrial Health*, 50(4): 267–78. <https://doi.org/10.2486/indhealth.MS1352>
- Lyu, Z., Yu, L., Liu, C., and Ma, T. (2024). 'When Temperatures Matter: Extreme Heat and Labor Share'. *Energy Economics*, 138: 107811. <https://doi.org/10.1016/j.eneco.2024.107811>
- Mendelsohn, R., Nordhaus, W.D., and Shaw, D. (1994). 'The Impact of Global Warming on Agriculture: A Ricardian Analysis'. *The American Economic Review*, 84(4): 753–71.
- Ministry of Statistics and Programme Implementation, Government of India (2023). 'Annual Survey of Industries'. New Delhi: MOSPI.
- Mutreja, P., Ravikumar, B., and Sposi, M. (2018). 'Capital Goods Trade, Relative Prices, and Economic Development'. *Review of Economic Dynamics*, 27: 101–22. <https://doi.org/10.1016/j.red.2017.11.003>
- Pankratz, N., Bauer, R., and Derwall, J. (2023). 'Climate Change, Firm Performance, and Investor Surprises'. *Management Science*, 69(12): 7352–98. <https://doi.org/10.1287/mnsc.2023.4685>
- Park, R.J., Pankratz, N., and Behrer, A.P. (2021). 'Temperature, Workplace Safety, and Labor Market Inequality'. Discussion Paper 14560. Bonn: IZA. <https://doi.org/10.2139/ssrn.3892588>
- Patz, J.A., Campbell-Lendrum, D., Holloway, T., and Foley, J.A. (2005). 'Impact of Regional Climate Change on Human Health'. *Nature*, 438(7066): 310–17. <https://doi.org/10.1038/nature04188>
- Ponticelli, J., Xu, Q., and Zeume, S. (2023). 'Temperature, Adaptation and Local Industry Concentration'. NBER Working Paper 31533. Cambridge, MA: National Bureau of Economic Research. <https://doi.org/10.3386/w31533>
- Qiu, X., and Yoshida, M. (2024). 'Climate Change and the Decline of Labor Share'. Discussion Paper 17485. Bonn: IZA. <https://doi.org/10.2139/ssrn.5041931>

- Rehdanz, K., and Maddison, D. (2005). 'Climate and Happiness'. *Ecological Economics*, 52(1): 111–25. <https://doi.org/10.1016/j.ecolecon.2004.06.015>
- Saha, B., Sen, K., and Maiti, D. (2013). 'Trade Openness, Labour Institutions and Flexibilisation: Theory and Evidence from India'. *Labour Economics*, 24: 180–95. <https://doi.org/10.1016/j.labeco.2013.08.008>
- Sankar, U. (1970). 'Elasticities of Substitution and Returns to Scale in Indian Manufacturing Industries'. *International Economic Review*, 11(3): 399–411. <https://doi.org/10.2307/2525320>
- Schlenker, W., Michael Hanemann, W., and Fisher, A.C. (2005). 'Will US Agriculture Really Benefit from Global Warming? Accounting for Irrigation in the Hedonic Approach'. *American Economic Review*, 95(1): 395–406. <https://doi.org/10.1257/0002828053828455>
- Somanathan, E., Somanathan, R., Sudarshan, A., and Tewari, M. (2021). 'The Impact of Temperature on Productivity and Labor Supply: Evidence from Indian Manufacturing'. *Journal of Political Economy*, 129(6): 1797–827. <https://doi.org/10.1086/713733>
- Soundararajan, V. (2019). 'Heterogeneous Effects of Imperfectly Enforced Minimum Wages in Low-Wage Labor Markets'. *Journal of Development Economics*, 140: 355–74. <https://doi.org/10.1016/j.jdeveco.2019.06.010>
- Tang, W., Yang, M., and Duan, H. (2023). 'Temperature and Corporate Tax Avoidance: Evidence from Chinese Manufacturing Firms'. *Energy Economics*, 117: 106486. <https://doi.org/10.1016/j.eneco.2022.106486>
- Upender, M (2009). 'Elasticity of Substitution Between Labour and Capital Across Twenty Six Major Industries in India During 2004–05'. *International Journal of Applied Econometrics and Quantitative Studies*, 6(1): 101–11.
- Zhang, J., Malikov, E., and Miao, R. (2024). 'Distributional Effects of the Increasing Heat Incidence on Labor Productivity'. *Journal of Environmental Economics and Management*, 125: 102998. <https://doi.org/10.1016/j.jeem.2024.102998>
- Zhang, P., Deschenes, O., Meng, K., and Zhang, J. (2018). 'Temperature Effects on Productivity and Factor Reallocation: Evidence from a Half Million Chinese Manufacturing Plants'. *Journal of Environmental Economics and Management*, 88: 1–17. <https://doi.org/10.1016/j.jeem.2017.11.001>
- Zivin, J.G., Song, Y., Tang, Q., and Zhang, P. (2020). 'Temperature and High-Stakes Cognitive Performance: Evidence from the National College Entrance Examination in China'. *Journal of Environmental Economics and Management*, 104: 102365. <https://doi.org/10.1016/j.jeem.2020.102365>

Appendix A: Annual Survey of Industries

A1 Data matching to generate ASI panel

In this section, we discuss the data matching methodology followed to construct a 22-year panel dataset from the ASI, received from the Ministry of Statistics and Programme Implementation, Government of India (2023). Keeping in mind the suitability and availability of the key variables of interest, we utilize the data between the financial years 1998–99 and 2019–20. The ASI data is available in two versions. The cross-section version, freely available at MOSPI's National Data Archive, provides 'district identifiers' of firms between 1998 and 2009 but no 'firm identifiers'. This prevents the user identifying firms uniformly across all the years. On the other hand, the restricted panel data received from MOSPI provides 'firm identifiers' for all the years but not 'district identifiers', which disables matching climate data to survey data.

For the years 1998–2009, we merge the versions using a unique matching methodology provided by Allcott et al. (2016) and Somanathan et al. (2021) and obtain location information of firms. To compute this matching, we concatenate a string using firm characteristics to generate a unique ID using the following firm characteristics: year of initial production, size classification (as per ASI), the five-digit NIC code, state location, rural/urban location, number of units owned, status of units, type of organization, ownership, and operational months. This provides location codes for most of the firm–year observations between 1998 and 2009. Further, we search for additional matches in each of these years individually because firms are not necessarily surveyed every year. As a second step, we obtain the location identifiers of firms between 2010 and 2019 using firm identifiers. At this stage, the dataset contains 1,050,055 firm–year observations, covering 306,942 firms. Out of this sample, we keep only 250,945 'operational' firms in the dataset, covering 899,005 firm–year observations.

A2 Data cleaning

We have undertaken some additional data cleaning steps to obtain our final dataset as follows:

1. Duplicates: At the data matching stage, a few duplicate firm identifiers are found in some years. These are dropped to avoid interruption in the data matching process.

2. Missing location identifiers: We keep only those firm–year observations in the sample where location identifiers could be matched. Around 237,979 firm–year observations are dropped with missing location identifiers. Note that Telangana was formed as a new state in 2014 and district codes provided by the ASI dataset are available up to 2009, which makes identification of districts under the jurisdiction of Telangana difficult. We drop 8,664 firm–year observations from the sample located in the state of Telangana.

3. Standardization of state codes, district codes, and NIC codes: We standardized the names of all states and districts as per the Census data and shapefile provided by Survey of India to incorporate changes in district and state boundaries between the study years. Further, the dataset provides the NIC codes for firms. The NIC codes were revised in 1998, 2004, and 2008. To have a uniform industrial classification throughout the analysis, we standardized the NIC codes for the years 1998–2007 in concordance with NIC 2008 using the information provided by MOSPI.

4. We drop 11,660 firm–year observations that report year of initial production (a proxy for age of firms) below 1900, above 2020, or greater than the current financial year.

5. Following Somanathan et al. (2021), we drop observations where the value of capital, sales, total inputs, workers, work days, wages, and total output are reported either missing, negative, or equal to zero. Similarly, we also drop a small number of implausible values reported for total wages (less than US\$300 per year), workers (over 10,000 workers in a factory), total capital (less than US\$2), and total sales (less than US\$250).

6. We drop a few observations where the labour share is either less than 0 or greater than 1.

7. We drop firm–year observations that reported industrial codes for non-manufacturing sectors. There were around 9,039 such firm–year observations.

8. We drop firms that are not surveyed at least twice.

9. We drop firms that report relocation from one district to another over time. This was done to prevent significant errors when assigning temperature data to these firms. The final dataset consists of 309,472 firm–year observations.

Appendix B: Heat Index (NOAA)

The Heat Index is calculated using the following formula provided by NOAA:

$$\begin{aligned} HI = & -42.379 + 2.04901523 T + 10.14333127 RH \\ & - 0.22475541 TRH \\ & - 0.00683783 T^2 - 0.05481717 RH^2 \\ & + 0.00122874 T^2 RH \\ & + 0.00085282 TRH^2 \\ & - 0.00000199 T^2 RH^2 \end{aligned} \tag{4}$$

where T is the hourly surface air temperature ($^{\circ}\text{C}$) and RH is the hourly relative humidity (%).

This formula is provided by NOAA and utilizes surface air temperature and relative humidity data to calculate the Heat Index. We use climate data from the ERA5-Land dataset provided by the ECMWF. Calculation of the Heat Index is done in R using the ‘weathermetrics’ package developed by Anderson et al. (2013), which provides an algorithm based on NOAA’s formula.

Appendix C: Wet-Bulb Globe Temperature

The Wet-Bulb Globe Temperature (WBGT) is measured using instruments such as a wetted thermometer, incorporating certain weather conditions. However, it can be approximated using empirically derived formulas that combine surface air temperature and relative humidity. We use the WBGT formula for indoor conditions, provided by Lemke and Kjellstrom (2012), as follows:

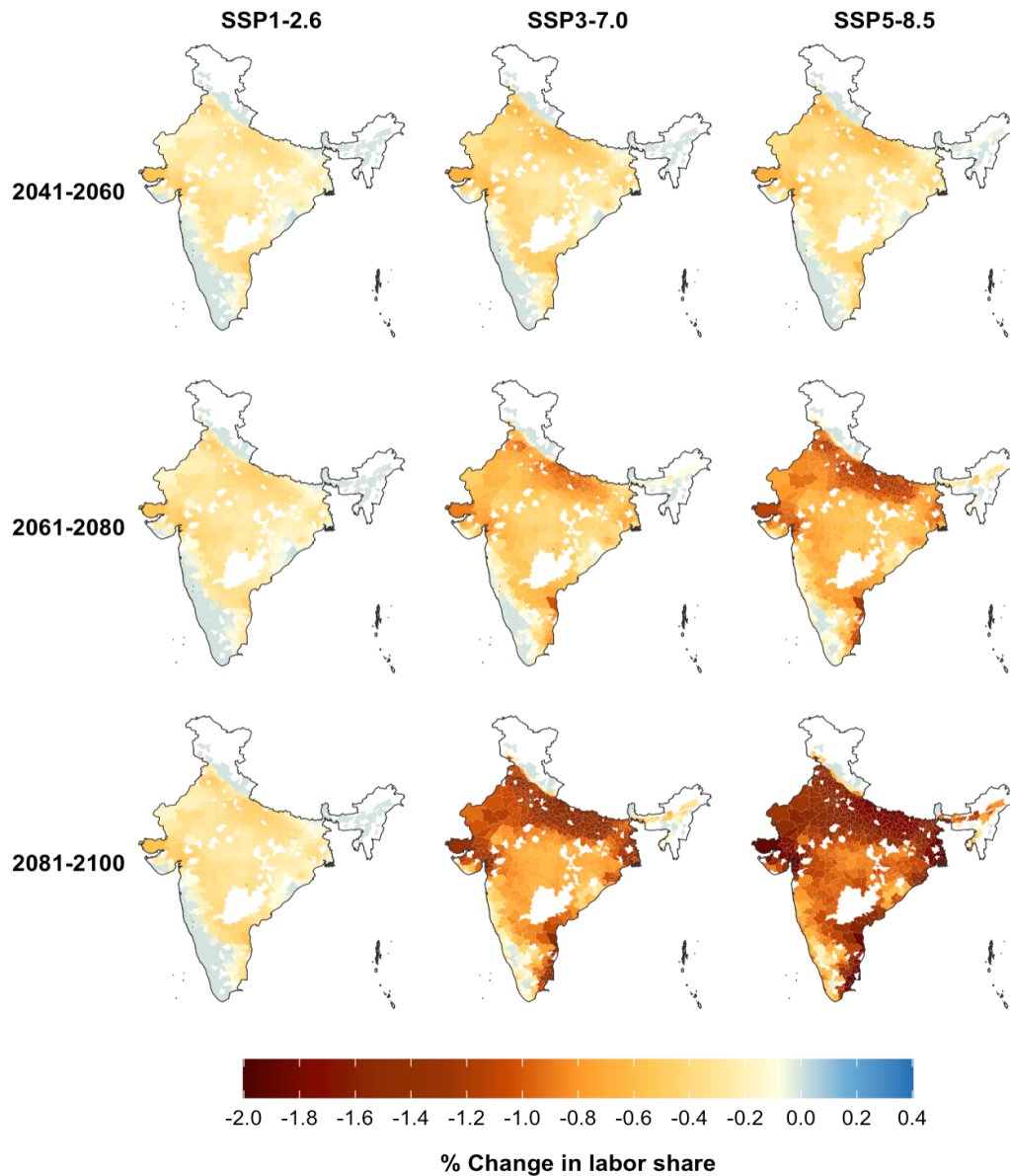
$$WBGT = 0.567T + 0.216\rho + 3.38 \quad (5)$$

where T is the hourly surface air temperature ($^{\circ}\text{C}$) and ρ is the water vapour pressure, which is calculated using relative humidity (RH) as follows:

$$\rho = \left(\frac{RH}{100} \right) \times 6.105 \exp \left(\frac{17.27 T}{237.7 + T} \right) \quad (6)$$

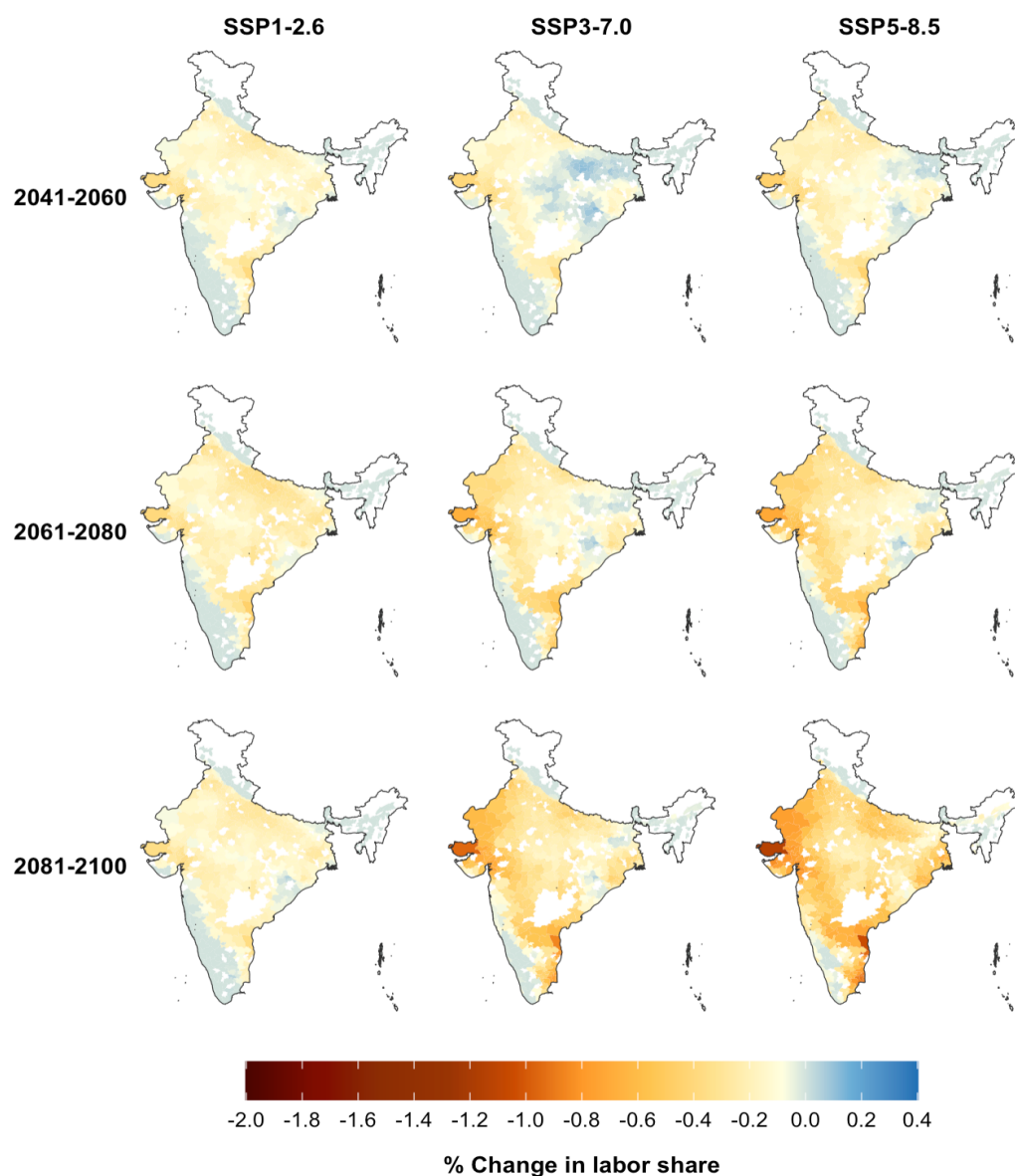
Appendix D: Additional tables and figures

Figure D1: Projected change in labour share using climate projections data from the global climate model IPSL-CM6A-LR for the largest temperature bin ($\geq 33^{\circ}\text{C}$)



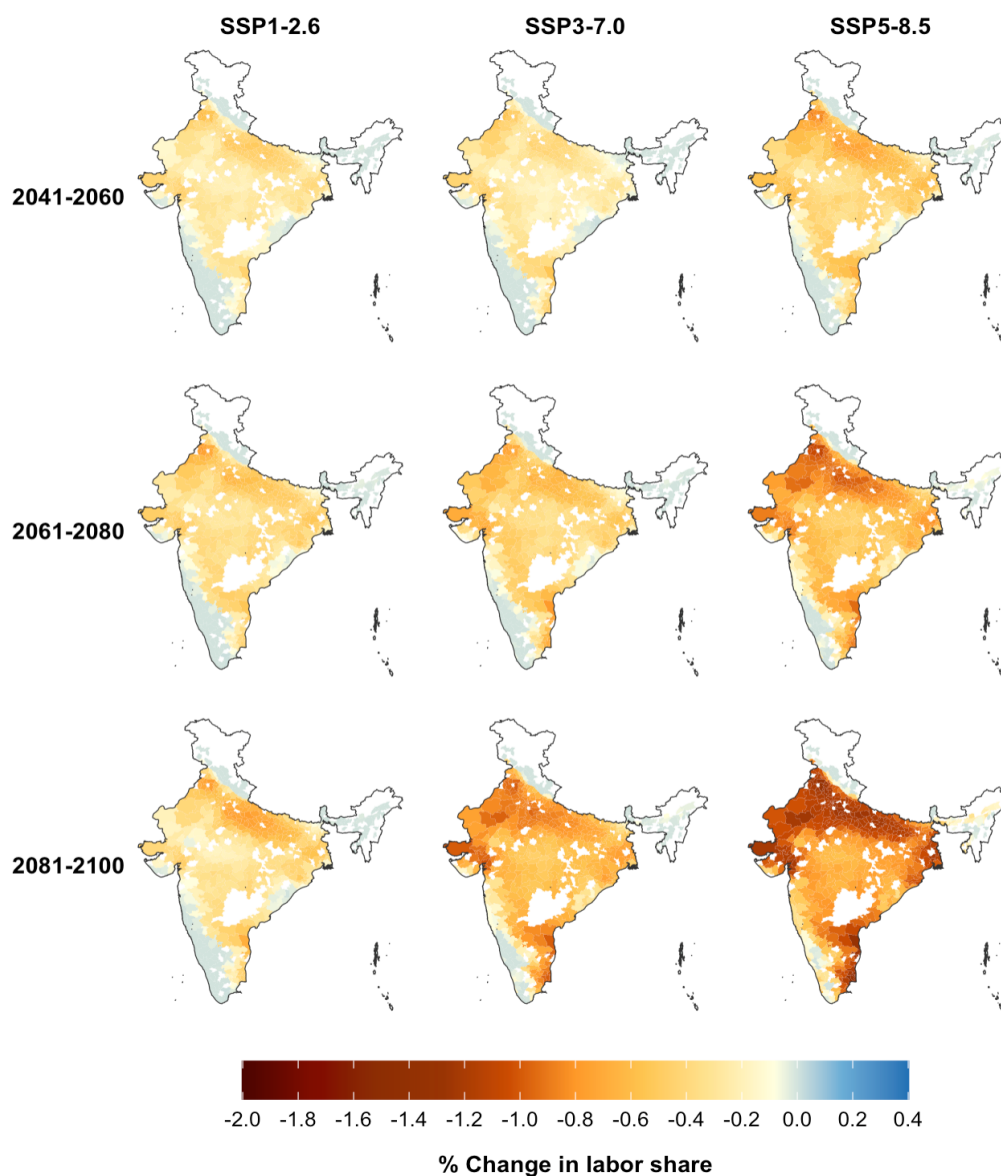
Note: reported are the projected analogues for the short run (2041–60), medium run (2061–80), and long run (2081–2100) under three warming scenarios: low emissions (SSP1-2.6), medium emissions (SSP3-7.0), and high emissions (SSP5-8.5). The maps are generated in R, using a shapefile provided by the Survey of India, Ministry of Science and Technology, India, at http://onlinemaps.surveyofindia.gov.in/Digital_Product_Show.aspx. Source: authors' calculation using ISIMIP data and estimated change in labour share (%).

Figure D2: Projected change in labour share using climate projections data from the global climate model MPI-ESM1-2-HR for the largest temperature bin ($\geq 33^{\circ}\text{C}$)



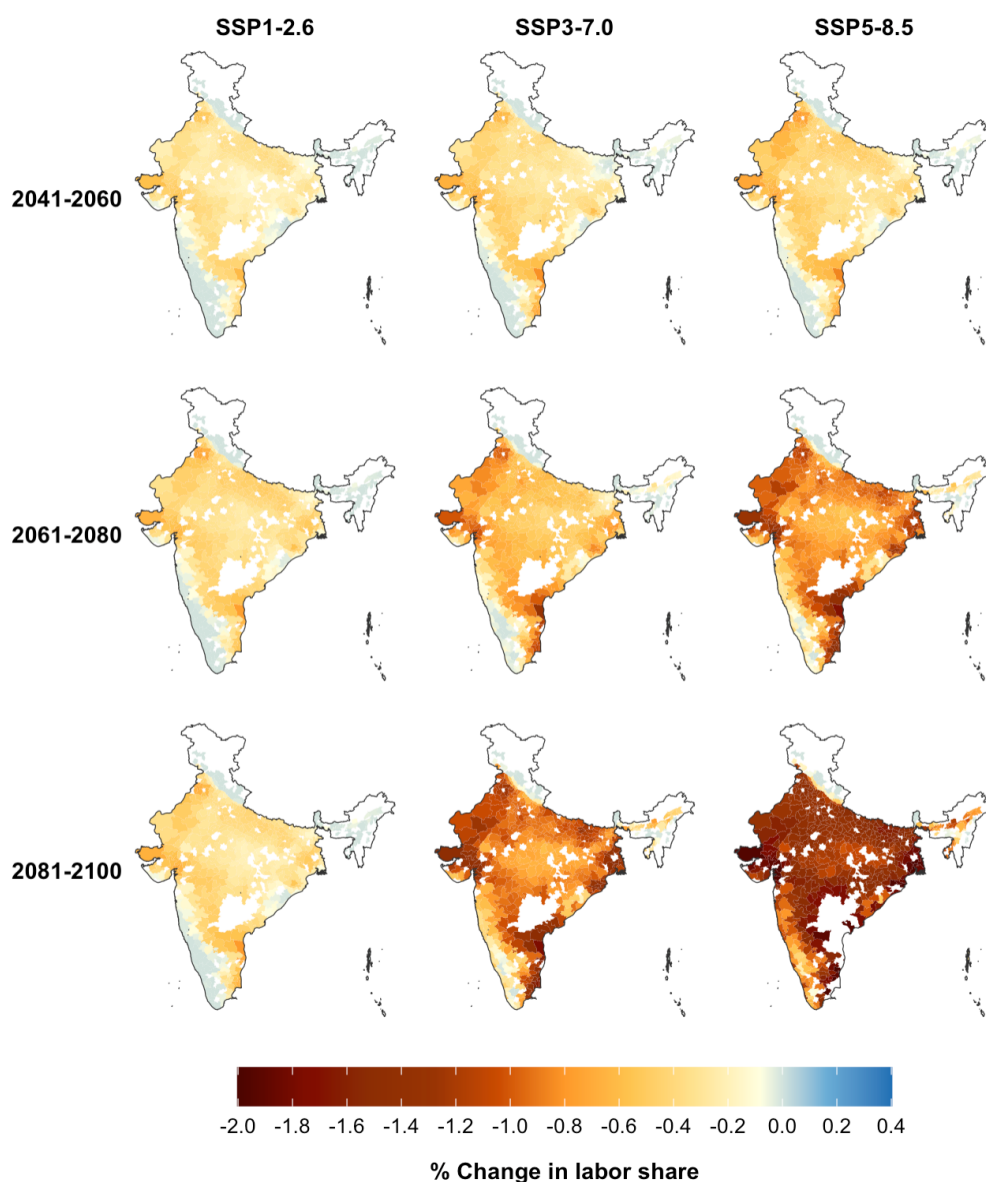
Note: reported are the projected analogues for the short run (2041–60), medium run (2061–80), and long run (2081–2100) under three warming scenarios: low emissions (SSP1-2.6), medium emissions (SSP3-7.0), and high emissions (SSP5-8.5). The maps are generated in R, using a shapefile provided by the Survey of India, Ministry of Science and Technology, India, at http://onlinemaps.surveyofindia.gov.in/Digital_Product_Show.aspx. Source: authors' calculation using ISIMIP data and estimated change in labour share (%).

Figure D3: Projected change in labour share using climate projections data from the global climate model MRI-ESM2-0 for the largest temperature bin ($\geq 33^{\circ}\text{C}$)



Note: reported are the projected analogues for the short run (2041–60), medium run (2061–80), and long run (2081–2100) under three warming scenarios: low emissions (SSP1-2.6), medium emissions (SSP3-7.0), and high emissions (SSP5-8.5). The maps are generated in R, using a shapefile provided by the Survey of India, Ministry of Science and Technology, India, at http://onlinemaps.surveyofindia.gov.in/Digital_Product_Show.aspx. Source: authors' calculation using ISIMIP data and estimated change in labour share (%).

Figure D4: Projected change in labour share using climate projections data from the global climate model UKESM1-0-LL for the largest temperature bin ($\geq 33^{\circ}\text{C}$)



Note: reported are the projected analogues for the short run (2041–60), medium run (2061–80), and long run (2081–2100) under three warming scenarios: low emissions (SSP1-2.6), medium emissions (SSP3-7.0), and high emissions (SSP5-8.5). The maps are generated in R, using a shapefile provided by the Survey of India, Ministry of Science and Technology, India, at http://onlinemaps.surveyofindia.gov.in/Digital_Product_Show.aspx. Source: authors' calculation using ISIMIP data and estimated change in labour share (%).

Table D1: Effect of extreme heat on labour share, robustness to alternative levels of clustering

Variables	(1)	(2)	(3)	(4)	(5)
$T_{mean}[<15^{\circ}\text{C}]$	-0.0009 (0.0044)	-0.0009 (0.0034)	-0.0009 (0.0049)	-0.0009 (0.0039)	-0.0009 (0.0041)
$T_{mean}[15-18^{\circ}\text{C}]$	0.0052* (0.0028)	0.0052** (0.0026)	0.0052 (0.0034)	0.0052** (0.0025)	0.0052* (0.0030)
$T_{mean}[18-21^{\circ}\text{C}]$	0.0008 (0.0023)	0.0008 (0.0020)	0.0008 (0.0019)	0.0008 (0.0023)	0.0008 (0.0025)
$T_{mean}[21-24^{\circ}\text{C}]$	0.0002 (0.0013)	0.0002 (0.0012)	0.0002 (0.0016)	0.0002 (0.0010)	0.0002 (0.0013)
$T_{mean}[27-30^{\circ}\text{C}]$	-0.0039** (0.0015)	-0.0039*** (0.0012)	-0.0039** (0.0017)	-0.0039** (0.0015)	-0.0039*** (0.0014)
$T_{mean}[30-33^{\circ}\text{C}]$	-0.0071*** (0.0022)	-0.0071*** (0.0016)	-0.0071*** (0.0024)	-0.0071** (0.0028)	-0.0071** (0.0030)
$T_{mean}[\geq 33^{\circ}\text{C}]$	-0.0091*** (0.0028)	-0.0091*** (0.0022)	-0.0091** (0.0034)	-0.0091*** (0.0032)	-0.0091*** (0.0032)
Observations	309,472	309,472	309,472	309,472	309,472
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes

Note: the table provides the estimated impacts of extreme heat on the dependent variable, that is, firm-level labour share. All columns provide an impact of one additional day recording average daily temperature in reference to the omitted bin $[24-27^{\circ}\text{C}]$. All models include firm and year fixed effects as well as total precipitation, age of firm, and firm size classification as per ASI as control variables. Column (1) provides estimates for the main specification with standard errors clustered at the district level. The robust standard errors, clustered at the firm level in column (2), district–industry level in column (3), and state level in column (4), are reported in parentheses. The Conley standard errors are reported in column (5). Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D2: Effect of extreme heat on labour share, robustness to time-varying state-level and sector-level factors, industrial disputes, alternative measures of labour share, and exclusion of firms with fewer than ten employees

Variables	(1)	(2)	(3)	(4)	(5)	(6)
$T_{mean}[<15^{\circ}\text{C})$	-0.0039 (0.0045)	-0.0012 (0.0047)	-0.0016 (0.0045)	-0.0050 (0.0037)	-0.0077* (0.0042)	-0.0002 (0.0047)
$T_{mean}[15-18^{\circ}\text{C})$	0.0021 (0.0027)	0.0045 (0.0028)	0.0042 (0.0028)	0.0040* (0.0023)	0.0042 (0.0028)	0.0072** (0.0032)
$T_{mean}[18-21^{\circ}\text{C})$	-0.0031 (0.0020)	0.0006 (0.0023)	0.0007 (0.0023)	0.0014 (0.0022)	0.0002 (0.0024)	0.0011 (0.0025)
$T_{mean}[21-24^{\circ}\text{C})$	-0.0007 (0.0014)	0.0001 (0.0013)	0.0000 (0.0013)	-0.0005 (0.0013)	-0.0013 (0.0014)	0.0014 (0.0014)
$T_{mean}[27-30^{\circ}\text{C})$	-0.0036** (0.0014)	-0.0041*** (0.0015)	-0.0041*** (0.0016)	-0.0023* (0.0013)	-0.0029** (0.0014)	-0.0041** (0.0016)
$T_{mean}[30-33^{\circ}\text{C})$	-0.0046** (0.0020)	-0.0068*** (0.0021)	-0.0070*** (0.0021)	-0.0045** (0.0020)	-0.0050** (0.0023)	-0.0080*** (0.0024)
$T_{mean}[\geq 33^{\circ}\text{C})$	-0.0068*** (0.0026)	-0.0085*** (0.0027)	-0.0088*** (0.0028)	-0.0056*** (0.0021)	-0.0069*** (0.0025)	-0.0095*** (0.0031)
Observations	309,472	309,472	309,472	309,472	309,472	274,208
Firm fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes	Yes
State fixed effects	Yes					
Year $\times$ state	Yes					
Year $\times$ two-digit industry		Yes				

Note: the table provides the estimated impacts of extreme heat on the dependent variable, that is, firm-level labour share. All columns provide an impact of one additional day recording average daily temperature in reference to the omitted bin $[24-27^{\circ}\text{C})$. All models include firm and year fixed effects as well as total precipitation, age of firm, and firm size classification as per ASI as control variables. The robust standard errors, clustered at the district level, are reported in parentheses. Column (1) controls for the state-specific time trends, and column (2) controls for sector-specific time trends. The minutes lost to industrial disputes are controlled for in column (3). In column (4), labour share is defined as total compensation/gross output, whereas in column (5) it is total compensation/value-added. Column (6) provides estimates for a subset of firms with a minimum of ten employees. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D3: Effect of extreme heat on labour share, robustness to alternative reference temperature bins

Variables	(1)	(2)
$T_{mean}[<15^{\circ}\text{C})$	-0.0011 (0.0041)	0.0030 (0.0045)
$T_{mean}[15-18^{\circ}\text{C})$	0.0051* (0.0027)	0.0091*** (0.0031)
$T_{mean}[18-21^{\circ}\text{C})$	0.0006 (0.0023)	0.0046* (0.0026)
$T_{mean}[21-24^{\circ}\text{C})$		0.0040** (0.0018)
$T_{mean}[24-27^{\circ}\text{C})$	-0.0002 (0.0013)	0.0039** (0.0015)
$T_{mean}[27-30^{\circ}\text{C})$	-0.0040** (0.0018)	
$T_{mean}[30-33^{\circ}\text{C})$	-0.0073*** (0.0023)	-0.0033 (0.0020)
$T_{mean}[\geq 33^{\circ}\text{C})$	-0.0093*** (0.0030)	-0.0053** (0.0023)
Observations	309,472	309,472
Firm fixed effects	Yes	Yes
Year fixed effects	Yes	Yes

Note: the table provides the estimated impacts of extreme heat on the dependent variable, that is, firm-level labour share. All models include firm and year fixed effects as well as total precipitation, age of firm, and firm size classification as per ASI as control variables. The robust standard errors, clustered at the district level, are reported in parentheses. Column (1) provides an impact of one additional day recording average daily temperature in reference to the omitted bin [21–24°C) and column (2) provides an impact in reference to the omitted bin [27–30°C). Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D4: Effect of extreme heat on labour share, robustness to alternative measures of extreme heat

Variables	(1)	(2)	(3)	(4)	(5)
$T_{max}[\leq 15^{\circ}\text{C}]$	0.0047 (0.0090)				
$T_{max}[15-18^{\circ}\text{C}]$	-0.0106** (0.0047)				
$T_{max}[18-21^{\circ}\text{C}]$	-0.0005 (0.0036)				
$T_{max}[21-24^{\circ}\text{C}]$	0.0004 (0.0027)				
$T_{max}[24-27^{\circ}\text{C}]$	0.0040** (0.0019)				
$T_{max}[30-33^{\circ}\text{C}]$	0.0000 (0.0013)				
$T_{max}[33-36^{\circ}\text{C}]$	-0.0034** (0.0015)				
$T_{max}[36-39^{\circ}\text{C}]$	-0.0062** (0.0026)				
$T_{max}[\geq 39^{\circ}\text{C}]$	-0.0049* (0.0029)				
Days count with mean temperature $>30^{\circ}\text{C}$		-0.0051*** (0.0019)			
Days count with maximum temperature $>30^{\circ}\text{C}$			-0.0027** (0.0011)		
Days count with maximum temperature $>32^{\circ}\text{C}$				-0.0046*** (0.0013)	
Days count with maximum temperature $>35^{\circ}\text{C}$					-0.0056*** (0.0018)
Observations	309,472	309,472	309,472	309,472	309,472
Firm fixed effects	Yes	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes	Yes

Note: the table provides the estimated impacts of extreme heat on the dependent variable, that is, firm-level labour share. All models include firm and year fixed effects as well as total precipitation, age of firm, and firm size classification as per ASI as control variables. The robust standard errors, clustered at the district level, are reported in parentheses. Column (1) provides an impact of one additional day recording daily maximum temperature in reference to the omitted bin $[27-30^{\circ}\text{C}]$. Column (2) provides an impact of one additional day recording average daily temperature above 30°C . Columns (3)–(5) provide an impact of one additional day recording daily maximum temperature above 30°C , 32°C , and 35°C , respectively. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D5: Effect of extreme heat on labour share, robustness to humidity-based measure of extreme heat (NOAA Heat Index)

Variables	(1)	(2)	(3)	(4)
HI[<10°C)	0.0058 (0.0063)			
HI[10–12°C)	–0.0043 (0.0053)			
HI[12–14°C)	0.0009 (0.0050)			
HI[14–16°C)	0.0016 (0.0038)			
HI[16–18°C)	0.0114*** (0.0033)			
HI[26°C–28°C)	0.0005 (0.0017)			
HI[28–30°C)	–0.0013 (0.0021)			
HI[30–32°C)	–0.0018 (0.0024)			
HI[32–34°C)	–0.0071** (0.0028)			
HI[34–36°C)	–0.0052* (0.0030)			
HI[≥36°)	–0.0100** (0.0040)			
Days count with Heat Index > 30°C		–0.0042*** (0.0016)		
Days count with Heat Index > 32°C			–0.0057*** (0.0020)	
Days count with Heat Index > 33°C				–0.0071*** (0.0022)
Observations	309,472	309,472	309,472	309,472
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Note: the table provides the estimated impacts of extreme heat on the dependent variable, that is, firm-level labour share. Column (1) provides an impact of one additional day recording NOAA Heat Index in reference to the omitted bin [18–26°C). Columns (2)–(4) provide an impact of one additional day recording NOAA Heat Index above 30°C, 32°C, and 33°C, respectively. All models include firm and year fixed effects as well as total precipitation, age of firm, and firm size classification as per ASI as control variables. The robust standard errors, clustered at the district level, are reported in parentheses. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D6: Effect of extreme heat on labour share, robustness to relative humidity-based measures of extreme heat (WBGT)

Variables	(1)	(2)	(3)	(4)
WBGT[<10°C)	0.0079 (0.0065)			
WBGT[10–12°C)	–0.0035 (0.0048)			
WBGT[18–20°C)	–0.0032 (0.0028)			
WBGT[20–22°C)	–0.0057* (0.0032)			
WBGT[22–24°C)	–0.0037 (0.0038)			
WBGT[24–26°C)	–0.0046 (0.0042)			
WBGT[26–28°C)	–0.0102** (0.0045)			
WBGT[≥28°C)	–0.0172*** (0.0065)			
Days count with WBGT >24°C		–0.0011 (0.0018)		
Days count with WBGT >25°C			–0.0031* (0.0017)	
Days count with WBGT >26°C				–0.0060*** (0.0021)
Observations	309,472	309,472	309,472	309,472
Firm fixed effects	Yes	Yes	Yes	Yes
Year fixed effects	Yes	Yes	Yes	Yes

Note: the table provides the estimated impacts of extreme heat on the dependent variable, that is, firm-level labour share. Column (1) provides an impact of one additional day recording WBGT in reference to the omitted bin [12–18°C). Columns (2)–(4) provide an impact of one additional day recording WBGT above 24°C, 25°C, and 26°C, respectively. All models include firm and year fixed effects as well as total precipitation, age of firm, and firm size classification as per ASI as control variables. The robust standard errors, clustered at the district level, are reported in parentheses. Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D7: Estimates of industry-level capital-labour substitution coefficients

Industry code	Industry	Coefficient	SE	Obs.	Sig.
23	Manufacture of other non-metallic mineral products	-3.6968401	0.1268230	29,805	***
33	Repair and installation of machinery and equipment	-3.5832870	1.3184709	231	***
52	Warehousing and support activities for transportation	-3.5263963	1.2278653	164	***
12	Manufacture of tobacco products	-2.8958228	0.2831845	2,416	***
31	Manufacture of furniture	-2.3874589	0.2297486	2,363	***
18	Printing and reproduction of recorded media	-2.2522640	0.3829993	4,630	***
13	Manufacture of textiles	-2.2513123	0.2129925	25,572	***
26	Manufacture of computer, electronic, and optical products	-1.8809690	0.2939924	7,665	***
14	Manufacture of wearing apparel	-1.8480380	0.2989150	9,559	***
29	Manufacture of motor vehicles, trailers, and semi-trailers	-1.8209146	0.1858399	9,980	***
21	Manufacture of pharmaceuticals	-1.8132289	0.1506217	9,952	***
20	Manufacture of chemicals and chemical products	-1.7440914	0.2508157	23,093	***
11	Manufacture of beverages	-1.7209205	0.1850659	5,462	***
15	Manufacture of leather and related products	-1.6539439	0.1539028	7,236	***
22	Manufacture of rubber and plastics products	-1.6254343	0.0730888	15,650	***
17	Manufacture of paper and paper products	-1.5175916	0.1030785	9,844	***
27	Manufacture of electrical equipment	-1.5094841	0.1110639	15,589	***
32	Other manufacturing	-1.4096628	0.2778722	5,832	***
25	Manufacture of fabricated metal products	-1.3626473	0.2289485	19,088	***
16	Manufacture of wood and products of wood	-1.3113465	0.1535569	5,626	***
24	Manufacture of basic metals	-1.3034173	0.0933312	21,543	***
30	Manufacture of other transport equipment	-1.1540206	0.3099332	5,890	***
28	Manufacture of machinery and equipment	-1.0766127	0.1232871	22,716	***
10	Manufacture of food products	-0.9153949	0.0822023	46,689	***
19	Manufacture of coke and refined petroleum products	-0.7655855	0.1398102	2,877	***

Source: authors' compilation.

Table D8: Effect of extreme heat on market concentration of sales and employment at district–industry–year level excluding single-firm markets

Variables	HHI(sales) (1)	CR1(sales) (2)	HHI(employment) (3)	CR1(employment) (4)
$T_{mean}[\leq 15^{\circ}\text{C}]$	0.0007*** (0.0002)	0.0690*** (0.0210)	0.0006*** (0.0001)	0.0547*** (0.0121)
$T_{mean}[15-18^{\circ}\text{C}]$	-0.0001 (0.0002)	-0.0093 (0.0152)	0.0001 (0.0001)	-0.0003 (0.0138)
$T_{mean}[18-21^{\circ}\text{C}]$	0.0002 (0.0002)	0.0146 (0.0145)	0.0002* (0.0001)	0.0163 (0.0127)
$T_{mean}[21-24^{\circ}\text{C}]$	0.0000 (0.0001)	0.0042 (0.0088)	0.0000 (0.0001)	0.0024 (0.0083)
$T_{mean}[27-30^{\circ}\text{C}]$	0.0001* (0.0001)	0.0110 (0.0076)	0.0003*** (0.0001)	0.0244*** (0.0069)
$T_{mean}[30-33^{\circ}\text{C}]$	0.0002 (0.0001)	0.0146 (0.0105)	0.0001 (0.0001)	0.0088 (0.0102)
$T_{mean}[\geq 33^{\circ}\text{C}]$	0.0001 (0.0001)	0.0041 (0.0116)	0.0002 (0.0001)	0.0101 (0.0112)
Observations	38,902	38,902	38,902	38,902
District fixed effects	Yes	Yes	Yes	Yes
Two-digit industry fixed effects	Yes	Yes	Yes	Yes

Note: the table provides estimates for the market concentration channel. The sample is restricted to markets with at least two firms. All columns provide an impact of one additional day recording average daily temperature in reference to the omitted bin $[24-27^{\circ}\text{C}]$. All models include district and industry (sector) fixed effects as well as total precipitation as a control variable. The robust standard errors, clustered at the district level, are reported in parentheses. The impact of heat on market concentration measured on the basis of sales is provided in columns (1) and (2) and on the basis of employment in columns (3) and (4). Significance level: * $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$.

Table D9: Projected impacts of climate change on labour share (using climate projections data from the global climate model IPSL-CM6A-LR)

Bin	SSP1-2.6			SSP3-7.0			SSP5-8.5		
	2041–60	2061–80	2081–2100	2041–60	2061–80	2081–2100	2041–60	2061–80	2081–2100
$T_{mean} [<15^{\circ}\text{C}]$	0.009	0.009	0.007	0.010	0.013	0.015	0.011	0.014	0.016
$T_{mean} [15–18^{\circ}\text{C}]$	–0.022	–0.024	–0.014	–0.028	–0.058	–0.080	–0.035	–0.073	–0.096
$T_{mean} [18–21^{\circ}\text{C}]$	–0.002	–0.002	–0.002	–0.003	–0.006	–0.012	–0.004	–0.009	–0.018
$T_{mean} [21–24^{\circ}\text{C}]$	–0.003	–0.004	–0.004	–0.004	–0.004	–0.005	–0.004	–0.005	–0.006
$T_{mean} [27–30^{\circ}\text{C}]$	–0.092	–0.122	–0.115	–0.078	–0.054	0.008	–0.071	–0.029	0.059
$T_{mean} [30–33^{\circ}\text{C}]$	–0.224	–0.245	–0.236	–0.297	–0.407	–0.448	–0.333	–0.437	–0.451
$T_{mean} [\geq 33^{\circ}\text{C}]$	–0.198	–0.223	–0.231	–0.301	–0.471	–0.842	–0.295	–0.652	–1.195

Table D10: Projected impacts of climate change on labour share (using climate projections data from global climate model MPI-ESM1-2-HR)

Bin	SSP1-2.6			SSP3-7.0			SSP5-8.5		
	2041–60	2061–80	2081–2100	2041–60	2061–80	2081–2100	2041–60	2061–80	2081–2100
$T_{mean}[\leq 15^{\circ}\text{C})$	0.006	0.006	0.006	0.004	0.009	0.012	0.007	0.012	0.014
$T_{mean}[15\text{--}18^{\circ}\text{C})$	0.000	–0.006	–0.003	0.019	0.000	–0.041	0.009	–0.035	–0.069
$T_{mean}[18\text{--}21^{\circ}\text{C})$	0.000	0.000	0.000	0.001	0.001	–0.002	0.000	–0.001	–0.008
$T_{mean}[21\text{--}24^{\circ}\text{C})$	–0.003	–0.003	–0.003	–0.003	–0.004	–0.004	–0.004	–0.004	–0.004
$T_{mean}[27\text{--}30^{\circ}\text{C})$	–0.086	–0.103	–0.104	–0.102	–0.118	–0.102	–0.111	–0.128	–0.096
$T_{mean}[30\text{--}33^{\circ}\text{C})$	–0.147	–0.172	–0.152	–0.159	–0.266	–0.392	–0.178	–0.309	–0.447
$T_{mean}[\geq 33^{\circ}\text{C})$	–0.114	–0.165	–0.132	–0.070	–0.157	–0.243	–0.112	–0.201	–0.348

Table D11: Projected impacts of climate change on labour share (using climate projections data from global climate model MRI-ESM2-0)

Bin	SSP1-2.6			SSP3-7.0			SSP5-8.5		
	2041–60	2061–80	2081–2100	2041–60	2061–80	2081–2100	2041–60	2061–80	2081–2100
$T_{mean} [<15^{\circ}\text{C}]$	0.009	0.009	0.009	0.009	0.012	0.013	0.012	0.013	0.015
$T_{mean} [15–18^{\circ}\text{C}]$	–0.013	–0.017	–0.022	–0.004	–0.040	–0.054	–0.037	–0.055	–0.082
$T_{mean} [18–21^{\circ}\text{C}]$	–0.001	–0.001	–0.001	0.000	–0.001	–0.004	–0.002	–0.004	–0.010
$T_{mean} [21–24^{\circ}\text{C}]$	–0.003	–0.003	–0.003	–0.003	–0.003	–0.004	–0.003	–0.004	–0.005
$T_{mean} [27–30^{\circ}\text{C}]$	–0.047	–0.062	–0.052	–0.062	–0.071	–0.043	–0.035	–0.045	–0.018
$T_{mean} [30–33^{\circ}\text{C}]$	–0.207	–0.225	–0.279	–0.232	–0.316	–0.349	–0.255	–0.327	–0.392
$T_{mean} [\geq 33^{\circ}\text{C}]$	–0.222	–0.295	–0.311	–0.196	–0.346	–0.533	–0.365	–0.530	–0.773

Table D12: Projected impacts of climate change on labour share (using climate projections data from global climate model UKESM1-0-LL)

Bin	SSP1-2.6			SSP3-7.0			SSP5-8.5		
	2041–60	2061–80	2081–2100	2041–60	2061–80	2081–2100	2041–60	2061–80	2081–2100
$T_{mean} [<15^{\circ}\text{C}]$	0.010	0.011	0.011	0.011	0.013	0.015	0.012	0.014	0.016
$T_{mean} [15–18^{\circ}\text{C}]$	–0.021	–0.038	–0.034	–0.032	–0.057	–0.078	–0.036	–0.075	–0.095
$T_{mean} [18–21^{\circ}\text{C}]$	–0.001	–0.002	–0.001	–0.003	–0.005	–0.010	–0.002	–0.009	–0.016
$T_{mean} [21–24^{\circ}\text{C}]$	–0.004	–0.004	–0.004	–0.004	–0.004	–0.005	–0.004	–0.005	–0.006
$T_{mean} [27–30^{\circ}\text{C}]$	–0.076	–0.092	–0.090	–0.080	–0.037	0.026	–0.060	0.009	0.091
$T_{mean} [30–33^{\circ}\text{C}]$	–0.246	–0.303	–0.314	–0.312	–0.477	–0.493	–0.326	–0.490	–0.431
$T_{mean} [\geq 33^{\circ}\text{C}]$	–0.211	–0.291	–0.273	–0.259	–0.474	–0.807	–0.314	–0.710	–1.268