The distributional and aggregate effects of factor-biased climate change

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Abstract

The distributional and aggregate effects of climate change depend on which factors of production climate change affects and the degree of substitutability between factor inputs. Using firm-level data from 32 countries in Europe and Asia, we find substantial factor bias in climate change. Extreme heat drives firms to shift expenditures from labor to capital, reducing the labor share of income. At aggregate and sectoral levels, this effect is driven by a combination of capital-labor complementarity, and climate change being biased toward damaging capital-augmenting productivity more than it damages labor-augmenting productivity. We use our estimates on the effects on labor- and capital- augmenting productivity to unpack the role of factor-biased climate change in aggregate income and the decline labor share of income over the last forty years. Factor-biased climate change has reduced aggregate global incomes by 2% since 1981 and explains 10% of the decline in the global labor income share. Conventional approaches that assume a unitary elasticity of substitution underestimate aggregate effects by up to 90% and find no effect of climate change on the labor share. Ignoring factor complementarity and biased impacts result in underestimating the negative effects of climate change.

1 Introduction

Measuring the distributional and aggregate effects of climate change is critical for a full understanding of its welfare impacts. Economists have spent several decades estimating the aggregate effects of a change in climate, predominantly using country-level data or quantified macroeconomic models. Recently, increasing attention has been paid to distributional consequences of climate change across countries and the income distribution. Researchers have accumulated a substantial body of evidence that climate change will reduce global income, and particularly labor income, and exacerbate global inequality.

In this paper we take a unified approach to estimating the aggregate effect of climate change and how it changes the distribution of income across labor and capital through its impact on factor productivity. In our analysis, we initially remain as agnostic as possible about the representation of the production function to minimize the role of specific modeling choices, and then we layer on additional structural assumptions that allow us to better understand the mechanisms through which climate change has particular impacts on the level and distribution of income. To do our analysis, we construct a firm-level dataset covering 10 million (primarily single-establishment) firms in 32 countries in Europe and Asia. These countries account for 41% of the global population, 39% of global GDP, and cover a wide range of climates and income levels. Our data report firm balance sheet information such as sales, costs of employees, number of employees, and capital stocks, that are critical for understanding how climate change impacts firms and the productivity of labor and capital.

In the first part of our analysis we provide reduced form evidence that extreme heat shocks reduces labor's share of income paid out by a firm. An additional day of the year above $30°$C relative to one between $10-15°$C decreases labor income relative to capital income by 0.17%. This effect is heterogeneous across firms operating in different sectors, as well as firms operating in different average climates and countries with different levels of economic development. Changes in relative incomes could be caused by changes in relative prices, relative quantities, or both, so we next estimate how extreme heat affects firm or regional ratios of wages to rental rates. Here we find a smaller impact. This indicates that most of the effect on relative incomes is driven by changes in the quantity of factors employed, not changes in prices.

These two results jointly provide evidence for two assertions about the economy and climate change that will inform our later analysis. The first is that, consistent with a recent empirical macroeconomics literature, the elasticity of substitution between labor and capital cannot be 1: production is not Cobb-Douglas. If it was, then then relative incomes would be fixed and invariant to changing temperatures. The vast majority of the climate economics literature has imposed a Cobb-Douglas form for tractability reasons. Our reduced form findings suggest that this assumption may not be appropriate and our later results will show that this assumption is not innocuous. Changing relative incomes is consistent with climate impacts being biased toward one of the two factors along with a non-unitary elasticity of substitution.

The second assertion is that relative income effects are caused by changing relative productivities. If extreme heat has little effect on the relative price of labor to capital, then relative income effects are predominantly driven by changes in relative quantities. Relative quantities

are chosen as a function of relative productivities if prices are held fixed. The role of changing relative productivities is the focus of our paper. If climate change affects capital- and labor-augmenting productivity and capital and labor have a non-unitary elasticity of substitution, our reduced form results can be explained by either (1) climate damages being biased toward labor and factors being substitutes, or (2) climate damages being biased toward capital and factors being complements.

In the second part of our analysis we take a Solow residual-based approach to estimate the effect of extreme heat on capital- and labor-augmenting productivities. This approach remains agnostic about the functional form of production and will allow us to understand whether extreme heat tends to harm capital or labor more. These estimates indicate that capital is much more sensitive to extreme heat. This result along with our finding that extreme heat reduces labor income relative to capital income suggests we are in a world where extreme heat harms capital productivity more than labor productivity–i.e. climate damages are biased toward capital–and the two factors are complements. Capital-labor complementarity is a well-founded result in the empirical macroeconomics literature (e.g. Raval 2019; Oberfield and Raval 2021; Berlingieri et al. 2024).[1] Capital-biased climate damages and capital-labor complementarity reconciles existing lines of evidence in these two disparate literatures.

Our final empirical analysis–the results of which we use for our counterfactual simulations–fully specifies the production function as constant elasticity of substitution (CES) with capital- and labor-augmenting productivities that may be affected by changes in temperature. We jointly estimate the elasticity of substitution and the effect of temperature on capital- relative to labor-augmenting productivity by regressing relative factor expenditures on temperature and relative prices. This specification arises from the firm first-order conditions for capital relative to labor. The coefficient on relative prices corresponds to the elasticity of substitution (minus 1), and we identify the elasticity using a granular instrumental variables strategy (Gabaix and Koijen 2024). The coefficient on temperature corresponds to the product of the elasticity of substitution (minus 1) times the relative effects on capital- versus labor-augmenting technology.

We estimate an average elasticity of substitution of 0.3 across all sectors and we can statistically reject elasticities greater than 0.75: capital and labor in our sample are, on average, complements. Along with this estimated complementarity, we find that extreme heat harms capital more than labor, consistent with our reduced form evidence. The combination of complementarity and a bias of extreme heat toward harming capital decreases the labor share of income as found in prior reduced form climate work and suggesting that climate change may be a driver of the observed global labor share trend (Karabarbounis 2024; Karabarbounis and Neiman 2013). We also estimate the elasticity of substitution and factor bias of climate change separately by sector. We find that for most sectors, and all the largest ones, labor and capital are complements and extreme heat damages capital productivity more than labor productivity. For half of the sectors, including manufacturing, construction, and services, we can statistically reject Cobb-Douglas. A non-unitary elasticity of substitution matters not only for the distribution of income across labor and capital, but also the effects on aggregate income. The greater the complementarity between factors, the less ability firms have to adjust inputs in response

1. Our aggregate estimate aligns well with the mean estimate in a recent meta-analysis (**?**).

to changes in productivity or prices. This means that when a firm faces negative productivity shocks from climate change, their impact is amplified, but if the firm faces positive productivity shocks, those impacts are dampened.

For our counterfactual simulations we require not just the effect of climate change on capital relative to labor, but the level impacts on both. To get these level effects, we specify demand as constant elasticity of substitution. We estimate the demand elasticity of substitution, which, along with our estimated production elasticity of substitution, we show allows us to finally identify the level effects on capital- and labor-augmenting technology rather than just the relative effect. Here we find that extreme heat harms both capital- and labor-augmenting productivity, but the effect on capital is three times that of labor.

We use the the level impact estimates on capital productivity and labor productivity to quantify the role of climate change in determining historical trends in the labor share and aggregate income since 1981. We find that factor-biased climate change has accounted for a 0.5pp decline in the labor share, a tenth of the overall decline during that time. The effects on the labor share are highly heterogeneous across countries, with some countries experiencing declines of up to 4pp, and others increases of up to 2pp. We also find that the factor bias of climate change and factor complementarity matter substantially for quantifying aggregate effects. Ignoring factor complementarity understates the negative effects of climate change by 90%.

Our paper contributes to an emerging literature on climate change damages. A common approach in this line of research is to estimate the average labor or total factor productivity losses due to higher temperatures, often imposing a Cobb-Douglas technology for tractability (Zhang et al. 2018; Somanathan et al. 2021; Acharya, Bhardwaj, and Tomunen 2023; Ponticelli, Xu, and Zeume 2023; Nath 2023). Cobb-Douglas is quite restrictive. Under such an assumption it does not matter whether extreme heat affects capital or labor more since productivity is factor-neutral. This precludes any changes in how income is shared between labor and capital.[2] We relax that assumption and show empirically that labor and capital are complements in firm-level production and that extreme heat disproportionately lowers capital productivity. These findings present a unified explanation for climate change harming labor incomes and capital-labor complementarity.

Our paper also adds to the literature on the declining labor share of income (Karabarbounis and Neiman 2013; Grossman and Oberfield 2022; Hubmer 2023; Karabarbounis 2024). Commonly cited causes include technical change, globalization, increased market power, reduced worker bargaining power, and changes in workforce composition.[3] Our paper highlights the role of environmental factors in driving changes in relative productivities and relative factor incomes. Changes in daily temperature distributions over the last four decades explain 10% of the observed labor share decline.

The rest of the paper is organized as follows. We describe our data and measurement strate-

2. Prior work does look at distributional issues of climate change but typically across countries or other spatial units with different income levels, not in the capital-labor sense (e.g. Dell, Jones, and Olken 2012; Diffenbaugh and Burke 2019; Carleton et al. 2022).

3. See Grossman and Oberfield (2022) for a comprehensive review on the explanations for the decline of labor share.

gies in Section 2. Our reduced form evidence are provided in Section 3. We define technical bias and take the Solow residual-based approach to estimate factor productivity bias in Section 4. Our structural estimations for the elasticity of substitution and the level of factor augmenting productivity are in in Section 5. We decompose the historical changes of labor share and projects the changes into the future in Section 6. We conclude in Section 7.

2 Data and Measurements

2.1 Firm data

We assemble a firm-level dataset from both developed and developing economies–namely 30 European countries, China, and India. These countries together account for about 40% of global GDP and global population. The data for the 30 European countries come from Bureau van Dijk's (BvD) Orbis database. For some countries like Spain and Italy, the coverage approaches census-level completeness. Each firm in the Orbis dataset is identified by its USSIC sector code, and we use its address information to match the firm to a specific NUTS3 region in Europe. We draw on official government survey data from China and India. For China, we use the China National Bureau of Statistics (NBS) Annual Survey of Industrial Firms, which covers all "above-scale" industrial firms—those with annual sales exceeding CNY 5 million (approximately USD 0.61 million)—from 1998 to 2007. This dataset includes firms in mining, manufacturing, and utilities, with manufacturing constituting over 90% of the observations. For India, we use the Annual Survey of Industries (ASI). The ASI is a census of large plants employing more than 100 workers and a random sample of approximately one-fifth of smaller plants registered under the Indian Factories Act. While its primary focus is on manufacturing, the ASI also covers repair services, gas and water supply, and cold storage.

We use address information to map firms to a prefecture in China, and a district in India. Each dataset contains detailed financial and operational information, including revenue, fixed assets, wage bills, and employment. These sources are commonly used in the literature and are considered nationally representative (see, for example, Kalemli- Özcan et al. (2024)).

Measurement of Capital Expenditure We measure a firm's capital stock K_{it} as its deflated book value of fixed assets. Following the standard Jorgenson (1963) formula, we compute the user cost of capital at the country-sector-year level as:

$$r_{c,s(i)t} = p^K_{c,s(i)t}\left[r^c_t + KRP_t - (1-\delta_{c,s(i)t})\left(\frac{p^K_{c,s(i)t-1}}{p^K_{c,s(i)t}}\right)\right],$$

where $p^K_{c,s(i)t}$ is the price of investment goods for country c and sector s in year t and r^c_t is the risk-free rate for country c. We obtain $p^K_{c,s(i)t}$ from EU KLEMS. We also adjust for the capital risk premium of $KRP_t = 7\%$ following Caballero, Farhi, and Gourinchas (2017). We compute the total user cost of capital for firm i as: $rK_{it} = r_{c,s(i)t}K_{it}$.

Measurement of Labor Expenditures To measure each firm's total wage bill, denoted by wL_{it}, we draw on consistent variables from different data sources. For European countries, we use the Orbis "cost of employees"; for India, the ASI's "total payments to labor"; and for China, the NBS's "total wage bills." These are comparable measures of labor expenditures across countries.

Measurement of Relative Expenditure Share. From the data on capital and labor expenditures we compute the firm-level relative expenditure shares for both factors as:

$$s_{Kit} = \frac{rK_{it}}{wL_{it} + rK_{it}} \qquad s_{Lit} = \frac{wL_{it}}{wL_{it} + rK_{it}}$$

2.2 Weather data.

We rely on ERA5-Land to construct historical climate variables for each region r. The ERA5-Land, produced by the European Centre for Medium-Range Weather Forecasts (ECMWF), is a reanalysis dataset that merges historical observations with model simulations to generate a consistent record of various climate indicators. Its main strength is its high temporal and spatial resolution, providing hourly data on surface variables at a 0.1°× 0.1°grid (about 9 km) worldwide. Our analysis uses air temperature measured two meters above the ground. We calculate the grid cell daily average temperature by averaging over the daily maximum and minimum. We then construct a set of 5°C temperature bin variables for each grid cell: $\mathbf{T}_{r,t} = \left\{\text{Tbin}_{r,t}^{<-5^\circ C}, \text{Tbin}_{r,t}^{-5\sim 0^\circ C}, ..., \text{Tbin}_{r,t}^{>30^\circ C}\right\}$.[4] These bins count the number of days in year t in which daily average temperature fell into that range of temperatures in each cell. The sum across all bins equals the number of days in the year. We then aggregate the bins to the region level using area weights, and all firms in a region have the same temperature bin variable values in a given year. This approach to measuring temperature allows us to better capture daily temperature extremes within a year, with more regional granularity.

3 Climate Shocks Affect Factor Shares: Reduced-form Evidence

We first present new empirical evidence on how firm-level factor shares respond to climate shocks. Our analysis shows that extreme heat significantly raises the ratio of capital to labor expenditures, decreasing the firm-level labor share. This finding is robust across virtually all sectors, regional climates, and regional income levels. A decreasing labor share at the firm level could result from either changes in relative input prices or relative productivity, the latter which we call the technical bias of climate change.[5] We will show that factor prices have an economically insignificant response to extreme temperature, indicating that there is a technical bias of climate change.

4. Binning daily temperatures or projecting them onto polynomials or splines is a relatively common approach for capturing within-year extremes for annual-level regressions (Deschênes and Greenstone 2011; Carleton et al. 2022; Rudik et al. 2021; Nath 2023).

5. Relative input prices would change independently of productivity, if, for example, temperature induced changes in labor supply through changing non-work amenities.

3.1 Empirical Strategy

Our baseline regression for estimating the effect of temperature on relative factor shares is:

$$\log\left(\frac{rK_{it}}{wL_{it}}\right) = \sum_{b \in B/(10\sim 15^{\circ}C)} \lambda^{b} \times \text{Tbin}^{b}_{r,t} + \delta_i + \eta_{c(r)s(i)t} + \varepsilon_{it} \tag{1}$$

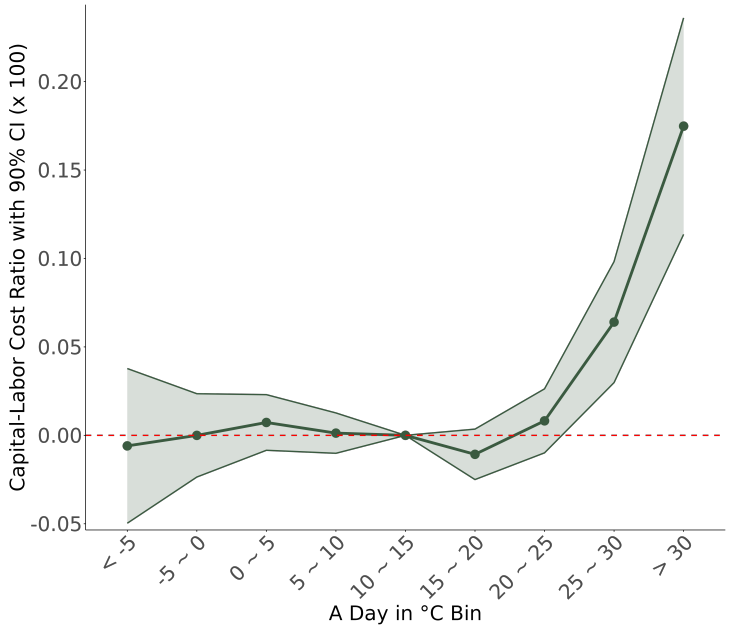
where the outcome variable, $\log\left(\frac{rK_{it}}{wL_{it}}\right)$, is the log ratio of capital expenditure to labor expenditure of firm i. As detailed in Section 2, capital expenditure is measured as the user cost of fixed assets and labor expenditure is the cost of employees. We include the full set of temperature bins $\text{Tbin}^{b}_{r,t}$, omitting the $10 \sim 15^{\circ}C$ interval as the reference category as it aligns with the average temperature for firms in Europe, China, and India in our sample. Thus, λ^{b} captures the average effect of replacing a day in the $10 \sim 15^{\circ}C$ range with a day in temperature range b on the annual (log) capital-to-labor expenditure ratio. We also include firm fixed effects δ_i and country-sector-year fixed effects $\eta_{c(r)s(i)t}$ where a sector is defined at USSIC 3 digit level.[6] The former absorbs all time-invariant firm-level characteristics, while the latter captures any unobserved factors common to firms within the same country and sector in a given year.

3.2 Heat Shocks Increase the K-to-L Expenditure Ratio and Reduce the Labor Share

Heat Shocks Increase the K-to-L Expenditure Ratio Figure 1 plots the estimated λ^{b} coefficients. The estimated effects of daily temperature below $25^{\circ}C$ are indistinguishable from a day between $25 \sim 30^{\circ}C$. However, we find that days above $25^{\circ}C$ result in firms spending markedly more on capital relative to labor. An additional day with temperatures above $30^{\circ}C$, compared to a $10 \sim 15^{\circ}C$ day increases the capital-to-labor expenditure ratio by 0.17%. Table A.1 column (1) reports the detailed estimates.

6. The country-sector-year fixed effects in the regressions all use USSIC 3 digit sector. The separate sector-level regressions are subsampled at USSIC Division (equivalent to 1 digit) level.

Figure 1: Daily Temperature Effect on $\log\left(rK_{it}/wL_{it}\right)$



Notes: The graph plots the estimated coefficients from equation (1), using $10\sim 15°C$ as the reference temperature bin. The shaded area is the 90% confidence interval computed from robust standard errors clustered at the regional level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects, where sector is at USSIC 3 digit level. The sample includes firms from 30 European countries, China and India from 1998 to 2018. 67,294,831 firm-year observations are included.

3.3 Heat Shocks Reduce the Labor Share

The relative increase in capital-to-labor expenditure implies a decline in the labor share. With a typical firm's labor share being around $s_i^L = 0.65$ (and thus $s_i^K = 0.35$), we can translate the estimates from equation (1) into the impact of climate shocks on the *level* of the labor share for the typical firm. Specifically, the average effect of an additional day in bin b on the labor share $\frac{ds_{Lit}}{d\,\mathrm{Tbin}_{r,t}^b}$ can be approximated by:

$$\frac{ds_{it}^L}{d\,\mathrm{Tbin}_{r,t}^b} = -s_{it}^L\left(1-s_{it}^L\right) \times \frac{d\ln\left(\frac{rK_{it}}{wL_{it}}\right)}{d\,\mathrm{Tbin}_{r,t}^b}, \tag{2}$$

where $\frac{d\ln\left(\frac{rK_{it}}{wL_{it}}\right)}{d\,\mathrm{Tbin}_{r,t}^b} = \lambda^b$ is the series of estimated coefficients from our regression in equation (1).

For context, a 30-day shift from $10\sim 15°C$ to $30°C$ —comparable to the warming experienced in Southern Spain over the past 70 years—would lower the average firm's labor share by about 1pp.[7] Hence, a firm starting with a labor share of 66% would see it drop to about

7. The calculation follows:

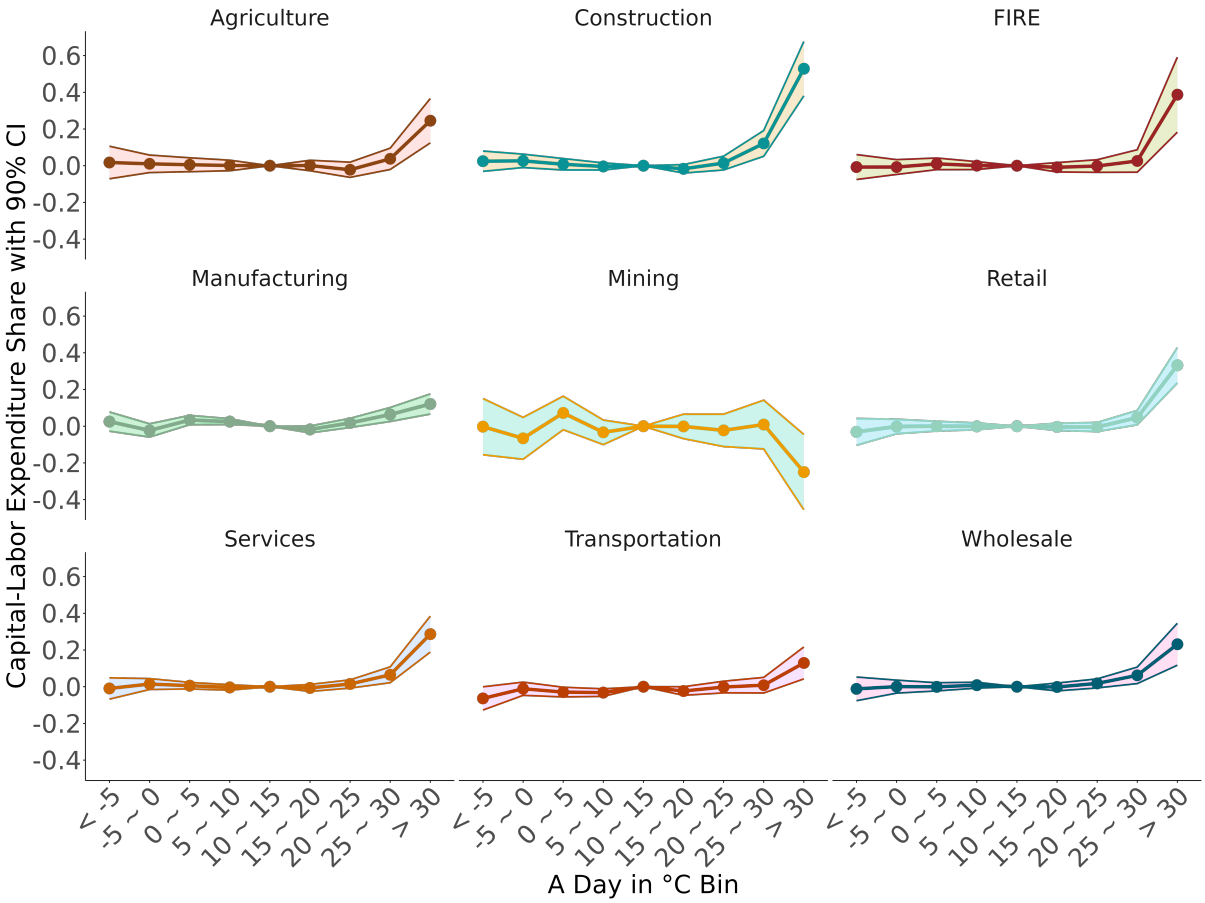
$$\Delta s_{Lit} = \frac{ds_{Lit}}{d\mathrm{Tbin}_{r,t}^{>30°\mathrm{C}}} \times 30 = -\underbrace{s_{Lit}\left(1-s_{Lit}\right)}_{0.35\times 0.65} \times \underbrace{\lambda^{>30°\mathrm{C}}}_{0.17\%} \times 30 = -0.01.$$

65%.

3.4 Heterogeneous Effects Across Sectors

Our baseline estimates average impacts across all sectors. However, production differs considerably in heat sensitivity, outdoor exposure, and factor requirements across different sectors. To investigate the resulting heterogeneity in how extreme heat affects relative factor shares, we separately estimate equation (1) for nine major sectors (USSIC Divisions): Agriculture, Construction, Finance/Insurance/Real Estate (FIRE), Manufacturing, Mining, Retail, Services, Transportation, and Wholesale.

Figure 2: Heterogeneous Impact of Climate Shocks on K-to-L Expenditure Ratio across Sectors



Notes: The graph plots the separately estimated coefficients from equation (1) for each sector. We use $10 \sim 15°C$ as the reference temperature bin. The shaded area is the 90% confidence interval computed from robust standard errors clustered at the regional level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-year fixed effects. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

Figure 2 presents these sector-specific estimates. A remarkably consistent pattern emerges across nearly all sectors (with mining the only exception), where the capital-to-labor expenditure ratio increases when daily temperatures exceed 25°C. Construction shows the most pronounced effect, with a 0.5% increase in the K-to-L expenditure ratio following an additional day over 30°C, likely reflecting increased reliance on heat-resistant machinery over human

labor in unfavorable outdoor conditions. FIRE, retail, and services also have substantial increases in capital-to-labor ratios at high daily temperatures, averaging around a 0.3% rise per additional day over 30°C. Manufacturing, agriculture, and transportation experience smaller increases, whereas Mining see a decrease of 0.3% capital-to-labor expenditure ratio. Overall, these results highlight that while extreme heat affects relative factor shares across most sectors – including major ones such as manufacturing, agriculture and services – the magnitude of the effect may vary considerably.

3.5 Heterogeneous Effects Across Regions

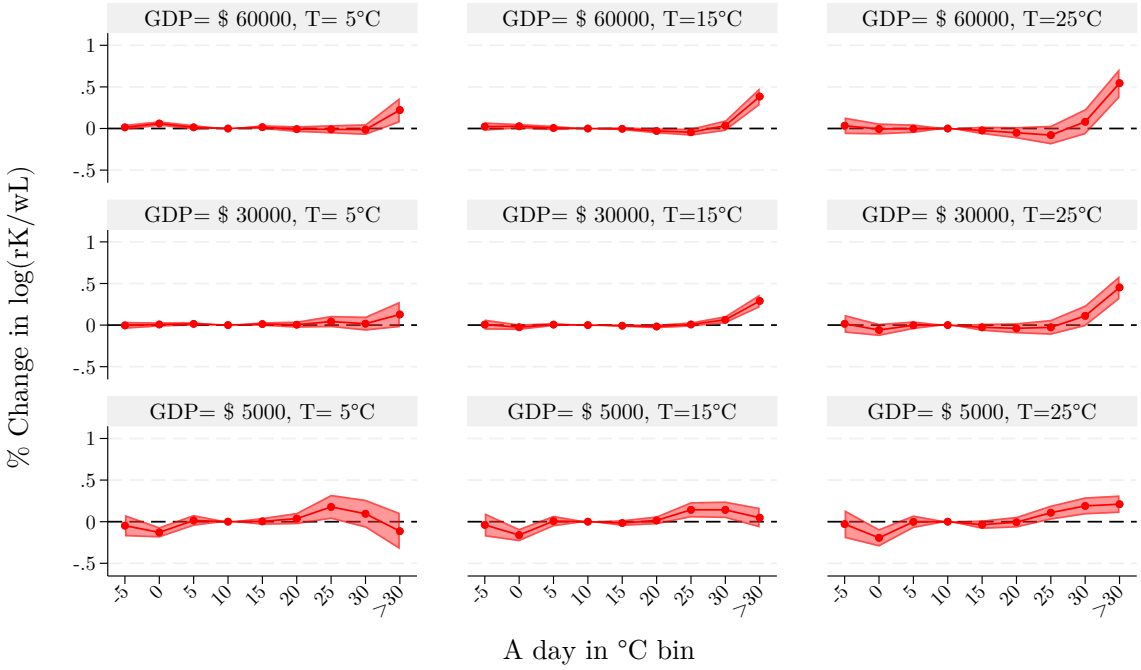
Our baseline estimates pool firms across all 32 countries in our sample, yet regions with different climatic conditions and access to adaptive resources may show distinct responses in their relative factor shares under climate shocks. To explore this, we follow the Carleton et al. (2022) approach and examine regional heterogeneity along two dimensions: long-run climate and long-run development. Specifically, we modify the baseline specification in (1) by interacting the set of temperature bins with their historical average temperatures and per-capita income levels,

$$\begin{aligned}\ln\left(\frac{rK_{it}}{wL_{it}}\right) = &\sum_{b\in B/(10\sim15^{\circ}C)} \lambda^{b} \times \text{Tbin}^{b}_{r,t} + \sum_{b\in B/(10\sim15^{\circ}C)} \lambda^{b}_{\overline{T}} \times \text{Tbin}^{b}_{r,t} \times \overline{T}_{r} \\ &+ \sum_{b\in B/(10\sim15^{\circ}C)} \lambda^{b}_{\text{GDP}_{\text{pc}}} \times \text{Tbin}^{b}_{r,t} \times \overline{\ln \text{GDP}_{\text{pc}}}_{r} + \delta_{i} + \eta_{c(r)s(i)t} + \varepsilon_{it},\end{aligned} \tag{3}$$

where $\overline{T}_r$ and $\overline{\ln \text{GDP}_{\text{pc}}}_r$ are the average annual temperature and (log) GDP per capita of region r from 1997-2018.[8] The coefficients $\lambda^{b}_{\overline{T}}$ and $\lambda^{b}_{\text{GDP}_{\text{pc}}}$ quantify whether warmer or more developed regions exhibit systematically different patterns in factor-share adjustment compared to cooler or less developed areas.

8. $\ln \overline{\text{GDP}_{\text{pc}}}_r$ is measured at the GADM-1 level from the DOSE dataset and cross-walked to regions in our sample.

Figure 3: Heterogeneous Impact of Climate Shocks on K-to-L Expenditure Ratio across Regions



Notes: The graphs plot the predicted effect of exposure to daily mean temperature bins on capital labor expenditure ratios at varying levels of income and climates from equation (3). We use 10 $\sim 15^{\circ}C$ as the reference temperature bin. The shaded area is the 90% confidence interval computed from robust standard errors clustered at the regional level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

Figure 3 presents the results from estimating equation (3), illustrating how extreme heat affects the K-to-L factor ratio across nine region types defined by three income levels and three baseline climate levels. Although nearly all regions exhibit some degree of shifting toward capital under high temperatures, the shift is notably larger in hotter and more developed areas. For instance, in southern Spain (GDP $\approx$ \$30,000, $\overline{T}_r = 25^{\circ}C$), an additional day above $30^{\circ}C$ raises the K-to-L expenditure ratio by about 0.5%, whereas India (GDP $\approx$ \$5,000, $\overline{T}_r = 25^{\circ}C$), which shares a similar baseline climate but is considerably poorer, experiences only a 0.1% increase. Conversely, India and Northeast China (GDP $\approx$ \$5,000, $\overline{T}_r = 5^{\circ}C$) have similar income levels but differ in climate; an extra day above $30^{\circ}C$ has no effect on the K-to-L factor share ratio in cooler Northeast China. These findings suggest that both a region's long-run climate and level of economic development could potentially shape how factor shares evolve under climate change.

3.6 Drivers of the Climate's Asymmetric Effect on Factor Expenditures

Our motivating exercises show that firms spend relatively more on capital in response to extreme heat shocks, pointing to a potential bias in how climate damages affect different factors of production. These exercises entangle two separate ways extreme heat may affect relative

factor shares: impacts on relative factor prices, and impacts on relative factor productivity. Relative factor prices may change, holding demand constant, if extreme heat changes the relative supply of capital to labor. [9] Relative factor productivity may change if one factor is more sensitive to extreme heat than the other.

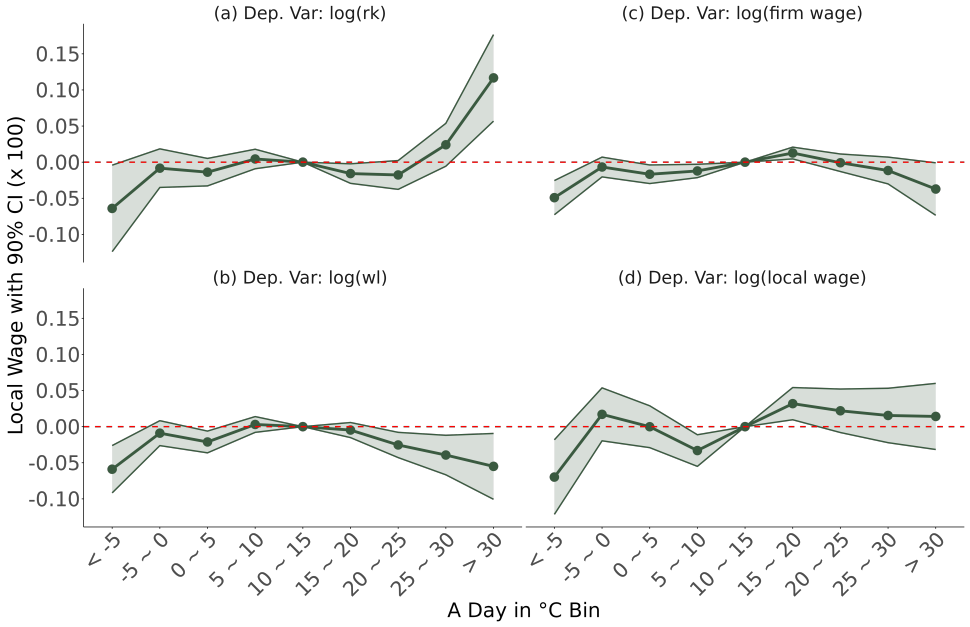
To shed light on whether our findings are driven by changes in relative prices or relative productivity, we re-estimate equation (2) but with relative factor prices (firm-level and regional wages) as the outcome variable.[10] Panel (c) and (d) in Figure 4 plot the effects on firm wage and local wage respectively and show that there is an economically and statistically insignificant effect. If relative prices do not respond to extreme heat, then relative productivity must be changing if capital-to-labor expenditure ratios are changing. Climate damages must exhibit a technical bias.[11]

9. Somanathan et al. (2021) provides micro-level evidence of heat-induced worker absenteeism, and Rode et al. (2024) shows that extreme heat leads to a same-week decline in labor supply. In a similar context, Hoffmann and Rud (2024) finds that heat causes a same-day decline in labor supply. However, it remains unclear whether these short-run channels generate large aggregate effects at the annual level, since labor supply can be substituted across weeks and days, and estimates of the intertemporal elasticity of labor supply at the daily or weekly levels are scarce.

10. Technically, we just have wages as the outcome variable, but since the user cost of capital does not vary within a country-sector-year, it is absorbed by our fixed effects.

11. Furthermore, the fact that extreme heat has a non-zero effect on relative factor shares also rules out Cobb-Douglas production functions, a common assumption in the climate economics literature.

Figure 4: Sources of the relative changes in K-L expenditure ratios



Notes: The graph plots the estimated coefficients by regressing the log of (a) fixed assets, (b) firm level wages, (c) cost of employees and (d) local wage, on temperature bins. Firm-level wage is calculated by dividing cost of employees with the number of employees. Local wage is obtained by estimating a residual wage for each firm after controlling for country-sector-year fixed effects and then averaged to region-year level. More details on the construction of local wage are provided in Section 5.2. We use $10 \sim 15°C$ as the reference temperature bin. The shaded area is the 90% confidence interval computed from robust standard errors clustered at the regional level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects except for (d), where the fixed effects are region and year. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

4 The Technical Bias of Climate Damages

We have provided reduced form evidence that climate damages exhibit a technical bias. We now formalize our notion of the technical bias of climate damages and develop a Solow residual-based approach to estimate the impacts of extreme heat on capital- and labor-augmenting productivity.

4.1 Definition

Here we formally define the technical bias of climate damages. A firm uses capital and labor to produce output $Y_{it} = F(A_{it}K_{it}, B_{it}L_{it})$ using a constant return to scale technology, where A_{it} is capital-augmenting productivity and B_{it} is labor-augmenting productivity. A_{it} and B_{it} may be affected by weather are thus functions of regional climate conditions $\mathbf{T}_{rt}$ and can be written as $A_{it} = A_i(\mathbf{T}_{rt}, \mathbf{X}_{it})$, $B_{it} = B_i(\mathbf{T}_{rt}, \mathbf{X}_{it})$, where $\mathbf{X}_{it}$ captures any additional factors such as time-varying firm characteristics. Firms are price-takers in input markets.

Without loss of generality, we arrange the vector $\mathbf{T}_{rt}$ so that its last N entries are temperature variables associated with heat, which are expected to increase under global warming.

We denote these entries collectively as $\mathbf{T}_{rt}^H$. In our reduced-form analysis, we specifically define $\mathbf{T}_{rt}^H = \left\{\text{Tbin}_{r,t}^{25\sim30^\circ C},\ \text{Tbin}_{r,t}^{>30^\circ C}\right\}$. For the effect of heat-related statistics ($\mathbf{T}_{rt}^H$) on factor-augmenting productivity, namely $\frac{d\log A_{it}}{d\mathbf{T}_{rt}^H}$ and $\frac{d\log B_{it}}{d\mathbf{T}_{rt}^H}$ - although not necessarily true quantitatively, we interpret these semi-elasticities to be negative, and refer to their effect as damages, for the ease of exposition.

Let $\sigma_{it} \equiv \frac{F_{Lit}F_{Kit}}{F_{LK,it}F_{it}}$ be the (local) elasticity of substitution between capital and labor for firm i. We can now define the technical bias of climate damages being capital-biased, labor-biased, or Hicks-neutral.

Definition 1 *Climate damages are **capital-biased** if:*

$$\frac{d\log\frac{A_{it}}{B_{it}}}{d\mathbf{T}_{rt}^H} < 0,$$

*that is, if log capital-augmenting productivity decreases more than labor augmenting productivity when climate increases. Climate damages are **labor-biased** if*

$$\frac{d\log\frac{A_{it}}{B_{it}}}{d\mathbf{T}_{rt}^H} > 0.$$

*Climate damages are **factor-neutral** if $\frac{d\log\frac{A_{it}}{B_{it}}}{d\mathbf{T}_{rt}^H} = 0$. If climate damages are factor-neutral or the elasticity of substitution between capital and labor is unitary ($\sigma_{it} = 1$), then climate damages are **Hicks-neutral.***

With this definition in hand, we can now formally establish why the technical bias of climate damages is a natural candidate to explain the large change in factor share observed in reduced form. Constant returns-to-scale in production implies that the relative factor shares must be $\frac{s_{Kit}}{s_{Lit}} = \frac{F_{Kit}K_{it}}{F_{Lit}L_{it}}$. When the relative price effect is very weak (as observed in Figure 4) such that $\frac{d\log\frac{F_{Kit}}{F_{Lit}}}{d\mathbf{T}_{rt}^H} \approx 0$, the firm's relative factor share adjustment must be coming from its input quantity adjustments, which themselves can be written as:

$$\frac{d\log\frac{F_{Kit}K_{it}}{F_{Lit}L_{it}}}{d\log\mathbf{T}_{rt}^H} \approx \frac{d\log\frac{K_{it}}{L_{it}}}{d\log\mathbf{T}_{rt}^H} = (\sigma_{it}-1)\frac{d\log\frac{A_{it}}{B_{it}}}{d\mathbf{T}_{rt}^H}.$$

Holding relative prices fixed, movements in factor shares must be due to a combination of a technical bias in climate damage and a non-unitary elasticity of substitution between labor and capital. Moreover, the direction in which climate change shifts the relative factor share depends on (1) whether capital and labor are gross complements or substitutes, and (2) the direction of the technical bias.

In Subsection 4.2, we will more directly test if the technical bias of climate change exists, and estimate the direction of the bias, without taking a stance on the elasticity of substitution σ_{it} using a flexible Solow residual approach. Later on, in Section 5, we will jointly estimate the sign of σ_{it} (using variation orthogonal to temperature shocks) and the technical bias of climate damage by imposing a constant elasticity of substitution production structure. This will allow

us to estimate both the extent of bias in climate damages and the extent of complementarity between labor and capital simultaneously.

4.2 Estimating the Technical Bias of Climate Damage via Solow Residuals

We develop an approach following the spirit of Hulten (1978) to estimate the climate damage on factor-augmenting productivity – and consequently the technical bias of climate damage– without taking a stand on the parametric form of production function.

Model Set-up Consider a large set of I^c firms operating in a country c which consists of a set of regions R^c. Each firm i resides in a specific region r in country c and produces a differentiated output Y_{it}. Firms produce output using labor and capital according to a production function: $Y_{it} = F_i(A_{it}K_{it}, B_{it}L_{it})$. The production technology F_i can vary across firms and is assumed to have constant returns to scale.

Consumers in country c have Dixit-Stiglitz preference across differentiated goods, consuming the bundle $Y_t^c = \left(\sum_{i\in I^c} Y_{it}^{\frac{\varepsilon-1}{\varepsilon}}\right)^{\frac{\varepsilon}{\varepsilon-1}}$. Utility maximization yields the demand for good i: $Y_{it} = \left(\frac{P_{it}}{P_t^c}\right)^{-\varepsilon} Y_t^c$, where P_{it} is the price of good i, $P_t^c = \left(\sum_{i\in I^c} P_{it}^{1-\varepsilon}\right)^{\frac{1}{1-\varepsilon}}$ is the aggregate price level and $\varepsilon > 1$ is the elasticity of substitution across goods. Log-differentiating the demand curve yields:

$$d\log P_{it}Y_{it} = \frac{\varepsilon-1}{\varepsilon} d\log Y_{it} + d\log P_t^c + \frac{1}{\varepsilon} d\log Y_t^c. \tag{4}$$

Facing isoelastic demand curves, firms are monopolistically competitive and maximize profits by choosing a price P_{it} and factor inputs K_{it} and L_{it} subject to the market wage w_{ct} and user cost of capital r_{ct}:

$$\begin{aligned} &\max_{P_{it},K_{it},L_{it}} P_{it}F_i(A_{it}K_{it}, B_{it}L_{it}) - w_{it}L_{it} - r_{ct}K_{it} \\ &\text{subject to : } Y_{it} = \left(\frac{P_{it}}{P_t^c}\right)^{-\varepsilon} Y_t^c. \end{aligned} \tag{5}$$

With the optimal Dixit-Stiglitz markup being $\frac{\varepsilon}{\varepsilon-1}$, the firm's profit maximization conditions imply the input elasticities of output must be proportional to the markup-adjusted factor shares:

$$\frac{d\log Y_{it}}{d\log K_{it}} = \frac{A_{it}F_{i1}K_{it}}{F_{it}} = \frac{\varepsilon}{\varepsilon-1}s_{it}^K, \quad \frac{d\log Y_{it}}{d\log L_{it}} = \frac{B_{it}F_{i2}L_{it}}{F_{it}} = \frac{\varepsilon}{\varepsilon-1}s_{it}^L. \tag{6}$$

Combining these expressions and totally differentiating the production function F_i yields,

$$d\log Y_{it} = \frac{A_{it}F_{i1}K_{it}}{Y_{it}}\left(d\log A_{it} + d\log K_{it}\right) + \frac{B_{it}F_{i2}L_{it}}{Y_{it}}\left(d\log B_{it} + d\log L_{it}\right), \tag{7}$$

and then combining with the expression for the demand curve in equation (4) gives us that:

$$d\log \text{Solow}_{it} = s_{it}^K d\log A_{it} + s_{it}^L d\log B_{it} + d\log P_{ct} + \frac{1}{\varepsilon} d\log Y_{ct}, \tag{8}$$

where $d\log \text{Solow}_{it} \equiv d\log P_{it}Y_{it} - s_{it}^K d\log K_{it} + s_{it}^L d\log L_{it}$ is the change in measured Solow (1957) residuals.

Functional Form Assumptions on Factor Productivity We now fully parametrize A_{it} and B_{it} to explicitly model how climate conditions damage both capital- and labor-augmenting productivity:

$$A_{it} = \tilde{A}_{it} \exp(\mathbf{a}_{rt} \cdot \mathbf{T}_{rt}), \quad B_{it} = \tilde{B}_{it} \exp(\mathbf{b}_{rt} \cdot \mathbf{T}_{rt}), \tag{9}$$

where $\tilde{A}_{it}$ and $\tilde{B}_{it}$ are firm-year specific technological components unrelated to climate. The terms $\mathbf{a}_{rt} \cdot \mathbf{T}_{rt}$ and $\mathbf{b}_{rt} \cdot \mathbf{T}_{rt}$ represent the total effects of different climate variables (number of hot days, number of cold days etc.) on capital- and labor-augmenting productivity, respectively. $\mathbf{a}_{rt}$ and $\mathbf{b}_{rt}$ are the region-specific semi-elasticities of factor productivity on $\mathbf{T}_{rt}$ in region r and year t. Naturally, our focus is on the heat-related statistics, $\mathbf{T}^H_{rt}$, and the sign and relative size of their corresponding semi-elasticities $\mathbf{a}^H_{rt}$ and $\mathbf{b}^H_{rt}$. From Definition 1, climate damages are capital-biased if $\mathbf{a}^H_{rt} - \mathbf{b}^H_{rt} < 0$ and labor biased if $\mathbf{a}^H_{rt} - \mathbf{b}^H_{rt} > 0$. If the production function is not locally Cobb-Douglas, then only when $\mathbf{a}^H_{rt} - \mathbf{b}^H_{rt} = 0$ could climate damage obtain a Hicks-neutral representation.

We now formalize how the change in a firm's Solow residual can be used to estimate the technical bias of climate damages.

Lemma 1 *With the functional forms assumed in (9), firm i's Solow residual can be written as*

$$d\log Solow_{it} = \mathbf{b}_{rt} \cdot d\mathbf{T}_{rt} + s^K_{it}(\mathbf{a}_{rt} - \mathbf{b}_{rt}) \cdot d\mathbf{T}_{rt} + \underbrace{d\varepsilon_{it}}_{\substack{s^L_{it} d\log \tilde{A}_{it} \\ +s^K_{it} d\log \tilde{B}_{it}}} + \underbrace{d\theta_{ct}}_{\substack{d\log P^c_t \\ +\frac{1}{\varepsilon} d\log Y^c_t}}. \tag{10}$$

Climate damage is capital-biased if and only if the climate damages decrease Solow residuals more for firms with higher capital shares:

$$\frac{d\frac{d\log Solow_{it}}{d\mathbf{T}^H_{r,t}}}{ds^K_{it}} < 0,$$

when holding fixed $\tilde{A}_{it}$ and $\tilde{B}_{it}$.

Proof. Equation (10) directly follows from equation (9) and equation (8). Taking derivatives with respect to heat shocks, we obtain $\frac{d\log \text{Solow}_{it}}{d\mathbf{T}^H_{r,t}} = \mathbf{b}^H_{rt} + s^K_{it}(\mathbf{a}^H_{rt} - \mathbf{b}^H_{rt})$. Further differentiating with respect to the capital share s^K_{it} gives $\frac{d}{ds^K_{it}}\left(\frac{d\log(\text{Solow}_{it})}{d\mathbf{T}^H_{r,t}}\right) = \mathbf{a}^H_{rt} - \mathbf{b}^H_{rt}$.

Hence, if $\mathbf{a}^H_{rt} - \mathbf{b}^H_{rt} < 0$, then $\frac{d}{ds^K_{it}}\left(\frac{d\log(\text{Solow}_{it})}{d\mathbf{T}^H_{r,t}}\right) < 0$, implying that climate damages disproportionately reduce the Solow residual for firms with larger capital shares. Conversely, if $\frac{d}{ds^K_{it}}\left(\frac{d\log(\text{Solow}_{it})}{d\mathbf{T}^H_{r,t}}\right) < 0$, then it must be that $\mathbf{a}^H_{rt} - \mathbf{b}^H_{rt} < 0$. ■

The decomposition in equation (10) highlights the heterogeneous response of firms' Solow residuals to temperature shocks can be used to identify the technical bias of climate damages. The term $s^K_{it}(\mathbf{a}_{rt} - \mathbf{b}_{rt}) \cdot d\mathbf{T}_{rt}$ shows that the interaction between the effect of a temperature change and a firm's capital share s_{Kcit} identifies the technical bias of climate damages. If a firm's capital share is higher, then capital is more important for production and capital-augmenting productivity thus becomes more important for that firm's technical efficiency. Thus, if the climate damage is indeed capital-biased, $(\mathbf{a}^H_{rt} - \mathbf{b}^H_{tr}) < 0$, then a firm that relies heavily on capital (and thus pays more to capital) would see a larger drop in their Solow

residual. We estimate this bias directly in the data.[12]

Mapping to Estimation For expositional clarity, we focus on estimating the average effect of temperature on capital-augmenting and labor-augmenting productivities, $\mathbf{a} \equiv \mathbb{E}_{rt}(\mathbf{a}_{rt})$ and $\mathbf{b} \equiv \mathbb{E}_{rt}(\mathbf{b}_{rt})$. We can write down a regression equation as the empirical analogue of equation (10):

$$\log\left(\widetilde{\text{Solow}}_{cit}\right) = \sum_{b \notin \{10\sim15°C\}} b^b \cdot T^b_{rt} + \sum_{b \notin \{10\sim15°C\}} (a^b - b^b) \cdot s^K_{it} \cdot T^b_{rt} + (a^{10\sim15°C} - b^{10\sim15°C}) \cdot s_{K_{it}} + \delta_i + \theta_{cst} + \varepsilon_{it}, \tag{11}$$

where $\widetilde{\text{Solow}}_{cit} = \frac{P_{it}Y_{it}}{K_{it}^{s^K_{it}} L_{it}^{1-s^K_{it}}}$ is the measured Solow residual. The idiosyncratic technological components are mapped into the firm fixed effect δ_i and error term ε_{it} while the aggregate states are absorbed in the county-sector-year fixed effects θ_{cst}.[13]

4.3 Climate Damages are Capital-Biased

The estimates for $\mathbf{a}$ and $\mathbf{a} - \mathbf{b}$ are reported in Table C.3. Column (1) shows our baseline results, where we use wage bills (adjusted by regional wages) as a measure of labor inputs to account for cross-firm human capital differences. Column (2) presents the results using the number of employees. Across both specifications, we find $\mathbf{a}^H - \mathbf{b}^H < 0$ in the high-temperature bins. For firms with higher capital shares, the impact of extreme heat on their Solow residual is correspondingly larger. According to Lemma 1, this pattern indicates that climate damage must be *capital-biased*.

The magnitude of the bias toward capital-augmenting productivity is greatest for days above $25°C$. With an estimated $\widehat{a^{>30°C} - b^{>30°C}} = -0.004$, all else being equal, an additional day above $30°C$ compared to a day in the $10°C \sim 15°C$ range results in 0.4% more damage to capital-augmenting productivity than to labor-augmenting productivity. Note that the level of $\mathbf{a}$ can also be recovered by linearly combining the estimates from equation (11). Figure 5a plots our estimates of $\mathbf{a}$ and $\mathbf{b}$ graphically in the baseline specification.

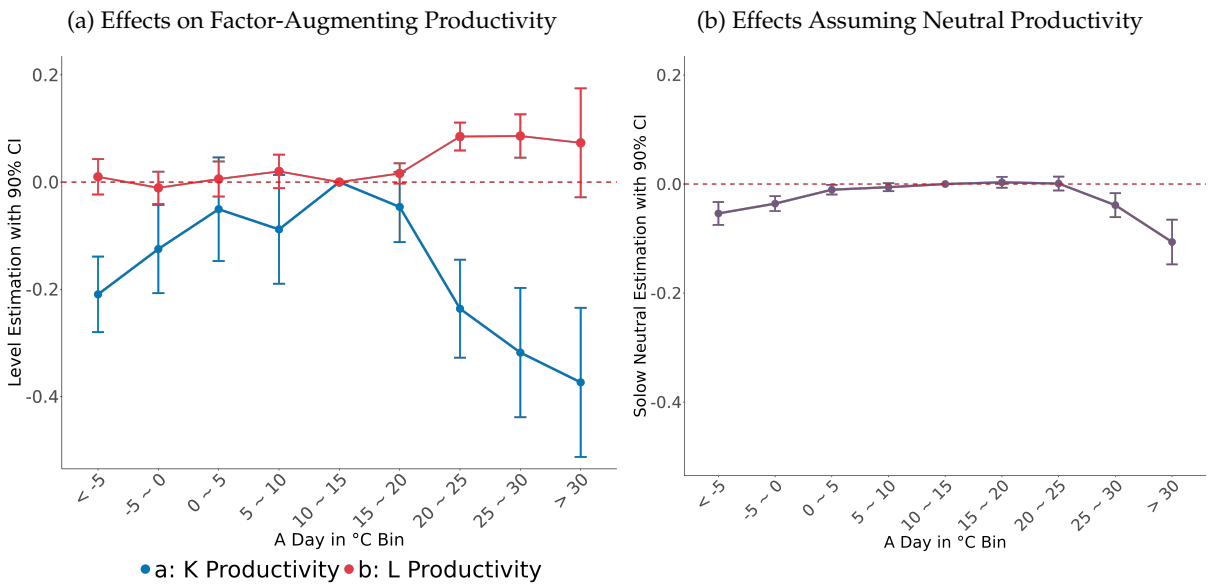
We estimate extreme heat (above 20°C) has a small positive effect on labor-augmenting productivity that is indistinguishable from zero in the hottest temperature bin. Labor-augmenting productivity remains largely unaffected by cold temperature shocks. In contrast, both extreme cold and heat causes substantial damage to capital productivity. Each additional day with temperatures below -5$°C$ leads to a 0.2% decline in capital-augmenting productivity, while each additional day above 30°C corresponds to a 0.4% decline. Indeed, any deviation from 10°C $\sim$ 15°C, whether extreme heat or cold, consistently damages capital productivity. Figure C.10 plots the productivity bias for each sector. Across mostly all sectors, capital productivity is significantly damaged under extreme heat whereas labor productivity see a small increase

12. Notice that we could rearrange $\mathbf{b}_r \cdot d\mathbf{T}_{rt} + s^K_{it}(\mathbf{a}_{rt} - \mathbf{b}_{rt}) \cdot d\mathbf{T}_{rt}$ to be $s^L_{it}\mathbf{b}_{rt} \cdot d\mathbf{T}_{rt} + s^K_{it}\mathbf{a}_{rt} \cdot d\mathbf{T}_{rt}$, and then the bias would be the difference between the effect of a change in temperature interacted with the firm's capital share and labor share.

13. As is standard practice, we include the uninteracted s_{Kit} term to have the full set of variables of the capital share-temperature interaction.

at above 20°C. The only exception is mining sector, which sees an increase of capital productivity and decrease in labor productivity, consistent with its decrease of capital share estimated in Figure 2.

Figure 5: Solow Residual Estimates of Productivity Effects



Notes: Panel (a) plots a_r^b and b_r^b by estimating equation (11). Panel (b) plots the coefficients from regressing log Solow residuals on temperature bins, under a Cobb–Douglas assumption. Standard errors in both estimations are clustered at the regional level. We use 10∼ 15°C as the reference temperature bin. The whisker is the 90% confidence interval where standard errors are calculated from the delta method. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects, where sector is at USSIC 3 digit level. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

Comparing with Previous Estimates. Our findings, while initially seeming at odds with existing research, are in fact consistent once we account for the assumptions used in prior work. For instance, Somanathan et al. (2021) impose a Cobb-Douglas specification and report that temperature shocks reduce the revenue elasticity of labor but increase that of capital—the so-called "labor channel" of climate change. However, labor's revenue elasticity in a Cobb-Douglas setting is precisely their output elasticity and labor share of income. A decline in the revenue elasticity of labor thus is the same as a drop in labor share, perfectly aligning with our reduced-form results. Our approach relaxes the strict Cobb-Douglas assumption common in the climate economics literature, is consistent with an empirical literature widely rejecting Cobb-Douglas (Gechert et al. 2022), and shows that the mechanism for the observed impacts on climate change on labor income may be different than commonly thought.

The Solow residual approach offers a flexible framework for revealing the novel fact that climate damage is primarily capital biased. This arises because temperature shocks chiefly affect capital-augmenting productivity, while labor-augmenting productivity remains largely invariant to such shocks.

5 Rationalizing the Bias of Climate Damages with CES Production

Our reduced-form results showed that firm-level relative factor shares respond to climate shocks and our Solow residual-based results showed that the climate damages exhibit a capital bias. Jointly, these suggest an elasticity of substitution between capital and labor that falls below unity. Now we rationalize our previous results in a CES production function framework. We estimate the technical bias of climate damages within the CES class of production functions and also estimate the elasticity of substitution. Using an instrumental variables strategy, we find that labor and capital are complements, and again that climate damages are capital-biased even with the additional CES structure. The CES estimates align well with our previous Solow residual-based estimates in Section 4.

5.1 Set-up

Production We maintain the same model set-up as Section 4.2, but additionally assume that each firm produces a differentiated output Y_{it} with labor and capital using a constant elasticity of substitution (CES) production function,

$$Y_{it} = \left[\gamma \left(A_{it}K_{it}\right)^{\frac{\sigma-1}{\sigma}} + (1-\gamma)\left(B_{it}L_{it}\right)^{\frac{\sigma-1}{\sigma}}\right]^{\frac{\sigma}{\sigma-1}}, \tag{12}$$

where σ is the elasticity of substitution between capital and labor. γ and $1-\gamma$ are the share parameters for capital and labor. Solving the firm's optimal choice of inputs in equation (5) with a CES production function as in equation (12) yields an expression for relative factor expenditures,

$$\log(\frac{r_{it}K_{it}}{w_{it}L_{it}}) = (\sigma-1)(\mathbf{a}_r - \mathbf{b}_r)\mathbf{T}_{r,t} + (\sigma-1)\log\frac{\tilde{A}_{it}}{\tilde{B}_{it}} + (\sigma-1)\log\frac{w_{it}}{r_{it}} + \log\left(\frac{\gamma}{1-\gamma}\right). \tag{13}$$

Relative factor expenditures depend on relative input prices and on how climate change interacts with the technical bias of climate damages (through relative factor productivity). The effect of relative input prices on relative expenditures is modulated by the elasticity of substitution. To gain intuition, suppose the price of labor rises relative to capital. When factors are gross substitutes ($\sigma > 1$), firms shift their input mix toward capital, increasing capital's share of spending. However, when factors are gross complements ($\sigma < 1$), firms cannot easily substitute away from labor in production, and end up spending more on labor as it becomes relatively more expensive. We will use plausibly exogenous variation in wages to identify σ.

How climate change affects relative factor spending depends on the technical bias of damages and the elasticity of substitution.[14] Suppose extreme heat reduces only capital-augmenting productivity (implying capital-biased damage). Then the firm's effective capital, $A_{it}K_{it}$, falls relative to its effective labor, $B_{it}L_{it}$. This triggers two responses: First, a *direct effect*: because lower capital productivity A_{it} reduces labor's marginal product, the firm cuts labor perfectly in proportion to the drop in effective capital. Second, a *substitution effect*: as capital becomes relatively more expensive $\left(r_{it}/A_{it}\right)$, the firm substitutes toward labor. The strength of this shift

14. The intuition described here follows closely that given in Raval (2019).

depends on σ. The combined effect of the two is $\sigma - 1$. If capital and labor are complements ($\sigma < 1$), the direct effect dominates, and the labor share falls. If they are substitutes ($\sigma > 1$), the substitution effect dominates, and the labor share rises. Under Cobb–Douglas ($\sigma = 1$), the two effects offset exactly, leaving the labor share unchanged.

Our reduced form and Solow residual results suggest that we are in a world with complementarity ($\sigma < 1$). Figure 5a shows that damages are capital-biased, combining this with Figure 1 showing that extreme heat increasing expenditures on capital relative to labor implies they are complements. We now estimate σ directly by isolating plausibly exogenous variation in wages.

5.2 Empirical Estimation

We jointly estimate the elasticity of substitution σ and the bias of climate damages using equation (13). The specification we use is:

$$\log(\frac{r_{it}K_{it}}{w_{it}L_{it}}) = \beta \log w_{rt} + \sum_b \beta^b T^b_{r,t} + \theta_{cou,s,t} + \gamma_i + \varepsilon_{it}, \tag{14}$$

where $\theta_{c(r)s(i)t}$ is a country-sector-year fixed effect and sector is a 3 digit USSIC sector. γ_i is firm fixed effect, and ε_{it} is a structural error term capturing firm-specific technological factors. $T^b_{r,t}$ are the same temperature bins as in our reduced-form analysis. We omit the rental rate for capital from our regression because it is unobserved, however this is not an issue for identification as long as the market for capital is not more granular than our country-3-digit-sector-year fixed effects $\theta_{c(r)s(i)t}$.[15]

Our coefficients of interest are β and β^b. Given our CES framework, $\beta = \sigma - 1$ and $\beta^b = (\sigma - 1)(a^b_r - b^b_r)$. An estimate of $\beta < 0$ would indicate that $\sigma < 1$ and that capital and labor are complements. Estimates of the bias can be recovered by manipulating estimates of β and β_b.

Identification of β^b follows standard arguments in the literature, where year-to-year variation in temperature within a firm, after controlling for unobserved country-sector shocks, is taken to be as good as random. Our identification strategy for σ is more involved as factor expenditures and prices are clearly endogenous. Our identification strategy follows closely to Oberfield and Raval (2021) where we will isolate plausibly exogenous variation in regional wages. We define a labor market to be at the region level, which is similar to the definition of commuting zone in the US context.[16] The appropriate measure of the local wage, $\log w_{rt}$, should reflect the cost of an efficiency unit of labor, and not capture skill premia nor differences from regional specialization of sectors (Combes, Duranton, and Gobillon 2008). Otherwise, it could correlate with unobserved firm characteristics (e.g., technology or workforce composition) and bias estimation of σ.[17] Thus, for each firm-year observation, we compute a firm's residual wage in a given year by regressing observed firm wages on country-sector-year fixed

15. Moreover, an instrumental variables approach can also address any omitted-variable bias if capital prices vary at a very granular level.

16. In fact, for European countries, the closest counterpart to commuting zones is the functional urban areas (FUAs), which are mostly defined at the NUTS-3 level, matching our definition of a region.

17. In practice, a skill-confounded wage measure can be viewed as a market wage measured with measurement errors, causing attenuation bias and potential weak instruments problems, as summarized by Hausman (2001).

effects and taking the residuals: $\tilde{w}_{it} = \hat{w}_{it} - w_{it}$. The implicit assumption underlying this residual wage approach is that within a narrowly defined sector in a country, the skills required for a worker and technologies of the firms will be similar, alleviating potential issues with skill premia and regional specialization. We then average this residual within each region to form a measure of local wage, $\log w_{rt} = \mathbb{E}_i[\tilde{w}_{it} | i \in I(r)]$. With the firm fixed effect present in the main regression, any persistent local skill premia will be absorbed as well.

Granular Instruments for Wages Even if our measure of regional wages have been purged of correlation with skill or firm's technology level, our measure of $\log w_{rt}$ may still be correlated with trends in technology or other shifts in labor demand at the region-year level such that $\text{Cov}(\log w_{rt}, \varepsilon_{it}) \neq 0$. We isolate plausibly exogenous variation in regional wages through "granular instrumental variables" in the spirit of Gabaix and Koijen (2024).[18]

Granular instruments are quite intuitive. Consider the regional (market) labor supply curve,

$$d \ln w_{rt} = \eta_r \cdot d \ln L_{rt} + d\varepsilon_{rt}$$

with η_r being the regional inverse Frisch elasticity of labor supply and $d\varepsilon_{rt}$ captures labor supply shocks. Labor demand for firm j in sector s in region r can be written as

$$d \ln L_{jt} = \kappa_{s(j),r} \cdot d \ln w_t + d\phi_{srt} + du_{jt}.$$

$\kappa_{s(j),r}$ is the firm j's labor demand elasticity, which is common to firms within a region-sector, $d\phi_{srt}$ captures other region-sector-year specific factors (e.g. the average substitution effect due to changes in capital rental rate) and du_{jt} is the firm's idiosyncratic labor demand shock, which originates from firm-level productivity or product demand shocks. Define firm j's steady-state employment share in its local labor market as s^r_{jt}. Aggregating the demand curve using the local labor market clearing condition $d \ln L_{rt} = \sum_{j \in I(r,t)} s^r_{jt} d \ln L_{jt}$, we have:

$$d \ln L_{rt} = \sum_{j \in I(r,t)} s_j \kappa_{s(j)r} d \ln w_t + \sum_{j \in I(r,t)} s_{jt} d\phi_{srt} + \sum_{j \in I(r,t)} s_{jt} du_{jt}.$$

Plugging this into the supply curve yields:

$$d \ln w_{rt} = \tilde{\eta}_{rt} \sum_{j \in I(r)} s_{jt} du_{jt} + \frac{\tilde{\eta}_{rt}}{\eta_r} \sum_{j \in I(r)} s_{jt} d\phi_{srt} + \frac{\tilde{\eta}_{rt}}{\eta_r} d\varepsilon_{rt} \tag{15}$$

where $\tilde{\eta}_{rt} = \frac{\eta_r}{1 - \eta_r \sum_{i \in I(r)} s_{it} \kappa_{s(i)r}}$ characterizes the pass-through of aggregated granular-level idiosyncratic demand shocks on wages. The regional wage is determined by a combination of idiosyncratic demand shocks, region-sector-year factors, and supply shocks. Since du_{jt} is idiosyncratic across firms within a region, $\text{Cov}(du_{jt}, du_{it}) = 0$, equation (15) shows that the share-weighted granular labor demand shocks, $\sum_{j \in I(r,t), j \neq i} s_{jt} du_{jt}$, can be used as an instru-

18. One common alternative approach is to isolate local labor supply shocks in a shift-share fashion from national-level shocks (Oberfield and Raval 2021). However, we lack of region-by-sector level employment data for the 32 countries from 1998-2018 in our sample. Eurostat only has very incomplete coverage of many countries before 2005 and with very aggregated sectoral definition. There is no harmonized prefecture-sector level dataset for India and China.

ment to isolate clean variation in $\ln w_{rt}$ in equation (14). The term "granular" arises from the idea that if a few large firms are big enough, their own idiosyncratic shocks (e.g., a sudden sales slump or a new product launch) can significantly move regional aggregates (like wages or employment). This type of movement acts as a firm-specific shock that is *exogenous* to *other* firms in the region, because it originates from the large firm's own circumstances rather than from local demand or policy affecting everyone.

To construct our granular instruments, we need to first estimate a set of firm-specific granular shocks $\widehat{u_{it}}$. Following Gabaix and Koijen (2024), we estimate these shocks as the residuals of regressing firm-level employment on firm fixed effects η_i and region-sector-year fixed effects:

$$\log(L_{it}) = \iota_i + \theta_{r,s,t} + u_{it}. \tag{16}$$

We then construct the granular instrument variable for firm i in year t as the difference between the share-weighted sum of granular shocks excluding firm i, and the average granular shock in the local labor market:

$$Z^{GIV}_{i,rst} = \sum_{j \in I(r,t), j \neq i} s^r_{jt} \hat{u}_{jt} - \frac{1}{|I(r,t)|} \sum_{j \in I(r,t)} \hat{u}_{jt}$$

where $s^r_{jt} = \frac{L_{jt}}{\sum_{k \in I(r)} L_{kt}}$ is the share of total observed local employment in the sample. If the firms-specific demand shocks used to construct the instrument $Z^{GIV}_{i,rst}$ are idiosyncratic, then they will only affect relative factor expenditures through how they affect the market wage, satisfying the exclusion restriction. The relevance of the instrument is clear from equation (15).

5.3 Capital and Labor are Complements and Climate Damages are Capital-Biased

Table 1 displays OLS and IV estimates of the capital-labor elasticity along with the jointly estimated effects of temperature on relative factor productivities. Column (1) shows an OLS estimate of 0.88 (SE: 0.01), and the remaining columns present IV results. Column (2) displays the main estimates of the average elasticity of substitution using all firms from all sectors in our sample. We estimate that the elasticity of substitution is $\hat{\sigma} = 0.3 < 1$. With a standard error of 0.23, it is statistically different from a unitary elasticity of substitution at the 1% significance level. On average, capital and labor are gross complements in production at the firm-level and we can rule out the commonly assumed Cobb-Douglas case of $\sigma = 1$. Our elasticity estimates across firms in the EU, India, and China align well with those of Oberfield and Raval (2021), who study the U.S., and Berlingieri et al. (2024), who study France (focusing on skilled labor), as well as with the mean elasticity found in the meta-study by Gechert et al. (2022).[19]

The estimates for the effects of temperature on relative factor productivities are quantitatively very similar to the estimates in the reduced form exercise (as in Figure 1), providing

19. See Chirinko (2008) for an earlier survey of this literature. Earlier work by Barnes, Price, and Barriel (2008) and Chirinko, Fazzari, and Meyer (2011) also found a micro elasticity of substitution below 1. Doraszelski and Jaumandreu (2018) reached similar conclusions using a more structural approach. Some estimates, such as those by Karabarbounis and Neiman (2013) and Hubmer (2023), based on variation across sectors and countries in aggregate data, suggest that the sector- or country-level aggregate elasticity of substitution can exceed 1. However, these estimates are conceptually different from the firm-level elasticity of substitution studied here.

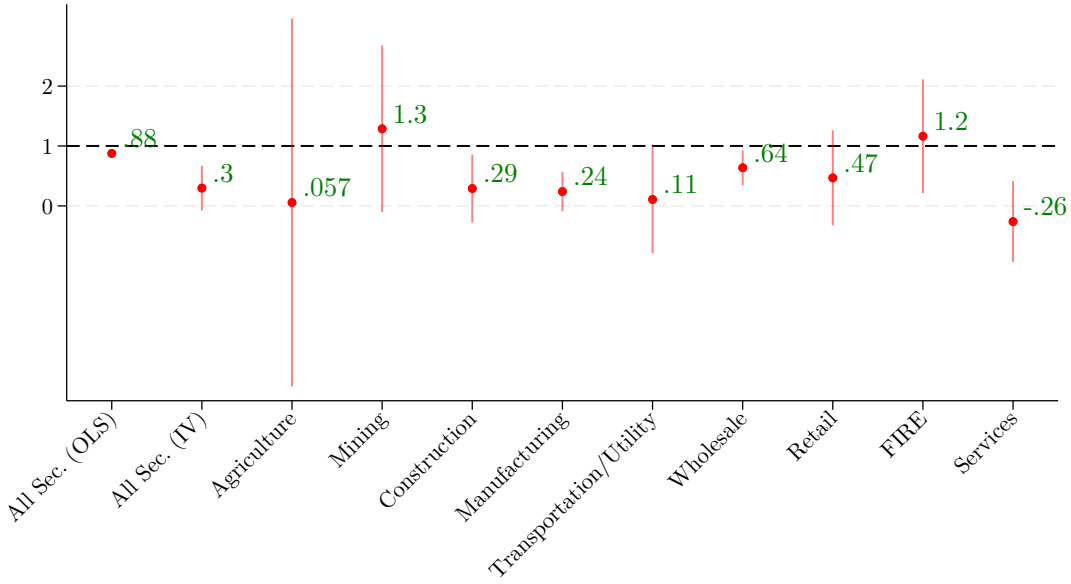
further evidence that effects through changes in relative prices are small.[20] Replacing one day of the year at $10 - 15°C$ with one above $30°C$ increases capital expenditures relative to labor expenditures by $\hat{\beta}^{>30°C} = 0.16\%$. Given our estimated elasticity of substitution, this implies a reduction in capital productivity relative to labor productivity of $\frac{\hat{\beta}^{>30°C}}{\hat{\sigma}-1} \approx -0.23\%$, as shown in the left panel of Figure 7a. This is about 60% of the relative productivity change implied by our Solow residual-based estimates, relatively close given the two distinct estimation strategies with different underlying assumptions. These estimates help explain why extreme heat reduces labor income while being consistent with the macroeconomic evidence on firm-level capital-labor complementarity.

Heterogeneity Across Sectors Table 1 also reports sector-specific estimates obtained by estimating the IV version of equation (14) on subsamples for each USSIC 1-digit sector. As with the results for all sectors, the sector-specific results are broadly consistent with the reduced form results in Figure 2, indicating that an additional day above $30°\text{C}$ raises the capital-to-labor expenditure ratio by about 1–5%. The point estimates of elasticity of substitution also generally remains below 1, implying that capital and labor are complements in most sectors. For about half of the sectors-—including manufacturing, services, and construction—we can statistically reject that the elasticity of substitution is greater than or equal to one.[21] Two sectors—Mining (1.3, SE: 0.84) and FIRE (1.2, SE: 0.58)—have point estimates for the elasticity of substitution above 1, although neither differs from 1 in a statistically significant way, and these two sectors account for a relatively small share of aggregate value added. Based on the point estimates, climate damage appears to be capital-biased in all sectors except FIRE. One point to note is that our instrument strength is generally good, with a first-stage F-statistic around 12 overall but reaching as high as 60 in manufacturing.

20. If effects through relative prices were first-order, we would expect the reduced form results to be substantially different since relative prices were omitted from the regression.

21. Note that estimates below 0, such as what we find for services, are not unusual. Although the point estimate is negative, we cannot reject that the elasticity for services is positive up to about 0.5.

Figure 6: Granular IV Estimates of the Elasticity of Substitution



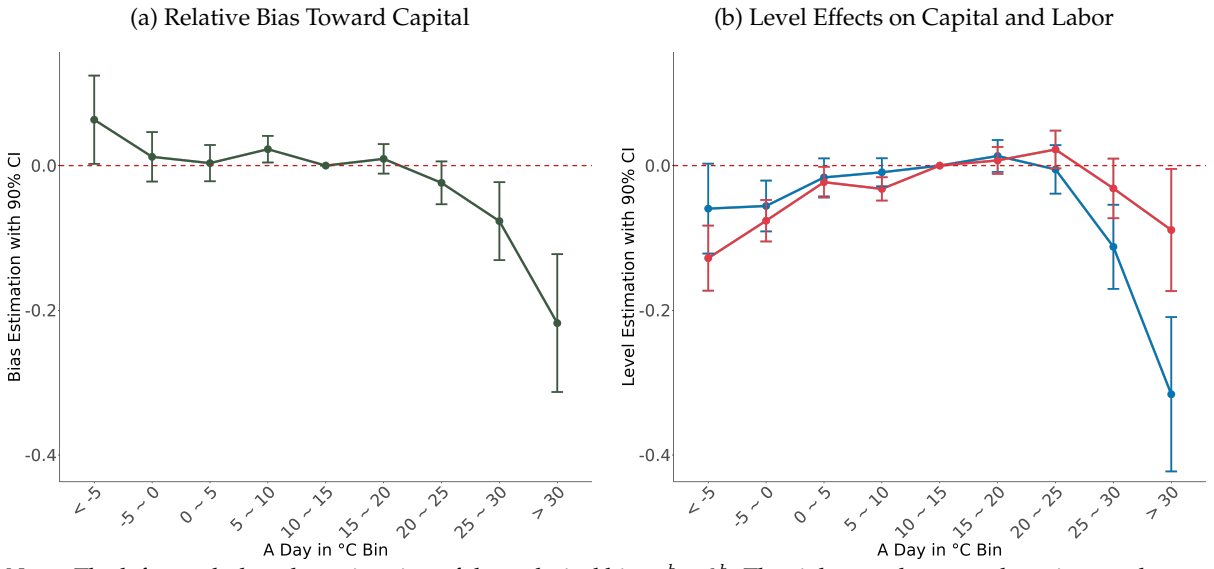
Notes: The graph plots the estimated average elasticities and elasticities by sector after instrumenting for local wage in equation (14). The whisker is the 90% confidence interval computed from robust standard errors clustered at the region level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects, where sector is at USSIC 3 digit level. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

Table 1: Granular IV Estimates by Sector

Sector	(1) All (OLS)	(2) All (IV)	(3) Agriculture	(4) Mining	(5) Construction	(6) Manufacturing	(7) Transp.+Utilities	(8) Wholesale	(9) Retail	(10) FIRE	(11) Services
< -5°C	-0.0002	-0.0004*	0.0000	-0.0001	0.0001	-0.0005	-0.0010**	-0.0003	-0.0006	0.0000	-0.0006*
	(0.0002)	(0.0002)	(0.0005)	(0.0010)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0004)	(0.0005)	(0.0004)
$-5 \sim 0$°C	-0.0000	-0.0000	0.0002	-0.0007	0.0003	-0.0001	-0.0002	-0.0001	-0.0001	-0.0000	-0.0000
	(0.0001)	(0.0001)	(0.0003)	(0.0008)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
$0 \sim 5$°C	0.0000	-0.0000	0.0002	0.0008	0.0001	0.0001	-0.0004*	-0.0000	-0.0001	0.0001	-0.0001
	(0.0001)	(0.0001)	(0.0003)	(0.0008)	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
$5 \sim 10$°C	-0.0000	-0.0001	0.0000	-0.0001	-0.0001	-0.0000	-0.0004***	0.0000	-0.0001	0.0000	-0.0002*
	(0.0001)	(0.0001)	(0.0002)	(0.0005)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0002)	(0.0001)
$15 \sim 20$°C	-0.0001	-0.0000	0.0002	-0.0001	-0.0001	-0.0001	-0.0001	0.0000	0.0000	-0.0001	-0.0000
	(0.0001)	(0.0001)	(0.0004)	(0.0005)	(0.0001)	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)
$20 \sim 25$°C	0.0001	0.0002	0.0000	-0.0003	0.0002	0.0004***	0.0002	0.0002	0.0000	-0.0000	0.0003*
	(0.0001)	(0.0001)	(0.0005)	(0.0007)	(0.0002)	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0002)
$25 \sim 30$°C	0.0006***	0.0006***	0.0006	0.0000	0.0011***	0.0007***	0.0000	0.0005**	0.0004*	0.0003	0.0006**
	(0.0001)	(0.0002)	(0.0004)	(0.0008)	(0.0003)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0003)	(0.0002)
> 30°C	0.0018***	0.0016***	0.0031***	-0.0032	0.0053***	0.0010***	0.0012**	0.0022***	0.0036***	0.0036***	0.0028***
	(0.0003)	(0.0003)	(0.0009)	(0.0023)	(0.0011)	(0.0002)	(0.0006)	(0.0007)	(0.0007)	(0.0010)	(0.0007)
$\log(\text{wage}_{rt})$	-0.1235***	-0.7029***	-0.9432	0.2873	-0.7098**	-0.7604***	-0.8919	-0.3636**	-0.5330	0.1630	-1.2620***
	(0.0107)	(0.2270)	(1.8663)	(0.8452)	(0.3441)	(0.2002)	(0.5448)	(0.1770)	(0.4818)	(0.5772)	(0.4106)
σ	0.8765***	0.2971***	0.0568	1.2873	0.2902**	0.2396***	0.1081	0.6364**	0.4670	1.1630	-0.2620***
	(0.0107)	(0.2270)	(1.8663)	(0.8452)	(0.3441)	(0.2002)	(0.5448)	(0.1770)	(0.4818)	(0.5772)	(0.4106)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Country-Sec.-Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	64448409	64327692	1,634,573	230,211	8,199,055	11094435	4,008,302	7,777,534	9,761,719	5,113,579	16508225
F-stat (KP)		11.723	5.727	28.470	8.197	59.442	16.766	17.766	4.100	9.553	7.746

Notes: Standard errors are two-way clustered at the firm and region-year level. The sector in country-sector-year fixed effects is defined at USSIC 3 digit level.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Figure 7: Factor Bias of Climate Change on Capital- vs. Labor-Augmenting Productivity



Notes: The left panel plots the estimation of the technical bias $a_r^b - b_r^b$. The right panel separately estimates the level of damage on capital productivity a_r^b (blue) and labor productivity b_r^b (red). We plug in the value of elasticity of substitution $\sigma = 0.3$, and the value of elasticity of demand $\varepsilon = 3.51$. The whisker is the 90% confidence interval where standard errors computed from robust standard errors clustered at the regional level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects, where sector is at USSIC 3 digit level.

Separate Identification of Factor-Augmenting Productivity Damage So far we have used the elasticity of substitution between capital and labor to back out the technical bias of climate damage from the response of *relative* factor shares and find them to be broadly consistent with reduced-form evidence. Next, we separately identify effects on the levels of capital- and labor-augmenting technology.

To separately identify effects on capital from those on labor, we need another equilibrium condition. Assuming that consumers exhibit CES demand with elasticity ϵ, we can insert the CES inverse demand curve into the firm's first-order conditions with respect to capital and labor in equation (5) and re-write them as two regression equations:

$$\frac{1}{\varepsilon - 1} \ln \left(P_{it} Y_{it} \right) - \frac{1}{\sigma - 1} \ln \left(\frac{P_{it} Y_{it}}{w_{it} L_{it}} \right) + \ln w_{rt} = \left[\sum_b b_r^b \cdot T_{r,t}^b \right] + \theta_{cou,s,t}^L + \gamma_i^L + \varepsilon_{it}^L, \tag{17}$$

$$\frac{1}{\varepsilon - 1} \ln \left(P_{it} Y_{it} \right) - \frac{1}{\sigma - 1} \ln \left(\frac{P_{it} Y_{it}}{r_{it} K_{it}} \right) = \left[\sum_b a_r^b \cdot T_{r,t}^b \right] + \theta_{cou,s,t}^K + \gamma_i^K + \varepsilon_{it}^K, \tag{18}$$

which are the optimality conditions stating that a firm's marginal revenue product of factor input, when divided by factor prices, must be proportional to the level of the factor's factor-augmenting productivity. All aggregate variables, including the price index, market rental rate of capital and aggregate outputs will be absorbed by the country-sector-year fixed effects and the firm-specific non-climate technology terms are in the error term. These two regressions pin down the levels of a_r^b and b_r^b rather than just their relative size.[22]

22. The intuition is that the firm's first-order conditions relate (unobserved) quantities of production to inputs

Constructing the dependent variables from equations (17) and (18) requires estimates of σ and ε. We estimate the demand elasticity ε using the common markup inversion approach. Given monopolistic competition à la Dixit-Stiglitz and constant returns-to-scale in firm-level production, the ratio of revenue over total cost in the data would correspond to the optimal markup $\frac{\varepsilon}{\varepsilon-1}$. We estimate the average markup as the cost-share-weighted average of firms' ratio of revenue over total cost, $\widehat{\frac{\varepsilon}{\varepsilon-1}} = \mathbb{E}^W_{it}[\frac{\text{Sales}_{it}}{\text{Total Cost}_{it}}]$ and then use the Delta method to obtain an estimate of $\hat{\varepsilon}$. Our baseline measure uses all firms in the sample and yields an estimate of $\hat{\varepsilon} = 3.51$ (SE: 0.01). Our estimated value for the demand elasticities in different sectors range from 2.31 to 10.[23]

Using the constructed dependent variables with the full sample estimates of $\hat{\varepsilon} = 3.51$ and $\hat{\sigma} = 0.3$, the estimates from equations (17) and (18) are reported in Columns (3) and (4) of Table E.5 and plotted on the right panel of Figure 7a, which shows the estimated capital productivity damage coefficients a^b and labor productivity damage coefficients b^b. We find that replacing a $10 \sim 15°C$ day with a hotter than 30° day decreases capital productivity by 0.3% and labor productivity by 0.09%. The left panel of Figure 7a shows the bias, i.e. the difference between the two effects. These estimates are highly consistent with those in Table 1 where the bias was estimated in one regression.

We have presented several lines of evidence that extreme heat reduces the labor share primarily because it damages capital more severely while capital and labor are complements. Next, we show why this distinction in mechanism matters by evaluating both the historical impact of climate change and anticipated future changes.

6 The Contribution of Climate Change to the Level and Distribution of Factor Income Since 1981

It is well documented that the labor share of income has declined globally. Using a global dataset on factor income shares from Bachas et al. (2022), we replicate the empirical findings of Karabarbounis and Neiman (2013), showing that the global labor share of net domestic product has steadily dropped by about 5pp since 1981, declining from 72.6% to 67.2% (red line in Figure 8b). In this section, we assess how climate change has contributed to this long-run decline in the labor share between 1981 and 2018 due to its bias toward damaging capital-augmenting productivity.

For these counterfactual simulations we will allow for heterogeneity across regions and over time by using an analogous specification to those in Carleton et al. (2022) and Nath (2023) where the effect of temperature may be heterogeneous across different long-run climates and different levels of economic development. Temperature shocks may be more harmful to capital at higher average temperatures if damages are convex in temperature. Similarly, extreme heat may disproportionately harm capital in developed countries if this capital is more sophisticated and sensitive to environmental change.

and input prices, technology, and climate variables. The demand equilibrium condition allows us to convert these into expenditures and sales which are observables.

23. We list these estimates in Figure D.11.

This approach also critically accounts for the effect of endogenous adaptation and directed technical change over the long run. For example, as a region warms over time, the local incentives for directed innovation might shift (Acemoglu 2002). Firms may direct their research towards more capital-specific, heat-adaptive technologies, thus mitigating the technical bias such that the actual effect is weaker in the long-run (See, for example, Moscona and Sastry 2023). By interacting daily temperature shocks with long-run baseline climate conditions and long-run income, we account for how the long-run incentives and efficiency of temperature-induced directed innovation might alter the strength of the bias of climate damages in different regions.

6.1 The Contribution of Climate Change to Labor Share Trends

Here we quantify the role of climate change in the decline of the labor share of income. First, notice that we can write the change in labor share as $ds^L_{rt} = s^L_{rt}\left(1-s^L_{rt}\right)\, d\ln\!\left(\frac{s^L_{rt}}{1-s^L_{rt}}\right)$. Combining this identity with equation (13), we can express this change as the sum of climate impacts and other channels:

$$ds^L_{rt} = \underbrace{s^L_{rt}\left(1-s^L_{rt}\right)\sum_b (\sigma-1)\left(a^b_{rt}-b^b_{rt}\right) d\,\text{Tbin}^b_{rt}}_{\text{Due to Factor-Biased Climate Change}} + \underbrace{\left(ds^L_{rt} - s^L_{rt}\left(1-s^L_{rt}\right)\sum_b (\sigma-1)\left(a^b_{rt}-b^b_{rt}\right) d\,\text{Tbin}^b_{rt}\right)}_{\text{Due to Residual Channels}}, \tag{19}$$

where now we explicitly allow the technology terms to be changing over space and time to capture how long run average climate and development may alter the impacts of changes in daily temperature. This first term in the expression measures how changes in climate ($d\text{Tbin}^b_{rt}$) affect the labor share through the bias of climate damages ($a^b_{rt}-b^b_{rt}$) and the elasticity of substitution. Our aim is to quantify this first term. Other changes such as changes in relative factor prices or other forms of technical progress unrelated to temperature are in the second, residual term. Notice that if production is Cobb-Douglas ($\sigma = 1$), then even if climate damages are biased, the labor share is invariant to a change in climate. Relaxing this common assumption is necessary for understanding climate change's distributional effects.

Discrete Approximation We must discretize equation (19) to take it to the data. Combining it with equation (14), we can approximate the climate-induced change in the regional-level labor share from t to $t+1$, which we denote as $\Delta^{\mathbf{T}}_{t,t+1}s^L_{rt}$, as:

$$\Delta^{\mathbf{T}}_{t,t+1}s^L_{rt} = \bar{s}^L_{rt,t+1}\cdot\left(1-\bar{s}^L_{rt,t+1}\right)\cdot\sum_b \overline{\left[(\sigma-1)\left(a^b_r-b^b_r\right)\right]}_{t,t+1}\;\Delta^{\mathbf{T}}_{t,t+1}\text{Tbin}^b_{rt}, \tag{20}$$

where $\bar{x}_{t,t+1} = \frac{x_t+x_{t+1}}{2}$ denotes the average of variable x over two adjacent years. The above expression measures how the labor share changes due to changes in the number of days in each temperature bin $\Delta^{\mathbf{T}}_{t,t+1}\text{Tbin}^b_{rt}$ interacted with the elasticity-adjusted bias term $\overline{\left[(\sigma-1)\left(a^b_r-b^b_r\right)\right]}_{t,t+1}$.

Next we need to estimate $(\sigma-1)\left(a^b_{rt}-b^b_{rt}\right)$ at the region-year level.[24] To do so, we estimate a variant of equation (14) that includes the interaction terms of temperature bins with both long-

24. For the decomposition we do not need to separately identify the bias from the elasticity of substitution. They are jointly identified by the coefficients on the temperature bins and they enter jointly into equation (20).

run average temperature $\overline{T}_r$ and with average (log) GDP per capita $\overline{\ln \text{GDP}_{\text{pc}_r}}$ as in equation (3). The predicted semi-elasticity for region r in year t to be used for decomposition is thus:

$$\widehat{(\sigma-1)\,(a^b_{rt}-b^b_{rt})} = \hat{\beta}^b + \hat{\beta}^b_{\overline{T}} \cdot \overline{T}_{rt} + \hat{\beta}^b_{\text{GDP}_{\text{pc}}} \cdot \ln \text{GDP}_{\text{pc}_{rt}}$$

where $\hat{\beta}^b_{\overline{T}}$ and $\hat{\beta}^b_{\text{GDP}_{\text{pc}}}$ are the estimated coefficients on the $\text{Tbin}^b_{r,t} \times \overline{T}_r$ and $\text{Tbin}^b_{r,t} \times \overline{\ln \text{GDP}_{\text{pc}_r}}$, respectively. We use the 5-year rolling average of $\overline{T}_{rt}$ and contemporaneous income $\ln \text{GDP}_{\text{pc}_{rt}}$ to obtain the estimates of past semi-elasticities.[25]

Aggregating the Global Cumulative Effect over Time Combining our estimates $\widehat{(\sigma-1)\,(a^b_{rt}-b^b_{rt})}$ with data on changes in temperature bins and data on the labor share allows us to compute the one-year-ahead change in regional labor share $\Delta^{\mathbf{T}}_{t,t+1} s^L_{rt}$. We then aggregate the year-to-year changes into cumulative changes in local labor shares due to climate from t_0 to t_1 by summing up each year-to-year change over time: $\Delta^{\mathbf{T}}_{t_0,t_1} s^L_{rt} = \sum_{t=t_0}^{t_1-1} \Delta^{\mathbf{T}}_{t,t+1} s^L_{rt}$.

We compute the global labor share as a weighted sum of local labor shares, $s^{\text{Global}}_{Lt} = \sum_c \theta^g_{rt} s^L_{rt}$, where θ^g_{rt} is region r's share in global GDP. The change in the global labor share from t_0 to t_1 caused by climate change is then:

$$\Delta^{\mathbf{T}}_{t_0,t_1} s^{\text{Global}}_{Lt} = \sum_r \left(\Delta^{\mathbf{T}}_{t_0,t_1} s^r_{L,t} \cdot \theta^g_{rt_0}\right) + \sum_r \left(\Delta^{\mathbf{T}}_{t_0,t_1} s^r_{L,t} \cdot \Delta^{\mathbf{T}}_{t_0,t_1} \theta^g_{rt}\right). \tag{21}$$

The first term sums over the change in a region's labor share due to changes in its climate, holding fixed its share of the global economy; while the second term further allows for how the change in a region's climate interacts with it's changing share of global economic activity. The former is the direct effect of a change in climate, the latter captures how this interacts with reallocation of production across regions.

6.1.1 Results from Historical Decomposition

We perform our decomposition of the trend in the global labor share from $t_0 = 1981$ to $t_1 = 2018$ using data of 142 countries.[26] Similar to Carleton et al. (2022), we use the heterogeneity in our estimates $\widehat{(\sigma-1)\,(a^b_{rt}-b^b_{rt})}$ to impute the effects of changing temperature on country-specific labor shares for countries outside our sample. We use the Bachas et al. (2022) dataset to benchmark observed factor shares at the country level and construct the aggregation weights θ^g_{rt} by combining region-level GDP data from Kummu, Kosonen, and Masoumzadeh Sayyar (2025) with World Bank GDP data. For each year, we then calculate the cumulative climate-induced change in labor share since 1981 at both the country and global levels. We compute this climate-induced change as the effect of the observed daily temperature distribution versus a counterfactual distribution held fixed at 1981 levels.

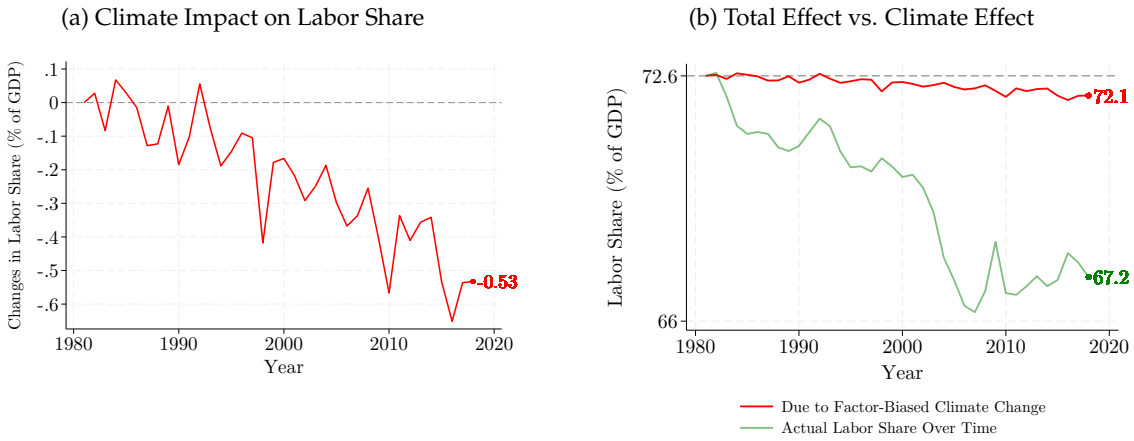
Figure 8a shows our decomposition results at the global level, plotting the time series of $\Delta^{\mathbf{T}}_{t_0,t} s^{\text{Global}}_{Lt}$. We find that factor-biased climate change has led to a steady decline in the global

25. We use the national-level data for $\ln \text{GDP}_{\text{pc}_{rt}}$ from World Bank when predicting the effects.
26. We cover all countries in the Bachas et al. (2022) dataset that have less than 15 years of missing data and can be matched with both the World Bank data and climate data.

labor share of about 0.01pp per year. Overall, climate change reduced the labor share by 0.53pp over 40 years, an economically significant figure.

How does this climate-driven decline compare with the actual global decline in labor share? Figure 8b contrasts the labor share trajectory accounting only for factor-biased climate change (red line) with the actual global labor share (green line). Factor-biased climate change accounts for a tenth of the overall decline in global labor share documented by Karabarbounis and Neiman (2013). If production was Cobb-Douglas or climate change was not factor-biased then it would have zero effect on the labor share.

Figure 8: Climate Change and the Global Decline of Labor Share

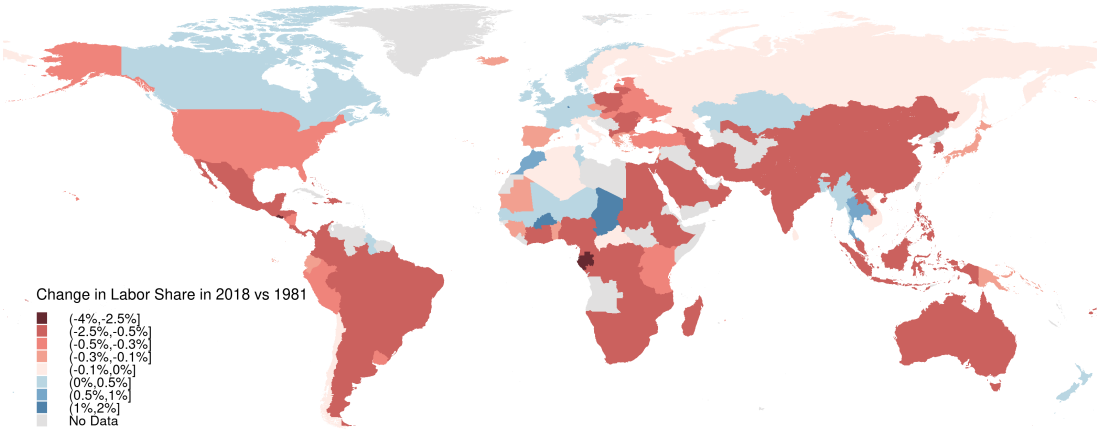


Notes:Panel (a) plots the cumulative change in global labor share, $\Delta^{\mathbf{T}}_{1981,2018} s^{\text{Global}}_{Lt}$, due to climate change from 1981 to 2018. $\Delta^{\mathbf{T}}_{1981,2018} s^{\text{Global}}_{Lt}$ is computed using equation (21). Panel (b) compares the actual decline in the global labor share (green line) with the path of labor share decline driven by climate change alone (red line). The actual decline in global labor share is computed from Bachas et al. (2022). The path of labor share decline driven by climate change is computed as $s^{\text{Global}}_{L,2018} + \Delta^{\mathbf{T}}_{1981,2018} s^{\text{Global}}_{Lt}$.

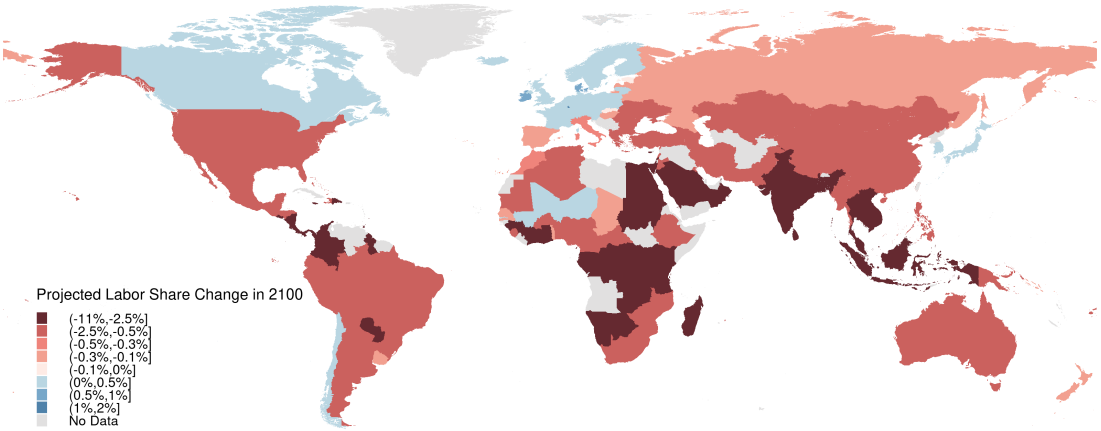
Heterogeneous Effects Across Countries Figure 9a shows the change in labor share attributed to climate change across various countries. These impacts range from a 4pp decline to a 2pp increase worldwide. In regions with hotter long-run average climates, the past 40 years of global warming has led to a substantial drop in labor share, primarily because (1) the frequency of extreme temperatures has increased, and (2) the jointly estimated semi-elasticities $\widehat{(\sigma - 1)\left(a^b_{rt} - b^b_{rt}\right)}$ are larger in hotter areas. Gabon experiences the most prominent climate-induced decline in labor share (about 3.7%). Major economies such as China and India see declines of roughly 1%, while the United States faces a decrease of about 0.4%. By contrast, some regions have a climate-induced *increase* in labor share. For instance, countries in northern Europe and Canada are experiencing fewer cold days and more moderate days. Moreover, some poorer yet hotter regions observe a slight rise in labor share because the capital bias of extreme heat (above $30°C$) is estimated to be smaller than that of moderate heat ($25 \sim 30°C$).

Figure 9: Historical Decomposition and Projection of Labor Share Changes

(a) Changes in Labor Share of income due to Climate Change: 1981-2018



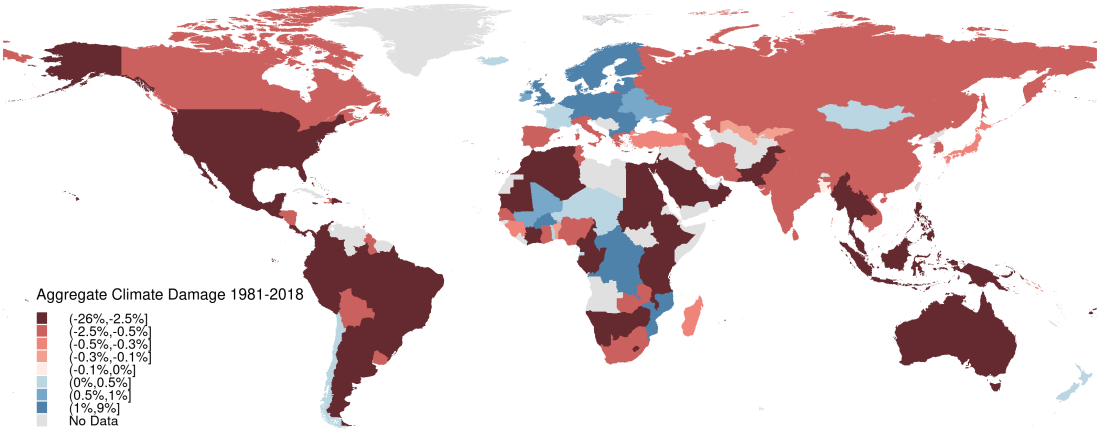
(b) Projected Changes in Labor Share of Income under RCP 4.5: 2018-2100



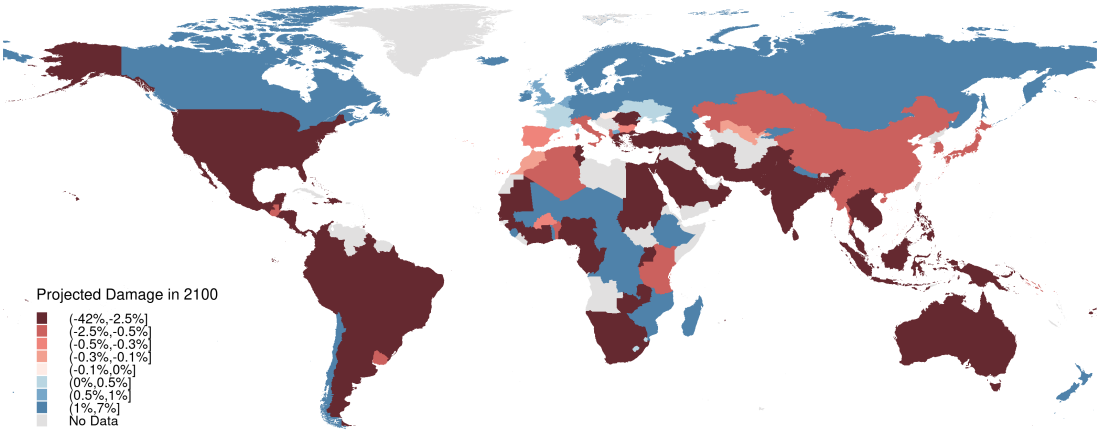
Notes: Panel (a) plots the values of $\Delta^{\mathbf{T}}_{1981,2018} s^c_{Lt}$, the changes in labor share of income due to climate change at the country level form 1981 to 2018. $\Delta^{\mathbf{T}}_{1981,2018} s^c_{Lt}$ is computed using equation (21), but with country-level GDP weights, θ^c_{rt}. Panel (b) plots the values of $\Delta^{\mathbf{T}}_{2020,2100} s^c_{Lt}$ under the RCP 4.5 scenario, also computed using equation (21), but with projected country-level GDP weights from Wang and Sun (2022). We use the projected global temperature distribution under the RCP 4.5 scenario from Copernicus Climate Change Service (2021).

Figure 10: Historical Decomposition and Projection of Climate Damages

(a) Historical Climate Damage from 1998 to 2018



(b) Projection of Climate Damage in 2100



Notes: Panel (a) plots the values of $\Delta^{\mathbf{T}}_{1981,2018} \log Y_{ct}$, which represent the changes in country-level aggregate income due to climate change from 1981 to 2018. $\Delta^{\mathbf{T}}_{1981,2018} \log Y_{ct}$ is computed as a cumulative weighted sum of region-level changes (see equation (22)), using Törnqvist weights $\bar{\theta}^{c}_{rt,t+1}$ over the 1981–2018 period. Panel (b) plots the values of $\Delta^{\mathbf{T}}_{2020,2100} s^{c}_{Lt}$ under the RCP 4.5 scenario, computed in a similar manner but with projected country-level GDP weights from Wang and Sun (2022). We use the projected global temperature distribution under the RCP 4.5 scenario from Copernicus Climate Change Service (2021).

6.2 The Contribution of Climate Change to Aggregate Income Trends

Next we study the contribution of climate change to changes in aggregate income and the importance of simultaneously accounting for factor-biased climate change and factor complementarity. To recover aggregate effects, we use a second-order approximation for the effect of a change in climate on regional income following Baqaee and Farhi (2019), which we then aggregate to changes in global income. We take our estimated micro elasticity of substitution $\hat{\sigma} = 0.3$ to be the region-level aggregate elasticity σ since the aggregation bias is likely small given the size of regions in our paper. The change in regional income due to climate shocks on productivity is given by:

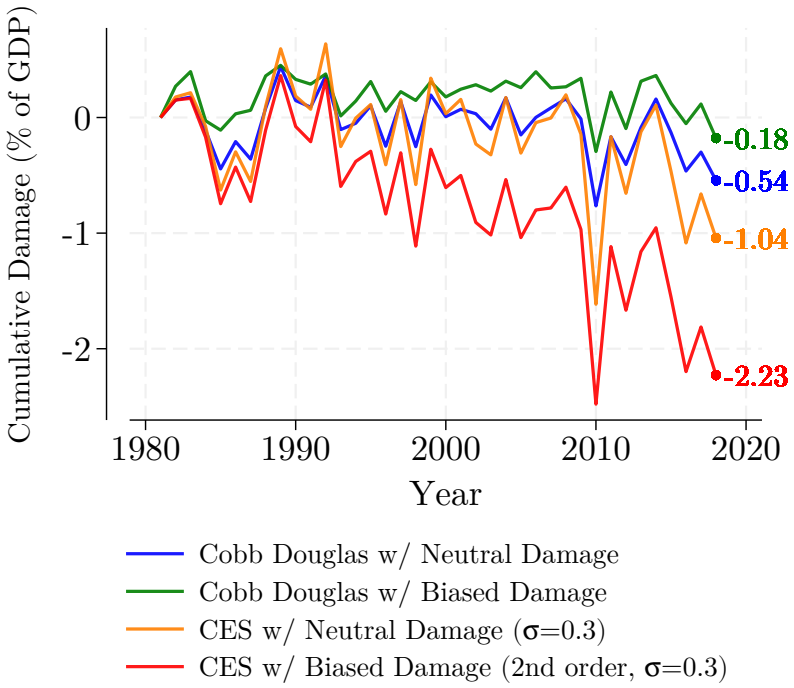
$$\begin{aligned}\Delta^{\mathbf{T}}_{t,t+1} \log Y_{rt} = {} & \bar{s}^K_{rt}\, \bar{\mathbf{a}}_{rt} \cdot \Delta^{\mathbf{T}}_{t,t+1}\mathbf{T}_{rt} + \bar{s}^L_{rt}\, \bar{\mathbf{b}}_{rt} \cdot \Delta^{\mathbf{T}}_{t,t+1}\mathbf{T}_{rt} \\ & + \frac{1}{2}\bar{s}^K_{rt}\, \bar{s}^L_{rt}\, (1 - \frac{1}{\sigma})\, (\bar{\mathbf{a}}_{rt} \cdot \Delta^{\mathbf{T}}_{t,t+1}\mathbf{T}_{rt})^2 \\ & + \frac{1}{2}\bar{s}^L_{rt}\, \bar{s}^K_{rt}\, (1 - \frac{1}{\sigma})\, (\bar{\mathbf{b}}_{rt} \cdot \Delta^{\mathbf{T}}_{t,t+1}\mathbf{T}_{rt})^2 \\ & + (\bar{s}^{L\,2}_{rt} - \bar{s}^L_{rt})\, (1 - \frac{1}{\sigma})\, (\bar{\mathbf{a}}_{rt} \cdot \Delta^{\mathbf{T}}_{t,t+1}\mathbf{T}_{rt})(\bar{\mathbf{b}}_{rt} \cdot \Delta^{\mathbf{T}}_{t,t+1}\mathbf{T}_{rt}).\end{aligned} \tag{22}$$

The first line captures first-order effects that are picked up by a Cobb-Douglas approach, the remaining lines capture second-order effects that are not. These second-order terms capture how capital-labor complementarity amplifies the overall effect of climate shocks on income. If capital and labor are gross complements in regional production ($\sigma < 1$), production becomes constrained by whichever input is relatively more damaged—think of it as "the weakest link." Consequently, when only effective capital is impaired, it lowers labor's marginal productivity even more, which gives rise to the negative coefficients on the squared terms $(\bar{\mathbf{a}}_{rt} \cdot \Delta^{\mathbf{T}}_{t,t+1}\mathbf{T}_{rt})^2$ and $(\bar{\mathbf{b}}_{rt} \cdot \Delta^{\mathbf{T}}_{t,t+1}\mathbf{T}_{rt})^2$. However, if both effective capital and labor are damaged simultaneously, this constraint binds less tightly than if only one factor were impaired on its own, which makes the cross-term coefficient positive. In other words, losing "two weak links" together can have a smaller marginal impact than losing each one separately, because neither factor alone ends up bottlenecking production to the same degree when both are reduced. In fact, when climate change is factor-neutral ($\bar{\mathbf{a}}_{rt} = \bar{\mathbf{b}}_{rt}$), the second order terms offset each other perfectly and become zero.

Figure 11 illustrates the cumulative change in global income from observed climate trends relative to a counterfactual scenario where the distributions of daily temperature in all regions were held fixed at the 1981 level. To highlight the roles of factor complementarity and factor-biased damage, we compare four scenarios. First, the blue line shows that if production was Cobb-Douglas and climate damages were factor-neutral, using the Solow residual estimates from Figure 5b, global income falls by only 0.54%. Next, the green line keeps the Cobb-Douglas structure but *allow* for factor-biased climate damage, drawing on Solow estimates from Figure 5a; this leads to a smaller global income loss of 0.18%, suggesting that unequal climate damage matters little under a production technology that does not force one damaged input to constrain the other. The orange lines, by contrast, permit a CES production function with factor complementarity but impose factor-neutral damage, which raises the loss

to 1.04%.[27] Finally, the red line combines factor complementarity ($\sigma = 0.3$) in CES production with factor-biased climate damage (using estimates in Figure 7), capturing all the second-order terms and revealing a much larger global income decline of 2.23%. In other words, correctly accounting for both factor complementarity and factor-biased climate damage raises estimated aggregate climate damage to be 4 times larger than following the common practices in the literature (Cobb-Douglas with neutral damage).

Figure 11: Factor Bias, Complementarity and Aggregate Climate Damage



Notes: All four lines plot the aggregate damage to global income computed from different cases of equation (22), under different model assumptions and estimates from different empirical specifications: (1) For the Cobb-Douglas case with neutral climate damage (blue line), we compute the region-level change as $\Delta^{\mathbf{T}}_{t,t+1} \log Y_{rt} = \bar{\mathbf{c}}_{rt} \cdot \Delta^{\mathbf{T}}_{t,t+1} \mathbf{T}_{rt}$, with the estimates of $\bar{\mathbf{c}}_{rt}$ similar to Figure 5b, but allowing for heterogeneous effects across climates and income levels as in equation (3). (2) For the Cobb-Douglas case with biased climate damage (green line), we compute the region-level change as $\Delta^{\mathbf{T}}_{t,t+1} \log Y_{rt} = \bar{s}^K_{rt}\ \bar{\mathbf{a}}_{rt} \cdot \Delta^{\mathbf{T}}_{t,t+1} \mathbf{T}_{rt} + \bar{s}^L_{rt}\ \bar{\mathbf{b}}_{rt} \cdot \Delta^{\mathbf{T}}_{t,t+1} \mathbf{T}_{rt}$, with the estimates of $\bar{\mathbf{a}}_{rt}$ and $\bar{\mathbf{b}}_{rt}$ similar to Figure 5a, but allowing for heterogeneous effects across climates and income levels as in equation (3). (3) For the CES case with neutral climate damage (orange line), we compute the region-level change as $\Delta^{\mathbf{T}}_{t,t+1} \log Y_{rt} = \bar{s}^K_{rt}\ \bar{\mathbf{a}}_{rt} \cdot \Delta^{\mathbf{T}}_{t,t+1} \mathbf{T}_{rt} + \bar{s}^L_{rt}\ \bar{\mathbf{b}}_{rt} \cdot \Delta^{\mathbf{T}}_{t,t+1} \mathbf{T}_{rt}$, with the estimates of $\bar{\mathbf{a}}_{rt}$ and $\bar{\mathbf{b}}_{rt}$ similar to Figure 7a, but allowing for heterogeneous effects across climates and income levels as in equation (3). (4) For the CES case with biased climate damage (red line), we compute the region-level change exactly as in equation (22) (second-order terms included), with the estimates of $\bar{\mathbf{a}}_{rt}$ and $\bar{\mathbf{b}}_{rt}$ similar to Figure 7a, again allowing for heterogeneous effects across climates and income levels as in equation (3). The plotted global aggregate damage in all four cases is then computed as a cumulative weighted sum of region-level changes using Törnqvist weights $\bar{\theta}^c_{rt,t+1}$ over the 1981–2018 period.

6.3 Future Global Labor Share and Aggregate Income under RCP 4.5

To gauge the implications of our new estimates for the future trajectory of the labor share and aggregate economic development, we combine our firm-level results with global income pro-

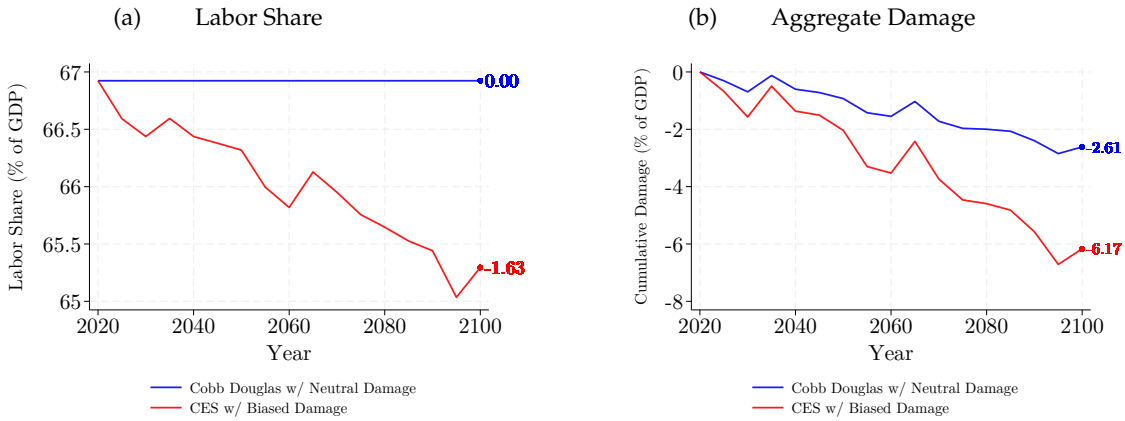
27. Factor-neutral damage with CES production is computed via estimates from (18) and (17) and then weighted by factor shares: $\bar{s}^K_{rt}\ \bar{\mathbf{a}}_{rt} + \bar{s}^L_{rt}\ \bar{\mathbf{b}}_{rt}$.

jections and climate forecasts. In particular, we adopt the RCP 4.5 scenario, associated with approximately 2-3$^{\circ}C$ of warming. We draw on RCP 4.5–consistent national income per capita forecasts from the SSP database—using the OECD EnvGrowth model (Dellink et al. 2017)—and corresponding GDP projections from Wang and Sun (2022), together with near-surface air temperature projections from the CMIP6 ensemble.

Figure 12 illustrates the evolution of the projected labor share and aggregate income under RCP 4.5. We estimate a 1.63–percentage-point drop in the global labor share by 2100, relative to the 2018 baseline, and a 6.17% loss in global aggregate income. In contrast, a canonical approach based on a Cobb-Douglas production function with factor-neutral climate damage would imply *no* decline in labor share and only a 2.61% reduction in global income.

Figures 9b and 10b show the projected heterogeneous effects on labor shares and aggregate income loss across different regions. We find that our approach captures strong nonlinearities compared to aggregate damage estimates in hotter regions, with the largest damage reaching 42%. Botswana, Guyana, Malaysia, and Paraguay each suffer more than 35% in aggregate losses, whereas a Cobb–Douglas model with neutral damage would predict only around 15%. These countries feature relatively high capital shares and significant capital bias, amplifying both the first-order effect of capital-biased damage and a second-order bottleneck effect in factor productivity. Meanwhile, in a few other regions, the Cobb–Douglas neutral-damage model slightly overstates damages, as lower capital shares actually reduce the importance of capital-biased harm.

Figure 12: Projected Change in Labor Share and Aggregate Income in 2100 under RCP 4.5



Notes: Panel (a) plots the projected change in global labor share using equation (21) under two different sets of assumptions: (1) For the Cobb-Douglas case with neutral climate damage (blue line), $\Delta^{\mathbf{T}}_{2020,2100} s^r_{L,t}$ is trivially zero. (2) For the CES case with biased climate damage (red line), the values of $\Delta^{\mathbf{T}}_{2020,2100} s^c_{Lt}$ are computed under the RCP 4.5 scenario, using the projected GDP weights of all regions from Wang and Sun (2022). Panel (b) plots the projected aggregate damage to global income, computed using two different cases of equation (22), under different model assumptions and empirical estimates: (1) For the Cobb-Douglas case with neutral climate damage (blue line), we compute the region-level change as $\Delta^{\mathbf{T}}_{t,t+1} \log Y_{rt} = \bar{\mathbf{c}}_{rt} \cdot \Delta^{\mathbf{T}}_{t,t+1} \mathbf{T}_{rt}$, with the estimates of $\bar{\mathbf{c}}_{rt}$ similar to Figure 5b, but allowing for heterogeneous effects across climates and income levels, as specified in equation (3). (2) For the CES case with biased climate damage (red line), we compute the region-level change exactly as in equation (22) (including second-order terms), using the estimates of $\bar{\mathbf{a}}_{rt}$ and $\bar{\mathbf{b}}_{rt}$ similar to Figure 7a, while also allowing for heterogeneous effects across climates and income levels, as specified in equation (3). The projected aggregate damage to global income in both cases is then computed as a cumulative weighted sum of region-level changes, using the projected Törnqvist weights $\bar{\theta}^c_{rt,t+1}$ over the 2020–2100 period. For both panels (a) and (b), we use the projected global temperature distribution under the RCP 4.5 scenario from Copernicus Climate Change Service (2021).

7 Conclusion

This paper provides the first systematic evidence that climate change is factor-biased: heat shocks induce firms to shift expenditures from labor to capital, reducing the labor share at the firm level. Our findings indicate that climate change significantly damages capital-augmenting productivity, with milder impacts on labor-augmenting productivity in a CES production function. As a result, factor bias emerges as a key mechanism through which climate change alters the distribution of income.

Our work also highlights several avenues for future research. First, the factor bias of climate change may change patterns of adaptation through migration and changing investment networks in ways that is inconsistent with current wisdom. Second, incorporating our empirical estimates into a heterogeneous-agent growth model calibrated to the global economy could shed light on how climate-induced productivity shocks interact with heterogeneity in both labor productivity and capital portfolios across households. Such an approach would illuminate the channels through which climate change influences income inequality in the long run.

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Appendix

A Additional Reduced Form Results

In this appendix, we present table results for estimations in Section 3.6 and Section 3.4. Table A.1 presents estimations in Equation 1 with five different outcome variables. Table A.2 presents separate estimations for Equation 1 from each sector.

Table A.1: Results from Reduced Form Estimation

Dependent Variables:	$\log(\frac{rK_{it}}{wL_{it}})$	$\log(rk_{it})$	$\log(wL_{it})$	Local Wage	$\log(w_{it})$
Model:	(1)	(2)	(3)	(4)	(5)
Variables					
< -5°C	-5.96×10^{-5}	-0.0006*	-0.0006***	-0.0007**	-0.0005***
	(0.0003)	(0.0004)	(0.0002)	(0.0003)	(0.0001)
$-5 \sim 0$°C	-1.71×10^{-7}	-8.3×10^{-5}	-9×10^{-5}	0.0002	-6.7×10^{-5}
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(8.31×10^{-5})
$0 \sim 5$°C	7.28×10^{-5}	-0.0001	-0.0002**	-9.06×10^{-7}	-0.0002**
	(9.56×10^{-5})	(0.0001)	(9.14×10^{-5})	(0.0002)	(7.8×10^{-5})
$5 \sim 10$°C	1.26×10^{-5}	4.4×10^{-5}	3.02×10^{-5}	-0.0003**	-0.0001**
	(6.93×10^{-5})	(8.19×10^{-5})	(6.62×10^{-5})	(0.0001)	(5.6×10^{-5})
$15 \sim 20$°C	-0.0001	-0.0002*	-4.71×10^{-5}	0.0003**	0.0001**
	(8.66×10^{-5})	(8.21×10^{-5})	(6.33×10^{-5})	(0.0001)	(4.94×10^{-5})
$20 \sim 25$°C	8.2×10^{-5}	-0.0002	-0.0003**	0.0002	-8.1×10^{-6}
	(0.0001)	(0.0001)	(0.0001)	(0.0002)	(7.36×10^{-5})
$25 \sim 30$°C	0.0006***	0.0002	-0.0004**	0.0002	-0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0001)
> 30°C	0.002***	0.001***	-0.0006**	0.0001	-0.0004*
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0002)
Fixed-effects					
firm_id	Yes	Yes	Yes		Yes
country_sic3_year	Yes	Yes	Yes		Yes
nuts_id				Yes	
country_year				Yes	
Fit statistics					
Observations	67,294,831	67,293,977	67,293,977	40,522	48,341,935
R^2	0.80204	0.88591	0.89365	0.66165	0.94461
Within R^2	1.09×10^{-5}	1.16×10^{-5}	7.77×10^{-6}	0.00080	1.23×10^{-5}

Notes: Standard errors clustered at the regional level (NUTS3 level for European countries, prefecture level for China, and district level for India).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table A.2: Results from Reduced Form Estimation by Sector

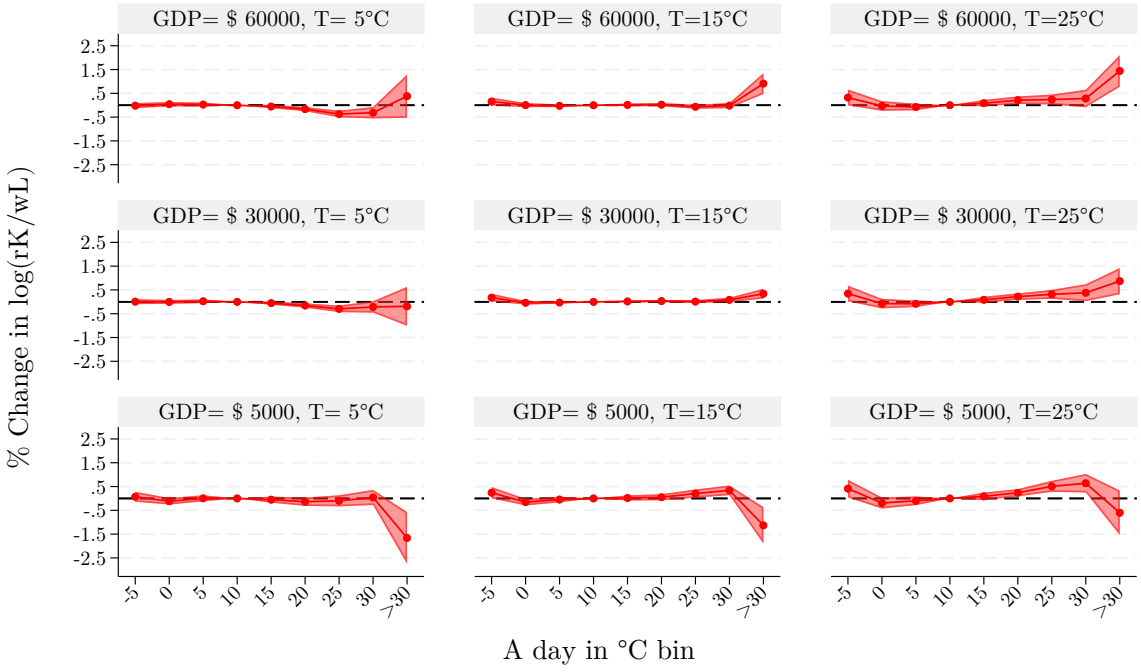
Dependent Variable:	$\log(\frac{rK_{it}}{wL_{it}})$								
Model:	Manufacturing (1)	FIRE (2)	Wholesale (3)	Construction (4)	Transportation (5)	Services (6)	Retail (7)	Mining (8)	Agriculture (9)
Variables									
< -5°C	0.0003	-7.3×10^{-5}	-0.0001	0.0002	-0.0006*	-9.45×10^{-5}	-0.0003	-2.43×10^{-5}	0.0002
	(0.0003)	(0.0004)	(0.0004)	(0.0003)	(0.0004)	(0.0004)	(0.0004)	(0.0009)	(0.0005)
$-5 \sim 0$°C	-0.0002	-7.24×10^{-5}	4.84×10^{-6}	0.0003	-0.0001	0.0001	-1.54×10^{-5}	-0.0007	0.0001
	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0007)	(0.0003)
$0 \sim 5$°C	0.0003**	0.0001	-6.26×10^{-6}	7.87×10^{-5}	-0.0003*	5.65×10^{-5}	2.8×10^{-6}	0.0007	5.27×10^{-5}
	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0002)	(0.0006)	(0.0002)
$5 \sim 10$°C	0.0003***	5.34×10^{-6}	8.4×10^{-5}	-4.1×10^{-5}	-0.0003***	-3.92×10^{-5}	-9.12×10^{-6}	-0.0003	1.32×10^{-5}
	(9.37×10^{-5})	(0.0001)	(9.59×10^{-5})	(0.0001)	(0.0001)	(8.84×10^{-5})	(0.0001)	(0.0004)	(0.0002)
$15 \sim 20$°C	-0.0002	-8.62×10^{-5}	-1.41×10^{-5}	-0.0002	-0.0002*	-6.66×10^{-5}	-3.58×10^{-5}	-1.07×10^{-5}	1.1×10^{-5}
	(0.0001)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0004)	(0.0002)
$20 \sim 25$°C	0.0002	-1.71×10^{-5}	0.0002	0.0001	-1.76×10^{-5}	0.0001	-4.42×10^{-5}	-0.0002	-0.0002
	(0.0001)	(0.0002)	(0.0001)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0005)	(0.0003)
$25 \sim 30$°C	0.0006***	0.0003	0.0006**	0.001***	8.26×10^{-5}	0.0006**	0.0005**	9.04×10^{-5}	0.0004
	(0.0002)	(0.0004)	(0.0003)	(0.0004)	(0.0003)	(0.0003)	(0.0002)	(0.0008)	(0.0004)
> 30°C	0.001***	0.004***	0.002***	0.005***	0.001**	0.003***	0.003***	-0.003**	0.002***
	(0.0003)	(0.001)	(0.0007)	(0.0009)	(0.0005)	(0.0006)	(0.0006)	(0.001)	(0.0007)
Fixed-effects									
firm_id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
country_sic3_year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	11,611,739	5,344,115	8,052,875	8,584,461	4,177,588	17,304,193	10,256,975	246,035	1,696,594
R^2	0.79483	0.85928	0.73447	0.76313	0.78271	0.78325	0.73534	0.77190	0.81581
Within R^2	3.14×10^{-5}	8.77×10^{-6}	8.04×10^{-6}	4×10^{-5}	8.43×10^{-6}	9.09×10^{-6}	1.55×10^{-5}	0.00012	1.84×10^{-5}

Notes: Standard errors clustered at the regional level (NUTS3 level for European countries, prefecture level for China, and district level for India).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

B Heterogeneous Effects Across Regions for Different Sectors

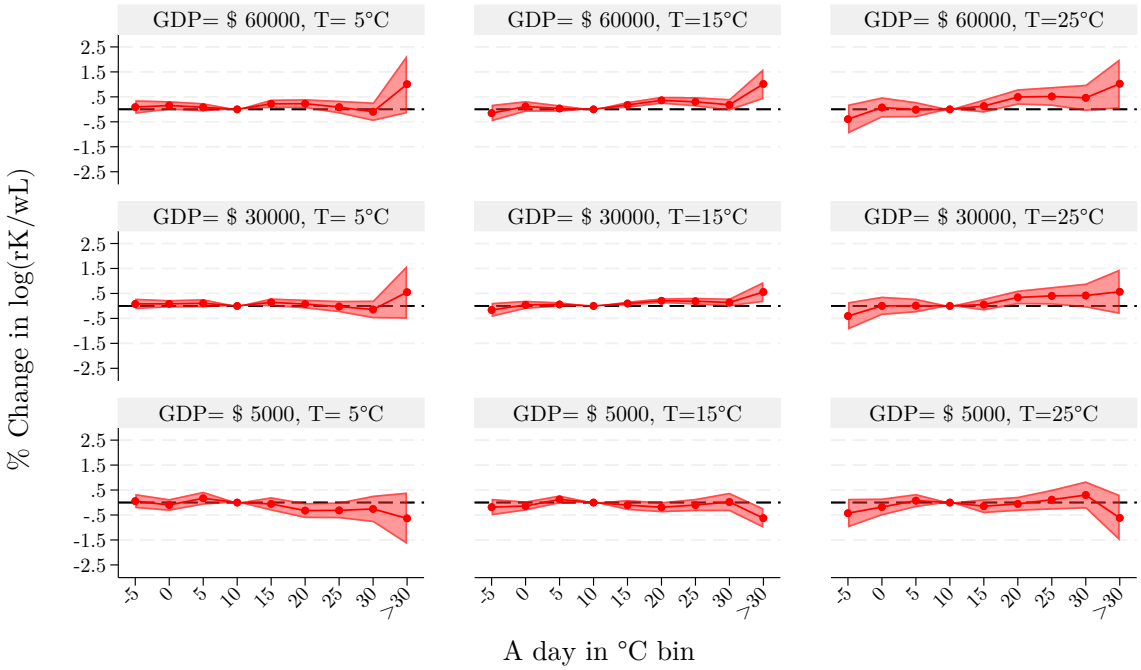
In this Appendix, we present sector-specific evidence of the heterogeneous effect of exposure to daily mean temperature bins on capital–labor expenditure ratios at varying levels of income and climate, based on separate estimations of Equation (3) for firms from nine SIC divisions. Across all sectors, we find consistent evidence that the increase in the capital–labor expenditure ratio, $\ln(\frac{rK_{it}}{wL_{it}})$, is notably larger in hotter and more developed areas. This also shows our results in Figure 3 are not driven by the sector compositions in our sample.

Figure B.1: Heterogeneous Impact of Climate Shocks on $\ln(\frac{rK_{it}}{wL_{it}})$ across Regions: Agriculture, Forestry, And Fishing (SIC Division A)



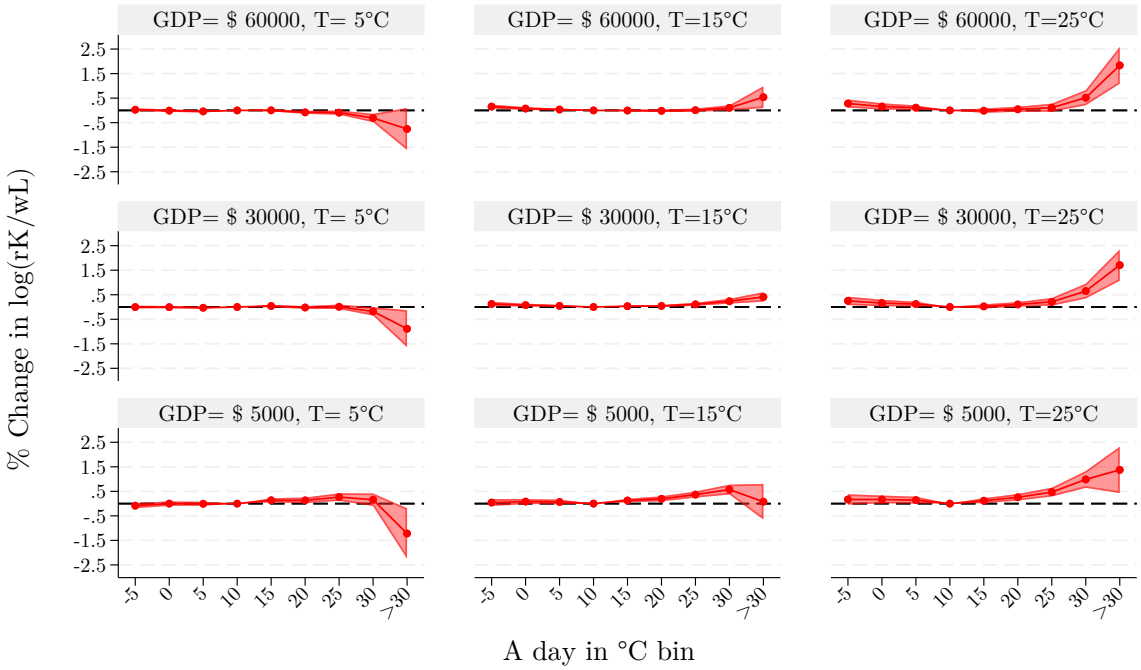
Notes: The graphs plot the predicted effect of exposure to daily mean temperature bins on capital labor expenditure ratios at varying levels of income and climates from Equation (3) with firms in SIC Division A (Agriculture, Forestry, And Fishing). We use 10 $\sim$15°C as the reference temperature bin. The shaded area is the 90% confidence interval computed from robust standard errors clustered at the regional level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

Figure B.2: Heterogeneous Impact of Climate Shocks on $\ln(\frac{rK_{it}}{wL_{it}})$ across Regions: Mining (SIC Division B)



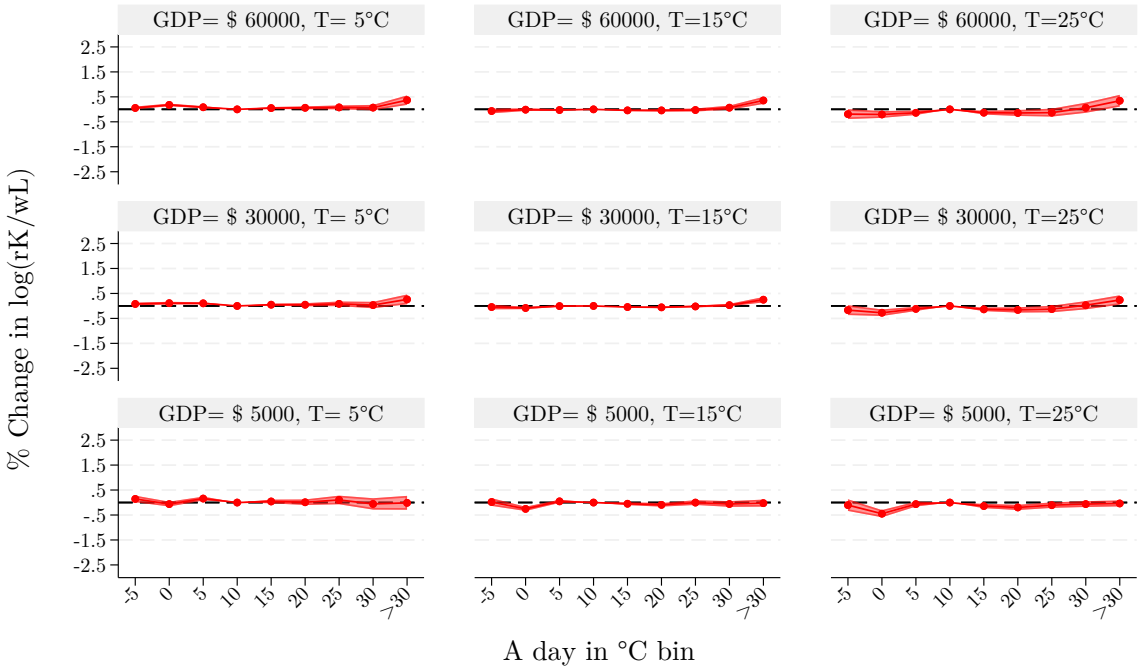
Notes: The graphs plot the predicted effect of exposure to daily mean temperature bins on capital labor expenditure ratios at varying levels of income and climates from Equation (3) with firms in SIC Division B (Mining). We use 10 $\sim$15°C as the reference temperature bin. The shaded area is the 90% confidence interval computed from robust standard errors clustered at the regional level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

Figure B.3: Heterogeneous Impact of Climate Shocks on $\ln(\frac{rK_{it}}{wL_{it}})$ across Regions: Construction (SIC Division C)



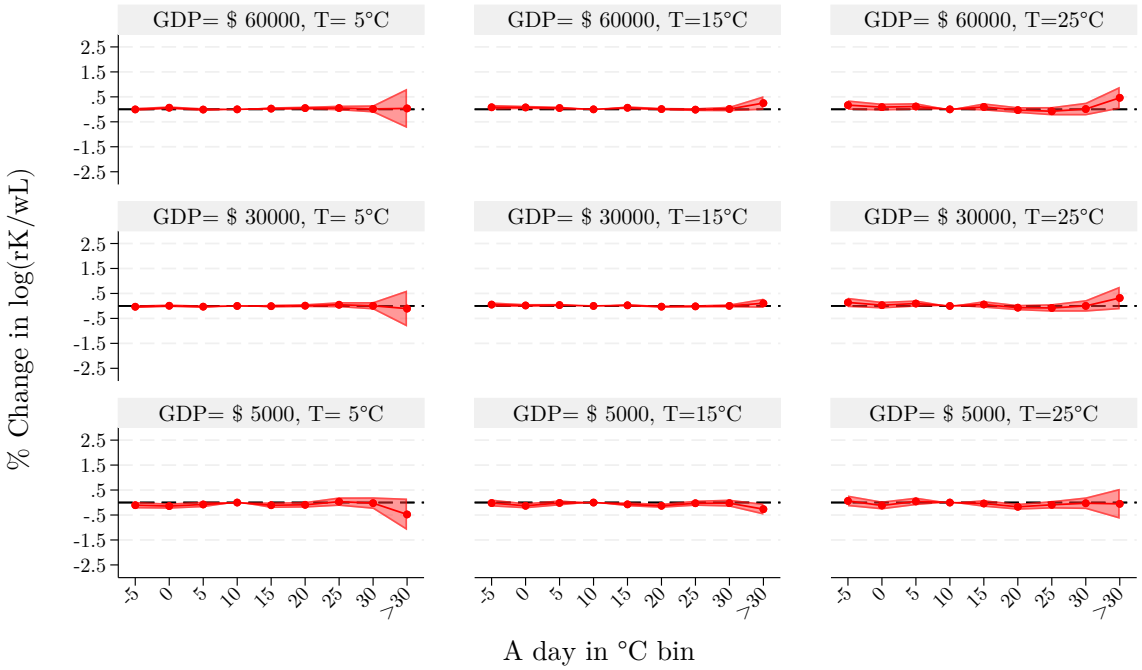
Notes: The graphs plot the predicted effect of exposure to daily mean temperature bins on capital labor expenditure ratios at varying levels of income and climates from Equation (3) with firms in SIC Division C (Construction). We use 10 $\sim$15°C as the reference temperature bin. The shaded area is the 90% confidence interval computed from robust standard errors clustered at the regional level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

Figure B.4: Heterogeneous Impact of Climate Shocks on $\ln(\frac{rK_{it}}{wL_{it}})$ across Regions: Manufacturing (SIC Division D)



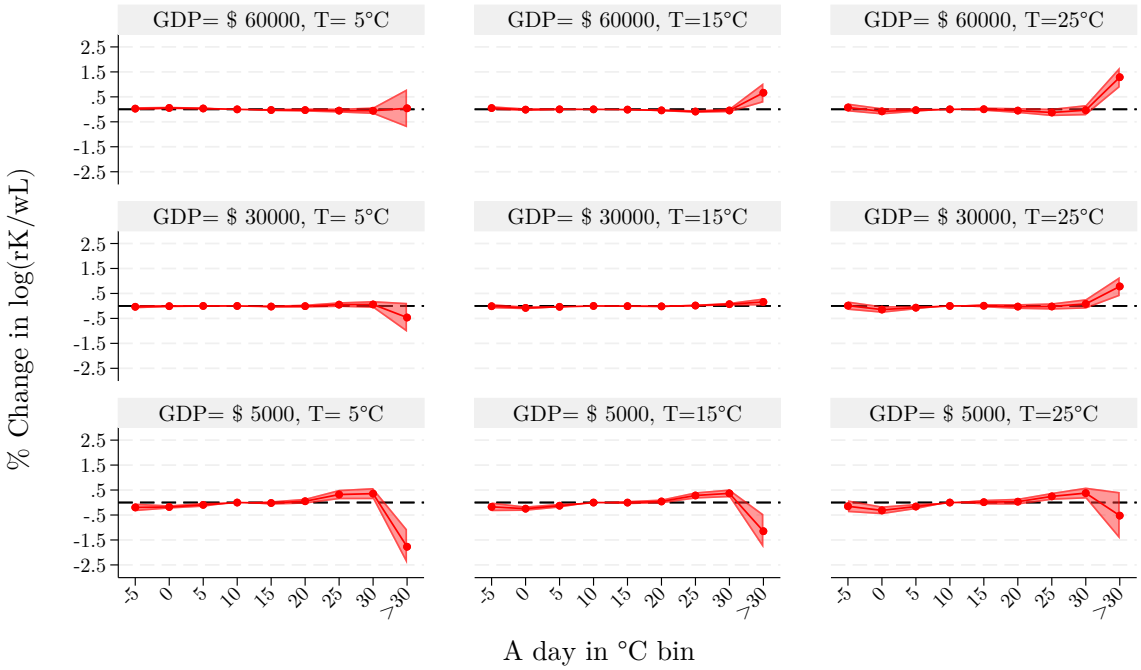
Notes: The graphs plot the predicted effect of exposure to daily mean temperature bins on capital labor expenditure ratios at varying levels of income and climates from Equation (3) with firms in SIC Division D (Manufacturing). We use 10 $\sim 15°C$ as the reference temperature bin. The shaded area is the 90% confidence interval computed from robust standard errors clustered at the regional level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

Figure B.5: Heterogeneous Impact of Climate Shocks on $\ln(\frac{rK_{it}}{wL_{it}})$ across Regions: Transportation, Communications, Electric, Gas, And Sanitary Services (SIC Division E)



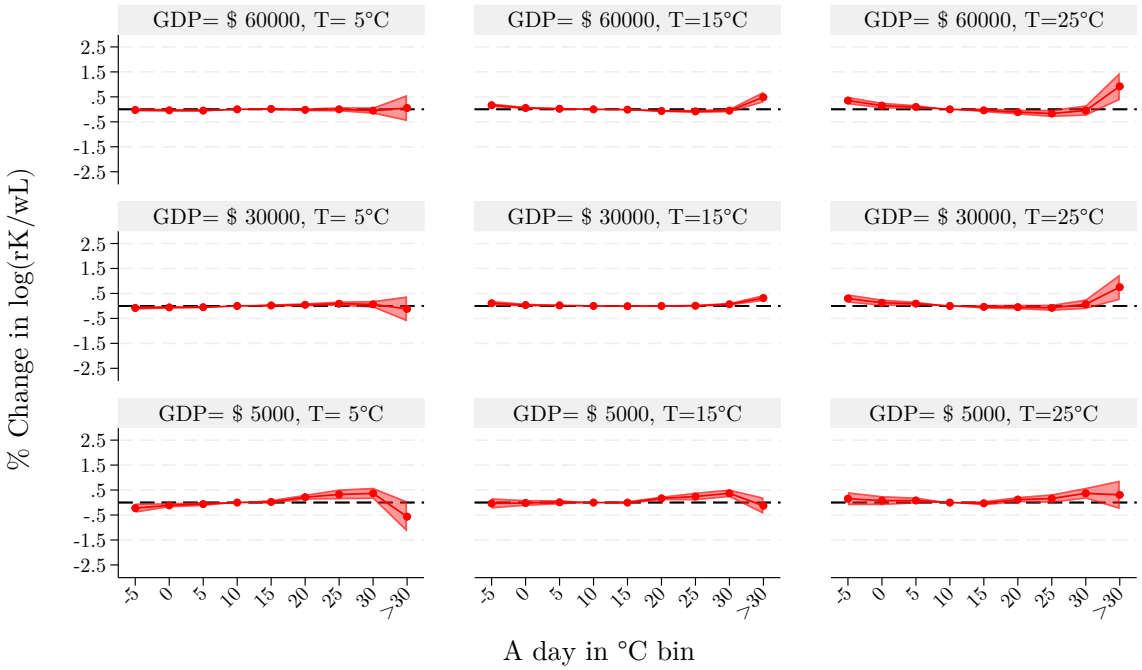
Notes: The graphs plot the predicted effect of exposure to daily mean temperature bins on capital labor expenditure ratios at varying levels of income and climates from Equation (3) with firms in SIC Division E (Transportation, Communications, Electric, Gas, And Sanitary Services). We use 10 $\sim 15°C$ as the reference temperature bin. The shaded area is the 90% confidence interval computed from robust standard errors clustered at the regional level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

Figure B.6: Heterogeneous Impact of Climate Shocks on $\ln(\frac{rK_{it}}{wL_{it}})$ across Regions: Wholesale Trade (SIC Division F)



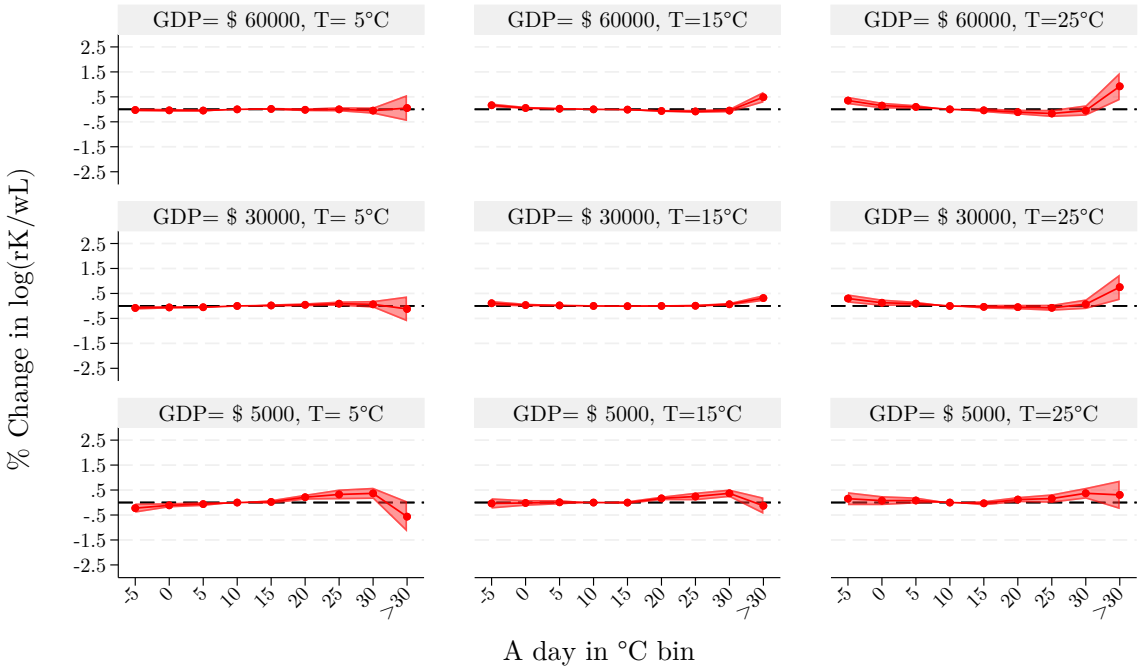
Notes: The graphs plot the predicted effect of exposure to daily mean temperature bins on capital labor expenditure ratios at varying levels of income and climates from Equation (3) with firms in SIC Division F (Wholesale Trade). We use 10 $\sim$15°C as the reference temperature bin. The shaded area is the 90% confidence interval computed from robust standard errors clustered at the regional level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

Figure B.7: Heterogeneous Impact of Climate Shocks on $\ln(\frac{rK_{it}}{wL_{it}})$ across Regions: Retail Trade (SIC Division G)



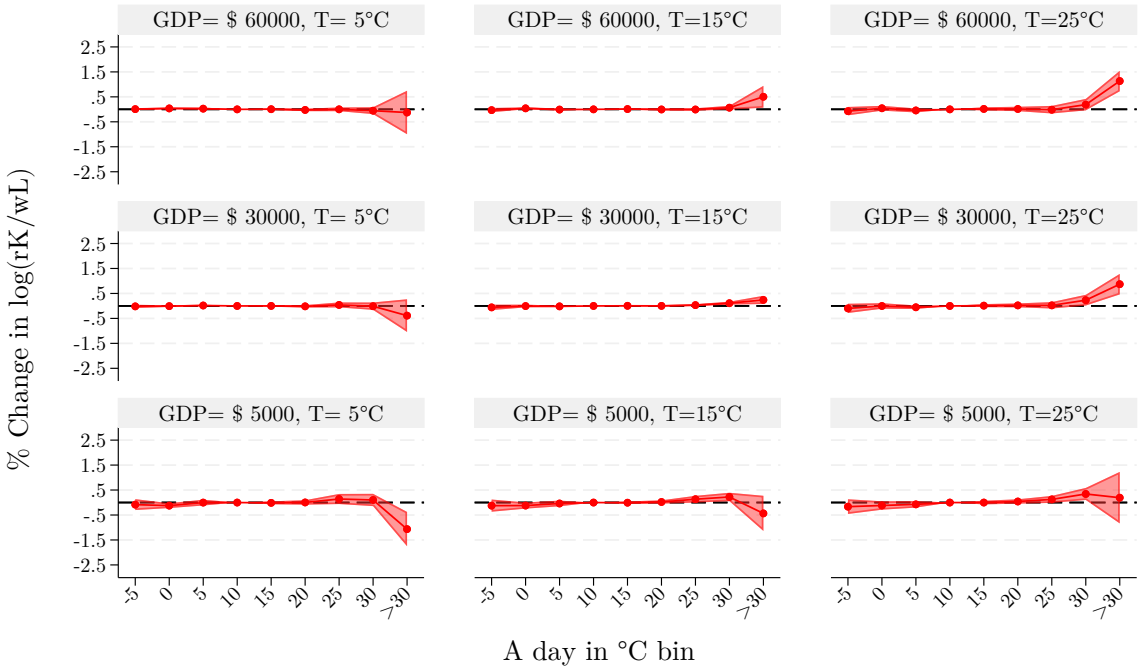
Notes: The graphs plot the predicted effect of exposure to daily mean temperature bins on capital labor expenditure ratios at varying levels of income and climates from Equation (3) with firms in SIC Division G (Retail Trade). We use 10 $\sim$15°C as the reference temperature bin. The shaded area is the 90% confidence interval computed from robust standard errors clustered at the regional level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

Figure B.8: Heterogeneous Impact of Climate Shocks on $\ln(\frac{rK_{it}}{wL_{it}})$ across Regions: Finance, Insurance, And Real Estate (SIC Division H)



Notes: The graphs plot the predicted effect of exposure to daily mean temperature bins on capital labor expenditure ratios at varying levels of income and climates from Equation (3) with firms in SIC Division H (Finance, Insurance, And Real Estate). We use 10 $\sim 15°C$ as the reference temperature bin. The shaded area is the 90% confidence interval computed from robust standard errors clustered at the regional level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

Figure B.9: Heterogeneous Impact of Climate Shocks on $\ln(\frac{rK_{it}}{wL_{it}})$ across Regions: Services (SIC Division I)



Notes: The graphs plot the predicted effect of exposure to daily mean temperature bins on capital labor expenditure ratios at varying levels of income and climates from Equation (3) with firms in SIC Division I (Services). We use 10 $\sim$15°C as the reference temperature bin. The shaded area is the 90% confidence interval computed from robust standard errors clustered at the regional level. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

C Additional Tables for Solow Residuals Estimates

The results from solow residual estimations from equation (11) are presented in Table C.3.

Table C.3: Results from Solow Residual Regressions

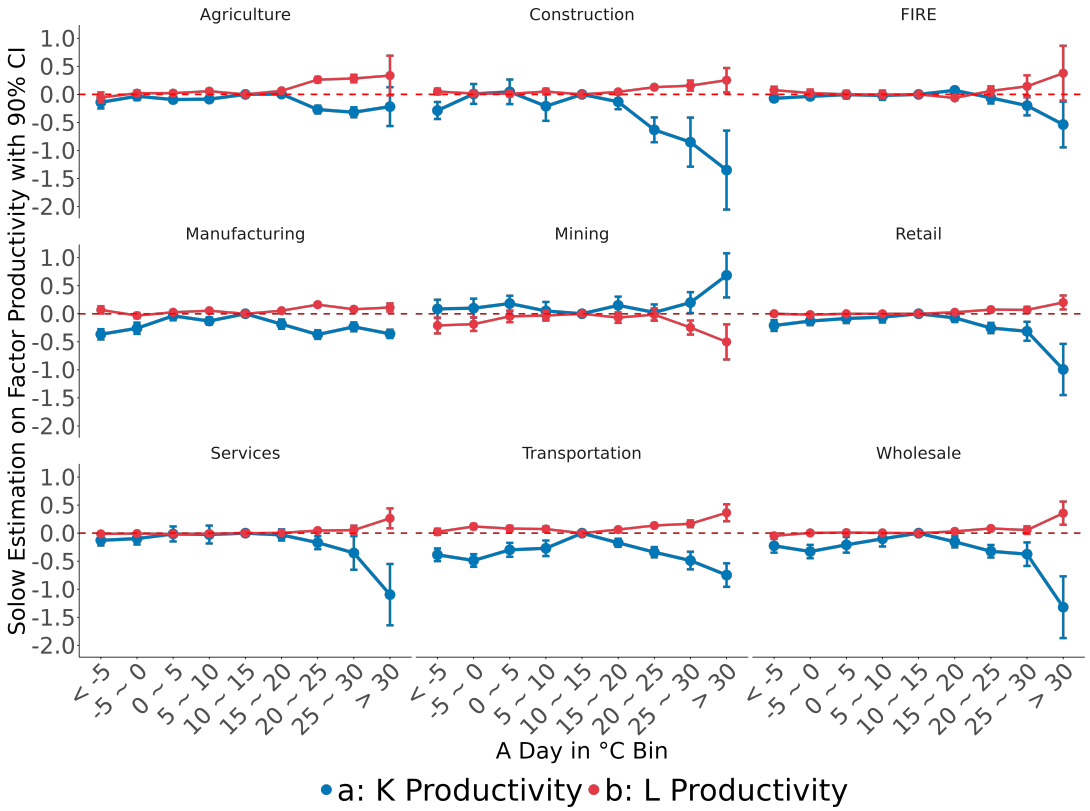
Dependent Variables:	Solow_{it} (wage bill)	Solow_{it} (employees)	Solow_{it} (wage bill)
Model:	(1)	(2)	(3)
Variables			
< -5°C	9.86×10^{-5}	-0.004***	-0.0005***
	(0.0002)	(0.0006)	(0.0001)
$-5 \sim 0$°C	-0.0001	-0.004***	-0.0004***
	(0.0002)	(0.0006)	(8.32×10^{-5})
$0 \sim 5$°C	5.72×10^{-5}	-0.002***	-0.0001*
	(0.0002)	(0.0005)	(5.38×10^{-5})
$5 \sim 10$°C	0.0002	-0.0001	-5.81×10^{-5}
	(0.0002)	(0.0004)	(4.45×10^{-5})
$15 \sim 20$°C	0.0002	-0.002***	3.15×10^{-5}
	(0.0001)	(0.0004)	(6.06×10^{-5})
$20 \sim 25$°C	0.0008***	-0.004***	8.71×10^{-6}
	(0.0002)	(0.0004)	(7.75×10^{-5})
$25 \sim 30$°C	0.0009***	-0.005***	-0.0004***
	(0.0002)	(0.0008)	(0.0001)
> 30°C	0.0007	0.006***	-0.001***
	(0.0006)	(0.002)	(0.0002)
$s_K \times < -5$°C	-0.002***	0.014***	
	(0.0006)	(0.002)	
$s_K \times -5 \sim 0$°C	-0.001*	0.015***	
	(0.0007)	(0.002)	
$s_K \times 0 \sim 5$°C	-0.0006	0.008***	
	(0.0008)	(0.002)	
$s_K \times 5 \sim 10$°C	-0.001	0.0006	
	(0.0008)	(0.002)	
$s_K \times 15 \sim 20$°C	-0.0006	0.008***	
	(0.0005)	(0.001)	
$s_K \times 20 \sim 25$°C	-0.003***	0.015***	
	(0.0007)	(0.002)	
$s_K \times 25 \sim 30$°C	-0.004***	0.017***	
	(0.0009)	(0.003)	
$s_K \times > 30$°C	-0.004***	-0.012***	
	(0.001)	(0.004)	
s_K	-1.18***	-14.0***	
	(0.136)	(0.314)	
Fixed-effects			
firm_id	Yes	Yes	Yes
country_sic3_year	Yes	Yes	Yes
Fit statistics			
Observations	60,901,653	43,778,727	60,901,653
R^2	0.81939	0.97689	0.79759
Within R^2	0.10769	0.83775	1.92×10^{-5}

Notes: Standard errors clustered at the regional level (NUTS3 level for European countries, prefecture level for China, and district level for India).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

C.1 Technical Bias of Climate Damage for Different Sectors: Solow Residuals Estimates

In this Appendix, we present the sector-specific estimates of the technical bias of climate damage obtained via the Solow residuals regression in equation (11). Figure C.10 shows the sector-specific estimates of the climate impact on capital-augmenting productivity **a** and labor-augmenting productivity **b**. We find that climate damage is capital-biased for all sectors except for Mining. The estimations are presented in Table C.4.

Figure C.10: Technical Bias of Climate Damage: Sectoral Evidence from Solow Residuals Estimates



Notes: Figure plots a^b_{cr} and b^b_{cr} by estimating Equation (11) separately for each sector. Standard errors are clustered at the regional level. We use $10\sim 15^{\circ}C$ as the reference temperature bin. The whisker is the 90% confidence interval where standard errors are calculated from the delta method. Regions are defined to be the NUTS 3 regions in Europe, prefectures in China, and districts in India. The estimates are conditioned on firm and country-sector-year fixed effects, where sector is at USSIC 3 digit level. The sample includes firms from 30 European countries, China and India from 1998 to 2018.

Table C.4: Results from Solow Residual Regressions By Sector

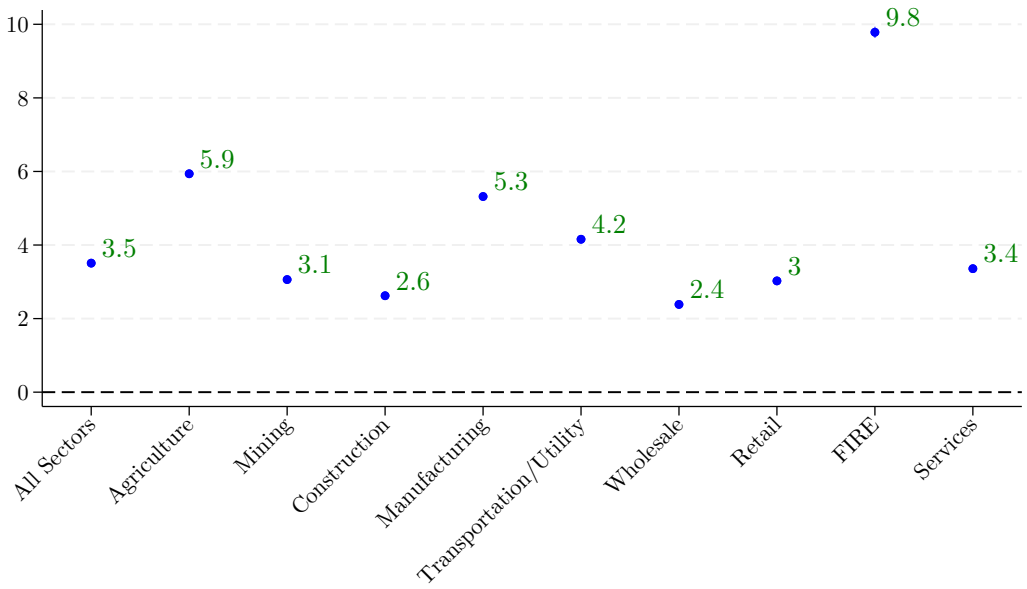
Dependent Variable:	Log Solow$_{it}$ (wage bill)								
Model:	Manufacturing (1)	FIRE (2)	Wholesale (3)	Construction (4)	Transportation (5)	Services (6)	Retail (7)	Mining (8)	Agriculture (9)
Variables									
< -5°C	0.0007*	0.0008**	-0.0005*	0.0005*	0.0002	-0.0001	6.29×10^{-6}	-0.002**	-0.0006
	(0.0004)	(0.0004)	(0.0003)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0009)	(0.0006)
$-5 \sim 0$°C	-0.0003	0.0002	4.42×10^{-5}	0.0002	0.001***	-6.96×10^{-5}	-0.0002	-0.002**	0.0002
	(0.0003)	(0.0004)	(0.0002)	(0.0002)	(0.0003)	(0.0002)	(0.0002)	(0.0007)	(0.0003)
$0 \sim 5$°C	0.0003	1.12×10^{-5}	9.35×10^{-5}	0.0001	0.0008***	-0.0001	-3.86×10^{-6}	-0.0005	0.0002
	(0.0002)	(0.0004)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0001)	(0.0006)	(0.0002)
$5 \sim 10$°C	0.0005***	-1.32×10^{-5}	4.95×10^{-5}	0.0005*	0.0007**	-8.33×10^{-5}	-9.64×10^{-6}	-0.0003	0.0006**
	(0.0001)	(0.0004)	(0.0002)	(0.0003)	(0.0003)	(0.0002)	(0.0002)	(0.0005)	(0.0002)
$15 \sim 20$°C	0.0005***	-0.0006***	0.0003*	0.0004***	0.0006***	4.54×10^{-5}	0.0003**	-0.0007	0.0006***
	(0.0002)	(0.0002)	(0.0002)	(0.0001)	(0.0001)	(0.0001)	(0.0001)	(0.0006)	(0.0002)
$20 \sim 25$°C	0.002***	0.0006	0.0008***	0.001***	0.001***	0.0005***	0.0007***	-0.0001	0.003***
	(0.0002)	(0.0005)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0002)	(0.0007)	(0.0003)
$25 \sim 30$°C	0.0008***	0.001	0.0006	0.002***	0.002***	0.0005	0.0007**	-0.002***	0.003***
	(0.0002)	(0.001)	(0.0004)	(0.0005)	(0.0004)	(0.0005)	(0.0003)	(0.0008)	(0.0004)
> 30°C	0.001**	0.004	0.004***	0.003*	0.004***	0.003**	0.002***	-0.005***	0.003
	(0.0004)	(0.003)	(0.001)	(0.001)	(0.0009)	(0.001)	(0.0008)	(0.002)	(0.002)
$s_K \times < -5$°C	-0.004***	-0.001**	-0.002**	-0.003***	-0.004***	-0.001*	-0.002***	0.003***	-0.0008
	(0.0007)	(0.0006)	(0.0009)	(0.001)	(0.0009)	(0.0007)	(0.0007)	(0.001)	(0.001)
$s_K \times -5 \sim 0$°C	-0.002***	-0.0006	-0.003***	-7.14×10^{-5}	-0.006***	-0.0009	-0.001**	0.003**	-0.0005
	(0.0008)	(0.0007)	(0.0009)	(0.001)	(0.0009)	(0.0008)	(0.0006)	(0.001)	(0.0006)
$s_K \times 0 \sim 5$°C	-0.0006	-5.13×10^{-5}	-0.002**	0.0004	-0.004***	1.1×10^{-5}	-0.0008	0.002**	-0.001**
	(0.0006)	(0.0008)	(0.001)	(0.002)	(0.001)	(0.001)	(0.0006)	(0.001)	(0.0005)
$s_K \times 5 \sim 10$°C	-0.002***	-0.0002	-0.001	-0.003	-0.003***	-0.0002	-0.0006	0.0008	-0.001***
	(0.0005)	(0.0009)	(0.001)	(0.002)	(0.001)	(0.001)	(0.0007)	(0.001)	(0.0005)
$s_K \times 15 \sim 20$°C	-0.002***	0.001***	-0.002**	-0.002*	-0.002***	-0.0004	-0.0010*	0.002	-0.0006
	(0.0006)	(0.0004)	(0.0007)	(0.0009)	(0.0006)	(0.0007)	(0.0005)	(0.001)	(0.0004)
$s_K \times 20 \sim 25$°C	-0.005***	-0.001	-0.004***	-0.008***	-0.005***	-0.002**	-0.003***	0.0004	-0.005***
	(0.0006)	(0.001)	(0.0008)	(0.002)	(0.0007)	(0.0009)	(0.0007)	(0.001)	(0.0006)
$s_K \times 25 \sim 30$°C	-0.003***	-0.003	-0.004***	-0.010***	-0.007***	-0.004*	-0.004***	0.004***	-0.006***
	(0.0006)	(0.002)	(0.002)	(0.003)	(0.001)	(0.002)	(0.001)	(0.001)	(0.0008)
$s_K \times > 30$°C	-0.005***	-0.009*	-0.017***	-0.016***	-0.011***	-0.014***	-0.012***	0.012***	-0.006
	(0.0007)	(0.005)	(0.004)	(0.005)	(0.002)	(0.004)	(0.003)	(0.004)	(0.004)
s_K	-0.959***	-2.69***	-0.852***	-0.545*	-0.577***	-1.02***	-0.975***	-2.76***	-1.60***
	(0.127)	(0.129)	(0.199)	(0.327)	(0.197)	(0.205)	(0.135)	(0.275)	(0.104)
Fixed-effects									
firm_id	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
country_sic3_year	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Fit statistics									
Observations	10,704,332	4,545,891	7,251,625	7,706,648	3,811,916	15,662,556	9,426,867	226,379	1,549,067
R^2	0.77967	0.87272	0.78341	0.69988	0.80003	0.75338	0.79456	0.80831	0.83719
Within R^2	0.13484	0.23808	0.09609	0.06607	0.13324	0.06937	0.11016	0.20507	0.20452

Notes: Standard errors clustered at the regional level (NUTS3 level for European countries, prefecture level for China, and district level for India).
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

D Elasticities of Demand for Different Sectors

This appendix presents estimated elasticities of demand for different sectors.

Figure D.11: Elasticities of Demand for Different Sectors (SIC division level)



Notes: All markup estimates are based upon inverting the average markup (weighted by the a firm's cost share within a country-SIC-division-year) across firms in an SIC division. We define the markup as sales divided by the total costs (the sum of user cost of capital, wage bill and material costs).

E Results from structural estimation

This appendix presents results from estimating equation (14), and equation (17) and (18) in Section 5.2.

Table E.5: Results from Structural Estimation

Dependent Variables:	$\log(\frac{rK_{it}}{wL_{it}})$	Rearranged Eq (14)	LHS Var of Eq (17)	LHS Var of Eq (18)
Model:	(1)	(2)	(3)	(4)
Variables				
< -5°C	-0.0001	0.0006*	-0.001***	-0.0006
	(0.0003)	(0.0004)	(0.0003)	(0.0004)
$-5 \sim 0$°C	-2.2×10^{-5}	0.0001	-0.0008***	-0.0006***
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
$0 \sim 5$°C	4.87×10^{-5}	3.42×10^{-5}	-0.0002*	-0.0002
	(9.39×10^{-5})	(0.0002)	(0.0001)	(0.0002)
$5 \sim 10$°C	-2.15×10^{-5}	0.0002**	-0.0003***	-9.26×10^{-5}
	(6.84×10^{-5})	(0.0001)	(9.8×10^{-5})	(0.0001)
$15 \sim 20$°C	-0.0001	9.32×10^{-5}	7.17×10^{-5}	0.0001
	(8.49×10^{-5})	(0.0001)	(0.0001)	(0.0001)
$20 \sim 25$°C	9.82×10^{-5}	-0.0002	0.0002	-5.26×10^{-5}
	(0.0001)	(0.0002)	(0.0002)	(0.0002)
$25 \sim 30$°C	0.0006***	-0.0008**	-0.0003	-0.001***
	(0.0002)	(0.0003)	(0.0003)	(0.0004)
> 30°C	0.002***	-0.002***	-0.0009*	-0.003***
	(0.0004)	(0.0006)	(0.0005)	(0.0006)
Local Wage	-0.140***			
	(0.020)			
Fixed-effects				
firm_id	Yes	Yes	Yes	Yes
country_sic3_year	Yes	Yes	Yes	Yes
Fit statistics				
Observations	67,243,459	67,242,605	62,296,290	62,296,290
R^2	0.80209	0.80189	0.76393	0.78798
Within R^2	4.99×10^{-5}	9.11×10^{-6}	1.68×10^{-5}	1.77×10^{-5}

Notes: Standard errors clustered at the regional level (NUTS3 level for European countries, prefecture level for China, and district level for India). The dependent variable in Column 1 is the log capital-labor expenditure ratio. Column 2 reports the estimation of the technical bias $a - b$. Columns 3 and 4 report the separate identifications of capital and labor productivity. The value of the parameters are chosen to be: $\sigma = 0.3, \varepsilon = 3.51$.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$