Weather shocks and sectoral labour reallocation in the European sub-national units

Federico Zilia [a], Paolo Nota [a], Alessandro Olper [a]

[a] Department of Environmental Science and Policy, University of Milan, Italy

Abstract

Climate change poses significant challenges to the productivity of the European agricultural sector, particularly in low-latitude regions such as the Mediterranean. The extent to which sectoral labour reallocation—shifting labour from agriculture to non-agricultural sectors—serves as an adaptation strategy to climate shocks remains an underexplored research question.
This paper examines how weather variability affects inter-sectoral labour reallocation among agriculture, construction, industry, and services across 1,149 European districts (NUTS3 level) from 1980 to 2022. In doing so, we also explore the extent to which weather-driven sectoral productivity shocks serve as a key mechanism. Leveraging this large and granular dataset, we employ flexible functional forms within a fixed-effects panel framework, where the impact of weather shocks is conditional on long-term climate. Unlike previous empirical research in climate economics, which primarily focused on inter-annual variations in average temperature, this study emphasizes the significant role of daily temperature variability. Temperature variability is particularly critical in warmer regions with low seasonal variability, which are more vulnerable to sudden temperature shifts or rainfall shocks. In hot regions with low seasonal variability—such as the Mediterranean—we find a robust adaptative response in the labour market, where workers shift from climate-sensitive agriculture to less affected sectors, such as industry and services. Interestingly, we also observe a labour reallocation effect in the opposite direction—from industry and services to agriculture—in the most cold and high-income districts. The heterogeneous impact of weather shocks on sectoral value-added growth across different climates appears to be a key mechanism driving this labour reallocation.

Keywords: climate change, labour reallocation, daily temperature variability, panel econometrics, European NUTS3.

1. Introduction

An extensive literature has adopted fixed effects panel models to study the impacts of temperature fluctuations on different economic outcomes, such as economic growth (Dell et al., 2009, 2012; Burke et al., 2015; Diffenbaugh and Burke, 2019), labour productivity (Deryugina and Hsiang, 2014; Dasgupta et al., 2021), human capital (Graff Zivin and Neidell, 2014; Graff Zivin et al., 2018; Fishman et al., 2019), energy demand (Auffhammer and Mansur, 2014; Wenz et al., 2017; van Ruijven et al., 2021), and crop yields (Schlenker and Roberts, 2009; Chen et al., 2016; Wing et al., 2021). Within this large literature, less effort has been devoted to study the impact of weather variation on labour market outcomes. This is quite surprising as across-sectoral labour reallocation is at the heart of the development process and could represent an important margin of adaptation to climate change (Colmer, 2021; Nath, 2023).

Previous research indicates that sectors more exposed to climate risks, such as agriculture and construction (i.e. outdoor activities) tend to suffer greater damage compared to less sensitive sectors, such as industry and services (Jessoe et al., 2018; Emerick, 2018; Colmer, 2021; Olper et al., 2022; Nath, 2023). This uneven impact creates disparities in the marginal returns to labour across different sectors. Consequently, workers at least in the short- to medium-run tend to shift from heavily affected sectors to those less vulnerable to climate change.[1] This channel of climate impact has been explored in developing countries (see Jessoe et al., 2018; Emerick, 2018; Colmer, 2021, Liu et al., 2023; Alfani et al., 2024; Musungu et al., 2024), while receiving little to no attention in developed ones, such as the European context.

This paper represents one of the first attempt to study how weather shocks can affect sectoral labour reallocation and value-added growth in Europe. To achieve these goals, we leverage an extensive dataset covering 29 European countries, working at a highly granular level across 1,149 NUTS3 sub-regional units over a 43-year period (1980–2022), comprising more than 49,000 data points.

Following the most recent climate-econometric literature (see Kalkuhl and Wenz, 2020; Hultgren et al., 2023; Kotz et al., 2024), instead of using the standard quadratic functional form, we employ a more flexible specification where each weather variables enter in the equation also interacted by the respective long-run mean (or climate), so that conditioning the effect of weather shocks with the climatic "state" of each sub-national units. This approach has two critical advantages. First, it directly accounts for the heterogeneity of the weather effects across different climatic conditions. Second, it is better suited to account for non-linearity and adaptation (see Hultgren et al., 2023).

[1] In the long run, things may change particularly for less developing countries because subsistence consumption needs (particularly when associated with high trade barriers) may create a "food problem" in which climate change instead intensifies agricultural specialization in more vulnerable regions (see Liu et al. 2023; Nath, 2023).

Our analysis incorporates cutting-edge weather variables from the latest climate-economic literature, particularly emphasizing day-to-day temperature variability (see Kotz et al., 2021). While many studies have shown that rising temperatures can reduce labour supply and productivity growth, most of them focus mainly on annual averages, which may not capture the full scenario. Losses from heat stress, for instance, occur on a daily basis, making daily temperature variability a better indicator of these impacts, particularly in regions less adapted to sudden heat stress (Kotz et al., 2024).

Main findings reveal that day-to-day temperature variability has indeed additional effects on sectoral labour share and productivity growth that are not captured by annual average temperatures. The labour reallocation effects of annual temperature shocks are small and statistically insignificant in the median district. Differently, day-to-day temperature variability, on average, induced a significantly labour reallocation effect from agriculture to, especially, the manufacturing and service sectors. These average effects are strongly heterogenous across different climate conditions. In very hot districts with low seasonal temperature variability, we observe a strong labour reallocation from agriculture to the services sector. However, in colder northern districts, we find some evidence of the opposite trend. The effect of temperature shocks on the sectoral gross value-added (GVA) growth seems to be a key mechanism driving this labour reallocation effects.

The rest of this paper is organized as follows: Section 2 summarizes the main potential mechanisms driving the weather-induced sectoral labour movement. Section 3 describes data and variables and the empirical strategy. Section 4 presents and discusses the main results and robustness checks; Finally, Section 5 concludes.

2. Theoretical background

The literature highlights at least three main potential economic channels to explain the sectoral labour reallocation driven by weather and climate shocks.

First, in the short-run, the stylized model described by Colmer (2021) examines how labour reallocates from agriculture to manufacturing (or services) in response to productivity shocks. The basic logic is the one of a two-sectors (specific-factor) economy where labour can move freely between sectors within each region, and (free-trade) market prices set equilibrium wages. When a negative shock, such as a severe weather event, lowers agricultural productivity, the value of agricultural output decreases. This decline reduces the demand for labour in agriculture, as farms use fewer workers to achieve lower output levels. As a result, agricultural workers can shift to non-agricultural sectors (manufacturing and services), which are less directly affected by the productivity shock. Importantly, the ability of non-agricultural sectors to absorb workers may play a key role in attenuating the economic consequences of agricultural productivity shocks. For India, Colmer (2021) estimates that, in the absence of labour reallocation, local economic losses from temperature shocks could be up to 69 percent higher.

A second possible, long-run, mechanism has been highlighted by Liu et al. (2023) emphasizing local demand effects as the key driver of labour reallocation due to sustained climate shocks. In this context, persistent warming reduces agricultural productivity, leading to lower farm incomes. In countries where the majority of workers are employed in agriculture and food consumption accounts for a large share of disposable income, this climate-driven income decline reduces demand for local non-agricultural goods and services. This reduced demand triggers a contraction in the non-agricultural labour force. Consequently, labour becomes more concentrated in agriculture, reinforcing sectoral immobility over time, creating a self-reinforcing cycle where the lack of alternative employment opportunities "locks" labour into agriculture (Liu et al., 2023).

An extension of this logic has been recently developed by Nath (2023) exploiting a global (spatial) quantitative trade model to analyse how climate-induced shifts in agricultural productivity might affect sectoral labour allocation. The model incorporates non-homothetic consumer preferences and high trade barriers, particularly relevant for low-income countries. The model highlights that subsistence needs, combined with high costs of importing food, create a "food problem" in these regions.

Finally, migration can play a vital role as a third mechanism. Rising temperatures could hinder rural-to-urban migration as lower agricultural incomes exacerbate liquidity constrain and thus workers' ability to relocate. Over extended periods, this mechanism restricts spatial mobility and maintains high labour shares in rural areas, even in the face of structural transformation pressures. This finding aligns with the limited impacts of adverse climate conditions on urbanization rates documented in low-income countries (see Cattaneo and Peri, 2016).

Clearly, the last two mechanisms – the consumption and migration channels – summarized above are less relevant in developed countries investigated here. Hence, in the empirical model discussed below our focus refers largely to the short-run labour reallocation effect proposed by Colmer (2021).

3. Data and empirical strategy

3.1 Data and variables

Dependent variables. Our key outcome variable of interest is the sectoral labour force share that is measured by dividing each sectoral employment by the total employment, considering agriculture, manufacturing, services and construction sectors. To study the key mechanism driving sectoral labour reallocation, we employ also the sectoral GVA growth at constant 2015 prices as outcome variable. Sectoral labour force and GVAs at constant prices at NUTS3 (and NUTS2) level, are all obtained from the Annual Regional Database of the European Commission's Directorate General for Regional and Urban Policy (ARDECO) dataset.[2]

Weather and climate variables. We followed recent literature to reconstruct a broad spectrum of climate variables whose impacts on micro and macroeconomic outputs have been widely identified in previous studies. The climate variables were processed using the Agrometeorological Indicators (AgERA5) dataset provided by Copernicus. AgERA5 data are aggregated to daily time steps in the local time zone and adjusted to a finer topography at a 0.1° spatial resolution and interpolated at a 0.1° x 0.1° grid level (e.g. around 11x11 km), considering both temperature and precipitation variables. In the aggregation process we assign different weights to the climate variables for each NUTS3 region, based on land use designated for agricultural or commercial activities, using the CORINE Land Cover dataset.

Because annual averages of climate variables can overlook important short-term variations such as daily heat or water stress, which affects productivity on a day-to-day basis (see Kotz et al., 2021), we also incorporated day-to-day temperature variability indicators.[3] Day-to-day temperature variability refers to the fluctuations in temperature within the same month (Linsenmeier, 2023), and we calculated it following the methodology outlined by Kotz et al. (2024).[4] We calculated also the seasonal temperature variability as the historical average of the differences between the maximum and minimum monthly temperatures for each given year.

---

[2] We focus on the following sectors: A (Agriculture, forestry, and fishing), B-E (Industry, mining and quarrying, electricity, water supply), and F (Constructions), while the remaining activities from G-U of the ARDECO classification are aggregated as total services.

[3] Measures like degree days, extensively used in previous applications, partially address this by accounting for temperature thresholds (Huang et al., 2020), but they still miss out on capturing daily variability.

[4] Formally, $\tilde{T}_{i,y} = \frac{1}{12}\sum_{m=1}^{12}\sqrt{\frac{1}{D_m}\sum_{d=1}^{D_m}(T_{i,d,m,y} - \bar{T}_{i,m})^2}$, where $\tilde{T}_{i,y}$ is the annual measures of daily variability; d is the distribution of daily temperature $T_{i,d,m,y}$ in the grid-cell (NUTS3 district) i within each month m, and year y. $\bar{T}_{i,m}$ is the monthly average temperature.

The final dataset encompasses approximately 49,407 observations across 1,149 European NUTS3 regions from 1980 to 2022. Table 1 reports summary statistics of the variables described above, while Figure 1 displays maps of the relevant temperature and precipitations variables used in the analysis.

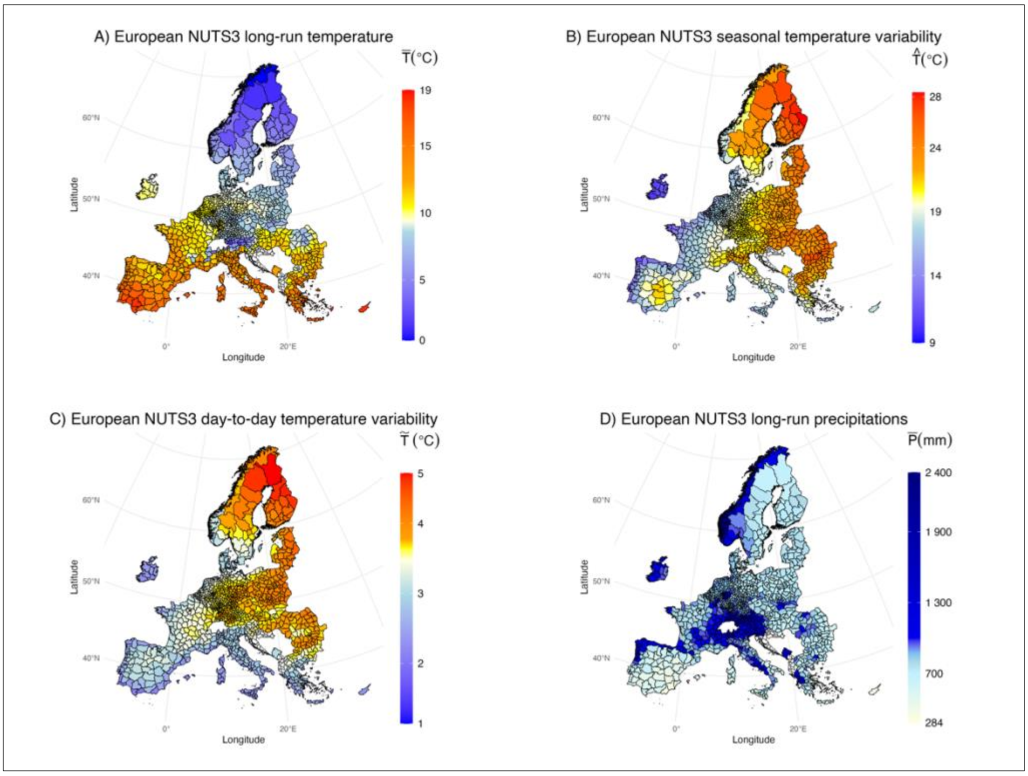
Two key patters in climate variables are worth noting. First, day-to-day temperature variability offers insights into how different districts, particularly those with smaller seasonal temperature differences (such as low-latitude regions like Mediterranean countries), are more vulnerable to temperature fluctuations (Figure 1, Panel B). In our sample, provinces with higher average temperature and the ones with low seasonal temperature variability significantly overlap (compare Panel A with Panel B and C).

Table 1. Summary statistics.

Variable	Obs.	Mean	Std. dev.	Min	Max
Employment share					
Labour share: Agriculture	44,794	0.0902	0.1133	0	0.8702
Labour share: Industry	44,808	0.2106	0.0970	0.0112	0.7940
Labour share: Services	44,808	0.6249	0.1383	0.0817	0.9563
Labour share: Constructions	44,808	0.0742	0.0271	0.0078	0.2966
Gross value added growth rate					
Growth of gross value added: Total	45,020	0.0152	0.0467	-2.1632	0.6579
Growth of gross value added: Agriculture	42,098	0.0050	0.1674	-3.3372	3.5803
Growth of gross value added: Industry	42,139	0.0176	0.0954	-1.1175	1.2722
Growth of gross value added: Services	42,162	0.0190	0.0416	-0.6709	0.5792
Growth of gross value added: Constructions	42,162	0.0025	0.1106	-3.2511	2.5770
Weather data					
Agricultural avg. annual temperature (°C)	49,407	10.2689	2.8341	-2.11	20.2
Agricultural avg. long-run temperature (°C)	49,407	10.2689	2.7192	0.15	19.15
Agricultural daily temperature variability (°C)	49,407	3.4328	0.5949	1.2912	6.5601
Agricultural total annual precipitations (cm)	49,407	87.0159	26.6841	16.046	319.53
Agricultural avg. long-run precipitations (cm)	49,407	86.0159	23.3801	28.866	243.248
Urban avg. annual temperature (°C)	49,407	10.3082	2.9146	-1.67	20.16
Urban avg. long-run temperature (°C)	49,407	10.3082	2.8034	0.5	19.15
Urban daily temperature variability (°C)	49,407	3.4217	0.6063	1.2915	6.52002
Urban total annual precipitations (cm)	49,407	87.3707	27.3725	15.727	308.563
Urban avg. long-run precipitations (cm)	49,407	87.3707	24.1175	28.382	240.039
Seasonal temperature (°C)	49,407	19.9589	2.7729	10.24	28.32

Notes: For variables description and sources see text.

Figure 1. Climate variables used in the analysis averaged over the 1980-2022 period



Notes: All variables shown in Figure 1 are graphically represented as average from 1980 to 2022. For variables description and sources see *Section 3.1*.

Figure 1, Panel C displays the average day-to-day temperature variation over the entire period. As seen when compared to Panel A, Central and Southern European regions show less daily variability than Northern countries, which are accustomed to significant climatic variations. These Northern regions may struggle to adapt to a consistent rise in average temperatures, but at the same time, they might be more resilient to daily fluctuations.

3.2 Econometric strategy

To estimates sectoral employment and growth equations, we build on the recent contributions of Kalkuhl and Wenz (2020) and Kotz et al. (2024), who introduced a more flexible reaction function to account for inter-annual weather variations in economic outcomes. The baseline equation allows the response of the weather to vary across districts, using interactions between the weather variables (annual averages and day-to-day variabilities) with their historical average (1980–2022) climatic conditions (long-term average and long-term seasonal variability). Hence, they simultaneously capture non-linearity in the weather-economic relations, and heterogenous effects across different climate, e.g. across cold and hot districts.

Formally, our strategy is to run regressions with the following empirical specification:

$$y_{it} = \beta_1 T_{it} + \beta_2(T_{it} * \bar{T}_i) + \beta_3 \tilde{T}_{it} + \beta_4(\tilde{T}_{it} * \hat{T}_i) + \beta_5 P_{it} + \beta_6(P_{it} * \bar{P}_i) + \alpha_i + \theta_t + \varepsilon_i \quad (1)$$

where the dependent variable, y_{it}, represents the sectoral labour force shares in district *i* and year *t*. $T_{i,t}$ is the average annual temperature, while $T_{it} \times \bar{T}_i$ is an interaction term between the average annual temperature and the average long-run temperature. The term $\tilde{T}_{it}$ represents daily temperature variability, and $\tilde{T}_{it} \times \hat{T}_i$ is the interaction between this variable and the seasonal temperature variability, $\hat{T}_i$. In the baseline specification, P_{it} represents the total precipitations, which is also interacted ($P_{it} \times \bar{P}_i$) with the average long-run precipitations, $\bar{P}_i$. Finally, $\alpha_i + \theta_t$ are district and time fixed effects, respectively.

Sectoral value-added growth equation is formally identically to (1), but the dependent variable is now the value-added growth rate in each sector, measured as the annual log level differences in sectoral GVAs, i.e. $\Delta y_{it} \equiv \log(y_{it}) - \log(y_{it-1})$.

Robust standard errors are clustered by NUTS3 level in the baseline specification, and at the NUTS2 level in the robustness checks, accounting for spatial correlation.

4. Results

4.1 Labour share equations: Main results

Given the non-linearity of our baseline specification and to simplify the interpretation of the results, in what follow we mainly discuss marginal effects.[5] These represent changes in sectoral labour share or GVA growth for a +1°C (or +1cm for precipitations) increase in average temperature, day-to-day temperature variability, and total precipitations, measured for different values of the respective moderating variable.[6]

Panel A of Figure 2 reports the marginal effects of average annual temperature in Cold (10th percentile), Median (50th percentile), and Hot (90th percentile) districts, based on the long-run temperature distribution. In the typical district, the marginal effect of temperature on the sectoral labour share is positive for agricultural and construction, and negative for industry and services. However, these effects are small and statistically insignificant.

Things change when moving to more extreme cold and hot districts. In coldest districts (10^{th} percentile), an increase in temperature of 1°C leads to +0.51 percentage points increase in agricultural labour share and an increase of +0.15 percentage points in constructions. In the same colder districts,

[5] Formally, marginal effect is computed as $\frac{\partial \hat{y}_i}{\partial \hat{x}_i} = \beta_1 + (\beta_2 \times x_i)$, with x_i is the level of the moderating variable at which the marginal effect is estimated.

[6] The Tables containing results of the estimated coefficients for each sector are omitted due to space constraints.

a +1°C temperature increase results in a labour share reduction of –0.14 percentage points in industry (not significant) and a –0.53 percentage points reduction in the services sector significant at the 1% level. Thus, the labour reallocation effects in colder district move mainly from the services to the agricultural and construction sectors, *ceteris paribus*.

Conversely, in the hottest districts (90th percentile), a +1°C increase in long-run temperature results in significantly reduction of –0.46 percentage points in agricultural labour share and a –0.26 drop in constructions. Here workers seem to shift mainly to the services sector, which experiences a significantly increase of +0.84 percentage points in the labour share. In these areas, located mainly in the Mediterranean basin, agriculture accounts on average for 13% of employment share, and the reallocation of labour to services may largely compensate for losses in agriculture and constructions.

Overall, these findings suggest that European workers are sensitive to temperature shocks only in extreme cold and hot districts, with labour reallocation moving from services to agriculture and constructions in the former, and from agriculture/constructions to services in the latter.

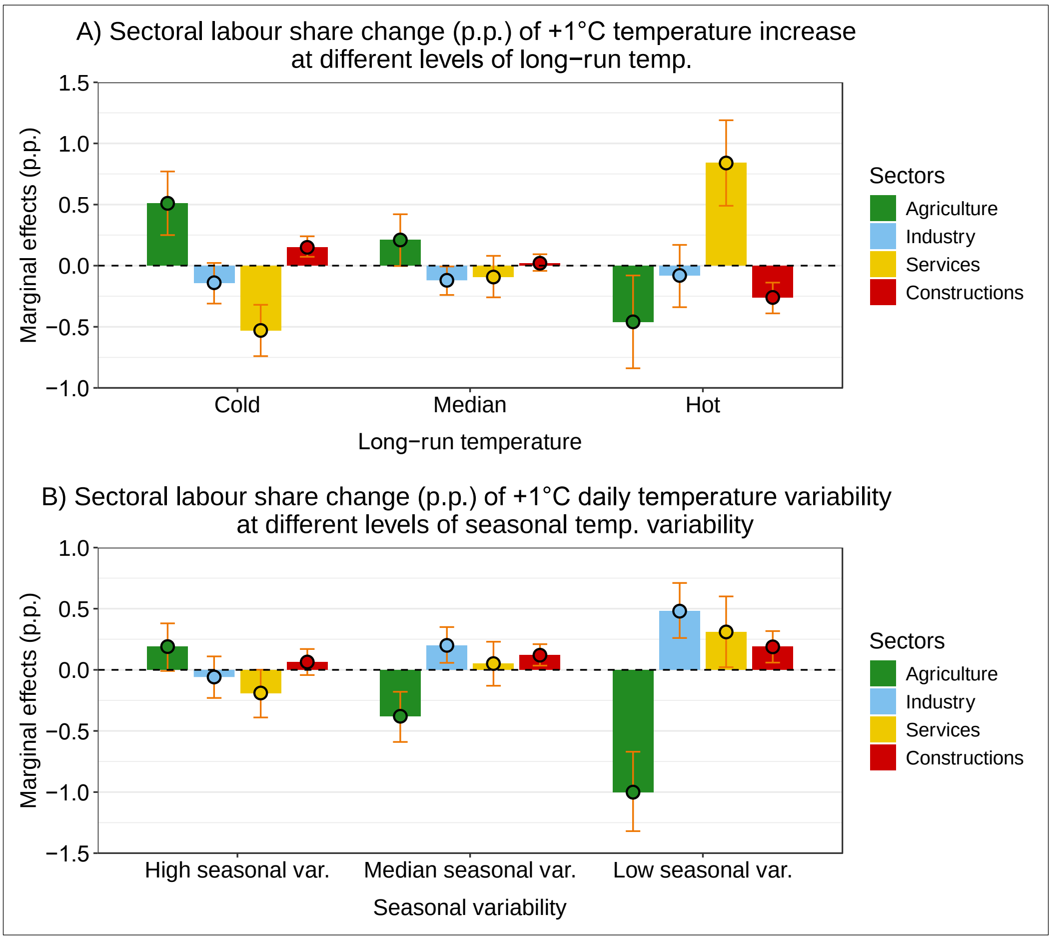
Moving to the impact of daily temperature variability, its effect appears independent from the one of annual temperature, although it moves in similar direction (see Figure 2, Panel B). An increase +1°C in day-to-day temperature variability, measured at high level of seasonal variability (10th percentile), poses no significant threat to any sector, as all exhibit marginal effects close to zero. Conversely, the marginal effects of day-to-day temperature variability on agricultural labour share is negative for the typical district (50th percentile), and equal to –0.38 percentage points. As expected, this negative marginal effect decreases up to –1 percentage point in provinces with low seasonal variability.

In the other sectors, on average, day-to-day temperature variability has positive and significant effects, moving in the opposite direction compared to agriculture. Specifically, a +1°C increase in day-to-day variability in provinces with low seasonal variability leads to a rise in labour share of +0.48 percentage points in industry, +0.31 in services, and +0.18 in constructions, all of which are statistically significant.

This finding aligns with the patterns discussed earlier in Figure 1, Panel A-C, regarding temperature effects in hot provinces. In these areas, the negative impact of warming on agricultural labour share tend to sum-up with the reallocation effects induced by daily temperature variability observed in districts with low seasonal variability. Taken together, these results suggest a compounding effect where workers increasingly transition from agriculture to services in response to changes in both annual temperature and day-to-day temperature variability.[7]

[7] We do not discuss the impact of precipitations. However, Table A.1 reports the associated coefficients and Figure A.1 shows the marginal effects of +1cm increase in precipitations on sectoral labour share.

Figure 2. Marginal effects of sectoral labour share.



Notes: The **upper panel A** shows the marginal effects of sectoral labour share change (percentage points) in response to a +1°C temperature increase relative to the long-run temperature, across different climate zones: cold (10th), median (50th), and hot (90th) NUTS3 regions. The corresponding average long-run temperatures are 7.8°C, 9.8°C, and 14.2°C. The **lower Panel B** depicts the marginal effects of sectoral labour share change (percentage points) in response to a +1°C day-to-day temperature variability relative to high (90th), median (50th), and low (10th) seasonal temperature variability NUTS3 regions. For all sectors, the seasonal temperatures are 23.5°C, 20.2°C, and 16.7°C, respectively.

Finally, it may be of interest to briefly discuss the marginal effects of precipitation on sectoral labour share (results not shown). As it is common in such analyses, the marginal effects of precipitation on sectoral labour share are approximately one order of magnitude smaller in absolute value than those of temperature. For instance, an increase of 1 cm in precipitations leads to a reduction in agricultural labour share of –0.012 percentage points in high-rainfall districts and of –0.018 percentage points in low-rainfall districts, both estimated with high precision. However, for all other sectors considered, the effect of precipitations is always positive and, as expected, smaller in magnitude than in agriculture.

4.2 Value-added equations: potential mechanism

In addition to estimating the effects of climate shocks on sectoral labour share, we also studied potential mechanisms. In the logic of the Colmer's (2021) model summarized in Section 2, a weather-driven negative growth effect in the more sensitive agricultural sector pushes downward the demand for labour in agriculture reducing equilibrium wage, potentially inducing a labour movement from agriculture toward less affected sectors.[8]

Results are summarized in Figure 4, Panel A and B, for temperature variables.[9] The marginal effect of sectoral GVA growth of +1°C temperature increase is consistently negative for agriculture and industry and become more negative moving from cold to particularly hot districts. In contrast, the services and constructions sectors exhibit positive and statistically significant growth effects of similar magnitude across climatic zones (see Table 4, Panel A).

Quantitatively, for the typical (median) district, a +1°C temperature increase induces a significantly negative growth effect in agriculture and industry of –0.99 and –0.47 percentage points, respectively. Meanwhile, the marginal effects are positive and significant for both the services and constructions sectors, with effects of around +0.38 and +0.98 percentage points, respectively.

These negative growth effects in agriculture and industry rise substantially (in absolute terms) in hotter provinces (90th percentile) causing a significant reduction in agricultural GVA growth of –2.03 percentage points. Regarding the other activities, the marginal effect in the industrial sector is also negative and significant, with a loss of –0.94 percentage points, while the services and constructions sectors show a steady, positive trend, with increases of +0.36 and +0.84 percentage points, respectively.

Figure 4, Panel B presents the marginal effects of sectoral GVA growth induced by day-to-day temperature variability at different levels of seasonal variability. These marginal effects are strongly negative particularly in the agriculture sector, with an effect potentially larger than the corresponding average temperature effect reported in Panel A. In districts with high seasonal variability (90th percentile), a +1°C increase in day-to-day temperature variability leads to a significant –5.90 percentage points reduction in agricultural GVA growth, an effect that shrink to –4.93 and –4.12 in the median and low seasonal variability. Note that, the 95% confidence interval of these effects overlap, suggesting that they are not statistically different from each other's.

In all other sectors, but industry in low seasonal variability districts, the corresponding marginal effects of day-to-day variability on GVA growth are several orders of magnitude smaller, often not

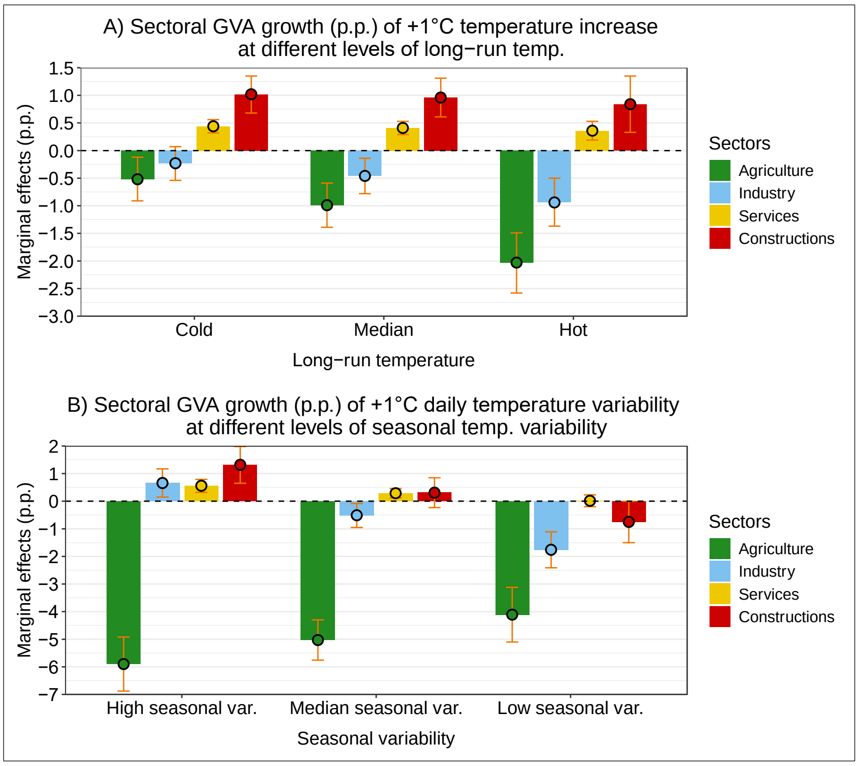
---

[8] We also test the growth equations by replacing sectoral gross value-added growth with sectoral labour productivity growth, obtaining very similar results.

[9] Marginal effects for precipitations, because small and often insignificantly in the GVA sectoral growth equations, are relegated in the Appendix.

statistically significant, and switching from positive to negative on moving from high to low seasonal variability.

Figure 4. Marginal effects of sectoral GVA growth.



Notes: The **upper Panel A** shows the marginal effects of sectoral GVA growth (p.p.) in response to a +1°C temperature increase relative to the long-run temperature, across different climate zones: cold (10^{th}), median (50^{th}), and hot (90^{th}) NUTS3 districts. The corresponding long-run temperatures are 7.8°C, 9.8°C, and 14.2°C. The **lower Panel B** depicts the marginal effects of sectoral GVA growth (p.p.) in response to a +1°C day-to-day temperature variability relative to high (90^{th}), median (50^{th}), and low (10^{th}) seasonal temperature variability NUTS3 districts. For all sectors, the seasonal temperatures are 23.5°C, 20.2°C, and 16.7°C, respectively.

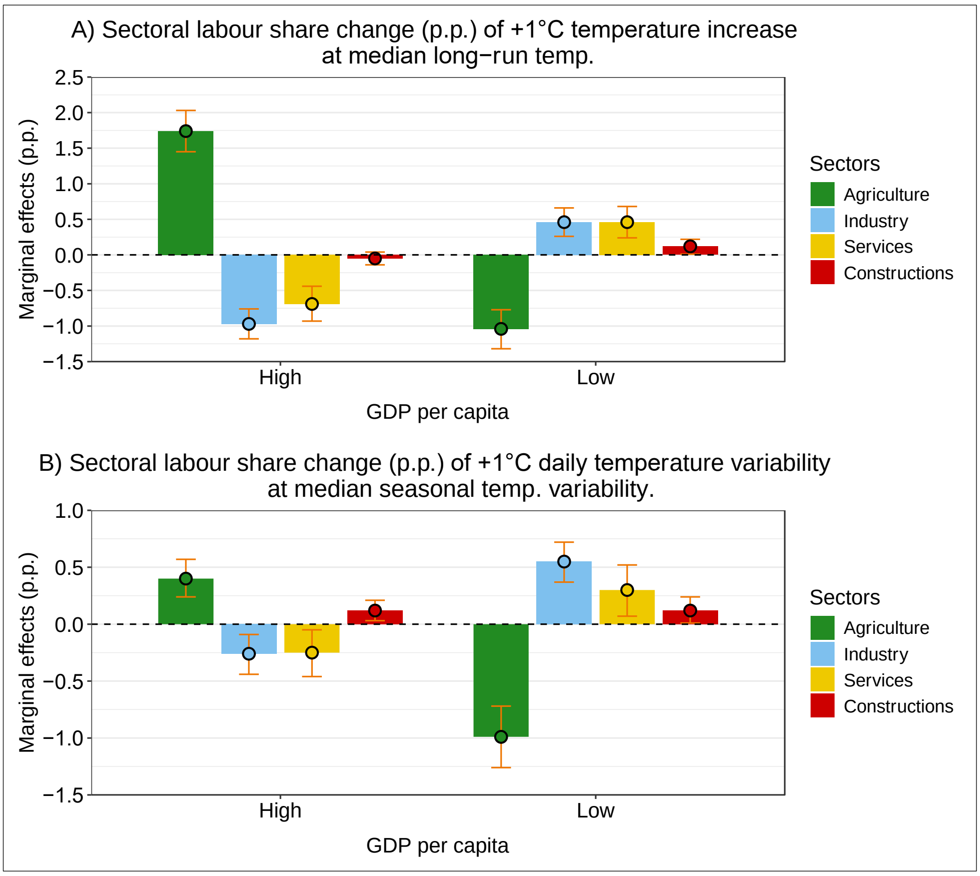
Interesting, these last findings differ strongly from Kotz et al. (2021), who observed that day-to-day temperature variability had similar negative effects on regional growth rates across all sectors considered (agriculture, industry and services). Thus, working with more granular and quality data, substantially change the conclusion about the effect of short-run temperature variability on economic activity.

Similar to Colmer (2021), the temperature-induced GVA growth effects in agriculture versus other sectors in Europe tend to align with the labour reallocation from agriculture to non-agricultural sectors, as discussed in Section 4.1. Thus, a key driver of this short-run labour reallocation can be attributed to the sectoral heterogeneity of weather-related productivity shocks, *ceteris paribus*.

4.3 Extension and robustness checks

Heterogeneity with respect to income. At the country level, it is well known that disentangling the effects of development from those of climate conditions is challenging due to the significant overlap between rich and poor countries and cold and hot regions (see Dell et al., 2014; Burke et al., 2015). A similar pattern applies at the European district level, where wealthier, colder northern districts and poorer, hotter southern districts partially overlap. However, the granularity of our sample, which includes 1,149 districts, make this identification less challenging.

Figure 5. Marginal effects of sectoral labour share: high- vs. low-GDP per capita NUTS3.



Notes: The **upper Panel A** shows the marginal effects of labour share (percentage points) in response to a +1°C temperature increase at the median (50th) long-run temperature between High- vs. Low-GDP per capita districts. The corresponding temperatures for agriculture and constructions in the High-GDP districts is 9.75°C, while for industry and services is 9.74°C. The corresponding temperatures for agriculture and constructions in the Low-GDP districts is 9.99°C, while for industry and services 9.96°C. The **lower Panel B** shows the marginal effects of labour share (percentage points) in response to a +1°C day-to-day temperature variability at the median (50th) seasonal variability between High- vs. Low-GDP per capita districts. The corresponding median seasonal temperature for all sectors in the High-GDP districts is 20.65°C, while in the Low-GDP districts is 19.79°C.

Thus, could be of some interest to study the heterogeneity across income groups by estimating our baseline labour share equations splitting the sample in high-GDP vs. low-GDP districts.[10] Figure 5, Panel A and B, summarize the results. The marginal effect of a +1°C temperature increase on the agricultural labour share at the median long-run temperature is positive, with a magnitude of +1.74 percentage points in high-GDP per capita districts, and negative, with a magnitude of –1.04 percentage points, in low-GDP districts. The opposite pattern is observed in the industry, services,

[10] This is done using the median value of average district' GDP per capita over the 43-year period.

and construction sectors, where the marginal temperature effects are significantly smaller in magnitude and have the opposite sign compared to the agricultural sector.

These patterns remain consistent when considering the marginal effects of day-to-day temperature variability on sectoral labour force shares, measured at the median seasonal variability (Figure 5, Panel B). As expected, while the observed heterogeneity across income levels partially mirrors the heterogeneity across climate, it emerges as particularly pronounced in predicting labour effects that display sharp differences on moving from high to low-income districts.

Aggregation at NUTS2 regional level. We have re-estimated the labour share equations using data at NUTS2 regional level. This can be of some interest because, on the one hand, economic and climate data at NUTS3 level, though more granular, can suffer of larger measurement errors eventually exacerbating attenuation bias in fixed effects panel models. On the other hand, this offers the possibility to learn something about the impact of aggregation bias, an issue sometime discussed in the climate economic literature (see Fezzi and Bateman, 2015). To this aim, we build a new dataset using economic variables from ARDECO at regional NUTS2 level, and climate variables were recalculated using the original daily gridded data from AgERA5, which were rescaled to NUTS2 boundaries.

Overall, although the results obtained at NUTS2 level are very close, some differences are worth noting. First, attenuation bias induced by error in variable, if anything, emerge mainly in the estimated impact of average temperature (and less so for day-to-day temperature variability), where the magnitude of the marginal effects tends to be slight larger (in absolute values) when estimated at NUTS2 vs. NUTS3 level. Differently, and not surprising, working at NUTS2 level the marginal effects are estimated with less precision than the ones estimated at NUTS3 level.

Alternative clustered standard errors. To address potential spatial correlation in the dependent and weather variables we re-run all the regressions using standard errors clustered at the NUTS2 level and by year. This introduces a higher degree of spatial and temporal aggregation, assuming correlations not only between provinces within the same NUTS2 region, but also within the same year. Although the estimated standard errors are sometime larger than before, all estimated marginal effects maintain a similar level of statistical significance.

Additional weather variables. As an additional robustness check, we included in the baseline specification additional weather variables more oriented to capture extreme events. Specifically, we considered the number of consecutive wet days where the rainfall is more than 1 mm per day at each station (see Abdila and Nugroho et al., 2021; McErlich et al., 2023 for calculation details), and extreme daily rainfall as sums of precipitation values for all days in year y, where the precipitation exceeds the 99th percentile threshold (see Martinez-Villalobos and Neelin, 2021; Kotz et al., 2024).

Main findings demonstrate the influence of these additional precipitation's shocks on sectoral labour share mainly in agriculture. However, the estimated marginal effects of temperature variables, overall, are quantitatively and qualitatively closed to the ones in the baseline specification.

Restricting the dataset at EU14 countries. Restricting the analysis to NUTS3 regions within the EU14 rather than including all 29 European countries allows us to focus on a subset of regions with more homogenous economic, institutional, and labour market conditions. The EU14 countries, being older members of the European Union, share relatively similar agricultural, industrial, and services sector dynamics, often influenced by long-standing policies such as the Common Agricultural Policy (CAP). Additionally, these regions are likely to have more reliable and consistent data, reducing potential biases introduced by variability in data quality or coverage across newer EU member states or other European countries.

The results in this restricted sample align well with those obtained for the full dataset, reinforcing the robustness of the main findings. Notably, the magnitude of the estimated coefficients for average annual temperature and daily temperature variability is generally slight lower, reflecting a possible reduced sensitivity of these sectors to weather fluctuations in the EU14. For instance, in agriculture, the positive impact of average annual temperature is slightly smaller compared to the broader sample, while remaining statistically significant. Similarly, in the services sector, the negative coefficient for average temperature is less pronounced but retains its significance level. This suggests that, even within the EU14, temperature changes influence sectoral labour reallocation, although potentially to a lesser extent than in the broader European sample.

5. Discussion and Conclusions

Building on recent climate economic literature, our study investigated the effects of weather shocks on sectoral labour reallocation and GVA growth using non-linear panel models. This approach enabled us to capture regional variations in weather responses by interacting weather variables with their historical average climatic conditions (1980–2022), thus accounting for non-linearities and heterogeneous effects across different climatic condition, such as cold versus hot European NUTS3 districts.

Our findings reveal that day-to-day temperature variability has additional effects on sectoral labour share and GVA growth that are not fully captured by annual average temperatures alone. Specifically, in median and hotter European districts, an increase of day-to-day temperature variability leads to a reduction in the agricultural labour share, with an impact magnitude twice that of the annual average temperature and moderated by expectations of seasonal temperature variability. Conversely, in Mediterranean and lower-latitude districts characterised by warmer climates and low seasonal variability, the labour share in services appears to benefit, driving a reallocation of labour from the more affected agricultural sector to the less exposed services sector, while the industry sector experiences a comparatively smaller shift as part of this adaptive response.

At the same time, in the colder-North and particularly high-income districts, our results indicate a labour reallocation effect in the opposite direction—shifting from the services and industry sectors toward agriculture. This finding, while novel, is somewhat unexpected and challenging to reconcile from an economic perspective. On one hand, global warming could increase agricultural productivity in northern and colder European districts by extending the growing season (see Van Passel et al., 2017). In addition, as recently argued by Hristov et al. (2024), the overall economic adjustment to heterogeneous climate-driven productivity shocks tends to benefit EU farmers, particularly in Northern regions. However, the extent to which these income gains lead to labour reallocation from non-agricultural sectors to agriculture remains difficult to interpret. Therefore, further analysis is needed to better assess the robustness of this finding.

The heterogeneous effects of weather shocks on sectoral GVA growth appear to be a possible mechanism driving labour reallocation from agriculture to the services sector. In the warmer, low-income regions of Europe with low seasonal variability, the industry and services sectors seem to act as a buffer, partially absorbing labour reallocated from agriculture. This finding underscores these sectors' capacity to mitigate employment losses in agriculture under specific income and climatic conditions.

As a potential limitation, our study highlights the need for further analysis to explore additional mechanisms driving labour reallocation, such as migration across regions and countries. Addressing this requires enhanced data on labour mobility flows within European regions and countries, as well as more timely unemployment information. Expanding data coverage to include various categories of mobile workers—such as temporary and seasonal employees, posted and self-employed workers, and cross-border commuters—would further enhance our understanding of climate-driven labour dynamics.

References

Abdila, W.P. and Nugroho, B.D.A. (2021). Trend analysis of extreme precipitation indices in the southern part of Java. *IOP Conference Series: Earth and Environmental Science,* 653: 012032.

Alfani, F., Molini, V., Pallante, G. and Palma, A. (2024). Job displacement and reallocation failure. Evidence from climate shocks in Morocco. *European Review of Agricultural Economics,* 51(1): 1-31.

Auffhammer, M. and Mansur, E.T. (2014). Measuring climatic impacts on energy consumption: a review of the empirical literature. *Energy Economics,* 46, 522-530.

Burke, M., Hsiang, S.M. and Miguel, E. (2015a). Global non-linear effect of temperature on economic production. *Nature,* 527: 235-239. http://doi.org/10.1038/nature15725

Burke, M., Hsiang, S.M. and Miguel, E. (2015b). Climate and Conflict. *Annual Review of Economics,* 7.

Cattaneo, C. and Peri, G. (2016). The migration response to increasing temperatures. *Journal of development economics*, 122, 127-146.

Chen, S., Chen, X. and Xu, J. (2016). Impacts of climate change on agriculture: evidence from China. *Journal of Environmental Economics and Management,* 76: 105-124.

Colmer, J. (2021). Temperature, labour reallocation, and industrial production: evidence from India. *American Economic Journal: Applied Economics*, 13(4): 101-124.

Dasgupta, S., van Maanen, N., Gosling, S.N., Piontek, F., Otto, C. and Schleussner, C.F. (2021). Effects of climate change on combined labour productivity and supply: an empirical, multi-model study. *Lancet Planet Health,* 5(7): 455-465. doi: 10.1016/S2542-5196(21)00170-4.

Dell, M., Jones, B.F. and Olken, B.A. (2009). Temperature and Income: Reconciling New Cross-Sectional and Panel Estimates. *American Economic Review,* 99(2): 198-204.

Dell, M., Jones, B.F. and Olken, B.A. (2014). What Do We Learn from the Weather? The New Climate-Economy Literature. *Journal of Economic Literature.*

Deryugina, T. and Hsiang, S.M. (2014). Does the environment still matter? Daily temperature and income in the United States. NBER Working Paper, 20750.

Diffenbaugh, N.S. and Burke, M. (2019). Global warming has increased global economic inequality. Proc. Natl. Acad. Sci. U.S.A. 116 (20) 9808-9813.

Emerick, K. (2018). Agricultural productivity and the sectoral reallocation of labour in rural India. *Journal of Development Economics,* 135(C): 488-503.

Fezzi, C. and Bateman, I. (2015). The Impact of Climate Change on Agriculture: Nonlinear Effects and Aggregation Bias in Ricardian Models of Farmland Values. Journal of the Association of Environmental and Resource Economists, 2(1).

Fishman, R., Carrillo, P. and Russ, J. (2019). Long-term impacts of exposure to high temperatures on human capital and economic productivity. *Journal of Environmental Economics and Management,* 93: 221-238.

Graff Zivin, J. and Neidell, M. (2014). Temperature and the Allocation of Time: Implications for Climate Change. *Journal of Labour Economics,* 32(1): 1-26. https://doi.org/10.1086/671766

Graff Zivin, J., Hsiang, S. and Neidell, M. (2018). Temperature and Human Capital in the Short and Long Run. *Journal of the Association of Environmental and Resource Economists,* 5.

Hristov, J., Pérez Domínguez, I., Fellmann, T. and Elleby, T. (2024). Economic impacts of climate change on EU agriculture: will the farmers benefit from global climate change? *Environmental Research Letter*, 19 – 014027.

Hultgren, A., Carleton, T., Delgado, M., Gergel, D.R., Greenstone, M. et al., (2023). Climate Change Impacts on Global Agriculture Accounting for Adaptation. Working paper.

Jessoe, K., Manning, D.T. and Taylor, J.E. (2018). Climate change and labour allocation in rural Mexico: evidence from annual fluctuations in weather. *The Economic Journal*, 128(608): 230-261.

Kalkuhl, M. and Wenz, L. (2020). The impact of climate conditions on economic production. evidence from a global panel of regions. *Journal of Environmental Economics and Management,* 103: 1-20.

Kotz, M., Levermann, A. and Wenz, L. (2024). The economic commitment of climate change. *Nature*, 628: 551-557. https://doi.org/10.1038/s41586-024-07219-0.

Kotz, M., Wenz, L., Stechemesser, A., Kalkuhl, M. and Levermann, A. (2021). Day-to-day temperature variability reduces economic growth. *Nature Climate Change*, 11: 319-325.

Linsenmeier, M. (2023). Temperature variability and long-run economic development. *Journal of Environmental Economics and Management,* 121: 102840.

Liu, M.Y., Shamdasani, Y. and Taraz, V. (2023). Climate change and labor reallocation: evidence from six decades of the Indian census. *American Economic Journal: Economic Policy*, 15(2): 395-423.

Martinez-Villalobos, C. and Neelin, J.D. (2021). Climate models capture key features of extreme precipitation probabilities across regions. *Environmental Research Letters*, 16(2): 024017.

McErlich, C., McDonald, A., Schuddeboom, A., Vishwanathan, G., Renwick, J. and Rana, S. (2023). Positive correlation between wet-day frequency and intensity linked to universal precipitation drivers. *Nature Geoscience,* 16: 410-415. https://doi.org/10.1038/s41561-023-01177-4

Musungu, A.L., Kubik, Z. and Qaim, M. (2024). Drought shocks and labour reallocation in rural Africa: evidence from Ethiopia. *European Review of Agricultural Economics*, 00: 1-24.

Nath, I. (2023). Climate Change, The Food Problem, and the Challenge of Adaptation through Sectoral Reallocation. Conference papers 333404, Purdue University, Center for Global Trade Analysis, Global Trade Analysis Project.

Olper, A., Zilia, F., Nota, P. and Raimondi, V. (2022). Adaptation to Weather Shocks Through Labour Reallocation: Evidence from Italy. *Politica Economica,* 3: 283-302.

Schlenker, W. and Roberts, D.L. (2009). Nonlinear Temperature Effects Indicate Severe Damages to U.S. Corn Yields Under Climate Change. *Proceedings of the National Academy of Sciences*, 106(37): 15594-15598.

Van Passel, S., Massetti, E. and Mendelsohn, R. (2017). A Ricardian analysis of the impact of climate change on European agriculture. *Environmental and Resource Economics,* 67(4), 725-760.

van Ruijven, B.J., De Cian, E. and Sue Wing, I. (2019). Amplification of future energy demand growth due to climate change. *Nature Communications*, 10: 2762. https://doi.org/10.1038/s41467-019-10399-3

Wenz, L., Levermann, A. and Auffhammer, M. (2017). North–south polarization of european electricity consumption under future warming. PNAS, 114(38): 7910–7918.

Wing, I.S., De Cian, E. and Mistry, M.N. (2021). Global vulnerability of crop yields to climate change. *Journal of Environmental Economics and Management*, 109: 1024.