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Heterogeneous effects of weather shocks on firm economic performance

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Abstract

This paper provides novel, firm-level estimates of the economic damages induced by temperature shocks. Leveraging European firm-level data, this study investigates the heterogeneity of damages across firms characteristics overlooked in aggregate analyses. The analysis consistently highlights negative (positive) impacts on the least (most) productive firms, contributing to both climate economics and the literature on aggregate productivity. Industry-specific effects indicate different susceptibilities across sectors to weather shocks. These results delve into the findings from the pooled sample which reveal a moderate U-shaped relationship between temperature and economic outcomes, suggesting significant adaptation for firms located in warmer areas. Temperature impacts on economic performance manifest with a lag, and varying persistence across firms. Methodologically, this work employs quantitative methods to address the potential drawbacks highlighted in the current climate econometrics discussion.

JEL codes: *D24, O13, O14, O44, O52, Q51, Q54, R11*
Keywords: *Weather, Climate Change, Firms, Climate Damages, Economic Performance.*

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1 Introduction

The increasing attention devoted to climate change is reflected in a growing body of academic research estimating its socioeconomic impacts (Carleton and Hsiang, 2016). Climate econometrics has emerged within this literature, estimating the costs of historical weather and climate events, generally defined as climate damages. These costs, in conjunction with climate projections, help quantify the present value of future climate change losses[1]. A key complexity in climate policies is the time mismatch between immediate emission reduction and future climate change costs. Estimating climate damages is essential to quantify future losses and set appropriate climate policies. These estimates are also crucial in refining the Social Cost of Carbon (SCC) (Stern, 2006; Pizer et al., 2014; Nordhaus, 2017; Rennert et al., 2022). Finally, identifying areas and entities with the highest costs of climate change allows policymakers to design adaptation policies effectively.

Climate econometrics leverages changes in weather realisations to identify the causal effect of climate on various socioeconomic variables (Dell et al., 2014)[2], industrial output (Graff Zivin and Kahn, 2016; Zappalà, 2023), labour productivity (Graff Zivin and Neidell, 2014; Somanathan et al., 2021), and economic growth (Dell et al., 2012; Burke et al., 2015). This literature relies on reduced form models exploiting exogenous weather variables and fixed effects (Hsiang, 2016) yielding plausibly exogenous variation of weather over time[3]. The relevant estimates are thus identified through idiosyncratic weather shocks[4]. Within this literature, Dell et al. (2012) uncovers negative linear effects of temperature shocks on aggregate output for poor countries , whereas Burke et al. (2015) shows that the global relationship between yearly average temperature and GDP growth is smooth, non-linear and concave. Therefore, it has been defined as inverted-U in the literature (Acevedo et al., 2020).

However, averaging local temperature at the country level leads to information loss, as different productive units are likely exposed to opposing temperature shocks, particularly in large countries with multiple climatic zones. This potentially introduces uncertainty and changes the true weather effect (Burke and Tanutama, 2019). Recently, strides have been made by focusing on more granular units of analysis, such as counties or regions (Burke and Tanutama, 2019; Kalkuhl and Wenz, 2020). Groom et al. (2023) find a nonlinear relationship opposite to the literature in Europe, highlighting the importance of disentangling aggregate effects. Nevertheless, regional analysis still lacks the granularity needed to capture critical economic dynamics affecting climate damages estimates. Moreover, identifying vulnerability heterogeneity at a more granular level provides policymakers with insights for tailoring adaptation policies, enhancing their effectiveness.

Since Melitz (2003) emphasized intra-industry heterogeneous firms' responses to economic shocks, firm-level analysis has become crucial in economic research, and it has recently been embraced in climate change economics. Results consistent with the aggregate studies are found for medium and large firms in China (Zhang et al., 2018; Chen and Yang, 2019) and in a sample of manufacturing and service firms from various countries (Nath, 2020), whereas no significant effect is found on public firm sales in the US (Addoum et al., 2020). Highlighting heterogeneous weather shocks across industries and regions helps understand how micro-level

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[1] Given the uncertainty of climate model projections (Murphy et al., 2004; Calel et al., 2020), enhancing our understanding of climate damages could reduce the overall uncertainty in these losses.

[2] Such as mortality (Deschênes and Greenstone, 2011; Barreca, 2012; Burgess et al., 2017; Carleton et al., 2022), violence and mental health (Card and Dahl, 2011; Carleton, 2017; Burke et al., 2018; Obradovich et al., 2018; Cunsolo et al., 2020), conflicts (Miguel et al., 2004; Burke et al., 2009; Harari and La Ferrara, 2018), agricultural output (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Burke and Emerick, 2016)

[3] Climate is the distribution of possible outcomes, whereas weather is its realization (Hsiang, 2016).

[4] Studies on economic growth initially relied on cross-sectional identifications (Mendelsohn et al., 1994; Nordhaus, 2006; Dell et al., 2009). To avoid bias from spurious associations of temperature with national characteristics (Acemoglu et al., 2002; Rodrik et al., 2004), the literature evolved towards panel data approaches.

impacts affect macro-level climate damages, as shown by Ponticelli et al. (2023), who highlights temperature impacts across firm size categories in the US.

In this paper, I conduct a firm-level analysis to explore the complex impact of weather shocks on the performance of European firms[5]. The European focus is particularly relevant because aggregate studies suggest that temperature variations do not significantly affect the European economy (Burke et al., 2015; Acevedo et al., 2020), and some even indicate a positive effect (Groom et al., 2023)[6]. Exploring sources of heterogeneity enables us to infer whether such damages are genuinely limited, or whether the aggregate estimates are confounded by different effects. In this regard, Groom et al. (2023) find heterogeneous damages across European regions, with temperature impacting the economy following a U-shaped relationship, in contrast with previous literature. By exploring the within-region distribution of economic activities, this analysis contributes to answering two main questions. First, whether aggregate results adequately capture the impact of temperature on economic outputs, or rather, whether they mechanically attenuate this effect by averaging out heterogeneous underlying responses. Second, if responses are heterogeneous, it seeks to identify their economic drivers.

To answer these question, I generate baseline results at the pooled level, providing a foundation for comparison with prior studies. These reveal a quasi-U-shaped relationship between temperature and economic outcomes. Although this result contrasts with previous literature, it is in line with Groom et al. (2023). This is reassuring since the findings are consistent across different levels of granularity within the European context. I further extend the analysis by incorporating interactions between weather variables and firm characteristics, highlighting substantial climate damages heterogeneity. Specifically, this study reveals that in general, high-productive firms appear to be better shielded from weather shocks. The marginal effect of an additional $1°C$ is either positive or not statistically significant for these firms, although high-productive firms exhibit negative marginal effects in the pooled sample when located in colder areas. In contrast, low-productive firms consistently experience negative impacts from rising temperature, albeit with some exceptions.

This paper contributes to different literature. First, the identification strategy section contributes to the climate econometrics literature by discussing the two econometric approaches commonly adopted in estimating the impacts of temperature shocks (temperature polynomials and temperature bins). Further, it addresses, in the firm-level context, methodological drawbacks that have been recently raised (Newell et al., 2021). Secondly, this work contributes to the climate economics literature by deepening our current understanding of the diverse ways firm heterogeneity influences climate damages. Thirdly, beyond its relevance to the applied climate economics literature, this research yields insights that are potentially valuable for the broader discussions on firm dynamism (Decker et al., 2016), firm inequality (De Loecker et al., 2022), and aggregate productivity (Foster et al., 2001). The analysis focusing on damages heterogeneity across firm productivity categories contributes to shedding some lights on the possible drivers of the aggregate productivity slowdown in Europe. The rest of this paper is structured as follows: section 2 presents the data, section 3 describes the identification strategy, section 4 reports and discusses results and section 5 concludes.

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[5] Despite its large share of the global GDP, Europe has not been previously analysed in firm-level studies.

[6] Europe is composed of developed countries with generally temperate temperature. Ceteris paribus, these characteristics are usually associated with lower climate damages.

2 Data

2.1 Economic Data

I use firm-level data from 1995 to 2020 derived from the administrative micro-level dataset Orbis Historical, provided by Bureau Van Dijk Electronic Publishing (BvD). These data have been extensively used in the literature focusing on firm dynamics (Bloom et al., 2016; Gopinath et al., 2017; Acharya et al., 2019; Autor et al., 2020). This database provides data on firm balance sheets and income statements for over 400 million companies worldwide, covering firms in all sectors of the economy. The main variables of interest in this analysis encompass real gross output (GO), real value added (VA), capital stock (K), number of employees (L), and total factor productivity (TFP). I estimate TFP using the Wooldridge (2009) method[7]. All financial variables, except for labour, are adjusted to 2010 prices using industry-level deflators from OECD STAN[8]. The most recent available deflators correspond to either 2019 or 2018. As the latest year in my sample is 2020, I adopt the most recent deflator for subsequent years[9]. Furthermore, I calculate the investment and capital stock using the Perpetual Inventory Method (PIM). Additionally, I adjust the financial variables by the OECD STAN PPP (LCU per US dollar) series to correct for price-level differences across countries. Finally, I winsorise the financial variables at the 1^{st} and the 99^{th} percentiles to mitigate the influence of outliers.

Kalemli-Ozcan et al. (2015) highlight the main challenges related to using Orbis data for research purposes. To minimise such issues, I follow and extend[10] the Kalemli-Ozcan et al. (2015) cleaning procedure. After this procedure, the total number of observations falls from 212,377,647 to 70,346,838. Table 2 reports descriptive statistics for the final dataset. Table 4 reports the total number of observations with at least one non-missing variable of interest (i.e. the union of observations with non-missing GO, VA and TFP) after the cleaning procedure (column 1) and the number of observations with non-missing GO (column 2), VA (column 3) and TFP (column 4)[11]. It is worth specifying that the panel is unbalanced. This is primarily due to the well-known enhancement in data availability and representativeness over time, a factor that should be considered when analysing the data. Furthermore, such improvement in data availability is not uniform across countries. Lastly, the decrease in observation availability in 2020 is a result of the reporting lag in Orbis.

Country-specific total numbers of observations are reported in table 3. I excluded Ireland and Luxembourg from the initial sample due to their favorable fiscal policies, which could introduce biases in the results. To gain insights into the distribution of firms, I present maps depicting the spatial distribution of firm-level variables aggregated at the Nuts 3 level. Figures 12 and 13 reveal significant heterogeneity between regions. While this visualization is informative for understanding firm characteristics within the sample, caution is needed when making inferences about the broader firm population due to potential non-random data availability, such as missing firms. A notable example is Germany, where regions have a low number of firms, leading to relatively low aggregate gross output and employment. Average values reveals that Germany consistently features large

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[7] Wooldridge (2009) extends the two-step estimation procedures from Olley and Pakes (1996) and Levinsohn and Petrin (2003), implementing a two-equations GMM estimation which solves an identification problem present in previous models and leads to more efficient estimators.

[8] Industry-level deflators are available at different NACE levels of aggregation for different industries. I defined an algorithm to identify and select the most granular available level of aggregation for each industry.

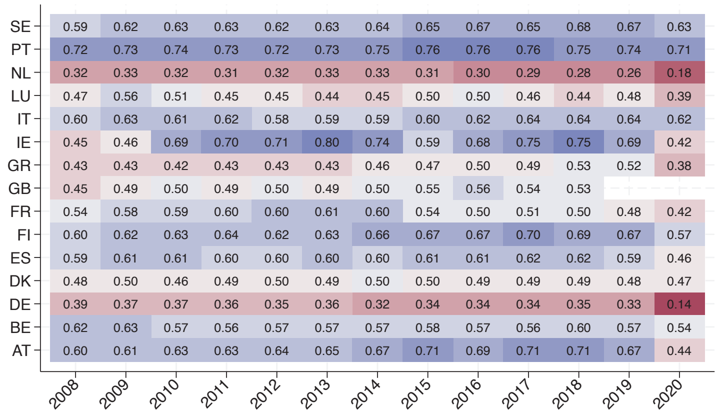
[9] I choose this approach for its likely conservatism compared to assuming a consistent growth rate as in previous years for imputed values.

[10] I extend the cleaning procedure by setting to missing implausible negative values for financial variables and unrealistic spikes in their growth rates.

[11] The number of available observations for TFP is lower than GO and VA because the Wooldridge (2009) TFP estimation procedure requires non-missing VA, K, L and cost of materials contemporaneously.

firms, with an under-representation of small firms. This should be considered when discussing the external validity of the estimates presented in this paper.

However, the total number of observations does not necessarily provide the full picture of how representative the sample is for the entire economy. Rather, it is good practice to assess representativeness in terms of coverage. That is, the ratio between aggregate economic output across all firms in the Orbis sample and aggregate values from official statistical offices. Figure 1 shows that, although the coverage is relatively stable over time within each country, there are non-negligible differences across countries. Specifically, notwithstanding the low coverage for Germany and the Netherlands, the coverage for the remaining countries is generally good, with most country-year values above 0.5. European countries generally have better coverage, as firms of all sizes face the same regulatory requirements to file most of the balance sheet variables included in the database.



	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
SE	0.59	0.62	0.63	0.63	0.62	0.63	0.64	0.65	0.67	0.65	0.68	0.67	0.63
PT	0.72	0.73	0.74	0.73	0.72	0.73	0.75	0.76	0.76	0.76	0.75	0.74	0.71
NL	0.32	0.33	0.32	0.31	0.32	0.33	0.33	0.31	0.30	0.29	0.28	0.26	0.18
LU	0.47	0.56	0.51	0.45	0.45	0.44	0.45	0.50	0.50	0.46	0.44	0.48	0.39
IT	0.60	0.63	0.61	0.62	0.58	0.59	0.59	0.60	0.62	0.64	0.64	0.64	0.62
IE	0.45	0.46	0.69	0.70	0.71	0.80	0.74	0.59	0.68	0.75	0.75	0.69	0.42
GR	0.43	0.43	0.42	0.43	0.43	0.43	0.46	0.47	0.50	0.49	0.53	0.52	0.38
GB	0.45	0.49	0.50	0.49	0.50	0.49	0.50	0.55	0.56	0.54	0.53		
FR	0.54	0.58	0.59	0.60	0.60	0.61	0.60	0.54	0.50	0.51	0.50	0.48	0.42
FI	0.60	0.62	0.63	0.64	0.62	0.63	0.66	0.67	0.67	0.70	0.69	0.67	0.57
ES	0.59	0.61	0.61	0.60	0.60	0.60	0.60	0.61	0.61	0.62	0.62	0.59	0.46
DK	0.48	0.50	0.46	0.49	0.50	0.49	0.50	0.50	0.49	0.49	0.49	0.48	0.47
DE	0.39	0.37	0.37	0.36	0.35	0.36	0.32	0.34	0.34	0.34	0.35	0.33	0.14
BE	0.62	0.63	0.57	0.56	0.57	0.57	0.57	0.58	0.57	0.56	0.60	0.57	0.54
AT	0.60	0.61	0.63	0.63	0.64	0.65	0.67	0.71	0.69	0.71	0.71	0.67	0.44

Figure 1: Coverage of the aggregate economy from Orbis data in terms of gross output. The values report for each country-year the ratio (bounded between 0 and 1) between aggregate gross output for the firms included in the sample and the economy-wide gross output. The economy-wide gross output values are only available since 2008. Source: Orbis and EUROSTAT.

While the overall number of observations provides some insight, the real focus of this work is on understanding the underlying heterogeneity. Table 5 breaks down observations across broadly defined sectors, aggregating the NACE revision 2 level 2 sectors into the broader NACE revision 2 level 1 for clarity. Notably, there are significant variations in data availability among industries. While these differences likely mirror the broader economic landscape, they should be considered when delving into industry-level heterogeneity, as they can impact standard errors and statistical significance. Given the modest number of observations for industries “O-Public administration and defence compulsory social security" and “U-Activities of extraterritorial organisations and bodies", firms belonging to these sectors are excluded from the analysis.

Another important aspect is firm size. Past research has underscored a significant positive correlation between size and productivity, albeit with variations across countries (Bartelsman et al., 2013). Orbis holds a distinct advantage over other firm-level data sources due to its inclusive coverage of Small and Medium Enterprises (SMEs). This is crucial because the exclusive focus on large firms would result in estimates with low external validity, leading to partial conclusions and misguided policy implications. Considering the geographical focus of this study, the inclusion of SMEs is particularly relevant given their significant contributions and substantial presence in the European economy. Table 6 outlines the number of observations for three periods in our sample, categorized by firm size[12]. Not only does the presence of SMEs increases over time, but their relative share

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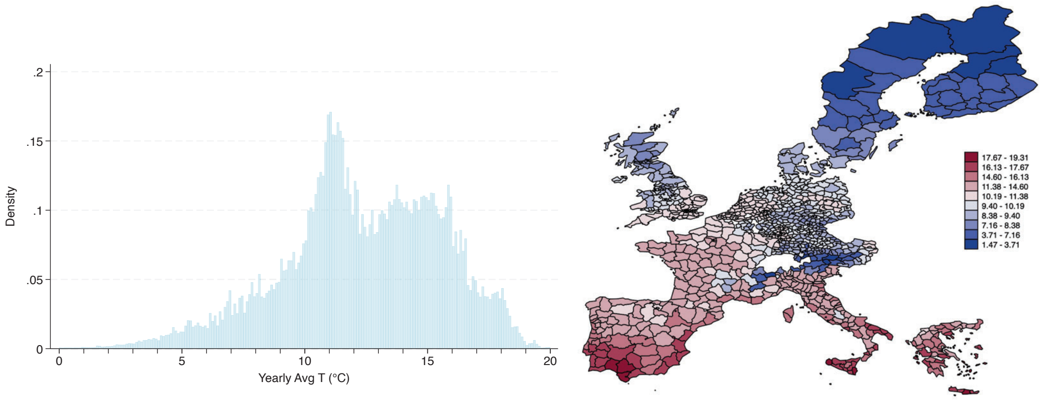
[12] Firm size is based on the number of employees according to the European Commission classification.

also grow. In this regard, it is worth highlighting that Orbis data suffer from underrepresentation of small firms, particularly before 2006 in countries like Germany, the Netherlands, and Ireland (Kalemli-Ozcan et al., 2015).

An additional multi-step process ensures the accuracy of reported coordinates[13]. I devised a simple procedure to remove implausible values at the Nuts 3 and city levels. After matching firms with Nuts 3-level shapefiles, I marked coordinates as missing if falling outside their region. Subsequently, I generated city-level coordinates and replaced firm coordinates with their city averages if the difference between the two exceeded 0.25 degrees. An additional procedure imputes the city-street level mode coordinates when these are missing. If multiple modes were present, I use the average coordinates unless the difference between the minimum and maximum mode exceeded 0.25 in absolute value. Testing these values with OpenCage geocoding consistently showed a correlation above 99%. For a detailed description, refer to Appendix 6.2.

2.2 Weather Data

I retrieve weather data from the Copernicus Climate Change Service (C3S) within the European Centre for Medium-Range Weather Forecasts (ECMRWF). I utilise hourly average temperature $(^\circ C)$ and total monthly precipitation (m) from the ERA5-Land product (Hersbach et al., 2020, 2019) which represents the fifth generation reanalysis of global climate and weather from 1950 onwards regridded to a regular latitude-longitude grid of 0.1 degrees ($\sim$ 9 km). Reanalysis combines model data with worldwide observations, resulting in a globally complete and consistent dataset according to the laws of physics. As meteorological measurements from station-based weather data are unevenly distributed globally, they can lead to inconsistencies between different areas. Such uneven distribution may introduce endogeneity in the estimation process, as the availability of meteorological stations is likely correlated with socioeconomic variables, which, in turn, are correlated with firms' performance. In contrast, reanalysis data are evenly available both over time and across space.



(a) Temperature Frequency (b) Temperature Spatial Distribution

Figure 2: Distribution (a) and Spatial distribution (b) of yearly average temperature across firm-year observations in Europe. Source: ECMWF.

Figure 2a plots the distribution of yearly average temperature for the firm-year observations included in the dataset. As is evident, the bulk of the observations is between $(8^\circ C)$ and $(19^\circ C)$. As expected, the distribution reports large varition in yearly average temperatures. Figure 2b reports the map of the the average temperature across the firm-year observations within each Nuts 3 region. In line with existing literature, I aggregate hourly average temperature to compute yearly average temperature and total monthly precipitation to compute yearly total precipitation. I match weather and firm-level data using the coordinates available in the two datasets.

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[13] Coordinates for AT, DE, FI, GR, and SE are unavailable in Orbis Historical, geocoded using OpenCage.

Employing an inverse-distance weighted matching procedure, I construct smoothed averages across space for the weather variables. Opting for inverse-distance weighting over matching based on the closest grid helps avoid potential inaccuracies in the assigned weather measures[14]. Additionally, this matching approach defines longitude-latitude-specific measures, introducing more variability than grid-specific measures. Due to computational limitations, I restrict this matching process to grids within a 10 km radius of the firm location. The spatial match is conducted based on geodetic distances (Picard, 2019).

A potential concern with this procedure is that firm locations may change over time, the physical and legal locations may differ, or the firm may have subsidiaries in different areas, potentially introducing bias to the estimates. The first concern is ruled out as BvD firm identifiers automatically change when a firm relocates to a different location. In addition, I rely on firm unconsolidated financial statements to exclude inflows from subsidiaries[15]. Moreover, the advantage of Orbis data lies in its extensive coverage of small and micro-firms, which are less likely to have different physical and legal locations (Fadic et al., 2019). While this assumption is reasonable for the scope of this work, further research should address and possibly rule out this concern.

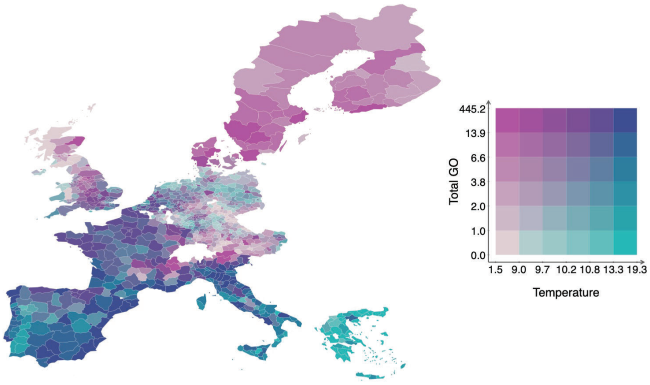

Figure 3: Bivariate Spatial distribution of yearly average temperature and total gross outpus across firm-year observations aggregated at the Nuts 3 level in Europe. The legend reports yearly average temperature on the X-axis and total GO on the Y-axis. Colours from bottom to top of the legend indicate higher total GO, whereas colours from left to right indicate higher yearly average temperatures. Source: Orbis and ECMWF.

To provide an overview of how the matched temperature and gross output are jointly spatially distributed, figure 3 reports the bivariate map of firm-level yearly average temperature and gross output aggregated at the Nuts 3 level. The figure reveals substantial heterogeneity in the interaction between these two variables across space[16]. This is relevant because it allows alleviate selection bias. For example, southern Europe is warmer and usually considered as less economically developed. However, the figure shows that in warmer areas both less-developed (south of Italy and Greece) and more-developed (south of Spain) areas are present.

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[14] Consider a firm in a temperate valley near the border of two grids. Using closest-distance matching, its coordinates might be closer to a grid's centroid that includes a mountain, resulting in a matched temperature significantly colder than its actual temperature.

[15] Unconsolidated financial statements are identified in Orbis as U1 and U2.

[16] The low values observed for total gross output and employment in German regions are driven by a low coverage and low number of firms as shown in figures 12a and 14a and discussed in previous section.

3 Identification and Model Selection

As highlighted in the introduction, the climate econometrics literature has evolved over time, refining methods to better capture various causal effects of temperature. Similarly to causal inference methods that exploit quasi-experimental settings, climate econometrics relies on exogenous variation in weather outcomes resulting from physics principles. Moreover, the inclusion of relevant fixed effects allows us to disentangle plausibly random weather fluctuations from long-term climate, which is likely correlated with other socioeconomic characteristics. These fixed effects ensure that constant unobserved components, which could introduce omitted variable bias if left unaccounted for, are incorporated into the estimation process.

Understanding the economic responses to climate change through the study of annual weather fluctuations is complex, and it is important to use the terms 'weather' and 'climate' carefully. 'Climate' refers to the distribution of outcomes, such as the range of temperatures experienced in an area, whereas 'weather' represents the realization of this distribution (Hsiang, 2016)[17]. Throughout this paper, I rely on weather fluctuations to identify the marginal effect of increasing temperature. These findings contribute to the broader discussion on climate damages, to the extent that climate change contributes to the observed increases in temperature reflected in weather fluctuations.

Over the last two decades two main approaches attempting at identifying the economic impacts of weather fluctuations have become the standard in the climate econometrics literature. One exploiting fluctuations in yearly average temperature (Dell et al., 2012; Burke et al., 2015), and another exploiting variation in the number of days in a year with daily average temperature within a certain interval (bin), first developed in Deschênes et al. (2009). The former estimates the marginal effect of an additional $1°C$ in yearly average temperature, whereas the latter estimates the marginal effect of an additional day with daily average temperature falling within a specific temperature bin compared to a temperate day. These models are not mutually exclusive, but rather complementary, and the choice between the two alternatives depends on the specific research question. The temperature bins specification is becoming particularly popular at the moment, possibly due to its straightforward causal identification and clearer interpretation.

Although more straightforward to interpret, the temperature bins models rely on the assumption that the impact of temperature on yearly production is a linear combination of daily average temperatures, with each day having the same weight. This is a plausible assumption in the case of analysis studying the effects of temperature on mortality. However, the assumption is weaker for firm-level production, since firms' production is usually not constant across days. For example, several firms adjust their production according to exogenous variation in demand, reduce their production during weekends or summer, and in some cases some firms temporarily interrupt production. Although this is not necessarily the case for some manufacturing firms which tend to produce at a mostly continuous rate - yet production can still slow-down in certain periods - it is more likely for firms in the agriculture, trade, retail or service sectors, which are a relevant part of the firms in my sample.

Moreover, estimates based on yearly average temperatures are relevant to the broader discussion on the estimation of the SCC, to the extent that these are used as inputs in general equilibrium macroeconomic models (Nordhaus, 1991). For these reasons, in this paper I rely on variation in firm-specific yearly weather fluctuations to identify the effect of higher temperature on firm economic performance. Specifically, I estimate the marginal effect of an additional $1°C$ in yearly average temperature using the following general model:

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[17] On this regard, Deryugina and Hsiang (2017) demonstrate that the marginal effect of long-run climate can be identified using only idiosyncratic weather variation, although under the strong assumption of efficient competitive markets.

$$\Delta Y_{i,t} = g(T_{i,t}) + f(P_{i,t}) + \sum_{\ell \geq 1} h(T_{i,t-\ell}) + \delta_i + \boldsymbol{\delta_{-i}} + \varepsilon_{i,t} \tag{1}$$

Where $\Delta Y_{i,t} = Y_{i,t} - Y_{i,t-1}$ represents the yearly growth rate of either either of the economic variables for firm i in year t. The function $g(T_{i,t})$ is a j^{th} order polynomial in temperature, capturing the impact of temperature on firm economic performance. It is defined as the dot-product between the $1 \times j$ row vector of marginal effects $\boldsymbol{\beta'}$ and the $j \times 1$ column vector of temperature $\boldsymbol{T_{i,t}}$, where j represents the degree of the polynomial in $T_{i,t}$,

$$g(T_{i,t}) = \underset{(1\times j)(j\times 1)}{\boldsymbol{\beta'} \;\; \boldsymbol{T_{i,t}}} \qquad \forall \quad j = 1, \ldots, J \tag{2}$$

expressing the vectors in matrix notation and applying the dot product between $\boldsymbol{\beta'}$ and $\boldsymbol{T_{i,t}}$, we can retrieve the underlying j^{th} order polynomial of temperature defined as

$$g(T_{i,t}) = \boldsymbol{\beta' T_{i,t}} = \underset{(1\times j)}{\begin{bmatrix} \beta_1 & \ldots & \beta_j \end{bmatrix}} \underset{(j\times 1)}{\begin{bmatrix} T_{i,t} \\ \vdots \\ T^j_{i,t} \end{bmatrix}} = \beta_1 T_{i,t} + \cdots + \beta_j T^j_{i,t} \qquad \forall \quad j = 1, \ldots, J \tag{3}$$

$f(P_{i,t})$ represents a k^{th} order polynomial capturing the effect of precipitation on firm economic performance and it is defined similar to $g(T_{i,t})$. Additionally, $\sum_{\ell > 1} h(T_{i,t-\ell})$ is a j^{th} order polynomial with the same degree as $g(T_{i,t})$. It is defined as the sum over the ℓ lags of the dot product between the $1 \times j$ row vector of marginal effects $\boldsymbol{\gamma'}$ and the $j \times 1$ column vector of temperature for lag l $\boldsymbol{T_\ell}$

$$\sum_{\ell \geq 1} h(T_{i,t-\ell}) = \sum_{\ell \geq 1} \underset{(1\times j)}{\boldsymbol{\gamma'_\ell}} \; \underset{(j\times 1)}{\boldsymbol{T_{i,t-l}}} \tag{4}$$

For $\ell = 1$ we have a j^{th} order polynomial of 1-lag temperature $\boldsymbol{T_{i,t-1}}$ defined analogously as $g(T_{i,t})$. Furthermore, δ_i is a firm fixed effect that accounts for firm-specific unobserved constant components, $\boldsymbol{\delta_{-i}}$ is a set of fixed effects complementary to δ_i, which can be adapted to the specific research design. For instance, in analyses at the establishment level, these could include spatial fixed effects. Given that the current analysis is based on firm-level observations, which are singularly located, spatial fixed effects would be nested under the firm fixed effect and consequently omitted to avoid multicollinearity. In this paper, I adopt the industry-year fixed effect $\lambda_{n,t}$ that accounts for unobserved time-varying Nace 2 industry-specific trends or shocks (Wooldridge, 2002). These could be common trends such as technological innovations or year-specific shocks, such as changes in energy prices or supply-chain shocks. I do not include time-trends in the preferred specification since these have no effects on the resulting firm-level estimates. Specifically, the results are robust to the inclusion of Nuts1-specific quadratic time trends. For an exhaustive discussion on the inclusion of time-trends in climate econometrics studies see Bearpak and Palomba (2024). Finally, $\varepsilon_{i,t}$ is the idiosyncratic error component, assumed to be exogenous to the weather-related covariates.

Specifically, given the temperature damage function identified in equation 1, the marginal effect of temperature on firm variables is defined as

$$\frac{\partial \Delta Y_{i,t}}{\partial T_{i,t}} = \frac{\partial g(T_{i,t})}{\partial T_{i,t}} \tag{5}$$

for the contemporaneous effect and

$$\frac{\partial \Delta Y_{i,t}}{\partial T_{i,t-\ell}} = \frac{\partial h(T_{i,t-\ell})}{\partial T_{i,t-\ell}} \tag{6}$$

for the effect of the ℓ^{th} lag. Therefore, the total cumulative effect, which identifies whether the effect of temperature variation is persistent (Dell et al., 2012) is defined as

$$\frac{\partial \Delta Y_{i,t}}{\partial T_{i,t}} + \sum_{\ell\geq 1} \frac{\partial \Delta Y_{i,t}}{\partial T_{i,t-\ell}} = \frac{\partial g(T_{i,t})}{\partial T_{i,t}} + \sum_{\ell\geq 1} \frac{\partial h(T_{i,t-\ell})}{\partial T_{i,t-\ell}} \tag{7}$$

In the case of a 2^{nd} order polynomial with 2 lags, the contemporaneous marginal effect is given by:

$$\frac{\partial Y_{i,t}}{\partial T_{i,t}} = \beta_1 + 2\beta_2 T_{i,t} \tag{8}$$

where the linear coefficient β_1 represents the marginal effect of an additional $1°C$ in terms of yearly average temperature for firms located in areas with an average yearly temperature of $0°C$. The coefficient of the quadratic term β_2 represents half of the additional marginal effect for firms located in areas with temperature different from $0°$. That is, half of the slope of the marginal effect function with respect to $T_{i,t}$. The persistence of the effect of increasing temperature is quantified by adding up the contemporaneous and lagged coefficients of the quadratic model. As emphasised by Newell et al. (2021) and further discussed by Klenow et al. (2023), if temperature has only a transitory effect on economic performance, the effects of lagged temperature should reverse the contemporaneous effect. This phenomenon would manifest in the contemporaneous $\boldsymbol{\beta'}$ and lagged $\sum_{\ell>1}^{L} \gamma_\ell$ effects having approximately equal magnitude but opposite sign (sign reversal).

The underlying identification assumption is that weather shocks, as identified by temperature fluctuations resulting after controlling for a polynomial of precipitation $f(P_{i,t})$ and the relevant fixed effects, are exogenous. If this assumption holds, then the estimated coefficients could be interpreted as the unbiased causal effect of an additional $1°C$ in temperature on firm economics performance. In terms of panel analysis and fixed effect model identification, this can be expressed as an adapted strict exogeneity assumption:

$$\mathbb{E}[\varepsilon_{i,t} \mid g(T_{i,t}), f(P_{i,t}), \{h(T_{i,t-1}), \ldots, h(T_{i,t-L})\}, \delta_i, \boldsymbol{\delta_{-i}}] = 0 \qquad \forall \quad t = 1, \ldots, T \tag{9}$$

As long as this assumption holds in the data, the estimates included in the $\boldsymbol{\beta'}$ vector can be considered as the causal marginal effect of an additional $1°C$ on firm economic performance. Previous works have relied on specific cases of the general identification strategy discussed in this section, with most analyses adopting the specification outlined in the seminal paper by Burke et al. (2015). Building on the Dell et al. (2012) paper, the authors model economic output as a quadratic function of temperature, allowing the marginal effect of temperature to vary over the temperature support.

Since the nonlinearity allows the units means to re-enter the estimation, in this model the marginal effect of increasing temperature is identified through both within-unit time series variation and between-units cross-sectional variation (McIntosh and Schlenker, 2006). Hence, the nonlinear specification allows us to estimate plausibly causal estimates of unanticipated short-term weather fluctuations, which incorporate adaptation responses to longer-term climate (Burke et al., 2015; Auffhammer, 2018). As highlighted by McIntosh and Schlenker (2006), the nonlinearity produced in a quadratic functional form with fixed-effects can be disentangled between a within nonlinearity (WNL) and a global nonlinearity (GNL)[18]. Nonlinear models with fixed-

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[18] The WNL has a centering point for each fixed-effect and identifies weather deviations from the mean of the fixed-effect group, whereas the GNL has only one centering point across the distribution of the weather variable and identifies deviations from the mean of the sample as a whole. The GNL implies that the marginal

effects accounting for GNL that fail to account for WNL when these are present are biased. Nevertheless, Mérel and Gammans (2021) show that such bias becomes negligible when cross-sectional variation in climate dominates locational weather fluctuations (within-units time series variation). WNL are potentially relevant in a small-N long-T country-level context but are likely to be modest in a large-N, short-T firm-level context. As highlighted in table 7, in the data of this analysis cross-sectional variation dominates time-series variation, therefore the coefficients estimated by the nonlinear model accounting for GNL only are likely to be unbiased.

Furthermore, concerns have arisen since the resulting inverted-U relationship could potentially be driven by the specific constraints that the functional form imposes on the parameters. In this analysis, I aim to provide preliminary empirical evidence to identify the functional form that most accurately captures the relationship between temperature and firm-level economic performance, utilising two distinct methodologies. Initially, I estimate a flexible model to glean preliminary insights into whether the effect of interest manifests as linear or non-linear. Subsequently, post-estimation tests are employed to determine the most appropriate order of the polynomial $\boldsymbol{\beta' T_{i,t}}$ and the number of lagged temperatures to include in the model. The flexible model is specified by replacing the quadratic term with an interaction between the linear temperature term and a categorical variable that classifies the firm's yearly average temperature $T_{i,t}$ into quintiles within the overall temperature distribution as follows:

$$\Delta Y_{i,t} = \beta_1 T_{i,t} + \beta_2 T_{i,t} \times Q_{i,t} + \boldsymbol{\psi' P_{i,t}} + \delta_i + \lambda_{n,t} + \varepsilon_{i,t} \tag{10}$$

where the main variables are defined as in equation 1 and $Q_{i,t}$ classifies firm's i temperature quintile in year t. Statistically significant differences in the marginal effect of linear temperature across different temperature quintiles would suggest the presence of nonlinearities in the effect of $T_{i,t}$. Figure 17 presents the results for this model, expressed as the additional marginal effect of a $1°C$ increase in yearly average temperature for firms situated in quintile $j = \{1, 2, 4, 5\}$ with respect to firms in the 3^{rd} quintile. While the contemporaneous additional marginal effects for the 1^{st} and 4^{th} quintiles are economically negligible and not statistically significant, those for the 2^{nd} and 5^{th} quintiles are negative and statistically significant at the 1% and 5% levels respectively (figure 17a). Furthermore, the analysis on how the marginal effect varies across different categories - the sum of β_1 and β_2 - yields a consistent pattern (figure 18a), although the estimate for the 5^{th} decile is significant only at the 10%. The analysis on lagged temperature provides preliminary insights on the persistence of the effect of temperature. These results highlight the importance of accounting for non-linearities and delayed (lagged) effects in the specification. However, this flexible model alone does not offer conclusive evidence on which specification, in terms of order of the polynomial and lagged temperatures, should be preferred.

To address these aspects, I conduct post-estimation tests on a subset of models characterised by different polynomial orders j and lags ℓ. I leverage two types of model selection criteria, i) canonical econometrics in-sample Information Criteria (IC) and ii) Machine Learning out-of-sample Cross Validation (CV). Appendix 6.3 discusses the main characteristics of these approaches. Given the large size of my sample, and the amount of computational resources required for these analysis, I limit this analysis to $\ell = \{1, \ldots, 5\}$ lags for each of the $j^{th} = \{1, \ldots, 4\}$ order polynomials[19]. The resulting measures of model performance are reported in table 8. The results from the model selection criteria are straightforward. Model performance is only marginally affected by the inclusion of higher-order polynomials, suggesting that they do not play a decisive role in improving model performance. In contrast, according to table 8 a more pronounced impact is observed with

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effect of $T_{i,t}$ on $Y_{i,t}$ varies across the $T_{i,t}$ distribution, whereas the WNL implies that the marginal effect of $T_{i,t}$ depends only on how $T_{i,t}$ moves away from the within groups mean $\overline{T_i}$.

[19] I used a cloud computing system set with 10 cores of CPU and 100 GB of RAM, which ran for 3 days, 3 hours and 38 minutes.

the inclusion of lagged temperature. However, selecting an appropriate order and number of lags presents a challenge, as both the IC and the CV values tend to continuously decrease without offering a definitive choice, likely influenced by the extensive sample size. Since direct comparisons based on absolute figures remains inconclusive, examining relative changes provides more insightful and rational selection criteria, suggesting a preference for models with two lags. This approach is similar to the elbow rule used in Machine Learning (e.g. clustering), where models are assessed according to their marginal benefit (James et al., 2013).

Within each polynomial order, including a second lag leads to a reduction of AIC and BIC values by approximately 25%, and CV means by approximately 10%. Further additions of lags result in diminishing returns, with IC reductions ranging from roughly 19% to 17% and CV averages from roughly 3.3% to 1.9%. Choosing the polynomial order remains complex, as different selection criteria do not always favour the same order when only models with two lags are considered. Within this framework, the AIC and the BIC indicate a third-order polynomial due to the most significant relative mean decrease by 0.00085% and 0.00079% respectively, whereas the CV tends towards a second-order polynomial, with its mean decreasing by 0.027%. Despite these slight discrepancies between IC and CV outcomes, a second-order polynomial is selected since the marginal improvement in CV is higher than in IC. A quadratic model balances providing adequate model flexibility and minimizing overfitting risks. Moreover, this model aligns with the established literature, facilitating comparisons with previous studies. Consequently, this study adopts a quadratic model to explore variations in the marginal effects of higher temperature across the temperature support. The model is defined as follows:

$$\Delta Y_{i,t} = \underset{(1\times2)}{\boldsymbol{\beta}'}\;\underset{(2\times1)}{\boldsymbol{T_{i,t}}} + \sum_{\ell=1}^{2} \underset{(1\times2)}{\boldsymbol{\gamma}'_{\boldsymbol{\ell}}}\;\underset{(2\times1)}{\boldsymbol{T_{i,t-l}}} + \underset{(1\times2)}{\boldsymbol{\psi}'}\;\underset{(2\times1)}{\boldsymbol{P_{i,t}}} + \delta_i + \lambda_{n,t} + \varepsilon_{i,t} \tag{11}$$

In this framework, the error term $\varepsilon_{i,t}$ is likely serially correlated within a firm over time and spatially correlated within a certain region. Such correlations may persist even after including the relevant fixed effects (Angrist and Pischke, 2009; Cameron and Miller, 2015). To address these concerns, I cluster standard errors at the regional level since each firm in the sample is located in one and only one region. Therefore, firm-level clusters are nested within regions. At this stage, another question naturally arises. Which is the optimal Nuts level the standard errors should be clustered at. Cameron and Miller (2015) highlight the relevant trade-off, analogous to the bias-variance trade-off common in estimation procedures[20]. Since large and few clusters have less bias but more variance, I cluster standard errors at the Nuts 3 level, providing a large number of sufficiently large clusters in both pooled and country-specific analyses.

Another issue related to these estimations concerns the potential non-stationarity of the variables' time series included in the analysis. If such series are non-stationary, the models become spurious as they are affected by three major issues: first, the regression estimates are inefficient; second, the forecasts based on these regressions are sub-optimal and; third, the usual significance tests on the coefficients are invalid (Granger and Newbold, 1974). A series

$$y_{i,t} = \rho_i y_{i,t-1} + \epsilon_{i,t} \tag{12}$$

is non-stationary when $\rho_i = 1$. That is, the series follows a random walk and has a unit-root. When series are non-stationary, they should be first-differenced when included in regressions. This issue has been raised

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[20] First, whenever the regressors and the error terms are potentially correlated within a cluster, the clustering level should be sufficiently broad to account for such correlation. Second, the clustered variance matrix of $\hat{\boldsymbol{\beta}}$ approximates the variance matrix of $\boldsymbol{\beta}$ only as the number of clusters gets large. Hence, if the defined clusters are too large, the resulting $V_{clu}[\hat{\boldsymbol{\beta}}]$ is a poor estimate of $V[\hat{\boldsymbol{\beta}}]$.

in climate econometrics by Burke et al. (2015)[21]. Newell et al. (2021) point out that the Burke et al. (2015) specification is still spurious since it only accounts for the non-stationarity in the GDP series but not in the temperature series, advocating that the temperature terms should be first-differenced as well. It is important to note in this context that there exists a distinct difference between country-level and firm-level analysis. Country-level works typically feature longer time series (T) and a lower number of entities (N), whereas firm-level analysis are characterised by shorter T and longer N. In the small T case of longitudinal microeconomic data sets, the time-series properties of the data are "a side issue that is usually of little interest" (Greene, 2003). However, when T increases as the same rate as n (e.g. cross-country studies) these properties become a central focus of the analysis. Although this paper falls into the first category (short T, long N), I conduct statistical tests to check for non-stationarity in the relevant series for completeness. All these tests strongly reject the null hypothesis of nonstationarity. The results of the tests and a detailed discussion can be found in section 6.5.

Finally, to identify the heterogeneous economic impacts of higher temperature I interact the variables in equation 11 with different variables identifying firms characteristics

$$\Delta Y_{i,t} = \underset{(1\times2)(2\times1)}{\boldsymbol{\beta}' \; \boldsymbol{T_{i,t}}} + \sum_{\ell=1}^{2} \underset{(1\times2)\ (2\times1)}{\boldsymbol{\gamma}'_{\boldsymbol{\ell}} \; \boldsymbol{T_{i,t-l}}} + (\underset{(1\times2)(2\times1)}{\boldsymbol{\beta}' \; \boldsymbol{T_{i,t}}}) \cdot C_{i,t} + (\sum_{\ell=1}^{2} \underset{(1\times2)\ (2\times1)}{\boldsymbol{\gamma}'_{\boldsymbol{\ell}} \; \boldsymbol{T_{i,t-l}}}) \cdot C_{i,t} + \underset{(1\times2)(2\times1)}{\boldsymbol{\psi}' \; \boldsymbol{P_{i,t}}} + \delta_i + \lambda_{n,t} + \varepsilon_{i,t} \tag{13}$$

where $C_{i,t}$ identifies firm i category in year t. The resulting marginal effects quantify the additional effect of an extra $1^{\circ}C$ in yearly average temperature for firms in a certain category, relative to firms in the base category, whose marginal effects are estimated by the non-interacted temperature variables. In the next section I initially discuss results from the non-interacted model (the pooled sample) to estimate the average effect of temperature fluctuations on firm economic performance, then I delve into heterogeneity analysis regarding different firm characteristics, such as productivity category, size and industry.

4 Results

Empirical evidence has demonstrated that higher temperatures can impact firm economic performance through various channels. For example, they can diminish labor supply through higher absenteeism (Graff Zivin and Neidell, 2014; Somanathan et al., 2021), potentially due to relocation towards leisure or inability to work. Higher temperatures also impair labor productivity (Graff Zivin et al., 2018; Somanathan et al., 2021), resulting from reduced cognitive or physical abilities. These impacts further extend to reduced capital productivity and stock. As highlighted by Zhang et al. (2018), higher temperatures adversely affect machine productivity through diminished lubrication capability (Mortier et al., 2010), higher failure rates (Collins, 1963), and reduced processing speed (Lilja, 2005). Unsustainable temperatures can also cause machinery breakdowns, reducing capital stock. Damages to production may also arise from reduced material supply due to supply chain shocks[22]. Additionally, impacts from higher temperatures can be indirect, involving increased energy or transportation costs. Higher temperatures lead to more use of AC and refrigerators, resulting in higher energy and fuel consumption. On extremely hot days, local aggregate energy consumption may exceed the grid's capacity, potentially causing blackouts and disrupting production. Finally, extreme weather shocks can directly reduce

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[21] They highlight how country-level GDP follows a random walk ($\rho_i = 0.999$) before being first-differenced

[22] While international supply chains may not be affected, many European firms depend on local supply chains, shown by local economic agglomerates, hence likely impacted by local weather shocks.

the stock of materials, requiring substitution to continue production. These results from previous research can be used to explain the empirical findings of this paper discussed in the following sections.

4.1 Temperature Average Damage, Timing, and Persistence

In this section I present and discuss empirical results for the model discussed in section 3 and the whole set of dependent variables, such as GO, VA, TFP, L, K and cost of materials (M). The estimates reported in this section refer to the average effect across the pooled sample (i.e. across all countries and firms characteristics). To avoid bias driven by outliers, I estimate the models by excluding firms located in areas belonging to the top and bottom percentiles of the temperature distribution. Table 1 reports the results from the quadratic model defined in equation 11. These results suggest that in general temperature affects GO mostly through TFP and M, whereas L and K have the same sign but a lower magnitude. This is potentially driven by higher adjustment costs for these two inputs. The main objective of this section is to shed light on the timing and persistence of the effect of higher temperature on firm economic performance. To do so, I focus on how the marginal effect of temperature on firm $Y_{i,t}$ varies across $T_{i,t-\ell}$ for $\ell = \{0, 1, 2\}$.

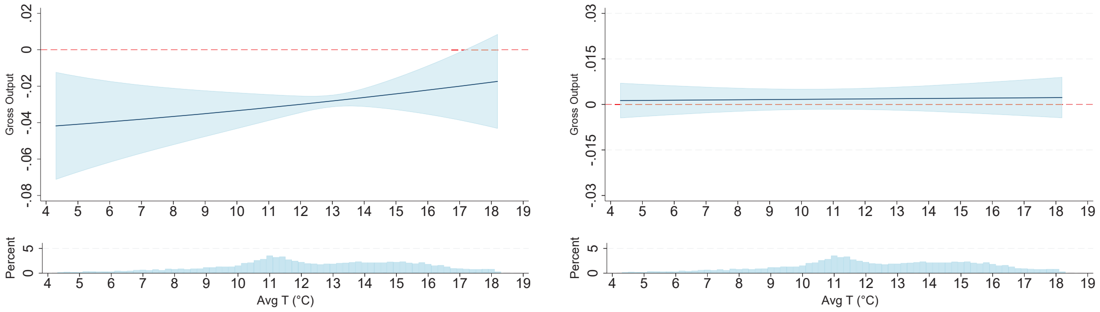
	(1) ΔGO	(2) ΔVA	(3) ΔTFP	(4) ΔL	(5) ΔK	(6) ΔM
T	0.000956	-0.00330	0.00731	-0.00660***	0.00357	-0.00166
	(0.00444)	(0.00578)	(0.00478)	(0.00229)	(0.00281)	(0.00477)
T^2	0.0000357	0.000237	-0.0000270	0.000321***	-0.000174	0.000241
	(0.000194)	(0.000234)	(0.000171)	(0.0000964)	(0.000112)	(0.000187)
$(\ell 1)T$	-0.0237***	-0.0383***	-0.0310***	-0.0160***	-0.00939***	-0.0241***
	(0.00420)	(0.00488)	(0.00415)	(0.00185)	(0.00213)	(0.00353)
$(\ell 1)T^2$	0.000383	0.000834***	0.000481**	0.000491***	0.000293**	0.000911***
	(0.000274)	(0.000271)	(0.000217)	(0.000124)	(0.000114)	(0.000233)
$(\ell 2)T$	-0.00517	-0.0202***	-0.00947**	-0.00599***	-0.0156***	0.00158
	(0.00503)	(0.00492)	(0.00449)	(0.00212)	(0.00237)	(0.00514)
$(\ell 2)T^2$	0.000445*	0.00106***	0.000389*	0.000455***	0.000511***	0.000267
	(0.000255)	(0.000258)	(0.000233)	(0.000135)	(0.000107)	(0.000232)
P	0.0169	-0.0276**	0.0133	-0.0000493	-0.0126**	-0.0181
	(0.0133)	(0.0125)	(0.0109)	(0.00643)	(0.00522)	(0.0122)
P^2	-0.00865*	0.0124***	-0.000636	0.00119	0.00699***	0.00792*
	(0.00485)	(0.00436)	(0.00343)	(0.00244)	(0.00185)	(0.00464)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind.-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.159	0.132	0.114	0.138	0.150	0.144
N	43,010,958	32,190,012	18,443,623	25,571,942	38,147,581	31,096,340

Standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 1: Point estimates and standard errors from the regressions of weather variables on the growth rates of GO, VA, TFP, L, K, and M. Results for the 2^{nd} order polynomial model with firm and industry-year FE, standard errors clustered at the Nuts 3 level.

The contemporaneous effect of temperature identified by $T_{i,t}$ is economically negligible and statistically not significant across all dependent variables except for L, likely because labour contracts are more elastic to economic shocks. The effect is larger and statistically significant for $T_{i,t-1}$, indicating a delayed impact on economic performance. This delay could be explained by the time lag inherent in the production and sales process, suggesting that temperature shocks to production manifest later in firm revenues[23]. Additionally, the lag in damages can be driven by how firms' production respond to higher temperature. Firms can absorb negative sales shocks in year t through stocks adjustments, with these shocks appearing in sales and revenues in year t+1 due to production constraints. In terms of costs, weather shock-induced increases in energy-related costs, especially heating costs at the end of year t, may be billed in year t+1. Finally, since GO identifies revenues and not production, this delay may be driven not only by economic factors but also by accounting practices, which can cause a temporal mismatch between the economic shock and the accounting realisation.

As discussed in section 3, comparing the estimates over time allows to understand whether the impact of weather shocks is persistent. If temperature has only a transitory effect, the effects of lagged temperature would reverse the contemporaneous effect. This would be evident if the contemporaneous $\boldsymbol{\beta'}$ and lagged $\sum_{\ell \geq 1}^{L} \gamma_\ell$ estimates have approximately equal magnitude but opposite sign. As is shown in table 1, the estimates for lagged temperature are negative for the linear terms and positive for the quadratic terms across all variables. The contemporaneous effects are positive but economically insignificant for GO, TFP and K, and negative for VA, L and M, with only L being statistically significant. These estimates suggest that temperatures impact production mostly through shocks in TFP and materials, although a reduction in materials has positive effects as it lowers costs. The negative contemporaneous estimates for VA and L, and positive but lower in magnitudes for the other variables, suggest persistent growth effects for VA and L. However, this result could be reversed by the positive quadratic terms for firms located in warmer areas. he remainder of this section plots the marginal effect across the temperature distribution and discusses the potential drivers of these differences.



(a) 2^{nd} order polynomial prediction

(b) 2^{nd} order polynomial marginal effect

Figure 4: Contemporaneous prediction (a) and marginal effect (b) of temperature on the growth rate of GO. Results from the 2^{nd} order polynomial model with firm and industry-year FE, standard errors clustered at the Nuts 3 level.

Figure 4 reports the contemporaneous prediction 4a and the marginal effect 4b of temperature on the growth rate of GO, holding the other covariates fixed at their average values. For presentational purposes, I plot the results excluding the top and bottom percentiles of the temperature distribution, even though these firms are present in the estimated sample. Figure 4a shows a quasi-U-shaped (increasing and convex) relationship between the two variables, in contrast with the commonly-reported inverted-U relationship. Firms throughout the temperature distribution are associated with negative growth rates, with more negative effects in areas with lower yearly average temperature. However, the predictions are not statistically different from 0 above an average temperature of $17°C$. The results from the quadratic model differ from a large part of previous literature focusing on global damages, but align with Groom et al. (2023) who analyse European regions. Since

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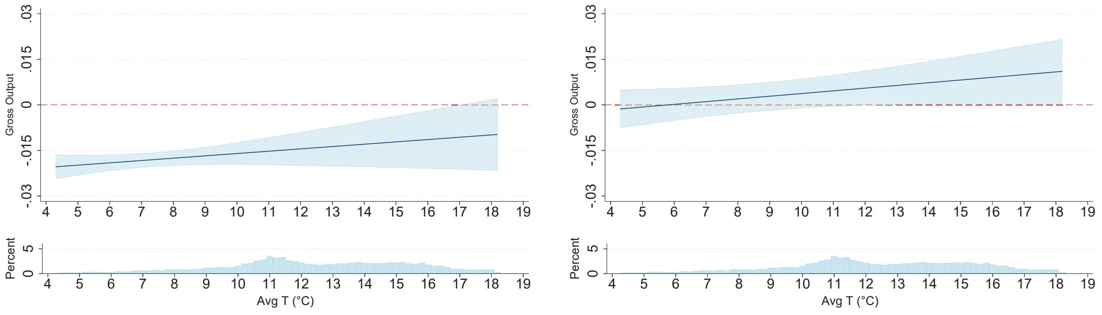
[23] In agriculture, weather shocks can affect crops during their initial stages, but the economic effects are only visible after harvest and commercialisation. Firms in construction or complex manufacturing activities can be characterised by long production processes, and in several industries payments are solved with a delay.

the marginal effects provide more intuitive insights, figure 4b reports the contemporaneous marginal effect of an additional $1°C$ in temperature across the temperature distribution. The marginal effect of temperature is mostly flat and neither economically nor statistically significant. The non-significance of the effect of $T_{i,t}$ is driven by several economic characteristics of the production process leading to a delayed impact of temperature.

Figure 5 reports the results for the lagged marginal effects of temperature on firm GO. The marginal effect of $T_{i,t-1}$ reported in figure 5a is consistently negative and statistically significant across the whole temperature distribution. Specifically, an additional $1°C$ reduces the growth rate of GO by -1.97% for firms located in areas with a yearly average temperature of $5°C$ and by -0.96% for firms located in areas with a yearly average temperature of $18°C$. The marginal effect of $T_{i,t-2}$ reported in figure 5b is marginally negative, although not statistically significant for firms located in areas with yearly average temperature below $5°C$ (-0.07% at $5°C$), and positive for firms located in the remaining part of the temperature distribution (1.11% at $18°C$), although statistically significant at the 5% only above $12°C$. Interestingly, the effect of $T_{i,t-2}$ partially reverses the effect of $T_{i,t-1}$, at least for firms located in warmer areas.



(a) lag-1 marginal effect

(b) lag-2 marginal effect

Figure 5: Lag-1 (a) and lag-2 (b) marginal effects of temperature on the growth rate of GO. Results from the 2^{nd} order polynomial model with firm and industry-year FE, standard errors clustered at the Nuts 3 level.

Figure 19a shows a quasi-U-shaped cumulative effect - the sum of the marginal effects over time. Firms in areas with lower temperature are associated with positive growth rates, while those in warmer areas are associated with negative growth rates. However, the predictions are not statistically different from 0 above a yearly average temperature of $16°C$. The cumulative marginal effect reported in figure 19b is generally negative and upward sloping. The effect is negative and statistically significant for firms in colder areas, indicating persistent growth effects. These estimates are not statistically significant above approximately $11°C$, suggesting that the damages are transitory for firms located in warmer areas. As discussed in the next section, the marginal effect of temperature is heterogeneous across firms, and the null average marginal effect may result from different effects across firms. This is supported by the presence of large standard errors. For example, warmer areas may have a higher presence of firms whose characteristics make them more resilient to temperature increases.

Previous literature has shown that such results are also driven by more developed or a higher penetration of adaptation strategies. Firms more exposed to higher temperature face larger damages, and have larger incentives to invest in adaptation. The results of this paper suggest that firms located in warmer areas have already undertaken, and potentially completed, adaptation strategies. Firms can adapt to higher temperatures by adopting air conditioning (Graff Zivin and Kahn, 2016), diversifying or transitioning their economic activities to less-impacted sectors, or ultimately relocating their establishments to less-impacted areas. Albert et al. (2021) provide evidence from Brazil of factor reallocation from agriculture and services to local manufacturing (in the short-run) or to the same sectors in less-affected areas (in the long-run) due to extreme dryness. As the authors study factors reallocation rather than firm decisions[24], further research is needed to explore these complementary strategies. Although relocation may not be considered as a form of adaptation from a local perspective, as it results in a loss of GDP for that area, it could be a viable form of adaptation from the firm's perspective.

Furthermore, comparing the estimates for the marginal effects of temperature between GO and VA can allow decoupling, at least partially, the total temperature damages from the economic impacts arising from variation in the costs of materials. The VA estimates thus identify the combined effect on L,K, and TFP. Since the estimates based on GO incorporate the full damage, whereas the estimates for VA are partially net of the effect on materials costs, the difference between β_{GO} and β_{VA} identifies the sign of the effects of higher temperature on costs. A positive (negative) difference $\beta_{GO} - \beta_{VA}$ suggests a reduction (increase) in costs of materials.

The impact of an additional $1°C$ is more pronounced for VA than for GO across the temperature distribution. The cumulative marginal effect on VA (figure 20) is more negative (positive) for firms in colder (warmer) regions, and follows a steeper function than the effect on GO presented in figure 19b. This highlighs persistent negative growth effects in colder areas and persistent positive (although not statistically significant) growth effects in warmer areas. The effect of temperature on materials costs mitigates the negative effect on production in colder areas, whereas it increases expenses, negatively impacting firms profitability in warmer areas[25]. Consistently with table 1, the reduction in materials costs seems to mitigate the negative (positive) effects of temperature on the other inputs in colder (warmer) areas.

The results presented thus far pertain to the model proposed by Burke et al. (2015) estimated on the pooled sample. However, the results from the pooled regressions are potentially confounded by the underlying heterogeneity in economic damages. Since the primary focus and contribution of this paper revolve around the significance of accounting for heterogeneous climate damages, I conduct the heterogeneity analysis relying on their established quadratic model, facilitating the comparison with previous work. Section 6.9.1 focuses on cross-country heterogeneity, highlighting differences in the damage function across countries, whereas next sections delve into damages heterogeneity in terms of firms characteristics.

4.2 Heterogeneity Analysis

Several factors may contribute to temperature damages across firms characteristics. Firms operating in sectors more exposed to temperature fluctuations, such as agriculture, mining, construction, are expected to be more sensitive to temperature fluctuations than sectors with a higher likelihood of indoor activities and a greater penetration of thermal control systems. Even within the same industry, more profitable firms are more likely to undertake the adaptation strategies mentioned above, since they have both higher opportunity costs of not adapting (in terms of lost profits) and more resources to invest. Firm size can also influence this dynamic. Larger firms are not only more profitable but, given the same level of profitability, face relatively lower adaptation costs due to economies of scale (i.e. lower per-worker costs). Productivity levels may also influence firm climate damages. Even within the same sector, more productive firms are more likely to rely on cognitive skills-based tasks, which are less affected compared to physical tasks, and often conducted in temperature-controlled environments, or with automated processes. These firms possess greater resources for adaptation as they employ fewer inputs for the same level of output. Finally, they may have better managers, who are able to mitigate productivity declines (Adhvaryu et al., 2022), likely to be more attentive, and to undertake

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[24] Factors reallocation could be determined by higher temperature but independent of firm decisions. For example, households may decide to change industry or migrate to colder areas for personal reasons.

[25] Since data availability could lead to selection bias if reporting VA is non-random, I estimate the model only for firms with both GO and VA available (table 11). The estimates are coherent with those in table 1.

investments in adaptation (Norris-Keiller and Van Reenen, 2024). In the following sections I discuss the heteorogeneous effects of weather shocks on firms' performance by productivity levels, size, and industry estimated using equation 13.

4.2.1 Productivity Heterogeneity

This section delves into the analysis of potential firm-level damages by assessing whether firm-specific productivity levels impact firms' responses to weather shocks. Figure 6 reports the point estimates for the regression of the growth rate of gross output on a second-order polynomial of temperature interacted with firm TFP category. The TFP categories are defined according to the firm average TFP percentile group, based on the first two years the firm is available in the sample, which are excluded from the estimation to avoid violating the strict exogeneity assumption (equation 9). Differently from the results on firm size, firm-level heterogeneity is clearly visible already at the European level. The function of the marginal effect of an additional $1°C$ in $T_{i,t}$ is upward-sloping in temperature for the three most productive categories, with positive values at high levels of the temperature distribution. On the contrary, firms belonging to the $[10^{th}; 25^{th})$ and $[25^{th}; 50^{th})$ categories are characterised by a flatter marginal effect function, which is slightly downward-sloping and generally upward-sloping for the $[10^{th}; 25^{th})$ and $[25^{th}; 50^{th})$ categories respectively. Finally, the marginal effect for the least productive firms (1^{st} decile) is strikingly downward-sloping.

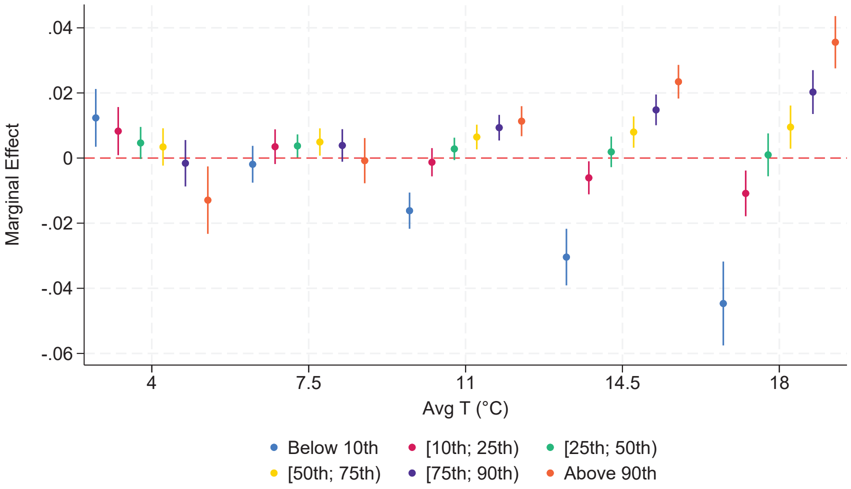
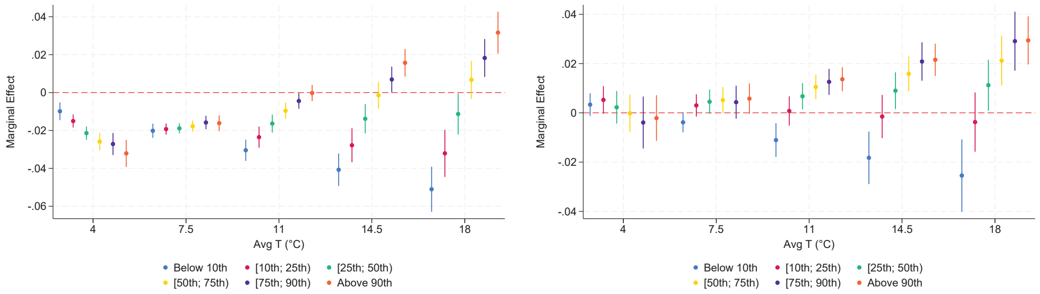


Figure 6: Marginal effect of an extra $1°C$ in contemporaneous yearly average temperature on the growth rate of gross output (log) accounting for productivity heterogeneity (firm grouped according to average TFP). Results from the quadratic model with firm and industry-year FE.

The dynamics between the least and most productive firms differ substantially according to whether we consider firms located in areas with colder or warmer yearly average temperature. For firms located in areas with an average yearly temperature of $4°C$, an additional $1°C$ in $T_{i,t}$ increases the growth rate of GO by 1.2% for firms belonging to the bottom (1^{st}) productivity decile, and reduces the growth rate of GO by 1.3% for firms belonging to the top (10^{th}) productivity decile. On the contrary, when considering firms located in areas with an average yearly temperature of $18°C$, an additional $1°C$ in $T_{i,t}$ decreases the growth rate of GO by -4.5% for firms belonging to the bottom (1^{st}) productivity decile and increases the growth rate of GO by 3.6% for firms belonging to the top (10^{th}) productivity decile.

The results for lagged temperatures $T_{i,t-1}$ and $T_{i,t-2}$ reported in figure 7 are largely consistent with those for contemporaneous temperature $T_{i,t}$. The marginal effects of $T_{i,t-1}$ are predominantly negative across the temperature distribution for all TFP categories, except for the most productive firms located in warmer areas which are positively impacted. The effect of $T_{i,t-1}$ is partially mitigated or reversed in $T_{i,t-2}$, despite the lasting negative (positive) effect on the least (most) productive firms. When considered collectively, the cumulative effects over the periods $t = \{0, 1, -2\}$ highlight persistent negative marginal effect for the most-productive firms located in colder areas and for the least-productive firms across the whole temperature distribution, and positive persistent marginal effects for most-productive firms located in warmer areas.

The persistent negative impacts of higher temperatures on the least-productive firms are not surprising. These firms tend to be more vulnerable to temperature variations because they are more likely to operate in sectors or engage in tasks that are more exposed to such fluctuations. Conversely, the most productive firms generally have better managers who are more likely to undertake adaptation investments or reallocate production factors to respond effectively to weather shocks. While these arguments explain why the most productive firms do not exhibit negative marginal effects, they do not address the presence of positive effects. These positive effects are potentially driven by a temperature-shock-induced reallocation of market shares and production factors from the least productive to the most productive firms. Consistent with the concept of market selection, the least productive firms experience significant negative shocks that likely decrease their competitiveness, leading to such reallocation. In line with the Schumpeterian notion of creative destruction, this effect might be considered economically efficient. However, assessing its macro effects, such as on aggregate productivity, is nontrivial.



(a) lag-1 marginal effect

(b) lag-2 marginal effect

Figure 7: Lag-1 (a) and lag-2 (b) marginal effects of temperature on the growth rate of gross output in the EU across different firm productivity categories. Results from the 2^{nd} order polynomial model with firm and industry-year FE, standard errors clustered at the Nuts 3 level.

Since these results are particularly striking when examining the effects on TFP growth (figure 39b), making a connection to the firm convergence and inequality literature is natural. From a convergence perspective in terms of TFP, higher temperature fosters convergence and reduce firm inequality for firms located in areas with colder yearly average temperature, and at the same time, slows down convergence and exacerbate firm-level inequality for firms located in areas with warmer yearly average temperature. The result related to colder areas could initially suggest a positive, and potentially welfare-enhancing effect, to the extent that lower inequality is usually associated with higher aggregate productivity growth and, consequently, long-run economic growth (De Loecker et al., 2022). Higher firm inequality is associated with higher factors misallocation and, therefore, lower aggregate output (Hsieh and Klenow, 2009).

However, in this case the reduction in firm inequality is not driven by a beneficial "catching-up" effect from lagging firms, but rather by a detrimental "slowing-down" effect determined by leading firms. Consequently, the net effect on aggregate productivity for firms located in colder areas is on average negative, and welfarereducing. Determining whether the marginal effect of temperature at the high end of the temperature distribution is welfare-enhancing or reducing is more complex. Since the effect is positive for more-productive firms and negative for low-productive firms, the assessment of the overall effect on aggregate productivity hinges on the relative shares of these firms within the economy and across the temperature support.

Section 6.9.6 delves into the heterogeneity of climate damages associated with firm-level productivity levels by analysing potential differences across countries. Unlike the other sources of heterogeneity analysed in this paper, the cross-country results focusing on firm-level productivity heterogeneity are consistent both with those estimated for the pooled sample and with each other. In almost all countries, the least-productive firms are negatively impacted by higher temperatures, whereas the impact on the most-productive firms is either positive or not statistically significant. The consistency of results across different samples suggests that differences in productivity levels are a credible source for identifying heterogeneity in firm-level climate damages. In addition to being a reasonable metric to pinpoint heterogeneous marginal effects from an econometric perspective, the identification of a single characteristic able to explain differences in economic responses to temperature offers new opportunities to design tailored climate policies.

4.2.2 Industry Heterogeneity

This section extends the discussion on the heterogeneity of the economic effects of temperature fluctuations, focusing on industry sectors. It is commonly believed that sectors like agriculture, mining, and, to a lesser degree, manufacturing, will be negatively impacted by rising temperatures, while the service industry is considered to be largely shielded from such effects. This is particularly relevant for developed countries, such as those in my sample, where firms, on average, possess more resources to insulate their economic activities against climate shocks. This section presents empirical evidence of industry-specific heterogeneous effects by estimating the within-industry marginal effects of higher temperature. I carry out the estimations interacting the temperature variables with the firm Nace Revision 2 level 1 industry category[26].

In this analysis I rely on a higher number of categories (21), which has implications for statistical power and significance. Thus, in this section I only report the statistically significant (at the 10%) point estimates. Figure 8 illustrates the resulting marginal effects of contemporaneous temperature $T_{i,t}$, where the colours reflect the sign and magnitude of the point estimates. Figures 27 and 28 provide the whole set of coefficients and the relevant p-values, respectively. These estimates are generally positive, with mostly downward-sloping industry-specific marginal effect functions. This suggests that the positive effect of an additional $1°C$ decreases in magnitude as temperature increases over the temperature support.

Nevertheless, a limited number of industries report negative coefficients, such as Construction (F) where the marginal effect is consistently negative although decreasing in magnitude as temperature increases. The marginal effect function is downward sloping for Mining and quarrying (B), Water supply sewerage waste management and remediation activities (E), Transportation and storage (H), Accommodation and food service activities (I), Professional scientific and technical activities (M), Administrative and support service activities (N), Education (P), Human health and social work activities (Q), Arts entertainment and recreation (R), and Other service activities (S). Conversely, the marginal effect function is upward sloping for Construction (F) and Financial and insurance activities (K).

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[26] This procedure necessitates particularly large computational power, as the estimation requires 200 Gb of RAM and runs for 167.5 hours.

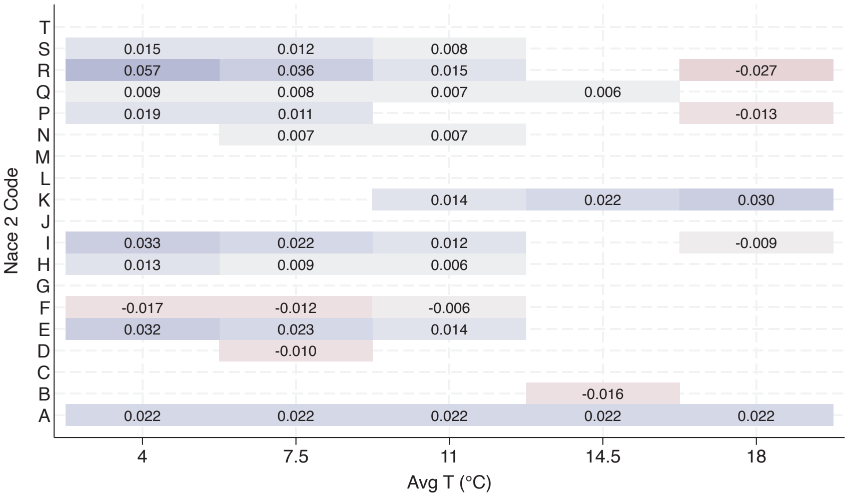


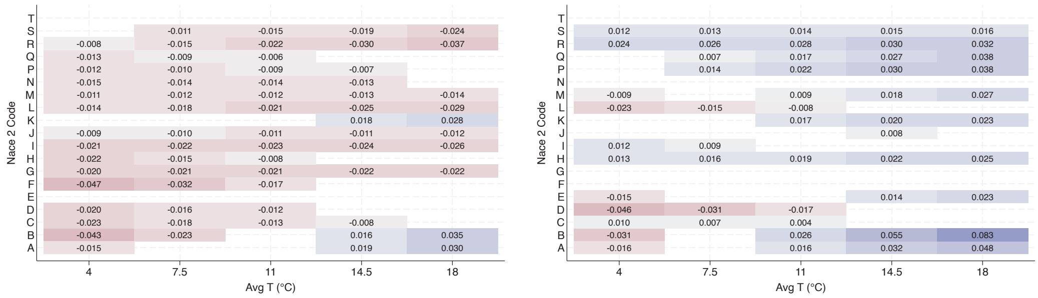
Figure 8: Marginal effect of an extra $1°C$ in contemporaneous yearly average temperature on the growth rate of gross output (log) accounting for industry heterogeneity (Nace 2 level 1). Results from the quadratic model with firm and industry-year FE.

Coherently with the results discussed in previous sections, these estimates highlight a delayed negative effect of higher temperature on firm GO (figure 9). The marginal effect of an extra $1°C$ in temperature is negative and statistically significant for most firms across the temperature distribution, although the number of significant estimates declines in warmer areas. On average, the industry-specific marginal effect functions are upward-sloping, except for Accommodation and food service activities (I), Information and Communication(J), Real estate activities (L), Professional scientific and technical activities (M), Arts entertainment and recreation (R), and Other service activities (S). Interestingly, the most negatively affected industries in colder areas, with negative marginal effects below -2% in magnitude are Mining and quarrying (B), Manufacturing (C), Electricity (D), Construction (F), Wholesale and retail trade of of motor vehicles (G), Transportation and storage (H), and Accommodation and food service activities (I).

This is an unexpected result because the majority of these industries rely on outdoor activities, which are expected to benefit from higher temperatures when located in colder areas. On the contrary, the most negatively affected industries in warmer areas, with negative marginal effects above 2% in magnitude are Wholesale and retail trade of motor vehicles (G), Accommodation and food service activities (I), Real estate activities (L), Arts entertainment and recreation (R), and Other service activities (S). The majority of these highly negatively-affected industries are related to tourism. The tourism sector can be particularly negatively impacted by higher temperatures because it is predominantly an outdoor-focused economic activity. Hence, adaptation possibilities are limited, and individuals would react to increases in temperatures by preferring cooler areas. On the contrary, Agriculture forestry and fishing (A), Mining and quarrying (B), and Financial and insurance activities (K) are characterised by positive marginal effects of approximately 3%.

This may not be surprising for the financial and insurance sector as it is primarily indoor-based and expected to be less affected by higher temperatures. Moreover, these firms are likely to engage in activities with clients not necessarily locally-based and therefore, partially not affected by local shocks. However, this result is unexpected for the outdoor agricultural and mining sectors. Given the nature of these sectors and the limited adaptation options, these sectors are expected to be negatively impacted by higher temperatures. However, since they are located in warmer areas, these firms are likely to have already undertaken adaptation strategies. Moreover, these positive marginal effects may be attributed to an increase in productivity due to milder winter temperatures, which might compensate for the potential reduction in productivity caused by warmer summer temperatures. This assumption is particularly relevant for agriculture, since a higher yearly average temperature can potentially increase production, provided that the number of growing degree days increases and the negative effects caused by torrid summer temperatures can be, at least to a certain extent, mitigated by increased irrigation. This result is supported by satellite observations showing vegetation greening in Europe (IPCC, 2019)[27].In this context, the agriculture-related results are specific to Europe and would not align with global estimates, since irrigation capabilities vary significantly between these regions.

The marginal effects of $T_{i,t-2}$ align with the sign-reversal hypothesis for firms located in the warmer part of the temperature distribution. Conversely, in colder areas the effect is negative and statistically significant solely for firms in the Agriculture (A), Mining (B), Electricity (D), Water supply (E), Real estate (L), and Professional scientific and technical activities (M) sectors, providing support for the presence of persistent negative effects in these areas. It is worth highlighting that in addition to these supply-side impacts, temperature shocks can affect firms' performance also through a reduction in demand. For example, if customers reduce outdoor shopping during particularly hot weather.



(a) lag-1 marginal effect

(b) lag-2 marginal effect

Figure 9: Lag-1 (a) and lag-2 (b) marginal effects of temperature on the growth rate of gross output in the EU across different firm industry categories. Results from the 2^{nd} order polynomial model with firm and industry-year FE, standard errors clustered at the Nuts 3 level.

The results discussed in this section disentangle different, and potentially opposing, heterogeneous effects of temperature which are averaged out in the marginal effects estimated in the pooled analysis previously discussed. Section 6.9.3 delves into unravelling potential underlying cross-country heterogeneity in industry-specific marginal effects. However, it is important to notice that many estimates reported in this section are not statistically different from zero. Such a lack of effect is likely driven by substantial within-industry variability in the relationship between temperature and economic performance. This variability may arise from either a genuine absence of a significant effect or the limitation that the industry-specific focus is not optimal to identify the relevant heterogeneity in the damage functions. Thus, there is a need to further investigate within-country and industry dynamics for a more comprehensive understanding.

4.2.3 Size Heterogeneity

This section extends the discussion on the heterogeneity of the economic effects of temperature fluctuations to firm characteristics, and firm size specifically, where size is defined with respect to the number of employees in

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[27] Causes of greening include combinations of an extended growing season, nitrogen deposition, Carbon Dioxide (CO2) fertilisation, and land management.

accordance with the European Commission classification. Figure 10 shows the marginal effect of an extra $1°C$ in contemporaneous temperature on the growth rate of gross output for each of the size categories, at different levels of the temperature support in the pooled sample. The results for this specification are generally consistent with the aggregate marginal effect reported in figure 4, although in this case the estimates for firms located in warmer areas are statistically significant at the 5% level, with the exception of smaller firms. Firms seem to be similarly impacted by increasing temperature across the different categories. Specifically, the marginal effect of an extra $1°C$ exhibits an upward-sloping and generally positive function across all size categories. Within each category, the effect is lower for firms located in colder areas and higher for firms located in warmer areas. However, the point estimates are economically small and characterised by relatively large confidence intervals.

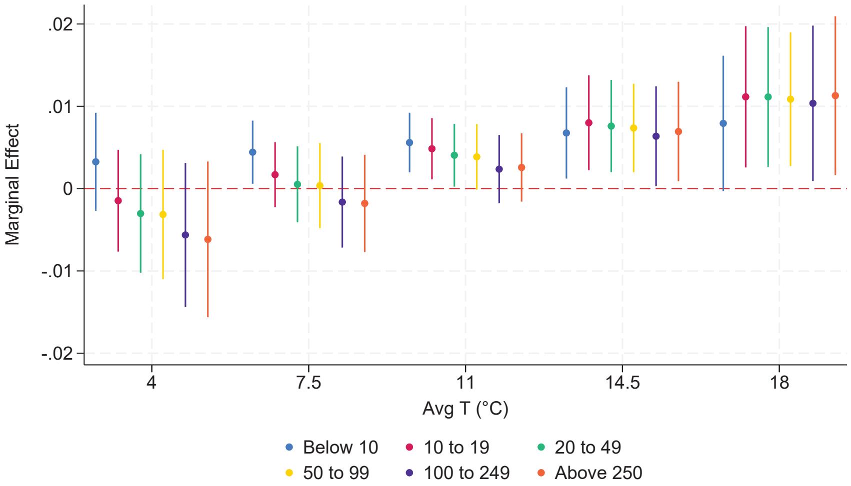
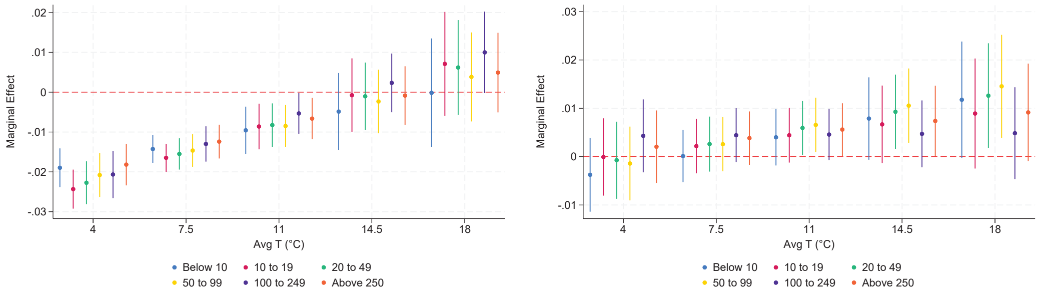


Figure 10: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output (log) across different firm size categories. Results from the quadratic model with firm and industry-year FE.

The results for the marginal effects of lagged temperature align with the average marginal effect reported in figure 5. The marginal effect function for $T_{i,t-1}$ shown in figure 11a is upward sloping and characterized by negative point estimates for firms situated in cooler regions and positive, albeit non-significant, point estimates for firms located in warmer regions. Notably, firms in the warmest areas tend to have larger confidence intervals that span both positive and negative values, indicating that even within a specific size category, there are considerable differences in impacts among firms. The case of the smallest size category (below 10 employees) is particularly striking, with a point estimate close to zero but a confidence interval ranging from approximately -0.013% to 0.012%. The marginal effect function for $T_{i,t-2}$, presented in figure 11b, is mostly flat and not statistically different from zero. Thus, in line with the cumulative average effects previously discussed, these findings suggest the existence of persistent negative effects for firms in cooler areas and positive, yet non-significant, effects for firms in warmer areas.



(a) lag-1 marginal effect

(b) lag-2 marginal effect

Figure 11: Lag-1 (a) and lag-2 (b) marginal effects of temperature on the growth rate of gross output in the EU across different firm size categories. Results from the 2^{nd} order polynomial model with firm and industry-year FE, standard errors clustered at the Nuts 3 level.

The size-specific estimates based on the pooled sample of European firms are noticeably similar to each other, suggesting a potentially consistent impact of weather fluctuations across different firm types. Thus, the firm size category does not appear to disentangle the heterogeneous and potentially opposite effects that higher temperatures may have on firm performance. However, as emphasized in previous sections, the estimates based on the pooled sample are likely influenced by other dynamics that tend to vary across countries, thereby attenuating, or potentially counteracting, the real effect of higher temperatures. This highlights the importance of conducting a more detailed cross-country analysis to isolate potential heterogeneity driven by country-specific factors. Section 6.9.4 reports country-specific estimates analysing potential size heterogeneity in climate damages.

The results discussed in these sections are relevant for two reasons, i) they show that, coherently with other strands of literature, focusing only on the average treatment effect could be misleading, as it likely overlooks important heterogeneous underlying dynamics; ii) they have policy implications which could be accounted for to design mitigation and adaptation policies. For instance, climate policies aimed at reducing the economic damages of climate shocks could be designed to target more vulnerable firms and require larger efforts in reducing emissions from better prepared or less affected ones.

5 Conclusions

This paper has presented and discussed estimates of economic damages induced by weather fluctuations based on a novel sample of European firms, which allows disentangling the heterogeneity of damages that is otherwise overlooked in aggregate-level analysis. This study delves into the Burke et al. (2015) specification, discussing its identification strategy and addressing, in the firm-level context, the potential drawbacks highlighted in the recent literature, such as nonstationarity. Furthermore, post-estimation model selection criteria allowed us to identify the optimal functional form in terms of both polynomial order and the number of temperature lags. The preferred model is a 2^{nd} order polynomial in temperature and precipitation with two lags, ensuring flexibility while avoiding overfitting. Additionally, the analysis explores the heterogeneity of climate impacts across countries and various firm characteristics, such as average productivity, industry, and size. This is the main contribution of this paper.

Contrary to prevailing literature (Burke et al., 2015; Chen and Yang, 2019; Acevedo et al., 2020), the empirical findings of this paper reveal a moderate U-shaped relationship between temperature and economic outcomes for the pooled European sample. Firms in colder areas exhibit negative marginal effects, challenging the results from previous aggregate studies that Europe, as a whole, is insulated from the negative impacts of rising temperature. As previously stressed, these results are generally coherent with other research focusing on Europe (Groom et al., 2023). The relationship unfolds divergently across countries, manifesting as either a U-shaped or an inverted-U-shaped relationship. Notably, the UK stands out as the only country where the marginal effect of an additional degree consistently manifests as negative across the entire temperature spectrum.

The analysis focusing on the heterogeneity across firm productivity levels highlights differential negative impacts on the least productive firms, offering consistent findings across several countries. This result not only yields empirical insights pertinent to the formulation of targeted adaptation strategies, but also bridges the gap between climate economics and the broader literature on aggregate productivity and firm dynamics. This study explores industry-specific effects, identifying certain sectors as particularly vulnerable to weather shocks, while other seem to benefit from higher temperature. Conversely, firm size seems not to be a characteristic influencing firm-level response to temperature fluctuations.

Nonetheless, this analysis faces certain limitations. While the internal validity of the results is adequate, as weather shocks — identified via temperature fluctuations after accounting for fixed effects — are plausibly exogenous, the external validity remains limited. European firms may not be representative of global firms, as they differ in resources and institutional frameworks for implementing adaptation policies. Considering the inertia in climate mitigation, climate adaptation becomes paramount for upholding adequate living standards. In this regard, the estimates presented in this paper pertain to the short- and medium-term economic damages arising from variations in temperature. As the impacts of rising temperatures become more pronounced, firms are likely to invest more substantially in adaptation, thereby attenuating their exposure to the effects of climate change. Moreover, while this paper studies the effect of average temperature, it does not account for temperature variability, a crucial factor for climate econometric analysis (Kotz et al., 2021; Linsenmeier, 2023).

The policy implications of this study may be profound. This work challenges prior research suggesting a lack of impact of higher temperature in Europe, thereby questioning the prevailing idea that the European green transition is purely motivated by between-continent equity reasons. Additionally, acknowledging the heterogeneity in climate impacts across firms emphasises the need for tailored climate policies. Taxation strategies, differentially applied to firms benefiting from or unaffected by higher temperature, could serve as a mean of redistributing funds to mitigate adverse effects on vulnerable firms. Furthermore, the paper highlights the importance of productivity-boosting policies. As higher productivity is associated with a reduction in the negative impacts of weather shocks, such policies have a dual benefit. Policymakers are urged to consider these findings when formulating strategies for a smooth and equitable transition, ensuring that climate policies align with the diverse vulnerabilities of firms in the European economic landscape.

6 Appendix

6.1 Summary Statistics

	Min	Median	Max	Mean	SD	N
Number of employees	1	4	599305	26.794	526.592	37,897,527
Real GO (log)	-2.488	12.847	24.654	12.858	2.151	66,624,037
Real VA (log)	-0.053	12.195	25.442	12.288	1.700	45,214,411
Number of employees (log)	0.000	1.386	13.304	1.650	1.383	37,897,527
Fixed assets (log)	-1.579	11.563	23.300	11.612	2.336	54,045,361
TFP	-12.170	10.010	48.412	9.923	1.025	29,580,376
Yearly Average T (°C)	-4.337	12.587	20.419	12.431	3.291	65,728,710
Yearly Total P (metres)	0.000	0.759	4.050	0.787	0.397	65,728,710

Table 2: Summary Statistics for different relevant variables. Source: Orbis and ECMRWF.

ISO	2000	2005	2010	2015	2020
AT	493	6,190	9,267	25,246	9,408
BE	72,783	23,138	40,275	35,342	25,896
DE	7,371	69,824	93,314	108,024	32,848
DK	17,583	31,672	26,845	22,393	16,120
ES	347,766	602,730	665,817	689,046	557,835
FI	49,816	76,884	129,014	139,635	107,334
FR	523,286	714,280	978,924	618,686	249,066
GB	235,576	279,813	213,585	167,831	111,439
GR	12,244	19,597	19,907	20,777	9,452
IT	119,876	504,692	791,868	827,547	715,271
NL	3,760	10,991	12,435	9,756	2,020
PT	27,157	223,522	257,219	273,756	284,717
SE	130,363	173,802	222,603	325,375	362,173

Table 3: Total number of observations by Country (ISO geographical areas). The full table can be found in section 6.1. Source: Orbis.

year	N	N Gross Output (log)	N Value Added (log)	N TFP (log)
1995	656,621	591,665	542,279	279,366
1996	883,005	823,365	722,371	366,875
1997	1,045,997	985,232	843,321	443,899
1998	1,296,358	1,232,357	994,963	559,348
1999	1,485,683	1,412,575	1,103,118	629,826
2000	1,646,362	1,548,074	1,249,236	727,215
2001	1,835,993	1,727,571	1,390,185	828,491
2002	2,081,454	1,937,880	1,519,259	888,050
2003	2,219,480	2,069,497	1,605,060	941,844
2004	2,576,967	2,415,462	1,948,151	1,042,245
2005	2,911,944	2,737,135	2,195,722	1,097,520
2006	3,091,646	2,905,526	2,314,636	1,378,497
2007	3,308,823	3,135,639	2,392,973	1,404,696
2008	3,464,151	3,280,756	2,495,579	1,505,656
2009	3,588,731	3,409,268	2,554,797	1,477,139
2010	3,643,531	3,461,073	2,581,186	1,407,666
2011	3,735,318	3,551,701	2,604,474	1,584,527
2012	3,788,124	3,604,949	2,608,281	1,522,490
2013	3,786,527	3,597,167	2,561,094	1,524,940
2014	3,702,227	3,511,815	2,355,801	1,543,117
2015	3,454,506	3,263,414	2,292,146	1,495,081
2016	3,368,576	3,224,585	2,118,766	1,451,505
2017	3,389,864	3,241,926	2,121,372	1,460,616
2018	3,425,572	3,274,297	2,121,650	1,457,707
2019	3,350,003	3,197,529	2,073,633	1,432,013
2020	2,609,375	2,483,579	1,627,159	1,130,047
Total	70,346,838	66,624,037	48,937,212	29,580,376

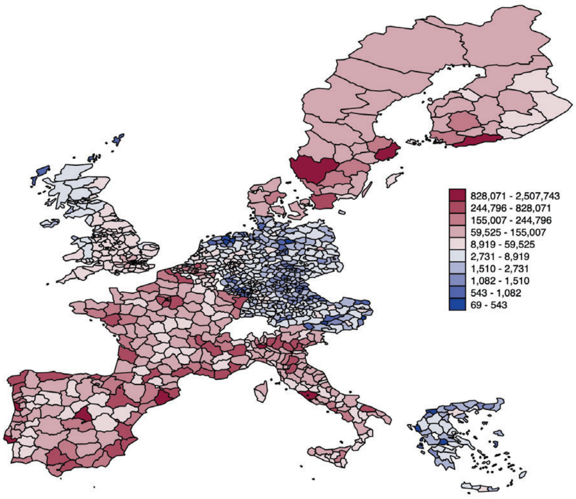
Table 4: Total number of observations across all the European countries available in the sample after the cleaning procedure. Columns 2 to 4 refer to observations with available GO, VA or TFP expressed in logs. Whereas column 1 is the their union (observations with at least one of these variables available). Source: Orbis

NACE2 1-digit	2000	2010	2020
A-Agriculture forestry and fishing	25,129	58,787	54,194
B-Mining and quarrying	4,923	7,174	4,560
C-Manufacturing	233,167	383,233	265,411
D-Electricity gas steam and air conditioning supply	4,129	21,133	23,767
E-Water supply sewerage waste management	5,905	14,921	11,703
F-Construction	201,733	498,560	300,410
G-Wholesale and retail trade repair of motor vehicles	385,209	744,214	485,038
H-Transportation and storage	58,885	124,987	97,082
I-Accommodation and food service activities	75,343	208,508	148,328
J-Information and communication	75,570	146,280	119,609
K-Financial and insurance activities	44,500	104,811	85,355
L-Real estate activities	120,510	335,598	252,419
M-Professional scientific and technical activities	138,312	365,279	295,435
N-Administrative and support service activities	72,921	161,534	115,258
O-Public administration and defence	395	915	632
P-Education	12,856	45,652	39,987
Q-Human health and social work activities	20,826	89,015	85,058
R-Arts entertainment and recreation	20,474	54,947	48,940
S-Other service activities	34,817	79,179	47,122
T-Activities of households as employers	12,418	16,145	3,161
U-Activities of extraterritorial organisations and bodies	52	201	110

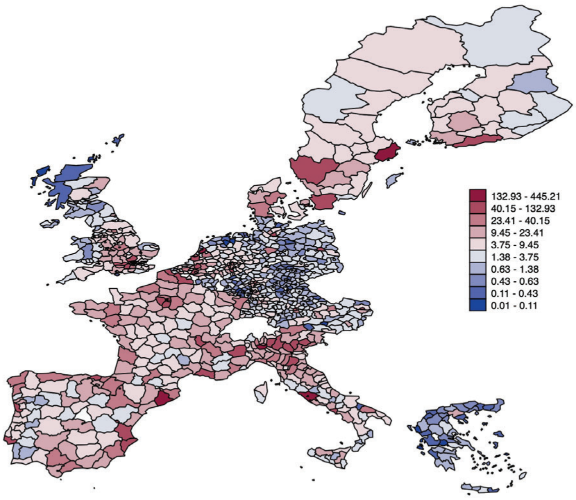
Table 5: Total number of observations by industry, defined by the NACE 2 level 1 sectors. Source: Orbis.

Size	2000	2005	2010	2015	2020
Below 10	527,852	888,874	1,293,442	1,477,137	1,231,760
10 to 19	131,003	166,521	201,246	236,791	198,870
20 to 49	105,164	126,856	135,134	158,540	134,658
50 to 99	35,286	44,491	52,030	58,905	48,642
100 to 249	22,826	30,383	35,841	42,126	33,831
Above 250	13,535	18,950	22,569	26,951	21,316

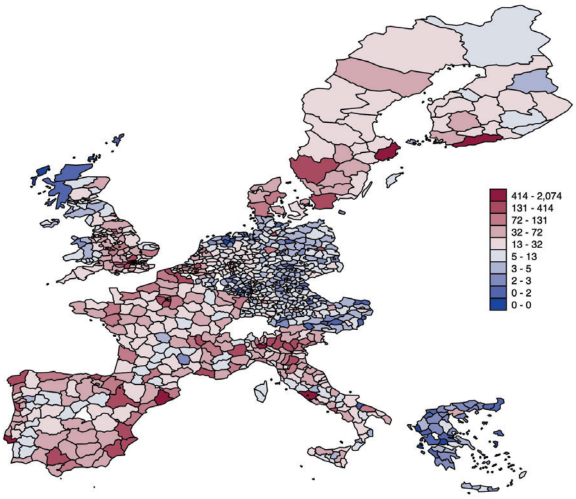
Table 6: Total number of observations by firm size (European Commission classification). For presentational purpose, I report a subset of the available years. Source: Orbis.



(a) Number of firms

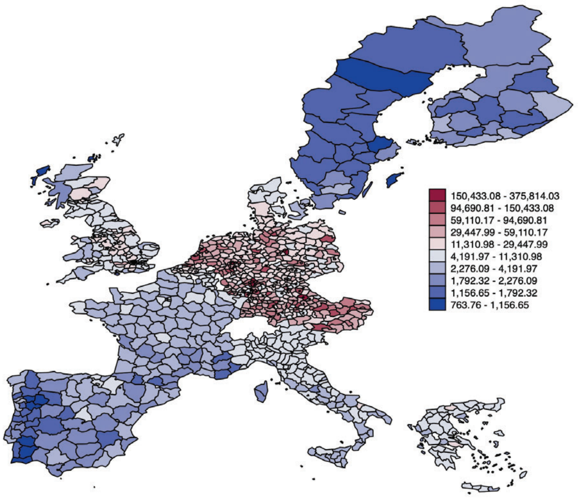


(b) Total gross output (billions of LCU)

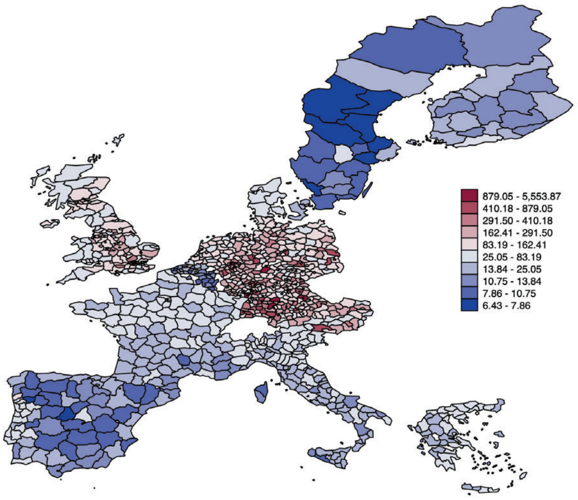


(c) Total number of employees (thousands)

Figure 12: Descriptive statistics by Nuts 3 areas. Source: Orbis.

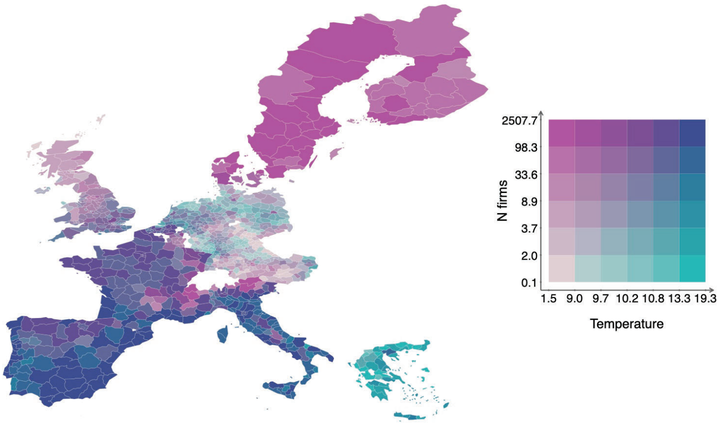


(a) Average gross output (thousands of LCU)

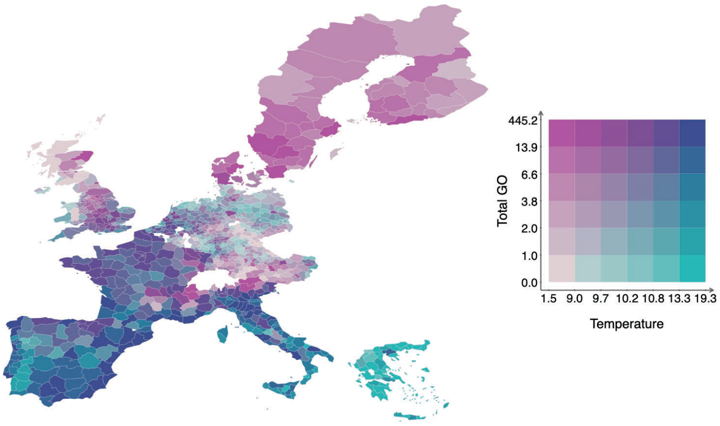


(b) Average number of employees

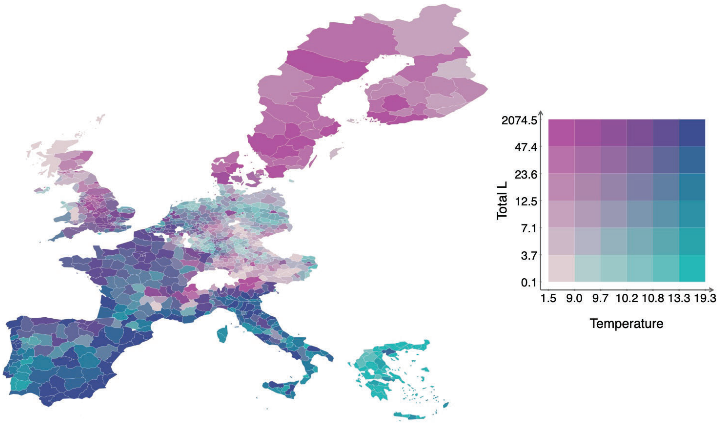
Figure 13: Descriptive statistics by Nuts 3 areas. Source: Orbis.



(a) Number of firms (thousands of units

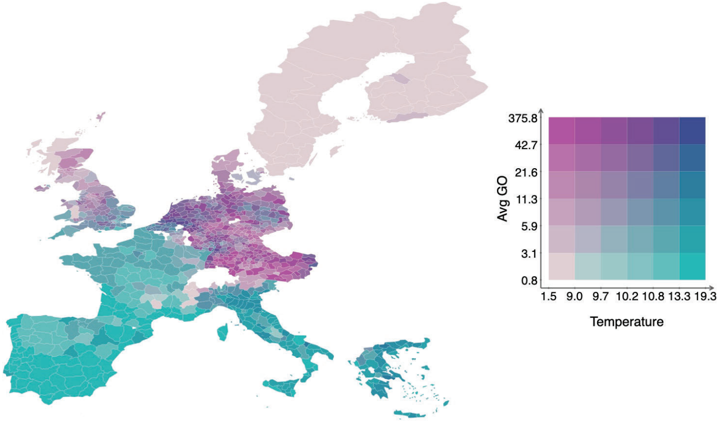


(b) Total gross output (billions of LCU)

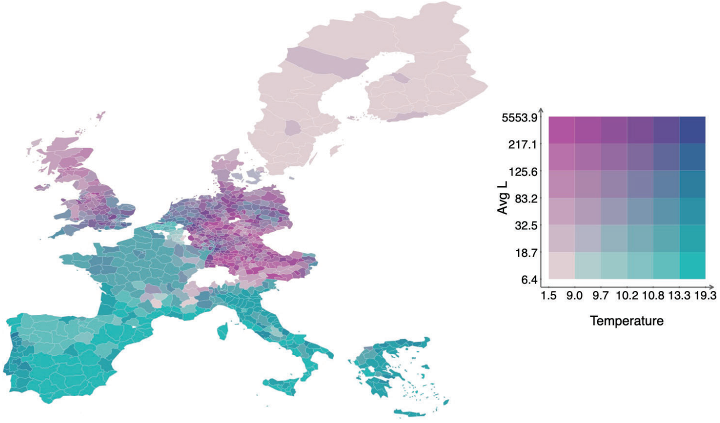


(c) Total number of employees (thousands)

Figure 14: Descriptive statistics by Nuts 3 areas. Bivariate map of yearly average temperature on the X-axis and main variable on the Y-axis. Source: Orbis and ECMWF.

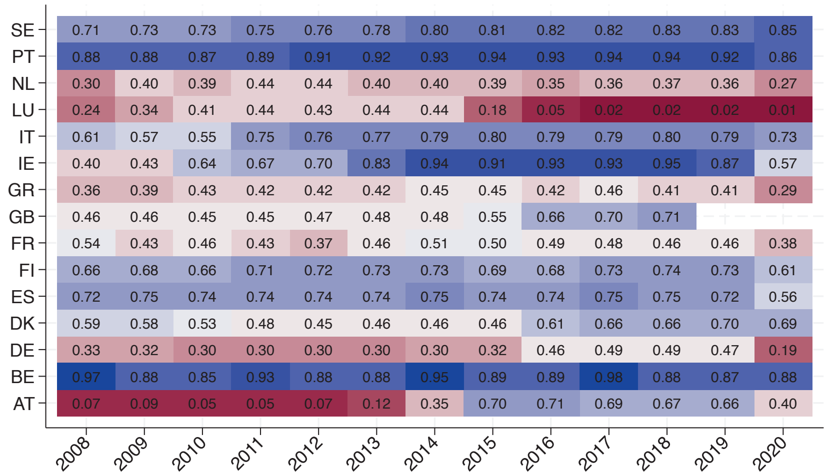


(a) Average gross output (millions of LCU)



(b) Average number of employees

Figure 15: Descriptive statistics by Nuts 3 areas. Bivariate map of yearly average temperature on the X-axis and main variable on the Y-axis. Source: Orbis and ECMWF.



	2008	2009	2010	2011	2012	2013	2014	2015	2016	2017	2018	2019	2020
SE	0.71	0.73	0.73	0.75	0.76	0.78	0.80	0.81	0.82	0.82	0.83	0.83	0.85
PT	0.88	0.88	0.87	0.89	0.91	0.92	0.93	0.94	0.93	0.94	0.94	0.92	0.86
NL	0.30	0.40	0.39	0.44	0.44	0.40	0.40	0.39	0.35	0.36	0.37	0.36	0.27
LU	0.24	0.34	0.41	0.44	0.43	0.44	0.44	0.18	0.05	0.02	0.02	0.02	0.01
IT	0.61	0.57	0.55	0.75	0.76	0.77	0.79	0.80	0.79	0.79	0.80	0.79	0.73
IE	0.40	0.43	0.64	0.67	0.70	0.83	0.94	0.91	0.93	0.93	0.95	0.87	0.57
GR	0.36	0.39	0.43	0.42	0.42	0.42	0.45	0.45	0.42	0.46	0.41	0.41	0.29
GB	0.46	0.46	0.45	0.45	0.47	0.48	0.48	0.55	0.66	0.70	0.71		
FR	0.54	0.43	0.46	0.43	0.37	0.46	0.51	0.50	0.49	0.48	0.46	0.46	0.38
FI	0.66	0.68	0.66	0.71	0.72	0.73	0.73	0.69	0.68	0.73	0.74	0.73	0.61
ES	0.72	0.75	0.74	0.74	0.74	0.74	0.75	0.74	0.74	0.75	0.75	0.72	0.56
DK	0.59	0.58	0.53	0.48	0.45	0.46	0.46	0.46	0.61	0.66	0.66	0.70	0.69
DE	0.33	0.32	0.30	0.30	0.30	0.30	0.30	0.32	0.46	0.49	0.49	0.47	0.19
BE	0.97	0.88	0.85	0.93	0.88	0.88	0.95	0.89	0.89	0.98	0.88	0.87	0.88
AT	0.07	0.09	0.05	0.05	0.07	0.12	0.35	0.70	0.71	0.69	0.67	0.66	0.40

Figure 16: Coverage of the aggregate economy from Orbis data in terms of number of employees. The values report for each country-year the ratio between the sum of the number of employees for the firms available in my sample and the economy-wide number of employees. By construction, values range between 0 (red) and 1 (blue). Source: EUROSTAT.

	Min	P1	P25	Median	P75	P99	Max	Mean	SD
Within Dev	0.000	0.000	0.148	0.318	0.552	1.575	3.171	0.398	0.341
Between Dev	-16.677	-8.541	-1.885	-0.005	2.493	6.050	8.078	0.000	3.252

Table 7: Distribution of firm-year temperature deviations from the mean of the fixed-effect group (within) and from the mean of the sample as a whole (between). Source: ECMRWF ERA5-Land.

6.2 Coordinates Imputation

In addition to coordinates, Nuts, city, zipcode and street are also available, which I use to impute the coordinate for the countries with available coordinates. The zipcode should not be used since the same zipcode sometimes refers to different cities.
Clean and homogenise firm' coordinate:

1. transform coordinates in degrees from the coordinates in degrees, minutes, seconds (consistent with the weather data coordinates);
2. homogenise streets addresses by removing numbers;
3. drop all firm with missing city and coordinates as we cannot impute them.

Remove implausible coordinates using a shapefile at the Nuts 3 granularity:

1. using the shapefile at the Nuts 3 level from EUROSTAT, I create min and max latitude and longitude for each Nuts 3 area;
2. merge the Orbis file with the shape file to obtain min and max coordinate for each Nuts 3 province;
3. for each firm, replace coordinate as missing if the coordinates lie outside of the min and $\max$ coordinates.

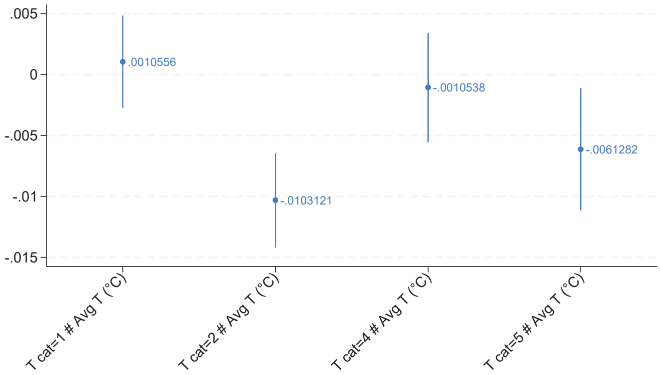
Generate average coordinate by city and replace firm's coordinates with city averages if the former is farther than 0.25 degrees from the latter. This procedure is quite conservative since it would drop only observation outside of a radius of approximately $25\ \mathrm{km}$ from the average coordinate in the city. Note that the average coordinate does not refer to the geographical centre of the city, but this step is intended to remove largely implausible values. At this stage, I impute firm' coordinates based on the coordinates of firm located in the same street in the same city. Given the resolution of the weather data $(0.1°)$, the imputation based on a city-street level seems to be relatively reasonable:

1. Impute firm coordinates using the mode of the city-street coordinate;
    - If multiple modes are present, I create min, max and average mode;
    - If the difference $\mid$ minmode $-$ maxmode $\mid< 0.25$, substitute the mode with the average mode, otherwise. If the difference $\mid$ minmode $-$ maxmode $\mid> 0.25$ firm in the city-street cluster are not imputed;
2. Substitute the coordinate with the mode if the coordinate is missing.

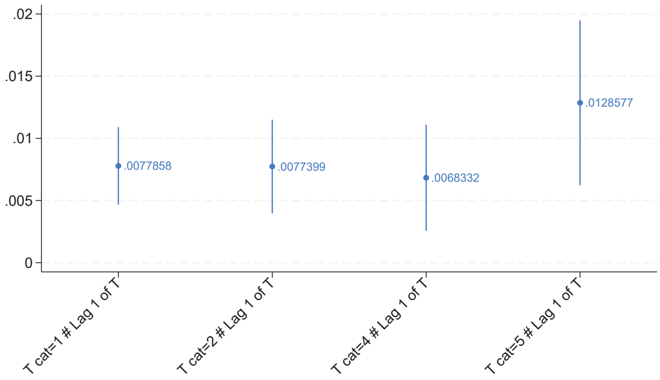
Finally, I run again the Nuts 3 level cleaning based on the shapefile to drop potential mismatch.

6.3 Model Selection

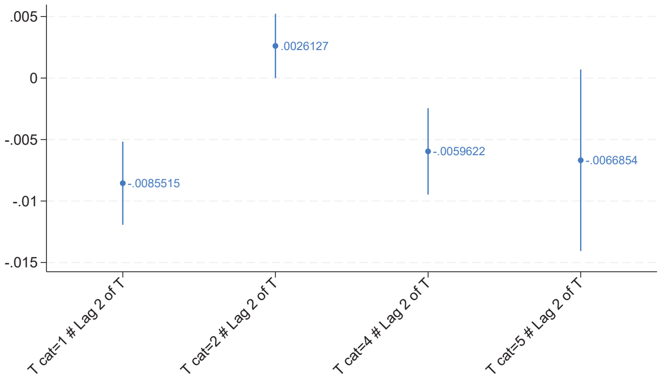
6.4 Flexible quintile-based estimation



(a) Contemporaneous effect

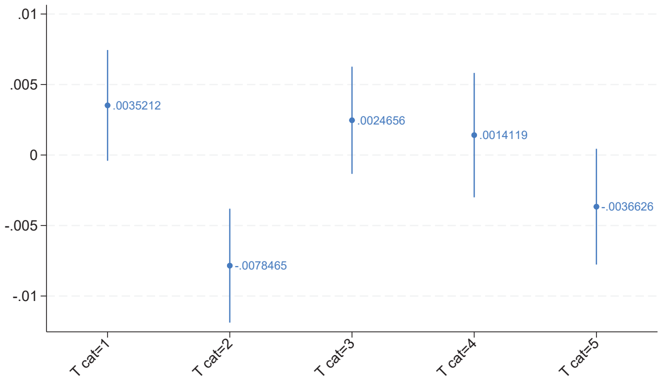


(b) 1-lag effect

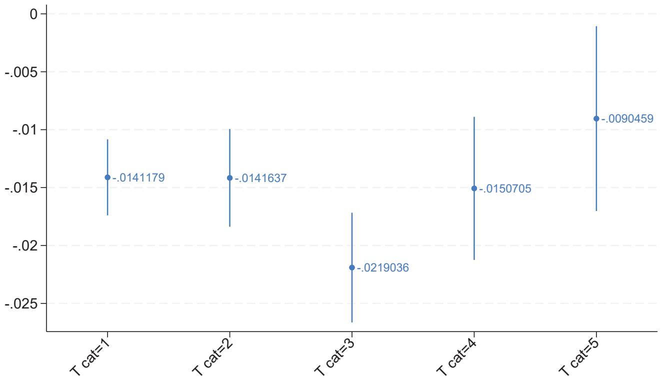


(c) 2-lag effect

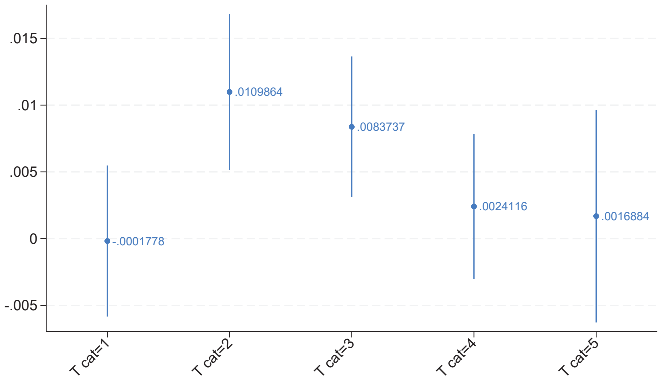
Figure 17: Contemporaneous (a), 1-lag (b), and 2-lags (c) additional marginal effects of an extra $1°C$ in yearly average temperature on the growth rate of gross output for firms located in decile i with respect to firms located in the 3^{rd} decile. Results from the flexible model obtained interacting yearly average temperature and a categorical variable identifying firm-level temperature decile, with firm and industry-year FE.



(a) Contemporaneous effect



(b) 1-lag effect



(c) 2-lag effect

Figure 18: Contemporaneous (a), 1-lag (b), and 2-lags (c) marginal effect of an extra $1^{\circ}C$ in yearly average temperature on the growth rate of gross output for firms located in decile i. Results from the flexible model obtained interacting yearly average temperature and a categorical variable identifying firm-level temperature decile, with firm and industry-year FE.

6.4.1 In-sample Information Criteria

Athey and Imbens (2019) point out that "In most discussions of linear regression in econometric textbook, there is little emphasis on model validation". In econometric model identifications, there may sometimes be a tendency to overfit the model, assuming that this would better explain the variation in the underlying data. However, the researcher has to trade off the improved fit to the current data with the increase in the variance of the forecast error (Greene, 2003). That is, the ability of the model to fit the in-sample data and produce a good out-of-sample fit. Although this issue is not of primary importance when estimating the effects of temperature on historical data to identify past damages, identifying the right model becomes of crucial importance when relying on the coefficients from such reduced-form models to produce climate damage projections. Additionally, relying on more parsimonious models is beneficial for its interpretation.

A preliminary guidance in this regard comes from the adjusted R^2, which differently from the R^2, penalises the model for the loss of degrees of freedom resulting from the inclusion of the new variables. However, it is not conclusive whether this penalty is sufficiently large to identify the correct model as the sample size increases (Greene, 2003). To potentially rule out this issue, Information Criteria (IC) have been introduced. These are log-likelihood criteria incorporating degrees of freedom adjustments, essentially balancing model fit measured by the maximised log-likelihood value and model parsimony incorporated into the degrees of freedom adjustments. The most notable and used IC are the Akaike Information Criterion (Akaike, 1973) and the Bayesian Information Criterion (Schwarz, 1978). Both measures reward an increase in the R^2 but, everything else constant, penalise more complex models (James et al., 2013). Hence, they favour models that achieve a certain fit with a lower number of variables.

Neither criterion has obvious advantages over the other. However, the Bayesian Information Criterion includes a larger penalty for the loss in degrees of freedom. Hence, would favour a more simple model[28]. This characteristic of the BIC makes it consistent. That is, as the sample size gets large, the model selection criterion would select the "true" model (or more likely its best approximation) with a probability approaching one. Consistency is achieved through penalising the loss of degrees of freedom. However, although it penalises such a loss, the AIC is not consistent even when the sample size gets large as the AIC tends to select "overparametrized" models. On the contrary, the BIC penalises the loss of degrees of freedom more heavily, and it is consistent. Nevertheless, this is not a conclusive argument. In fact, the AIC is asymptotically efficient whereas the BIC is not.

Moreover, a model selection method is consistent if it asymptotically selects the correct model from a set of possible models. On the other hand, a model selection method is conservative if it asymptotically always selects a model that nests the correct model. The minimum-BIC-based model selection procedure is a consistent model selection procedure, whereas a minimum-AIC-based model selection procedure is a conservative model selection procedure (Leeb and Pötscher, 2005). In practical work, both criteria are reported and usually identify the same model. When this is not the case, Diebold (1998) recommends using the more parsimonious model selected by the BIC.

However, in the climate econometrics discussion Newell et al. (2021) highlight that in-sample fit information criteria tend to select over-fitted models, especially when higher-order polynomials are included (Chatfield, 1996). Therefore, similar with Newell et al. (2021), I discuss and rely on model Cross-Validation (CV) as well to assess the accuracy of different models in fitting out-of-sample data.

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[28] For an extensive discussion on information criteria see Greene (2003), Cameron and Trivedi (2005)

6.4.2 Machine Learning out-of-sample Cross-Validation

Cross-Validation (CV) techniques estimate different models on a sub-sample of the data, defined as the training set. Their accuracy is then assessed by fitting the same model out-of-sample. That is, in a different subset of the data excluded from the training set, defined as the test set. This procedure has advantages compared to in-sample validation methods. It provides a direct estimate of the test error, and at the same time makes fewer assumptions about the true underlying model (James et al., 2013). Information Criterion methods were preferred in the past due to the high computational power needed by CV methods. However, nowadays CV have become more widely accessible and therefore more attractive in econometric and statistical analysis. In my specific case, although the number of predictors and/or models is relatively limited compared to other Machine Learning tasks, the relatively large sample size requires a sufficiently performative machine and long computational time. Specifically, I used a cloud-based high-performance computer set with 10 cores of CPU and 100 GB of RAM, which ran for 3 days, 3 hours and 38 minutes.

One of the main methods used for CV is the K-fold CV method, introduced by Geisser (1975). The original sample is randomly split into K equally-sized sub-samples (usually 5 or 10) and the model is assessed through K iterations. In each iteration $i = 1, \dots, K$, the i^{th} sub-sample is used as the test set, whereas the complementary $(K - i)$ sub-samples are used as the training set. There is no replacement in the sub-samples, therefore each observation is used (K-1) times in the training sets and only 1 time in the test set. Every model is estimated on each of the K sets and each iteration provides a measure of predictive ability (i.e. the predictor quality), usually the Mean Squared Error (MSE). The lower the MSE, the more precisely the model fits the out-of-sample data. Therefore, the model with the lowest MSE should be chosen. For each model, the resulting CV measure is the average of the K MSE:

$$\mathrm{CV}_K = \frac{1}{K}\sum_{j=1}^{K}\mathrm{MSE}_{(j)}\,, \tag{14}$$

with

$$\mathrm{MSE}_{(j)} = \frac{1}{N - k_j}\sum_{i=1}^{N-k_j}\left(y_i - \widehat{y}_i\right)^2. \tag{15}$$

Where $MSE_{(j)}$ is the MSE for fold j, based on estimates excluding observations belonging to fold j. Once the researcher identifies the preferred model through CV, the model is estimated on the full sample.

The K-fold CV method is applied by Newell et al. (2021), among forecats and backcats, in their CV exercise. They find that model performance assessed through this method is largely invariant to how temperature is modelled or whether it is excluded, with a RMSE varying by less than 1% across temperature functions. Noticeably, the RMSE is insensitive to whether temperature lags are included or not and to the inclusion of GDP growth or level effects. Moreover, the RMSE in their work is minimised for models including region-year fixed effects and excluding parametric trends. However, they point out that "K-fold ignores the time-series nature of the data and yields an optimistic estimate of the model fit if data are serially correlated. This is a relevant concern considering that both economic measures and temperature are likely to be serially correlated.

6.4.3 Model selection criteria results

	Information Criteria		Cross Validation	
	Akaike IC	Bayesian IC	CV Mean	CV SD
poly 1 lag 0	96666180.21	96666243.25	0.69367565	0.00063269
poly 1 lag 1	96665325.27	96665404.08	0.69355397	0.00063970
poly 1 lag 2	72071995.82	72072089.32	0.61998115	0.00055934
poly 1 lag 3	58401353.32	58401461.25	0.59890321	0.00042714
poly 1 lag 4	48108591.74	48108713.79	0.58396111	0.00040914
poly 1 lag 5	39916264.3	39916400.17	0.57248304	0.00069127
poly 2 lag 0	96666182.1	96666260.91	0.69368113	0.00063410
poly 2 lag 1	96665289.37	96665399.69	0.69354666	0.00063865
poly 2 lag 2	72071573.81	72071714.06	0.61981421	0.00055961
poly 2 lag 3	58400848.6	58401018.2	0.59834296	0.00042389
poly 2 lag 4	48107893.89	48108092.22	0.58379824	0.00042059
poly 2 lag 5	39914923.51	39915149.96	0.57270432	0.00070848
poly 3 lag 0	96666017.79	96666112.35	0.69371646	0.00063443
poly 3 lag 1	96665119.37	96665261.22	0.69353645	0.00063848
poly 3 lag 2	72070959.72	72071146.73	0.61976578	0.00055941
poly 3 lag 3	58399903.34	58400134.61	0.59842587	0.00042197
poly 3 lag 4	48106216.74	48106491.35	0.58416069	0.00041515
poly 3 lag 5	39913349.05	39913666.09	0.5729878	0.00070571
poly 4 lag 0	96665752.1	96665862.42	0.69370251	0.00063410
poly 4 lag 1	96664723.52	96664896.88	0.69354793	0.00063781
poly 4 lag 2	72070448.54	72070682.3	0.61970471	0.00055881
poly 4 lag 3	58399434.33	58399727.28	0.59849412	0.00041998
poly 4 lag 4	48105759.53	48106110.43	0.58422745	0.00041491
poly 4 lag 5	39912912.54	39913320.15	0.57305402	0.00071425

Table 8: Results from the Model Selection Criteria analysis. The first two columns refer to the Akaike and Bayesian in-sample IC, the remaining two refer to out-of-sample CV, where the 10-fold MSE mean and standard deviation are reported for each model.

6.5 Non-stationarity

Although testing for unit-roots in time-series setting is common practice, its application to panel data is relatively more recent. These tests are analogs of the Augmented Dickey Fueller unit-root test and, the resulting statistics are averages of the bias-adjusted t statistics for each panel. An extensive discussion of the different models and their specific issues can be found in Baltagi (2008). In this paper, I focus on two different tests which are more appropriate for the characteristics of my data. The Im et al. (2003) test relaxes some requirements of previous tests by allowing ρ_i to be heterogeneous across panels and propose a testing procedure that averages the individual test statistics. The null hypothesis is that the panel contains a unit root for all i (i.e. $H_0 : \rho_i = 1 \; \forall \; i$), whereas the alternative hypothesis is that at least one of the individual series is stationary (i.e. $H_1 : \exists \; i \; s.t. \; \rho_i < 1$).

One limitation of the Im et al. (2003) test in this context relates to the definition of the alternative hypothesis. The presence of one stationary panel would lead the test to reject the null hypothesis, which is limiting with high N. Choi (2001) propose a Fisher-type test that extends previous tests and relaxes this assumption among others. When N is finite, this test is consistent against the alternative that at least one panel does not have a unit root. When N is infinite, the number of panel which do not have a unit root should grow at the same rate as N for the tests to be consistent. It is evident how this test is more appropriate for the panel of this study. In the remaining of this section I will present and discuss results from both the Im et al. (2003) and Choi (2001) tests.

The main criticism of the Burke et al. (2015) model raised by Newell et al. (2021) refers to overlooking the nonstationarity of the temperature variables. Since, consistent with Burke et al. (2015), I include the dependent economic variables in first differences (growth rates), these variables do not need to be tested. Therefore, I only test the potential nonstationarity of temperature. On this regard, although the panels of my analysis are at the firm-level, testing all these panels would not be feasible in terms of computational power. Hence, I conduct the tests at the weather variable grid level. This is a reasonable approximation to the extent that the firm-specific temperature values are a weighted average of the neighbouring grids.

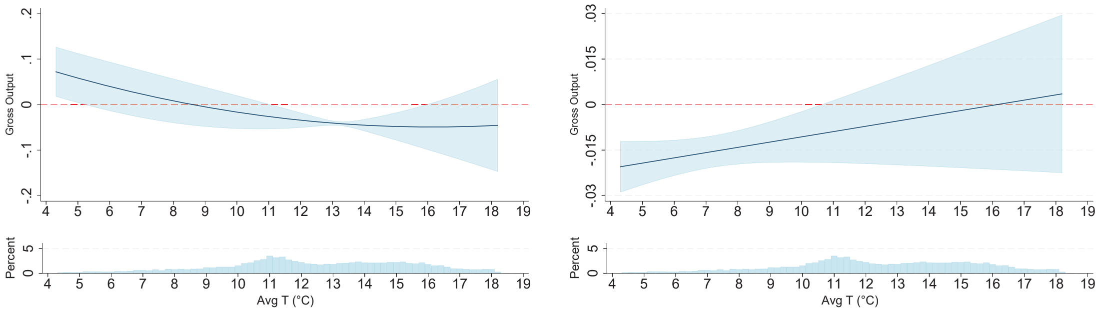
	Statistic	p-value
Z-ttilde-bar	-456.806	0.000
W-t-bar	-334.724	0.000
Inverse chi-squared	242315.259	0.000
Inverse normal	-247.420	0.000
Inverse logit	-256.954	0.000
Modified inv. chi-squared	257.904	0.000

Table 9: Panel unit-root Augmented Dickey Fueller tests results. Test statistics and p-values reported. Source: Copernicus Climate Change Service (C3S) ERA5-Land.

Table 9 reports the statistics and p-values of the various tests. The first row refers to the Im et al. (2003) test, where multiple tests are run to identify the number of lags to include in order to account for serial correlation, such that the Akaike (1973) information criteria is minimised. The average number of lags that should be included across the panels is 0.54. The resulting p-value of this test is 0.0000, hence the test strongly rejects the null hypothesis of nonstationarity. The remaining three rows refer to the Choi (2001) test, where, consistent with the previous test, I include one lag to account for serial correlation. The inverse χ^2 is the most relevant statistics in this case, since it is a transformation that is suitable for when N tends to infinity. Also in this case, all tests have a p-value of 0.0000, hence rejecting the null hypothesis on nonstationarity.

This section has discussed whether the nonstationarity issue relevant in long T and short N country-level panels highlighted in Burke et al. (2015) and (Newell et al., 2021) is relevant in long T and short N firm-level panels. I argued that in this panel nonstationarity should not be a concern given the limited length of the time series (Greene, 2003). Nevertheless, I formally tested the validity of this argument using the the Im et al. (2003) and Choi (2001) tests that extend the Augmented Dickey Fueller unit root test to panel data. All these tests consistently have p-values of 0.0000, strongly rejecting the null hypothesis of nonstationarity. Therefore, the temperature variables could be included in the analysis in levels and not necessarily firs differenced, unless the specific research setting requires that.

6.6 Additional Results Cumulative Effect



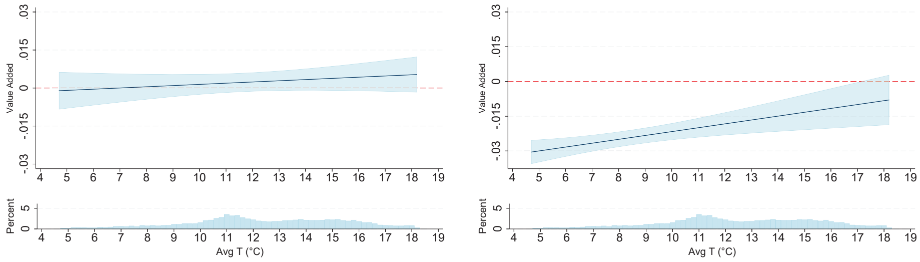
(a) Cumulative response

(b) Cumulative marginal effect

Figure 19: Cumulative marginal effects of temperature on the growth rate of GO. Results from the 2^{nd} order polynomial model with firm and industry-year FE, standard errors clustered at the Nuts 3 level.

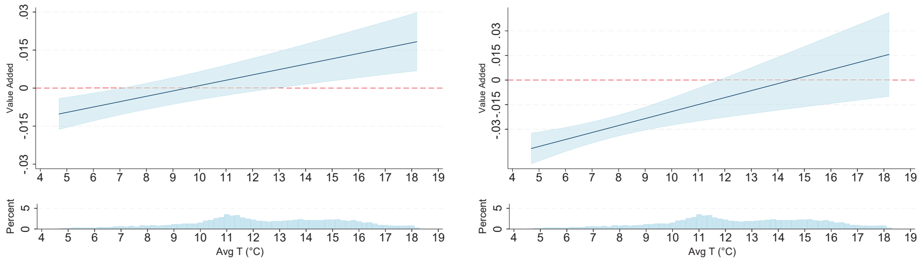
6.7 Additional Results Value Added

As for GO, the effect of $T_{i,t}$ is generally not significant. The effect of $T_{i,t-1}$ is more pronounced, whereas the marginal effect function of $T_{i,t-2}$ has a lower intercept (in absolute value) and a steeper slope than $T_{i,t-1}$. As higher temperature in $t-2$ negatively (positively) impact VA in areas with temperature below (above) $9°C$, the effect of $T_{i,t-2}$ reverses the effect of $T_{i,t-1}$ in warmer areas and exacerbates it in colder areas as shown in figure 20d.



(a) Contemporaneous marginal effect

(b) lag-1 marginal effect



(c) lag-2 marginal effect

(d) Cumulative marginal effect

Figure 20: Contemporaneous (a) lag-1 (b) lag-2 (c) and cumulative (d) marginal effects of temperature on the growth rate of gross output in the EU. Results from the 2^{nd} order polynomial model with firm and industry-year FE, standard errors clustered at the Nuts 3 level.

6.8 Additional Results TFP and Value Added Sample

	(1) ΔGO	(2) ΔVA	(3) ΔTFP	(4) ΔL	(5) ΔK	(6) ΔM
T	-0.0019	-0.0054	0.0071	-0.015***	-0.0080***	-0.0011
	(0.0042)	(0.0046)	(0.0044)	(0.0027)	(0.0031)	(0.0041)
T^2	0.00043**	0.00055***	-0.000021	0.00068***	0.00044***	0.00044***
	(0.00018)	(0.00019)	(0.00016)	(0.00012)	(0.00011)	(0.00017)
$(\ell 1)T$	-0.032***	-0.053***	-0.033***	-0.023***	-0.020***	-0.025***
	(0.0029)	(0.0048)	(0.0039)	(0.0020)	(0.0024)	(0.0029)
$(\ell 1)T^2$	0.0011***	0.0013***	0.00061***	0.00083***	0.00082***	0.0011***
	(0.00021)	(0.00026)	(0.00020)	(0.00012)	(0.00012)	(0.00021)
$(\ell 2)T$	-0.012**	-0.024***	-0.011**	-0.014***	-0.022***	-0.0036
	(0.0048)	(0.0054)	(0.0043)	(0.0017)	(0.0036)	(0.0049)
$(\ell 2)T^2$	0.00082***	0.0011***	0.00043*	0.00085***	0.00087***	0.00053**
	(0.00023)	(0.00028)	(0.00023)	(0.000098)	(0.00014)	(0.00023)
P	-0.00059	0.012	0.012	-0.0015	0.0051	-0.0040
	(0.011)	(0.014)	(0.011)	(0.0062)	(0.0084)	(0.011)
P^2	0.0046	0.0022	0.00036	0.0023	0.0032	0.0047
	(0.0041)	(0.0045)	(0.0034)	(0.0024)	(0.0031)	(0.0042)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Ind-Year-FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.20	0.15	0.11	0.14	0.17	0.16
N	16203021	16203021	16203021	16203021	16203021	16203021

Standard errors in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

Table 10: Point estimates and standard errors from the regressions of weather variables on the growth rates of GO, VA, and TFP. Results refer to the subsample of firms with available TFP. Results for the 2^{nd} order polynomial model with firm and industry-year FE, standard errors clustered at the Nuts 3 level.

	(1) dGO	(2) dVA
T (°C)	-0.00493	-0.00618
	(0.00496)	(0.00555)
T^2 (°C)	0.000347*	0.000368*
	(0.000191)	(0.000219)
$(\ell 1)T$ (°C)	-0.0268***	-0.0394***
	(0.00323)	(0.00473)
$(\ell 1)T^2$ (°C)	0.000813***	0.000834***
	(0.000218)	(0.000260)
$(\ell 2)T$ (°C)	-0.00501	-0.0192***
	(0.00498)	(0.00517)
$(\ell 2)T^2$ (°C)	0.000530**	0.00100***
	(0.000232)	(0.000261)
P	-0.0177*	-0.0176
	(0.0102)	(0.0121)
P^2	0.00905**	0.00914**
	(0.00370)	(0.00410)
Firm FE	Yes	Yes
Industry-Year-FE	Yes	Yes
R^2	0.180	0.133
N	28,359,459	28,359,459

Standard errors in parentheses

* $p < 0.1$, ** $p < 0.05$, *** $p < 0.01$

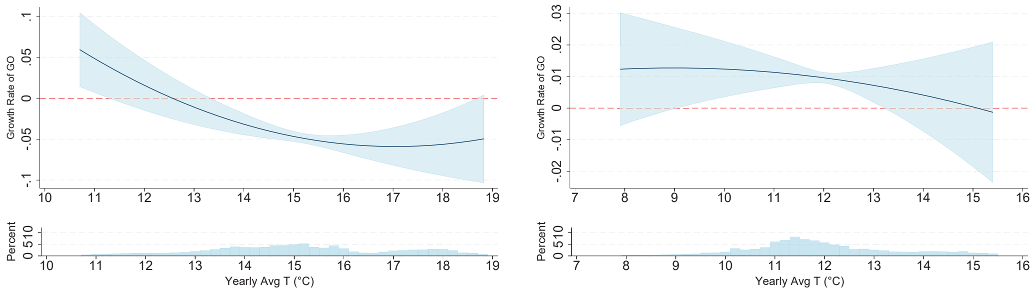
Table 11: Point estimates and standard errors from the regressions of weather variables on the growth rates of GO and VA. Results refer to the subsample of firms with available VA. Results for the 2^{nd} order polynomial model with firm and industry-year FE, standard errors clustered at the Nuts 3 level. Note that the new sample is constructed as the intersection between firms with available GO and VA, hence the total number of observations is lower than those with available either GO or VA in the main regressions.

6.9 Additional Results Heterogeneity

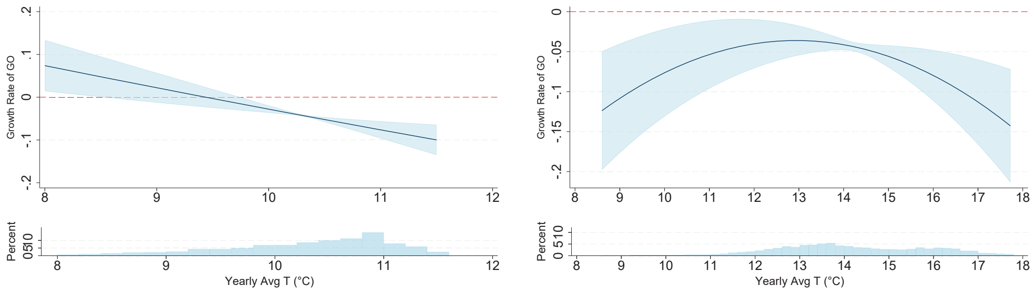
6.9.1 Cross-Country Heterogeneity

This setion focuses on cross-country heterogeneity. While results for all countries in the sample are presented, the discussion focuses on France, Italy, Spain and the UK as they constitute the major and most relevant countries in my sample. I exclude Germany from the main discussion due to the previously discussed issues related to the poor coverage in Orbis Historical. This applies to all sections focusing on cross-country heterogeneity in the paper.

Consistent with Burke et al. (2015), the results from the quadratic model (equation 11) for Italy and France in figure 22 show an inverted-U relationship. The predicted effect of temperature on the growth rate of gross output is a smooth function which is negative at all levels of the temperature distribution for Italy and positive for France, with a larger effect in magnitude at the two tails of the temperature distribution. Firms located in the coldest and warmest areas have on average a lower growth rate of output than firms located in areas with milder temperature. On the contrary, the response function for Spain reports a U-shaped and convex relationship, characterised by positive predicted growth rates at lower temperature and negative rates at temperate and higher temperature. Also in this case, possible explanations could be related to a higher presence of firms with specific characteristics or to a higher level of adaptation. Interestingly, the UK is characterised by a downward-sloping and linear relationship. In this case, the temperature support is particularly narrow, therefore the UK-specific estimator is negatively impacted by the low variability in the variable of interest. Nevertheless, to understand how much economic production is affected by increasing temperature, the marginal effects reported in figure 22 below are more informative.



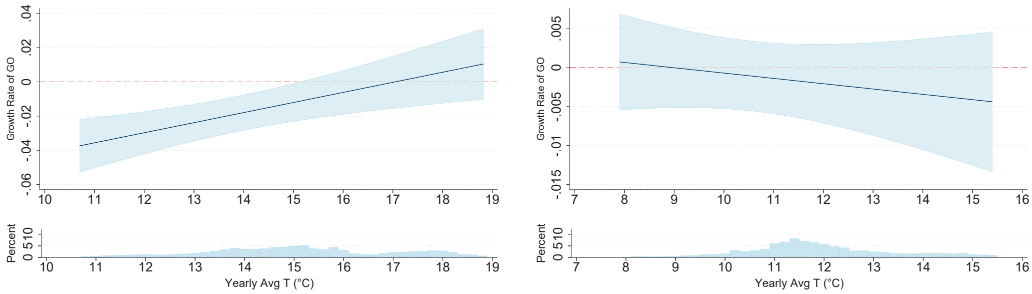
(a) Prediction ES (b) Prediction FR



(c) Prediction GB (d) Prediction IT

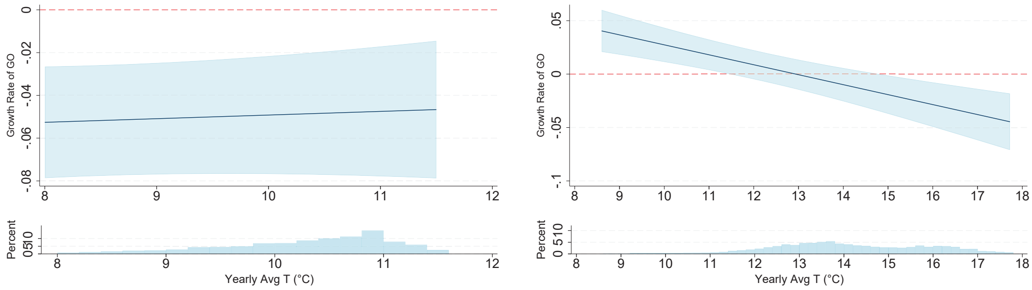
Figure 21: Predicted effect of temperature on the growth rate of gross output in Spain, France, Italy and Great Britain. Results from the quadratic model with firm and industry-year FE estimated excluding the bottom and top 1% of the temperature distribution.

Figure 22 reports the marginal effect of an extra 1°C against the temperature support. As is evident, the marginal effect varies largely across Countries, being upward sloping for Italy (figure 22d) and France (figures 22b), slightly downward sloping for Great Britain (figure 22c) and upward sloping for Spain (figure 22a). An extra $1°C$ in yearly average temperature in Italy increases the growth rate of gross output by approximately 0.067 log-points (6.9%) for firms located in areas with a yearly average temperature of $6°C$ and decreases the growth rate of gross output by 0.051 log-points (5.2%) for firms located in areas with a yearly average temperature of $18°C$. These effects may initially seem excessively large. However, it is unlikely that yearly average temperature will increase by $1°C$ in a year. Rather, they will increase by a fraction of $1°C$, and the marginal impact will also be a fraction of the reported values. The results for France are generally consistent with, although lower in magnitude than those for Italy. According to figure 22b the marginal effect of an extra $1°C$ in yearly average temperature is generally not statistically significant. Nevertheless, it is still important to consider the point estimates as they can provide insights on general trends. An extra $1°C$ in yearly average temperature has a positive impact of 0.004 log-points (0.4%) for firms located in areas with average yearly temperature of $6°C$ and -0.0065 log-points (-0.65%) for firms located in areas with average yearly temperature of $15.5°C$.



(a) Marginal Effect ES

(b) Marginal Effect FR



(c) Marginal Effect GB

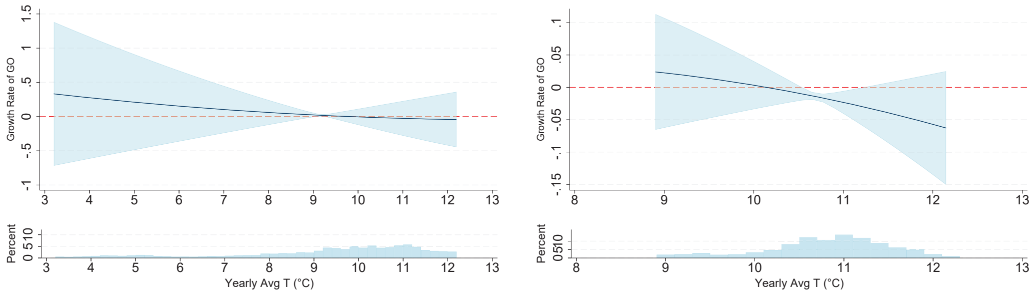
(d) Marginal Effect IT

Figure 22: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in Spain, France, Italy and Great Britain. Results from the quadratic model with firm and industry-year FE estimated excluding the bottom and top 1% of the temperature distribution.

The results for Spain reported in figure 22a differ substantially from those for Italy and France, although they are consistent with the pooled-EU marginal effects. The estimated marginal effect of temperature on the growth rate of gross output panel is increasing over the temperature distribution, although not statistically significant above $15°C$. The marginal effect of temperature is negative for firms located at lower temperature and positive for firms located at higher temperature. Specifically, an extra $1°C$ in yearly average temperature has a positive impact of -0.042 log-points (-4.3%) for firms located in areas with average yearly temperature of $10°C$ and -0.013 log-points (-1.38%) for firms located in areas with average yearly temperature of $19°C$. Moreover, the UK is a peculiar case as the marginal effect is consistently negative and statistically significant over the whole temperature distribution. An extra $1°C$ in yearly average temperature has a negative impact of -0.051

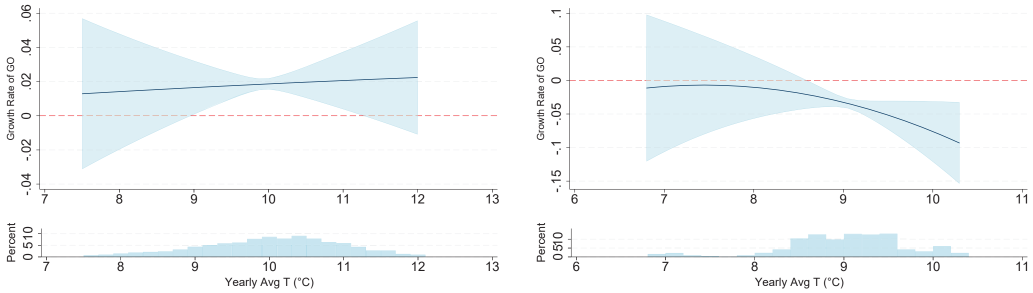
log-points (-5.2%) for firms located in areas with average yearly temperature of $8°C$ and -0.057 log-points (-5.8%) for firms located in areas with average yearly temperature of $11.5°C$.

The figure below report the marginal effects for the remaining countries. Results for these countries are characterised by large confidence intervals, likely due to a lower number of observations, making these results not statistically significant for most countries over a large part of the temperature distribution. The marginal effect function is downward sloping for Belgium, Denmark, Finland, and the Netherlands. Apart from the Netherlands, the marginal effect is negative over the whole temperature support. On the contrary, the marginal effect function is upward-sloping for Austria, Germany, Greece, Portugal, and Sweden. The function is characterised by positive point estimates for all countries, with the exception of Austria and the colder areas in Sweden.



(a) Prediction AT

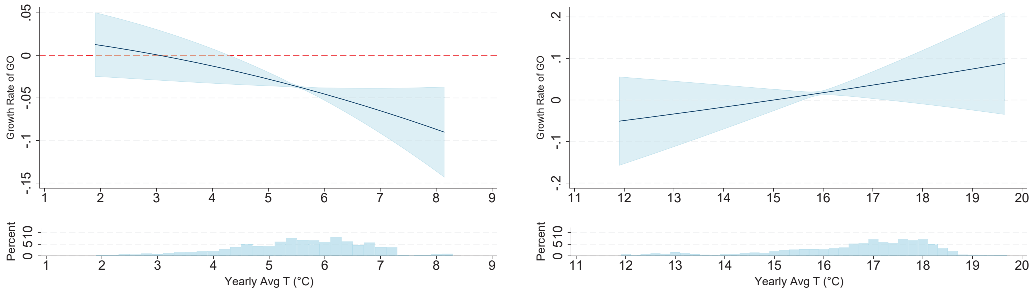
(b) Prediction BE



(c) Prediction DE

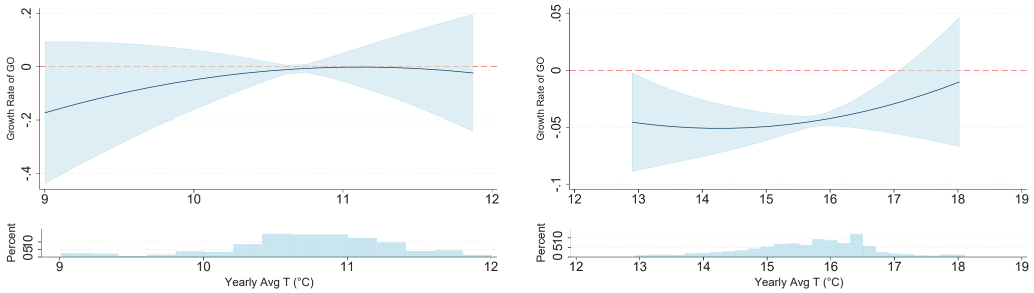
(d) Prediction DK

Figure 23: Predicted effect of temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE estimated excluding the bottom and top 1% of the temperature distribution.



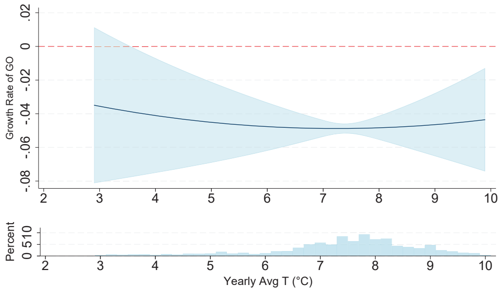
(a) Prediction FI

(b) Prediction GR



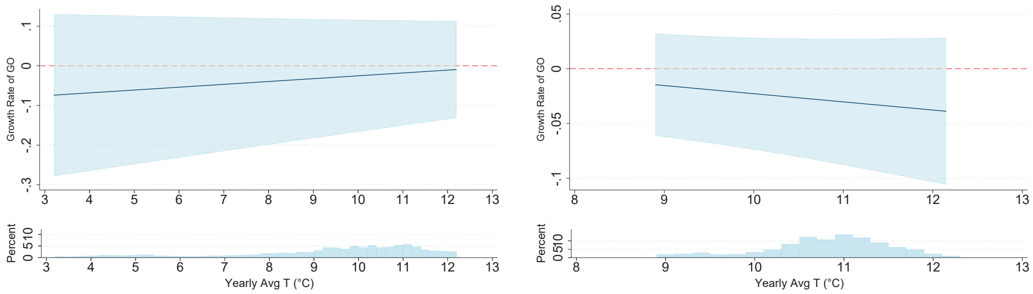
(c) Prediction NL

(d) Prediction PT



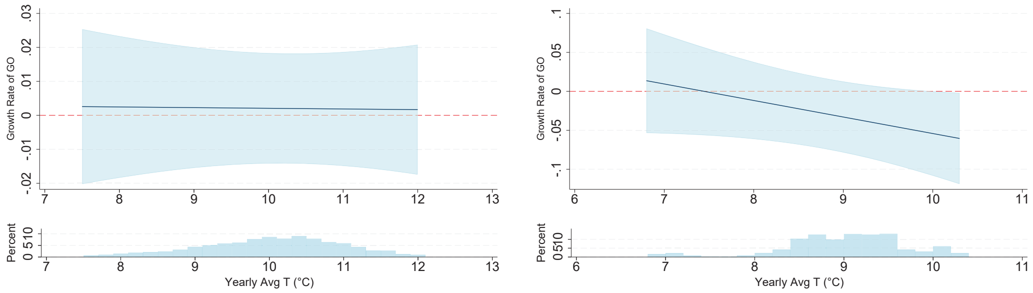
(e) Prediction SE

Figure 24: Predicted effect of temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE estimated excluding the bottom and top 1% of the temperature distribution.



(a) Marginal Effect AT

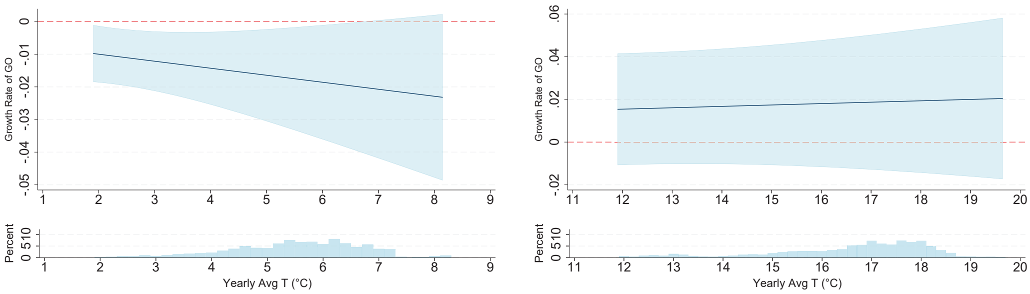
(b) Marginal Effect BE



(c) Marginal Effect DE

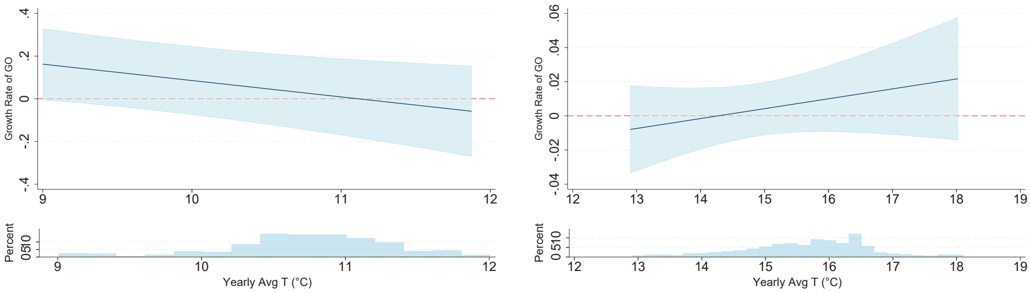
(d) Marginal Effect DK

Figure 25: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the temperature distribution.



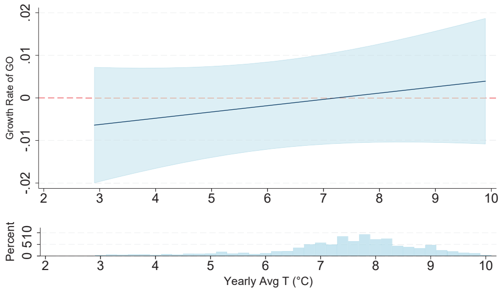
(a) Marginal Effect FI

(b) Marginal Effect GR



(c) Marginal Effect NL

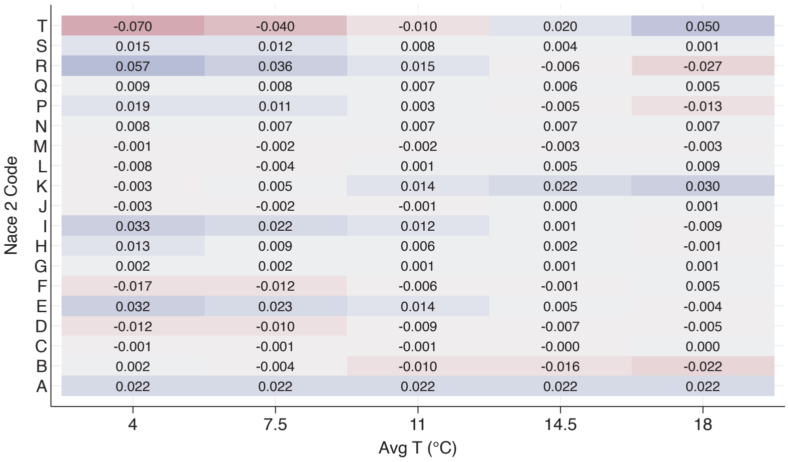
(d) Marginal Effect PT



(e) Marginal Effect SE

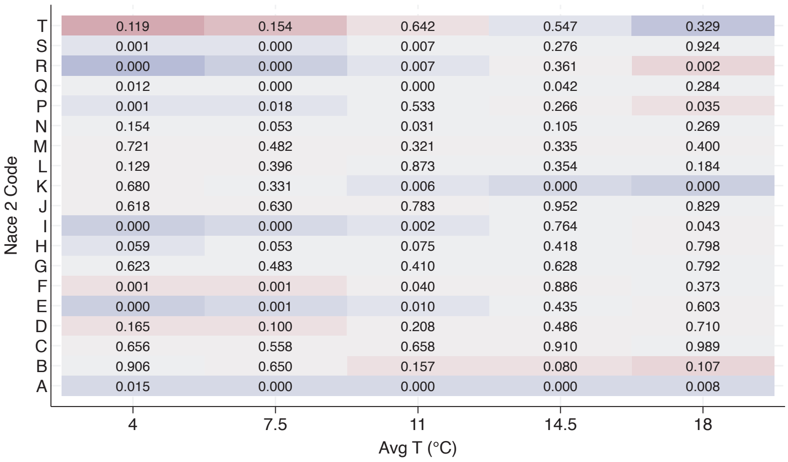
Figure 26: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the temperature distribution.

6.9.2 Pooled EU additional results, industry heterogeneity



Nace 2 Code	4	7.5	11	14.5	18
T	-0.070	-0.040	-0.010	0.020	0.050
S	0.015	0.012	0.008	0.004	0.001
R	0.057	0.036	0.015	-0.006	-0.027
Q	0.009	0.008	0.007	0.006	0.005
P	0.019	0.011	0.003	-0.005	-0.013
N	0.008	0.007	0.007	0.007	0.007
M	-0.001	-0.002	-0.002	-0.003	-0.003
L	-0.008	-0.004	0.001	0.005	0.009
K	-0.003	0.005	0.014	0.022	0.030
J	-0.003	-0.002	-0.001	0.000	0.001
I	0.033	0.022	0.012	0.001	-0.009
H	0.013	0.009	0.006	0.002	-0.001
G	0.002	0.002	0.001	0.001	0.001
F	-0.017	-0.012	-0.006	-0.001	0.005
E	0.032	0.023	0.014	0.005	-0.004
D	-0.012	-0.010	-0.009	-0.007	-0.005
C	-0.001	-0.001	-0.001	-0.000	0.000
B	0.002	-0.004	-0.010	-0.016	-0.022
A	0.022	0.022	0.022	0.022	0.022

Figure 27: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output (log) accounting for industry heterogeneity (Nace 2 level 2). Results from the quadratic model with firm and industry-year FE.



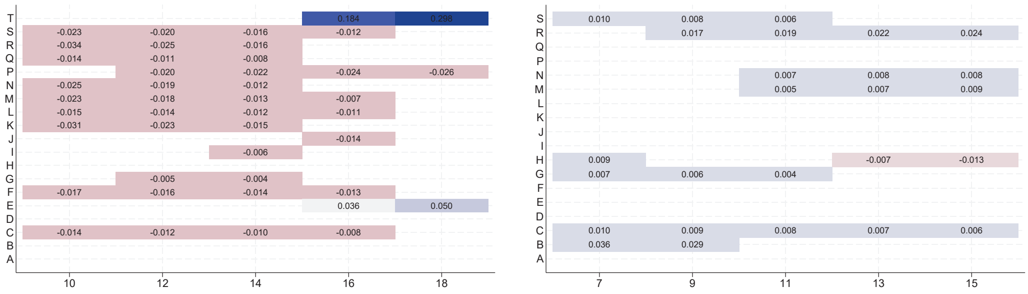
Nace 2 Code	4	7.5	11	14.5	18
T	0.119	0.154	0.642	0.547	0.329
S	0.001	0.000	0.007	0.276	0.924
R	0.000	0.000	0.007	0.361	0.002
Q	0.012	0.000	0.000	0.042	0.284
P	0.001	0.018	0.533	0.266	0.035
N	0.154	0.053	0.031	0.105	0.269
M	0.721	0.482	0.321	0.335	0.400
L	0.129	0.396	0.873	0.354	0.184
K	0.680	0.331	0.006	0.000	0.000
J	0.618	0.630	0.783	0.952	0.829
I	0.000	0.000	0.002	0.764	0.043
H	0.059	0.053	0.075	0.418	0.798
G	0.623	0.483	0.410	0.628	0.792
F	0.001	0.001	0.040	0.886	0.373
E	0.000	0.001	0.010	0.435	0.603
D	0.165	0.100	0.208	0.486	0.710
C	0.656	0.558	0.658	0.910	0.989
B	0.906	0.650	0.157	0.080	0.107
A	0.015	0.000	0.000	0.000	0.008

Figure 28: P-values for coefficients of figure 27 for the marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output (log) accounting for industry heterogeneity (Nace 2 level 2). The heat map colours refer to the values of the point estimates. Results from the quadratic model with firm and industry-year FE.

6.9.3 Cross-country heterogeneity, industry-level

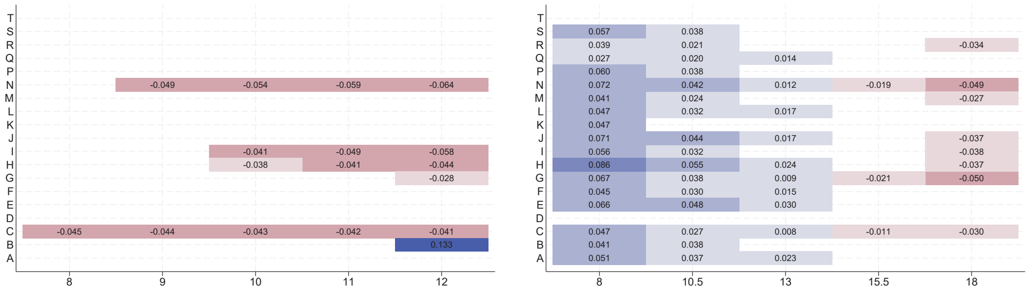
The marginal effect for Spain reported in 29a is a negative and upward-sloping function of temperature. Among the industry categories whose effects are statistically significant, Manufacturing (C), Construction (F), Financial and insurance activities (K), Real estate activities (L), Professional scientific and technical activities (M), Education (P), and Other service activities (S) are the industries that seem to be more consistently negatively impacted over most part of the temperature distribution. For industries such as Manufacturing (C) and Construction (F), this is an expected result since these activities are usually less likely to be sheltered from higher temperature. Whereas, for the remaining industries, this is a less obvious result because service-related activities are classified as low-risk since they tend to be better sheltered against weather shocks (Graff Zivin and Neidell, 2014).

The results for France reported in figure 29b are generally not statistically significant and, within the set of industries where the effect is significant, the marginal effect function is upward sloping for the services (M and N) and the Arts entertainment and recreation (R) sectors and downward sloping for Mining and quarrying (B), Manufacturing C, Wholesale and retail trade repair of motor vehicles and motorcycles (G), Transportation and storage (H), and Other service activities (S). The effect is positive in sign across all these industries, with the exception of Transportation and storage (H), where the effect becomes negative at higher temperature.



(a) Marginal Effect ES

(b) Marginal Effect FR



(c) Marginal Effect GB

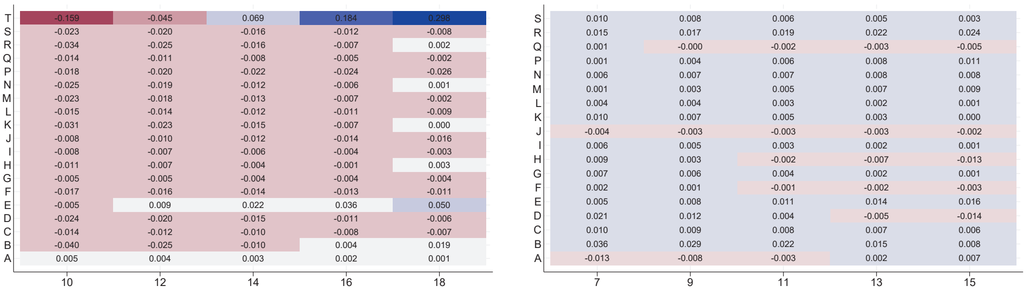
(d) Marginal Effect IT

Figure 29: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output accounting for industry heterogeneity. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, plotted over country-specific temperature supports.

The United Kingdom is an interesting case because, as reported in figure 29c, although only a limited amount of industries are significantly affected by higher temperature, those reporting statistically significant estimates are considerably impacted. The marginal effect of an additional $1°C$ for firms located in areas with an average yearly temperature of $12°C$ is -4.2% for manufacturing (C), -2.8% for Wholesale and retail trade repair of motor vehicles and motorcycles (G), -4.5% for transportation and storage (H), -6% for the Accommodation and food service activities (I), and -6.6% for the Administrative and support service activities (N).

Finally, the results for Italy reported in figure 29d are consistent with the results from the pooled analysis, as they show the expected downward-sloping marginal effect across all industries. In addition, in the Italian case, a significant share of the point estimates is statistically significant. The two most affected sectors at high temperature are Wholesale and retail trade repair of motor vehicles and motorcycles (G) and Administrative and support service activities (N), with marginal effects of -5.1% and -5% respectively. The remaining significantly impacted sectors are manufacturing (C), Transportation and storage (H), Accommodation and food service activities (I), Information and communication (J), Professional scientific and technical activities (M), and Arts entertainment and recreation (R), with damages ranging between -2.7% and -3.8%.

The industry-specific estimates for the remaining reported countries are not easy to interpret given the considerable amount of country-industry-specific point estimates to take into account. The heat map colours are particularly convenient in this case because they provide a broad overview of the different signs and magnitudes. The main result arising from the plots in this section is that industry-specific marginal effects are generally consistently negative across countries, although with significant differences in magnitude as highlighted by the different colour intensities.

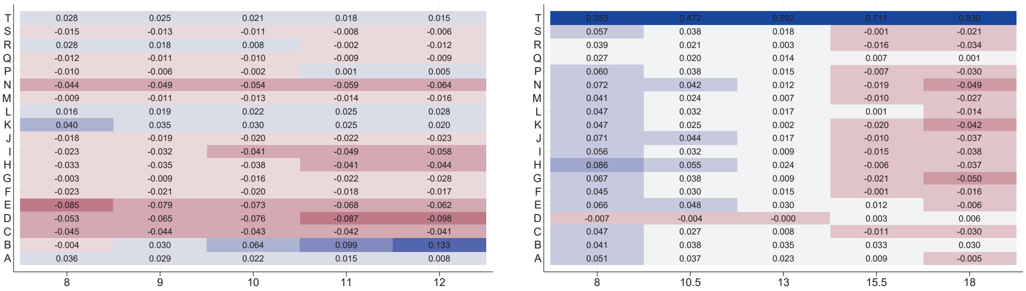


	10	12	14	16	18
T	-0.159	-0.045	0.069	0.184	0.298
S	-0.023	-0.020	-0.016	-0.012	-0.008
R	-0.034	-0.025	-0.016	-0.007	0.002
Q	-0.014	-0.011	-0.008	-0.005	-0.002
P	-0.018	-0.020	-0.022	-0.024	-0.026
N	-0.025	-0.019	-0.012	-0.006	0.001
M	-0.023	-0.018	-0.013	-0.007	-0.002
L	-0.015	-0.014	-0.012	-0.011	-0.009
K	-0.031	-0.023	-0.015	-0.007	0.000
J	-0.008	-0.010	-0.012	-0.014	-0.016
I	-0.008	-0.007	-0.006	-0.004	-0.003
H	-0.011	-0.007	-0.004	-0.001	0.003
G	-0.005	-0.005	-0.004	-0.004	-0.004
F	-0.017	-0.016	-0.014	-0.013	-0.011
E	-0.005	0.009	0.022	0.036	0.050
D	-0.024	-0.020	-0.015	-0.011	-0.006
C	-0.014	-0.012	-0.010	-0.008	-0.007
B	-0.040	-0.025	-0.010	0.004	0.019
A	0.005	0.004	0.003	0.002	0.001

	7	9	11	13	15
S	0.010	0.008	0.006	0.005	0.003
R	0.015	0.017	0.019	0.022	0.024
Q	0.001	-0.000	-0.002	-0.003	-0.005
P	0.001	0.004	0.006	0.008	0.011
N	0.006	0.007	0.007	0.008	0.008
M	0.001	0.003	0.005	0.007	0.009
L	0.004	0.004	0.003	0.002	0.001
K	0.010	0.007	0.005	0.003	0.000
J	-0.004	-0.003	-0.003	-0.003	-0.002
I	0.006	0.005	0.003	0.002	0.001
H	0.009	0.003	-0.002	-0.007	-0.013
G	0.007	0.006	0.004	0.002	0.001
F	0.002	0.001	-0.001	-0.002	-0.003
E	0.005	0.008	0.011	0.014	0.016
D	0.021	0.012	0.004	-0.005	-0.014
C	0.010	0.009	0.008	0.007	0.006
B	0.036	0.029	0.022	0.015	0.008
A	-0.013	-0.008	-0.003	0.002	0.007

(a) Marginal Effect ES

(b) Marginal Effect FR



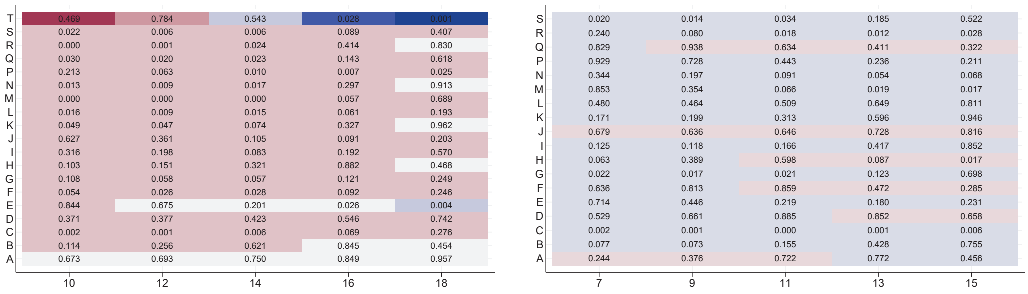
	8	9	10	11	12
T	0.028	0.025	0.021	0.018	0.015
S	-0.015	-0.013	-0.011	-0.008	-0.006
R	0.028	0.018	0.008	-0.002	-0.012
Q	-0.012	-0.011	-0.010	-0.009	-0.009
P	-0.010	-0.006	-0.002	0.001	0.005
N	-0.044	-0.049	-0.054	-0.059	-0.064
M	-0.009	-0.011	-0.013	-0.014	-0.016
L	0.016	0.019	0.022	0.025	0.028
K	0.040	0.035	0.030	0.025	0.020
J	-0.018	-0.019	-0.020	-0.022	-0.023
I	-0.023	-0.032	-0.041	-0.049	-0.058
H	-0.033	-0.035	-0.038	-0.041	-0.044
G	-0.003	-0.009	-0.016	-0.022	-0.028
F	-0.023	-0.021	-0.020	-0.018	-0.017
E	-0.085	-0.079	-0.073	-0.068	-0.062
D	-0.053	-0.065	-0.076	-0.087	-0.098
C	-0.045	-0.044	-0.043	-0.042	-0.041
B	-0.004	0.030	0.064	0.099	0.133
A	0.036	0.029	0.022	0.015	0.008

	8	10.5	13	15.5	18
T	0.353	0.472	0.592	0.711	0.830
S	0.057	0.038	0.018	-0.001	-0.021
R	0.039	0.021	0.003	-0.016	-0.034
Q	0.027	0.020	0.014	0.007	0.001
P	0.060	0.038	0.015	-0.007	-0.030
N	0.072	0.042	0.012	-0.019	-0.049
M	0.041	0.024	0.007	-0.010	-0.027
L	0.047	0.032	0.017	0.001	-0.014
K	0.047	0.025	0.002	-0.020	-0.042
J	0.071	0.044	0.017	-0.010	-0.037
I	0.056	0.032	0.009	-0.015	-0.038
H	0.086	0.055	0.024	-0.006	-0.037
G	0.067	0.038	0.009	-0.021	-0.050
F	0.045	0.030	0.015	-0.001	-0.016
E	0.066	0.048	0.030	0.012	-0.006
D	-0.007	-0.004	-0.000	0.003	0.006
C	0.047	0.027	0.008	-0.011	-0.030
B	0.041	0.038	0.035	0.033	0.030
A	0.051	0.037	0.023	0.009	-0.005

(c) Marginal Effect GB

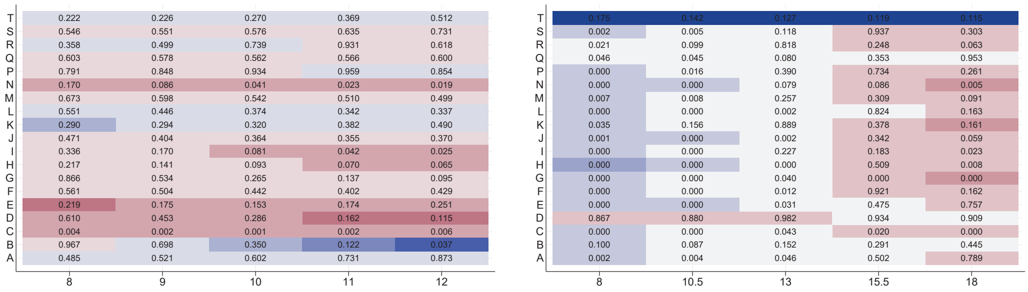
(d) Marginal Effect IT

Figure 30: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output accounting for firm industry heterogeneity - estimates with a statistical significance of at least 90%. Results from the quadratic model with firm and industry-year FE plotted over country-specific temperature supports.



(a) P-values ES

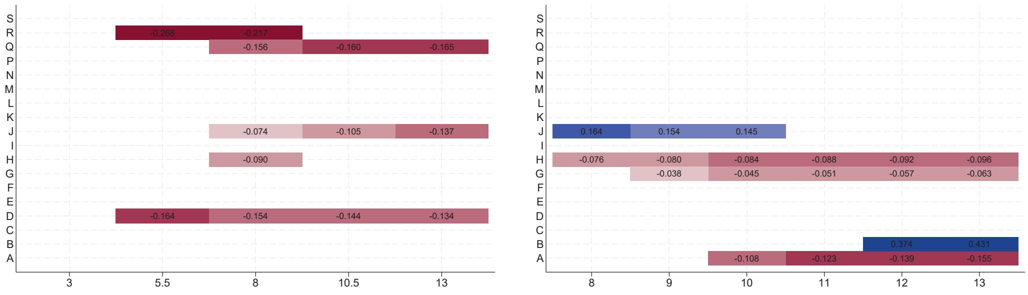
(b) P-values FR



(c) P-values GB

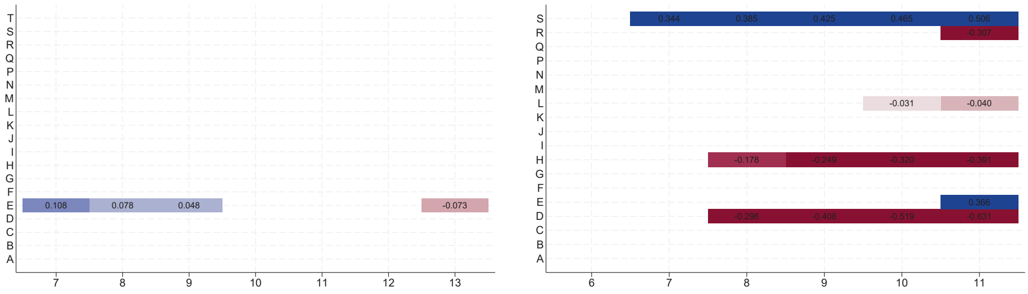
(d) P-values IT

Figure 31: Relevant p-values for the marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output accounting for firm industry heterogeneity. Results from the quadratic model with firm and industry-year FE plotted over country-specific temperature supports.



(a) Marginal Effect AT

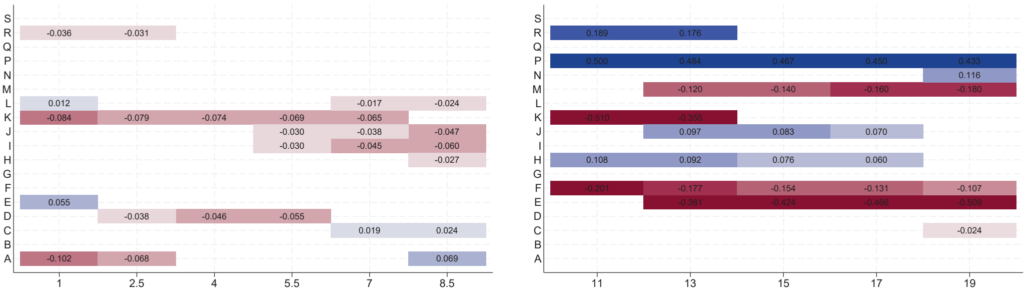
(b) Marginal Effect BE



(c) Marginal Effect DE

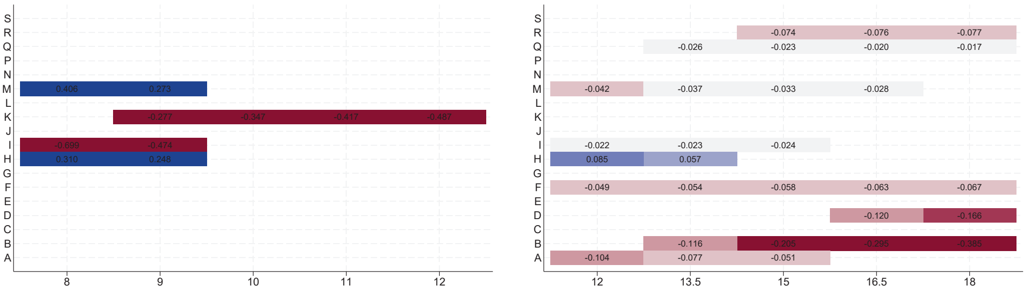
(d) Marginal Effect DK

Figure 32: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the temperature distribution.



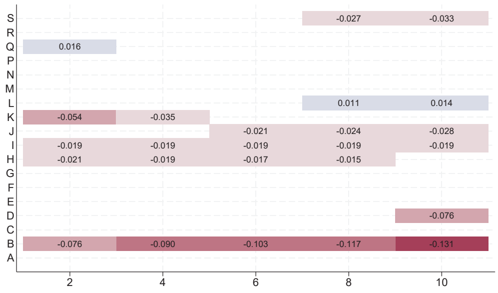
(a) Marginal Effect FI

(b) Marginal Effect GR



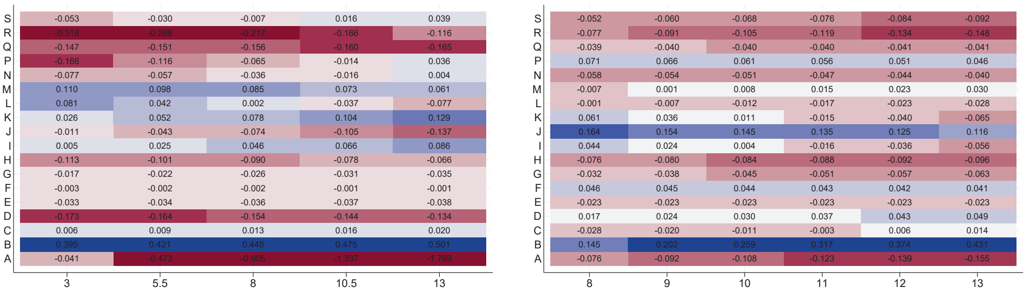
(c) Marginal Effect NL

(d) Marginal Effect PT



(e) Marginal Effect SE

Figure 33: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the temperature distribution.

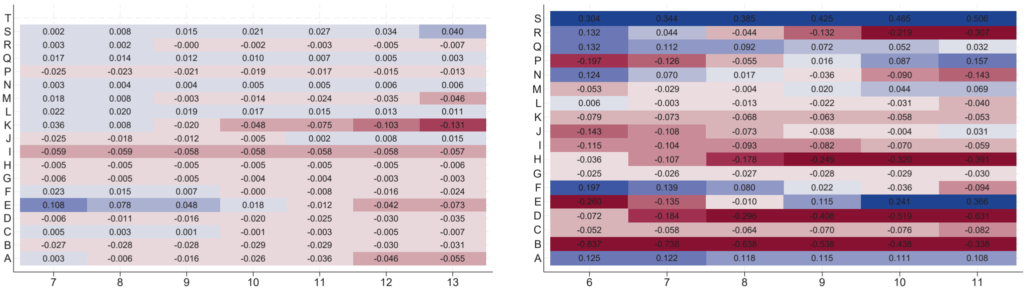


	3	5.5	8	10.5	13
S	-0.053	-0.030	-0.007	0.016	0.039
R	-0.318	-0.268	-0.217	-0.166	-0.116
Q	-0.147	-0.151	-0.156	-0.160	-0.165
P	-0.166	-0.116	-0.065	-0.014	0.036
N	-0.077	-0.057	-0.036	-0.016	0.004
M	0.110	0.098	0.085	0.073	0.061
L	0.081	0.042	0.002	-0.037	-0.077
K	0.026	0.052	0.078	0.104	0.129
J	-0.011	-0.043	-0.074	-0.105	-0.137
I	0.005	0.025	0.046	0.066	0.086
H	-0.113	-0.101	-0.090	-0.078	-0.066
G	-0.017	-0.022	-0.026	-0.031	-0.035
F	-0.003	-0.002	-0.002	-0.001	-0.001
E	-0.033	-0.034	-0.036	-0.037	-0.038
D	-0.173	-0.164	-0.154	-0.144	-0.134
C	0.006	0.009	0.013	0.016	0.020
B	0.395	0.421	0.448	0.475	0.501
A	-0.041	-0.473	-0.905	-1.337	-1.769

(a) Marginal Effect AT

	8	9	10	11	12	13
S	-0.052	-0.060	-0.068	-0.076	-0.084	-0.092
R	-0.077	-0.091	-0.105	-0.119	-0.134	-0.148
Q	-0.039	-0.040	-0.040	-0.040	-0.041	-0.041
P	0.071	0.066	0.061	0.056	0.051	0.046
N	-0.058	-0.054	-0.051	-0.047	-0.044	-0.040
M	-0.007	0.001	0.008	0.015	0.023	0.030
L	-0.001	-0.007	-0.012	-0.017	-0.023	-0.028
K	0.061	0.036	0.011	-0.015	-0.040	-0.065
J	0.164	0.154	0.145	0.135	0.125	0.116
I	0.044	0.024	0.004	-0.016	-0.036	-0.056
H	-0.076	-0.080	-0.084	-0.088	-0.092	-0.096
G	-0.032	-0.038	-0.045	-0.051	-0.057	-0.063
F	0.046	0.045	0.044	0.043	0.042	0.041
E	-0.023	-0.023	-0.023	-0.023	-0.023	-0.023
D	0.017	0.024	0.030	0.037	0.043	0.049
C	-0.028	-0.020	-0.011	-0.003	0.006	0.014
B	0.145	0.202	0.259	0.317	0.374	0.431
A	-0.076	-0.092	-0.108	-0.123	-0.139	-0.155

(b) Marginal Effect BE



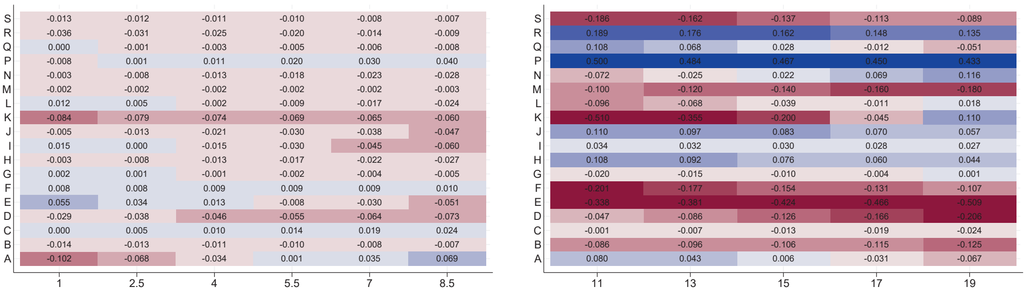
	7	8	9	10	11	12	13
T							
S	0.002	0.008	0.015	0.021	0.027	0.034	0.040
R	0.003	0.002	-0.000	-0.002	-0.003	-0.005	-0.007
Q	0.017	0.014	0.012	0.010	0.007	0.005	0.003
P	-0.025	-0.023	-0.021	-0.019	-0.017	-0.015	-0.013
N	0.003	0.004	0.004	0.005	0.005	0.006	0.006
M	0.018	0.008	-0.003	-0.014	-0.024	-0.035	-0.046
L	0.022	0.020	0.019	0.017	0.015	0.013	0.011
K	0.036	0.008	-0.020	-0.048	-0.075	-0.103	-0.131
J	-0.025	-0.018	-0.012	-0.005	0.002	0.008	0.015
I	-0.059	-0.059	-0.058	-0.058	-0.058	-0.058	-0.057
H	-0.005	-0.005	-0.005	-0.005	-0.005	-0.005	-0.006
G	-0.006	-0.005	-0.005	-0.004	-0.004	-0.003	-0.003
F	0.023	0.015	0.007	-0.000	-0.008	-0.016	-0.024
E	0.108	0.078	0.048	0.018	-0.012	-0.042	-0.073
D	-0.006	-0.011	-0.016	-0.020	-0.025	-0.030	-0.035
C	0.005	0.003	0.001	-0.001	-0.003	-0.005	-0.007
B	-0.027	-0.028	-0.028	-0.029	-0.029	-0.030	-0.031
A	0.003	-0.006	-0.016	-0.026	-0.036	-0.046	-0.055

(c) Marginal Effect DE

	6	7	8	9	10	11
S	0.304	0.344	0.385	0.425	0.465	0.506
R	0.132	0.044	-0.044	-0.132	-0.219	-0.307
Q	0.132	0.112	0.092	0.072	0.052	0.032
P	-0.197	-0.126	-0.055	0.016	0.087	0.157
N	0.124	0.070	0.017	-0.036	-0.090	-0.143
M	-0.053	-0.029	-0.004	0.020	0.044	0.069
L	0.006	-0.003	-0.013	-0.022	-0.031	-0.040
K	-0.079	-0.073	-0.068	-0.063	-0.058	-0.053
J	-0.143	-0.108	-0.073	-0.038	-0.004	0.031
I	-0.115	-0.104	-0.093	-0.082	-0.070	-0.059
H	-0.036	-0.107	-0.178	-0.249	-0.320	-0.391
G	-0.025	-0.026	-0.027	-0.028	-0.029	-0.030
F	0.197	0.139	0.080	0.022	-0.036	-0.094
E	-0.260	-0.135	-0.010	0.115	0.241	0.366
D	-0.072	-0.184	-0.296	-0.408	-0.519	-0.631
C	-0.052	-0.058	-0.064	-0.070	-0.076	-0.082
B	-0.837	-0.738	-0.638	-0.538	-0.438	-0.338
A	0.125	0.122	0.118	0.115	0.111	0.108

(d) Marginal Effect DK

Figure 34: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the temperature distribution.

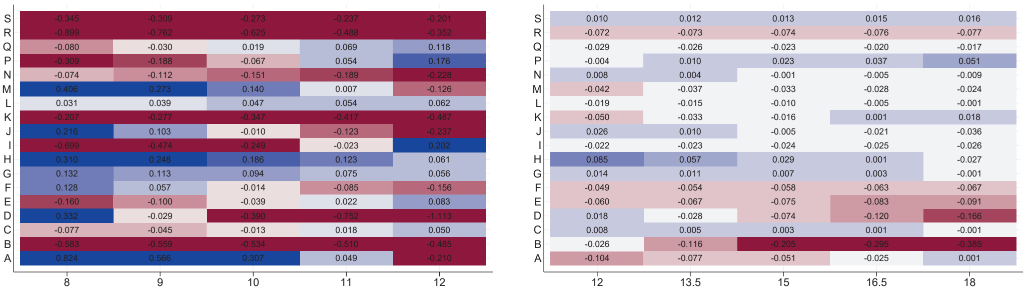


	1	2.5	4	5.5	7	8.5
S	-0.013	-0.012	-0.011	-0.010	-0.008	-0.007
R	-0.036	-0.031	-0.025	-0.020	-0.014	-0.009
Q	0.000	-0.001	-0.003	-0.005	-0.006	-0.008
P	-0.008	0.001	0.011	0.020	0.030	0.040
N	-0.003	-0.008	-0.013	-0.018	-0.023	-0.028
M	-0.002	-0.002	-0.002	-0.002	-0.002	-0.003
L	0.012	0.005	-0.002	-0.009	-0.017	-0.024
K	-0.084	-0.079	-0.074	-0.069	-0.065	-0.060
J	-0.005	-0.013	-0.021	-0.030	-0.038	-0.047
I	0.015	0.000	-0.015	-0.030	-0.045	-0.060
H	-0.003	-0.008	-0.013	-0.017	-0.022	-0.027
G	0.002	0.001	-0.001	-0.002	-0.004	-0.005
F	0.008	0.008	0.009	0.009	0.009	0.010
E	0.055	0.034	0.013	-0.008	-0.030	-0.051
D	-0.029	-0.038	-0.046	-0.055	-0.064	-0.073
C	0.000	0.005	0.010	0.014	0.019	0.024
B	-0.014	-0.013	-0.011	-0.010	-0.008	-0.007
A	-0.102	-0.068	-0.034	0.001	0.035	0.069

(a) Marginal Effect FI

	11	13	15	17	19
S	-0.186	-0.162	-0.137	-0.113	-0.089
R	0.189	0.176	0.162	0.148	0.135
Q	0.108	0.068	0.028	-0.012	-0.051
P	0.500	0.484	0.467	0.450	0.433
N	-0.072	-0.025	0.022	0.069	0.116
M	-0.100	-0.120	-0.140	-0.160	-0.180
L	-0.096	-0.068	-0.039	-0.011	0.018
K	-0.510	-0.355	-0.200	-0.045	0.110
J	0.110	0.097	0.083	0.070	0.057
I	0.034	0.032	0.030	0.028	0.027
H	0.108	0.092	0.076	0.060	0.044
G	-0.020	-0.015	-0.010	-0.004	0.001
F	-0.201	-0.177	-0.154	-0.131	-0.107
E	-0.338	-0.381	-0.424	-0.466	-0.509
D	-0.047	-0.086	-0.126	-0.166	-0.206
C	-0.001	-0.007	-0.013	-0.019	-0.024
B	-0.086	-0.096	-0.106	-0.115	-0.125
A	0.080	0.043	0.006	-0.031	-0.067

(b) Marginal Effect GR

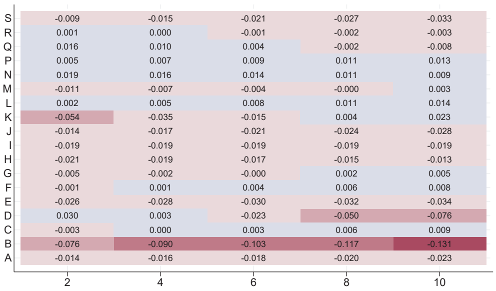


	8	9	10	11	12
S	-0.345	-0.309	-0.273	-0.237	-0.201
R	-0.899	-0.762	-0.625	-0.488	-0.352
Q	-0.080	-0.030	0.019	0.069	0.118
P	-0.309	-0.188	-0.067	0.054	0.176
N	-0.074	-0.112	-0.151	-0.189	-0.228
M	0.406	0.273	0.140	0.007	-0.126
L	0.031	0.039	0.047	0.054	0.062
K	-0.207	-0.277	-0.347	-0.417	-0.487
J	0.216	0.103	-0.010	-0.123	-0.237
I	-0.699	-0.474	-0.249	-0.023	0.202
H	0.310	0.248	0.186	0.123	0.061
G	0.132	0.113	0.094	0.075	0.056
F	0.128	0.057	-0.014	-0.085	-0.156
E	-0.160	-0.100	-0.039	0.022	0.083
D	0.332	-0.029	-0.390	-0.752	-1.113
C	-0.077	-0.045	-0.013	0.018	0.050
B	-0.583	-0.559	-0.534	-0.510	-0.485
A	0.824	0.566	0.307	0.049	-0.210

(c) Marginal Effect NL

	12	13.5	15	16.5	18
S	0.010	0.012	0.013	0.015	0.016
R	-0.072	-0.073	-0.074	-0.076	-0.077
Q	-0.029	-0.026	-0.023	-0.020	-0.017
P	-0.004	0.010	0.023	0.037	0.051
N	0.008	0.004	-0.001	-0.005	-0.009
M	-0.042	-0.037	-0.033	-0.028	-0.024
L	-0.019	-0.015	-0.010	-0.005	-0.001
K	-0.050	-0.033	-0.016	0.001	0.018
J	0.026	0.010	-0.005	-0.021	-0.036
I	-0.022	-0.023	-0.024	-0.025	-0.026
H	0.085	0.057	0.029	0.001	-0.027
G	0.014	0.011	0.007	0.003	-0.001
F	-0.049	-0.054	-0.058	-0.063	-0.067
E	-0.060	-0.067	-0.075	-0.083	-0.091
D	0.018	-0.028	-0.074	-0.120	-0.166
C	0.008	0.005	0.003	0.001	-0.001
B	-0.026	-0.116	-0.205	-0.295	-0.385
A	-0.104	-0.077	-0.051	-0.025	0.001

(d) Marginal Effect PT



	2	4	6	8	10
S	-0.009	-0.015	-0.021	-0.027	-0.033
R	0.001	0.000	-0.001	-0.002	-0.003
Q	0.016	0.010	0.004	-0.002	-0.008
P	0.005	0.007	0.009	0.011	0.013
N	0.019	0.016	0.014	0.011	0.009
M	-0.011	-0.007	-0.004	-0.000	0.003
L	0.002	0.005	0.008	0.011	0.014
K	-0.054	-0.035	-0.015	0.004	0.023
J	-0.014	-0.017	-0.021	-0.024	-0.028
I	-0.019	-0.019	-0.019	-0.019	-0.019
H	-0.021	-0.019	-0.017	-0.015	-0.013
G	-0.005	-0.002	-0.000	0.002	0.005
F	-0.001	0.001	0.004	0.006	0.008
E	-0.026	-0.028	-0.030	-0.032	-0.034
D	0.030	0.003	-0.023	-0.050	-0.076
C	-0.003	0.000	0.003	0.006	0.009
B	-0.076	-0.090	-0.103	-0.117	-0.131
A	-0.014	-0.016	-0.018	-0.020	-0.023

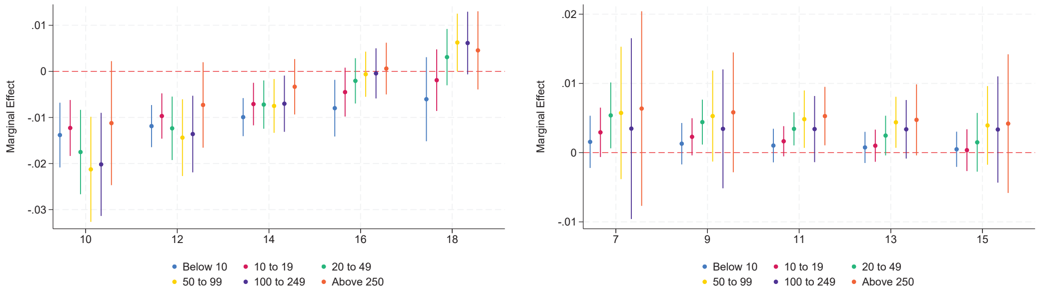
(e) Marginal Effect SE

Figure 35: Marginal effect of an extra 1°C in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the temperature distribution.

6.9.4 Country-level additional results, size heterogeneity

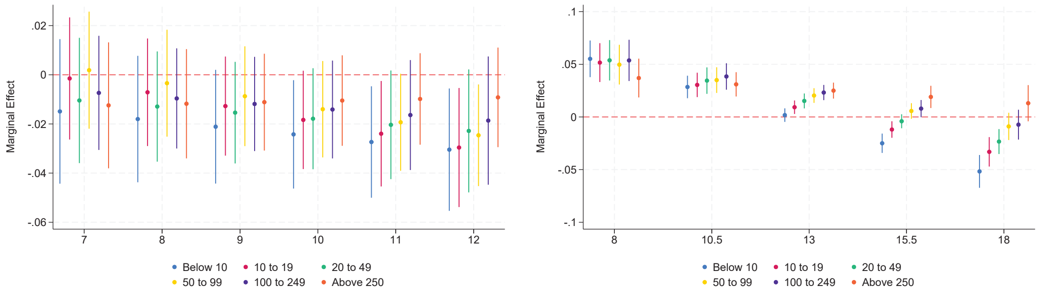
Figure 36 reports the marginal effect of an additional $1^\circ C$ on the growth rate of gross output for the quadratic model in equation 11 for different firm size in selected Countries. Consistent with the country-level average estimates, there are notable differences across countries. It is worth starting the discussion with the results for Italy as they are more evident than for other countries and help to provide the underlying intuition.

The size-specific results for Italy are generally in line with the average marginal effect reported in figure 22d. The point estimates reported in figure 36d are not significantly different from each other at lower temperature. Nevertheless, the coefficients become statistically different from each other at medium and higher temperature. These differences are particularly evident in the two warmest sections of the temperature support. Moreover, when focusing on the highest part of the temperature support an important result emerges. Although small and medium firms are negatively impacted by increasing temperature, we fail to reject the null hypothesis of a marginal effect equal to 0 for larger firms (more than 50 employees). That is, the marginal effect of higher yearly average temperature is not statistically different from 0 at the 5% significance level. Specifically, the impact of an additional $1^\circ C$ on firm gross output growth rate is -5.3% for the first category (below 10), -3.4% for the second category (10 to 19) and -2.4% for the third category (20 to 49). The estimates for the three largest categories are neither economically, nor statistically significant (at the 5% level).



(a) Marginal Effect ES

(b) Marginal Effect FR



(c) Marginal Effect GB

(d) Marginal Effect IT

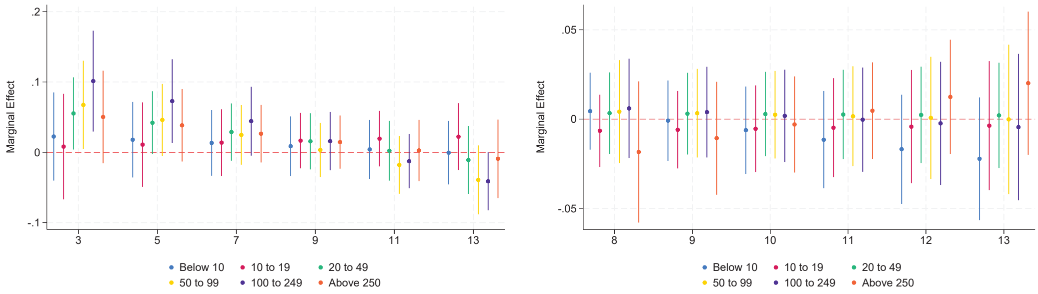
Figure 36: Marginal effect of an extra $1^\circ C$ in yearly average temperature on the growth rate of gross output accounting for firm size heterogeneity. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, plotted over country-specific temperature supports.

There are several reasons why larger firms may not be affected, on average, by higher temperature. First of all, larger firms usually tend to have higher revenues and profits, which determine a lower relative cost of implementing, and a larger opportunity cost of refraining from adaptation strategies. Examples of these adaptation strategies are adopting or expanding air conditioning (Graff Zivin and Kahn, 2016), and improving thermal insulation for the plants where production is carried out. Moreover, given their larger resources, these firms can undertake more radical adaptation strategies, such as changing their economic activity towards less impacted sectors or relocate to areas with milder temperature.

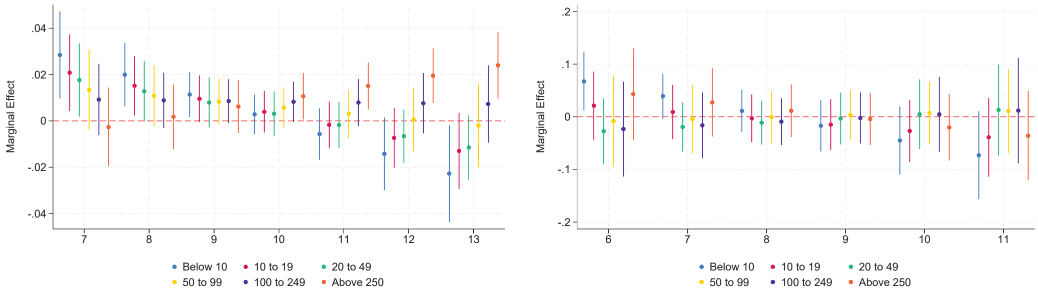
The results for the remaining countries in figure 36 are less clear than, and somehow contrasting with those for Italy. Consistent with the aggregate results from figure 22a, the size-specific results for Spain reported in figure 36a show an upward-sloping marginal effect function over the temperature support across all firm size groups. The point estimates are negative for all groups over the first half of the support. At higher temperature, they remain negative for smaller firms and become positive for larger firms. The estimates are generally statistically significant in the lower part of the temperature distribution and become insignificant at higher temperatures, apart from the largest size group which seems to be not significantly affected by higher temperature over the whole support. Although with substantial differences, the results for Spain seem to be coherent with those for Italy to the extent that smaller firms seem to be negatively impacted by higher temperature, whereas larger firms seem not to be impacted by, or even benefit from higher temperature.

The results for France and the UK reported in figures 36b and 36c respectively, are characterised by larger confidence intervals and, therefore, larger uncertainty than those just discussed. Although the results for France are consistently not significant over the whole temperature support and across all size categories, the estimates for the UK provide insightful information nonetheless. The negative estimates, which are not significant for the larger size groups at all levels of the support, become significant at the 95% level for the smaller groups. Suggesting that, differently from larger firms which seem not to be affected by higher temperature, the evidence indicates that smaller firms are negatively affected by higher temperature. Specifically, an additional $1°C$ in yearly average temperature reduces the growth rate of gross output for firms in the first (below 10) and second (10 to 19) categories by -3% and -2.9% respectively.

The results for the remaining countries reported in figures 37 and 38 are generally consistent with the finding that smaller firms tend to be more negatively (positively) impacted by higher temperatures when located in warmer (colder) areas. Although with different level of statistical significance, these results are particularly relevant because they show that even when located in areas with different absolute temperatures across countries, smaller firms tend to be more vulnerable to higher temperature when located in relatively warmer areas compared to the specific country-level distribution. This has again implications for the pooled results since it shows that the average effects estimated when pooling all firms together, average out different and often opposing effects within the same level of the temperature distribution. Therefore, relying on the European-level results without acknowledging the underlying country-level heterogeneity, might lead to incorrectly infer that size heterogeneity does not play a role in explaining climate damages.

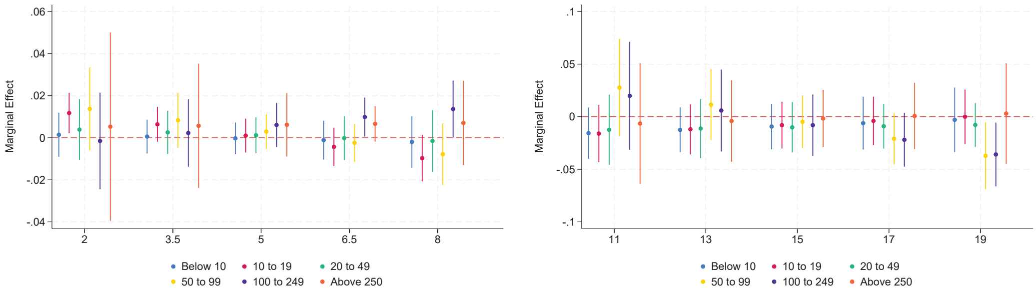


(a) Marginal Effect AT (b) Marginal Effect BE

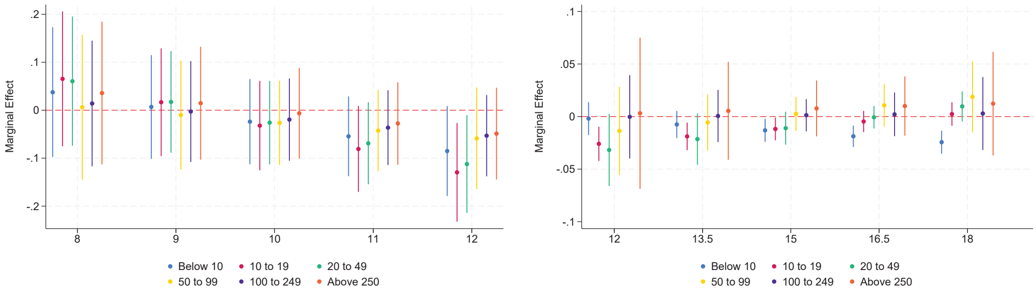


(c) Marginal Effect DE (d) Marginal Effect DK

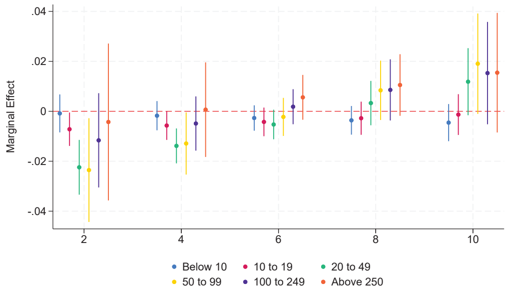
Figure 37: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the temperature distribution.



(a) Marginal Effect FI (b) Marginal Effect GR



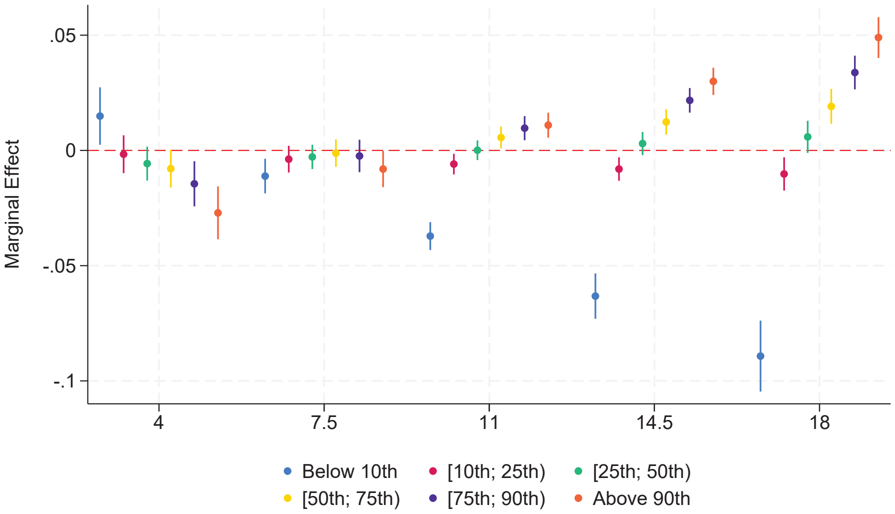
(c) Marginal Effect NL (d) Marginal Effect PT



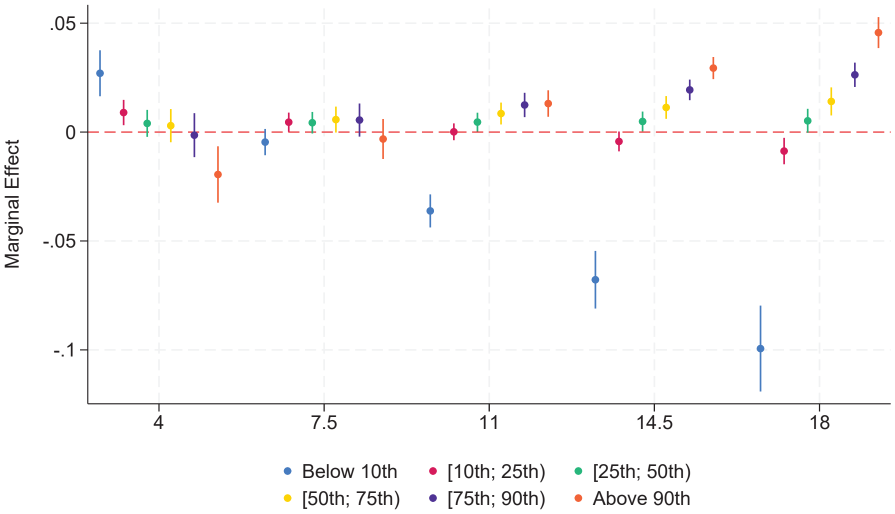
(e) Marginal Effect SE

Figure 38: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the temperature distribution.

6.9.5 Pooled EU additional results, productivity heterogeneity (VA and TFP)



(a) Marginal effect VA

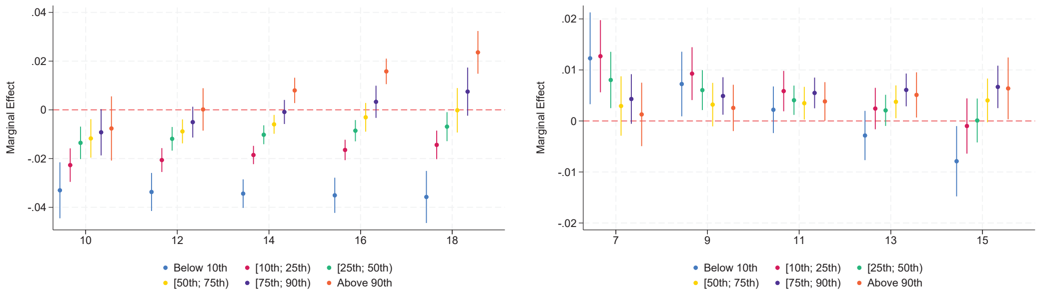


(b) Marginal effect TFP

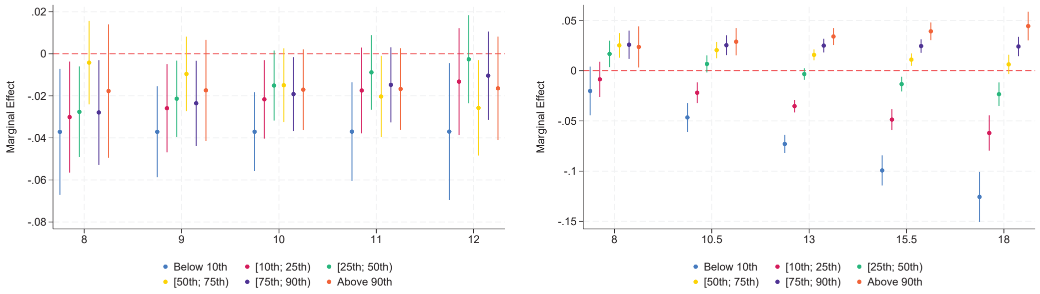
Figure 39: Marginal effect of an extra $1^{\circ}C$ in yearly average temperature on the growth rate of value added (a) and TFP (b) accounting for productivity heterogeneity (firm grouped according to their average TFP). Results from the quadratic model with firm and industry-year FE.

6.9.6 Country-level additional results, TFP heterogeneity

The country-specific damages heterogeneity related to the TFP categories reported in figure 40 are generally consistent with both the country-level pooled analysis and the other sources of damages heterogeneity highlighted so far, with relevant differences between the analysed countries. Similar to the pooled results presented in the previous section, the disaggregated country-level estimates related to TFP categories are unequivocal. On the one hand, most productive firms seem to be generally shielded by, or even benefit from, higher temperature across the whole temperature support, characterised by either positive or non-significant effects. On the other hand, least productive firms are consistently negatively impacted across most countries and over a large part of the temperature support.



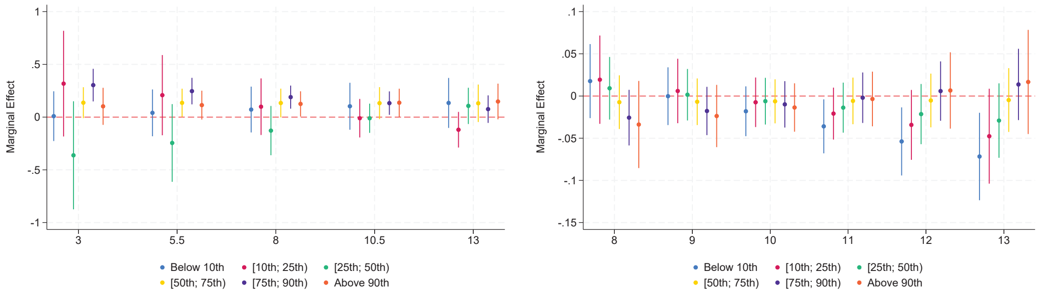
(a) Marginal Effect ES (b) Marginal Effect FR



(c) Marginal Effect GB (d) Marginal Effect IT

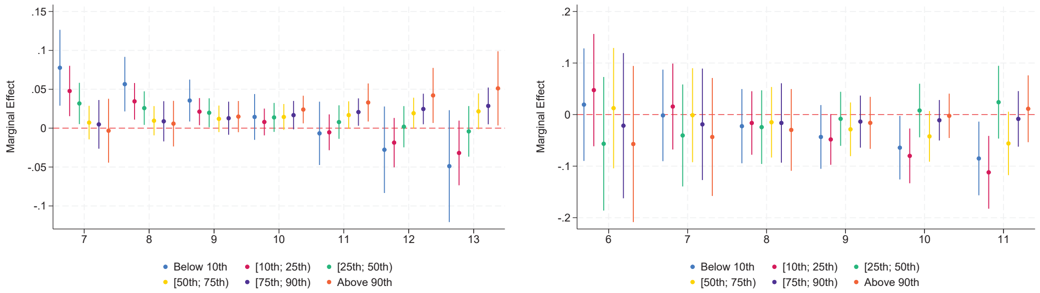
Figure 40: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output accounting for firm size heterogeneity. Results from the quadratic model with firm and industry-year and standard errors clustered at the Nuts 3 level, FE plotted over country-specific temperature supports.

Specifically, in terms of the four countries discussed in the main body, least productive firms are significantly negatively impacted by higher temperature across the whole temperature support in Italy (figure 40d), Spain (figure 40a), and the UK (figure 40c). In France (figure 40b) this effect is negative only at higher temperature and positive at lower temperature. Most productive firms instead, seem to be positively affected by higher temperature over the whole distribution in Italy, and at high temperature in France and Spain. These "leaders" firms are not significantly affected by higher temperature in the colder areas of Spain and in generally in the UK. It is worth highlighting that, although the results in the UK are clear for least productive firms, they are more uncertain for the other TFP categories. The results for the remaining countries reported in figures 41 and 42 are also consistent with both the pooled results and the previous country-level analysis. In general, the marginal effect of an additional $1°C$ in yearly average temperature is positive or not statistically significant for most productive firms and negative, and usually statistically significant for least productive firms.



(a) Marginal Effect AT

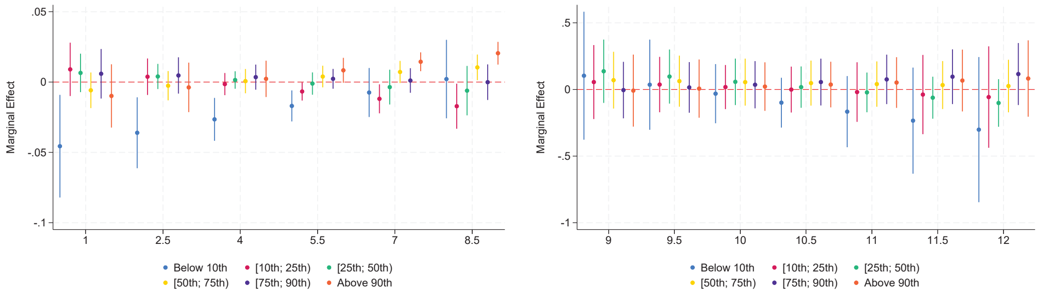
(b) Marginal Effect BE



(c) Marginal Effect DE

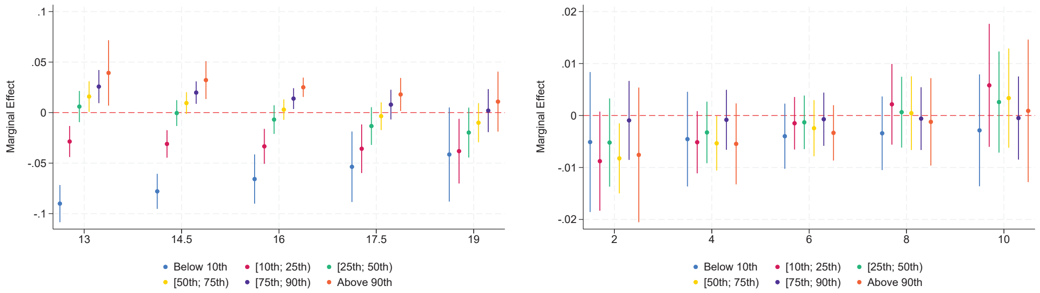
(d) Marginal Effect DK

Figure 41: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the temperature distribution.



(a) Marginal Effect FI

(b) Marginal Effect NL



(c) Marginal Effect PT

(d) Marginal Effect SE

Figure 42: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the temperature distribution.

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