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Heterogeneous effects of weather shocks on firm economic performance

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Latest Version

Abstract

This paper provides novel firm-level estimates of the economic damages caused by temperature shocks to European firms. I rely on a panel data analysis to show wide heterogeneities in the impact of temperature shocks, which depend on firm characteristics. This paper reveals the importance of micro-level data to reduce the uncertainty in climate damages estimates, as the average relationship between temperature and economic outcomes masks firms' different susceptibilities to weather shocks. These create both winners and losers, harming less productive and smaller firms, particularly those in warmer regions, while benefiting more productive ones. This paper highlights the distributional effects of climate change, and offers insights for targeted adaptation policies.

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

Climate change, with its profound socioeconomic impacts (Carleton and Hsiang, 2016), has been described as the greatest market failure in history (Stern, 2006). As CO_2 emitters fail to internalise the socioeconomic costs of their emissions, government intervention becomes essential. Identifying optimal climate policies is particularly challenging, especially given the temporal mismatch between immediate CO_2 reduction and future climate damages, which requires careful trade-offs. Because climate damages are crucial to informing climate policies, accurately quantifying these damages is essential for an effective policy intervention[1]. However, modelling climate damages has proven to be complex, widely debated (Weitzman, 2009; Pindyck, 2013; Dietz and Stern, 2015; Stern and Stiglitz, 2021), and subject to considerable uncertainty (National Academies of Sciences, 2017). Given the uncertainty in climate projections (Murphy et al., 2004; Calel et al., 2020), advancing our understanding of climate damages is essential to reducing the overall uncertainty surrounding future damages (Auffhammer, 2018; Rising et al., 2022).

Existing climate damages estimates, derived from historical weather and climate events (Hsiang, 2016), exhibit significant uncertainty and substantial variation across studies (Burke et al., 2015; Klenow et al., 2023; Kotz et al., 2024; Bilal and Känzig, 2024). A primary source of this uncertainty lies in the underlying heterogeneity of weather effects, as averaging-out diverse impacts can potentially lead to imprecise estimates. Beyond statistical concerns, exploring this heterogeneity is crucial for understanding the distributional effects of climate change. If damages disproportionately impact economically disadvantaged and socially vulnerable communities, climate change will exacerbate social inequalities[2]. Finally, identifying the areas and entities facing the highest costs of climate change enables policymakers to design targeted and effective adaptation strategies.

This paper provides the first firm-level analysis of the effects of weather shocks on the performance of European firms. The European focus is relevant because aggregate studies often suggest that temperature fluctuations do not significantly affect the European economy (Burke et al., 2015; Acevedo et al., 2020)[3], with some even indicating positive impacts in certain areas (Groom et al., 2023). Exploring sources of heterogeneity enables us to determine whether such damages are genuinely limited, or whether different effects confound aggregate estimates. This firm-leval analysis delves into the within-region distribution of economic activities, to determine whether aggregate results adequately capture the impact of temperature on economic outputs, or if they instead mechanically average out heterogeneous underlying responses[4]. Furthermore, if heterogeneous responses are present, this paper identifies their economic drivers, thereby clarifying how climate effects diverge across firms.

To address these question, I generate baseline results at the pooled level, establishing a foundation for comparison with prior studies. Consistent with previous research, these results reveal an inverted-U-shaped relationship between temperature and economic outcomes, although the marginal effects are statistically insignificant. I further introduce interactions between weather variables and firm characteristics, revealing substantial heterogeneity in climate damages that potentially explains the insignificance of the pooled results. Low-productive firms consistently experience negative impacts from rising temperature, albeit with some exceptions. In contrast, high-productive firms generally appear to be better shielded from weather shocks. Importantly, accounting for TFP heterogeneity significantly reduces the uncertainty around climate damages, as indicated by narrower

[1] Climate damages are also a key input to the Social Cost of Carbon (SCC), which guides optimal carbon pricing (Stern, 2006; Pizer et al., 2014; Nordhaus, 2017; Rennert et al., 2022).

[2] Although between-country heterogeneity is well-documented, within-country evidence remains limited.

[3] Europe's developed economies and temperate climates are usually associated with lower climate damages.

[4] Additionally, as discussed in section 2.2, firm-level data enable a closer match between economic activity and relevant weather data, reducing aggregation bias (Burke and Tanutama, 2019).

confidence intervals, potentially lowering the overall uncertainty in climate damage projections.

This paper contributes to different literature. First, this work contributes to climate economics by exploring how firm heterogeneity shapes climate damages, enhancing our understanding of micro-level impacts on macro-level outcomes. This result has relevant policy implications as it allows policymakers to target adaptation policies towards the most impacted firms. Second, it contributes to climate econometrics by discussing the two primary econometric approaches for estimating temperature impacts - temperature polynomials and temperature bins - and addresses, in the firm-level context, methodological drawbacks raised in recent studies (Newell et al., 2021). Third, beyond its relevance to the applied climate economics literature, this research contributes to the broader discussions on firm dynamism (Decker et al., 2016), firm inequality (De Loecker et al., 2022), and aggregate productivity (Foster et al., 2001)[5]. By examining climate impacts across productivity categories, this analysis sheds light on the possible drivers of the aggregate productivity slowdown in Europe.

Climate econometrics leverages changes in weather realisations to identify the causal effect of climate on various socioeconomic variables (Dell et al., 2014)[6], agricultural output (Deschênes and Greenstone, 2007; Schlenker and Roberts, 2009; Burke and Emerick, 2016), industrial output (Graff Zivin and Kahn, 2016), labour productivity (Graff Zivin and Neidell, 2014; Somanathan et al., 2021), natural capital (Benmir et al., 2024), and economic growth (Dell et al., 2012; Burke et al., 2015; Acevedo et al., 2020). This literature relies on reduced form models exploiting exogenous weather variables and fixed effects (Hsiang, 2016) yielding plausibly exogenous variation of weather over time[7]. The relevant estimates are thus identified through idiosyncratic weather shocks[8]. Within this literature, Dell et al. (2012) identify negative linear effects of temperature on aggregate output for poor countries, while Burke et al. (2015) find that the global relationship between temperature and GDP growth is non-linear and concave, following an inverted-U shape.

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 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). In Europe, Groom et al. (2023) report a nonlinear relationship opposite to the literature, highlighting the importance of disentangling aggregate effects. Nevertheless, regional analysis still lacks sufficient granularity to capture critical economic dynamics affecting climate damages estimates. Moreover, identifying vulnerability heterogeneity at a more granular level provides policymakers with insights for tailoring more effective adaptation policies.

Since Melitz (2003) emphasised intra-industry heterogeneous firms' responses to economic shocks, firm-level analysis has become central in economic research. Climate econometrics has recently embraced this approach. Results consistent with the aggregate studies are found for medium and large firms in China (Zhang et al., 2018; Chen and Yang, 2019), in a sample of manufacturing and service firms from various countries (Nath, 2020), and in Italian firms (Caggese et al., 2023), whereas no significant effect appears on public firm sales in the US (Addoum et al., 2020). Highlighting how weather shocks vary across industries and regions shed light on how

[5] Caggese et al. (2023) estimate aggregate productivity losses from firm-level damages.

[6] 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)

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

[8] 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.

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

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[9]. All financial variables, except for labour, are adjusted to 2010 prices using industry-level deflators from OECD STAN[10]. 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[11]. 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[12] 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)[13]. 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

[9] Wooldridge (2009) extends the two-step estimation procedures from Olley and Pakes (1996) and Levinsohn and Petrin (2003), implementing a two-equations GMM estimation leading to more efficient estimators.

[10] 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.

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

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

[13] 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.

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 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.

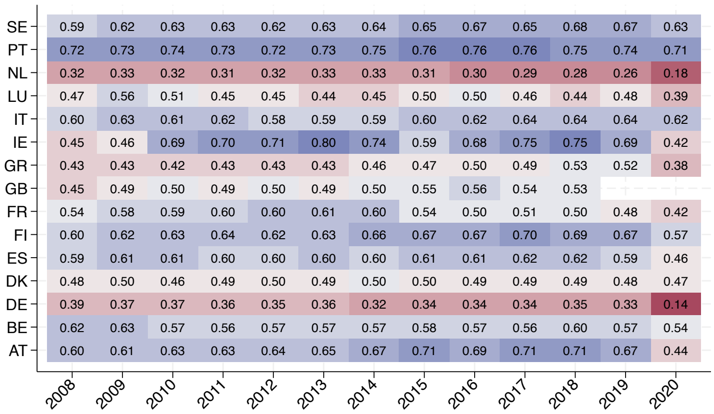


Figure 1: Coverage of the aggregate economy from Orbis data in terms of gross output. The values report for each country-year the ratio (bounded between 0 and 1) between aggregate gross output for the firms included in the sample and the economy-wide gross output. The economy-wide gross output values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

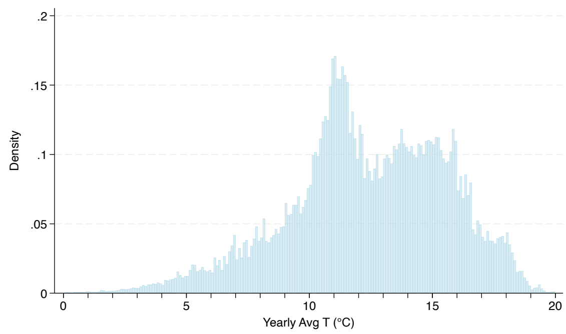
While the overall number of observations provides some insight, the real focus of this work is on understanding the underlying heterogeneity. Table 5 breaks down observations across broadly defined sectors, aggregating the NACE revision 2 level 2 sectors into the broader NACE revision 2 level 1 for clarity. 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[14]. Not only does the presence of SMEs increases over time, but their relative share 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).

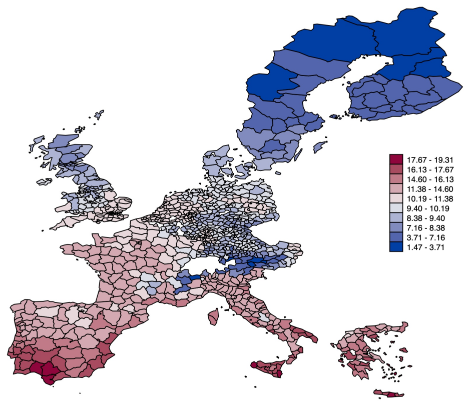
An additional multi-step process ensures the accuracy of reported coordinates[15]. I devised a simple procedure to remove implausible values at the Nuts 3 and city levels. After matching firms with Nuts 3-level shapefiles, I marked coordinates as missing if falling outside their region. Subsequently, 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 B.

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 $(°C)$ 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 $(8°C)$ and $(19°C)$. As expected, the distribution

[14]Firm size is based on the number of employees according to the European Commission classification.
[15]Coordinates for AT, DE, FI, GR, and SE are unavailable in Orbis Historical, geocoded using OpenCage.

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. 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[16]. 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[17]. 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.

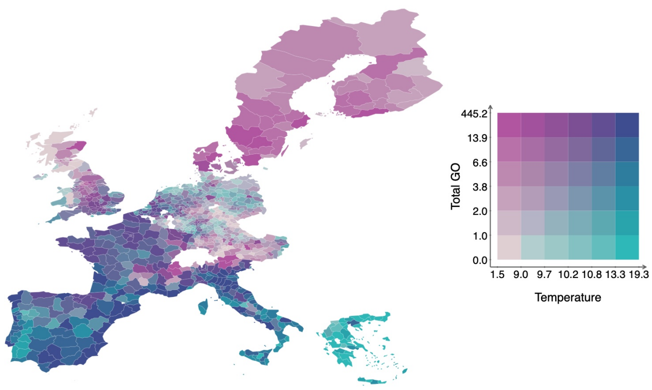


Figure 3: Bivariate Spatial distribution of yearly average temperature and total gross outpus across firm-year observations aggregated at the Nuts 3 level in Europe. The legend reports yearly average temperature on the X-axis and total GO on the Y-axis. Colours from bottom to top of the legend indicate 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[18]. 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.

[16]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.

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

[18]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)[19]. 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:

[19] 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 $T_{i,t}$,

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

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

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

$f(P_{i,t})$ 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 restrictive country-industry-year fixed effect $\lambda_{c,n,t}$ that accounts for unobserved time-varying, and country-specific 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 which are allowed to differ across countries and accounting for macroeconomic 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, on the growth rate of firms' economic variables (in percentage points), 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)[20]. Nonlinear models with fixed-

[20]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

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 identify the functional form that most accurately captures the relationship between temperature and firm-level economic performance. I employ post-estimation tests 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. 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 C 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[21].

The results from the model selection criteria reported in table 8 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, a more pronounced impact is observed with 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 3.5% to 1.9%. When only models with two lags are considered, all the selection criteria tend to favour a second-order polynomial, due to the most significant relative mean decrease by 0.00012%, 0.000057%, and 0.00944% for the AIC, BIC, and CV respectively. A quadratic model provides adequate model flexibility 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:

$$\Delta Y_{i,t} = \underset{(1\times2)(2\times1)}{\boldsymbol{\beta'}\ \boldsymbol{T_{i,t}}} + \sum_{\ell=1}^{2} \underset{(1\times2)\ (2\times1)}{\boldsymbol{\gamma'_\ell}\ \boldsymbol{T_{i,t-l}}} + \underset{(1\times2)(2\times1)}{\boldsymbol{\psi'}\ \boldsymbol{P_{i,t}}} + \delta_i + \lambda_{c,n,t} + \varepsilon_{i,t} \tag{10}$$

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

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variable and identifies deviations from the mean of the sample as a whole. The GNL implies that the marginal 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 $\overline{T_i}$.

[21] I used a cloud computing system set with 2 cores of CPU and 80 GB of RAM, which ran for 4 days, 17 hours and 32 minutes.

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[22]. 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

$$y_{i,t} = \rho_i y_{i,t-1} + \epsilon_{i,t} \tag{11}$$

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 in climate econometrics by Burke et al. (2015)[23]. 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 D.

Finally, to identify the heterogeneous economic impacts of higher temperature I interact the variables in equation 10 with different variables identifying firms characteristics

$$\Delta Y_{i,t} = \underset{(1\times2)}{\boldsymbol{\beta'}}\underset{(2\times1)}{\boldsymbol{T_{i,t}}} + \sum_{\ell=1}^{2} \underset{(1\times2)}{\boldsymbol{\gamma'_\ell}}\underset{(2\times1)}{\boldsymbol{T_{i,t-l}}} + (\underset{(1\times2)}{\boldsymbol{\beta'}}\underset{(2\times1)}{\boldsymbol{T_{i,t}}}) \cdot C_{i,t} + (\sum_{\ell=1}^{2} \underset{(1\times2)}{\boldsymbol{\gamma'_\ell}}\underset{(2\times1)}{\boldsymbol{T_{i,t-l}}}) \cdot C_{i,t} + \underset{(1\times2)}{\boldsymbol{\psi'}}\underset{(2\times1)}{\boldsymbol{P_{i,t}}} + \delta_i + \lambda_{c,n,t} + \varepsilon_{i,t} \tag{12}$$

where $C_{i,t}$ identifies firm i category in year t. The resulting marginal effects quantify the additional effect of an extra $1°C$ 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

[22]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 $V[\hat{\boldsymbol{\beta}}]$.

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

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[24]. 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 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 presented here represent the average effect across the pooled sample, which includes all countries and firms characteristics. To mitigate bias from extreme values, I exclude firms located in areas falling within the top and bottom percentiles of the temperature distribution. Table 1 reports the results from the quadratic model defined in equation 10. According to these estimates, temperature does not seem to have a substantial effect on firms' economic performance. The marginal effects of temperature on the growth rate of these variables, in terms of percentage points, are generally not statistically significant. Moreover, even when statistical significance is present - such as for GO and K - the effects are economically negligible. The primary objective of this section is to explore the timing and persistence of temperature impacts on firms' economic outcomes.

The contemporaneous effect of temperature $T_{i,t}$ is economically negligible and statistically insignificant across all dependent variables except for GO and K. Given the similar magnitude of these two effects, K may be the primary channel through which temperature shocks impact GO. The effect on K can be attributed to reductions in capital stock being more readily observable by firms, and accounted for in their balance sheets. In contrast, negative labor shocks, although likely to affect firm performance, are mitigated by rigid labor contracts that are less responsive to short-term weather fluctuations. For $T_{i,t-1}$, the effects are generally not statistically significant, indicating that past temperature shocks do not seem to have a lasting impact on firms' performance. Once again, the only exception is K, which consistently shows statistically significant estimates over time. This persistence may be driven by the fact that negative shocks to capital are more difficult to restore, possibly due to limited financial resources or greater financial constraints.

[24]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.

	(1) ΔGO	(2) ΔVA	(3) ΔTFP	(4) ΔL	(5) ΔK	(6) ΔM
T	0.0098**	0.0043	0.0015	0.00063	0.0096***	0.0015
	(0.0042)	(0.0037)	(0.0029)	(0.0027)	(0.0027)	(0.0030)
T^2	-0.00040**	-0.00024	-0.00013	-0.000066	-0.00035***	-0.00011
	(0.00016)	(0.00015)	(0.00011)	(0.00012)	(0.00011)	(0.00012)
$(\ell 1)T$	0.00078	-0.0056	-0.0029	-0.0088***	0.0097***	-0.0049
	(0.0051)	(0.0048)	(0.0045)	(0.0024)	(0.0032)	(0.0040)
$(\ell 1)T^2$	-0.00011	0.000031	0.000033	0.00011	-0.00034***	0.00012
	(0.00021)	(0.00020)	(0.00018)	(0.00011)	(0.00012)	(0.00016)
$(\ell 2)T$	0.0047	0.0012	-0.00090	0.0011	0.011***	0.0049*
	(0.0042)	(0.0045)	(0.0046)	(0.0023)	(0.0032)	(0.0029)
$(\ell 2)T^2$	-0.00023	-0.000099	-0.0000044	-0.000024	-0.00037***	-0.00015
	(0.00020)	(0.00021)	(0.00020)	(0.00010)	(0.00013)	(0.00014)
P	-0.017***	-0.014**	-0.013**	-0.0081*	0.0023	-0.017***
	(0.0062)	(0.0072)	(0.0065)	(0.0047)	(0.0038)	(0.0060)
P^2	0.0057***	0.0049**	0.0044*	0.0018	0.0015	0.0055***
	(0.0022)	(0.0025)	(0.0023)	(0.0018)	(0.0012)	(0.0021)
$Constant$	-0.087	0.063	0.052	0.091**	-0.17***	0.013
	(0.073)	(0.068)	(0.060)	(0.037)	(0.052)	(0.052)
Firm FE	Yes	Yes	Yes	Yes	Yes	Yes
Cou-Ind-Year FE	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.16	0.14	0.12	0.14	0.15	0.15
N	43,010,224	32,189,101	18,442,532	25,570,937	38,146,624	31,095,285

Standard errors in parentheses
$^{*}\ p < 0.10$, $^{**}\ p < 0.05$, $^{***}\ p < 0.01$

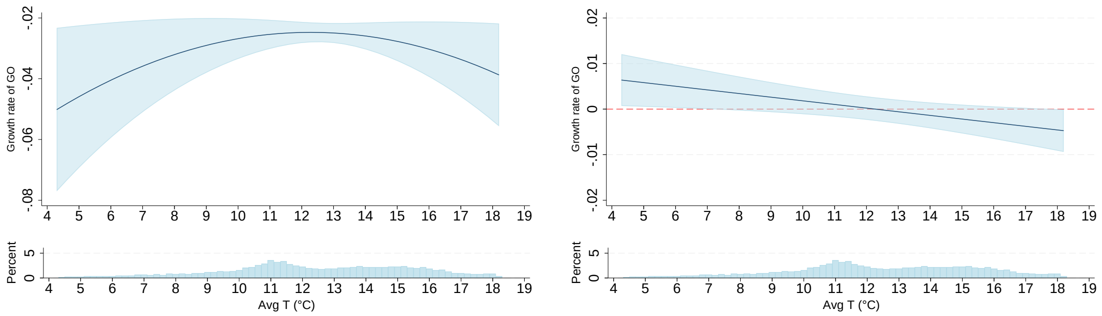
Table 1: Point estimates and standard errors from the regressions of weather variables on the growth rates of GO, VA, TFP, L, K, and M. Results for the 2^{nd} order polynomial model with firm and country-industry-year FE, standard errors clustered at the Nuts 3 level.

As discussed in section 3, comparing the estimates over time helps to determine 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 β' and lagged $\sum_{\ell \geq 1}^{L} \gamma_\ell$ estimates had approximately equal magnitudes but opposite signs. As shown in table 1, the linear estimates for $T_{i,t-1}$ are positive for GO and K and negative for VA, TFP, L, and M, while those for $T_{i,t-2}$ are positive for all variables except TFP. Although generally not statically significant, these results seem to suggest persistent growth effects for GO and K, while VA, TFP[25], L, and M exhibit more transitory effects due to the observed sign-reversal. However, this finding may be reversed for firms located in warmer areas by the positive quadratic terms. To better understand how these effects vary across the temperature distribution, the remainder of this section presents the marginal effect over the temperature support, discussing the potential drivers of these differences.

Figure 4 presents the contemporaneous prediction 4a and the marginal effect 4b of temperature on the growth rate of GO. For presentational purposes, I plot the results excluding the top and bottom percentiles of the temperature distribution, although these firms are present in the estimated sample. Figure 4a presents the predicted outcomes from equation 10, with temperature varying across its distribution while holding the other covariates constant at their average values. The figure shows an inverted-U-shaped (concave) relationship between the two variables, consistently with the findings from the existing literature. Firms throughout the temperature distribution are associated with negative growth rates, with more pronounced negative effects observed in areas with

[25] Although the marginal effect of $T_{i,t-2}$ is negative for TFP, its magnitude is approximately zero.

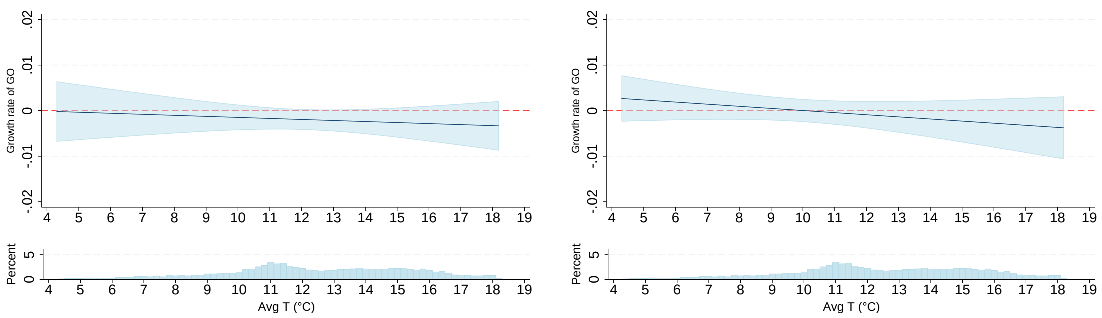
both lower and higher yearly average temperature. However, as marginal effects provide more valuable insights, figure 4b reports the contemporaneous marginal effect of a $1°C$ increase in temperature across the temperature distribution. In line with previous research, the marginal effect of temperature is downward-sloping, though it is generally economically insignificant. Moreover, since the relationship is flat in the middle, the overall effect - combining the linear and quadratic coefficients - is generally statistically insignificant.



(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 country-industry-year FE, standard errors clustered at the Nuts 3 level.

Figure 5 reports the lagged marginal effects of temperature on firm GO. The marginal effects of $T_{i,t-1}$ and $T_{i,t-2}$ (figures 5a and 5b respectively) are downward-sloping and statistically not significant across the whole temperature distribution, with $T_{i,t-2}$ generally larger in magnitude and exhibiting a steeper slope. Figure 17a highlights an inverted-U-shaped cumulative effect, where firms are associated with negative growth rates throughout the temperature distribution. These predictions are either not statistically different from zero or show large standard errors, reinforcing the conclusion that these estimates are not effective in precisely identifying the effect of weather on firms' performance.



(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 country-industry-year FE, standard errors clustered at the Nuts 3 level.

The cumulative marginal effect reported in figure 17b is generally downward sloping, with positive (negative) estimates in colder (warmer) areas, although statistically insignificant across the entire temperature distribution. Despite being statistically insignificant, these estimates are consistent in sign, showing the lack of the so-called sign-reversal and providing suggestive evidence for the presence of persistent growth effects. As discussed, the marginal effect of temperature is heterogeneous across firms. In this paper, I argue that the overall null average marginal effect may be the result of these heterogeneous impacts, as further supported by the presence of large standard errors, which motivates the empirical analysis presented in the following sections.

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 the European firms present in this sample seem to be more likely to 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[26], 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.

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 E.4.1 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 they also 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 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 12.

[26]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.

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). Unlike 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 1^{st} decile and the $[10^{th}; 25^{th})$ and $[25^{th}; 50^{th})$ categories are characterised by downward-sloping marginal effect functions, with the least-productive firms (1^{st} decile) being remarkably negatively affected when located in warmer areas. This result is particularly relevant to discussions on climate damages uncertainty. As shown by the narrower confidence intervals, accounting for TFP heterogeneity produces more precise estimates, significantly reducing uncertainty.

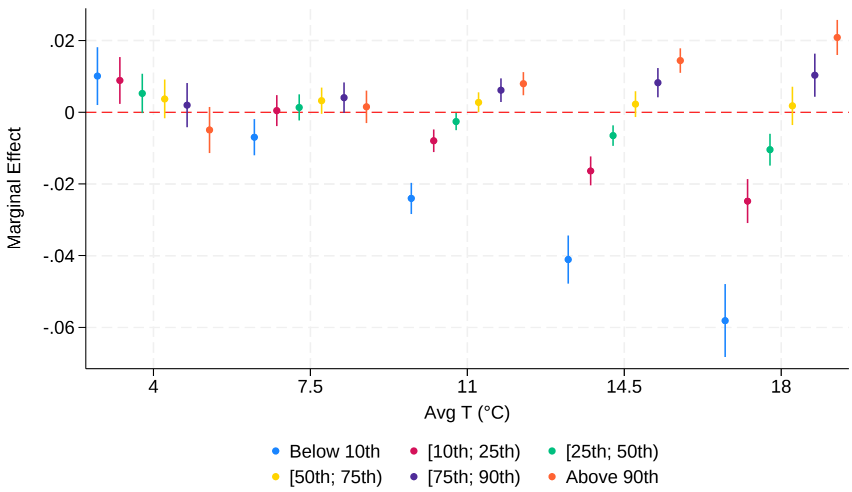
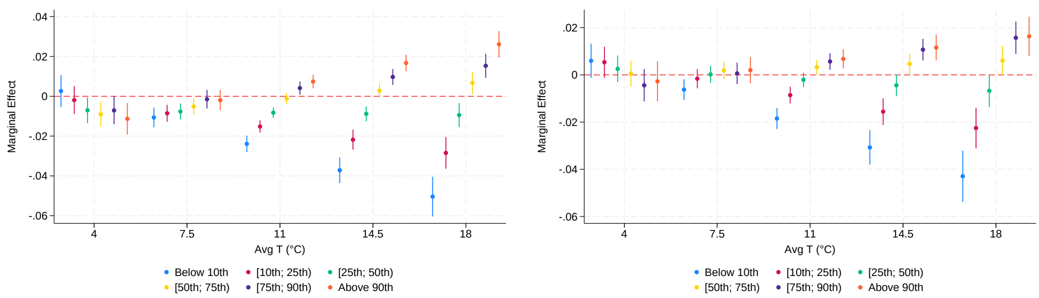


Figure 6: Marginal effect of an extra $1°C$ in contemporaneous yearly average temperature on the growth rate of gross output (log) accounting for productivity heterogeneity (firm grouped according to average TFP). Results from the quadratic model with firm and country-industry-year FE.

The dynamics between the least and most productive firms differ substantially across the temperature distribution. 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 percentage points for firms belonging to the bottom (1^{st}) productivity decile, and reduces the growth rate of GO by 0.5 percentage points for firms belonging to the top (10^{th}) productivity decile, although this result is not significant. When considering areas with an average yearly temperature of $18°C$, an additional $1°C$ in $T_{i,t}$ decreases the growth rate of GO by -5.8 percentage points for firms in the bottom (1^{st}) productivity decile and increases the growth rate of GO by 2.1 percentage points for firms in the top (10^{th}) productivity decile. Although large climate damages estimates are not uncommon in the literature (Ricke et al., 2018; Bilal and Känzig, 2024; Kotz et al., 2024), it is important to clarify that the estimates in this paper reflect the impact of a $1°C$ increase, whereas yearly average temperatures typically fluctuate by only a fraction of a degree.

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 $T_{i,t-2}$ is similar to $T_{i,t-1}$, although the estimates are not significant or precisely zero for most firms located in colder areas. When considered collectively, the cumulative effects over the periods $t = \{0, -1, -2\}$ highlight persistent, although economically negligible, 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. Nevertheless, apart from the signs, the difference in magnitude between the marginal effects of the least and most productive firms is substantial. One concern is that these results could reflect industry composition rather than firms' relative TFP ranking. As TFP distributions vary by industry, TFP categories may correlate with industry-specific exposure to climate damages, potentially biasing the estimates. To address this, section E.4.4 presents additional results in which TFP categories are defined within each industry, accounting for average TFP differences across industries. The estimates remain largely unchanged, confirming that the results presented in this section effectively capture climate damage heterogeneity across TFP categories

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. Furthermore, lower factor misallocation leads to higher aggregate output (Hsieh and Klenow, 2009). However, assessing the related 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 country-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 27b), 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., 2024).

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 welfare-reducing. 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 E.4.5 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 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 accordance with the European Commission classification. Figure 8 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 small firms located in warmer areas are negative and statistically significant. However, even when they are significant, the point estimates are economically small and characterised by relatively large confidence intervals.

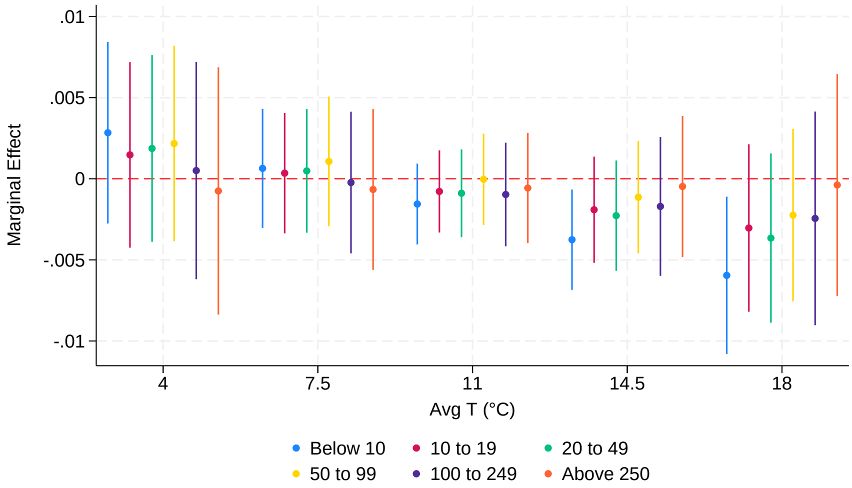
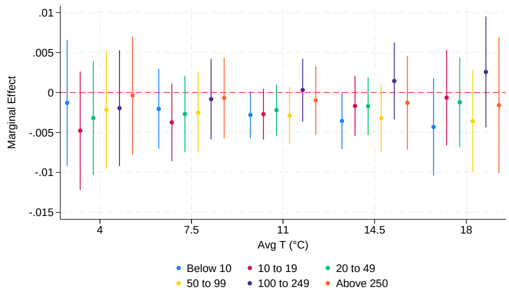
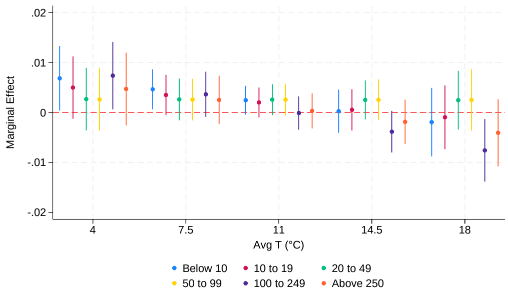


Figure 8: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output (log) across different firm size categories. Results from the quadratic model with firm and industry-year FE.

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 9a is generally flat for all categories throughout the temperature support. Notably, several point estimates tend to have large 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 marginal effect function for $T_{i,t-2}$, presented in figure 9b, is downward-sloping and mostly 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 small firms in warmer areas and insignificant effects for the remaining firms.



(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 size categories. Results from the 2^{nd} order polynomial model with firm and country-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 E.4.6 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.

4.2.3 Industry Heterogeneity

This section extends the discussion on the heterogeneity of the economic effects of temperature fluctuations, with a focus on industry sectors. It is commonly believed that sectors like agriculture, mining, and, to a lesser degree, manufacturing are more vulnerable to rising temperatures, while the service sector is generally considered to be largely insulated from these effects. This is particularly relevant for developed countries, such as those in my sample, where firms typically have greater resources to insulate their economic activities against climate shocks. In this section, I present empirical evidence of industry-specific heterogeneous effects by estimating the marginal effect of higher temperatures within each industry. These estimations are performed by interacting the temperature variables with industry categories[27]. To enhance the clarity and informativeness of the analysis, I aggregate the Nace Revision 2 level 1 industry into six broader industries.

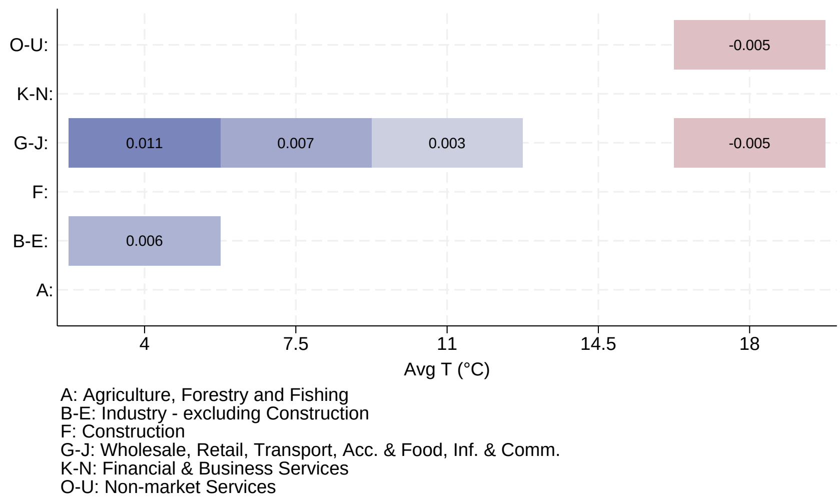


Figure 10: Marginal effect of an extra $1°C$ in contemporaneous yearly average temperature on the growth rate of gross output (log) accounting for industry heterogeneity (Nace 2 level 1). Results from the quadratic model with firm and country-industry-year FE.

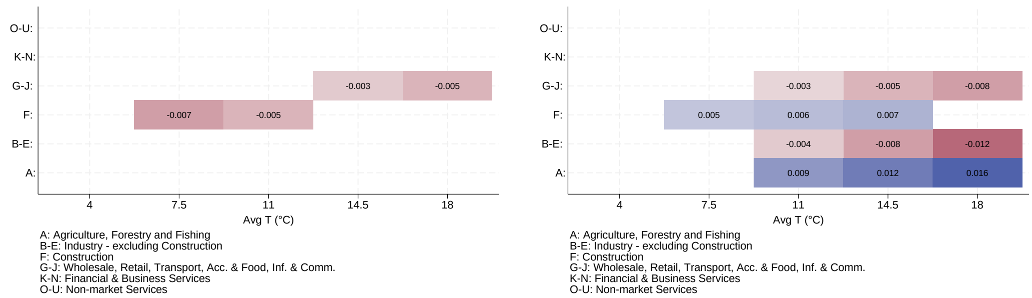
These broadly defined sectors are likely characterized by significant heterogeneity in underlying climate damages, affecting both statistical power and significance. Thus, in this section I only report the statistically significant (at the 10%) point estimates. Figure 10 illustrates the resulting marginal effects of contemporaneous temperature $T_{i,t}$, where the colours reflect the sign and magnitude of the point estimates. Figures 25 and

[27]This procedure requires substantial computational power, as the estimation requires 200 Gb of RAM and runs for 167.5 hours.

26 provide the whole set of coefficients and the relevant p-values, respectively. These estimates are generally positive (negative) in cold (warm) areas, and mostly characterised by downward-sloping industry-specific marginal effect functions over the temperature support. However, these estimates are only significant for the G-J (Wholesale, Retail, Transport, Accommodation & Food, Information & Communication) industry groups, B-E (Industry - excluding Construction) in cold areas and O-U (Non-market Services) in warm areas.

The industry-specific estimates highlight a delayed negative effect of higher temperature on firm GO (figure 11), particularly with respect to $T_{i,t-2}$ in the warmer part of the temperature distribution. The marginal effect of an extra $1°C$ in temperature is negative and statistically significant for the sectors B-E and G-J, while it is positive for F (Construction) and A (Agriculture Forestry and Fishing). The lack of significant effects for the service sectors is unsurprising, as these activities are typically conducted indoors in temperature-controlled environments. The negative estimates for sectors B-E and G-J are intuitive and align with expectations. These sectors are characterised, on average, by a lower penetration of adaptation technologies, such as AC, and are often more dependent on local supply-chain, which are also vulnerable to the same local weather shocks.

It is worth highlighting, especially for the wholesale and retail sectors within the G-J group, that temperature shocks can affect firm performance not only through supply-side impacts but also through a reduction in demand. For example, customers may reduce outdoor shopping during periods of extreme heat. Moreover, a significant portion of the G-J sectors is comprised of industries related to tourism. The tourism sector is particularly vulnerable to higher temperatures because it predominantly involves outdoor activities, limiting adaptation possibilities. As a result, individuals may respond to rising temperatures by opting for cooler destinations, further dampening demand.



(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 industry categories. Results from the 2^{nd} order polynomial model with firm and country-industry-year FE, standard errors clustered at the Nuts 3 level.

On the contrary, the outdoor Agriculture forestry and fishing (A) and the Construction (F) sectors are unexpectedly characterised by positive marginal effects. Given their outdoor nature and their limited adaptation options, these sectors would typically be expected to suffer from higher temperatures. However, since these firms are located in warmer regions, it is likely they have already implemented adaptation strategies. Additionally, the positive marginal effects may be driven by increased productivity during milder winter temperatures, which could offset the productivity loss during hotter summer months. This assumption is particularly relevant for agriculture, where higher average annual temperatures can boost production—provided the number of growing degree days increases and the negative effects of extreme summer heat can be mitigated, at least partially, through irrigation. This finding is supported by satellite observations showing vegetation greening in Europe

(IPCC, 2019)[28]. It is important to note that these agriculture-related results are specific to Europe and may not align with global estimates, as irrigation capabilities vary significantly between regions.

The results discussed in this section disentangle different, and potentially opposing, heterogeneous effects of temperature that are averaged out in the marginal effects estimated in the pooled analysis. Section E.4.7 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. This lack of effect is likely due to substantial within-industry variability in the relationship between temperature and economic performance. Such variability may stem from either the genuine absence of a significant effect or the limitation that the industry-specific focus may not be the optimal lens to identify the relevant heterogeneity in the damage functions. Thus, further investigations within countries and industry dynamics, such as those presented in previous sections, become necessary to fully understand the relationship between temperature and firms' economic performance.

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 analysis. This study delves into the Burke et al. (2015) specification, discussing its identification strategy and addressing, in the firm-level context, the drawbacks highlighted in the recent literature. 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.

Consistent with prevailing literature (Burke et al., 2015; Chen and Yang, 2019; Acevedo et al., 2020), the empirical findings of this paper reveal an inverted-U-shaped relationship between temperature and economic outcomes for the pooled European sample. However, the pooled estimates are statistically insignificant across the temperature distribution, suggesting that Europe, as a whole, is insulated from the negative impacts of rising temperature. 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. Accounting for TFP heterogeneity produces more precise estimates, significantly reducing climate damages uncertainty. 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. Firm size seems to be relevant only for small firms located in warmer areas, which are negatively impacted by higher temperature. This study explores industry-specific effects, identifying certain sectors as particularly vulnerable to weather shocks, while other seem to benefit from higher temperature.

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

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

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.

References

Acemoglu, D., Johnson, S., and Robinson, J. A. (2002). Reversal of fortune: Geography and institutions in the making of the modern world income distribution. *The Quarterly journal of economics*, 117(4):1231–1294.

Acevedo, S., Mrkaic, M., Novta, N., Pugacheva, E., and Topalova, P. (2020). The effects of weather shocks on economic activity: what are the channels of impact? *Journal of Macroeconomics*, 65:103207.

Acharya, V. V., Eisert, T., Eufinger, C., and Hirsch, C. (2019). Whatever it takes: The real effects of unconventional monetary policy. *The Review of Financial Studies*, 32(9):3366–3411.

Addoum, J. M., Ng, D. T., and Ortiz-Bobea, A. (2020). Temperature shocks and establishment sales. *The Review of Financial Studies*, 33(3):1331–1366.

Adhvaryu, A., Kala, N., and Nyshadham, A. (2022). Management and shocks to worker productivity. *Journal of Political Economy*, 130(1):1–47.

Akaike, H. (1973). Maximum likelihood identification of gaussian autoregressive moving average models. *Biometrika*, 60(2):255–265.

Albert, C., Bustos, P., and Ponticelli, J. (2021). The effects of climate change on labor and capital reallocation. Technical report, National Bureau of Economic Research.

Angrist, J. D. and Pischke, J.-S. (2009). *Mostly harmless econometrics: An empiricist's companion*. Princeton university press.

Athey, S. and Imbens, G. W. (2019). Machine learning methods that economists should know about. *Annual Review of Economics*, 11:685–725.

Auffhammer, M. (2018). Quantifying economic damages from climate change. *Journal of Economic Perspectives*, 32(4):33–52.

Autor, D., Dorn, D., Katz, L. F., Patterson, C., and Van Reenen, J. (2020). The fall of the labor share and the rise of superstar firms. *The Quarterly Journal of Economics*, 135(2):645–709.

Baltagi, B. H. (2008). *Econometric analysis of panel data*, volume 4. Springer.

Barreca, A. I. (2012). Climate change, humidity, and mortality in the united states. *Journal of Environmental Economics and Management*, 63(1):19–34.

Bartelsman, E., Haltiwanger, J., and Scarpetta, S. (2013). Cross-country differences in productivity: The role of allocation and selection. *American economic review*, 103(1):305–334.

Bearpak, T. and Palomba, F. (2024). Time trends in climate impact studies. *Forthcoming*.

Benmir, G., Mori, A., Josselin, R., and Tarsia, R. (2024). Beneath the trees: The influence of natural capital on shadow price dynamics in a macroeconomic model with uncertainty. *Working Paper*.

Bilal, A. and Känzig, D. R. (2024). The macroeconomic impact of climate change: Global vs. local temperature. Technical report, National Bureau of Economic Research.

Bloom, N., Draca, M., and Van Reenen, J. (2016). Trade induced technical change? the impact of chinese imports on innovation, it and productivity. *The review of economic studies*, 83(1):87–117.

Burgess, R., Deschenes, O., Donaldson, D., and Greenstone, M. (2017). Weather, climate change and death in india. *University of Chicago*, pages 577–617.

Burke, M. and Emerick, K. (2016). Adaptation to climate change: Evidence from us agriculture. *American Economic Journal: Economic Policy*, 8(3):106–140.

Burke, M., González, F., Baylis, P., Heft-Neal, S., Baysan, C., Basu, S., and Hsiang, S. (2018). Higher temperatures increase suicide rates in the united states and mexico. *Nature climate change*, 8(8):723–729.

Burke, M., Hsiang, S. M., and Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, 527(7577):235–239.

Burke, M. and Tanutama, V. (2019). Climatic constraints on aggregate economic output. Technical report, National Bureau of Economic Research.

Burke, M. B., Miguel, E., Satyanath, S., Dykema, J. A., and Lobell, D. B. (2009). Warming increases the risk of civil war in africa. *Proceedings of the national Academy of sciences*, 106(49):20670–20674.

Caggese, A., Chiavari, A., Goraya, S., and Villegas-Sanchez, C. (2023). Climate change, firms, and aggregate productivity. Technical report, Working Paper.

Calel, R., Chapman, S. C., Stainforth, D. A., and Watkins, N. W. (2020). Temperature variability implies greater economic damages from climate change. *Nature communications*, 11(1):5028.

Cameron, A. C. and Miller, D. L. (2015). A practitioner's guide to cluster-robust inference. *Journal of human resources*, 50(2):317–372.

Cameron, A. C. and Trivedi, P. K. (2005). *Microeconometrics: methods and applications*. Cambridge university press.

Card, D. and Dahl, G. B. (2011). Family violence and football: The effect of unexpected emotional cues on violent behavior. *The quarterly journal of economics*, 126(1):103–143.

Carleton, T., Jina, A., Delgado, M., Greenstone, M., Houser, T., Hsiang, S., Hultgren, A., Kopp, R. E., McCusker, K. E., Nath, I., et al. (2022). Valuing the global mortality consequences of climate change accounting for adaptation costs and benefits. *The Quarterly Journal of Economics*, 137(4):2037–2105.

Carleton, T. A. (2017). Crop-damaging temperatures increase suicide rates in india. *Proceedings of the National Academy of Sciences*, 114(33):8746–8751.

Carleton, T. A. and Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, 353(6304):aad9837.

Chatfield, C. (1996). Model uncertainty and forecast accuracy. *Journal of Forecasting*, 15(7):495–508.

Chen, X. and Yang, L. (2019). Temperature and industrial output: Firm-level evidence from china. *Journal of Environmental Economics and Management*, 95:257–274.

Choi, I. (2001). Unit root tests for panel data. *Journal of international money and Finance*, 20(2):249–272.

Collins, J. (1963). On the calculation of the temperature variation of the coefficient of thermal expansion for materials of cubic structure. *Philosophical Magazine*, 8(86):323–332.

Cunsolo, A., Harper, S. L., Minor, K., Hayes, K., Williams, K. G., and Howard, C. (2020). Ecological grief and anxiety: the start of a healthy response to climate change? *The Lancet Planetary Health*, 4(7):e261–e263.

De Loecker, J., Obermeier, T., and Van Reenen, J. (2022). Firms and inequality. *Centre for Economic Performance Discussion Paper, London School of Economics and Poiltical Science*.

De Loecker, J., Obermeier, T., and Van Reenen, J. (2024). Firms and inequality. *Oxford Open Economics*, 3(Supplement):i962–i982.

Decker, R. A., Haltiwanger, J., Jarmin, R. S., and Miranda, J. (2016). Declining business dynamism: What we know and the way forward. *American Economic Review*, 106(5):203–207.

Dell, M., Jones, B. F., and Olken, B. A. (2009). Temperature and income: reconciling new cross-sectional and panel estimates. *American Economic Review*, 99(2):198–204.

Dell, M., Jones, B. F., and Olken, B. A. (2012). Temperature shocks and economic growth: Evidence from the last half century. *American Economic Journal: Macroeconomics*, 4(3):66–95.

Dell, M., Jones, B. F., and Olken, B. A. (2014). What do we learn from the weather? the new climate-economy literature. *Journal of Economic literature*, 52(3):740–798.

Deryugina, T. and Hsiang, S. (2017). The marginal product of climate. Technical report, National Bureau of Economic Research.

Deschênes, O. and Greenstone, M. (2007). The economic impacts of climate change: evidence from agricultural output and random fluctuations in weather. *American economic review*, 97(1):354–385.

Deschênes, O. and Greenstone, M. (2011). Climate change, mortality, and adaptation: Evidence from annual fluctuations in weather in the us. *American Economic Journal: Applied Economics*, 3(4):152–185.

Deschênes, O., Greenstone, M., and Guryan, J. (2009). Climate change and birth weight. *American Economic Review*, 99(2):211–217.

Diebold, F. X. (1998). *Elements of forecasting*. Citeseer.

Dietz, S. and Stern, N. (2015). Endogenous growth, convexity of damage and climate risk: how nordhaus' framework supports deep cuts in carbon emissions. *The Economic Journal*, 125(583):574–620.

Fadic, M., Garda, P., and Pisu, M. (2019). The effect of public sector efficiency on firm-level productivity growth: The italian case.

Foster, L., Haltiwanger, J. C., and Krizan, C. J. (2001). Aggregate productivity growth: Lessons from microeconomic evidence. In *New developments in productivity analysis*, pages 303–372. University of Chicago Press.

Geisser, S. (1975). The predictive sample reuse method with applications. *Journal of the American statistical Association*, 70(350):320–328.

Gopinath, G., Kalemli-Özcan, Ş., Karabarbounis, L., and Villegas-Sanchez, C. (2017). Capital allocation and productivity in south europe. *The Quarterly Journal of Economics*, 132(4):1915–1967.

Graff Zivin, J., Hsiang, S. M., and Neidell, M. (2018). Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists*, 5(1):77–105.

Graff Zivin, J. and Kahn, M. E. (2016). Industrial productivity in a hotter world: the aggregate implications of heterogeneous firm investment in air conditioning. Technical report, National Bureau of Economic Research.

Graff Zivin, J. and Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, 32(1):1–26.

Granger, C. W. and Newbold, P. (1974). Spurious regressions in econometrics. *Journal of econometrics*, 2(2):111–120.

Greene, W. H. (2003). *Econometric analysis*. Pearson Education India.

Groom, B., Linsenmeier, M., and Roth, S. (2023). Some like it cold: Heterogeneity in the temperature-economy relationships of europe.

Harari, M. and La Ferrara, E. (2018). Conflict, climate, and cells: a disaggregated analysis. *Review of Economics and Statistics*, 100(4):594–608.

Hersbach, H., Bell, B., Berrisford, P., Biavati, G., Horányi, A., Muñoz Sabater, J., Nicolas, J., Peubey, C., Radu, R., Rozum, I., et al. (2019). Era5 monthly averaged data on single levels from 1979 to present. *Copernicus Climate Change Service (C3S) Climate Data Store (CDS)*, 10:252–266.

Hersbach, H., Bell, B., Berrisford, P., Hirahara, S., Horányi, A., Muñoz-Sabater, J., Nicolas, J., Peubey, C., Radu, R., Schepers, D., et al. (2020). The era5 global reanalysis. *Quarterly Journal of the Royal Meteorological Society*, 146(730):1999–2049.

Hsiang, S. (2016). Climate econometrics. *Annual Review of Resource Economics*, 8:43–75.

Hsieh, C.-T. and Klenow, P. J. (2009). Misallocation and manufacturing tfp in china and india. *The Quarterly journal of economics*, 124(4):1403–1448.

Im, K. S., Pesaran, M. H., and Shin, Y. (2003). Testing for unit roots in heterogeneous panels. *Journal of econometrics*, 115(1):53–74.

IPCC (2019). Climate change and land: an ipcc special report on climate change, desertification, land degradation, sustainable land management, food security, and greenhouse gas fluxes in terrestrial ecosystems. *In press*.

James, G., Witten, D., Hastie, T., Tibshirani, R., et al. (2013). *An introduction to statistical learning*, volume 112. Springer.

Kalemli-Ozcan, S., Sorensen, B., Villegas-Sanchez, C., Volosovych, V., and Yesiltas, S. (2015). How to construct nationally representative firm level data from the orbis global database: New facts and aggregate implications. Technical report, National Bureau of Economic Research.

Kalkuhl, M. and Wenz, L. (2020). The impact of climate conditions on economic production. evidence from a global panel of regions. *Journal of Environmental Economics and Management*, 103:102360.

Klenow, P. J., Nath, I. B., and Ramey, V. A. (2023). How much will global warming cool global growth? Technical report, Working paper.

Kotz, M., Levermann, A., and Wenz, L. (2024). The economic commitment of climate change. *Nature*, 628(8008):551–557.

Kotz, M., Wenz, L., Stechemesser, A., Kalkuhl, M., and Levermann, A. (2021). Day-to-day temperature variability reduces economic growth. *Nature Climate Change*, 11(4):319–325.

Leeb, H. and Pötscher, B. M. (2005). Model selection and inference: Facts and fiction. *Econometric Theory*, 21(1):21–59.

Levinsohn, J. and Petrin, A. (2003). Estimating production functions using inputs to control for unobservables. *The review of economic studies*, 70(2):317–341.

Lilja, D. J. (2005). *Measuring computer performance: a practitioner's guide*. Cambridge university press.

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

McIntosh, C. T. and Schlenker, W. (2006). Identifying non-linearities in fixed effects models. *UC-San Diego Working Paper*.

Melitz, M. J. (2003). The impact of trade on intra-industry reallocations and aggregate industry productivity. *econometrica*, 71(6):1695–1725.

Mendelsohn, R., Nordhaus, W. D., and Shaw, D. (1994). The impact of global warming on agriculture: a ricardian analysis. *The American economic review*, pages 753–771.

Mérel, P. and Gammans, M. (2021). Climate econometrics: Can the panel approach account for long-run adaptation? *American Journal of Agricultural Economics*, 103(4):1207–1238.

Miguel, E., Satyanath, S., and Sergenti, E. (2004). Economic shocks and civil conflict: An instrumental variables approach. *Journal of political Economy*, 112(4):725–753.

Mortier, R. M., Orszulik, S. T., and Fox, M. F. (2010). *Chemistry and technology of lubricants*, volume 107115. Springer.

Murphy, J. M., Sexton, D. M., Barnett, D. N., Jones, G. S., Webb, M. J., Collins, M., and Stainforth, D. A. (2004). Quantification of modelling uncertainties in a large ensemble of climate change simulations. *Nature*, 430(7001):768–772.

Nath, I. B. (2020). The food problem and the aggregate productivity consequences of climate change. Technical report, National Bureau of Economic Research.

National Academies of Sciences (2017). *Valuing climate damages: updating estimation of the social cost of carbon dioxide*. National Academies Press.

Newell, R. G., Prest, B. C., and Sexton, S. E. (2021). The gdp-temperature relationship: implications for climate change damages. *Journal of Environmental Economics and Management*, 108:102445.

Nordhaus, W. D. (1991). To slow or not to slow: the economics of the greenhouse effect. *Economic Journal*, 101(407):920–937.

Nordhaus, W. D. (2006). Geography and macroeconomics: New data and new findings. *Proceedings of the National Academy of Sciences*, 103(10):3510–3517.

Nordhaus, W. D. (2017). Revisiting the social cost of carbon. *Proceedings of the National Academy of Sciences*, 114(7):1518–1523.

Norris-Keiller, A. and Van Reenen, J. (2024). Disaster management. Technical report, Centre for Economic Performance, LSE.

Obradovich, N., Migliorini, R., Paulus, M. P., and Rahwan, I. (2018). Empirical evidence of mental health risks posed by climate change. *Proceedings of the National Academy of Sciences*, 115(43):10953–10958.

Olley, G. S. and Pakes, A. (1996). The dynamics of productivity in the telecommunications equipment industry. *Econometrica*, 64(6):1263–1297.

Picard, R. (2019). Geonear: Stata module to find nearest neighbors using geodetic distances.

Pindyck, R. S. (2013). Climate change policy: what do the models tell us? *Journal of Economic Literature*, 51(3):860–872.

Pizer, W., Adler, M., Aldy, J., Anthoff, D., Cropper, M., Gillingham, K., Greenstone, M., Murray, B., Newell, R., Richels, R., et al. (2014). Using and improving the social cost of carbon. *Science*, 346(6214):1189–1190.

Ponticelli, J., Xu, Q., and Zeume, S. (2023). Temperature and local industry concentration. Technical report, National Bureau of Economic Research.

Rennert, K., Errickson, F., Prest, B. C., Rennels, L., Newell, R. G., Pizer, W., Kingdon, C., Wingenroth, J., Cooke, R., Parthum, B., et al. (2022). Comprehensive evidence implies a higher social cost of co2. *Nature*, 610(7933):687–692.

Ricke, K., Drouet, L., Caldeira, K., and Tavoni, M. (2018). Country-level social cost of carbon. *Nature Climate Change*, 8(10):895–900.

Rising, J., Tedesco, M., Piontek, F., and Stainforth, D. A. (2022). The missing risks of climate change. *Nature*, 610(7933):643–651.

Rodrik, D., Subramanian, A., and Trebbi, F. (2004). Institutions rule: the primacy of institutions over geography and integration in economic development. *Journal of economic growth*, 9:131–165.

Schlenker, W. and Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to us crop yields under climate change. *Proceedings of the National Academy of sciences*, 106(37):15594–15598.

Schwarz, G. (1978). Estimating the dimension of a model. *The annals of statistics*, pages 461–464.

Somanathan, E., Somanathan, R., Sudarshan, A., and Tewari, M. (2021). The impact of temperature on productivity and labor supply: Evidence from indian manufacturing. *Journal of Political Economy*, 129(6):1797–1827.

Stern, N. (2006). Stern review: The economics of climate change. *Cambrdige University Press*.

Stern, N. and Stiglitz, J. E. (2021). *The social cost of carbon, risk, distribution, market failures: An alternative approach*, volume 15. National Bureau of Economic Research Cambridge, MA, USA.

Weitzman, M. L. (2009). On modeling and interpreting the economics of catastrophic climate change. *The review of economics and statistics*, 91(1):1–19.

Wooldridge, J. M. (2002). Econometric analysis of cross section and panel data. *MIT press, Cambridge, MA*, 108(2):245–254.

Wooldridge, J. M. (2009). On estimating firm-level production functions using proxy variables to control for unobservables. *Economics letters*, 104(3):112–114.

Zhang, P., Deschenes, O., Meng, K., and Zhang, J. (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million chinese manufacturing plants. *Journal of Environmental Economics and Management*, 88:1–17.

Appendix A 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 A. 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

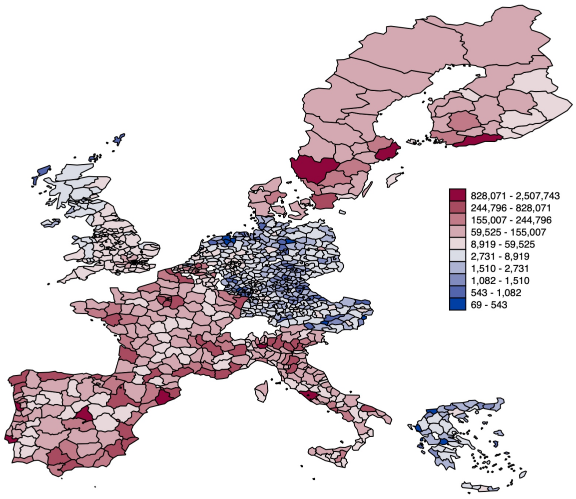
Table 4: Total number of observations across all the European countries available in the sample after the cleaning procedure. Columns 2 to 4 refer to observations with available GO, VA or TFP expressed in logs. Whereas column 1 is the their union (observations with at least one of these variables available).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

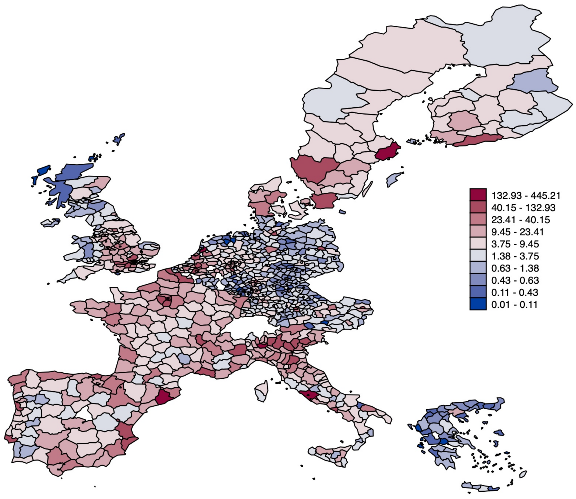
Table 5: Total number of observations by industry, defined by the NACE 2 level 1 sectors. Source: Orbis.

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

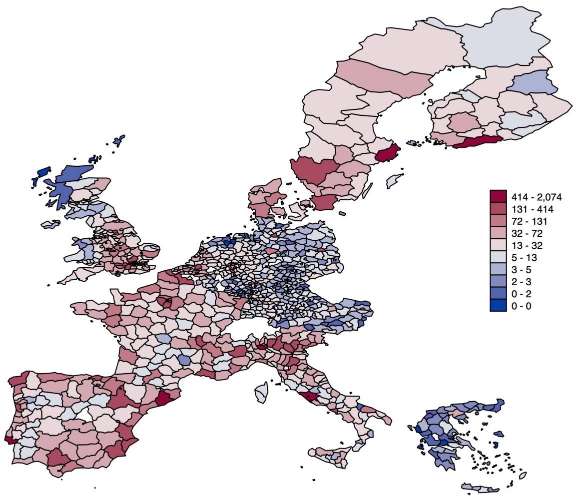
Table 6: Total number of observations by firm size (European Commission classification). For presentational purpose, I report a subset of the available years. Source: Orbis.



(a) Number of firms

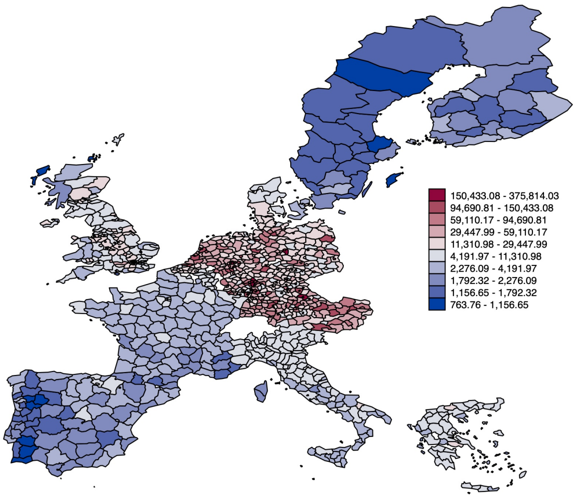


(b) Total gross output (billions of LCU)

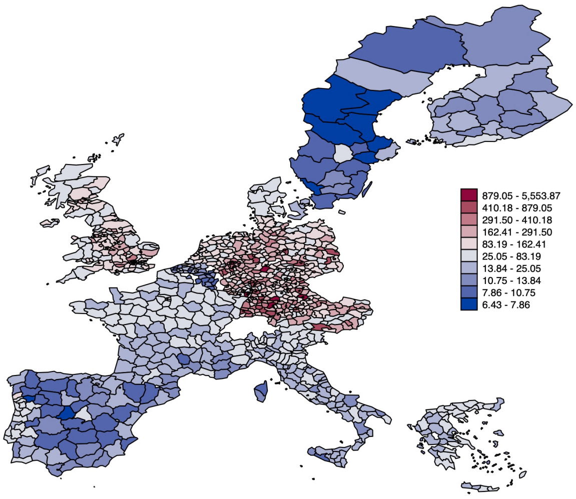


(c) Total number of employees (thousands)

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

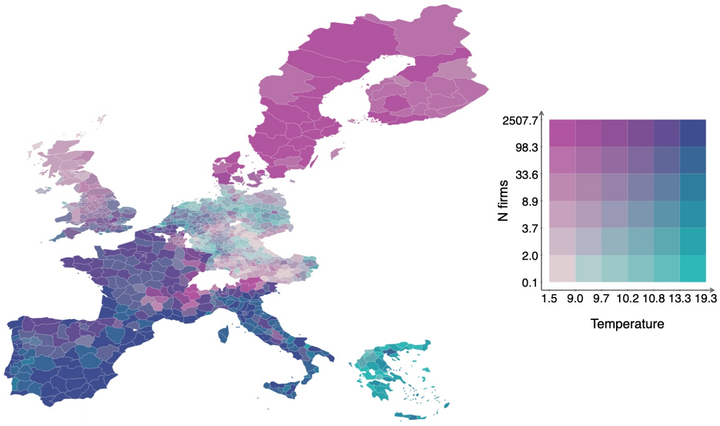


(a) Average gross output (thousands of LCU)

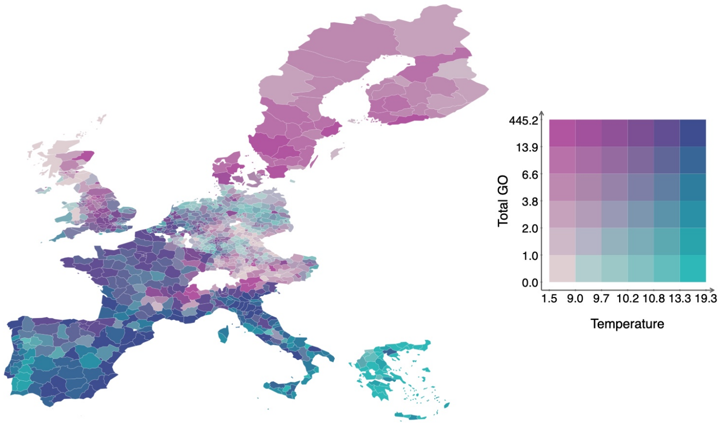


(b) Average number of employees

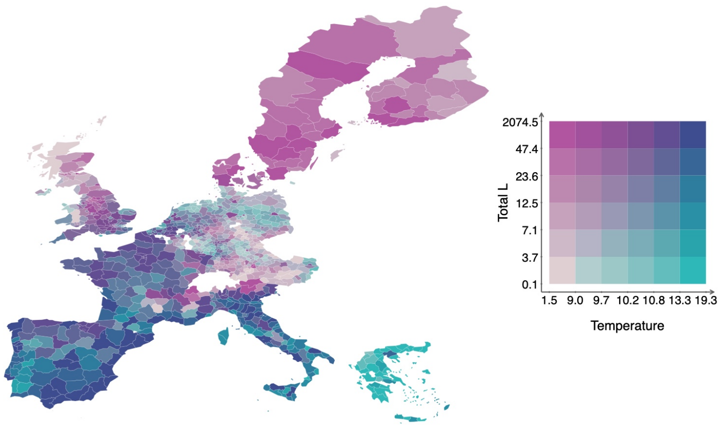
Figure 13: Descriptive statistics by Nuts 3 areas. Source: Orbis.



(a) Number of firms (thousands of units

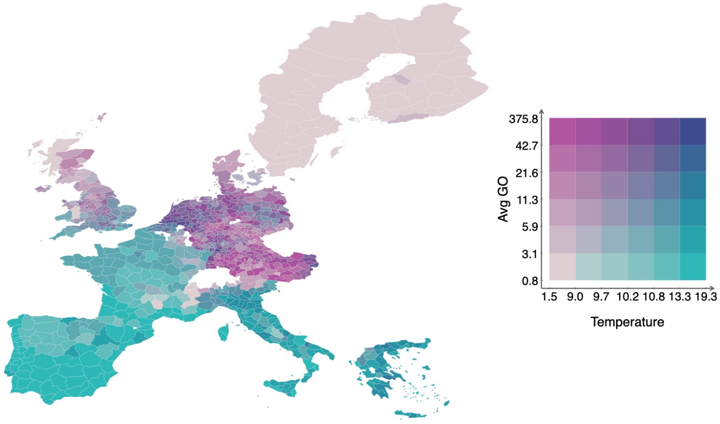


(b) Total gross output (billions of LCU)

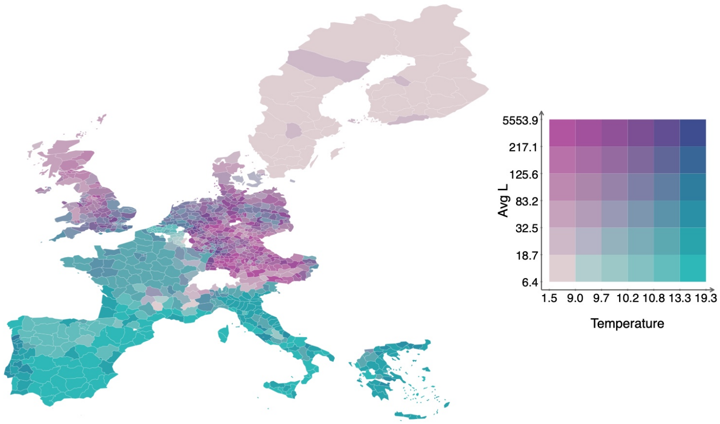


(c) Total number of employees (thousands)

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.

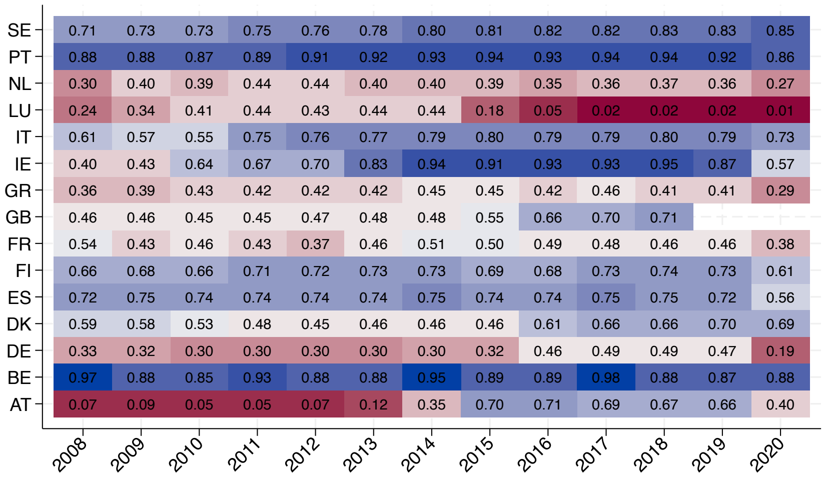


Figure 16: Coverage of the aggregate economy from Orbis data in terms of number of employees. The values report for each country-year the ratio between the sum of the number of employees for the firms available in my sample and the economy-wide number of employees. By construction, values range between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

Appendix B 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 | 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.

Appendix C Model Selection

C.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[29]. 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

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

to assess the accuracy of different models in fitting out-of-sample data.

C.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 $i = 1, \ldots, K$, 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:

$$\mathrm{CV}_K = \frac{1}{K}\sum_{j=1}^{K} \mathrm{MSE}_{(j)}\,, \tag{13}$$

with

$$\mathrm{MSE}_{(j)} = \frac{1}{N-k_j}\sum_{i=1}^{N-k_j} (y_i - \widehat{y}_i)^2\,. \tag{14}$$

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 forecasts 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.

C.3 Model selection criteria results

	Information Criteria		Cross Validation	
	Akaike IC	Bayesian IC	Mean	SD
poly 1 lag 0	96,246,866	96,246,929	0.69358186	0.00074038
poly 1 lag 1	96,246,868	96,246,947	0.69357927	0.00074092
poly 1 lag 2	71,755,475	71,755,569	0.61942618	0.00058512
poly 1 lag 3	58,126,088	58,126,196	0.59742817	0.00040273
poly 1 lag 4	47,867,591	47,867,713	0.58367275	0.00049614
poly 1 lag 5	39,709,263	39,709,399	0.57427776	0.00036762
poly 2 lag 0	96,246,596	96,246,675	0.69363934	0.00074288
poly 2 lag 1	96,246,457	96,246,568	0.69376047	0.00074541
poly 2 lag 2	71,755,388	71,755,528	0.61936773	0.00058616
poly 2 lag 3	58,125,968	58,126,138	0.59734969	0.00040642
poly 2 lag 4	47,867,460	47,867,658	0.58355948	0.00050144
poly 2 lag 5	39,709,128	39,709,354	0.57423643	0.00037318
poly 3 lag 0	96,246,506	96,246,601	0.69363498	0.00074250
poly 3 lag 1	96,246,366	96,246,508	0.69373925	0.00074524
poly 3 lag 2	71,755,382	71,755,569	0.61936904	0.00058617
poly 3 lag 3	58,125,947	58,126,178	0.59731763	0.00040354
poly 3 lag 4	47,867,443	47,867,717	0.58345314	0.00050233
poly 3 lag 5	39,709,092	39,709,409	0.57393991	0.00036960
poly 4 lag 0	96,246,500	96,246,610	0.69364369	0.00074306
poly 4 lag 1	96,246,343	96,246,517	0.69378355	0.00074678
poly 4 lag 2	71,755,265	71,755,499	0.61936615	0.00058748
poly 4 lag 3	58,125,798	58,126,091	0.59735727	0.00040871
poly 4 lag 4	47,867,263	47,867,614	0.58356162	0.00050331
poly 4 lag 5	39,708,932	39,709,340	0.57405486	0.00037542

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.

Appendix D 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

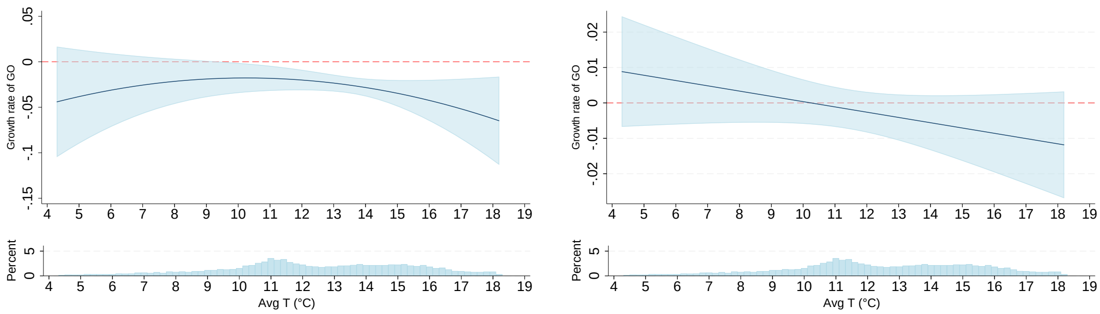
Table 9: Panel unit-root Augmented Dickey Fueller tests results. Test statistics and p-values reported. Source: Copernicus Climate Change Service (C3S) ERA5-Land.

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.

Appendix E Additional Results

E.1 Additional Results Cumulative Effect



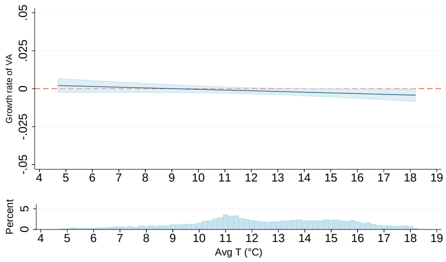
(a) Cumulative response

(b) Cumulative marginal effect

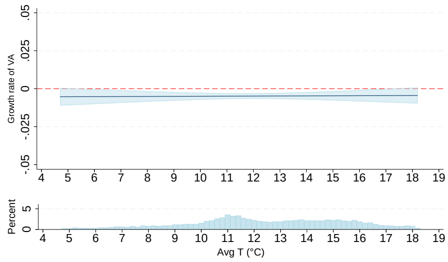
Figure 17: Cumulative marginal effects of temperature on the growth rate of GO. Results from the 2^{nd} order polynomial model with firm and industry-year FE, standard errors clustered at the Nuts 3 level.

E.2 Additional Results Value Added

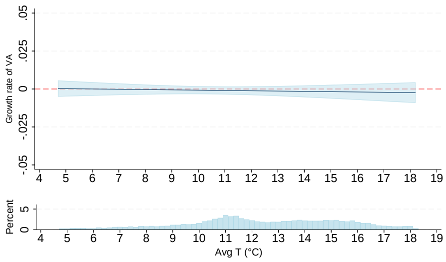
As for GO, the effect of $T_{i,t}$ is generally not significant. The effect of $T_{i,t-1}$ is more pronounced, whereas the marginal effect function of $T_{i,t-2}$ has a lower intercept (in absolute value) and a steeper slope than $T_{i,t-1}$. As higher temperature in $t-2$ negatively (positively) impact 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 18d.



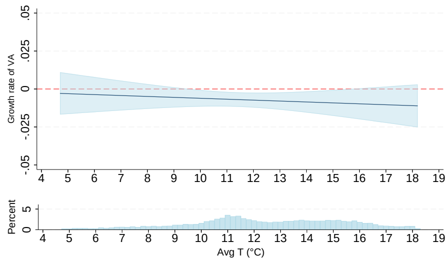
(a) Contemporaneous marginal effect



(b) lag-1 marginal effect



(c) lag-2 marginal effect



(d) Cumulative marginal effect

Figure 18: 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.

E.3 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) ΔGO	(2) ΔVA
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

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

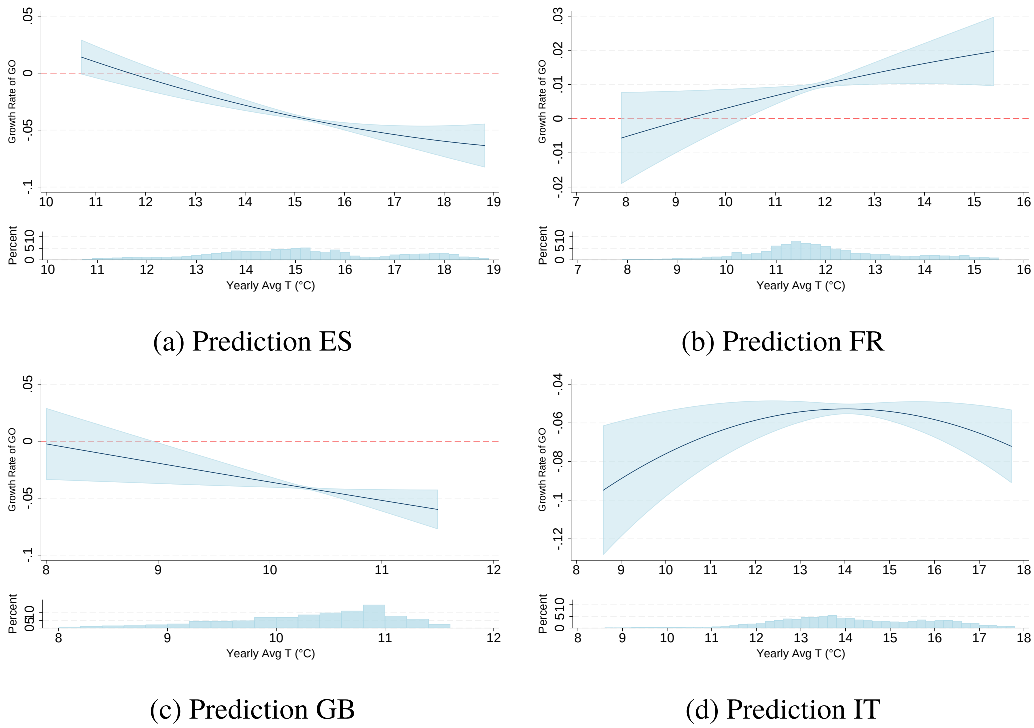
Table 11: Point estimates and standard errors from the regressions of weather variables on the growth rates of GO and VA. Results refer to the subsample of firms with available VA. Results for the 2^{nd} order polynomial model with firm and industry-year FE, standard errors clustered at the Nuts 3 level. 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.

E.4 Additional Results Heterogeneity

E.4.1 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 10) for Italy and France in figure 20 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 20 below are more informative.



(a) Prediction ES

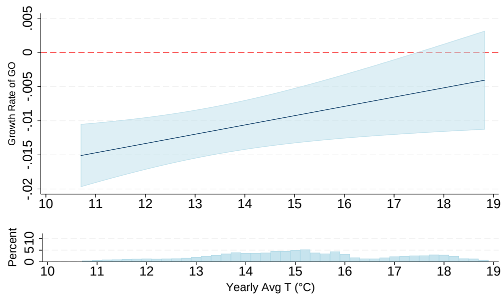
(b) Prediction FR

(c) Prediction GB

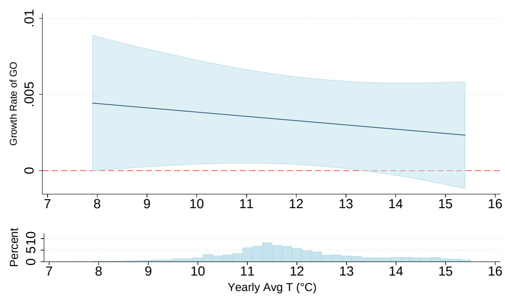
(d) Prediction IT

Figure 19: 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.

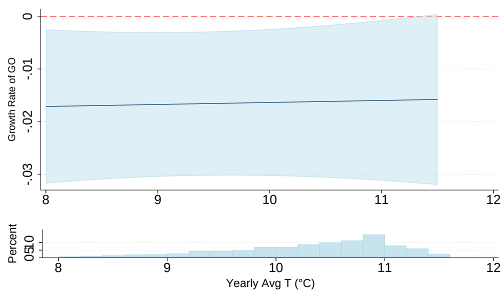
Figure 20 reports the marginal effect of an extra $1°C$ against the temperature support. As is evident, the marginal effect varies largely across Countries, being upward sloping for Italy (figure 20d) and France (figures 20b), slightly downward sloping for Great Britain (figure 20c) and upward sloping for Spain (figure 20a). 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 20b 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 $15.5°C$.



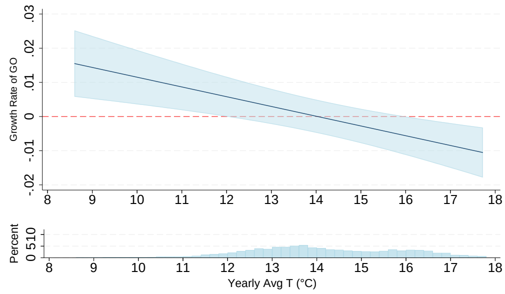
(a) Marginal Effect ES



(b) Marginal Effect FR



(c) Marginal Effect GB



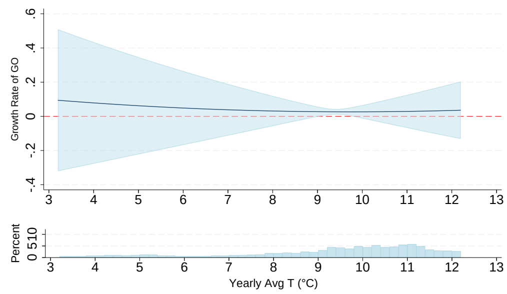
(d) Marginal Effect IT

Figure 20: 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.

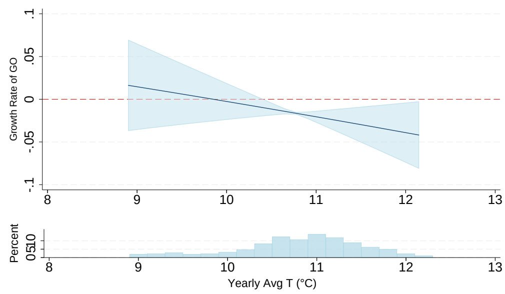
The results for Spain reported in figure 20a differ substantially from those for Italy and France, although they are consistent with the pooled-EU marginal effects. The estimated marginal effect of temperature on the growth rate of gross output panel is increasing over the temperature distribution, although 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 $11.5°C$.

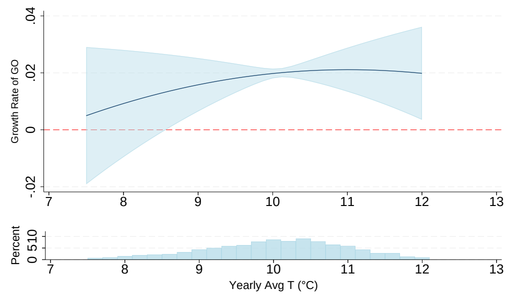
The figure below report the marginal effects for the remaining countries. Results for these countries are characterised by large confidence intervals, likely due to a lower number of observations, making these results not statistically significant for most countries over a large part of the temperature 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.



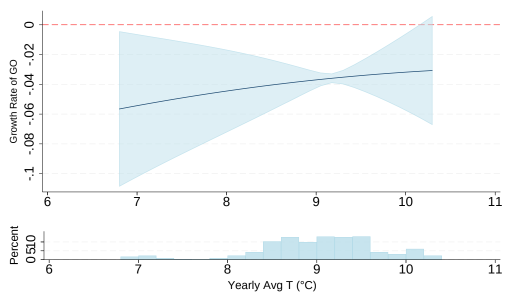
(a) Prediction AT



(b) Prediction BE

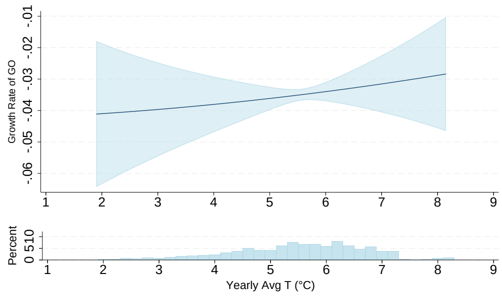


(c) Prediction DE

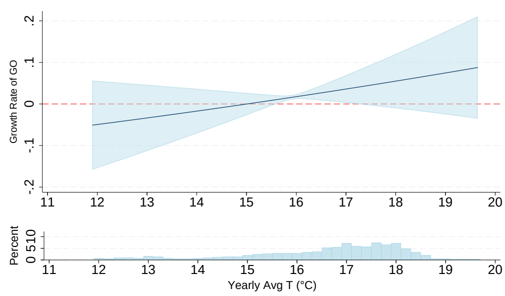


(d) Prediction DK

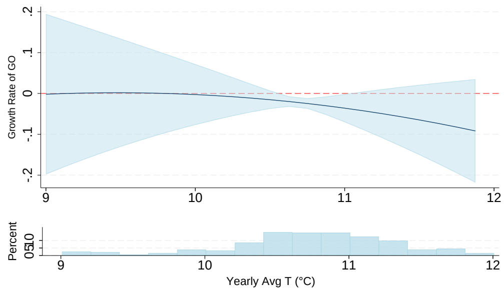
Figure 21: Predicted effect of temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE estimated excluding the bottom and top 1% of the temperature distribution.



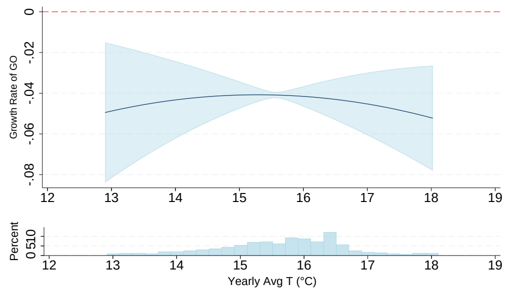
(a) Prediction FI



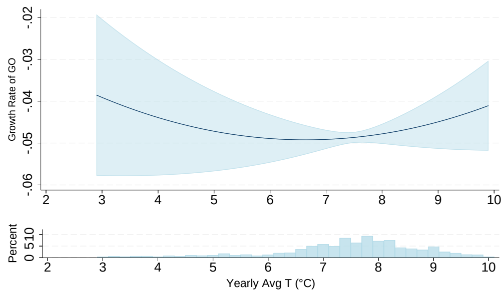
(b) Prediction GR



(c) Prediction NL

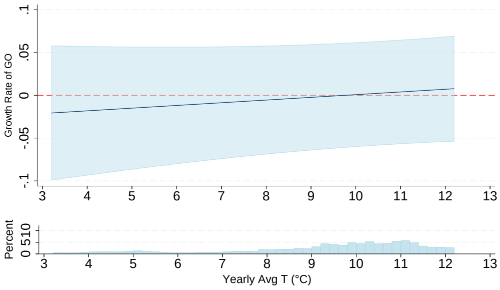


(d) Prediction PT

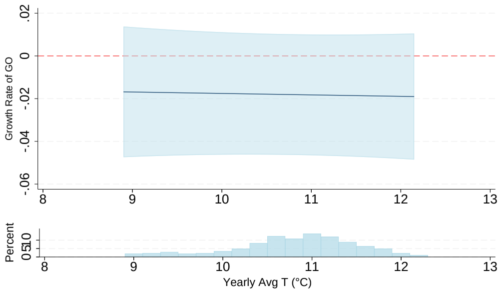


(e) Prediction SE

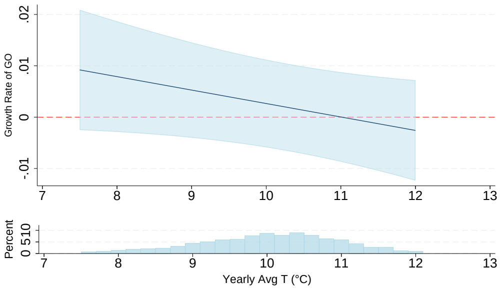
Figure 22: Predicted effect of temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE estimated excluding the bottom and top 1% of the temperature distribution.



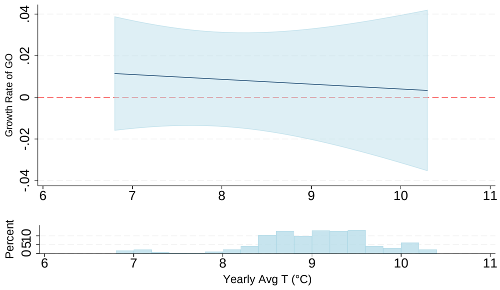
(a) Marginal Effect AT



(b) Marginal Effect BE

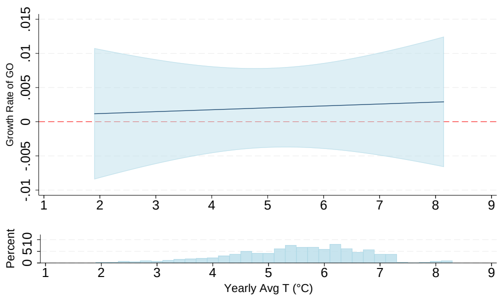


(c) Marginal Effect DE

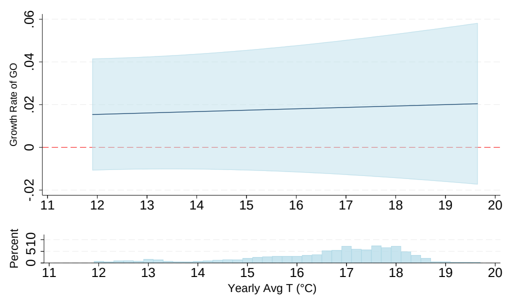


(d) Marginal Effect DK

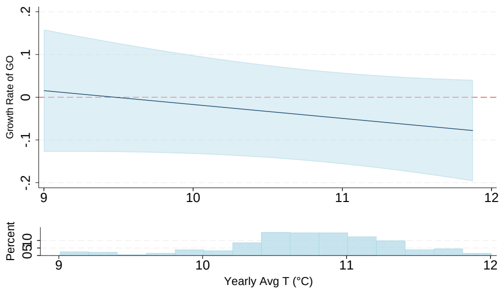
Figure 23: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the temperature distribution.



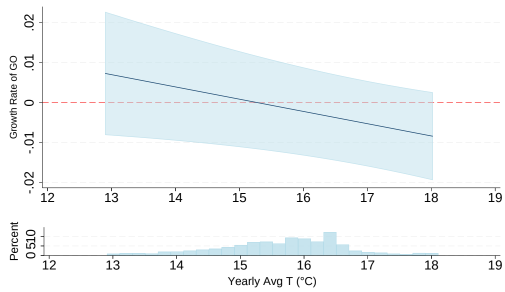
(a) Marginal Effect FI



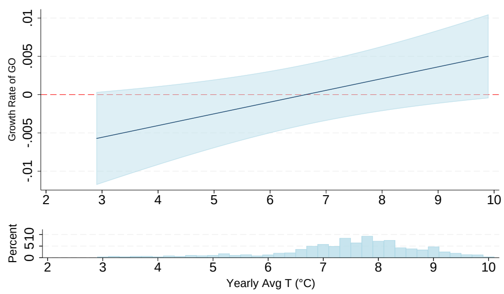
(b) Marginal Effect GR



(c) Marginal Effect NL



(d) Marginal Effect PT



(e) Marginal Effect SE

Figure 24: 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.

E.4.2 Pooled EU additional results, industry heterogeneity

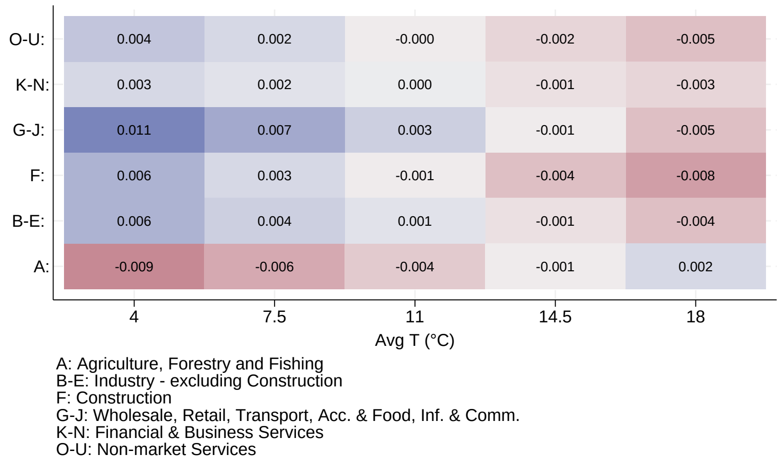


Figure 25: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output (log) accounting for industry heterogeneity (Nace 2 level 2). Results from the quadratic model with firm and industry-year FE.

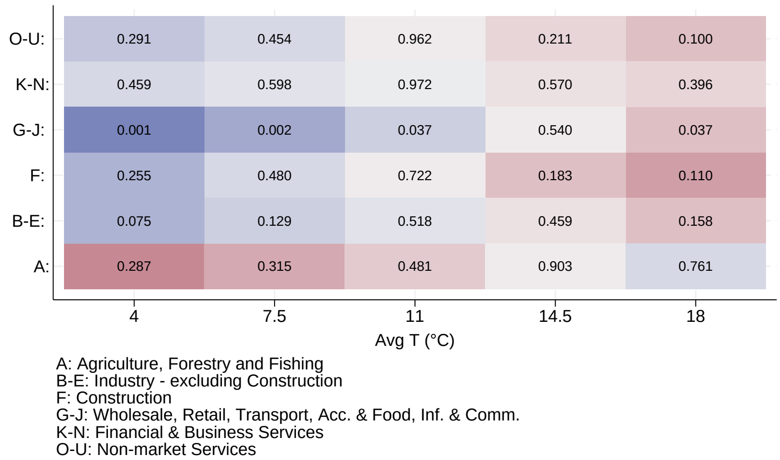
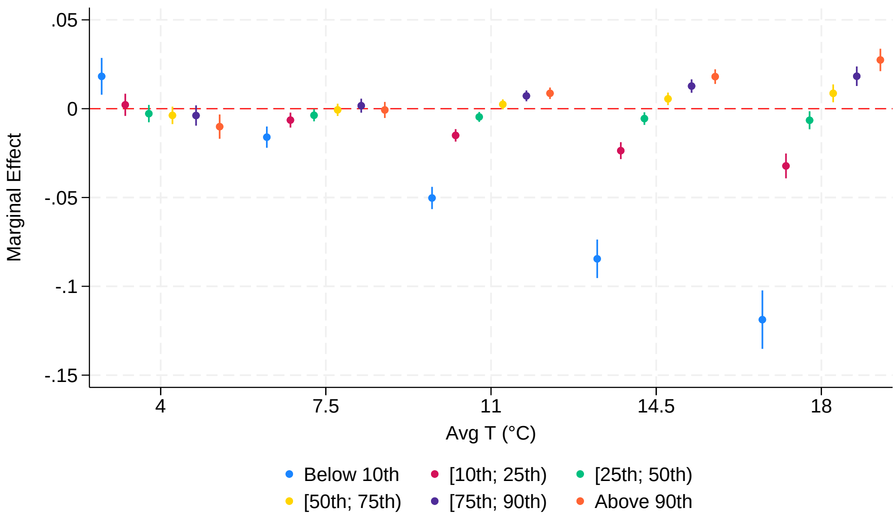
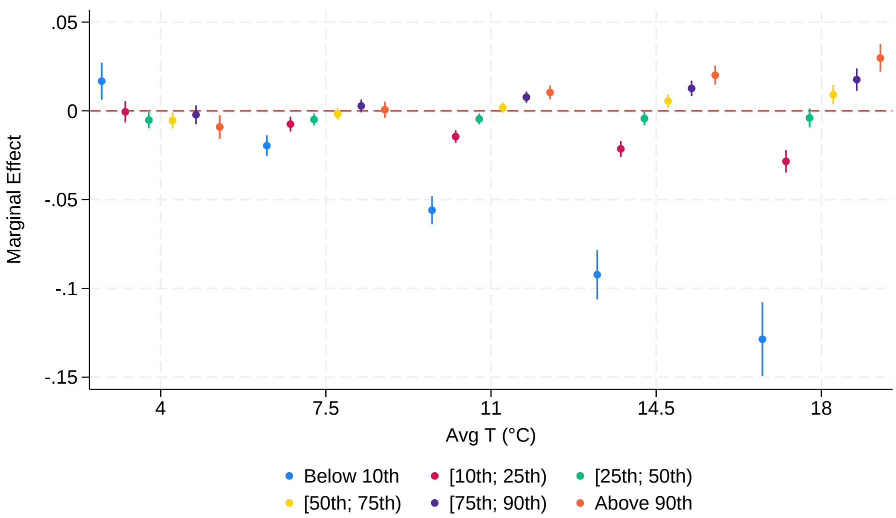


Figure 26: P-values for coefficients of figure 25 for the marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output (log) accounting for industry heterogeneity (Nace 2 level 2). The heat map colours refer to the values of the point estimates. Results from the quadratic model with firm and industry-year FE.

E.4.3 Pooled EU additional results, productivity heterogeneity (VA and TFP)



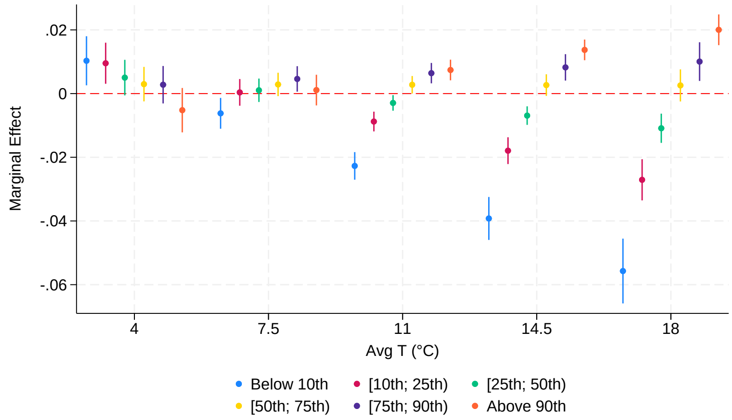
(a) Marginal effect VA



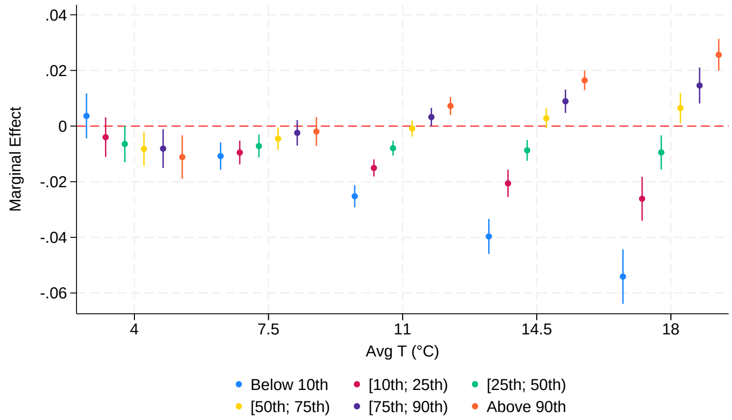
(b) Marginal effect TFP

Figure 27: Marginal effect of an extra $1°C$ 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.

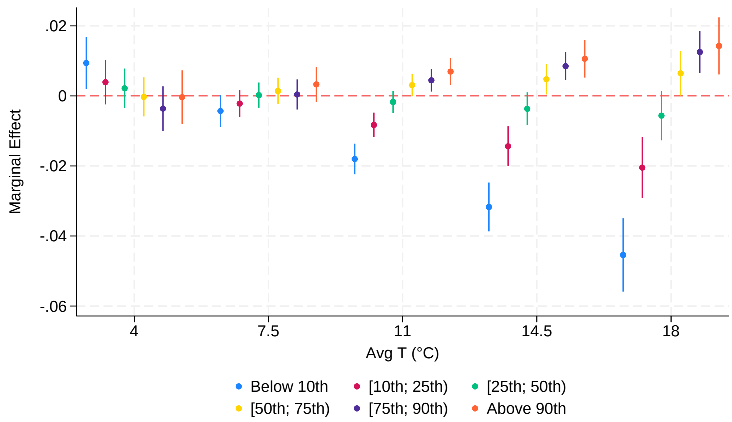
E.4.4 Pooled EU additional results, productivity heterogeneity by within-industry productivity category



(a) Marginal effect



(b) Lag-1 marginal effect

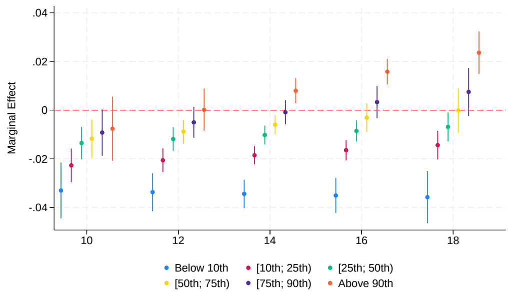


(c) Lag-2 marginal effect

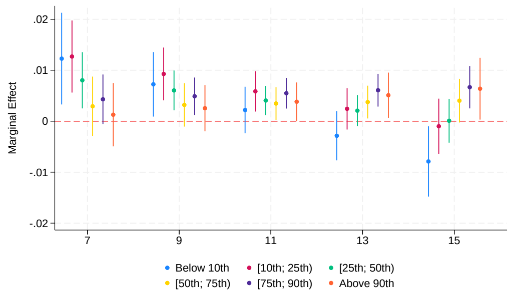
Figure 28: Contemporaneous (a), lag-1 (b), and lag-2 (c) marginal effects of an extra $1°C$ in yearly average temperature on the growth rate of gross output accounting for productivity heterogeneity (within each industry). Results from the quadratic model with firm and industry-year FE.

E.4.5 Country-level additional results, TFP heterogeneity

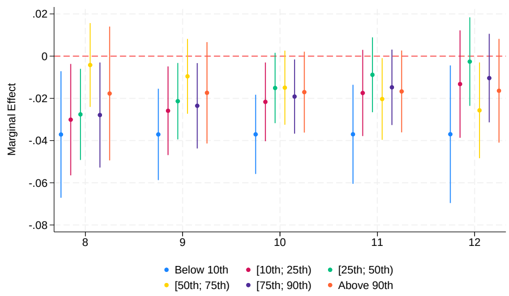
The country-specific damages heterogeneity related to the TFP categories reported in figure 29 are generally consistent with both the country-level pooled analysis and the other sources of damages heterogeneity highlighted so far, with relevant differences between the analysed countries. Similar to the 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.



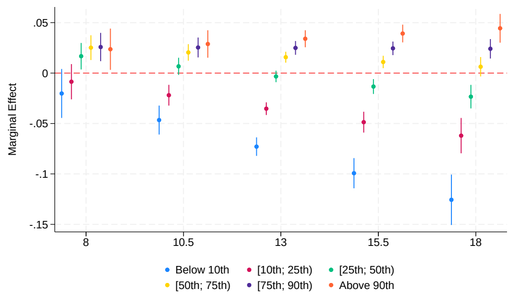
(a) Marginal Effect ES



(b) Marginal Effect FR



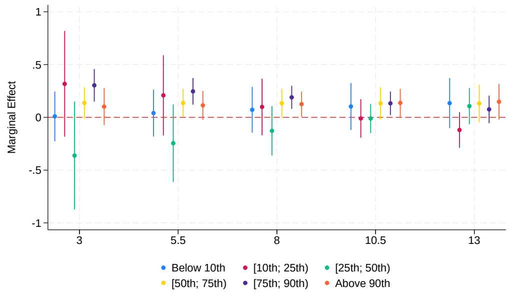
(c) Marginal Effect GB



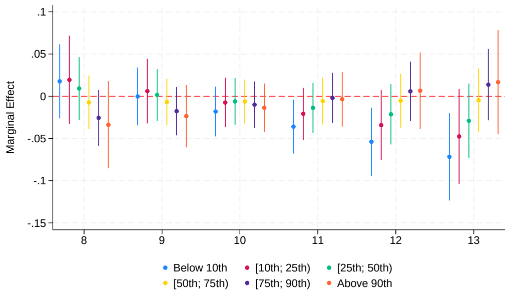
(d) Marginal Effect IT

Figure 29: 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.

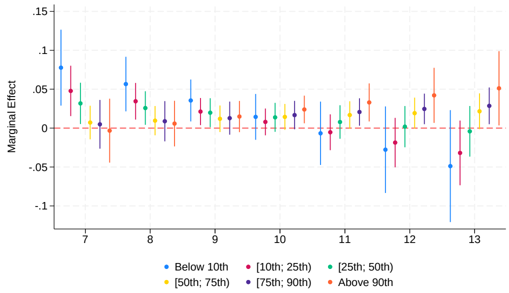
Specifically, in terms of the four countries discussed in the main body, least productive firms are significantly negatively impacted by higher temperature across the whole temperature support in Italy (figure 29d), Spain (figure 29a), and the UK (figure 29c). In France (figure 29b) this effect is negative 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 30 and 31 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.



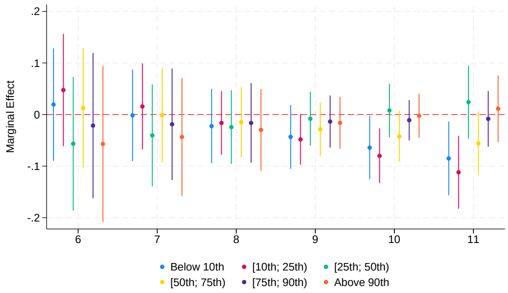
(a) Marginal Effect AT



(b) Marginal Effect BE

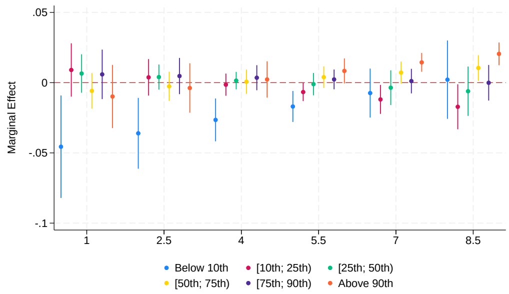


(c) Marginal Effect DE

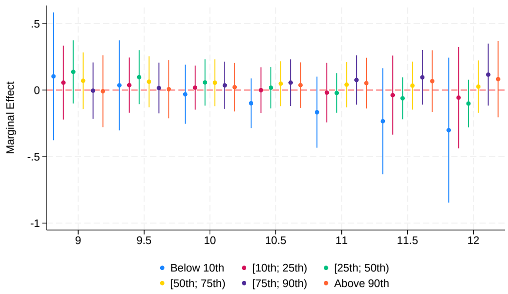


(d) Marginal Effect DK

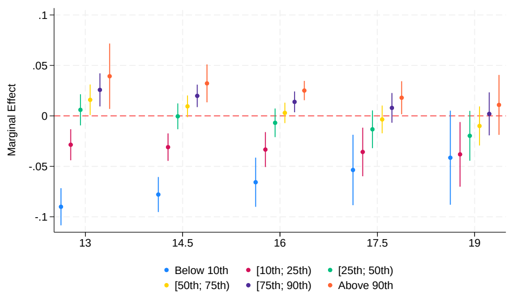
Figure 30: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the temperature distribution.



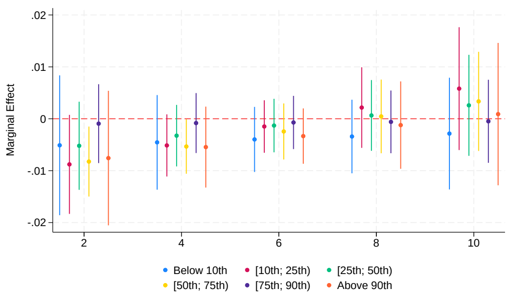
(a) Marginal Effect FI



(b) Marginal Effect NL



(c) Marginal Effect PT



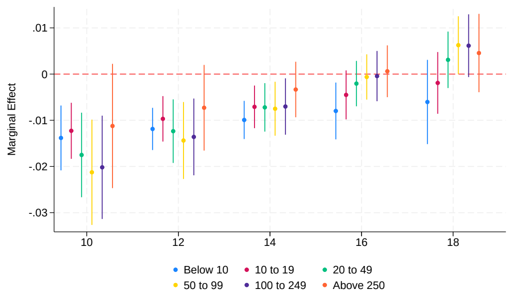
(d) Marginal Effect SE

Figure 31: 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.

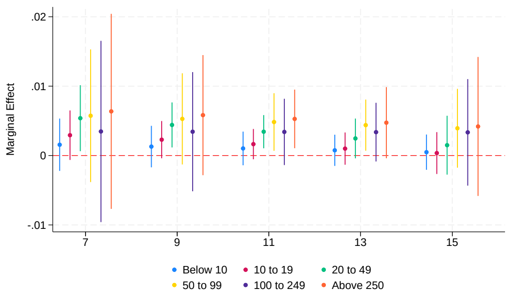
E.4.6 Country-level additional results, size heterogeneity

Figure 32 reports the marginal effect of an additional $1^{\circ}C$ on the growth rate of gross output for the quadratic model in equation 10 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.

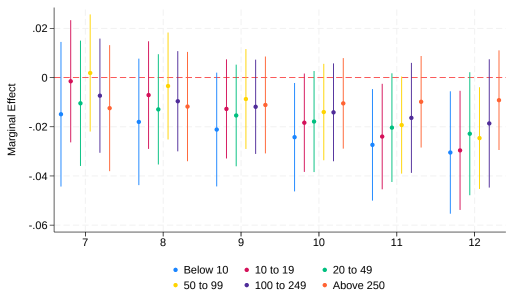
The size-specific results for Italy are generally in line with the average marginal effect reported in figure 20d. The point estimates reported in figure 32d are not significantly different from each other at lower temperature. Nevertheless, the coefficients become statistically different from each other 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

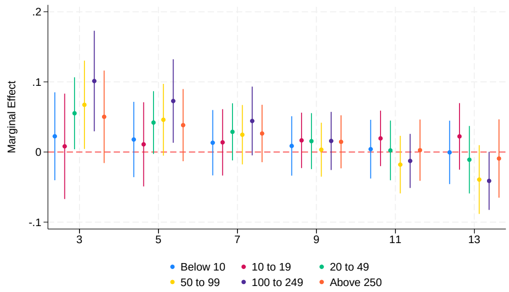
Figure 32: Marginal effect of an extra $1^{\circ}C$ in yearly average temperature on the growth rate of gross output accounting for firm size heterogeneity. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, plotted over country-specific 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.

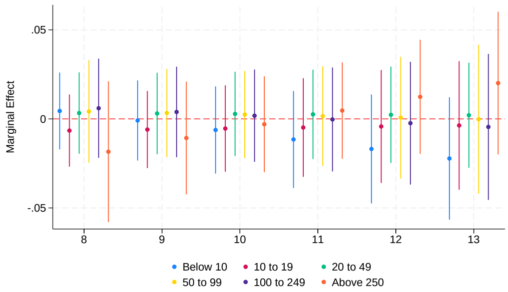
The results for the remaining countries in figure 32 are less clear than, and somehow contrasting with those for Italy. Consistent with the aggregate results from figure 20a, the size-specific results for Spain reported in figure 32a show an upward-sloping marginal effect function over the temperature 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 32b and 32c 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.

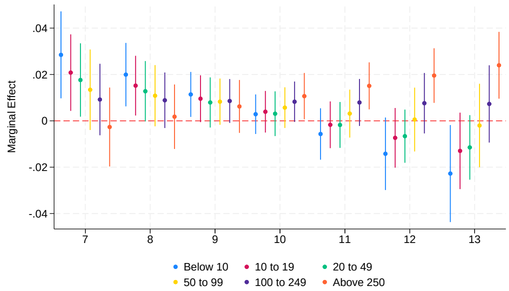
The results for the remaining countries reported in figures 33 and 34 are generally consistent with the finding that smaller firms tend to be more negatively (positively) impacted by higher temperatures when located in warmer (colder) areas. Although with different level of statistical significance, 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.



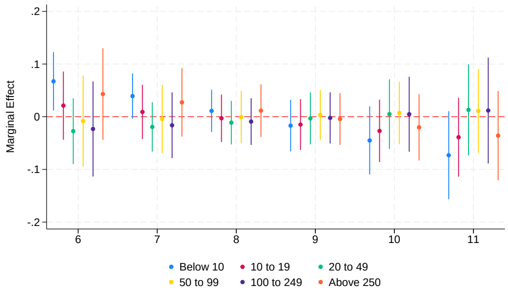
(a) Marginal Effect AT



(b) Marginal Effect BE

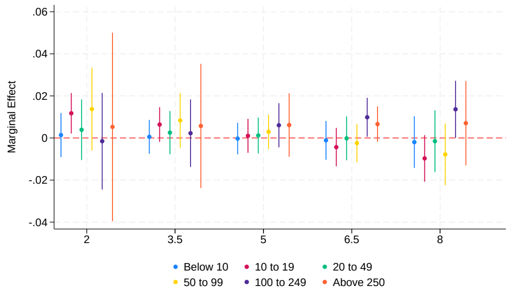


(c) Marginal Effect DE

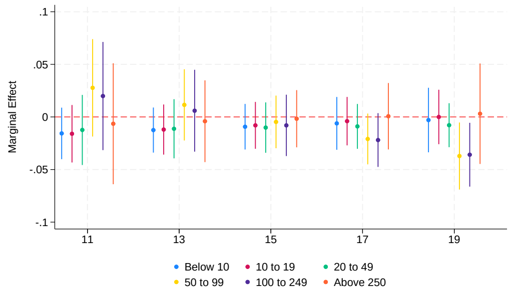


(d) Marginal Effect DK

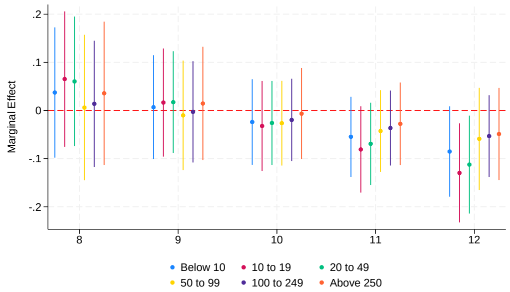
Figure 33: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the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



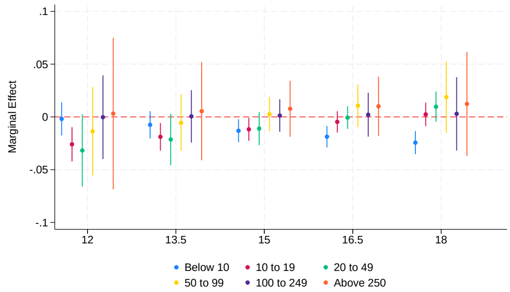
(a) Marginal Effect FI



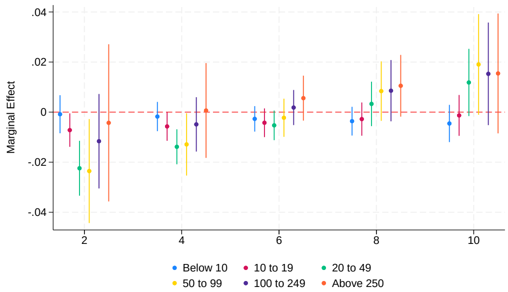
(b) Marginal Effect GR



(c) Marginal Effect NL



(d) Marginal Effect PT

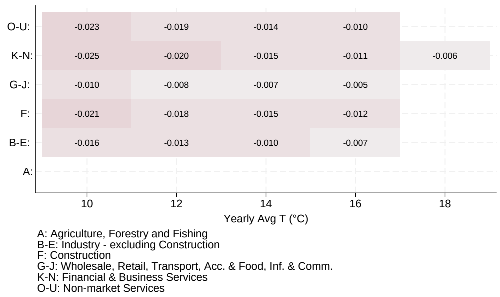


(e) Marginal Effect SE

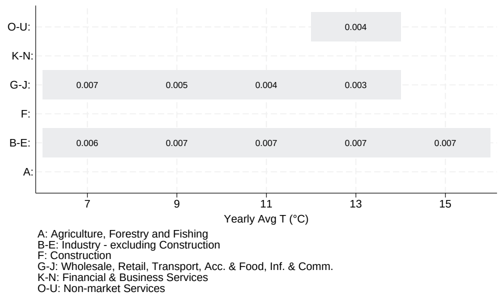
Figure 34: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the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

E.4.7 Cross-country heterogeneity, industry-level

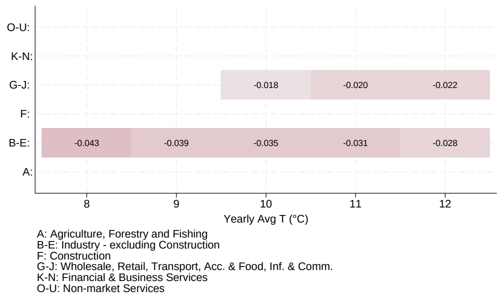
The marginal effect for Spain reported in 35a is a negative and upward-sloping function of temperature. The results for France reported in figure 35b are generally not statistically significant and, within the set of industries where the effects are positive. The United Kingdom is an interesting case because, as reported in figure 35c, although only a limited amount of industries are significantly affected by higher temperature, those reporting statistically significant estimates are considerably impacted. Finally, the results for Italy reported in figure 35d 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. T



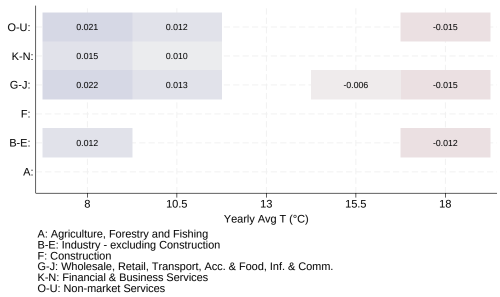
(a) Marginal Effect ES



(b) Marginal Effect FR



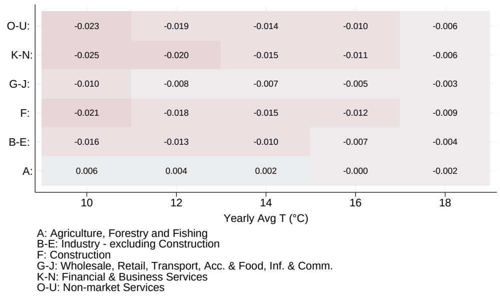
(c) Marginal Effect GB



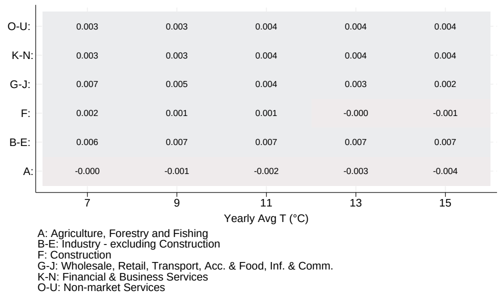
(d) Marginal Effect IT

Figure 35: 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.

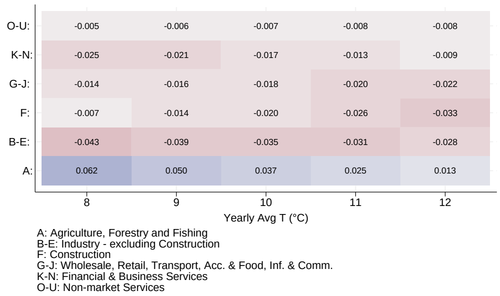
The industry-specific estimates for the remaining reported countries are not easy to interpret given the considerable amount of country-industry-specific point estimates to take into account. The heat map colours are particularly convenient in this case because they provide a broad overview of the different 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.



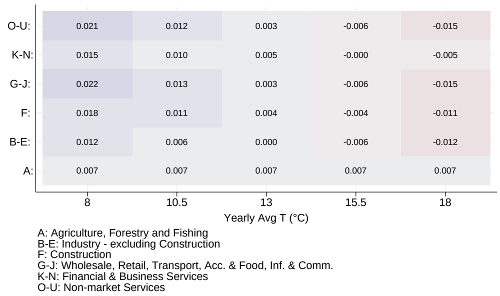
(a) Marginal Effect ES



(b) Marginal Effect FR

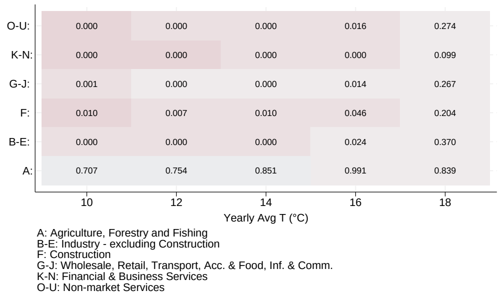


(c) Marginal Effect GB

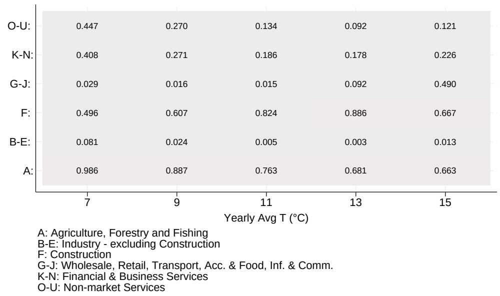


(d) Marginal Effect IT

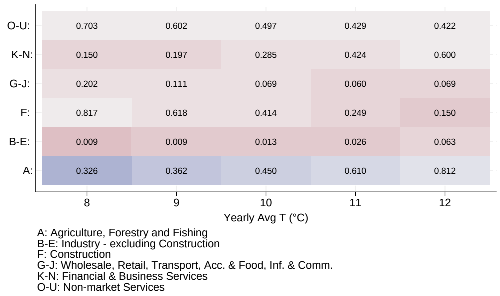
Figure 36: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output accounting for firm industry heterogeneity - estimates with a statistical significance of at least 90%. Results from the quadratic model with firm and industry-year FE plotted over country-specific temperature supports.



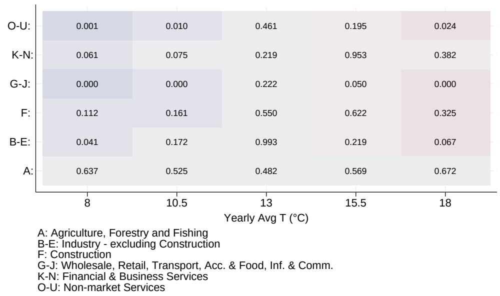
(a) P-values ES



(b) P-values FR

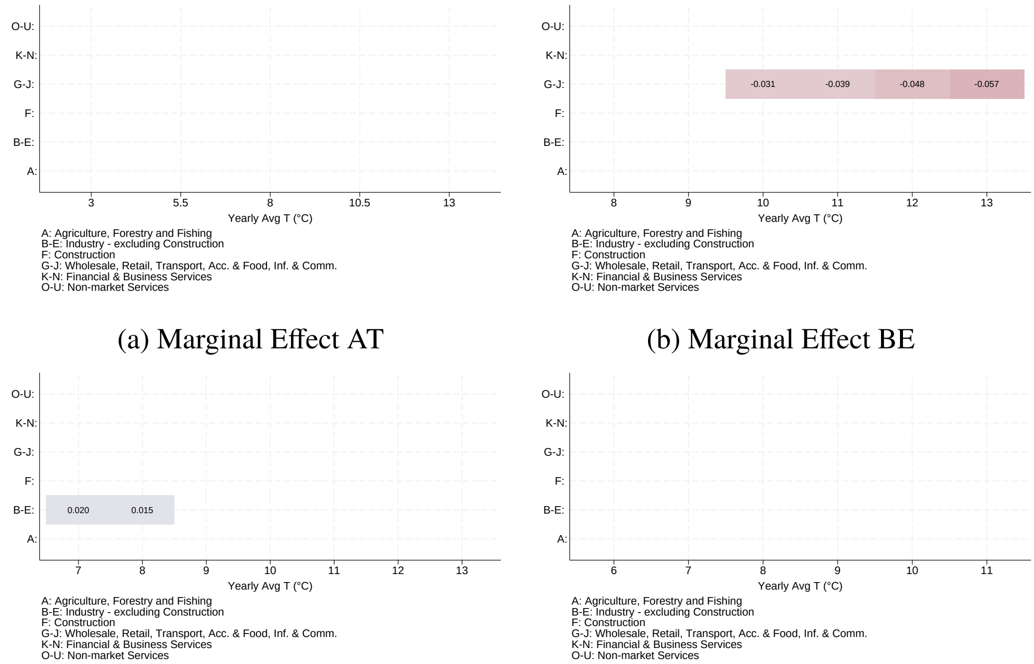


(c) P-values GB



(d) P-values IT

Figure 37: 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.



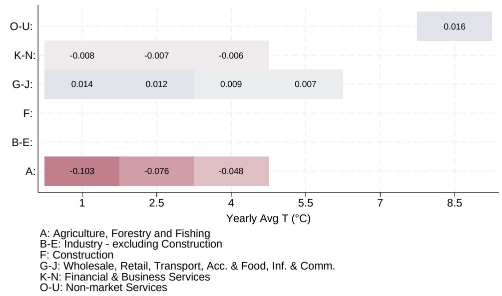
(a) Marginal Effect AT

(b) Marginal Effect BE

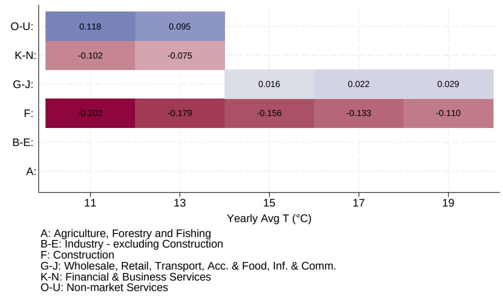
(c) Marginal Effect DE

(d) Marginal Effect DK

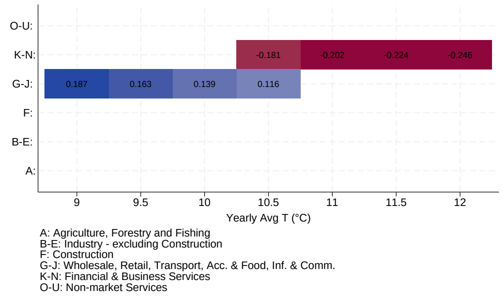
Figure 38: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the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



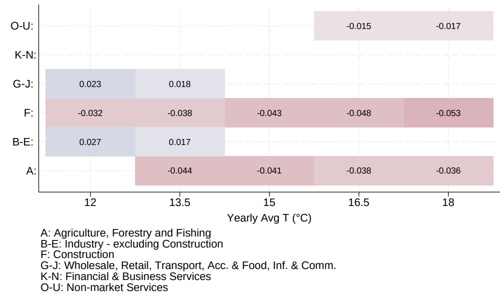
(a) Marginal Effect FI



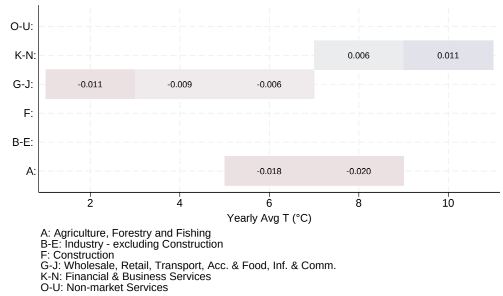
(b) Marginal Effect GR



(c) Marginal Effect NL

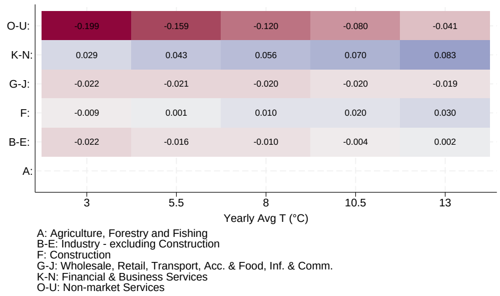


(d) Marginal Effect PT

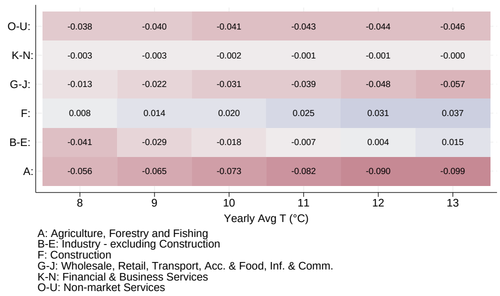


(e) Marginal Effect SE

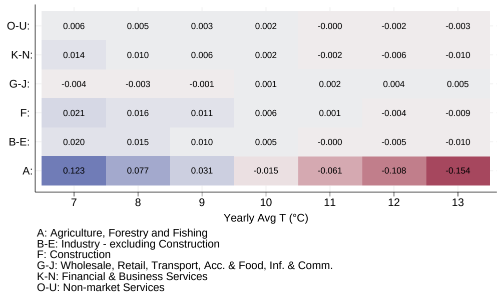
Figure 39: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the temperature distribution.



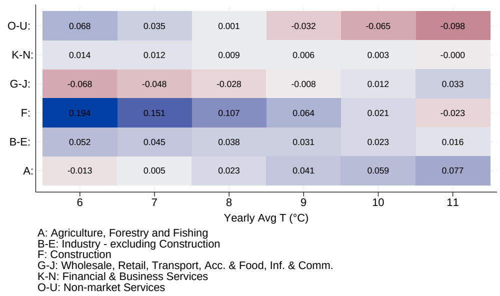
(a) Marginal Effect AT



(b) Marginal Effect BE

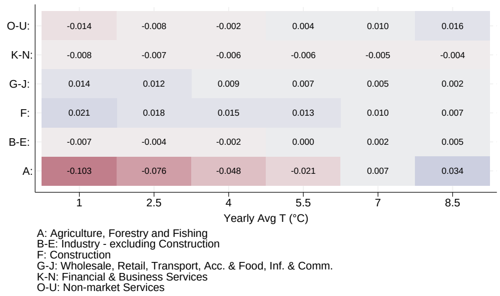


(c) Marginal Effect DE

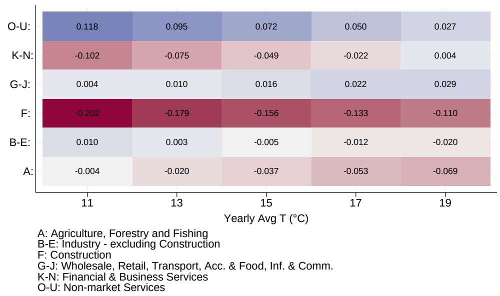


(d) Marginal Effect DK

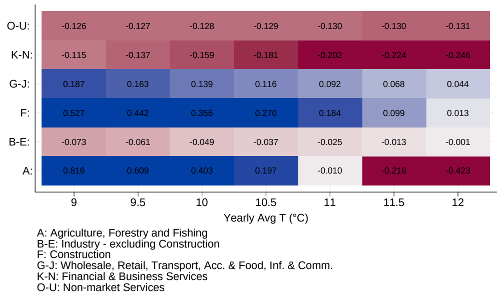
Figure 40: Marginal effect of an extra $1°C$ in yearly average temperature on the growth rate of gross output in other European countries. Results from the quadratic model with firm and industry-year FE and standard errors clustered at the Nuts 3 level, estimated excluding the bottom and top 1% of the temperature distribution.



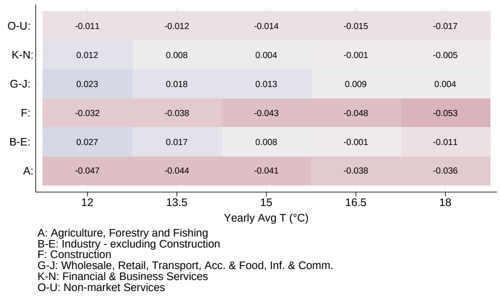
(a) Marginal Effect FI



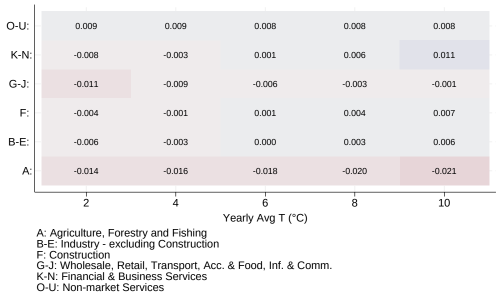
(b) Marginal Effect GR



(c) Marginal Effect NL



(d) Marginal Effect PT



(e) Marginal Effect SE

Figure 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.