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THE PRODUCTIVITY IMPACT OF GLOBAL WARMING: FIRM-LEVEL EVIDENCE FROM EUROPE

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The Productivity Impact of Global Warming: Firm-Level Evidence for Europe

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Abstract

In this paper, we investigate the impact of rising temperatures on firm productivity using longitudinal firm-level balance-sheet data from private sector firms in 14 European countries, combined with detailed weather data, including temperature. We begin by estimating firms' total factor productivity (TFP) using control-function techniques. We then apply multiple-way fixed-effects regressions to assess how higher temperature anomalies affect firm productivity – measured via TFP, labor productivity, and capital productivity. Our findings reveal that global warming significantly and negatively impacts firms' TFP, with the most adverse effects occurring at higher anomaly levels. Labor productivity declines markedly as temperatures rise, while capital productivity remains unaffected – indicating that TFP is primarily affected through the labor input channel. Our moderating analyses show that firms involved in outdoor activities, such as agriculture and construction, are more adversely impacted by increased warming. Manufacturing, capital-intensive, and blue-collar-intensive firms, compatible with assembly-line production settings, also experience significant productivity declines. Geographically, the negative impact is most pronounced in temperate and mediterranean climate areas, calling for widespread adaptation solutions to climate change across Europe.

Keywords: Climate change, Global warming, Firm productivity, Total factor productivity (TFP), Semiparametric methods to estimate production functions, Longitudinal firm-level data.

JEL Classification: D24, J24, Q54.

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1. Introduction

Climate change has emerged as one of the biggest challenges that the world has ever faced. According to the Sixth Assessment Report of the Intergovernmental Panel on Climate Change (IPCC, 2023), global temperatures have already risen by 1.1°C above pre-industrial levels, with Europe heating around twice the global rate. The increase in temperatures has particularly intensified over the last decade and is expected to continue in the near term and beyond, mainly due to heightened cumulative greenhouse gas (GHG) emissions and inertia in the climate system. Unless large-scale climate mitigation measures are implemented, there is an increasing likelihood that the Paris Agreement targets will not be met.[1] Every increment of global warming is further expected to intensify multiple and concurrent extreme weather events, such as severe heatwaves, heavy precipitation, floods, and droughts, with potentially dire consequences for human life and natural systems. Each climate-related disaster will also put additional strain on the economy, through loss of productivity, direct damage, reduced growth potential, and pressure on public budgets (EEA, 2024; Gagliardi et al., 2022).

In this paper, we focus on the economic dimension of climate change impacts as we explore the impact of rising temperatures on firm productivity, while providing a European perspective.

Recent years have witnessed a growing interest in the macro- and micro-economic effects of rising temperatures. At the macro level, higher temperatures have generally been found to be associated with reduced economic output in both developed and developing countries (Burke et al., 2015; Dell et al., 2012; Deryugina and Hsiang, 2014; Hsiang, 2010). For instance, evidence from 28 Caribbean-basin countries shows that a 1°C increase in temperature leads to a 2.5% decrease in national output (Hsiang, 2010). Substantial output reductions on hotter days have also been documented in the US (Deryugina and Hsiang, 2014). Moreover, there is evidence that both rich and poor countries respond non-linearly to temperature changes, with an inverted U-shaped relationship (Burke et al., 2015).[2] If future adaptation follows the pattern of past adaptation, unmitigated warming is expected to transform the global economy, leading to a reduction in average global output by approximately 23% by 2100 (Burke et al., 2015).

The existing country- and/or regional-level studies are based on aggregate production functions, which cannot be fully suggestive of the underlying micro-mechanisms linking

[1] The Paris Agreement is a legally binding international treaty that entered into force on November 4, 2016, following the UN Climate Change Conference (COP21) in Paris. The agreement establishes long-term goals for all nations to significantly reduce global greenhouse gas emissions. Its primary objective is to limit the global temperature increase this century to well below 2°C above pre-industrial levels, with efforts to limit the rise to 1.5°C, recognizing that achieving these targets would greatly reduce the risks and impacts of climate change. According to the IPCC (2023), at the current GHG emissions rates, there is an increasing likelihood that the 1.5°C target will already be reached in the near term.

[2] Burke et al., (2015) find that overall economic productivity is non-linear in temperature for all countries, with productivity peaking at an annual average temperature of 13°C and declining strongly at higher temperatures. The relationship is globally generalizable, for agricultural and non-agricultural activity, in both rich and poor countries.

temperature and economic activity. However, a deep understanding of the latter remains crucial to designing optimal adaptation policies and withstanding the unavoidable adverse impacts of climate change. Some studies have thus been developed to provide informed micro-level evidence (Deschênes, 2023). Higher temperatures are generally found to reduce output either via (i) direct productivity effects[3] or (ii) due to constraints on factor reallocations[4]. The former mechanism is the primary focus of this paper.

Recent research based on integrated assessment models (IAMs; Dietz and Stern, 2015; Stern, 2013) has theorized the potential altering impact of climate change on total factor productivity (TFP), with adverse implications for long-run economic growth and development (Syverson, 2011). Preliminary empirical country-level evidence has further established both a negative linear relationship (Letta and Tol, 2019) and a non-linear concave relationship (Bijnens et al., 2024; Kumar and Maiti, 2024; Kumar and Khanna, 2019) between temperature and TFP (or labor productivity) growth rates.

However, few studies offer a micro perspective on how higher temperatures influence TFP (and its main channels - that is, labor and capital productivity) and none, to our knowledge, focuses on Europe. To date, there are micro-level studies for Chinese firms (Zhang et al., 2018; Zhang et al., 2023a), US firms (Chen et al., 2019), and African firms (Traore and Foltz, 2018). All of them point to economically meaningful and statistically significant negative relationships between high temperature and TFP.

Some recent micro-level studies focus on the connection between temperature and labor productivity, considering both intensive margins, related to thermal stress, and extensive margins, linked to absenteeism and labor supply. Thermal stress is generally found to trigger thermoregulatory responses, affecting body and brain functioning via physiological and psychological discomfort and strain, thus adversely affecting cognitive and physical skills. This may impact labor productivity in terms of reduced work intensity and quality of labor input. At the same time, higher temperatures may increase workers' absenteeism or reduce the time allocated to work (Lai et al., 2023). Overall, the existing empirical evidence suggests a negative and/or inverted U-shaped relationship[5] between temperature and labor productivity, consistent across various

[3] In this review, we focus on studies examining firm productivity (particularly, TFP and its main channels - labor and capital productivity). However, an emerging strand of research has also highlighted the adverse impact of higher temperatures on firm-level financial performance (Cathcart et al., 2022; Custodio et al., 2021; He et al., 2021; Addoum et al., 2020).

[4] As global warming changes the overall productivity distribution, economic activity naturally reallocates towards sectors and/or regions gaining comparative advantage (Albert et al., 2023). At the same time, firms may respond to higher temperatures by adjusting the composition of factor inputs (e.g., shifting between labor and capital inputs; Zhang et al., 2018). However, existing capital and labor market frictions may constrain any temperature-driven reallocation via higher adjustment costs.

[5] Studies pointing to an inverted-U-shaped relationship highlight how both extreme cold and extreme heat have significant negative impact on productivity. For instance, Cai et al., (2018) show that extreme cold (heat) with a daily maximum temperature below 60°F (over 95°F) causes an 11% (8.5%) reduction in productivity compared to the reference bin (75-80°F).

sectors and production settings (e.g., Cai et al., 2018; Chen and Yang, 2019; Somanathan et al., 2021; Zhang et al., 2023b).[6]

On the contrary, the relationship between temperature and capital productivity remains largely unexplored. Engineering studies suggest that capital stock might become less efficient or perform poorly under extreme heat due to factors such as increased friction between mechanical components (Mortier et al., 2010), higher failure rates from input material deformation (Collins, 1963), or reduced processing speed of computers (Lilja, 2005). Tentative analyses using various proxies of capital productivity suggest some adverse impacts of temperature (Zhang et al., 2018, for Chinese firms; Traore and Foltz, 2018, for African companies).

All in all, the existing micro-level evidence appears largely focused on developing countries and to not systematically address the impact of global warming on TFP and across its key components (i.e., labor and capital productivity). In addition, the existing empirical studies may lack some generalizability in assessing the broad effects of global warming, as they focus exclusively on the impact of annual variations in absolute temperatures (either measured as average temperature or through "temperature bins").[7] However, in climate research, temperature anomalies are found to be far more relevant than absolute temperatures, since anomalies inform us about changes (both positive and negative) *relative* to a historical temperature baseline (the so-called "climate normal" - usually established by averaging several decades of temperature data (Samborska, 2024; WMO, 2017). This provides a better frame of reference to calculate temperature trends more accurately as well as to perform consistent comparison across locations.[8]

In this paper, we contribute to the existing debate by performing a robust and large-scale empirical assessment of the micro-economic impact of global warming on firm productivity. To the best of our knowledge, we are the first to provide such evidence on European firms.

To perform our empirical analysis, we construct a unique data set based on (i) firm-level balance-sheet information derived from ORBIS - Bureau Ban Dijk and (ii) high-resolution gridded weather information derived from E-OBS – Copernicus from the European Union's Space

[6] Most studies focus on labor-intensive non-agricultural industries. Cai et al. (2018) identify significant negative labor productivity impacts of extreme temperatures in Chinese manufacturing firms, attributed to thermal stress during production. Chen and Yang (2019) estimate a 3.4-4.5% decrease in Chinese firm-level labor productivity with a 1°C increase in summer temperatures. Somanathan et al. (2021) observe reduced productivity and increased absenteeism on hot days in Indian manufacturing settings, despite climate control efforts. Other studies examine outdoor and non-industrial activities. For example, Zhang et al. (2023b) analyze Chinese enterprises in the construction sector, revealing significant inverted U-shaped relationships between temperature and labor productivity. In particular, the labor productivity in construction enterprises reaches its highest when the average temperature is 24.90° C and corrodes when the temperature is either too high or too low.

[7] The so-called "bin approach" (Deryugina and Hsian, 2014; Deschênes and Greenstone, 2011) consists in discretizing the annual distribution of daily temperatures into a fixed series of temperature bins (measured in °C or °F), with each bin representing the number of days, in a given country and year, falling into the n^{th} temperature bin.

[8] Additionally, the use of anomalies allows researchers to account for missing direct temperature observations (NASA, 2024; NOAA, 2024). This may be due to an uneven distribution of temperature measurement stations. Relatedly, the large amounts of required interpolation for data-sparse regions further increases uncertainty surrounding absolute temperature measurements (NOAA, 2024).

programme. We then conduct a computationally intensive work of geographical matching between the firm and weather data sources, obtaining a data set of more than 7 million firm-year observations matched with detailed NUTS-3 level weather data referring to the period 2013-2020.

In addition, we measure global warming by considering annual temperature anomalies (measured in °C), as opposed to simple variations in absolute temperatures. In particular, the rich historical information provided in our weather data allows us to compute positive annual temperature anomalies - namely, instances when the yearly temperature is found to exceed its long-term historical reference baseline (i.e., a 30-year historical period, 1980-2010 in our case), thus enhancing the accuracy of the measure.

As concerns our dependent variable, we consider three different indicators of firm productivity: TFP, labor productivity, and capital productivity. This allows us to explore the key channels through which overall firm productivity - as captured by TFP - is impacted by global warming and, more specifically, whether the effect is related to labor and/or capital inputs to production. Moreover, we obtain consistent estimates of firms' TFP using the control-function method proposed by Ackerberg et al. (2015), which accounts for the simultaneity of inputs in the estimation of production functions.

We examine the impact of temperature anomalies on firm productivity via multiple-way fixed-effects regressions, accounting for unobserved firm heterogeneity, multiple interaction fixed effects at various levels, detailed time-varying controls on potentially relevant weather aspects (e.g., precipitation, relative humidity, and air quality), and other time-varying firm-level controls (e.g., size). Through these regressions, we investigate the presence of both linear and curvilinear (i.e., inverted U-shaped) impacts. In addition, we examine potential heterogeneous effects to determine whether, and to what extent, the impact varies based on geographical, sectoral, and firm characteristics.

The analyses show that a higher temperature anomaly significantly reduce TFP. A 1°C increase in temperature anomaly is estimated to lead to a decrease in TFP ranging from 0.3% to 0.4%. This negative impact is slightly curvilinear, with the most severe effects observed at temperature anomalies between 1°C and 1.5°C, and exceeding 1.5°C, respectively - indicating a consistently worsening effect as temperatures increases approach the main Paris Agreement reference target (see Footnote 1). The main driver underlying the reduction in TFP is a significant decline in labor productivity, which drops by 1.2% for each 1°C increase in anomaly, while capital productivity remains unaffected. The impact on TFP and, correspondingly, on labor productivity is highly heterogeneous. Geographical variations are critical, as firms located in temperate and mediterranean climate areas are found to experience more severe productivity losses from increasing warming. Sectoral differences are also evident, with firms engaged in outdoor activities, such as agriculture and construction, experiencing substantial negative impacts. Firms in the manufacturing sector, as well as firms that are more capital-intensive and with a high proportion of blue-collar workers – all contexts compatible with assembly-line production settings – also appear to suffer the impact of higher temperature anomalies. Focusing on size - micro and small firms and, to a lesser extent, medium-sized firms appear to be the most adversely impacted.

Overall, our findings highlight the need to step up the fight against climate change by implementing credible, effective, and large-scale policy mitigation and adaptation actions, with the aim to curb any potentially adverse economic, social, and environmental implication on our society. In this context, targeted measures to mitigate and adapt to the adverse effects of rising temperatures, tailored to the specific needs of various sectors and regions, can more effectively tackle the productivity challenges posed by climate change.

The remainder of this article is organized as follows. Section 2 presents the data and main descriptive statistics. Section 3 presents our empirical model and estimation strategy. Section 4 presents and discusses the econometric results. Section 5 concludes the work, drawing policy implications and discussing avenues for future research.

2. Data, variables, and descriptive statistics

2.1 Firm-level data and computation of productivity indicators

We collect firm-level data from ORBIS, a comprehensive harmonized cross-country longitudinal data set provided by Bureau Van Dijk (a Moody's company). ORBIS includes detailed financial and other firm-level information on over 200 million firms, both private and publicly listed, across more than 200 countries worldwide, including European nations. In addition to balance-sheet data (such as value added, tangible fixed assets, and expenditure on intermediate inputs), ORBIS offers detailed information on a firm's location, economic sector (NACE Rev. 2 classification), and number of employees, among other variables.

Using the data available in ORBIS, we calculate our firm productivity indicators – namely TFP, labor productivity, and capital productivity – as follows.

As concerns TFP, we consider the following production function:

$$Y_{it} = f(L_{it}, K_{it}, A_{it}) \tag{1}$$

where the output of firm *i* at time *t* (Y_{it}) is modeled as a function of its labor (L_{it}) and capital (K_{it}) inputs, and A_{it} is the TFP. In particular, A_{it} is that part of the output that is not explained by labor and capital inputs. It can be thought of as containing several aspects of the firm, such as its productive, organizational, and logistic performance. In sum, TFP captures the overall productivity level of a firm. We then retrieve the TFP estimates according to:

$$A_{it} = f^{-1}(Y_{it}, L_{it}, K_{it}) \tag{2}$$

We assume that the production function in Equation (1) is a log-transformed value-added Cobb-Douglas function.

A critical and well-known issue in the estimation of production functions is the simultaneity of inputs, that is, inputs are endogenous since they respond to a firm's productivity level (Ackerberg et al., 2015). For example, a highly productive firm will produce more, using more input. Similarly, a productivity improvement (e.g., due to the introduction of a process innovation) will lead to an increase in the usage of inputs. This simultaneity problem makes the OLS estimates of the input contributions - and, therefore, of TFP - inconsistent. A fixed-effects (FE) estimation (Mundlak, 1961) cannot solve the issue either, although it removes the fixed firm-specific productivity level.[9] Therefore, a method is needed that can control for a more articulated framework, whereby the unobserved productivity level can fluctuate over time, and production inputs are allowed to respond to such fluctuations. The control-function approach proposed by Ackerberg et al. (2015) (ACF, hereafter) represents a solution to the problem of simultaneity. In a nutshell, this estimation method uses a firm's demand for intermediate inputs to proxy for its unobserved productivity level. The rationale is that intermediate inputs can capture unobserved productivity because firms can easily adjust their use of intermediate inputs in response to productivity shocks.[10] The ACF method is discussed in detail in Appendix A.

We measure a firm's output (Y_{it}) with its value added. The labor input (L_{it}) is measured by considering the number of employees. We measure capital (K_{it}) by referring to the physical capital stock (i.e., tangible fixed assets), computed through a version of the permanent inventory method.[11] The intermediate input demand (used to proxy a firm's unobserved productivity level)

[9] Such a method would only deliver consistent estimates under two unrealistic assumptions: (i) the omitted variable bias is derived exclusively from unobserved time-invariant variables and (ii) inputs do not respond to unobserved (by the econometrician) productivity fluctuations.
[10] The ACF method is part of the larger family of the so-called "control-function estimators", introduced in the seminal work of Olley and Pakes (1996). These methods have been and are still widely used in applied studies, and they represent the standard way of estimating firm-level production functions (Ackerberg et al., 2015).
[11] This version of the permanent inventory method, which is also implemented in Card et al. (2014), applies a constant depreciation rate equal to 5%. The benchmark in the first year is given by the book value of tangible fixed assets. Since direct information on investments is unavailable in our data, these are computed as the difference between a firm's tangible fixed assets in two contiguous years.

is measured by the intermediate input items of the profit and loss accounts, which include both intermediate goods and services used in the production process.

We estimate a separate production function for each economic sector, as defined by the 2-digit NACE Rev. 2 classification. This allows us to account for any structural differences in the production processes among different industries. In total, we pursue the estimation of 73 different production functions. All these estimations control for year, firm location (NUTS-3 region), sector (3-digit NACE Rev. 2), and size (4 classes). They also include interactions for year-region, year-sector, and year-size. In sum, our TFP estimates are the (log) residuals from the ACF estimation of these sector-specific production functions.

We then compute two additional measures of firm output. On the one hand, the labor productivity of the firms, as the log of value added over the number of employees. On the other hand, capital productivity, computed as the log of value added over the capital stock - as derived from the permanent inventory method described above. While TFP provides an indicator of the overall productive performance of a company, labor and capital productivity focus on two critical inputs of the production process, providing specific information about the efficiency and quality of human and physical capital, respectively. In turn, this allows us to evaluate whether any warming-related impact on overall productivity is attributable to a specific input to the production process or whether it stems from a more widespread impact.

2.2 Weather data and variables

We extract temperature and other meteorological data from the Climate Data Store of the Copernicus Climate Change Service, one of the six thematic services provided by the European Union's Copernicus Programme.[12] More specifically, we extract data from E-OBS, a high-resolution daily gridded meteorological data set for Europe ranging from 1950 to present. Unlike weather station-based data sets, gridded data sets have the advantage of providing a precise characterization of the weather variables within a certain territory and, at the same time, a complete data series that allows for long-term analyses (Škrk et al., 2021; Dell et al., 2014). E-OBS is a unique data set in Europe because of the high horizontal grid spacing, the daily resolution, the provision of multiple variables, and the longitudinal length.

To construct the temperature-related variable, we start from the information on daily maximum air temperatures contained in E-OBS. These are measured near the surface, usually at a height of 2 meters, and are based on a 0.1° x 0.1° horizontal resolution for each latitude and longitude pair.

[12] Copernicus is the Earth observation component of the European Union Space Programme, managed by the European Commission. Copernicus provides information services derived from Earth observation satellites and in-situ (non-space) data.

Relying on daily maximum temperatures (as opposed to daily average temperatures, which combine both the maximum and minimum temperatures of a day) has the advantage of better capturing the actual temperatures felt during the daytime, when most jobs are performed (Lai et al., 2023; Somanathan et al., 2021), thus improving the accuracy of our estimated economic impact.

Starting from this information, we construct our regressor of interest, $anomaly_{rit}$. This is an indicator of absolute temperature anomaly (measured in degree °C), referring to a given NUTS-3 *r*, where the firm *i* is placed, in each year *t*. Specifically, $anomaly_{rit}$ is calculated as the absolute difference between the yearly average maximum temperature, observed in a given NUTS-3 region where the firm is located, and a corresponding long-term reference trend (or "climate normal").[13] The reference trend is defined as the average maximum temperature observed in the specific NUTS-3 region over a 30-year historical period (in our case, from 1980 to 2010).[14]

In this paper, we aim to capture the effect of *pure* global warming, and therefore focus exclusively on positive temperature anomalies - namely, instances when the yearly average maximum temperature is found to exceed its long-term historical value (i.e., when temperature anomaly is greater than zero).[15] Figure 1 illustrates the observed yearly average temperature anomaly in each NUTS-3 region of the European Union from 2013 to 2020 (i.e., our observation window), based on our computations using the E-OBS data set. These graphs report the full range of temperature anomalies, including negative values (shaded in blue) that indicate "cooling conditions" relative to the long-term reference trend. As shown in Figure 1, throughout the considered years, most of Europe has experienced positive temperature anomalies. The majority of countries indeed appear as red-shaded across the entire period, thus highlighting a widespread warming trend in most European regions – and further supporting the focus of this paper on the potential economic implications of higher warming conditions.

From E-OBS, we extract additional meteorological data, typically correlated with temperature, on precipitation and humidity.[16] Additionally, we rely on the European Environment Agency (EEA) for data on air quality, measured by the average concentration of the pollutant PM2.5.[17]

[13] In this paper, we choose to rely on the absolute temperature anomaly as main regressor of interest, since this provides an intuitive interpretation (i.e., a measurement in °C) of the impact of global warming on firm productivity. However, an absolute temperature anomaly may not necessarily and fully capture the exceptionality of a given anomaly event in a certain area. For this reason, relying on a "standardized" temperature anomaly may be more appropriate. This issue is discussed and tested in Appendix C.

[14] The choice of a 30-year historical period based on the years 1980-2010 to compute the long-term "climate normal" in our sample is in line with standard international practice, relying on the World Meteorological Organization (WMO, 2017) guidelines.

[15] Observations associated with positive temperature anomalies represent around 94% of our sample.

[16] We also extracted data on windspeed, but due to its very limited geographical coverage, we had to exclude it from our analyses.

[17] Air quality and climate change are closely related. Aside from GHGs, most human activities result in the co-emissions of gaseous and particulate pollutants that modify the composition of the atmosphere, leading to degradation of air quality as well as to climate change. These air pollutants are also "short-lived climate forcers" – substances that affect the climate but remain in the atmosphere for shorter periods (days to decades) than long-lived greenhouse gases like carbon dioxide (IPCC, 2023). In our analyses, we rely on the pollutant PM2.5 (i.e., particulate matter less than 2.5 micrometers in diameter) as this is commonly used as proxy for air pollution (and considered the most harmful type of air pollution, with severe health and environmental implications) affecting 99% of the global population breathing outdoor air which breaches WHO air quality standards (WHO, 2022; 2021).

Starting from the raw information in E-OBS and EEA data sets[18], we construct year- and NUTS-3-specific variables on precipitation (millimeters; PR_{rit}), relative humidity (percentage; HU_{rit}), and air quality (μg/m^3; AQ_{rit}). As detailed in Section 3, these variables are used as controls in our regression analyses.

2.3 The matching process, country selection, and the final data set

We merge the firm-level data from ORBIS with the temperature and other meteorological variables constructed from E-OBS and EEA data sets, using the information on firms' locations provided by ORBIS. Our matching process, along with the construction of weather variables, is conducted at the year and NUTS-3 level. The reasons are twofold. First, since the firm-level data is reported on an annual basis, all our weather variables are calculated as yearly average values, as outlined above. Second, the NUTS-3 level represents the smallest geographical unit applicable for each firm in ORBIS.[19]

In ORBIS, we consider firms active in the last year of observations available at the moment of data extraction (that is, beginning of 2022) and go back to 2013. Overall, we rely on a panel data set from 2013 to 2020.[20] We focus on observations for which we can compute relevant variables for the estimation, including TFP (e.g., available information on the number of employees, value added, tangible fixed assets, and intermediate inputs).[21] Finally, we remove firms belonging to sectors in which the level of public intervention is substantial, namely, education, human health, social work activities, and arts, entertainment, and recreation.[22]

As previously noted, ORBIS is a unique data set that provides comprehensive financial information, as well as detailed firm characteristics such as employee counts, sector classification, and geographical location, for over 200 million companies globally. Bureau van Dijk compiles these data from a variety of sources, primarily national business registers, and standardizes them into an internationally comparable format. Given its status as the largest data set of its kind, ORBIS is widely utilized for analyzing a range of firm-level issues (e.g., Adalet McGowan et al., 2018;

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[18] Consistent with the temperature variable, the additional meteorological indicators on precipitation and humidity from E-OBS are reported daily, based on gridded data sets with a 0.1° x 0.1° horizontal resolution for each latitude and longitude pair. Air quality data, obtained from the EEA data set, is reported annually at the NUTS-3 level.

[19] In principle, ORBIS provides detailed information about a firm's location, including precise latitude and longitude coordinates. In practice, these coordinates are missing from our download. As an alternative, we could have used the city where each firm is located, information that is available in ORBIS. However, we chose to rely on the larger NUTS-3 areas to avoid losing a significant number of observations, especially due to the unavailability of gridded information from E-OBS for several (smaller) cities. Note that a 0.1° latitude by 0.1° longitude grid (as provided by E-OBS) corresponds to approximately 11.1 x 11.1 kilometers at the Equator, decreasing as one moves toward the poles (for example, at 45° latitude, the grid measures about 11.1 x 7.8 kilometers).

[20] In theory, ORBIS provides a 10-year history of firms. However, at the time of data extraction, information for 2012 has become largely unavailable, and data for 2021 was still largely missing.

[21] This includes the requirement for firms to have at least two consecutive years of observations, which is essential for applying the ACF method.

[22] The rationale is derived from the standard production theory and its requirement that prices must be economically meaningful.

Alviarez et al., 2017; Li and Wu, 2020). However, despite its strengths - including rich informational depth, flexibility, and broad cross-country breadth - ORBIS is not without limitations. Most importantly, it encompasses only a sample of all firms, with coverage rates varying significantly: over 50% in well-represented countries, but considerably lower in others (Bajgar et al., 2020). These considerable cross-country disparities in coverage rates are primarily influenced by the specific requirements in each country regarding which firms must submit balance-sheet information to business registers, which Bureau van Dijk uses as the basis for data collection.[23]

In our empirical analysis, we initially downloaded data from ORBIS for firms located in each of the European Union (EU27) member countries. To address the issue of disparities in cross-country coverage rates in ORBIS, we adopted a cleaning process inspired by Bajgar et al. (2020). This process involved selecting countries where the ORBIS sample more accurately represented the underlying population, particularly after eliminating unusable observations.[24] Our screening procedure therefore involved calculating coverage rates by comparing ORBIS data with official statistics from Eurostat on gross value added and the number of employees in each country, respectively. Based on the obtained coverage rates, we retained data for firms in the following countries: Belgium, Bulgaria, Croatia, Czechia, Estonia, Finland, Hungary, Italy, Portugal, Romania, Slovakia, Slovenia, Spain, and Sweden. Appendix B provides further details on the procedure of country selection.[25]

It is crucial to emphasize that our findings are specific to the countries analyzed and may not be necessarily generalized to the entire EU27. While the selection of countries with better representativeness in ORBIS results in the exclusion of some, this approach significantly enhances the accuracy and reliability of our results (Bajgar et al., 2020; Kalemli-Ozcan et al., 2015). Moreover, the countries included in this study are sufficiently representative of the diverse climate regions in Europe (see Section 2.4), thus enabling us to conduct a comprehensive assessment of heterogeneous effects across different climate areas.

The final merged data set, resulting from the matching process and sample selection outlined above, includes 7,720,588 firm-year observations for a total of 1,660,180 firms observed from 2013 to 2020. Using this sample, we calculate our productivity indicators as outlined in Subsection 2.1

[23] Kalemli-Ozcan et al. (2015) provide a table in Appendix A.6 (Table A.6.1) detailing company filing requirements and data providers for several countries available in ORBIS.

[24] In addition to Bajgar et al. (2020), most studies utilizing ORBIS implement some form of country selection to address issues of limited representativeness (e.g., Adalet McGowan et al., 2018).

[25] Additionally, as discussed in Section 3, we weigh all our estimates by the inverse of the average coverage rates, computed for each year and country, and derived from comparing both gross value added and the number of employees between ORBIS and Eurostat data sources. This procedure, discussed in Appendix B, further addresses potential discrepancies in ORBIS data coverage across countries.

and evaluate the impact of warming on firm productivity. The results of the econometric analysis are presented in Section 4. Before that, we provide relevant descriptive statistics in the following subsection and outline the empirical model in Section 3.

2.4 Descriptive statistics

Table 1 presents general summary statistics of the sample. On average, firms employ about 20 workers and produce a value added of around 1 million euros per year. However, half of the sample is composed of firms with less than 5 employees and 157 thousand euros per year of value added. Consistently, micro (fewer than 10 employees) and small (10 to 49 employees) firms account for the majority of the sample, representing approximately 94%, which aligns with the structure of the European industrial landscape. The value added per worker stands at an average of around 49 thousand euros per year. Concerning the sectoral distribution, services and trade, followed by manufacturing and construction collect the largest number of firms - accounting respectively for around 33%, 29%, 20%, and 15% of the sample. Around 3% of the companies operate in the agricultural sector.

We then categorize countries (and, consequently, firms) based on their climate type, utilizing a climate classification system from the EEA.[26] More specifically, we identify five climate areas in our sample, broadly covering the types of climate characterizing Europe: cold (including Finland), cold-temperate (including Sweden), temperate (including Belgium, Czechia, Estonia, Hungary, Romania, and Slovakia), mediterranean-temperate (including Croatia, Bulgaria, and Slovenia), and mediterranean (collecting Italy, Portugal, and Spain). Approximately 63% of the sample firms are located in countries with a typical mediterranean climate, while about 19% are in areas with a temperate climate. Around 10% are found in regions with a combination of temperate and cold climate, 5% in areas with a mix of temperate and mediterranean climate conditions, and 4% in regions with a predominantly cold climate.

The yearly average maximum temperature for the entire panel is 17.53°C, with a standard deviation of 3.98°C. The yearly average precipitation is 2.05 millimeters, and the average relative humidity is 72.64%. Additionally, the average air quality, measured by PM 2.5, is 12.35 μg/m³.

Regarding our main regressor, $anomaly_{rit}$, which indicates the extent to which the yearly average maximum temperature exceeds its long-term baseline trend, the average throughout the panel stands at 1.29°C. Table 2 further elaborates on this. Across all examined years, average

[26] The European Environment Agency (EEA) serves as the European Union's primary agency for providing knowledge and data to support environmental and climate goals. It offers a country-based classification of Europe's main climate types, which are divided into four primary groups. Each of these groups is further subdivided into color-coded categories. Such information is not available at the NUTS-3 level. The color-coding has therefore been used as a basis to create a climate classification based on the countries available in our sample. For more details, see https://www.eea.europa.eu/data-and-maps/figures/climate.

$anomaly_{rit}$ ranged from a minimum of 0.71°C in 2013 to a maximum of around 1.5°C in four out of the eight years considered in the paper (i.e., 2015, 2017, 2019, and 2020).

3. Empirical model

Our empirical analysis is based on two steps. After obtaining TFP estimates and constructing the necessary variables for our estimations (see Subsection 2.1), we then examine the impact of temperature anomalies on firm productivity. Our baseline model takes the following form:

$$productivity_{it} = \alpha + \beta anomaly_{rit} + \gamma X_{rit} + \delta C_{it} + u_{it} \tag{3}$$

The dependent variable, $productivity_{it}$, represents the productivity of firm i in year t. This variable alternates between the estimated (log) TFP (i.e., $\hat{A}_{it}$), (log) labor productivity, and (log) capital productivity, as defined in Subsection 2.1. Our regressor of interest, $anomaly_{rit}$, identifies the temperature anomaly (measured in °C) for the NUTS-3 area r, where firm i is located, in year t, and is calculated as described in Subsection 2.2.

The term X_{rit} is a vector of additional weather-related variables, defined at the NUTS-3 level for each year. These variables include precipitation amount (PR_{rit}), relative humidity (HU_{rit}), and air quality (AQ_{rit}), as detailed in Subsection 2.2. While these variables may be linked to firm productivity, they are also typically correlated with temperature (Lai et al., 2023), making them important controls to include in our regressions.

The term C_{it} includes multiple fixed effects. Firstly, it incorporates firm fixed effects to account for unobserved firm-level time-invariant heterogeneity, such as structural and persistent differences in productivity across firms. Secondly, it includes fixed effects for year, firm size (4 classes), region (NUTS-3), and sector (3-digit NACE Rev. 2). Additionally, it includes interactions for year-size, year-region, and year-sector, allowing us to control for any differential trends in firm productivity over time across these dimensions.

Finally, u_{it} is the error term of the regression. Throughout the analysis, we cluster standard errors at the region (NUTS-3) and year level to address potential spatial and serial correlation in the error term (Cameron et al., 2011).

Additionally, we weigh all our estimates by the inverse of the average coverage rates, computed for each year and country, and derived from comparing both gross value added and the number of employees between ORBIS and Eurostat data sources. Specifically, we use the average of the coverage rates as detailed in Appendix B (particularly in Tables B.1 and B.2). This weighting procedure serves as an additional precaution (on top of the country selection procedure described in Subsection 2.3) to address any potential discrepancies in the coverage of the ORBIS data set across our selected countries.

Our coefficient of interest, β, represents the percentage change in firm productivity for each additional degree (°C) increase in temperature anomaly relative to the long-term reference trend. This coefficient is obtained after accounting for the weather-related time-varying variables and multiple (interaction) fixed effects as described above, as well as for unobserved firm-level heterogeneity.

Endogeneity issues in this context are relatively limited (Dell et al., 2012). Temperature anomaly is unlikely to be influenced by a single firm and its productivity, substantially reducing concerns of simultaneity bias. Moreover, we thoroughly control for possible confounding factors, specifically linked to other weather-related variables (i.e., precipitation, humidity, and air quality - Hsiang, 2016). Additionally, the inclusion of multiple-way fixed effects, particularly interactions, helps capture potentially confounding differential trends in firm productivity across different locations, firm sizes, and sectors.

A residual issue pertains to the location choices of firms, which may respond to warming and potentially affect the estimates. There could be a selection issue if, for instance, more productive firms decided to relocate to areas which are less affected by significant temperature anomalies. However, in our specific context, this seems relatively unlikely for at least three reasons. First, while it might be a viable - though arguably unlikely - option for more structured and larger firms to relocate to less warm areas, smaller firms face far more stringent constraints. Micro and small enterprises, which constitute the majority of European firms (and of our sample), experience limited mobility and relocation possibilities (Beck et al., 2005). Second, the localization of firms is generally influenced by numerous other factors such as the entrepreneur's place of birth, the institutional context, infrastructure availability, agglomeration effects, and general economic opportunities – thus making temperature anomaly an arguably minor factor in these decisions (Arauzo-Carod et al., 2010). Third, before potentially considering any re-localization choice, firms affected by higher temperatures may first naturally opt for investments in climate resilience mechanisms.[27]

In summary, our empirical analysis examines, via multiple-way fixed-effects regressions, the impact of warming on firm productivity by estimating Equation (3) using three different dependent

[27] This is likely to be particularly the case in Europe, where ambitious regulatory action (e.g., the European Green Deal, EU Climate Law, EU Adaptation Strategy to Climate Change) to catalyze the fight and adaptation to climate change has been put in place. According to a recent survey by the European Investment Bank (EIB, 2023), more than half of EU firms are worried about the physical impacts of climate change. However, around 33% of those firms (particularly, 42% of large firms and 25% of SMEs) have already invested in some form of climate adaptation option. In addition, around 88% of firms (particularly, 94% of large firms and 81% of SMEs) are also investing in green technological solutions and changing processes to increase resilience to physical risks from climate change.

variables: TFP, labor productivity, and capital productivity. We further test for the presence of heterogeneous effects by estimating Equation (3) (with TFP and labor productivity as dependent variables only)[28], using split samples under various moderating analyses.

4. Results and discussion

4.1. The overall impact of temperature anomaly on firm productivity

In this subsection, we show the results obtained from the estimation of Equation (3), aimed at measuring the overall impact of warming on firm productivity, that is both on TFP and its key channels (i.e., labor and capital productivity).

In Table 3, we first report the estimates on TFP. The coefficient in Column (1) associated with temperature anomaly is negative and highly significant. Our estimates indicate that a 1°C increase in temperature anomaly - with respect to the corresponding long-term reference trend - leads to a decrease in TFP of -0.3%, on average.

We then investigate the potential curvilinear relationship between temperature anomalies and TFP. Specifically, in Column (2) of Table 3, we assess whether the impact of additional warming differs depending on the underlying average anomaly level to which firms are already exposed. To achieve this, we construct four dummy variables for each temperature anomaly threshold: below 0.5°C, between 0.5°C and 1°C, between 1°C and 1.5°C, and above 1.5°C. We then interact these dummy variables with the actual temperature anomaly (i.e., measured as a continuous variable). Overall, our findings show that the impact of warming on TFP is small and not significant when firms already experience relatively low levels of temperature anomalies (i.e., the first two bins). However, at higher levels of temperature anomalies (i.e., the third and fourth bins), the negative impact on TFP becomes substantial and statistically significant. This indicates that the effect of warming intensifies at higher anomaly levels. Specifically, an additional 1°C increase in warming results in a -0.4% impact on TFP when the average temperature anomaly ranges between 1°C and 1.5°C. This adverse impact slightly decreases to -0.3% for anomalies starting at 1.5°C and above - although remaining highly significant.[29] Conversely, for anomalies below 1°C, our results indicate no significant impact on TFP.

In Table 4, we analyze the impact of temperature anomaly on labor and capital productivity. Interestingly, our results point to a strongly significant and negative impact on labor productivity. As shown in Column (1), a 1°C increase in temperature anomaly is estimated to lead to a decrease

[28] See Subsection 4.1. Capital productivity does not appear to be affected by higher temperature anomalies. This result holds across all moderating analyses. Consequently, for ease of exposition, only TFP and labor productivity are used as dependent variables when presenting their corresponding results in Section 4 and related tables.

[29] The difference between the two coefficients is not found to be statistically significant. This implies that the adverse impacts of additional warming on productivity is overall similar, once the underlying average temperature anomaly threshold of 1°C is reached.

in labor productivity by as much as -1.2%. On the contrary, no significant impact is found for capital productivity, indicating that the labor input is the mostly affected by warming.[30]

All in all, the results from our analysis thus far indicate that warming has a significant negative impact on a firm's TFP, with the effect intensifying at higher overall anomaly levels. While temperature anomalies might dampen a firm's TFP through various channels, including negative effects on organizational, logistic, and productive performance, the pronounced negative impact on labor productivity suggests that the labor input is a primary channel through which warming affects overall firm productivity. This may be due to decreases in individual labor productivity caused by thermal stress (both via physical and cognitive fatigue) and/or heightened workers' absenteeism, which leads to substantial direct and indirect losses for the organization (Grinza and Rycx, 2020).

4.2. The diversified impact of geographical, sectoral, and firm characteristics

In this subsection, we conduct a set of moderating analyses to explore the impact of temperature anomaly on firm productivity by relevant geographical, sectoral, and firm characteristics. As specified in Section 3, we rely on the estimation of Equation (3), using TFP and labor productivity as dependent variables only, and perform the estimations on split samples.

Given the variety of European countries in our sample (and their underlying climate types), a key moderating factor to consider is arguably whether the impact of higher temperature anomalies on productivity differs significantly across regions. A priori, the expected overall impact is not clear-cut. Rising temperatures are generally seen as detrimental to economic activity across countries. In the specific case of Europe, existing trends and projections point to southern regions as likely to experience much larger negative impacts (notably via the effects of heatwaves, droughts, and forest fires), compared to areas relatively up north. At the same time, some minor economic opportunities may be observed in northern and central parts of Europe (e.g., via specific benefits to the agriculture and tourism sectors, or decreased heating demand). However, the overall positive effects of climate change are expected to be fewer than the negative ones, and typically limited to specific instances. Furthermore, the impact in a specific region and/or sector will also strictly depend on the extent and type of mitigation and adaptation measures at play (IPCC, 2022b; EEA,

[30] As mentioned in Footnote 13, this paper relies on an indicator of "absolute" temperature anomaly as main regressor of interest, since this provides a more intuitive interpretation (i.e., a measurement in °C) on the impact of global warming. However, this may not necessarily and fully capture the exceptionality of a given anomaly event in a certain area. This is particularly relevant when performing cross-country analyses, where average local variability in temperature should also be considered. We tackle such issues by assessing the sensitivity of our results to the use of a "standardized" temperature anomaly (see discussion in Appendix C). Our findings (presented in Appendix C) are fully in line with Tables 3 and 4. In particular, we find a negative and significant relationship between the "standardized" anomaly, TFP and labor productivity. No significant impact is instead found for capital productivity. Results also hold across the entire estimation spectrum (i.e., our moderating analyses) and are available upon request.

2017).[31] To test for this, we categorize the countries in our sample into major climate areas, based on the classification provided by the EEA (as detailed in Subsection 2.4 and Footnote 26). We identify five distinct climate areas in our sample, as outlined in Table 1: cold, cold-temperate, temperate, mediterranean-temperate, and mediterranean. We perform our standard estimations for each climate-specific sample. Results are presented in Table 5.

Interestingly, our results point to a large and significant negative impact for temperate climate areas (-1.2% for TFP and -2.4% for labor productivity) and a relatively smaller - but still highly significant - negative impact in mediterranean climates (-0.3% for TFP and -1.2% for labor productivity). These findings suggest that global warming has the potential to exert negative economic consequences across various regions of Europe – especially in those areas generally accustomed to milder temperate conditions. These regions may experience more severe impacts from higher-than-normal temperature rises, potentially due to lower underlying levels of preparedness and adaptive capacities to climate change. As shown in Figure 1, more temperate areas in Europe seem to have been indeed exposed to some of the highest warming trends over recent years, compared to other countries.

As for other areas, our results highlight that countries featuring a typical mediterranean climate (and therefore accustomed to warmer underlying conditions) still appear to suffer – albeit to a lesser extent – from higher-than-expected temperatures (particularly on the labor productivity side). Such findings appear to be in line with the projected adverse climate predictions for southern countries in Europe (IPCC, 2022b). At the same time, they also seem to point to some potential limitations in the adaptation responses currently in place in such areas, thus calling for a more widespread and effective implementation of better-designed mechanisms to counteract the adverse economic impacts of a changing climate.

At the same time, we find a weakly significant[32] and positive impact on labor productivity in countries featuring a combination of both mediterranean and temperate climate conditions, although this effect does not seem to extend to TFP. While not too robust, such result may nevertheless highlight some potential economic opportunities of warmer temperatures in specific regions and/or industries. In contrast, no economically significant effects are observed in either cold or cold-temperate climates. This may be attributable to the fact that, despite higher

[31] Alongside potential economic benefits to some northern and central parts of Europe, studies equally point to the negative impact of additional warming for such regions, due to more intense and frequent extreme weather events (e.g., via intense storms and floods) affecting sectors across the board and expected to outweigh the specific opportunities that may emerge from a warmer climate (EEA, 2024; IPCC, 2022b). Additional negative impacts on the agricultural and forestry ecosystems in the north of Europe may occur, for instance, through increasing risks of pests and diseases, nutrient leaching, and reduced soil organic matter (EEA, 2012). Southern European countries are expected to suffer the most, due to decreased precipitation and increased temperature (e.g., affecting water availability and crop yields), increased energy demand for cooling, and less favorable conditions for tourism.

[32] The estimated impact is only marginally significant at the 10% level and should therefore be interpreted with caution.

temperature anomalies *relative* to historical trends observed thus far, these countries continue to experience overall naturally cooler conditions, which may allow for a relatively smoother conduct of economic activity.

Another relevant moderating factor to consider is whether a certain firm's activities are conducted outdoors or indoors. Intuitively, activities primarily performed outdoors entail prolonged direct exposure to heat combined with higher physical work intensity – compared to activities performed indoors – where temperature control systems (such as air conditioning) are easier to implement, and physical work intensity may be relatively more moderate. The following moderating analysis focuses on such aspects. In line with existing literature (Zhang et al., 2023b; ILO, 2019; Traore and Foltz, 2018), we classify as "outdoor activities" those firms involved in activities belonging to the agriculture and construction sectors (NACE A and NACE F sectors based on the NACE Rev. 2 classification).

Results are presented in Table 6. As expected, our evidence points to a clear-cut negative and highly significant impact of warming on the productivity of firms performing most of their activities outdoors. For these activities, a 1°C increase in temperature anomaly is estimated to lead to a -0.7% decrease in TFP. The impact on labor productivity is notably greater, standing at -2.4%, in line with the overall finding of our sample that labor productivity tends to be more affected than TFP. Indoor activities appear to be equally at risk, although relatively less, with a highly significant decrease of -0.3% in TFP and -1% in labor productivity.

In Table 7, we examine the diversified effects based on a macro-sectoral classification. While we anticipate negative impacts for outdoor sectors (i.e., agriculture and construction), this analysis aims to determine whether significant differences mainly exist among the primarily indoor sectors. We thus divide the sample according to the six macro-sectors (based on 2-digit Rev.2 NACE classification) outlined in Table 1: agriculture, mining and quarrying, manufacturing, construction, trade, and services. As expected, a 1°C increase in temperature anomaly has a substantial negative impact on TFP in outdoor sectors, with agriculture experiencing a -1.6% effect and construction a -0.5% effect. Among the remaining sectors, manufacturing faces a notable -0.6% impact, while trade experiences a smaller decline of -0.4%.[33] In contrast, no statistically significant impact is observed for mining and quarrying or services. A similar trend is observed for labor productivity, but with a more pronounced effect. The negative and significant impact of increased temperature anomalies is -3.5% for agriculture, -2.1% for construction, -1.7% for manufacturing, and -1% for

[33] The difference between the coefficients across these two sectors does not appear to be statistically significant. This implies that the effect of a higher temperature anomaly on TFP is statistically similar across the two sectors.

trade. As for TFP, the estimated effect is not significant for mining and quarrying as well as for services.

The negative impacts on agriculture and construction are consistent with their reliance on activities mostly performed in outdoor settings.[34] In contrast, when focusing on indoor activities, the most adverse effects are observed in manufacturing - particularly for labor productivity. This is again explained by manufacturing typically involving a substantial amount of manual labor, which is arguably more sensitive to heat compared to cognitive tasks. Additionally, temperature control in manufacturing environments may be especially challenging due to the substantial heat generated by machinery, coupled with specific standards concerning workwear, working time regulations, and/or with building design issues (e.g., poor ventilation, inadequate insulation). Similarly, the adverse impact on the trade sector may be attributed to its heavy reliance on manual activities and the inherent difficulties in maintaining effective temperature control. For instance, retail stores with frequent door openings face continuous challenges with regulating indoor temperatures. Such aspects appear less prominent in service-based sectors - where machinery heating and physical work intensity are minimal - and effective adaptive systems/behaviors may be more easily implemented. Across the entire industrial spectrum, higher heat levels may still further dampen productivity by impairing cognitive skills and increasing mental fatigue (ILO, 2019).

To better understand the factors driving the sector-specific estimates, we explore two additional dimensions of firms' production processes: capital intensity and blue-collar intensity. For the first dimension, we define capital-intensive firms as those with a capital-to-labor ratio higher than the sample median (computed within a given NUTS-3 and year). The capital-to-labor ratio is calculated using the capital stock, computed with the permanent inventory method as described in Subsection 2.1, divided by the number of employees. We then divide the sample and separately examine the impact of interest for capital-intensive versus non-capital-intensive firms. The results presented in Table 8 show that the productivity impact is only significant for capital-intensive firms, with estimates indicating a -0.5% impact on TFP and -1.4% on labor productivity. Conversely, no significant impact is observed for non-capital-intensive firms.

For the second dimension, we identify blue-collar-intensive firms as those with a higher share of blue-collar workers than the sample median computed within a given NUTS-3 and year.[35] We

[34] Moreover, such results are in line with evidence that rising temperatures are expected to lead to significant productivity losses in agriculture, such as by affecting crop yields, making some lands unproductive, and displacing farming communities (IPCC, 2022a). The agricultural sector alone accounted for 83 per cent of global working hours lost to heat stress in 1995 and is projected to account for 60 per cent of such loss in 2030. Similarly, while the construction sector accounted for just 6 per cent of global working hours lost to heat stress in 1995, this share is expected to increase to 19 per cent by 2030 (ILO, 2019).

[35] The share of blue-collar workers is not provided by ORBIS. We extract such data from the Labor Force Survey (LFS) data set provided by Eurostat. More specifically, we rely on annual data on employment (by sex, age, occupation, and economic activity)

then split the sample and analyze the impact on blue-collar-intensive versus non-blue-collar-intensive firms. The results, presented in Table 9, show that the negative impact on firm productivity due to temperature anomalies is particularly pronounced for blue-collar-intensive firms, with an estimated -0.6% impact on TFP and -1.9% on labor productivity. Conversely, non-blue-collar-intensive firms exhibit small and insignificant coefficients for both TFP and labor productivity.

Taken together, these findings highlight that firms characterized by high capital intensity and a high proportion of blue-collar workers suffer the most from higher warming. This provides direct evidence that firms with predominantly manual work, heavily relying on machinery and technical equipment (and therefore more sensitive to temperature control issues) face more challenges in adapting to rising temperatures. Such production processes are often also found in outdoor sectors like agriculture and construction but equally in manufacturing firms - with typical indoor activities based on assembly-line settings.

Our analysis finally explores the moderating role of firm size. We divide the sample into four size categories as outlined in Table 1: micro firms (less than 10 employees), small firms (10 to 49 employees), medium-sized firms (50 to 249 employees), and large firms (250 or more employees). The results, reported in Table 10, show that the negative impact of temperature anomalies on firm productivity progressively diminishes as firm size increases. The impact is negative and significant, with a relatively high magnitude, for both TFP and labor productivity in micro and small enterprises. The TFP impact ranges between -0.3% for micro firms and -0.4% for small firms. The labor productivity impact is correspondingly larger, at -1.1% for micro firms and -0.9% for small firms. For medium-sized firms, the impact is statistically significant only for labor productivity, while the coefficient for TFP is not significant. Finally, large firms display non-significant coefficients for both TFP and labor productivity. This result is in line with the idea that typically smaller firms, which face more stringent financial and organizational constraints, may find it more difficult to invest in effective systems to counteract the negative productivity effects of rising temperatures. Conversely, larger firms may be better equipped to steadily implement adaptation solutions.

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which are matched - at the country-sector (1-digit NACE Rev. 2)-year level with our data set. Starting from the LFS, the share of blue-collar workers is constructed, for each country-sector-year pair, by computing the ratio of the number of workers in commonly identified blue-collar occupations (i.e., categories 6-9 according to the ISCO-08 classification - skilled agricultural, forestry and fishery workers; craft and related trades workers; plant and machine operators and assemblers; and elementary occupations) over the total number of workers therein.

5. Conclusion

This paper has contributed to the ongoing debate on the micro-economic impact of global warming by conducting a robust, large-scale empirical assessment of how global warming affects firm productivity. This is the first study to provide comprehensive evidence on European firms.

We have created a unique data set by combining firm-level balance-sheet information from ORBIS - Bureau van Dijk with high-resolution gridded weather data from E-OBS – Copernicus (European Union Space Programme). This has involved matching firm data with rich weather information, notably on yearly average maximum temperature, resulting in over 7 million firm-year observations with detailed NUTS-3 level weather data from 2013 to 2020.

In our study, we have measured global warming using positive temperature anomalies (i.e., instances when the yearly average maximum temperature is found to exceed its long-term historical value), which provide a more adequate measure of changing climate conditions, compared to annual variations in absolute temperature. In line with international guidelines, we have calculated annual anomalies *relative* to a 30-year historical baseline (i.e., 1980-2010), enhancing measurement accuracy. We have measured firm productivity using three dependent variables: TFP, labor productivity, and capital productivity, allowing us to explore the impact of warming on overall firm productivity and its effect might be mediated through labor and/or capital inputs. We have obtained consistent TFP estimates using the control-function method by Ackerberg et al. (2015), which accounts for the simultaneity of inputs in production function estimation.

We have analyzed the impact of temperature anomalies on firm productivity using multiple-way fixed-effects regressions. These regressions account for unobserved firm heterogeneity, interaction fixed effects at various levels, detailed time-varying weather controls (such as precipitation, relative humidity, and air quality), and other time-varying firm-level controls (such as size). We have examined both linear and curvilinear impacts and assessed potentially heterogeneous effects, based on geographical and sectoral characteristics. We have also considered other relevant firm characteristics, including firm size and production process type.

The study has highlighted a substantial and nuanced impact of global warming on firm productivity. Overall, rising temperatures negatively impact TFP, with the effect of additional warming becoming notably more intense as the underlying average anomalies to which firms are exposed approach the main Paris Agreement reference target. Specifically, a 1°C increase in temperature anomaly is estimated to lead to a decrease in TFP ranging from 0.3% to 0.4%. This negative impact is slightly curvilinear, with the most severe effects observed at average temperature anomalies between 1°C and 1.5°C, and exceeding 1.5°C, respectively. We have also found that labor productivity is particularly sensitive to warming, declining by 1.2% for each 1°C increase in the temperature anomaly. This suggests that the primary channel through which warming affect overall productivity is the labor input, most likely due to factors such as thermal stress and/or increased worker absenteeism. In contrast, capital productivity does not show significant change, highlighting the unique vulnerability of human labor to climatic conditions.

We have found that geographical variation nuances the relationship. Firms located in countries with a typically temperate climate seem to experience the largest negative impacts, suggesting lower preparedness and adaptive capacity to face the increased warming exposure faced over recent years. Interestingly, mediterranean countries are still found to experience significant challenges from additional warming, thus highlighting the need to refine and/or enhance the current adaptation practices in place. In contrast, no significant effect is found for either cold or cold-temperate climate areas.

Sectoral differences also play a crucial role. Firms engaged in outdoor activities, such as agriculture and construction, are disproportionately affected. These sectors experience significant declines in both TFP and labor productivity, with agriculture facing the most severe impact. Conversely, indoor sectors, while still negatively affected, suffer less severe declines, reflecting the effectiveness of some level of adaptation (such as temperature control) systems.

The study has also revealed that firm characteristics, such as the type of production process and size, moderate the impact of warming. Capital-intensive and blue-collar-intensive firms are particularly vulnerable, experiencing notable declines in productivity. This is consistent with the intuition that workers involved in moderately intensive physical tasks – and who also employ machinery and other equipment subject to heating – tend to be more adversely affected. As for size, we have found that smaller firms face more severe impacts, compared to larger firms. This may be driven by financial and organizational constraints hindering adequate investments in effective adaptation measures to withstand the adverse productivity impact of rising temperatures.

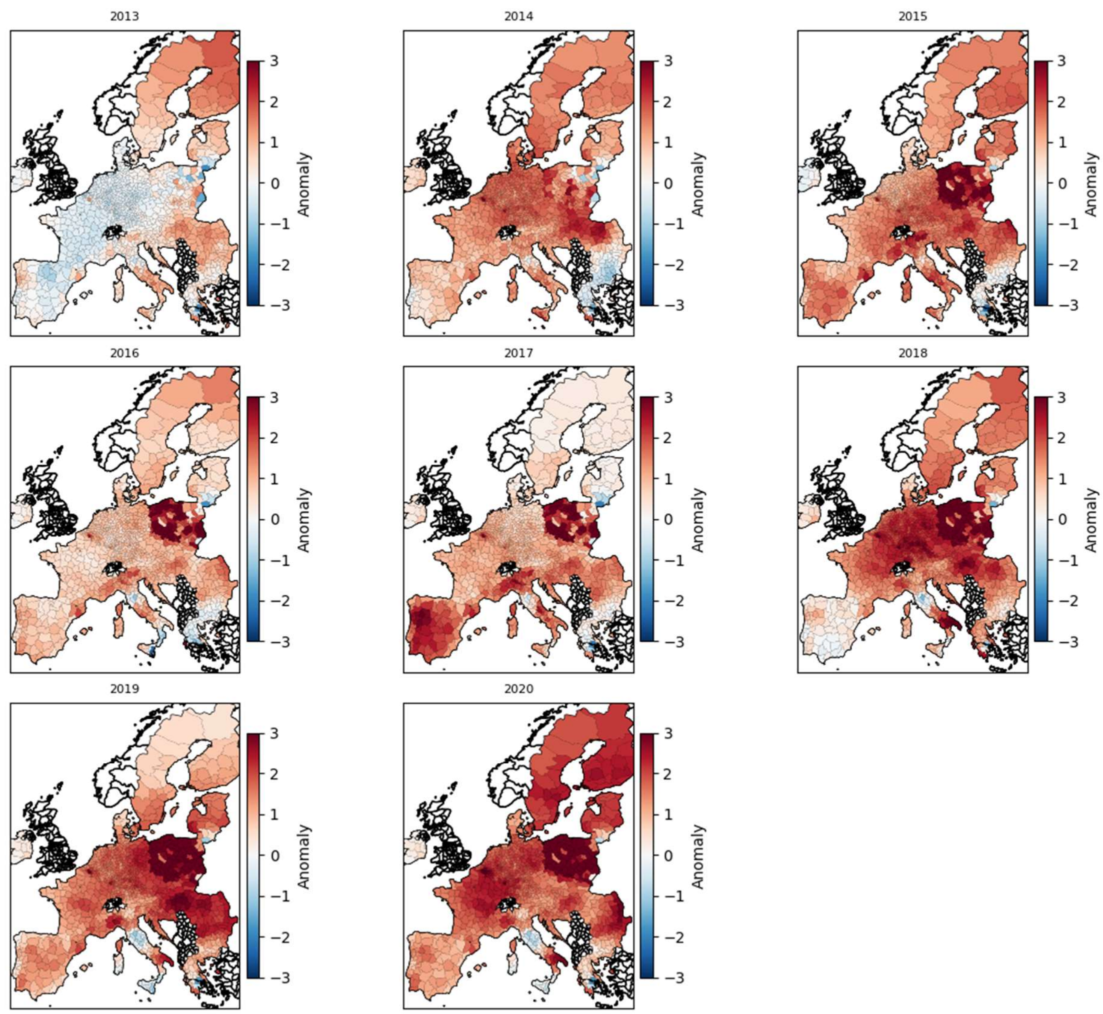
Overall, we have shown that climate change has the potential to negatively affect the economic system in various regions across Europe. Without adequate and large-scale mitigation and adaptation policies, additional temperature increases, more frequent and intense extreme weather events, and sea-level rise are all expected to affect – directly or indirectly – our economic sectors in the coming decades (Gagliardi et al., 2022; Batten, 2018). To protect our environment and support a fair, modern and competitive economy, the European Union has set forth ambitious climate policy action over recent years. The European Green Deal, launched in December 2019, is a package of policy initiatives aiming to set the EU on the path to a green transition, with the ultimate goal of reaching the legally binding target of climate neutrality by 2050, delivering on the commitments under the Paris Agreement.

Addressing the negative impact of rising temperatures on firm productivity, particularly in sectors such as agriculture, construction, and manufacturing, requires swift and appropriate climate adaptation measures. In this context, governments, employers, and workers all play an equally relevant role. From the government side, it is essential to establish and enforce well-designed regulatory frameworks that encourage employers and workers to adopt practices that mitigate heat stress on the workplace. These may range from clearly prescribed standards (e.g., equipment, maximum level of temperature exposure) to measures promoting the adoption of specific technologies and technical standards to ensure adequate temperature control in buildings. At the same time, employers should take an active role in ensuring that working conditions conform to existing standards and regulations. Furthermore, in order to provide safe and healthy workplaces, infrastructure investments in adaptation should be tailored to both indoor (e.g., building design improvement) and outdoor activities (e.g., protective equipment, increase mechanization to reduce physical effort). Additional measures may relate to working hour adjustment, increased breaks, and workwear. Training programs can be equally effective to help workers take individual action in the workplace to reduce their sensitivity to heat and reduce its negative impact on their productivity. In this context, social dialogue remains critical to reach consensus on adequate adaptation solutions (ILO, 2019).

Similarly, geographical differences on rising temperatures impacts point to the relevance of region-specific adaptation strategies to maintain productivity levels. Firms in temperate and mediterranean climates, which experience the most substantial productivity losses, may need more focused support. This could include the design of specific regional policies and incentives for investments in infrastructure upgrades, the promotion and adoption of innovative climate-resilient practices and setting up region-specific regulations and standards.

While this study provides valuable insights, several avenues for future research emerge. Expanding the analysis beyond Europe to include firms in other countries could uncover differences in global patterns and provide insights into varying resilience and adaptive capacities to temperature increases. Additionally, adopting a comprehensive longitudinal approach that examines data over a longer period and incorporates predictions about future climate change, including on extreme weather events, is crucial for further investigation. Furthermore, a deeper exploration of firm-level characteristics, such as management practices and workforce composition, could shed light on how these factors affect a firm's ability to adapt to the adverse productivity impacts of warming. Overall, depending on data availability, an examination across types of implemented adaptation measures may provide a clearer understanding on the effectiveness of existing strategies, their vulnerabilities, and potential ways forward.

Figure 1 – Temperature anomaly (°C) in the European Union, by NUTS-3 and year



Notes: The anomaly (°C) is computed as the deviation of the yearly average maximum temperature, observed in a given NUTS-3 region, from the corresponding long-term reference trend (measured as the average of the maximum temperature observed over the period 1980-2010 in the same NUTS-3 region).
Source: E-OBS Copernicus (years: 2013-2020).

Table 1 – Sample summary statistics: overall variables

Variable	Mean	Std. Dev.	25th perc.	Median	75th perc.
Employees	19.659	189.170	2	5	12
Value added (1,000 euros)	1056.794	16,744.19	56	157	460.86
Capital (1,000 euros, permanent inventory method)	1,123.504	146,621.5	11	47	231.93
Expenditure on intermediate inputs (1,000 euros)	2,696.905	78,083.66	36	160	642
Value added over employees (VA/L; 1,000 euros)	49.184	552.970	16.961	32.210	54.214
log (VA/L) (labor productivity)	3.359	1.011	2.830	3.472	3.992
TFP (log)	1.076	0.409	0.953	1.167	1.309
Agriculture (%)	0.033	-	-	-	-
Mining and quarrying (%)	0.002	-	-	-	-
Manufacturing (%)	0.200	-	-	-	-
Construction (%)	0.145	-	-	-	-
Trade (%)	0.287	-	-	-	-
Services (%)	0.330	-	-	-	-
Less than 10 employees (%)	0.693	-	-	-	-
Between 10 and 50 employees (%)	0.250	-	-	-	-
Between 50 and 250 employees (%)	0.046	-	-	-	-
More than 250 employees (%)	0.008	-	-	-	-
Cold (%)	0.037	-	-	-	-
Cold-Temperate (%)	0.095	-	-	-	-
Temperate (%)	0.185	-	-	-	-
Mediterranean-Temperate (%)	0.051	-	-	-	-
Mediterranean (%)	0.628				
Maximum temperature (°C)	17.530	3.975	15.337	18.317	20.412
Temperature anomaly (°C)	1.293	0.632	0.841	1.270	1.705
Precipitation (mm)	2.051	0.901	1.462	1.845	2.478
Relative humidity (%)	72.642	6.301	68.323	73.076	77.588
Air quality (PM2.5 - $\mu g/m^3$)	12.354	5.430	8.271	11.65	15.842
Observations: 7,720,588					

Notes: Sampling weights are used as discussed in Appendix B.
Source: ORBIS, E-OBS Copernicus, *EEA* (years: 2013-2020).

Table 2 – Temperature anomaly (°C), by year

Year	Mean	Median	Min	Max
2013	0.707	0.733	0.002	1.851
2014	1.211	1.222	0.033	3.185
2015	1.540	1.565	0.143	2.835
2016	1.024	0.933	0.028	2.613
2017	1.457	1.433	0.012	3.192
2018	1.273	1.371	0.012	3.941
2019	1.466	1.417	0.076	3.389
2020	1.528	1.460	0.062	4.275
Observations: 7,720,588				

Notes: The anomaly (°C) is computed as the deviation of the yearly average maximum temperature, observed in a given NUTS-3 region where the firm is located, from the corresponding long-term reference trend (measured as the average of the maximum temperature observed over the period 1980-2010 in the same NUTS-3 region). Sampling weights are used as discussed in Appendix B.
Source: ORBIS, E-OBS Copernicus, *EEA* (years: 2013-2020).

Table 3 – The impact of temperature anomaly (°C) on TFP

Variable	(1)	(2)
	TFP	**TFP**
Temperature anomaly (°C)	-0.003**	
	(0.001)	
Temperature anomaly, by range (°C):		
Less than 0.5°C	-	-0.002
		(0.003)
Between 0.5°C and 1°C	-	-0.002
		(0.002)
Between 1°C and 1.5°C	-	-0.004**
		(0.001)
1.5°C and above	-	-0.003**
		(0.001)
Precipitation	-0.002	-0.002
	(0.002)	(0.002)
Precipitation – squared	0.000	0.000
	(0.000)	(0.000)
Humidity	0.003	0.003
	(0.002)	(0.002)
Humidity – squared	-0.000	-0.000
	(0.000)	(0.000)
Air quality	-0.002**	-0.002**
	(0.001)	(0.001)
Air quality - squared	0.000*	0.000*
	(0.000)	(0.000)
Year FE	Yes	Yes
Region FE	Yes	Yes
Industry FE	Yes	Yes
Size FE	Yes	Yes
Year-Region FE	Yes	Yes
Year-Industry FE	Yes	Yes
Year-Size FE	Yes	Yes
Firm FE	Yes	Yes
Observations	7,720,588	7,720,588

Notes: Standard errors, reported in parentheses, are robust and clustered at the region (NUTS-3)-year level. ***, **, and * denote the 1%, 5 %, and 10% significance levels, respectively. The anomaly (°C) is computed as the deviation of the yearly average maximum temperature, observed in a given NUTS-3 region where the firm is located, from the corresponding long-term reference trend (measured as the average of the maximum temperature observed over the period 1980-2010 in the same NUTS-3 region).The region dummies are at the 3-digit level of the NUTS classification; the industry dummies are at the 3-digit level of the NACE Rev. 2 classification; the size dummies collect four classes of firm size (as outlined in Table 1). In Column (2), we investigate the potential curvilinear relationship between the temperature anomaly and TFP by interacting four dummy variables (i.e., representing average temperature anomaly intervals) and the actual temperature anomaly (i.e., measured as a continuous variable). Sampling weights are used as discussed in Appendix B.
Source: ORBIS, E-OBS Copernicus, *EEA* (years: 2013-2020).

Table 4 – Labor productivity versus capital productivity

Variable	(1)	(2)
	Labor productivity	Capital productivity
Temperature anomaly (°C)	-0.012**	0.007
	(0.004)	(0.006)
Precipitation	-0.007	-0.001
	(0.006)	(0.009)
Precipitation – squared	0.000	0.000
	(0.000)	(0.001)
Humidity	0.006	0.008
	(0.005)	(0.007)
Humidity – squared	-0.000	-0.000
	(0.000)	(0.000)
Air quality	-0.001	-0.001
	(0.002)	(0.003)
Air quality - squared	0.000	-0.000
	(0.000)	(0.000)
Year FE	Yes	Yes
Region FE	Yes	Yes
Industry FE	Yes	Yes
Size FE	Yes	Yes
Year-Region FE	Yes	Yes
Year-Industry FE	Yes	Yes
Year-Size FE	Yes	Yes
Firm FE	Yes	Yes
Observations	7,720,588	7,720,588

Notes: Standard errors, reported in parentheses, are robust and clustered at the region (NUTS-3)-year level. ***, **, and * denote the 1%, 5 %, and 10% significance levels, respectively. The anomaly (°C) is computed as the deviation of the yearly average maximum temperature, observed in a given NUTS-3 region where the firm is located, from the corresponding long-term reference trend (measured as the average of the maximum temperature observed over the period 1980-2010 in the same NUTS-3 region). The region dummies are at the 3-digit level of the NUTS classification; the industry dummies are at the 3-digit level of the NACE Rev. 2 classification; the size dummies collect four classes of firm size (as outlined in Table 1). Sampling weights are used as discussed in Appendix B.
Source: ORBIS, E-OBS Copernicus, *EEA* (years: 2013-2020).

Table 5 – By climate area

Variable	(1)	(2)
	TFP	**Labor productivity**
Cold		
Temperature anomaly (°C)	-0.005	-0.021
	(0.005)	(0.018)
Observations: 164,718		
Cold-Temperate		
Temperature anomaly (°C)	-0.004	-0.010
	(0.003)	(0.010)
Observations: 490,354		
Temperate		
Temperature anomaly (°C)	-0.012**	-0.024**
	(0.005)	(0.010)
Observations: 1,488,708		
Mediterranean-Temperate		
Temperature anomaly (°C)	0.006	0.020*
	(0.006)	(0.012)
Observations: 612,143		
Mediterranean		
Temperature anomaly (°C)	-0.003**	-0.012**
	(0.001)	(0.005)
Observations: 4,964,665		

Notes: Standard errors, reported in parentheses, are robust and clustered at the region (NUTS-3)-year level. ***, **, and * denote the 1%, 5 %, and 10% significance levels, respectively. The anomaly (°C) is computed as the deviation of the yearly average maximum temperature, observed in a given NUTS-3 region where the firm is located, from the corresponding long-term reference trend (measured as the average of the maximum temperature observed over the period 1980-2010 in the same NUTS-3 region). The same set of controls as in Table 3 are used. Sampling weights are used. The climate areas are categorized as follows: mediterranean (comprising Italy, Portugal, and Spain), temperate (including Belgium, Czechia, Estonia, Hungary, Romania, and Slovakia), mediterranean-temperate (covering Croatia, Bulgaria, and Slovenia), cold-temperate (encompassing Sweden), and cold (including Finland).
Source: ORBIS, E-OBS Copernicus, *EEA* (years: 2013-2020).

Table 6 – Outdoor versus indoor activities

Variable	(1)	(2)
	TFP	**Labor productivity**
Outdoor activities		
Temperature anomaly (°C)	-0.007***	-0.024***
	(0.002)	(0.006)
Observations: 1,333,557		
Indoor activities		
Temperature anomaly (°C)	-0.003**	-0.010**
	(0.001)	(0.004)
Observations: 6,387,031		

Notes: Standard errors, reported in parentheses, are robust and clustered at the region (NUTS-3)-year level. ***, **, and * denote the 1%, 5 %, and 10% significance levels, respectively. The anomaly (°C) is computed as the deviation of the yearly average maximum temperature, observed in a given NUTS-3 region where the firm is located, from the corresponding long-term reference trend (measured as the average of the maximum temperature observed over the period 1980-2010 in the same NUTS-3 region). The same set of controls as in Table 3 are used. Sampling weights are used. Outdoor activities are classified based on sectors whose activities are prevalently performed outdoors (i.e., agriculture and construction - NACE A and NACE F based on the NACE Rev. 2 classification). Indoor activities are classified based on sectors whose activities are prevalently performed indoors (i.e., all sectors with the exclusion of agriculture and construction, as previously defined).
Source: ORBIS, E-OBS Copernicus, *EEA* (years: 2013-2020).

Table 7 – By sectoral aggregation

Variable	(1) TFP	(2) Labor productivity
Agriculture		
Temperature anomaly (°C)	-0.016**	-0.035**
	(0.007)	(0.015)
Observations: 262,102		
Mining and Quarrying		
Temperature anomaly (°C)	0.002	-0.000
	(0.011)	(0.029)
Observations: 20,560		
Manufacturing		
Temperature anomaly (°C)	-0.006***	-0.017***
	(0.001)	(0.004)
Observations: 1,545,758		
Construction		
Temperature anomaly (°C)	-0.005**	-0.021***
	(0.002)	(0.006)
Observations: 1,071,455		
Trade		
Temperature anomaly (°C)	-0.004**	-0.010**
	(0.002)	(0.004)
Observations: 2,257,638		
Services		
Temperature anomaly (°C)	-0.000	-0.005
	(0.002)	(0.006)
Observations: 2,563,075		

Notes: Standard errors, reported in parentheses, are robust and clustered at the region (NUTS-3)-year level. ***, **, and * denote the 1%, 5 %, and 10% significance levels, respectively. The anomaly (°C) is computed as the deviation of the yearly average maximum temperature, observed in a given NUTS-3 region where the firm is located, from the corresponding long-term reference trend (measured as the average of the maximum temperature observed over the period 1980-2010 in the same NUTS-3 region). The same set of controls as in Table 3 are used. Sampling weights are used. The six macro-sectors are identified on the basis of a 2-digit Rev.2 NACE classification.
Source: ORBIS, E-OBS Copernicus, *EEA* (years: 2013-2020).

Table 8 – Capital-intensive versus non-capital-intensive firms

Variable	(1)	(2)
	TFP	**Labor productivity**
Capital-intensive		
Temperature anomaly (°C)	-0.005***	-0.014***
	(0.001)	(0.004)
Observations: 3,859,027		
Non-capital-intensive		
Temperature anomaly (°C)	-0.000	-0.006
	(0.001)	(0.004)
Observations: 3,861,561		

Notes: Standard errors, reported in parentheses, are robust and clustered at the region (NUTS-3)-year level. ***, **, and * denote the 1%, 5 %, and 10% significance levels, respectively. The anomaly (°C) is computed as the deviation of the yearly average maximum temperature, observed in a given NUTS-3 region where the firm is located, from the corresponding long-term reference trend (measured as the average of the maximum temperature observed over the period 1980-2010 in the same NUTS-3 region). The same set of controls as in Table 3 are used. Sampling weights are used. Capital-intensive firms are defined as those firms whose capital-to-labor ratio is above the median of the corresponding region (NUTS-3)-year pair.
Source: ORBIS, E-OBS Copernicus, *EEA* (years: 2013-2020).

Table 9 – Blue-collar-intensive versus non-blue-collar-intensive firms

Variable	(1)	(2)
	TFP	**Labor productivity**
Blue-collar-intensive		
Temperature anomaly (°C)	-0.006***	-0.019***
	(0.001)	(0.004)
Observations: 3,740,903		
Non-blue-collar-intensive		
Temperature anomaly (°C)	-0.001	-0.008
	(0.002)	(0.005)
Observations: 3,979,685		

Notes: Standard errors, reported in parentheses, are robust and clustered at region (NUTS-3)-year level. ***, **, and * denote the 1%, 5 %, and 10% significance levels, respectively. The anomaly (°C) is computed as the deviation of the yearly average maximum temperature, observed in a given NUTS-3 region where the firm is located, from the corresponding long-term reference trend (measured as the average of the maximum temperature observed over the period 1980-2010 in the same NUTS-3 region). The same set of controls as in Table 3 are used. Sampling weights are used. Blue-collar-intensive firms are defined as those firms whose share of blue collar workers is above the median of the corresponding country-year pair.
Source: ORBIS, E-OBS Copernicus, *EEA* (years: 2013-2020).

Table 10 – By size

Variable	(1) TFP	(2) Labor productivity
Micro		
Temperature anomaly (°C)	-0.003**	-0.011**
	(0.001)	(0.005)
Observations: 5,356,188		
Small		
Temperature anomaly (°C)	-0.004**	-0.009**
	(0.001)	(0.004)
Observations: 1,934,806		
Medium-sized		
Temperature anomaly (°C)	-0.003	-0.013**
	(0.002)	(0.004)
Observations: 362,836		
Large		
Temperature anomaly (°C)	0.002	-0.018
	(0.005)	(0.012)
Observations: 66,758		

Notes: Standard errors, reported in parentheses, are robust and clustered at the region (NUTS-3)-year level. ***, **, and * denote the 1%, 5 %, and 10% significance levels, respectively. The anomaly (°C) is computed as the deviation of the yearly average maximum temperature, observed in a given NUTS-3 region where the firm is located, from the corresponding long-term reference trend (measured as the average of the maximum temperature observed over the period 1980-2010 in the same NUTS-3 region). The same set of controls as in Table 3 are used. Sampling weights are used. The firms are categorized by size as follows: micro firms (fewer than 10 employees), small firms (10 to 49 employees), medium-sized firms (50 to 249 employees), and large firms (250 or more employees).
Source: ORBIS, E-OBS Copernicus, *EEA* (years: 2013-2020).

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Appendices

Appendix A. The empirical framework and the ACF method

We here present a discussion on our empirical framework in the context of the ACF estimations. For details on the underlying assumptions - which we summarize hereafter - and their implications, the reader may refer to Ackerberg et al. (2015).

We estimate the following augmented production function (we omit control variables for ease of exposition):

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + \omega_{it} + \varepsilon_{it} \tag{A.1}$$

First, it is assumed that the firm's information set at t, I_{it}, includes the current and past productivity levels, $\{\omega_{i\tau}\}_{\tau=0}^{t}$, but not future productivity levels, $\{\omega_{i\tau}\}_{\tau=t+1}^{\infty}$. Furthermore, it is assumed that the transitory shock, ε_{it}, cannot be predicted by the firm (i.e., $E[\varepsilon_{it}|I_{it} = 0]$).

Second, it is assumed that the unobserved productivity level, ω_{it}, evolves according to the distribution:

$$p(\omega_{it+1}|I_{it}) = p(\omega_{it+1}|\omega_{it}), \tag{A.2}$$

which is known to the firm. Equation (A.2) implies that the productivity level evolves according to a first-order Markov process.

These two assumptions imply that it is possible to decompose ω_{it} into its conditional expectation at $t-1$ and an innovation term $\omega_{it} = E[\omega_{it}|I_{it-}\ ] + \xi_{it} = E[\omega_{it}|\omega_{it-1}] + \xi_{it} = g(\omega_{it-1}) + \xi_{it}$, where, by construction, $E[\xi_{it}|I_{it-1}] = 0$. Hence, $g(\omega_{it-1})$ is that part of ω_{it} that the firm can predict at $t-1$, whereas ξ_{it} is the innovation in ω_{it}, observed by the firm at t and, by construction, is not predictable at $t-1$. In practice, firms observe ω_{it} at t and construct expectations about ω_{it} at $t-1$ using $g(\cdot)$.

Third, it is assumed that firms accumulate capital according to:

$$k_{it} = \kappa(k_{it-1}, i_{it-1}),$$

where investments, i_{it-1}, are chosen at $t-1$. This implies that the firm decides upon the level of capital to use at t one period earlier, at $t-1$ (i.e., $k_{it} \in I_{it-1}$). This assumption entails that a full period is required for new capital to be ordered, delivered and installed. Moreover, it implies that capital has dynamic implications, in the sense that the firm's choice of capital for period t has an impact on the firm's future profits. We assume that the firm decides upon the level of labor to use at t one period earlier, at $t-1$, thereby allowing it to have dynamic implications.

Fourth, it is assumed that the firm's demand for intermediate inputs, m_{it}, is a function of labor, capital, and a firm's unobserved productivity level:

$$m_{it} = f(l_{it}, k_{it}, \omega_{it}). \tag{A.3}$$

Lastly, it is assumed that the function in (A.3) is strictly increasing in ω_{it}. Intuitively, this means that, conditional on labor and capital, the higher the unobserved productivity level is, the larger the demand for intermediate inputs. At this point, ACF outlines a two-step estimation method. Given the assumptions discussed above, f can be inverted to deliver an expression of ω_{it}, which is unobservable, as a function of l_{it}, k_{it}, and m_{it}, which are instead observable:

$$\omega_{it} = f^{-1}(l_{it}, k_{it}, m_{it}).$$

The inverted intermediate input demand function $f^{-1}(\cdot)$ is the key to Control-Function Estimation (CFE): it allows the unobserved productivity level to be controlled once inserted into the production function. Hence, substituting $f^{-1}(\cdot)$ in Equation (A.1) results in the following first-stage equation:

$$y_{it} = \alpha + \beta_l l_{it} + \beta_k k_{it} + f^{-1}(l_{it}, k_{it}, m_{it}) + \epsilon_{it} = \Phi(l_{it}, k_{it}, m_{it}) + \epsilon_{it}. \tag{A.4}$$

As is common practice in the literature, we proxy the function Φ with a third-order polynomial in l_{it}, k_{it}, and m_{it} (Ackerberg et al., 2015). The parameters β_l and β_k, are clearly not identified at this stage and are subsumed into $\Phi(l_{it}, k_{it}, m_{it}) = \alpha + \beta_l l_{it} + \beta_k k_{it} + \omega_{it}$. However, the estimation of (A.4) produces the estimate $\widetilde{\Phi}(l_{it}, k_{it}, m_{it})$ of $\Phi(l_{it}, k_{it}, m_{it})$.[36]

From given guesses of β_l and β_k denoted as β_l^* and β_k^*, it is possible to recover the implied ω_{it}, $\widetilde{\omega}_{it}(\beta_l^*, \beta_k^*)$, as:

$$\widetilde{\omega}_{it}(\beta_l^*, \beta_k^*) = \widetilde{\Phi}(l_{it}, k_{it}, m_{it}) - \beta_l^* l_{it} - \beta_k^* k_{it}. \tag{A.5}$$

As ω_{it} is assumed to follow a first-order Markov process (i.e., $\omega_{it} = g(\omega_{it-1}) + \xi_{it}$), and given $\widetilde{\omega}_{it}(\beta_l^*, \beta_k^*)$, it is possible to compute the implied innovations, $\tilde{\xi}_{it}(\beta_l^*, \beta_k^*)$, as the residuals of a regression of $\widetilde{\omega}_{it}(\beta_l^*, \beta_k^*)$ on $g(\widetilde{\omega}_{it-1}(\beta_l^*, \beta_k^*))$. Following the standard practice, we proxy the function $g(\cdot)$ with a third-order polynomial in $\widetilde{\omega}_{it-1}(\beta_l^*, \beta_k^*)$. The second step of the procedure now recovers the parameters of interest by evaluating the sample analogues of the moment conditions stemming from the previously stated timing assumptions:

$$\frac{1}{N}\frac{1}{T}\sum_i \sum_t \tilde{\xi}_{it}(\beta_l^*, \beta_k^*)\, k_{it} = 0$$

$$\frac{1}{N}\frac{1}{T}\sum_i \sum_t \tilde{\xi}_{it}(\beta_l^*, \beta_k^*)\, l_{it} = 0 \tag{A.6}$$

The search over $\beta_l^*$and β_k^*,continues until $\widetilde{\beta}_l$ and $\widetilde{\beta}_k$ are found, in order to the satisfy the conditions in (A.6). These are the ACF estimates of β_l and β_k.

[36] Note that these are just the values predicted from the regression in Equation (A.4).

Appendix B. Coverage rate

The coverage rates in Table B.1 have been computed by taking the ratio of gross value added (current prices, million euros) as reported by Eurostat for the population of EU countries over the period 2013-2020 (series: *nama_10_a10)* and the corresponding data reported in ORBIS over the same period. The coverage ratios in Table B.2 have been computed based on the total number of employees (thousand persons) reported by Eurostat for the population of EU countries over the period 2013-2020 (series: *nama_10_a10_e)* and the corresponding data reported in ORBIS over the same period.

In our sample, we choose to retain countries with an average coverage rate above 30%. However, to have some representativeness of Nordic European countries, we then further extend to countries with a coverage above 20%. This allows for the inclusion of Finland and Sweden (and, by extension, Slovakia). In our sample, we do not retain Denmark, Ireland, Greece, Cyprus, Lithuania, Malta, and The Netherlands (whose coverage rates are not reported in Tables B.1 and B.2) due to significant missing observation on key variables used to compute firm productivity. The inverse of the average coverage rates, computed for each year and country (and derived from comparing both gross value added and the number of employees between ORBIS and Eurostat data sources), is used as a sampling weight in our analyses.

Table B.1 – Coverage rate by country, based on gross value added

Country	2013	2014	2015	2016	2017	2018	2019	2020	Average
BE	0.307	0.32	0.314	0.327	0.316	0.380	0.335	0.304	0.326
BG	0.547	0.591	0.594	0.591	0.618	0.605	0.608	0.607	0.595
CZ	0.375	0.405	0.411	0.418	0.432	0.402	0.338	0.134	0.364
DE	0.097	0.101	0.101	0.099	0.115	0.107	0.114	0.084	0.102
EE	0.381	0.397	0.414	0.417	0.400	0.395	0.383	0.360	0.393
ES	0.320	0.343	0.341	0.349	0.356	0.359	0.373	0.341	0.348
FR	0.004	0.006	0.004	0.003	0.002	0.001	0.000	0.000	0.003
HR	0.389	0.431	0.446	0.462	0.474	0.497	0.520	0.547	0.471
IT	0.265	0.288	0.289	0.298	0.308	0.322	0.335	0.317	0.303
LV	0.026	0.026	0.024	0.026	0.031	0.034	0.032	0.031	0.029
LU	0.180	0.227	0.120	0.008	0.003	0.003	0.001	0.001	0.068
HU	0.338	0.369	0.384	0.367	0.396	0.400	0.372	0.367	0.374
AT	0.001	0.026	0.172	0.203	0.210	0.203	0.190	0.151	0.145
PL	0.016	0.023	0.021	0.082	0.153	0.143	0.146	0.126	0.089
PT	0.368	0.382	0.393	0.394	0.406	0.410	0.404	0.380	0.392
RO	0.315	0.343	0.358	0.378	0.370	0.380	0.379	0.383	0.363
SI	0.463	0.485	0.497	0.486	0.490	0.494	0.500	0.509	0.490
SK	0.263	0.208	0.202	0.228	0.243	0.239	0.254	0.200	0.230
FI	0.242	0.265	0.171	0.157	0.156	0.159	0.165	0.157	0.184
SE	0.208	0.227	0.263	0.208	0.212	0.218	0.221	0.221	0.222
EU	0.255	0.273	0.275	0.275	0.284	0.287	0.283	0.261	0.274

Source: EUROSTAT and *ORBIS* (years: 2013-2020).

Table B.2 – Coverage rate by country, based on the total number of employees

Country	2013	2014	2015	2016	2017	2018	2019	2020	Average
BE	0.310	0.319	0.321	0.319	0.317	0.319	0.317	0.308	0.316
BG	0.691	0.725	0.750	0.742	0.756	0.753	0.742	0.708	0.733
CZ	0.410	0.432	0.419	0.419	0.417	0.404	0.335	0.145	0.373
DE	0.087	0.092	0.089	0.090	0.095	0.099	0.098	0.077	0.091
EE	0.488	0.542	0.541	0.544	0.521	0.528	0.528	0.488	0.522
ES	0.430	0.452	0.454	0.467	0.476	0.485	0.477	0.445	0.461
FR	0.008	0.010	0.008	0.005	0.003	0.001	0.001	0.000	0.004
HR	0.574	0.582	0.600	0.610	0.610	0.621	0.648	0.631	0.609
IT	0.399	0.423	0.440	0.451	0.461	0.474	0.485	0.458	0.449
LV	0.023	0.025	0.025	0.025	0.025	0.026	0.027	0.028	0.025
LU	0.167	0.169	0.057	0.018	0.003	0.003	0.001	0.001	0.052
HU	0.308	0.326	0.326	0.307	0.312	0.308	0.305	0.293	0.311
AT	0.001	0.027	0.162	0.200	0.199	0.187	0.179	0.138	0.137
PL	0.020	0.029	0.026	0.102	0.210	0.194	0.201	0.179	0.120
PT	0.554	0.558	0.565	0.571	0.576	0.588	0.587	0.553	0.569
RO	0.537	0.559	0.567	0.570	0.566	0.558	0.551	0.522	0.554
SI	0.548	0.564	0.574	0.575	0.570	0.585	0.586	0.573	0.572
SK	0.315	0.260	0.249	0.291	0.306	0.306	0.288	0.247	0.283
FI	0.348	0.376	0.254	0.217	0.225	0.233	0.244	0.229	0.266
SE	0.290	0.309	0.320	0.284	0.289	0.293	0.301	0.289	0.297
EU	0.325	0.338	0.337	0.340	0.346	0.348	0.344	0.315	0.337

Source: EUROSTAT and *ORBIS* (years: 2013-2020).

Appendix C. Standardized anomaly

The results presented in this paper have been based on absolute temperature anomalies (measured in °C), which has been computed as the absolute difference between the yearly average maximum temperature, observed in a given NUTS-3 region where the firm is located, and a corresponding long-term reference trend (measured as the average maximum temperature, in the same NUTS-3 specific region, over the period 1980-2010). However, while absolute anomalies provide a more intuitive interpretation of the impact of warming, they may not necessarily and fully capture the exceptionality of a given anomaly event in a certain area.

This aspect may be particularly relevant when performing cross-country analyses, where average local variability in temperature should also be considered.[37] This issue may be easily overcome by "standardizing" temperature anomalies – that is, in our specific case, by scaling the absolute temperature anomaly (computed as discussed above) with respect to the standard deviation of yearly maximum temperature observed in the specific NUTS-3 region over the long-term reference period (i.e., 1980-2010). This measure provides more significance to the magnitude of the anomalies, since any influences of local average temperature dispersion have been removed.

To test for this, we run an additional sensitivity analysis where we replace our main regressor of interest in Equation (3), $anomaly_{rit}$, with the standardized temperature anomaly – measured as discussed above in Appendix C. In Table C.1, we present results based on the overall sample, and run using TFP, labor productivity, and capital productivity as dependent variables. As shown, the results based on the standardized anomaly remain fully consistent with those of Table 3. In particular, we find a detrimental and highly significant impact of -0.026 (on TFP) and -0.078 (for labor productivity). No significant impact is instead found for capital productivity. Such results also hold consistently across the entire estimation spectrum (i.e., our moderating analyses). Results are available upon request.

[37] For instance, an anomaly of +1°C may be more relevant in areas with normally stable temperatures, as opposed to areas with typically large variability. On the contrary, a standardized anomaly of 1 has the same relative significance across locations.

Table C.1 – The overall impact on TFP, Labor Productivity, and Capital Productivity

Variable	**(1)**	**(2)**	**(3)**
	TFP	**Labor productivity**	**Capital productivity**
Standardized anomaly	-0.026**	-0.078**	0.059
	(0.013)	(0.037)	(0.050)
Precipitation	-0.002	-0.006	-0.001
	(0.002)	(0.006)	(0.009)
Precipitation – squared	0.000	0.000	0.000
	(0.000)	(0.000)	(0.001)
Humidity	0.003*	0.007	0.007
	(0.002)	(0.005)	(0.007)
Humidity – squared	-0.000*	-0.000	-0.000
	(0.000)	(0.000)	(0.000)
Air quality	-0.002**	-0.002	-0.001
	(0.001)	(0.002)	(0.003)
Air quality - squared	0.000*	0.000	-0.000
	(0.000)	(0.000)	(0.000)
Year FE	Yes	Yes	Yes
Region FE	Yes	Yes	Yes
Industry FE	Yes	Yes	Yes
Size FE	Yes	Yes	Yes
Year-Region FE	Yes	Yes	Yes
Year-Industry FE	Yes	Yes	Yes
Year-Size FE	Yes	Yes	Yes
Firm FE	Yes	Yes	Yes
Observations	7,720,588	7,720,588	7,720,588

Notes: Standard errors, reported in parentheses, are robust and clustered at the region (NUTS-3)-year level. ***, **, and * denote the 1%, 5 %, and 10% significance levels, respectively. The standardized anomaly is defined by scaling the absolute temperature anomaly with respect to the standard deviation of yearly maximum temperature observed in the specific NUTS-3 region over the long-term reference period (i.e., 1980-2010). The region dummies are at the 3-digit level of the NUTS classification; the industry dummies are at the 3-digit level of the NACE Rev. 2 classification; the size dummies collect four classes of firm size (as outlined in Table 1). Sampling weights are used as discussed in Appendix B.
Source: ORBIS, Copernicus (years: 2013-2020).