Climate Change, Firms, and Aggregate Productivity*

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Abstract: This paper employs a general equilibrium framework to analyze how temperature affects firm-level demand, productivity, and input allocative efficiency, informing aggregate productivity damages due to climate change. Using data from Italian firms and detailed climate data, it uncovers a sizeable negative effect of extreme temperature on firm-level productivity and revenue-based marginal product of capital. Based on these estimates, the model generates aggregate productivity losses higher than previously thought, ranging from 0.60 to 6.82 percent depending on the scenario and the extent of adaptation. Additionally, climate change exacerbates Italian regional disparities.

Keywords: Climate Change, Aggregate Productivity, Firms, Allocative Efficiency.

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1 Introduction

The rising levels of CO_2 in the atmosphere are causing significant increases in global temperatures and altering weather patterns, leading to climate change (IPCC, 2021). The aggregate economic costs associated with climate change and the formulation of effective policies to address it have attracted the interest of academics and policymakers, triggering broad public debate. The economic costs, as well as the potential policies to confront them, are largely contingent upon the relationship between temperature and aggregate productivity damages (Nordhaus, 1977; Cruz and Rossi-Hansberg, 2021; Barrage and Nordhaus, 2023; Desmet and Rossi-Hansberg, 2024). These aggregate productivity damages are likely influenced by the disruptions faced by firms operating in areas most affected by extreme temperatures. Therefore, in order to evaluate them correctly, it is crucial to analyze the heterogeneous effects of climate shocks across firms, the potential reallocation effects, and their aggregate implications.

This paper makes two significant contributions to the literature. First, we quantify the relative importance of three different channels determining the impact of climate change on firm outcomes: (i) the demand channel, (ii) the productivity channel, and (iii) the reallocation channel. Second, we develop a structural framework that allows us to estimate *aggregate* productivity losses from these *firm-level* effects.

Anecdotal evidence suggests that higher temperatures can shift consumer spending patterns across firms in different sectors. Similarly, there is ample empirical evidence that extreme temperatures decrease productivity.[1] We refer to these as the direct effects of temperature on firms. However, if inputs can reallocate from firms experiencing extreme temperatures to those in less affected locations, the damage from direct effects would be mitigated. Conversely, if the reallocation process is slow or hindered by frictions, the direct effects may be amplified. We refer to these reallocation of inputs as the indirect effects. Empirical evidence on the reallocation of inputs across firms is somehow limited.[2]

However, while the literature has made progress in identifying separate sources of firm-level damages, their interaction and aggregation remain unclear. To address this, we propose a novel methodology to measure aggregate productivity damages due to temperature rise

[1] See Somanathan et al., 2021 for labor productivity in India; Zhang et al. (2018) for TFP in China; Seppanen et al. (2006) for office productivity; and Lobell and Field (2007) for agricultural yields

[2] Reduced-form evidence on county-level labor mobility are provided in Leduc and Wilson (2023), while on labor mobility across agricultural and non-agricultural sectors in emerging markets are provided by Colmer (2021) and Albert et al. (2021)

grounded on causally estimated firm-level outcomes. Our methodology allows for the interplay of direct and indirect effects and their causal identification using commonly available firm-level datasets. Additionally, this framework allows for a closed-form characterization of aggregate productivity damages in general equilibrium.

In our structural framework, we model monopolistically competitive firms similarly to a closed-economy version of Melitz (2003). These firms' demand and productivity may depend on the temperature at their location and other factors. This allows temperature to directly affect the scale at which firms operate. Additionally, to capture the indirect effects of slow input reallocation or frictions in reduced-form, we incorporate input-specific wedges following Restuccia and Rogerson (2008) and Hsieh and Klenow (2009), and allow them to potentially depend on temperature and other factors. These wedges represent the gap between the revenue-based marginal product of each input and its user cost, influencing the relative holding of each input. Thus, if the reallocation of a particular input is slow or frictional after a firm experiences extreme temperatures, the firm will be stuck with more of that input relative to others, resulting in an relative decline in the given wedge.

Our framework leads to the following identification structure. By deriving the first-order conditions of the firm's problem, we show that the relationship between sales and local temperature depends on demand, productivity, and input-specific wedges. However, the revenue-based marginal productivity of each input is affected solely through its wedge, allowing us to separately identify these factors. By netting out the effect of the wedges, the remaining temperature-dependent variation in sales is driven only by demand and productivity. To further separate these two effects, we assume (and test) that the temperature-dependent demand factor does not affect firms operating in tradable sectors, as the demand for their products is geographically dispersed and not influenced by local temperature. Thus, by comparing the effect of temperature on the revenues of tradable and non-tradable firms, we disentangle the effect of demand and productivity.[3]

One notable advantage of our framework is that it allows for the closed-form characterization of the link between aggregate productivity damages and temperature via the firm-level

[3]This identification strategy is derived directly from findings in empirical trade literature. For example, the lower demand sensitivity of sales for firms selling tradable goods has been documented by Almunia et al. (2021) for the Great Recession episode. Furthermore, considering this dimension in our data appears to be a natural choice, especially considering that a significant portion of Italian firms self-select into exporting, as documented in Caggese and Cuñat (2013).

channels described above. Moreover, it also allows to separate the contribution of the direct channel, i.e., demand and productivity, to aggregate productivity damages from the indirect channel, i.e., slow inputs reallocation and frictions, similarly to Hsieh and Klenow (2009), Gopinath et al. (2017), and Baqaee and Farhi (2020). Importantly, our methodology does not rely on knowing equilibrium input prices, thus remaining robust to general equilibrium considerations and circumventing the missing intercept problem.

We demonstrate how to implement our model using the case of Italy, which provides an ideal setting for our purpose. Because of its latitude, it often suffers episodes of very high temperatures, especially in recent years.[4] Moreover, its geography exhibits considerable diversity across regions both in terms of climate as well as regional development. Furthermore, by comparing locations differently exposed to extreme temperature fluctuations, we are able to estimate adaptation effects and quantify their aggregate impact.

We exploit Orbis, provided by Bureau van Dijk, between the years 1999-2013, a firm-level quasi-census dataset covering around 75 percent of Italy's aggregate gross output (Kalemli-Özcan et al., 2024). We pair the firm-level data with gridded climate data obtained from the Copernicus Climate Change Services. The climate data provides daily temperature in degree Celsius (C) and rainfall measurements at an approximately 11x11 km resolution. Copernicus data highlight substantial variation in within-grid-cell average yearly temperature, ranging from approximately 0 to 23 degrees Celsius. The pairing is done by assigning to each firm in Orbis the temperature and rainfall corresponding to the nearest grid cell in which the postcode of the firm headquarters is situated.[5]

Empirically, we follow the methodology in Somanathan et al. (2021), aggregating the daily temperatures at each grid point to the annual level by counting the number of days falling within different temperature ranges. We find strong evidence of an inverted U-shaped effect, indicating that extreme temperatures, whether high or low, lower firm-level output, labor, and material inputs, but not capital. The negative impact of high temperatures is particularly pronounced and nonlinear. Relative to the reference temperature interval (0°C, 30°C], an ex-

[4]European temperatures increased at more than twice the global average over the past 30 years, the highest increase among all continents (source: Report on the State of the Climate in Europe, 2021, by the World Meteorological Association.)

[5]The majority of our sample consists of small and medium-sized firms that are single establishments. However, we perform extensive robustness exercises showing that large firms, firms reporting consolidated accounts, or foreign firms—i.e., those more likely to have multiple plants, which could lead to misclassification based on the headquarters zip code—do not drive our results.

tra day with temperatures between 35°C and 40°C reduces sales by 0.05 percent, while an extra day above 40°C reduces sales by 0.81 percent. We estimate a significant temperature-dependent input wedge that reduces the marginal productivity of capital at extreme temperatures, while no significant effects are found for other input wedges. This suggests that extreme temperatures depress firms' output and inputs, with firms able to adjust labor and material use but not capital due to the presence of frictions that prevent its reallocation. Lastly, our analysis indicates that the non-tradable sector does not experience significant additional effects, suggesting that productivity plays a more influential role than demand.

We then proceed to quantify the aggregate productivity losses resulting from different warming scenarios using the firm-level causally estimated effects for each channel. We consider several alternative scenarios of temperature increase between now and the year 2100, including a 1-degree Celsius increase, a 2-degree Celsius increase (regarded as the baseline in line with the Paris Agreement objectives), and a 4-degree Celsius increase.[6] To simulate these warming scenarios, we assign the corresponding temperature increases to each day and grid cell in our climate data. Under a 1-degree Celsius increase, aggregate productivity drops by 0.77 percent. Under the 2-degree Celsius baseline warming scenario, aggregate productivity lowers by 1.68 percent. Doubling the temperature increase to 4-degree Celsius, the drop becomes nearly four times larger, reaching 6.82 percent. Additionally, using predictions from the RCP 4.5 and RCP 8.5 climate models gives us an aggregate productivity loss of 1.64 and 5.35 percent, respectively. We find that the role of direct productivity effects and indirect missing capital reallocation effects contribute equally to the aggregate productivity losses.

How do our predicted aggregate productivity losses relate with the damage functions assumed in recent Integrated Assessment Models (IAM), such as for example Barrage and Nordhaus (2023)? Even though they both quantify the effects of temperature fluctuations on productivity, they are not directly comparable, because our exercise focuses on firm-level channels only and one specific country, while the latter attempts to summarise the world-level impact of several channels, quantified from different studies and methodologies. Nonetheless, we can make two observations: First, we describe a theory-based methodology that aggregates micro-level climate-change channels into aggregate general equilibrium effects, and which could be applied to other countries and contexts and become a building block of damage functions in future versions of IAM models. Second, the channels we explore are

[6]The DICE (Dynamic Integrated Climate-Economy) models use 2100 as the time horizon of reference.

only partially included in the drivers of climate change usually summarised in those damage functions, and find effects quantitatively large relative to them. Therefore, incorporating such channels in IAM models is likely to significantly revise upwards the economic costs of climate change, and the social cost of carbon.

Our quantitative findings have potential caveats. We primarily estimate short- to medium-term effects of local temperature. In the long run, future advancements or increased investment in climate-mitigating technologies could enhance firms' ability to handle extreme temperatures. Although quantifying the former is challenging, concerning the latter, we demonstrate through an additional empirical exercise that including this margin of adaptation reduces our damages by around 20-30 percent.[7] Additionally, improvements in allocative efficiency in the long run may mitigate damages as capital reallocation frictions may ease with time. Though estimating these dynamics is challenging with our short panel, our framework provides an upper bound, gauged by changes in allocative efficiency. Finally, in our framework, we chose to omit considerations on firm entry and exit due to the limited information on these in our data. Neglecting this margin may bias our results, as discussed in detail in the main text. However, our findings on the relative importance of different channels provide valuable inputs for future models of firm dynamics aiming to incorporate extensive margin effects of climate change.

Finally, we investigate the regional impact of climate change on productivity across Italian provinces, uncovering heterogeneous effects that can lead to both mildly positive and severely negative outcomes. Our analysis indicates that as poorer regions in the south are anticipated to experience shifts towards more extreme temperature ranges, climate change may exacerbate existing regional inequality in Italy. This is highlighted by our findings, which demonstrate a negative relationship between expected productivity losses and current GDP per capita.

Literature Review. The paper is related to the literature pioneered by Nordhaus (1977) that studies the macroeconomic impact of climate change and recently extended in Krusell and Smith (2022) and Barrage and Nordhaus (2023), among others.[8] Further, it contributes to the

[7] To measure adaptation through the use of climate-mitigating technologies, we compare firm-level losses between grid-cells accustomed to extreme temperatures, which we assume are already adapted through this channel, and those not.

[8] Another strand of the literature studies the aggregate consequences of climate change empirically, e.g., Dell et al. (2012, 2014); Burke et al. (2015); Hsiang et al. (2017); Burke and Tanutama (2019); Kalkuhl and Wenz (2020); Kahn et al. (2021); Newell et al. (2021); Bastien-Olvera et al. (2022); Casey et al. (2023); Nath et al. (2023);

emerging body of research that combines detailed granular data with quantitative macroeconomic models to analyze the economic aspects of climate change (e.g., Desmet and Rossi-Hansberg, 2015; Balboni, 2019; Barrage, 2020; Cruz and Rossi-Hansberg, 2021; Conte, 2022; Conte et al., 2022; Fried, 2022; Nath, 2022, Bilal and Rossi-Hansberg, 2023). Our contribution emphasizes firm heterogeneity. Our model establishes a direct link between firm-level temperature-semielasticities and aggregate productivity losses within a general equilibrium framework. This reveals a novel channel related to firm-level allocative efficiency adjustments in response to temperature changes. This channel can be assessed using micro-data and has significant aggregate effects.

We build our empirical strategy on Zhang et al. (2018) and Somanathan et al. (2021).[9] We complement these papers by proposing a model that allows for a structural interpretation of temperature-semielasticities. This, together with the novel estimate of the temperature-semielasticity of the marginal product of inputs at the firm level, permits the aggregation of the micro estimates to perform aggregate counterfactuals in general equilibrium.

This paper also relates to the literature on resource misallocation, pioneered by Hopenhayn and Rogerson (1993), Restuccia and Rogerson (2008), and Hsieh and Klenow (2009). Our structural framework builds upon insights from Osotimehin (2019); Baqaee and Farhi (2020); Bau and Matray (2020); and Sraer and Thesmar (2023); enabling a connection between aggregate productivity in general equilibrium and the reduced-form firm-level temperature-semielasticities of productivity, demand, and marginal products. Our analysis shows that input-related wedges, often interpreted as frictions in this literature, constitute a substantial channel through which extreme temperatures operate. Thus, revealing that the insights from this literature are important for understanding the adverse effects associated with climate change.

Outline. The rest of the article is organized as follows. Section 2 describes a theoretical model that guides measurement and interpretation of results. Section 3 describes data and measurement. Section 4 lays the empirical strategy. Section 5 presents the main results on temperature's impact on firm outcomes. Section 6 quantifies the aggregate effects. Section 7

and Leduc and Wilson (2023).

[9]Other papers studying empirically the micro-level impact of climate change are Deschênes and Greenstone (2011); Kala et al. (2012); Graff Zivin and Neidell (2014); Cohn and Deryugina (2018); Diffenbaugh and Burke (2019); Addoum et al. (2020); Colmer (2021); Albert et al. (2021); Pankratz and Schiller (2021); Custodio et al. (2022); Cascarano et al. (2022); Acharya et al. (2023); and Ponticelli et al. (2024).

concludes.

2 Structural Framework

In this section, we present a framework to study the effect of temperature on firms' outcomes and on aggregate productivity.

2.1 Firm-Level Variables

We build our framework on the work of Hsieh and Klenow (2009).[10] We consider an economy at time t populated by a large number N of monopolistically competitive firms i, producing differentiated varieties, operating in a grid-cell g.[11] In this economy, aggregate output Y is a CES aggregate of N firms:

$$Y_t = \left(\sum_{i=1}^{N_t} \left(e^{d_{it}(T_{g(i)t})} Y_{it} \right)^{\frac{\sigma-1}{\sigma}} \right)^{\frac{\sigma}{\sigma-1}}, \tag{1}$$

where Y_{it} is the output of firm i, $e^{d_{it}(T_{g(i)t})}$ is a *temperature-dependent demand shifter* with $T_{g(i)t}$ being the temperature in a grid-cell g, and σ denotes the elasticity of substitution between varieties. The notation $g(i)$ means that the grid-cell g varies for different firms i. The presence of a temperature-dependent demand shifter $e^{d_{it}(T_{g(i)t})}$ implies that temperature changes in a given grid-cell may affect the demand faced by the firms in that grid-cell. Nonetheless, the functional form assumed for $d_{it}(T_{g(i)t})$, and for the other temperature-dependent frictions in the model, allows for the possibility that they are influenced by factors other than grid-cell-level temperature. Section 4 explains in detail the functional forms assumed in the empirical analysis.

We denote by P_{it} the price of firm i and by P_t the price of aggregate output Y_t. The

[10] As in Hsieh and Klenow (2009), also this model is static, and firm decisions in time t do not depend on past choices, nor they affect future outcomes. Nonetheless, for convenience, we introduce from the beginning the time subscript, which is useful because, in the empirical application, we will use panel data.

[11] The grid-cell is the finest geographical unit for which we have data on temperatures. It coincides with an area of 0.1deg^2, which corresponds approximately to 121km^2. This is approximately the size of Turin (130km^2) and $1/10th$ the size of Rome ($1,285\text{km}^2$). Section 3 describes the data in more detail.

demand faced by each firm i is given by

$$Y_{it} = \left(e^{d_{it}(T_{g(i)t})}\right)^{\sigma-1} \left(\frac{P_{it}}{P_t}\right)^{-\sigma} Y_t. \tag{2}$$

The production function of each firm is Cobb-Douglas in productivity, capital, labor, and materials:

$$Y_{it} = e^{z_{it}(T_{g(i)t})} \prod_{X \in \mathcal{X}} X_{it}^{\alpha^X}, \quad \text{with} \quad \sum_{X \in \mathcal{X}} \alpha^X = 1, \tag{3}$$

where $e^{z_{it}(T_{g(i)t})}$ is the *temperature-dependent productivity* for firm i in grid-cell g and $\mathcal{X} \equiv \{K, L, M\}$ with K being capital, L being labor, and M being materials. This term, $e^{z_{it}(T_{g(i)t})}$, implies that temperature changes in a given grid cell may affect the productivity at which the firms in that grid cell operate.

The problem of a firm is given by

$$\begin{aligned} \Pi_i = & \max_{\{P_{it}, Y_{it}\}} P_{it} Y_{it} - \mathcal{C}(Y_{it}), \\ \text{s.t.} \quad & Y_{it} = \left(e^{d_{it}(T_{g(i)t})}\right)^{\sigma-1} \left(\frac{P_{it}}{P_t}\right)^{-\sigma} Y_t; \end{aligned} \tag{4}$$

where

$$\mathcal{C}(Y_{it}) = \min_X \left\{ \sum_{X \in \mathcal{X}} e^{\tau_{it}^X (T_{g(i)t})} P_t^X X_{it} \quad \middle| \quad Y_{it} - e^{z_{it}(T_{g(i)t})} \prod_{X \in \mathcal{X}} X_{it}^{\alpha^X} \right\}, \tag{5}$$

where $e^{\tau_{it}^X (T_{g(i)t})}$ are *temperature-dependent input-specific wedges* for firm i in grid-cell g and P_t^X is the price of input X. These wedges represent frictions that affect the marginal products or costs of specific inputs, including factors like adjustment costs, spatial and financial frictions, among others. Temperature changes in the grid-cells where firms operate can influence these wedges. Our main objective is to estimate how these wedges react to temperature changes and quantify their impact on aggregate productivity.

Profit maximization yields the standard condition that the firm's output price is a fixed markup over its marginal cost:

$$P_{it} = \mathcal{M} \cdot \mathcal{C}'(Y_{it}), \tag{6}$$

where $\mathcal{M} \equiv \sigma/(\sigma-1)$. The solution of the minimization problem is given by

$$\mathcal{C}(Y_{it}) = \prod_{X\in\mathcal{X}} \left(\frac{e^{\tau_{it}^X(T_{g(i)t})} P_t^X}{\alpha^X}\right)^{\alpha^X} \frac{Y_{it}}{e^{z_{it}(T_{g(i)t})}}. \tag{7}$$

Combining equations (2), (6), and (7), firm i sales can hence be expressed just as a function of the primitives of the model as

$$P_{it}Y_{it} = \left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1} \left(\mathcal{M} \prod_{X\in\mathcal{X}} \left(\frac{e^{\tau_{it}^X(T_{g(i)t})} P_t^x}{\alpha^X}\right)^{\alpha^X}\right)^{-(\sigma-1)} P_t^\sigma Y_t, \tag{8}$$

with

$$e^{\tilde{z}_{it}(T_{g(i)t})} \equiv e^{d_{it}(T_{g(i)t})} e^{z_{it}(T_{g(i)t})}, \tag{9}$$

where $e^{\tilde{z}_{it}(T_{g(i)t})}$ is defined through the rest of the paper as the firm level *temperature-dependent demand-adjusted productivity*, and combines the firm productivity and the demand shifter responses to temperature. Taking logarithms in equation (8) we recover the following log-linear relation:

$$\begin{aligned} p_{it}y_{it} = (\sigma-1)\left(\tilde{z}_{it}(T_{g(i)t}) - \sum_{X\in\mathcal{X}} \alpha^X \tau_{it}^X(T_{g(i)t})\right) \\ -(\sigma-1)\left(\mu + \sum_{X\in\mathcal{X}} \alpha^X \left(p_t^X - \log\alpha^X\right)\right) + \sigma p_t + y_t, \end{aligned} \tag{10}$$

with lowercase letters indicating logarithms. $p_{it}y_{it}$ is the logarithm of sales for firm i in period t. In Section 4 we explain how we estimate an empirical counterpart of equation (10). Importantly, our theoretical framework has the advantage to identify the different channels trough which temperature shocks affect firm-level revenues. More specifically, sales may respond to temperature because this can affect (i) the firm demand-adjusted productivity through $\tilde{z}_{it}(T_{g(i)t})$ or (ii) the input-specific wedges through $\tau_{it}^X(T_{g(i)t})$. Formally, the temperature-semielasticity of sales is given by

$$\frac{\partial p_{it}y_{it}}{\partial T_{g(i)t}} = (\sigma-1)\left(\frac{\partial \tilde{z}_{it}(T_{g(i)t})}{\partial T_{g(i)t}} - \sum_{X\in\mathcal{X}} \alpha^X \frac{\partial \tau_{it}^X(T_{g(i)t})}{\partial T_{g(i)t}}\right) \tag{11}$$

Equation (11) shows that conditional on a measure of the elasticity of substitution between varieties σ and the production function elasticities α^X if one can measure the temperature-semielasticity of the input-specific wedges, $\partial\tau_{it}^X(T_{g(i)t})/\partial T_{g(i)t}$, one can recover the temperature-semielasticity of the demand-adjusted productivity, $\partial\tilde{z}_{it}(T_{g(i)t})/\partial T_{g(i)t}$ and vice versa. We can leverage this intuition since the optimality conditions of our model imply that individual input demand is given by:

$$e^{\tau_{it}^X(T_{g(i)t})}P_t^X X_{it} = \alpha^X \mathcal{C}(Y_{it}), \quad \forall X \in \mathcal{X}, \tag{12}$$

which can be rearranged, using equation (6), as

$$MRPX_{it} \equiv \alpha^X \frac{P_{it}Y_{it}}{X_{it}} = \mathcal{M}e^{\tau_{it}^X(T_{g(i)t})}P_t^X. \tag{13}$$

Taking logarithms in equation (13) we recover the following log-linear relation:

$$\log MRPX_{it} = \tau_{it}^X(T_{g(i)t}) + \mu + p_t^X. \tag{14}$$

Equations (13) and (14) have two important insights. First, as shown by Hsieh and Klenow (2009), conditional on the production function elasticity α^X, the revenue-based marginal product of input X ($MRPX$) of firm i can be measured just by observing firm-level sales $P_{it}Y_{it}$ and firm-level input quantities $X_{it} \in \{K_{it}, L_{it}, M_{it}\}$. Second, in equilibrium the effect of temperature on $\log MRPX_{it}$ only depends on its input-specific wedge $\tau_{it}^X(T_{g(i)t})$, and not on the other input-specific frictions.[12]

Hence, having the necessary data to empirically measure firm-level sales and $MRPX$, we can use equations (10) and (14) to estimate the temperature-semielasticity of sales and of input-specific wedges, and then use equation (11) to recover the temperature-semielasticity of the demand-adjusted productivity. We provide a detailed procedure for this in Section 4.

[12] It also relies on the logarithm of the markup μ, and of the input price p_t^X. Regarding the latter, to the extent that its variations are similar across all firms in a given industry, they are absorbed by sector-year effects in our empirical specification. Regarding the former, assuming a CES aggregator in our model rules out any direct effect of temperature on markups. However, while this channel might be accommodated by the temperate-dependent input-specific wedges, in the empirical analysis in Section 5 we find no *prima facie* effect of temperature on the revenue-based marginal product of materials and labor (which are common measures of firm-level markups used by the literature; see Loecker and Warzynski, 2012), validating the CES assumption. Furthermore, the empirical specification of equation (14) will further generalize this formula to account for other potential factors.

2.2 Aggregate Variables

To quantify the effects of temperatures on aggregate productivity and make predictions about when rising temperatures will reduce an economy's aggregate productivity, we use changes in the Solow residual as a proxy for changes in aggregate productivity. Appendix A reports the details of all the calculations.

Before introducing the Solow residual in our framework, we demonstrate that aggregate gross output TFP can be expressed as

$$TFP_t = \frac{Y_t}{\prod_{X\in\mathcal{X}} X_t^{\alpha^X}}, \tag{15}$$

$$= \left(\sum_{i=1}^{N_t} \left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{-(\sigma-1)\alpha^X} \right)^{\frac{\sigma}{\sigma-1}}$$

$$\times \prod_{X\in\mathcal{X}} \left(\sum_{i=1}^{N_t} \frac{\left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1}}{e^{\tau_{it}^X(T_{g(i)t})}} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{-(\sigma-1)\alpha^X} \right)^{-\alpha^X}; \tag{16}$$

with $X_t = \sum_{i=1}^{N_t} X_{it}$ standing for real aggregate capital, labor, and materials. Equation (16) shows that conditional on the elasticity of substitution between varieties σ and the production function elasticities α^X, aggregate gross output TFP is just a function of two measurable objects: $e^{\tilde{z}_{it}(T_{g(i)t})}$ and $e^{\tau_{it}^X(T_{g(i)t})}$. The firm-level demand-adjusted productivity $e^{\tilde{z}_{it}(T_{g(i)t})}$ can be expressed, employing the structural assumptions on demand and production used to arrive at equation (16), as

$$e^{\tilde{z}_{it}(T_{g(i)t})} = \left(\frac{(P_t Y_t)^{-\frac{1}{\sigma-1}}}{P_t} \right) \left(\frac{(P_{it} Y_{it})^{\frac{\sigma}{\sigma-1}}}{\prod_{X\in\mathcal{X}} X_{it}^{\alpha^X}} \right). \tag{17}$$

As noted in Hsieh and Klenow (2009), conditional on a measure of the elasticity of substitution between varieties σ and the production function elasticities α^X, Equation (17) can be measured just with data on nominal aggregate output $P_t Y_t$, the aggregate price deflator P_t, firm-level sales $P_{it} Y_{it}$, and firm-level inputs X_{it}. Moreover, firm-level input-specific wedges $e^{\tau_{it}^X(T_{g(i)t})}$ can be measured using equation (13), as explained above. Hence, using standard firm-level data and leveraging the structure of our framework, we can measure empirically each element in equation (16).

Taking logs and differentiating equation (16), we can derive the following expression relating changes in aggregate gross output TFP to changes in grid-cell-level temperatures:

$$
\begin{aligned}
\Delta \log TFP_t &\equiv \Delta \log TFP_t \left(e^{\tilde{z}_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}, \Delta T_{g(i)t}\right) \\
&\approx \sum_{i=1}^{N_t} \lambda_{it}\left(e^{\tilde{z}_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}\right) \sum_{X\in\mathcal{X}} \frac{\alpha^X}{e^{\tau_{it}^X(T_{g(i)t})}} \Omega_t^X\left(e^{\tilde{z}_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}\right) \\
&\times \left[\left(\sigma \frac{e^{\tau_{it}^X(T_{g(i)t})}}{\Omega_t^X\left(e^{\tilde{z}_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}\right)} - (\sigma-1)\right)\left(\frac{\partial \tilde{z}_{it}(T_{g(i)t})}{\partial T_{g(i)t}} - \sum_{X\in\mathcal{X}} \alpha^X \frac{\partial \tau_{it}^X(T_{g(i)t})}{\partial T_{g(i)t}}\right) + \frac{\partial \tau_{it}^X(T_{g(i)t})}{\partial T_{g(i)t}}\right] \\
&\times \Delta T_{g(i)t}, \qquad (18)
\end{aligned}
$$

where $\lambda_{it}(\cdot,\cdot)$ is a firm-level weight and $\Omega_t^X(\cdot,\cdot)$ is an aggregate object. Both are described in Appendix A.1. Equation (18) allows calculating *counterfactual* changes in aggregate TFP due to changes in grid-cell-level temperatures $\Delta T_{g(i)t}$. In particular, to calculate this counterfactual, we need information about three types of objects: (i) $e^{\tilde{z}_{it}(T_{g(i)t})}$ and $e^{\tau_{it}^X(T_{g(i)t})}$, which can be measured using firm-level data as explained above; (ii) $\partial \tilde{z}_{it}(T_{g(i)t})/\partial T_{g(i)t}$ and $\partial \tau_{it}^X(T_{g(i)t})/\partial T_{g(i)t}$, which are temperature-semielasticities of the demand-adjusted productivity and of input-specific wedges; and (iii) grid-cell-level temperature changes $\Delta T_{g(i)t}$, which are the objects of interest to vary in the counterfactual.

We highlight that as in Hsieh and Klenow (2009) and Gopinath et al. (2017), we can use equation (16) to also recover the upper bound of aggregate gross output TFP in this economy. This is obtained by equalizing all input-specific wedges $e^{\tau_{it}^X(T_{g(i)t})}$ across firms. The resulting expression is given by

$$TFP_t^* = \left(\sum_{i=1}^{N_t} \left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1}\right)^{\frac{1}{\sigma-1}}. \qquad (19)$$

This represents the upper bound of aggregate TFP in a counterfactual frictionless scenario. In the rest of the paper, we are going to compare the actual changes in TFP to the changes in this ideal TFP that we call, with a slight abuse of terminology, efficient.[13] As above, taking logs and differentiating equation (19), we can derive the following expression relating changes in

[13]We label this counterfactual TFP as efficient but avoid using it for normative considerations. The reason is that this level of TFP does not have to always lay within the set of achievable allocations. For instance, if part of the frictions we measure in the data result from technological constraints like adjustment costs, then this counterfactual TFP cannot be attained.

efficient aggregate gross output TFP to changes in grid-cell-level temperatures:

$$\Delta \log TFP_t^* \equiv \Delta \log TFP_t^* \left(e^{\tilde{z}_{it}(T_{g(i)t})}, \Delta T_{g(i)t}\right)$$
$$\approx \sum_{i=1}^{N_t} \lambda_{it}^* \left(e^{\tilde{z}_{it}(T_{g(i)t})}\right) \frac{\partial \tilde{z}_{it}(T_{g(i)t})}{\partial T_{g(i)t}} \Delta T_{g(i)t}, \tag{20}$$

where $\lambda_{it}^*(\cdot)$ is a firm-level weight described in Appendix A.1.

Equation (20) allows calculating *counterfactual* changes in the efficient gross output TFP due to changes in grid-cell-level temperatures $\Delta T_{g(i)t}$. In particular, to calculate this counterfactual change, we again just need information on three objects: (i) $e^{\tilde{z}_{it}(T_{g(i)t})}$, which can be measured using firm-level data as explained above; (ii) $\partial \tilde{z}_{it}(T_{g(i)t})/\partial T_{g(i)t}$, which is firm-level temperature-semielasticity of the demand-adjusted productivity; and (iii) grid-cell-level temperature changes $\Delta T_{g(i)t}$, which are the objects of interest to vary in the counterfactual.[14]

Now we have all the elements to decompose the change in aggregate gross output TFP into the change in an efficient component and the change in a component associated with input-related frictions. The final expression for changes in aggregate gross output TFP is the following:

$$\Delta \log TFP_t = \underbrace{\Delta \log TFP_t^*}_{\Delta \text{ Technology}} - \underbrace{\left(\Delta \log TFP_t^* - \Delta \log TFP_t\right)}_{\Delta \text{ Allocative Efficicency}}. \tag{21}$$

The first term captures changes in efficient TFP, as described above. The second term captures changes in the allocation relative to the efficient allocation, which goes back to Debreu (1951) and Farrell (1957), and recently Baqaee and Farhi (2020); therefore, we label it as allocative efficiency. Intuitively, $\Delta \log TFP_t^*$ measures the changes in aggregate TFP caused by the impact of temperature on demand-adjusted productivity for an economy that is not affected by any allocative problem (that is, aggregate output cannot be increased just by reallocating inputs across productive units). By contrast, the second term in equation (21) measures the additional negative effect on aggregate TFP caused by the fact that temperature shocks can worsen allocative efficiency. Interestingly, this latter term is potentially affected both by changes in firm-level demand-adjusted productivity and in input-specific wedges, be-

[14]One useful property of our theoretical framework is that equations (18) and (20) do not depend on any aggregate prices, which are market clearing objects in general equilibrium. Thus, our analysis is robust to general equilibrium considerations and to the missing intercept problem. In other words, to perform the aggregate counterfactuals of interest, only $\partial \tilde{z}_{it}(T_{g(i)t})/\partial T_{g(i)t}$ and $\partial \tau_{it}^X(T_{g(i)t})/\partial T_{g(i)t}$ are needed. Understanding how to estimate them in the data is the objective of the empirical strategy outlined in Section 4.

cause these terms interact at the firm level and their covariance matters, as similarly noted in Gopinath et al. (2017).

As an example, consider two geographical locations A and B, where firms are equally productive in both locations, but those in A are subject to larger input-specific wedges. In this case, an increase in demand-adjusted productivity in location A would reduce allocative efficiency, by increasing the covariance between productivity and wedges, even if the latter do not change.

Finally, since we are interested in the effect of climate change on the Solow residual, which is defined on value-added, and not on aggregate gross output TFP per se, we adjust (21) following the insights in Jones (2011), as explained in Appendix A.2. This gives the following measure for changes in the Solow residual:

$$\Delta \log Solow_t \approx \frac{Y_t}{GDP_t} \left(\Delta \log TFP_t^* - \left(\Delta \log TFP_t^* - \Delta \log TFP_t \right) \right), \tag{22}$$

where Y_t is gross output and GDP_t is value-added, i.e., gross output net of materials.

Therefore, to compute the counterfactual impact of climate change on aggregate productivity and to separate its effect into an efficient component and a component associated with resource reallocation, we can simultaneously employ equations (18), (20), and (22).

3 Data

This section presents the two main data sources used for the empirical analysis and the merging procedure used to combine them.

3.1 Firm-Level Data

The Italian firm-level data is obtained from Orbis, provided by Bureau van Dijk between the years 1999-2013. Orbis offers harmonized cross-country financial information for both private and public firms collected from various national data sources, primarily business registers. The dataset covers, on average, 75 percent of the official Italian gross output reported in Eurostat. One major advantage of Orbis over other datasets is that it includes many small private firms. In fact, Gopinath et al. (2017) show that Orbis closely mimics the official size distribution reported in Eurostat Structural and Business Statistics (SBS). The cleaning process follows

Kalemli-Özcan et al. (2024) and is explained in Appendix B.

The final dataset includes information on approximately 4.3 million observations corresponding to 1 million firms. We measure sales (PY) by operating revenue, materials (M) by expenditure on materials, labor (L) by the cost of employment, and capital (K) by the book value of tangible fixed assets. All monetary values are deflated using Eurostat two-digit industry price deflators, and capital is deflated using the country-specific price of investment from the World Development Indicators. The dataset also provides the main sector of economic activity at the four-digit industry level and crucially includes firm-level zip codes that allow for geolocation, which we use to link to the climate data discussed in the next subsection.

We use the financial information reported in the database to compute the marginal revenue product of input $X \in \{L, M, K\}$ following equation (13). We measure α^X, the elasticity of output with respect to the input X, following the cost shares approach as in Foster et al. (2008) and take the median firm-level cost share within each four-digit industry, as in De Loecker et al. (2020), to account for measurement error and for short-run adjustment frictions.[15] The production function elasticities are given by $\alpha^M = \text{med}\left\{\frac{P_t^M M_{it}}{r_t K_{it}+W_t L_{it}+P_t^M M_{it}}\right\}$, $\alpha^L = \text{med}\left\{\frac{W_t L_{it}}{r_t K_{it}+W_t L_{it}+P_t^M M_{it}}\right\}$, $\alpha^K = 1-\alpha^L-\alpha^M$, where $r_t K_{it}$ is the rental cost of tangible capital, $W_t L_{it}$ is the wage bill, and $P_t^M M_{it}$ is the expenditure on materials.[16] We recover median production function elasticities $\{\alpha^X\}_{X\in\{M,L,K\}}$ equal to $\{0.53, 0.36, 0.11\}$, well within the range found by the literature.[17] For instance, Gandhi et al. (2020) reports values for materials, labor, and capital ranging from 0.50-0.67, 0.22-0.52, and 0.04-0.16, respectively.

3.2 Climate Data

The meteorological data are obtained from Copernicus, the European Union's Earth Observation Programme, using E-OBS, a daily gridded land-only observational dataset over Europe.[18] For more details on the dataset, refer to Cornes et al. (2018) and Appendix B.1. This dataset is

[15]Notice that we use the production function elasticities both to calculate our aggregate counterfactual based on equation (18), and to compute the revenue-based marginal products in equation (13). Regarding the latter, given that our regression framework is saturated with firm and sector-time fixed effects, as explained below, these elasticities are absorbed by the error term in the log-linear equations, and therefore are irrelevant to identify the temperature-semielasticity of each revenue-based marginal product.

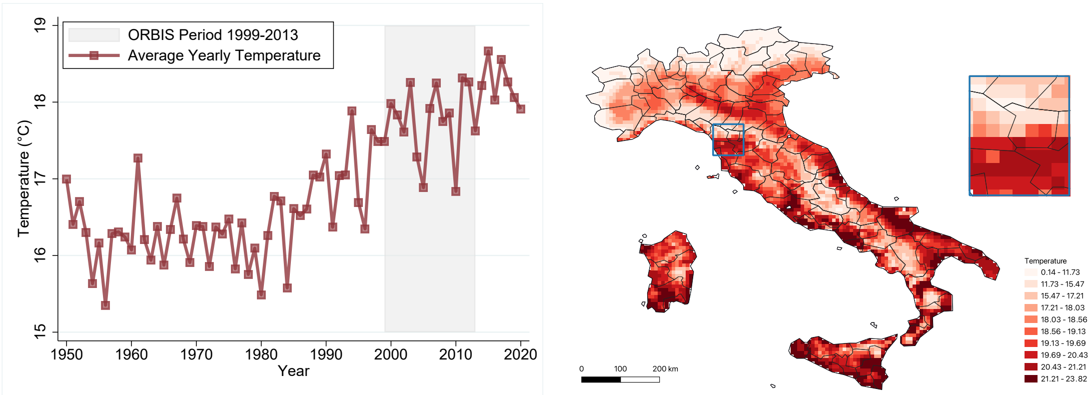
[16]We measure the user cost of capital as $r_t = i_t - \mathbb{E}_t\pi_{t+1} + \delta + RP$. We use the real interest, $i_t - \mathbb{E}_t\pi_{t+1}$, from Gopinath et al. (2017), a depreciation rate, δ, of 10% as usually done in the literature, and a risk premium, RP, of 5% as calculated in Caballero et al. (2017).

[17]The inclusion of aggregate median elasticities in the text serves the sole purpose of facilitating a meaningful comparison with the existing literature. However, in the calculations, only the sector-level elasticities are used.

[18]See https://doi.org/10.24381/cds.151d3ec6

based on observations from meteorological stations across Europe provided by the National Meteorological and Hydrological Services (NMHSs) and other data-holding institutes. The station data are provided by 84 participating institutions, and the ECA&D dataset contains over 23,000 meteorological stations. More information is available in Appendix B.2.1.

Figure 1: Average Yearly Temperature



(a) 1950-2020 Trend **(b) 1999 Cross Section**

Note. Figure 1a shows the evolution of the average yearly temperature in Italy between 1950-2020. The grey areas show the time frame (1999-2013) for which Orbis data is available. Figure 1b shows the average yearly temperature across all the grid-cells in Italy in 1999. It also plots regional boundaries at the NUTS 3 level.

We obtain daily temperatures and rainfall with a horizontal grid resolution of 0.1° (0.1deg^2), corresponding to grid cells of around 11km×11km (121km^2), spanning the period 1950-2020. Daily temperatures are recorded in degrees Celsius (°C), and rainfall is measured in millimeters (mm). Consistent with Somanathan et al. (2021), we characterize daily temperature using the maximum temperature, which typically occurs during working hours and serves as a proxy for heat exposure during peak daily economic activities. Rainfall is measured as the total daily precipitation, including rain, snow, and hail, expressed as the equivalent height of liquid water in a square meter. Our primary variable of interest is temperature, while rainfall serves as a control variable in our empirical analysis, as detailed in Section 4.

Figure 1a shows the evolution of the average yearly maximum temperature over the entire sample period. The average yearly maximum temperature is volatile and rising over time. Table 1 presents summary statistics of our climate data for the period 1999-2013, which corresponds to the subperiod for which we have firm-level data and thus constitutes the data used in our analysis. Table B.2 in Appendix B.2.3 provides summary statistics for the entire sample period. Additionally, Figure 1b displays the average yearly temperature in 1999 for each grid cell alongside the boundaries of NUTS 3 regions of Italy. The average yearly temperature ranges from 0.14°C to 23.82°C, showcasing considerable temperature variation across both grid cells and regions within Italy. The significant temperature variation observed in Italy makes it an exceptional laboratory for studying the economic impact of climate change. The co-existence of broad temperature gradients with diverse geographical economic activity locations (ranging from production sites in cold environments like the Alps to warm areas such as the coast) offers a distinctive opportunity to examine how firm respond to various climatic conditions.

Table 1: Summary Statistics of Climate Data (1999-2013)

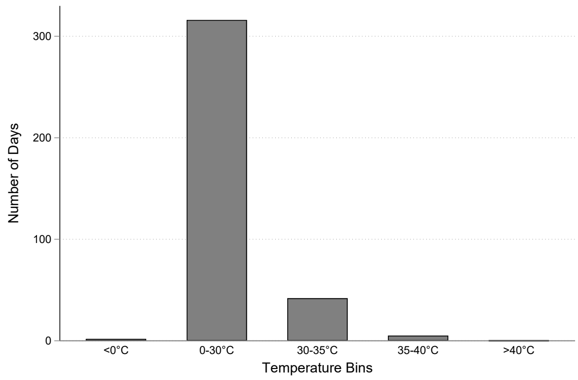
	Overall		**Within Grid-Cell**	
	Temperatures (°C)	Rainfalls (mm)	Temperatures (°C)	Rainfalls (mm)
Mean	17.74	2.28	17.74	2.28
Median	17.65	0.00	17.51	1.01
Min	-24.94	0.00	0.35	0.00
Max	43.71	258.40	33.62	26.99

Note. Table 1 shows summary statistics of temperature in degrees Celsius (°C) and rainfalls in millimeters (mm) for the period 1999-2013. The first two columns report statistics for the overall sample. The last two columns report statistics on the variation within the average grid-cell, that is, they show the average temperature distribution among the different grid-cells.

Our main empirical specification follows Somanathan et al. (2021) and aggregate daily temperatures, measured in degrees Celsius, up to the annual level using counts of the number of days in the year falling within different temperature bins. We use temperature bins $\{(-\infty, 0°\text{C}], (0°\text{C}, 30°\text{C}], (30°\text{C}, 35°\text{C}], (35°\text{C}, 40°\text{C}], (40°\text{C}, +\infty)\}$. To summarize the temperature distribution over the year, we construct a vector $\boldsymbol{T} = \{T^1, T^2, T^3, T^4, T^5\}$, which counts the number of days in each of these bins. This is calculated for every grid-cell and each year. Taken together, these bins are nonoverlapping and span the observed range of temperatures in the data, so that any given day is assigned to exactly one bin. For robustness, as explained in Section 5, we adopt an alternative specification of daily maximum temperatures, based on a degree-day measure.

Figure 2 shows the distribution of days within each temperature bin of the vector $\boldsymbol{T}$ averaged across grid-cells and years. Most of the days clearly belong to the $[0°\text{C}, 30°\text{C})$ range, which we will use as the reference bin in the regression framework described in Section 4. Importantly, all temperature bins have a non-zero average number of days. Table B.3 in Appendix B.3 reports summary statics for the distribution of days within each temperature bin across grid-cells.

Figure 2: Average Distribution of Days Within Temperature Bins



Note. Figure 2 shows the number of days per year within each temperature bin of the vector $\boldsymbol{T}$. We construct this figure averaging across all grid-cells and years.

3.3 Main Combined Data

To construct our final dataset, we merge the Orbis firm-level data with the Copernicus temperature data. This requires assigning each firm in the Orbis dataset to a specific grid-cell within the Copernicus dataset. While the Copernicus data provides latitude and longitude information for its grid-cells, geolocating the firms presents a set of challenges.

To determine the geographical coordinates corresponding to each firm, we rely on the headquarters postcode information available in the business registry. The postcode serves as a unique identifier for a specific location, allowing us to narrow down the firm's position. We convert these postcodes into actual geographical coordinates using the Python package "pgeocode."[19] Once we have the geographical coordinates for the firms and the latitude and longitude information for the Copernicus grid-cells, we proceed with the matching process. Our objective is to assign each firm to the grid-cell that is closest to its geographical location. To do this, we calculate the minimum distance between each firm's postcode location and the grid-cell locations and select the grid-cell with the shortest distance.

One limitation of our data is that we only have information about the address of the firm's headquarters and lack details on their production plants. For instance, if a firm's headquarters is located in a different grid cell than its production plant, we might incorrectly assign the temperature data. Such scenarios are more likely for large multi-plant firms. In our sample of Orbis-Italian firms, only 1 percent are publicly listed, while 3-4 percent are foreign-owned,

[19] The pgeocode package (https://pypi.org/project/pgeocode/) provides geographical information associated with postcodes from an open-source project known as GeoNames (https://www.geonames.org), which offers comprehensive data on postal codes and their corresponding locations.

and 2 percent have some form of consolidated financial statements. Although these statistics indicate that such potentially problematic firms constitute a small minority in our dataset, through a series of robustness, we consistently show that they do not determine our results. Additionally, if a firm's production location is inaccurately assigned to a grid cell, the firm's response to the erroneously assigned temperature should be weaker or zero, biasing our results downward. This suggests a more benign view of this potential source of mismeasurement, as it would go against the effect we are after.

4 Empirical Strategy

This section outlines the empirical strategy and explains our approach for identifying the firm-level effects that temperature may have on demand-adjusted productivity and on input-specific wedges.

So far we left the various temperature-dependent factors in Section 2 unspecified functions. Here, we make explicit the functional forms that we adopt in the empirical analysis for the demand-adjusted productivity and for the input-specific wedges. In particular, we assume that firm-level outcomes and input-specific wedges have a temperature-dependent component, $F(T_{g(i)t})$, and a temperature-independent component, $\mathbf{W}_{it}$, such that:

$$e^{\tilde{z}_{it}(T_{g(i)t})} \equiv e^{F^{\tilde{z}}(T_{g(i)t})+G^{\tilde{z}}(\mathbf{W}_{it})}, \tag{23}$$

$$e^{\tau^X_{it}(T_{g(i)t})} \equiv e^{F^{\tau^X}(T_{g(i)t})+G^{\tau^X}(\mathbf{W}_{it})}, \quad \text{with} \quad \forall X \in \mathcal{X}; \tag{24}$$

where $F(\cdot)$ is a non-linear function of temperature in the grid-cell to which firm i belongs and $G(\mathbf{W}_{it})$ is a linear function of alternative explanatory variables.

Thus, to measure the effect of changes in temperature on firm-level outcomes, we estimate the following equation:

$$Outcome_{it} = \sum_{\ell} \beta_\ell T^{\ell}_{g(i)t} + \delta Rain_{g(i)t} + \boldsymbol{\lambda}'\mathbf{X}_{r(i)t} + \gamma_{s(i)t} + \alpha_i + \varepsilon_{it}, \tag{25}$$

where i denotes a firm, t stands for year and $g(i)$ denotes the grid-cell to which firm i belongs. $Outcome_{it}$ denotes log firm-level outcomes or log revenue-based marginal product of a given input X, $\log MRPX_{it}$. We approximate the non-linear temperature function $F(\cdot)$

by the variable $T^{\ell}_{g(i)t}$, denoting the number of days in temperature bin ℓ, that each grid cell $g(i)$ experienced during a given year (see Section 3.2 for a description). We set the interval $[0°\text{C}, 30°\text{C})$ as the reference temperature bin since it covers the average range of temperature faced by most grid-cells in our data.

$G(\mathbf{W}_{it})$ includes potential confounding factors at the firm, grid-cell, region, and sector level. In particular, outcome variables may respond to other climate factors related to temperature, to control for this possibility we use $Rain_{g(i)t}$ to indicate the average yearly rainfalls in each grid-cell. We also include firm fixed effects α_i to control for firm time-invariant unobserved characteristics (α_i). To account for regional shocks we include regional trends captured by $\mathbf{X}_{r(i)t}$, consisting of time trends at the regional level ($r(i)$ denotes the NUTS 2 region to which firm i belongs) and regional-level Great Recession (GR: 2008-2009) and Sovereign Debt Crisis (SDC: 2012-2013) dummies to account for the fact that the mid-2000s crises in Italy had an uneven effect across regions. Similarly, to guard against differences in output being driven by different sectoral productivity trends we include sector-time fixed effects $\gamma_{s(i)t}$ that control for sectoral and aggregate fluctuations ($s(i)$ denotes the NACE 4 sector to which firm i belongs). Standard errors are clustered at the grid-cell level to account for any serial correlation that might bias our standard errors downwards.[20]

The regression specification given by equation (25) is the empirical counterpart of equations (10) and (14). Equations (10) and (14) indicate the effect of a change in temperature on firm-level sales and on the firm-level revenue-based marginal product of input X. Equation (25) precisely measures this in the data. The coefficient of interest is β_ℓ, which captures the effect of an extra day into the temperature bin ℓ relative to the reference temperature bin. Thus, $\beta_\ell < 0$ implies that the given firm-level outcome declines β_ℓ percent for each extra day into the temperature bin ℓ relative to the reference temperature bin.

Our coefficient of interest, β_ℓ, is identified by comparing two firms with similar time-invariant characteristics, facing the same level of grid-cell rainfalls, the same regional development patterns, the same regional exposition to the GR and the SDC as well as, similar sector developments but exposed to different grid-cell level changes in temperature over time. The main identification assumption is that, after controlling for a series of regional and sectoral fixed effects, temperature fluctuations are exogenous to any other time-varying factors that

[20]To address concerns on the spatial correlation of shocks, weather shocks might be regionally correlated, we verified results are robust to including regional trends and clustering standard errors at the NUTS 3 level.

affect demand, productivity, or inputs.

There are at least three potential challenges to validity. However, as we discuss next, they do not all align well with our findings and they would tend to bias our results downwards. First, there exists the possibility of an alternative contemporaneous shock that impacts both temperatures and productivity simultaneously. For instance, in regions experiencing a surge in economic activity, factors such as congestion or pollution may escalate, resulting in a simultaneous decline in productivity and a rise in temperatures. This scenario does not entirely align with our findings, as we observe a decrease in output linked to elevated temperatures. A second identification challenge arises from shocks that influence both productivity and its responsiveness to temperature. For instance, higher firm unionization might lead to tougher bargaining discussions, including grievances about working under extreme temperatures. In this scenario, there is a potential for overestimating the impact of temperatures, as it may also encompass the effects of unionization itself. However, by controlling for sector-year fixed effects and considering that these phenomena are widespread across all firms in a sector, concerns should be mitigated. Third, if firms could precisely anticipate temperature increases across grid-cells and consequently decide their location accordingly, it would have implications for regional selection. The inclusion of regional trends addresses this concern as we are estimating deviations from the trend, capturing the effects of unanticipated shocks, and suggesting our estimates should be best interpreted as short- or medium-run elasticities.

5 Results

In this section, we present the firm-level effects of temperature on several objects of interest and we discuss potential channels and heterogenous effects.

5.1 Sales, Inputs, and Marginal Revenue Products

We estimate the effect of temperature on firm-level outcomes using the regression specification from equation (25). While our primary focus is on observing the effect of temperature on sales, we also examine its impact on firms' inputs, such as materials, labor, and capital, to inform the response of marginal revenue input products that will be analyzed later. Table 2 reports the results.

Table 2: Average Effect of Temperature on Sales and Inputs

Dependent Variable	**Sales** (1)	**Materials** (2)	**Labor** (3)	**Capital** (4)
Temperature Bins				
$(-\infty, 0°\mathrm{C}]$	-0.094***	-0.068**	-0.070***	-0.036*
	(0.019)	(0.029)	(0.019)	(0.021)
$(30°\mathrm{C}, 35°\mathrm{C}]$	-0.017*	-0.022	0.002	0.003
	(0.009)	(0.014)	(0.007)	(0.010)
$(35°\mathrm{C}, 40°\mathrm{C}]$	-0.046***	-0.060**	-0.003	0.004
	(0.017)	(0.025)	(0.016)	(0.019)
$(40°\mathrm{C}, +\infty]$	-0.807***	-0.557**	-0.369**	0.033
	(0.194)	(0.242)	(0.187)	(0.217)
Fixed Effects				
Firm	✓	✓	✓	✓
Sector × Year	✓	✓	✓	✓
GR and SDC × Region	✓	✓	✓	✓
Controls				
Rainfalls	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓
Observations	4,687,524	4,687,524	3,767,578	4,328,710

Note. All dependent variables are in logs. Temperature bins are constructed as explained in Section 3.2. Rows 1-4 present the effect on the log of the dependent variable of adding an extra day in the given temperature range respectively. Standard errors are clustered at the grid-cell level and reported in parentheses. *, **, and *** denote 10, 5, and 1% statistical significance respectively.

The estimates indicate that temperature has an inverted U-shaped effect on sales, materials, and labor, implying that extreme temperatures, either high or low, tend to depress those firm-level outcomes. For example, our estimates suggest that one extra day above 40 degrees Celsius reduces sales by 0.807 percent, while one extra day below 5 degrees Celsius reduces sales by 0.094 percent.[21] All these losses are relative to the reference temperature bin $[0°\mathrm{C}, 30°\mathrm{C})$. The response of capital is less strong, especially for higher temperatures. This is particularly relevant to our analysis because it suggests that while materials and, to a lesser extent, labor respond significantly and meaningfully to additional days of extreme temperature, capital does so less, which is consistent with the widely held view that this input is subject to greater adjustment frictions than materials and labor.[22]

[21] Assuming that production is evenly distributed over all effective working days of the year (which in Italy are approximately 220, i.e., 250 working days net of 30 days of holidays), these patterns imply that one extra day above 40 degrees Celsius produces almost a two-day loss in sales ($100 \times 2/220 \approx 0.807$), while one extra day below 5 degrees Celsius produces a one-third-day loss in sales ($100 \times 0.3/220 \approx 0.094$).

[22] We highlight that, for our interpretation to be correct, it is sufficient that factors of production are relatively flexible. This seems unlikely for capital, which consists largely of structures, and hence its rigidity in the data. However, it seems plausible that, even in a relatively rigid labor market like that of Italy, labor input can be flexibly adjusted by firms. On the one hand, firms have extensive margins of labor adjustment (changes in numbers of hours worked) which are reflected in the wage bill, which is the variable we use to measure labor input. On the other hand, it is worth noting that a large literature has shown that, since the mid-90s, labor reform in Italy has made it easier to hire workers with fixed-term contracts, which have been used to increase employment flexibility in reaction to shocks (Caggese and Cuñat, 2008).

Next, we estimate the effect of temperature on the firm-level revenue-based marginal product of each input using the regression specification from equation (25). Table 3 reports the results. The estimates indicate that temperature has an inverted U-shaped effect, although statistically significant and substantial only for $MRPK$, implying that extreme temperatures, either high or low, tend to depress the revenue-based marginal product of inputs. Looking at the revenue-based marginal product of capital, our estimates suggest that one extra day above 40 degrees Celsius reduces it by 0.578 percent, while one extra day below 5 degrees Celsius reduces it by 0.030 percent.

Table 3: Average Effect of Temperature on Revenue-Based Marginal Product of Inputs

Dependent Variable	**MRPM** (1)	**MRPL** (2)	**MRPK** (3)
Temperature Bins			
$(-\infty, 0°C]$	-0.018	0.008	-0.030
	(0.019)	(0.013)	(0.022)
$(30°C, 35°C]$	0.006	-0.012**	-0.014
	(0.008)	(0.006)	(0.010)
$(35°C, 40°C]$	0.011	-0.021	-0.045**
	(0.014)	(0.013)	(0.021)
$(40°C, +\infty)$	-0.209	-0.019	-0.578**
	(0.156)	(0.145)	(0.231)
Fixed Effects			
Firm	✓	✓	✓
Sector × Year	✓	✓	✓
GR and SDC × Region	✓	✓	✓
Controls			
Rainfalls	✓	✓	✓
Region Trends	✓	✓	✓
Observations	4,687,524	3,767,578	4,328,710

Note. All dependent variables are in logs. Temperature bins are constructed as explained in Section 3.2. Rows 1-4 present the effect on the log of the dependent variable of adding an extra day in the given temperature range respectively. Standard errors are clustered at the grid-cell level and reported in parentheses. *, **, and *** denote 10, 5, and 1% statistical significance respectively.

While the main pattern is qualitatively evident for all revenue-based marginal products, only the capital product exhibits a statistically significant and substantial pattern. This outcome is not unexpected, as the behavior of each revenue-based marginal product in Table 3 aligns with the behavior of each input in Table 2. Specifically, we observe that $MRPM$ and $MRPL$ do not respond to changes in temperature because both inputs respond to it, similar to sales. One plausible interpretation of this finding is that these inputs are more flexible and can be adjusted until the revenue-based marginal product equalizes the marginal cost of the input. However, this process does not occur for capital, which is subject to larger adjustment costs, implying that its revenue-based marginal product does not equal its marginal cost, thus becoming sensitive to temperature changes, as we see in the data. Overall, these results suggest that following a temperature change in a given grid-cell, labor and materials are optimally adjusted by the affected firms, while capital is not, potentially lowering the allocative efficiency of the economy.[23] In Section 6, we use our theoretical framework to quantify the aggregate allocative effects of temperature shocks.

Tables C.4 and C.5 in Appendix C.1 show that the results hold for different robustness tests. First, we verify that our result are robust to controlling for the age of the firm that has been empirically established as one of the most significant predictors of firm heterogeneity (Fort et al., 2013). Second, we explore the robustness of the results to alternative temperature specifications. In particular, we describe a model that is piece-wise linear in degree days, as in Somanathan et al. (2021). Third, we use a specification that controls for rainfalls nonlinearly, instead of linearly. Finally, we study how sensitive results are to temperature bins being defined at the grid-cell level by alternatively defining temperature bins at the region (NUTS 3) level. We find that the results of these additional robustness exercises are very similar to the benchmark case reported in this section.

Moreover, Tables C.6 and C.7 in Appendix C.2 present additional specifications to assess the sensitivity of our estimates to the presence of firms that could potentially be assigned to incorrect temperatures, as discussed in Section 3.3. These specifications exclude certain types of firms, including foreign firms, listed firms, firms reporting consolidated accounts, and large firms. The details of the exclusion criteria are provided in Appendix C.2. Importantly, our analysis reveals that none of our estimates are affected by the inclusion or exclusion of these types of firms. This finding suggests that the concerns raised in Section 3.3 regarding potentially misclassified firms do not significantly impact our overall results.

5.2 Demand-Adjusted Productivity

Having estimated both the effect of temperature on sales and on the revenue-based marginal product of inputs, we can rely on the structural framework and use equation (11) to recover the effect of temperature on firm-level demand-adjusted productivity.

[23]It is worth noting that the model assumes no unemployed inputs. Therefore, when firms are hit by a temperature shock and reduce their labor and material inputs, these inputs are assumed to be reallocated within the year to where they are most productive. In reality, some of these inputs might remain unemployed for a while. However, while this would be relevant for aggregate output, it is less so for aggregate productivity, which is what we focus on.

To compute this, we require estimates of the elasticity of substitution σ across varieties and of the production function elasticities α^X. We use the production function elasticities described in Section 2 and assume an elasticity of substitution between varieties equal to σ = 4. This implies an average cost-weighted markup of 33%, in line with the estimates from De Loecker et al. (2020), and is the mean value from Broda and Weinstein (2006).[24] This number is also in line with many firm-level estimates and macroeconomic studies. Bernard et al. (2003) find a value of σ = 3.79 in a model of firm-level export. Among macroeconomic studies Christiano et al. (2015) estimate a New-Keynesian model with financial frictions and find an elasticity of σ = 3.78. Additionally, we obtain the temperature-semielasticities of sales and revenue-based marginal products from Tables 2 and 3, and we set the temperature-semielasticity of $MRPM$ and $MRPL$ to zero as they are statistically insignificant and small in size.[25]

Table 4 summarizes the effect of temperature on demand-adjusted productivity, under the parameters specified above. Notice that the temperature-semielasticities of the demand-adjusted productivity vary across sectors as production function elasticities are sector-specific. Thus, we report both an unweighted average and a sales-weighted average across sectors.[26]

Table 4: Average Effect of Temperature on Demand-Adjusted Productivity

	Temperature Bins			
	$(-\infty, 0°\text{C}]$	$(30°\text{C}, 35°\text{C}]$	$(35°\text{C}, 40°\text{C}]$	$(40°\text{C}, \infty)$
Variable				
β_ℓ^{z}, unweighted	-0.031	-0.005	-0.021	-0.337
β_ℓ^{z}, weighted	-0.031	-0.005	-0.019	-0.321

Note. Table 4 reports the temperature-semielasticity for demand-adjusted wedges for each temperate bin. Temperature bins are constructed as explained in Section 3.2. Row 1 reports the unweighted average across sectors. Row 2 reports the sales-weighted average across sectors.

We observe that the temperature-semielasticity of demand-adjusted productivity follows the inverted U-shaped pattern identified previously. This finding is not entirely surprising, as equation (11) indicates that this semielasticity is merely a linear combination of the preceding ones, up to a rescaling. On the quantitative side, our finding suggests that one extra day above 40 degrees Celsius reduces the demand-adjusted productivity by 0.337 percent, while one extra day below 0 degrees Celsius reduces it by 0.031 percent. Hence, we conclude that extreme temperatures, either high or low, have a substantial effect on the demand-adjusted

[24] Three-digit goods (SITC-3), over the period 1990-2001.

[25] We do the same for the calculation implemented in Section 6.

[26] Table C.8 in the appendix C.3 shows how the effect of temperature on demand-adjusted productivity varies across sectors. High capital intensive sectors experience larger losses.

productivity in the data.

5.3 Different Channels and Adaptation Effects

This section investigates potential differences between tradable and non-tradable sectors, shedding light on the roles of demand versus efficiency. Additionally, it explores the possibility of firm adaptation to climate change.

5.3.1 Demand versus Productivity

Although the model does not ask for the separation of demand from productivity to perform the aggregate counterfactual from equation (21), we are nonetheless interested in understanding which of these two margins is more influenced by temperature. Therefore, in here, we extend our empirical strategy to disentangle the effects of temperature on firms' demand and productivity. While firms producing in a given area are likely to face similar productivity effects of extreme temperatures, we notice that firms selling tradable goods are likely to be less subject to local temperature-related demand shocks, because most of their demand comes from elsewhere, potentially abroad.[27] Therefore, if the temperature changes in the grid-cell where their production is located, their productivity will be affected but their demand will either remain unaffected or be less affected because these firms do not rely heavily on sales in that grid-cell.

Thus, we set to identify the effect of temperature on demand and productivity separately using the following regression specification:

$$\begin{aligned} Outcome_{it} = &\sum_{\ell} \beta_{1,\ell} T^{\ell}_{g(i)t} + \delta_1 Rain_{g(i)t} + \boldsymbol{\lambda_1'} \mathbf{X}_{r(i)t} \\ &+ \left(\sum_{\ell} \beta_{2,\ell} T^{\ell}_{g(i)t} + \delta_2 Rain_{g(i)t} + \boldsymbol{\lambda_2'} \mathbf{X}_{r(i)t} \right) \times I^{NT}_{s(i)} + \gamma_{s(i)t} + \alpha_i + \varepsilon_{it}, \end{aligned} \tag{26}$$

where $I^{NT}_{s(i)}$ is an indicator function that takes the value of one if firm i belongs to sectors s selling non-tradable goods, as described below, and the other variables are described in the

[27]For example, the lower demand-sensitivity of sales of firms selling tradable goods has been documented empirically by Almunia et al. (2021) for the Great Recession episode. Moreover, looking at this dimension in our data seems a natural choice given that a sizeable fraction of Italian firms select into the production of tradable goods and exporting, as documented in Caggese and Cuñat (2013).

main specification in Section 4.

In this specification, the estimated coefficients $\beta_{1,\ell}$ capture the temperature-semielasticity of sales, which is common to firms both in the tradable and non-tradable sectors and that therefore captures common productivity effects. Instead, the coefficients $\beta_{2,\ell}$ capture the differential effect of temperature for firms in the non-tradable sector and we interpret it as the semielasticity of the demand effect.

We employ three distinct measures to classify firms into tradable and non-tradable sectors. We start by using the World Input-Output Database (WIOD), identifying the tradable sectors as those with a proportion of exports in the total value-added for each NACE 2-digit sector in Italy exceeding the median. Subsequently, recognizing that international trade is just one facet of tradability in our context, our focus shifts to pinpointing firms whose goods and services are predominantly demanded locally, indicating low tradability within the country. Toward this end, we employ two alternative metrics. First, we use the classification provided by Gervais and Jensen (2019) which utilizes a unique dataset on the distribution of output and demand across regions of the United States to construct measures of trade costs for nearly a thousand service and manufacturing industries.[28] Secondly, we adapt the tradability measure proposed by Mian and Sufi (2014), which examines regional employment concentration in the US and argues that sectors with high economic activity concentration are more tradable. We adopt a similar methodology, measuring the geographical (NUTS 2) concentration of each sector (NACE 2) in Italy and defining a sector as tradable if above the median geographical concentration.

Table 5 reports the results. Column 1 in Table 5 reports the estimates of the average effect of temperature on sales as reported in Table 2. Columns 2 to 4 report (i) the coefficient capturing the common effect of temperature on sales for both tradable and non-tradable sectors and (ii) the coefficients capturing the additional effect of temperature on the sales of non-tradable sectors only, which captures the effect of demand. Column 2 defines tradable sectors as those with a proportion of exports from WIOD in the total value-added for each NACE 2-digit sector above the median. Column 3 uses the tradability measure from Gervais and Jensen (2019). Column 4 uses the tradability measure in Mian and Sufi (2014) adapted to the Italian context using wage bill data.

We observe that the interaction coefficient is largely insignificant and modest in size

[28]We thank Antoine Gervais for sharing his data with us.

Table 5: Effect of Temperature on Sales of Tradable versus Non-Tradable Sectors

Dependent Variable	Sales (1)	Sales (2)	Sales (3)	Sales (4)
Temperature Bins				
$(-\infty, 0°\text{C}]$	-0.094***	-0.090***	-0.096***	-0.113***
	(0.019)	(0.024)	(0.024)	(0.026)
$(30°\text{C}, 35°\text{C}]$	-0.017*	-0.006	-0.006	-0.025**
	(0.009)	(0.009)	(0.011)	(0.010)
$(35°\text{C}, 40°\text{C}]$	-0.046***	-0.017	-0.013	-0.024
	(0.017)	(0.019)	(0.020)	(0.021)
$(40°\text{C}, +\infty)$	-0.807***	-0.758***	-0.835***	-1.046***
	(0.194)	(0.260)	(0.297)	(0.310)
Temperature Bins$\times I^{NT}_{s(i)}$				
$(-\infty, 5°\text{C}]$		-0.006	0.005	0.032
		(0.030)	(0.026)	(0.029)
$(30°\text{C}, 35°\text{C}]$		-0.019	-0.016	0.014
		(0.015)	(0.012)	(0.012)
$(35°\text{C}, 40°\text{C}]$		-0.049*	-0.046*	-0.036
		(0.027)	(0.023)	(0.023)
$(40°\text{C}, +\infty)$		-0.087	0.022	0.385
		(0.352)	(0.357)	(0.383)
Fixed Effects				
Firm	✓	✓	✓	✓
Sector × Year	✓	✓	✓	✓
GR and SDC × Region	✓	✓	✓	✓
Controls				
Rainfalls	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓
Observations	4,687,524	4,684,661	4,593,020	4,687,524

Note. All dependent variables are in logs. Temperature bins are constructed as explained in Section 3.2. The variable $I^{NT}_{s(i)}$ is an indicator function that takes the value of one if firm i belongs to a sector s selling non-tradable goods, as described in Section 3. Particularly, column 2 uses the WIOD to define tradable sectors as those with a proportion of exports in the total value-added for each NACE 2-digit sector above the median. Column 3 uses the tradability measure from Gervais and Jensen (2019). Column 4 uses the tradability measure in Mian and Sufi (2014) adapted to the Italian context using wage bill data. Rows 1-4 present the effect on the log of sales of adding an extra day in the given temperature range respectively. Rows 5-8 present the extra effect for non-tradable goods on the log of sales of adding an extra day in the given temperature range respectively. Standard errors are clustered at the grid-cell level and reported in parentheses. *, **, and *** denote 10, 5, and 1% statistical significance respectively.

across intervals, except for the $(35°\text{C}, 40°\text{C}]$ interval, where it is significant and negative in two out of three specifications. Conversely, the common coefficient is highly significant for extreme temperatures, substantial in size, and close to the average effect. Thus, our findings suggest that non-tradable firms are only marginally more affected by temperature, indicating a minor, albeit nonzero, role of temperature in demand and a more significant role in productivity. Consequently, our results imply that the majority of the effect of temperature on the demand-adjusted productivity wedge arises from its impact on productivity, consistent with existing studies from other contexts that highlight temperature's predominant effect on firm productivity (Seppanen et al., 2006 and Somanathan et al., 2021).

5.3.2 Adaptation

In the next section, we use the estimates presented in Section 5.1 to predict the aggregate productivity effects of temperature increases resulting from climate change. For this purpose, it is important to consider adaptation. If firms adopt climate-mitigating measures in response to climate change, we may overestimate its effect.[29] Therefore, we introduce an additional analysis exploring the potential differential impact of operating in grid-cells with varying exposure to extreme temperatures. The rationale is that firms located in different Italian regions face markedly different climates, not only in terms of average temperature but also in terms of temperature variability throughout the year. Consequently, firms confronting more frequent extreme temperatures may exhibit greater adaptation to them, resulting in distinct temperature semielasticities. In this context, we believe it is crucial to model regional adaptation as a function of temperature dispersion rather than average temperature, for at least two reasons. First, in a geographically diverse country like Italy, higher average temperature over the year might be a poor proxy of adaptation to extreme heat. Many coastal areas have relatively high yearly average temperatures but experience overall milder climates due to their proximity to the sea, thereby encountering fewer extreme temperatures compared to inland regions that are on average cooler. Second, climate scientists have provided strong evidence that climate change will lead to increases in both average temperatures and temperature variability (Seneviratne et al., 2021).

In order to test this possibility we estimate the following regression:

$$\begin{aligned} Outcome_{it} = & \sum_{\ell} \beta_{1,\ell} T^{\ell}_{g(i)t} + \delta_1 Rain_{g(i)t} + \boldsymbol{\lambda_1'} \mathbf{X}_{r(i)t} \\ & + \left(\sum_{\ell} \beta_{2,\ell} T^{\ell}_{g(i)t} + \delta_2 Rain_{g(i)t} + \boldsymbol{\lambda_2'} \mathbf{X}_{r(i)t} \right) \times I^H_{g(i)} + \gamma_{s(i)t} + \alpha_i + \varepsilon_{it}, \end{aligned} \tag{27}$$

where $I^H_{g(i)}$ is an indicator function that takes the value of one if firm i belongs to adapted grid-cells g, defined as those that experience more extreme temperatures during the year,

[29]Note that our model and empirical strategy already incorporate two aspects of adaptation discussed in the literature. First, the model permits input reallocation, as revealed by empirical analysis, showing that materials and labor reallocate in response to temperature changes, while capital does not. Second, given that our firm-level measures are annual while our temperature measures are daily, any measures firms take to boost production to cope with temperature increases, such as extending working hours during cooler periods, are already reflected in our semielasticities

and the other variables are described in equation (25).[30] In particular, columns 2 and 5 of Table 6 use an indicator variable that equals one if the number of extreme temperature days in that grid-cell exceeds the national mean, while columns 3 and 6 present results using the national median as the threshold. In this specification, the estimated coefficients $\beta_{1,\ell}$ capture the temperature-semielasticity of sales, which is common to firms in regions exposed to high and low extreme temperatures. Instead, the coefficients $\beta_{2,\ell}$ capture the differential effect of temperature for firms in more adapted grid-cells. Results in Table 6, columns 2 and 3, show that this differential effect is positive for the number of days above 40 degrees. In other words, firms in more adapted regions experience a less negative effect of extremely high temperatures on output compared to firms in less adapted regions. They also experience a lower fall in their marginal return to capital, although this coefficient is imprecisely estimated. Conversely, we find smaller and insignificant effects of adaptation regarding the exposure to high but less extreme temperatures. Overall, we take these results are suggestive evidence of relatively small adaptation effects, broadly in line with those found in the literature (Nath, 2022).

6 Aggregate Effects

This section documents the aggregate productivity losses resulting from various warming scenarios and highlights their heterogeneous regional impact.

6.1 Aggregate Productivity Loss

While our reduced-form estimates suggest that climate change reduces firm-level productivity and loweres the revenue-based marginal product of capital, they do not tell us whether this had economically meaningful effects on aggregate productivity. To measure this, we estimate the effect of climate change on the Solow residual, a proxy for aggregate productivity, using

[30] More specifically, we consider as extreme the days with maximum temperatures above 30 degrees or below 0 degrees. Then for each location and year we compute the ratio between number of days with extreme temperatures and the number of days with moderate temperatures (daily maximum between 0 and 30 degrees). Adapted locations are those that over the whole of our sample period have an average yearly ratio above the mean (or median) ratio at the national level.

Table 6: Effect of Temperature on Sales and MRPK Conditional on Adaptation

Dependent Variable	**Sales** (1)	**Sales** (2)	**Sales** (3)	**MRPK** (4)	**MRPK** (5)	**MRPK** (6)
Temperature Bins						
$(-\infty, 0°C]$	-0.094***	-0.080***	-0.079***	-0.030	-0.004	-0.001
	(0.019)	(0.021)	(0.021)	(0.022)	(0.027)	(0.028)
$(30°C, 35°C]$	-0.017*	-0.029***	-0.023**	-0.014	-0.019	-0.018
	(0.009)	(0.010)	(0.009)	(0.010)	(0.012)	(0.013)
$(35°C, 40°C]$	-0.046***	-0.035	-0.024	-0.045**	-0.049	-0.061
	(0.017)	(0.033)	(0.037)	(0.021)	(0.036)	(0.042)
$(40°C, +\infty)$	-0.807***	-1.864***	-2.039***	-0.578**	-1.225**	-1.393***
	(0.194)	(0.505)	(0.524)	(0.231)	(0.536)	(0.551)
Temperature Bins$\times I^H_{g(i)}$						
$(-\infty, 0°C]$		-0.019	-0.019		-0.039	-0.041
		(0.028)	(0.027)		(0.031)	(0.031)
$(30°C, 35°C]$		0.018	0.009		0.017	0.019
		(0.011)	(0.011)		(0.014)	(0.013)
$(35°C, 40°C]$		-0.003	-0.012		0.025	0.042
		(0.032)	(0.036)		(0.038)	(0.043)
$(40°C, +\infty)$		1.146**	1.344**		0.653	0.826
		(0.540)	(0.559)		(0.581)	(0.595)
Fixed Effects						
Firm	✓	✓	✓	✓	✓	✓
Sector × Year	✓	✓	✓	✓	✓	✓
GR and SDC × Region	✓	✓	✓	✓	✓	✓
Controls						
Rainfalls	✓	✓	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓	✓	✓
Observations	4,687,524	4,687,503	4,687,503	4,328,710	4,328,689	4,328,689

Note. All dependent variables are in logs. Temperature bins are constructed as explained in Section 3.2. In columns 2 and 5 the variable $I^H_{g(i)}$ is an indicator function that takes the value of one if firm i belongs to a grid-cell g with the number of extreme days above the national mean. In columns 3 and 6 the variable $I^H_{g(i)}$ is an indicator function that takes the value of one if firm i belongs to a grid-cell g with the number of extreme days above the national median. Rows 1-4 present the effect on the log of sales of adding an extra day in the given temperature range respectively. Rows 5-12 present the extra effect coming from being exposed to extreme temperatures. Standard errors are clustered at the grid-cell level and reported in parentheses. *, **, and *** denote 10, 5, and 1% statistical significance respectively.

equations (18), (20), and (22). We re-state compactly these equations as

$$\Delta \log Solow_t \approx \frac{Y_t}{GDP_t}\Bigg(\underbrace{\Delta \log TFP^*_t\left(e^{\tilde{z}_{it}(T_{g(i)t})}, \Delta T_{g(i)t}\right)}_{\Delta\text{Technology}} - \underbrace{\left(\Delta \log TFP^*_t\left(e^{\tilde{z}_{it}(T_{g(i)t})}, \Delta T_{g(i)t}\right) - \Delta \log TFP_t\left(e^{\tilde{z}_{it}(T_{g(i)t})}, e^{\tau^X_{it}(T_{g(i)t})}, \Delta T_{g(i)t}\right)\right)}_{\Delta\text{Allocative Efficiency}} \Bigg). \tag{28}$$

Equation (28) indicates that to quantify the counterfactual effect of climate change on aggregate productivity, we require: (i) the demand-adjusted productivity $e^{\tilde{z}_{it}(T_{g(i)t})}$ and their temperature-semielasticity; (ii) input-specific wedges $e^{\tau^X_{it}(T_{g(i)t})}$ and their temperature-semielasticity;

and (iii) counterfactual changes in grid-cell-level temperatures $\Delta T_{g(i)t}$. For the elasticity of substitution between the varieties σ and the production function elasticities α^X we use the same values as in Section 5.2. We next turn to explain how we use the empirical results from Section 5 to measure each of these elements.

6.1.1 Measurement and Identification

Demand-adjusted productivity. We compute demand-adjusted productivity in the data using equation (17). For the temperature-semielasticity of the demand-adjusted productivity, we follow the calculations in Section 5.2 as reported in Table 4.

Input-specific wedges. We compute input-specific wedges with our firm-level data using equation (13) as explained in Section 3. To calculate the temperature-semielasticity of the input-specific wedges we use the findings from Section 5.1 and proceed as follows: (i) we set to zero the temperature-semielasticity of labor and materials inputs since we did not observe significant effects of temperature (see Table 3), and (ii) we set the temperature-semielasticity of capital input equal to estimates from Table 3.

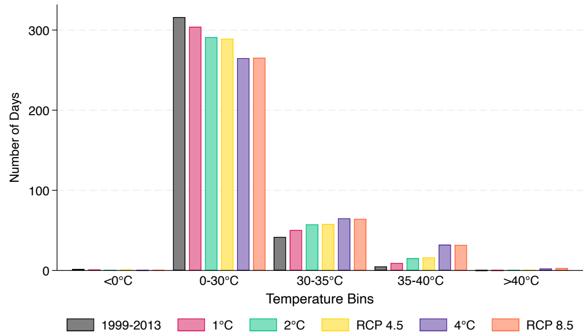
Counterfactual changes in grid-cell-level temperatures. The final component required to calculate productivity losses due to climate change across various warming scenarios is the counterfactual changes in temperatures at the grid-cell level. We derive the counterfactual change in the grid-cell-level temperature distribution for different climate scenarios, including mean temperature increases of 1-, 2- (baseline), and 4-degrees Celsius. We choose a mean temperature increase of 2-degrees Celsius as the benchmark scenario, aligning with the objectives of the Paris Agreement, while considering other temperature increases as robustness checks.[31] Additionally, we incorporate as additional robustness the RCP4.5 and RCP8.5 scenarios from the Copernicus project climate models, representing approximate average increases of 2- and 4-degrees Celsius, respectively.[32] These scenarios offer the advantage of capturing non-linear and heterogeneous temperature increases across different regions (NUTS3), aligning closely with realistic climate change models.

To calculate the counterfactuals for these different warming scenarios, we add the specified degree Celsius increase to the temperature of each grid-cell for each day of the year.

[31] https://unfccc.int/process-and-meetings/the-paris-agreement.

[32] https://climate.copernicus.eu/sites/default/files/2021-01/infosheet3.pdf.

Figure 3: Counterfactual Average Distribution of Days Within Temperature Bins



Note. Figure 3 shows the average number of days per year within each temperature bin of the vector $\boldsymbol{T}$. The number of days within each bin is an average across grid-cells. The first column (grey) reports the data for the period 1999-2013. The second column (pink) reports the warming scenario where the daily temperature increases by 1-degree Celsius. The third column (green) reports the warming scenario where the daily temperature increases by 2-degrees Celsius. The fourth column (orange) reports the warming scenario from the RCP4.5 where temperature increases by approximately 2-degrees Celsius. The fifth column (blue) reports the warming scenario where the daily temperature increases by 4-degrees Celsius. The sixth column (red) reports the warming scenario from the RCP8.5 where temperature increases by approximately 4-degrees Celsius.

This yields a new distribution of the number of days with the counterfactual temperature for each grid-cell under each of the different scenarios. We then partition this distribution into different temperature bins, as described in Section 3.2, represented by the vector $\boldsymbol{T_c} = \{T_c^\ell\}_\ell$. Figure 3 illustrates the counterfactual average distributions of the number of days within each temperature bin across grid-cells. Table D.9 in Appendix D.1 provides the complete counterfactual distribution of days within each temperature bin for all grid-cells under each warming scenario. Then, using this partition, we compute the counterfactual changes in the number of days per temperature bin across grid-cells, relative to those measured in Section 3.2, which we use to perform our counterfactuals. Table D.10 in Appendix D.1 presents the full counterfactual distribution of changes in the number of days within each temperature bin across all grid-cells under each warming scenario.

6.1.2 Results

In this section, we quantify the aggregate productivity losses resulting from climate change across various climate scenarios, distinguishing between the effects of pure technology and changes in allocative efficiency.

Baseline. Under the baseline warming scenario of a 2-degrees Celsius increase in average temperature, we find that the aggregate productivity loss is 1.68 percent (Table 7, row 1).[33]

[33]To minimize the influence of high short-run temperature volatility (as shown in Figure 1a for the years 1999-

This loss can be attributed to two main factors: 48 percent arises from firm-level productivity reductions, while the remaining 52 percent is due to a decrease in allocative efficiency. Translating this into economic terms, it corresponds to a GDP loss of approximately 35.37 billion US dollars in 2021, based on the Italian GDP of approximately 2.108 trillion US dollars in the same year.[34]

Alternative scenarios and robustness. To understand better the relation between the magnitude of temperature shocks and the associated economic damages, as well as to assess the robustness of our findings, we explore five alternative scenarios outlined in Table 7. These scenarios include a 1-degree and a 4-degree Celsius increase in average temperature, along with the RCP4.5 and RCP8.5 scenarios of the Copernicus project climate model. Additionally, we consider the baseline scenario of a 2-degree Celsius increase while controlling for adaptation forces.

Table 7: Effect of Climate Change on Aggregate Productivity

		Aggregate Productivity Loss		
		Δ*Total*	Δ*Technology*	Δ*Allocative Efficiency*
Baseline	2°C	1.68%	0.81%	0.87%
	1°C	0.77%	0.31%	0.46%
	2°C, Adaptation	1.21%	0.53%	0.68%
Robustness	4°C	6.82%	3.33%	3.49%
	RCP4.5	1.64%	0.85%	0.79%
	RCP8.5	5.35%	2.75%	2.60%

Note. This table reports the productivity losses due to climate change. Column 1 reports the total losses, column 2 reports the losses due to due to reductions in firm-level productivity, and column 3 reports the losses due to allocative efficiency. Row 1 reports the losses under the baseline scenario of a 2-degree Celsius increase in average temperature. Rows 2 to 6 report the robustness exercises. Row 2 reports the losses under the scenario of 1 degrees Celsius increase in average temperature. Row 3 reports the losses under the scenario of a 2-degrees Celsius increase in average temperature conditional on adaptation as explained in the main text. Row 4 reports the losses under the scenario of a 4-degrees Celsius increase in average temperature. Row 5 reports the losses under the scenario of an approximately 2-degrees Celsius increase from the RCP4.5 climate model. Row 6 reports the losses under the scenario of an approximately 4-degrees Celsius from the RCP8.5 climate model.

On the one hand, in the 1-degree Celsius scenario (row 2), aggregate productivity losses amount to 0.77 percent, with 40 percent attributed to firm-level productivity reductions and 60 percent to decreased allocative efficiency. On the other hand, in the 4 degrees Celsius scenario (row 4), the productivity losses increase to 6.82 percent, with 49 percent originating from

2013), we calculate the counterfactual aggregate productivity loss for each year within the sample and subsequently compute the average weighted by the number of observations.

[34]To calculate the GDP loss, we multiply the 2021 Italian GDP in US dollars (2.108 trillion US dollars) by the percentage loss (1.56 percent): 0.0168×2.108 trillion US dollars = 35.37 billion US dollars.

firm-level productivity reductions and 51 percent from decreased allocative efficiency. The two scenarios imply a GDP loss in US dollars of 16.27 billion and 143.88 billion, respectively.

These alternative scenarios highlight the nonlinear and convex nature of the impact of climate change on productivity losses. In part, this is due to the inverted U-shaped relation between temperature and firm-level economic outcomes identified in Section 5, which implies that a linear increase in hot days causes a convex increase in productivity losses. But in addition to that, climate change itself implies that the number of regions exposed to extreme temperatures increases exponentially as average temperature increases. This is shown in Table D.9 in the appendix. The average number of days of the year with +40 temperatures increases from 0.04 to 0.41 in the 2-degree Celsius scenario, while its increase is much more dramatic, from 0.04 to 2.55, in the 4-degree Celsius scenario. In Section 6.2 below, we compare our findings with the losses derived from damage functions employed in Integrated Assessment Models.

In the RCP4.5 scenario (row 5) and RCP8.5 scenario (row 6), corresponding to an average increase of 2 and 4 degrees Celsius, aggregate productivity losses amount to 1.64 percent to 5.35 percent, with 48 percent and 49 percent attributed to decreased allocative efficiency, respectively, and the rest to firm-level productivity losses. The two scenarios imply a GDP loss in US dollars of 34.58 billion and 112.72 billion, respectively. Thus, using counterfactual temperature changes from realistic climate models produces similar aggregate productivity losses compared to our simpler counterfactual scenarios.

Finally, we evaluate how firm-level adaptation influences our aggregate findings. Using the estimates provided in Table 6 in Section 5.3.2, for our baseline 2-degree Celsius temperature increase (row 3), we observe that aggregate productivity losses amount to 1.21 percent, which is 28 percent lower than in our baseline scenario. Of this reduction, 57 percent is attributed to declining allocative efficiency, with the remainder stemming from firm-level productivity losses. This scenario implies a GDP loss in US dollars of 25.44 billion. The effects of adaptation in the other scenarios are reported in Appendix D.2.[35]

[35]We find adaptation to mitigate relatively less the damage in the scenarios with higher increase in temperature (4-degree celsius and RCP8.5) than in the benchmark scenario. This is because we find that 81 percent of the firms that were not already adapted, i.e., those in grid-cells with a below-median number of days with extreme temperatures, will already adapt in our baseline 2-degree Celsius scenario. Therefore, additional projected increases in temperature imply modest increases in adaptation. We also estimated alternative adaptation models in which the predicted change in the number of extreme days is based on the historical relationship between average temperatures and their dispersion, obtaining very similar results. These additional estimates are available upon request.

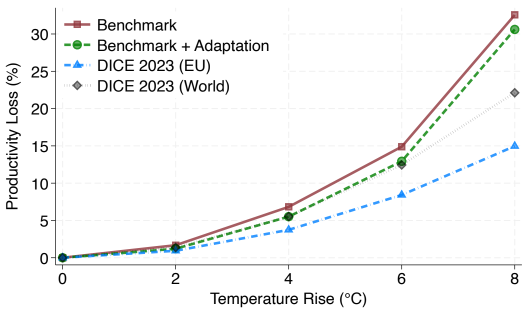
6.2 Discussion

In this section, we discuss how our results compare with the existing literature, and what are the main caveats of our framework.

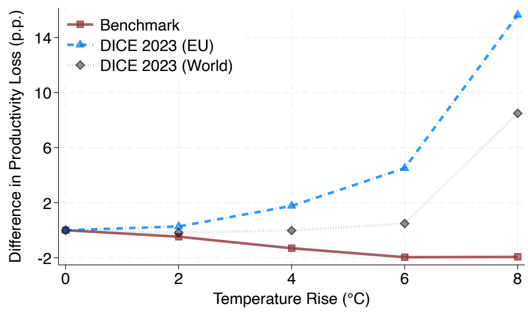
6.2.1 Comparison With The Literature

Figure 4a and Figure 4b compare our aggregate productivity losses, with and without adaptation, to the damage functions summarizing productivity losses in the most up-to-date iteration of the DICE model, i.e., Barrage and Nordhaus (2023).[36] Their damage function for the world is given by $0.003467 \times \Delta T^2$. However, to compare their damages with ours, which are based on a European country, we adjust their calibration downward by premultiplying their world damage function by 0.677.[37] This adjustment is based on the recurrent finding in aggregate studies using different approaches (e.g., Nordhaus and Yang, 1996; Dell et al., 2012) that lower aggregate productivity damages are typical for Europe. The detailed computations for our productivity losses are elaborated in Section 6.1.1.

Figure 4: Differences Across Productivity Loss Functions



(a) Productivity Loss Across Models



(b) Difference in Productivity Loss Across Models

Note. Figure 4a compares the productivity losses in percent due to a temperature increase between our model without adaptation (red line with squares), our model with adaptation (dashed green line with circles), the European-adjusted losses from the DICE model (dash-dotted blue line with triangles), and the world losses from the DICE model (dotted gray line with diamonds). Figure 4b shows the percentage point difference between the productivity losses from our model with adaptation and those from our model without adaptation (red line with squares) and the losses from the DICE model adjusted for Europe (dash-dotted blue line with triangles) and for the world (dotted gray line with diamonds). The DICE model used as a reference is from Barrage and Nordhaus (2023).

[36] We consider our losses with and without adaptation to perform a fair comparison with the DICE model's calibrations, which tend to incorporate adjustments for adaptation.

[37] This number is based on the regional damages reported in Nordhaus and Yang (1996). Specifically, we take the ratio of their European damages to their world damages, obtained as the GDP-weighted average of all regional damages from the numbers reported in their Table 2 on page 746.

The left figure illustrates the productivity losses across different models, while the right figure displays the differences between our losses with adaptation and our losses without adaptation, as well as those for Europe and the world from the DICE model. We find that all models exhibit a convex non-linear relationship that becomes steeper with higher temperature increases. When recast into the functional form of an aggregate damage function, our model implies the following loss: $0.00444 \times \Delta T^2$. Thus, productivity losses are estimated to be larger in our framework, particularly for more extreme climate change scenarios.

It is important to interpret the evidence presented here accurately. We are not suggesting that our estimated losses are a better proxy for the loss function modeled in the above-mentioned papers. The objective of those works is to assess the relationship between temperature increases and overall economic damage stemming from various channels, such as changes in mortality, crop yields, coastal erosion, and labor supply, among others. Instead, our findings, revealing substantial losses caused by one specific channel largely independent of those considered in the literature, underscore the significance of focusing on detailed evidence from micro-data to reassess the overall magnitude of these economic costs. Nevertheless, we acknowledge that a comprehensive assessment that integrates all these effects into a unified framework and distinguishes the relative importance of each component is beyond the scope of our study.

6.2.2 Interpretation of The Results

Our quantitative findings are subject to potential caveats. Following the literature that estimates the effect of local temperature fluctuations using micro-data, we focus on the short-run effects. However, the short-run effects may differ from the long-run effects due to technological adaptation. In the future, firms may be better equipped to handle extreme temperatures due to technological advancement or increased investment in existing climate-mitigating technologies. Although quantifying the former is challenging, concerning the latter, we demonstrate in Sections 5.3.2 and 6.1.2 that including this margin of adaptation reduces our estimated productivity costs of climate change by around 20-30 percent.

Furthermore, the long-run effects might be reduced due to improvements in allocative efficiency as short-term capital reallocation frictions subside. Although estimating these dynamics is challenging within our short panel, our framework offers an upper bound on this potential bias in aggregate productivity losses. Specifically, if we assume that firm-level productivity losses are long-lasting but all capital reallocation frictions are resolved in the long run, then the frictionless term in equation (20) provides an estimate of the minimum aggregate productivity loss attainable in a scenario where all capital is fully mobile.

Additionally, our framework is static. Although we have detailed the advantages of this choice, a limitation is that it does not capture the extensive margin, such as the entry and exit of firms. We chose not to incorporate this margin due to limited information on firm entry and exit in our data. Neglecting this margin likely biases our results through two channels. First, in affected regions, unproductive firms may exit, thus improving the selection of firms. Second, firms in affected areas might choose to close and relocate all their capital to cooler regions, enhancing capital allocative efficiency in the long run (we find limited evidence for this channel in our sample). We emphasize that our findings on the relative importance of different channels and wedges provide valuable inputs for future models addressing the extensive margin effects of climate change.[38]

6.3 Regional Heterogeneity

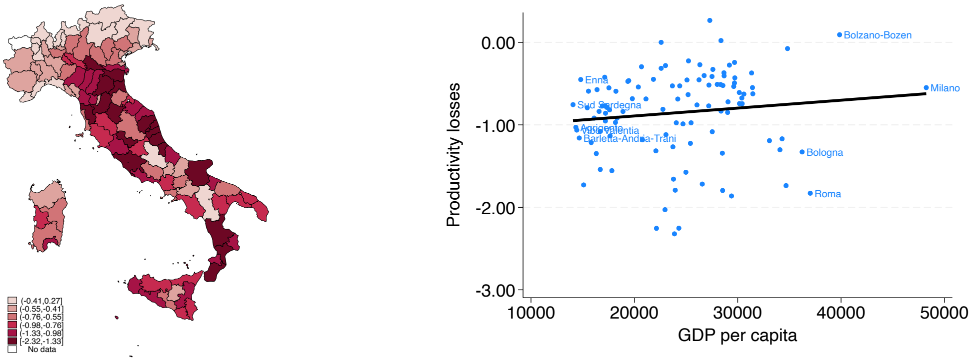
This section examines the impact of climate change on productivity losses at the province level (NUTS 3) in Italy. Using the methodology described in Section 2, we apply equation (22) to each province to estimate the magnitude and spatial distribution of these losses under the baseline warming scenario of 2 degrees Celsius.

The results presented in Figure 5a highlight significant variations in productivity losses among Italian provinces under the 2 degrees Celsius warming scenario. Although climate change has an overall negative effect on productivity across Italy, the impact is not uniform. Some regions experience positive effects, with a modest productivity increase of 0.27 percent, while others face substantial reductions, with the maximum loss reaching 2.32 percent.

Our analysis reveals regional disparities between the southern and northern regions of Italy in climate change-induced productivity losses. Southern regions experience pronounced negative impacts due to increased extreme heat days. In contrast, northern alpine areas benefit from fewer days below 0 degrees Celsius, resulting in moderate productivity losses or even

[38] This is because it is well known in the misallocation literature that different input wedges and productivity factors, of the types quantified in this paper, affect firms' value, and therefore both entry and exit decisions, in different ways (Restuccia and Rogerson, 2017).

Figure 5: Regional Productivity Losses for 2°C Warming Scenario



(a) Regional Productivity Losses **(b) Regional Losses and GDP Per Capita**

Note. Figure 5a shows the productivity losses across NUTS 3 regions due to a 2 degrees Celsius increase in temperature, calculated using equation (18), adjusted with the ratio of gross output to value added. Productivity losses are in percent, and darker colors represent larger losses. Figure 5b plots the same regional losses against average GDP per capita in our sample, showing a negative correlation of 0.232.

modest increases. In Appendix D.3, Figures D.2a-D.2b display regional productivity losses under the four alternative warming scenarios. Overall, we find that the most severe impact of climate change in southern regions carries on across different scenarios. Moreover, the RCP4.5 and RCP8.5 scenarios, that include more accurate predictions of local temperature changes, and imply a larger increase in temperature in the south relative to the north, predict wider disparities in productivity losses between northern and southern regions.

These findings underscore how firm-level losses, characterized by an inverted U-shape pattern, translate into substantial regional differences depending on historical temperatures. To show more clearly the relation between predicted productivity losses and inequality, in Figure 5b we relate productivity losses to GDP per capita and find a significantly positive relation, confirming that climate change is expected to increase inequality across regions in Italy. Importantly, this positive relation is much stronger for the more accurate RCP4.5 and RCP8.5 scenarios (Figures D.3d and D.3e in the Appendix D.3).

7 Conclusion

This paper examines the impact of temperature fluctuations on firm-level outcomes in Italy and presents a general equilibrium framework to analyze their aggregate implications. The framework establishes the link between firm-level losses due to rising temperatures and aggregate productivity losses in general equilibrium. Our model identifies three key channels through which climate change impacts aggregate productivity: (i) the firm-level demand channel, (ii) the firm-level productivity channel, and (iii) the reallocation channel. We develop an empirical strategy for measuring these channels and demonstrate how the estimates can be utilized to quantify the aggregate implications.

By leveraging a combination of Italian firm-level data and detailed climate data, we estimate the temperature-semielasticities that are essential inputs for our model. Our empirical findings reveal an inverted U-shaped pattern for temperature-associated losses, with more significant effects observed at extreme temperature levels. Specifically, we observe contractions in sales, materials, and labor costs during extreme temperatures, but not in capital. This pattern is reflected in the behavior of revenue-based marginal products, which contract at extreme temperatures only for capital, but not for materials and labor. These empirical results suggest that climate change negatively affects firm-level sales, leading to the reallocation of materials and labor, but not of capital, to less affected areas, potentially lowering the allocative efficiency of the economy.

Finally, using the estimated firm-level temperature semielasticities, we employ the model to compute aggregate productivity losses under different climate change scenarios. Our analysis indicates that under a two-degree Celsius warming scenario, productivity is estimated to decline by 1.68%, which can be moderated to 0.77% with a one-degree Celsius temperature increase. However, in the event of a doubled temperature increase to four degrees Celsius, the drop in productivity becomes four times larger, reaching around 6.77%. This non-linear and convex relationship between temperature and aggregate productivity highlights the significantly larger productivity losses associated with higher warming scenarios. Notably, roughly half of the aggregate productivity losses are attributed to reductions in firm-level productivity, while the remaining half is ascribed to a decline in allocative efficiency. We broadly confirm the magnitude of these finding using temperature change predictions from the RCP 4.5 and RCP 8.5 climate models. Furthermore, in a robustness exercise we measure adaptation by comparing firm-level losses in grid cells with different different extreme temperature exposure. Including this adaptation margin reduces projected aggregate damages by 20-30 percent. Our analysis also reveals that climate change impacts productivity differently across Italian provinces, contributing to regional inequality, as we find a negative relationship between expected productivity losses and current GDP per capita.

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Climate Change, Firms, and Aggregate Productivity

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Carolina Villegas-Sanchez

Online Appendix

Contents

A Structural Framework

In this section, we show the derivations of the equations in Section 2.2.

A.1 Aggregate Gross Output TFP

To derive the equations (18) and (20), we start from the definition of aggregate gross output TFP, given by

$$TFP_t = \left(\frac{\prod_{X \in \mathcal{X}} X_t^{\alpha^X}}{Y_t} \right)^{-1}, \tag{29}$$

$$= \prod_{X \in \mathcal{X}} \left(\frac{X_t}{Y_t} \right)^{-\alpha^X}; \tag{30}$$

where aggregate real inputs are defined as

$$X_t = \sum_{i=1}^{N_t} X_{it}. \tag{31}$$

To characterize aggregate real inputs X_t, we now need to derive the demand for each input X_{it}. We start recalling that the minimized cost function is given by

$$\mathcal{C}(Y_{it}) = \frac{Y_{it}}{e^{z_{it}(T_{g(i)t})}} \prod_{X \in \mathcal{X}} \left(\frac{e^{\tau_{it}^X(T_{g(i)t})} P^X}{\alpha^X} \right)^{\alpha^X}, \tag{32}$$

$$= \prod_{X \in \mathcal{X}} \left(\frac{P_t^X}{\alpha^X} \right)^{\alpha^X} \frac{Y_{it}}{e^{z_{it}(T_{g(i)t})}} \prod_{X \in \mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})} \right)^{\alpha^X}, \tag{33}$$

$$= C_t \frac{Y_{it}}{e^{z_{it}(T_{g(i)t})}} \prod_{X \in \mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})} \right)^{\alpha^X}; \tag{34}$$

where

$$C_t = \prod_{X \in \mathcal{X}} \left(\frac{P_t^X}{\alpha^X} \right)^{\alpha^X}. \tag{35}$$

Given that the first-order conditions for each input are given by

$$e^{\tau^X_{it}(T_{g(i)t})} P^X_t X_{it} = \alpha^X \mathcal{C}(Y_{it}), \tag{36}$$

$$= \alpha^X C_t \frac{Y_{it}}{e^{z_{it}(T_{g(i)t})}} \prod_{X \in \mathcal{X}} \left(e^{\tau^X_{it}(T_{g(i)t})}\right)^{\alpha^X}; \tag{37}$$

we obtain the following input demand function:

$$X_{it} = \alpha^X \frac{C_t}{P^X_t} \frac{Y_{it}}{e^{\tau^X_{it}(T_{g(i)t})} e^{z_{it}(T_{g(i)t})}} \prod_{X \in \mathcal{X}} \left(e^{\tau^X_{it}(T_{g(i)t})}\right)^{\alpha^X}, \tag{38}$$

This implies the following aggregate level for each input X_t:

$$X_t = \alpha^X \frac{C_t}{P^X_t} \sum_{i=1}^{N_t} \frac{Y_{it}}{e^{\tau^X_{it}(T_{g(i)t})} e^{z_{it}(T_{g(i)t})}} \prod_{X \in \mathcal{X}} \left(e^{\tau^X_{it}(T_{g(i)t})}\right)^{\alpha^X}. \tag{39}$$

Substituting equation (39) back into equation (30) we obtain the following:

$$TFP_t = \prod_{X \in \mathcal{X}} \left(\alpha^X \frac{C_t}{P^X_t} \sum_{i=1}^{N_t} \frac{1}{e^{\tau^X_{it}(T_{g(i)t})} e^{z_{it}(T_{g(i)t})}} \frac{Y_{it}}{Y_t} \prod_{X \in \mathcal{X}} \left(e^{\tau^X_{it}(T_{g(i)t})}\right)^{\alpha^X}\right)^{-\alpha^X}, \tag{40}$$

$$= \prod_{X \in \mathcal{X}} \left(\alpha^X \frac{C_t}{P^X_t}\right)^{\alpha^X} \left(\sum_{i=1}^{N_t} \frac{1}{e^{\tau^X_{it}(T_{g(i)t})} e^{z_{it}(T_{g(i)t})}} \frac{Y_{it}}{Y_t} \prod_{X \in \mathcal{X}} \left(e^{\tau^X_{it}(T_{g(i)t})}\right)^{\alpha^X}\right)^{-\alpha^X}, \tag{41}$$

$$= \prod_{X \in \mathcal{X}} \left(\sum_{i=1}^{N_t} \frac{1}{e^{\tau^X_{it}(T_{g(i)t})} e^{z_{it}(T_{g(i)t})}} \frac{Y_{it}}{Y_t} \prod_{X \in \mathcal{X}} \left(e^{\tau^X_{it}(T_{g(i)t})}\right)^{\alpha^X}\right)^{-\alpha^X}; \tag{42}$$

where the last equality holds because of the definition of C_t in equation (35). Notice that now aggregate gross output TFP in equation (42) depends only on wedges and on each firm relative size Y_{it}/Y_t. Hence, to obtain an expression for aggregate gross output TFP that depends only on wedges, we need to express the relative size of each firm as a function of wedges only. We start by defining a firm's relative size using the demand function:

$$\frac{Y_{it}}{Y_t} = \left(e^{d_{it}(T_{g(i)t})}\right)^{\sigma-1} \left(\frac{P_{it}}{P_t}\right)^{-\sigma}. \tag{43}$$

Now, recall that the firms' prices are given by

$$P_{it} = \mathcal{MC}'(Y_{it}), \tag{44}$$

$$= \mathcal{M}C_t \frac{1}{e^{z_{it}(T_{g(i)t})}} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{\alpha^X}; \tag{45}$$

Moreover, we can substitute firm-level prices from equation (45) into the aggregate price index and obtain

$$P_t = \left(\sum_{i=1}^{N_t}\left(\frac{P_{it}}{e^{d_{it}(T_{g(i)t})}}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}, \tag{46}$$

$$= \left(\sum_{i=1}^{N_t}\left(\mathcal{M}C_t \frac{1}{e^{d_{it}(T_{g(i)t})}e^{z_{it}(T_{g(i)t})}} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{\alpha^X}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}, \tag{47}$$

$$= \mathcal{M}C_t \left(\sum_{i=1}^{N_t}\left(\frac{1}{e^{\tilde{z}_{it}(T_{g(i)t})}} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{\alpha^X}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}; \tag{48}$$

Finally, substituting equations (45) and (48) into equation (43), we obtain an expression for firms' relative size as a function of wedges only, given by

$$\frac{Y_{it}}{Y_t} = \left(e^{d_{it}(T_{g(i)t})}\right)^{\sigma-1} \left(\frac{\frac{1}{e^{z_{it}(T_{g(i)t})}} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{\alpha^X}}{\left(\sum_{i=1}^{N_t}\left(\frac{1}{e^{\tilde{z}_{it}(T_{g(i)t})}} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{\alpha^X}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}}\right)^{-\sigma} \tag{49}$$

Now, we can substitute equation (49) into equation (42) to obtain the following:

$$TFP_t = \prod_{X\in\mathcal{X}} \left(\sum_{i=1}^{N_t} \frac{\left(e^{d_{it}(T_{g(i)t})}\right)^{\sigma-1}}{e^{\tau_{it}^X(T_{g(i)t})} e^{z_{it}(T_{g(i)t})}} \left(\frac{\frac{1}{e^{z_{it}(T_{g(i)t})}} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{\alpha^X}}{\left(\sum_{i=1}^{N_t} \left(\frac{1}{e^{\tilde{z}_{it}(T_{g(i)t})}} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{\alpha^X}\right)^{1-\sigma}\right)^{\frac{1}{1-\sigma}}} \right)^{-\sigma} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{\alpha^X} \right)^{-\alpha^X}, \tag{50}$$

$$= \left(\sum_{i=1}^{N_t} \left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{-(\sigma-1)\alpha^X} \right)^{\frac{\sigma}{\sigma-1}}$$

$$\times \prod_{X\in\mathcal{X}} \left(\sum_{i=1}^{N_t} \frac{\left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1}}{e^{\tau_{it}^X(T_{g(i)t})}} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{-(\sigma-1)\alpha^X} \right)^{-\alpha^X}. \tag{51}$$

Hence, taking logs in equation (51) we obtain the following:

$$\log TFP_t = \frac{\sigma}{\sigma-1} \log \left(\sum_{i=1}^{N_t} \left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{-(\sigma-1)\alpha^X} \right)$$
$$- \sum_{X\in\mathcal{X}} \alpha^X \log \left(\sum_{i=1}^{N_t} \frac{\left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1}}{e^{\tau_{it}^X(T_{g(i)t})}} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{-(\sigma-1)\alpha^X} \right). \tag{52}$$

Equation 52 shows that aggregate gross output TFP in this framework can be expressed as just a function of (i) firm-level wedges, $e^{\tilde{z}_{it}(T_{g(i)t})}$ and $e^{\tau_{it}^X}(T_{g(i)t})$; (ii) the elasticity of substitution across goods σ; and (iii) the production function elasticities α^X.

Notice that if the revenue-based marginal products equalize across firms, i.e., if $e^{\tau_{it}^X(T_{g(i)t})} = 1$, then equation (52) reduces to the efficient aggregate gross output TFP, given by

$$\log TFP_t^* = \frac{1}{\sigma-1} \log \left(\sum_{i=1}^{N_t} \left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1} \right). \tag{53}$$

This concludes the derivations to get equations (16) and (19), which define respectively the inefficient and the efficient aggregate gross output TFP. Using these two equations, we can now derive equations (18) and (20). We start by differentiating equation (52) to obtain a relation linking changes in aggregate gross output TFP to changes in grid-cell-level temperatures, given by

$$d\log TFP_t = \sigma \sum_{i=1}^{N_t} \underbrace{\left(\frac{\left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{-(\sigma-1)\alpha^X}}{\sum_{i=1}^{N_t} \left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{-(\sigma-1)\alpha^X}} \right)}_{\equiv \lambda_{it}\left(e^{\tilde{z}_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}\right)}$$

$$\times \left(\frac{\partial \tilde{z}_{it}(T_{g(i)t})}{\partial T_{g(i)t}} - \sum_{X\in\mathcal{X}} \alpha^X \frac{\partial \tau_{it}^X(T_{g(i)t})}{\partial T_{g(i)t}} \right) dT_{g(i)t}$$

$$- \sum_{X\in\mathcal{X}} \alpha^X \sum_{i=1}^{N_t} \left(\frac{\frac{\left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1}}{e^{\tau_{it}^X(T_{g(i)t})}} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{-(\sigma-1)\alpha^X}}{\sum_{i=1}^{N_t} \frac{\left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1}}{e^{\tau_{it}^X(T_{g(i)t})}} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{-(\sigma-1)\alpha^X}} \right)$$

$$\times \left((\sigma-1)\frac{\partial \tilde{z}_{it}(T_{g(i)t})}{\partial T_{g(i)t}} - \frac{\partial \tau_{it}^X(T_{g(i)t})}{\partial T_{g(i)t}} - \sum_{X\in\mathcal{X}} (\sigma-1)\alpha^X \frac{\partial \tau_{it}^X(T_{g(i)t})}{\partial T_{g(i)t}} \right) dT_{g(i)t}, \tag{54}$$

$$= \sigma \sum_{i=1}^{N_t} \lambda_{it}\left(e^{\tilde{z}_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}\right)$$

$$\times \left(\frac{\partial \tilde{z}_{it}(T_{g(i)t})}{\partial T_{g(i)t}} - \sum_{X\in\mathcal{X}} \alpha^X \frac{\partial \tau_{it}^X(T_{g(i)t})}{\partial T_{g(i)t}} \right) dT_{g(i)t}$$

$$- \sum_{X\in\mathcal{X}} \alpha^X \sum_{i=1}^{N_t} \underbrace{\left(\frac{\sum_{i=1}^{N_t} \left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{-(\sigma-1)\alpha^X}}{\sum_{i=1}^{N_t} \frac{\left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1}}{e^{\tau_{it}^X(T_{g(i)t})}} \prod_{X\in\mathcal{X}} \left(e^{\tau_{it}^X(T_{g(i)t})}\right)^{-(\sigma-1)\alpha^X}} \right)}_{\equiv \Omega_t^X\left(e^{\tilde{z}_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}\right)} \lambda_{it}\left(e^{\tilde{z}_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}\right)$$

$$\times \frac{1}{e^{\tau_{it}^X(T_{g(i)t})}} \left((\sigma-1)\frac{\partial \tilde{z}_{it}(T_{g(i)t})}{\partial T_{g(i)t}} - \frac{\partial \tau_{it}^X(T_{g(i)t})}{\partial T_{g(i)t}} - \sum_{X\in\mathcal{X}} (\sigma-1)\alpha^X \frac{\partial \tau_{it}^X(T_{g(i)t})}{\partial T_{g(i)t}} \right) dT_{g(i)t}, \tag{55}$$

$$= \sum_{i=1}^{N_t} \lambda_{it}\left(e^{\tilde{z}_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}\right) \left[\sigma \left(\frac{\partial \tilde{z}_{it}(T_{g(i)t})}{\partial T_{g(i)t}} - \sum_{X\in\mathcal{X}} \alpha^X \frac{\partial \tau_{it}^X(T_{g(i)t})}{\partial T_{g(i)t}} \right) dT_{g(i)t} \right.$$

$$- \sum_{X\in\mathcal{X}} \frac{\alpha^X}{e^{\tau_{it}^X(T_{g(i)t})}} \Omega_t^X\left(e^{\tilde{z}_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}\right)$$

$$\left. \times \left((\sigma-1)\frac{\partial \tilde{z}_{it}(T_{g(i)t})}{\partial T_{g(i)t}} - \frac{\partial \tau_{it}^X(T_{g(i)t})}{\partial T_{g(i)t}} - \sum_{X\in\mathcal{X}} (\sigma-1)\alpha^X \frac{\partial \tau_{it}^X(T_{g(i)t})}{\partial T_{g(i)t}} \right) dT_{g(i)t} \right], \tag{56}$$

$$= \sum_{i=1}^{N_t} \lambda_{it}\left(e^{\tilde{z}_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}\right) \sum_{X\in\mathcal{X}} \frac{\alpha^X}{e^{\tau_{it}^X(T_{g(i)t})}} \Omega_t^X\left(e^{\tilde{z}_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}\right)$$

$$\times \left[\left(\sigma \frac{e^{\tau_{it}^X(T_{g(i)t})}}{\Omega_t^X\left(e^{\tilde{z}_{it}(T_{g(i)t})}, e^{\tau_{it}^X(T_{g(i)t})}\right)} - (\sigma-1) \right) \left(\frac{\partial \tilde{z}_{it}(T_{g(i)t})}{\partial T_{g(i)t}} - \sum_{X\in\mathcal{X}} \alpha^X \frac{\partial \tau_{it}^X(T_{g(i)t})}{\partial T_{g(i)t}} \right) + \frac{\partial \tau_{it}^X(T_{g(i)t})}{\partial T_{g(i)t}} \right]$$

$$\times dT_{g(i)t}; \tag{57}$$

which is exactly the expression in equation (18) in Section (2). We can now follow the strategy as above and differentiate equation (53) to obtain a relation linking changes in efficient aggregate gross output TFP to changes in grid-cell-level temperatures, given by

$$d\log TFP_t^* = \sum_{i=1}^{N_t} \underbrace{\left(\frac{\left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1}}{\sum_{i=1}^{N_t}\left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)^{\sigma-1}} \right)}_{\equiv \lambda_{it}^*\left(e^{\tilde{z}_{it}(T_{g(i)t})}\right)} \frac{\partial \tilde{z}_{it}(T_{g(i)t})}{\partial T_{g(i)t}} dT_{g(i)t}, \tag{58}$$

$$= \sum_{i=1}^{N_t} \lambda_{it}^* \left(e^{\tilde{z}_{it}(T_{g(i)t})}\right) \frac{\partial \tilde{z}_{it}(T_{g(i)t})}{\partial T_{g(i)t}} dT_{g(i)t}; \tag{59}$$

which is exactly the expression in equation (20) in Section (2).

A.2 Solow Residual

The model presented in Section 2 has three productive inputs: capital, labor, and materials. This implies that its notion of output is a gross measure, hence, its implied TFP is defined on gross output. However, when normally thinking about productivity as defined by Solow (1957), we think of a concept related to net output, i.e., to GDP. Here, we show how to adjust our measurement to be able to study the effect of climate change on aggregate net output TFP, i.e., on the Solow residual. Our strategy is reminiscent of the insights from Jones (2011).

We start by the definition of GDP, given by

$$GDP_t = Y_t - \frac{P_t^M}{P_t} M_t, \tag{60}$$

$$= TFP_t K^{\alpha^K} L^{\alpha^L} M^{\alpha^M} - \frac{P_t^M}{P_t} M_t; \tag{61}$$

i.e., GDP is defined as gross output net of the aggregate real value of materials. Given equation (61), we can defined the Solow residual as

$$Solow_t = \frac{TFP_t K^{\alpha^K} L^{\alpha^L} M^{\alpha^M} - \frac{P_t^M}{P_t} M_t}{K^{\widehat{\alpha}^K} L^{\widehat{\alpha}^L}}, \tag{62}$$

where $\widehat{\alpha}^K$ and $\widehat{\alpha}^L$ are the aggregate capital and labor elasticities of value added. Taking logs gives

$$\log Solow_t = \log\left(TFP_t K^{\alpha^K} L^{\alpha^L} M^{\alpha^M} - \frac{P^M_t}{P_t} M_t\right) - \log\left(K^{\widehat{\alpha}^K} L^{\widehat{\alpha}^L}\right). \tag{63}$$

Since we are interested in a counterfactual that assesses the implications of a medium- or long-run phenomenon such as climate change, we abstract from the fluctuations in aggregate capital and labor due to it and assume that these two aggregate quantities are fixed in the medium- or long-run, i.e., $K_t = \overline{K}$ and $L_t = \overline{L}$. Notice that this assumption is coherent with the model being in general equilibrium, it just implies that aggregate capital and labor supplies are supplied inelastically. Under these two assumptions, we can differentiate equation (63) and obtain the following:

$$d\log Solow_t = \frac{1}{GDP_t} TFP_t K^{\alpha K} L^{\alpha L} M^{\alpha M} \frac{dTFP_t}{TFP_t} + \frac{\alpha^M}{GDP_t} TFP_t K^{\alpha K} L^{\alpha L} M^{\alpha M} \frac{dM_t}{M_t} - \frac{\frac{P^M_t}{P_t} M_t}{GDP_t} \frac{dM_t}{M_t}, \tag{64}$$

$$= \frac{Y_t}{GDP_t} d\log TFP_t + \alpha^M \frac{Y_t}{GDP_t} d\log M_t - \frac{\frac{P^M_t}{P_t} M_t}{Y_t} \frac{Y_t}{GDP_t} d\log M_t, \tag{65}$$

$$= \frac{Y_t}{GDP_t}\left(d\log TFP_t + \left(\alpha^M - \frac{\frac{P^M_t}{P_t} M_t}{Y_t}\right) d\log M_t\right). \tag{66}$$

The equation (66) says that a percentage change in the Solow residual is proportional to the linear combination of the percentage changes in aggregate gross output TFP and aggregate materials. We further approximate equation (66) by assuming that $\alpha^M - P^M M_t / P_t Y_t$ is close to zero. This assumption is convenient since it allows us to solve the model in closed form.[39] We emphasize two things about this additional assumption: (i) In the likely scenario where the general equilibrium temperature-semielasticity of the aggregate materials is negative, this assumption should be considered conservative because it goes against the effect of temperature on the Solow residual; and (ii) when we test this hypothesis empirically by measuring the difference between α^M and $P^M M_t / P_t Y_t$, we find that it is less than 0.1 in our data.[40] Hence,

[39]Notice that, while aggregate gross output TFP does not depend on aggregate prices, aggregate materials do depend on them. Therefore, to know their response to changes in temperature we would have to infer the general equilibrium effect of temperature, i.e., their effect on the user cost of capital and wages, which is beyond the scope of our analysis and difficult because of the constraints imposed by the short time frame of our data.

[40]This implies that, even if the temperature-semielasticity of aggregate materials is x, which we consider an unlikely upper bound, given that this is our estimate of partial equilibrium temperature-semielasticity found

with this additional assumption at hand, we can derive the following adjustment to our gross output TFP measure:

$$d\log Solow_t = \frac{Y_t}{GDP_t} d\log TFP_t, \tag{67}$$

which is exactly equation (22) in Section (2).

B Data

B.1 Firm-Level Data

To ensure data quality, we employ firm-level balance sheet information from Orbis, following the data construction and cleaning methodologies outlined by Kalemli-Özcan et al. (2024) and Gopinath et al. (2017). The following steps are implemented: (1) Removal of Missing Information: We drop firm-year observations that have missing data on total assets, operating revenue, sales, and employment. (2) Exclusion of Negative Values: Firms reporting negative values for assets, tangible fixed assets, employment, or sales are excluded from the analysis. (3) Limiting Extreme Values: To enhance the robustness of our findings, we compute three ratios: sales to total assets, employment to total assets, and employment to sales. We then remove observations that fall below the 0.1 percentile or above the 99.9 percentile of the distribution of these ratios. By doing so, we mitigate the potential influence of extreme values on our analysis.

For this specific project, we apply additional filters and exclusions. (1) Removal of Missing Zipcode Information: Firms with missing zipcode information are dropped from the dataset. This ensures that we can accurately associate firms with specific geographic regions. (2) Exclusion of Finance, Insurance, and Utility Sectors: To maintain focus on the sectors relevant to our analysis, we exclude firms operating in the finance and insurance sectors, as well as the utility sector. (3) Exclusion of Firms with Negative Age or Exceeding 100: Firms with negative age or those exceeding 100 years are excluded from the analysis. (4) Time Period Selection: We keep observations from 1999 to 2013.

The final sample used for our analysis consists of approximately 4.3 million observations, representing 1 million unique firms. To account for changes in prices and maintain compa-

in Table 2 and that normally general equilibrium effects dampen partial equilibrium estimates, we would lose at *most* 0.1*x percentage points relative to our main results.

rability over time, we deflate operating revenue, material expenditure, and wage bill using gross output price indices at the two-digit industry level, with the base year of 2005 (sourced from the Eurostat database). Additionally, the capital stock is deflated using the economy-wide price of investment goods obtained from the World Development Indicators database. Table B.1 provides an overview of the main variables in our analysis, based on the final Orbis dataset.

Table B.1: Summary Statistics (1999-2013)

	Sales	Materials	Wage Bill	Employees	Capital	MRPM	MRPL	MRPK
Mean	13.33	11.61	11.66	1.88	11.14	1.72	2.03	2.30
Median	13.34	12.02	11.82	1.79	11.05	1.01	1.77	2.39
Min	5.92	3.55	4.35	0	5.51	-0.04	-0.05	-4.26
Max	17.78	17.32	16.08	5.76	16.68	8.09	7.52	7.27
No. Obs.	4,823,392	4,823,392	3,875,031	2,545,857	4,444,668	4,823,392	3,875,031	4,444,668

Note. Summary statistics of cleaned Orbis dataset between 1999 and 2013. All variables are in logs. All monetary values are deflated using Eurostat two-digit industry price deflators, and capital is deflated using the country-specific price of investment from the World Development Indicators.

B.2 Climate Data

B.2.1 Description of E-OBS data

E-OBS is a land-only gridded daily observational dataset that provides information on precipitation, temperature, sea level pressure, global radiation, wind speed, and relative humidity in Europe.[41] The dataset is derived from meteorological observations collected by the National Meteorological and Hydrological Services (NMHSs) and other data-holding institutes across Europe.

E-OBS is presented on regular latitude-longitude grids with spatial resolutions of 0.1°. It covers a significant portion of the European continent, spanning from northern Scandinavia to southern Spain and extending from Iceland to 40°E in the Russian Federation. Over time, the coverage of E-OBS has progressively expanded since its inception in the 1950s, encompassing a larger area of the European continent due to an increasing number of contributing meteorological stations. The dataset undergoes comprehensive updates twice a year, with provisional monthly updates accessible through the E-OBS website.[42]

[41] Official E-OBS website: https://cds.climate.copernicus.eu.

[42] E-OBS monthly updates: http://surfobs.climate.copernicus.eu/dataaccess/access_eobs_months.php.

Originally developed in 2008 as a validation tool for Europe-wide climate model simulations within the European Union ENSEMBLES project, E-OBS has evolved into a resource for monitoring climate conditions across Europe (Klein Tank et al., 2002). The position of E-OBS in Europe is unique due to its relatively high spatial resolution, daily temporal resolution, multiple variables, and the extensive length of the dataset. The station-level data on which E-OBS is based can be accessed through the webpages of the European Climate Assessment & Dataset (ECA&D), subject to data permissions.[43]

The dataset is daily, meaning the observations cover a 24-hour period per time step. The specific 24-hour period may vary across regions and data providers. The reason for this is that some data providers measure between midnight to midnight while others might measure from morning to morning. Since E-OBS is an observational dataset, no attempts have been made to adjust the time series for this 24-hour offset. However, it ensures that the largest part of the measured 24-hour period corresponds to the day attached to the time step in E-OBS and ECA&D

B.2.2 Distribution of Meteorological Stations

The station data used in the E-OBS dataset are sourced from 84 participating institutions and encompass over 23,000 meteorological stations. For a considerable number of countries, the number of stations used in the E-OBS dataset represents their complete national network, resulting in a much higher density compared to the station network routinely shared among NMHSs, which forms the basis of other gridded datasets.

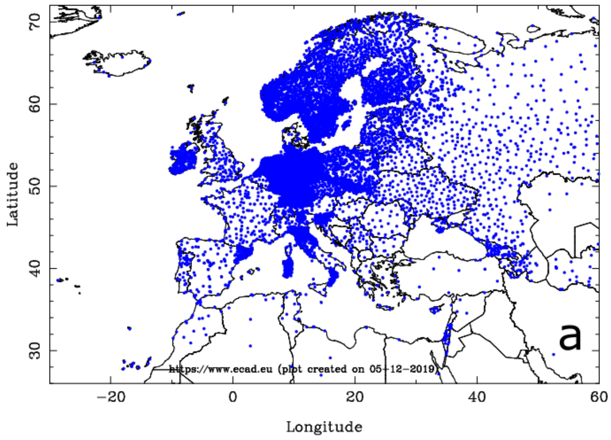
Figure B.1 presents the distribution of meteorological stations used by E-OBS. This map showcases the station coverage in ECA&D, which serves as the basis for the E-OBS precipitation dataset v20.0e., regardless of their start or stop dates. The figure illustrates the high density of stations in many parts of Europe.

B.2.3 Climate Data Summary Statistics

Table B.2 displays the distribution of temperatures and rainfall across Italy and within the average grid-cell of Italy. It reveals significant variation in temperature throughout Italy, ranging from a minimum of -25 degrees Celsius to a maximum of 45 degrees Celsius, with an

[43]ECA&D website: www.ecad.eu.

Figure B.1: Distribution of Meteorological Station Used by E-OBS



Note. Figure B.1 shows the map with the station coverage in ECA&D which is the basis for the E-OBS precipitation dataset v20.0e.

average temperature of 17 degrees Celsius.

Table B.2: Summary Statistics of Climate Data (1950-2020)

	Overall		Within Grid-Cell	
	Temperatures (°C)	Rainfalls (mm)	Temperatures (°C)	Rainfalls (mm)
Mean	16.88	2.28	16.88	2.28
Median	16.73	0.00	16.50	1.09
Min	-25.43	0.00	-2.60	0.00
Max	45.82	308.20	35.02	31.71

Note. Table 1 shows summary statistics of temperature in degrees Celsius (°C) and rainfalls in millimeters (mm) for the period 1999-2013. The first two columns report statistics for the overall sample. The last two columns report statistics on the variation within the average grid-cell, i.e., they show the average temperature distribution among the different grid-cells.

Examining the variation within grid-cells, which is the crucial one to identify our effects, we find slightly lower but still significant temperature variation. Specifically, the average minimum temperature within grid-cells is -3 degrees Celsius, and the average maximum is 35 degrees Celsius, with an average temperature within grid-cells of 17 degrees Celsius.

B.3 Temperature bins

Table B.3 reports summary statistics on the distribution of the number of days across grid-cells within each temperature bin for the period 1999-2013. Several points can be highlighted from these statistics.

First, despite the considerable variation in the data, all temperature bins have a positive number of days on average, with the exception of the bin capturing temperatures above 40

Table B.3: Summary Statistics of Days Within Temperature Bins (1999-2013)

	Temperature Bins				
	$(-\infty, 0°C]$	$(0°C, 30°C]$	$(30°C, 35°C]$	$(35°C, 40°C]$	$(40°C, \infty)$
Mean	1.90	316.10	41.87	5.19	0.04
Median	0	317	43	3	0
Min	0	201	0	0	0
Max	164	365	95	56	10

Note. Table B.3 shows the summary statistics on the number of days across grid-cells within each temperature bin for the period 1999-2013.

degrees Celsius. This shows that there is some representation for each bin across the grid-cells. Second, there is significant variation within each temperature bin across different grid cells. Even in the reference temperature bin $(0°C, 30°C]$, the number of days ranges from a minimum of 201 to a maximum of 365. This observation underscores the substantial variability present across grid-cells, which is important for our regression analysis. Third, it is worth noting that certain grid-cells exhibit a particularly high number of days with temperatures that are typically considered extreme. For instance, the maximum number of days below 0 degrees Celsius can reach as high as 164. This is not surprising considering Italy's diverse geography, which includes areas in the Alps (in the northern part of Italy) that frequently experience subzero temperatures. Additionally, some grid-cells experience a significant number of days with temperatures above 40 degrees Celsius, with some areas recording up to 10 such days.

C Empirical Results

C.1 Additional Controls and Alternative Independent Variables

In this section of the appendix, we present additional regression models to further validate the extent of the robustness of our results obtained from equation (25).

First, we augment the regression framework in equation (25) with a quadratic control for age. Age it has been shown empirically to be an important predictor of firm-level differences related to demand, productivity, and differences in financial frictions (see Fort et al., 2013; Cloyne et al., 2018; and Colciago et al., 2019). Columns 1, 5, 9, and 13 of Table C.4 and columns 1, 5, and 9 of Table C.5 present the estimates of this specification.

Moreover, we also use alternative functions of daily maximum temperatures over the year, such as the piece-wise linear degree days measure used in Somanathan et al. (2021). The calculation of degree days is best explained with an example. A day with a temperature of 35 degrees Celsius contributes 30 degrees Celsius to the first bin (0°C,30°C], 5 degrees Celsius to the third bin (30°C, 35°C], and 0 degree Celsius to the fourth bin (35°C, 40°C]. Thus, when a single day moves from 35 degrees Celsius to 40 degrees Celsius there is an increase of 5 degrees Celsius in the fourth-degree-day bin and no change in other bins.

More formally, denote the endpoints of our five temperature bins by $[T^{1\ell}, T^{2\ell})$, ℓ = 1,2,. . . , 5. A daily temperature T contributes positive degree days to all those bins for which $T > T^{1\ell}$ and zero to all others. If $T \geq T^{2\ell}$, the day contributes $T^{2\ell} - T^{1\ell}$ to bin ℓ. If $T^{1\ell} < T \leq T^{2\ell}$, it contributes $T - T^{1\ell}$ to bin ℓ. We now sum the degree days in each bin over the year to obtain D^{ℓ}_{it} for each unit i and estimate the following model:

$$Outome_{it} = \sum_{\ell} \beta_\ell D^{\ell}_{it} + \delta Rain_{g(i)t} + \boldsymbol{\lambda}'\mathbf{X}_{r(i)t} + \gamma_{s(i)t} + \alpha_i + \varepsilon_{it}. \tag{68}$$

Columns 2, 6, 10, and 14 of Table C.4 and columns 2, 6, and 10 of Table C.5 present the estimates of this specification.

Additionally, we also estimate equation (25) allowing for a semiparametric specification of rainfalls instead of the linear baseline one. This allows us to capture the non-linear effects of rainfalls. We use ten different bins, capturing P10, P20, ..., P100. Columns 3, 7, 11, and 15 of Table C.4 and Columns 3, 7, and 11 of Table C.5 present the estimates of this specification.

Finally, we also estimate equation (25) using the same benchmark definition for temperature bins, but we define them at a coarser geographical level, i.e., NUTS 3 level. Columns 4, 8, 12, and 16 of Table C.4 and Columns 4, 8, and 12 of Table C.5 present the estimates of this specification.

Tables C.4 and C.5 consistently confirm our main findings through the outlined robustness exercises. Specifically, we observe that extreme temperatures harm sales, materials, and labor, while they do not affect capital substantially. Consequently, the revenue-based marginal products of materials and labor exhibit much sensitivity to extreme temperatures, whereas that of capital does.

We also conducted an additional robustness check where we split our benchmark (0,30] temperature bin into two additional bins: (0,15] and (15,30]. We found results consistent with those of the benchmark analysis. Although we do not report them here due to space constraints, they are available upon request.

[h!]

Table C.4: Average Effect of Temperature on Sales and Inputs—Robustness

Dependent Variable	Sales				Materials				Labor				Capital			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Temperature Bins																
$(-\infty, 0°C]$	-0.088***	0.011**	-0.084***	-0.058***	-0.063**	0.010	-0.061**	-0.051**	-0.065***	0.006	-0.065***	-0.027	-0.034	-0.001	-0.035	-0.028
	(0.019)	(0.005)	(0.018)	(0.021)	(0.028)	(0.007)	(0.028)	(0.024)	(0.019)	(0.004)	(0.019)	(0.017)	(0.021)	(0.005)	(0.022)	(0.022)
$(30°C, 35°C]$	-0.019**	-0.011***	-0.013	-0.028***	-0.024*	-0.012***	-0.018	-0.045***	-0.000	0.001	0.005	-0.003	0.002	-0.000	0.004	-0.044**
	(0.009)	(0.003)	(0.008)	(0.008)	(0.014)	(0.004)	(0.013)	(0.013)	(0.008)	(0.003)	(0.008)	(0.008)	(0.010)	(0.004)	(0.010)	(0.001)
$(35°C, 40°C]$	-0.043**	-0.019*	-0.042**	-0.099***	-0.058**	-0.027*	-0.055**	-0.120***	0.002	-0.006	0.002	-0.053**	0.005	-0.008	0.007	-0.062**
	(0.017)	(0.010)	(0.017)	(0.024)	(0.025)	(0.014)	(0.025)	(0.036)	(0.016)	(0.009)	(0.017)	(0.023)	(0.019)	(0.011)	(0.020)	(0.026)
$(40°C, +\infty)$	-0.722***	-0.969***	-0.720***	-1.634***	-0.473**	-0.519*	-0.467*	-1.000	-0.257	-0.438**	-0.374*	-0.883*	0.063	0.128	-0.020	0.086
	(0.190)	(0.250)	(0.196)	(0.498)	(0.236)	(0.297)	(0.246)	(0.778)	(0.197)	(0.206)	(0.197)	(0.479)	(0.221)	(0.198)	(0.227)	(0.430)
Fixed Effects																
Firm	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
GR and SDC × Region	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls																
Rainfalls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Age^2	✓				✓				✓				✓			
Observations	4,687,503	4,687,503	4,687,503	4,687,503	4,687,503	4,687,503	4,687,503	4,687,503	3,767,558	3,767,558	3,767,558	3,767,558	4,328,689	4,328,689	4,328,689	4,328,689

Note. All dependent variables are in logs. Columns 1, 5, 9, and 13 provide estimates from the baseline specification in equation (25), with temperature bins constructed as explained in Section 3.2, augmented with a quadratic age control. Columns 2, 6, 10, and 14 present estimates from the degree-day model in equation (68). Columns 3, 7, 11, and 15 provide estimates from the baseline specification in equation (25), with temperature bins constructed as explained in Section 3.2, where rainfall controls are defined semiparametrically by ten bins instead of the linear specification in the benchmark case. Columns 4, 8, 12, and 16 provide estimates from the baseline specification in equation (25), with temperature bins constructed as explained in Section 3.2 but at the NUTS 3 level instead of the grid-cell level. Rows 1-4 present the effect on the log of the dependent variable of adding an extra day in the given temperature range respectively. Standard errors are clustered at the grid-cell level and reported in parentheses. *, **, and *** denote 10, 5, and 1% statistical significance respectively.

[h!]

Table C.5: Average Effect of Temperature on Revenue-Based Marginal Products of Inputs—Robustness

Dependent Variable	**MRPM**				**MRPL**				**MRPK**			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Temperature Bins												
$(-\infty, 0°C]$	-0.018	-0.000	-0.016	-0.006	0.007	0.000	0.007	-0.003	-0.026	0.005	-0.023	-0.009
	(0.019)	(0.005)	(0.019)	(0.015)	(0.013)	(0.003)	(0.013)	(0.010)	(0.022)	(0.004)	(0.022)	(0.020)
$(30°C, 35°C]$	0.006	0.001	0.006	-0.018**	-0.011*	-0.006***	-0.012**	-0.010	-0.015	-0.008**	-0.012	0.022**
	(0.008)	(0.003)	(0.007)	(0.007)	(0.006)	(0.002)	(0.006)	(0.006)	(0.011)	(0.004)	(0.010)	(0.010)
$(35°C, 40°C]$	0.011	0.005	0.010	0.017	-0.022*	-0.002	-0.025*	0.005	-0.044**	-0.009	-0.046**	-0.016
	(0.014)	(0.008)	(0.015)	(0.023)	(0.013)	(0.007)	(0.013)	(0.018)	(0.022)	(0.013)	(0.022)	(0.026)
$(40°C, +\infty)$	-0.209	-0.412**	-0.212	-0.518	-0.049	-0.034	0.060	-0.392	-0.523**	-0.803***	-0.443**	-1.628***
	(0.156)	(0.179)	(0.157)	(0.511)	(0.148)	(0.169)	(0.138)	(0.370)	(0.225)	(0.246)	(0.227)	(0.523)
Fixed Effects												
Firm	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
GR and SDC × Region	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls												
Rainfalls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Age^2	✓				✓				✓			
Observations	4,687,503	4,687,503	4,687,503	4,687,503	3,767,558	3,767,558	3,767,558	3,767,558	4,328,689	4,328,689	4,328,689	4,328,689

Note. All dependent variables are in logs. Columns 1, 3, and 5 provide estimates from the baseline specification in equation (25), with temperature bins constructed as explained in Section 3.2, augmented with a quadratic age control. Columns 2, 4, and 6 present estimates from the degree-day model in equation (68). Columns 3, 7, and 11 provide estimates from the baseline specification in equation (25), with temperature bins constructed as explained in Section 3.2, where rainfall controls are defined semiparametrically by ten bins instead of the linear specification in the benchmark case. Columns 4, 8, and 12 provide estimates from the baseline specification in equation (25), with temperature bins constructed as explained in Section 3.2 but at the NUTS 3 level instead of the grid-cell level. Rows 1-4 present the effect on the log of the dependent variable of adding an extra day in the given temperature range respectively. Standard errors are clustered at the grid-cell level and reported in parentheses. *, **, and *** denote 10, 5, and 1% statistical significance respectively.

C.2 Additional Sample Cuts

In this section, we address the challenge posed by multiplant firms, as discussed in Section 3.3. To mitigate concerns associated with the presence of these firms, we conduct regression analysis where we exclude specific subsets of firms from our sample. First, we exclude all foreign firms, as presented in Columns 1, 5, 9, and 13 of Table C.6 and Columns 1, 5, and 9 of Table C.7. Next, we exclude all listed firms, as displayed in Columns 2, 6, 10, and 14 of Table C.6 and Columns 2, 6, and 10 of Table C.7. Furthermore, we exclude all firms that report consolidated accounts, as illustrated in Columns 3, 7, 11, and 15 of Table C.6 and Columns 3, 7, and 11 of Table C.7. Finally, we drop firms within the top 5 percent of the sales distribution, as depicted in Columns 4, 8, 12, and 16 of Table C.6 and Columns 4, 8, 12 of Table C.7.

Tables C.6 and C.7 consistently indicate that extreme temperatures adversely affect sales, materials, and labor, but not capital. Consequently, the revenue-based marginal products of materials and labor display no systematic sensitivity to extreme temperature fluctuations, in contrast to capital. Notably, our estimates are if anything larger, confirming the downward bias produced by firms more likely to be multiplant. Nevertheless, the consistency of results across these specifications underscores that the presence of multiplant firms does not significantly impact our fundamental conclusions.

Table C.6: Average Effect of Temperature on Sales and Inputs—Robustness II

Dependent Variable	Sales				Materials				Labor				Capital			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)	(15)	(16)
Temperature Bins																
$(-\infty, 0°C]$	-0.095***	-0.095***	-0.092***	-0.085***	-0.070**	-0.069**	-0.065**	-0.057*	-0.070***	-0.070***	-0.069***	-0.069***	-0.033	-0.036*	-0.037*	-0.035
	(0.020)	(0.019)	(0.019)	(0.020)	(0.022)	(0.029)	(0.029)	(0.031)	(0.021)	(0.019)	(0.020)	(0.020)	(0.022)	(0.021)	(0.021)	(0.022)
$(30°C, 35°C]$	-0.017*	-0.017*	-0.017*	-0.018**	-0.023	-0.022	-0.020	-0.023	-0.001	0.002	0.004	0.002	-0.000	0003	0.004	0.004
	(0.009)	(0.009)	(0.009)	(0.009)	(0.014)	(0.014)	(0.014)	(0.014)	(0.008)	(0.008)	(0.008)	(0.008)	(0.010)	(0.011)	(0.011)	(0.011)
$(35°C, 40°C]$	-0.050***	-0.046***	-0.047***	-0.045***	-0.068**	-0.060**	-0.057**	-0.056**	-0.010	-0.003	-0.003	-0.004	0.001	0.004	0.006	0.006
	(0.017)	(0.017)	(0.017)	(0.017)	(0.026)	(0.025)	(0.026)	(0.025)	(0.017)	(0.017)	(0.017)	(0.017)	(0.019)	(0.019)	(0.020)	(0.020)
$(40°C, +\infty)$	-0.827***	-0.806***	-0.829***	-0.889***	-0.571**	-0.560**	-0.554**	-0.645**	-0.433**	-0.367**	-0.363*	-0.456**	0.040	0.033	0.024	0.001
	(0.191)	(0.194)	(0.194)	(0.200)	(0.243)	(0.242)	(0.243)	(0.254)	(0.194)	(0.187)	(0.190)	(0.195)	(0.204)	(0.216)	(0.220)	(0.211)
Fixed Effects																
Firm	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
GR and SDC × Region	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls																
Rainfalls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4,463,602	4,685,250	4,603,410	4,394,813	4,463,602	4,685,250	4,603,410	4,394,813	3,576,070	3,765,341	3,687,667	3,480,405	4,120,335	4,326,444	4,246,524	4,040,241

Note. All dependent variables are in logs. Columns. Columns 1, 6, 9, and 13 provide estimates from the baseline specification in equation (25) excluding foreign firms. Columns 2, 6, 10, and 14 provide estimates from the baseline specification in equation (25) excluding listed firms. Columns 3, 7, 11, and 15 provide estimates from the baseline specification in equation (25) excluding firms reporting consolidated accounts. Columns 4, 8, 12, and 16 provide estimates from the baseline specification in equation (25) excluding firms with sales above top 5%. Rows 1-4 present the effect on the log of the dependent variable of adding an extra day in the given temperature range respectively (temperature bin coefficients). Standard errors are clustered at the grid-cell level and reported in parentheses. *, **, and *** denote 10, 5, and 1% statistical significance respectively.

Table C.7: Average Effect of Temperature on Revenue-Based Marginal Products of Inputs—Robustness II

Dependent Variable	MRPM				MRPL				MRPK			
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
Temperature Bins												
$(-\infty, 0°\text{C}]$	-0.016	-0.018	-0.019	-0.021	0.005	0.008	0.009	0.014	-0.034	-0.030	-0.027	-0.025
	(0.020)	(0.019)	(0.020)	(0.21)	(0.014)	(0.013)	(0.013)	(0.014)	(0.023)	(0.022)	(0.022)	(0.024)
$(30°\text{C}, 35°\text{C}]$	0.007	0.006	0.004	0.006	-0.010*	-0.012**	-0.012**	-0.011*	-0.012	-0.014	-0.014	-0.015
	(0.007)	(0.008)	(0.008)	(0.008)	(0.006)	(0.006)	(0.006)	(0.006)	(0.010)	(0.010)	(0.010)	(0.011)
$(35°\text{C}, 40°\text{C}]$	0.014	0.011	0.007	0.009	-0.021	-0.021	-0.022*	-0.017	-0.046**	-0.045**	-0.048**	-0.048**
	(0.015)	(0.014)	(0.015)	(0.015)	(0.013)	(0.013)	(0.013)	(0.014)	(0.020)	(0.021)	(0.022)	(0.022)
$(40°\text{C}, +\infty)$	-0.220	-0.206	-0.234	-0.217	-0.016	-0.020	-0.017	0.001	-0.638***	-0.579**	-0.583**	-0.604***
	(0.160)	(0.156)	(0.162)	(0.164)	(0.148)	(0.145)	(0.149)	(0.152)	(0.217)	(0.231)	(0.239)	(0.229)
Fixed Effects												
Firm	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Sector × Year	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
GR and SDC × Region	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Controls												
Rainfalls	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Region Trends	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓	✓
Observations	4,463,602	4,685,250	4,603,410	4,394,813	3,576,070	3,765,341	3,687,667	3,480,405	4,120,335	4,326,444	4,246,524	4,040,241

Note. All dependent variables are in logs. Columns provide estimates from the baseline specification in equation (25). Columns 1, 5, and 9 estimate from the baseline specification in equation (25) excluding foreign firms. Columns 2, 6, and 10 provide estimates from the baseline specification in equation (25) excluding listed firms. Columns 3, 7, and 11 provide estimates from the baseline specification in equation (25) excluding firms reporting consolidated accounts. Columns 4, 8, and 12 provide estimates from the baseline specification in equation (25) excluding firms with sales above top 5%. Rows 1-4 present the effect on the log of the dependent variable of adding an extra day in the given temperature range respectively (temperature bin coefficients). Standard errors are clustered at the grid-cell level and reported in parentheses. *, **, and *** denote 10, 5, and 1% statistical significance respectively.

C.3 Additional Demand-Adjusted Productivity Results

Table C.8 presents sector-level losses in demand-adjusted productivity due to a 2-degree Celsius increase in temperature.

Table C.8: Sector-Level Demand-Adjusted Productivity Losses

Sector	NACE 1	Sector-level loss	α^K
Wholesale and Retail Trade	G	-0.344	0.027
Manufacturing	C	-0.343	0.075
Construction	F	-0.382	0.084
Other Service Activities	S	-0.446	0.121
Information and Communication	J	-0.436	0.127
Transporting and Storage	H	-0.395	0.132
Administrative and Support Service Activities	N	-0.442	0.136
Professional, Scientific and Technical Activities	M	-0.400	0.138
Mining and Quarrying	B	-0.423	0.206
Accommodation and Food Service Activities	I	-0.495	0.216
Arts, Entertainment and Recreation	R	-0.511	0.231
Agriculture, Forestry and Fishing	A	-0.490	0.267
Real Estate Activities	L	-0.699	0.548

Note. Table C.8 presents sector-level losses in demand-adjusted productivity due to a 2-degree Celsius increase in temperature. Column 1 lists the sector names, Column 2 provides the corresponding NACE codes, Column 3 shows the loss levels, and Column 4 indicates the capital intensity.

To obtain these numbers, we applied equation (11) using our estimates from Tables 2 and 3, along with the sector-level production function elasticities as explained in Section 3. For conciseness, we report a single number summarizing the sector-level losses. This was done by applying the temperature bin-specific semiparametric losses for each sector to the homogeneous 2-degree Celsius temperature increase from our benchmark scenario explained in Section 6.1.1. Our losses are broadly in line with those reported in the literature, such as the high damages to agriculture and lower damages for manufacturing noted by Addoum et al. (2020) and Ponticelli et al. (2024).

D Aggregate Results

D.1 Counterfactual Temperature Distributions

This appendix describes the counterfactual distribution of days within temperature bins under different warming scenarios compared to the observed data. Table D.9 provides summary statistics of the distribution of days within temperature bins, while Table D.10 presents the changes in the distribution of days under each warming scenario.

Table D.9: Summary Statistics of Counterfactual Distribution of Days Within Temperature Bins

		Temperature Bins				
		$(-\infty, 0°C]$	$(0°C, 30°C]$	$(30°C, 35°C]$	$(35°C, 40°C]$	$(40°C, +\infty)$
Warming Scenario	*Variable*					
1999-2013	Mean	1.90	316.10	41.87	5.08	0.04
	Median	0	317	44	3	0
	Min	0	201	0	0	0
	Max	164	365	95	56	10
1°C	Mean	1.14	304.04	50.38	9.31	0.13
	Median	0	304	51	6	0
	Min	0	212	0	0	0
	Max	153	365	105	64	17
2°C	Mean	0.66	291.22	57.53	15.18	0.41
	Median	0	289	59	11	0
	Min	0	221	0	0	0
	Max	140	365	105	70	32
4°C	Mean	0.23	265.02	65.142	32.06	2.55
	Median	0	264	65	31	1
	Min	0	198	0	0	0
	Max	111	365	117	87	52
RCP4.5	Mean	0.83	298.21	57.89	16.37	0.7
	Median	0	289	59	11	0
	Min	0	208	0	0	0
	Max	142	365	113	74	37
RCP8.5	Mean	0.30	265.37	64.46	31.92	2.95
	Median	0	266	65	30	0
	Min	0	190	0	0	0
	Max	104	365	122	92	58

Note. Table D.9 summarizes the distribution of days within temperature bins in the data and under different warming scenarios. It includes statistics such as mean, median, minimum, and maximum values for each temperature bin. The temperature bins range from below 0 degrees Celsius to 40 degrees Celsius or higher as defined in Section 3.2.

Table D.9 summarizes the distribution of days within temperature bins for the observed data and various warming scenarios. The temperature bins are categorized from below 0 degrees Celsius to 40 degrees Celsius or higher, as explained in Section 3.2. The table includes statistical measures such as mean, median, minimum, and maximum values for each temperature bin.

The first four rows present the distribution of days within each temperature bin in the data for the period 1999-2013. The second four rows present the distribution of days within each temperature bin for the 1-degree Celsius temperature increase counterfactual scenario. The third four rows present the distribution of days within each temperature bin for the 2-degree Celsius temperature increase counterfactual scenario. The fourth four rows present the distribution of days within each temperature bin for the 4-degree Celsius temperature increase counterfactual scenario. The fifth four rows present the distribution of days within each temperature bin for the RCP4.5 counterfactual scenario. The sixth four rows present the distribution of days within each temperature bin for the RCP8.5 counterfactual scenario. Overall, we see that the more extreme the counterfactual warming scenario, the larger the shift in the number of days toward higher temperatures.

Table D.10: Summary Statistics of Counterfactual Change in Distribution of Days Within Temperature Bins

		Temperature Bins				
		$(-\infty, 0°C]$	$(0°C, 30°C]$	$(30°C, 35°C]$	$(35°C, 40°C]$	$(40°C, +\infty)$
1°C	Mean	-0.76	-12.07	8.51	4.23	0.09
	Median	0	-12	9	3	0
	Min	-27	-33	-21	-2	0
	Max	0	27	33	25	10
2°C	Mean	-1.24	-24.88	15.66	10.10	0.37
	Median	0	-251	17	8	0
	Min	-56	-64	-31	-10	0
	Max	0	56	57	39	22
4°C	Mean	-1.67	-51.09	23.27	26.98	2.51
	Median	0	-52	24	27	1
	Min	-84	-100	-48	-15	0
	Max	0	84	86	71	44
RCP4.5	Mean	-1.07	-26.89	16.02	11.28	0.66
	Median	0	-24	16	8	0
	Min	-71	-79	-41	-10	0
	Max	0	71	70	57	35
RCP8.5	Mean	-1.60	-50.82	22.59	26.83	2.91
	Median	0	-51	23	25	0
	Min	-100	-120	-49	-22	0
	Max	0	101	100	85	56

Note. Table D.10 presents the changes in the distribution of days within temperature bins under various warming scenarios. It provides statistical measures such as mean, median, minimum, and maximum values for each temperature range. The values indicate the deviation in the number of days compared to the data. Negative values indicate a decrease, while positive values represent an increase in the number of days.

Table D.10 presents the changes in the distribution of days within temperature bins under different warming scenarios. The values indicate the deviation in the number of days compared to the observed data. Negative values represent a decrease, while positive values indicate an increase in the number of days.

The first four rows present the change relative to the data in the distribution of days within each temperature bin for the 1-degree Celsius temperature increase counterfactual scenario. The second four rows present the change relative to the data in the distribution of days within each temperature bin for the 2-degree Celsius temperature increase counterfactual scenario. The third four rows present the change relative to the data in the distribution of days within each temperature bin for the 4-degree Celsius temperature increase counterfactual scenario.

The fourth four rows present the change relative to the data in the distribution of days within each temperature bin for the RCP4.5 counterfactual scenario. The fifth four rows present the change relative to the data in the distribution of days within each temperature bin for the RCP8.5 counterfactual scenario. Overall, we see that the more extreme the counterfactual warming scenario, the larger the increase in the number of days with higher temperatures and the decline in the number of days with lower temperatures.

D.2 Additional Robustness Main Results

Table D.11: Climate Change Impact on Aggregate Productivity With Adaptation

	Aggregate Productivity Loss	
	Without Adaptation	*With Adaptation*
1°C	0.77%	0.60%
4°C	6.82%	5.51%
RCP4.5	1.64%	1.32%
RCP8.5	5.35%	4.18%

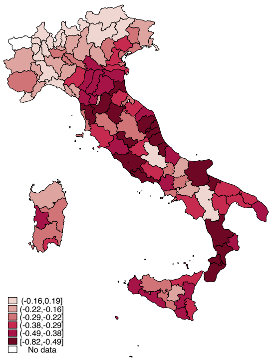
Note. Column 1 reports the aggregate productivity losses without adaptation for the scenarios in the robustness exercises in Table 7. Column 2 reports the effect of adding adaptation effects to each of these scenarios.

Table D.11 presents the impact of controlling for adaptation on the scenarios used as robustness exercises in Section 6.1.2. Introducing adaptation in the 1-degree Celsius scenario reduces productivity losses to 0.60, and in the 4-degree Celsius scenario, it decreases losses to 5.51. Finally, adaptation reduces productivity losses from the RCP4.5 and RCP8.5 scenarios to 1.32 and 4.18, respectively. Overall, we find that adaptation lowers the aggregate productivity losses of the different scenarios by an average of 20 percent.

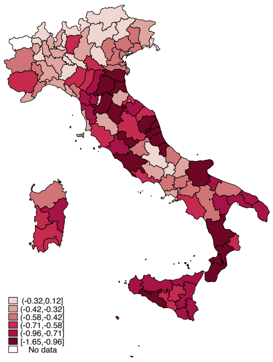
D.3 Regional Heterogeneity

This appendix section explores the impact of climate change on productivity losses at the province level (NUTS 3) in Italy, examining four alternative warming scenarios: a 1-degree Celsius increase, a 4-degree Celsius increase, and increases according to the RCP4.5 and RCP8.5 scenarios. Moreover, we explore the role of adaptation for regional economic losses. We employ the methodology described in Section 2 and apply the same approach used in Section 6.3 to assess productivity losses for each province under these different warming scenarios.

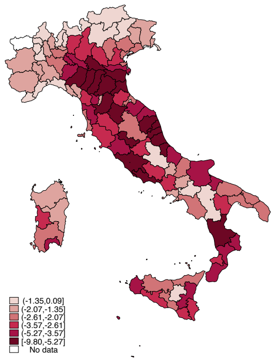
Figure D.2: Regional Productivity Losses for Alternative Warming Scenarios



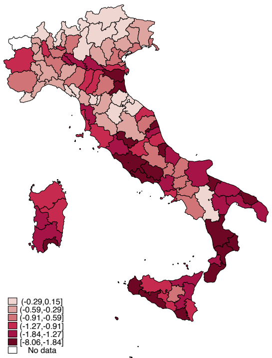
(a) 1°C



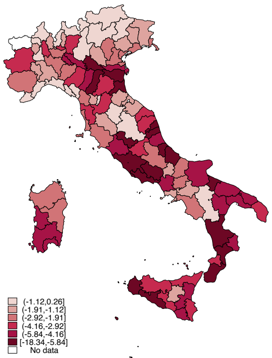
(b) 2°C w. Adaptation



(c) 4°C



(d) RCP4.5



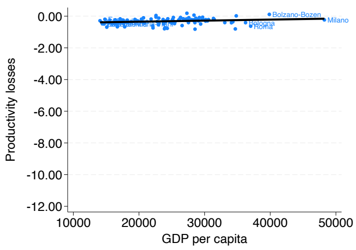
(e) RCP8.5

Note. Figure D.2a shows the productivity losses across NUTS 3 regions due to a 1-degrees Celsius increase in temperature, calculated using equation (18), adjusted with the ratio of gross output to value added. Figure D.2b shows the productivity losses across NUTS 3 regions due to the 2-degrees Celsius increase in temperature but in the presence of adaptation, calculated using equation (18), adjusted with the ratio of gross output to value added. Figure D.2c shows the productivity losses across NUTS 3 regions due to a 4-degrees Celsius increase in temperature, calculated using equation (18), adjusted with the ratio of gross output to value added. Figure D.2d shows the productivity losses across NUTS 3 regions due to the RCP4.5 scenario, calculated using equation (18), adjusted with the ratio of gross output to value added. Figure D.2e shows the productivity losses across NUTS 3 regions due to the RCP8.5 scenario, calculated using equation (18), adjusted with the ratio of gross output to value added. Productivity losses are in percent, and darker colors represent larger losses.

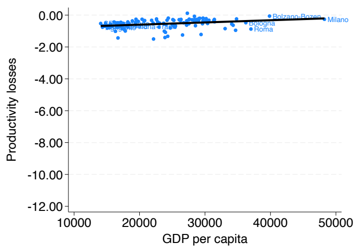
Figures D.2a, D.2c, D.2d, D.2e, and D.2b display regional productivity changes under various warming scenarios. In the 1-degree Celsius warming scenario (D.2a), Italian provinces show diverse outcomes, with some experiencing gains of up to 0.19 percent and others facing losses of up to 0.82 percent. Under the 4-degree Celsius scenario (D.2c), variations are even more pronounced, ranging from slight increases of 0.09 percent to severe reductions of up to 9.80 percent. The RCP4.5 and RCP8.5 scenarios (D.2d, D.2e) also exhibit varying degrees of change, with some provinces seeing gains and others facing losses, particularly severe under RCP8.5, reaching -13.23 percent. The RCP4.5 and RCP8.5 scenarios exhibit the most significant regional variations due to the non-uniform distribution of temperature increases, predicting larger in southern regions compared to the north. In the 2-degree Celsius warming scenario with adaptation (D.2b), regional differences persist, with increases of 1.55 percent in the least affected areas and decreases of 2.80 percent in the most affected ones.

The relationship between GDP per capita in our sample and future productivity losses is depicted in Figure D.3. With the exception of the 4-degree Celsius scenario, which shows no significant relation, all other scenarios predict increasing inequality due to climate change.

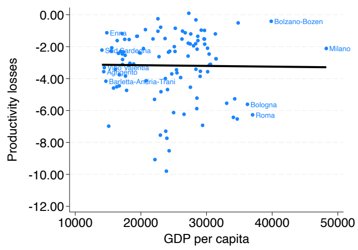
Figure D.3: Correlation Between Regional Losses and GDP Per Capita



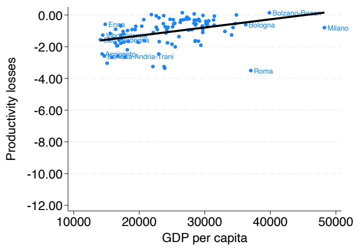
(a) 1°C



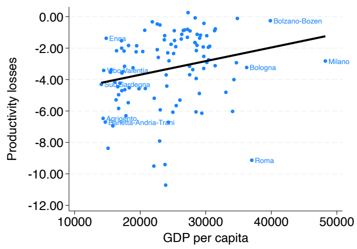
(b) 2°C w. Adaptation



(c) 4°C



(d) RCP4.5



(e) RCP8.5

Note. Figure D.3a scatters the productivity losses across NUTS 3 regions due to a 1-degrees Celsius increase in temperature against GDP per capita in the data. Figure D.3b shows the productivity losses across NUTS 3 regions due to a 2-degrees Celsius increase in temperature in the presence of adaptation against GDP per capita in the data. Figure D.3c scatters the productivity losses across NUTS 3 regions due to a 4-degrees Celsius increase in temperature against GDP per capita in the data. Figure D.3d scatters the productivity losses across NUTS 3 regions due to a the RCP4.5 scenario against GDP per capita in the data. Figure D.3e scatters the productivity losses across NUTS 3 regions due to the RCP8.5 scenario against GDP per capita in the data. Light blue dots are NUTS 3 regions and the black line represents the best fit.