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Abstract

Climate change has long run effects on the size and composition of a country's corporate sector. Using administrative data on the universe of Italian firms, we find that an increase in the incidence of very hot days over a multiyear period persistently reduces the growth rate of active firms in the market. This is due to a drop in firm entry and an increase in firm exit, with relocation playing a minor role. A firm-level investigation reveals a dichotomy between smaller firms, which suffer from high temperatures, and larger firms that successfully adapt, increasing production and net revenues. According to an average climatic scenario, the projected evolution of local temperatures will impact corporate demography further, also exacerbating the divergent effects across warmer and colder areas over the current decade.

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Keywords: climate change, temperatures, firm dynamics

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1 Introduction

The literature on the economic effects of climate change actively debates on whether fluctuations in temperatures and extreme events such as heat waves affect firms' output. Performance over the year can drop because workers in heat-exposed occupations can be less productive or more absent in hot days or, more generally, because hot temperatures increase overall production costs. These effects might exist for a large set of firms. However, on a longer time span, they may vanish and stimulate adaptation and technological advancement for some firms while, at the opposite, they can accumulate and become persistent for others. This divergence might be not inconsequential for market structure.

While the question of whether firms adapt to a changing climate is central to understand its longer run economic effects, the evidence is still scant. Recent contributions focus on impacts and adaptation policies of large, listed firms with complex supply chains and multiple local units. No evidence is available, to our knowledge, on the scope of temperature effects on the entire corporate sector, which can ultimately be shaped by climate-related entry-exit choices or by defaults of the most vulnerable entities. Using administrative data for the universe of Italian firms (excluding sole proprietorship) between 2005 and 2019, we take a broader perspective and explore medium-run implications of climate change on firm demography. In particular, we estimate the effect of the increasing incidence of high temperatures over a multiyear period on the number of active firms in the market, disentangling the effects on entry, exit and relocation rates at local level.

We find that positive variations in the number of hot days within the year reduce, in the medium run, the growth rate of active firms in the same area. These effects are strikingly persistent, with enduring impacts extending up to at least 12 years ahead. By decomposing this effect in its components, it turns out that a significant reduction in entry rates of new firms and, to a lower extent, an increase in exit rates drive results, while relocation plays a minor role. Implications on entry and exit prove to be heterogeneous across geographic areas: entries fall and exits rise in Mediterranean (warmer) areas while effects are milder —if anything, of opposite sign— in temperate (colder) ones, confirming that areas with high average temperature levels are those suffering the most from climate change. We show that these effects are not driven by pre-existing differences between Northern and Southern regions. At sector level, manufacturing, construction and retail are impacted almost as agriculture, both in terms of lower entries and higher exits. The fact that there is no clear correspondence at sector level between exits (or missing entries) in Mediterranean areas and entry in temperate ones is another evidence that any form of climate-induced firm mobility is at least of secondary importance. In the near future, climatic developments will exacerbate the trends highlighted by our results: based on an average scenario on the evolution of local temperatures until 2030, we show that the cumulative reduction in the growth rate of active firms between 2020 and 2031 would add to 0.2 percentage points, quite a sizable impact with respect to an average annual increase in the size of the corporate sector by 1.5%. Moreover, additional calculations show that these effects would be substantially magnified for warmer areas.

Results on firm demography show how the structure of the corporate sector is affected by hot temperatures, but cannot inform on the characteristics of exiting firms or potential newcomers. To investigate how climatic events unravel through firm's activity, we rely on detailed balance sheet data from the Company Account Database of Cerved Group: by encompassing almost 10 million firm-year observations from 2005 to 2019, our analysis is based on one of the largest single country dataset in the literature, as far as we know. This data set, which comprehends all publicly listed firms as well as all non-listed limited liability companies, including single worker and micro firms (with less than 10 employees) that file their balance sheet at the Italian Business Registry, is ideal to identify differentiated temperature effects across various firm dimensions.

We show that, within the Cerved sample, a permanent rise in temperature increases net revenues and production, driving up profitability in the longer term. These effects depend on the fact that the sample only includes those firms who survived to hot temperatures for at least the period under analysis (3 to 12 years), which therefore might be selected among those that display a higher propensity to adapt to climate shocks. However, differentiating these results by firm size reveals a substantial heterogeneity: while temperatures have positive impacts on medium and large firms, they instead have a negative impact on the very small ones, who reduce investments in the longer run. This finding marks a stark difference in the resilience to climate change across firms, suggesting that global warming might be stimulating a reallocation of production shares within the business sector. All in all, our results of a negative medium-run effect of hot temperatures on firm demography, and of a climate-induced divergence both across areas with different temperatures and across firms with different size stand out in the literature.

The negative impact of temperatures on the economic performance of firms can have multiple drivers. As the one with more solid ground in the literature is that of heat stress, we investigate whether structural differences in workers' heat exposure across firms might also matter in the long run. We construct an indicator for this purpose as the share of blue collars – plausibly more exposed to hot temperatures – to the total firm workforce and find that climate change effects are positive for firms with an above average share and negative for below-average ones. This implies that having few blue collars (relative to firm size) makes firms less able to diversify risk if those employees carry out vital activities for firms' business, suggesting a connection between our results and a well-known transmission channel of climate change.[1] All in all, our results on firm demography and on the enduring balance sheet effects of hot temperatures contribute to the literature by shedding light on the aggregate market dynamics in an increasingly hot world, previously disregarded, in which adaptation to climate change and lack thereof can play a pivotal role.

This paper is organized as follows. Section 2 documents the contribution of the paper in the literature. Section 3 describes the data used in the empirical analyses. Section 4 details the

[1]Beside workers' heat stress, other reasons for a differentiated effect of temperature across firms might be related, for example, to a larger impact on non-labor (e.g., energy-related) costs for small firms, or to factors related to demand such as higher geographical proximity to producers entailing exposure to same temperature risks. Exploring all possible drivers is out of the scope for this paper.

empirical strategy to asses long run effects of temperatures on firm demography and comments on the obtained results. Section 5 presents firm-level estimates. Section 6 concludes.

2 Related literature

The effects of climate change on the global economy are found to be multifaceted. High temperatures substantially reduce activity and growth, especially —but not exclusively— in poor countries (Dell et al., 2012; Burke et al., 2015; Acevedo et al., 2020), entailing multiple effects, including migration (Hornbeck, 2012 and Peri and Sasahara, 2019, among others; see Dell et al., 2014 for a review of the literature). Effects on advanced economies have been analyzed mainly regarding the United States, where sizable effects have first been found in agriculture (Burke and Emerick, 2016) and, more recently, in a wider range of industries (Colacito et al., 2019), with income per capita losses being concentrated during business days (Deryugina and Hsiang, 2014). The economic consequences of high temperatures are mainly channeled through reduced hours worked in climate-exposed industries and time allocated to outdoor leisure in hot days (Graff Zivin and Neidell, 2014) and by a reduction in labor productivity and an increase in absenteism (Somanathan et al., 2021).

The literature on the long-run effects of climate change is emerging, but it is still scant. At firm level, while most of the analysis is focused on short-run impacts —where results are still mixed— one strand of literature investigates how firms implement medium-run adaptation policies to fight climate change.[2] For example, large firms are found to reduce the number of employees and firm establishments in the medium run because of high temperatures (Jin et al., 2021), and downstream firms in the supply chain terminate existing relationships with their suppliers if the latter underperform due to high temperatures (Pankratz and Schiller, 2021). These papers focus on large, publicly listed firms, with complex firm structures and supply chain

[2]Regarding short-run effects, some papers do not find any consequence of high temperatures on firm sales and labor productivity (Addoum et al., 2020), while others document negative effects on sales of upstream firms in the supply chain (Custódio et al., 2021). Further evidence suggests that firm-level effects can be of opposite signs in different sectors and seasons (Addoum et al., 2021).

relationships. While specific adaptation mechanisms are uncovered, these papers do not allow to draw conclusions on the longer run effects of temperature on the whole country's corporate sector because the most vulnerable entities, which are also the least able to adapt to high temperatures, are for sure out of those selected firm samples. Moreover, limiting the analyses to the pool of incumbent firms in the market do not allow to consider extreme adaptation mechanisms — missing entry or premature exit— which are possible only with comprehensive firm demography data. Because of our focus on aggregate dynamics, our paper displays similarities with Barreca et al. (2016), who analyze the relationship between temperatures, mortality and household demography.

Another strand of literature explores long-run implications of climate change by focusing on the geographic dimension of global warming. Some papers carry out multi-country level analyses (Hsiang and Narita, 2012; Kahn et al., 2021, among others), suggesting that adaptation might limit, but not offset weather impacts. Others propose spatial equilibrium models taking into account differential effects on productivity, trade, migration and policy response across geographic areas (Costinot et al., 2016; Desmet and Rossi-Hansberg, 2015; Balboni, 2019; Conte et al., 2020). At local level, Albert et al. (2021) empirically find that drought events in Brazil had negative long run effects in affected areas through lower credit granted, and spillovers via out-migration flows. With respect to this work, which focuses on geographic redistribution via labor mobility, our analysis is complementary as it studies implications of climate change on corporate demography, showing that in the domain of firms mobility is less relevant than entry-exit choices.

Our paper also connects to the literature on the determinants of firms' entry and exit in the market (Agarwal and Gort, 1996; Audretsch, 1991; Sutaria and Hicks, 2004; Bartelsman et al., 2005; Santarelli and Vivarelli, 2007; Clementi and Palazzo, 2016, among others). With respect to this broad body of literature, we highlight an additional determinant of firm dynamics, showing that heat stress to firm activity might play a non-negligible role. As entry and exit are fundamental drivers of productivity dynamics (Melitz and Polanec, 2015), our findings suggest a potential channel connecting climate change and aggregate productivity, which might deserve further investigation.

3 Data

We combine data on temperatures, weather, firm demography and firm balance sheets from different sources. In the following sections we account for these sources, providing the relevant stylized facts on our sample.

3.1 Temperatures, precipitations and extreme events

We use the JRC MARS Meteorological Database (EU AGRI4CAST project) that contains meteorological observations from weather stations interpolated on a 25x25 km grid, on a daily basis from 1979 to 2019, for the EU and neighbouring countries. In this work we use temperature (maximum and average) and precipitation data for Italy from 1993 to 2019. We linearly interpolate data from 25x25 km2 to a 5x5 km2 raster to calculate daily data, averaged at the level of local labor market (LLM).[3]

The measure of extreme temperature we rely on is the number of days with a maximum temperature above 30°C within a year. This is a widely exploited measure in the literature on the economic effects of extreme temperatures (Bauer et al. (2019); Addoum et al. (2020)). Its utilization rests on the observation that 30°C is a critical threshold, above which individual productivity starts dropping at increasing rates (Fisk et al. (2006); Somanathan et al. (2021)). Hence, it is likely that at this threshold most of the economic consequences of temperatures might start to emerge, for example as a consequence of firms increasing their costs for cooling

[3] A local labor market is a partition of the Italian territory that maximizes the self-containment of home-to-work commuting flows. As such, it identifies relatively homogeneous areas representing the center of interest for most of the residents. From the perspective of the firms, it is the geographic extension of the labor market pool from which they draw their employees. We use the 2011 classification provided by the National Institute of Statistics, which singles out 611 LLMs, with an average size larger than that of a municipality but smaller than that of a province. More information available at https://www.istat.it/it/informazioni-territoriali-e-cartografiche/sistemi-locali-del-lavoro.

needs or reorganizing production processes to react to the lower individual efficiency.

Over the 27 years considered in this paper, the number of extreme heat days registered on average in Italian LLMs has considerably increased: at the end of the observation period, there were around 15 days of extreme temperatures more than at the beginning (Figure 1). Despite the large erraticness of the series, a clear upward trend is perceivable especially in the first half of the sample, before a substantial stabilization at the high levels reached around 2007. This broad figure masks a sizable heterogeneity at the geographic level, which clearly emerges from the summary statistics in Table 1. The across-LLM variability in the number of extreme heat days has been increasing over time, but even within single years the realizations of temperature are not evenly spread across geographic units: while in all years there is at least a LLM not experiencing any extreme heat event, there are other LLMs that can suffer as much as 105 days with maximum temperature above 30°C.

Contrary to expectations, the LLMs with a higher frequency of extreme temperature events are not entirely concentrated in the South. Figure 2 panel (a), shows the distribution of extreme heat days at the beginning of the sample.[4] While certain Southern areas —such as South Sardinia, Eastern Sicily, Campania and Northern Apulia— ranked high in the number of extreme heat days, they shared this destiny with other areas in Central and Northern Italy, especially Tuscany and vast stretches of the Po Valley. Clearly, the mountainous LLMs belonging to the Alpine Arc and to the highest zones of the Apennines display the lowest level of extreme heat incidence. Over the period observed in this paper, the increase in the frequency of extreme temperatures has also been highly heterogeneous across LLMs, as Figure 2 panel (b) shows. The largest increases affected Sardinia, Eastern Sicily, the Po Valley, Southern Apulia and Rome and its surroundings. Mildest increases have also hit the Western Alps, while some LLMs in the South have been spared from this tendency (Campania, Calabria, Northern Apulia).

The measure of precipitation we use is calculated by cumulating for each year the total daily

[4]To avoid highlighting spurious spikes in temperatures, in Figure 2 we consider 5-years averages of the number of extreme heat days.

precipitation in millimeters, averaged at the LLM level. In the econometric analyses we use this measure in logarithm.

For certain extensions to our results, we use data on extreme events from the European Severe Weather Database (ESWD), which provides detailed information on localized disruptive weather events. The database includes a variety of events, that can be broadly grouped in the following categories: strong winds, snow, hail, avalanches, lightnings and precipitations. Data is available from 1979, but their reliability has been increasing in time, as the number of reporting entities grew. Preliminary inspection reveals that data prior to 2008 are not sufficiently reliable for our purposes. As a consequence, we only use information from that year onward, which significantly limits the scope of application of these data. We will include the events reported in ESWD as additional controls in our estimates, with the exclusion of severe precipitations, for which we have more accurate data in millimeters, as discussed above.

3.2 Firm demography data

We draw information on entry year, exit year, geographic location and sector of firms from the Infocamere dataset, which contains administrative registry data for the universe of Italian firms, excluding one-person companies. The dataset covers all sectors of activity for the years between 2005 and 2019. Overall, the firms included in our sample are representative of more than three quarters of total employees in Italy.

As many other administrative sources, the Infocamere dataset requires intensive data cleaning. The most relevant step concerns the activity status of the firm. Registered companies can go through different activity statuses during their lives: they can be either active (when production is normally taking place), suspended (when the firm undergoes a temporary interruption of production) or inactive (when all activities cease). A firm can switch status multiple times and it is not automatically cancelled from the registry, even if it remains inactive for several years. Throughout our data cleaning process, we have tried to single out the dates in which the firms operated the strategic decision of entering the market in a certain location or to exit, disregarding temporary switches across statuses. To do that, this is how we treated the most relevant cases:

- The years in which a firm is suspended are considered as activity years and are not dropped from the sample.
- Firms that never turn active throughout their lives are entirely dropped from the sample. These are entities that were registered for motivations unrelated to production activity and therefore are not to be included in our analysis.
- The years of inactivity that some firms experience right after their entry are kept in the sample: even if the firm does not immediately start producing, the decision of entering the market is taken when the firm enrolls in the registry.
- When firms undergo a stretch of inactivity before exiting the market, those years are dropped from the sample and the exit year of the firm is adjusted (anticipated) accordingly: a closed firm might remain in the registry for various reasons (potentially also related to the lengthiness of the bankruptcy procedures), but we are interested in the date in which it stops producing.

After data cleaning is carried out and after excluding non-market services, our sample contains on average around 2.1 million active firms per year (Table A.1).[5] The vast majority of them belongs to the market services sector. Manufacturing and construction are roughly equally represented.

Since our empirical strategy will rely on extreme temperature variations at the local labor market level, we collapse the relevant firm demography information (active firms, entry and exit) to this geographic aggregation, based on the geographic location of firms' headquarters. Since

[5] With 'active firms' we refer to the truly active firms, excluding the ones that have temporarily suspended production and the new-born ones that are still inactive.

extreme temperature episodes might push firms to move to less-affected places, we also keep track of relocations to and from other LLMs.

By definition, when we collapse our data at the local labor market level, the following equality holds for each LLM in all years t:

$$A_t = A_{t-1} + E_t - X_t + R_t^{\text{in}} - R_t^{\text{out}} + Z_t \tag{1}$$

where A is the number of active firms; E and X are firms entering and exiting the market, respectively; R^{in} and R^{out} are firms relocating from and to other LLMs, respectively. The last term Z is a residual —typically negligible— which compounds relocations from/to foreign countries or undefined locations.

Rearranging the terms, we can express the growth rate of active firms as a function of entry, exit and relocation rates, as defined in the following expression:

$$\dot{A}_t = \frac{E_t}{A_{t-1}} - \frac{X_t}{A_{t-1}} + \frac{R^{\text{in}}}{A_{t-1}} - \frac{R^{\text{out}}}{A_{t-1}} + \frac{Z_t}{A_{t-1}} = e_t - x_t + r_t^{\text{in}} - r_t^{\text{out}} + z_t \tag{2}$$

where lowercase letters represent rates.

Figure 3 shows the aggregate dynamics of these components in the years covered by our data. Net natality shrunk significantly in the first part of the sample, as a consequence of a sizable drop in entry and a more moderate but relevant increase in exit. From 2012 on, net natality remained stable at a low but positive level. The same trends are displayed with greater detail in Table 2, which reports the average values of demographic components across LLM, highlighting the substantial amount of variability between territorial units. However, no clear geographic pattern emerges in the demographic dynamics of firms. The two maps in Figure 4 illustrate the variation in entry and exit rates between the beginning and the end of our observation period. The changes are fairly dispersed across LLMs, with some of the largest decreases in the entry rates observed in certain parts of the Western coast (Campania, Calabria) and in Piedmont;

instead, entry remained roughly stable or increased in some area of Sicily, Sardinia, Apulia, and North-East Alps. The variation in exit rates is equally spread out, with some large increases in Eastern Sicily, Northern Sardinia, Tuscany and Western Alps. In general, it is difficult to eyeball a clear relationship between temperature variations and firm demographic dynamics: both sets of data are characterized by a substantial amount of variation, that we will try to discipline with our empirical strategy.

3.3 Firm balance-sheet data

As for firm's information we use data provided by Cerved Group, which collects companies' balance sheets and indicators for a very large portion of Italian limited liabilities companies. Our firms' dataset encompasses more than 10 million firm-year observations from 2004 to 2019 (Table 3). We filter the Cerved database according to two rules. First, we select only firms for which we know their location according to their head office. In this way we are able associate to each firm a time-varying measure of temperature that it experiences. Then we consider only active firms, i.e. such that their turnover and assets are strictly positive.

4 The effect of extreme temperatures on firm demography and localization

In this section we analyze the a link between extreme temperature events and firm demography and localization, exploiting variability at the LLM level. Below we describe our empirical strategy, define the temperature variable that we take into account and present the results.

4.1 Empirical strategy

The effects of extreme temperatures on firm demography arguably take some time to build up. The decision process leading to events such as the entry into the market or the relocation of activity to a more favorable place is unlikely to be significantly altered by an isolated temperature event hitting a LLM in a certain year. The same argument applies to the exit decision of a firm: unless the extreme heat event is particularly disruptive, a company has plenty of potential instruments to absorb a single negative shock (for example using its own liquidity, increasing the use of credit, reorganizing production processes, or adjusting the number of employees). As repeated adverse temperature events accumulate in a certain place, they might start undermining the fundamental growth expectations of incumbent and prospective firms, thus affecting the medium-run considerations on the profitability of locating or remaining in that place. To gauge these effects, we have to both elaborate a specification that takes into account this medium-run decision horizon and define the relevant temperature variation for the firms' choices.

To net from short-run variations and to account for a relatively long time span in a parsimonious way, we first bin our data into 9 three-years periods over the entire observation sample. For each LLM-period cell, we compute the average growth rate of active firms, along with its average components (entry, exit and relocation rates) from equation 2. Notice that the addition property over the components is preserved by the binning procedure. We then estimate by OLS a distributed lag model on the binned data, where the coefficients of interest are the ones on the temperature variable that we will define shortly. Our baseline model is the following:

$$y_{ip} = \sum_{k=1}^{3} \beta_k \Delta T_{i,p-k} + \sum_{k=1}^{3} \gamma_k \Delta \ln \left(\text{prec}\right)_{i,p-k} + X_{ip} + \delta_i + \delta_p + \varepsilon_{ip} \tag{3}$$

where i indexes LLMs and p indexes periods. The dependent variable $y_{ip} \in \left\{\overline{A}, \overline{e}, \overline{x}, \overline{r^{\text{in}}}, \overline{r^{\text{out}}}\right\}$ is the bin average of either the growth rate of active firms or of one of its components. $\Delta T_{i,p-k}$ is the temperature variation hitting LLM i at lag k from period p. Three lags of the variation in the log millimeters of precipitations are included in the regression in the same fashion. δ_i and δ_p are fixed effects, while X_{ip} contains additional controls that we occasionally add to our regressions. Depending on the specification, these might include area$\times$year or population quartile$\times$year dummies, in order to control for trends differentially affecting certain geographic zones or rural vs urban LLMs.[6] In an extension we also use the number of extreme events from the ESWD database as an additional control. Since these data are only reliable from 2008 on (see section 3), we can only include them with two lags; even so, using these data entails a substantial loss of observations. Standard errors are clustered at the LLM level.

Notice that, since the decomposition in 2 is exact and is preserved by our binning strategy, the coefficients of the regression using the growth rate of active firms as a dependent variable can be obtained as the sum of the coefficients of all other regressions. This allows us to gauge the relative importance of the various demographic components in determining the evolution of active firms.

As stated above, the coefficients of interest are those attached to the three lags of the temperature variable ΔT. Since heat waves might be correlated with other types of potentially disruptive weather events, we deem important to control for precipitations in order to isolate the pure effect of temperature variations on our variables of interest.[7] Having a long series of temperature and weather observations (starting in 1993) allows us to deploy a rich lag structure while exploiting the full information on firm demography.

We perform a number of heterogeneity exercises throughout the paper. One of them investigates the stability of the coefficient estimates across different climatic zones. The purpose is to evaluate if the effect of extreme heat differentially affects places that are ex-ante characterized by a higher average temperature. To do that, we interact the temperature and precipitation variables by a categorical variable indicating whether the LLM belongs to the temperate or to the Mediterranean climatic zone.[8] Another exercise aims at assessing what are the sectors that react the most to heat waves. In this case, we slightly modify the structure of our data, collapsing demographic information into LLM×sector×period cells and estimating the following

[6]The areas considered here are North West, North East, Center and South (including Islands). Population quartile is assigned to each LLM based on its population in 1999.

[7]Adding the ESWD extreme events data as additional controls responds to the same concern.

[8]The two zones are depicted in Figure B.1. They are defined on the basis of the Istat classification at https://www.istat.it/it/archivio/224780.

equation:

$$y_{isp} = \sum_{j=1}^{S}\sum_{k=1}^{3}\beta_{jk}\Delta T_{i,p-k} \times \mathbb{1}(j=s) + \sum_{j=1}^{S}\sum_{k=1}^{3}\gamma_{jk}\Delta \ln\left(\text{prec}\right)_{i,p-k} \times \mathbb{1}(j=s) + X_{isp} + \delta_i + \delta_p + \varepsilon_{isp} \tag{4}$$

where s indexes sectors (defined according to the Nace Rev. 2 classification), $\mathbb{1}()$ is an indicator function identifying sectors, and X_{isp} also contains sector×period fixed effects. In this case, standard errors are clustered at the LLM-sector level.

Having laid our empirical strategy, the only block that is yet to be defined is the temperature variable ΔT used in our regressions. We have already discussed in section 3 why we choose the number of days with a maximum temperature above 30°C as a measure of the frequency of heat waves. We now want to define what we deem to be the relevant temperature variable affecting firms' decision. We propose the time difference in the number of extreme heat days as a a measure of the amount of innovation to the distribution of maximum temperatures known to the firms. In the context of our binned data exercise, for each LLM we define the temperature variable as follows:

$$\Delta T_p = \frac{\overline{M}_p^{>30} - \overline{M}_{p-1}^{>30}}{365} \tag{5}$$

where $\overline{M}_p^{>30}$ is the average number of days with maximum temperature above 30°C in period p. We rescale the difference by 365 to convert it to a share, in order to facilitate the reading of regression results. Figure 5 displays the distribution of ΔT over our 3-years period and across the temperate and Mediterranean climatic zones. Both zones follows roughly the same pattern over time, even though the Mediterranean one displays a little more variability and a slightly higher incidence of outliers.

Incumbent and prospective firms might be intrinsically different across LLMs characterized by a different temperature distribution: for example, incumbent (prospective) firms might have adapted (planned) their production processes to be able to cope with a certain amount of heat waves per year. By looking at the difference in the number of heat waves, the aim is to isolate the temperature component that is new to the firms' information set: when a new draw of temperatures realizes, the firms' initial belief is confirmed or proved wrong, a new belief on maximum temperature distribution is formed, and the optimal dynamic choices of firms are updated accordingly. The idea behind this kind of Bayesian updating mechanism has also been exploited by the related paper of Pankratz and Schiller (2021), in the context of a different empirical framework.

Interestingly, this specification for the temperature variable also gives us the opportunity to interpret the estimates of our distributed lag model as the parameters of an impulse response function, following a permanent increase in temperatures: supposing an isolated 1% variation in temperature takes place in a certain period, the associated change in the dependent variable after p periods will be equal to the coefficient attached to the p^{th} lag of the explanatory variable.

Overall, the empirical strategy laid out in this section can be interpreted as a halfway compromise between a pure panel structure and the "long difference approach", proposed by Burke and Emerick (2016) to net from short-run responses to weather events. In our model, the parsimonious distributed lag structure over time-averaged variables performs the same function of muting the erratic short-run effects, while at the same time highlighting the medium-term responses that determine the transition to a new equilibrium. We will show in the section dedicated to robustness exercises that adopting a long differences approach returns qualitatively very similar results.

4.2 Results

The baseline results obtained from the estimation of equation 3 on the growth rate of active firms and its components are displayed in Table 4. We directly report the most demanding specification, which includes LLM, period, area×period and population quartile×period fixed effects.

An increase in the number of extreme heat days leads to a decrease in the growth rate of active firms. The effect starts to pick up from the second lag, when it grows in size and becomes significant, and it persists in the following lag. The overall result is the composition of a decrease in the entry rate and a concurrent —though fainter— increase in the exit rate. Relocation does not appear to be equally relevant. Relocation to and from other LLMs provides a positive and significant contribution in the second lag, but its magnitude is negligible with respect to the other components. The effect of precipitations on the growth rate of active firms is negative and mostly mediated by the entry rate component. The exit rate component is negatively affected by precipitations, although to a very limited extent. Since precipitations are not our main focus, we will not always report them in the presented tables, even though they are always included as a control.

As we could expect given the potentially secondary role played by climate variables in firms' strategic decisions, the size of the effects is not massive: a 1% increase in the share of extremely hot days (equivalent to 3.5 days more) reduces the growth rate of active firms by 0.04 percentage points after three periods (the average growth rate is 1.5 percent); it reduces the entry rate by 0.03 percentage points (5 percent on average) and increases the exit rate by 0.02 percentage points (3.5 on average). Nonetheless, the sign and significance of these estimates are robust across different specifications. Moreover, given the highly demanding specification, the variability explained by temperature and precipitation variables is not irrelevant —at least in the case of the entry rate—, as suggested by the within R^2 statistics.

The reduced-form model adopted in our empirical strategy can be thought as capturing the net impact of a host of firm-level and general equilibrium adjustments occurring over the medium run. Isolating each of these channels is out of the scope of this paper, but the overall impact on firm demography that we are able to identify compounds technology adjustments and other forms of medium-run adaptation of firms (e.g., capital reallocation across business units), as well as general equilibrium effects such as climate-induced labor mobility or changes in relative prices.

If the heat waves were correlated with other disruptive extreme weather events, there might be the concern that our results are picking up the effect of these adverse occurrences rather than that of extreme temperatures. To resolve this doubt, we include as additional controls the count of different extreme events from the ESWD database, as described in the data section above. Given the already discussed limitations of the ESWD data, it is possible to include only two lags of the severe weather events. Results are reported in Table 5. The only significant coefficient estimates are those on hail and avalanches, possibly the most disruptive events in the dataset; as expected, their effect is negative on active firms, and it mostly unravels through a higher exit rate. Our baseline results on extreme temperature remain unaffected in most of its main indications, with an even stronger drop in the growth rate of active firms and in the entry rate. Instead, the coefficient estimates on exit rate reduce in magnitude and become non-significant. This might be due on one side to the fact that the previously singled out effects could have been mediated by other extreme events and were not imputable to extreme temperatures alone; on the other side, it is worth remembering that the limited time span of the ESWD data imply a substantial loss of observations (the estimation sample gets more than halved), potentially giving to rise to less precisely estimated parameters.

With this caveat in mind, it is however useful to compare the relative size of the effects of high temperatures, precipitations and extreme events. To do that, we have computed the impact that two consecutive and equally-sized variations in the explanatory variables would have on firm demography. To favor the comparison between the different phenomena, we have set the size of the variation to the one experienced by the average LLM. Table 6 collects the results. Precipitations are the event that imply a stronger adjustment in the growth rate of active firms, followed by the increase in temperatures. In both cases, the response essentially unravels through the entry rate. The extreme events are comparatively less relevant, also because they less frequently affect the average LLM. Among the two type of events considered, avalanches are the ones that have a slightly more pronounced effect on the demography of firms, leading to both a lower entry and a higher exit. Hail tends to increase firm exit only. Given the vast amount of information that we lose to include extreme events in our regressions, we do not deem these estimates to be the most solid ones we can provide. For this reason, and having shown that including extreme events does not significantly affect the qualitative implications of our estimates, we will drop the ESWD events from our analysis in what follows.

Going back to the baseline results in Table 4, we have then expanded them to allow for potential heterogeneity in the average effects detected. A first exercise has looked across climatic zones, to investigate if the rise in temperature has different effects in areas characterized by different ex-ante climatic conditions. We only consider two climatic zones: (i) the Mediterranean one —including the two main Islands and all the coasts, except the North Eastern ones—, typically characterized by higher average temperatures; and (ii) the temperate one —including the rest of the country—, characterized by milder summers and colder winters.[9] Results are displayed in Table 7. They show that the baseline results discussed above are essentially driven by the Mediterranean zone, where an increase in extreme temperatures leads to a clear drop in the growth rate of active firms, as a consequence of both a decrease in entry and an increase in exit. In the temperate zone the effect are less stark, but are if anything reversed: the growth rate of active firms increases as a consequence of the rise in temperatures, essentially through a lower exit rate. These results are broadly consistent with certain arguments brought about by the economic geography literature, claiming that regions might be unequally affected by climate change, with initially colder areas benefiting from a net inflow of population and economic activity at the expenses of initially warmer zones (see Cruz and Rossi-Hansberg (2021), who apply this argument at a global scale).

To provide a further test for this claim and unveil one of the causes at the root of the documented difference between Mediterranean and temperate zones, we have performed a similar heterogeneity exercise, distinguishing between the LLMs above and below the median average

[9]A map of these climatic zones is provided in Figure B.1.

temperature in the years 1999–2001. Results displayed in Table A.4 confirms that the initial temperature might be a differentiation margin, showing that the effects are concentrated in the LLMs characterized by a higher average temperature. Their magnitudes are also close tho the ones presented in Table 7 for the Mediterranean climate zone. A potential concern is that climate zones or average temperatures are essentially discriminating between Northern and Southern regions, which might be characterized by different pre-trends. To address this issue, we first repeat our estimates adding LLM-specific linear trends. Table A.5 shows that the effects are even starker under this alternative specification. In Table A.6, instead, we repeat the same estimates as in Table 7, but only within Southern regions. The number of observations drops, hence the precision is somewhat diminished. However, the same patterns emerge, with Mediterranean LLMs experiencing a reduction in the growth rate of active firms over the medium term. If anything, the differences between the two areas are even more pronounced, with the temperate zone benefiting from the temperature rise.

Another heterogeneity exercise involves estimating the differential effect of extreme temperatures across sectors. To do that, we have estimated the model in equation 4, with the full set of fixed effects discussed above. Given the large number of parameters to report, we have preferred to provide a graphical representation to summarize the main results.[10] Under the hypothesis that a 1% increase in the share of extreme heat days occurred in three consecutive periods, the effect on entry, exit and relocation rates would be given by the sum of the coefficients on the three lags of ΔT. The histogram in Figure 6 provides these linear combinations of coefficient estimates, together with their standard errors. On one side, entry rate significantly drops for agriculture, manufacturing, construction and retail. All of them are sectors considered as particularly exposed to temperature shocks by the existing literature (Graff Zivin and Neidell, 2014). On the other side, exit rate increases significantly again for manufacturing, construction and

[10]Since the coefficient on the growth rate of active firms can be obtained as the sum of all other coefficients, we will not report it in what follows.

retail. Once more, relocation plays no sizable role.[11] Overall, the affected sectors are in line with expectations, given the nature of the activities carried out.

A richer picture emerges if we add another layer of heterogeneity, looking at how coefficients vary across sector and climate zones. Figure 7 displays a heatmap where blue colors indicate decreases and red colors increases; the intensity of the shading is proportional to the magnitude of the coefficient. White cells indicate non-significant values. The reported coefficient is again the linear combination of the three lags, supposing three consecutive 1% increases in heat days. This representation allows a more granular representation of sectors. Again, it is apparent that most of the action takes place in the Mediterranean zone, where the entry rate decrease significantly for agriculture, mining, manufacturing, construction and retail. It also decreases for transportation and professional and support activities, probably indicating potential second-order effects, as these businesses depend on the activity of other firms. The Mediterranean zone also sees an increase in exit rates for manufacturing, construction and retail. Fainter effects can be acknowledged for the temperate zone. It is worth noting, however, that the entry rate in the agriculture sector decreases also in this area, probably signalling that these activities suffer from heat waves, independently from the initial climate conditions. Moreover, the tourism sector in the temperate region experiences a sizable increase in entry (only partly counterbalanced by an increase in exit), probably because higher temperatures allow to reduce the seasonality of trade flows.

4.3 The implications for firm demography of temperature rise in the current decade

The JRC MARS Meteorological Database provides us with a scenario for the evolution of precipitations and temperatures until 2030, according to the ETHZ CLM regional climate model projections run by the Swiss Federal Institute of Technology (see Jaeger et al. (2008)

[11] The slight increase for the relocation rate from other LLMs among the 'other sectors' category is essentially driven by the electricity, gas, steam and air conditioning supply sector.

and Duveiller et al. (2017) for a discussion, and Figure B.2 for a graphical representation of the scenario). It is therefore a natural step to provide a rough quantification of the effects that these changes would imply on firm demography, according to our estimates. To do that, we have computed the estimated variation in the growth rate of active firms and its components between the years 2020 and 2031, as a consequence of the evolution of temperatures and precipitations forecast by the ETHZ scenario.

The results of this back-of-the-envelope calculations are displayed in Table 8. For Italy, the JRC data predict that in 2028 the share of days with maximum temperature above 30°C will be 4.1 percentage points higher than in 2011, while the precipitations will increase by 1.45%.[12] According to our estimates in Table 4, these temperatures and precipitations dynamics would translate into a cumulative variation of -0.22 percentage points in the growth rate of active firms. This figure is the composition of a (cumulative) entry rate drop by -0.15 percentage points and a (cumulative) exit rate increase by 0.09. The relocation terms are quantitatively less relevant. As a term of comparison, over the same time window precipitations are predicted to have a lower impact than temperatures on firm demographics: a -0.07 percentage points decrease in the entry rate is almost entirely counterbalanced by an almost equally-sized decrease in the exit rate.

The lower panel of Table 8 displays how these figures vary across climate zones, once we apply the estimates obtained in Table 7. In the Mediterranean climatic zone, the evolution of temperatures would command a sharper decrease in the growth rate of active firms (-0.36 p.p.), again as a consequence of both a decrease in entry (-0.2) and an increase in exit (0.18). In the temperate climatic zone the effects are reversed in sign, with the exit playing a relatively stronger role. Precipitations are also acquire more relevance in the Mediterranean zone, as a consequence of the more pronounced precipitation dynamics which is expected to characterize this area. Overall, this rough quantification exercise points to non-negligible effects of temperatures on

[12] The time span 2011–28 is the one that needed to project our estimates forward in the periods 2020–22, 2023–25, 2026–28 and 2029–31.

the firms' entry and exit decisions over the current decade.

4.4 Robustness checks

In this section we perform some exercise to show the robustness of our findings. A first concern might be that, even though our battery of fixed effects allows us to capture differences in levels, it fails to control for potentially different trends characterizing the LLMs in our sample. To address this point, we have estimated the model in equation 3 including a linear LLM-specific trend. The results displayed in Table 9 are, if anything, more solid. The coefficients on entry and exit increase both in magnitude and significance.

A second source of worry is that the three-year window adopted to bin our data is of course arbitrary. Existing literature offers no clue on the optimal bin width for this kind of exercise. To support our specification, we show that the obtained results still hold even if we stretch the bin width to the whole sample period. In other words, we adopt a pure long difference approach in the spirit of Burke and Emerick (2016) and estimate our effects on the cross section of the LLMs. The growth rate of (average) active firms between 2005–07 and 2017–19 is regressed against the variation in the (average) share of days above 30°C between 2002–04 and 2014–16. Given that we are now dealing with a cumulative growth rate over a 12-years time window, when we use entry, exit and relocation rates as dependent variables they will also be cumulated over the same period. The accounting identity linking the demographic variables is still satisfied. Results are displayed in Table 10. Again, the effect on the growth rate of active firms is negative and significant; it mainly unfolds through the entry rate, and to a lesser extent through the exit rate. Also precipitations negatively affect the growth rate of active firms, essentially through the entry channel.

Another arbitrary choice —although motivated by extensive literature— is the one related to the 30°C threshold adopted to compute the explanatory variable ΔT. Hence, we have repeated our estimates changing the threshold. The results are graphically displayed in Figure 8. In the same spirit as the heterogeneity exercises presented above, we display —for each temperature choice— the linear combination of the coefficients on the three lags, corresponding to the effect of three consecutive 1% increases in the temperature variable. For the sake of brevity, we only have performed this exercise for the growth rate of active firms, entry and exit. The results are robust to the choice of the temperature threshold. The effects tend to slightly increase in magnitude in the range between 29 and 32°C, consistently with the indications derived from the existing literature. For temperatures above 32°C the variation in the explanatory variable abruptly reduces, pushing down the precision of our estimates. These patterns emerge even more starkly if we repeat the heterogeneity exercise conducted on the climate zones and focus on the estimated effects in the Mediterranean one (column b).

5 Extreme temperatures and firm performance

The results discussed in the previous section indicate that high temperatures entail a reduction in the number of active firms in the medium-run, driven both by a lower entry rate and by a higher exit rate. To document whether temperatures also affect the activity of the firms that are not involved in entry and exit decisions, we make use of balance sheet data at the firm level for the subset of incorporated firms, recorded in the Company Account Database (CAD) provided by Cerved Group SpA. This dataset contains full balance-sheet information on the universe of incorporated businesses (i.e. limited liability companies) in Italy, which encompass large multinational companies as well as small firms with only one worker. Such a wide variety is crucial to inspect possible divergent effects of high temperatures on firms' activity.[13] Balance-sheet data allow us to inspect temperature effects on firms that are in the market, i.e. which survive to extreme temperature exposure at least during our sample period.

[13]The CAD dataset is richer than other data sources commonly used for non-financial firms balance sheet analysis in economic research, as the latter typically comprehend publicly listed firms only.

5.1 Empirical strategy

To assess the impact of temperature shocks on firms' fundamentals, we adopt a similar estimation strategy as the one in Section 4.1. As before, we bin our data into three-year periods over the observation sample. Then we use OLS to estimate the following distributed lag model:

$$y_{fp} = \sum_{k=0}^{2} \beta_k \Delta T_{f,p-k} + \sum_{k=0}^{2} \gamma_k \Delta \ln\left(\text{prec}\right)_{f,p-k} + \delta_f + \delta_{sp} + \delta_{dp} + \varepsilon_{fp} \tag{6}$$

where f indexes the firm, s and d denote respectively the firm sector and size and p the period. We define firm sector s as the 2-digit NACE rev.2 classification code of each firm. We split our pool of firms in three categories, according to the value of total assets: small firms are those with less than 10 million euros assets; medium firms are those between 10 and 50 million and large firms above 50 million euros assets. $\Delta T_{f,p-k}$ is the temperature variation hitting the LLMs where each firm f is located at lag k from period p. Three lags of the variation in the log millimeters of precipitations are included in the regression as controls. $\delta_\star$ are fixed effects at the $\star$-level. With respect to the specification adopted previously, we here also include contemporaneous effects of temperature variations, in order to capture short-run effects that would have been unrealistic in the previous exercise.

We use the specification in Equation 6 for a range of dependent variables, including some firm fundamentals (total assets, equity, net revenues, production), the total number of workers, and some indices of profitability, investments, liquidity and leverage. All these variables are averaged over the three year windows.

5.2 Results

Table 12 reports the estimated coefficients of the model in Equation 6. The effects of temperatures on balance-sheet variables manifest with no lag and appear, on average, significantly positive: a permanent increase in the incidence of hot days stimulate production (Column 4) and increases net revenues (Column 3), affecting the total value of assets (column 1). At the same time, the number of employees per firm is found to increase, as companies increase their workforce to expand production. This clearly shows that global warming is beneficial for resilient firms, spurring successful adaptation mechanisms that enhance firm value.

To complement this evidence, we also run our regression model on a set of firm indices including investments, earnings, liquidity and leverage over total firms' assets. All of them —excluding investments— are calculated in variation with respect to the previous period. Table 13 shows that, in line with previous results, extreme heat events increase profitability (column (2)), although near-zero within R^2 suggests a limited explanatory power for these specifications. Liquidity rises (Column 3) and investments fall (Column 1), suggesting that firms' adaptation to higher temperatures does not pass mainly through investments: on balance, giving up investment projects outstrips a possible increase in adaptation investment, and firms live with higher liquidity buffers to face higher costs induced by climate change. These results are coherent with no effects on leverage at any lag.

Interacting temperatures with firm size reveals an important heterogeneity: across all fundamentals reported in Table 12, the cumulative effect of hot temperatures is estimated to be positive across all size classes, except for the micro firms, for which production, revenues, equity and total assets significantly fall, and the number of workers decrease. This result shows a dichotomy between resilient and non-resilient firms even in the selected sample of those who survived hot temperatures for many years. Looking at the results on firms' indicators at the same level of breakdown documents a decrease in investments and an increase in liquidity only for micro firms, suggesting a clear explanation for the puzzling effect found on average (Figure 9).

5.3 A measure of heat stress exposure

All in all, results highlight a stark difference in the effect of hot temperatures on existing firms of different size, where medium and large ones appear to benefit in the long run, maybe triggering technological advancements and productivity gains, while micro firms find no way to adapt. As this result appears robust, the next step is to investigate some relevant drivers of this difference and, in particular, possible causes of firms' vulnerability. We take up this issue by investigating the most popular explanation, which is linked to workers' heat stress. To assess its potential role in deteriorating firms' businesses, we exploit the available breakdown of workers for each firm, which are divided in blue collars, white collars and management. Information is based on the workers' contracts and is available from records provided by the Italian National Institute for Social Security. We expect that blue collars, who cover manual tasks and lower skilled occupations, are more exposed to extreme temperatures than white collars and the management, who mainly spend their work time in offices with air conditioned. According to that, we construct an indicator of Workers' Heat Exposure (WHE henceforth) as the ratio of the number of blue collars over the total number of workers for each firm, as

$$\text{WHE}_{fp} = \text{blue collars}_{fp} \ / \ \text{total workers}_{fp} \tag{7}$$

By averaging the WHE over time, we get $W\bar{H}E_f$ that is used to sort firms according to the share of workers exposed. A dummy variable identifying firms with $W\bar{H}E_f$ above the median is then used as interaction term in our regression. Figure 11 displays the results over the subset of firms providing the workers breakdown —75 percent of total, mainly medium and larger ones. Firms with a larger share of exposed workers are find to benefit from hot temperatures while on the contrary, those with a small share suffer significantly, lowering production, revenues and the number of employees.

This dichotomy combines with the estimates made on the other set of indices. In particular,

Figure 12 shows that both profitability and liquidity increase only for firms with a large share of blue collars, while investment decrease with the other ones. All of the above results are striking, considering that differences in firm size are already net out by means of size class fixed effects. One possible explanation for these findings is that having less blue collars in the work team, who are vital to carry out production activities but at the same time more exposed to high temperatures, entails a lower ability for the firm to diversify climate risk, generating a higher probability of business disruptions in times of high temperatures. In the long-run, firms with a low share of blue collars are structurally exposed. This result suggests that human heat stress alone, *ceteris paribus* any other temperature effects (e.g., on firms' costs), might be able to explain a divergent path in the corporate sector. Investigating this non-linearity further can be considered as a promising avenue for further research.

6 Conclusions

In this paper we investigate medium-run implications of climate change on the corporate sector, using data on the universe of Italian firms. We find that a permanent increase in hot temperatures ends up reducing the entry rate of new firms and increasing exit rate. Results vary substantially, based on the sector and geographic area to which firms belong to. A balance-sheet level analysis on the subset of incorporated firms also reveals a differential impact of climate change on firms' business depending on their size, as temperatures have negative effects for small firms only, while it appears to be beneficial for larger ones, probably the ones having a greater propensity to adapt to the varying climatic conditions.

Our findings might have relevant policy implications. First, as global warming may turn beneficial for the firms in the higher part of the firm size distribution, policy makers might meditate on the opportunity to target policies to smaller firms, in order to assist them in their adaptation process to varying climate conditions. Second, the documented heterogeneity across geographic areas might signal potential effects of temperatures on regional disparities. In Italy, for example, the future evolution of heat waves might exacerbate the existing divide between the North and the South (Mediterranean areas are mostly located in the South). In that case, additional efforts could be placed on the leveling of non-climate related differences in the business environment, that may act as a resilience device to contrast the effects of rising temperatures on the production structure. Finally, our findings call for additional research on the repercussion of climate-induced entry and exit dynamics on aggregate productivity at the local level.

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Tables

Table 1: Number of extreme heat days, summary statistics

year	mean	median	std. dev.	minimum	maximum
1993	23.10	23	14.77	0	72
1994	38.90	39	20.55	0	90
1995	18.47	17	12.51	0	47
1996	12.98	11	10.14	0	61
1997	17.89	13	15.80	0	73
1998	36.27	39	18.03	0	70
1999	25.63	26	15.64	0	67
2000	29.23	29	16.84	0	65
2001	35.29	36	19.03	0	86
2002	22.27	22	13.51	0	67
2003	63.78	69	23.58	0	96
2004	29.34	29	18.87	0	79
2005	26.19	25	14.66	0	63
2006	36.21	38	15.92	0	75
2007	34.49	36	18.96	0	79
2008	41.76	46	25.25	0	84
2009	42.57	46	22.57	0	81
2010	31.35	32	18.93	0	77
2011	36.96	37	21.89	0	90
2012	53.59	61	26.08	0	105
2013	34.80	36	20.00	0	75
2014	20.11	14	17.63	0	89
2015	45.46	47	18.80	0	80
2016	31.01	31	21.13	0	77
2017	44.97	47	21.34	0	90
2018	33.29	32	20.02	0	95
2019	46.03	49	23.44	0	97
Total	33.78	33	22.18	0	105

Notes: The table displays some summary statistics for the number of extreme heat days across LLMs. Extreme heat days are defined as those in which the maximum temperature exceeds 30°C.

Table 2: Summary statistics for the components of firm demography

year	$\dot{A}$	e	x	r^{in}	r^{out}
2006	0.0497	0.0688	0.0194	0.0030	0.0028
	(0.0233)	(0.0204)	(0.0090)	(0.0031)	(0.0026)
2007	0.0334	0.0640	0.0305	0.0034	0.0035
	(0.0214)	(0.0165)	(0.0105)	(0.0028)	(0.0031)
2008	0.0251	0.0591	0.0337	0.0051	0.0054
	(0.0234)	(0.0176)	(0.0133)	(0.0035)	(0.0035)
2009	0.0161	0.0516	0.0349	0.0055	0.0060
	(0.0213)	(0.0157)	(0.0115)	(0.0038)	(0.0036)
2010	0.0162	0.0521	0.0356	0.0048	0.0051
	(0.0254)	(0.0165)	(0.0178)	(0.0034)	(0.0031)
2011	0.0113	0.0466	0.0352	0.0047	0.0048
	(0.0202)	(0.0136)	(0.0116)	(0.0031)	(0.0030)
2012	0.0043	0.0431	0.0388	0.0047	0.0046
	(0.0170)	(0.0129)	(0.0132)	(0.0030)	(0.0029)
2013	0.0073	0.0434	0.0363	0.0036	0.0035
	(0.0176)	(0.0136)	(0.0106)	(0.0026)	(0.0026)
2014	0.0059	0.0446	0.0387	0.0036	0.0035
	(0.0198)	(0.0148)	(0.0110)	(0.0060)	(0.0027)
2015	0.0077	0.0453	0.0373	0.0031	0.0034
	(0.0201)	(0.0151)	(0.0112)	(0.0024)	(0.0027)
2016	0.0106	0.0467	0.0359	0.0033	0.0035
	(0.0179)	(0.0138)	(0.0102)	(0.0026)	(0.0027)
2017	0.0112	0.0485	0.0373	0.0035	0.0035
	(0.0277)	(0.0199)	(0.0108)	(0.0087)	(0.0081)
2018	0.0093	0.0464	0.0364	0.0040	0.0046
	(0.0464)	(0.0168)	(0.0112)	(0.0243)	(0.0295)
2019	0.0059	0.0420	0.0361	0.0040	0.0041
	(0.0202)	(0.0148)	(0.0120)	(0.0053)	(0.0054)
Total	0.0153	0.0502	0.0347	0.0037	0.0039
	(0.0270)	(0.0179)	(0.0128)	(0.0076)	(0.0087)

Notes: The table displays the average values across LLMs of the components of firm demography, as defined in equation 2. Standard deviations are displayed in parentheses.

Table 3: Firms in Cerved database by year

	Number of firms
2005	544,401
2006	568,240
2007	590,149
2008	604,578
2009	628,189
2010	640,675
2011	650,939
2012	648,907
2013	646,180
2014	646,906
2015	661,624
2016	673,300
2017	681,416
2018	686,984
2019	720,116

Notes: Authors' elaboration on Cerved data.

Table 4: Firm demography regressions, baseline results

	$\dot{A}$	e	x	r^{in}	r^{out}
ΔT_{p-1}	-0.013	-0.010	0.003	0.004	0.001
	[0.012]	[0.009]	[0.008]	[0.003]	[0.003]
ΔT_{p-2}	-0.033**	-0.026**	0.003	0.005**	0.007*
	[0.016]	[0.012]	[0.010]	[0.002]	[0.004]
ΔT_{p-3}	-0.043**	-0.029**	0.019*	-0.002	-0.008
	[0.021]	[0.012]	[0.010]	[0.006]	[0.012]
$\Delta \ln(\text{prec})_{p-1}$	-0.011**	-0.015***	-0.005***	0.002	0.003
	[0.005]	[0.002]	[0.002]	[0.002]	[0.003]
$\Delta \ln(\text{prec})_{p-2}$	-0.001	-0.006***	-0.006***	0.001	0.002
	[0.004]	[0.002]	[0.002]	[0.001]	[0.002]
$\Delta \ln(\text{prec})_{p-3}$	-0.008***	-0.010***	-0.002	0.001	0.002*
	[0.003]	[0.002]	[0.001]	[0.001]	[0.001]
Obs.	3,055	3,055	3,055	3,055	3,055
R^2	0.609	0.756	0.758	0.334	0.246
Within R^2	0.016	0.055	0.010	0.003	0.004

Notes: Estimation results for the model in equation 3. Column names indicate the dependent variable of each regression. LLM, period, area×period and population quartile×period fixed effects included in all specifications. Coefficients on entry, exit and relocation rates regressions might not add up to the coefficients in the first columns, because the residual term in equation 2 is not reported in the table. Standard errors clustered at the LLM level in parentheses * p<0.10, ** p<0.05, *** p<0.01

Table 5: Firm demography regressions, controlling for extreme events

	$\dot{A}$	e	x	r^{in}	r^{out}
ΔT_{p-1}	-0.047*	-0.062***	-0.000	0.012	-0.003
	[0.025]	[0.020]	[0.013]	[0.008]	[0.008]
ΔT_{p-2}	-0.110**	-0.107***	-0.007	0.025	0.035
	[0.047]	[0.028]	[0.019]	[0.015]	[0.023]
ΔT_{p-3}	-0.125***	-0.120***	0.017	0.002	-0.011
	[0.044]	[0.030]	[0.017]	[0.007]	[0.020]
hail_{p-1}	-0.012	0.006	0.016	-0.004	-0.002
	[0.032]	[0.021]	[0.018]	[0.006]	[0.009]
hail_{p-2}	-0.064*	-0.017	0.052***	0.014	0.009
	[0.034]	[0.022]	[0.019]	[0.011]	[0.007]
avalanches_{p-1}	-0.446***	-0.106	0.321***	0.007	0.024
	[0.112]	[0.085]	[0.097]	[0.023]	[0.034]
avalanches_{p-2}	-0.829***	-0.436***	0.374**	-0.001	0.019
	[0.212]	[0.130]	[0.174]	[0.044]	[0.079]
Obs.	1,222	1,222	1,222	1,222	1,222
R^2	0.726	0.838	0.808	0.517	0.511
Within R^2	0.079	0.215	0.041	0.012	0.016

Notes: Estimation results for the model in equation 3, augmented with additional controls for extreme events. Column names indicate the dependent variable of each regression. Coefficients on precipitations are not reported. LLM, period, area×period and population quartile×period fixed effects included in all specifications. Standard errors clustered at the LLM level in parentheses * p<0.10, ** p<0.05, *** p<0.01

Table 6: Comparing the size of the effects of temperatures, precipitations and extreme events

	$\dot{A}$	e	x	r^{in}	r^{out}
ΔT	-0.078**	-0.085***	-0.004	0.018	0.016
$\Delta \ln(\text{prec})$	-0.263**	-0.218***	-0.001	0.038	0.084
hail	-0.034	-0.005	0.031**	0.004	0.003
avalanches	-0.047***	-0.020***	0.026***	0.000	0.002

Notes: For each dependent variable, this table reports the effect of two consecutive temperature, precipitation or extreme event (hail or avalanche) realizations of the size experienced by the average LLM. All coefficients are expressed in percentage points.

Table 7: Firm demography regressions, climate zone heterogeneity

	$\dot{A}$	e	x	r^{in}	r^{out}
$\Delta T_{p-1} \times$ temperate	0.029	0.008	-0.024**	0.010	0.014
	[0.021]	[0.013]	[0.010]	[0.006]	[0.009]
$\Delta T_{p-2} \times$ temperate	0.052**	0.014	-0.034***	0.005	0.008
	[0.021]	[0.014]	[0.013]	[0.005]	[0.006]
$\Delta T_{p-3} \times$ temperate	0.037*	0.015	-0.023*	0.006	0.009*
	[0.021]	[0.014]	[0.014]	[0.004]	[0.005]
$\Delta T_{p-1} \times$ Mediterranean	-0.026*	-0.011	0.016*	0.001	-0.004
	[0.015]	[0.011]	[0.010]	[0.003]	[0.003]
$\Delta T_{p-2} \times$ Mediterranean	-0.061***	-0.034**	0.020	0.005*	0.005
	[0.020]	[0.015]	[0.013]	[0.003]	[0.004]
$\Delta T_{p-3} \times$ Mediterranean	-0.073***	-0.043***	0.038***	-0.005	-0.016
	[0.027]	[0.015]	[0.013]	[0.008]	[0.016]
Obs.	3,055	3,055	3,055	3,055	3,055
R^2	0.613	0.760	0.761	0.336	0.248
Within R^2	0.024	0.069	0.023	0.005	0.006

Notes: Estimation results for the model in equation 3, with parameters being allowed to be heterogeneous across climate zones. Column names indicate the dependent variable of each regression. Coefficients on precipitations are not reported. LLM, period, area×period and population quartile×period fixed effects included in all specifications. Coefficients on entry, exit and relocation rates regressions might not add up to the coefficients in the first columns, because the residual term in equation 2 is not reported in the table. Standard errors clustered at the LLM level in parentheses * p<0.10, ** p<0.05, *** p<0.01

Table 8: Estimated changes in firm demography variables in the 2020 decade, under a potential scenario for temperatures and precipitations

	$\dot{A}$	e	x	r^{in}	r^{out}
	All LLMs				
cumulative ΔT 2011–28 (p.p.)=4.102	-0.223	-0.154	0.085	0.002	-0.025
cumulative $\Delta \ln(\text{prec})$ 2011–28 (%)=1.454	-0.010	-0.074	-0.067	0.011	0.024
	Temperate climate zone				
cumulative ΔT 2011–28 (p.p.)=3.978	0.271	0.094	-0.180	0.047	0.073
cumulative $\Delta \ln(\text{prec})$ 2011–28 (%)=-2.459	0.116	0.079	-0.030	-0.000	-0.001
	Mediterranean climate zone				
cumulative ΔT 2011–28 (p.p.)=4.273	-0.356	-0.207	0.181	-0.019	-0.067
cumulative $\Delta \ln(\text{prec})$ 2011–28 (%)=7.488	-0.203	-0.325	-0.144	0.031	0.066

Notes: This table reports back of the envelope calculations based on the results displayed in tables 4 and 7. For each dependent variable, the reported coefficients represent the cumulated change in the period 2020–2031, as predicted by our estimates. All coefficients are expressed in percentage points. The future evolution of temperatures and precipitations is defined according the ETHZ CLM regional climate model projections.

Table 9: Firm demography regressions, adding LLM-specific linear trends

	$\dot{A}$	e	x	r^{in}	r^{out}
ΔT_{p-1}	-0.012	-0.010	-0.001	0.003	0.002
	[0.017]	[0.013]	[0.011]	[0.005]	[0.003]
ΔT_{p-2}	-0.063***	-0.044***	0.014	0.007	0.010*
	[0.024]	[0.015]	[0.015]	[0.005]	[0.005]
ΔT_{p-3}	-0.069***	-0.042***	0.030**	-0.001	-0.005
	[0.025]	[0.014]	[0.012]	[0.006]	[0.013]
$\Delta \ln(\text{prec})_{p-1}$	-0.010	-0.013***	-0.005**	0.002	0.004
	[0.007]	[0.002]	[0.002]	[0.003]	[0.005]
$\Delta \ln(\text{prec})_{p-2}$	-0.005	-0.007**	-0.003	0.003	0.004
	[0.008]	[0.003]	[0.003]	[0.003]	[0.005]
$\Delta \ln(\text{prec})_{p-3}$	-0.011*	-0.010***	-0.001	0.001	0.004
	[0.006]	[0.002]	[0.002]	[0.002]	[0.004]
Obs.	3,055	3,055	3,055	3,055	3,055
R^2	0.751	0.836	0.819	0.626	0.612
Within R^2	0.374	0.365	0.260	0.439	0.488

Notes: Estimation results for the model in equation 3. Column names indicate the dependent variable of each regression. LLM, period, area×period and population quartile×period fixed effects included in all specifications. LLM-specific linear trends included in all specifications. Coefficients on entry, exit and relocation rates regressions might not add up to the coefficients in the first columns, because the residual term in equation 2 is not reported in the table. Standard errors clustered at the LLM level in parentheses * p<0.10, ** p<0.05, *** p<0.01

Table 10: Firm demography regressions, long differences approach

	$\dot{A}$	e	x	r^{in}	r^{out}
ΔT	-0.160***	-0.128**	0.037*	-0.006	-0.007
	[0.061]	[0.054]	[0.022]	[0.008]	[0.011]
$\Delta \ln(\text{prec})$	-0.075***	-0.078***	-0.000	0.004***	0.004***
	[0.010]	[0.010]	[0.004]	[0.001]	[0.001]
Obs.	611	611	611	611	611
R^2	0.111	0.124	0.006	0.015	0.014

Notes: Estimation results using a long differences approach as in Burke and Emerick (2016). Column names indicate the dependent variable of each regression. $\dot{A}$ computed as the variation between the average number of active firms in the periods 2005–07 and 2017–19. Entry, exit and relocation rates are averages over the whole 2005–2019 period. ΔT and $\Delta \ln(\text{prec})$ are variations between average values in the periods 2002–04 and 2014–16. Coefficients on entry, exit and relocation rates regressions might not add up to the coefficients in the first columns, because the residual term in equation 2 is not reported in the table. Robust standard errors in parentheses * p<0.10, ** p<0.05, *** p<0.01

Table 11: Firms' balance sheet data - Descriptive Stats

	mean	sd	min	p25	p50	p75	max
Total assets (1)	10.076	53.944	-848.208	-11.887	7.363	31.749	904.271
Net worth (1)	21.916	74.539	-869.915	-7.333	16.345	51.083	974.993
Net revenues (1)	-3.089	92.880	-1455.255	-25.131	1.923	26.448	1,233.859
Val. of product. (1)	-4.342	84.416	-1044.128	-25.335	1.814	26.048	1,062.801
Nr. of employees (1)	1.826	46.655	-827.054	-10.162	0.000	16.900	633.471
Investments (2)	-1.028	10.503	-113.158	-2.038	-0.227	1.007	36.705
EBITDA (3)	-2.723	22.711	-315.992	-6.886	-1.087	3.278	315.992
Liquidity (3)	0.166	11.893	-90.700	-3.468	-0.002	3.645	90.700
Leverage (4)	-3.560	54.100	-646.474	-14.360	0.000	7.138	646.474
Observations	2,442,128						

Notes: Author's elaboration on Cerved Data. All variables are presented in percentage points. (1) Variables are calculated in growth rate. (2) Over total assets. (3) Over total assets and in difference with respect to the previous period. (4) Variable calculated in difference with respect to the previous period.

Table 12: Firms' fundamentals regressions

	(1) Total assets	(2) Equity	(3) Net revenues	(4) Value of production	(5) Number of employees
ΔT_p	0.00020***	0.00015	0.00063***	0.00071***	0.00023***
	[0.00007]	[0.00011]	[0.00012]	[0.00011]	[0.00006]
ΔT_{p-1}	0.00040***	0.00055***	0.00098***	0.00100***	0.00030***
	[0.00008]	[0.00012]	[0.00014]	[0.00013]	[0.00007]
ΔT_{p-2}	-0.00022***	0.00002	0.00019	0.00024*	0.00010
	[0.00008]	[0.00012]	[0.00014]	[0.00012]	[0.00007]
$\Delta \ln (\text{prec})_p$	2.53091***	-0.97495	2.97066***	2.90170***	2.66107***
	[0.41456]	[0.67665]	[0.80027]	[0.70248]	[0.39646]
$\Delta \ln (\text{prec})_{p-1}$	7.15609***	5.94782***	15.34286***	14.33842***	9.37148***
	[0.40668]	[0.64334]	[0.73491]	[0.65784]	[0.38636]
$\Delta \ln (\text{prec})_{p-2}$	0.81684**	-1.66857***	5.54830***	5.27323***	3.98231***
	[0.32888]	[0.53631]	[0.61793]	[0.54692]	[0.31392]
Obs.	2442128	2095169	2442128	2434421	2402292
R^2	0.454	0.350	0.372	0.401	0.393
Within R^2	0.00028	0.00015	0.00032	0.00036	0.00046

Notes: Column names indicate the dependent variable of each regression. Each variable is calculated in log-difference with respect to the previous period. Coefficients on lagged precipitations are not reported. Firm, sector×period, size×period fixed effects included in all specifications. Standard errors clustered at the firm level in parentheses * p<0.10, ** p<0.05, *** p<0.01

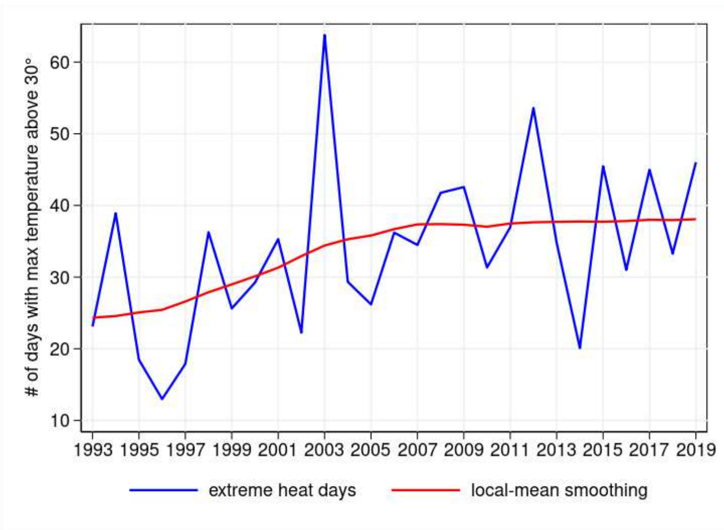
Table 13: Firm indices regressions

	(1) Investments	(2) EBITDA	(3) Liquidity	(4) Leverage
ΔT_p	-0.00003**	-0.00001	0.00005***	0.00005
	[0.00001]	[0.00003]	[0.00002]	[0.00008]
ΔT_{p-1}	-0.00001	0.00010***	0.00005**	0.00006
	[0.00002]	[0.00004]	[0.00002]	[0.00008]
ΔT_{p-2}	-0.00003**	0.00002	0.00004**	-0.00012
	[0.00002]	[0.00004]	[0.00002]	[0.00009]
$\Delta \ln(\text{prec})_p$	0.40391***	0.34542*	-0.51699***	0.93497*
	[0.08774]	[0.20061]	[0.10574]	[0.50659]
$\Delta \ln(\text{prec})_{p-1}$	0.40684***	1.09393***	-0.36985***	0.92705**
	[0.08316]	[0.18106]	[0.09646]	[0.44170]
$\Delta \ln(\text{prec})_{p-2}$	-0.17780**	1.04326***	-0.03429	-0.20489
	[0.06911]	[0.15828]	[0.08298]	[0.39273]
Obs.	2385905	2442128	2442128	2438141
R^2	0.373	0.294	0.272	0.213
Within R^2	0.00007	0.00004	0.00004	0.00001

Notes: Column names indicate the dependent variable of each regression. Each dependent variable is winsorized at $(0.5, 99.5)$. The variables in the last three columns calculated in difference with respect to the previous period. The variables in the first three columns are calculated as ratio over total assets. Liquidity is computed as the sum of cash and financial assets. Leverage is defined as the ratio of financial debts and the sum of financial debts and capital. Firm, sector×period, size×period fixed effects included in all specifications. Standard errors clustered at the firm level in parentheses * p<0.10, ** p<0.05, *** p<0.01

Figures

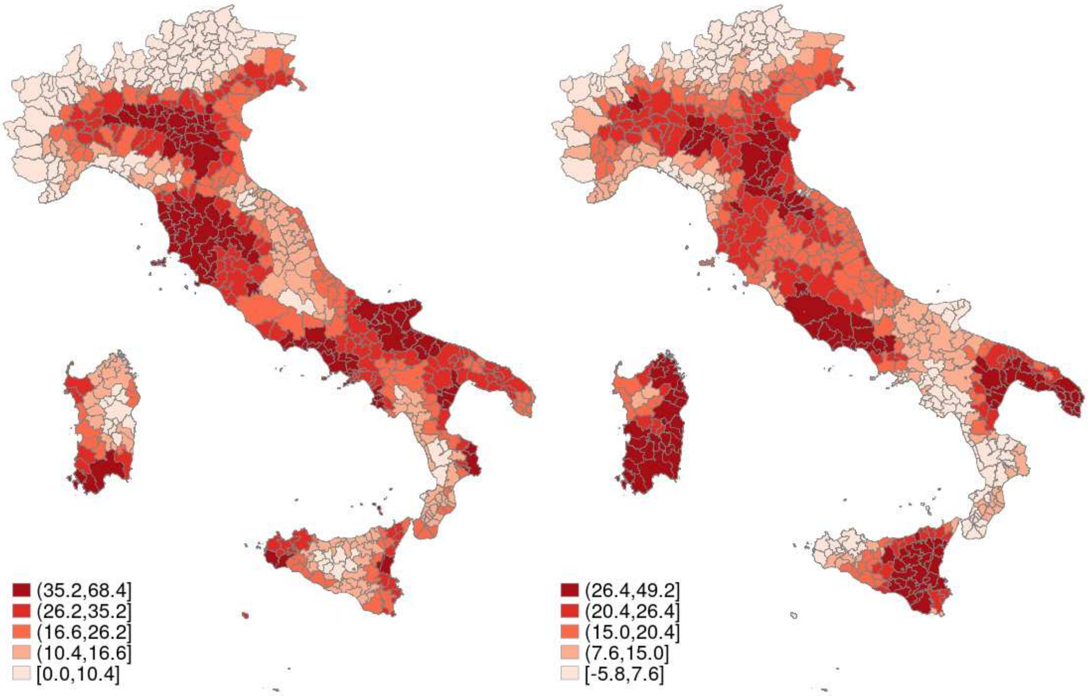
Figure 1: The evolution of extreme heat days in Italy



Notes: Average number of extreme heat days across LLMs. Extreme heat days are defined as those in which the maximum temperature exceeds 30°C.

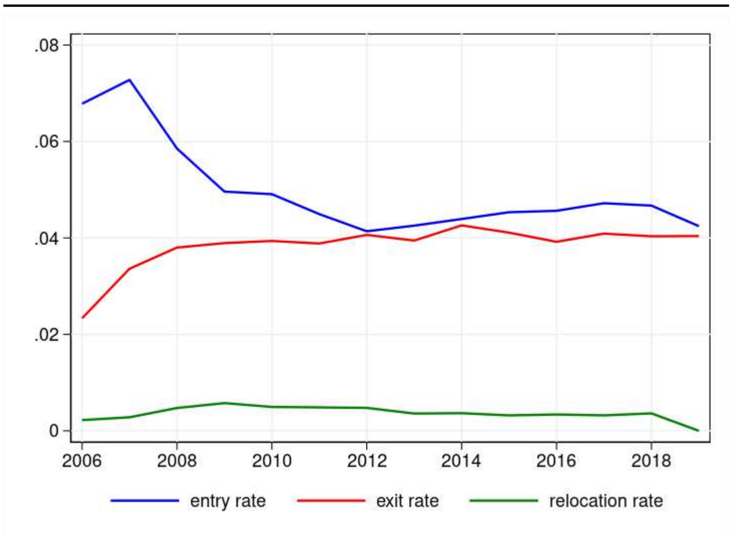
Figure 2: The distribution of extreme heat days in Italy

(a) average # of days > 30°C, 1993–97	(b) variation between 1993–97 and 2015–19



Notes: Extreme heat days are defined as those in which the maximum temperature exceeds 30°C. Data are averaged over 5-years windows to smooth erratic variations in the number of extreme heat days. Panel (a) represents the average number of extreme heat days for each local labor market in the period 1993–97. Panel (b) represents the variation in the average number of extreme heat days between 1993–97 and 2015–19. In both panels, data have been grouped in five equally populated classes.

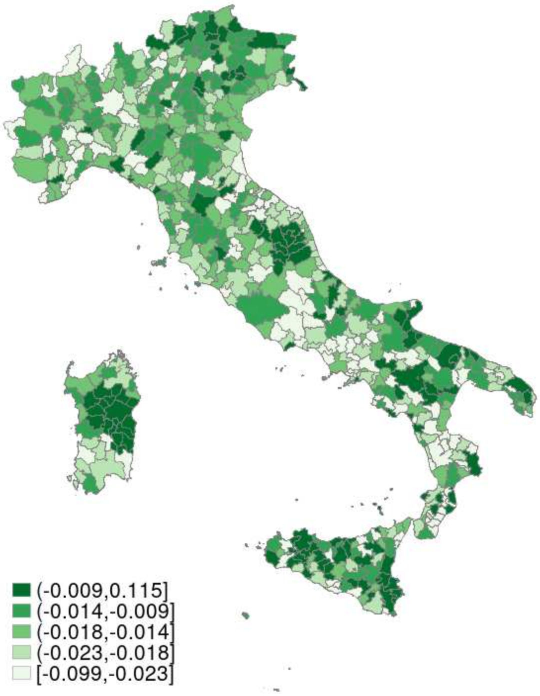
Figure 3: The evolution of firm demography components in Italy

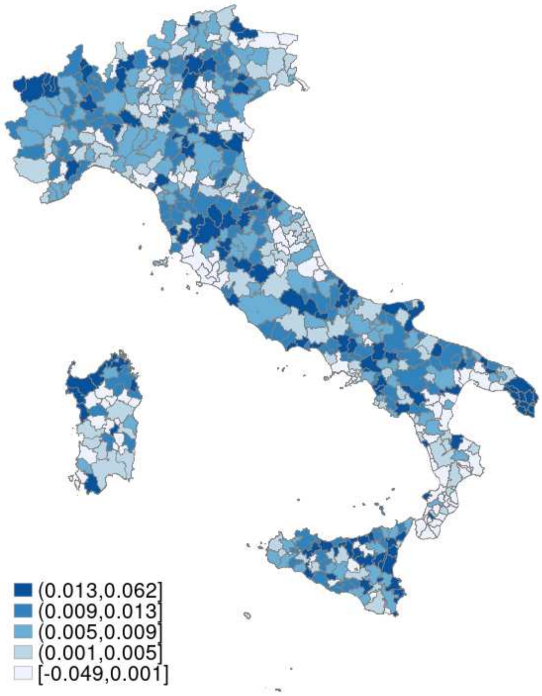


Notes: Aggregate entry, exit and relocation rates, as defined in equation 2. We only draw one relocation component, since in the aggregate the relocation to other LLMs and from other LLMs are equal by definition.

Figure 4: The variation of entry and exit rates, 2005–07 to 2017–2019

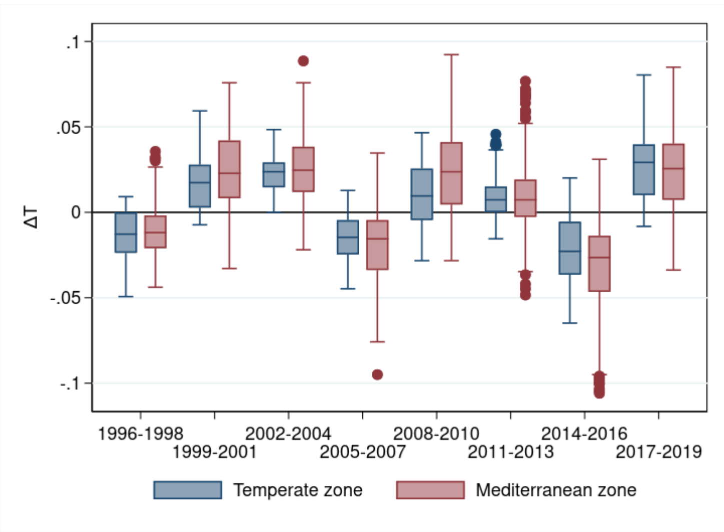
(a) Δ entry rate	(b) Δ exit rate





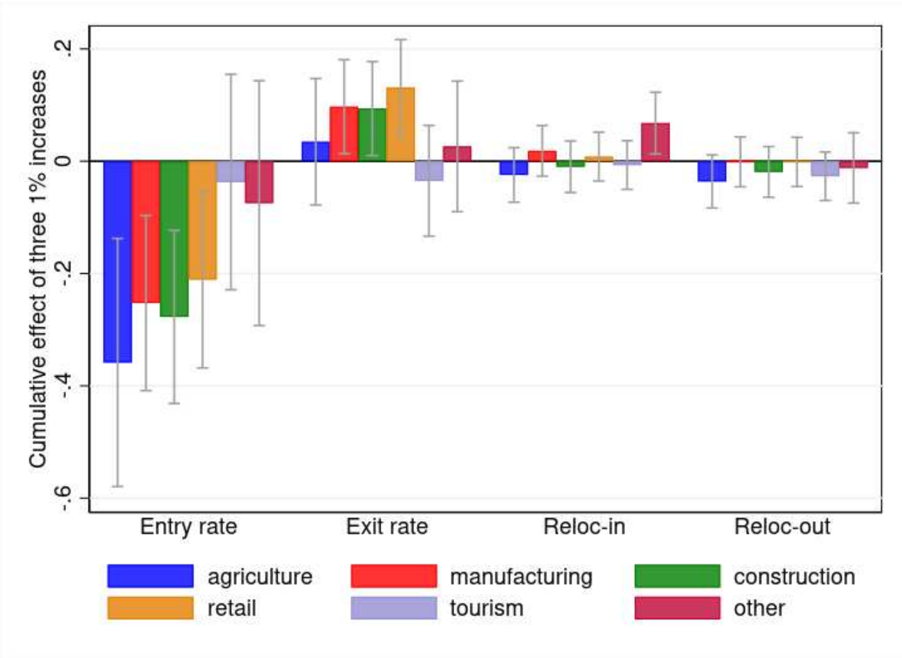
Notes: Entry and exit rates are defined as in equation 2. Data are averaged over 3-years windows to smooth short-run variations in entry and exit rates. Panel (a) represents the variation of the average entry rate between the years 2005–07 and 2017–2019. Panel (b) represents the variation of the average exit rate between the years 2005–07 and 2017–2019. In both panels, data have been grouped in five equally populated classes.

Figure 5: Distribution of ΔT over time and across climate zones



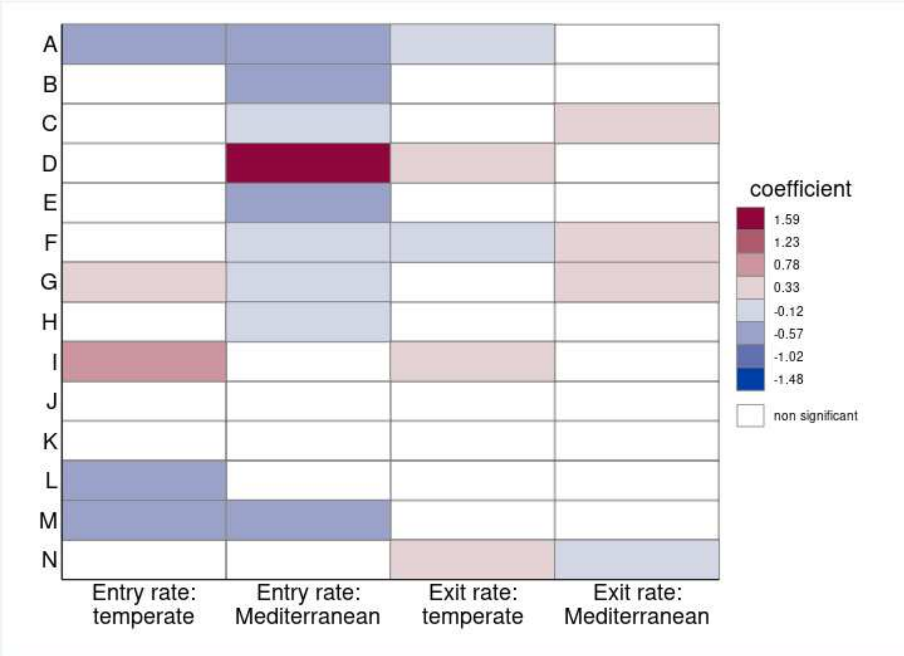
Notes: The figure represents a box and whiskers plot for the variable ΔT, as defined in equation 5. Climate zones are defined according to Istat classification, as in Figure B.1.

Figure 6: The effect of extreme temperature events across sectors



Notes: The graph is a visual representation of the coefficients obtained estimating the model in equation 4. The reported bars depict the linear combination of the three coefficients on lagged ΔT, hypothesizing a 1% increase in the number of extreme heat days in three consecutive periods. The horizontal axis displays the dependent variable used in the regression. The gray bars are confidence intervals at the 95% significance level.

Figure 7: The effect of extreme temperature events across sectors and climate zones



Notes: The graph is a heatmap providing a visual representation of the coefficients obtained estimating the model in equation 4, allowing for the coefficients to be heterogeneous across climate zones. The color of the cells varies according to the values of the linear combination of the three coefficients on lagged ΔT, hypothesizing a 1% increase in the number of extreme heat days in three consecutive periods. Empty cells indicate non-significant estimates at the 95% significance level. The columns of the matrix are labeled by the dependent variable of the regression and the climate zone to which the coefficient estimate is referred. The rows of the matrix indicate the sector according to the Nace Rev. 2 classification: A. Agriculture, Forestry and Fishing; B. Mining and Quarrying; C. Manufacturing; D. Electricity, Gas, Steam and Air Conditioning Supply; E. Water Supply, Sewerage, Waste Management and Remediation Activities; F. Construction; G. Wholesale and Retail Trade, Repair of Motor Vehicles and Motorcycles; H. Transportation and Storage; I. Accommodation and Food Service Activities; J. Information and Communication; K. Financial and Insurance Activities; L. Real Estate Activities; M. Professional, Scientific and Technical Activities; N. Administrative and Support Service Activities.

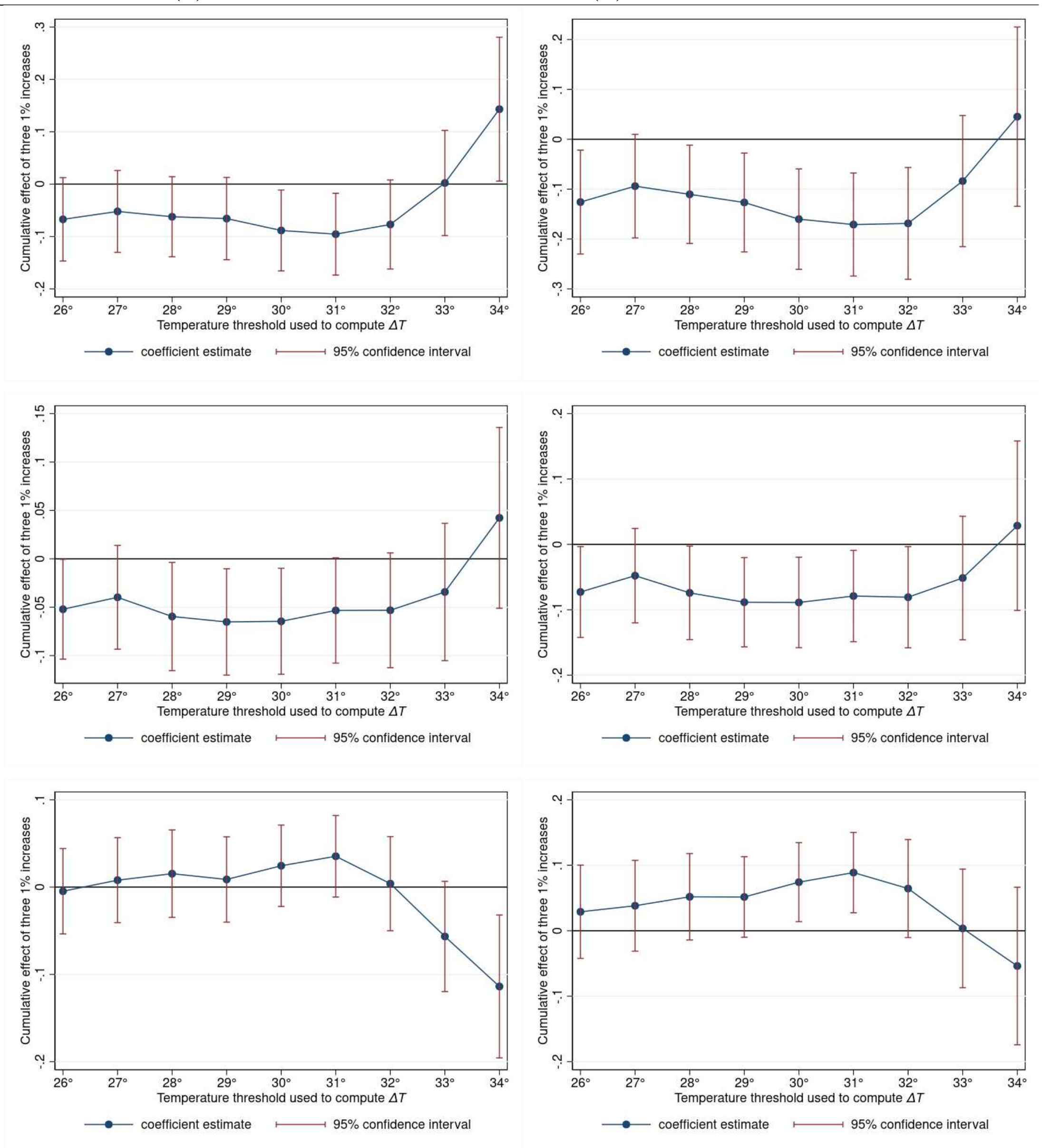
Figure 8: Coefficient stability for different temperature thresholds for ΔT

(a) Full sample | (b) Mediterranean climate zone

growth rate of active firms $\dot{A}$

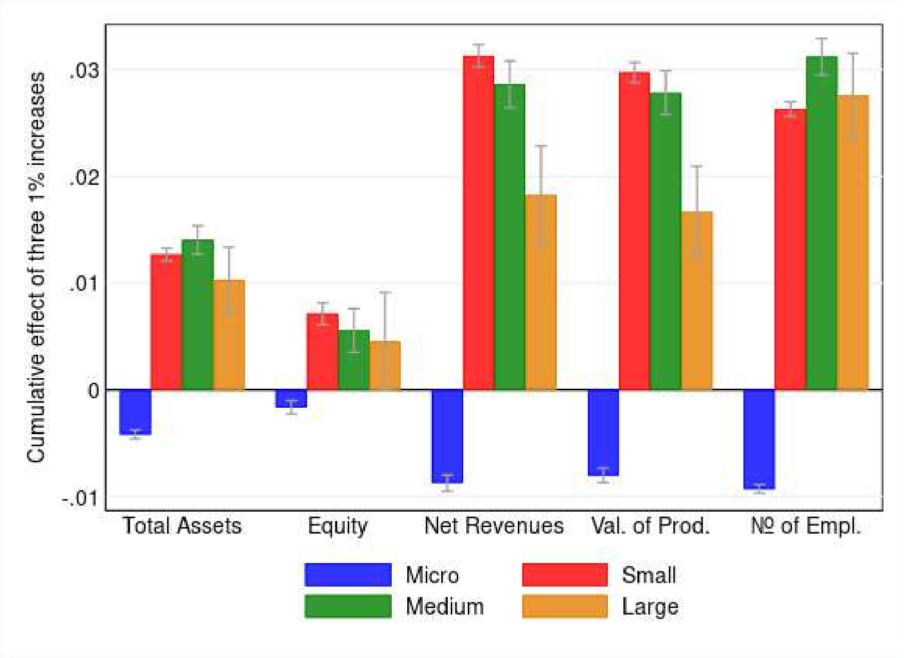
entry rate e

exit rate x



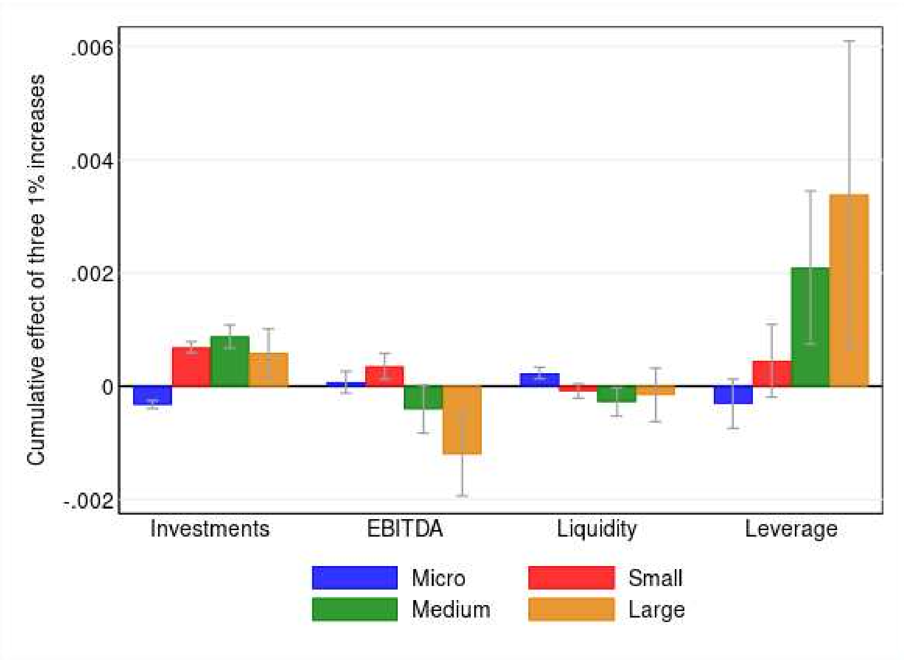
Notes: The graphs display the regression coefficients obtained estimating the model in equation 3 using different thresholds for the temperature variable ΔT. The threshold used is displayed in the horizontal axis of each graph. Each row collects the results obtained from a different dependent variable (growth rate of active firms, entry rate, exit rate). The two columns represent the results obtained for the full sample or the Mediterranean climate zone, under an heterogeneity exercise similar to the one in Table 7.

Figure 9: The effect of extreme temperature events on firms' fundamentals across sizes



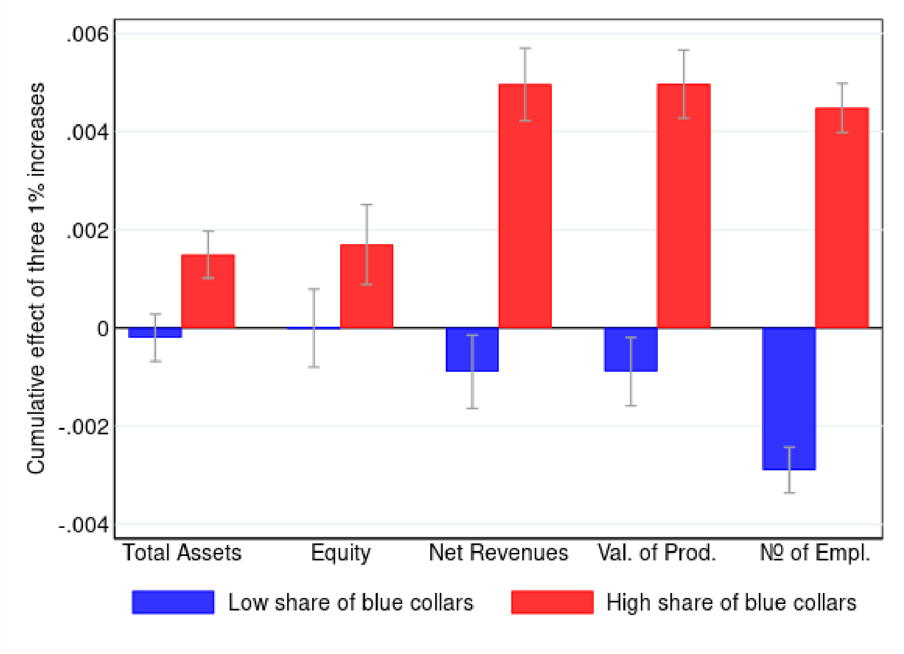
Notes: The graph is a visual representation of the coefficients obtained estimating the model in equation 6. The reported bars depict the linear combination of the three coefficients on lagged ΔT, hypothesizing a 1% increase in the number of extreme heat days in three consecutive periods. The horizontal axis displays the dependent variable used in the regression. Each variable is calculated in log-difference with respect to the previous period. The gray bars are confidence intervals at the 95% significance level.

Figure 10: The effect of extreme temperature events on firms' indices across sizes



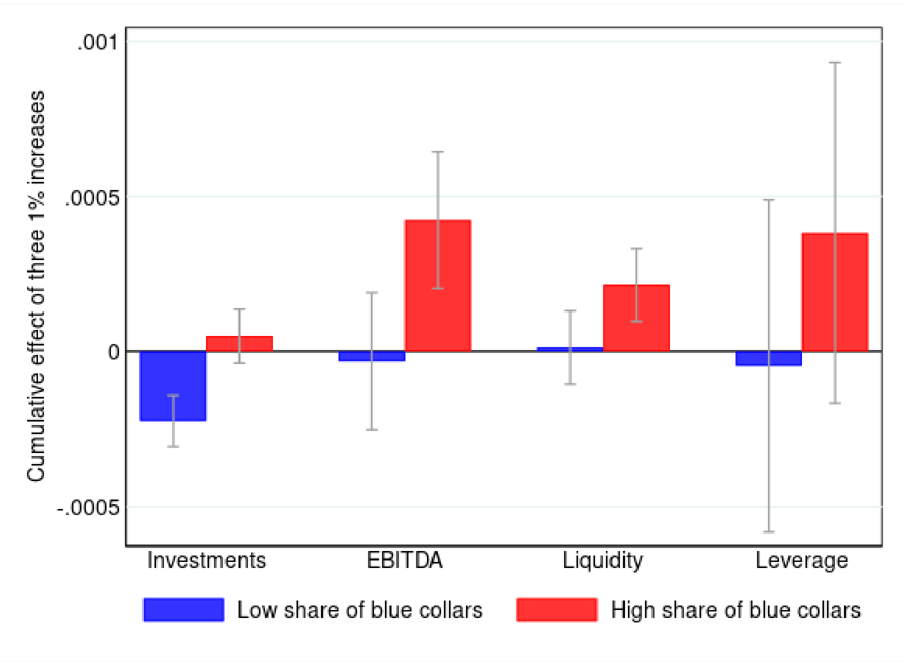
Notes: The graph is a visual representation of the coefficients obtained estimating the model in equation 6. The reported bars depict the linear combination of the three coefficients on lagged ΔT, hypothesizing a 1% increase in the number of extreme heat days in three consecutive periods. The horizontal axis displays the dependent variable used in the regression. Each variable is winsorized at $(0.5, 99.5)$. The last three variables are calculated in difference with respect to the previous period. The variables in the first three groups are calculated as ratio over total assets. Liquidity is computed as the sum of cash and financial assets. Leverage is defined as the ratio of financial debts and the sum of financial debts and capital. The gray bars are confidence intervals at the 95% significance level.

Figure 11: The effect of extreme temperatures on firms' fundamentals across the WHE indicator



Notes: The graph is a visual representation of the coefficients obtained estimating the model in equation 6. The reported bars depict the linear combination of the three coefficients on lagged ΔT, hypothesizing a 1% increase in the number of extreme heat days in three consecutive periods. The horizontal axis displays the dependent variable used in the regression. Each variable is calculated in log-difference with respect to the previous period. The gray bars are confidence intervals at the 95% significance level.

Figure 12: The effect of extreme temperatures on firms' indices across the WHE indicator



Notes: The graph is a visual representation of the coefficients obtained estimating the model in equation 6. The reported bars depict the linear combination of the three coefficients on lagged ΔT, hypothesizing a 1% increase in the number of extreme heat days in three consecutive periods. The horizontal axis displays the dependent variable used in the regression. Each variable is calculated in log-difference with respect to the previous period. The gray bars are confidence intervals at the 95% significance level.

A Additional tables

Table A.1: Infocamere sample, by sector and year

year	manufacturing	construction	market services	other	total
2005	316,464	276,865	1,144,147	139,178	1,876,654
2006	323,379	294,319	1,206,746	140,676	1,965,120
2007	334,334	316,180	1,285,638	133,454	2,069,606
2008	351,023	337,867	1,381,245	106,939	2,177,074
2009	351,824	344,858	1,405,702	102,214	2,204,598
2010	343,775	338,175	1,388,130	105,025	2,175,105
2011	339,891	339,655	1,402,923	107,924	2,190,393
2012	335,261	337,566	1,411,222	109,670	2,193,719
2013	331,727	336,928	1,422,642	111,587	2,202,884
2014	327,858	334,428	1,429,038	113,144	2,204,468
2015	325,010	334,110	1,442,765	115,223	2,217,108
2016	322,300	334,337	1,457,504	119,265	2,233,406
2017	319,494	334,876	1,472,881	122,906	2,250,157
2018	316,628	336,206	1,488,019	125,818	2,266,671
2019	311,547	337,851	1,496,395	127,881	2,273,674

Notes: The table displays the number of firms in the Infocamere dataset, after data cleaning. Non-market services are excluded from the sample. The column 'other' groups firms belonging to agriculture, mining and utilities.

Table A.2: Cerved sample, by size and year

			Nr. of firms			
year	Micro	Small	Medium	Large	NA	Total
2005	391,781	110,954	23,327	4,653	13,686	544,401
2006	411,847	112,631	23,144	4,598	16,020	568,240
2007	423,267	122,118	25,070	5,245	14,449	590,149
2008	437,952	122,626	24,783	5,157	14,060	604,578
2009	458,313	124,557	24,441	5,097	15,781	628,189
2010	473,699	122,056	24,747	5,325	14,848	640,675
2011	483,425	123,059	24,596	5,272	14,587	650,939
2012	482,318	121,500	24,039	5,168	15,882	648,907
2013	486,571	116,376	23,698	5,316	14,219	646,180
2014	488,880	116,173	23,375	5,285	13,193	646,906
2015	501,814	116,569	23,281	5,228	14,732	661,624
2016	506,859	126,508	26,048	5,924	7,961	673,300
2017	516,656	126,257	25,729	5,873	6,901	681,416
2018	523,296	125,798	25,226	5,762	6,902	686,984
2019	540,061	133,280	27,312	6,256	13,207	720,116

Notes: Authors' elaboration on Cerved Data.The size classes are those defined by Eurostat, namely (1) micro enterprises as with less than 10 persons employed; (2) small enterprises as with 10 to 49 persons employed; (3) medium-sized enterprises as those with 50 to 249 persons employed; (4) large enterprises as those with 250 or more persons employed.

Table A.3: Cerved sample, by sector and year

			Nr. of firms				
Year	Agriculture	Manufacturing	Construction	Retail	Tourism	Other	Total
2005	9,762	112,447	82,548	134,906	51,339	153,399	544,401
2006	10,219	114,387	89,865	139,204	54,471	160,094	568,240
2007	10,357	116,491	96,397	142,954	57,389	166,561	590,149
2008	10,678	116,437	101,616	144,708	59,325	171,814	604,578
2009	11,522	118,609	106,762	149,458	62,201	179,637	628,189
2010	11,989	118,978	107,754	151,903	64,252	185,799	640,675
2011	12,534	118,821	107,625	153,921	66,077	191,961	650,939
2012	12,978	117,221	104,191	153,919	66,541	194,057	648,907
2013	13,172	115,910	100,413	153,929	67,267	195,489	646,180
2014	13,208	115,671	98,011	154,730	68,846	196,440	646,906
2015	13,581	116,805	97,740	157,976	72,789	202,733	661,624
2016	13,697	117,796	97,115	161,142	76,329	207,221	673,300
2017	14,004	117,566	96,425	162,535	79,688	211,198	681,416
2018	14,047	118,063	95,742	163,823	81,980	213,329	686,984
2019	14,871	120,936	101,472	170,212	88,450	224,175	720,116

Notes: Authors' elaboration on Cerved Data.

Table A.4: Firm demography regressions, heterogeneity by initial average temperature

	$\dot{A}$	e	x	r^{in}	r^{out}
ΔT_{p-1} × low temperature	0.037	-0.010	-0.009	0.007	-0.030
	[0.043]	[0.014]	[0.011]	[0.005]	[0.034]
ΔT_{p-2} × low temperature	0.031	0.014	-0.018	0.004	0.010
	[0.030]	[0.020]	[0.017]	[0.005]	[0.008]
ΔT_{p-3} × low temperature	0.033	0.009	0.003	0.005	-0.021
	[0.046]	[0.020]	[0.018]	[0.004]	[0.031]
ΔT_{p-1} × high temperature	-0.031	-0.006	0.009	0.003	0.014
	[0.023]	[0.012]	[0.010]	[0.003]	[0.015]
ΔT_{p-2} × high temperature	-0.056***	-0.034**	0.012	0.006**	0.011
	[0.021]	[0.015]	[0.013]	[0.003]	[0.008]
ΔT_{p-3} × high temperature	-0.072***	-0.040***	0.026**	-0.004	-0.001
	[0.021]	[0.014]	[0.013]	[0.008]	[0.004]
Obs.	3,055	3,055	3,055	3,055	3,055
R^2	0.611	0.759	0.759	0.336	0.251
Within R^2	0.021	0.066	0.014	0.006	0.010

Notes: Estimation results for the model in equation 3, with parameters being allowed to be heterogeneous for LLMs below or above the median of average temperatures in the period 1999–2001. Column names indicate the dependent variable of each regression. Coefficients on precipitations are not reported. LLM, period, area×period and population quartile×period fixed effects included in all specifications. Coefficients on entry, exit and relocation rates regressions might not add up to the coefficients in the first columns, because the residual term in equation 2 is not reported in the table. Standard errors clustered at the LLM level in parentheses * p<0.10, ** p<0.05, *** p<0.01

Table A.5: Firm demography regressions, climate zone heterogeneity and LLM-specific linear trend

	$\dot{A}$	e	x	r^{in}	r^{out}
ΔT_{p-1} × temperate	0.028	0.006	-0.028	0.017*	0.023
	[0.035]	[0.021]	[0.017]	[0.009]	[0.014]
ΔT_{p-2} × temperate	0.039	0.004	-0.038**	0.015	0.020*
	[0.035]	[0.023]	[0.018]	[0.009]	[0.010]
ΔT_{p-3} × temperate	0.032	0.009	-0.029*	0.016**	0.021***
	[0.029]	[0.020]	[0.017]	[0.007]	[0.007]
ΔT_{p-1} × Mediterranean	-0.018	-0.008	0.009	-0.001	-0.004
	[0.020]	[0.015]	[0.013]	[0.004]	[0.004]
ΔT_{p-2} × Mediterranean	-0.097***	-0.056***	0.036*	0.005	0.007
	[0.028]	[0.018]	[0.019]	[0.006]	[0.005]
ΔT_{p-3} × Mediterranean	-0.105***	-0.057***	0.056***	-0.007	-0.014
	[0.032]	[0.017]	[0.015]	[0.007]	[0.017]
Obs.	3,055	3,055	3,055	3,055	3,055
R^2	0.755	0.839	0.823	0.628	0.614
Within R^2	0.383	0.378	0.274	0.443	0.490

Notes: Estimation results for the model in equation 3, with parameters being allowed to be heterogeneous across climate zones. Column names indicate the dependent variable of each regression. Coefficients on precipitations are not reported. LLM, period, area×period and population quartile×period fixed effects included in all specifications. LLM-specific linear trends included in all specifications. Coefficients on entry, exit and relocation rates regressions might not add up to the coefficients in the first columns, because the residual term in equation 2 is not reported in the table. Standard errors clustered at the LLM level in parentheses * p<0.10, ** p<0.05, *** p<0.01

Table A.6: Firm demography regressions, climate zone heterogeneity in the Southern regions

	$\dot{A}$	e	x	r^{in}	r^{out}
ΔT_{p-1} × temperate	0.214***	0.137**	-0.105***	0.012	0.028
	[0.075]	[0.054]	[0.027]	[0.018]	[0.029]
ΔT_{p-2} × temperate	0.080	0.057	-0.055	-0.010	0.016
	[0.102]	[0.069]	[0.044]	[0.014]	[0.019]
ΔT_{p-3} × temperate	0.095	-0.001	-0.125***	-0.010	-0.000
	[0.094]	[0.066]	[0.044]	[0.015]	[0.023]
ΔT_{p-1} × Mediterranean	-0.016	-0.006	0.010	0.001	-0.004
	[0.016]	[0.012]	[0.010]	[0.004]	[0.003]
ΔT_{p-2} × Mediterranean	-0.044**	-0.024	0.013	0.001	0.003
	[0.021]	[0.017]	[0.014]	[0.003]	[0.004]
ΔT_{p-3} × Mediterranean	-0.068**	-0.045***	0.031**	-0.008	-0.019
	[0.030]	[0.016]	[0.013]	[0.009]	[0.019]
Obs.	1,405	1,405	1,405	1,405	1,405
R^2	0.405	0.633	0.693	0.268	0.229
Within R^2	0.042	0.114	0.034	0.009	0.008

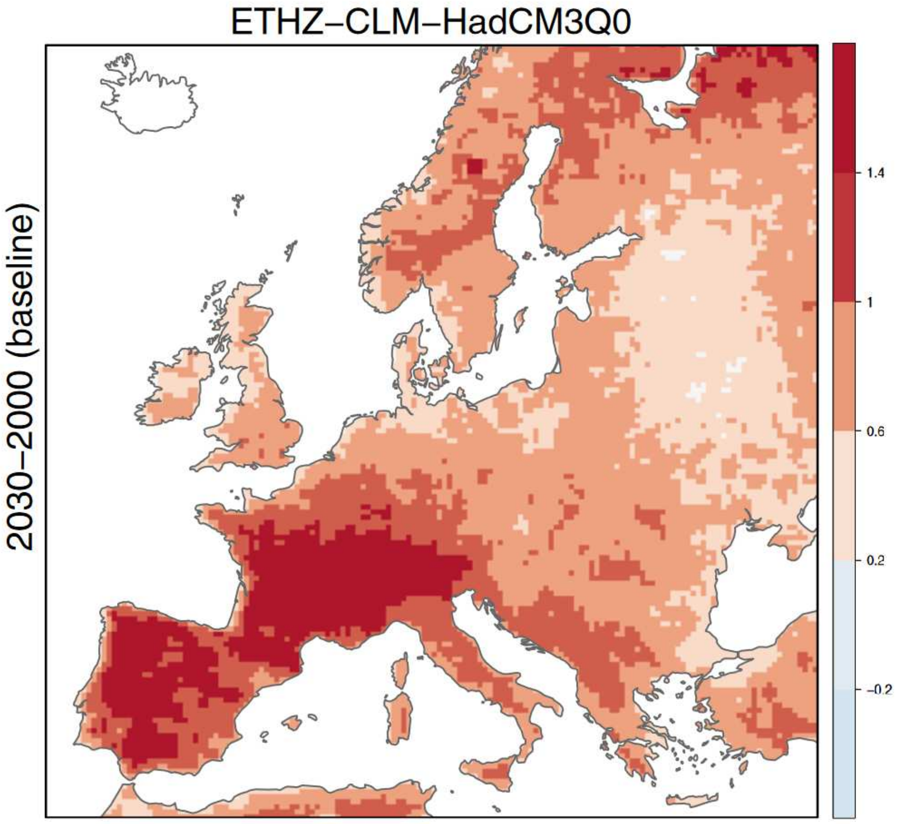
Notes: Estimation results for the model in equation 3, with parameters being allowed to be heterogeneous across climate zones. Column names indicate the dependent variable of each regression. Coefficients on precipitations are not reported. LLM, period, area×period and population quartile×period fixed effects included in all specifications. Coefficients on entry, exit and relocation rates regressions might not add up to the coefficients in the first columns, because the residual term in equation 2 is not reported in the table. Standard errors clustered at the LLM level in parentheses * p<0.10, ** p<0.05, *** p<0.01

B Additional figures

Figure B.1: Climate zones in Italy

Notes: Local labor markets have been classified into temperate and mediterranean climate zones according to the Istat classification (https://www.istat.it/it/archivio/224780).

Figure B.2: Difference of average maximum temperature during the period from April to September



Notes: The graph represents the difference in mean maximum temperature, averaged over the 30 synthetic years and for the period going from 1 April until 30 September, from 2000 to 2030, according to the model ETHZ-CLMHadCM3Q0. Adapted from Figure 6 of Duveiller et al. (2017) under the terms of the Creative Commons Attribution 4.0 International License (http://creativecommons.org/licenses/by/4.0/).