# Climate Change and Market Power

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**Abstract**

Using manufacturing sector firm-level data from Orbis for 2000–2020, we examine the effects of temperature shocks on industry market power across 12 European countries. Our analysis shows that temperature extremes reduce firm productivity, with significant heterogeneity across firms. Small firms experience larger productivity declines, leading to a reallocation of market share toward larger firms. As a result, temperature shocks increase industry concentration and aggregate markups. To quantify the welfare costs arising from both the productivity impact and the increase in market power, we develop an equilibrium model of heterogeneous firms with a variable elasticity of substitution that endogenizes markups. Based on the estimated marginal effects of temperature shocks on firm productivity and markups, the model suggests that the observed changes in the temperature distribution between 2000 and 2020—relative to a counterfactual scenario in which the temperature distribution remained constant—resulted in heterogeneous welfare effects across EU countries. Spain, which experienced the largest temperature increase over this period, incurred the largest welfare loss, equivalent to 0.44 percent of manufacturing sector GDP. A model that does not endogenize markups would miss over 40 percent of the welfare loss from extreme heat. Our findings underscore the importance of incorporating firm-level heterogeneity and market power into climate impact assessment.

**Keywords:** Climate Change, Market Power, Markups, Productivity

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# 1 Introduction

Rising temperatures and increasingly frequent heatwaves are among the most prominent and well-documented manifestations of climate change. Temperature shocks such as extreme heat have been shown to negatively affect a wide range of social and economic outcomes (Hsiang and Kopp, 2018; Carleton et al., 2022). Among the climate impact literature, an emerging line of work demonstrates that extreme heat reduces firm productivity (Zhang et al., 2018; Somanathan et al., 2021; Xie, 2024), but the effects of these productivity shocks on market power remain largely unexplored. This represents an important research gap, as shifts in market power can carry substantial welfare implications (De Loecker et al., 2021; Edmond et al., 2023).

Our study aims to fill this gap by examining the impact of temperature on market power and the resulting welfare implications, using an empirical analysis guided by a theoretical model. In doing so, we bridge two important strands of literature: one on the economic impacts of climate change, and the other on the causes and consequences of rising market power. Our empirical analysis draws on detailed firm-level balance sheet and geo-location data from ORBIS, combined with high-resolution weather information, covering 12 European countries from 2000 to 2020. We begin by analyzing how temperature extremes affect firm market shares and market concentration, metrics that can be readily constructed from firm revenue data. The results provide strong and robust evidence that extreme heat increases local market concentration by shifting market share from smaller to larger firms.

While informative and straightforward to analyze, changes in market concentration do not directly reveal the direction or magnitude of the impact of climate shocks on market power and social welfare (Syverson, 2019). To better interpret our empirical findings on concentration and more importantly to quantify their implications for market power and welfare, we develop a stylized heterogeneous firm model à la Melitz (2003), which links climate-induced productivity shocks to aggregate outcomes such as concentration and market power. Informed by insights from the literature and our empirical findings, the model explicitly incorporates the heterogeneous effects of climate shocks on firm productivity across different firm sizes. To capture how these heterogeneous impacts lead to market share reallocation and changes in firm markups—a robust measure of market power—we adopt a variable elasticity of substitution (VES) framework which allows for endogenous markups following Atkeson and Burstein (2008). In this setting, climate shocks not only reduce average firm productivity (TFP) but also amplify within-industry across-firm productivity dispersion, leading to a reallocation of market shares toward more productive, higher-markup firms. This reallocation, in turn, raises the aggregate markup and results in welfare losses. The overall welfare loss arises from two channels: the direct productivity loss and the increase in markups due to market share reallocation. While the constant elasticity of substitution (CES) framework commonly used in the literature can capture the former, our approach endogenizes markups and therefore incorporates the latter, an empirically significant channel.

The theoretical model illustrates that the overall welfare effects of climate shocks critically depend on changes in both firm productivity (specifically quantity-based TFP, or TFPQ) and markups. Guided by this insight, our empirical analysis is set to quantify how temperature extremes affect TFPQ and markups, i.e., the gradients of TFPQ and markups with respect to temperature extremes. As is common in the literature, our firm-level data include information on revenue but not product quantity, which prevents the direct estimation of TFPQ and markups. Our empirical approach relies on the fact that gradient estimates can still be obtained, provided that TFPQ and markups are recoverable up to a normalizing constant.

Our empirical analysis proceeds as follows. We first estimate revenue-based TFP (TFPR) from the production function estimation following the approach of Ackerberg et al. (2015), and then estimate revenue-based markups based on the production function estimation following De Loecker and Warzynski (2012).[1] Although these revenue-based markup estimates may not be informative of the level of true markups (Bond et al., 2021), they can still be informative of the true dispersion (De Ridder et al., 2022). In our baseline model, which features a Cobb-Douglas production function and heterogeneous demand elasticities, revenue-based markups equal true markups scaled by an industry-specific constant. As a result, the semi-elasticity of true markups with respect to temperature extremes can be consistently estimated using revenue-based markups in a semi-log regression with industry fixed effects.

A similar challenge exists for the gradient estimate of TFPQ: we cannot directly estimate the impact of temperature extremes on TFPQ based on the estimated TFPR as that would capture the impact not only on TFPQ but also on product prices. Instead, we recover the dispersion of TFPQ based on a key theoretical result under the VES framework: the market share of a firm in a given year is a function of its markup and TFPQ normalized by a market-year level scale factor.[2] Therefore, with observed market shares and estimated revenue-based markups, we can recover relative TFPQ, which is the true TFPQ up to a market-year level constant. The semi-elasticity of relative TFPQ with respect to temperature extremes can then be estimated based on the recovered relative TFPQ in a semi-log regression with market by year fixed effects.

Our empirical analysis shows that extreme heat reduces firm productivity while increasing the average markup. Specifically, a day with maximum temperature of 100°F would decrease the average firm-level TFPQ by 0.0128 percent and increase the average markup by 0.0046 percent compared to a day within the moderate range between 40°F and 80°F. The estimated effects on productivity are closely aligned with findings from the literature using similar model specifications (Nath, 2025). The effects are heterogeneous across firms: small firms experience declines in both productivity and markup, whereas large firms see increases in both. The increase in the aggregate markup could be driven by both the reallocation of market share from small to large (or from low- to high-markup) firms and rising markups among larger firms.

Using the estimated marginal effects of temperature shocks on productivity and markups, we conduct a quantification exercise to address two key questions. First, what is the welfare loss resulting from the predicted productivity changes and market share reallocation caused by the observed changes in the temperature distribution between 2000 and 2020? Second, how does assuming a standard CES demand framework, which

[1] This approach relies on the fact that markups can be written as the ratio of the output elasticity of a variable input (such as labor) over the input's revenue share. The output elasticity can be obtained after the estimation of the production function. With revenue instead of quantity data, the estimated elasticity may not be equal to the output elasticity, thus introducing measurement error in markups.

[2] A market is defined as a country by NACE-4 industry in our baseline.

does not account for observed markup heterogeneity affect the welfare measurement?

Two model parameters are central to answering these questions— the within-sector elasticity of substitution and across-sector elasticity of substitution. These parameters govern the degree of reallocation and changes in markup dispersion in response to heat-induced productivity shocks. Specifically, they determine how changes in relative prices translate into market share movement, as well as how sensitive markups adjustments are to market share changes. We draw on the literature that estimates the two elasticity parameters (De Loecker et al., 2021; Edmond et al., 2023) for our baseline analysis. Additionally, we calibrate these parameters using a simulated method of moments (SMM) approach, as described in Appendix E. The calibrated values are consistent with those reported in the literature.

For each firm, we predict changes in TFPQ based on the response to shifts in the temperature distribution between 2000 and 2020, using our estimates from Equation (4). The resulting counterfactual TFPQ in 2020—reflecting the impact of temperature changes—is then used to solve for the model's counterfactual equilibrium market shares and markups at the firm level. We aggregate these results to compute sector- and country-level changes in aggregate TFPQ and markups, and use them to simulate welfare losses according to Equation (17).

Our quantification exercise shows significant cross-country heterogeneity in welfare effects under the observed temperature changes from 2000 to 2020. In Spain, which experienced the largest temperature increase in terms of annual cooling degree days, the welfare loss is equivalent to 0.44 percent of manufacturing sector GDP, whereas in Hungary, which experienced a decrease in cooling degree days, welfare increases by about 0.38 percent. More importantly, if we ignore the role of reallocation and endogenous markups, we can misstate the welfare cost of climate change. Such misstatement arises because climate-induced market power leads to additional misallocation of inputs across firms and consequently affects labor demand and wages through quantity distortions. A standard CES approach overlooks these key reallocation channels and underestimates the welfare loss in Spain by about 42 percent.

To gauge the relative magnitude of our welfare loss estimates, we compare our numbers to the related literature on estimating the GDP loss of climate change due to increases in temperature. For studies estimating GDP impact of extreme temperature in Europe, IPCC (2014) and IPCC (2022) document GDP losses in Europe on the order of 0.1–0.7% under roughly 0.5°C of warming, with Southern Europe more negatively affected than Northern and Eastern Europe. For the US, Hsiang et al. (2017) finds that each additional 0.5°C reduces aggregate GDP by about 0.6%. While many of these studies focus on multiple impacts – for example, agriculture, coastal flooding, and health – our welfare losses stem from a single channel : *heat-driven productivity shocks*, and focus exclusively on the manufacturing sector. Our welfare loss estimates for Spain – 0.44 percent under an increase of 1.08 °C in the mean of daily maximum temperature – thus appears substantial when viewed alongside these broader estimates. More importantly, markups play a significant role in the measurement of our welfare loss. A comparison of welfare loss estimated under VES versus CES demand highlights the role of markups in the measurement of climate damage – CES could underestimate the welfare loss of heat-driven productivity loss by over 40 percent, as it fails to take into account the endogeneity of markups and the effect of the consequent changes in misallocation on aggregate productivity.

In sum, our findings emphasize the importance of firm heterogeneity, market structure dynamics, and endogenous market power for the welfare cost of climate change. By showing that extreme temperature shocks can exacerbate market power and reduce welfare, our study points to potentially important yet underappreciated economic consequences of climate change, as well as another factor contributing to the rise of market power.

Our paper contributes to three strands of literature. The first is the emerging literature that documents that temperature extremes exhibit a negative effect on firm-level productivity and that the effect may be heterogeneous across firms due to differences in their ability to adapt (Bustos et al., 2016; Zhang et al., 2018; Somanathan et al., 2021; Ponticelli et al., 2023; Xie, 2024; Bilal and Känzig, 2024; Shi and Zhang, 2025).[3] We contribute to this literature by examining how heterogeneous productivity impacts lead to changes in market structure and aggregate welfare. In particular, we focus on the effects of temperature extremes on market power, an important but underexplored dimension in the climate economics literature. Among these studies, our paper is perhaps most closely related to Ponticelli et al. (2023), which documents rising local market concentration in U.S. counties with larger temperature shocks. In contrast to their focus on market concentration, our analysis examines markups, a more direct measure of market power, and quantifies the associated welfare costs. This welfare-based approach provides a more informative assessment of the importance of market power as a channel through which climate shocks affect the overall economy.

Second, our paper adds to the literature on understanding the causes and consequences of changing market power over time and across space (De Loecker et al., 2020; Rossi-Hansberg et al., 2020). The literature identifies several market and regulatory forces behind the rise of market power, and develops framework to quantify the economic and welfare impacts from market power change.[4] Two papers are particularly relevant: De Loecker et al. (2021) build an endogenous markup model to quantify how changes in market structure and technology can lead to movements in market power, labor share, and job reallocation. Edmond et al. (2023) develop a model of endogenous markup and quantifies the welfare costs of markups by comparing them against a markup-free efficient benchmark. Our study contributes to this literature by identifying climate shocks as a driver for changing market power, and quantifying the resulting welfare implications in a framework of endogenous markups.

Third, this study fits into the important literature on measuring the economic costs of climate change (i.e., the social cost of carbon) using the Integrated Assessment Models (IAMs) (Nordhaus, 1992; Hope et al., 1993; Tol, 1995). We contribute to this strand of literature by examining the role of demand assumption on the measurement of the cost of climate change. Existing IAM literature and climate-macro literature (Nath, 2025;

[3]For instance, Somanathan et al. (2021) and Zivin and Kahn (2016) show that larger firms are more inclined to invest in climate-control technologies like air conditioning, while Ponticelli et al. (2023) documents that smaller firms incur comparatively greater productivity losses and that larger manufacturers mitigate local shocks by operating multiple plants.

[4]These underlying forces include the emergence of superstar firms (Autor et al., 2020), globalization (Van Reenen, 2018), antitrust policy (Van Reenen, 2018), changes in product substitutability (Syverson, 2004), search cost (Goldmanis et al., 2010), entry costs (Asplund and Nocke, 2006), and technological change (De Loecker et al., 2021).

Cruz and Rossi-Hansberg, 2021; Rudik et al., 2022) adopt CES demand elasticity assumption and thus abstract away any welfare effect of climate shocks that can derive from movements of profit margins and associated misallocation. Following the insights of the trade literature exploring the role of markups in quantifying welfare implication of trade (Arkolakis and Morlacco, 2017; Arkolakis et al., 2019), our paper adopts a *variable-elasticity* (VES) approach to show that climate-driven productivity losses intensify reallocation and markup dispersion, thus resulting in additional misallocation and higher welfare costs than CES models would predict. By applying a VES framework to extreme heat shocks, we highlight the importance of relaxing demand assumption and allowing for endogenous markup on the measurement of economic cost of climate change.

The remainder of the paper is structured as follows. Section 2 describes our data sources and presents descriptive evidence on market concentration. In Section 3, we develop a stylized framework that connect temperature shock to changes in concentration and markups, highlighting the role of *variable demand elasticity* in driving reallocation and market power dynamics. Section 4 introduces the estimation of firm-level markups and productivity, offering additional empirical evidence on how extreme temperature affects both markups and productivity at the firm and market levels. Section 5 then outlines our model calibration and quantifies the welfare implications of the observed productivity shock, underscoring the importance of accounting for endogenous markups by comparing welfare outcomes under CES and VES assumptions. Section 6 concludes.

# 2 Data and Descriptive Evidence on Concentration

In this section, we first provide details on our data sources. We then show reduced-form evidence on how extreme temperature affects market concentration and leads to market share reallocation.

## 2.1 Data Sources

### 2.1.1 Firm Data

To measure firm-level economic outcomes, we use the Orbis Database provided by Bureau van Dijk.[5] It is compiled from firm-level financial statements and balance sheets collected by different national information providers. We use data on annual revenue, labor costs, capital, the number of employees, and materials costs.[6] We also use firm-level geographical information, such as address, longitude, and latitude, to match the Orbis data with the weather data.

We process the data using the the cleaning and imputation procedures in Kalemli-Ozcan et al. (2015), Bajgar et al. (2020), and Gal (2013), but we use more lenient data filtering and retain firm observations with

[5] Orbis has been widely used in the literature studying firm-level performance (Bajgar et al., 2019a,b; De Haas and Poelhekke, 2019; Autor et al., 2020).

[6] Within Orbis, we measure output using the operating revenue. Labor costs are measured by the total costs of employees including wages and salaries plus employer social-security/pension charges and other staff benefits. Capital is measured by the book value of tangible fixed assets, including property, plant & equipment. Material costs capture the consumption or purchases of raw materials, goods and energy.

fewer employees. Because our analysis focuses on the within-firm response to temperature shocks and the heterogeneity of that response across firm sizes, maximizing coverage is essential for capturing as much cross-firm variation as possible. See Appendix A for more details on the cleaning and imputation procedure.

### 2.1.2 Weather Data

**Temperature** Our climate variable of interest is *daily maximum temperature*.[7] The daily maximum temperature data comes from *NOAA Physical Science Laboratory*, which provides global gridded data with a 0.5° × 0.5° resolution (around 55 km at mid-latitudes). We assign daily maximum temperature to each firm based on its recorded longitude and latitude.[8]

We transform daily temperature into cooling degree days (CDD) above 80°F and heating degree days (HDD) below 40°F. CDD in some day of year $d$ in year $t$ is given by $CDD_{dt} = 1(T_{dt} \leq 40) \times (40 - T_{dt})$ while heating degree days are given by $HDD_{dt} = 1(T_{dt} \leq 40) \times (40 - T_{dt})$, where $T_{dt}$ is daily maximum temperature on day $d$ of year $t$. To match the temporal resolution of the Orbis data we aggregate these to the annual level by summing across days of the year so that $AHDD_t = \sum_{d=1}^{365} HDD_{dt}$ and $ACDD_t = \sum_{d=1}^{365} CDD_{dt}$. In Section 2.2 we explain how using ACDDs and AHDDs as right-hand-side variables allows us to interpret our estimates as the slopes of a piecewise linear spline similar to the approach in Nath (2025).

ACDDs and AHDDs essentially sum up temperatures above 80°F and below 40°F for the year, creating a measure of total exposure to extreme heat and cold. We focus on extreme temperature because it is the dominant weather hazard for the European countries in our sample. Europe has warmed almost twice as fast as the global average, and heatwaves have become more common and intense (IPCC, 2021). Echoing this trend, the *European Climate Risk Assessment 2024* ranks heat-stress as the climate risk at "critical" levels (European Environment Agency, 2024). In robustness checks we use temperature bins as an alternative measure of extreme temperature exposure. The temperature bins are constructed by grouping daily maximum temperatures into eight 10°F intervals: <30°F, 30–40°F, 40–50°F, 50–60°F, 60–70°F, 70–80°F, 80–90°F, and ≥90°F. We then count the number of days in a year during which an firm experiences a maximum temperature within each bin, with the total across all bins summing to 365.

**Precipitation** The precipitation data are from *NOAA Physical Science Laboratory*. It is a global gridded data product with a 0.5° × 0.5° resolution. We extract precipitation at the location of each firm based on its geographic information, and average daily precipitation to yearly level.

[7] We use daily maximum temperature because it captures daytime temperatures that workers face while on the job, and therefore it better reflects the true exposure compared to other temperature measures such as daily averages (Graff Zivin and Neidell, 2014; Somanathan et al., 2021; Gagliardi et al., 2024; Lai et al., 2023). We discuss how our mechanisms could extend to other climate shocks in Section 6.

[8] For firms in our sample that do not have longitude and latitude information, we use the average of the daily maximum temperature within the zipcode where the firm is located.

### 2.1.3 Final Sample

Our final sample consists of manufacturing firms in 12 European countries from 2000 to 2020. These countries have the most complete firm-level Orbis data, as well as the geographic information needed to match the climate variables.[9]

Our sectoral focus is the manufacturing sector, which the prior literature has found is impacted by extreme temperatures (Graff Zivin and Neidell, 2014; Zhang et al., 2018; Nath, 2025). Under the Statistical Classification of Economic Activities in the European Community (NACE), sectors are classified in four levels. The manufacturing sector corresponds to the Level 1 sector, labeled C. It comprises 23 Level 2 industries, hereafter referred to as NACE2 industries; and 302 Level 4 industries, hereafter referred to as NACE4 industries.[10] Throughout the paper, we use *sector* to refer to the top level of the NACE classification, and *NACE2* and *NACE4* to refer to the Level 2 and Level 4 NACE industry classification.

After applying the data cleaning procedure outlined in Appendix A, our full sample consists of 5.04 million firm-year observations. The sample is unbalanced, with data coverage varying across countries and years, as shown in panel (a) of Figure F1. We use the full sample to construct measures of market concentration for each market-year and provide descriptive evidence on the effects of temperature shocks on market concentration.

In some analyses we use a balanced sample restricted to firms that entered the dataset before 2000 and remained throughout the entire sample period. This balanced sample, illustrated in panel (b) of Figure F1, consists of 1.07 million observations, accounting for approximately 21% of the full sample. We use the balanced sample to examine the impact of temperature changes on firm-level productivity and markups. This approach allows us to better isolate effects on the intensive margin—how existing firms adjust their performance—rather than confounding these effects with changes on the extensive margin, such as firm entry and exit, which are not reliably captured in the Orbis database. Our firm-level results remain robust to using the full sample.

Table 1 reports the summary statistics of the data used for analysis. The first panel presents summaries of our climate data. The average firm is exposed to about 400 cooling degree days and only 160 heating degree days, but with substantial variation as reflected in the standard deviation and the range between the minimum and maximum values. The bottom panel presents summaries of firm-level outcomes, some of which are computed and not directly from the data. The panel shows that there is substantial variation in TFPQ and TFPR across firms. On average, firms have a 1% market share and a 13% markup, but some may be much larger.

[9] These countries are: Belgium, Denmark, Germany, Estonia, Spain, Finland, France, Croatia, Hungary, Italy, Poland, Slovakia.

[10] NACE is a hierarchically structured four-digit code system used in the European Union to classify industries, similar to NAICS in North America: https://en.wikipedia.org/wiki/Statistical_Classification_of_Economic_Activities_in_the_European_Community. Within the manufacturing sector, NACE2 industries include activities such as the manufacturing of food products, beverages, and textiles. NACE4 are more granular classifications, such as processing and preserving of meat, processing and preserving of potatoes, manufacturing of ice cream, and manufacturing of carpets and rugs.

Table 1: Summary Statistics

| Variable | Mean | Std. Dev. | Min. | Max. | N |
|---|---|---|---|---|---|
| **Climate variables** (Firm $\times$ Year) | | | | | |
| ACDD | 417 | 370 | 0 | 6035 | 5043223 |
| AHDD | 159 | 332 | 0 | 4528 | 5043223 |
| # days [<30F] | 4.9 | 13 | 0 | 157 | 5043223 |
| # days [30-40F] | 23 | 25 | 0 | 161 | 5043223 |
| # days [40-50F] | 50 | 25 | 0 | 135 | 5043223 |
| # days [50-60F] | 77 | 21 | 0 | 195 | 5043223 |
| # days [60-70F] | 78 | 19 | 1 | 194 | 5043223 |
| # days [70-80F] | 70 | 18 | 0 | 285 | 5043223 |
| # days [80-90F] | 49 | 26 | 0 | 135 | 5043223 |
| # days [>=90F] | 14 | 18 | 0 | 225 | 5043223 |
| Precipitation | 1.9 | 0.79 | 0.014 | 5.8 | 5043223 |
| **Market outcomes** (Country$\times$ NACE4 $\times$ year) | | | | | |
| HHI | 3450 | 3086 | 7.46 | 10000 | 51041 |
| CR4 | 0.73 | 0.28 | 0.02 | 1.00 | 51041 |
| CR8 | 0.82 | 0.24 | 0.03 | 1.00 | 51041 |
| **Firm outcomes** (Firm $\times$ Year) | | | | | |
| log(TFPR) | 1.6 | 1.26 | -9.68 | 12.7 | 5043223 |
| log(TFPQ) | -0.096 | 0.42 | -3.09 | 4.07 | 5043223 |
| Markup | 1.19 | 1.45 | 0.491 | 19.4 | 5043223 |
| Market share | 0.0081 | 0.044 | 1.27e-10 | 1.00 | 5043223 |

*Notes:* This table reports the summary statistics of climate variables, establishment outcomes, and market outcomes. A market is defined as a combination of country-NACE4 industry cell. ACDD represents annual cooling degree days above 80°F, and AHDD represents annual heating degree days below 40°F.

## 2.2 Market Concentration

In our main analysis we define a "market" at a relatively narrow level, country-by-NACE4 industry. This approach aligns with our theoretical framework in Section 3, where we model an oligopolistic structure of finite firms confronting local shocks. Our results remain robust when markets are defined at a broader level—by country and NACE2 industry.

We measure market concentration using two common, sales-based metrics: the *Concentration Ratio* (CR) and the *Herfindahl–Hirschman Index* (HHI). The $CR_N$ is defined as the share of total sales captured by the top $N$ firms in a market-year, while the HHI is the sum of squared market shares of all firms in that market. Both measures capture the dominance of larger firms and the degree of overall concentration. However, we acknowledge the caveat that Orbis data does not provide universal coverage of all firms and tends to be biased toward larger, older, and more productive firms (Kalemli-Ozcan et al., 2015; Bajgar et al., 2020). As a result, the market concentration measures may overstate the true level of concentration.

When analyzing market-level outcomes, we aggregate firm-level temperature and precipitation data to the market-level by calculating weighted averages, using each firm's market share as the weight.

The mid panel of Table 1 shows summaries of market-level outcomes. In the average market, the top 4 or 8 firms hold three-quarters or greater of the market share, again with significant heterogeneity across markets.

#### 2.2.1 Descriptive Evidence on Market Concentration

In this section, we present descriptive, reduced-form evidence for how extreme temperature affects market concentration. We examine two underlying margins of adjustment that lead to changing concentration: market share reallocation and firm exit.

**Market Concentration** Let $j$ index markets and $t$ index years. $d$ indexes day-of-year for the weather variables that will be aggregated to the annual level. We use the following specification to estimate the effect of extreme temperature on market concentration:

$$y_{jt} = F(T_{jdt};\boldsymbol{\beta}) + G(R_{jdt};\iota) + \delta_j + \xi_t + \varepsilon_{jt}, \tag{1}$$

where the unit of observation is a market-year (i.e., country-NACE4-year). The dependent variable will be either log(HHI) and log(CR4). $T_{jt}$ and $R_{jt}$ are the temperature exposure and precipitation in market $j$ and year $t$. The response function $F(\cdot)$ captures the relationship between the outcome $y_{jt}$ and our measure of temperature in year $t$, which we formally defined below. $G(\cdot)$ is a second-order polynomial of the average daily precipitation in order to allow for non-linear effects. We include market fixed effects ($\delta_j$) to capture the baseline differences across industries and locations and year fixed effects ($\xi_t$) to capture common macroeconomic shocks. Standard errors are clustered two ways at the country-year level and market (i.e., country-industry) level to account for spatial correlation across industries within a country-year and serial correlation over time within a market.

The recent literature finds that the marginal effect of temperature is negligible in the moderate temperature range, with impacts primarily deriving from extreme heat or extreme cold exposure (Lai et al., 2023; Ponticelli et al., 2023; Carleton et al., 2022). We follow Nath (2025) and adopt a piecewise linear spline in daily maximum temperature $T_{jdt}$:[11]

$$f(T_{jdt}) = \beta_1 \underbrace{\mathbf{1}(T_{jdt} \leq 40)(40 - T_{jdt})}_{HDD} \quad + \quad \beta_2 \underbrace{\mathbf{1}(T_{jdt} \geq 80)(T_{jdt} - 80)}_{CDD}, \tag{2}$$

where moderate degree days between 40°F and 80 °F are omitted. We can then sum the daily splines over all

[11] In the literature, three different approaches have been recently used to capture the annual effects of daily temperature: temperature bins (e.g. Ponticelli et al., 2023; Zhang et al., 2018), global polynomials (e.g. Carleton et al., 2022; Addoum et al., 2023), and splines (e.g. Nath, 2025). Each approach has different benefits and limitations so present results using temperature bins and global polynomials as robustness checks in the Appendix.

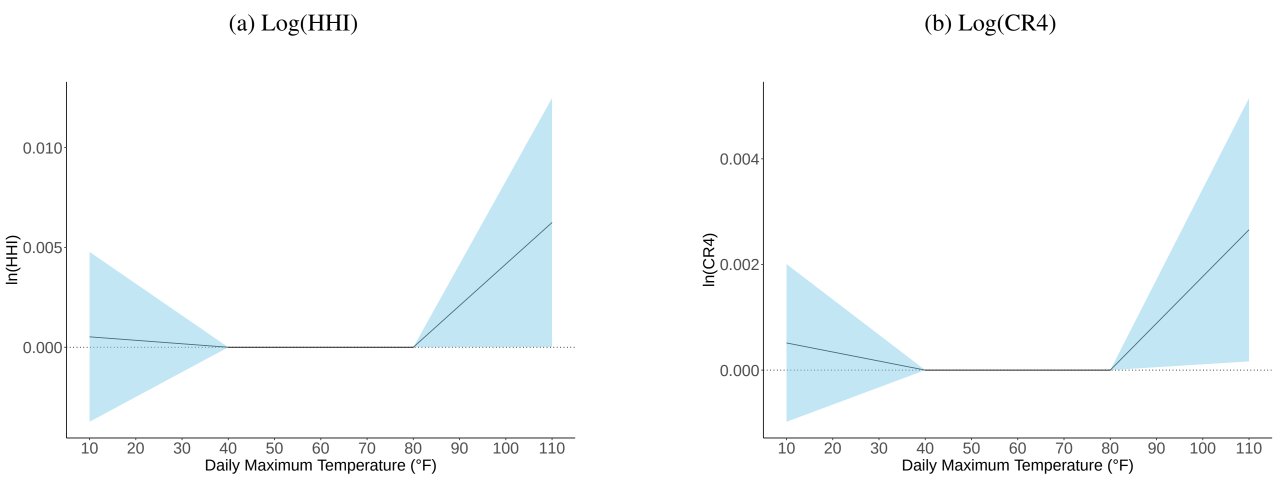
days in a year to obtain the annual temperature response function $F(T_{jdt};\boldsymbol{\beta})$:

$$F(T_{jdt};\boldsymbol{\beta}) = \sum_{d=1}^{365} \left\{\beta_1(40 - T_{jdt})\mathbf{1}(T_{jdt} < 40) + \beta_2(T_{jdt} - 80)\mathbf{1}(T_{jdt} > 80)\right\} = \beta_1 AHDD_{jt} + \beta_2 ACDD_{jt}, \quad (3)$$

where AHDD and ACDD denote the annual heating degree days (below 40°F) and cooling degree days (above 80°F). $\beta_1$ and $\beta_2$ correspond to the slopes on the two outer linear components of the piecewise spline. Given some daily maximum temperature $T_{jdt}$, the effect of a day of the year at that temperature relative to the omitted 40°F - 80°F range is $(40 - T_{jdt}) \times \beta_1$ if $T_{djt} < 40$ and $(T_{jdt} - 80) \times \beta_2$ if $T_{jdt} > 80$.

Figure 1 plots the estimated effects of daily maximum temperature on HHI and CR4. Additional days in a year above 80°F are associated with greater market concentration in that year, but additional degree days below 40°F have a small and imprecise relationship with market concentration. Table G2 reports regression results, which suggest that a day with maximum temperature of 100°F would increase HHI by 0.42% and increase CR4 by 0.18% relative to a day in the moderate range 40°F to 80°F. This result is consistent with Ponticelli et al. (2023), which, in the context of the United States, finds that higher temperatures can lead to an increase in local industrial concentration.

Figure 1: Effect of Temperature Change on Market Concentration




*Notes*: This figure reports the effect of the temperature change on market concentration. The coefficients are estimated from Equation (1). The market is defined at the country-NACE4 industry level. The dependent variables are log(HHI) and log(CR4). The blue bands show the 95% confidence interval. Standard errors are two-way clustered at the country-year and market levels.

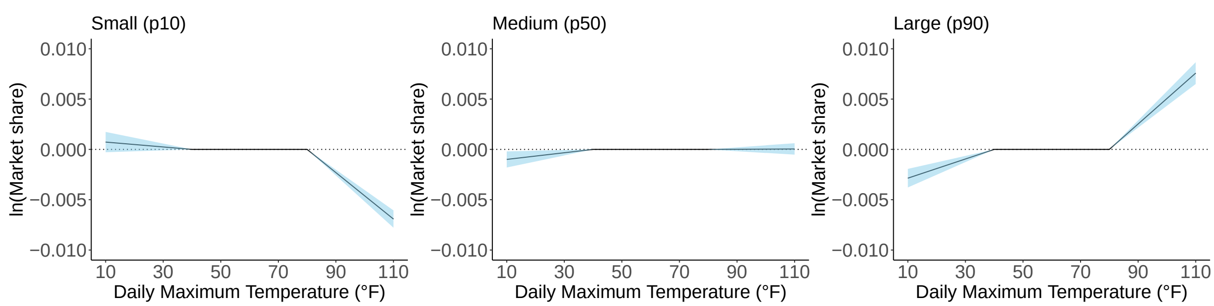
**Market Share Reallocation** Our results above indicate that extreme temperature increases market concentration. Next we provide supporting, firm-level evidence that extreme temperature shocks result in a reallocation of market share from small firms to large ones. To do so, we use the following specification:

$$s_{ijt} = F(T_{ijdt};\boldsymbol{\beta}) + F(T_{ijdt};\boldsymbol{\beta}) \times \ln(\overline{Rev}_i) + G(R_{ijdt};\boldsymbol{\iota}) + G(R_{jdt};\boldsymbol{\iota}) \times \ln(\overline{Rev}_i) + \alpha_i + \delta_{jt} + \varepsilon_{ijt}, \quad (4)$$

where $i$ indexes firms and the daily weather variables are now measured at the firm-level. $s_{ijt}$ is the logarithm of a firm $i$'s market share, calculated as the ratio of the value added of firm $i$ in year $t$ to the total value added of all firms in market $j$ in the same year. To capture heterogeneous effects, we interact the response function $F(T_{ijdt})$ with the logarithm of the average total revenue for each firm over the sample period, $\ln(\overline{Rev_i})$. The functions $F$ and $G$ are the same as the previous section. We include firm fixed effects ($\alpha_i$) to absorb time-invariant unobserved firm heterogeneity. To more flexibly control for time-varying shocks, we include market-year fixed effects $\delta_{jt}$. Standard errors are two-way clustered at the firm and market-year levels, to allow for serial correlation within a firm across years and spatial correlation across firms within a market-year.

Figure 2 presents the predicted changes in the logarithm of market share in response to the daily maximum temperature, based on estimates from Equation (4). The panels capture the effect of temperature on firms of three different sizes—small, medium, and large—corresponding to the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. The results show that daily maximum temperatures above 80°F tend to reduce the market share of small firms while increasing the market share of large firms, indicating a reallocation of market share from smaller to larger firms, consistent with our evidence for increasing concentration in Figure 1.

Figure 2: Heterogeneous Effects of Temperature Change on Market Share




*Notes*: This figure reports the heterogeneous effects of temperature change on firm market share by firm size. Coefficients are estimated from Equation (4). The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the country-year and market levels. The blue bands show the 95% confidence interval.

**Firm Exits** In addition to examining market share reallocation, we analyze the impact of temperature on firm exits using Equation (4). We construct a dummy variable for firm exit, defined as a firm not appearing in the dataset after a given year.[12] Our results, presented in Figure F2, show that extreme heat increases the exit rate for small firms but decreases it for large firms. However, given that data coverage in Orbis varies over time and across countries, the observed exits may not fully reflect actual firm closures. As such, we interpret these results with caution.

[12] A challenge with using Orbis data for studying entry and exist is that it does not record the precise year of entry or exit (Bajgar et al., 2020). Some firm "entries" may merely reflect improvements in data coverage, but spurious firm exits are unlikely, making the exit metric more reliable. Accordingly, our empirical analysis focuses on firm-level exit as the main proxy for industry turnover.

# 3 A Model of Climate-Induced Market Power

Our reduced form evidence shows that extreme heat increases local market concentration and reallocates market share from small to large firms. We next develop an equilibrium model of heterogeneous firms consistent with this evidence to examine how extreme temperature affects market power and social welfare.

## 3.1 Supply Side: Heterogeneous Firms and Climate Shocks

We consider an economy with heterogeneous firms à la Melitz (2003). Firm $i$ produces a unique variety under a constant returns to scale technology and incurs a fix cost $f$ to operate. Firm productivity is drawn from a Pareto distribution with shape parameter $\xi$. Firm $i$'s baseline productivity is denoted as $\varphi_i$. If it hires $l_i$ units of labor at wage $W = 1$, it produces $y_i = \varphi_i l_i$.

Extreme temperature $T$ affects firm productivity, reducing a firm's baseline productivity $\varphi_i$ to an "effective" level $\tilde{\varphi}_i(T)$. We model this via a *temperature-induced productivity shock factor* $\gamma_i(T)$:

$$\tilde{\varphi}_i(T) = \frac{\varphi_i}{\gamma_i(T)}, \tag{5}$$

where $\gamma_i(T)$ captures the adverse impact of temperature. We assume $\gamma_i(T^*) = 1$ at the ideal temperature $T^*$ and $\frac{\partial \gamma_i(T)}{\partial T} > 0$ for $T > T^*$. Thus, hotter-than-ideal conditions increase $\gamma_i(T)$, reducing effective productivity.

Marginal cost, $MC_i$, is then the inverse of effective productivity:

$$MC_i = \frac{1}{\tilde{\varphi}_i(T)} = \gamma_i(T)\frac{1}{\varphi_i}. \tag{6}$$

Consistent with our reduced-form findings in the empirical section below, we allow for firm-level heterogeneity in temperature responsiveness. More specifically, smaller firms (i.e., those with lower $\varphi_i$) experience disproportionately larger cost increases under extreme heat $\tilde{T} > T^*$ and thus tend to lose market share. [13]

Firm $i$'s per-period profit is

$$\pi_i(\varphi_i, T) = P_i y_i - \frac{\gamma_i(T)}{\varphi_i} y_i - f,$$

where $P_i$ is the price. Firms are assumed to engage in Cournot competition, and the markup is

$$\mu_i \equiv \frac{P_i}{MC_i} = \frac{\varepsilon_i}{\varepsilon_i - 1},$$

where $\varepsilon_i$ is firm $i$'s demand elasticity, which we derive below.

[13] The literature examines how climate change affects firms differently, with heterogeneity arising from adaptation costs, firm size, and managerial capabilities. Traore and Foltz (2018) develops a model of climate adaptation, predicting that more productive firms are more likely to invest in climate-control technology, thereby reducing their vulnerability to heat shocks. Ponticelli et al. (2023) attributes the heterogeneous effects to differences in energy costs, managerial skills, and access to finance, showing that small firms suffer disproportionately from rising temperatures, while large firms are better equipped to adapt. Somanathan et al. (2021) and Zivin and Kahn (2016) provide empirical evidence that air conditioning can significantly mitigate heat-related productivity losses in manufacturing, but larger firms are more likely to adopt such technology. In addition, differences in labor intensity of production across firms can also lead to heterogeneous productivity response when shocks are factor-biased.

### 3.2 Demand Side

We use two types of demand specifications which have different implications for how markups respond to climate shocks:

- **Constant Elasticity (CES)**: $\varepsilon_i = \sigma$, yielding a constant markup that does not respond to reallocation nor temperature shocks,
- **Variable Elasticity (VES)**: $\varepsilon_i = \varepsilon(s_i)$, allowing markups to endogenously vary with firm market shares and temperature shocks.

#### 3.2.1 Demand under Constant Elasticity (CES)

There is a continuum of firms indexed by $i \in [0,1]$, operating under monopolistic competition. Under CES demand with elasticity of substitution $\sigma$, each firm faces the residual demand

$$y_i = E\left(\frac{P_i}{P}\right)^{-\sigma},$$

where $E$ is aggregate expenditure and $P$ is the aggregate price index. In this setting, the demand elasticity is constant across firms, $\varepsilon_i = \sigma$, implying a *constant* markup:

$$\mu_i = \frac{\sigma}{\sigma - 1}, \quad \forall i. \tag{7}$$

Although CES demand admits changing firm market shares caused by heterogeneous effects of temperature on firm productivity, it cannot generate heterogeneous impacts on markups. This limitation becomes critical when analyzing how climate shocks affect market power.

#### 3.2.2 Demand under Variable Elasticity (VES)

To capture the heterogeneous impacts of climate shocks on markups, we relax the CES assumption in favor of the VES demand structure following Atkeson and Burstein (2008).[14] Consider a continuum of sectors $j \in [0,1]$, each containing a finite number of $n_j$ firms, where some firm $i$ in sector $j$ is indexed by $ij$. Across sectors, the demand elasticity is $\eta$, while within a sector it is $\rho$, with $\rho > \eta$. The sector-level and firm-level composites are:

$$Y = \left[\int_0^1 y_j^{\frac{\eta-1}{\eta}}\, dj\right]^{\frac{\eta}{\eta-1}}, \quad y_j = \left[\sum_{i=1}^{n_j} y_{ij}^{\frac{\rho-1}{\rho}}\right]^{\frac{\rho}{\rho-1}}. \tag{8}$$

Under Cournot competition, firm $ij$'s choice affects the sector-level price index $P_j$ due to the finite nature of firms in the sector, yielding oligopolistic competition.

[14]The core qualitative demand feature we leverage — that a firm's demand elasticity falls with its market share — also arises in Kimball or Addilog demand which are commonly adopted in models of endogenous markups (Edmond et al., 2023; Arkolakis and Morlacco, 2017).

In this setting, the demand elasticity varies across firms, leading to firm-specific markups:

$$\mu_{ij} = \frac{\varepsilon_{ij}}{\varepsilon_{ij}-1},$$

where

$$\varepsilon_{ij} \equiv \varepsilon(s_{ij}) = \left[\frac{1}{\rho}(1-s_{ij}) + \frac{1}{\eta}s_{ij}\right]^{-1}. \tag{9}$$

Equation (9) shows that firm demand elasticity is decreasing in market shares – larger firms face more inelastic demand. The market share $s_{ij}$ is determined by the firm's relative price:

$$s_{ij} = \frac{(P_{ij})^{1-\rho}}{\sum_{k=1}^{n_j}(P_{kj})^{1-\rho}} = \left(\frac{P_{ij}}{P_j}\right)^{1-\rho}. \tag{10}$$

In the VES setup, it is the *dispersion* of the productivity distribution—rather than its level—that determines the equilibrium distribution of market shares and markups. Firms with higher productivity $\varphi_{ij}$ *relative to other firms in the same market* capture larger shares $s_{ij}$ and charge higher markups $\mu_{ij}$.[15] Unlike CES (constant markups), markups vary with shocks that *alter dispersion*: a mean-preserving spread in productivity increases the dispersion, raises concentration, and increases aggregate markup.

### 3.3 Model Predictions

We outline some qualitative predictions on how climate change affects market outcomes based on the model. Take temperature shocks as an example, we assume extreme temperature exerts differential productivity damages across firms, captured by the *temperature-induced productivity shock* $\gamma_i(T)$ as shown in Equation (5). Our predictions and simulations focus on the market share reallocation but abstract away from entry and exit in the VES environment.[16]

**Qualitative Predictions** Under our VES setting, equilibrium outcomes do not admit a closed-form solution. Nonetheless, the model delivers three broad qualitative predictions of the impacts of *temperature-induced productivity shock* given some simplifying assumptions:

- Reallocation of market shares toward larger (high-productivity) firms;
- A rise in the aggregate (sales-weighted) markup;
- An increase in industry concentration (HHI).

[15] Empirically, we observe the same pattern in our data. Table G1 documents the positive within–market correlation between productivity, market share, and markups.

[16] We focus on the intensive margin for four reasons. First, data limitations make exit/entry measurement less precise. Second, existing literature has comparatively less focus on the intensive reallocation of market share. Third, as shown by Edmond et al. (2023), the net effect of entry on aggregate markup can be quantitatively small, whereas exit can raise concentration. Thus omitting extensive-margin responses provides a conservative (lower-bound) estimate of climate's effect on market power. Finally, a balanced sample of incumbents simplifies our theoretical and empirical analysis of markup adjustments.

The intuition is straightforward: under extreme temperature, when smaller and less-productive firms are hit by disproportionately larger productivity shocks, as we have shown in our reduced-form results, they lose market share further to larger incumbents. As market share shifts toward these already high-markup firms, the sector's average markup rises. Appendix C.2.2 shows mathematically that this occurs through a between-firm reallocation effect and a within-firm effect. The between-firm effect is from market share shifting to higher-markup firms, holding markups constant, while the within-firm effect is from larger firms increasing their markups due to facing a less elastic component of the aggregate demand curve. Consequently, between-firm reallocation leads to larger firms becoming even more dominant, the sales distribution becoming more dispersed, and raising the Herfindahl–Hirschman Index as shown in Appendix C.2.3.

Because VES models do not admit simple closed-form solutions for key outcomes like the aggregate markup, we complement these predictions with a simulation of a single-industry VES equilibrium in Appendix D. We show that a productivity-decreasing shock generates the reallocation patterns consistent with the qualitative predictions described above.

### 3.4 The Welfare Cost of Climate-Induced Market Power

Building on the VES framework introduced in Section 3.2.2, this section examines how climate change impacts welfare through firm-level reallocation and changes in market power. In our model, climate change affects welfare through two key channels. First, it raises the aggregate markup, which acts like an output tax–i.e., a gap between marginal product and factor income–reducing input use, wages, and total production. Second, it increases the dispersion in markups across firms, leading to a misallocation of resources away from the most productive producers and thereby lowering aggregate productivity. Technical details are provided in Appendix C.4.1.

**Aggregate Markup and Employment** From the pricing equation (3.1), firms set prices above labor costs by a factor of the markup. At the aggregate level, the aggregate markup can be interpreted as a labor wedge: for a given marginal product of labor (MPL), the real wage is

$$\frac{W}{P} = \frac{1}{\mathscr{M}}\text{MPL}.$$

A higher aggregate markup, denoted by $\mathscr{M}$, reduces the real wage (holding MPL fixed). By reducing workers' effective return to labor, it depresses labor supply, leading to lower aggregate employment, output, and consumption. A higher $\mathscr{M}$ thus works much like an output tax, lowering labor usage and shrinking overall economic activity. [17]

**Markup Dispersion and Aggregate Productivity** Markup dispersion will matter for welfare through how it alters aggregate productivity. Under our production function $y = \varphi \cdot l$, sectoral productivity is defined as

[17] Aggregate employment decreases in the aggregate markup in equilibrium as shown in Appendix C.3 for more details.

the relative output-weighted harmonic average of productivities across firms within a sector, and aggregate productivity is the relative output-weighted harmonic average of sectoral productivities:

$$\varphi_j = \left(\sum_i^{n_j} \frac{q_{ij}}{\varphi_{ij}}\right)^{-1}, \quad \varphi = \left(\int_0^1 \frac{q_j}{\varphi_j}\right)^{-1}, \tag{11}$$

where $q_{ij}$ is the output share of firm $i$ within sector $j$, and $q_j$ is the output share of sector $j$ in the total economy:

$$q_{ij} = \frac{y_{ij}}{y_j}, \quad q_j = \frac{y_j}{Y}. \tag{12}$$

Given these definitions, how does markup dispersion affect aggregate productivity? Since firm productivities are model primitives, markup dispersion affects aggregate productivity only if it distorts the distribution of market shares across firms. If there is no dispersion in markups ($\mu_{ij} = \mu$), the *efficient* firm and sectoral relative size allocations, $q^*_{ij}$ and $q^*_j$, are functions of productivity only:[18]

$$q^*_{ij} = \left(\frac{\varphi^*_j}{\varphi_{ij}}\right)^{-\rho}, \quad q^*_j = \left(\frac{\varphi^*}{\varphi^*_j}\right)^{-\eta}, \tag{13}$$

which allows us to express the efficient sectoral and aggregate productivity as:

$$\varphi^*_j = \left(\sum_i^{n_j} (\varphi_{ij})^{\rho-1}\right)^{\frac{1}{\rho-1}}, \ \varphi^* = \left(\int_0^1 (\varphi^*_j)^{\eta-1} dj\right)^{\frac{1}{\eta-1}}. \tag{14}$$

However, in the presence of markup dispersion, the equilibrium firm and sectoral allocations are:

$$q^D_{ij} = \left(\frac{\mu_{ij}}{\mu_j}\frac{\varphi_j}{\varphi_{ij}}\right)^{-\rho}, \quad q^D_j = \left(\frac{\mu_j}{\mathscr{M}}\frac{\varphi}{\varphi_j}\right)^{-\eta}, \tag{15}$$

and equilibrium market shares are distorted by a firm or sector's relative markup size. With markup dispersion, a firm with a higher markup, holding productivities fixed, results in an inefficiently low output share. Given these output shares, the sectoral and aggregate productivities are:

$$\varphi^D_j = \left(\sum_i^{n_j} \left(\frac{\mu_{ij}}{\mu_j}\right)^{-\rho} (\varphi^D_{ij})^{\rho-1}\right)^{\frac{1}{\rho-1}}, \ \varphi^D = \left(\int_0^1 \left(\frac{\mu_j}{\mathscr{M}}\right)^{-\eta} (\varphi^D_j)^{\eta-1} dj\right)^{\frac{1}{\eta-1}}. \tag{16}$$

Comparing the two scenarios, the key difference in equilibrium size allocation as shown in Equations (13) and Equations (15) is $\frac{\mu_{ij}}{\mu_j}$ and $\frac{\mu_j}{\mathscr{M}}$. These two ratios capture the fact that markup heterogeneity distorts the relative size allocation—large and high-markup firms are producing too little and small and low-markup firms are producing too much. This leads to misallocation of production inputs from more productive to less productive

[18]Even if there exist uniform markups, this still does not reduce aggregate productivity because uniform markups do not change relative prices across firms.

firms, resulting in aggregate productivity loss as shown in Equations (14) and (16).

**Climate Change and Consumption-Equivalent Welfare** To quantify the overall welfare impact of climate-induced reallocation and market power, we adopt a *consumption-equivalent* metric in the spirit of Edmond et al. (2023). This metric represents the percentage of baseline consumption that the representative household would need to forgo permanently to avoid the climate-induced productivity shock. Under the model, the consumption-equivalent welfare loss under climate change ($cc$) is derived as

$$1 - \left(\frac{\varphi_{cc}}{\varphi}\right)\left(\frac{\mathscr{M}_{cc}}{\mathscr{M}}\right)^{-\frac{1}{1+\nu}}, \tag{17}$$

where $\varphi_{cc}$ and $\mathscr{M}_{cc}$ denote the new aggregate productivity and markup after climate change, while $\varphi$ and $\mathscr{M}$ are their baseline values. [19]

Equation (17) captures three channels through which climate change undermines welfare via its effects on productivity and market power. First, climate change can directly lower firm-level productivity, which, even absent markup distortions, reduces aggregate productivity (i.e., $\varphi_{cc} < \varphi$). Second, greater dispersion in markups, due to the climate-induced reallocation, leads to a misallocation of production inputs away from the most productive firms, further reducing aggregate productivity. Third, a rise in the aggregate markup (i.e., $\mathscr{M}_{cc} > \mathscr{M}$) acts like an output tax—suppressing input usage, employment, and overall production. Together, these effects reduce consumption-equivalent welfare.[20]

While our framework highlights the welfare losses from both aggregate markups and markup dispersion, other studies such as Shi and Zhang (2025) emphasize the potential for selection and reallocation effects to raise aggregate productivity following climate shocks. However, their conclusions rely on a CES demand system, which assumes constant markups and may overstate the net gains in aggregate productivity from reallocation, as they abstract from markup distortions that can limit output expansion by large firms. In contrast, our variable-elasticity framework captures the endogenous increase in markups by large firms, which limits their output expansion and amplifies misallocation—thus reducing the extent to which reallocation can offset aggregate productivity losses.

Our model rationalizes the observed empirical patterns of market share reallocation and resulting concentration changes through the heterogeneous productivity impacts of climate change across firms. However, an alternative—and observationally equivalent—mechanism may also be at play: *heterogeneity in cost pass-through*. Even if firms face similar productivity (and thus cost) shocks, differences in pass-through behavior can lead to similar reallocation outcomes. In models with endogenous markups, larger firms exhibit greater

[19] Appendix C.4.3 details the derivation. $\nu$ is the inverse of the Frisch elasticity of labor supply, which we set to 1 following (Edmond et al., 2023).

[20] Changes in aggregate productivity reflect both a level effect—the direct decline in firm-level productivity—and a share effect, which captures how output shares shift across firms. Even if average shocks are negative, reallocation toward more productive firms could partially offset the loss in aggregate productivity. However, this offsetting share effect is weaker in our setting because markups respond endogenously: more productive firms also raise markups and restrict output, limiting the potential aggregate productivity gains from reallocation and reinforcing misallocation.

markup flexibility, allowing them to pass through less of the cost shock to prices. This enables them to better stabilize prices, maintain competitiveness, and gain market share, reinforcing their advantage over smaller firms. Following Arkolakis and Morlacco (2017), we show in Appendix C.1 that pass-through is inversely related to the level of markups in a simplifying case of local shocks. While our baseline model emphasizes supply-side heterogeneity, both mechanisms—heterogeneous shocks and heterogeneous pass-through—can lead to similar patterns in markup and market share dynamics.

# 4 Empirical Analysis of Productivity and Markups

Our results in Section 2.2.1 show the reduced-form effect of temperature on concentration and market share reallocation, but we cannot rely on concentration changes to gauge welfare impacts because the relationship between market concentration and welfare is ambiguous.[21] The theoretical model shows that the welfare impact of climate shocks depends on how they affect economy-wide productivity and markups. We now formally estimate the marginal effects of temperature on these two outcomes. We use our firm-level revenue and input data to first recover productivity and markups at the firm level (up to a scale factor). Logarithmic transformations of these variables will then serve as the dependent variables in regressions on temperature with appropriate controls (e.g., fixed effects) to absorb the unobserved scale factor. The quantification exercise in the next section will then use the estimated firm-level effects of temperature to quantify aggregate welfare measures.

## 4.1 Estimating Firm Markups

Measuring markups directly is challenging, as firm-level prices and marginal costs are rarely observed simultaneously. To estimate markups, we follow the production-function-based approach of De Loecker and Warzynski (2012), which infers markups from firms' input choices under the assumption of cost minimization. Specifically, the markup of a firm $i$ at time $t$ is expressed as the ratio of the output elasticity of a variable input $x$ to that input's cost share in total revenue: $\mu_{ijt} = \frac{\alpha^x_{ijt}}{\theta^x_{ijt}}$. The output elasticity $\alpha^x_{ijt}$ is recovered from an estimated production function, while the revenue share $\theta^x_{ijt}$ is directly computed from firm-level data on revenues and input expenditures.

We first estimate a Cobb-Douglas production function at the country by NACE4 industry level as our baseline specification, using the control function approach of Ackerberg et al. (2015). From the estimated production function, we obtain estimates of output elasticities, which, when combined with each firm's input cost shares, allow us to compute firm-level markups. Further technical details on the production function

[21] While markups offer a direct proxy of market power by capturing the extent to which price exceeds marginal costs, the relationship between concentration and market power depends on specific demand and supply factors (Van Reenen, 2018; Bajgar et al., 2019b; Afrouzi et al., 2023; Berry et al., 2019). Traditional Cournot models predict a positive correlation between concentration and market power (Tirole, 1988), whereas competition-driven consolidation may indicate lower markups (Melitz and Ottaviano, 2008; Asplund and Nocke, 2006). Syverson (2019) provides a comprehensive overview on the linkage between concentration and market power.

specification, the two-stage estimation procedure, and related identification assumptions are provided in Appendix B. In our main analysis we Winsorize estimated markups at the 1st and 99th percentiles, as is common practice in the literature (Weche and Wambach, 2021; De Loecker et al., 2016).

A key challenge in this procedure arises from the fact that we observe only revenue, not physical output, which introduces measurement error into the estimation of output elasticities and markups. In an imperfectly competitive environment, changes in firm revenue reflect changes not only in output quantity but also in prices. While Bond et al. (2021) question the informativeness of revenue-based markups, De Ridder et al. (2022) show that although the average level of revenue-based markups may be biased, the dispersion of these markups is informative of the true dispersion in settings with heterogeneous demand elasticities. Under a Cobb-Douglas production function, revenue-based markup estimates are equal to true markups up to a market-specific constant.[22]

Since our focus is on the marginal effect of temperature on markups rather than just markup levels, we can address this measurement error by including market-year fixed effects in a semi-log regression. This approach yields a consistent estimate of the semi-elasticity of markups with respect to temperature. Under a more flexible production function, such as a translog specification, revenue-based markups are equal to true markups multiplied by a non-linear function of input usage (De Ridder et al., 2022). In this case, we can still identify the semi-elasticity by controlling flexibly for input usage in the semi-log regression.

### 4.2 Estimating Firm Productivity

Estimating the production function using revenue data yields revenue-based total factor productivity (TFPR), which is measured as the residual between revenue output and inputs.[23] In an imperfectly competitive environment, temperature shocks influence both the quantity of output and the price at the firm level so that the estimated TFPR impacts of temperature will reflect not only genuine changes in productivity, but also changes in prices. To properly compute the consumption-equivalent welfare effects of temperature we need to separate the effects on TFPQ from the associated price response, so we must directly recover TFPQ.

Here we show how to recover TFPQ based on market shares and estimated markups, given our model assumptions. In the VES framework of Section 3.2.2, each firm's equilibrium market share $s_{ijt}$ can be expressed as a combination of its markup $\mu_{ijt}$ and its productivity $\varphi_{ijt}$ (TFPQ):

$$s_{ijt} = \frac{\mu_{ijt}^{1-\rho}\,\varphi_{ijt}^{\rho-1}}{\sum_{\ell=1}^{n_{jt}} \mu_{\ell jt}^{1-\rho}\,\varphi_{\ell jt}^{\rho-1}}, \tag{18}$$

where $\rho$ is the relevant elasticity parameter in the VES demand system. As mentioned in Section 3.2.2, this equation implies that market shares are governed by the *dispersion* of productivity across firms within a market-year (Atkeson and Burstein, 2008; De Loecker et al., 2021; Edmond et al., 2015, 2023). If all firms'

[22] The constant is equal to the weighted average of inverse markup among firms sharing the same production function, i.e., firms in the same country by NACE4 industry group in our production function estimation.

[23] Appendix B provides details on the estimation of TFPR.

productivity are scaled by a common market-year factor, their market shares remain unchanged. Therefore, when we recover firm productivity $\varphi_{ijt}$ with the observed market shares and revenue-based markups (estimated up to a constant at the market level) using fixed point iterations, we can only recover the dispersion of TFPQ, but cannot pin down the absolute level of TFPQ for each firm.

In a semi-log regression with logarithm productivity as the outcome variable, the market-year fixed effects absorb the market-year level scale that contains the information of the absolute level of productivity within a market-year. To the extent that the market-year fixed effects (i.e., the scale of the productivity) vary with temperature, the regression based on relative TFPQ can only allow us consistently estimate the effect of temperature on firm relative TFPQ.

### 4.3 Temperature Effects on Productivity and Markup

**Empirical Specification** We use the following model to estimate the effect of temperature on firm-level productivity and markups:

$$y_{ijt} = F(T_{ijdt}; \beta) + G(R_{ijdt}; \iota) + \alpha_i + \delta_{jt} + \varepsilon_{ijt}, \tag{19}$$

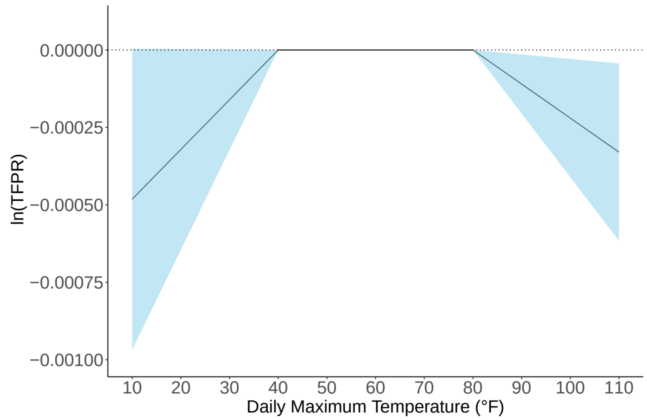
where $y_{ijt}$ is the log of TFPR, revenue-based markups for firm $i$ in market $j$ at year $t$. $F(\cdot)$ and $G(\cdot)$ are the same as the prior specifications. We control for firm fixed effects ($\alpha_i$) to capture time-invariant unobservables at the firm-level, and market-year fixed effects $\delta_{jt}$ to capture market-specific trends and to absorb the normalizing constant. Standard errors are clustered two ways at the firm-level and market-year level to allow for serial correlation within a firm across years and spatial correlation across firms within a market-year.

**Temperature Effects on Productivity** Figure 3 presents estimated effects of temperature on firm TFPR using Equation (19). The figure shows that TFPR has an inverted U-shape relationship with temperature: extreme heat and extreme cold significantly reduce firm TFPR. Table G3 reports the estimated coefficients in Column (1).The estimates indicate that replacing a day between 40°F and 80°F with one at 100°F would decrease firm TFPR by 0.022 percent.

The magnitude of our estimated effects on productivity is consistent with findings from the existing literature. The most straightforward comparison is to Nath (2025), which finds that a day with a maximum temperature of either –5°C or 40°C reduces annual revenue-based labor productivity in the manufacturing sector by approximately 0.03 percent, relative to a day in the moderate temperature range of 5°C to 30°C. Similarly, our results indicate that a day with a maximum temperature of 40°C reduces firm-level TFPR by 0.022 percent.

Another common approach to measuring temperature impacts is to use bins of daily temperature. We test the robustness of our results to using temperature bins instead of splines in Figure F14. Our results suggest that an additional 10 days per year above 90°F instead of at 50-60°F reduces firm-level TFPR by 0.20 percent.In comparison, Costa et al. (2024), using Orbis firm-level data from 23 OECD countries, finds that 10

Figure 3: Average Effect of Temperature Change on Firm TFPR




*Notes*: This figure shows the average effect of temperature change on firm TFPR. Coefficients are estimated from Equation (19) with the dependent variable being the log of firm TFPR. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

additional extremely hot days (above 86°F) per year reduce labor productivity by 0.16 percent. Based on U.S. manufacturing data, Ponticelli et al. (2023) report that 10 additional days above 27°C (80.6°F) lower total factor productivity (TFP) by 0.4 percent and labor productivity by 0.7 percent. Using Chinese manufacturing data, Zhang et al. (2018) estimate that 10 additional days above 90°F reduce TFP by 5.6 percent. Our estimated effects are closely aligned with findings from studies focused on European countries and the United States, but are smaller than those reported in studies of China. These differences may stem from specification differences, such as reference temperature bins, fixed effects, TFP estimation methods, or differences between Europe and China in baseline climate conditions and adaptation capacities.

The above results show the *average* effect of extreme temperature on firms TFPR, an outcome that may reflect changes in both TFPQ and prices. Next, we use Equation (18) to recover relative TFPQ and estimate *heterogeneous* effects of temperature on relative TFPQ across firms of different sizes. Specifically, we interact the temperature response function with the logarithm of each firm's average revenue over the sample period, as specified in Equation (4). Column (2) of Table G4 reports the estimated results. The coefficient on annual cooling degree days (ACDD), defined as the difference between the daily maximum temperature and 80°F, is negative, indicating that high temperature reduces relative TFPQ for the baseline firm with a log average revenue of zero. The interaction term between ACDD and the logarithm of firm revenue over the sample period, $\ln(\overline{Rev})$, is positive and statistically significant, suggesting that the negative effect of high temperatures on relative TFPQ is smaller in magnitude for larger firms.

Panel (a) of Figure 4 illustrates the predicted change of logarithm of relative TFPQ in response to daily maximum temperature for firms at the 10th, 50th, and 90th percentile of the distribution of total revenue across all firms, representing small, medium, and large firms. We find that extreme heat significantly reduces relative TFPQ for small firms, has no effect on medium firms, and significantly increases relative TFPQ for large firms. Since the dependent variable captures the relative distribution of TFPQ rather than its absolute level, the results suggest that large firms are more resilient to extreme heat shocks, moving upward in the productivity distribution relative to smaller firms. It is possible that temperature shocks reduce the absolute level of TFPQ for all firms to varying degrees. However, our model only captures changes in the distribution of TFPQ and cannot identify changes in its absolute level. Simulation results in Figure D3 illustrate this scenario. Panel (a) shows that absolute TFPQ decreases for all firms under a temperature shock, but the decline is less severe for large firms. Panel (b) depicts how relative TFPQ changes across the firm size distribution: small firms experience a decline in relative TFPQ, while large firms see an increase.[24]

As discussed above, the market-year fixed effects in Equation (4) absorb the market-level scale, removing variation related to the absolute level of TFPQ. As a result, the estimated effects reflect changes in relative TFPQ. Panel (b) of Figure 4 presents results from an alternative specification that includes firm and year fixed effects, allowing us to exploit some variation at the market-year level. The figure shows that small firms experience a significant decline in TFPQ, medium-sized firms show a smaller decline, and large firms are largely unaffected. While we do not interpret this as direct evidence on levels of TFPQ, the results suggest that productivity may be declining across all firms, with disproportionately larger effects on smaller firms.

The literature has documented similar heterogeneity in the impact of temperature on firm productivity, showing that smaller firms are more vulnerable to extreme heat shocks than larger firms (Ponticelli et al., 2023; Costa et al., 2024; Gagliardi et al., 2024). Several factors may contribute to this pattern. Larger firms typically have more resources to adapt to climate risks, such as installing temperature control systems (Zivin and Kahn, 2016; Somanathan et al., 2021). They may also have better access to finance and stronger managerial capabilities. In addition, they may use higher-quality capital—such as better-insulated buildings and newer, more energy-efficient machinery that is less prone to overheating (Ponticelli et al., 2023).

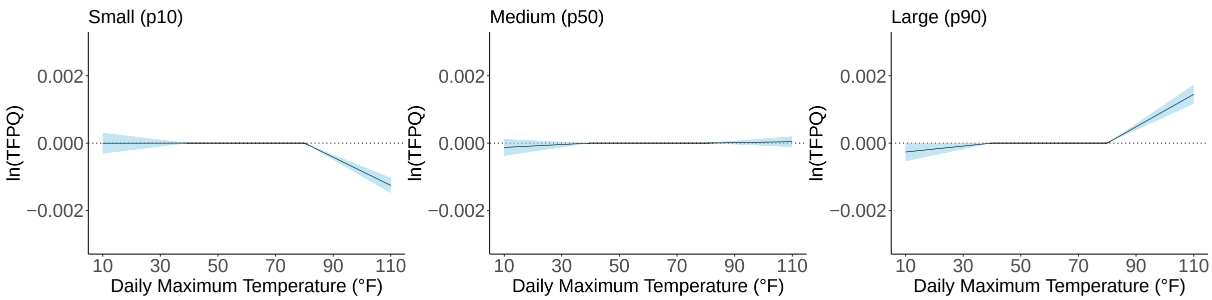
Our results suggest that large firms, such as those in the top 10 percent of the revenue distribution, experience more resilience under extreme heat. As discussed above, large firms, with better access to finance, are more capable of responding to extreme heat shocks by investing in productivity-enhancing technologies or higher-quality capital (e.g., air conditioning or automation). This resilience may lead to a relative productivity advantage for large firms over smaller ones, resulting in a reallocation of market share, as shown in Section 2.2. Specifically, large firms may expand input usage while smaller firms contract. Supporting this mechanism, Figures F3 and F4 show that large firms increase both labor and capital inputs in response to extreme heat, whereas small firms reduce them.

The mechanism discussed above hinges on the idea that large firms are better able to invest in new capital that makes production more resilient to extreme heat. To investigate this channel, we note that while our data lack information on capital quality or vintage, newer entrants are more likely to adopt modern technologies than incumbents. Therefore, we split the sample into firms that entered the market earlier versus those that entered later. If newer firms tend to employ more modern and productive capital, we would expect them to experience a stronger productivity gain from extreme heat—particularly among larger firms. The results,

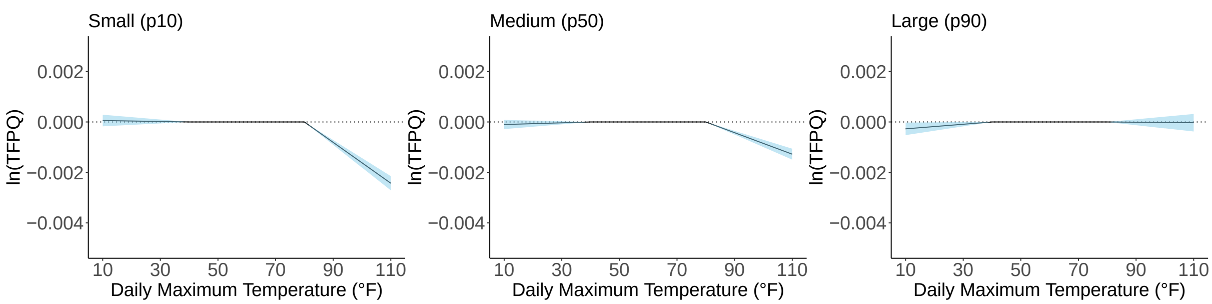
[24] In the simulation, relative TFPQ is defined as $\tilde{\varphi}_{ijt}^{(\mathrm{rel})} = \tilde{\mu}_{ijt}(s_{ijt})^{\frac{1}{\rho-1}}$, where $\tilde{\mu}_{ijt}$ is the estimated revenue-based markups.

Figure 4: Heterogeneous Effects of Temperature Change on Firm Relative Productivity

(a) Baseline Specification




(b) Alternative Specification



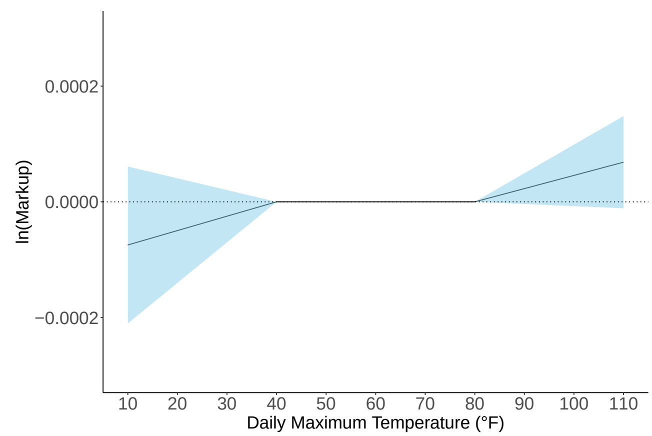

*Notes*: This figure shows the heterogeneous effects of temperature change on firm relative TFPQ by size. The coefficients of Panel (a) are estimated from Equation (4). The coefficients of Panel (b) are estimated from an alternative specification similar to Equation (4) but include firm and year fixed effects. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

presented in Table G6, support this hypothesis. The coefficients on the interaction between cooling degree days and the log of average revenue are positive and statistically significant for both older firms (entered before 2005) and newer ones (entered after 2005). However, the coefficient for newer firms is nearly three times larger than that for older firms, suggesting a stronger positive response to extreme heat among newer firms, likely as a result of adopting newer and better technologies.

**Temperature Effects on Markups** We estimate Equation (19) with the dependent variable being the logarithm of firm markups. As noted in De Ridder et al. (2022) and discussed in Section 4.1, revenue-based markups are subject to bias from measurement error, with the extent of the bias depending on the joint distribution of inputs and the elasticities of both demand and output. When regressing revenue-based markups on temperature, this bias term enters the error term and may be correlated with temperature, potentially leading to biased estimates. To address this concern, we flexibly control for input usage by including second-order polynomials of both labor and material costs in the regression model.

The average effects are reported in Figure 5 and column (3) in Table G3. The results show that extreme heat tends to increase firm markups on average: a day with a maximum temperature of 100°F raises firm markups by approximately 0.0046 percent, compared to a day with a maximum temperature at the middle range between 40°F to 80 °F.

Figure 5: Average Effect of Temperature Change on Firm Markup




*Notes*: This figure reports the average effect of temperature changes on firm markup. Coefficients are estimated from Equation (19), with additional controls of second-order polynomial in variable input costs, including labor costs and material costs. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

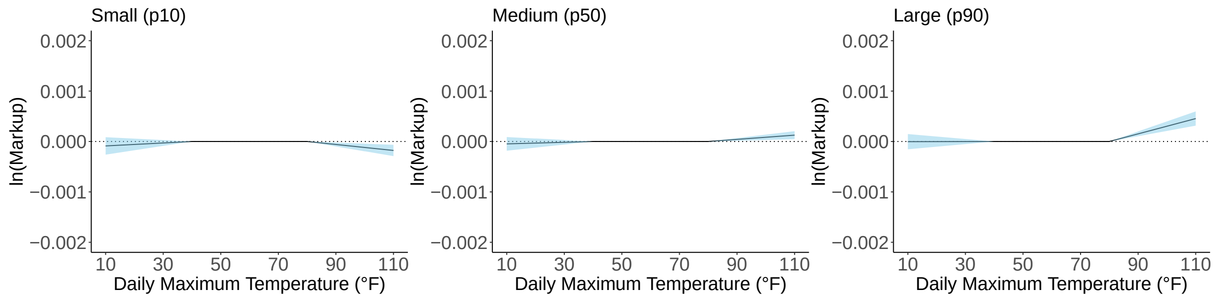
The heterogeneous effects are particularly noteworthy, as shown in Figure 6 and column (3) of Table G4. In Table G4, the coefficient on extreme heat for the baseline firm is negative and statistically significant. In contrast, the interaction term between annual cooling degree days and the log of average revenue is positive and significant, indicating that the adverse impact of heat on markup diminishes—and even reverses—for larger firms. Figure 6 illustrates the predicted change in log of markup for firms at the 10th, 50th, and 90th percentiles of the average revenue distribution, showing that high temperatures reduce markups for small firms but increase them for large firms.

### 4.4 Robustness Checks

**Broader Market Definition** Our main specification defines a market at the country-NACE4 industry level. We also conduct the above analyses by defining a broader market at the country-NACE2 industry level. The results are robust. We see similar concentration-increasing (F5), market share reallocation (F6), heterogeneous effects on firm productivity (F7), and heterogeneous effects on firm markup (F8) under a broader industry classification.

**Full Sample** Our baseline results are based on a balanced sample that includes firms that present in the dataset throughout the sample period. For robustness, we perform firm-level analyses using the full sample.

Figure 6: Heterogeneous Effects of Temperature Change on Firm Markup




*Notes*: This figure reports the heterogeneous effects of temperature changes on firm markup. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

The result, presented in Figures F9, F10, and F11, confirm the main findings. We observe similar patterns of heterogeneity in market share reallocation, firm productivity, and markups.

**Alternative Temperature Response Functions** We adopt two alternative specifications for the temperature response function. The first approach uses temperature bins. We group daily maximum temperatures into eight 10-degree Fahrenheit bins: <30°F, 30–40°F, 40–50°F, 50–60°F, 60–70°F, 70–80°F, 80–90°F, and 90°F. Each bin represents the number of days in a year that a firm experiences a daily maximum temperature within that range, and the sum across all bins equals 365. This specification captures how changes in the distribution of daily temperatures affect annual outcomes. In the regression analysis, we use the 50–60°F bin as the omitted reference category. The response function is defined as: $F(T) = \sum_{b \neq [50-60F)} \beta_b \cdot \text{Bin}^b$, where $\text{Bin}^b$ represents the number of days in a year a firm experiences a daily maximum temperature within bin $b$.

Figure F12 shows that extreme high temperatures increase market concentration, measured by HHI and CR4. Figures F13, F15, and F16 display the heterogeneous effects of temperature on firms' market share, relative TFPQ, and markup, respectively, for firms at the 10th, 50th, and 90th percentiles of the revenue distribution. These figures reveal clear heterogeneity between large and small firms in response to extreme heat, consistent with our baseline findings.

The second approach uses global polynomials. Following Carleton et al. (2022), we specify the temperature response function as a fourth-order polynomial of the annual sum of daily maximum temperature. Figures F17, F18, and F19 show the heterogeneous effects on firm market share, relative TFPQ, and markup, respectively. These heterogeneous patterns align with our main findings.

**Alternative Markup and Productivity Estimations** A growing literature on production-function estimation highlights how modeling choices—for instance, functional form (Cobb–Douglas vs. Translog vs. CES), the use of revenue versus quantity data, the choice of variable input for markup calculation, and whether productivity is factor-neutral or factor-augmenting—can all influence both estimated output elasticities and the resulting markups (De Ridder et al., 2022; Raval, 2023). Figures F20 and F21 present the average and heterogeneous effects on firm productivity estimated using a Translog production function. Similarly, Figures F22 and F23 report the corresponding effects on firm markups estimated using a Translog production function. These results are consistent with our main findings based on productivity and markup estimated from a Cobb-Douglas production function specification.

### 4.5 More Evidence from Developing Countries

The above results are based on data from 12 EU countries, which are mostly developed economies located in relatively temperate climate zones. To evaluate the external validity of our findings, we extend the analysis by incorporating data from China and India, two representative developing countries that encompass extensive regions with substantially hotter climates than those observed in most EU countries.

For China, firm-level data are drawn from the National Tax Survey Database. The dataset is jointly collected by the Ministry of Finance and the State Administration of Taxation using a stratified random sampling design. The data cover 2009–2015 and contain detailed annual information on inputs, outputs, employment, and financial outcomes. Because the database is collected for tax administration and policy evaluation, key variables are highly accurate, and the sample is representative across industries and firm sizes. The dataset has been widely used in recent economics research (Liu and Mao, 2019; Chen et al., 2021, 2023; Li and Wang, 2025).

For India, we use firm-level data from the Annual Survey of Industries (ASI) covering the period 1999–2022. The ASI is conducted annually by the Ministry of Statistics and Programme Implementation (MoSPI), Government of India. Compared with alternative data sources, such as the Census of Manufacturing Industries (CMI) and the Sample Survey of Manufacturing Industries (SSMI), the ASI offers substantially broader coverage and is broadly comparable to manufacturing surveys used in the United States and other industrialized countries. The ASI provides annual data on output, the value of fixed assets, debt, cash on hand, inventories, input expenditures, and the employment of workers and management. Owing to its wide coverage and data quality, the ASI has been widely used in literature (Somanathan et al., 2021; Colmer, 2021; Nath, 2025).

We apply a series of standard data-cleaning procedures to construct the final analysis sample. First, we restrict the sample to manufacturing firms to be consistent with data from other countries. Second, we drop observations with missing or non-positive values for key variables (employment, material costs, labor costs, and tangible fixed assets), exclude newly established firms, remove industries with fewer than 100 firms. To avoid extreme values, we also winsorize key variables at the 1st and 99th percentiles.

The results are consistent with our main findings. In both countries, we define a market at the 4-digit industry level. In China, Figure F24 shows evidence of increasing market concentration, measured by HHI and CR4, in response to extreme high temperatures. Figure F25 presents heterogeneous effects on firm market share: small firms lose market share while large firms gain market share following extreme heat shocks. Regarding productivity, average TFPR does not exhibit a significant decline (see Figure F26). However, we find substantial heterogeneity in relative TFPQ across firm sizes. As shown in Figure F27, small firms' relative TFPQ decreases, whereas large firms' relative TFPQ increases under extreme heat. Figure F28 displays the average effect on firm markups. We observe a significant increase in average markups in Panel (a), although the effect becomes insignificant once measurement-error controls are added in Panel (b). Consistent with our main results, we again find heterogeneous effects across firm sizes: large firms' markups increase under extreme heat (see Figure F29).

For India, Figure F30 shows a similar increasing pattern of market concentration in response to high-temperature shocks.[25] Figure F31 documents heterogeneous effects on firm market share, with small firms losing market share while large firms gain market share following extreme heat shocks. We also find suggestive evidence of heterogeneous productivity responses: smaller firms experience declines in TFPR, whereas larger firms exhibit increases in TFPR under extreme heat (see Figure F33). It is important to note that the India data come with several limitations. First, the dataset does not include firm identifiers, which prevents us from estimating firm-level regressions with firm fixed effects; we are only able to control for state fixed effects. Second, because firm geolocations are unavailable, temperature exposure can only be extracted at the state level, which reduces spatial variation in the temperature measure. For these reasons, we interpret the firm-level results for India with caution.

### 4.6 Discussion: Beyond Temperature Shocks

These empirical findings illustrate how climate-induced productivity shocks reshape market structure in a manner consistent with our endogenous markup framework. Smaller establishments, more vulnerable to extreme heat and possessing fewer resources for adjustment, experience sharper productivity declines and lose market share to larger incumbents. As production concentrates among larger firms, these firms move into less elastic segments of demand and raise markups, while smaller firms—facing tighter margins and limited pricing flexibility—see their markups compress. The net effect is an increase in aggregate market power driven by climate-induced reallocation.

More broadly, the mechanisms we uncover are not specific to temperature shocks but speak to a general class of climate disruptions that disproportionately affect smaller firms. Any shock that raises production costs, disrupts labor supply, or introduces operational frictions—such as energy price spikes, supply chain disruptions, or extreme weather events—can generate heterogeneous responses by firm size. Smaller firms, with more limited buffers, adjustment capacity, and financial constraint, are often less able to absorb such shocks, leading to sharper declines in productivity, output, or market presence. In contrast, larger firms, endowed with greater financial flexibility, diversified operations, and pricing power, are better positioned to withstand or offset these shocks. The heterogeneous patterns we document under extreme temperature conditions thus reflect a more general vulnerability of small firms to adverse climate shocks and a corresponding tendency for market power to become more concentrated during periods of disruption.

[25] Because India has a higher average temperature, we use 50°F–90°F as the baseline temperature range.

A further amplifying channel is endogenous adaptation. The literature has documented various margins of adjustment to climate stress, including air conditioning adoption (Somanathan et al., 2021), directed innovation toward heat-resistant technologies in agriculture (Moscona and Sastry, 2023), and supply chain diversification (Castro-Vincenzi et al., 2024). However, these adaptation measures typically involve substantial fixed costs—capital expenditures, R&D investments, or coordination costs—that are more easily borne by large firms with greater financial capacity and the ability to spread fixed costs over larger output. When adaptation is costly and scale-dependent, pre-existing productivity dispersion can become self-reinforcing: firms that are already large and productive invest in adaptation, partially insulating themselves from future shocks, while smaller firms remain exposed. The result is a dynamic in which climate shocks not only reallocate market share in the short run but also widen the productivity gap over time, further entrenching market concentration.

# 5 Model Quantification

Our model in Section 3 illustrates how climate-induced productivity shocks can reshape market concentration, raise aggregate markups, and reduce overall welfare. The empirical analysis in Sections 2.2.1 and 4 documents the impacts of extreme heat on concentration, productivity, and markups. In this section, we quantify the welfare implication of such impacts.

We begin by discussing the key model parameters needed to capture the welfare implications of heat-induced productivity losses and market power, along with our choice to borrow parameter values from the existing literature. We then use the structure of the model to simulate how extreme heat affects aggregate productivity, markups, and welfare. Finally, we compare welfare outcomes under two different demand assumptions (CES versus VES) to show how reallocation-driven market power affects the welfare costs of extreme heat shock.

## 5.1 Demand Elasticity Parameters

In our climate-induced reallocation framework, heterogeneous productivity shocks drive the reallocation of market shares across firms. Under a VES structure, this reallocation alters firms' demand elasticities and thus their markups. The final welfare impact depends on the change in aggregate productivity and aggregate markup (equation (17)). Two elasticity parameters are central to this mechanism: the within-sector elasticity of substitution, $\rho$, and the across-sector elasticity of substitution, $\eta$. Equation (10) illustrates that $\rho$ governs the sensitivity of a firm's market share to its relative price. When $\rho$ is high, goods within a sector are highly substitutable, so small price differences can lead to sizable shifts in market shares. Meanwhile, $\eta$ captures how responsive sectoral shares are to changes in relative prices across different sectors. In short, $\rho$ and $\eta$ together determine how market shares respond to cost or price shocks.

These two elasticity parameters also bound firms' markups. Specifically, $\rho$ and $\eta$ imply that the firm-level markup must lie between $\frac{\rho}{\rho-1}$ and $\frac{\eta}{\eta-1}$. In the limit where a firm's market share approaches zero (making it a very small player in its sector), it faces fierce intra-sector competition and charges a low markup close to $\frac{\rho}{\rho-1}$. In contrast, when a firm's market share is close to one, it behaves more like a monopolist competing mainly across sectors, so its markup approaches $\frac{\eta}{\eta-1}$.

In addition to bounding the markup level, $\rho$ and $\eta$ jointly determine how sensitive markup changes in response to changes in market share. From (9), we have:

$$\frac{1}{\mu_{ijt}} = \left(1 - \frac{1}{\rho}\right) - \left(\frac{1}{\eta} - \frac{1}{\rho}\right) s_{ijt},$$

so the difference $\frac{1}{\eta} - \frac{1}{\rho}$ governs how strongly a firm's markup changes with its market share.

To calibrate $\rho$ and $\eta$, we draw on the key literature that estimates the two substitution elasticities. Edmond et al. (2023) report values for $\rho = 7.16$ and for $\eta = 1.15$ while De Loecker et al. (2021) estimate $\rho = 5.75$ and $\eta = 1.2$. For our baseline, we take a midpoint between these values and set our parameters as $\rho = 6.45$ and $\eta = 1.18$. With these two elasticities, we can fully characterize how temperature-driven productivity shocks translate into market share shifts and markup changes, and thus quantify their aggregate impact on social welfare following Equation (17).

In Appendix E, we also present an alternative calibration where we estimate the two substitution elasticities from our data using a simulated method of moments, following the procedure in Edmond et al. (2023). The resulting parameter estimates align well with those reported in the literature, underscoring the robustness of our chosen values.

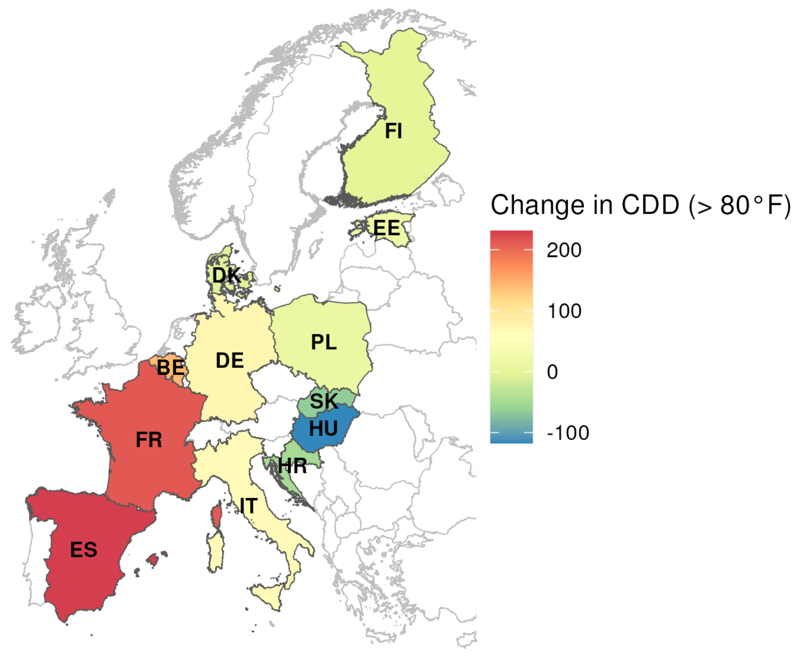
## 5.2 Welfare Quantification

In this section, we quantify the welfare implications of climate-induced productivity shocks. We do so by employing an oligopolistic competition model with VES (variable elasticity of substitution) demand and feeding the observed firm-level productivity shock from heat into the model to calculate changes in welfare. To underscore the role of markups and reallocation in quantifying the welfare loss of climate-induced productivity shock, we also compare the VES-based welfare costs to those generated under a CES framework, where markups remain constant by construction.

The scenario we consider in this paper is the observed shifts in the distribution of daily maximum temperature between 2000 and 2020, relative to a counterfactual scenario in which the temperature distribution remained constant. Figure 7 depicts the change in cooling degree days above 80°F across countries. The extent of temperature change varies significantly across countries during this period. For example, countries such as Spain and France have experienced increased exposure to extreme heat, while others, like Hungary, have seen reduced exposure.

**Simulation Method** To measure how climate-induced temperature shocks affect aggregate productivity, concentration, and markups, and to translate these changes into welfare outcomes, we first draw on the firm-level productivity responses estimated in our regression analysis. Specifically, we use the size-specific impacts

Figure 7: Temperature Change between 2000 and 2020




*Notes*: This figure illustrates the change in the degree days per year with daily maximum temperature exceeding 80°$F$ by country between 2000 and 2020.

of temperature shocks on firm TFPQ reported in Panel (b) of Figure 4, which controls only for firm and year fixed effects. Recall that the TFPQ measure $\varphi$ recovered from Equation (18) reflects true TFPQ scaled by a market-level constant. When we include market-year fixed effects in the regression, this market-level aggregate is fully absorbed, and the coefficients identify effects on relative TFPQ—that is, firm-level TFPQ relative to the market-average level. In contrast, when we omit market-year fixed effects and control only for year fixed effects, the market-level component is not fully absorbed. As a result, the estimated coefficients partially capture changes in the level of TFPQ, though we acknowledge that these are not clean estimates of true level effects. As a next step, we plan to obtain a subset of the data with quantity information, which would allow us to recover true TFPQ levels and estimate level effects more directly.

Mirroring the nested demand structure in our VES model, we treat each country as a standalone economy composed of multiple sectors (country × NACE4). For each country, we fed the observed temperature changes between 2000 and 2020 into our estimated response functions described above to simulate the corresponding predicted changes in firm TFPQ and markups. Predicted post-shock outcomes are constructed by adding these simulated changes to the baseline firm-level values as of 2000. Finally, we aggregate the firm-level outcomes to obtain aggregate TFPQ, aggregate markups, and consumption-equivalent welfare at the country level, as described in Appendix C.4.3, for both the baseline year 2000 and the year 2020.

Table 2 presents the simulation results under the observed shifts in the daily maximum temperature distribution between 2000 and 2020. The first row shows the GDP-weighted country-level averages, while the second row (in brackets) indicates the minimum and maximum range across countries. Overall, country-level simulations suggest that GDP-weighted aggregate TFP increases by 0.197%, the average markup rises by 0.101%, and the consumption-equivalent welfare increases by 0.146%. As discussed in Section 4.2, our method recovers firm-level TFPQ only up to a market-year constant (equation 18), meaning we identify changes in *relative* productivity across firms rather than absolute levels. To the extent that heat also reduces productivity through channels common to all firms within a market—as existing evidence suggests—the aggregate TFP effects reported here likely understate the true productivity damage from rising temperatures. The changes in productivity *dispersion* and the resulting reallocation across firms, however, are well identified, and it is this heterogeneity—and its implications for markups and welfare—that we emphasize in what follows in Section 5.3.

Table 2: Summary of Simulated Welfare Change

| | TFP Change | Markup Change | Welfare Change |
|---|---|---|---|
| GDP-weighted Mean | 0.197 | 0.101 | 0.146 |
| Range | [-0.338,0.486] | [-0.059,0.215] | [-0.441,0.452] |

*Notes*: This table shows the changes in aggregate TFP, aggregate markup, and welfare under observed changes in daily maximum distribution from 2000 to 2020 . We treat each country as a separate economy and simulate markup and welfare changes at the country level. The first row within each panel shows the average change across country, weighted by Country-specific GDP in 2020. The second row shows the minimum and maximum across countries. Welfare loss is *Consumption-Equivalent* Welfare Loss, as defined in Appendix C.4.3.

Table 3: Summary of Country-Specific Changes

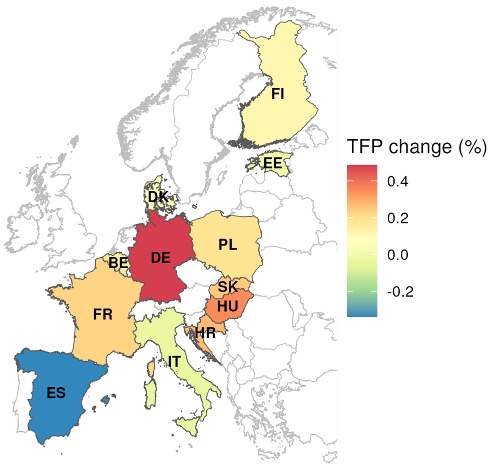
| Country | TFP Change | Markup Change | Welfare Change |
|---|---|---|---|
| Spain | -0.338 | 0.207 | -0.441 |
| Italy | -0.035 | 0.027 | -0.049 |
| Estonia | -0.003 | 0.050 | -0.028 |
| Denmark | 0.042 | -0.001 | 0.043 |
| Finland | 0.113 | 0.020 | 0.103 |
| France | 0.231 | 0.215 | 0.123 |
| Belgium | 0.166 | 0.076 | 0.128 |
| Poland | 0.193 | 0.025 | 0.181 |
| Slovakia | 0.252 | -0.022 | 0.263 |
| Croatia | 0.276 | -0.021 | 0.287 |
| Hungary | 0.351 | -0.059 | 0.381 |
| Germany | 0.486 | 0.068 | 0.452 |

*Notes*: This table summarizes the percentage change in Aggregate TFP, Aggregate Markup, and Consumption-Equivalent Welfare for each country. Observations are ordered in the order of decreasing welfare loss.

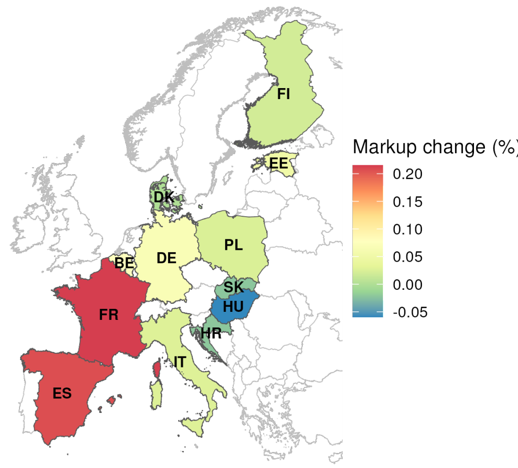
Consistent with existing evidence on spatial heterogeneity of climate impact (Dell et al., 2012; Burke et al., 2015), these temperature-driven productivity shocks and their aggregate effects vary significantly across Europe. As shown in Table 5, Western and Southern European countries such as Spain and Italy experience

Figure 8: Predicted TFPQ Change and Markup Change between 2000 and 2020

(a) TFPQ

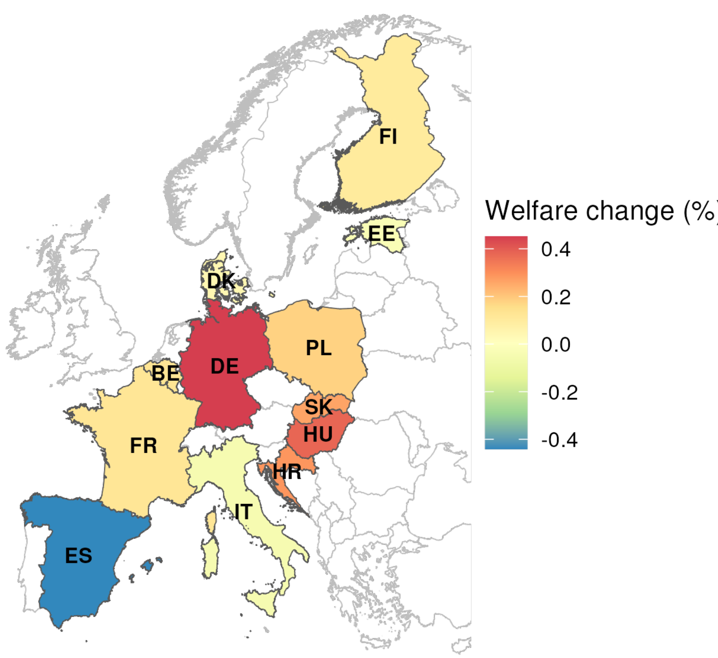



(b) Markup




*Notes*: This figure illustrates the welfare change predicted by the VES model by country between 2000 and 2020.

Figure 9: Predicted Welfare Change between 2000 and 2020




*Notes*: This figure illustrates the welfare change predicted by the VES model by country between 2000 and 2020.

the bulk of the welfare losses, whereas Eastern and Northern European countries (e.g., Croatia and Hungary) enjoy net welfare gains. The direction of the welfare change largely reflects whether productivity is boosted or reduced by the climate shock: countries experiencing negative productivity impacts incur welfare losses.

Additionally, changes in markups introduce a further channel of welfare fluctuation—for instance, in Spain, the adverse productivity effect is compounded by an increase in markups, exacerbating the overall welfare loss.

It is noteworthy that our approach endogenizes market power, revealing that climate shocks can alter markups and thereby amplify or mitigate the welfare effects of productivity changes from temperature extremes. In countries where productivity declines, the rise in markups can worsen consumer welfare beyond the pure productivity loss, whereas in regions benefiting from mild productivity gains, lower markups may partly buffer households from extreme temperature events. In the following subsection, we highlight the importance of the market power channel in quantifying welfare loss by examining how these results may be shaped by a key modeling choice: the assumption of variable versus constant markups. By contrasting our baseline VES framework with a CES setting, we show that holding markups constant can significantly misstate the true welfare cost of temperature shocks.

### 5.3 Role of Demand Assumption: CES vs. VES

In estimating the economic costs of climate change, the climate economics literature has largely relied on the Integrated Assessment Models (IAMs) (Nordhaus, 1992; Hope et al., 1993; Tol, 1995). These models as well as those used in more recent studies (Nath, 2025; Cruz and Rossi-Hansberg, 2021; Rudik et al., 2022) have adopted the CES demand system because of its tractability and its well-documented ability to fit macro-level relationship. Similarly, some recent firm-level empirical studies (Caggese et al., 2024; Shi and Zhang, 2025) incorporate heterogeneous productivity impacts of temperature shocks, but they likewise maintain a CES demand assumption. CES demand models implies constant markups and thus fail to account for welfare changes due to potential markup changes from climate shocks. Recent studies in trade and macro have examined the welfare implications of CES vs. VES demand (Arkolakis et al., 2019; Edmond et al., 2015; Macedoni and Weinberger, 2022). A key finding is that the quantitative significance of using VES (relative CES) demand crucially hinges on the degree of pre-existing dispersion and firm heterogeneity.

Our empirical analysis suggests a significant degree of heterogeneity not only in the level of firm productivity but also in the impact on productivity from temperature shocks. To better understand the role of VES demand in estimating the welfare cost of temperature shocks, we compare climate-induced consumption-equivalent welfare losses under two alternative demand structures: (1) a CES framework, in which reallocation does not affect either the distribution or the aggregate level of markups, and (2) our baseline VES framework, in which climate-driven reallocation does raise markup dispersion and the aggregate markup.[26] Both scenarios are driven by the same heterogeneous productivity shocks at the firm level, which are quantified through our empirically observed heat-to-productivity damage function in Section 4.3. The key difference lies in how markups are determined: under CES, markups are constant and market shares depend only on relative productivity; under VES, markups and market shares are jointly determined in equilibrium, with markups

[26] See Appendix C.4.3 for the details of the welfare loss formula in each specification.

varying endogenously with firm size. As discussed in Section 5.1, the sensitivity of markups to market share—governed by the gap between the two demand elasticities ($\frac{1}{\eta} - \frac{1}{\rho}$)—determines the degree of markup-induced misallocation and the change in the aggregate output tax.

Given the VES model framework and consumption-equivalent welfare metrics, we can decompose the difference between welfare costs under VES and CES into two parts: the changes in *misallocation* from the changing markup dispersion and the change *output tax* from the changes in aggregate markup.[27] Equation (20) summarizes this intuition:

$$\underbrace{\left[\text{Welfare Loss}_{\text{VES}} - \text{Welfare Loss}_{\text{CES}}\right]}_{\text{(CES's Welfare (Over)Underestimation)}} \approx \underbrace{\left[\text{TFP loss}_{\text{VES}} - \text{TFP loss}_{\text{CES}}\right]}_{\text{Misallocation}} + \underbrace{\tfrac{1}{2} \times \Delta(\text{markup})}_{\text{Output tax}}. \tag{20}$$

The first term on the right hand side captures how changes in markups due to climate change can either magnify or mitigate TFP losses by changing the degree of markup-induced misallocation across firms, while the second term reflects that a change in the *aggregate* markup can change employment and output via the labor wedge channel. For example, in countries where temperature shocks have negative impacts and lead to increased productivity dispersion, welfare calculation under VES is able to take into account the additional misallocation and output tax induced by climate shocks and thus results in a higher welfare loss than in CES. In other words, whether CES under or overestimate welfare costs of climate induced market power depends on whether the realized shock increase or decrease markups dispersion and level.

Table 6 summarizes the decomposition of Equation (20) at the country level: the first column ("Welfare Loss (VES-CES)") shows whether CES over- or underestimates the welfare cost for each country, and the subsequent columns ("Misalloc" and "Output Tax") report the two decomposition components. The 'Misalloc' column captures the aggregate productivity loss attributed to markup dispersion, while the 'Output Tax' column captures how changes in the aggregate markup changes the labor wedge and therefore total output. Positive entries in the first column indicate that CES underestimates the welfare loss relative to VES, whereas negative entries indicate an overestimate. Some countries, such as Spain, see an increase in aggregate markups ("Output Tax") as well as increased misallocation, amplifying the welfare cost under VES and thus leading CES to understate the damage. Others experience a drop in equilibrium markups, causing CES to overshoot. In all cases, the final welfare difference reflects contributions of comparable magnitude from two channels: the misallocation channel, tied to differential TFP losses, and changes in the aggregate markup.[28] For the more affected countries, the magnitude of this underestimation is substantial: in Spain, CES misses over **40** percent of the total welfare cost from heat exposure.[29]

Our quantitative findings indicate that temperature shocks could lead to a non-negligible welfare loss via the productivity shock channel where the direct productivity loss is amplified by endogenously rising

[27] Appendix C.4.3 provides details on the derivation of this decomposition

[28] Changes in aggregate markup can further be decomposed into the between-firm and within-firm effects. G9 shows the country-specific decomposition of aggregate markup. Both the within and between components are important in explaining changes in aggregate markup.

[29] Calculated as the ratio of the CES-VES welfare difference to the total welfare loss under VES (0.189/0.441).

Table 4: Summary of Simulated Welfare Change (CES) version

| | ΔTFP(%) | ΔMarkup(%) | ΔWelfare(%) |
|---|---|---|---|
| GDP-weighted Mean | 0.231 | 0 | 0.231 |
| Range | [-0.252,0.497] | [0,0] | [-0.252,0.497] |

*Notes*: This table shows the changes in aggregate TFP, aggregate markup, and welfare under observed changes in daily maximum distribution from 2000 to 2020 . We treat each country as a separate economy and simulate markup and welfare changes at the country level. The first row within each panel shows the average change across country, weighted by Country-specific GDP in 2020. The second row shows the minimum and maximum across countries. Welfare loss is *Consumption-Equivalent* Welfare Loss, as defined in Appendix C.4.3.

Table 5: Summary Of Country-Specific Changes (CES)

| Country | TFP Change | Markup Change | Welfare Change |
|---|---|---|---|
| Spain | -0.252 | 0 | -0.252 |
| Italy | -0.038 | 0 | -0.038 |
| Estonia | 0.012 | 0 | 0.012 |
| Denmark | 0.043 | 0 | 0.043 |
| Finland | 0.113 | 0 | 0.113 |
| Belgium | 0.188 | 0 | 0.188 |
| Poland | 0.200 | 0 | 0.200 |
| Slovakia | 0.249 | 0 | 0.249 |
| Croatia | 0.265 | 0 | 0.265 |
| France | 0.324 | 0 | 0.324 |
| Hungary | 0.339 | 0 | 0.339 |
| Germany | 0.497 | 0 | 0.497 |

*Notes*: This table summarizes the percentage change in Aggregate TFP, Aggregate Markup, and Consumption-Equivalent Welfare for each country. The calculation is based on a CES demand environment where markup is exogenously determined, by construction. Observations are ordered in the order of decreasing welfare loss.

market power (higher markups) and the resulting misallocation of resources. By using a VES demand system, our analysis uncovers welfare effects that a standard CES model would miss. In particular, the CES and VES comparison reveals that ignoring heterogeneous markup adjustments can either understate or overstate the true welfare impact, depending on how such distortions manifest. In doing so, our framework brings into climate economics literature insights from trade and industrial organization on firm heterogeneity and misallocation.

**Discussion: Comparison with Trade Literature** Our CES-VES comparison connects to the recent trade literature that quantifies gains from trade under endogenous markups (Edmond et al., 2015; Arkolakis et al., 2019). A key finding from this literature is that, contrary to the intuition that trade-induced competition should reduce markups and amplify welfare gains, CES and VES frameworks yield quantitatively similar welfare estimates for trade liberalization. Arkolakis et al. (2019) show that this similarity arises because trade opening generates two offsetting forces: as foreign firms gain market access, their markups rise, while

Table 6: Comparison of Welfare under CES and VES

| Country | Welfare Loss (VES - CES) | Misallocation | Output Tax |
|---|---|---|---|
| France | 0.200 | 0.093 | 0.108 |
| Spain | 0.189 | 0.086 | 0.104 |
| Belgium | 0.059 | 0.021 | 0.038 |
| Germany | 0.046 | 0.012 | 0.034 |
| Estonia | 0.040 | 0.015 | 0.025 |
| Poland | 0.020 | 0.007 | 0.012 |
| Italy | 0.011 | -0.003 | 0.014 |
| Finland | 0.010 | 0.0003 | 0.010 |
| Denmark | -0.0001 | 0.0003 | -0.0004 |
| Slovakia | -0.015 | -0.004 | -0.011 |
| Croatia | -0.022 | -0.012 | -0.011 |
| Hungary | -0.042 | -0.012 | -0.030 |

*Notes*: This table compares simulated welfare outcomes under VES and CES. For each country, we report the difference in welfare losses ( $\text{Welfare Loss}_{\text{VES}} - \text{Welfare Loss}_{\text{CES}}$ ) alongside its decomposition into a *misallocation* channel and an *output-tax* channel, as given by Equation (20). A positive value in the Welfare Difference column indicates that the climate-induced welfare cost is *larger* in the VES model—i.e., the *CES* specification *underestimates* the overall welfare loss. The "Misallocation" component corresponds to the difference in aggregate TFP losses between the two specifications, while the "Output Tax" component captures one-half of the difference in aggregate markups, reflecting how markup variation can amplify or mitigate the overall climate shock.

domestic firms facing increased competition see their markups fall. These opposing movements largely cancel in aggregate, rendering the CES-VES distinction quantitatively modest.

Our setting differs in a fundamental way. Climate shocks have no analogous two-sided structure—there is no "foreign" and "domestic" moving in opposite directions. Instead, extreme heat operates as a one-directional force on the productivity distribution: it disproportionately harms small firms while leaving large firms relatively unaffected. This asymmetric shock increases productivity dispersion, shifts market share toward high-markup incumbents, and raises aggregate markups without a countervailing pro-competitive effect. As shown in Table 6, failing to account for endogenous markups leads to understated welfare losses (or overstated welfare gains) from heat exposure in EU manufacturing.

More broadly, our findings suggest a condition under which the CES-VES distinction becomes quantitatively important: when shocks differ systematically by firm size in a way that interacts with and amplifies pre-existing productivity dispersion. As documented in Section 4.3, extreme heat disproportionately reduces productivity for small firms while leaving large firms relatively unaffected—a pattern likely driven by costly adaptation, financial constraints, and other size-dependent channels. Such shocks widen the gap between high- and low-productivity firms, generating systematic reallocation toward high-markup incumbents. Accounting for the resulting misallocation through a VES framework can matter substantially for quantifying aggregate productivity damages.

## 6 Conclusion

This paper examines the impact of temperature shocks on market structure and market power, and quantifies the associated welfare costs. Using firm-level data from the manufacturing sector in 12 EU countries, we find that extreme heat reduces firm productivity and increases markups on average. However, the effects vary across firms of different sizes, both in magnitude and direction. Productivity increases among the largest firms but declines among smaller firms. These heterogeneous impacts lead to a reallocation of market share from small to large firms, resulting in greater market concentration and higher aggregate markups. Taking into account both the productivity and markup channels, we find substantial variation in welfare effects across countries, with the direction depending on local temperature exposures. Notably, our findings underscore the importance of endogenizing markups: comparing welfare losses under VES versus CES demand, we show that standard CES frameworks can substantially understate the true welfare cost of temperature shocks. In Spain, for example, CES misses over 40 percent of the welfare loss. This underestimation arises because extreme heat shock disproportionately harms small firms while leaving large firms relatively unaffected—systematically shifting market share toward high-markup incumbents.

Our study contributes to the literature on the economic costs of climate change by examining how temperature shocks affect firm productivity and, importantly, market power. Methodologically, it highlights the importance of endogenizing markups by moving beyond the conventional constant elasticity of substitution demand framework. In doing so, the paper bridges the climate economics literature with the macroeconomics and industrial organization literature that seeks to understand the causes and consequences of rising market power.

While our evidence centers on extreme heat, the scale-biased nature of climate change extends beyond direct temperature shocks to encompass both adaptation investments and environmental policy responses. Consider coastal flooding: flood-protection investments—such as the raised-floor distribution centers built in Bangkok's logistics parks after the 2011 floods, or the perimeter flood walls now common around U.S. coastal factories—are capital-intensive and therefore more accessible to large, multi-site firms. Early work, such as Fatica et al. (2024) on European floods and Seetharam (2018) on U.S. hurricanes, documents within-firm reallocation and differential exit patterns across firm sizes, yet the sign and magnitude of concentration changes vary by hazard and context. Similarly, compliance with environmental regulations—whether emission standards, carbon taxes, or mandated abatement technologies—often entails substantial fixed costs that disproportionately burden smaller producers. To the extent that climate policy tightens in response to warming, these regulatory channels may further amplify the market-power effects we document. If these channels similarly generate forces favoring larger firms, the CES-VES distinction we identify—and the resulting underestimation of welfare costs under standard frameworks—would apply broadly. Determining whether such amplification is a general cost of climate change—across hazards, adaptation margins, and policy instruments—therefore remains an open research agenda.

We acknowledge two important limitations of our study related to the temporal and spatial scope of the analysis, and we discuss directions for future research. First, our analysis focuses on short-term impacts by examining reallocation driven by contemporaneous temperature shocks. Over the longer term, however, increased market concentration may reduce incentives to innovate in climate-resilient technologies, dampening industry dynamism and slowing technological progress. Future research could incorporate data on investment, industry turnover, and adaptation mechanisms to better understand the long-term effects on market structure.

Second, our current analysis focuses on 12 European economies. Although we uses China and India data as robustness checks, our analysis does not cover a broad range of the developing world. On one hand, many developing countries, especially those near the equator, face more intense and frequent heat extremes (Dell et al., 2012; Burke et al., 2015), and higher baseline temperatures may imply a greater marginal impact on productivity as warming occurs. On the other hand, adaptation to climate shocks may be more constrained in developing countries by weaker financial systems, pervasive informality, and limited managerial capacity (Bloom et al., 2013; Hsieh and Klenow, 2009). These factors could exacerbate the heterogeneous productivity effects and the resulting market share reallocation. Therefore, it stands to reason that the climate impact and associated welfare loss, through both productivity and markup channels, may be even larger in developing countries than what we estimate in the European context. We are currently extending our analysis to a broader set of countries.

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# Online Appendix

## Climate Change and Market Power

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## Table of Contents

# A Orbis Data

**Data Cleaning** There are several type of firm accounts available in our Orbis dataset: Consolidated(consolidation code C1, C2), Unconsolidated(U1,U2), and Limited Financial(LF). We use only Unconsolidated accounts data from Orbis, as we want to match the economic variables of a plant to its specific location and the local temperature shock it experiences, as well as to avoid double counting. Restricting the sample to be only unconsolidated accounts also better approximates specific product market, which further validates the production function estimation approach. On the other hand, consolidated accounts observations might not reflect the output of the local plant, as it can be balance sheet data of a headquarter, instead of a specific plant.

Using only unconsolidated accounts information can understate the level of concentration measure, since it can ignore firm-to-firm linkages within different business group (Kalemli-Ozcan et al., 2015). The literature has adopted different approaches when it comes to measuring concentration: whether it is at the individual firm-level or the business group level. Each of these approach has its advantages and limitations, depending on the data availability and research questions [30]. However, in our context, we believe focusing on individual plants' performances are more appropriate for analyzing the effect of local temperature shock. In addition, across most countries and industries, unconsolidated firms account for more than majority of the market shares (Bajgar et al., 2020).The broad trend of concentration change in the EU carry through, regardless of different unit of measures, though the trajectory is a bit different(Bajgar et al., 2019b).[31]

From our production function estimation, our data cleaning procedure closely follows Weche and Wambach (2021) and Ganglmair et al. (2020), albeit a bit less restrictive. Observations that have missing or insensible data in these variables are dropped : *OPERATING_REVENUE_TURNOVER*, *NUMBER_OF_EMPLOYEES*. We also keep only unconsolidated accounts, as in the context of production function estimation unconsolidated accounts are closer to a product market compared to consolidted.

Many researchers using Orbis tend to impose a fixed cutoff threshold for number of employees to address the problem of Orbis under-representing small firms. Doing so can ensure a more stable coverage over time and a better defined distribution. However, it would also diminish the ability to approximate the true distribution of firms, especially for the micro firms, which can be more vulnerable to climate change. Imposing a fixed cutoff threshold across different country-industries can also be misleading, as it can cutoff different parts of the firm distribution in different country-industries. Therefore, in the context of our research questions, we think it's also crucial to analyze how smaller firms are affected by climate change. Thus, we adopt a less restrictive data cleaning approach than the literature and do not impose any size restrictions at the moment.

The climate data extraction procedure requires data on geographical locations. Our preferred geographical variables are longitude and latitude of a plant. When those are not available, we use street address or postcode to geocode the location. Observations that do not have any of these geographical variables are dropped.

**Deflator** For output measures, we use Producer Price Index data from Eurostat, which is available at the country by NACE 2-digit industries level. For labor cost, we use Labor Cost Index at the same country by NACE 2-digit industries level.

[30] For a more complete discussion on the accounts types in Orbis, see Bajgar et al. (2020)

[31] For more discussions on different approaches to calculate concentration in EU, see Bajgar et al. (2019b)

**Imputation** Following Gal (2013), we perform internal imputation for the Value-added and Material Costs variable before the production function estimation. As suggested by Bajgar et al. (2020) ,imputation of value added using information on wage bill and earnings can partially improve the representativeness of Orbis data, which has been a well-documented problem with Orbis. In particular, the mean characteristics and the representativeness of the bottom half of firm distribution is closer to that of the true population after imputation. So far our imputation is internal, using information from within the Orbis data. External imputation, which requires industry level wage bill data, is also possible. However, the effect of external imputation is minimal and can diminishes the dispersion within industries (Bajgar et al., 2020). Hence, we plan to incorporate the external imputation in the later versions of the draft as a further robustness check, while keeping the internal imputation as our primary imputation method.

# B Production Function and Markup Estimation

This section describes our empirical approach to estimate the production function and markups based on firm-level revenue and input data following the approach in De Loecker and Warzynski (2012).

**Cost-minimization** Consider the following production function for firm $i$ in time $t$:

$$Q_{it} = F(X^1_{it},...,X^V_{it},K_{it};\beta)exp(\omega_{it}), \tag{B.1}$$

where $\omega_{it}$ is the productivity. Under cost-minimization,

$$L(X^1_{it}...X^V_{it},K_{it}) = \sum_{v=1}^{V} P^{X^v}_{it} X^v_{it} + r_{it}K_{it} + \lambda_{it}(Q_{it} - Q_{it}(\cdot)), \tag{B.2}$$

where $\lambda_{it}$ is the marginal cost of changing output. The first-order condition with respect to variable input $X^v_{it}$ implies:

$$P^{X^V}_{it} = \lambda_{it}\frac{\partial Q_{it}(\cdot)}{\partial X^V_{it}}. \tag{B.3}$$

Given the definition of output elasticity of variable input ($\theta^{X^V}_{it}$),

$$\theta^{X^V}_{it} = \underbrace{\frac{\partial Q_{it}(\cdot)}{\partial X^V_{it}}\frac{X^V_{it}}{Q_{it}}}_{\text{Output elas. wrt var. input}} = \underbrace{\frac{1}{\lambda_{it}}}_{\text{1/MC}}\underbrace{\frac{P^{X^V}_{it}X^V_{it}}{Q_{it}}}_{\text{var. exp. share}} = \mu_{it}\frac{P^{X^V}_{it}X^V_{it}}{P_{it}Q_{it}}, \tag{B.4}$$

where the last equality follows from $\mu = \frac{P}{MC}$. This implies:

$$\mu_{it} = \frac{\theta^{X^V}_{it}}{\alpha^{X^V}_{it}}. \tag{B.5}$$

That is, firm markup can be written as the output elasticity of variable input $X^V$, $\theta^{X^V}_{it}$, over the revenue share of input $X^V$, $\alpha^{X^V}_{it}$. The latter is defined as the total cost of $X^V$ over total revenue.

**Production Function and Output elasticity** Consider the following production function, where $Q_{it}$ is denoted as the output of firm $i$ in time $t$; $X^m_{it}$ as the variable input $m$, $K_{it}$ as the capital, $\omega_{it}$ as the productivity, and $\varepsilon_{it}$ as idiosyncratic shocks.

$$Q_{it} = F(X^1_{it},...,X^V_{it},K_{it};\beta)exp(\omega_{it})exp(\varepsilon_{it}), \tag{B.6}$$

Take logarithm on both sides,

$$q_{it} = f(x^1_{it},...,x^V_{it},k_{it};\beta) + \omega_{it} + \varepsilon_{it}. \tag{B.7}$$

Production Function $F(\cdot)$ is Cobb-Douglas, with labor being the variable inputs and capital being the dynamic input.

$$q_{it} = \beta_l l_{it} + \beta_k k_{it}. \tag{B.8}$$

Under this specification of the production function, we can then calculate the output elasticity of labor input as the following:

$$\hat{\theta}_{it}^{L} = \frac{\partial \ln F(\cdot)}{\partial \ln L_{it}} = \frac{\partial f(\cdot)}{\partial l_{it}} = \hat{\beta}_l \tag{B.9}$$

We estimate the production function at the country by NACE4 industry level, i.e., firms in the same country by NACE4 industry share the same production function. We follow the proxy method and two-stage procedure in De Loecker and Warzynski (2012). Given the estimated production function coefficients, we can then use the output elasticity at the country by NACE4 industry level, and the firm level labor and capital input to calculate firm-level output elasticity, from which we can then calculate markups.

From Equation (B.5),

$$\hat{\mu}_{it} = \hat{\theta}_{it}^{L} \cdot \frac{P_{it} Q_{it}}{W_{it} L_{it}}. \tag{B.10}$$

Firm-level markup is the product of industry output elasticity with respect to labor and the inverse of firm's labor revenue share.

**Two-step GMM** The estimation procedure consists of two steps. The first stage is for purging out measurement errors $\varepsilon$. The second step uses moments conditions to estimate the $\beta$ coefficients. The proxy variable, material costs in our case, is assumed to be a function of productivity and capital inputs. The inversion of the material demand function gives:

$$\omega_{it} = h_t(k_{it}, m_{it}, z_{it}),$$

where $z_{it}$ are additional industry and time fixed effects that can affect material demand other than productivity and inputs. The production function then becomes

$$y_{it} = \underbrace{f(l_{it}, k_{it}) + \overbrace{h_t(m_{it}, k_{it}, \mathbf{z}_{it})}^{\text{Productivity } \omega_{it}}}_{\text{Expected Output } \hat{\phi}_{it}(l_{it}, k_{it}, m_{it}, z_{it})} + \varepsilon_{it}.$$

The residuals from the first-stage is then

$$\hat{\varepsilon}_{it} = y_{it} - \hat{\phi}_{it}(l_{it}, k_{it}, m_{it}, z_{it}),$$

and the productivity can be expressed as a function of $\beta$'s

$$\omega_{it}(\beta) = \hat{\phi}_{it}(l_{it}, k_{it}, m_{it}, z_{it}) - f(l_{it}, k_{it}).$$

Productivity is assumed to follow a first-order Markov Process:

$$\omega_{it} = g(\omega_{it-1}) + \xi it,$$

where $\xi_{it}$ is the productivity shock. The key identification assumption comes from the orthogonality between current productivity shock and current state variable (capital), as well as between current productivity shock and lagged free variable (labor). Namely, capital inputs are decided dynamically, while labor adjusts more freely and respond to contemporaneous productivity shock. Therefore, in the second stage, $\hat{\beta}$ are derived from Moments conditions:

$$E\left(\xi_t(\beta)\cdot\begin{pmatrix}K_t\\L_{t-1}\end{pmatrix}\right) = 0.$$

Once $\hat{\beta}$ is estimated, we can then derive firm-level productivity $\hat{\omega}_{it}$ and output elasticity $\hat{\theta}_l$ and $\hat{\theta}_k$.

**Discussion on limitation** Production quantity data is needed for production function estimation in order to estimate the level of markups. However, standard firm-level data sets like ours only contain revenue but not quantity. As shown by De Ridder et al. (2022), revenue-based markup estimates contain useful information about the dispersion of markup and the trend of markup over time, as they correlates with key variables such as market shares. In particular, revenue-based markups can be used to obtain one of our empirical objectives, to estimate the gradient of firm markups with respect to temperature shocks with appropriate controls such as the industry fixed effects.

# C Model

## C.1 Additional Details

**Profits and Exit** Using $MC_i = \gamma_i(T)\,\frac{W}{\varphi_i}$ and the constant-markup pricing, firm $i$'s profit function becomes

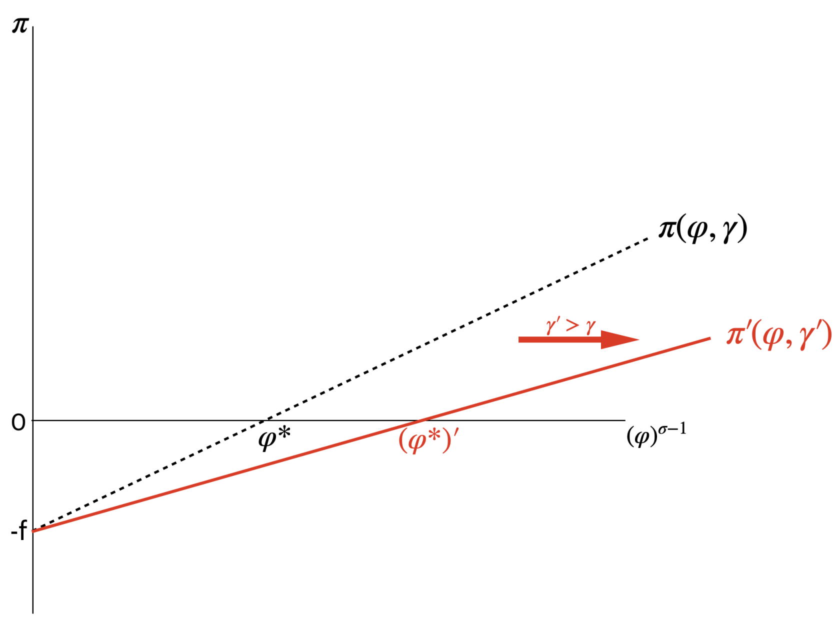
$$\pi(\varphi_i) \;=\; \gamma_i(T)^{1-\sigma}\,\frac{1}{\sigma}\,E\left(P\,\frac{\sigma}{\sigma-1}\right)^{\sigma-1}\varphi_i^{\sigma-1} \;-\; f, \tag{C.11}$$

Following Melitz (2003), there is a unique productivity cutoff $\varphi^*$ at which profits are zero:

$$\pi(\varphi_i^*) \;=\; 0 \quad\Longrightarrow\quad \varphi_i^* \;=\; \gamma_i(T)\left(\frac{f\,\sigma}{E}\right)^{\frac{1}{\sigma-1}}\frac{\sigma-1}{\sigma\,P}. \tag{C.12}$$

**Proposition 1.** *An increase in $\gamma_i(T)$ (e.g., higher temperature) raises the zero-profit cutoff, thus pushing out lower-productivity firms.*

Figure C1: Exit Cutoff Under Climate-Induced Cost (CES)




*Note:* This figure plots firm profit as a function of productivity $\varphi$ in the CES setting. $\varphi^*$ is the zero-profit threshold below which firms exit the market.

**Heterogeneous Pass-Through and Markup Elasticity** The previous analysis emphasized the impact of industry-wide temperature shocks on equilibrium outcomes, reflecting our empirical setting in which local temperature fluctuations affect all firms in a particular region. Nonetheless, it is also useful to introduce the concept of differential pass-through under an endogenous-markup model, where individual firms' pricing decisions respond to *idiosyncratic* cost shocks.[32] Recognizing heterogeneity in cost pass-through across firms

[32]This discussion is partial-equilibrium in nature, keeping competitors' prices fixed and focusing on how a single firm adjusts its own price in response to its own cost shocks.

of different sizes can provide insights into the mechanisms behind shifts in market structure. Our notation follows Arkolakis and Morlacco (2017).

Let $\Gamma(s)$ denote the elasticity of the markup $\mu_{ij}$ with respect to the firm's market share $s_{ij}$:

$$\Gamma(s_{ij}) \;\equiv\; \frac{\partial \log \mu_{ij}}{\partial \log s_{ij}} \;=\; \frac{(\rho-\eta)\,s_{ij}}{\rho - s_{ij}(\rho-\eta)}, \tag{C.13}$$

where $\Gamma(s_{ij}) > 0$ and increases with $s_{ij}$ for the relevant range of market shares observed in the data. Intuitively, *larger firms' markups become more sensitive* to changes in market share.

Define $\Phi_{ij}$ as the elasticity of firm-level prices with respect to the temperature-induced productivity shock $\gamma_{ij}(T)$, holding the aggregate price index constant:

$$\Phi_{ij} \;=\; \left.\frac{\partial \log P_{ij}}{\partial \log \gamma_{ij}}\right|_{P_j}, \tag{C.14}$$

where $P_{ij}$ is the firm's price and $P_j$. Under partial equilibrium, one can show from the firm's optimal pricing equation that markup elasticity and cost pass-through are inversely related:

$$\Phi_{ij}(s_{ij}) \;=\; \frac{1}{1+\Gamma(s_{ij})}. \tag{C.15}$$

Because $\Gamma'(s) > 0$, it follows that $\Phi'(s) < 0$: *larger firms have higher markup elasticity and therefore lower cost pass-through*. In the face of an idiosyncratic productivity shock, larger firms can more flexibly adjust their markups, stabilizing both price and market share. In contrast, smaller firms face less flexible markups and must pass on a greater share of their cost increases to final prices. Thus, higher markup elasticity serves as a buffer against cost shocks and reflects the degree of market power a firm has.

To illustrate, decompose the firm's log price change:

$$\hat{P}_{ij} \;=\; \underbrace{\Gamma(s_{ij})\cdot \hat{s}_{ij}}_{\text{market power channel}} \;+\; \underbrace{\hat{mc}_{ij}}_{\text{productivity channel}},$$

where $\hat{mc}_{ij} > 0$ captures the increase in marginal cost following a negative productivity shock. Larger firms (high $\Gamma$) absorb more of this shock by reducing their markups, thereby mitigating the impact on $\hat{P}_{ij}$ and $\hat{s}_{ij}$. Smaller firms lack this margin of adjustment and must raise prices more, losing additional market share.

In contrast, under standard CES ($\Gamma = 0$ and $\Phi = 1$), markups are constant and cost pass-through is complete, leaving no room for heterogeneous price adjustments across firms. This assumption contradicts empirical findings of variable pass-through rates and underscores the importance of modeling endogenous markups when analyzing reallocation and market structure. Nonetheless, because climate shocks typically affect all firms within a given geographical region, it can be challenging to empirically disentangle the 'market power channel' from the 'productivity channel.' Observed changes in prices and market shares likely combine both forces.

## C.2 Derivations of Qualitative Predictions

### C.2.1 Derivation of Proposition 1 on Exit Cutoff

*Proof.*

$$\frac{\partial \varphi^*}{\partial T} = \frac{\partial}{\partial T}\left(\gamma(\frac{f\sigma}{E})^{\frac{1}{\sigma-1}}\frac{\sigma-1}{\sigma P}\right) \tag{C.16}$$

$$= \left((\frac{f\sigma}{E})^{\frac{1}{\sigma-1}}\frac{\sigma-1}{\sigma P}\right)\cdot\frac{\partial\gamma}{\partial T} \tag{C.17}$$

Given that extremely hot temperature decrease productivity more ($\frac{\partial\gamma}{\partial T} > 0$), the partial derivative of exit cutoff with respect to temperature is also positive. The climate-induced productivity shock $\gamma$ essentially increases the ex-ante productivity needed to earn the same profit. ■

### C.2.2 Derivation of Changes in Aggregate Markup under Climate Shocks

*Proof.* Let $\mu \equiv \sum_i^N s_i \cdot \mu_i$ be defined as the sales-share weighted aggregate markup. Taking the total derivative of aggregate markup with respect to the temperature-induced productivity shock $\gamma(T)$, we have

$$\frac{d\mu}{d\gamma} = \sum_i^N \left(\underbrace{\frac{ds_i}{d\gamma}\cdot\mu_i}_{\text{Between}} + \underbrace{s_i\cdot\frac{d\mu_i}{d\gamma}}_{\text{Within}}\right) \tag{C.18}$$

The between component captures the effect of temperature shock on market share changes, holding firm markup constant. It measures the contribution of reallocation of market shares to aggregate markup change. The within component measures the aggregate effect of firm-level markup change, holding market share fixed.

From equation (9), we can show that demand elasticity is decreasing and convex in market share

$$\frac{d\varepsilon_i}{ds_i} = \frac{\eta\rho(\eta-\rho)}{(\eta(s_i-1)-\rho s_i)^2} < 0, \quad \text{given } \rho > \eta > 1 \tag{C.19}$$

$$\frac{d^2\varepsilon_i}{d{s_i}^2} = 2\left(\frac{1}{\eta}-\frac{1}{\rho}\right)^2\cdot\left(\frac{1-s_i}{\rho}+\frac{s_i}{\eta}\right)^{-3} > 0 \tag{C.20}$$

Likewise, from equation (9), we can also show that markup is increasing and convex in market share ($\frac{d\mu_i}{ds_i} > 0$ and $\frac{d^2\mu_i}{d{s_i}^2} > 0$)

**Between Component**

$$\text{Between} = \sum_{i=1}^N \frac{ds_i}{d\gamma}\cdot\mu_i. \tag{C.21}$$

From the market share equation (10), the effect of changes in temperature shock $\gamma$ can be expressed as

$$\frac{ds_i}{d\gamma} = (1-\rho)\cdot s_i \left(\frac{d\ln P_i}{d\gamma} - \sum_{j=1}^{N} s_j \frac{d\ln P_j}{d\gamma}\right). \tag{C.22}$$

Without loss of generality, suppose that $\frac{d\ln P_i}{d\gamma}$ is smaller (less negative) for larger firms, under the assumption of productivity-decreasing shock. This implies that larger firms' prices increase less compared to smaller firms when $\gamma$ increases, decreasing their relative prices and increasing their market share.

Given that larger firms gain market share ($\frac{ds_i}{d\gamma} > 0$ for large $s_i$) and have higher markups (since $\mu_i$ increases with $s_i$), while smaller firms lose market share ($\frac{ds_i}{d\gamma} < 0$ for small $s_i$) and have lower markups, the overall sum is likely positive.

**Within Component**

$$\text{Within} = \sum_{i=1}^{N} s_i \cdot \frac{d\mu_i}{d\gamma} = \sum_{i=1}^{N} s_i \cdot \frac{d\mu_i}{ds_i}\cdot\frac{ds_i}{d\gamma}. \tag{C.23}$$

Since $\frac{d\mu_i}{ds_i} > 0$ and $\frac{d^2\mu_i}{ds_i^2} > 0$, and larger firms have large $s_i$ and $\frac{ds_i}{d\gamma} > 0$, their contributions to the within component are positive and weighted more heavily due to larger $s_i$. Smaller firms contribute negatively, but their $s_i$ are smaller, so their negative contributions are less significant.

Combining the positive effect on both the *Between* and *Within* components, we conclude that aggregate markup will likely increase under a productivity decreasing temperature shock $\gamma$. The convexity of demand is crucial for this conclusion. We further test this prediction in our simulation section. ■

### C.2.3 Derivation of Changes in HHI Under Climate Shocks

Let $N$ be the total number of firms in the market. Let $s_i$ denote the market share of firm $i$, where $s_i \geq 0$ and $\sum_{i=1}^{N} s_i = 1$. The **Herfindahl-Hirschman Index (HHI)** is defined as:

$$\text{HHI} = \sum_{i=1}^{N}(s_i \times 100)^2 = 10{,}000 \times \sum_{i=1}^{N} s_i^2. \tag{C.24}$$

Under the assumption of productivity-decreasing shock and Proposition **??**, temperature shock essentially leads to a **mean-preserving spread** of a market share distribution. More specifically, while the mean of market share is constant in a balanced sample ($\bar{s} = \frac{1}{N}\sum_{i=1}^{N} s_i = \frac{1}{N}$ ), the variance of market share increases.

The variance of market share is defined as

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N}(s_i - \bar{s})^2 = \frac{1}{N}\sum_{i=1}^{N} s_i^2 - \bar{s}^2 \tag{C.25}$$

Rewriting equation (C.25) as

$$\sum_{i=1}^{N} s_i^2 = N\sigma^2 + N\bar{s}^2 = N\sigma^2 + \frac{1}{N}. \tag{C.26}$$

From (C.26), it is evident that industry HHI is an increasing function of the variance of market shares. Intuitively, the more dispersed the market share, the larger gap between large and small firms, the more concentrated an industry is.

Under a temperature shock that leads to reallocation and mean-preserving spread of market share distribution, variance of market share $\sigma$ increases, increasing the aggregate HHI.

## C.3 Derivation of Labor Demand

Labor demand is the sum of production labor as well as labor used for overhead. Time subscripts are dropped for clearer exposition. Let $\tilde{l}$ be labor used for production, $l^F$ be the labor used for overhead. $\Xi$ denotes the misallocation forces.

**Firm Production Labor Demand**

$$\begin{aligned}\tilde{l}_{ij}^d &= \frac{y_{ij}}{\varphi_{ij}} \\ &= \frac{Y}{\varphi_{ij}} \cdot \left(\frac{\frac{\mu_j}{\varphi_j}}{\frac{\mu_{ij}}{\varphi_{ij}}}\right)^{\rho} \cdot \left(\frac{\mu_j \frac{W}{\varphi_j}}{P}\right)^{-\eta}\end{aligned}$$

**Sectoral Labor Demand**

$$\begin{aligned}l_j^d &= \sum_{i=1}^{n_{ij}} \tilde{l}_{ij}^d + l_j^F \\ &= \sum_{i=1}^{n_{ij}} \tilde{l}_{ij}^d + n_{ij} f \\ &= \left(\frac{Y}{\varphi_j}\right) \cdot \left(\frac{P\varphi_j}{W\mu_j}\right)^{\eta} \cdot \underbrace{\sum_{i=1}^{n_{ij}} \left[\left(\frac{\mu_{ij}}{\mu_j}\right)^{-\rho} \left(\frac{\varphi_{ij}}{\varphi_j}\right)^{\rho-1}\right]}_{\Xi_j}\end{aligned}$$

**Aggregate Labor Demand**

$$\begin{aligned}L^d &= \int_j l_j^d dj + \int_j n_j f dj \\ &= \frac{Y}{\varphi} \cdot \left(\frac{P\varphi}{\mathscr{M} W}\right)^{\eta} \cdot \underbrace{\left[\int_j \left(\frac{\varphi_j}{\varphi}\right)^{\eta-1} \left(\frac{\mu_j}{\mathscr{M}}\right)^{-\eta} \Xi_j dj\right]}_{\Xi} + \int_j n_j f dj.\end{aligned}$$

## C.4 Full Model Details

In this section, we present the complete model setup, following Section 5.2, and include intermediate inputs and capital in production. Our framework closely follows Edmond et al. (2023).

Our goal is not to provide methodological or theoretical innovations on the model of Edmond et al. (2023). Rather, we use their endogenous markup framework to emphasize a different aspect of interest in our setting. First, we discuss the definition of *TFPR* in the presence of endogenous markups—something their paper does not explicitly highlight but is of particular interest to our setting[33]. Second, while Edmond et al. (2023) is primarily concerned with how heterogeneous markups distort the decentralized economy relative to a planner's efficient (markup-free) allocation, our focus lies in comparing how different assumptions about market structure (constant vs. endogenous markups) influence the quantification of the welfare impact of a productivity shock.

### C.4.1 Model Setup

*Representative consumer*.—The representative consumer maximizes:

$$\sum_{t=0}^{\infty} \beta^t \left( \log C_t - \psi \frac{L_t^{1+\nu}}{1+\nu} \right), \tag{C.27}$$

subject to:

$$C_t + I_t = W_t L_t + R_t K_t + \Pi_t, \tag{C.28}$$

where $C_t$ is aggregate consumption, $i_t$ investment, $W_t$ wage, $R_t$ rental rate, $\Pi_t$ aggregate profits, and $L_t$ labor supply.

The labor supply condition is:

$$\psi C_t L_t^{\nu} = W_t. \tag{C.29}$$

*Final-good producers*.—The final good $Y_t$ can be used for consumption $C_t$, Investment $I_t$, and Materials $M_t$:

$$Y_t = C_t + I_t + X_t \tag{C.30}$$

The final good $Y_t$ is a CES bundle of sector outputs $y_{jt}$ for sectors $j \in [0,1]$:

$$Y_t = \left( \int_0^1 y_{jt}^{\frac{\eta-1}{\eta}} dj \right)^{\frac{\eta}{\eta-1}}, \tag{C.31}$$

where $\eta > 1$ is the across-sector elasticity. Final good is the numeraire, and sector price index $P_{jt}$ satisfies:

$$1 = \left( \int_0^1 P_{jt}^{1-\eta} dj \right)^{\frac{1}{1-\eta}}. \tag{C.32}$$

[33] Our climate induced reallocation story essentially boils down to a TFPQ to TFPR distribution change

*Within sectors*.—Sector $j$ consists of $n_{jt}$ firms producing differentiated goods $y_{ijt}$ aggregated via CES:

$$y_{jt} = \left( \sum_{i=1}^{n_{jt}} y_{ijt}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \tag{C.33}$$

where $\rho > \eta > 1$ is the within-sector elasticity.

Relative prices satisfy:

$$\frac{P_{ijt}}{P_{jt}} = \left( \frac{y_{ijt}}{y_{jt}} \right)^{-\frac{1}{\rho}}, \quad P_{jt} = \left( \sum_{i=1}^{n_{jt}} P_{ijt}^{1-\rho} \right)^{\frac{1}{1-\rho}}. \tag{C.34}$$

*Technology*.—Firms enter by paying a sunk cost $\kappa$ in units of labor and then obtain a one-time productivity draw $\varphi_{ij} \sim G(z)$ in a random sector $s$. We assume $G(z)$ to be pareto with tail parameters $\xi$.A firm's *gross output* is then

$$y_{ij} = \varphi_{ij} \left[ \phi^{1/\theta} v_{ij}^{(\theta-1)/\theta} + (1-\phi)^{1/\theta} x_{ij}^{(\theta-1)/\theta} \right]^{\theta/(\theta-1)}, \tag{8}$$

where $v_{ij}$ is the firm's *value-added*, a Cobb-Douglas composite of capital and labor,

$$v_i = k_{ij}^{\alpha} l_{ij}^{1-\alpha}. \tag{9}$$

*Input Demand*.—Taking input prices as given, cost minimization gives the labor and capital demands:

$$R_t k_{ijt} = \alpha \left[ \left( \frac{R_t}{\alpha} \right)^{\alpha} \left( \frac{W_t}{1-\alpha} \right)^{1-\alpha} \right] v_{ijt} \tag{C.35}$$

$$W_t l_{ijt} = (1-\alpha) \left[ \left( \frac{R_t}{\alpha} \right)^{\alpha} \left( \frac{W_t}{1-\alpha} \right)^{1-\alpha} \right] v_{ijt}, \tag{C.36}$$

and the demand for value-added composite and materials are given by:

$$v_{ijt} = \phi \left\{ \frac{(R_t/\alpha)^{\alpha} (W_t/(1-\alpha))^{1-\alpha}}{\Omega_t} \right\}^{-\theta} \frac{y_{ijt}}{\varphi_{ijt}} \tag{C.37}$$

$$x_{ijt} = (1-\phi) \left( \frac{1}{\Omega_t} \right)^{-\theta} \frac{y_{ijt}}{\varphi_{ijt}}, \tag{C.38}$$

where $\Omega_t$ is the input cost index:

$$\Omega_t = \left\{ \phi \left[ \left( \frac{R_t}{\alpha} \right)^{\alpha} \left( \frac{W_t}{1-\alpha} \right)^{1-\alpha} \right]^{1-\theta} + (1-\phi) \right\}^{\frac{1}{1-\theta}}. \tag{C.39}$$

*Marginal Cost*.—We incorporate a *temperature-induced productivity shock* factor, $\gamma_{ij}(T_t)$, which reduces firm $i$'s baseline productivity $\varphi_{ijt}$ to an effective level:

$$\tilde{\varphi}_{ijt}(T_t) = \frac{\varphi_{ijt}}{\gamma_{ij}(T_t)}.$$

Consequently, marginal cost takes the form:

$$MC_{ijt} = \frac{\Omega_t}{\tilde{\varphi}_{ijt}(T_t)} = \gamma_{ij}(T_t)\,\frac{\Omega_t}{\varphi_{ijt}}. \tag{C.40}$$

We assume $\gamma_{ij}(T^*) = 1$ at the ideal temperature $T^*$ and $\partial\gamma_{ij}(T_t)/\partial T_t > 0$ for $T_t > T^*$. Intuitively, higher temperatures increase $\gamma_{ij}(T_t)$, lowering a firm's effective productivity and thus raising its marginal cost.

*Profits*.—Firm $i$'s profits at time $t$ are given by:

$$\pi_{ijt} = P_{ijt}\,y_{ijt} - MC_{ijt}\,y_{ijt}. \tag{C.41}$$

*Firm pricing and markups*.—Firms price as a markup over marginal cost:

$$P_{ijt} = \mu_{ijt} \cdot MC_{ijt}, \quad \mu_{ijt} = \frac{\varepsilon_{ijt}}{\varepsilon_{ijt} - 1}, \tag{C.42}$$

profit maximization under Cournot competition[34] gives the firm-specific elasticity of demand as a decreasing function of market share:

$$\varepsilon_{ijt} = \left[\frac{1}{\rho}(1 - s_{ijt}) + \frac{1}{\eta}s_{ijt}\right]^{-1}. \tag{C.43}$$

From the CES aggregator within-sectors Equations (C.33), market share can be expressed as:

$$s_{ijt} = \frac{(P_{ijt})^{1-\rho}}{\sum_{k=1}^{n_{ijt}}(P_{ikt})^{1-\rho}} = \left(\frac{P_{ijt}}{P_{jt}}\right)^{1-\rho} \tag{C.44}$$

We can then write firm markup as a function of market share

$$\mu_{ijt} = \frac{1}{1 - \left[\frac{1}{\rho}(1 - s_{ijt}) + \frac{1}{\eta}s_{ijt}\right]} \tag{C.45}$$

and market share as a function of markup

$$s_{ijt} = \frac{\mu_{ijt}^{1-\rho}\,\varphi_{ijt}^{\rho-1}}{\sum_{i=1}^{n_{jt}}\mu_{ijt}^{1-\rho}\,\varphi_{ijt}^{\rho-1}} \tag{C.46}$$

Given a productivity distribution for sector $j$, Equations (C.45) and (C.46) form a system of $2n_{jt}$ equations that can allow us to solve for industry equilibrium market shares and markup.

[34] Under Bertrand: $\varepsilon_{ijt} = \rho(1 - s_{ijt}) + \eta s_{ijt}$.. Both Bertrand and Cournot features size-decreasing elasticity.

*TFPR*.— Firm TFPR by definition is

$$\mathrm{TFPR}_{ijt} \equiv \frac{P_{ijt}\, y_{ijt}}{F(\ell,k,x)} = \mu_{ijt} \times \Omega_t, \tag{C.47}$$

where $\mu_{ijt}$ is the firm-specific markup and $\Omega_t$ is an aggregate cost index capturing wages and input prices. Because $\Omega_t$ is *common* to all firms at time $t$, cross-firm differences in TFPR stem from differences in markups $\mu_{ijt}$. In other words, heterogeneity in TFPR reflects heterogeneity in market power (i.e. markups), rather than purely physical efficiency. [35] Furthermore, dispersion of TFPR therefore reflects the markup dispersion and negatively correlates with Aggregate TFP.

*Labor Shares*.— Combining a firm's labor demand from Equations (C.36) and (C.37) with markup pricing (C.42), a firm's labor share can be written as

$$\frac{W_t l_{ijt}}{p_{jt} y_{jt}} = \frac{(1-\alpha)\zeta_t}{\mu_{ijt}} \tag{C.48}$$

where $\zeta_t$ denotes the elasticity of output with respect to value-added,

$$\zeta_t = \frac{[\phi/(1-\phi)]\left\{(R_t/\alpha)^{\alpha}\,[W_t/(1-\alpha)]^{1-\alpha}\right\}^{1-\theta}}{1+[\phi/(1-\phi)]\left\{(R_t/\alpha)^{\alpha}\,[W_t/(1-\alpha)]^{1-\alpha}\right\}^{1-\theta}}. \tag{C.49}$$

This elasticity is common to all firms but in general varies over time. All cross-sectional variation in labor shares is due to cross-sectional variation in markups $\mu_{ijt}$.

*Aggregate Productivity*.— Let $k_{jt}$, $l_{jt}$, and $x_{jt}$ denote sector-level capital, labor, and materials, respectively. These are the sums of $k_{ijt}$, $l_{ijt}$, and $x_{ijt}$ over $i$ within $j$. We can then write the gross output of sector $j$ as

$$y_{jt} = \varphi_{jt} F\left(k_{jt}, l_{jt}, x_{jt}\right) \tag{C.50}$$

where

$$F(k,l,x) = \left[\phi^{1/\theta}\left(k^{1-\alpha}\right)^{(\theta-1)/\theta} + (1-\phi)^{1/\theta}\left(x^{(\theta-1)/\theta}\right)\right]^{\theta/(\theta-1)} \tag{C.51}$$

and where sector-level productivity satisfies

Sectoral productivity $\varphi_{jt}$ by definition of production function:

$$\varphi_{jt} = \left(\sum_{i}^{n_{jt}} \frac{q_{ijt}}{\varphi_{ijt}}\right)^{-1}. \tag{C.52}$$

[35] Under this definition, a firm can have *lower* TFPQ (physical productivity) but still see *higher* TFPR if its markup $\mu_{ijt}$ grows large enough to outweigh any shifts in $\Omega_t$. The aggregate cost index $\Omega_t$ moves *uniformly* for all firms, so it does not create dispersion *across* them—it only scales TFPR *up or down together*.

, where $q_{ijt}$ is the relative size of firm $i$ in sector $j$:

$$q_{ijt} = \frac{y_{ijt}}{y_{jt}} \tag{C.53}$$

and market share can be written as a function of relative sizes

$$s_{ijt} = q_{ijt}^{\frac{\rho-1}{\rho}} \tag{C.54}$$

*Aggregate Markup*.— Let $\mu_{jt}$ denote the sector-level markup, implicitly defined by the sector-level labor share

$$\frac{W_t L_{jt}}{p_{jt} y_{jt}} = \frac{(1-\alpha)\zeta_t}{\mu_{jt}}. \tag{C.55}$$

Combining the sector-level labor share with its firm-level counterpart (Equation (C.48)), we can write the sales share of firm $i$ in sector $s$ as

$$\frac{p_{ijt} y_{ijt}}{p_{jt} y_{jt}} = \frac{\mu_{ijt}}{\mu_{jt}} \times \frac{l_{ijt}}{l_{jt}}. \tag{C.56}$$

When both sides are summed across firms, the sector-level markup can be written as a market share-weighted harmonic average of firm-level markups:

$$\mu_{jt} = \left( \sum_{i=1}^{n_{jt}} \frac{1}{\mu_{ijt}} s_{ijt} \right)^{-1}. \tag{C.57}$$

From either of these and the expression for sector-level productivity $\varphi_{jt}$, we see that the sector-level markup satisfies

$$p_{jt} = \mu_{jt} \cdot \frac{\Omega_t}{\varphi_{jt}};$$

that is, the sector price index can be expressed as the sector-level markup over marginal cost.

Likewise, let $\mathscr{M}$ denote the aggregate, economy-wide markup. Following the same steps, this can be written either as an employment-weighted arithmetic average or a sales-weighted harmonic average of sector-level markups,

The aggregate markup is:

$$\mathscr{M}_t = \left( \int_0^1 \frac{1}{\mu_{jt}} s_{jt}\, dj \right)^{-1}. \tag{C.58}$$

*Markup Dispersion and Productivity*.— To see how markup dispersion affects productivity, observe from Equation (C.31) and $P_t = 1$ that sector size $q_{jt} = \frac{y_{jt}}{Y_t}$ satisfies $q_{jt} = p_{jt}^{-\eta}$, and since $p_{jt} = \mu_{jt}\Omega_t/\varphi_{jt}$ and $1 = \mathscr{M}_t\Omega_t/Z_t$, we can write

$$q_{ijt} = \left( \frac{\mu_{jt}}{\mathscr{M}_t} \frac{\varphi_t}{\varphi_{jt}} \right)^{-\eta}. \tag{C.59}$$

Equation (C.59) shows how heterogeneous markup impact the relative size of the firm. Compare to a social planner whose allocation based on relative productivity only, in a decentralized equilibrium, the largest firm (also high-markup firms) is too small. Furthermore, a shock that increase the productivity dispersion will lead to greater markup heterogeneity, further increasing such misallocation forces.

Combining Equation (11) and (C.59), we have the sectoral productivity $\varphi_{jt}$ accounted for markup dispersion:

$$\varphi_{jt} = \left( \sum_{i=1}^{n_{jt}} \left( \frac{\mu_{ijt}}{\mu_{jt}} \right)^{-\rho} \varphi_{ijt}^{\rho-1} \right)^{\frac{1}{\rho-1}}. \tag{C.60}$$

Similarly, aggregate productivity is then:

$$\varphi_t = \left( \int_0^1 \left( \frac{\mu_{jt}}{\mathscr{M}_t} \right)^{-\eta} \varphi_{jt}^{\eta-1} dj \right)^{\frac{1}{\eta-1}}. \tag{C.61}$$

*Entry and Exit*.—Firms enter by paying a sunk cost $\kappa$ in units of labor and then obtain a one-time productivity draw $z_t(s) \sim G(z)$ in a randomly allocated sector $s \in [0,1]$. Let $N_t = \int_0^1 n_t(s)\, ds$ denote the aggregate mass of firms, and let $M_t = \int_0^1 m_t(s)\, ds$ denote the aggregate mass of entrants.

With a continuum of sectors, entry per sector $m_t(s)$ is IID (independently and identically distributed) Poisson, with rate parameter $M_t^*$. Firms operate in their sector, obtaining a stream of profits $\pi_t(s)$, until they are hit with an IID exit shock, which happens with probability $\delta$ per period. For each sector $s$, we then have

$$n_{jt+1} = (1-\delta)n_{jt} + m_{jt}$$

and hence the aggregate mass of firms evolves according to

$$N_{t+1} = (1-\delta)N_t + M_t.$$

*Free-entry condition*.—Firms enter by paying a sunk cost $\kappa W_t$ and draw productivity $\delta_{ijt}$ from $G(\delta)$. The free-entry condition is:

$$\kappa W_t = \beta \mathbb{E} \sum_{j=1}^{\infty} (1-\delta)^{j-1} \frac{C_t}{c_{t+j}} \pi_{ijt}. \tag{C.62}$$

### C.4.2 Equilibrium

Given an initial mass of firms $n_j0$ per sector and an aggregate capital stock $K_0$, an *equilibrium* is (i) a sequence of firm prices $p_{ij}$ and allocations $y_{ij}$, $k_{ij}$, $l_{ij}$, $x_{ij}$ and (ii) aggregate gross output $Y$, consumption $C$, investment $I$, materials $X$, labor $L$, wage rate $W$, rental rate $R$, and mass of entrants $M$, such that firms and consumers optimize and the labor, capital, and goods markets all clear. In particular,

$$L_t = \int_0^1 [\sum_i^{n_{jt}} l_{ijt}] \, dj + \kappa M \tag{C.63}$$

$$K_t = \int_0^1 [\sum_i^{n_{jt}} k_{ijt}] \, dj \tag{C.64}$$

$$X_t = \int_0^1 [\sum_i^{n_{jt}} x_{ijt}] \, dj \tag{C.65}$$

Note that $\kappa M$ denotes labor used in the entry of new firms.

### C.4.3 Consumption-equivalent Welfare Loss

*Static welfare loss*.—We derive a simple formula for the welfare losses from markups in a steady-state version of our model. Suppose that the representative consumer has preferences

$$U(C,L) = \frac{C^{1-\sigma}}{1-\sigma} - \frac{L^{1+\nu}}{1+\nu} \tag{C.66}$$

Suppose also that labor is the only factor of production and that there is a representative firm with production function $Y = \varphi L$. Markups distort allocations by reducing aggregate productivity $\varphi$ and by introducing a wedge $\mathscr{M}$ between the wage and marginal product of labor, $W = \varphi/\mathscr{M}$. Labor supply is given by $C^{\sigma} L^{\nu} = W = \varphi/\mathscr{M}$. Using goods market clearing $C = Y = \varphi L$, employment and consumption in the distorted allocation are given by

$$L = \mathscr{M}^{-\frac{1}{\sigma+\nu}} \varphi^{\frac{1-\sigma}{\sigma+\nu}}, \quad C = \mathscr{M}^{-\frac{\sigma}{\sigma+\nu}} \varphi^{\frac{1+\nu}{\sigma+\nu}}. \tag{C.67}$$

The associated level of utility is

$$U(C,L) = \left( \frac{1}{1-\sigma} - \frac{1}{1+\nu} \right) \mathscr{M}^{-\frac{\sigma}{\sigma+\nu}} \varphi^{\frac{(1+\nu)(1-\sigma)}{\sigma+\nu}}. \tag{C.68}$$

Let $\mathscr{W}$ denote the level of consumption solving $U(\mathscr{W},0) = U(C,L)$ for the distorted allocation, namely

$$\mathscr{W} = \left( 1 - \frac{1-\sigma}{1+\nu} \mathscr{M} \right)^{\frac{1}{1-\sigma}} \mathscr{M}^{-\frac{\sigma}{\sigma+\nu}} \varphi^{\frac{1+\nu}{\sigma+\nu}}. \tag{C.69}$$

Similarly, let $\mathscr{W}_{cc}$ denote the level of consumption solving $U(\mathscr{W}_{cc},0) = U(C,L)$ for the climate change shock.

$$\mathscr{W}_{cc} = \left( 1 - \frac{1-\sigma}{1+\nu} \mathscr{M}_{cc} \right)^{\frac{1}{1-\sigma}} \mathscr{M}_{cc}{}^{-\frac{\sigma}{\sigma+\nu}} \varphi_{cc}{}^{\frac{1+\nu}{\sigma+\nu}}. \tag{C.70}$$

Hence the *consumption-equivalent losses from climate change-induced reallocation and changed in markup* can be written as

$$\frac{\mathscr{W}_{cc}}{\mathscr{W}} = \left( \frac{\left(1 - \frac{1-\sigma}{1+\nu}\mathscr{M}_{cc}\right)}{\left(1 - \frac{1-\sigma}{1+\nu}\mathscr{M}\right)} \right)^{\frac{1}{1-\sigma}} \left( \frac{\varphi_{cc}}{\varphi} \right)^{\frac{1+\nu}{\sigma+\nu}} \left( \frac{\mathscr{M}_{cc}}{\mathscr{M}} \right)^{-\frac{\sigma}{\sigma+\nu}}. \tag{C.71}$$

With logarithmic utility, $\sigma \to 1$, as in the main text, this simplifies to

$$\frac{\mathscr{W}_{cc}}{\mathscr{W}} = \left( \frac{\varphi_{cc}}{\varphi} \right) \left( \frac{\mathscr{M}_{cc}}{\mathscr{M}} \right)^{-\frac{1}{1+\nu}}. \tag{C.72}$$

The lower the new aggregate TFP $\varphi_{cc}$ and the higher the new aggregate markup $\mathscr{M}_{cc}$, the lower and consumption and welfare, and therefore higher the consumption-equivalent welfare loss.

Aggregate welfare loss from climate change-induced reallocation is therefore:

$$1 - \frac{\mathscr{W}_{cc}}{\mathscr{W}} = 1 - \left( \frac{\varphi_{cc}}{\varphi} \right) \left( \frac{\mathscr{M}_{cc}}{\mathscr{M}} \right)^{-\frac{1}{1+\nu}}. \tag{C.73}$$

The first ratio $\frac{\varphi_{cc}}{\varphi}$ represents the change in aggregate productivity under climate change productivity shock. There are two reasons why climate change can lead to lower aggregate productivity ($\varphi_{cc} < \varphi$). The first channel is the *productivity effect*: if all firms are negatively affected, so will the aggregate. The second channel is the *misallocation channel*: climate-induced higher market power and markup can lead to less efficient allocation of production input across firms and therefore greater misallocation.

The second ratio $\frac{\mathscr{M}_{cc}}{\mathscr{M}}$ represent the "aggregate tax" of markups. If climate change leads to more reallocation and higher market power, then aggregate markup will increase ($\mathscr{M}_{cc} > \mathscr{M}$), further curbing overall labor demand and aggregate output.

**Role of Demand Assumption**

In our baseline model with VES demand, climate change shocks affect the distribution of markups across heterogeneous firms, ultimately altering both aggregate productivity $\varphi_{cc}$ and the aggregate markup $\mathscr{M}_{cc}$. This *reallocation channel* is central to our results. A useful benchmark for comparison is a model with *constant elasticity of substitution* (CES) demand, which is commonly adopted in quantitative analysis related to climate change due to its tractability.

Under the CES specification, reallocation *does not* change markup dispersion nor the aggregate markup, because each firm faces a residual demand elasticity that is constant and invariant to firm-level shocks. Specifically, if $\sigma$ denotes the elasticity of substitution at the variety level, the markup each firm charges is simply

$$\mu_{\text{CES}} = \frac{\sigma}{\sigma - 1},$$

which is constant across all firms. Consequently, the only impact on aggregate variables under climate change comes from the uniform shift in productivity levels. In other words, under CES, there is no additional misallocation arising from changes in the distribution of markups across firms.

Our primary focus is on how climate shocks (or any size-dependent heterogeneous shocks) propagate differently under these two demand assumptions, rather than on measuring any baseline (pre-shock) markup distortions. Under CES, the markup is uniform and remains unchanged when a shock hits, implying that any variation in firm productivity does not alter either the dispersion of markups or the resulting misallocation. In contrast, under VES, the demand elasticity (and hence each firm's markup) can respond endogenously to shocks, changing the distribution of markups. As a result, using CES may systematically *underestimate* the overall welfare impact of climate change shocks, because it abstracts from the additional inefficiencies arising from changes in markup dispersion and from an increase in the aggregate markup itself.

To illustrate the quantitative implications of these different market structures in the context of climate-induced productivity shocks, we compare the *consumption-equivalent* welfare losses in each case. As before, we measure welfare losses by the ratio of the distorted consumption level to some baseline reference. Under VES, climate change raises the dispersion in markups (as high-productivity firms charge higher markups), *lowers* aggregate productivity through both a *productivity effect* and a *misallocation effect*, and further reduces aggregate output and consumption through a higher aggregate markup (a labor wedge). Under CES, welfare losses come only from the uniform productivity drop, with no amplification via markups. Formally, let $\mathscr{W}_{\text{cc}}^{\text{CES}}$ be the welfare level under the CES assumption, and let $\mathscr{W}^{\text{CES}}$ be the corresponding baseline welfare. Then the consumption-equivalent welfare loss under CES is:

$$1 - \frac{\mathscr{W}_{\text{cc}}^{\text{CES}}}{\mathscr{W}^{\text{CES}}} = 1 - \left(\frac{\varphi_{cc}}{\varphi}\right), \tag{C.74}$$

which depends *only* on the change in aggregate productivity, $\varphi_{cc}/\varphi$, and not on any change in markups.

By construction, the CES benchmark *shuts down* the endogenous markup-dispersion channel. Any *additional* welfare losses observed under the VES setup therefore reflect the reallocation of market shares toward firms with higher markups, the accompanying reduction in aggregate TFP, and the rise in the aggregate markup. In this way, comparing the VES and CES welfare losses highlights the importance of incorporating endogenous markups into climate-change quantification.

**Decomposition of the VES–CES Difference.** To see why the difference between VES and CES can be attributed to both *TFP misallocation* and an *output-tax* effect, consider the VES welfare loss:

$$1 - \frac{\mathscr{W}_{\text{cc}}}{\mathscr{W}} = 1 - \left(\frac{\varphi_{cc}}{\varphi}\right)\left(\frac{\mathscr{M}_{cc}}{\mathscr{M}}\right)^{-\frac{1}{1+\nu}}.$$

Assuming $\nu = 1$, the markup term enters as $\left(\mathscr{M}_{cc}/\mathscr{M}\right)^{-1/2}$. Hence a small percentage *increase* in $\mathscr{M}_{cc}/\mathscr{M}$ translates into roughly *half* that size of a percentage *decrease* in the product $(\varphi_{cc}/\varphi)\left(\mathscr{M}_{cc}/\mathscr{M}\right)^{-1/2}$. Subtracting the CES expression in (C.74) from the VES expression above then gives an approximate decomposition:

$$\left[\text{Welfare Loss}_{\text{VES}} - \text{Welfare Loss}_{\text{CES}}\right] \approx \underbrace{\left[\text{TFP loss}_{\text{VES}} - \text{TFP loss}_{\text{CES}}\right]}_{\text{additional misallocation}} + \underbrace{\tfrac{1}{2} \times \Delta(\text{markup})}_{\text{aggregate markup (tax) effect}}, \tag{C.75}$$

where $\Delta$(markup) is the percentage change in the aggregate markup between the baseline and post-climate-shock allocations.[36]

In short, a higher markup under VES both worsens misallocation and acts like an output tax that reduces total employment and output. By neglecting this mechanism, CES underestimates the true welfare cost of climate change shocks.

[36]Strictly speaking, (C.75) is a first-order approximation that holds exactly for small changes in $\mathscr{M}_{cc}/\mathscr{M}$, or in the limit as $\nu \to 1$. For larger changes, second-order terms may appear, but the decomposition remains a good guide to the relative contributions of TFP vs. markup.

# D Simulation of a single-industry heterogeneous temperature shock

This section presents a single-industry simulation to illustrate how a market-level temperature shock affects market structure. Our results deliver two main insights: (1) a heterogeneous, productivity-reducing shock increases within-industry productivity dispersion, and (2) this heightened dispersion widens the gap between large and small firms, reallocating market shares toward the largest firm and thereby raising overall concentration and markups. These findings are consistent with the theoretical predictions outlined in Section 3.2.2 and inform the design of our empirical analysis.

**Simulation Setup** The simulation setting directly follow section 3.2.2, incorporating a heterogeneous firms model under endogenous markup. Demand features nested CES, with the within-industry elasticity of substitution $\rho$ higher than across-industry elasticity of substitution $\eta$ . Firm level productivity $\varphi$ are drawn from a Pareto distribution with a shape parameter $\theta$. We fix the set of model parameters throughout the simulation and focus on the equilibrium behavior of a single market.

In this framework of endogenous markup, the distribution of productivity determines the distribution of the relative prices, which in turn determines market shares and markup distribution. Two demand elasticity $\rho$ and $\eta$ bounds the range of markup. Largest firm have the lowest relative prices, highest market shares, and charges higher markup.

In order to model the impact of market-level temperature shock, we introduce the climate productivity shifter $\gamma$, which is greater or equal to 1[37]. Such shifter changes the effective productivity of firms:

$$\varphi_{\text{ij,effective}} = \frac{\varphi_{ij}}{\gamma_{ij}}.$$

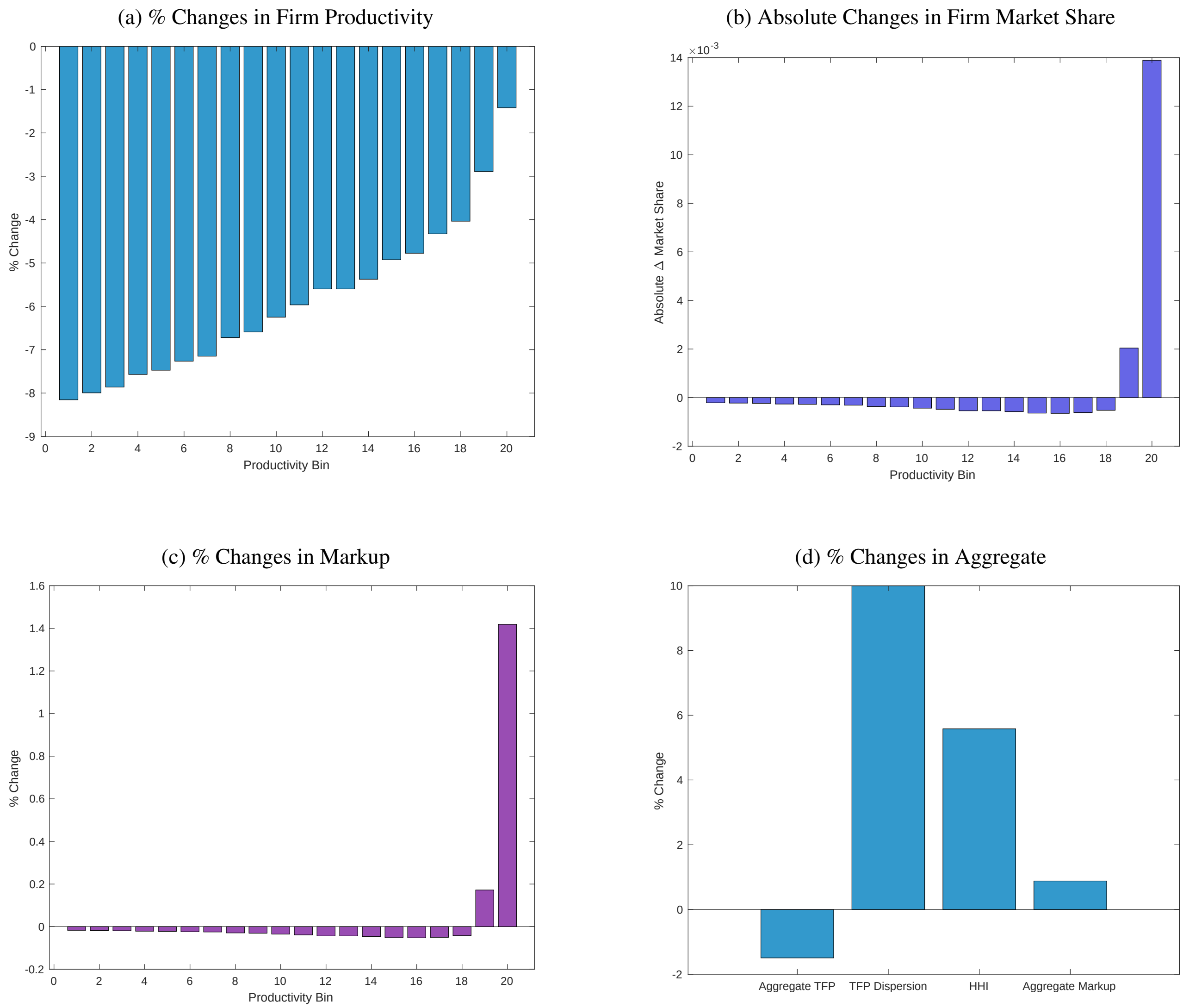
We also assume that the productivity shifter is heterogeneous and decreasing in productivity $(\gamma(\varphi)' < 0)$, which captures the costly nature of adaptation and that larger firms are likely less affected by climate shocks.

Figure D2 summarizes the simulation result. Figure 2(a) to 2(c) shows the changes in three *firm-level* outcomes: *firm productivity*, *firm market share*, and *firm markups*. We group firms within an industry into 20 productivity bins, increasing from left to right. Figure 2(a) shows the negative and productivity-decreasing nature of the shock, by construction. Figure 2(b) shows the differential response of market share across firms of different size bins: while many small to medium firms lose market shares, the largest firms gain significant market shares. This shows a reallocation of shares from small to large firms. As market shares determine equilibrium markup in our framework, figure 2(c) shows similar story for the markup change: largest firm that gain market share can also charge higher markup, while small firms' markup drop due to loss of market share.

As for the aggregate impact of such heterogeneous shock, we see results consistent with predictions in section 3.2.2. Figure 2(d) shows the changes in four *aggregate* outcomes: *Aggregate Productivity*, *Productivity Dispersion*, *HHI*, and *Aggregate Markup*. Given that the shocks are negative for all firms, aggregate

[37]This assumption is based on the overall negative productivity impact of temperature shock we observed in our sample, as well as empirical evidence on the heterogeneous productivity impacts (Zivin and Kahn, 2016; Shi and Zhang, 2025; Somanathan et al., 2021) . In this model of reallocation, homogeneous shock will not lead to reallocation and markup changes

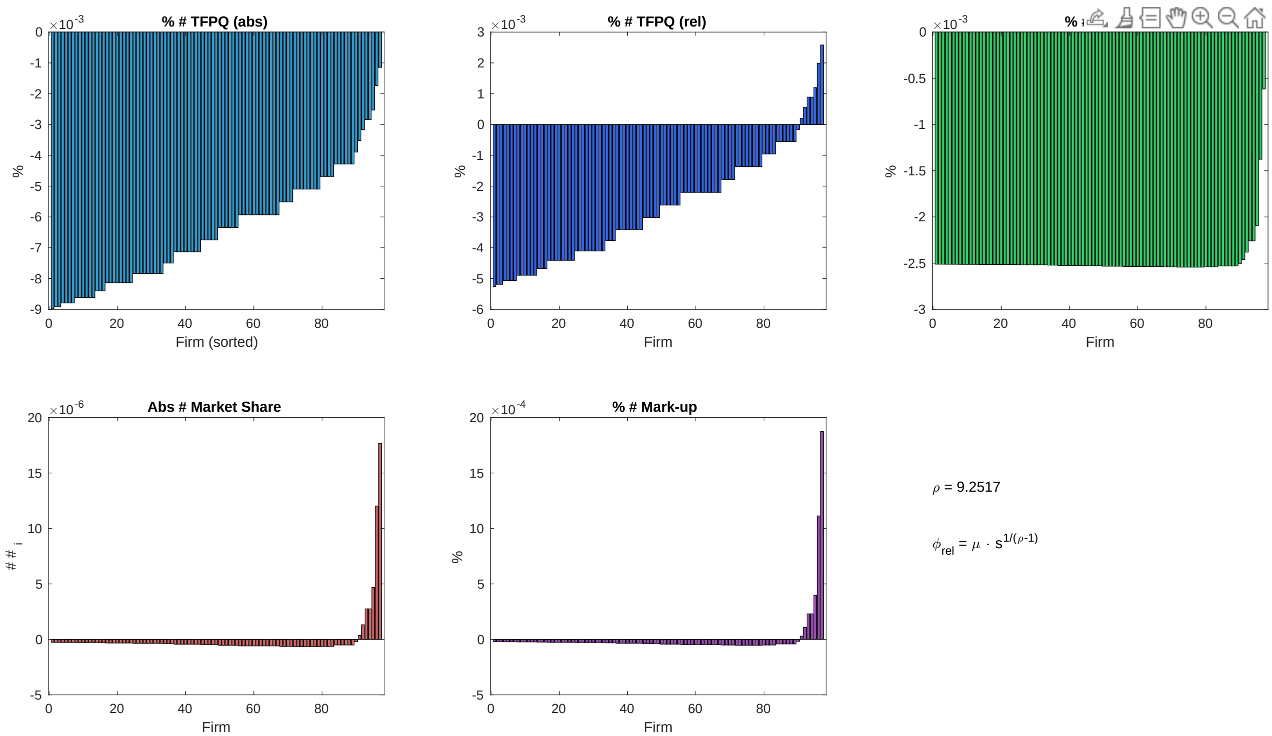
Figure D2: Simulation Result of a Productivity-Decreasing Shock




*Notes*: This figure reports the simulation result of a productivity-decreasing shock. Panel (a),(b), and (c) shows the change in key *firm-level* outcomes, while Panel (d) summarizes changes in key *aggregate* outcomes. For the firm-level, we show the average percentage changes in Productivity (a), absolute changes in Market Share(b), and percentage changes in Markup(c) across different productivity bins resulting from a productivity-decreasing shock within a single market. On the horizontal axis of panel (a) to (c), productivity(firm size) increases from left to right. We use absolute changes for market share in order to better highlight the reallocation channel. Panel (d) shows the percentage change in aggregate TFP, TFP(log-normalized) dispersion, HHI, and aggregate Markup.

productivity drops as expected. For the dispersion of within-industry productivity (which is calculated based on normalized productivity in order to remove the level effect), although all firms are getting a negative shock, the heterogeneous nature of the shock increases the relative gap between large and small firms, creating larger dispersion. Such increase in productivity dispersion fuels the reallocation of market shares from small to large firms, resulting in higher concentration and higher aggregate markup.

Figure D3: Simulation Result of a Productivity-Decreasing Shock




*Notes*: This figure reports the simulation result of a productivity-decreasing shock. Panel (a),(b), and (c) shows the change in key *firm-level* outcomes, while Panel (d) summarizes changes in key *aggregate* outcomes. For the firm-level, we show the average percentage changes in Productivity (a), absolute changes in Market Share(b), and percentage changes in Markup(c) across different productivity bins resulting from a productivity-decreasing shock within a single market. On the horizontal axis of panel (a) to (c), productivity(firm size) increases from left to right. We use absolute changes for market share in order to better highlight the reallocation channel. Panel (d) shows the percentage change in aggregate TFP, TFP(log-normalized) dispersion, HHI, and aggregate Markup.

# E Alternative Calibration

In this appendix, we detail our simulated method of moments (SMM) approach to calibrate the nested CES framework, providing a consistency check for the baseline parameter values borrowed from the literature. Following Edmond et al. (2023), we calibrate four parameters: the within-sector elasticity $\rho$, the across-sector elasticity $\eta$, the Pareto shape parameter $\xi$, and the average number of firms $N$ in each sector. These parameters jointly determine the level and dispersion of markups in the model, as well as the degree of market concentration. Intuitively, $\rho$ and $\eta$ govern how firm-level market shares translate into firm-level and aggregate markups, $\xi$ controls the extent of productivity dispersion (and thus sales concentration), and $N$ affects the intensity of competition within each sector.

We match four empirical moments to their model-implied counterparts. First, we target the top-4 and top-20 concentration ratios observed in our data (calculated at the country-by-4-digit NACE industry level). A lower $\xi$ (i.e., a heavier Pareto tail) generates more skewed productivity draws, leading to higher concentration. Second, we use an indirect inference approach to capture the relationship between firm-level markups and market shares, leveraging the slope coefficient $\hat{b} = -0.16$ from a regression similar to Edmond et al. (2023). From equation (9), we have

$$\frac{1}{\mu_{ijt}} = \left(1 - \frac{1}{\rho}\right) - \underbrace{\left(\frac{1}{\eta} - \frac{1}{\rho}\right)}_{b} s_{ijt}, \tag{E.76}$$

where $\hat{b} = -0.16$ identifies the gap between $\frac{1}{\eta}$ and $\frac{1}{\rho}$. Third, we ensure that the model's sales-weighted aggregate markup aligns with the empirical average. Finally, we choose $N$ alongside the other parameters to match overall patterns of concentration and markups.

Table G8 summarizes our calibration targets and the estimated parameter values under this oligopoly setting. The model replicates both the aggregate markup and the markup–market-share coefficient closely, indicating that the elasticities $\eta$ and $\rho$ are accurately pinned down.

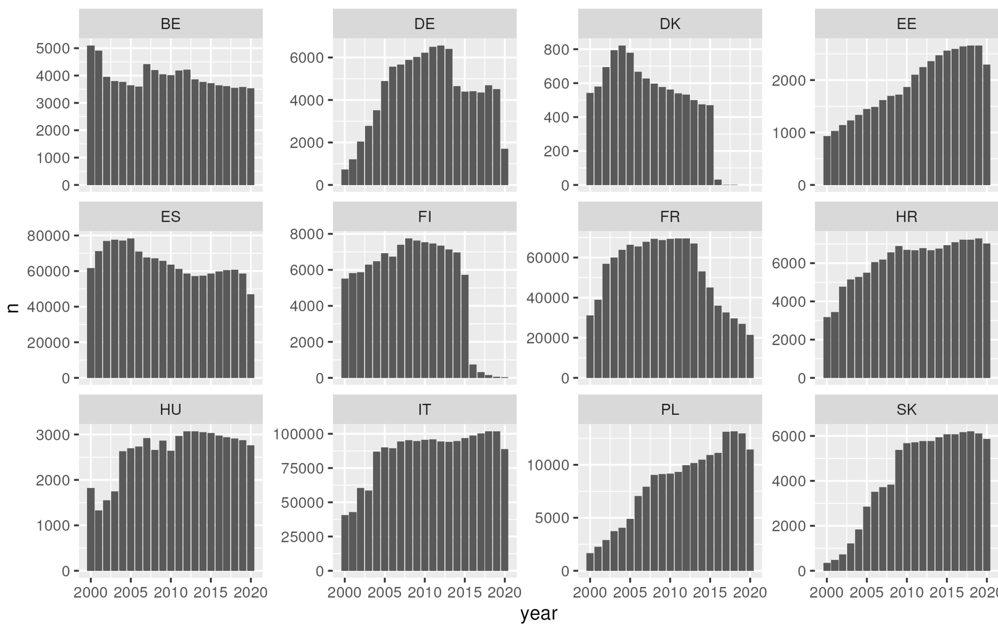
**Comparison with the Literature.** Our within-sector elasticity $\rho = 9.25$ falls within the broad range of 5.21–59.69 reported by Edmond et al. (2023), which corresponds to their different calibration scenarios targeting aggregate markups of 1.05 to 1.35. It is also somewhat higher than the 5.75 estimate in De Loecker et al. (2021), yet remains consistent with the range of values typically used in nested CES models. Likewise, our across-sector elasticity $\eta = 1.21$ aligns with the 1.0–1.62 range reported by Edmond et al. (2023) and is close to the 1.20 estimate in De Loecker et al. (2021). Given that our observed aggregate markup is around 1.3, these elasticity estimates appear both internally consistent and broadly in line with previous studies of oligopolistic competition under nested CES demand.

Overall, our SMM-based parameter estimates confirm that the chosen demand elasticities are robust to the data and consistent with estimates in related literature. This exercise thus reinforces that our baseline parameters—adapted from Edmond et al. (2023) and De Loecker et al. (2021)—are appropriate for analyzing how climate-induced productivity shocks affect market concentration, markups, and welfare.

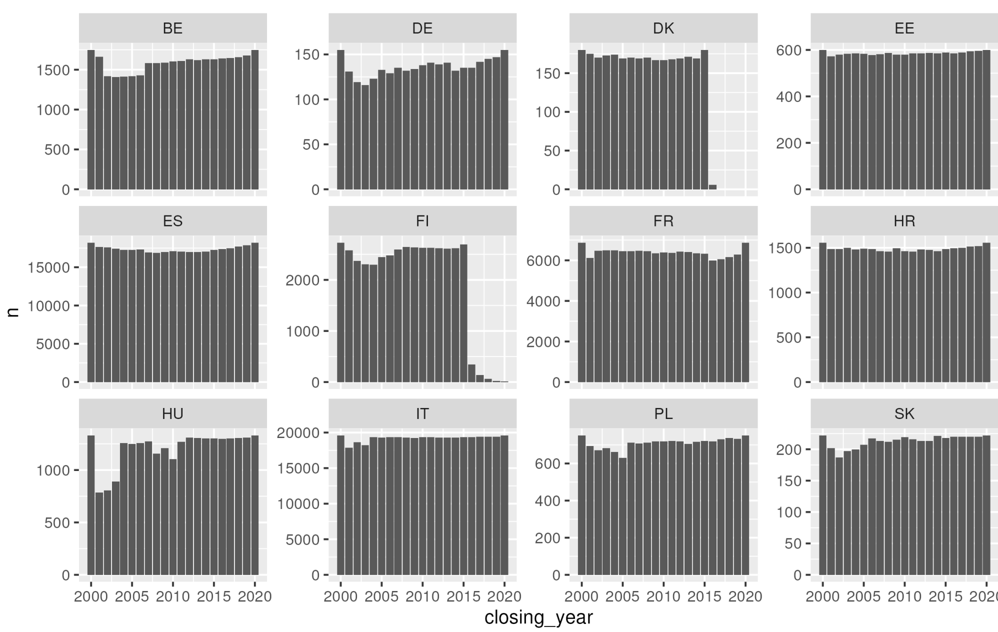
# F Additional Figures

Figure F1: Number of Observations by Country-Year

(a) Full sample

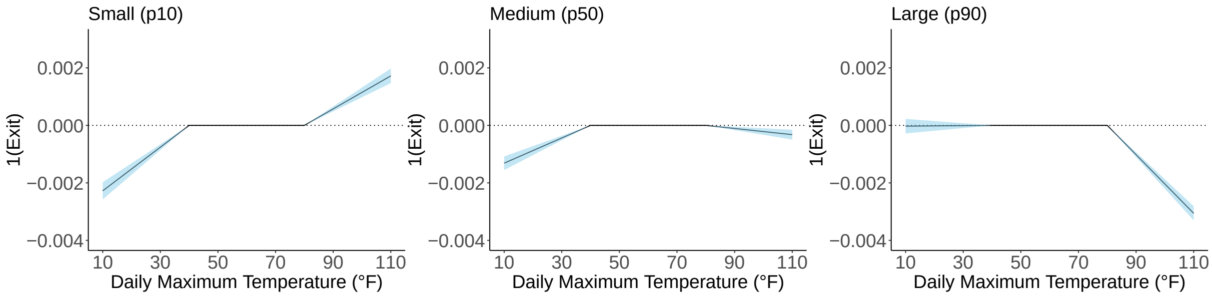



(b) Balanced sample



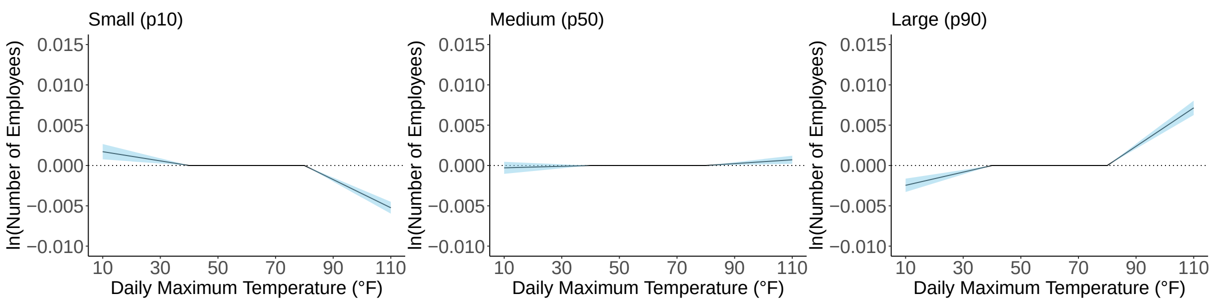

*Notes*: This figure presents the number of observations in the manufacturing sector sample for 12 European countries over the period 2000–2020. Panel (a) shows the full sample, which includes 5.06 million observations. Panel (b) restricts the sample to firms that entered the dataset before 2000 and remained throughout the entire sample period.

Figure F2: Effect of Temperature Change on Firm Exits



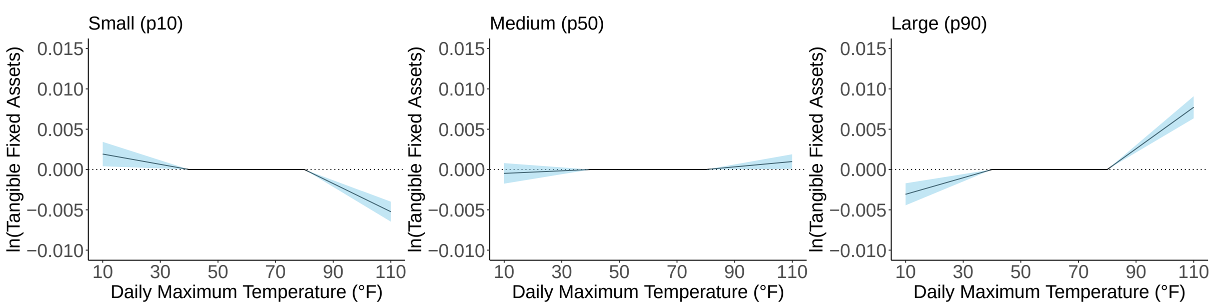

*Notes*: This figure reports the effect of temperature change on firm exits by firm size. Coefficients are estimated from Equation (4) with the dependent variable being a dummy that equals one if a firm exits the market in a given year between 2000 and 2020. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F3: Effect of Temperature Change on Firm Labor



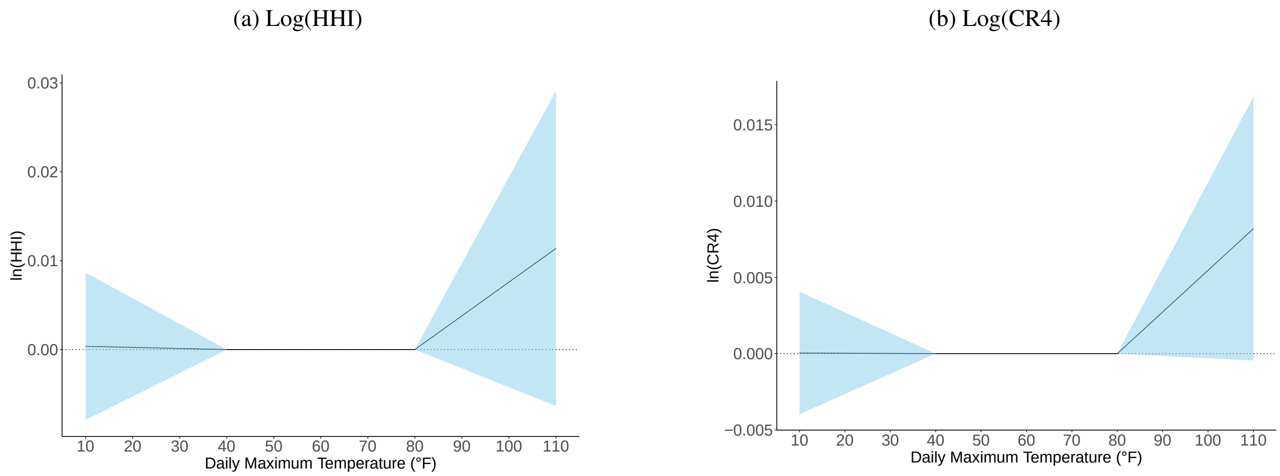

*Notes*: This figure reports the effect of temperature change on labor usage by firm size. Coefficients are estimated from Equation (4) with the dependent variable being the logarithm of the number of employees for each firm. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F4: Effect of Temperature Change on Firms Capital



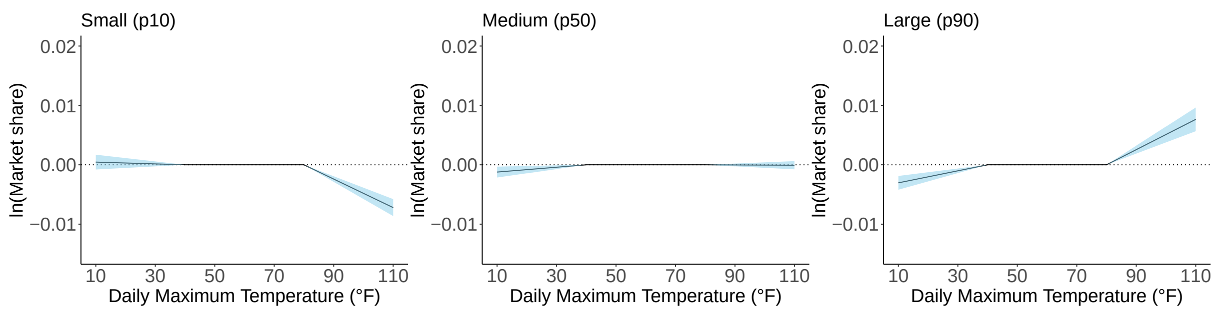

*Notes*: This figure reports the effect of temperature change on capital by firm size. Coefficients are estimated from Equation (4) with the dependent variable being the logarithm of tangible fixed assets for each firm. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F5: Effect of Temperature Change on Market Concentration (Country-NACE2)



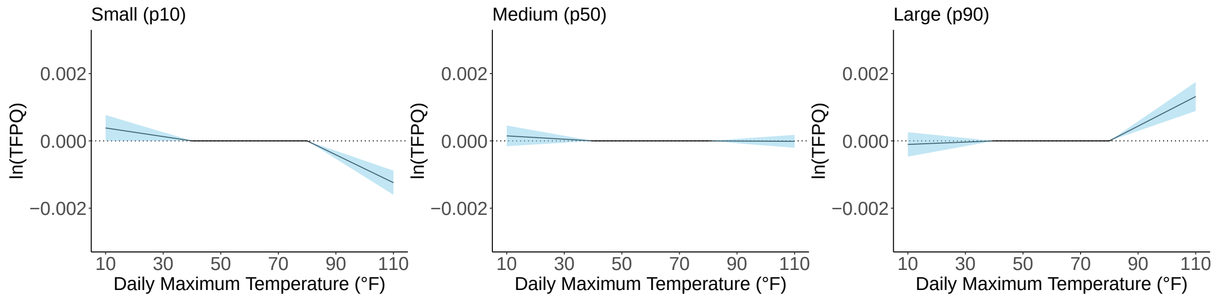

*Notes*: This figure reports the effect of the temperature change on market concentration. The coefficients are estimated from Equation (1). The dependent variables are log(HHI) and log(CR4). A market is defined at the country-NACE2 industry level. The blue bands show the 95% confidence interval. Standard errors are two-way clustered at the country-year and market levels.

Figure F6: Heterogeneous Effects of Temperature Change on Firm Market Share (Country-NACE2)



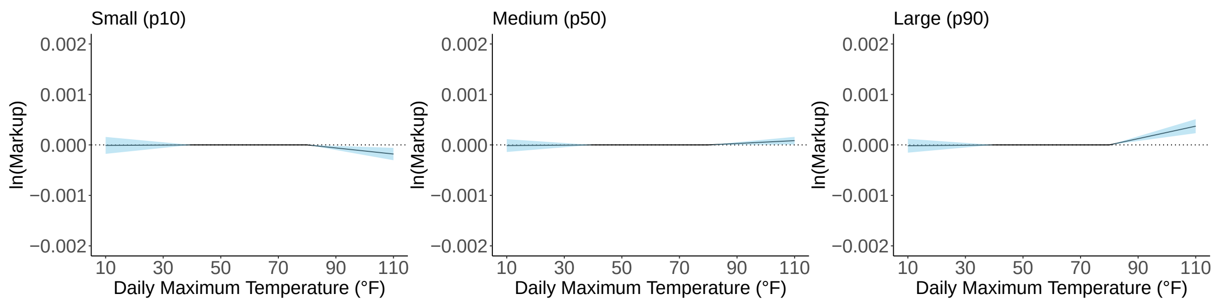

*Notes*: This figure reports the heterogeneous effects of temperature change on firm market share by firm size. Coefficients are estimated from Equation (4) with the dependent variable log of market share. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. A market is defined at the country-NACE2 industry level. The blue bands show the 95% confidence interval. Standard errors are two-way clustered at the firm and market-year levels.

Figure F7: Heterogeneous Effects of Temperature Change on Firm Productivity (Country-NACE2)



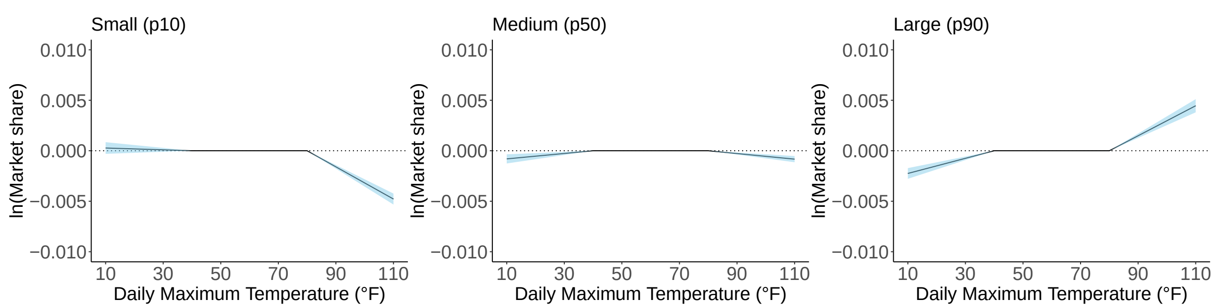

*Notes*: This figure reports the heterogeneous effects of the temperature change on firm productivity by firm size. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. A market is defined at the country-NACE2 industry level. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F8: Heterogeneous Effects of Temperature Change on Firm Markup (Country-NACE2)



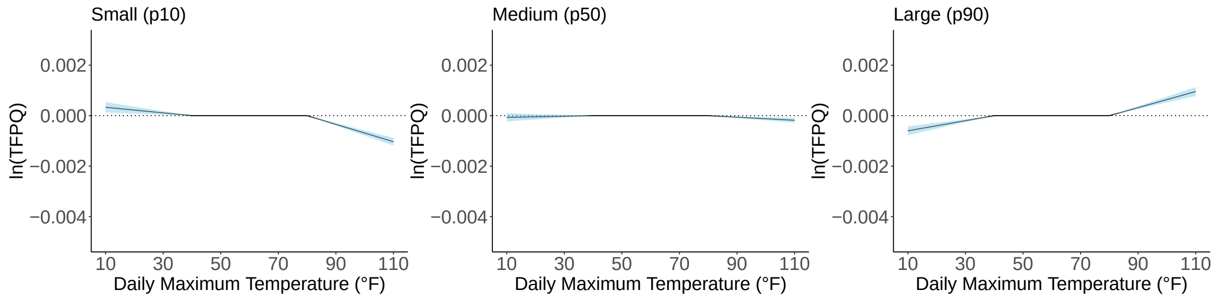

*Notes*: This figure reports the heterogeneous effects of temperature changes on firm markup by firm size. Coefficients are estimated from Equation (4) with the dependent variable as the log of markup. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. A market is defined at the country-NACE2 industry level. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F9: Heterogeneous Effects of Temperature Change on Market Share (Full Sample)



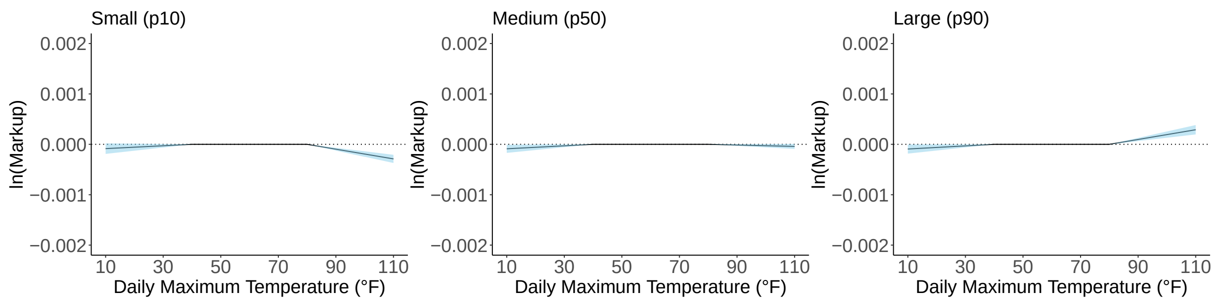

*Notes*: This figure reports the heterogeneous effects of temperature change on firm market share by firm size. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. The blue bands show the 95% confidence interval.

Figure F10: Heterogeneous Effects of Temperature Change on Firm Productivity (Full Sample)




*Notes*: Panels (a) to (d) show the heterogeneous effects of temperature change on firm TFP by firm size. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

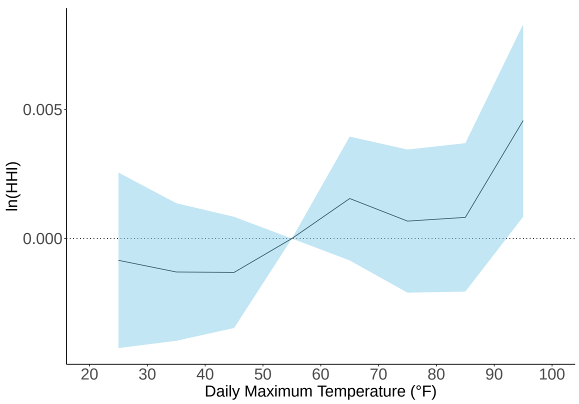
Figure F11: Heterogeneous Effects of Temperature Change on Firm Markup (Full Sample)



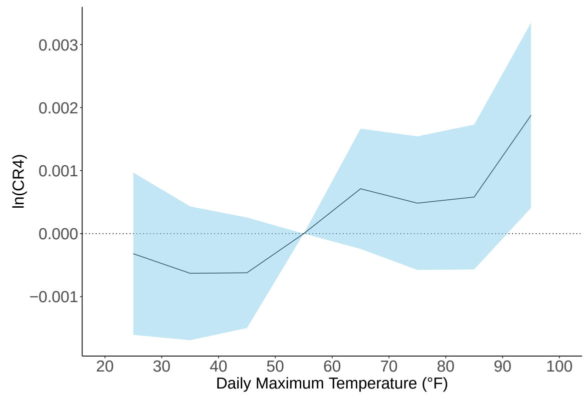

*Notes*: The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. The blue bands show the 95% confidence interval.

Figure F12: Effect of Temperature Change on Market Concentration

(a) Log(HHI)

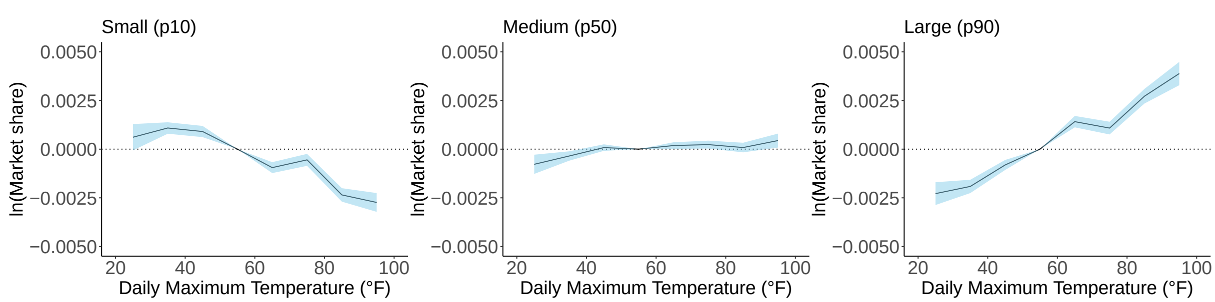



(b) Log(CR4)




*Notes*: This figure reports the effect of temperature changes on market concentration. The coefficients are estimated from Equation (1), using the temperature bin specification for the response function. Daily maximum temperatures are grouped into eight 10-degree Fahrenheit bins: <30°F, 30–40°F, 40–50°F, 50–60°F, 60–70°F, 70–80°F, 80–90°F, and 90°F. Each bin represents the number of days in a year that a firm experiences a daily maximum temperature within that range. The 50–60°F bin is omitted in the regressions as the reference category. The market is defined at the country-NACE4 industry level. The blue bands show the 95% confidence interval. Standard errors are two-way clustered at the country-year and market levels.

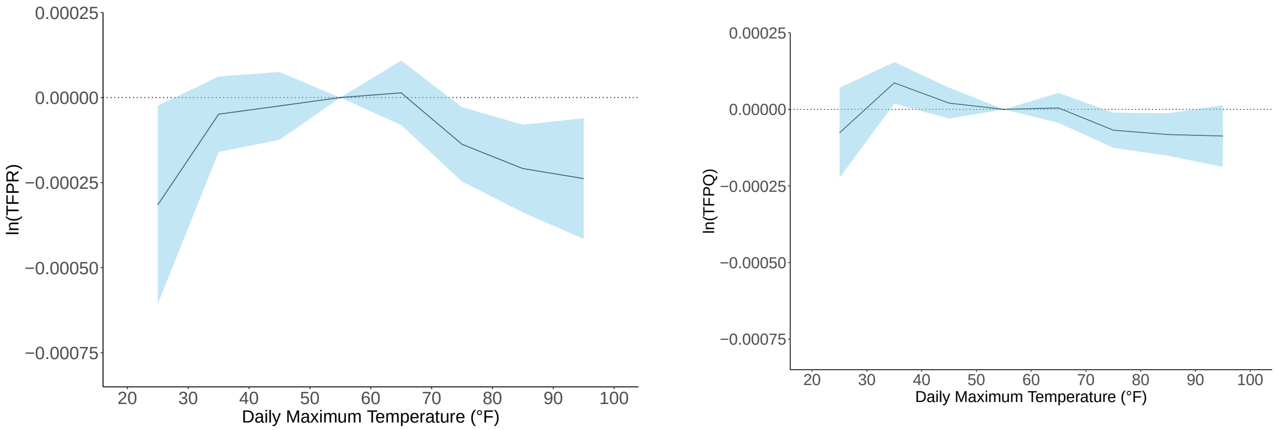
Figure F13: Heterogeneous Effects of Temperature Change on Market Share




*Notes*: This figure reports the heterogeneous effects of temperature change on market share by firm size. Coefficients are estimated from Equation (4) with the dependent variable log of market share, using the temperature bin specification for the response function. Daily maximum temperatures are grouped into eight 10-degree Fahrenheit bins: <30°F, 30–40°F, 40–50°F, 50–60°F, 60–70°F, 70–80°F, 80–90°F, and 90°F. Each bin represents the number of days in a year that a firm experiences a daily maximum temperature within that range. The 50–60°F bin is omitted in the regressions as the reference category. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the country-year and market levels. The blue bands show the 95% confidence interval.

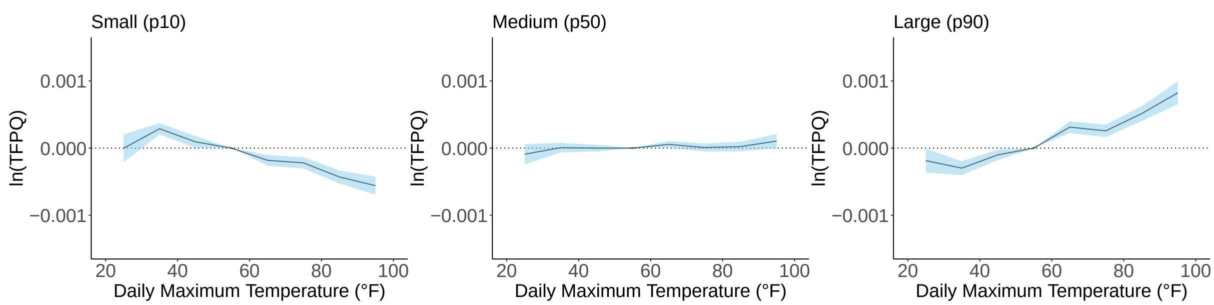
Figure F14: Average Effect of Temperature Change on Firm Productivity

(a) TFPR (b) TFPQ



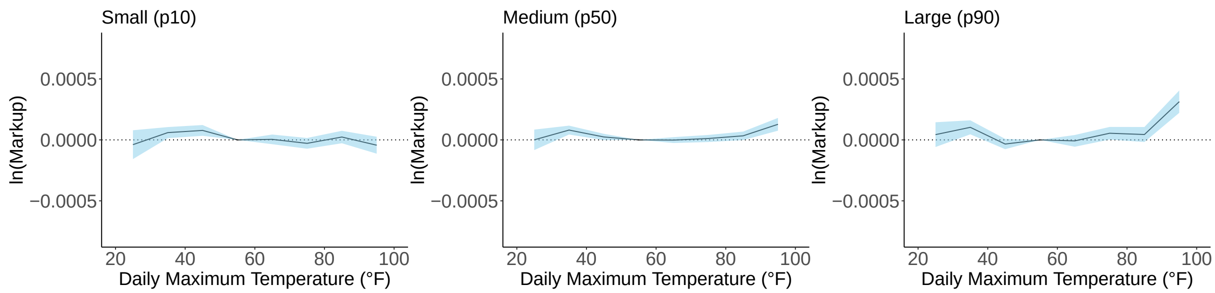

*Notes*: Panel (a) and Panel (b) show the average effect of temperature change on firm TFPR and TFPQ, respectively. Coefficients are estimated from Equation (19) with the dependent variable being the log of firm TFPR and TFPQ. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F15: Heterogeneous Effects of Temperature Change on Firm Productivity



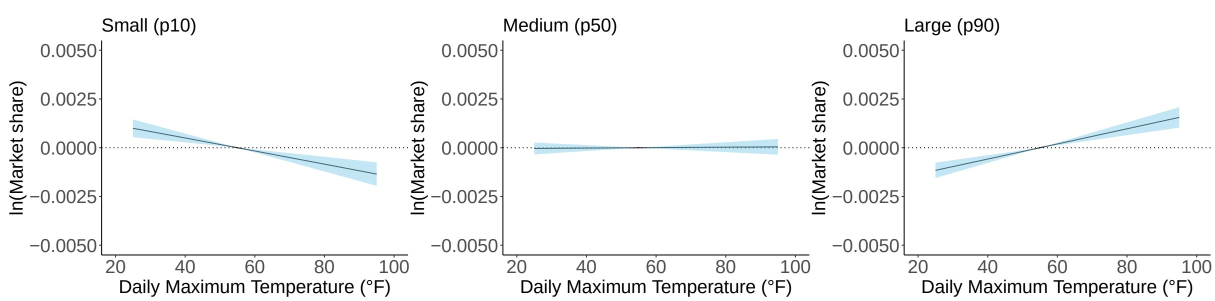

*Notes*: This figure shows the heterogeneous effects of temperature change on firm TFPQ by size. Coefficients are estimated from Equation (4), using the temperature bin specification for the response function. Daily maximum temperatures are grouped into eight 10-degree Fahrenheit bins: <30°F, 30–40°F, 40–50°F, 50–60°F, 60–70°F, 70–80°F, 80–90°F, and 90°F. Each bin represents the number of days in a year that a firm experiences a daily maximum temperature within that range. The 50–60°F bin is omitted in the regressions as the reference category. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F16: Heterogeneous Effects of Temperature Change on Firm Markup



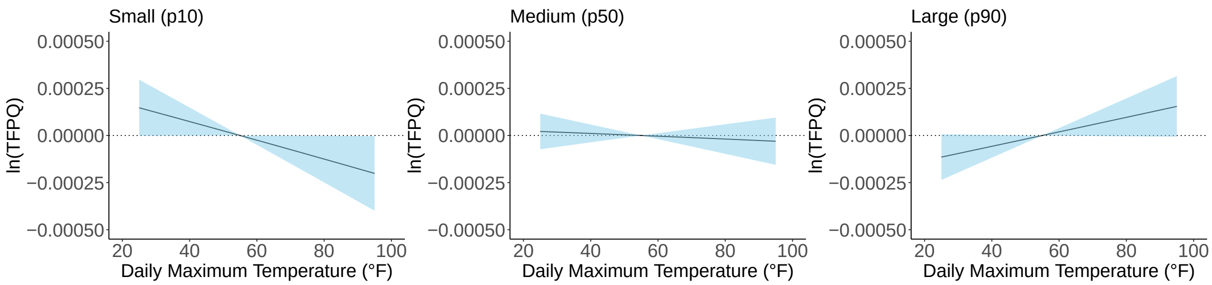

*Notes*: This figure reports the heterogeneous effects of temperature changes on firm markup. Coefficients are estimated from Equation (4), using the temperature bin specification for the response function. Daily maximum temperatures are grouped into eight 10-degree Fahrenheit bins: <30°F, 30–40°F, 40–50°F, 50–60°F, 60–70°F, 70–80°F, 80–90°F, and 90°F. Each bin represents the number of days in a year that a firm experiences a daily maximum temperature within that range. The 50–60°F bin is omitted in the regressions as the reference category. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F17: Heterogeneous Effects of Temperature Change on Market Share



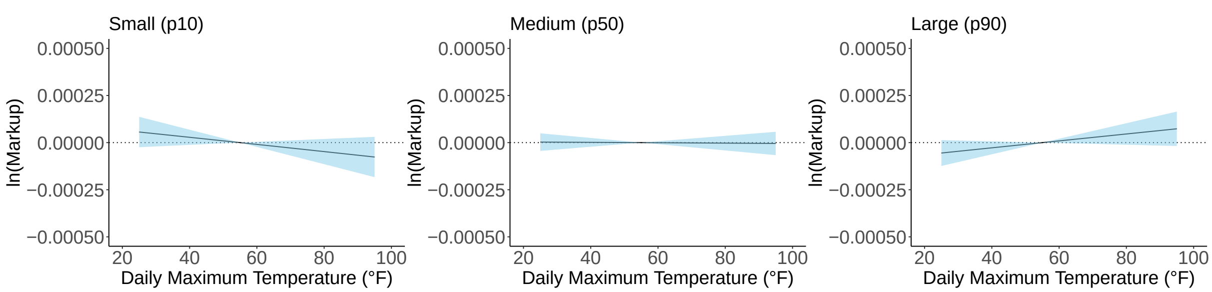

*Notes*: This figure reports the heterogeneous effects of temperature changes on firm market share. The coefficients are estimated from Equation (4), where the temperature response function is specified as a fourth-order polynomial of the annual sum of daily maximum temperatures. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F18: Heterogeneous Effects of Temperature Change on Firm Productivity



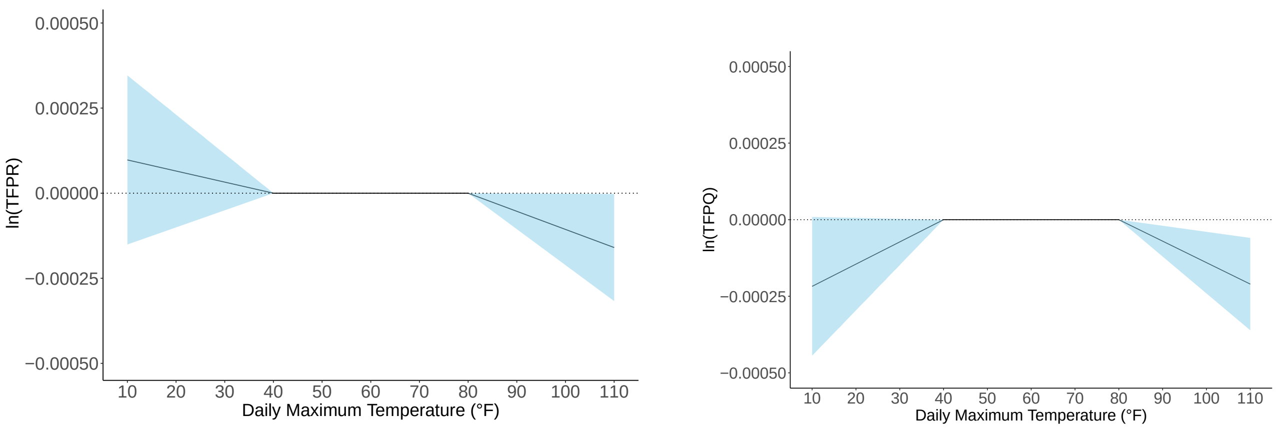

*Notes*: This figure reports the heterogeneous effects of temperature changes on firm TFPQ. The coefficients are estimated from Equation (4), where the temperature response function is specified as a fourth-order polynomial of the annual sum of daily maximum temperatures. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F19: Heterogeneous Effects of Temperature Change on Firm Markup



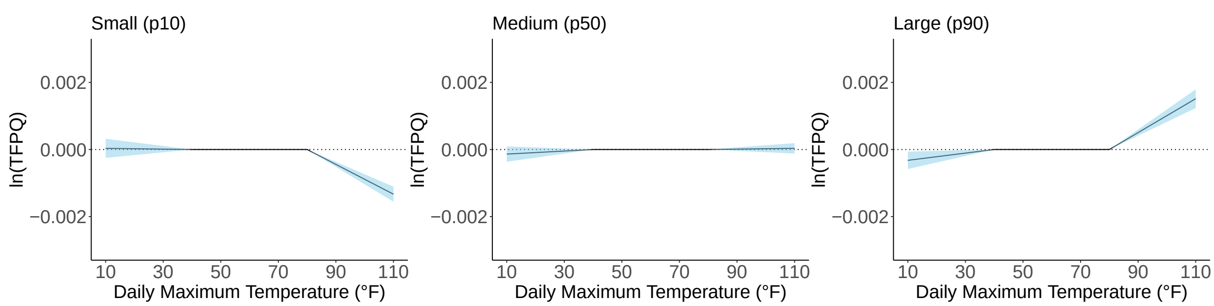

*Notes*: This figure reports the heterogeneous effects of temperature changes on firm markup. The coefficients are estimated from Equation (4), where the temperature response function is specified as a fourth-order polynomial of the annual sum of daily maximum temperatures. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F20: Average Effect of Temperature Change on Firm Productivity



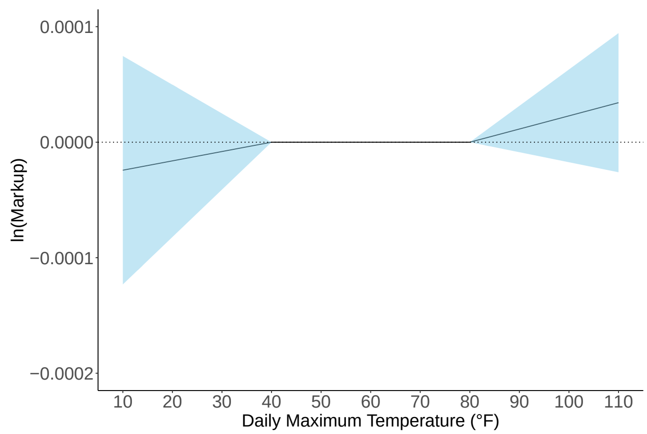

*Notes*: Panel (a) and Panel (b) show the average effect of temperature change on firm TFPR and relative TFPQ, respectively. Coefficients are estimated from Equation (4) with the dependent variable being the log of firm TFPR and relative TFPQ. TFRP is estimated from the translog production function, and relative TFPQ is calculated with the estimated markup from the translog production function and the market share using Equation (18). Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F21: Heterogeneous Effects of Temperature Change on Firm Productivity



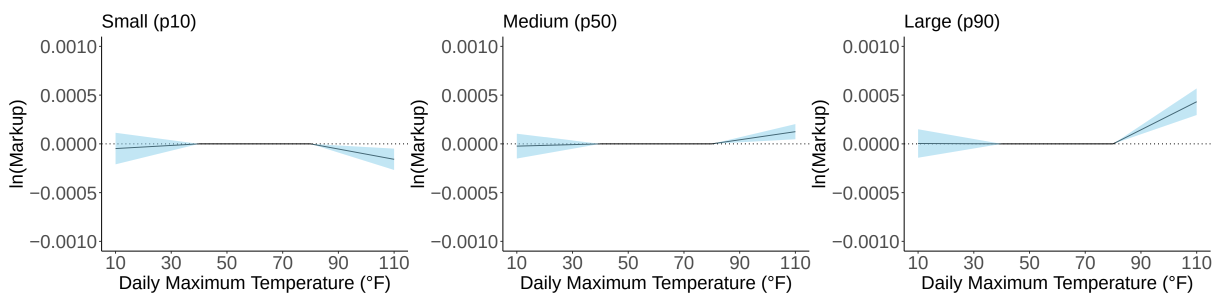

*Notes*: This figure shows the heterogeneous effects of temperature change on firm relative TFPQ by size. Coefficients are estimated from Equation (4). Relative TFPQ is calculated with the estimated markup from the translog production function and the market share using Equation (18). The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F22: Average Effect of Temperature Change on Firm Markup




*Notes*: This figure shows the average effect of temperature change on firm markup. Coefficients are estimated from Equation (19) with the dependent variable being the log of firm markup estimated from the translog production function, controlling for second order polynomial of input costs. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

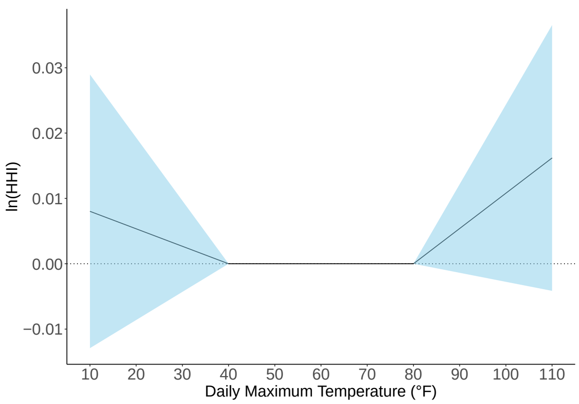
Figure F23: Heterogeneous Effects of Temperature Change on Firm Markup



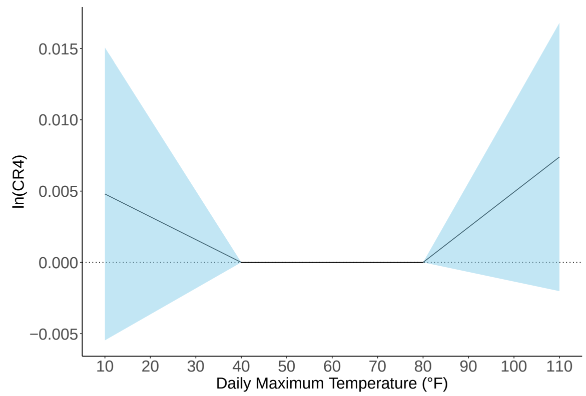

*Notes*: This figure shows the heterogeneous effects of temperature change on firm markup by size. Coefficients are estimated from Equation (4), with the dependent variable being the log of firm markup estimated from the translog production function, controlling for second order polynomial of input costs. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F24: Effect of Temperature Change on Market Concentration in China

(a) Log(HHI)

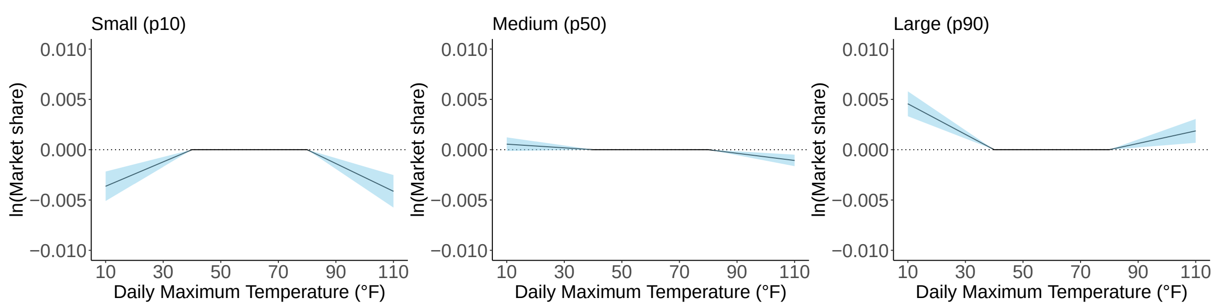



(b) Log(CR4)



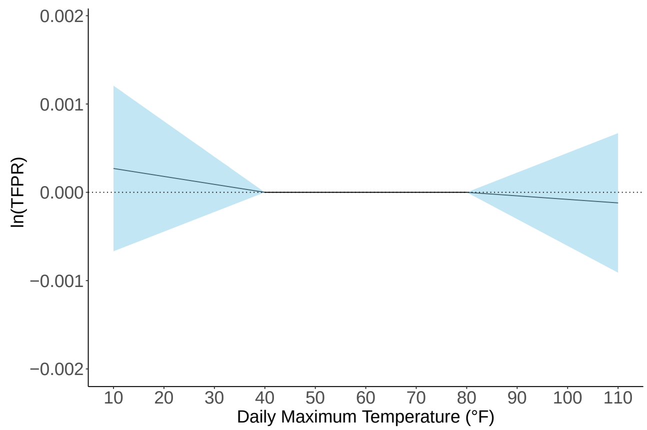

*Notes*: This figure reports the effect of temperature changes on market concentration in China. The coefficients are estimated from Equation (1). The market is defined at the China 4-digit industry level. The blue bands show the 95% confidence interval. Standard errors are two-way clustered at the country-year and market levels.

Figure F25: Heterogeneous Effects of Temperature Change on Firm Market Share in China



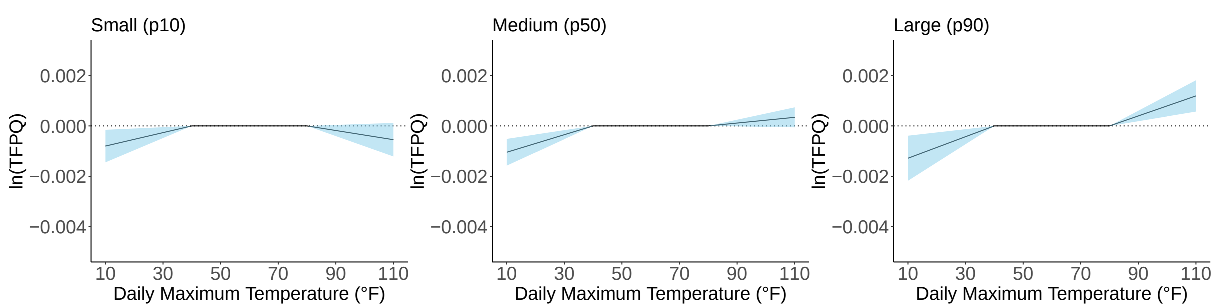

*Notes*: This figure shows the heterogeneous effects of temperature change on firm market share by size. Coefficients are estimated from Equation (4). The market is defined at the China 4-digit industry level. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F26: Average Effect of Temperature Change on Firm TFPR in China




*Notes*: This figure shows the average effect of temperature change on firm productivity. Coefficients are estimated from Equation (4) with the dependent variable being the log of firm TFPR. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F27: Heterogeneous Effects of Temperature Change on Firm Productivity in China

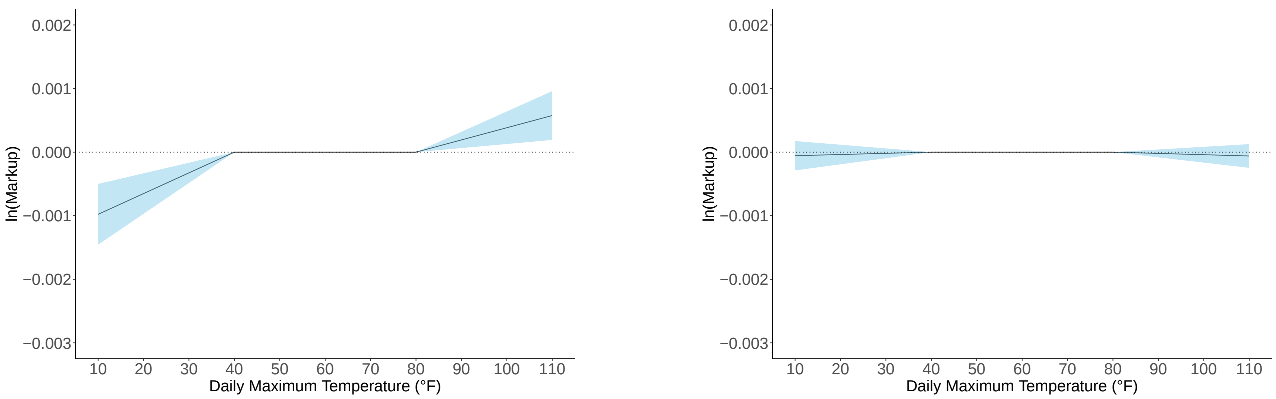



*Notes*: This figure shows the heterogeneous effects of temperature change on firm relative TFPQ by size. Coefficients are estimated from Equation (4). Relative TFPQ is calculated with the estimated markup from the CD production function and the market share using Equation (18). The market is defined at the China 4-digit industry level. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F28: Average Effect of Temperature Change on Firm Markup in China

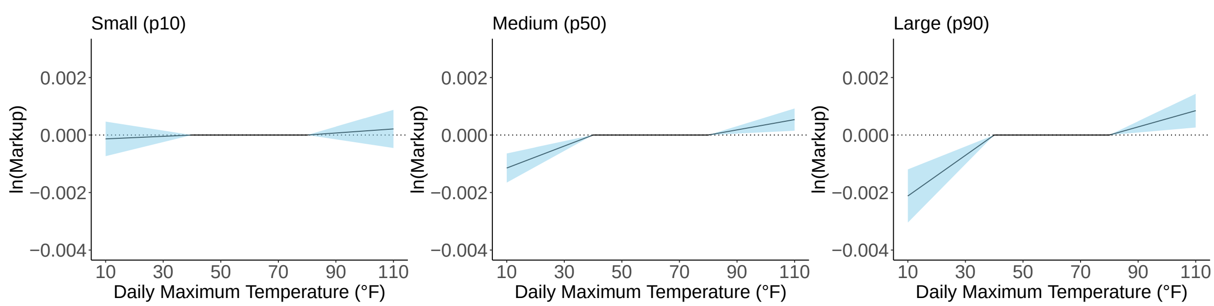
(a) Not control for measurement error

(b) Control for measurement error



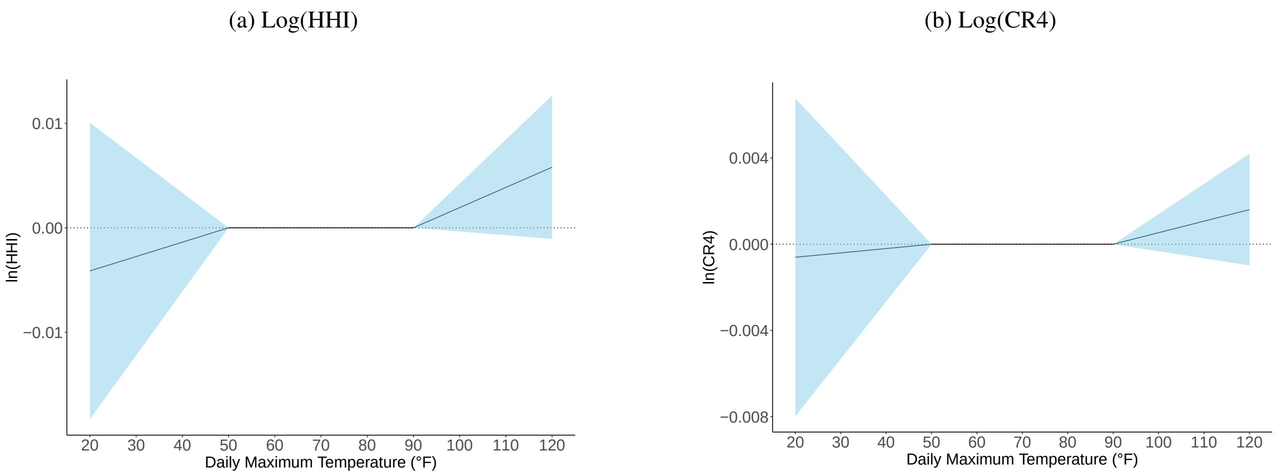

*Notes*: This figure shows the average effect of temperature change on firm markup. Coefficients are estimated from Equation (19) with the dependent variable being the log of firm markup. Panel (a) does not control for order polynomial of input costs, while Panel (b) controls for second order polynomial of input costs. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F29: Heterogeneous Effects of Temperature Change on Firm Markup in China



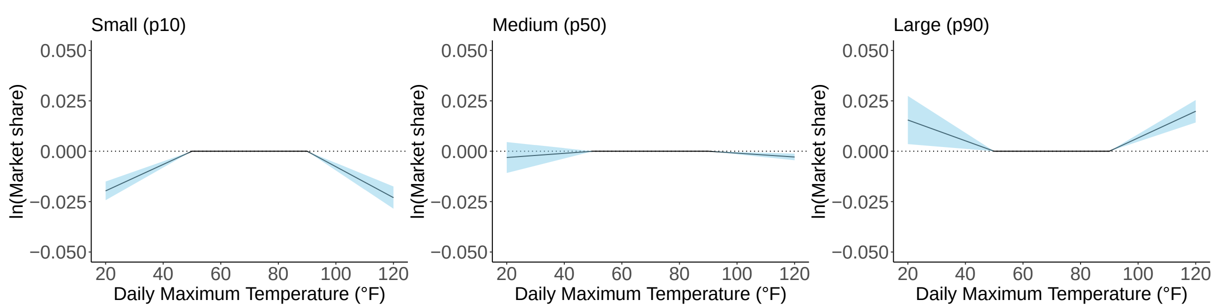

*Notes*: This figure shows the heterogeneous effects of temperature change on firm markup by size. Coefficients are estimated from Equation (4), with the dependent variable being the log of firm markup. The labels p10, p50, and p90 refer to firms whose average revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the firm and market-year levels. The blue bands show the 95% confidence interval.

Figure F30: Effect of Temperature Change on Market Concentration in India



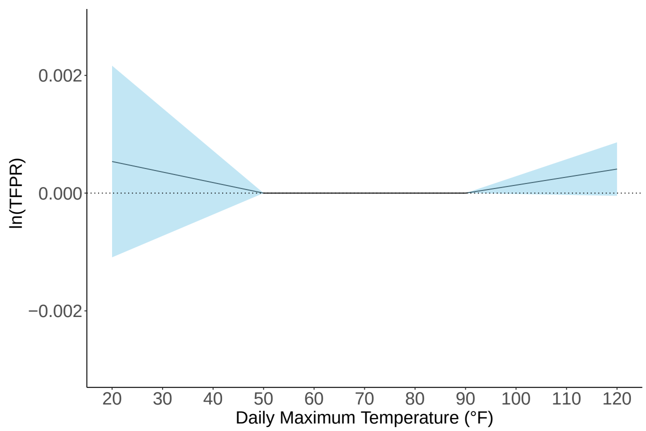

*Notes*: This figure reports the effect of temperature changes on market concentration in India. The coefficients are estimated from Equation (1). The market is defined at the 4-digit industry level. The blue bands show the 95% confidence interval. Standard errors are two-way clustered at the year and market levels.

Figure F31: Heterogeneous Effects of Temperature Change on Firm Market Share in India



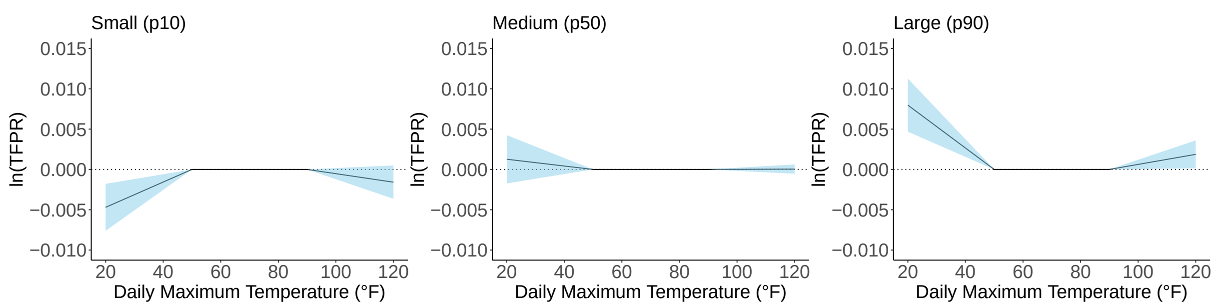

*Notes*: This figure shows the heterogeneous effects of temperature change on firm market share by size. Coefficients are estimated from Equation (4), controlling for state and market-year fixed effects. The market is defined at the 4-digit industry level. The labels p10, p50, and p90 refer to firms whose revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the state and market-year levels. The blue bands show the 95% confidence interval.

Figure F32: Average Effect of Temperature Change on Firm TFPR in India




*Notes*: This figure shows the average effect of temperature change on firm productivity. Coefficients are estimated from Equation (4) with the dependent variable being the log of firm TFPR. Standard errors are two-way clustered at the state and market-year levels. The blue bands show the 95% confidence interval.

Figure F33: Heterogeneous Effects of Temperature Change on Firm Productivity in India




*Notes*: This figure shows the heterogeneous effects of temperature change on firm TFPR by size. Coefficients are estimated from Equation (4), controlling for state and market-year fixed effects. The market is defined at the 4-digit industry level. The labels p10, p50, and p90 refer to firms whose revenue falls at the 10th, 50th, and 90th percentiles, respectively, of the revenue distribution across all firms. Standard errors are two-way clustered at the state and market-year levels. The blue bands show the 95% confidence interval.

# G Additional Tables

Table G1: Correlation between Productivity, Market Share, and Markup

| Dep. Var.: | Log(Market Share) | Log(Markup) |
|---|---|---|
| | (1) | (2) |
| Log(TFP) | 0.1609*** | 1.303*** |
| | (0.0266) | (0.0274) |
| Firm FE | Yes | Yes |
| Country-year FE | Yes | Yes |
| NACE2-year FE | Yes | Yes |
| Observations | 31,125,699 | 31,125,699 |

*Notes:* Standard-errors in parentheses are clustered at the country-NACE 4-digit industry level. ***: 0.01, **: 0.05, *: 0.1.

Table G2: Effect of Contemporaneous Temperature Change on Market Concentration

| | Log(HHI) | Log(CR4) | Log(CR8) |
|---|---|---|---|
| | (1) | (2) | (3) |
| ACDD ('000) | 0.2083* | 0.0886** | 0.0719** |
| | (0.1060) | (0.0424) | (0.0306) |
| AHDD ('000) | 0.0174 | 0.0171 | 0.0169 |
| | (0.0724) | (0.0254) | (0.0174) |
| Observations | 51,041 | 51,041 | 51,041 |
| Market FE | ✓ | ✓ | ✓ |
| Year FE | ✓ | ✓ | ✓ |

*Notes:* AHDD and ACDD denote the annual sum of heating degree days (below 40°F) and that of cooling degree days (above 80°F) based on daily maximum temperature. AHDD=$\sum_{d=1}^{365}(T_d-80)*\mathbf{1}(T_d>80)$ and ACDD=$\sum_{d=1}^{365}(40-T_d)*\mathbf{1}(T_d<40)$, where $T_d$ is the daily maximum temperature. ACDD and AHDD are divided by 1000 to make the results more readable. Standard errors are two-way clustered at the country-year and market levels. $^{*}$ $p<0.10$, $^{**}$ $p<0.05$, $^{***}$ $p<0.01$.

Table G3: Average Effect of Temperature on Productivity and Markups

| | Log(TFPR) | Log(TFPQ) | Log(Markup) |
|---|---|---|---|
| | (1) | (2) | (3) |
| ACDD('000) | -0.0110$^{**}$ | -0.0064$^{**}$ | 0.0023$^{*}$ |
| | (0.0049) | (0.0027) | (0.0014) |
| AHDD('000) | -0.0161$^{*}$ | -0.0066 | -0.0025 |
| | (0.0083) | (0.0042) | (0.0023) |
| Observations | 1,065,260 | 1,065,260 | 1,065,260 |
| Polynomials of precipitation | Y | Y | Y |
| Polynomials of input costs | | | Y |
| Establishment FE | Y | Y | Y |
| Market-year FE | Y | Y | Y |

*Notes:* This table reports the average effect of temperature change on establishment productivity and markups. AHDD and ACDD denote the annual sum of heating degree days (below 40°F) and that of cooling degree days (above 80°F) based on daily maximum temperature. AHDD and ACDD are divided by 1000 to make the results more readable. For all regressions, we control for second-order polynomials of precipitation. Column (3) further controls for second order polynomials of labor and material costs. Standard errors are clustered at the firm and market-year level. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table G4: Heterogeneous Effects by Firm Size

| | Market Share | Log(TFPQ) | Log(Markup) |
|---|---|---|---|
| | (1) | (2) | (3) |
| ACDD('000) | -1.762$^{***}$ | -0.3279$^{***}$ | -0.0727$^{***}$ |
| | (0.0975) | (0.0245) | (0.0121) |
| AHDD('000) | 0.4031$^{***}$ | 0.0276 | -0.0118 |
| | (0.0719) | (0.0204) | (0.0119) |
| ACDD('000) $\times$ $\ln(\overline{Rev})$ | 0.1165$^{***}$ | 0.0217$^{***}$ | 0.0051$^{***}$ |
| | (0.0065) | (0.0016) | (0.0008) |
| AHDD('000) $\times$ $\ln(\overline{Rev})$ | -0.0288$^{***}$ | -0.0021$^{*}$ | 0.0007 |
| | (0.0046) | (0.0013) | (0.0007) |
| Observations | 1,065,260 | 1,065,260 | 1,065,260 |
| Polynomials of precipitation | Y | Y | Y |
| Polynomial of input costs | | | Y |
| Establishment FE | Y | Y | Y |
| Market-year FE | Y | Y | Y |

*Notes:* This table reports the heterogeneous effects of temperature on market share, productivity, and markups. AHDD and ACDD denote the annual sum of heating degree days (below 40°F) and that of cooling degree days (above 80°F) based on daily maximum temperature. AHDD and ACDD are divided by 1000 to make the results more readable. $\overline{Rev}$ denotes the average revenue of an establishment during the sample period. For column (3), we control for second order polynomials of labor and material costs. Standard errors are two-way clustered at the firm and market-year levels. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table G5: Summary Statistics by Firm Size for the Balanced Sample

| Firm size | Number of employees | Tangible fixed assets($) | Revenue($) |
|---|---|---|---|
| 10th Pct. | 5.67 | 4222 | 512358 |
| 50th Pct. | 12.4 | 323185 | 3774366 |
| 90th Pct. | 76.7 | 5997518 | 33261439 |

*Notes:* This table presents the values for the number of employees, tangible fixed assets and operating revenue for three establishments at the 10th, 50th, and 90th percentile of the average revenue distribution across all establishments.

Table G6: Heterogeneous Effects on Productivity by Establishment Age

| Dep. var. | Log(TFPQ) | |
|---|---|---|
| | Before 2005 | After 2005 |
| | (1) | (2) |
| ACDD('000) | -0.1668$^{***}$ | -0.4409$^{***}$ |
| | (0.0177) | (0.0415) |
| AHDD('000) | 0.0577$^{***}$ | 0.2325$^{***}$ |
| | (0.0160) | (0.0306) |
| ACDD('000) $\times$ ln($\overline{Rev}$) | 0.0113$^{***}$ | 0.0322$^{***}$ |
| | (0.0012) | (0.0030) |
| AHDD('000) $\times$ ln($\overline{Rev}$) | -0.0039$^{***}$ | -0.0170$^{***}$ |
| | (0.0010) | (0.0020) |
| Observations | 3,772,085 | 1,270,348 |
| Establishment FE | ✓ | ✓ |
| Market-year FE | ✓ | ✓ |

*Notes:* This table reports the heterogeneous effects of temperature shocks on establishment productivity. We divide the full sample into two subsamples: establishments that entered the market before 2005 and those that entered after 2005. AHDD and ACDD denote the annual sum of heating degree days (below 40°F) and that of cooling degree days (above 80°F) based on daily maximum temperature. $\overline{Rev}$ denotes the average revenue of an establishment during the sample period. Columns (1) and (2) present coefficients estimated from Equation (4) for each subsample, respectively. Standard errors are two-way clustered at the establishment and market-year levels. $^{*}$ $p < 0.10$, $^{**}$ $p < 0.05$, $^{***}$ $p < 0.01$.

Table G7: Assigned Parameters

| **Parameter** | **Value** |
|---|---|
| Discount factor, $\beta$ | 0.96 |
| Depreciation rate, $\delta$ | 0.06 |
| Exit rate, $\varphi$ | 0.04 |
| Elasticity of value-added to capital, $\alpha$ | $\frac{1}{3}$ |
| Elasticity of labor supply, $\nu$ | 1 |
| Elasticity of substitution between value-added and materials, $\theta$ | 0.5 |

*Notes*: This table shows the assigned parameters that are fixed through the quantification exercise. We directly use the parameters values of Table 1 in Edmond et al. (2023).

Table G8: Model Calibration

| | Data | Prediction |
|---|---|---|
| **Calibration targets:** | | |
| Aggregate markup, $\mathscr{M}$ | 1.29 | 1.29 |
| Top-4 sales share, CR4 | 0.67 | 0.64 |
| Top-20 sales share, CR20 | 0.86 | 0.90 |
| Regression coefficient, $\hat{b}$ | -0.16 | -0.16 |
| **Parameter Estimates:** | | |
| Pareto tail, $\xi$ | | 4.42 |
| Elasticity of substitution within sectors, $\rho$ | | 9.25 |
| Elasticity of substitution between sectors, $\eta$ | | 1.21 |
| Average number of firms per sector, $N$ | | 115 |

*Notes*: This table reports our calibrated target and parameters values. We calibrate the Pareto tail $\xi$ and the within- and between-sector elasticities of substitution $\rho$ and $\eta$ to match the empirical targets on markups and concentration. $\hat{b}$ is the coefficient on market share of regression based on Equation (E.76) and is used to pin down the gap between $\rho$ and $\eta$.

Table G9: Decomposition of changes in Country Aggregate Markup

| Country | Markup Change | Within Component | Between Component | Cross Component |
|---|---|---|---|---|
| France | 0.215 | 0.132 | 0.081 | 0.003 |
| Spain | 0.207 | 0.124 | 0.080 | 0.004 |
| Belgium | 0.076 | 0.045 | 0.030 | 0.001 |
| Germany | 0.068 | 0.049 | 0.019 | 0.0004 |
| Estonia | 0.050 | 0.032 | 0.017 | 0.0004 |
| Italy | 0.027 | -0.004 | 0.026 | 0.005 |
| Poland | 0.024 | 0.016 | 0.009 | 0.0001 |
| Finland | 0.020 | 0.005 | 0.015 | 0.0003 |
| Denmark | -0.001 | -0.001 | -0.0003 | 0 |
| Croatia | -0.021 | -0.016 | -0.007 | 0.001 |
| Slovakia | -0.022 | -0.015 | -0.007 | 0.0001 |
| Hungary | -0.059 | -0.040 | -0.020 | 0.0005 |

*Notes*: This table decomposes the percentage change in country-specific markup into Between, Within, and Cross Component. We first decompose the sector (county by NACE 4-digit) aggregate markup based on: $\Delta\mu_j = \sum_i \omega_{ij}(\mu_{ij}^{cc} - \mu_{ij}) + \sum_i \mu_{ij}(\omega_{ij}^{cc} - \omega_{ij}) + \sum_i(\omega_{ij}^{cc} - \omega_{ij})(\mu_{ij}^{cc} - \mu_{ij})$, where $\mu^{cc}$ and $\omega^{cc}$ are the new firm-level markup and market share after the Climate Change Shock. The sector level decomposition is then further aggregated into country level using the equilibrium sector share.