Climate Change and Market Power

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Abstract

Using establishment-level data from Orbis during 2000-2020, we study the effect of extreme temperature shocks on local industry market power. We document that extreme temperature exacerbates local market power, increasing industry concentration and aggregate markup. This increase in market power was driven by the heterogeneous responses of firms to temperature-induced productivity shocks across different firm sizes. Small firms are more vulnerable to temperature shocks compared to large firms, thus leading to a reallocation of market shares from small to large firms under climate change. We rationalize the empirical finding with a model of reallocation and endogenous markup. By calibrating the model to the observed aggregate markup and concentration, we further quantify the welfare loss of climate-induced productivity shocks. Our findings underscore the importance of incorporating market dynamics and firm-level heterogeneity into assessment of the economic impacts of climate change.

Keywords: Climate Change, Market Power, Markups, Productivity

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1 Introduction

Rising temperatures are one of the most significant and well-documented features of climate change. The IPCC's 2023 Synthesis Report indicates that global surface temperatures have risen by 1.1°C from the period of 1850-1900 to the most recent decade, 2011-2020 (Calvin et al., 2023). While existing studies highlight the negative impacts of higher temperatures on firm productivity (Zhang et al., 2018; Bustos et al., 2016; Xie, 2024; Somanathan et al., 2021), the aggregate consequences of firm-level shocks on industry market power are less understood.

Given the increasing availability of firm-level panel data and recent advances in production function estimation (De Loecker and Warzynski, 2012), there is a resurgence of interest in estimating and studying market power. Studying market power is essential because it ties closely with key economic outcomes such as labor share (Autor et al., 2020), innovation (Aghion et al., 2009), misallocation (Edmond et al., 2023; Baqaee and Farhi, 2020) etc., with important implications for both consumer welfare and economic efficiency (Edmond et al., 2023; De Loecker et al., 2021). Theoretically, markups (i.e., price over marginal cost) serve as a core proxy for market power, and evidence suggests that global markups have increased over the past four decades, from around 1.15 in 1980 to about 1.6 in 2016 (De Loecker and Eeckhout, 2018). As the literature shows that rising temperature could affect economic activities at the micro level, this paper examines the implications of rising temperature on market power and social welfare, as well as the underlying channels of impact.

We start by developing a stylized heterogeneous firm model that link temperature-induced productivity shocks to key aggregate outcomes for market structure. Different from previous studies, we focus on the intensive margin of reallocation that could drive changes in market concentration and markup. To capture the intensive margin of reallocation, we employ an endogenous markup framework following Atkeson and Burstein (2008). In this framework, heterogeneous temperature shocks increase within-industry productivity dispersion, leading to the reallocation of market shares toward more productive, higher-markup firms and thereby increasing aggregate markup.

We empirically test these predictions in the context of the European Union (EU). Using establishment-level data from Orbis (2000-2020), we exploit detailed firm-level balance sheet data (e.g., annual revenue, labor costs, capital costs, number of employees), as well as geographic information such as address and latitude/longitude. Our analysis focuses on 16 EU countries with the most comprehensive firm records and seven sectors that are particularly sensitive to heat. We acknowledge that the data still suffer from incomplete coverage, that firms included are disproportionately larger, older, and more productive. We alleviate this concern in two ways. First, we improve the representativeness of our sample by imputing value added using information on wage bill and earnings following the procedures in Kalemli-Ozcan et al. (2015), Bajgar et al. (2020), and Gal (2013). 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. Second, instead of capturing the economy-wide concentration trend, our analysis focuses more on within-firm responses to temperature shock and the heterogeneity of this response between firm sizes. As Bajgar et al. (2020) point out, Orbis data is

more suitable for studies that focus on mean-performance or within-firm changes.

With these detailed data, we measure the firm-level markup using the production function estimation approach following De Loecker and Warzynski (2012). The production function approach exploits the cost-minimization condition and therefore does not require any demand-side assumption, making it suitable for multi-industry macro analysis. Our estimate shows a steady increase in aggregate markup in our EU sample, consistent with the recent literature on macro-market power (De Loecker and Eeckhout, 2018; Bajgar et al., 2019). We also observe that the firm-level markup distribution has become more dispersed, particularly in the upper tail, with a subset of firms earning significantly higher markups. Meanwhile, for the majority of firms in the lower tail, markups have changed relatively little.

Next, we examine the impact of temperature change on local industry market power. The markets we consider are narrowly defined — NACE 4-digit industry within a country for a given year.[1] To capture the non-linearity of the impacts of temperature, we group the maximum daily temperature into eight bins, each spanning 10°F intervals, ranging from below 30°F to above 90°F. We then count the number of days that fall into each temperature bin per year at each firm location and aggregate it to the market level.

We regress market level outcomes on the number of days within each temperature bin, omitting the 60-70°F bin, and controlling for precipitation. We include country-by-year fixed effects to capture country specific trends, such as macroeconomic policy or demand shocks at the country level. We control for sector-by-year fixed effects to absorb sector specific trend, such as technology advance or sector wise demand shocks over time. The estimation assumption is that temperature shocks for each market are exogenous to potential unobserved factors that might affect market outcomes after controlling for these fixed effects. We find that extreme high temperature would increase within-market productivity dispersion, degree of concentration, and aggregate markup in local industries.

Furthermore, we analyze firm-level data to explore the mechanisms driving the observed effect on market power and market concentration. We study the impact of temperature on firm productivity, revenue, market share, markup, and exit, by regressing firm-level outcomes on the number of days within different temperature bins. We control for firm fixed effects to use variations within each firm across years. We include country-by-NACE 2-digit industry-by-year fixed effects to absorb country-industry wide shocks that change over time. The identification assumption is that the year-to-year temperature shock for each firm is not correlated to unobserved confounding factors that may affect firms' productivity, revenue, market share, and exit behavior.

We find that extreme high temperatures reduce firm productivity and revenue. On average, firm productivity, measured by revenue total factor productivity (TFP), decreases by 0.96 percent for every additional 100 days in the above-90-degree bin, while firm revenue decreases by 8.96 percent. More importantly, these effects are heterogeneous across firm sizes, with smaller firms experiencing more pronounced negative impacts. The larger reductions in productivity for smaller firms result in market share reallocation toward larger firms.

[1] NACE is the abbrivation for the Statistical Classification of Economic Activities in the European Community. It has four levels. Level 1 includes 21 sections identified by alphabetical letters A to U, and level 4 includes 615 classes identified by 4-digit numerical codes.

Specifically, for an additional 100 days in the above-90-degree bin, the market share of small firms declines by 8.29 percent, that of medium firms declines by 5.97 percent, while the market share of large firms increases by 22.67 percent. Additionally, large firms experience increases in markups, whereas small and medium firms do not.

These results align with the predictions of our stylized model, an endogenous markup model in which productivity and market share distribution determines concentration and aggregate markup. Under such environment, in the presence of a size-dependent productivity shock, smaller firms are facing larger shocks and are limited by a lower cost pass-through. The consequent reallocation of market share towards larger firms increases market concentration and aggregate markup.

Building on our empirical findings and stylized model, we conclude by asking how relaxing the standard CES assumption used in much of the environmental literature—and allowing for heterogeneous markups—affects the measurement of climate-change welfare costs. To address this question, we compare the welfare loss under our baseline VES (Variable Demand Elasticity) framework with the loss under the standard CES assumption. The results show that ignoring reallocation and variable demand elasticity can underestimate the welfare cost of climate change by approximately 17 percent. This underestimation arises because climate-induced market power leads to additional misallocation of inputs across firms and depresses labor demand and wages through quantity distortions. A standard CES approach overlooks these key reallocation channels, potentially masking important welfare consequences of climate change.

In sum, our findings emphasize the need to incorporate firm heterogeneity, market structure dynamics, and endogenous market power into assessments of the 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.

Related Literature Our paper speaks to three strands of literature. The first examines the short-run and long-run effect of climate change on economic activities, with one of the key economic variables of interest being firm productivity. This body of work consistently documents the negative effect of extreme temperature shock on TFP or labor productivity (Zhang et al., 2018; Bustos et al., 2016; Xie, 2024; Somanathan et al., 2021; Bilal and Känzig, 2024). Aside from empirical evidence on firm-level response, recent environmental literature has given more attention to the aggregate impact of such firm-level productivity response (Xie, 2024; Ponticelli et al., 2023; Shi and Zhang, 2023). We contribute to this literature by studying the aggregate impact on market power across multiple sectors in European countries. To the best of our knowledge, we are the first to study temperature shock's impact on market power and markup.

In addition to the adverse impact on firm-level and aggregate activity, more focuses have been directed to the heterogeneity in firms' response to climate change. Somanathan et al. (2021) and Zivin and Kahn (2016) find that larger firms have a higher incentive to invest in Air Conditioning. Ponticelli et al. (2023) finds that smaller firms suffer more in terms of productivity and suggests that larger manufacturing firms adapt better

since they have plants across multiple locations to help hedging against the local temperature shock. In this paper, we study the aggregate consequences of such firm-level heterogeneity in climate adaptation, which drives reallocation of market shares towards larger firms whose suffer relatively smaller negative impacts. While these literature mostly focus on the role of supply side heterogeneity and adopt CES demand, we contribute to this debate by looking at the role of demand side primitives (Variable Demand Elasticity) in shaping reallocation, market structure dynamics, and welfare loss.

Our paper also speaks to the recent discussion of rising market power and market concentration (Autor et al., 2020; De Loecker and Eeckhout, 2018). This strand of literature takes advantage of the recent emergence of detailed firm-level data and estimates firm level markup using production function estimation approach (De Loecker and Warzynski, 2012). As market concentration is an economic outcome of underlying demand and supply structures, there are multiple potential causal paths leading towards an increase in market concentration: the rise of superstar firm (Autor et al., 2020), globalization (Van Reenen, 2018), antitrust policy (Van Reenen, 2018), changes in product substitutability (Syverson, 2004), changes in search cost (Goldmanis et al., 2010), changes in entry costs (Asplund and Nocke, 2006), and technological change (De Loecker et al., 2021). Depending on the root causes, each of these paths can have very different implications on welfare and efficiency gain of the rise in concentration and market power. For example, while in some cases concentration increase can be due to technological development or increased competition, in other cases it can result from large firms exerting market power, which undermines consumer welfare (Bighelli et al., 2023). The potential tradeoff between efficiency and deadweight loss makes understanding the cause of concentration increase crucial for evaluating the impact on aggregate productivity and consumer welfare. We contribute to this debate by proposing another source of concentration increase: climate shocks. We argue that such climate-induced concentration increase raises concentration at the expense of exacerbating the degree of market power and creating additional misallocation, while the efficiency gain is minimal compared to the competition-driven concentration increase. Looking ahead, given the current projection of future climate scenario, the extent and frequencies of extreme climate events will only continue to exacerbate, which further reinforce and magnify the climate-induced impact of climate change on market concentration. Furthermore, our climate change setting can be generalized to other productivity shocks which, when interacting with firm-heterogeneity and costly shock-mitigation measures, changes productivity dispersion and therefore market concentration and markup.

Two papers in this field are particularly relevant to our paper. De Loecker et al. (2021) develops and quantify an endogenous markup model where both the changes in market structure and technology can lead to movements in market power, labor share, and job reallocation. The empirical setting in our paper - the extreme weather productivity shock - falls into the technology channel of their model, which features a change in the variance of productivity shock that changes within-industry productivity dispersion. While their paper models a mean-preserving dispersion change of productivity, our setting features not only an increase in productivity dispersion, but also a decrease in overall level. Intuitively, given a negative shock, the heterogeneity across different firms can lead to differential realization of the shock, changing the productivity dispersion.

The second closely-related paper is Edmond et al. (2023), which quantifies the welfare cost of markup and decompose it into three channels of (i)uniform tax, (ii) misallocation, and (iii) inefficient entry. We closely follow their model settings and calibration strategy for our welfare quantification. While their paper focuses on quantifying the welfare costs of markups distortion itself and studying the relative importance of the three channels, we use the setting to quantify the cost of climate change related productivity shock under an endogenous markup framework and ask to what extent is relaxing CES assumption and allowing for variable demand elasticity important to such quantification.

In addition, our paper is related to the literature on Variable Demand Elasticity (VES) and heterogeneous cost pass-through (Amiti et al., 2014, 2016; Arkolakis and Morlacco, 2017; Edmond et al., 2023). These papers build on demand systems that deviate from the traditional CES and monopolistic competition structure commonly used in trade literature, allowing firms to differ in demand primitives such as demand elasticity. One of the main empirical findings from these papers is that more productive firms face more inelastic demand, have higher market shares, charge higher markups, and have lower cost pass-through. While these papers mostly focus on the exchange rate shock that changes input costs, our paper applies such demand framework on another cost shock that is becoming more and more relevant: climate change cost shocks. In the environmental economics literature, most of the modeling frameworks assume the traditional CES+monopolistic competition demand framework. While such framework is highly tractable, it overlooks important dynamics regarding how large and small firms are reacting to climate change differently and on what the aggregate implications of these reallocation are for market power. Our analysis highlights that allowing for a more flexible demand system introduces new dimensions to the discussion on the economic impact of climate change.

Our paper is most closely related to Ponticelli et al. (2023), which studies the impact of temperature shock on local Commuting Zone concentration. While the focus of that paper is more on concentration and the potential mechanisms, we focus on the effect on local market power and directly proxy it by estimating firm level markup, which is theoretically the best measure for market power. As the interpretation of concentration change can be challenging , we used multiple measures of market power, including concentration and markup, in order to isolate the cause behind concentration change (we will discuss this in more detail in Section 3). The estimation of markup is also helpful, as it allows us to observe the change in pricing behavior amid temperature shock, and is thus informative on the demand side factors that potentially shape market concentration change, such as the movements in market shares. In addition to the differences in the focus of our papers, our data samples also differ. While Ponticelli et al. (2023) documents that extreme temperature increases concentration in the manufacturing sector in the US at the county level, our analysis finds significant impact on concentration across multiple sectors in 16 EU countries at the level of narrowly-defined industry. Comparison of a cross-section of different industries allows us to identify industry-specific characteristics that determine the degree of concentration change due to temperature shock.

There are a couple of other papers that study the impact of temperature on industry dynamics. Xie (2024) and Cascarano et al. (2023) focus on the impact of extreme temperature on the extensive margin of plants' entry and exit, while Shi and Zhang (2023) emphasizes the impact of extreme hot temperature on aggregate

productivity. Our analysis differs in that, though we also study the extensive margin, our main focus is on the intensive margin of reallocation, fueled by the heterogeneity in firm responses. We emphasize more on the reallocation channel rather than extensive dynamics because of data limitation, and more importantly, because it is a dimension less understood in the literature and it has important interaction with variable demand elasticity.

The paper is structured as follows. In Section 2, we cover details of our firm-level data used for markup estimation and temperature data. Section 3 talks about how we measure market power and define various indicators. In Section 4, we show some stylized facts on different measures of market power, including our markup estimates. In Section 5, we provide some theoretical foundations to explain the potential mechanism at work. In Section 6, we estimate the effect of temperature change on market power and concentration, as well as discuss the mechanism by providing empirical evidence at the firm level. We calibrate our model and calculate welfare loss of climate change productivity shock in Section 7. Finally, we conclude this paper with Section 8.

2 Data

2.1 Establishments data

To measure firm-level economic activities, we use the Orbis Database provided by the Bureau van Dijk. It is compiled from firm-level financial statements and balance sheets collected by different national information providers. It covers more than 200 countries around the world and a wide range of industrial sectors. In particular, we exploit information on annual revenue, labor costs, capital costs, and number of employees. We also take advantage of firm-level geographical information, such as address, longitude, and latitude, to match the Orbis data with the weather data. We further estimate revenue TFP[2] and markup at the firm level, following De Loecker and Warzynski (2012). Appendix G: provides more details on the estimation of the production function.

In response to the concerns raised by the existing literature that Orbis exhibits bias towards larger, older, and more productive firms (Kalemli-Ozcan et al., 2015; Bajgar et al., 2020), we improve the representativeness of our sample and to recover the true distribution of firms by cleaning the data and imputing missing values following the procedures in Kalemli-Ozcan et al. (2015), Bajgar et al. (2020), and Gal (2013). As the exact data cleaning and imputation procedure should depend on the research context, our data cleaning approach aims to recover a wider range of firm observation across different firm sizes and is less restrictive than the approach generally adopted in the literature. Contrary to the strand of macro market power literature which focuses on getting the *macroeconomic* trend of aggregate market power and thus requires the data to be representative of the true firm distribution, our analysis focus more on within-firm response to temperature

[2]Revenue TFP (or TFPR) is a measure of total factor productivity derived from firms' revenue, rather than physical output, thereby reflecting not only underlying production efficiency but also price and markup variations.

shock and the heterogeneity of such response across firm sizes. See Appendix A.1 for more details on the cleaning and imputation procedure.

2.2 Weather data

We use multiple sources to measure various weather variables.

Temperature The daily temperature data comes from *NOAA Physical Science Laboratory*, which provides global gridded data with $1^\circ \times 1^\circ$ resolution. We extract both the daily *maximum* temperature and the daily *average* temperature for each firm based on their recorded longitude and latitude.[3] We use *maximum* as our main temperature variable. Compared to daily average temperature, daily maximum temperature can better capture the temperature workers experience during the day, and therefore can be a better proxy for extreme high temperature shock (Graff Zivin and Neidell, 2014).

To better capture the change in the temperature distribution experienced by each firm, we group the daily temperature 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, >=90°F. Each bin represents the number of days in a year in which a firm experiences a daily maximum temperature within that bin. In the regression analysis later, we drop the bin 60-70°F, which is used as a reference bin.

Precipitation The precipitation data are provided by *NOAA Physical Science Laboratory*. It is a global gridded data with a resolution of $0.5^\circ \times 0.5^\circ$ resolution. We extract precipitation at the location of each firm based on its geographic information, and average daily precipitation to yearly level. Annual average precipitation at the firm's location is included in the regression analysis as a climate control variable to isolate the impact of temperature shocks, as temperature shocks are often correlated with other disruptive weather events.

2.3 Final Sample

The final data sample covers 16 European countries[4] from 2000 to 2020, which have the most complete firm-level data, as well as the geographic information needed to match the climate variables. In terms of sector coverage, we focus on seven sectors that are more exposed to heat (Graff Zivin and Neidell, 2014): Agriculture, forestry, and fishing (NACE code A); Mining and quarrying (B); Manufacturing(C); Electricity, gas, steam and air conditioning supply(D); Water supply; sewerage; waste managment and remediation activities(E); Construction(F); Transportation (H). We include firms that entered the dataset before 2000. Our final sample includes roughly 2.2 million firm-year observations.

[3]For firms in our sample that do not have longitude and latitude information, we average the temperature at the zipcode level where the firm is located, and use it as a proxy for firm temperature exposure.

[4]Austria, Belgium, Denmark, Germany, Estonia, Spain, Finland, France, Croatia, Hungary, Ireland, Italy, Luxembourg, Netherlands, Poland, Slovakia.

3 Measuring market power

Market power generally refers to the firm's ability to charge a price that is higher than marginal cost. It has significant implications for consumer welfare, innovation, employment, and TFP growth etc. (Gutiérrez and Philippon, 2017; Berry et al., 2019; De Loecker and Eeckhout, 2018; Ganapati, 2018). Measuring market power can be challenging, as many of the potential proxies are the products of multiple forces at play. In this section, we discuss different ways to empirically measure market power, each proxy's pros and cons, and our approach to best measure market power using multiple proxies. We then briefly go over related literature on measuring market power and conclude with our definition of a market.

3.1 Market Power Proxies

Concentration Ratio (CR) Defined as the sales percentage of the top N firms within a market in year t.

$$CR_{N,t} = \frac{\sum_{i \in \text{Top N}} \text{sales}_{i,t}}{\sum_{i \in I} \text{sales}_{i,t}}$$

The value of Concentration Ratio ranges from 0 to 1, with higher value representing more market shares for the top firms and therefore higher concentration. The calculation of Concentration Ratio is data-friendly, in the sense that it only requires firm-level sales data, which are relatively available. However, since it only captures the performance of the top firms and ignores the rest, CR does not necessarily capture the entire distribution of firm performance within a market.

Herfindahl–Hirschman index (HHI) Defined as

$$HHI = \sum_{i=1}^{N} s_i^2$$

where: s_i is the market share of firm i, in percentage term.

Compared to CR, HHI can better capture shape of the entire distribution of sales, as it includes information of all firms within a market. Under some specific forms of competition structure such as Cournot, HHI can also contain direct information on demand primitives (demand elasticity).

The value of HHI ranges from 0, representing perfect competition, to 10000, which infers monopoly. The criterion for measuring the degree of concentration varies by different regulatory entities, but an HHI level above 2500 is generally considered to be highly concentrated.

Each of these concentration measures (CR and HHI) has its own pros and cons. While CR measures might not reflect the entire distribution of firms in an industry, HHI can be biased if the coverage of firms varies over time (Bajgar et al., 2019). However, our measure of CR and HHI are highly correlated, with an average correlation between HHI and CR4 of 0.82 (Figure B1 shows the high correlation between HHI and CR measures). Throughout the paper, we proxy concentration using both measures and our main results do not depend on this particular selection. To the extent that larger firms, compared with smaller firms, are relatively

well covered and that large firms typically represent the majority of an industry's activity (Kalemli-Ozcan et al., 2015), we believe that both of these measures are adequately indicative of market concentration.

Markup Defined as

$$\mu_i = \frac{P_i}{MC_i}$$

Markup measure is theoretically the direct measure of firm's pricing power, as it measures the gap between price and marginal costs. To understand how markup can proxy for market power, it is also useful to express markup in an alternative way. From the first order condition of profit maximization, we have

$$\mu \equiv \frac{P}{MC} = \frac{\varepsilon}{\varepsilon - 1}$$

Markup is thus directly related to the price elasticity of demand ε. Producers facing less elastic demand (smaller ε) can charge higher prices above marginal costs, exerting greater market power.

However, direct measurement of markup is almost impossible as we can rarely observe both prices and marginal costs. As an alternative, researchers rely on estimation of markup, which can also be challenging. While IO researchers typically derive markup from demand estimation, such estimation is usually conducted at a narrow industry setting where a specific competition conduct is assumed. In light of our setting of climate change, which affects the economy across space and sectors, we tend to the production function estimation approach to estimate firm-level markup, following De Loecker and Warzynski (2012). The advantage of this approach is that it does not require any demand-side assumption, as this method is based on the cost-minimization condition. We document the specifics of the production function estimation in Appendix G:.

Industry Turnover Another way to measure the degree of market power is by measuring industry dynamism, including entry rates, exit rates, and churn rate (Bajgar et al., 2020; Cavalleri et al., 2019). Industry turnover can be informative on the degree of market power, as lower entry rates and higher exit rates are often associated with industries with higher concentration. In models of heterogeneous firms and firm dynamics such as Melitz (2003), entry and exit decisions also rely crucially on the degree of competition.

One caveat of using Orbis data to analyze entry and exit is that the data itself may not reflect true entry and exit, as it does not include information on the year of entry/exit (Bajgar et al., 2020). As the next best option, we identify entry and exit as the first year and the last year when we observe the firms in our sample. An entry under our definition can either represent true entry, or merely changes in data coverage. However, given that spurious exit is less likely than spurious entry, the results on exit are more informative than those on entry. In our empirical exercise, we focus on the firm level exit status as the main proxy for measuring industry turnover.

3.2 Challenges in Identifying True Market Power

As discussed above, even though each of these measures can be correlated with market power, they are not convincingly informative by themselves. Using only one of of these measures can lead to misleading conclusions on change in market power.

Even though markup is, by its definition, theoretically the best proxy for market power, empirically inferring market power change simply from changes in markup can be also misleading. On one hand, markup increase can represent the increasing gap between price and marginal costs, implying true pricing power. On the other hand, higher markup can also be associated with an increase in fixed cost rather than a higher market power. If such fixed costs increases lead to product quality increase or marginal cost decrease, then the impact on welfare can be ambiguous (Berry et al., 2019).

Furthermore, the relationship between changes in concentration and shifts in market power is not immediately clear. Depending on the specific demand and supply settings, a higher concentration can be correlated with either higher or lower market power (Van Reenen, 2018; Bajgar et al., 2019; Afrouzi et al., 2023; Berry et al., 2019). For example, while traditional Cournot Oligopoly model generates a positive correlation between concentration and market power (Tirole, 1988), competition-driven increase in concentration can actually infer lower market power (Melitz and Ottaviano, 2008; Asplund and Nocke, 2003). The correlation between concentration and market power depends on the demand and supply primitives, which usually vary by industries[5]. Therefore, in order to paint a comprehensive picture of market power as accurately as possible, we look at all different available metrics, including *concentration, markups, and industry turnover*. The joint movements of these metrics can provide valuable insights into the sources of market power changes and help the assessment of welfare implications.

3.3 Defining Markets: Scope and Implications

In the recent discussion of accurately measuring concentration trends in EU and US, the level at which researchers define the relevant market has been the point of contention. The narrowness of industries and the decision between local and national market all matters for the trend of concentration (Cruz and Rossi-Hansberg, 2021; OECD, 2018). However, it is important to highlight that the accuracy and representativeness at which we describe aggregate concentration trend is not the focus of this paper. Instead, we tend our focus to the within-market firm reallocation dynamics on a more disaggregated level and the potential drivers of such dynamics.

In our research context, since different locations—particularly across countries—experience significantly varying temperature shocks, and we aim to focus on the effects of local temperature shocks, we restrict our market to a more geographically compact area. This ensures that firms and industries within a given cell are likely exposed to similar temperature shocks. Balancing the trade-off between accurately capturing a market and measuring the degree of local temperature shock, we define a market as a *country by 4-digit* (or 2-digit)

[5]For a more comprehensive discussion on concentration and market power, see Syverson (2019) and OECD (2018)

industry by year cell [6]. Restricting a market to be relatively compact also connects to the theoretical settings in Section 5 where we model an oligopoly competition structure with finite number of firms.

To the extent that countries in EU are relatively integrated and that demand is likely geographically diverse, defining a market in such geographically compact manner also means that the demand factors are relatively orthogonal to the local temperature shock, isolating the role of supply side cost shocks.

When aggregating firm-level variables such as productivity and markups, we use value-added shares as weights, as this is the most readily available variable after data imputation. We also experiment with using sales shares and employment shares as weights, yielding very similar results. In the industry level analysis in Section 6.2, we include results on both unweighted and weighted average of these aggregate outcome, as the difference of the results on these two aggregates can be informative on the between-within mechanism. For example, if the impact on the weighted markup is higher than that on unweighted markup, then it is indicative of a reallocation of shares at play.

4 Descriptive Summary

In this section, we summarize the data pattern of our main dependent and independent variables of interest, while comparing our observed pattern to those in the literature.

4.1 Temperature

Year-to-year temperature change Figure 1 shows the change in temperature distribution in our sample, with each row representing the time-series of bin values for that specific temperature bin. For the colder end of the temperature distribution, such as bin [<30F] and bin [30-40F], there is a decreasing trend from 2000 to 2020, whereas the increasing frequency of extreme hot days are evident by the upper right corner of the heatmap, where there are increasingly more hotter days over time. Together these imply a rightward shift of the temperature distribution, and such shifts seem to concentrate among Southern and Western Europe — in countries such as Spain(ES), Italy (IT), and France (FR).

The change in daily maximum distribution is also heterogeneous across space and time. Figures H4, Table H4, and H5 provide the breakdown of the changes in temperature distribution across countries and times.

Long term temperature change In addition to the year-to-year temperature variations, we see that the temperature has increased in the long run. Figure 2 illustrates the change in the average decadal temperature between 2000-2009 and 2010-2020 by country. The maximum daily temperature has increased by nearly 1°F in countries such as France, Croatia, Poland, Slovakia, and Hungary (panel (a)). Furthermore, the number of extremely hot days (temperature above 86°F) has increased by 4 to 6 days per year in Spain, France, Slovakia,

[6] Our main results are qualitatively similar for different choices of industry levels

and Hungary (Panel (b)). Northern countries, such as Finland, Estonia, and Denmark, have seen a more moderate increase in temperature.

4.2 Market Power

Although there have been extensive studies on the evolution of market power in the U.S., less is known in the EU context as the evidence so far shows mixed results (Cavalleri et al., 2019; De Loecker and Eeckhout, 2018; Bajgar et al., 2019). This inconsistency of the results can be largely attributed to the coverage and representativeness of the data researchers use and the data cleaning procedures implemented. While the focus of these papers is to representatively capture the economy-wide concentration trend, we tend our focus towards the changes of various market power indicators on a more granular scale and focus more on the potential drivers behind concentration change. Nonetheless, our data patterns look similar to related literature using Orbis data (Weche and Wambach, 2021; De Loecker and Eeckhout, 2018).

Markup Consistent with recent literature on macro market power (De Loecker and Eeckhout, 2018; Bajgar et al., 2019), Figure 3 shows a steady rise in aggregate markup in our EU sample [7], albeit some disruptions in the middle likely due to the financial crisis in 2008. Recently, there has been a sharp rise in aggregate markup in the 2010s. There is some heterogeneity in the magnitude of this trend across countries and across sectors [8], but the general rising trend is consistent throughout.

When it comes to the distribution of the firm-level markups, Figure 4 shows a fattening of the upper tail and an increasingly dispersed markup distribution. In particular, there are more firms earning increasingly higher markup, while, for the majority of firms in the lower tail, the level of markup has not changed much. Consequently, the rising trend in aggregate markup can be attributed to the largest firm earning higher markup, a story consistent with the recent macro market power discussion (De Loecker and Eeckhout, 2018).

Concentration As discussed before, the literature on concentration trend in EU has not yet reached a consensus, as different researchers use different data sources and the result is really sensitive on the exact data cleaning procedures, which differ for each researcher (for example, whether to restrict sample to include consolidated accounts or unconsolidated accounts, whether to correct for multi-national or foreign ownership, the decision on employment size cutoff, etc.). Due to our different research focuses and our less restrictive sample section criterion, our data sample will inevitably differ. Figure H8 shows the concentration trend in our sample. It shows the change in HHI index for the mean 4-digit industries in our sample. No clear rising trend is detected throughout the entire sample period. However, there has been a steady increase in concentration post financial crisis, a period of increasing trend that seems to be consistent with recent literature.[9] The

[7] Following the standard in the literature, we winsorize our markup data at the 2% level when calculating aggregate summary

[8] See Figure H5 and H6 in the Appendix for more details on the heterogeneity across countries and sectors

[9] Figure 14 in Bajgar et al. (2019) shows such increasing trend from 2005 onward; Bighelli et al. (2023) also documents a 43 percent increase in EU concentration from 2009 to 2016

aggregate trend masks significant heterogeneity across sectors. Figure H10 shows the concentration change for the mean industry by sectors. Among the 6 sectors in our sample, *Mining and Quarrying(B)*, *Electricity (D)*, and *Manufacturing(C)* experience more concentration increase, especially for the later part of the sample period.

Industry Exit Rates Figure H9 shows the trend in mean 4-digit industry exit rates in our sample, which have been rising. This increasing trend is consistent across broader definition of industry (2-digit) or market definition.

Table 1 reports the summary statistics of the data used for analysis.

5 A Stylized Model

This section provides theoretical foundations for incorporating the effect of temperature into a model of firm dynamics. We start with a simple CES framework to illustrate how temperature affects the extensive margins of exit. Next, we relax the CES assumption, allowing the intensive margin of reallocation to influence both firm- and aggregate-level markups. To incorporate such reallocation dynamics, we adopt a model of endogenous markup following Atkeson and Burstein (2008), from which we make predictions on market share reallocation, changes in market concentration, and the aggregate level of markup under climate-induced productivity shocks. We end this section by simulating a single-industry endogenous markup model, which provides insights that guide our empirical design in Section 6.

Climate changes can enter economic models in various ways, such as through a productivity shifter (Xie, 2024; Nath, 2020) or a change in the capital depreciation rate (Bilal and Känzig, 2024). To fix ideas and demonstrate the basic mechanism, we model the effect of temperature shocks as firm-specific productivity shocks. There is a wealth of empirical evidence documenting the effect of temperature on either labor productivity or total factor productivity (Zhang et al., 2018; Bustos et al., 2016; Dell et al., 2014; Burke and Emerick, 2016; Somanathan et al., 2021). In particular, the effect of temperature on productivity is non-linear, and extreme temperatures are likely to lower productivity.

5.1 Extensive margin: CES [10]

We begin with the standard static model of heterogeneous firms à la Melitz (2003), focusing on how temperature affects the extensive margin of exit.

Demand is CES across varieties $i \in I$, which gives each firm i the inverse demand function:

$$y_i = E \cdot \left(\frac{p_i}{P}\right)^{-\sigma}, \tag{1}$$

[10] Equilibrium objects under CES framework have closed-form solutions and thus offers intuitive comparative statics insights.

where $\sigma > 1$ is the elasticity of substitution, E is the aggregate real expenditure, P is the aggregate price index, and p_i is the price for firm i.

Each firm draws productivity φ_i from a distribution $G(\varphi)$ and pays a fixed overhead production cost f before producing. Production is constant returns to scale and linear in labor, so $y_i = \varphi_i l_i$.

Building on Melitz (2003), we introduce an additional climate-induced marginal cost shifter $\gamma_i(T)$, so that the new marginal cost under climate change becomes:

$$\gamma_i(T)\frac{W}{\varphi_i} \tag{2}$$

where W is the wage (normalized to 1). The climate shock factor $\gamma_i(T)$ can be interpreted as the additional inputs required to produce the same unit of output due to a temperature shock that lowers productivity. We assume that there is no damage at the optimal temperature T^* ($\gamma_i(T^*) = 1$) and that higher temperature exacerbates productivity losses ($\frac{\partial \gamma_i(T)}{\partial T} > 0$).

Profit Maximization Firms choose y_i to maximize profits:

$$\max_{y_i} \ \pi(\varphi_i, T) \ = \ p_i y_i \ - \ \frac{\gamma_i(T)}{\varphi_i} y_i \ - \ f. \tag{3}$$

Solving the firm's problem yields the optimal price:

$$p_i(\varphi_i) \ = \ \frac{\sigma}{\sigma - 1}\frac{\gamma_i(T)}{\varphi_i}. \tag{4}$$

Thus, firm-level prices feature a constant markup $\mu_i = \frac{\sigma}{\sigma-1}$ above the firm-specific marginal cost. The resulting profit function is

$$\pi(\varphi_i) \ = \ \gamma_i(T)^{1-\sigma}\frac{1}{\sigma}E\left(P\frac{\sigma}{\sigma-1}\right)^{\sigma-1}\varphi_i^{\sigma-1} \ - \ f, \tag{5}$$

which is decreasing in the magnitude of the climate shock $\gamma_i(T)$ and increasing in the firm's productivity φ_i.

Since σ is constant in the CES framework, the demand elasticity does not vary with output, and markups remain fixed. Hence, any reallocation of market shares does not affect markups.

Exit A firm exits the market if it cannot earn a positive profit. Because the profit function is increasing in φ_i, there is a unique zero-profit (exit) productivity cutoff φ_i^* defined by:

$$\pi(\varphi_i^*) = 0. \tag{6}$$

Solving this condition gives

$$\varphi_i^* \ = \ \gamma_i(T)\left(\frac{f\sigma}{E}\right)^{\frac{1}{\sigma-1}}\frac{\sigma-1}{\sigma P}. \tag{7}$$

A simple comparative statics exercise shows that an increase in temperature raises marginal costs through $\gamma_i(T)$, thereby increasing the zero-profit cutoff.

Proposition 1. *The increase in temperature increases the zero-profit productivity cutoff*

$$\frac{\partial \varphi_i^*}{\partial T} > 0$$

Proof. See Appendix C.1 ■

Intuitively, as temperature rises, firms face higher marginal costs. To remain profitable, they must have sufficiently high productivity. Consequently, the zero-profit cutoff increases, forcing lower-productivity firms to exit. Figure 6 illustrates this mechanism.

5.2 Intensive margin: extension to endogenous markup

The workhorse model of international trade and firm dynamics typically adopts a CES demand structure with monopolistic competition (Melitz, 2003). While this setup is analytically tractable, its assumption of constant markups and perfect pass-through is at odds with empirical evidence showing that markups vary across firms and that cost pass-through rates are often heterogeneous and incomplete (De Loecker and Eeckhout, 2018; Amiti et al., 2016). Although non-CES demand structures have increasingly been adopted in international trade studies (e.g., exchange rate pass-through), they remain relatively underexplored in the context of environmental and climate-change economics.

One key implication of the CES assumption is that a climate-induced shock does not fundamentally change markups at either the firm or the industry level. Consequently, CES models cannot capture how heterogeneous shocks and subsequent reallocation of market share might endogenously alter markups and market power. Allowing for differential markups and varying pass-through rates is essential to align models more closely with the empirical reality that climate impacts can differ substantially across firms of different sizes. This heterogeneity in response to climate shocks may play a significant role in shaping market concentration and overall welfare, a point that becomes particularly salient when examining rising market concentration in recent debates.

To address these concerns, we extend the model to feature endogenous markups using a nested-CES demand structure, following Atkeson and Burstein (2008). In this framework, the distribution of firm productivity directly influences market shares, which in turn determine markups and aggregate outcomes. Hence, when climate change alters the productivity distribution, it triggers a reallocation of market shares that can affect both market concentration and average markups. By incorporating endogenous markups, this VES framework provides a richer lens through which to understand the economic repercussions of climate shocks, offering new insights into how climate-driven productivity changes can reshape market power dynamics in ways that the CES model cannot.

Demand Demand features a nested CES structure[11]. In the outer nest, we have a continuum of sectors indexed $j \in [0,1]$, whose elasticity of substitution is η. In the inner nest, within sectors, we have n_j firms producing distinct products. The elasticity within sectors is ρ. We impose $\rho > \eta$ to reflect that goods within sectors are more substitutable than those across sectors.

To illustrate the key mechanism determining equilibrium markups, here we focus on single industry static equilibrium. Time subscripts are dropped for clearer notation. Aggregate output Y is a CES bundle over a continuum of industry output y_j, which is a CES composite of firms i output y_{ij} within industry j.

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

. In contrast to between-sectors, firms within sectors are granular and recognize their impact on aggregate price index and output. The finite number of firms within a sector also imply that firms exert market power. Such oligopolistic structure also connects to our empirical settings where markets are narrowly defined at a more disaggregated level.

Under the CES structure, the inverse demand for goods within sector and for the sector aggregate are given by

$$\frac{P_{ij}}{P_j} = \left(\frac{y_{ij}}{y_j}\right)^{-1/\rho}, \quad \frac{P_j}{P} = \left(\frac{y_j}{Y}\right)^{-1/\eta} \tag{9}$$

Production On the production side, firms are heterogeneous in productivity φ. Production is CRS and labor is the only production input: $y_{ij} = \varphi_{ij} \cdot l_{ij}$. Firms must pay f units of overhead labor in order to produce. Firms plays a static *Cournot quantity* competition game.[12] Profit maximization gives the optimal pricing formula:

$$P_{ij} = \mu_{ij} \cdot MC_{ij} \tag{10}$$

where $MC_{ij} = \gamma_{ij}(T) \cdot \frac{W}{\varphi_{ij}}$ is the marginal costs taken into account the impact of temperature on productivity. $\gamma_{ij}(T) > 1$ can be interpreted as the additional amount of inputs (labor) needed to produce the same amount of output. When production environment is at an ideal temperature T^*, then there is no productivity discounting ($\gamma(T = T^*) = 1$) and this collapse to the regular marginal costs settings . To fix ideas, we focus on extremely hot temperature and assume $\frac{\partial \gamma}{\partial T} > 0$. The higher the temperature, the more severe the impact on productivity, and thus a higher the marginal costs.

Optimal markup is

$$\mu_{ij} = \frac{\varepsilon(s_{ij})}{\varepsilon(s_{ij}) - 1} \tag{11}$$

[11]The key qualitative feature of demand systems that we leverage in our theoretical prediction is productivity-decreasing demand elasticity. Such feature holds for a broad class of endogenous markup model including Kimball and Addilog preference. For a more comprehensive review of demand elasticity and pass-through, see Arkolakis and Morlacco (2017)

[12]The same qualitative result carry through under price competition. We use Cournot specifications as it allows for greater markup variation, which we observe in our estimation. Amiti et al. (2016)

which depends on firm specific demand elasticity, which is a function of its market share:

$$\varepsilon_{ij} = \left[\frac{1}{\rho}(1 - s_{ij}) + \frac{1}{\eta}s_{ij}\right]^{-1} \tag{12}$$

The demand elasticity is decreasing ($\varepsilon'(s) < 0$) and convex in market share ($\varepsilon''(s) > 0$).

In contrast to CES setting, the variable demand elasticity feature here (thus the variable markup feature) dictates that movements in relative prices and market shares can generate movements in firm-specific demand elasticity and markup, potentially impacting aggregate variables such as market concentration and market power.

Under the nested CES structure, market share can be expressed directly as relative prices.

$$s_{ij} = \frac{(P_{ij})^{1-\rho}}{\sum_{k=1}^{K}(P_{ik})^{1-\rho}} = \left(\frac{P_{ij}}{P_j}\right)^{1-\rho} \tag{13}$$

In particular, the more productive firms can charge lower prices and grab larger market share. The higher the market share, the more inelastic the demand ($\varepsilon(s)' < 0$), and the higher markup a firm can charge ($\mu(s)' > 0$). Within-sector demand elasticity $\rho > 1$ magnifies the relative price differences into differences in market share. In markets where goods are highly substitutable, small price differences translates into large differences in market shares.

In our data, we also see the qualitative correlation consistent with the model's prediction. In particular, higher productivity is correlated with higher market share and higher markup. Table B1 shows the correlation between productivity, market share, and markup.

Impact of a market-wise heterogeneous temperature shock Assume that extreme temperature will lower productivity and lead to higher marginal cost. This can be, for example, through the impact of extreme heat on labor productivity. In particular, we assume the impact to be *productivity-decreasing*: smaller firms (low productivity and low market share) receive a larger cost shock than large firm (high productivity and high market share). This assumption is based on our empirical observation on firm-level productivity where small firms' productivity is more negatively affected by extreme temperature shocks than large firms, as well as on the empirical evidence in related literature that attribute such heterogeneity to the qualities of managers, differences in input mix and quality, access to external finance, different climate-control investments, skill intensity, etc (Ponticelli et al., 2023; Xie, 2024; Somanathan et al., 2021). Given the focus of our paper, we abstract away from modelling such heterogeneity and instead focus on the aggregate implication of such heterogeneity on market power. The assumption on the heterogeneity of cost shock is also necessary to generate movements in relative prices and market shares. Furthermore, to isolate the intensive margin of reallocation after temperature shock, we abstract away from entry and exit. [13]

[13]The rationale behind the focus on intensive margin is fourfold. First is data limitation, as discussed in section 2 and 3. Secondly, while extensive margin of exit and entry has been studied empirically, intensive margin of reallocation is less understood in the literature. Thirdly, given our focus on the impact of welfare stemming from changes in market power and markup, the intensive margin

While the endogeneity of key variables and the presence of strategic complementarity complicate clean comparative statics, we propose some qualitative and testable predictions on the direction of reallocation, changes in market concentration, and aggregate markup, which will be tested using simulation in Section 5.2.1 and examined empirically in Section 6.2.

Proposition 1. *There will be a reallocation of market shares from small (low-productivity) firms to large (high-productivity) firms.*

Given the differential exposure to cost shocks for small and large firms, the relative prices for larger firms will fall. Consequently, there will be a reallocation of market shares from small firms to large firms.

Proposition 2. *Aggregate markup will likely rise in equilibrium.*

In the endogeneous markup setting, the distribution of market shares determines the distribution of markup. Low-productivity firms have lower market shares and thus have lower markup. Consequently, Proposition 1 also implies the reallocation of market shares from low-markup firms to high-markup firms, increasing aggregate markup.

Proof. See Appendix C.2

■

Proposition 3. *Industry concentration (HHI) will rise.*

Proof. See Appendix C.3

■

Intuitively, the increase in market shares for large firms is magnified by existing large market share. Larger firms grow larger and smaller firms shrink, causing the market to be more concentrated. The implied increase in market share dispersion translates to higher concentration, given the convexity nature of the concentration definition.

Idiosyncratic Cost 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.[14] Recognizing heterogeneity in cost pass-through across firms

is qualitatively and quantitatively more important - Edmond et al. (2023) points out that entry has both the direct and compositional effect on aggregate markup, making the net effect of entry on aggregate markup quantitatively negligible. Exit, on the other hand, can increase concentration and markup. Therefore, to that end, we view our reallocation story as a lower bound of the aggregate effect of climate change on concentration and markup. Lastly, abstracting away from entry and exit allows us to maintain a balanced sample environment that allows for cleaner theoretical predictions on concentration and markup as well as sharper empirics on market share reallocation.

[14]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 μ with respect to the firm's market share s:

$$\Gamma(s) \equiv \frac{\partial \log \mu}{\partial \log s} = \frac{(\rho - \eta)s}{\rho - s(\rho - \eta)}, \tag{14}$$

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

Define Φ as the elasticity of firm-level prices with respect to the climate-induced cost shifter $\gamma(T)$, holding the aggregate index constant:

$$\Phi = \left.\frac{\partial \log P}{\partial \log \gamma}\right|_{P}, \tag{15}$$

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

$$\Phi(s) = \frac{1}{1 + \Gamma(s)}. \tag{16}$$

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 Γ) 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.

5.2.1 Simulation of a single-industry heterogeneous temperature shock

Because models with endogenous markups and strategic complementarities typically do not admit closed-form solutions for key equilibrium outcomes, 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 5.2 and inform the design of our empirical analysis.

Simulation Setup The simulation setting directly follow section 5.2, incorporating a heterogeneous firms model under endogenous markup. Demand features nested CES, with the within-industry elasticity of substitution ρ higher than across-industry elasticity of substitution η . Firm level productivity φ are drawn from a Pareto distribution with a shape parameter θ. 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 ρ and η 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 γ, which is greater or equal to 1[15]. 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 7 summarizes the simulation result. Figure 7(a) to 7(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 7(a) shows the negative and productivity-decreasing nature of the shock, by construction. Figure 7(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 7(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.

[15]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, 2023; Somanathan et al., 2021) . In this model of reallocation, homogeneous shock will not lead to reallocation and markup changes

As for the aggregate impact of such heterogeneous shock, we see results consistent with predictions in section 5.2. Figure 7(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 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.

While we abstract away from the micro-foundation of the productivity-decreasing nature of such market wise shock, it is also important to consider the potential mechanisms that might explain such heterogeneity. One potential mechanism could be the story of climate-control technology adoption (a flavor of Bustos (2011)). In such model of technology adoption, adaptation measures are costly and therefore only the more productive firms have the capacity to invest in climate-control investment that mitigates their heat exposure and alleviates the negative impact on productivity. Such heterogeneity in adaptation capabilities could be a potential driver of the widening productivity gap. Zivin and Kahn (2016); Shi and Zhang (2023); Somanathan et al. (2021); Ponticelli et al. (2023) provide similar empirical evidence regarding adaptation friction and heterogeneity of productivity impacts across firms.

An additional insight from our stylized model and simulation is that both the absolute level of the productivity shock and its heterogeneity across firms play a crucial role in determining industry outcome. Even modest shocks can significantly alter market structure if they disproportionately affect smaller firms. Therefore, for our empirical analysis in Section 6.3, we pay specific attentions to the heterogeneity of firm-level response to temperature shock.

6 Empirical Results

6.1 Model Specifications

We use two models to estimate the effect of temperature on market-level and firm-level outcomes. For the market-level outcomes, we use the following model:

$$y_{kjt} = \sum_{\substack{b \in B \\ b \neq [60-70F)}} \beta_b \cdot \text{Bin}^b_{kjt} + X_{kjt} + \alpha_{kt} + \alpha_{st} + \varepsilon_{kjt} \tag{17}$$

where k represents a country, j represents a NACE 4-digit industry, and t represents a year. Dependent variables include log of different measures of market concentration and within-market dispersion. Bin^b_{kjt} is the number of days in country k, industry j, and year t whose average daily maximum temperature is within a certain bin b. We divide the temperature into eight bins, each with an interval of 10°F, ranging from 30°F and below, to 90°F and above. The temperature bin 60-70°F is dropped in the specification, so the estimated

$\hat{\beta}_b$ represents the effect of one additional day with average temperature in the corresponding bin b relative to one additional day with average temperature 60-70°F on the outcome. X_{kjt} is the precipitation in country k, NACE 4-digit industry j, at year t. We include country-by-year fixed effects (α_{kt}) to capture country specific trends, such as macroeconomic policy or demand shock at the country level. We control for sector-by-year fixed effects (α_{st}) to absorb sector-specific trend, such as technology advance or sector-wise demand shock over time. Therefore, our identification leverages two sources of variation: local shocks within a country-year between industries and shocks within a sector-year between countries.

For the firm level outcomes, we use the model:

$$y_{ijkt} = \sum_{\substack{b \in B \\ b \neq [60-70F)}} \beta_b \cdot \text{Bin}^b_{ijkt} + X_{ijkt} + \alpha_i + \alpha_{kt} + \alpha_{lt} + \varepsilon_{ijkt} \tag{18}$$

where y_{ijkt} is the outcome of firm i which belongs to a NACE 4-digit class j and locates in country k in year t. Dependent variables include measures for firm productivity, revenue, market share, and markup. $\text{Bin}^b_{i(jk)t}$ is the number of days that firm i exposes to daily maximum temperature within a certain bin b in year t. The temperature bin 60-70°F is dropped, so the estimated $\hat{\beta}_b$ represents the effect of one additional days in temperature bin b relative to one additional day in temperature bin 60-70°F on the outcome. X_{ijt} is the precipitation in the location of firm i, industry j, at year t. We include country-by-year fixed effects (α_{kt}) to absorb common trends in different countries, and industry-by-year fixed effects (α_{lt}) to capture any industry-specific trends experienced by different NACE 2-digit industries.

6.2 Temperature on market outcomes

Average markup weighted by market share We begin our empirical analysis by examining the effect of temperature on markup. We estimate Equation (18) with the dependent variable log of firm markup, weighted by firms' market shares. We use the weights of relative size (market share) in order to proxy for the aggregate impact on industry average markup, as larger firms' markup change would contribute more towards industry aggregate markup change. The results are reported in Table 2. We start from controlling for the standard two-way fixed effects, firm fixed effects and year fixed effects. By controlling for firm fixed effects, the temperature variation used for identification is the temperature deviation from the mean temperature for the location of each firm. The year fixed effects captures the common trends of temperature changes over time for all locations. The estimated coefficient for the above 90 degree temperature bin is -0.1209 and insignificant. Column (2) controls for NACE 2-digit industry-by-year fixed effects to capture time-varying industry-specific shocks. The coefficient for the above 90 degree bin is -0.1199 and significant at the 10 percent level. Column (3) adds county-by-year fixed effect to capture time-varying country-specific shocks. The estimate for the above 90 degree bin becomes 0.0417 and significant at the 10 percent level. Column (4) controls for country-sector-year fixed effects to capture shocks within a county-sector that change over time. Column (5) controls for country-NACE 2-digit industry-year fixed effects that capture shocks within a country and NACE 2-digit

industry. The results across columns (3) to (5) are qualitatively similar.

We select model (5) as our preferred specification, and its coefficients are visualized in Figure 8. The estimate for the above 90 degree bin is 0.0345 and significant at the 10 percent level, implying that 100 more days per year in the temperature bin above 90°F would increase market share-weighted average markup by about 3 percent.

Market concentration Next, we examine the effect of temperature changes on market concentration. We estimate Equation (17) using different measures of market concentration, log(HHI), log(CR4), and log(CR8) as the dependent variable.

The results are reported in Table 3. For each dependent variable, we use two sets of fixed effects, country-by-year fixed effects alone, and country-by-year fixed effects and sector-by-year fixed effects. The results between different fixed effects are qualitatively similar, and all showing that extreme high temperature has a positive effect on the markets concentration. Using our preferred specification by controlling for country-by-year fixed effects and sector-by-year fixed effects, the results show that one more day per year in the temperature bin above 90°F would increase market HHI by 1.68 percent, CR4 by 0.81 percent, and CR8 by 0.56 percent. These results are illustrated in panels (a), (b), and (c) in Figure 9.

As mentioned in Section 4, HHI captures the entire distribution of firms in a market, while CR4 and CR8 reflect the top 4 or 8 firms. Our result that extreme high temperature has a positive effect on HHI indicates that the market becomes more concentrated, and the positive effect on CR4 and CR8 further indicates that the largest firms obtain more market shares in this process. This is consistent with the theoretical prediction that high temperature may lead to reallocation of market shares towards the largest firms and therefore a higher market concentration.

Within-market dispersion In models of heterogeneous firms and endogenous market markups, one of the key determinants of market concentration and the degree of market power is the within-industry dispersion of productivity. The larger the dispersion, the larger the gap between small and large firms, leading to more dominant positions and higher market power for the big firms. Therefore, we also directly look at how industry dispersion changes due to extreme weather shock.

We estimate Equation (17) using two dependent variables that measure the within-industry dispersion of productivity, the standard deviation of log-normalized productivity, and the difference between the 90th and the 10th percentile of productivity.

The results are reported in Table 4. For each dependent variable, we use two sets of fixed effects, country-by-year fixed effects alone, and country-by-year fixed effects and sector-by-year fixed effects. The estimates are qualitatively similar and indicate that extreme high temperature increases the within-market dispersion in productivity.

Our preferred specification is columns (2) and (4). The results in column (2) suggest that an additional day per year in the temperature bin above 90°F would increase the within-market standard deviation by 0.0013,

which is about 0.45 percent increase. The results in column (4) imply that one more day per year in the temperature bin above 90°F would increase would increase the gap of 90th-10th percentile in productivity by 0.0022, which is about 0.37 percent increase. These results are also visualized in Figure 10, panels (a) and (b).

The increased within-industry productivity dispersion means that larger firms are relatively more competitive than smaller firms. Combining with the results on concentration and aggregate markup, we see an apparent pattern: extreme high temperature shock creates larger within-industry dispersion, larger local market concentration, and higher aggregate markup.

Placebo test We conduct a placebo test to demonstrate that our results are not driven by the model specification or other potential confounding factors. Our market data are a panel of different markets (country-NACE4 industry) spanning from years 2000 to 2020. We reshuffle the temperature exposure for each market year from the temperature bin distributions across all market years. We rerun equation (17) 500 times using pseudo datasets with fake temperature data. Figure D1 reports the distribution of the 500 pseudo estimates of the coefficient of the temperature bin above 90°F on aggregate markup, HHI, CR4, CR8, standard deviation of TFP, and the 90th-10th percentile gap in TFP. As shown in all panels, the distributions of the pseudo estimates are centered around 0, and our true estimates lie at the far right of the distributions, suggesting that our baseline results are unlikely to be driven by the model specification or other potential confounding factors.

6.3 Mechanisms at the intensive margin

As indicated by the stylized model in Section 5, under the endogenous markup framework, firms' markup is determined by their demand elasticity, and their demand elasticity is a function of their market shares. Firms with a larger market share face a more inelastic demand and therefore can maintain a higher markup. When facing a temperature shock, larger firms' productivity is less affected, and their price increase would be smaller relative to small firms. Such heterogeneity in productivity impacts will change relative prices and market shares, leading to market share reallocation from smaller firms to larger firms. With a higher market share, larger firms would face even more inelastic demand and could maintain higher markup, while smaller firms' markup would decrease.

We test these theoretical predictions with firm-level analysis in this section. To focus on the intensive margin, we restrict our sample to the firms that enter the dataset before 2000. We examine the effect of the temperature change on firms' productivity, revenue, market shares, and markup. Furthermore, we investigate heterogeneous effects across firms of different sizes.

Firm productivity First, we examine the impact of temperature change on individual firm productivity, measured by revenue TFP (*Total Factor Productivity*). The results are reported in Table 5. All coefficients are multiplied by 100 to increase readability. Column (1) controls for firm fixed effects which absorb time invariant characteristics of each firm that may affect their productivity, and year fixed effects that capture

common shocks that affect all firms' productivity at different years. The estimated coefficient for the temperature bin above 90 °F is -0.0256 and significant at the 1 percent level, implying that if the number of days with temperature in the bin above 90 °F increases by 100, firms' productivity would decrease by 2.6 percent. Column (2) controls for firm fixed effects and NACE 2-digit industry-by-year fixed effects. NACE 2-digit industry-by-year fixed effects capture industry-level shocks in different years, such as industry technology advancement and macroeconomic policy. The coefficient for the temperature bin above 90 °F is -0.237 and significant at the 1 percent level. Column (3) adds an additional set of fixed effects, country-by-year fixed effects, which further control for country-level shocks that vary year by year, such as country-wide policy. The coefficient on the above-90-degree bin changes to -0.0119, and is still significant. Column (4) controls for firm fixed effects and country-sector-year fixed effects. Country-sector-year fixed effects capture shocks within a country-sector in different years. Column (5) controls for country-NACE 2-digit industry-year fixed effects, which capture shocks within a country-industry in different years. Column (5) uses the most stringent fixed effects and is our preferred specification. The estimated coefficients suggest that an additional 100 days in above 90 °F temperature bin would reduce firms' productivity by about 0.96 percent. The results of column (5) are visualized in Figure 11.

Next, we examine whether the effects on firm productivity vary by firm size. Firms are categorized as small, medium, or large based on their market shares as of 2000: small firms have market shares below the 80th percentile, medium firms fall between the 80th and 97th percentiles, and large firms have market shares above the 97th percentile.

Table 6 reports the heterogeneous effects by firm size with a full set of fixed effects. We only report the results for the top two temperature bins to make the table easier to read. Columns (1) to (3) show the results on productivity for small, medium, and large firms. For an additional 100 days in the above-90-degree temperature bin, productivity decreases by 1.06 percent for small firms, decreases by 0.53 percent but insignificant for medium firms, and increases by 2.21 percent but insignificant for large firms. The complete results for all temperature bins are visualized in Figure 11 panel (b).

The heterogeneity between firms' sizes is consistent with the findings in the literature that smaller firms are more vulnerable to extreme high-temperature shocks relative to larger firms (Ponticelli et al., 2023). From our stylized model with endogenous markup, such heterogeneity in cost shocks is the source of market share movements, which in turn causes reallocation and changes in aggregate concentration and markup.[16]

Firm revenue Then we examine the effect of temperature on firm revenue. The results are reported in Table 7 and visualized in panel (a) of Figure 12. By including five different sets of fixed effects as in the regressions for firm productivity, the estimates are qualitatively similar, indicating that extreme high temperature reduces

[16]Equation F.32 in Appendix F.1 defines the model-implied revenue productivity ($TFPR$) and decomposes it into two channels - the *Markup* channel and the *Cost* channel, the former of which explains the heterogeneity of (revenue) productivity responses across firms. By the definition of revenue productivity ($TFPR = P \cdot TFPQ$), revenue productivity not only includes information on efficiency change ($TFPQ$) but also on the market reallocation outcomes and market structure. Under a negative shock, largest firms' revenue productivity can increase given a large reallocation of shares and the consequent increase in markup.

firms' revenue. Under our preferred specification with firm fixed effects and country-industry-year fixed effects, for an additional 100 days in the above-90-degree temperature bin, firm revenue decreases by 8.96 percent. This effect is significant at the 1 percent level.

The heterogeneous impacts on the productivity of different size firms transfer into large heterogeneity in firms revenue. As shown in Table 8 and panel (b) of Figure 12, under the shock of an additional 100 days in the above 90 degree temperature bin, small firms' revenue would reduce by 8.99 percent, medium firms' revenue reduce by 2.5 percent, but large firms' revenue would increase by 22.5 percent.

Firm market share Next, to examine whether heterogeneous shocks on firm productivity could lead to market share reallocation between small and large firms, we examine the heterogeneous effects of temperature on firm market shares across firm sizes. As shown in Table 9 and Panel (a) of Figure 13, for an additional 100 days in the above 90 degree bin, the market share for small firms declines by 8.29 percent, the market share for medium firms declines by 5.97 percent, while the market share for large firms increases by 22.67 percent. All the coefficients are significant at the 5 percent level.

Firm markup Lastly, we examine heterogeneous effects of temperature on firm markup across firm sizes. As shown in Table 10 and Panel (b) of Figure 13, small and medium firms' markups increase by 0.17 percent and 0.19 percent, and the markup of large firms increases by 2.97 percent facing an additional 100 days in the above 90 degree bin. However, all coefficients are not significant.

To summarize our empirical findings at the intensive margin, we find that high-temperature shocks lead to reductions in firm productivity and revenues. However, the impact varies across firms of different sizes. Smaller firms experience more pronounced negative effects on productivity and revenue, causing them to lose market share. Conversely, larger firms gain market share from smaller firms, increase their markups, and boost their revenues. This market share reallocation contributes to greater within-market dispersion, higher aggregate market markups, and increased market concentration.

Overall, the aggregate effects mask significantly heterogeneous impacts, which are decreasing in firm sizes. In addition, the majority of the heterogeneity happens at the two tails of the firm distribution - very small firms and extremely big firms. Firms in the middle are less affected.

6.4 Firm exits

The analyses above focus on the intensive margin. According to the theoretical model, extreme temperature shocks can also impact market concentration via the extensive margin, through increasing the exit cutoff and toughening selection. While Orbis data don't cover all firms, Bajgar et al. (2020) notes that Orbis exit rates are closer to actual exit rates than entry rates. Moreover, as Orbis coverage improves over time, spurious exits are less common than spurious entries. For this reason, we focus on exit rates in our firm-level extensive margin analysis. This section explores the effect of temperature on firm exits.

Table 11 reports the results with five sets of fixed effects discussed above. The estimated coefficients for the above-90-degree bin in columns (1) and (2) are similar, both negative and insignificant. However, when we add country-by-year fixed effects, or country-sector-year fixed effects, or country-industry-year fixed effects, the coefficients become positive and significant. The result indicates that the likelihood of a firm that exits the market would increase by 0.85 percent for an additional 100 days in the above-90-degree days per year. The results are visualized in Figure 14 panel (a).

Table 12 reports the heterogeneous effects. We find that extreme high temperature has a positive and significant effect on small firms, increasing their probability of exit by 0.93 percent, while the effect on medium and large firms are insignificant. These results are illustrated in Figure 14, panel (b).

6.5 Robustness checks

Broader market definition Our main specification defines a market at the country-4-digit industry level. We also conduct the above analyses by defining a broader market at the country-2-digit industry level. The results are robust (see Appendix D:). We see similar concentration-increasing and markup-increasing pattern under broader industry classification. Nonetheless, the effects are relatively less significant. We attribute this pattern to the *aggregation bias* - when we broaden our market definition to more aggregated levels, we also cover a wider range of geography and temperature distributions. Consequently, aggregation of heterogeneous temperature distributions can lead to a loss of variation.

Alternative markup and productivity estimations A growing literature on production function estimation has examined how different production-function specifications can affect the estimated output elasticities, and thus the resulting markups (De Ridder et al., 2022; Raval, 2023). The choices surrounding functional form (e.g., Cobb–Douglas vs. Translog vs. CES), the use of revenue versus quantity output data, the particular input assumed to be variable in the markup calculation, and whether productivity is factor-neutral or factor-augmenting all influence the accuracy and interpretation of estimated markups. Despite these concerns, our baseline specification seeks primarily to capture the dispersion of markups in the cross-section and the within-firm changes over time—factors that are crucial for understanding the reallocation dynamics in our setting. In addition, given that our markup estimates still correlate strongly with key firm-level outcomes such as market share, which is the key determinant of markup in models of endogenous markup, we view our baseline approach as informative for capturing the forces of reallocation we study. Moreover, markup is only one of the dimensions in our broader empirical analysis of how reallocation manifests through various industry- and firm-level measures—such as concentration and firm market shares.

Nonetheless, to reinforce the robustness of our findings, future versions of this draft will incorporate additional markup and productivity estimates derived from alternative approaches. By comparing results across different specifications, we will further validate that our main insights are not driven by any single methodological choice.

Industry Heterogeneity As our sample includes a wide variety of industries of different characteristics, we also explore heterogeneity of the effects across industries. We show our result in Appendix Appendix E:.

Motivated by our stylized model, We consider two dimensions of industry characteristics: *labor intensity* and *industry dispersion*. We measure the degree of industry labor intensity as the industry average of firm-level output-to-labor elasticity from the production function estimation, and then group country-4 digit industries into terciles based on the average labor intensity. We proxy the within-industry dispersion as the standard deviations of firm-level productivity in an industry, and group industries into terciles.

We find that firms in all industries experiences negative effects from extreme high temperature on productivity and revenue, but the effect is the most pronounced for the most labor intensive industry (Figure E1). These heterogeneity results are consistent with the productivity channel that extreme temperature shocks could have a larger impact on firms that are more reliant on labor in production.

In the dimension of industry dispersion, we find that firms in the most dispersed industries see the largest decline in overall market share. The more pronounced market share reallocation would also transfer to a larger increase in markup. The most dispersed industries also experience the largest increase in industry markup (Figure E2). Such results highlight the fact that in industries where big firms are much bigger than smaller firms, the same extreme temperature shock can have vary different realization on each firm's productivity, pricing, market shares, and markups.

7 Welfare

In this section, we examine the welfare implications of a climate-induced productivity shock, asking whether standard assessments of climate change costs might understate the role of reallocation and heterogeneous markups. To do so, we conduct a quantitative exercise using an oligopolistic competition model with VES demand. We then highlight the importance of markup heterogeneity and misallocation by comparing the welfare cost under the VES framework to that obtained under a CES assumption where reallocation does not affect markups.

7.1 Welfare cost of markup

Recent literature has identified several key channels through which markups leads to welfare loss. In particular, three components stand out. First, higher aggregate markups act like a uniform tax on production, dampening overall input demand, wages and consumption (Edmond et al., 2023; De Loecker et al., 2021). Studies such as Autor et al. (2020) and De Loecker et al. (2021) also attribute the fall in the labor share to the rise in market power.

Second, markup dispersion across firms leads to misallocation, as high-markup (and often more productive) firms underproduce relative to the social optimum, while low-markup firms overproduce, leading to a

drag on aggregate productivity. (Baqaee and Farhi, 2020; De Loecker et al., 2021; Edmond et al., 2023). Baqaee and Farhi (2020) finds that eliminating such distortions can yield considerable productivity gains.

Finally, markups can also lead to inefficient entry as markup drives a wedge between firms' the incentive to enter and planner's incentive to create new varieties (Edmond et al., 2023).

7.1.1 Markup and key equilibrium objects

Here, building on the single-industry equilibrium setting outlined in Section 5.2, we highlight several key equilibrium outcomes crucial to understanding how climate-induced reallocation and the resulting changes in markups influence aggregate welfare. Our modeling environment closely follows Edmond et al. (2023). Details of the full model setup are provided in Appendix F.1.

Labor Demand and Aggregate Markup From the markup-pricing equation (eq 10) in the labor-only model, firms set prices above marginal cost by a factor of the markup. At the aggregate level, this markup can be interpreted as a labor wedge: for a given marginal product of labor (MPL), the real wage is effectively

$$\frac{W_t}{P_t} = \frac{1}{\mathscr{M}_t}\,\mathrm{MPL}_t,$$

so that a higher aggregate markup $\mathscr{M}_t$ increases the relative price of final output to variable labor, reducing the real wage (holding MPL fixed). This depresses the equilibrium labor demand[17] and—given typical household preferences—also reduces labor supply, leading to lower aggregate employment, output, and consumption.

The aggregate markup $\mathscr{M}_t$ thus directly impacts welfare by lowering both equilibrium labor and consumption. In a representative-consumer framework, one can see $\mathscr{M}_t$ as a deviation from the first-best condition

$$\underbrace{\frac{\partial U/\partial \ell}{\partial U/\partial c}}_{\mathrm{MRS}_{\ell,c}} = \frac{W_t}{P_t},$$

because $\frac{w_t}{P_t}$ is now $\frac{1}{\mathscr{M}_t}\mathrm{MPL}_t$ instead of simply MPL_t. As $\mathscr{M}_t$ grows, the real wage for workers falls (relative to MPL), discouraging labor and reducing welfare.

Productivity and markup dispersion Given the sector and aggregate production function $y = \varphi \cdot F(l,k,x)$, the sector and aggregate productivity is defined as the relative size-weighted firm (sector) productivity harmonic average:

$$\varphi_{jt} = \left(\sum_i^{n_{jt}} \frac{q_{ijt}}{\varphi_{ijt}}\right)^{-1}, \quad \varphi_t = \left(\int_0^1 \frac{q_{jt}}{\varphi_{jt}}\right)^{-1}. \tag{19}$$

[17] It can be shown that equilibrium aggregate labor demand is decreasing in equilibrium aggregate markup. See appendix C.4 for more details.

where q_{ijt} (q_{jt}) is the relative size of firm (sector) in terms of output:

$$q_{ijt} = \frac{y_{ijt}}{y_{jt}}, \quad q_{jt} = \frac{y_{jt}}{Y_t}. \tag{20}$$

Aggregate (Sector) Productivity is therefore the relative size-weighted harmonic average of sector (firm) productivity.

To see how markup dispersion impact aggregate TFP, it is useful to compare the equilibrium allocation under the *efficient economy* (q^*_{jt}) and the *decentralized equilibrium* (q_{jt}).

Under efficient allocation with no markup dispersion ($\mu = 1$), the efficient allocation q^*_{ijt} is given by:

$$q^*_{jt} = \left(\frac{\varphi^*_t}{\varphi^*_{jt}}\right)^{-\eta}. \tag{21}$$

In the decentralized equilibrium, using the CES aggregator and the markup pricing equation, we can rewrite relative size in terms of markup dispersion:

$$q_{jt} = \left(\frac{\mu_{jt}}{\mathscr{M}_t}\frac{\varphi_t}{\varphi_{jt}}\right)^{-\eta}. \tag{22}$$

The comparison of relative size under efficient (eq 21) and decentralized equilibrium (eq 22) highlights how markup heterogeneity affects aggregate productivity through distorting the relative size of sectors or firms.

Sectoral productivity φ_{jt} and Aggregate productivity φ_t in the decentralized economy can then be expressed as

$$\varphi_t = \left(\int_0^1 \left(\frac{\mu_{jt}}{\mathscr{M}_t}\right)^{-\eta} \varphi_{jt}^{\eta-1}\, dj\right)^{\frac{1}{\eta-1}}, \tag{23}$$

$$\varphi_{jt} = \left(\sum_i^{n_{jt}} \left(\frac{\mu_{ijt}}{\mu_{jt}}\right)^{-\rho} \varphi_{ijt}^{\rho-1}\right)^{\frac{1}{\rho-1}}. \tag{24}$$

where the first term represents the misallocation channel of endogenous markups—the distribution of productivity and the consequent distribution of markups determines the aggregate productivity. Markup dispersion therefore affects aggregate productivity and output through distorting the relative size distribution-more productive (larger) firms are employing and producing too little, and less productive (small) firms are employing and producing too much.

To summarize the welfare cost of markup, the aggregate markup $\mathscr{M}_t$ affects equilibrium labor and consumption by acting as a wedge between the real wage and the marginal product of labor, while markup dispersion across firms or sectors misallocates production inputs and reduces aggregate productivity. Both channels reduce welfare relative to a markup-free benchmark.

Consumption-equivalent welfare We follow welfare calculation from Edmond et al. (2023) and defines the consumption-equivalent welfare loss as

$$1 - \left(\frac{\varphi_{CC}}{\varphi}\right) \cdot \left(\frac{\mathscr{M}_{CC}}{\mathscr{M}}\right)^{-\frac{1}{1+\nu}} \tag{25}$$

where φ_{CC} and $\mathscr{M}_{CC}$ are the new aggregate TFP and Markup, and ν is the elasticity of the marginal disutility of labor, which is assumed to be 1 [18].

To illustrate the intuition, supposed we are in a climate change scenario (CC) where $(\varphi_{CC} < \varphi)$ and $(M_{CC} > M)$, as shown by our simulation and empirical result. Then both the lower aggregate TFP φ' and the higher aggregate markup $\mathscr{M}'$ lead to a larger consumption-equivalent welfare loss.

7.2 Calibration

Our calibration procedure follows closely with Edmond et al. (2023), under the oligopolistic competition framework. While the focus of Edmond et al. (2023) is the welfare costs of markup distortion and misallocation, we focus on the quantifying the cost under a climate change productivity shock, taking into account the role of reallocation, markup heterogeneity, and misallocation.

In such framework, the two demand elasticities - within-sector (ρ) and between-sector (η) - governs the relationship between firm-level market share and firm-level markup, as well as determining the overall level of aggregate markup. With respect to concentration, it is closely related to the degree of firm productivity dispersion within industry, which is governed by the Pareto tail parameters (ξ). These three parameters are crucial in determining market power and dispersion of markup. We use the average Concentration ratio (CR4,CR20) across country by 4-digit NACE industries in our sample to pin down tail parameters ξ, while using regression coefficients between firm-level markup and market-share to pin down the gap between η and ρ, following equation 26:

$$\frac{1}{\mu_{ijt}} = \left(1 - \frac{1}{\gamma}\right) - \left(\frac{1}{\eta} - \frac{1}{\gamma}\right) s_{ijt}. \tag{26}$$

. We also calculated the sales-weighted aggregate markup from our sample as another calibration target.

Table 14 shows our calibration targets and calibrated parameters under the oligopoly setting. The model can target aggregate markup and the regression coefficient well, which means that the key demand parameters η and ρ are well calibrated. In terms of the concentration, the model can target top 4 concentration (CR4) relatively well, while the top 20 ones are harder to match well. Comparing to Edmond et al. (2023)'s target concentration of 43 percent CR4 and 72 percent CR20, our Orbis data sample over-represents larger firms and the average concentration is much higher. While Edmond et al. (2023) defines industry as US 6-digit NAICS, our industry are country by 4 digit NACE industry across multiple EU countries, which is a much smaller market scale in comparison.

[18] For more details on the derivation of consumption-equivalent welfare, see appendix F.3

7.3 Welfare Loss of Climate Change

How do climate-induced shifts in the temperature distribution affect aggregate productivity, concentration, and markups in our endogenous-markup model, and what does that imply for welfare? To answer this question, we first construct a simulated productivity shock that aligns with our empirical observations. We then feed this shock into our model to solve for the new steady state and quantify the corresponding welfare loss.

7.3.1 Simulating heterogeneous productivity shock

Recall that we model the impact of extreme weather through a firm-specific productivity shifter γ_{ijt}. The marginal cost function of each firm then becomes

$$MC_{ijt} = \gamma_{ijt} \cdot \frac{W_t}{\varphi_{ijt}}$$

where W is the wage and φ_{ijt} represents baseline firm productivity in industry j at time t. Our empirical analysis uncovers two key properties of these shocks: (i) a negative average (level) effect on firm-level productivity, and (ii) a size-dependent heterogeneity wherein smaller firms experience larger shocks relative to bigger, more resilient firms.

Because our data do not include data on adaptation measures, we adopt a reduced-form approach to capture both the overall negative impact of climate change and the associated firm-level heterogeneity. Specifically, we assume the shock factor is:

$$\gamma_{ijt} \;=\; (1 + \frac{a}{100}\,\varphi_{ijt}^{-b})^{-1}, \quad (a \geq 0, b \geq 0) \tag{27}$$

where a is the baseline shock scale and b determines how strongly smaller firms are impacted. This functional form ensures $\gamma_{ijt} \geq 1$ (firms are receiving non-positive shock) and that shocks are less severe with larger firms. We then calibrate $\{a, b\}$ to match two key data moments: (i) the average productivity loss, and (ii) the change in within-industry productivity dispersion.

Intuitively, under endogenous markups, the welfare impact of a productivity shock hinges on two main factors: the average productivity loss and the shift in within-industry productivity dispersion, the latter of which amplifies markup dispersion and thus misallocation. We capture these two dimensions in our measured productivity shock, feed them into the model, and solve for the new equilibrium.

For the level-effect, we use the target of -0.01 percent, which is the average firm-level productivity shock under the observed daily maximum distribution change in our sample. For the dispersion, we use the target of 2.1 percent increase, which is the average changes in within-industry productivity dispersion under the observed changes in daily maximum distribution in our sample. Table H7 summarizes the result of our calibration of the shock function.

7.3.2 Simulation Summary

From equation 25, it is clear that welfare impact of climate change is more than the productivity shock itself - once the role of reallocation and heterogeneous markup is taken into account, climate change also leads to lower aggregate TFP through misallocation, while also lowers employment and consumption through the higher aggregate Markup.

Table 15 summarizes the result under the climate change shock. By construction, firm level TFP drops by 0.1 percent, matching our empirical findings on the average productivity impact. Aggregate Markup increases by 0.01 percent. As discussed in section 5 and 5.2.1, a negative and heterogeneous productivity shock can lead to an reallocation of markup shares from low-markup firms to high-markup firms. As high-markup firms gain market shares, they can move to an more inelastic portion of the demand curve and further charge higher markup. Both the within and between components contribute to a higher aggregate markup. Given the reallocation, concentration (HHI) also increases 0.1 percent. The consumption-equivalent welfare loss is 0.08 percent.

7.4 Role of Demand Assumption: CES or VES

Many quantification exercises in climate-change studies adopt the CES demand system due to its tractability and its success in capturing macro-level relationships. However, by assuming constant markups, CES can miss critical reallocation effects associated with heterogeneous markups. In particular, it does not capture the link between increased productivity dispersion, rising markup dispersion, and an increasing aggregate markup—an important mechanism through which climate shocks can amplify welfare losses.

Are we underestimating the cost of climate change by assuming the CES structure and imposing constant markups? How important is the role of reallocation and markup dispersion in quantifying the welfare cost of climate change[19]?

To address these questions, we calculate the welfare cost under both the *CES framework*, where reallocation does not change the distribution or the aggregate level of markups, and our baseline *VES oligopolistic framework*, where climate-induced reallocation increases both markup dispersion and the aggregate markup.[20]

In both models, a climate shock reduces average firm-level productivity, which in turn lowers aggregate TFP. However, the CES framework fails to capture how the resulting *reallocation of market shares* can change markups. In contrast, with heterogeneous markups, high-productivity firms typically charge higher markups but produce *too little* relative to an efficient benchmark. This additional misallocation channel further reduces aggregate TFP and welfare. As shown in Column (3) of Table 16, the decline in aggregate TFP due to climate change is larger under the heterogeneous-markup (VES) environment than under CES.

[19] Edmond et al. (2023) points out that assuming CES can overstate the degree of misallocation, because the planner's allocation is less concave in productivity than in VES. While their emphasis is on the magnitude of the markup distortion itself relative to an efficient no-markup world, our focus is on the *shock* scenario and how markup heterogeneity shapes its impact.

[20] See Appendix F.3 for the details on the welfare cost measure.

As for the aggregate markup, under the CES assumption there is no change by construction. In a heterogeneous-markup framework, however, the climate shock triggers both a *between-firm* effect—shifting market share from low-markup to high-markup firms—and a *within-firm* effect—higher markups among those more productive firms. Together, these effects increase the *aggregate* markup, which acts like a uniform output tax that depresses employment and output for all firms.

From Equation 25, both the lower aggregate TFP *and* the higher aggregate markup translate into a larger consumption-equivalent welfare loss. The last column of Table 16 indicates that by neglecting these reallocation effects and the resulting markup heterogeneity, one can underestimate the cost of climate change by 18%, which is a sizable difference.

8 Conclusion

In this paper, we examine how extreme temperature shocks shape local industry market concentration and market power across 16 EU countries. We find that these shocks disproportionately weaken the productivity of smaller firms, triggering a reallocation of market shares toward larger, more resilient firms. As a result, local industries become more concentrated and exhibit higher markups following extreme temperature events.

We quantify these effects using an endogenous-markup framework that explicitly captures the roles of reallocation and market power—an often-overlooked channel in the analysis of climate change costs. Our key contribution lies in showing that models assuming constant markups (e.g., under CES) underestimate the welfare implications of climate change. In contrast, our VES-based approach reveals that within-industry reallocation exacerbates the welfare loss from temperature shocks, in part by amplifying resource misallocation and intensifying market power. We also contribute to the literature on market power by documenting a novel mechanism through which extreme temperatures can increase industry concentration and aggregate markups.

Because our data lack extensive-margin information on entry and exit, an important avenue for future research is to investigate how climate-induced reallocation and market power evolve when firm turnover is explicitly considered. Over a longer horizon, increased concentration might also dampen the incentives for climate-adaptation innovations, potentially hindering long-run growth through reduced industry turnover.

Taken together, our findings underscore a structural channel through which climate change affects economic outcomes: by magnifying the heterogeneous vulnerabilities of firms to extreme temperatures, it reshapes industry dynamics and market power. Future studies of climate change costs should therefore incorporate firm heterogeneity, within-industry reallocation, and endogenous markups. Moreover, examining the accessibility and effectiveness of climate-adaptation measures across firms of varying sizes is likely to be critical for mitigating the adverse consequences of climate change.

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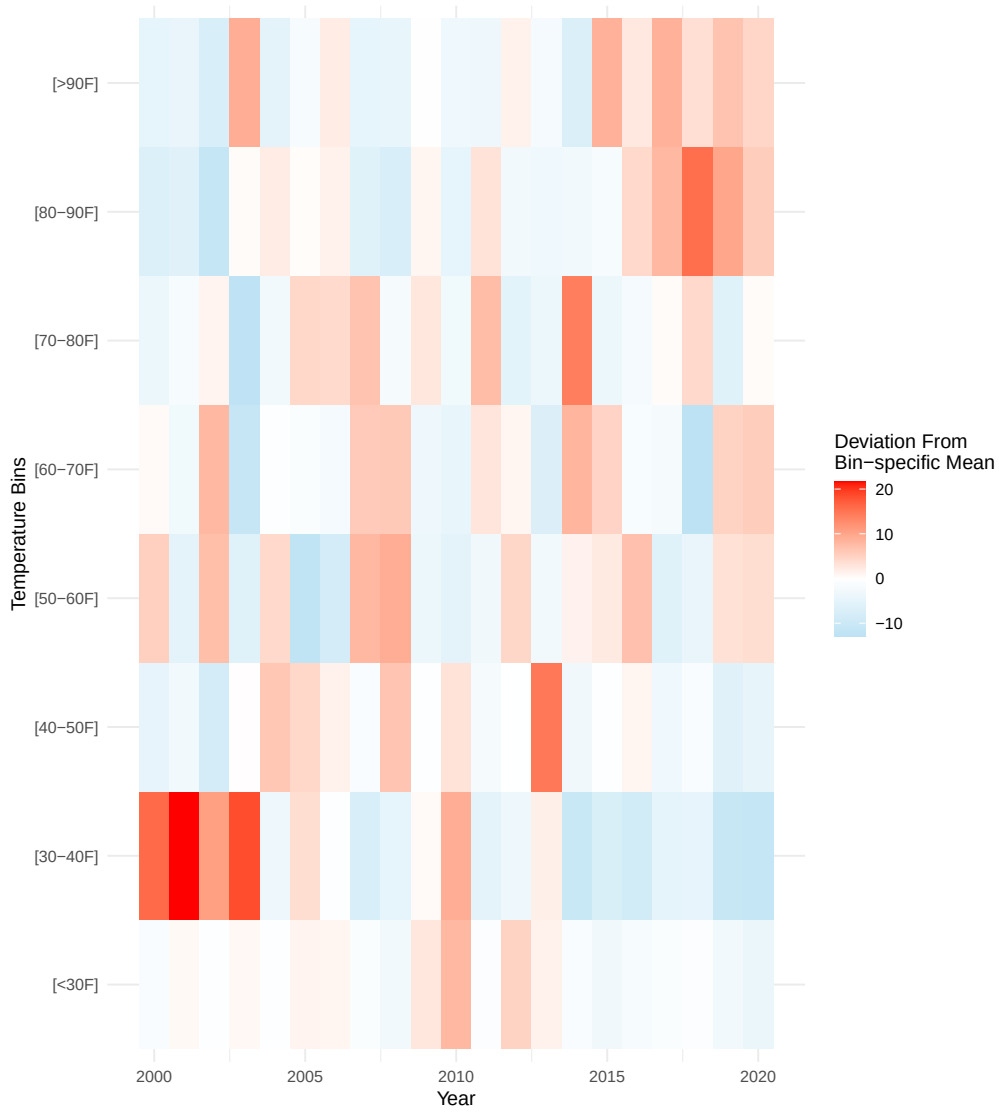
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Figures and Tables

Figure 1: Change in daily maximum bin distribution over time

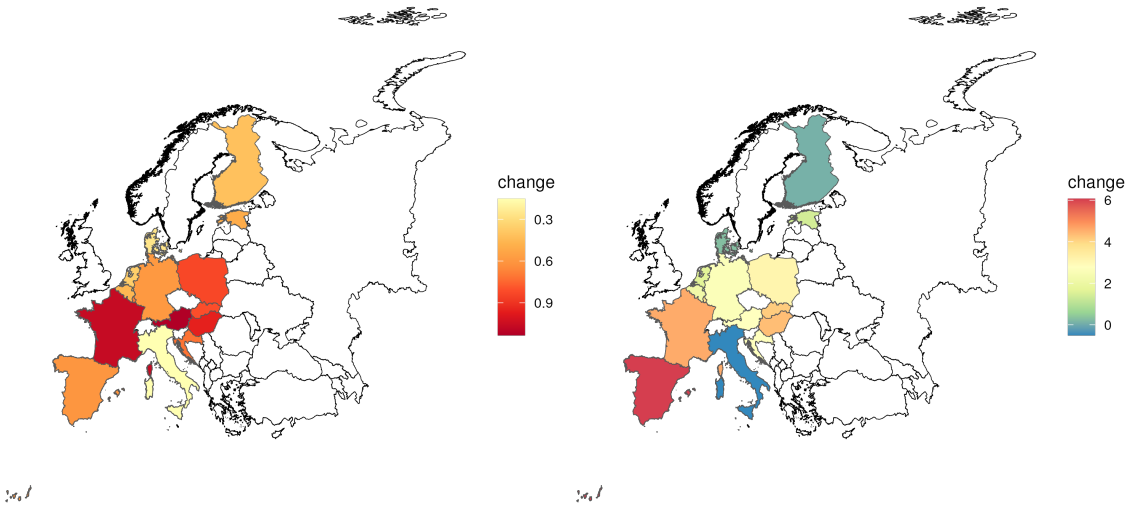


Notes: This figure shows the change in values within each daily maximum bin temperature bins. Each row represent a temperature bin, while each column represents a year. The cell value is the deviation from bin-specific mean across sample periods. The change in bin values within each row from left to right can be interpreted as the change in temperature distribution observed in our sample.

Figure 2: Temperature Change between 2000s and 2020s

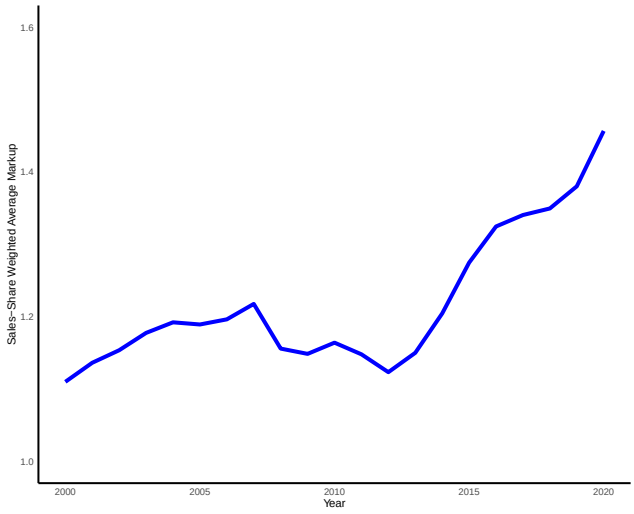
(a) Daily max temperature

(b) Number of extremely hot days



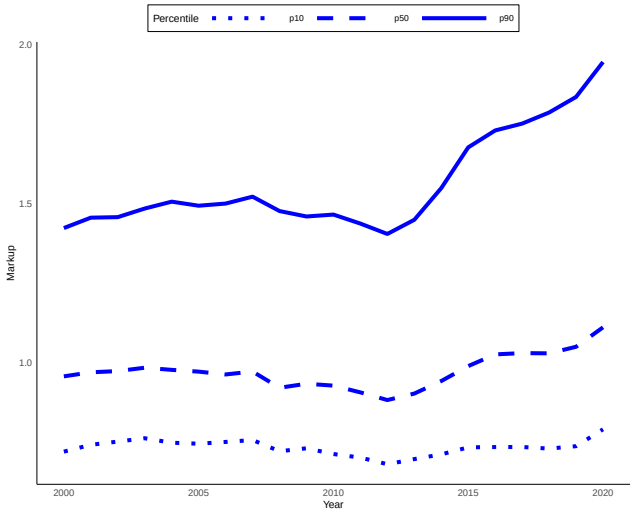
Notes: Data source: NOAA Physical Sciences Laboratory Gridded Climate Data.
This figure shows the long-run temperature change in degrees Fahrenheit by country from 2000 to 2020. Panel (a) presents the change in daily maximum temperature, while Panel (b) shows the change in the number of extremely hot days per year (daily max temperature above 86°F). Both panels compare the decadal averages of 2000-2009 and 2010-2020.

Figure 3: Aggregate Markup Trend



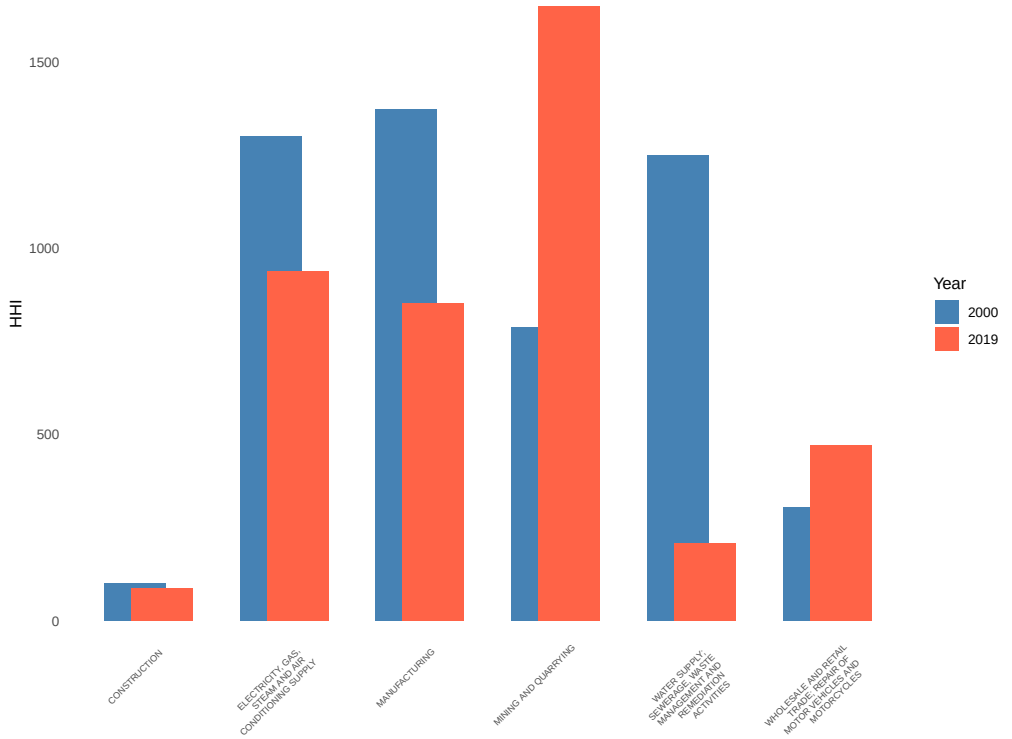
Notes: This figure shows the change in aggregate markup within our sample. Aggregate markup is calculated by the sales-share weighted average of firm-level markup in each year, winsorized at 1 %.

Figure 4: Markup Percentile Distribution Over Time



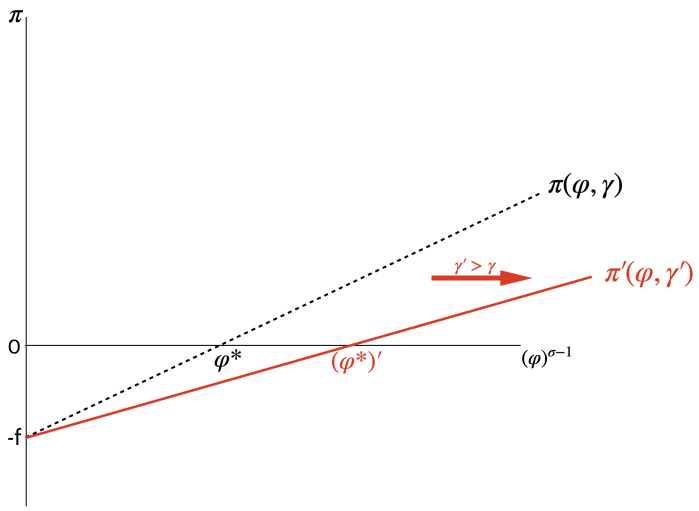
Notes: This figure shows the change in the dispersion of markup distribution. For each year, we group firms into percentile based on their markup in that year. In this figure, we plot the time series of markup for firms in 10-percentile, 50 percentile, and 90 percentile of the yearly markup distribution.

Figure 5: HHI measure by sector in 2000 and 2019



Notes: This figure shows the average HHI (Herfindahl–Hirschman index) for country by 4-digit NACE industries in year 2000 and 2019, for six major sectors: Construction (NACE F), Electricity, Gas, Steam and Air Conditioning Supply (NACE D), Manufacturing (NACE C), Mining and Quarrying (NACE B), Water Supply; Sewerage, Waste Management and Remediation Activities (NACE E), Wholesale and Retail Trade; Repair of Motor Vehicles and Motorcycles (NACE G).

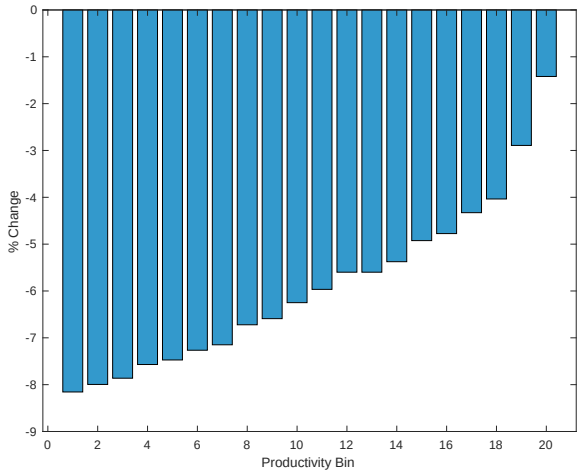
Figure 6: Exit Cutoff under Climate-Induced Cost in CES



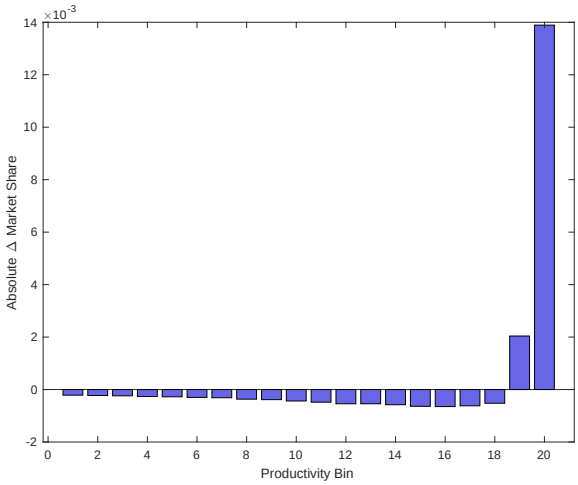
Note: This figure plots firm profit as a function of productivity φ under CES setting. φ^* represents the exit productivity threshold, below which firms are earning negative profit and therefore exit.

Figure 7: Simulation Result of a Productivity-Decreasing Shock

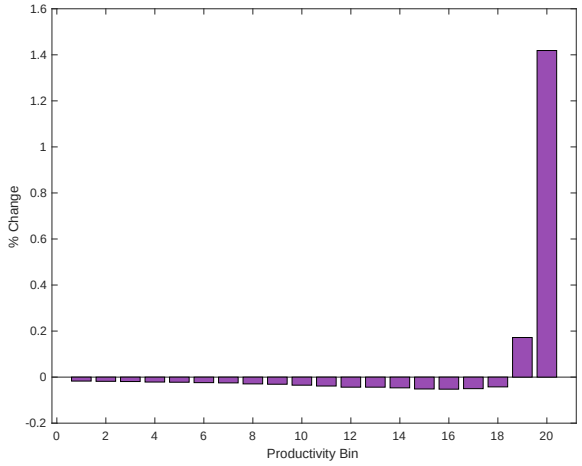
(a) % Changes in Firm Productivity



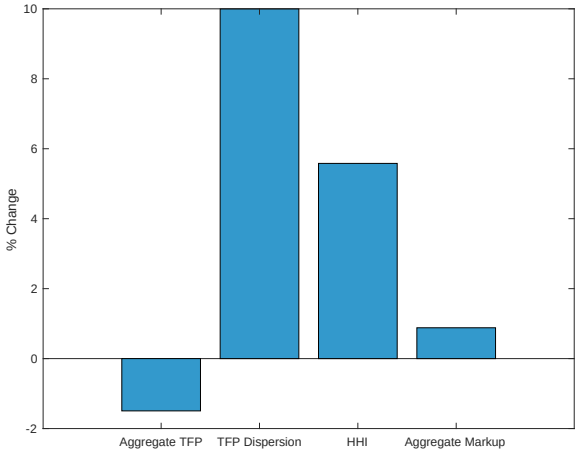
(b) Absolute Changes in Firm Market Share



(c) % Changes in Markup

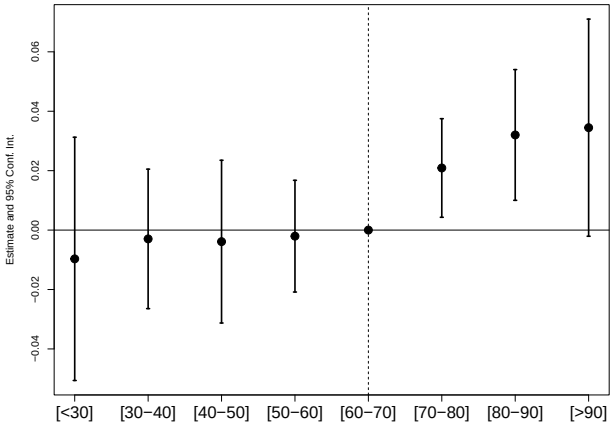


(d) % Changes in Aggregate



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.

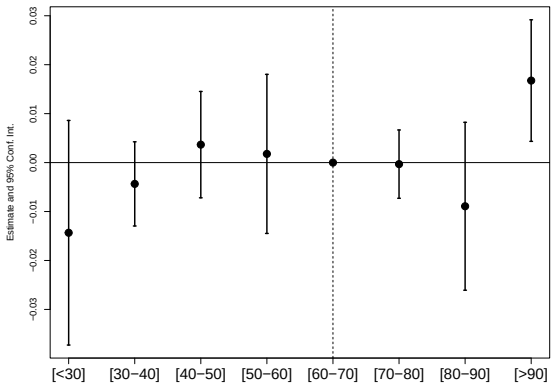
Figure 8: Effect of Temperature Change on Weighted Markup



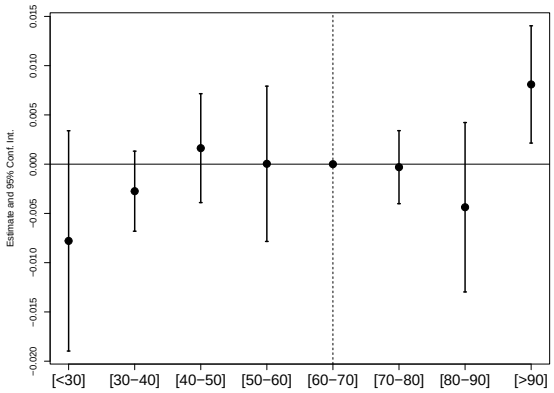
Notes: This figure reports the effect of temperature change on firm markup weighted by firms' market shares as of 2000. Coefficients are estimated from Equation (18) with the dependent variable being the firm markup. The vertical lines show the 95% confidence interval. The standard error is clusters at the country-by-sector level.

Figure 9: Effect of Temperature Change on Market Concentration

(a) Log(HHI)



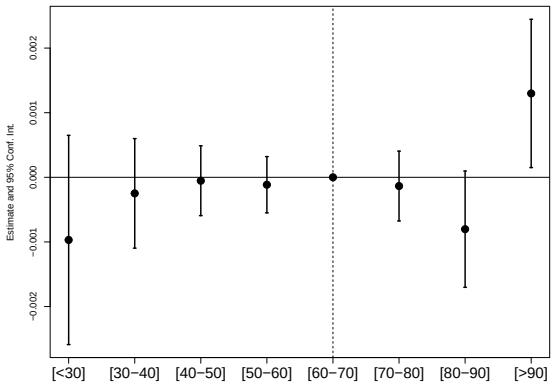
(b) Log(CR4)



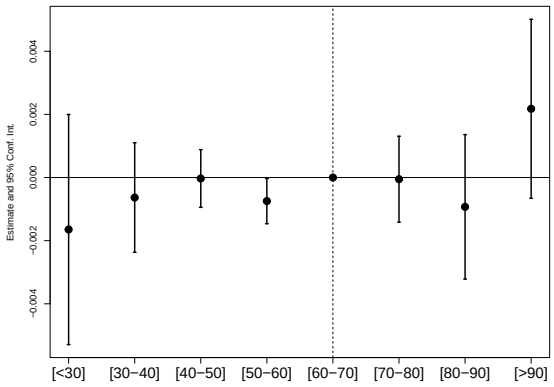
Notes: This figure reports the effect of the temperature change on market concentration. The coefficients are estimated from Equation (17). The market is defined as an NACE 4-digit class within a country in a given year. The dependent variables are log(HHI) and log(CR4). The vertical lines show the 95% confidence interval. The standard error is clusters at the country level.

Figure 10: Effect of Temperature Change on Within Market Dispersion

(a) Productivity SD



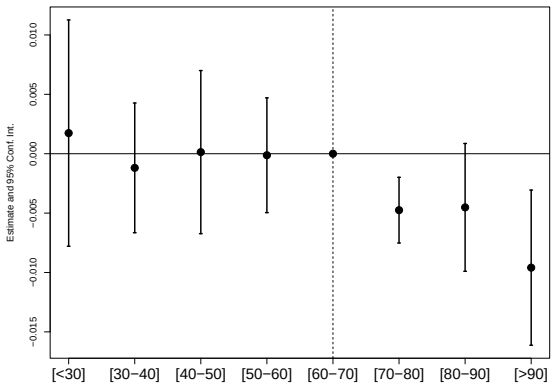
(b) Productivity 90th-10th percentile gap



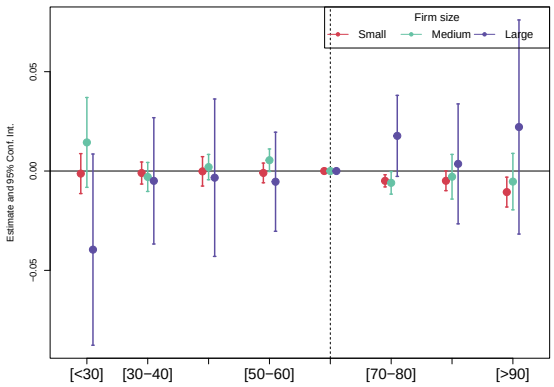
Notes: This figure reports the effect of the temperature change on within market productivity dispersion. The coefficients are estimated from Equation (17). The market is defined as an NACE 4-digit industry within a country in a given year. The dependent variables are two indices that measure the distribution of productivity within a market: log of standard deviation of productivity, and log of the gap between the 90th and the 10th percentile of the productivity. The vertical lines show the 95% confidence interval. The standard error is clusters at the country level.

Figure 11: Effect of Temperature Change on Firm Productivity

(a) Full sample



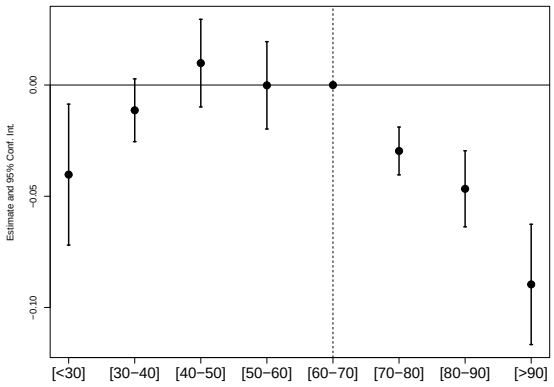
(b) By firm size



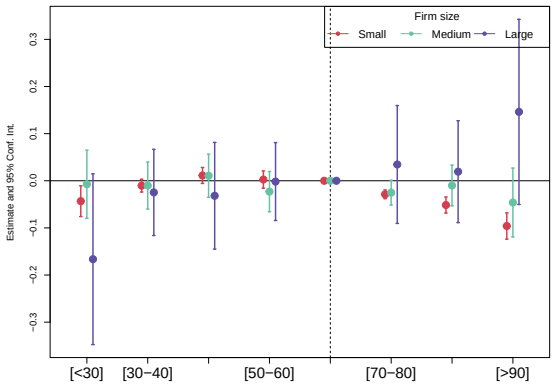
Notes: This figure reports the effect of temperature change on firm revenue TFP. Coefficients are estimated from Equation (18) with the dependent variable being the log of firm revenue TFP. Firms are categorized as small, medium, or large based on their market shares as of 2000: small firms have market shares below the 80th percentile, medium firms fall between the 80th and 97th percentiles, and large firms have market shares above the 97th percentile. The standard error is clusters at the country-by-sector level.

Figure 12: Effect of Temperature Change on Firm Revenue

(a) Full sample



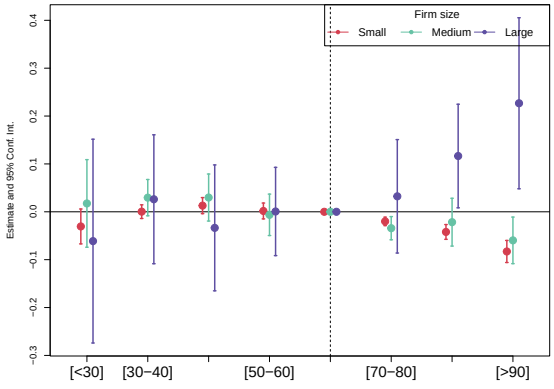
(b) By firm size



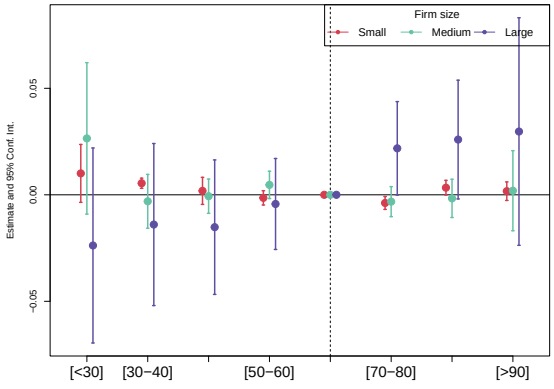
Notes: This figure reports the effect of temperature change on firm revenue. Coefficients are estimated from Equation (18) with the dependent variable being the log of revenue. Firms are categorized as small, medium, or large based on their market shares as of 2000: small firms have market shares below the 80th percentile, medium firms fall between the 80th and 97th percentiles, and large firms have market shares above the 97th percentile. The standard error is clusters at the country-by-sector level.

Figure 13: Heterogeneous Effects of Temperature Change on Firm Market Share and Markup

(a) Market share



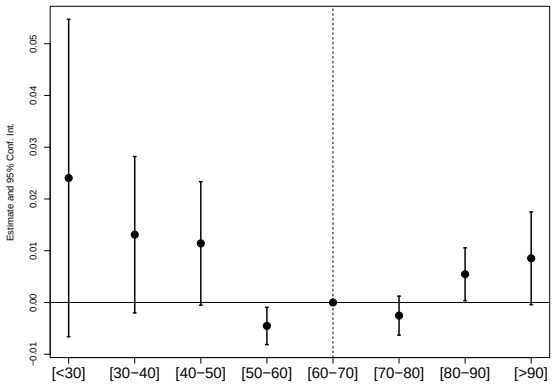
(b) Markup



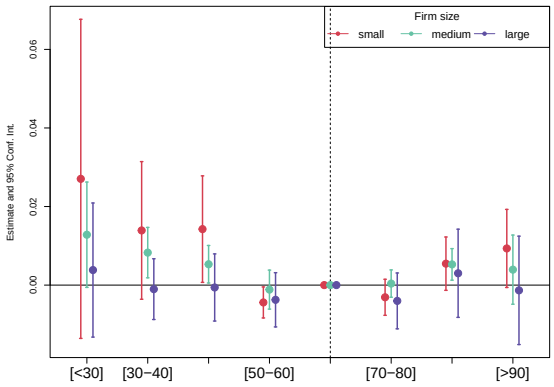
Notes: This figure reports the heterogeneous effects of temperature change on firm market share and markup. Coefficients are estimated from Equation (18) with the dependent variable being the log of market share and log of markup. Firms are categorized as small, medium, or large based on their market shares as of 2000: small firms have market shares below the 80th percentile, medium firms fall between the 80th and 97th percentiles, and large firms have market shares above the 97th percentile. The standard error is clusters at the country-by-sector level.

Figure 14: Effect of Temperature Change on Firm Exit

(a) Full sample



(b) By firm size



Notes: This figure reports the effect of temperature change on firm exit. Coefficients are estimated from Equation (18) with the dependent variable being a dummy that equals one if a firm exits the market in a given year between 2000 and 2020. Firms are categorized as small, medium, or large based on their market shares as of 2000: small firms have market shares below the 80th percentile, medium firms fall between the 80th and 97th percentiles, and large firms have market shares above the 97th percentile. The vertical lines show the 95% confidence interval. The standard error is clusters at the country-by-sector level.

Table 1: Summary Statistics

Variable	Mean	Std. Dev.	Min.	Max.	N
Climate variables (Firm × Year)					
# days [<30F]	4	11	0	154	2279071
# days [30-40F]	23	26	0	161	2279071
# days [40-50F]	48	26	0	135	2279071
# days [50-60F]	77	22	0	195	2279071
# days [60-70F]	80	20	1	194	2279071
# days [70-80F]	70	18	0	285	2279071
# days [80-90F]	49	26	0	135	2279071
# days [>90F]	16	20	0	131	2279071
Precipitation	1.8	0.82	0.012	5.8	2279071
Firm outcomes (Firm × Year)					
log(TFP)	1.8	1.3	-2.5	13	2279071
log(Revenue)	15	1.7	0	26	2278690
Markup	1.1	0.68	0.56	9.5	2279071
Market share (%)	1.3	6.5	0.0000000016	100	2278690
Market outcomes (Country× NACE4 × year)					
HHI	1503	1541	2.94	9962	44060
CR4	0.528	0.242	0.0139	0.999	44060
CR8	0.665	0.25	0.0224	1	44060
Aggregated markup	1.24	0.402	0.559	6.49	44060
Aggregated markup weighted by market shares	1.2	0.539	0.559	9.18	44060
S.D. of TFP	0.3	0.165	0.0272	2.97	44060
Gap between 90th and 10th percentile of TFP	0.599	0.301	0.057	5	44060

Notes: This table reports the summary statistics of climate variables, firm outcomes, and market outcomes. A market is defined as a combination of country-NACE 4-digit industry-year cell.

Table 2: Effect of Temperature Change on Firm Markup Weighted by Market Share

	Log(Markup)				
	(1)	(2)	(3)	(4)	(5)
<30	-0.1617*	-0.1550	-0.0322	-0.0046	-0.0097
	(0.0943)	(0.0981)	(0.0238)	(0.0193)	(0.0206)
30-40	0.0862	0.0877	-0.0147	-0.0097	-0.0030
	(0.0640)	(0.0651)	(0.0153)	(0.0151)	(0.0118)
40-50	0.1314**	0.1332**	-0.0107	-0.0044	-0.0039
	(0.0618)	(0.0637)	(0.0146)	(0.0142)	(0.0138)
50-60	0.0664*	0.0659*	-0.0120	-0.0089	-0.0020
	(0.0343)	(0.0358)	(0.0106)	(0.0099)	(0.0095)
70-80	-0.0281	-0.0306	0.0175*	0.0161*	0.0209**
	(0.0406)	(0.0445)	(0.0096)	(0.0093)	(0.0083)
80-90	0.0465	0.0415	0.0325***	0.0344***	0.0320***
	(0.0597)	(0.0553)	(0.0114)	(0.0110)	(0.0111)
>=90	-0.1209	-0.1199*	0.0417*	0.0332	0.0345*
	(0.0738)	(0.0720)	(0.0224)	(0.0227)	(0.0184)
Observations	2,278,854	2,278,854	2,278,854	2,278,854	2,278,854
R^2	0.77636	0.78626	0.82979	0.84035	0.86350
Firm FEs	✓	✓	✓	✓	✓
Year FEs	✓				
Industry-Year FEs		✓	✓		
Country-Year FEs			✓		
Country-Sector-Year FEs				✓	
Country-Industry-Year FEs					✓

Notes: This table reports the effect of temperature change on firm markup weighted by market share. The independent variables are number of days per year that falls in the corresponding temperature bins. The bin of 60-70 °F is omitted. All coefficients are multiplied by 100 to improve readability. Standard errors are two-way clustered at the country-by-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 3: Effect of Contemporaneous Temperature Change on Market Concentration

	Log(HHI)		Log(CR4)		Log(CR8)	
	(1)	(2)	(3)	(4)	(5)	(6)
<30	-0.0134	-0.0143	-0.0071	-0.0078	-0.0056	-0.0063
	(0.0102)	(0.0107)	(0.0049)	(0.0052)	(0.0039)	(0.0042)
30-40	-0.0033	-0.0044	-0.0020	-0.0027	-0.0018	-0.0025
	(0.0040)	(0.0040)	(0.0019)	(0.0019)	(0.0014)	(0.0014)
40-50	0.0073	0.0037	0.0038	0.0016	0.0029	0.0011
	(0.0057)	(0.0051)	(0.0028)	(0.0026)	(0.0021)	(0.0020)
50-60	0.0033	0.0018	0.0008	3.74×10^{-5}	0.0004	-0.0002
	(0.0088)	(0.0076)	(0.0042)	(0.0037)	(0.0034)	(0.0030)
70-80	0.0007	-0.0003	0.0003	-0.0003	-2.81×10^{-6}	-0.0005
	(0.0033)	(0.0033)	(0.0017)	(0.0017)	(0.0014)	(0.0014)
80-90	-0.0079	-0.0089	-0.0037	-0.0044	-0.0030	-0.0036
	(0.0086)	(0.0080)	(0.0043)	(0.0040)	(0.0036)	(0.0033)
>=90	0.0158**	0.0168**	0.0074**	0.0081**	0.0049*	0.0056**
	(0.0064)	(0.0058)	(0.0030)	(0.0028)	(0.0023)	(0.0021)
Observations	44,060	44,060	44,060	44,060	44,060	44,060
R^2	0.10407	0.17342	0.10826	0.17790	0.12897	0.20276
Country-Year FEs	✓	✓	✓	✓	✓	✓
Sector-Year FEs		✓		✓		✓

Notes: The market is defined as the combination of country-NACE 4-digit industry-year. The independent variables are number of days per year that falls in the corresponding temperature bins. The bin of 60-70 °F is omitted. Standard errors are clustered at the country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 4: Effect of Contemporaneous Temperature Change on Within-Market Dispersion

	TFP S.D.		TFP 90th-10th Gap	
	(1)	(2)	(3)	(4)
<30	-0.0009	-0.0010	-0.0013	-0.0016
	(0.0007)	(0.0008)	(0.0016)	(0.0017)
30-40	-0.0006	-0.0002	-0.0012	-0.0006
	(0.0007)	(0.0004)	(0.0013)	(0.0008)
40-50	-0.0007	-5.27×10^{-5}	-0.0012	-3.08×10^{-5}
	(0.0004)	(0.0003)	(0.0008)	(0.0004)
50-60	-0.0002	-0.0001	-0.0008	-0.0007**
	(0.0003)	(0.0002)	(0.0005)	(0.0003)
70-80	-0.0004**	-0.0001	-0.0005	-5.24×10^{-5}
	(0.0002)	(0.0003)	(0.0005)	(0.0006)
80-90	-0.0012**	-0.0008*	-0.0018	-0.0009
	(0.0005)	(0.0004)	(0.0012)	(0.0011)
>=90	0.0021***	0.0013**	0.0039**	0.0022
	(0.0007)	(0.0005)	(0.0014)	(0.0013)
Observations	44,060	44,060	44,060	44,060
R^2	0.17850	0.30008	0.23118	0.41816
Country-Year FEs	✓	✓	✓	✓
Sector-Year FEs		✓		✓

Notes: The market is defined as the combination of country-NACE 4-digit industry-year. TFP S.D. is the standard deviation of the TFP within a market. TFP 90th-10th is the gap between the 90th and the 10th percentile of the TFP distribution within a market. TFP 10th is the 10th percentile of the TFP distribution of a market. The independent variables are number of days per year that falls in the corresponding temperature bins. The bin of 60-70 °F is omitted. Standard errors are clustered at the country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 5: Effect of Temperature Change on Firm Productivity

	Log(TFP)				
	(1)	(2)	(3)	(4)	(5)
80-90	-0.0318***	-0.0307***	-0.0052*	-0.0054*	-0.0045*
	(0.0072)	(0.0054)	(0.0028)	(0.0028)	(0.0027)
>=90	-0.0256***	-0.0237***	-0.0119***	-0.0107***	-0.0096***
	(0.0097)	(0.0073)	(0.0034)	(0.0032)	(0.0033)
Observations	2,279,071	2,279,071	2,279,071	2,279,071	2,279,071
R^2	0.98671	0.98678	0.98690	0.98693	0.98708
Firm FEs	✓	✓	✓	✓	✓
Year FEs	✓				
Industry-Year FEs		✓	✓		
Country-year FEs			✓		
Country-Sector-Year FEs				✓	
Country-Industry-Year FEs					✓

Notes: This table reports the effect of temperature change on firm productivity, measured by TFP. The independent variables are number of days per year that falls in the corresponding temperature bins. The bin of 60-70 °F is omitted. All coefficients are multiplied by 100 to improve readability. Standard errors are clustered at the country-by-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 6: Heterogeneous Effects of Temperature Change on Firm Productivity

	Log(TFP)		
Firm size	Small	Medium	Large
	(1)	(2)	(3)
80-90	-0.0049*	-0.0029	0.0036
	(0.0025)	(0.0057)	(0.0152)
>=90	-0.0106***	-0.0053	0.0221
	(0.0038)	(0.0071)	(0.0271)
Observations	1,807,794	402,864	68,196
R^2	0.98672	0.98829	0.98701
Firm FEs	✓	✓	✓
Country-Industry-Year FEs	✓	✓	✓

Notes: This table reports heterogeneous effects of temperature change on firm productivity across different firm sizes. Firms are categorized as small, medium, or large based on their market shares as of 2000: small firms have market shares below the 80th percentile, medium firms fall between the 80th and 97th percentiles, and large firms have market shares above the 97th percentile. The independent variables are number of days per year that falls in the corresponding temperature bins. The bin of 60-70 °F is omitted. All coefficients are multiplied by 100 to improve readability. Standard errors are clustered at the country-by-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 7: Effect of Temperature Change on Firm Revenue

	Log(Revenue)				
	(1)	(2)	(3)	(4)	(5)
80-90	-0.0736**	-0.0611***	-0.0504***	-0.0516***	-0.0466***
	(0.0326)	(0.0221)	(0.0086)	(0.0084)	(0.0086)
>=90	-0.2181**	-0.1799***	-0.0926***	-0.0970***	-0.0896***
	(0.0882)	(0.0485)	(0.0168)	(0.0136)	(0.0136)
Observations	2,278,690	2,278,690	2,278,690	2,278,690	2,278,690
R^2	0.92357	0.92730	0.93031	0.92957	0.93196
Firm FEs	✓	✓	✓	✓	✓
Year FEs	✓				
Industry-Year FEs		✓	✓		
Country-Year FEs			✓		
Country-Sector-Year FEs				✓	
Country-Industry-Year FEs					✓

Notes: This table reports the effect of temperature change on firm markup. The independent variables are number of days per year that falls in the corresponding temperature bins. The bin of 60-70 °F is omitted. All coefficients are multiplied by 100 to improve readability. Standard errors are clustered at the country-by-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 8: Heterogeneous Effects of Temperature Change on Firm Revenue

	Log(Revenue)		
Firm size	Small	Medium	Large
	(1)	(2)	(3)
80-90	-0.0469***	-0.0227**	0.0824**
	(0.0143)	(0.0098)	(0.0363)
>=90	-0.0899***	-0.0250*	0.2252***
	(0.0050)	(0.0139)	(0.0484)
Observations	1,813,589	401,187	38,555
R^2	0.90955	0.96414	0.97820
Firm FEs	✓	✓	✓
Country-Industry-Year FEs	✓	✓	✓

Notes: This table reports heterogeneous effects of temperature change on firm markup across different firm sizes. Firms are categorized as small, medium, or large based on their market shares as of 2000: small firms have market shares below the 80th percentile, medium firms fall between the 80th and 97th percentiles, and large firms have market shares above the 97th percentile. The independent variables are number of days per year that falls in the corresponding temperature bins. The bin of 60-70 °F is omitted. All coefficients are multiplied by 100 to improve readability. Standard errors are clustered at the country-by-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 9: Heterogeneous Effects of Temperature Change on Firm Market Share

	Log(Market Share)		
Firm size	Small	Medium	Large
	(1)	(2)	(3)
80-90	-0.0421***	-0.0217	0.1165**
	(0.0077)	(0.0251)	(0.0544)
>=90	-0.0829***	-0.0597**	0.2267**
	(0.0116)	(0.0245)	(0.0898)
Observations	1,807,486	402,842	68,190
R^2	0.92379	0.83937	0.84351
Firm FEs	✓	✓	✓
Country-Industry-Year FEs	✓	✓	✓

Notes: This table reports heterogeneous effects of temperature change on firm market share across different firm sizes. Firms are divided into three groups according to their market share. Firms are categorized as small, medium, or large based on their market shares as of 2000: small firms have market shares below the 80th percentile, medium firms fall between the 80th and 97th percentiles, and large firms have market shares above the 97th percentile. The independent variables are number of days per year that falls in the corresponding temperature bins. The bin of 60-70 °F is omitted. All coefficients are multiplied by 100 to improve readability. Standard errors are clustered at the country-by-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 10: Heterogeneous Effects of Temperature Change on Firm Markup

	Log(Markup)		
Firm size	Small	Medium	Large
	(1)	(2)	(3)
80-90	0.0033*	-0.0017	0.0259*
	(0.0017)	(0.0045)	(0.0140)
>=90	0.0017	0.0019	0.0297
	(0.0022)	(0.0095)	(0.0269)
Observations	1,807,794	402,864	68,196
R^2	0.77059	0.83606	0.87352
Firm FEs	✓	✓	✓
Country-Industry-Year FEs	✓	✓	✓

Notes: This table reports heterogeneous effects of temperature change on firm markup across different firm sizes. Firms are categorized as small, medium, or large based on their market shares as of 2000: small firms have market shares below the 80th percentile, medium firms fall between the 80th and 97th percentiles, and large firms have market shares above the 97th percentile. The independent variables are number of days per year that falls in the corresponding temperature bins. The bin of 60-70 °F is omitted. All coefficients are multiplied by 100 to improve readability. Standard errors are clustered at the country-by-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 11: Effect of Temperature Change on Firm Exit

	1(Exit)				
	(1)	(2)	(3)	(4)	(5)
80-90	-0.0023	-0.0072	0.0055**	0.0061**	0.0055**
	(0.0183)	(0.0146)	(0.0027)	(0.0026)	(0.0026)
>=90	-0.0219	-0.0299	0.0091*	0.0091*	0.0085*
	(0.0357)	(0.0311)	(0.0051)	(0.0048)	(0.0045)
Observations	10,939,961	10,939,961	10,939,961	10,939,961	10,939,961
R^2	0.27069	0.27755	0.30859	0.30931	0.31196
Firm FEs	✓	✓	✓	✓	✓
Year FEs	✓				
Industry-Year FEs		✓	✓		
Country-year FEs			✓		
Country-Sector-Year FEs				✓	
Country-Industry-Year FEs					✓

Notes: This table reports the effect of temperature change on firm exit. The independent variables are number of days per year that falls in the corresponding temperature bins. The bin of 60-70 °F is omitted. All coefficients are multiplied by 100 to improve readability. Standard errors are clustered at the country level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 12: Heterogeneous Effects of Temperature Change on Firm Exit

	1(Exit)		
Firm size	Small	Medium	Large
	(1)	(2)	(3)
80-90	0.0055	0.0053**	0.0030
	(0.0034)	(0.0020)	(0.0056)
>=90	0.0093*	0.0039	-0.0013
	(0.0050)	(0.0044)	(0.0069)
Observations	8,016,526	2,445,593	472,811
R^2	0.31603	0.29159	0.35287
Firm FEs	✓	✓	✓
Country-Industry-Year FEs	✓	✓	✓

Notes: This table reports heterogeneous effects of temperature change on firm exit across different firm sizes. Firms are categorized as small, medium, or large based on their market shares as of 2000: small firms have market shares below the 80th percentile, medium firms fall between the 80th and 97th percentiles, and large firms have market shares above the 97th percentile. The independent variables are number of days per year that falls in the corresponding temperature bins. The bin of 60-70 °F is omitted. All coefficients are multiplied by 100 to improve readability. Standard errors are clustered at the country-by-sector level. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table 13: Assigned Parameters

Parameter	Value
Discount factor, β	0.96
Depreciation rate, δ	0.06
Exit rate, φ	0.04
Elasticity of value-added to capital, α	$\frac{1}{3}$
Elasticity of labor supply, ν	1
Elasticity of substitution between value-added and materials, θ	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 14: Calibration

	Data	Model
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, $\hat{b}$	-0.21	-0.20
Parameter values:		
Pareto tail, ξ		4.42
Elasticity of substitution within sectors, ρ		9.25
Elasticity of substitution between sectors, η		1.21

Notes: This table reports our calibrated target and parameters values. We calibrate the Pareto tail ξ and the within- and between-sector elasticities of substitution ρ and η to match the empirical targets on markups and concentration. The cross-sectional regression is of the change over time in sector-level labor shares on the change in sector-level HHIs, following Edmond et al. (2023).

Table 15: Climate Change Simulation Summary

Scenario	Firm TFP (%)	Aggregate Markup (%)	HHI (%)	Welfare Loss (%)
Climate Change	-0.1	0.016924	0.10757	0.083484

Notes: This table summarizes the change in aggregate outcomes under a simulated climate change productivity shock. Aggregate Markup is the sales-share weighted harmonic average markup. HHI is the average of industry HHI. Welfare loss is the static consumption-equivalent welfare loss discussed in the main text and defined in F.3.

Table 16: Welfare cost of climate change and the role of heterogeneous markup

Markup Assumption	Firm TFP(%)	Aggregate TFP(%)	Aggregate Markup(%)	Welfare(%)
Heterogeneous Markups	-0.1	-0.075029	0.016924	-0.083484
Constant Markups(CES)	-0.1	-0.068734	0	-0.068734

Notes: This table compares the changes in aggregate outcomes under VES and CES assumption. For more details on the quantification under CES, see Online Appendix F.3.

Online Appendix

Climate Change and Market Power

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Appendix A: Data

A.1 Orbis

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 [21]. 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., 2019).[22]

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

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

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

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.

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.

Appendix B: Descriptive Summary

Table B1: Correlation between Productivity, Market Share, and Markup

Dependent Variables:	Log(Market Share) (1)	Log(Markup) (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
R^2	0.92530	0.89165
Within R^2	0.00277	0.61144

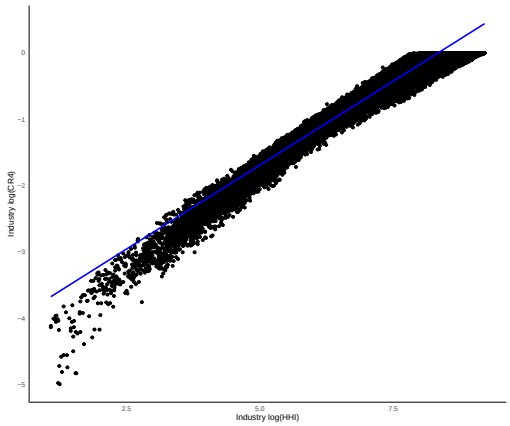
Note: Standard-errors in parentheses are clustered at the country-NACE 2-digit industry level. ***: 0.01, **: 0.05, *: 0.1.

Table B2: Correlation between different concentration measures

	HHI	CR4	CR8
HHI	1.00	0.83	0.72
CR4	0.83	1.00	0.97
CR8	0.72	0.97	1.00

Notes: Correlation table for the levels of HHI, CR4, and CR8. Concentration is calculated at the level of country by 4-digit industries.

Figure B1: Correlation between HHI measure and CR4 measure



Note: Correlation between country by 4-digit industries level logged HHI and logged CR4, the market share of the 4 largest firm in a country-industry cell.

Observed correlation between Markup, Concentration, and Productivity Table B3 shows the correlation between concentration, markup, and productivity in our sample. Columns (1) and (2) show that higher concentration is associated with lower aggregate markup. Columns (3) and (4) show that higher concentration level is correlated with a higher level of aggregate productivity. [23]

As discussed in Section 3, there are many potential causes for concentration change, each of them leading to different conclusions on efficiency and welfare. At first glance, the positive correlation between concentration and aggregate productivity shows that the net effect of these forces is consistent with the competition-driven concentration increase story in which increased competition lowers margin, reallocate market shares towards the largest and most productive firms (Melitz and Ottaviano, 2008). If such winner-takes-all forces dominate, then an increase in concentration should be correlated with higher aggregate productivity and lower aggregate markup. Our paper proposes a counteracting concentration-increasing force that can be welfare-decreasing.

Table B3: Correlation between Concentration and Markup

Dependent Variable:	HHI			
	(1)	(2)	(3)	(4)
Avg Markup	-0.0284***			
	(0.0032)			
Weighted Avg Markup		-0.0422***		-0.1436***
		(0.0062)		(0.0072)
Weighted Avg TFP			0.8496***	0.9960***
			(0.0398)	(0.0364)
Year FE	Yes	Yes	Yes	Yes
Country-NACE4 FE	Yes	Yes	Yes	Yes
Observations	104,119	104,119	104,119	104,119
R^2	0.86205	0.86211	0.87507	0.87848
Within R^2	0.00192	0.00238	0.09613	0.12078

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

[23] The same directional result holds given different concentration measures and different definition of industries, either country-wise or EU-wise.

Appendix C: Proof to theoretical model

C.1 Proof of Proposition 1 on exit cutoff

Proof.

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

$$= \left((\frac{f\sigma}{E})^{\frac{1}{\sigma-1}}\frac{\sigma-1}{\sigma P}\right)\cdot\frac{\partial\gamma}{\partial T} \tag{C.2}$$

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 γ essentially increases the ex-ante productivity needed to earn the same profit. ■

C.2 Proof of Proposition 2 on aggregate markup

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

$$\frac{d\boldsymbol{\mu}}{d\gamma} = \sum_i^N \left(\underbrace{\frac{ds_i}{d\gamma}\cdot\mu_i}_{\text{Between}} + \underbrace{s_i\cdot\frac{d\mu_i}{d\gamma}}_{\text{Within}}\right) \tag{C.3}$$

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

$$\frac{d\varepsilon_i}{ds_i} = \frac{\eta\rho(\eta-\rho)}{(\eta(s_i-1)-\rho s_i)^2} < 0, \quad \text{given } \rho > \eta > 1 \tag{C.4}$$

$$\frac{d^2\varepsilon_i}{ds_i{}^2} = 2\left(\frac{1}{\eta}-\frac{1}{\rho}\right)^2\cdot\left(\frac{1-s_i}{\rho}+\frac{s_i}{\eta}\right)^{-3} > 0 \tag{C.5}$$

Likewise, from equation (11) and (12), we can also show that markup is increasing and convex in market share ($\frac{d\mu_i}{ds_i} > 0$ and $\frac{d^2\mu_i}{ds_i{}^2} > 0$)

Between Component

$$\text{Between} = \sum_{i=1}^N \frac{ds_i}{d\gamma}\cdot\mu_i. \tag{C.6}$$

From the market share equation 13, the effect of changes in temperature shock γ can be expressed as

$$\frac{ds_i}{d\gamma} = (1-\rho)\cdot s_i \left(\frac{d\ln P_i}{d\gamma} - \sum_{j=1}^{N} s_j \frac{d\ln P_j}{d\gamma} \right). \tag{C.7}$$

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 γ 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 μ_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

$$\text{Within} = \sum_{i=1}^{N} s_i \cdot \frac{d\mu_i}{d\gamma} = \sum_{i=1}^{N} s_i \cdot \frac{d\mu_i}{ds_i} \cdot \frac{ds_i}{d\gamma}. \tag{C.8}$$

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 γ. The convexity of demand is crucial for this conclusion. We further test this prediction in our simulation section. ■

C.3 Proof of Proposition 3 on HHI

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:

$$\text{HHI} = \sum_{i=1}^{N} (s_i \times 100)^2 = 10,000 \times \sum_{i=1}^{N} s_i^2. \tag{C.9}$$

Under the assumption of productivity-decreasing shock and Proposition 1, 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

$$\sigma^2 = \frac{1}{N}\sum_{i=1}^{N} (s_i - \bar{s})^2 = \frac{1}{N}\sum_{i=1}^{N} s_i^2 - \bar{s}^2 \tag{C.10}$$

Rewriting equation (C.10) as

$$\sum_{i=1}^{N} s_i^2 = N\sigma^2 + N\bar{s}^2 = N\sigma^2 + \frac{1}{N}. \tag{C.11}$$

From (C.11), 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 σ increases, increasing the aggregate HHI.

C.4 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. Ξ 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

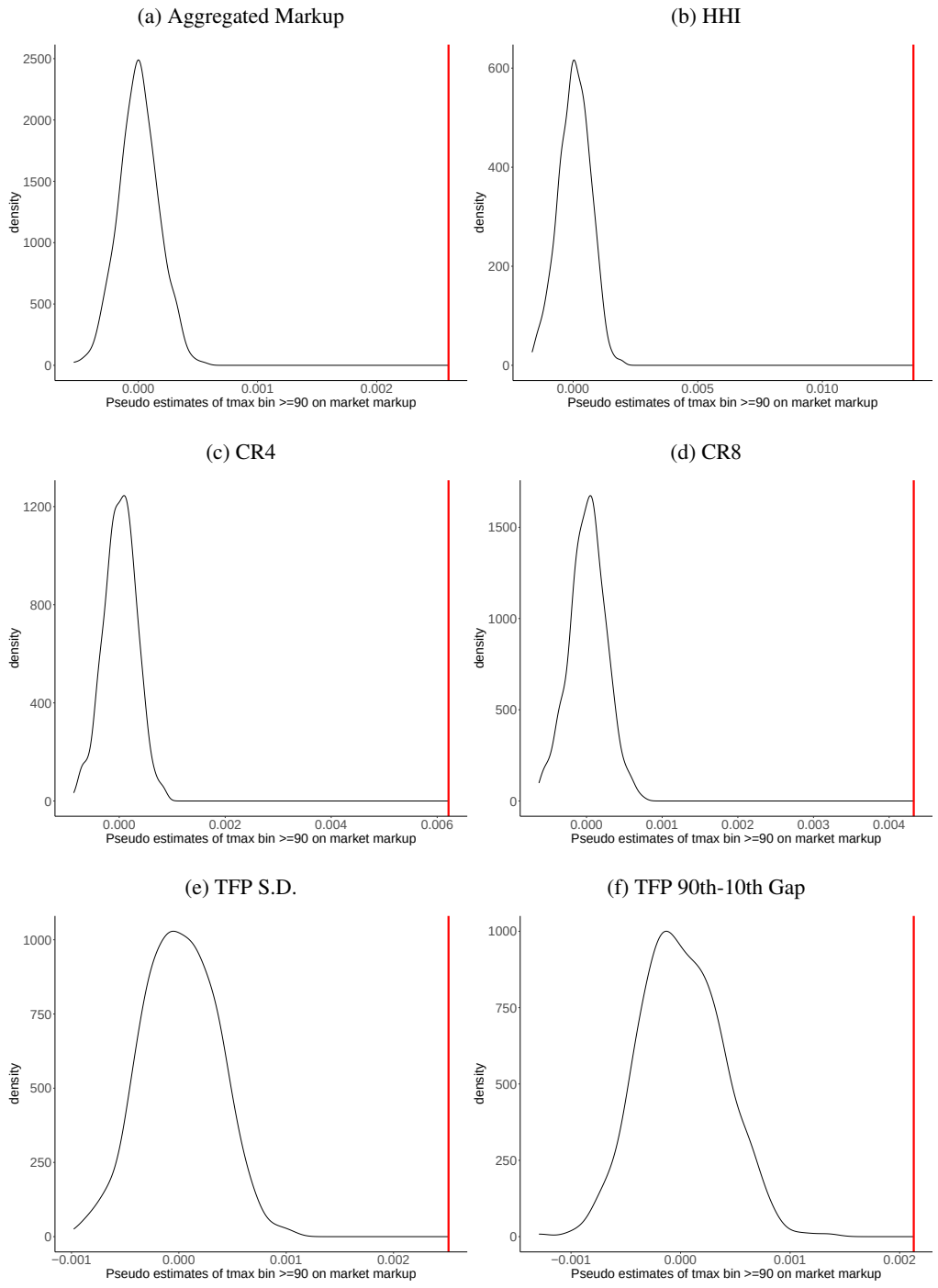
$$\begin{aligned}l_j^d &= \sum_{i=1}^{n_{ij}} \tilde{l}_{ij}^d + l_j^F \\ &= \sum_{i=1}^{n_{ij}} \tilde{l}_{ij}^d + n_{ij} f \\ &= \left(\frac{Y}{\varphi_j}\right) \cdot \left(\frac{P\varphi_j}{W\mu_j}\right)^{\eta} \cdot \underbrace{\sum_{i=1}^{n_{ij}} \left[\left(\frac{\mu_{ij}}{\mu_j}\right)^{-\rho}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

Aggregate Labor Demand

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

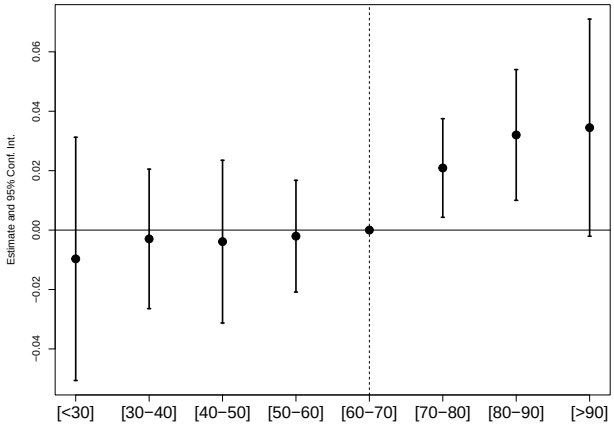
Appendix D: Robustness Checks

Figure D1: Placebo Test of the Effect of Temperature Change on Market Outcomes



Notes: The figures show the placebo test on the estimated coefficient of the temperature bin above 90°F on market concentration and within market dispersion. We rerun equation (17) 500 times using pseudo datasets generated by reshuffling temperature bins across country-class-year. The figures shows the distribution of the 500 pseudo estimates. The red vertical bar is where the true estimate of the temperature bin above 90°F is.

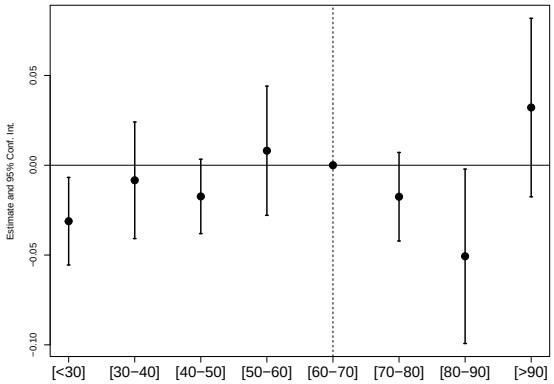
Figure D2: Effect of Temperature Change on Weighted Markup



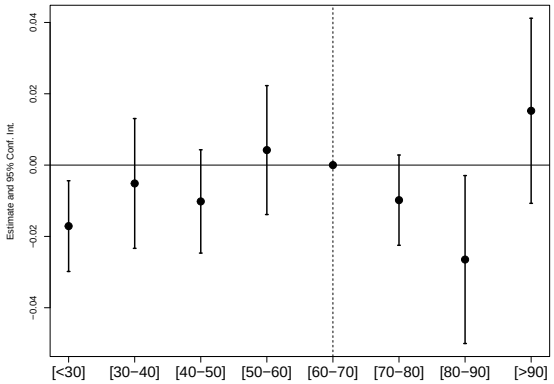
Notes: This figure reports the effect of temperature change on firm markup weighted by market shares. Coefficients are estimated from Equation (18) with the dependent variable being the log of markup. The vertical lines show the 95% confidence interval. The standard error is clusters at the country-by-sector level.

Figure D3: Effect of Temperature Change on Market Concentration

(a) Log(HHI)



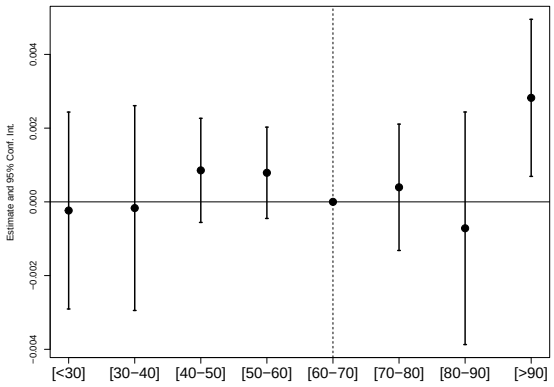
(b) Log(CR4)



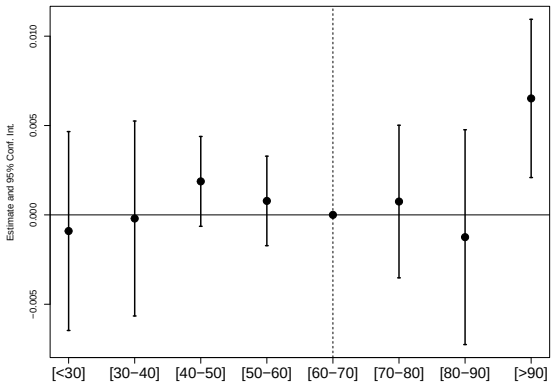
Notes: This figure reports the effect of the temperature change on market concentration. The coefficients are estimated from Equation (17). The market is defined as an NACE 2-digit industry within a country in a given year. The dependent variables are log(HHI), log(CR4), and log(CR8). The vertical lines show the 95% confidence interval. The standard error is clusters at the country level.

Figure D4: Effect of Temperature Change on Within Market Dispersion

(a) Productivity SD



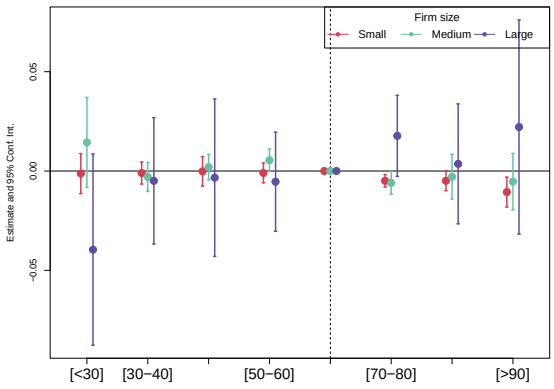
(b) Productivity 90th-10th percentile Gap



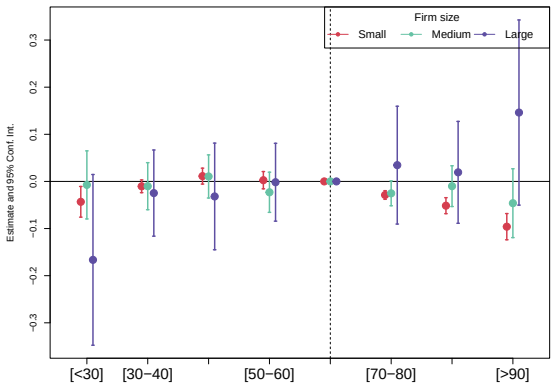
Notes: This figure reports the effect of the temperature change on within market productivity dispersion. The coefficients are estimated from Equation (17). The market is defined as an NACE 2-digit industry within a country in a given year. The dependent variables are two indices that measure the distribution of productivity within a market: log of standard deviation of productivity, and log of the gap between the 90th and the 10th percentile of the productivity. The vertical lines show the 95% confidence interval. The standard error is clusters at the country level.

Figure D5: Heterogeneous Effects of Temperature Change on Firm Productivity and Revenue

(a) Productivity



(b) Revenue

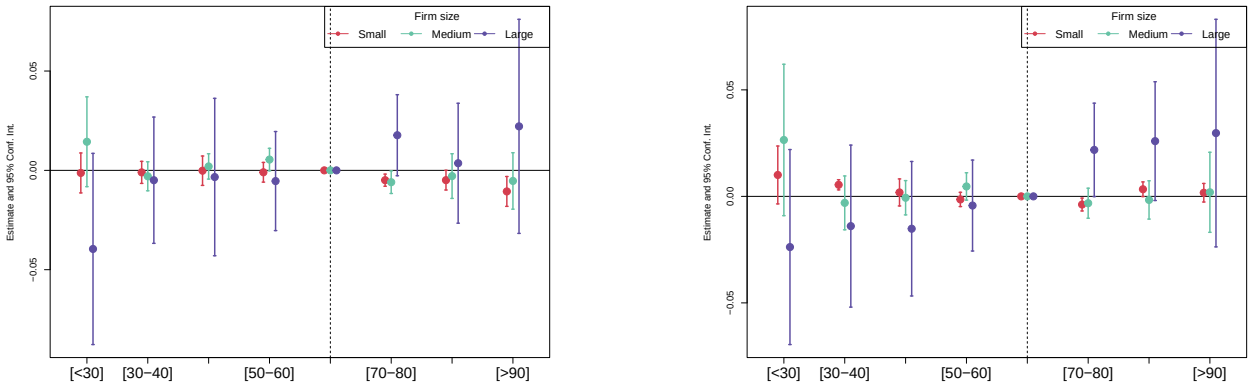


Notes: This figure reports the effect of temperature change on firm productivity measured by revenue TFP and on firm revenue. Coefficients are estimated from Equation (18) with the dependent variable being the log of revenue TFP and revenue. Firms are categorized as small, medium, or large based on their market shares as of 2000: small firms have market shares below the 80th percentile, medium firms fall between the 80th and 97th percentiles, and large firms have market shares above the 97th percentile. The vertical lines show the 95% confidence interval. The standard error is clusters at the country-by-sector level.

Figure D6: Heterogeneous Effects of Temperature Change on Firm Market Share and Markup

(a) Market share

(b) Markup



Notes: This figure reports the effect of temperature change on firm market share and markup. Coefficients are estimated from Equation (18) with the dependent variable being the log of market share and log of markup. Firms are categorized as small, medium, or large based on their market shares as of 2000: small firms have market shares below the 80th percentile, medium firms fall between the 80th and 97th percentiles, and large firms have market shares above the 97th percentile. The vertical lines show the 95% confidence interval. The standard error is clusters at the country-by-sector level.

Appendix E: Heterogeneity by industry[24]

The empirical analysis in Section 6 focuses on economy-wide concentration change. We find that extreme temperature, on average, reallocates market shares from small firms to larger firms, increasing aggregate concentration and markups.

Nonetheless, it is also important to recognize the considerable heterogeneity across different industries. On the production side, industries differ in their production technology and the capital or labor intensity. For example, while labor-intensive construction industry is exposed to heat shocks, less labor-intensive telecommunications industry is relatively shielded from heat shocks. On the demand side, the degree of within-industry dispersion and market power can also determine the heterogeneity of pass-through across firms and therefore the magnitude of the reallocation after shocks.

Does the aggregate result hold for different industries? Which industries experience more severe reallocation than others and what are some industry characteristics that are informative? In this section, we utilize the cross-section of industry data and delve deeper into the industry heterogeneity.

E.1 Discussion on relevant industry characteristics

Motivated by our stylized model in section 5, we propose different dimensions of industry characteristics that are potentially relevant for determining the degree of concentration change across industries. We discuss the intuition behind each of these dimensions, and how we measure them from our data.

Labor Intensity One of the channels through which climate change impacts production is through the labor productivity channel (Dell et al., 2014; Somanathan et al., 2021), thus we would expect to see larger productivity impact in industries that rely heavily on labor for production. As productivity shock generates reallocation in our stylized model in section 5, larger productivity shock can lead to greater reallocation.

We measure the degree of industry labor intensity as the industry average of firm-level output-to-labor elasticity (θ_l) from the production function estimation, defined by Equation G.68. We then group industries into terciles based on the average labor intensity. For more details on the estimation of output elasticity, see Section Appendix G:.

Industry Dispersion High within-industry dispersion implies a greater discrepancy between large firms and small firms, potentially leading to different levels of adaptation capabilities and productivity response to heat shock. For example, in industries where firms are highly dispersed, larger firms have higher market power and larger financial capacity to pay the upfront cost for cooling equipment to shield production process from heat shocks, while smaller firms are more financially restricted and are therefore more exposed to heat shocks. Furthermore, in model of endogenous markup and heterogeneous pass-through, larger productivity dispersion also implies greater dispersion in firm-level cost pass-through. In our data, we proxy the within-industry dispersion as the standard deviations of firm-level productivity in an industry.

[24] Result on industry heterogeneity is preliminary, and will be updated in later versions of the draft.

E.2 Heterogeneity results

Labor intensity We group country-4 digit industries into three terciles based on each industry's average labor intensity. Figure E1 shows the heterogeneous effects on firm productivity and revenue from the least to the most labor intensive industries. As shown in Panel (a), firms in all industries experiences negative effects from extreme high temperature on productivity, and the effect is the most pronounced for the most labor intensive industry. Similarly, panel (b) shows that firms in the most labor intensive industries experience the largest decline in their revenue. These heterogneity results are consistent with the productivity channel that extreme temperature shocks could have a larger impact on firms that are more reliant on labor in production.

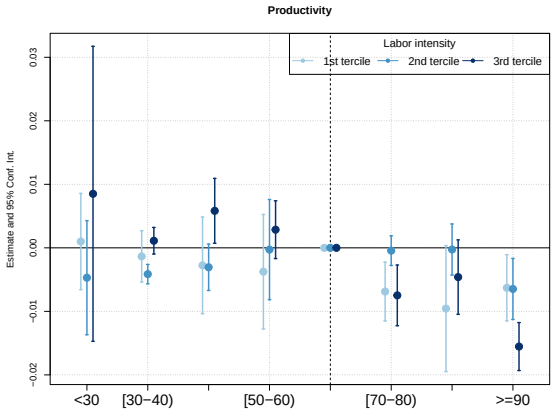
Industry Dispersion We also group industries into three terciles based on the level of within-industry dispersion, which is calculated as the standard deviations of firm-level revenue TFP in an industry. According to our stylized model, more dispersed industries are composed of firms with greater diversity in size and market share, thus it is more likely that market share will be reallocated from smaller firms to larger firms. This is what we see in panel (a) of Figure E2, that firms in the most dispersed industries see the largest decline in their market share. The more pronounced market share reallocation would also transfer to a larger increase in markup. As we see in panel (b) of Figure E2, firms in the most dispersed industries experience the largest and significant increase in firm markup, while the effect for firms in the least dispersed industries is not significantly different from zero.

In Section 6.3, we examine the effect of temperature on firm market share and markup between firm sizes. We find that small and medium firms' market share declines, while large firms' market share increases, suggesting market share reallocation. We also find that small and medium firms' markup do not change significantly under extreme high temperature shocks, but large firms' markup increases significantly.

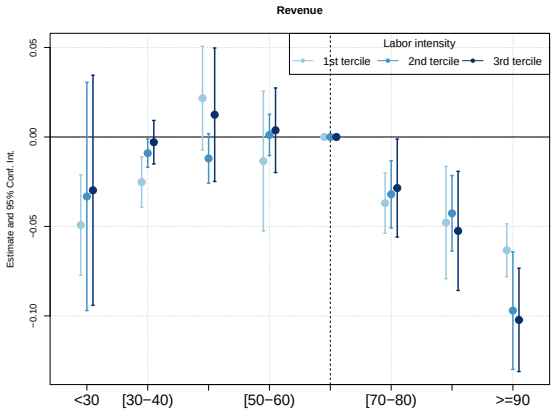
Now we redo these analyses in sub-samples of varying industry dispersion. As mentioned above, the most dispersed industries should see the largest heterogeneity in market share reallocation and markup change. Figure E3 shows the results. The dependent variable for panel (a) is the log of market share, and the dependent variable for panel (b) is the log of firm markup. From left to right, panels show results for the 1st, 2nd, and 3rd tercile of industries based on revenue TFP dispersion. Small firms are those whose market share is below 0.5 percent, and large firms are those whose market share is above 15 percent. Both in panel (a) and panel (b), we see that the heterogeneity across firm size is the most pronounced in the most dispersed industries, which is consistent with the model prediction.

Figure E1: Heterogeneity by industry labor intensity

(a) TFP



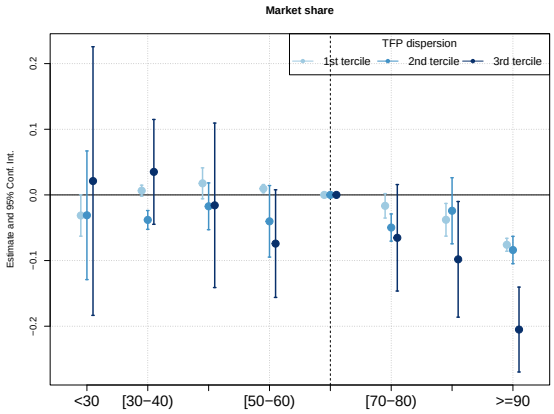
(b) Revenue



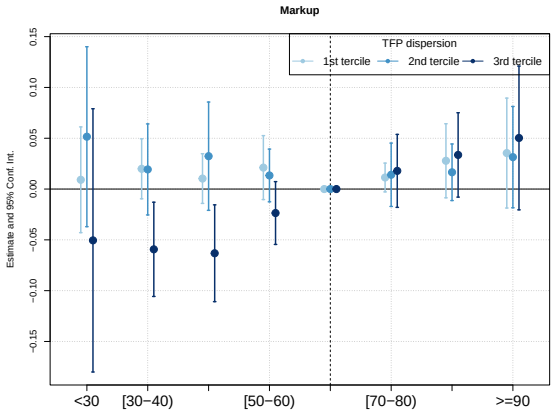
Notes: This figure reports the heterogeneous effects of temperature on firm productivity and revenue by industry labor intensity. The vertical lines show the 95% confidence interval. The standard error is clusters at the country level.

Figure E2: Heterogeneity by industry dispersion

(a) Market share



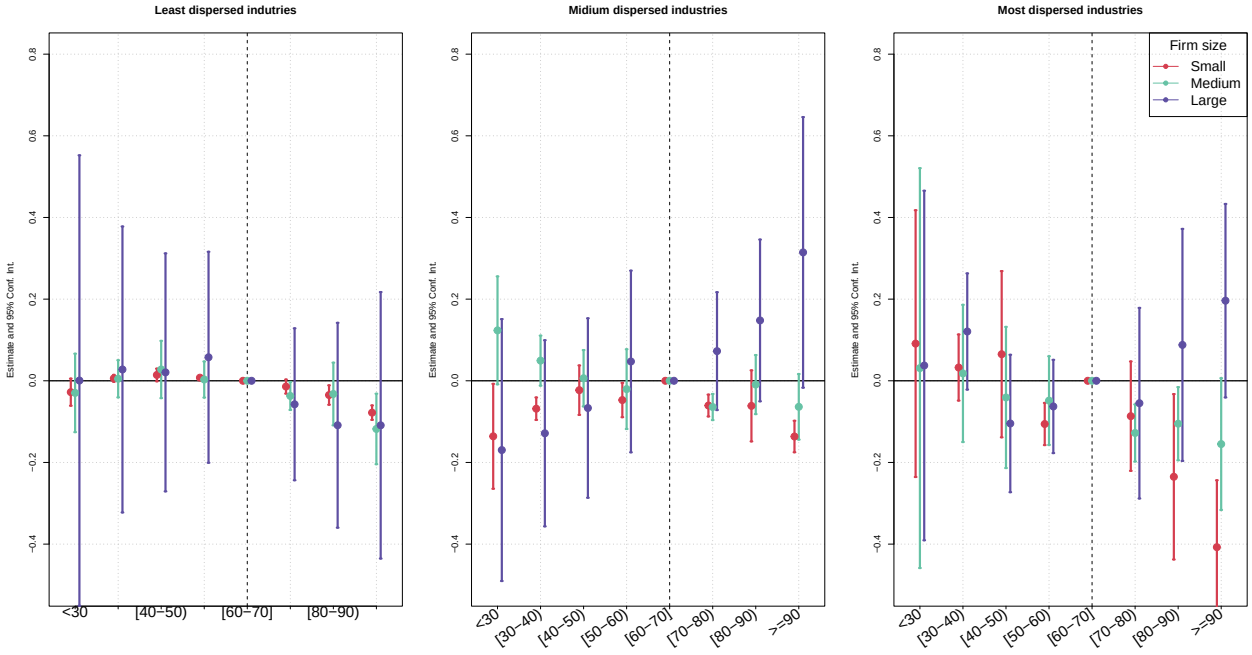
(b) Markup



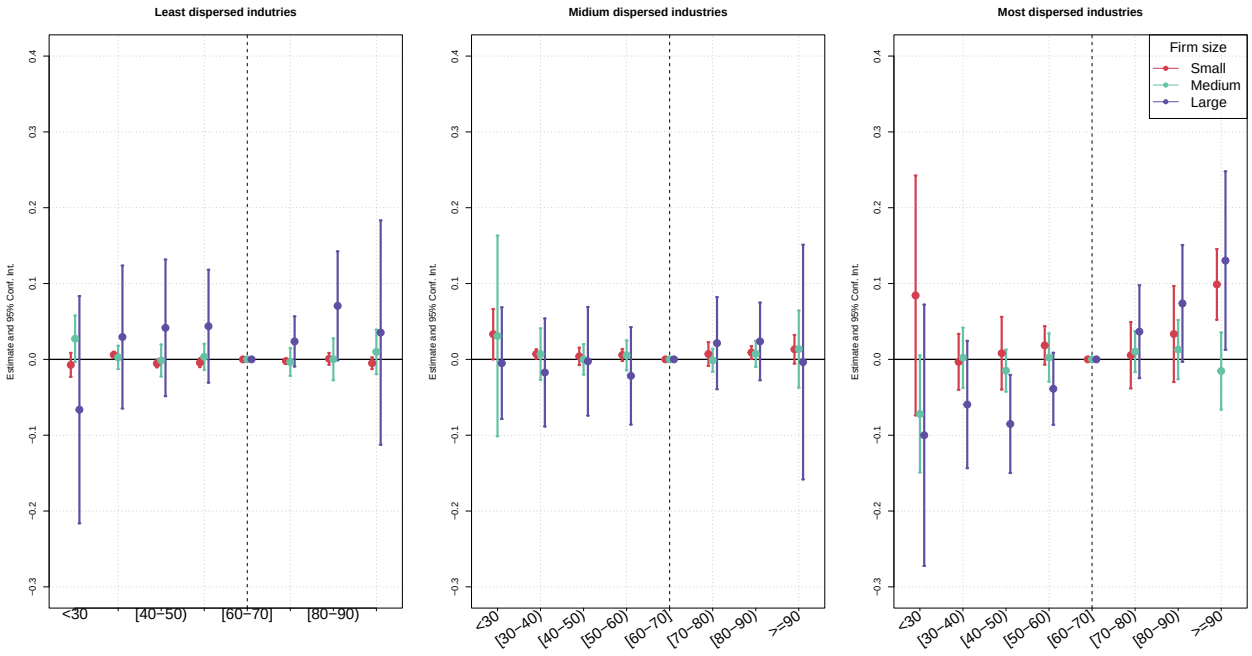
Notes: This figure reports the heterogeneous effects of temperature on firm market share and markup by industry revenue TFP dispersion. The vertical lines show the 95% confidence interval. The standard error is clusters at the country level.

Figure E3: Heterogeneity by industry dispersion across firm sizes

(a) Market share



(b) Markup



Notes: The dependent variables for panel (a) and panel (b) are log of market share and log of markup. Country-digit 4 industries are classified into three terciles based on their average revenue TFP dispersion. From left to right, panels show results for the 1st, 2nd, and 3rd tercile of industries based on revenue TFP dispersion. Firms are classified into small, medium, and large size based on their market shares. Firms are categorized as small, medium, or large based on their market shares as of 2000: small firms have market shares below the 80th percentile, medium firms fall between the 80th and 97th percentiles, and large firms have market shares above the 97th percentile. The standard error is clusters at the country level.

Appendix F: Full Model Details

In this section, we present the complete model setup, following Section 7, 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[25]. 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.

F.1 Model Setup[26]

Representative consumer.—The representative consumer maximizes:

$$\sum_{t=0}^{\infty} \beta^t \left(\log C_t - \psi \frac{L_t^{1+\nu}}{1+\nu} \right), \tag{F.12}$$

subject to:

$$C_t + I_t = W_t L_t + R_t K_t + \Pi_t, \tag{F.13}$$

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

The labor supply condition is:

$$\psi C_t L_t^{\nu} = W_t. \tag{F.14}$$

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

$$Y_t = C_t + I_t + X_t \tag{F.15}$$

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

$$Y_t = \left(\int_0^1 y_{jt}^{\frac{\eta-1}{\eta}} dj \right)^{\frac{\eta}{\eta-1}}, \tag{F.16}$$

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

[26] For clearer exposition, we suppress the time subscript t whenever there is no ambiguity.

where $\eta > 1$ is the across-sector elasticity. Prices P_{jt} satisfy:

$$1 = \left(\int_0^1 P_{jt}^{1-\eta} dj \right)^{\frac{1}{1-\eta}}. \tag{F.17}$$

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

$$y_{jt} = \left(\sum_{i=1}^{n_{jt}} y_{ijt}^{\frac{\rho-1}{\rho}} \right)^{\frac{\rho}{\rho-1}}, \tag{F.18}$$

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

Relative prices satisfy:

$$\frac{P_{ijt}}{P_{jt}} = \left(\frac{y_{ijt}}{y_{jt}} \right)^{-\frac{1}{\rho}}, \quad P_{jt} = \left(\sum_{i=1}^{n_{jt}} P_{ijt}^{1-\rho} \right)^{\frac{1}{1-\rho}}. \tag{F.19}$$

Technology.—Firms enter by paying a sunk cost κ 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 ξ.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:

$$R_t k_{ijt} = \alpha \left[\left(\frac{R_t}{\alpha} \right)^{\alpha} \left(\frac{W_t}{1-\alpha} \right)^{1-\alpha} \right] v_{ijt} \tag{F.20}$$

$$W_t l_{ijt} = (1-\alpha) \left[\left(\frac{R_t}{\alpha} \right)^{\alpha} \left(\frac{W_t}{1-\alpha} \right)^{1-\alpha} \right] v_{ijt}, \tag{F.21}$$

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

$$v_{ijt} = \phi \left\{ \frac{(R_t/\alpha)^{\alpha} (W_t/(1-\alpha))^{1-\alpha}}{\Omega_t} \right\}^{-\theta} \frac{y_{ijt}}{\varphi_{ijt}} \tag{F.22}$$

$$x_{ijt} = (1-\phi) \left(\frac{1}{\Omega_t} \right)^{-\theta} \frac{y_{ijt}}{\varphi_{ijt}}, \tag{F.23}$$

where Ω_t is the input cost index:

$$\Omega_t = \left\{ \phi \left[\left(\frac{R_t}{\alpha} \right)^{\alpha} \left(\frac{W_t}{1-\alpha} \right)^{1-\alpha} \right]^{1-\theta} + (1-\phi) \right\}^{\frac{1}{1-\theta}}. \tag{F.24}$$

Marginal cost.—Marginal cost includes a climate cost shifter $\gamma(T_t)$:

$$MC_{ijt} = \gamma_{ij}(T_t) \frac{\Omega_t}{\varphi_{ijt}}. \tag{F.25}$$

Profits.—Firm i's profits are:

$$\pi_{ijt} = P_{ijt} y_{ijt} - MC_{ijt} y_{ijt}. \tag{F.26}$$

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

$$P_{ijt} = \mu_{ijt} \cdot MC_{ijt}, \quad \mu_{ijt} = \frac{\varepsilon_{ijt}}{\varepsilon_{ijt} - 1}, \tag{F.27}$$

profit maximization under Cournot competition[27] gives the firm-specific elasticity of demand as a decreasing function of market share:

$$\varepsilon_{ijt} = \left[\frac{1}{\rho}(1 - s_{ijt}) + \frac{1}{\eta} s_{ijt} \right]^{-1}. \tag{F.28}$$

From the CES aggregator within-sectors (eq F.18), market share can be expressed as:

$$s_{ijt} = \frac{(P_{ijt})^{1-\rho}}{\sum_{k=1}^{n_{ijt}} (P_{ikt})^{1-\rho}} = \left(\frac{P_{ijt}}{P_{jt}} \right)^{1-\rho} \tag{F.29}$$

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

$$\mu_{ijt} = \frac{1}{1 - \left[\frac{1}{\rho}(1 - s_{ijt}) + \frac{1}{\eta} s_{ijt} \right]} \tag{F.30}$$

and market share as a function of markup

$$s_{ijt} = \frac{\mu_{ijt}^{1-\rho} \varphi_{ijt}^{\rho-1}}{\sum_{i=1}^{n_{jt}} \mu_{ijt}^{1-\rho} \varphi_{ijt}^{\rho-1}} \tag{F.31}$$

Given a productivity distribution for sector j, equations F.30 and F.31 form a system of $2n_{jt}$ equations that can allow us to solve for industry equilibrium market shares and markup.

TFPR.— Firm TFPR by definition is

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

$$\text{TFPR}_{ijt} \equiv \frac{P_{ijt}\, y_{ijt}}{F(\ell,k,x)} = \mu_{ijt} \times \Omega_t, \tag{F.32}$$

where μ_{ijt} is the firm-specific markup and Ω_t is an aggregate cost index capturing wages and input prices. Because Ω_t is *common* to all firms at time t, cross-firm differences in TFPR stem from differences in markups μ_{ijt}. In other words, heterogeneity in TFPR reflects heterogeneity in market power (i.e. markups), rather than purely physical efficiency. [28] Furthermore, dispersion of TFPR therefore reflects the markup dispersion and negatively correlates with Aggregate TFP.

Revenue.— Labor Shares.— Combining a firm's labor demand from equations F.21 and F.22 with markup pricing F.27, a firm's labor share can be written as

$$\frac{W_t l_{ijt}}{p_{jt} y_{jt}} = \frac{(1-\alpha)\zeta_t}{\mu_{ijt}} \tag{F.33}$$

where ζ_t denotes the elasticity of output with respect to value-added,

$$\zeta_t = \frac{[\phi/(1-\phi)]\left\{(R_t/\alpha)^{\alpha}\left[W_t/(1-\alpha)\right]^{1-\alpha}\right\}^{1-\theta}}{1+[\phi/(1-\phi)]\left\{(R_t/\alpha)^{\alpha}\left[W_t/(1-\alpha)\right]^{1-\alpha}\right\}^{1-\theta}}. \tag{F.34}$$

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 μ_{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

$$y_{jt} = \varphi_{jt} F\left(k_{jt}, l_{jt}, x_{jt}\right) \tag{F.35}$$

where

$$F(k,l,x) = \left[\phi^{1/\theta}\left(k^{1-\alpha}\right)^{(\theta-1)/\theta} + (1-\phi)^{1/\theta}\left(x^{(\theta-1)/\theta}\right)\right]^{\theta/(\theta-1)} \tag{F.36}$$

and where sector-level productivity satisfies

Sectoral productivity φ_{jt} by definition of production function:

$$\varphi_{jt} = \left(\sum_{i}^{n_{jt}} \frac{q_{ijt}}{\varphi_{ijt}}\right)^{-1}. \tag{F.37}$$

[28] Under this definition, a firm can have *lower* TFPQ (physical productivity) but still see *higher* TFPR if its markup μ_{ijt} grows large enough to outweigh any shifts in Ω_t. The aggregate cost index Ω_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:

$$q_{ijt} = \frac{y_{ijt}}{y_{jt}} \tag{F.38}$$

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

$$s_{ijt} = q_{ijt}^{\frac{\rho-1}{\rho}} \tag{F.39}$$

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

$$\frac{W_t L_{jt}}{p_{jt} y_{jt}} = \frac{(1-\alpha)\zeta_t}{\mu_{jt}}. \tag{F.40}$$

Combining the sector-level labor share with its firm-level counterpart (eq F.33), we can write the sales share of firm i in sector s as

$$\frac{p_{ijt} y_{ijt}}{p_{jt} y_{jt}} = \frac{\mu_{ijt}}{\mu_{jt}} \times \frac{l_{ijt}}{l_{jt}}. \tag{F.41}$$

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:

$$\mu_{jt} = \left(\sum_{i=1}^{n_{jt}} \frac{1}{\mu_{ijt}} s_{ijt} \right)^{-1}. \tag{F.42}$$

From either of these and the expression for sector-level productivity φ_{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:

$$\mathscr{M}_t = \left(\int_0^1 \frac{1}{\mu_{jt}} s_{jt} \, dj \right)^{-1}. \tag{F.43}$$

Markup Dispersion and Productivity.— To see how markup dispersion affects productivity, observe from equation F.16 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

$$q_{ijt} = \left(\frac{\mu_{jt}}{\mathscr{M}_t} \frac{\varphi_t}{\varphi_{jt}} \right)^{-\eta}. \tag{F.44}$$

Equation F.44 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 19 and F.44, we have the sectoral productivity φ_{jt} accounted for markup dispersion:

$$\varphi_{jt} = \left(\sum_{i=1}^{n_{jt}} \left(\frac{\mu_{ijt}}{\mu_{jt}} \right)^{-\rho} \varphi_{ijt}^{\rho-1} \right)^{\frac{1}{\rho-1}}. \tag{F.45}$$

Similarly, aggregate productivity is then:

$$\varphi_t = \left(\int_0^1 \left(\frac{\mu_{jt}}{\mathscr{M}_t} \right)^{-\eta} \varphi_{jt}^{\eta-1} dj \right)^{\frac{1}{\eta-1}}. \tag{F.46}$$

Entry and Exit.—Firms enter by paying a sunk cost κ 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 δ 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 κW_t and draw productivity δ_{ijt} from $G(\delta)$. The free-entry condition is:

$$\kappa W_t = \beta \mathbb{E} \sum_{j=1}^{\infty} (1-\delta)^{j-1} \frac{C_t}{c_{t+j}} \pi_{ijt}. \tag{F.47}$$

F.2 Equilibrium

Given an initial mass of firms $n_j 0$ 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,

$$L_t = \int_0^1 [\sum_i^{n_{jt}} l_{ijt}]\, dj + \kappa M \tag{F.48}$$

$$K_t = \int_0^1 [\sum_i^{n_{jt}} k_{ijt}]\, dj \tag{F.49}$$

$$X_t = \int_0^1 [\sum_i^{n_{jt}} x_{ijt}]\, dj \tag{F.50}$$

Note that κM denotes labor used in the entry of new firms.

F.3 Consumption-equivalent Welfare

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

$$U(C,L) = \frac{C^{1-\sigma}}{1-\sigma} - \frac{L^{1+\nu}}{1+\nu} \tag{F.51}$$

Suppose also that labor is the only factor of production and that there is a representative firm with production function $Y =$. Markups distort allocations by reducing aggregate productivity φ 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

$$L = \mathscr{M}^{-\frac{1}{\sigma+\nu}} \varphi^{\frac{1-\sigma}{\sigma+\nu}}, \quad C = \mathscr{M}^{-\frac{\sigma}{\sigma+\nu}} \varphi^{\frac{1+\nu}{\sigma+\nu}}. \tag{F.52}$$

The associated level of utility is

$$U(C,L) = \left(\frac{1}{1-\sigma} - \frac{1}{1+\nu}\right) \mathscr{M}^{-\frac{\sigma}{\sigma+\nu}} \varphi^{\frac{(1+\nu)(1-\sigma)}{\sigma+\nu}}. \tag{F.53}$$

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

$$\mathscr{W} = \left(1 - \frac{1-\sigma}{1+\nu}\mathscr{M}\right)^{\frac{1}{1-\sigma}} \mathscr{M}^{-\frac{\sigma}{\sigma+\nu}} \varphi^{\frac{1+\nu}{\sigma+\nu}}. \tag{F.54}$$

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

$$\mathscr{W}_{CC} = \left(1 - \frac{1-\sigma}{1+\nu}\mathscr{M}_{CC}\right)^{\frac{1}{1-\sigma}} \mathscr{M}_{CC}{}^{-\frac{\sigma}{\sigma+\nu}} \varphi_{CC}{}^{\frac{1+\nu}{\sigma+\nu}}. \tag{F.55}$$

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

$$\frac{\mathscr{W}_{CC}}{\mathscr{W}} = \left(\frac{\left(1 - \frac{1-\sigma}{1+\nu}\mathscr{M}_{CC}\right)}{\left(1 - \frac{1-\sigma}{1+\nu}\mathscr{M}\right)} \right)^{\frac{1}{1-\sigma}} \left(\frac{\varphi_{CC}}{\varphi} \right)^{\frac{1+\nu}{\sigma+\nu}} \left(\frac{\mathscr{M}_{CC}}{\mathscr{M}} \right)^{-\frac{\sigma}{\sigma+\nu}}. \tag{F.56}$$

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

$$\frac{\mathscr{W}_{CC}}{\mathscr{W}} = \left(\frac{\varphi_{CC}}{\varphi} \right) \left(\frac{\mathscr{M}_{CC}}{\mathscr{M}} \right)^{-\frac{1}{1+\nu}}. \tag{F.57}$$

The lower the new aggregate TFP φ_{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:

$$1 - \frac{\mathscr{W}_{CC}}{\mathscr{W}} = 1 - \left(\frac{\varphi_{CC}}{\varphi} \right) \left(\frac{\mathscr{M}_{CC}}{\mathscr{M}} \right)^{-\frac{1}{1+\nu}}. \tag{F.58}$$

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 φ_{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 γ denotes the elasticity of substitution at the variety level, the markup each firm charges is simply

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

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 due to differential markup changes 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 the dispersion of markups and the degree of misallocation. By 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 aggregate markup.

To illustrate the quantitative implications of these different market structures on the quantification of the climate-induced productivity shock, we can compare the consumption-equivalent welfare losses in each case. As before, we measure welfare losses by the ratio of the distorted consumption level relative to some reference baseline. Under VES, climate change raises the markup dispersion and aggregate markup, lowering aggregate productivity through both a *productivity effect* and a *misallocation effect*, as well as lowering aggregate output and consumption through a higher aggregate markup and higher *labor wedge*. Under CES, welfare losses come from only the *productivity effect*. Formally, let $\mathscr{W}_{\text{CC}}^{\text{CES}}$ be the welfare level (in consumption-equivalent terms) under the CES assumption, and let $\mathscr{W}^{\text{CES}}$ be the corresponding baseline welfare. Then the consumption-equivalent welfare loss due to climate change under CES is

$$1 - \frac{\mathscr{W}_{\text{CC}}^{\text{CES}}}{\mathscr{W}^{\text{CES}}} = 1 - \left(\frac{\varphi_{CC}}{\varphi} \right), \tag{F.59}$$

which depends *only* on the change in aggregate productivity under the climate shock, and not on any change in markups and markup distribution.

By construction, the CES benchmark shuts down the endogenous markup dispersion channel. Hence any additional welfare losses observed in the VES setup are caused by the reallocation of market shares toward firms with higher markups, the corresponding reduction in aggregate productivity, and the resulting increase in the aggregate markup. In this way, the comparison of welfare losses under VES assumption and CES assumption quantifies the importance of incorporating endogenous markups in quantifying the cost of climate change.

Appendix G: Production Function Estimation

Here we introduce an empirical setting where we estimate industry-level production function, industry-level output elasticity of variable input, and firm-level markup.

We follow the specifications in De Loecker and Warzynski (2012) where they use cost-minimization condition to estimate markup.

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

$$Q_{it} = F(X_{it}^1, ..., X_{it}^V, K_{it}; \beta) exp(\omega_{it}) \tag{G.60}$$

where ω_{it} is the productivity.

Then under cost-minimization, we have that

$$L(X_{it}^1 ... X_{it}^V, K_{it}) = \sum_{v=1}^{V} P_{it}^{X^v} X_{it}^v + r_{it} K_{it} + \lambda_{it}(Q_{it} - Q_{it}(\cdot)) \tag{G.61}$$

where λ_{it} is the marginal cost of changing output. Under first order condition with respect to variable input X_{it}^v, we have that

$$P_{it}^{X^V} = \lambda_{it} \frac{\partial Q_{it}(\cdot)}{\partial X_{it}^V} \tag{G.62}$$

And given the definition of output elasticity of variable input ($\theta_{it}^{X^V}$), we have

$$\theta_{it}^{X^V} = \underbrace{\frac{\partial Q_{it}(\cdot)}{\partial X_{it}^V} \frac{X_{it}^V}{Q_{it}}}_{\text{Output elas wrt var input}} = \underbrace{\frac{1}{\lambda_{it}}}_{\text{1/MC}} \underbrace{\frac{P_{it}^{X^V} X_{it}^V}{Q_{it}}}_{\text{var exp share}} \tag{G.63}$$

Write equation (G.63) as a function of markup $\mu = \frac{P}{mc}$, we have

$$\theta_{it}^X = \mu_{it} \frac{P_{it}^X X_{it}}{P_{it} Q_{it}} \Longleftrightarrow \mu_{it} = \frac{\theta_{it}^X}{\alpha_{it}^X} \tag{G.64}$$

Using the cost-minimization FOC, we can derive markup as the output elasticity of variable input X (θ_{it}^X) over input X's revenue share(α_{it}^X), which is defined by X's total variable cost over total revenue.

Production Function and Output elasticity Consider the following production function, where Q_{it} is the output of firm i in time t, X_{it}^V is the variable input v, K_{it} is the capital,

$$Q_{it} = F(X_{it}^1, ..., X_{it}^V, K_{it}; \beta) exp(\omega_{it}) \tag{G.65}$$

and the log version

$$q_{it} = f(x_{it}^1, ..., x_{it}^V, k_{it}; \beta) + \omega_{it} + \varepsilon_{it} \tag{G.66}$$

We follow the specification of De Loecker and Warzynski where $f(\cdot)$ to be a translog production function with second order polynomial plus interaction, with labor being the variable inputs and capital being the dynamic input

$$q_{it} = \beta_l l_{it} + \beta_k k_{it} + \beta_{ll} l_{it}^2 + \beta_{kk} k_{it}^2 + \beta_{lk} l_{it} k_{it} \tag{G.67}$$

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

$$\hat{\theta}_{it}^L = \frac{\partial \ln F(\cdot)}{\partial \ln L_{it}} = \frac{\partial f(\cdot)}{\partial l_{it}} = \hat{\beta}_l + 2\hat{\beta}_{ll} l_{it} + \hat{\beta}_{lk} k_{it} \tag{G.68}$$

Markup We estimate the production function coefficients at the NACE Level 2 industry level using the proxy method and two-stage procedure in line with De Loecker and Warzynski (2012). Given the estimated production function coefficients, we can then use the industry production output elasticity and the firm level labor and capital input to calculate firm-level output elasticity, from which we can then calculate markup.

From (G.64) , we have:

$$\hat{\mu}_{it} = \hat{\theta}_l \cdot \frac{P_{it} Q_{it}}{W_{it} L_{it}} \tag{G.69}$$

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 ε. The second step uses moments conditions to estimate the β coefficients.

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:

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

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

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

First-stage error is then

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

and Productivity can be expressed as a function of β'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 ξ_{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 solved for, we can then derive firm-level productivity $\hat{i}$ and output elasticity $\hat{\theta}_l$ and $\hat{\theta}_k$. Under ACF procedure, observed output($\tilde{Q}$) should be corrected by measurement errors derived in the first stage: $Q_{it} = \frac{\tilde{Q}_{it}}{\exp(\varepsilon_{it})}$. We then use this correction when calculating markups from input cost shares.

Implication of data limitations and estimation assumption As pointed out by De Ridder et al. (2022), although quantity data is the most optimal for production function estimation and getting the level of aggregate markup right, revenue data can suffice for analysis that focuses on the dispersion of markup and the trend of markup over time, as revenue-based markup still correlates with key variables such as market shares. Given our paper's focus on the mechanism behind the change in markups overtime and across firms, we believe using the revenue data to estimate markup is appropriate for our study.

Appendix H: Additional Figures and Tables

Table H4: Distribution of daily maximum temperature by Year

Year	[<30F]	[30-40F]	[40-50F]	[50-60F]	[60-70F]	[70-80F]	[80-90F]	[>90F]
2000	3.4	38.6	42.0	83.6	82.0	66.6	40.0	9.7
2001	5.5	44.3	44.1	73.0	78.5	68.6	40.8	10.2
2002	4.3	33.3	38.4	85.5	89.3	71.6	35.7	7.0
2003	5.6	41.1	46.9	71.9	70.4	58.1	47.3	23.7
2004	4.4	19.4	53.1	82.4	80.9	67.6	49.0	9.3
2005	6.0	26.4	51.1	66.4	80.3	74.7	47.2	12.9
2006	5.8	22.1	48.3	69.8	79.3	74.5	48.4	16.8
2007	3.7	15.1	45.3	86.2	87.3	77.1	40.6	9.7
2008	2.3	17.8	53.2	87.4	87.4	68.3	39.3	10.1
2009	7.5	23.2	46.1	74.5	78.0	73.1	47.9	14.6
2010	12.8	31.7	49.9	72.9	76.9	67.5	41.9	11.4
2011	4.0	17.4	44.8	75.3	84.3	77.9	50.1	11.3
2012	9.8	19.4	46.5	82.8	82.5	64.9	44.0	16.2
2013	6.4	24.5	61.4	75.5	74.5	66.6	43.7	12.4
2014	3.4	12.3	43.7	79.6	89.7	84.4	44.2	7.7
2015	1.8	15.3	46.2	80.6	86.2	66.6	44.9	23.3
2016	3.0	13.7	47.8	85.2	79.9	68.2	51.1	17.2
2017	3.7	17.5	43.6	71.9	79.5	70.8	54.7	23.3
2018	4.1	17.9	45.2	73.8	68.5	74.6	62.5	18.3
2019	2.0	12.1	40.6	81.6	86.4	64.1	56.7	21.3
2020	0.8	11.6	42.1	82.0	87.1	70.8	52.5	19.3

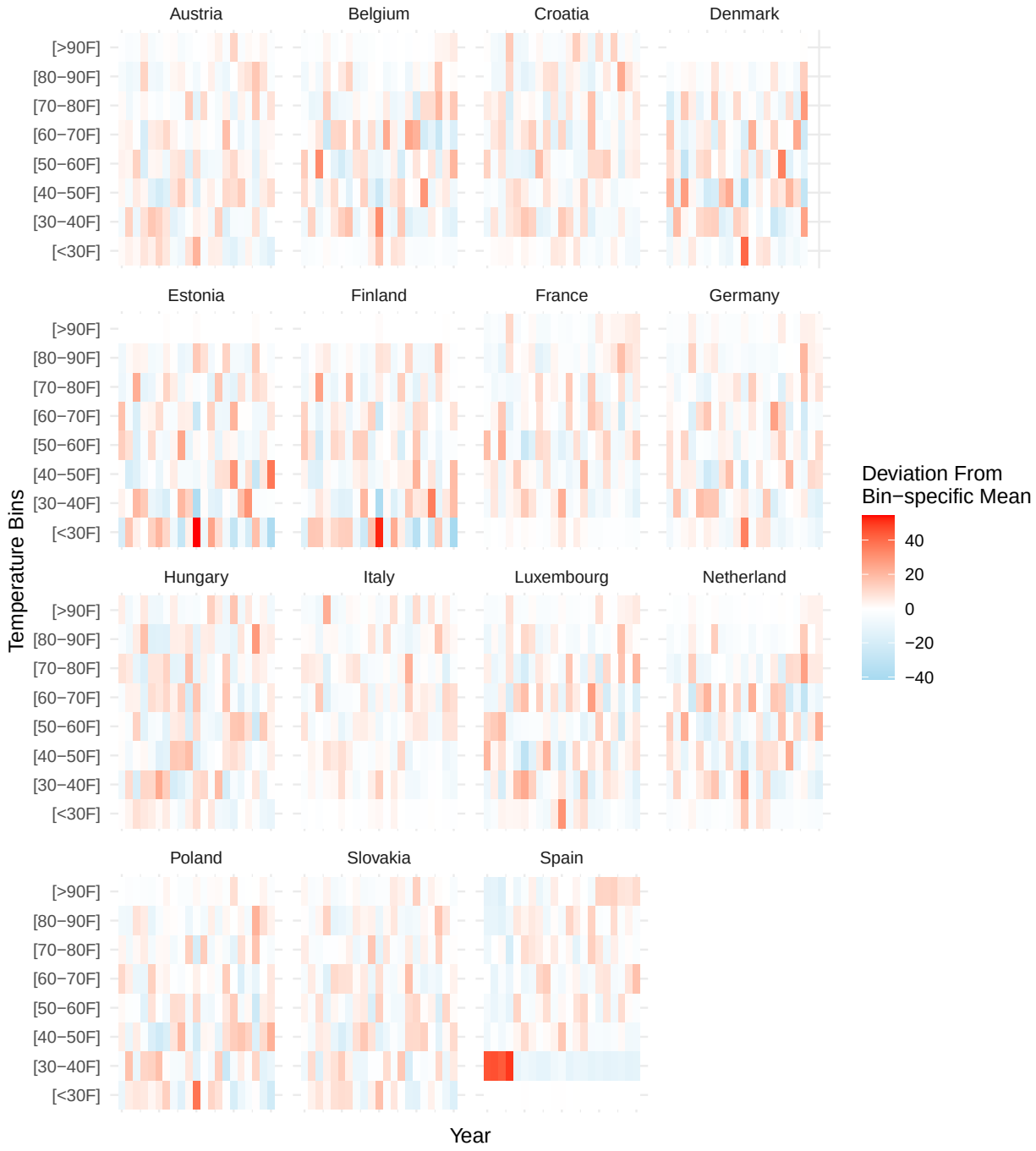
Note: Each cell shows the average number of days in a year in which a location experience daily maximum temperature within that bin.

Table H5: Distribution of daily maximum temperature by Countries

Country	[<30F]	[30-40F]	[40-50F]	[50-60F]	[60-70F]	[70-80F]	[80-90F]	[>90F]	Avg Temp[F]
Spain	0.1	13.5	26.0	76.4	85.9	73.5	60.4	29.3	60.8
Italy	1.8	14.2	49.2	77.3	75.2	71.3	61.8	14.5	59.6
Croatia	7.0	28.8	50.0	70.4	71.0	72.2	53.5	12.3	55.6
France	2.8	20.9	57.4	86.4	86.3	73.0	32.5	6.0	54.3
Hungary	14.5	44.1	55.1	55.5	60.8	71.1	51.2	13.1	52.8
Netherland	3.7	28.2	81.0	84.0	98.0	55.8	13.1	1.5	52.1
Belgium	3.5	28.3	76.8	84.0	92.3	61.3	16.6	2.4	51.8
Germany	13.1	46.4	72.3	69.6	78.6	60.1	21.8	3.3	50.3
Slovakia	20.6	54.1	59.6	57.5	64.2	65.0	37.2	7.1	50.0
Poland	22.4	54.6	66.2	58.8	68.9	63.0	28.2	3.2	49.6
Luxembourg	9.7	46.2	75.1	68.6	81.7	58.9	20.9	4.0	48.8
Denmark	12.0	55.5	86.3	74.9	88.8	41.8	6.0	0.0	48.7
Austria	16.9	50.7	66.2	63.7	68.8	60.6	33.1	5.4	48.5
Estonia	44.6	78.5	61.4	53.2	73.1	43.9	10.4	0.2	44.1
Finland	65.7	76.9	56.9	56.1	65.0	36.9	7.6	0.1	41.9

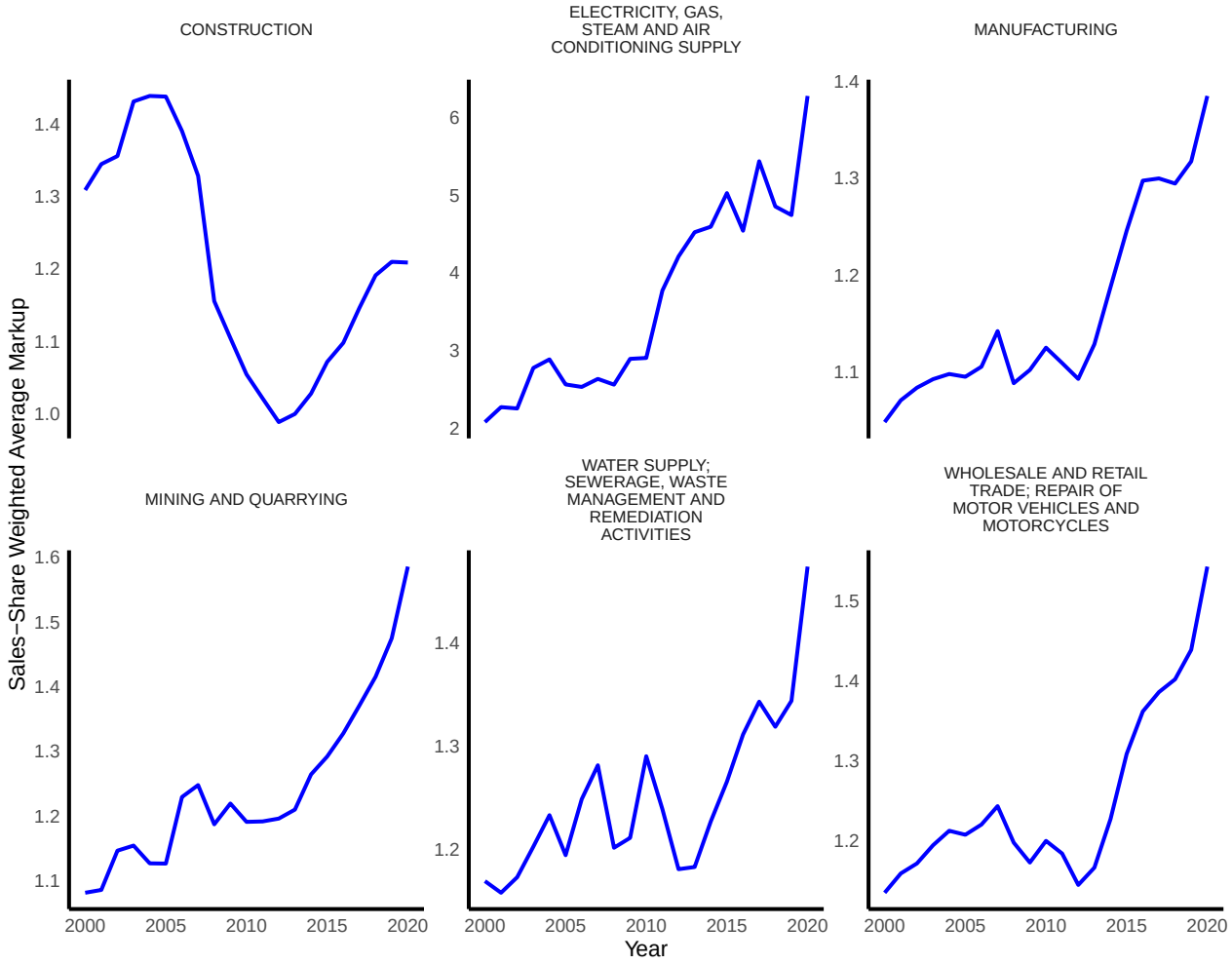
Note: Bin variables represent the sample average number of days in a year in which a location in that country experience daily maximum temperature within that bin. The last column is the sample average temperature for each country in Fahrenheit

Figure H4: Change in daily maximum bin distribution over time



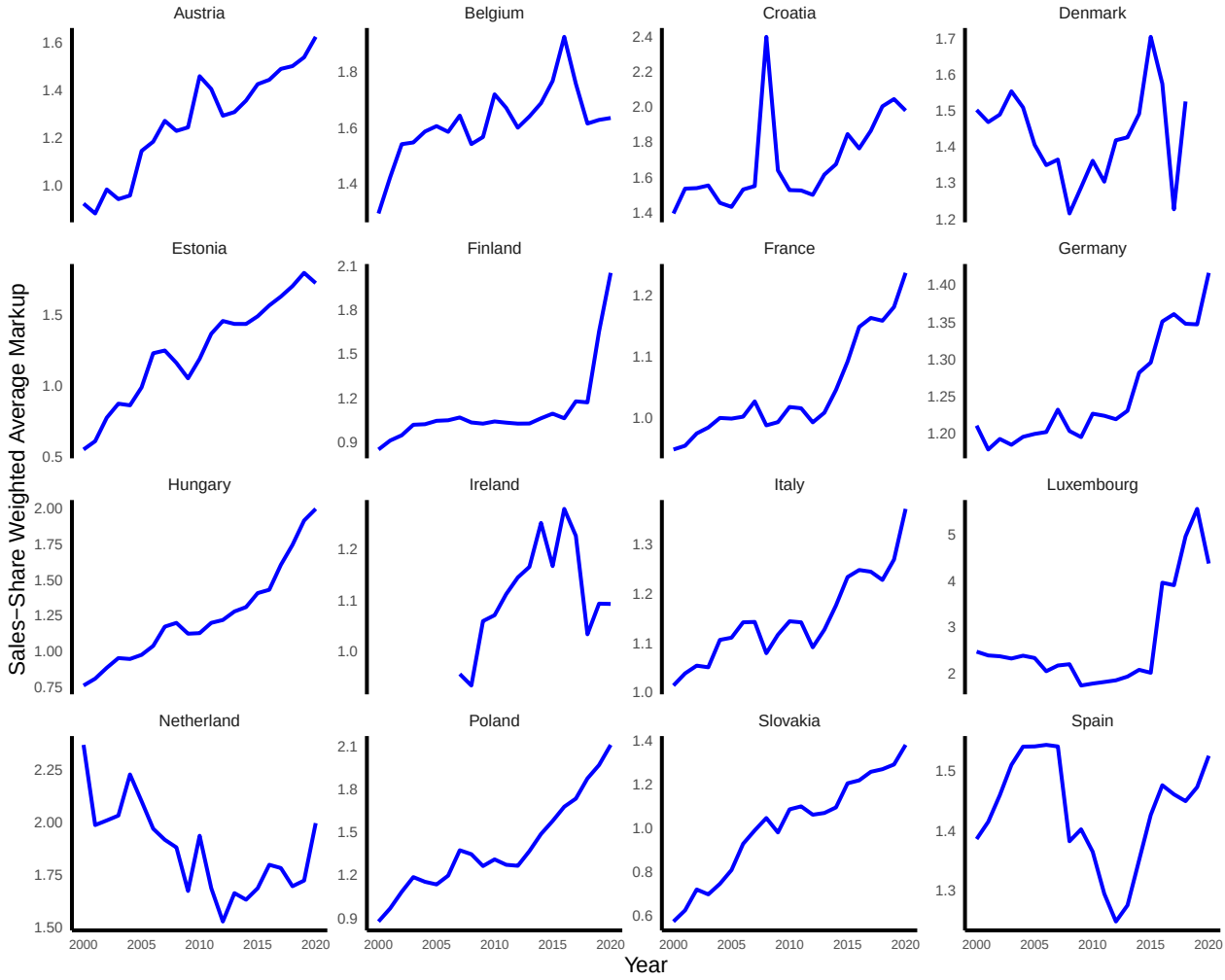
Notes: This figure shows the change in values within each daily maximum bin temperature bins, for each country in our sample. Each row represent a temperature bin, while each column represents a year. The cell value is the deviation from bin-specific mean across sample periods. The change in bin values within each row from left to right can be interpreted as the change in temperature distribution observed in our sample.

Figure H5: Aggregate Markup Trend by Sector



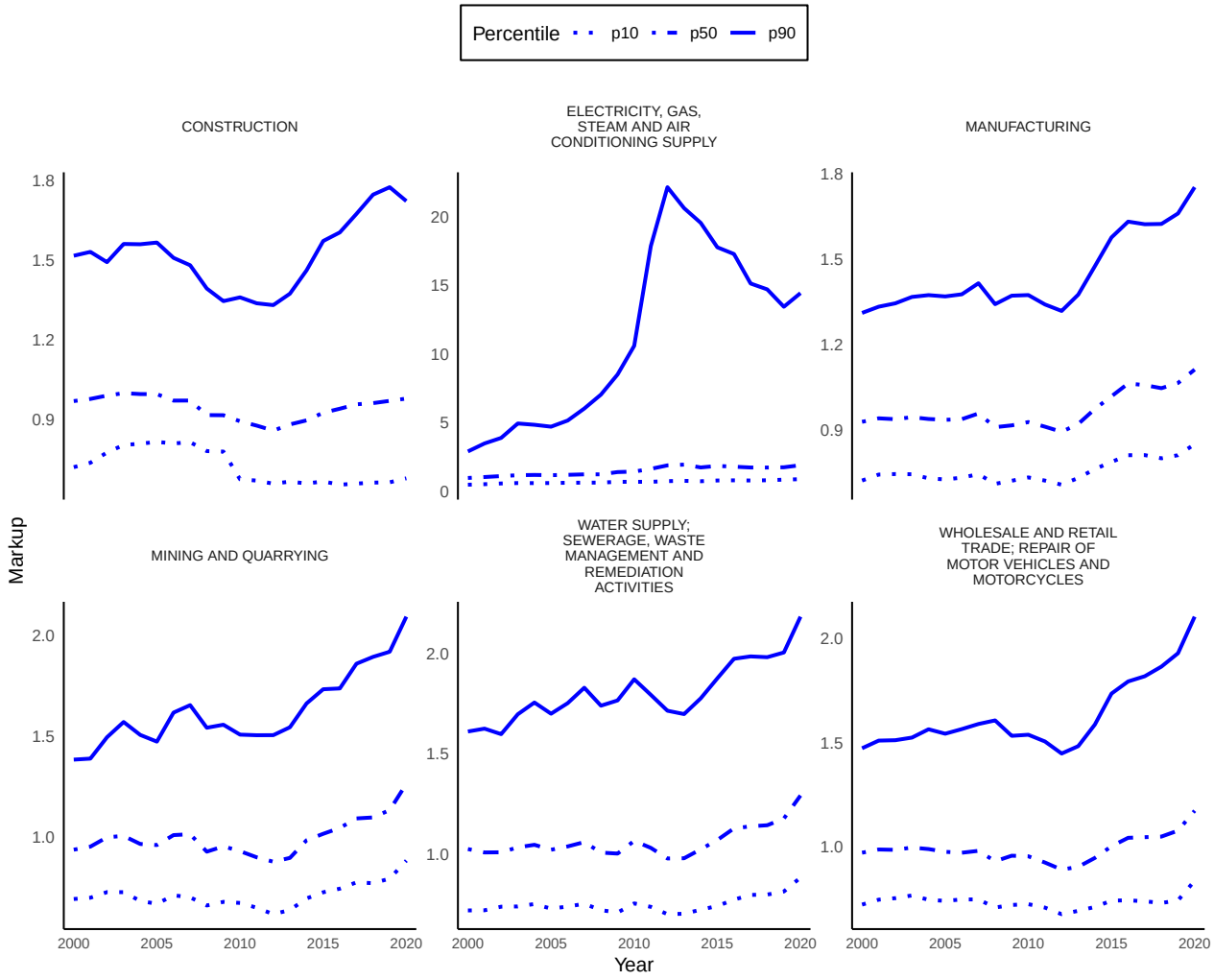
Notes: This figure shows the change in aggregate markup, for each NACE 1-digit sector. Aggregate markup is calculated by the sales-share weighted average of firm-level markup in each year, winsorized at 1 %.

Figure H6: Aggregate Markup Trend by Countries



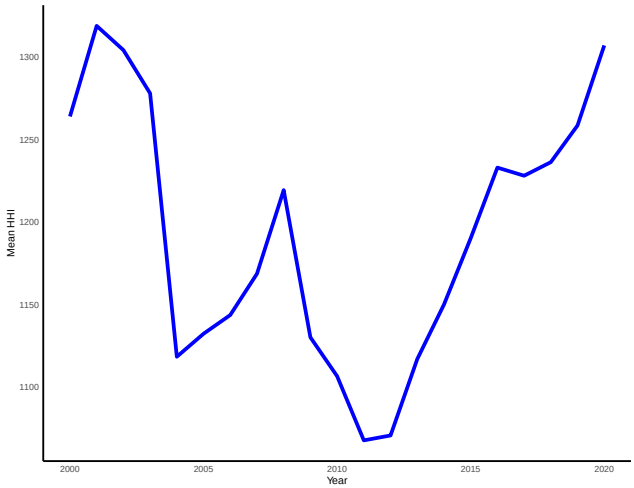
Notes: This figure shows the change in aggregate markup, for each country in our sample. Aggregate markup is calculated by the sales-share weighted average of firm-level markup in each year, winsorized at 1 %.

Figure H7: Markup Percentile over time



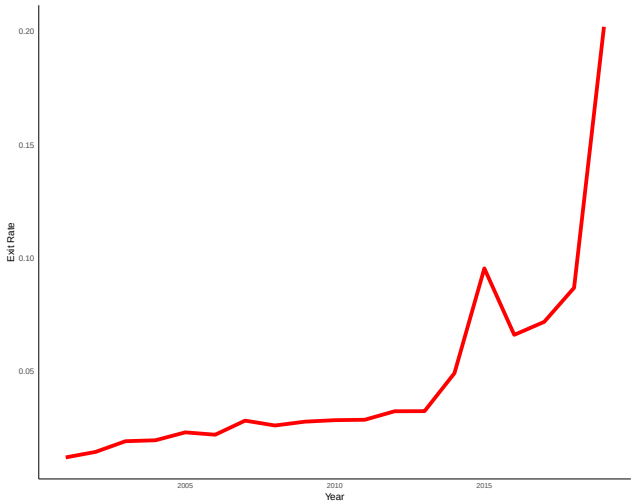
Notes: This figure shows the change in the dispersion of markup distribution, for each NACE 1-digit Sector. For each year, we group firms into percentile based on their markup in that year. In this figure, we plot the time series of markup for firms in 10-percentile, 50 percentile, and 90 percentile of the yearly markup distribution.

Figure H8: Concentration Trend in our EU sample



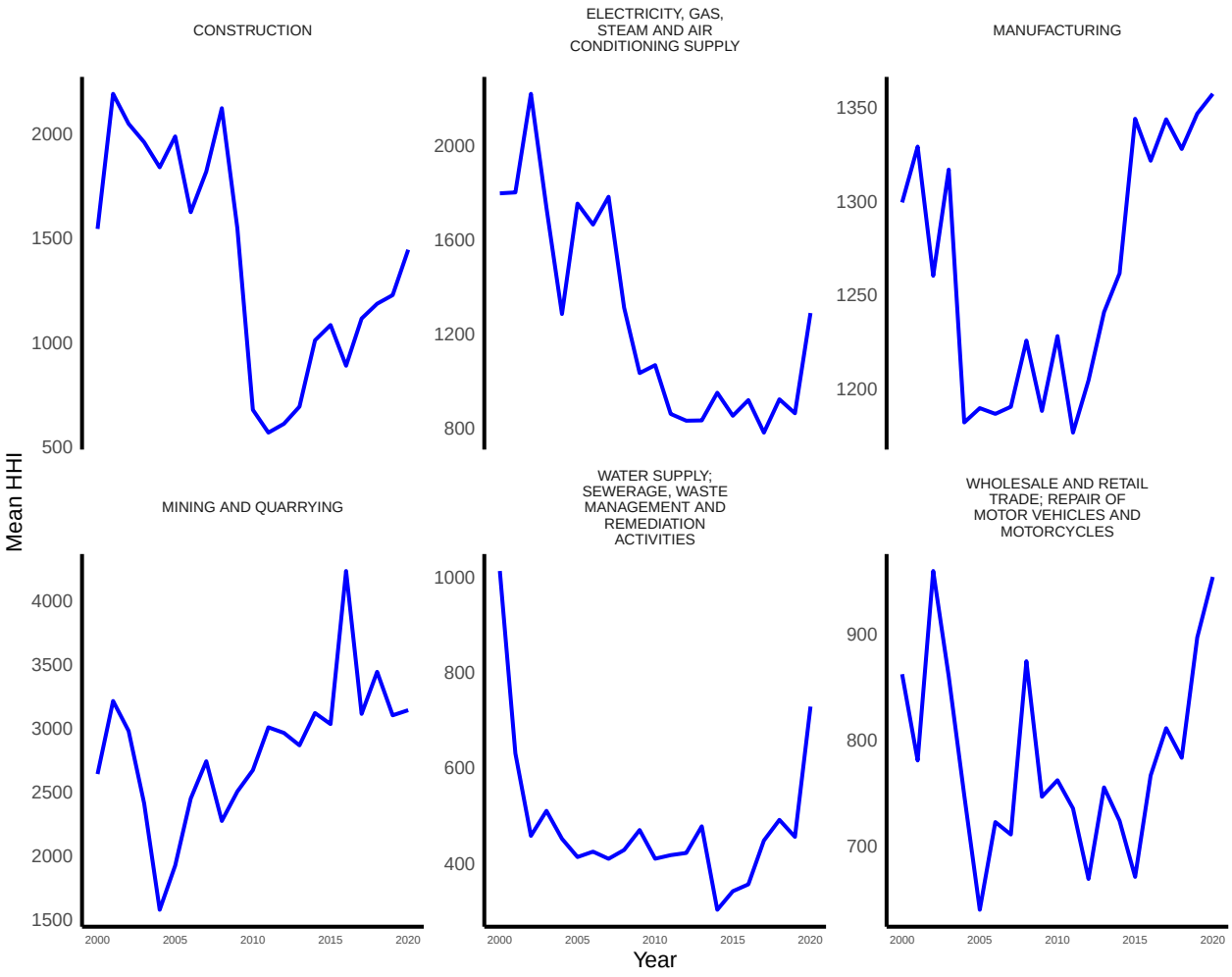
Notes: This figure shows the change in HHI index for the mean 4-digit industries in EU using the Orbis data. It is similar to Figure 14 in Bajgar et al. (2019).

Figure H9: Trend of Industry Exit Rates



Notes: This figure shows the mean exit rates for each year. Markets is defined as the same as in our industry analysis - country by 4-digit industries. We exclude the first and last year to exclude selection into data sample that contaminate exit.

Figure H10: Mean HHI by sectors



Notes: This figure shows the change in HHI index for the mean 4-digit industries in each sector in EU using the Orbis data.

Table H6: Relationship between Firm Markup and Market Share

Dependent Variable:	1/markup
Model:	(1)
Variables	
Constant	1.041^{***}
	(5.85×10^{-5})
market share	-0.1608^{***}
	(0.0015)
Fit statistics	
Observations	26,904,044

Notes: Market shares are calculated within each country by industry (NACE 4 digit) cell each year. Industry $\times$ Year fixed effect is included to control for industry-specific demand shock or macroeconomic shock. Firm fixed effects are also included to control for time-invariant component of demand. Standard errors (in parentheses) are clustered at the country $\times$ industry level.

Table H7: Calibration of shock parameters

Targets/Parameters	value
Firm Productivity Target	-0.1
Industry Dispersion Target	2.1
Parameter (a)	1.0991e-14
Elasticity Parameter (b)	30.4733

Notes: This table shows the calibration result corresponding to Equation 27. The first two rows summarize our shock calibration targets, which help pin down the overall level and heterogeneity of the climate-induced productivity shock. Row three and four shows the result of our calibrated parameters.