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Abstract

We study how extreme (high) temperatures affect firm dynamics—entry, exit, and aggregate productivity—in Chinese manufacturing sectors. Existing studies focus on the effects on incumbent firms (intensive margin), while we examine the effects on entry and exit (extensive margin), and their relationship with the aggregate productivity. Extreme temperatures lower the productivity of incumbent firms (productivity effects), while selecting firms with higher productivity to survive (selection effect). Exploiting a unique data set on the registration information of the universe of firms allows us to document this novel general equilibrium mechanism, whereby resources released by eliminated low-productivity firms are reallocated to firms with higher productivity. Thus, the combined effects on aggregate productivity are muted, a finding that differs from the consensus in the literature that extreme (high) temperatures worsen productivity and economic outcomes. We quantify these effects using a heterogeneous firm framework a la Melitz (2003). The results shed light on the importance of firm dynamics in stipulating climate policies.

JEL Classification: C15, D21, D22, E23, Q56

Keywords: extreme (high) temperature, climate policy, firm dynamics, productivity effect, selection effect, productivity

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1 Introduction

Global warming and associated climate policies are a central issue for policymakers since high temperatures hurt firm productivity. However, the policy implications may differ when productivity is measured at different, individual or aggregate, levels. In this paper, we provide the first empirical analysis in the literature of how extreme temperatures affect firm dynamics, including entry, exit, and aggregate productivity. While the existing research on the effects of temperature on firms focuses on incumbent firms (Chen and Yang, 2019; Zhang et al., 2018), which correspond to the intensive margin, we examine the effects on entry and exit, which correspond to the extensive margin, and how those effects contribute to aggregate productivity. Supporting the existing literature that suggests that extreme high temperatures might harm incumbent firms' productivity (*productivity effects*), we contribute by arguing that such high temperatures have *selection effects*, leaving firms with higher productivity in the market, while driving firms with lower productivity out of the market. Thus, the distribution of surviving firms shifts rightward, leading to an increase in aggregate productivity. The combined effects (the negative productivity effect and the positive selection effect) on aggregate productivity are not definitely negative.

We reevaluate the productivity effects of extreme high temperatures from the perspective of firm dynamics, and argue that climate policy based on the effects of high temperatures on *aggregate productivity* may yield completely different results than policy based on the effects on *individual incumbent productivity.* This paper focuses on Chinese manufacturing, a sector that experienced high-speed productivity growth during the sample period (2001-2012), but it is still comparable to the manufacturing sector in several other developing countries. [1]

Previous studies have focused strictly on the effects of high temperatures on incumbent firms, in part because researchers did not have high-quality data on entry and exit. However, this paper exploits a novel data set that has such information. With these data, we aim to reevaluate the productivity effects of high temperatures. We emphasize the general equilibrium channel, or the selection effect, whereby the resources eliminated by low-productivity firms are reallocated to the surviving high-productivity firms (a channel that is also documented in a recently published paper Xie (2018)[2]). This channel can be considered only by using the unique data that have information on the entry and exit of the universe of firms in China.

Our main contributions are twofold. First, on the empirical side, we document that there is a discrepancy in the effects of high temperatures on productivity at the aggregate level and at the incumbent individual firm level. We attribute such a discrepancy to firm dynamics and heterogeneity and interfirm reallocation. In particular, firm dynamics—firm entry and exit—is a new outcome of interest in the studies of the effects of high temperatures. We separately identify and estimate the productivity effect and the selection effect. Second, on the theoretical/quantitative side, we estimate a heterogenous-firm and firm dynamics model a la Melitz (2003), and quantify the different effects associated with firm dynamics. This is our major distinction compared to Zhang et al. (2018) and Xie (2018), which mainly contain reduced-form empirical analysis.[3]

[1]For a comprehensive discussion, see Appendix C.

[2]In Xie (2018), she focuses on Indonesia, and does not discuss deeply productivity and aggregate productivity. She also does not provide a model for quantitative analysis.

[3]Xie (2018) has a theory appendix a la Melitz (2003), but she does not have a quantitative model and

Throughout this paper, we highlight the importance of the response of ***aggregate*** productivity rather than ***individual*** incumbent productivity. We do so because aggregate productivity is important in its own right: aggregate productivity is closely related to the overall welfare of the entire economy, and its related concept, gross domestic product, is of great interest in the popular media and policymaking processes. Aggregate productivity combines information on incumbent firms and the distribution of all surviving firms. The previous literature focuses mainly on the former, while our paper sheds light on the latter.

In the reduced-form empirical analysis of this paper, which provides the motivation, we regress the entry and exit in a certain city-sector-year cell against the number of days of different temperature intervals in a certain city-year cell. The effects of temperatures are identified from their variations within a city across years after adjusting for covariates and annual shocks common to all the cities. Due to the unpredictability of temperature fluctuations, it is reasonable to presume that this variation is orthogonal to the unobserved determinants of firm dynamics, especially conditional on (high-dimensional) fixed effects.[4] Therefore, we follow the tradition of the literature and use OLS regressions with high-dimensional fixed effects throughout this paper. We find that extreme high temperatures lead to less entry and more exit. The results are robust to different sets of control variables and the inclusion of high-dimensional fixed effects. The results are also robust to non-linear estimation strategies such as Poisson and negative binomial.[5] We further find that the effects are more salient for labor-intensive sectors and sectors with work environments that are more sensitive to temperature. Moreover, we also regress the weighted (and unweighted for robustness checks) average of productivity of individual surviving firms in a specific city-sector-year cell, as a measure of aggregate productivity, against the number of days of different temperature intervals. Such a measure of aggregate productivity is consistent with the literature (Chambers and Pope, 1996; Basu and Fernald, 2002; Duarte and Restuccia, 2010). The result is that extreme high temperatures do not reduce, and actually have very small effects on, aggregate productivity. Such results contrast with the results regarding the productivity effects on incumbent firms, and with the traditional wisdom that extreme temperatures may lower productivity (Chen and Yang, 2019; Seppanen et al., 2006; Zhang et al., 2018; Chen and Yang, 2019; Somanathan et al., 2021).

Regarding mechanisms, we find that the main reason that entry decreases and exit increases is that extreme high temperatures lower the productivity of incumbent firms (measured by TFP (OP, LP, GMM), as proposed by Olley and Pakes, 1996, Levinsohn and Petrin, 2003, Ackerberg et al., 2015, and Yu, 2015;[6] labor productivity (revenue or output divided by employment); and Solow residual[7]), a finding that corroborates the existing research (Zhang et al., 2018; Adhvaryu et al., 2020; Colmer, 2021). This is the productivity effect of extreme high temperatures. In the theoretical model, we propose two mechanisms by which extreme high temperatures may reduce productivity: (1) extreme

analysis.

[4]We use a city-sector-year panel data set in which the identifying variations are at the city-year level. However, our results are still robust when we control for city-year trends, province-year fixed effects, and sector-year fixed effects.

[5]We only report the baseline results with non-linear estimation. Other results, although not reported to keep the paper short, are also mostly robust with non-linear estimation.

[6]All TFP measures are log(TFP).

[7]Due to data limitations, all the productivity measures are related to revenue productivity, not physical productivity.

high temperatures cause worker discomfort, and, thus, reduce productivity (direct productivity effect); and (2) firms have to use more resources to mitigate the harm of extreme high temperatures, which is a non-productive purpose (indirect productivity effect). In addition, we find that extreme high temperatures have heterogeneous effects on entry and exit in terms of firm productivity: they drive firms with lower productivity out of the market. We find that the effects on entry and exit are larger for smaller firms and firms with lower measured productivity, and such a pattern is not sensitive to productivity measures. This is the selection effect of extreme high temperatures. Thus, extreme high temperatures cause a reallocation of resources from low-productivity firms to high-productivity firms. This reallocation channel accounts for the general equilibrium effects of extreme high temperatures. Moreover, firms are both backward- and forward-looking. Their decisions are partly based on the temperatures of the past. In addition, since global warming is a common trend, temperatures in the past can predict those in the future, thus again affecting the decisions of forward-looking firms. In this paper, we build and estimate a firm dynamics model, trying to quantify the importance of these effects. Finally, high temperatures may also lead to general equilibrium feedback effects, whereby the wage rate and the capital rental rate respond to high temperatures. On the empirical side, we control for province-year and sector-year fixed effects to separate out these effects. On the theoretical/quantitative side, we also find such effects are not quantitatively important and do not change any qualitative results. Finally, we rule out several alternative mechanisms, including (1) intersectoral factor reallocation, (2) spatial linkages, (3) input-output linkages, (4) innovation and productivity dynamics, and (5) local demand.

One caveat in interpreting our results is that we use a relatively short sample (of 12 years, 2001-2012[8]) and, thus, cannot perfectly inform policymakers of the long-term scenario, in which firms can flexibly adjust for large fixed costs, such as adapting their technology. However, we also estimate the cumulative or relatively longer-term effects of high temperatures by regressing outcome variables on the average annual number of days in certain temperature bins in the past three to five years. The coefficients are still statistically and economically significant, suggesting that our core mechanisms still exist in a longer time frame. Finally, we exploit a long sample period (1990-2020, 31 years) to examine the effects of high temperatures on entry, exit, and aggregate city-level socioeconomic outcomes.[9] It is arguable that firms can make adaptations more flexibly given such a longer time period. We find that the effects on entry and exit still exist, while null effects on aggregate city outcomes, thus corroborating the above analysis on firm dynamics and aggregate productivity.

In addition, we build a theoretical/quantitative model to rationalize the empirical findings and provide quantitative results. The model is built on Melitz (2003), using a heterogeneous-firm framework.[10] Extreme high temperatures impose a larger flow cost and a fixed cost on firms, leading to a negative productivity effect and a positive selection effect, as the reduced-form analysis suggests. The flow cost, for example, consists of the daily operation of cooling equipment, and the fixed cost, for example, consists of the one-time installation of such equipment. The model can provide theoretical

[8]We use this sample period mainly because of the availability of firm-level data. The results still hold for other sample periods.

[9]We do not have data on productivity in such a sample.

[10]The model is a static model in which firms do not innovate to improve productivity. We assume so because empirically we find that extreme high temperatures do not affect firms' innovation decisions (Table B10) and productivity dynamics (Table B11).

propositions that are all consistent with the empirical findings. Moreover, the quantitative analysis using the model estimates suggests that the effects of extreme high temperatures on aggregate productivity are exaggerated if one overlooks firm dynamics. Thus, our analysis sheds light on the role of firm dynamics in evaluating climate policy. Finally, we make three extensions of the baseline model: (1) size-varying temperature damages; (2) costly factor reallocation; (3) long-run adaptation; and (4) production with capital. The extensions yield the same qualitative implications but different quantitative results. Based on the quantitative analysis, we conduct a back-of-the-envelope cost-benefit analysis. We find that policymakers ought not to base their climate policies simply on the effects of high temperatures on individual incumbent firms. Since aggregate productivity is a better indicator of societal welfare, policymakers should take into consideration the selection effect and aggregate productivity to make better-informed and better-rounded policies. Our model does not embody the following alternative mechanisms, including (1) intersectoral factor reallocation, (2) spatial linkages, (3) input-output linkages, (4) innovation and productivity dynamics, and (5) local demand, since our empirical analysis fails to detect them.

This paper is related to three strands of the literature. First, it speaks directly to the effects of environmental factors on firms, especially on productivity. In Zhang et al. (2018), the paper most closely related to our research, the authors find that extreme high temperatures reduce firm productivity. We build on the results of their paper, further arguing that the effects on aggregate productivity might differ if we take into consideration the effects on entry and exit, which are the extensive margin. This paper is also related to Xie (2018), who finds that climate changes cause reallocation of resources across firms. Compared to Xie (2018), we delve deeper by documenting the discrepancy between the effects of high temperatures on individual incumbent productivity and aggregate productivity, which may stem from the same reallocation mechanism. Our paper is also related to Rudik et al. (2022) and Cruz and Rossi-Hansberg (2024), who find a welfare loss induced by climate change. Comparing with these two papers, our paper provides a more detailed micro-level analysis and focuses on (aggregate) productivity, not total economic output or welfare. Finally, our paper is also related to two recent papers on the effects of high temperatures on firm entry and exit (Cascarano et al., 2022; Li et al., 2023). Comparing with these two papers, our paper delves deeper into the mechanisms of firm dynamics and heterogeneity and aggregate productivity.

More broadly speaking, this paper contributes to the literature on the determinants of productivity (Aw et al., 2008; Syverson, 2011; Topalova and Khandelwal, 2011) and firm dynamics (Jovanovic, 1982; Hopenhayn, 1992; Pavcnik, 2002; Melitz, 2003; Acemoglu et al., 2018; Akcigit et al., 2021). Our paper studies the effects on aggregate productivity through the lens of firm dynamics, hence is related to Foster et al. (2008). Moreover, the selection effect is already mentioned in papers such as Pavcnik (2002) and Melitz (2003). Our paper provides an example of how such a selection channel might be found in environmental economics. Moreover, this paper employs a heterogeneous-firm framework used extensively in the trade literature to analyze the impact of an environmental factor and, thus, speaks to Shapiro and Walker (2018) and Shapiro (2021).

Our findings also shed light on the various consequences of extreme temperatures. Extreme temperatures can raise the mortality rate (Barreca et al., 2016; Deschenes and Moretti, 2009; Deschênes and Greenstone, 2011; Yu et al., 2019) and the hospital admissions rate (White, 2017; Karlsson and

Ziebarth, 2018; Agarwal et al., 2021), increase the risk of mental illness (Obradovich et al., 2018; Mullins and White, 2019) and suicidal behaviors (Burke et al., 2018), impede cognitive performance in both low- and high-stakes exams (Graff Zivin et al., 2018; Garg et al., 2020; Garg et al., 2020; Park et al., 2020; Park, 2020), and reduce the labor supply (Deschenes, 2014; Graff Zivin and Neidell, 2014) as well as agricultural income and nutrition (Deschênes and Greenstone, 2007; Shah and Steinberg, 2017).

The remainder of this paper is organized as follows. Section 2 lays out the conceptual framework that establishes the hypotheses to be tested by empirical analysis and formalized by the model. Section 3 describes the data. Section 4 presents and analyzes the reduced-form descriptive evidence on the relationship between temperatures and firm dynamics and productivity. Section 5 introduces the quantitative model of temperature and firm dynamics. Section 6 discusses the estimation of the model. Section 7 conducts several quantitative exercises and policy experiments. Section 8 concludes the paper.

2 Conceptual Framework

In this section, we lay out a conceptual framework that establishes several hypotheses to be tested by the empirical analysis. We further formalize these hypotheses in Section 5 with a model.

It is a well-established argument that extreme high temperatures reduce labor productivity. They may cause discomfort to workers and, thus, worsen firm performance. Moreover, to combat the negative effects of high temperatures, firms have to devote more inputs to non-productive purposes, such as purchasing cooling equipment. In all, the link between temperature and productivity has been discussed extensively in many papers, especially Zhang et al. (2018), who focus on the case of Chinese manufacturing as we do. Therefore, we have Hypothesis 1.

Hypothesis 1. *(The productivity effect of extreme high temperatures) extreme high temperatures lower the productivity of incumbent firms. There are two causes: (1) high temperatures directly reduce labor productivity, which is the direct productivity effect; and (2) high temperatures induce firms to use more resources to mitigate the damage of high temperatures, which is the indirect productivity effect.*

In this paper, we examine the effects of extreme high temperatures on entry and exit. Due to the above-mentioned productivity effect, we may hypothesize that high temperatures induce less entry and more exit, as firms may find it less profitable to enter and stay in the market because of lower productivity. Moreover, as is illustrated by the quantitative model below, extreme high temperatures may also increase firms' entry cost, since upon entry, firms have to purchase machines and equipment to mitigate the negative effects of high temperatures. Combining the two channels of reducing productivity and increasing entry cost, we have Hypothesis 2.

Hypothesis 2. *Extreme high temperatures induce less entry and more exit.*

Next, we establish several hypotheses regarding the heterogeneous effects of extreme high temperatures. First, the negative effects of high temperatures are more salient for labor-intensive firms, because the reduction in labor productivity is a cause of the negative effects. Second, the negative effects of high temperatures are more salient for low-productivity firms, because these firms are more sensitive to raising entry cost and flow costs to mitigate the effects of high temperatures. Therefore, we have Hypotheses 3 and 4.

Hypothesis 3. *The effects of extreme high temperatures are more pronounced for labor-intensive firms.*

Hypothesis 4. *(The selection effect) The negative effects of extreme high temperatures are more pronounced for low-productivity firms. Extreme high temperatures shift the distribution of surviving firms rightward, leading to an increase in aggregate productivity.*

In this paper, we focus on the effects of extreme high temperatures on aggregate productivity. We do so because aggregate productivity is more closely related to the aggregate resource of the economy and the overall welfare of the society. However, different from the effects on individual incumbent firms' productivity, the effects on aggregate productivity might be muted due to the countervailing productivity effect and selection effect. Therefore, we have Hypothesis 5.

Hypothesis 5. *(The combination of countervailing productivity and selection effects) the effects of extreme high temperatures on aggregate productivity are muted or even positive.*

In the empirical analysis, we can show that all of the above five hypotheses can be supported by the data. The hypotheses can also be rationalized by a model shown below.

3 Data

In the empirical analysis, we use two major data sets: (1) a city-sector-year (balanced) panel data set and (2) a firm-year micro (unbalanced) panel data set. The first data set is compiled using the Chinese firm registration database, while the second data set is compiled using the Annual Survey of Industrial Firms (ASIF).

The main focus of our analysis is firm dynamics in China, especially firm entry and exit, which are calculated using the Chinese firm registry database. This database provides registry information on all firms in China (about 21.368 million firms), including the location, the year it was established, the year of exit (if any), and the value of registry capital.[11] From individual registration records, we can calculate how many firms enter and exit in a specific city-sector-year cell. Note that if the firm simply stops production or relocates but does not deregister, then it is not deemed to exit in our data set. However, we also merge the registration data set with the ASIF data set that has information on production, with a matching rate of 81%. The matched sample is still representative in the sense that the summary statistics of key variables are the same for the entire sample and the matched sample. If we take into account the fact that a firm may stop production and count this case as an exit, the new exit should be 2.24% larger, whereas all of the results on exit still hold. Moreover, this study is concerned only with the industrial sectors in the economy—39 in total. The summary statistics for log(1+entry) and log(1+exit) are shown in Table A1. We use the total number of firms to measure

[11] The registry capital is not the firm's fixed assets. However, according to Chinese Business Law, the registry capital should be proportional to the scale (and the assets) of the firm. During our sample period, the government agency verified the registry capital reported upon registration and made sure that the registry capital would finally be equal to the paid-in capital.

entry and exit, and they are the main outcome variables in the descriptive analysis. The details of the compilation of the data set are discussed in Appendix B.

The registration database has information on the size of each registered firm's registry capital, and, thus, we can calculate entry and exit for larger and smaller firms. Moreover, we link the registration data with the ASIF data to track the productivity of each registered firm. We use TFP (OP, ACF corrected), TFP (LP, ACF corrected), as calculated in Olley and Pakes (1996), Levinsohn and Petrin (2003), and Ackerberg et al. (2015), as two productivity measures.[12] Due to data limitations, we only have data on these measures for the sample period before 2007. In addition, we classify the firms according to whether their performance is above or below average and calculate the entry and exit for each category. These data are used to demonstrate that extreme temperatures have the selection effect, and will be discussed in detail below.

The weather data are obtained from the China National Meteorological Data Service Center (CMDC), part of the National Meteorological Information Center of China. The data set contains consecutive daily weather records of 824 monitoring stations along with their longitudes and latitudes in China. The data report daily maximum, minimum, and mean temperatures. Other weather variables include wind speed, precipitation, relative humidity, sunshine duration, and atmospheric pressure. Following a similar procedure with Agarwal et al. (2021), we transform weather data from station to city level by calculating the mean values of weather variables from all the monitoring stations within each city. As an alternative matching method, we interpolate the weather data from the stations into a $0.1° \times 0.1°$ grid level using the inverse-distance weighting (IDW) method and extract the value of the weather measures based on the boundaries of each city from the gridded data. Our main findings still hold using this matching approach. The details of the matching process of the weather data and the robustness of our results are discussed in Appendix B.

The concentration of PM2.5 is obtained from the Modern-Era Retrospective Analysis for Research and Applications version 2 (MERRA-2) released by the U.S. National Aeronautics and Space Administration (NASA). We aggregate all the grids within each city and calculate their annual mean values. This data set has been widely used in previous studies (Deschenes et al., 2020; Fu et al., 2021), and validated with air pollution data from ground-based monitoring stations in China (Chen et al., 2022).

Following the general practice used in the latest literature (Deschênes and Greenstone, 2011; Zhang et al., 2018), we calculate the number of days falling into each 10°F-wide bin by city and year to allow for substantial flexibility and nonlinear relationships between the firm dynamics and temperature exposure. Specifically, we divide the temperature spectrum into ten bins, with the lowest bin including all temperatures below 10°F and the highest bin including all temperatures above 90°F due to data sparseness at the extremities of the distribution. Figure A1 shows the share of days with extreme high temperatures. Temperatures can also be measured using the Celsius scale, and our results are not sensitive to the different measurement scales. Finally, there are no significant increasing or decreasing trends for the share of days with extreme high temperatures in our sample period.

[12] All TFP measures are log(TFP).

4 Reduced-form Empirical Analysis

4.1 Empirical Strategy

The main specification of the descriptive empirical analysis in this section takes the form of equation (1), which follows the previous literature (Zhang et al., 2018):

$$y_{ijt} = \sum_{group, group \neq 5} \beta_{group} D_{group,it} + X_{ijt}\gamma + \lambda_{ij} + \lambda_t + \lambda_i \times t + \lambda_j \times t + u_{ijt}, \tag{1}$$

where y_{ijt} is the outcome variable, including entry and exit, in city i, sector j, and year t, $D_{group,it}$ is the number of days in the city i and year t that fall into the temperature interval (T$\geq$ 90°F, 80°F$\leq$T<90°F, 70°F$\leq$T<80°F, 60°F$\leq$T<70°F, 40°F$\leq$T<50°F, 30°F$\leq$T<40°F, 20°F$\leq$T<30°F, 10°F$\leq$T<20°F, and T<10°F), with the fifth group 50°F$\leq$T<60°F being excluded as the base group. [13] X_{ijt} is a vector of weather controls, including wind speed, precipitation, sunshine duration, relative humidity, atmospheric pressure, and PM2.5 levels, along with their squared terms. We also estimate the baseline specification (1) with alternative sets of control variables, especially those with plausibly endogenous "bad controls," such as log per capita GDP, log population, and log lagged total sectoral registry capital. Omitting these variables may cause an omitted variable bias, but may also alleviate the issue of correlation between these control variables and the error term. However, it is reassuring that, no matter the choice of control variables, the results remain qualitatively similar. λ_{ij} is city-sector fixed effects; λ_t is year fixed effects; $\lambda_i \times t$ is city-specific linear year trends; $\lambda_j \times t$ is sector-specific linear year trends. For robustness checks, we also control for sector-year fixed effects and province-year fixed effects, and the results remain robust. u_{ijt} is the error term. Standard errors are two-way clustered at the city and sector levels. The statistical significance does not change if we cluster the standard errors at the city or city-by-sector level.

β_{group} are identified from the variations in temperatures within a city-sector across years after adjusting for covariates, annual shocks common to all the cities, as well as city-specific and sector-specific time-varying confounding factors. Due to the unpredictability of temperature fluctuations, it seems reasonable to presume that this variation is orthogonal to the unobserved determinants of firm dynamics. Therefore, we use OLS regressions throughout this paper.

4.2 Baseline Results

Table 1 displays the baseline results. Columns (1) and (2) present a parsimonious specification including temperature exposures, city-sector fixed effects, and year fixed effects. We find a strong negative effect of exposure to high temperatures (T$\geq$ 90°F) on firm entry and a positive effect on firm exit. The pattern continues to hold when weather controls, city-specific year trends, and sector-specific year trends are further added in columns (3) and (4). In addition, we also calculate the standard errors in different ways: (1) two-way cluster at the city and sector levels; (2) cluster at the city level; and (3) cluster at the city-by-sector level. As revealed in Table 2, the statistical significance remains the

[13]Transforming to the Celsius scale, the ten temperature bins are: T$\geq$32.2°F, 26.7°C$\leq$T<32.2°C, 21.1°C$\leq$T<26.7°C, 15.6°C$\leq$T<21.1°C, 10°C$\leq$T<15.6°C, 4.4°C$\leq$T<10°C, -1.1°C$\leq$T<4.4°C, -6.7°C$\leq$T<-1.1°C, -12.2°C$\leq$T<-6.7°C, and T<-12.2°C.

same given different ways of clustering.

Figure 1 plots the estimated results of the preferred specification in columns (3) and (4) of Table 1. Figure 1(a) corresponds to firm entry, while Figure 1(b) corresponds to firm exit. Each figure reveals the estimated coefficients for the ten temperature bins defined in equation (1), together with their 95% confidence intervals. The reference temperature bin is 50-60°F. As revealed in Figure 1(a), high temperatures significantly hinder firm entry. A one-standard-deviation (SD) increase in the number of days with a temperature above 90°F, relative to a day in the 50-60°F range, reduces firm entry by 1.1%. Extreme low temperatures also hinder firm entry, but the effects are less statistically significant. Figure 1(b) further presents the estimated effect on firm exit. We find that high temperatures expedite firm exit. A one SD increase in the number of days with a temperature above 90°F, relative to the reference temperature bin, raises firm exit by 1.6%. Extreme low temperatures do not have significant effects on exit, but more mildly low temperatures have small but negative effects on exit.

For robustness checks, we explore the possibility of adding an alternative set of controls and adding more high-dimensional fixed effects in Table 2, and the results are stable across the board. In particular, the plausibly endogenous control variables, such as the level of economic development and sectoral size, which can be deemed "bad controls," do not alter our main results. Moreover, since we have controlled for province-year fixed effects and sector-year fixed effects, we rule out the case that the general equilibrium responses of wages and prices to high temperatures are the main driver of our main results, as wages and prices can be seen as regional-time specific and sector-time specific, and these variations are already absorbed by the fixed effects. For robustness checks, we use other measures of entry and exit, including log(0.01+entry) and arcsinh(entry), and the results, as reported in Table 3, are qualitatively similar to the baseline results. Moreover, we also employ two nonlinear models, including the Poisson Pseudo Maximum Likelihood (PPML) and the negative binomial model to deal with such count data as the number of entries and exits. The results, in particular the marginal effects, are reported in Table 4. The results are still qualitatively similar. We also replicate all the empirical analysis below with such non-linear estimation strategies. The results are mostly robust, whereas they are not reported to keep the paper short.

As an alternative temperature-location matching method, we interpolate the weather data from the stations into a $0.1° \times 0.1°$ grid level using the IDW method and extract the value of the weather measures based on the boundaries of each city from the gridded data. Interpolating the weather data from stations into the grid level enables us to match the weather data following the exact boundaries for each city. This can help ameliorate concerns about potential measurement errors caused by the imprecise matching radius for some geographically large or small cities when using the IDW method. Using this data set, we re-estimate the baseline specification and report the results in Table A2. The results are qualitatively similar to the previous main results.

Next, we conduct three more robustness checks. First, we use several alternative measures (the definition can be found in table notes) of high temperatures and estimate their effects on entry and exit. The results in Table 5 are still robust. Second, we use the temperature bins of the daily maximum and minimum temperatures as the independent variables. According to Table A3, the results remain robust. Third, we use the Celsius measure of temperatures to measure temperature bins. The results in Table A4 indicate that the main findings are not sensitive to different measures of the temperatures.

Next, we estimate the lag effects of high temperatures on firm dynamics, using lagged temperature bins as the dependent variables. According to Table 6, the effects on entry decay significantly as the time lag increases, whereas the effects on exit are quite stable. This is because firms may not make immediate responses in exit to high temperatures, but this is not the case for entry. Finally, we also estimate the effects on the agriculture and service sectors and report the results in Table A5. The effects on the agriculture and service sectors are still statistically significant, while the effects on the service sectors are larger in magnitude. Such results indicate that our analysis can also be extended to sectors other than the manufacturing sector. However, due to the lack of data on productivity for the agriculture and service sectors, our analysis still mainly focuses on the manufacturing sector in this paper.

4.3 Heterogeneity

Next, we look at the heterogeneous effects of high temperatures on firm dynamics. We first explore the heterogeneity in firm ownership. The results in Table A7 show that the coefficients on "T$\geq$ 90°F" are larger and statistically significant only for private firms. This might be due to the fact that private firms do not receive aid from the government, and thus are more vulnerable to extreme temperatures.

We then examine the heterogeneity in firm size, which is measured using the amount of registry capital. We define a firm as large if its size belongs in the top 10%, as medium if its size belongs in the top 10%-50%, and as small if its size belongs in the bottom 50%, in the corresponding city-sector-year cell. The results are presented in Table 7. In columns (1) through (3), the coefficient on "T$\geq$ 90°F" is the largest for small firms. In columns (4) through (6), the coefficient on "T$\geq$ 90°F" is also the largest for small firms. Such results indicate that extreme high temperatures have a "selection effect" that reduces the entry and increases the exit of small firms, which are typically less productive. Finally, we estimate the effects on firm entry and exit for different size percentiles. According to the results in Table A6, the negative effects on entry and the positive effects on exit are more salient when firms are smaller. For example, the negative effect on the entry of the bottom 10% smallest firms is 1.5 times larger than that of the bottom 50%.

Following Table 7, we further examine the heterogeneity in firm performance. We classify the firms into two categories: revenue/labor above and below the median of the city-sector-year cell. Table 8 displays the results. For both entry and exit, the coefficients on "T$\geq$ 90°F" are larger for firms with worse performance. Such results, again, imply that extreme high temperatures have a "selection effect" on firms: they induce firms with higher productivity to survive and stay in the market, while driving firms with lower productivity out of the market. Moreover, if we classify firms according to alternative measures, such as value added per worker and output per worker, the results remain robust (Table A8). Thus, extreme high temperatures cause a reallocation of resources from low-productivity firms to high-productivity firms. This reallocation channel is the general equilibrium effect of extreme high temperatures. Also, note that in estimating the selection effect, we control for province-year and sector-year fixed effects. Thus, the selection effect is not driven by the responses of wages and prices to high temperatures.

We then focus on sectoral heterogeneity. First, we look at the heterogeneity in the technological intensity of different sectors. We define a sector as either high-tech or non-high-tech, following the same criteria used by the National Bureau of Statistics. [14] We interact a dummy variable, 1(High Tech), with the number of days in different temperature intervals. The results are presented in Table A9. For firm entry, the coefficient on 1(High Tech)*(T≥ 90°F) is positive and statistically significant, implying that high-tech industries are less negatively affected by extreme high temperatures. For firm exit, the interaction term is not statistically significant. Such results are consistent with Zhang et al. (2018), who find that the effects of high temperatures on productivity are not different for high-tech and non-high-tech firms.

Second, we explore the heterogeneity in the labor intensity and temperature sensitivity of different sectors. Again, we interact the dummy variable, 1(High labor intensity)[15], with the numbers of days of different temperature intervals. The results are shown in Table 9. For both firm entry and exit, the coefficient on the interaction term 1(High labor intensity)*(T≥ 90°F) is statistically significant, implying that the labor intensity does affect firms' vulnerability to extreme high temperatures. Furthermore, the results in Table A10 indicate that noon high temperatures (daily maximum) have more salient effects than night-time temperatures (daily minimum) in labor-intensive sectors, since the coefficients are larger in magnitude for noon temperatures. Such results indicate that the reduction of labor productivity due to high temperatures is the main driver of the main empirical findings. In addition, we examine whether sectors in which the workers are subject to stronger influences of temperatures exhibit larger effects in entry and exit. To meet this end, we interact the temperature bins with 1(Sensitive to temperature), which equals 1 if the sector is mining or smelting. The effects, according to Table 10, are indeed more salient for these sectors.

4.4 Mechanisms

Then, we examine the effects of extreme temperatures on incumbent firms, replicating the results in Zhang et al. (2018). First, we test whether high temperatures reduce the productivity of incumbent firms. The results are displayed in Table A11. As in Zhang et al. (2018), we find that the extreme high temperatures significantly reduce firm productivity, for all six measures of productivity—TFP (OP), TFP (LP),[16] TFP (GMM), log(revenue/L), log(output/L), and log(Solow residual). Thus, we find that extreme high temperatures have negative *productivity effects* on incumbent firms. We propose two mechanisms by which extreme high temperatures may reduce productivity: (1) extreme high temperatures cause discomfort of workers, and, thus, reduce productivity (direct productivity effect); and (2) firms have to use more resources to mitigate the harm of extreme high temperatures, which is a non-productive purpose (indirect productivity effect). The above results on labor intensity and temperature sensitivity imply that the first mechanism is at play. The results below regarding labor-capital substitution imply that the second mechanism is also at play. We further examine whether the negative effects on individual firm-level outcomes are different for high- versus low-productivity

[14]See `http://www.stats.gov.cn/tjsj/tjbz/201310/P020131021347576415205.pdf` for details. High-technology industries include medicine manufacturing, electronic and telecommunication manufacturing, aviation and aerospace manufacturing, computer manufacturing, medical equipment manufacturing, and information chemicals manufacturing.

[15]High labor intensity is defined according to whether the labor-capital ratio of a sector is larger than the sample median of the corresponding city-year cell.

[16]TFP (OP and LP) are ACF corrected.

firms. The results are reported in Table 11. The effect on labor use is negative for low-productivity firms, whereas positive for high-productivity firms; the effect on capital use is more positive for high-productivity firms than for low-productivity firms, suggesting that low-productivity firms tend to substitute labor with capital more; the effect on revenue is more negative for low-productivity firms, suggesting that low-productivity firms are more vulnerable to high temperatures. Thus, high temperatures induce low-productivity firms to use more capital, and their revenues are more negatively affected. All of these findings support the argument that selection effects are at play.

Next, we look at the effects on input use. The results are shown in Table 12. We find that extreme high temperatures increase both labor and capital inputs. This may be due to the fact that such high temperatures increase exit and decrease entry, reducing the number of firms in the market and, thus, the wage rate and capital rental rate. As a result, firms use more labor and capital as inputs. Moreover, firms may hire more labor to overcome the negative effects of extreme high temperatures. As a result, the inputs that each firm in the market uses will increase. Again, this result is consistent with Zhang et al. (2018). However, the labor-capital ratio responds negatively to extreme high temperatures, implying that firms use more capital, which is not sensitive to high temperatures, to substitute for labor. In particular, in Table 12, columns (1) through (3), we do not control for province-year fixed effects and sector-year fixed effects. Thus, the estimated coefficients embody the combination of the two channels: (1) reduction of wage and rental rate due to more exit; and (2) increasing input use to combat high temperatures. In Table 12, columns (4) through (6), we further control for province-year and sector-year fixed effects. The coefficients are still positive and statistically significant, whereas the magnitude is smaller. Since the variations in wages and interest rates are absorbed by province-year and sector-year fixed effects, these estimates embody only the second channel, and this is why the magnitude is smaller.

Then, we exploit the firm-registration data set to construct a firm-year panel data set, in which the main dependent variable is a dummy indicating whether the firm exits in a certain year. If the firm exits, then it disappears from the sample from then on. We estimate the effects on firm-level exit and report the results in Table A12. The effects on exit are positive and statistically significant, supporting the city-sector-year-level analysis of firm exit.

Next, we examine the effects of extreme high temperatures on aggregate productivity. We focus on six measures of aggregate productivity: the weighted[17] average of TFP (OP, ACF corrected), TFP (LP, ACF corrected), TFP (GMM), log(revenue/labor), log(output/labor), and log Solow residual of all surviving firms in the city-sector cell. TFP (OP, LP, GMM) includes only data from 2000 to 2007. TFP (OP and LP) are ACF corrected. TFP (GMM) is calculated using the method proposed in Yu (2015). The results are shown in Table 13. Such a measure is consistent with the literature on aggregate productivity (Chambers and Pope, 1996; Basu and Fernald, 2002; Duarte and Restuccia, 2010). For all measures of aggregate productivity, extreme high temperatures do not have statistically significant effects. The effects of extreme high temperatures on aggregate productivity, unlike on individual incumbent productivity, are muted, because of the selection effect: they leave firms with better performance surviving and staying in the market, and, thus, the effects on aggregate productivity are nearly zero. Thus, different aspects of productivity yield completely different results, which also lead

[17]The weight is the revenue share of one firm in the associated city-sector-year cell.

to different policy implications. Moreover, we use unweighted productivities as the dependent variable and estimate the same specification. We report the results in Table A13, which still indicate a null effect.

We also decompose the aggregate productivity by the contribution of entry, exit, and incumbent, in the same fashion as Haltiwanger (1997) and Griliches and Regev (1995)[18], and estimates the effects of extreme temperatures on these contributions. Results in Table 14 suggest that extreme high temperatures increase the productivity of the entrants, and reduce the productivity of the incumbents. These results are thus consistent with the story of selection effects, and the model presented in the next section. It is also noteworthy that we control for province-year and sector-year fixed effects, which absorb the variations of wages and interest rates, and, therefore, the impacts of the general equilibrium adjustment of factor prices are separated out. In all, the discrepancy of the effects on incumbent and aggregate productivity can be reconciled by the existence of the selection effect. The reason is that extreme high temperatures raise the cutoff of productivity for new entrants, and drive firms with low productivity out of the market. The model in the next section will illustrate this idea.

In the final descriptive empirical analysis in this section, we estimate the effects of temperatures on (aggregate) city-level outcomes. Table A14 indicates that extreme high temperatures have no significant impacts on these outcomes. When we use a longer sample period (1990-2020), we find, as shown in Table A14, that high temperatures do not significantly affect city-level aggregate socio-economic outcomes, echoing the previous results on aggregate productivity. We then estimate the cumulative and long-term effects of high temperatures on entry, exit, and productivity, and present the results in Table A15. The number of days in each temperature bin corresponds to the average annual number of days in the past 3 or 5 years. The estimates indicate that high temperatures still have statistically and economically significant impacts on entry, exit, and productivity. However, the magnitude of the coefficients is smaller. Thus, in the long run when firms can adjust input use and make decisions regarding fixed or sunk costs more flexibly, extreme high temperatures still have significant, but smaller, effects on firm dynamics. Finally, we use a long sample period of 31 years (1990-2020) in the regression analysis. According to Table A16, the estimated coefficients for entry and exit are still both economically and statistically significant, indicating that the main findings also exist in the long run. Thus, these results add credibility to our policy implications that exploit temperature projections many years later.

4.5 Other Channels

In this section, we investigate other channels, including (1) inter-sectoral factor reallocation within locations, (2) spatial linkages, (3) input-output linkages, (4) innovation and productivity dynamics, and (5) local demand.

[18]The equation of decomposition is $\Delta y_{st} = \sum_{i\in C}(\bar{s}_i \Delta y_{it} + \Delta s_{it}(\bar{y}_i - y_{st-k})) + \sum_{i\in E} s_{it}(y_{it} - y_{st-k}) - \sum_{i\in X} s_{it-k}(y_{it-k} - y_{st-k})$, where C, E, and X denote the sets of continuing, entering, and exiting firms, respectively, in industry s. We normalize the current level of outcome y of firm i by y_{st-k}. The notation follows Griliches and Regev (1995).

4.5.1 Inter-sectoral Factor Reallocation Within Locations

It is possible in theory that extreme high temperatures may induce reallocation of labor and capital between sectors (agricultural, manufacturing, and service) ***within a certain location***. To meet this end, we exploit the Chinese National Tax Survey Database (CNTSD), which encompasses firms in all sectors (other than manufacturing). Using this database, we calculate the share of capital and labor in the agricultural, manufacturing, and service sectors and use it as the dependent variable. We still estimate our baseline specification (1). We present the results in Table B4. High temperatures do not affect intersectoral factor reallocation. Thus, the result justifies our model that only contains the manufacturing sector.

4.5.2 Spatial Linkages

We next investigate whether extreme high temperatures may induce the reallocation of resources across space. We focus on two types of spatial linkages: capital flows and migration flows. It is possible in theory that capital and labor flow to regions less affected by high temperatures. To meet this end, we use data on intercity capital flows (as in Shi, 2021; Shi et al., 2021; and Liu and Shi, 2023) and migration flows, and estimate the following specification

$$Flow_{ijt} = \alpha Temperature_{ijt} + \lambda_{ij} + \lambda_t + u_{ijt}, \tag{2}$$

where $Flow_{ijt}$ is a measure of capital or migration flows from city i to city j in year t, $Temperature_{ijt}$ measures the difference[19] in temperatures of cities i and j in year t, λ_{ij} and λ_t are city-dyad and year fixed effects, and u_{ijt} is the error term. We cluster the standard errors at the city-dyad level. We report the results in Tables B5, B6, and B7. High temperatures do not affect capital and migration flows. Thus, the result justifies our model that only contains a single location.

4.5.3 Input-output Linkages

In this section, we investigate the role of input-output linkages. It is possible in theory that extreme high temperatures may affect input-output linkages and, then affect firm dynamics and factor reallocations.[20] To show that our results are still robust taking into account input-output linkages, we use the method in Shi (2022) to capture the role of input-output linkages. Specifically, we calculate a weighted sum of entry and exit, in which the weight is the input or output share obtained from the input-output table.[21] We first calculate an input-entry/input-exit index as follows:

[19]The difference of mean temperatures in cities j and i, and the difference of the number of days of T$\geq$ 90°F and 80°F$\leq$T$<$90°F in city j and city i.

[20]Unfortunately, we do not have city-level input-output data, so we cannot examine the effects of high temperatures on input-output linkages.

[21]The input-output data only contain 1997, 2002, 2007, and 2012, and thus we use the input-output data of 1997 to construct the sample of 1997-2001, 2002 to construct 2002-2006, 2007 to construct 2007-2011, 2012 to construct 2012.

$$\begin{aligned} InputEntry_{cit} &= \sum_j \frac{Flow_{jipt}}{\sum_k Flow_{kipt}} \log(Entry)_{cjt} = \sum_j InputShare_{ijt} \log(Entry)_{cjt}, \\ InputExit_{cit} &= \sum_j \frac{Flow_{jipt}}{\sum_k Flow_{kipt}} \log(Exit)_{cjt} = \sum_j InputShare_{ijt} \log(Exit)_{cjt}. \end{aligned} \tag{3}$$

where $Flow_{jipt}$ is the input-output flow from sector j to sector i, $\log(Entry)_{cjt}$ ($\log(Exit)_{cjt}$) is the log number of firm entry (exit) in city c (which is in province p) and sector j. This variable measures the supply of inputs by all sectors demanded by sector i.[22] To capture the role of output demand, we construct a variable as follows:

$$\begin{aligned} OutputEntry_{cit} &= \sum_j \frac{Flow_{ijpt}}{\sum_k Flow_{ikpt}} \log(Entry)_{cjt} = \sum_j OutputShare_{ijt} \log(Entry)_{cjt}, \\ OutputExit_{cit} &= \sum_j \frac{Flow_{ijpt}}{\sum_k Flow_{ikpt}} \log(Exit)_{cjt} = \sum_j OutputShare_{ijt} \log(Exit)_{cjt}. \end{aligned} \tag{4}$$

Using these measures, we estimate the effects of high temperatures on entry and exit weighted by input-output linkages. We still estimate our baseline specification (1). We report the estimation results in Table B8. The results are qualitatively similar when we use entry and exit weighted by input/output shares. Thus, the input-output linkages do not bias our main results. Thus, the result justifies our model that does not take into account input-output linkages.

4.5.4 Innovation and Productivity Dynamics

In this section, we examine whether extreme high temperatures affect innovation and input and productivity dynamics. We estimate our baseline specification (1), using innovation, input growth, and productivity growth as the dependent variable. We report the results in Tables B9, B10, and B11. We find null effects. Thus, high temperatures do not affect firms' input and productivity dynamics. This result justifies the static feature of our model.

4.5.5 Local Demand

In theory, it is possible that extreme high temperatures may affect consumer preferences and local demand shifters. For example, high temperatures may affect preferences and marginal rate of substitutions between agricultural goods and manufacturing goods. To examine this channel, we utilize the city-level price indices that contain demand-side information and the number of firms that contains supply-side information. The price indices are constructed using the China Price Yearbooks. We estimate equation (1), use the price index as the dependent variable, and at the same time control for the lagged number of firms that proxies the supply side.[23] We report the results in Table B12. High temperatures do not have significant effects on the local demand that is captured by price indices

[22] The input-output tables contain 38 sectors. To maintain consistency, all sector-level analyses contain the same number of sectors.

[23] We use the lagged number of firms to alleviate endogeneity issues.

in the agricultural, manufacturing, and service sectors. Thus, the result justifies our model that does not take into account shifts in consumer preferences.

5 Quantitative Model

We first lay out the baseline model in which we impose several simplifying assumptions. In particular, we establish a framework with (1) a single sector, (2) a single location, (3) no interregional migration flows and capital flows, (4) no input-output linkages, (5) no input/productivity dynamics and innovation, and (6) no endogenous local demand shifter. Such restrictions are consistent with the empirical results in Section 4.5. In particular, the model is essentially a static one since we do not detect input/productivity dynamics empirically.

Next, we relax these assumptions and make three extensions: (1) size-varying temperature damages; (2) factor reallocation cost; (3) long-run firm adaptation; and (4) production with capital. The model renders a framework for quantitative analysis, and it produces four theoretical propositions that are all consistent with the conceptual framework and the empirical findings.

5.1 Baseline Model

In this section, we introduce the quantitative model which depicts how extreme temperatures may affect firm dynamics and productivity. This model combines elements of Melitz (2003), Acemoglu et al. (2018), and Akcigit et al. (2021). It is a static model in which firms do not innovate to improve productivity. We assume so because empirically we find that extreme high temperatures do not affect firms' innovation decisions (Table B10), input accumulation (Table B9), and productivity dynamics (Table B11). Thus, we abstract away the innovation process, input accumulation, and productivity dynamics.

In this model time is discrete: $t = 0, 1, 2, ...$ The representative household's preference is standard CRRA preference: $U = \sum_{t=0}^{\infty} \beta^t \frac{C_t^{1-\gamma}-1}{1-\gamma}$. The household supplies one unit of labor inelastically in each period, which earns wage w_t. The final good, Y_t, which is the numeraire, is a CES composite of a unit continuum of varieties: $Y_t = (\int_0^1 y_{jt}^{\frac{\epsilon-1}{\epsilon}} dj)^{\frac{\epsilon}{\epsilon-1}}$. The resource constraint is $Y_t = C_t$.

The household's budget constraint is standard: $C_t + A_{t+1} = R_t A_t + w_t$, where R_t is the interest rate. We set $R_0 = 1$. A_t is the stock value of firms in the market. Suppose that the no-Ponzi condition holds. From now on we omit the time index when possible.

The firm might earn profit from production, which is denoted by π_f. The production function of each variety j and firm f is $y_{jf} = \psi z_f l_{jf}^P$, where ψz_f is the efficiency, ψ the effects of temperature on productivity, z_f the own idiosyncratic efficiency draw, l_{jf}^P the labor input in production. We assume that labor is the only factor for production. While adding capital to the production function may better illustrate the labor-capital substitution of the firms, it introduces the dynamic programming problem of capital accumulation and, thus, makes the model untractable and difficult to compute. While without capital, we cannot model the substitution of labor and capital, we can examine whether labor is more intensively used in production and in combating the negative impacts of high temperatures, which is introduced below. This said, however, we do relax this assumption by adding static inputs of capital in production in Section 5.2.4, without further introducing capital accumulation and investment in the model. The main theoretical results still follow, but the quantitative results are different.

Suppose that the price of good j by firm f is p_{jf}. Then, the profit from production is $\pi_f = p_{jf}y_{jf} - w(l^P_{jf} + l^R_{jf}) - \tau E(y_{jf}, l^R_{jf})$, where τ is the unit cost induced by extreme temperature, l^R_{jf} is the labor used to reduce the damage of extreme temperatures, and $E(y_{jf}, l^R_{jf}) = y_{jf}(\lambda_0 + \lambda_1(l^R_{jf})^{-\lambda_2})$ is the damage caused by extreme temperatures. Again, τ is an exogenously set parameter that describes the unit damage of high temperatures. It resembles the role of corporate tax since it causes losses of revenue to the firm. However, the damage (or "revenue") of high temperatures simply "dissipates" and does not turn into revenue in others' pockets, as the tax does. For ease of computation, we impose restrictions on the functional form for the $E(\cdot)$ function. In the model, τE corresponds to the flow cost induced by high temperatures. We also make three assumptions here. We first assume that the unit cost is homogeneous across firms, and then relax this assumption in the model extension part. Second, we assume that labor released by exiting firms can be costlessly reallocated to surviving firms, but we relax this assumption in the model extension. We finally assume that firms cannot make long-run adaptation to the high temperatures, but we allow for decreasing damage of high temperatures to model long-run adaptation in the model extension part. The profit maximization problem for firm f is $\max_{p_{jf}, l^P_{jf}, l^R_{jf}} \pi_f$. Given the production function of the final good, the inverse demand function is $p_{jf} = Y^{\frac{1}{\epsilon}} y_j^{-\frac{1}{\epsilon}}$.

In each period, there is a measure one of potential entrants. To enter the market, each entrant has to pay a fixed cost f_e in terms of labor. If labor reallocation is costly, then upon entry, firms have to pay an extra labor reallocation cost. We make this extension in the model extension section below. After drawing its productivity from PDF $g(z)$ (whose CDF is $G(z)$), each entrant decides whether to enter. If it does so, the firm pays the fixed entry cost.[24]

For simplicity, assume that after gaining the productivity draw, the idiosyncratic productivity z remains fixed over time. Therefore, the model is essentially a static one that abstracts away all productivity dynamics. In the empirical analysis, we find that firms' innovation decisions are not affected by high temperatures. Since innovation is related to productivity growth, such evidence adds credibility to this lack of productivity dynamics in the model. Moreover, productivity dynamics are not needed to illustrate the two main theoretical channels: productivity effect and selection effect. Therefore, we abstract away the productivity dynamics. The net value of entry conditional on productivity z_f is, thus, $V(z_f) = \sum_{t=0}^{\infty}(\prod_{s=0}^{s=t} \frac{1}{R_s})\pi_f(\psi z_f) - wf_e$.

There is a productivity cutoff z^*, above which the firm will enter the market, and below which the firm will not enter the market: $\sum_{t=0}^{\infty}(\prod_{s=0}^{s=t} \frac{1}{R_s})\pi_f(\psi z^*) - wf_e = 0$. The distribution of productivity for firms in the market is

$$\mu_t(z) = \begin{cases} \dfrac{g(z)}{1 - G(z_t^*)}, & if\ z > z^* \\ 0, & if\ otherwise. \end{cases} \tag{5}$$

Thus, in each period t, a $1 - G(z_t^*)$ measure of firms enter the market, and an $M_{t-1}(1 - G(z_{t-1}^*)) -$

[24] When entering the market, each firm naively assumes that the cost parameters will remain constant over time. However, these parameters may be subject to change at some point in time. Once they change, each firm will assume that they will remain at the new level from then on. This assumption is imposed for the tractability of the model since it does not affect the illustration of the main mechanisms in this model.

$(M_t(1-G(z_t^*))$ measure of firms exit the market, where M is the total measure of firms in the market. Households' asset holdings satisfy $A = \int_{z^*}^{\infty} V(z)\mu(z)dz$.

A stationary competitive equilibrium is defined as follows: a tuple of $\Delta \equiv \{C, Y, A, R, p_{jf}, w, l_{jf}^P(z), y_{jf}, z^*, M\}$ such that (1) the household's Euler equation holds in the steady state: $\beta R = 1$; (2) incumbent firms solve the profit maximization problem for $\{l_{jf}^P, l_{jf}^R\}$; (3) the final product market clears: $Y = C$; and (4) the labor market clears: $M(\int_{z^*}^{\infty}(l_{jf}^P(z) + l_{jf}^R(z))\mu(z)dz + f_e) = 1^{25}$.

Extreme temperatures lead to an increase in flow cost τ and sunk cost f_e. We have the following propositions, which are all consistent with the conceptual framework and the empirical findings. We provide proofs in Appendix E, and we provide detailed explanations of their logic and intuition here. We can also further verify these propositions with the quantitative exercises below. To begin with, with more extreme high temperatures:

Proposition 1. *Incumbent firms' performance worsens:* $\frac{p_{jf}y_{jf}}{l_{jf}^P + l_{jf}^R}$ *decreases. This may result from using more labor to reduce the damage caused by extreme temperatures (indirect productivity effect, or adjustment effect), and reduced* ψ *draw (direct productivity effect).*

Proposition 1 holds since (1) firms use more labor inputs for non-productive purposes, and, thus, productivity decreases; and (2) extreme high temperatures directly reduce TFP (ψ). Combining these two aspects, we get Proposition 1 that incumbent firms' performance will worsen under extreme high temperatures. This proposition is consistent with Hypothesis 1, and is supported by Table A11. In the quantitative analysis, the productivity effect is obtained by calculating the change in mean productivity due to the direct and indirect productivity effects defined above. Moreover, since firms that use more labor to combat the negative effects are more negatively affected, this proposition is also consistent with Hypothesis 3. Proposition 1 is also further verified by the quantitative analysis since Figure 3 (a) indeed finds that increasing temperatures may harm productivity at the firm level.

Proposition 2. *Productivity cutoff* z^* *increases. This means that entry decreases and exit increases (selection effect).*

Proposition 2 holds since the entry cost f_e and flow cost τ both increase under more extreme high temperatures. Thus, it is less profitable for firms with lower productivity to enter. Moreover, firms with low productivity may reduce their loss by exiting, since their operating costs increase. Moreover, the distribution of surviving firms is improved, due to the increase in cutoff z^*. Proposition 2 is consistent with Hypotheses 2 and 4. This proposition is also supported by Table 8. In the quantitative analysis, the selection effect is obtained by calculating the change in the mean of productivity distribution due to the change in productivity cutoff z^*. Proposition 2 is also verified by the quantitative analysis since Figure 2 shows that increasing temperatures will shift the productivity cutoff z^* to the right side. It can also be verified by Figure 3 (b), which shows a positive selection effect.

Proposition 3. *Input use for each firm that stays in the market increases (adjustment effect).*

Proposition 3 holds since the damage of extreme high temperature is larger as there are more days of high temperatures ($\tau E(y_{jf}, l_{jf}^R)$ is larger). Thus, it is more profitable for firms to use labor

[25] We assume that labor supply is homogeneous across cities because we find that extreme high temperatures do not affect migrants, with either high skills or low skills. The results are shown in Table B6

inputs to reduce the damage of extreme high temperatures. This proposition is consistent with Table 12. It is also consistent with the second part of Hypothesis 1. Proposition 3 is further verified by the quantitative analysis since Figure 2 implies that surviving firms under high temperatures are larger, due to the right shift of z^* and a fixed supply of labor inputs.

Proposition 4. *The change in aggregate productivity is uncertain (the combination of the direct and indirect productivity effect and the selection effect).*

Proposition 4 holds due to the combination of Proposition 1 and 2. On the one hand, the productivity of incumbent firms decreases. On the other hand, the distribution of all surviving firms improves. The "tax," or $\tau E(\cdot)$ in the model, does not lead to an improvement of individual productivity. However, it will drive low-productivity firms out of the market and leave high-productivity firms surviving and staying in the market. Thus, in terms of aggregate productivity, such a tax may have a positive effect. Combining these two aspects of Propositions 1 and 2 yields Proposition 4. This proposition is supported by Table 13 and Table 14, which indicate that the effects of high temperatures on aggregate productivity are muted and that this fact results from the response of firm dynamics. To be more specific, Table 13 indicates the null effect of high temperatures on aggregate productivity; Table 14 indicates that the null effect is driven by the combination of the productivity effect and the selection effect. This proposition is consistent with Hypothesis 5. Proposition 4 is also further verified by the quantitative exercise since Figure 3 (c) points out that the net effect is much smaller than the productivity effect.

5.2 Model Extensions

5.2.1 Size-varying Temperature Damages

In the above baseline version of the model, we assume that high temperatures have uniform effects on firms' profits. Now we relax this restriction and allow that the productivity effect can be heterogeneous with respect to firm size. Specifically, we assume that the negative effect on profit is larger for smaller firms: τ should be an increasing function of l^P. We let $\tau = \tau_0 \times \tau_{size}$, where τ_0 is the τ parameter in the baseline model, and τ_{size} is the size-varying part of temperature damages. We further assume that the partial effect of $\log(\tau_{size})$ with respect to D_{group}, where D_{group} is the number of days in a certain group of temperature intervals, should be a linear function of $\log(l^P)$: $\frac{\partial \log(\tau_{size})}{\partial D_{group}} = \beta_{group,\tau_{size}} \log(l^P)$. We estimate $\tau_{size,group}$ using indirect inference. The selection effect may be more salient since the negative damages are more pronounced for firms with lower productivity. Finally, all of the four above theoretical propositions still hold, but the quantitative importance of different mechanisms may be different. We provide the results of quantitative analysis in Figure C1.

5.2.2 Costly Factor Reallocation

In the above version of the model, we assume that labor can be costlessly reallocated across firms. Now we relax this assumption, by stipulating that firms pay an extra labor reallocation cost upon entry. To follow the line of the literature on the factor adjustment costs, and for simplicity, we assume that the labor reallocation cost C^R is a convex quadratic function of labor inputs, and it is paid upon entry. Specifically, the functional form is $C^R(l^P) = w \times c^R \times (l^P)^2$, where c^R is a parameter to be estimated. Thus, the total entry cost is $wf_e + wc^R(l^P)^2$. We estimate c^R using indirect inference together with other parameters. The productivity effect and the selection effect are both more salient, since firms have to use more labor inputs for non-productive purposes, and firms with lower productivity are deterred from entry more intensively. The effects on entry and exit are also more salient, because firms have less incentive to enter and more incentive to exit, given the factor reallocation cost. Finally, all of the four above propositions still hold, but the quantitative importance of different mechanisms may be different. We provide the results of quantitative analysis in Figure C2.

5.2.3 Long-run Adaptation

In the long run, firms may come up with ways to cope with high temperatures or global warming. Thus, firms may be more efficient in reducing the harm of high temperatures. Therefore, we assume that in the long run, the unit damage caused by high temperatures may be $\alpha \times \tau$, where $\alpha \in [0, 1)$. Thus, $\pi_f = p_{jf}y_{jf} - w(l^P_{jf} + l^R_{jf}) - \alpha\tau E(y_{jf}, l^R_{jf})$. We try different values of α to model the adaptation of firms in time frames with various lengths. Specifically, we set $\alpha \in \{0.1, 0.3, 0.5, 0.7, 0.9\}$ and examine the quantitative implications respectively. Smaller α corresponds to a longer time frame, in which firms can adjust to high temperatures more flexibly. Thus, the effects of extreme high temperatures on entry, exit, and productivity are less salient, due to firms' flexible coping mechanisms. In the quantitative analysis below, we indeed find that these effects are quantitatively less pronounced. We provide the results of quantitative analysis in Figures C3-C7.

5.2.4 Production with Capital

In this section, we change the model by allowing firms to use capital for production. In this case, the production function is $y_{jf} = \psi z(l^P_{jf})^a(k^P_{jf})^{1-a}$, where a is the output elasticity to be estimated in a production function estimation approach.[26] We also assume that capital is an input just like labor that cannot be accumulated by firms and can only be purchased from the capital market. This is because we find that high temperatures do not affect the accumulation or change in capital, labor, and labor-capital ratio over time, as Table B9 suggests. It is easy to show that the main propositions still hold. The quantitative results, however, may differ. We provide the results of quantitative analysis in Figure C8.

6 Model Estimation

In this section, we introduce how we estimate the quantitative model. First, we parameterize the unknown functions and distributions: (1) parameterize $\log \tau = \tau_0 + \sum_{group,group\neq 5} \beta_{group,\tau} D_{group}$; (2) parameterize the entry cost f_e as $\log f_e = f_{e0} + \sum_{group,group\neq 5} \beta_{group,f_e} D_{group}$; (3) parameterize $\log \tau_{size} = \sum_{group,group\neq 5} \beta_{group,\tau_{size}} D_{group}$, where D_{group} is the number of days in a certain group of temperature intervals; and (4) parameterize z following a log-normal distribution with mean μ (=0, by construction) and variance σ^2 (the cumulative density function is $G(z)$).

[26] We use OP (ACF corrected) as the approach of production function estimation in the quantitative analysis.

In this model, there is a set of parameters to be externally calibrated, $\Theta_1 = \{\epsilon, \beta, \gamma\}$, and a set of parameters to be estimated: $\Theta_2 = \{\beta_{group,\psi}, \beta_{group,\tau}, \beta_{group,f_e}, \mu, \sigma^2, f_{e0}, \tau_0, \lambda_0, \lambda_1, \lambda_2\}$. Let $\Theta = (\Theta_1, \Theta_2)$. Given each set of parameters, we can solve the model as a function of parameters: $l^P_{jf}(\Theta), l^R_{jf}(\Theta), z^*(\Theta), M(\Theta), w(\Theta), R(\Theta), Y(\Theta)$.

We conduct the external calibration as follows: $\epsilon = 2.9$ (according to Broda and Weinstein, 2006; Acemoglu et al., 2018),$\beta = 0.997$ (according to Song et al., 2011), and $\gamma = 2$ (according to Song et al., 2011; Acemoglu et al., 2018).

We can also fit some parameters using microdata and reduced-form regressions. First, we estimate $\beta_{group,\psi}$ by reduced form regressions with firm-level productivity (controlling for fixed effects). Then, we estimate $\mu(= 0), \sigma$ by fitting the residual of the regression to log-normal distribution, since by Figure A2 the distribution of the log of productivity resembles a normal distribution.

We next use indirect inference to estimate the rest of the structural parameters. We match the model-generated data to the following targeted reduced form estimates: (1) entry, whole sample; (2) exit, whole sample; (3) entry, below median performance; (4) entry, above median performance; (5) exit, below median performance; (6) exit, above median performance; (7) entry, large firms; (8) entry, medium firms; (9) entry, small firms; (10) exit, large firms; (11) exit, medium firms; (12) exit, small firms.

Here is the estimation algorithm: we simulate $10000 \times 295 \times 39 \times 12$ firms (in 295 cities, 39 industries, and 12 years) drawing the productivity from $G(z)$. Given the parameters Θ, we solve the model as a function of parameters: $l^P_{jf}(\Theta), l^R_{jf}(\Theta), z^*(\Theta), M(\Theta)$. Specifically, we first solve the allocation given prices and then use market-clearing conditions to solve the prices. This is a fixed point problem as in Atkeson and Burstein (2010). After solving the firm-level outcomes, we aggregate the data to the city-sector-year level, and then run reduced-form regressions. Using the model-simulated data, we can estimate the reduced-form parameters $\Psi^s(\Theta)$. The estimates of the model parameters Θ^* should minimize the distance of Ψ^r and Ψ^s: $\Theta^* = \arg\min_\Theta ||(\Psi^s(\Theta) - \Psi^r)'(\Psi^s(\Theta) - \Psi^r)||$. We calculate the standard errors by Bootstrap.

The calibrated parameters and the parameters estimated externally are shown in Table A17. For $\beta_{\psi 1}$ to $\beta_{\psi 10}$, the subscript corresponds to the temperature interval of T$\geq$ 90°F, 80°F$\leq$T<90°F, 70°F$\leq$T<80°F, 60°F$\leq$T<70°F, 40°F$\leq$T<50°F, 30°F$\leq$T<40°F, 20°F$\leq$T<30°F, 10°F$\leq$T<20°F, and T<10°F. As above, the estimate for $\beta_{\psi 1}$ is negative and statistically significant, implying that extreme high temperatures reduce firm productivity.

Then, we present the results of parameter estimation obtained through indirect inference in Table A18. For $\beta_{\tau 1}$ to $\beta_{\tau 10}$, and for $\beta_{f_e 1}$ to $\beta_{f_e 10}$, the subscript corresponds to the temperature intervals of T$\geq$ 90°F, 80°F$\leq$T<90°F, 70°F$\leq$T<80°F, 60°F$\leq$T<70°F, 40°F$\leq$T<50°F, 30°F$\leq$T<40°F, 20°F$\leq$T<30°F, 10°F$\leq$T<20°F, and T<10°F. The estimates of $\beta_{\tau 1}$ and $\beta_{f_e 1}$ are positive and statistically significant, implying that extreme high temperatures increase the flow costs and the sunk costs.[27]

The goodness of fit for the model is shown in Table A19. We compare the actual regression coefficients on T$\geq$ 90°F with the model-generated coefficients, and find that they are quite close to each other.

Moreover, for the parameters in the extensions of the baseline model, we report the estimation

[27]Since τ and f_e cannot be directly observed in the data, we have to rely on simulation-based estimation for calibration.

results in Table A20. All the estimates are statistically significant, and the estimates of $\beta_{k,\tau_{size}}$ ($k \neq 5$) indeed indicate that the negative productivity effects are more salient for smaller firms. The estimate of c^R is significantly greater than zero, indicating that the labor reallocation cost is positive and convex.

7 Implications of climate change and climate policies

In this section, we explore the implications of climate change. Using the reduced-form estimates and the structural estimates, we predict changes in entry, exit, and aggregate productivity when the temperature rises to the predicted level for 2070-2099.

We rely on predictions based on the Hadley Centre Global Environment Model version 2 (HadGEM2-ES), which is used in the Fifth Assessment Intergovernmental Panel on Climate Change (IPCC) Report. The HadGEM2-ES provides predicted values of daily mean temperature for each $1.25° \times 1.875°$ grid over a wide time-span at different Representative Concentration Pathways (RCPs).[28] Following Agarwal et al., 2021, we focus on RCP8.5, which assumes that global greenhouse gas emissions will rise continuously at the current emissions growth rates (i.e., "business-as-usual") throughout the 21st century. We obtain the daily predictions of mean temperature for 2070-2099 and aggregate the values from the grid level to the city level. Finally, we calculate the average number of days in each temperature bin per year for each city during 2070-2099.

The distribution of days in different temperature bins for the period of 2001-2012 and 2070-2099 is shown in Figure A3. We can see that there will be more days of extreme high temperatures during 2070-2099 than there were during 2001-2012.

Figure A4 shows the counterfactual results on the predicted change in entry and exit. The predicted warming may hinder entry and induce exit in most areas. The areas hit hardest are the Huabei and Huazhong areas.

Figure 3 shows the counterfactual results on the predicted changes in aggregate productivity, and two related channels: productivity effect and selection effect. The productivity effect is obtained by calculating the change in mean productivity due to the direct and indirect productivity effects defined above. The selection effect is obtained by calculating the change in the mean of productivity distribution due to the change in productivity cutoff z^*. [29] Technically, the productivity effect and the selection effect are calculated by treating wages and prices as floating; in other words, these two effects also contain the general equilibrium feedback effects generated by floating wages and prices in response to the high temperatures. However, in Figure 2, in the case in which we treat either wages or prices or both as fixed, the newly calculated productivity and selection effects are quantitatively similar to one another. Thus, the general equilibrium feedback effect, or the adjustment of wages and prices, does not alter our main quantitative findings. The reason why general equilibrium feedback effects are not quantitatively important is that they are not the first-order consequences (which should be changes in productivity and entry cost), but only the second-order consequences.

[28] The data are available at https://cera-www.dkrz.de/WDCC/ui/cerasearch/.

[29] The mathematical formula for productivity effect is: $ProductivityEffect = \Delta(\log(\frac{py}{l^P+l^R})$; the mathematical formula for selection effect is: $SelectionEffect = \Delta(E(z)))$, where the expectation is calculated using the truncated distribution associated with z^*.

According to Figure 3, we can see that the productivity effects on aggregate productivity are mostly negative, while the selection effects on aggregate productivity are mostly positive. Therefore, the combined effects on aggregate productivity are muted compared to the productivity effects alone. Therefore, the harm of global warming might be overestimated if we do not take firm dynamics into account.

Next, we conduct the quantitative analysis based on three model extensions: (1) size-varying temperature damages; (2) costly factor reallocation; (3) long-run firm adaptation; and (4) production with capital. The results are shown in Figures C1-C8. With size-varying temperature damages, the selection effects are larger and more positive, whereas the productivity effects are quantitatively similar. Thus, the net effects are more positive. With costly factor reallocation, the effects on entry and exit are both more negative; the productivity effects are more negative, and the selection effects are more positive. Moreover, allowing for long-run firm adaptation leads to less salient effects on entry and exit, and less pronounced productivity and selection effects. As α becomes smaller, the adaptation is stronger, and the effects are more attenuated. Finally, adding capital to production increases the productivity effects, since capital productivity is also negatively affected, and firms tend to substitute labor with capital under higher temperatures. All of these results are consistent with the theoretical propositions in Section 5.2.

Based on the quantitative analysis, we conduct a back-of-the-envelope cost-benefit analysis. We find that policymakers ought not to base their climate policies simply on the effects of high temperatures on incumbent firms. Since aggregate productivity is a better indicator of societal welfare, policymakers should take into consideration the selection effect to avoid overreacting to global warming. Following the method of cost-benefit analysis proposed by He et al. (2020), we find that, using the technology of 2012, the spatial distribution of the damage of high temperatures is depicted by Figure 4. The average damage in a city calculated using individual incumbent productivity effects is 2.2 billion RMB, while it is 1.6 billion RMB if calculated using aggregate productivity effects. It can be easily found that basing the cost-benefit analysis on the effects of temperatures on individual incumbent productivity and aggregate productivity produces completely different results. The costs would be much higher if we focus on individual incumbent productivity. Moreover, if we further allow for long-run adaptation by firms, the cost would be even smaller. The results are reported in Figures C9-C13.

8 Conclusion

In this paper, we study how extreme temperatures affect firm dynamics in the Chinese manufacturing sector, focusing on the following three aspects: entry, exit, and (aggregate) productivity. While the existing literature focuses mainly on the effects of extreme temperatures on incumbent firms (intensive margin), we study their effects on entry and exit (extensive margin), and how they contribute to aggregate productivity. We find that extreme high temperatures lower the productivity of incumbent firms (individual incumbent productivity effects), which is consistent with the existing literature. At the same time, however, we find that such temperatures leave firms with higher productivity staying in the market (selection effect) and, thus, the combined effect on aggregate productivity is muted.

We estimate a firm-dynamics model by indirect inference, and quantify the importance of different mechanisms. Finally, we discuss the implications of global warming by conducting counterfactual experiments using the estimates of the model. The harm of global warming might be quantitatively different, to a great extent, if we do not take firm dynamics into account.

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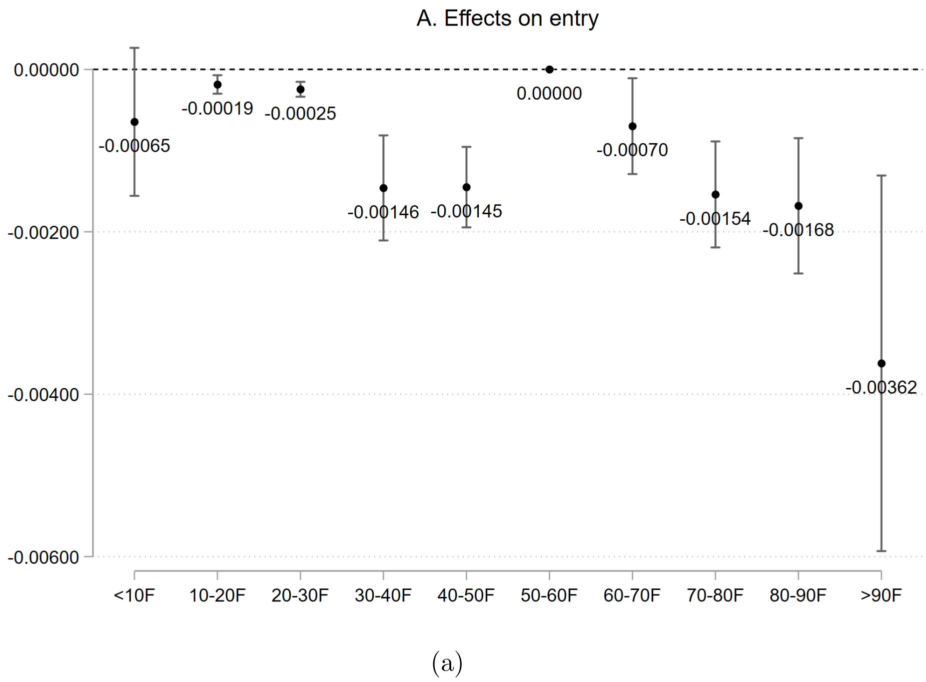
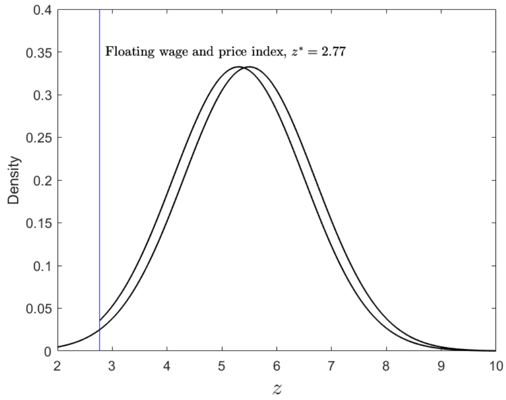
Figure 1: The impact of temperatures on firm dynamics

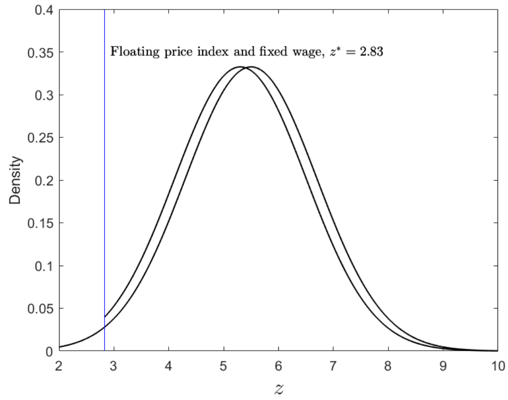


Notes: These figures plot the coefficients on temperature bins based on the results in columns (3) and (4) of Table 1. Each dot represents the regression coefficient. The vertical line around each dot represents the 95% confidence interval. Standard errors are two-way clustered at city and sector levels.

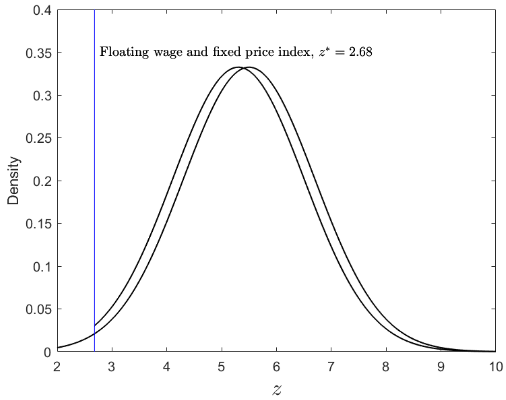
Figure 2: The channel of general equilibrium feedback effects



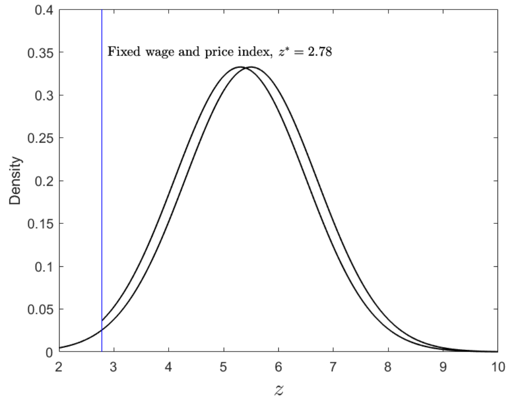
(a)



(b)



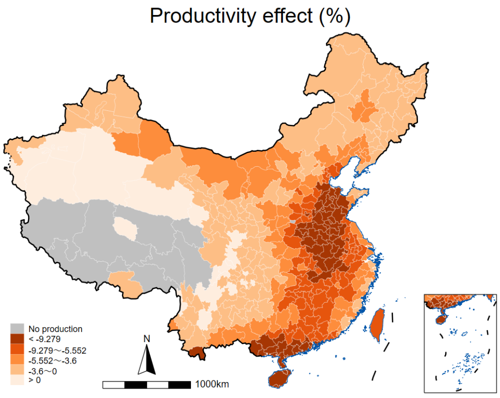
(c)



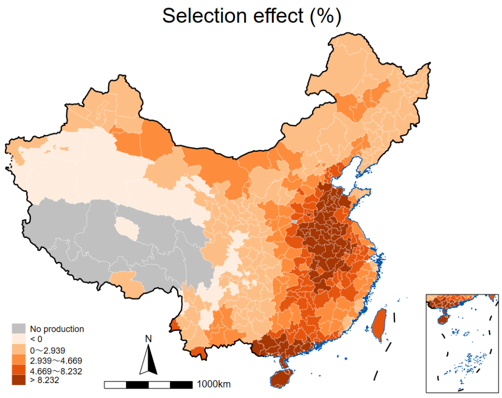
(d)

Notes: These four subfigures plot the general equilibrium feedback effects, with the changes in wages and prices (determined in general equilibrium) taken into account. We fix wages and price indices (as exogenously set, not endogenously determined), either, neither, or both, compared to the baseline scenario. The untruncated distribution corresponds to the case without productivity and selection effects, and the truncated distribution corresponds to the case with projection using the temperatures of 2070-2099 compared to 2001-2012. The vertical line corresponds to the lower bar of productivity to enter the economy, or z^* in the model, and corresponds to the selection effect.

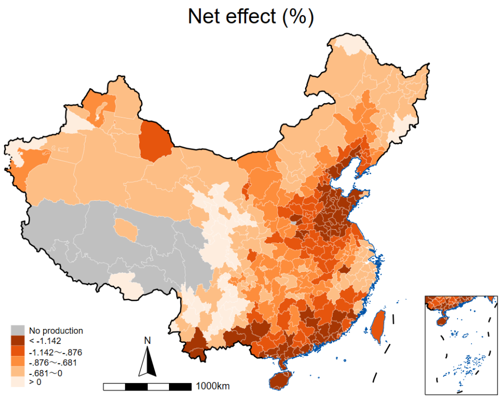
Figure 3: The predicted impacts of climate change on productivity



(a)



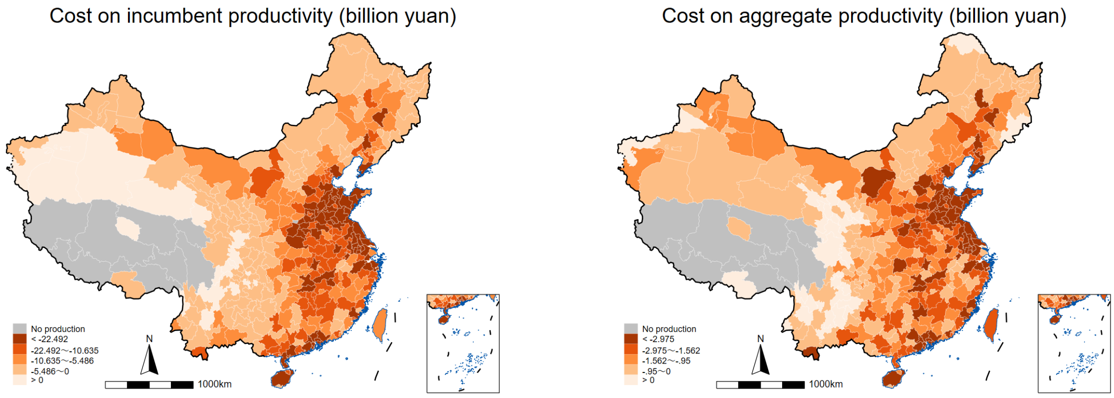
(b)



(c)

Notes: Figure 3 (a) shows the predicted impacts of climate change on aggregate productivity through the productivity effect. Figure 3 (b) shows the predicted impacts of climate change on aggregate productivity through the selection effect. Figure 3 (c) shows the combined effects of the productivity and selection effects. The productivity effect is obtained by calculating the change in mean productivity due to the direct and indirect productivity effects defined above. The selection effect is obtained by calculating the change in the mean of productivity distribution due to the change in productivity cutoff z^*. *The net effect is calculated by adding the productivity effect and the selection effect. All effects are measured in percentage points.*

Figure 4: The damage of global warming



(a) (b)

Notes: Figure 4 (a) shows the damage of global warming on value added of the manufacturing sector, using the individual incumbent productivity effects. Figure 4 (b) shows the damage of global warming on value added of the manufacturing sector, using the aggregate productivity effects. The method of calculation is based on He et al. (2020).

Table 1: Baseline results

	(1)	(2)	(3)	(4)
	log(1+Entry)	log(1+Exit)	log(1+Entry)	log(1+Exit)
T≥90°F	-0.00358***	0.00526***	-0.00362***	0.00524***
Two-way clustered	(0.00131)	(0.00141)	(0.00118)	(0.00125)
City-level clustered	(0.00129)***	(0.00140)***	(0.00115)***	(0.00125)***
City-by-sector-level clustered	(0.00127)***	(0.00135)***	(0.00114)***	(0.00123)***
80°F≤T<90°F	-0.00163***	0.00427***	-0.00168***	0.00439***
Two-way clustered	(0.000493)	(0.000508)	(0.000425)	(0.000515)
City-level clustered	(0.000490)***	(0.000504)***	(0.000422)***	(0.000512)***
City-by-sector-level clustered	(0.000490)***	(0.000501)***	(0.000420)***	(0.000511)***
70°F≤T<80°F	-0.00152***	0.00286***	-0.00154***	0.00296***
	(0.000378)	(0.000412)	(0.000333)	(0.000356)
60°F≤T<70°F	-0.000659**	0.000724**	-0.000699**	0.000736**
	(0.000224)	(0.000340)	(0.000301)	(0.000304)
40°F≤T<50°F	-0.00126***	-0.000687**	-0.00145***	-0.000673**
	(0.000226)	(0.000321)	(0.000253)	(0.000310)
30°F≤T<40°F	-0.00142***	-0.00412***	-0.00146***	-0.00414***
	(0.000318)	(0.000392)	(0.000330)	(0.000375)
20°F≤T<30°F	-0.000216***	-0.000186	-0.000245***	-0.000183
	(0.0000485)	(0.000540)	(0.0000469)	(0.000543)
10°F≤T<20°F	-0.000197***	-0.00254***	-0.000186***	-0.00245***
	(0.0000598)	(0.000672)	(0.0000581)	(0.000642)
T< 10°F	-0.000647	0.00163	-0.000646	0.00165
	(0.000466)	(0.00482)	(0.000465)	(0.00471)
City-sector FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
City-year trends	N	N	Y	Y
Sector-year trends	N	N	Y	Y
Weather Controls	N	N	Y	Y
Observations	132444	132444	132444	132444
R-squared	0.017	0.081	0.021	0.088
Number of city-sectors	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. Entry and exit are measured by the number of firm entries and exits, respectively. When not specified, we cluster robust standard errors at the city and sector levels and present them in parentheses. We also report the standard errors clustered at the city and city-by-sector levels for the first two independent variables. Since the significance level does not change using other standard errors, we omit the standard errors clustered at city and city-sector level for other independent variables to save space. Weather controls include wind speed, precipitation, sunshine duration, relative humidity, atmospheric pressure, and PM2.5 levels, along with their squared terms. *** p<0.01, ** p<0.05, * p<0.1.

Table 2: Including alternative control variables and fixed effects

	Panel A: Entry				
	(1)	(2)	(3)	(4)	(5)
	log(1+Number of entry)				
T≥90°F	-0.00369***	-0.00345***	-0.00396***	-0.00378***	-0.00390***
	(0.00103)	(0.00100)	(0.00110)	(0.00104)	(0.00118)
80°F≤T<90°F	-0.00168***	-0.00182***	-0.00136***	-0.00182***	-0.00177***
	(0.000340)	(0.000313)	(0.000312)	(0.000312)	(0.000300)
City-sector FE	Y	Y	Y	Y	Y
Year FE	Y	Y	N	N	N
Province-year FE	N	N	Y	Y	Y
Sector-year FE	N	N	N	Y	Y
Economic Controls	N	Y	N	N	Y
Weather Controls	Y	N	N	N	Y
Observations	132444	132444	132444	132444	132444
R-squared	0.017	0.017	0.016	0.033	0.034
Number of city-sectors	11154	11154	11154	11154	11154
	Panel B: Exit				
	(1)	(2)	(3)	(4)	(5)
	log(1+Number of exit)				
T≥90°F	0.00556***	0.00554***	0.00590***	0.00588***	0.00567***
	(0.00115)	(0.00136)	(0.00178)	(0.00130)	(0.00120)
80°F≤T<90°F	0.00459***	0.00438***	0.00457***	0.00441***	0.00433***
	(0.000500)	(0.000474)	(0.000464)	(0.000501)	(0.000511)
City-sector FE	Y	Y	Y	Y	Y
Year FE	Y	Y	N	N	N
Province-year FE	N	N	Y	Y	Y
Sector-year FE	N	N	N	Y	Y
Economic Controls	N	Y	N	N	Y
Weather Controls	Y	N	N	N	Y
Observations	132444	132444	132444	132444	132444
R-squared	0.081	0.081	0.080	0.102	0.103
Number of city-sectors	11154	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Economic controls include log per capita GDP, log population, and log lagged total sectoral registry capital. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 3: Using different transformations of entry and exit

	(1)	(2)	(3)	(4)
	log(0.01+No. of entry)	log(0.01+No. of exit)	arcsinh(entry)	arcsinh(exit)
T≥90°F	-0.00366***	0.00551***	-0.00376***	0.00522***
	(0.00136)	(0.00163)	(0.00124)	(0.00117)
80°F≤T<90°F	-0.00169***	0.00442***	-0.00183***	0.00490***
	(0.000482)	(0.000514)	(0.000405)	(0.000532)
City-sector FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
City-year trends	Y	Y	Y	Y
Sector-year trends	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Observations	132444	132444	132444	132444
R-squared	0.021	0.088	0.021	0.088
Number of city-sectors	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 4: Using non-linear estimation method

	(1)	(2)	(3)	(4)
	Entry		Exit	
	PPML	Negative Binomial	PPML	Negative Binomial
	Marginal effects are reported below			
T≥90°F	-0.00295**	-0.00283***	0.00475***	0.00386***
	(0.00132)	(0.000412)	(0.00113)	(0.000622)
80°F≤T<90°F	-0.00138***	-0.000683**	0.00365***	0.00225***
	(0.000161)	(0.000299)	(0.000433)	(0.000414)
City-sector FE	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y
Sector-year FE	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Observations	132444	132444	132444	132444
Pseudo R-squared	0.022	0.017	0.029	0.022
Number of city-sectors	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 5: Alternative temperature measures

	(1)	(2)	(3)	(4)
	log(1+Number of entry)		log(1+Number of exit)	
Consecutive hot days>90°F	-0.00423***		0.00389***	
	(0.00101)		(0.00203)	
Temperature>Mean+2SD		-0.00398***		0.00392***
		(0.000542)		(0.000329)
City-sector FE	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y
Sector-year FE	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Observations	132444	132444	132444	132444
R-squared	0.022	0.017	0.029	0.042
Number of city-sectors	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. Consecutive hot days>90°F are measured by the number of consecutive days with a daily mean temperature above 90°F. Temp>mean+2SD are measured by the number of days with daily mean temperature above the historical mean+2SD of daily temperatures during 1980-2000 for each city. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 6: Lag effects of high temperatures

	Panel A: Entry				
	(1)	(2)	(3)	(4)	(5)
	log(1+Number of entry)				
	lag 1	lag 2	lag 3	lag 4	lag 5
T≥ 90°F	-0.00168**	-0.000645	-0.000322	-0.000325	-0.000112
	(0.000512)	(0.000800)	(0.000415)	(0.000604)	(0.000138)
80°F≤T<90°F	-0.000681**	-0.000521	-0.000236	-0.000220	-0.0000774
	(0.000333)	(0.000399)	(0.000447)	(0.000212)	(0.000115)
Observations	132444	132444	132444	132444	132444
R-squared	0.017	0.017	0.016	0.033	0.034
Number of city-sectors	11154	11154	11154	11154	11154

	Panel B: Exit				
	(1)	(2)	(3)	(4)	(5)
	log(1+Number of exit)				
	lag 1	lag 2	lag 3	lag 4	lag 5
T≥ 90°F	0.00399***	0.00375***	0.00306***	0.00269***	0.00250***
	(0.000813)	(0.000710)	(0.000789)	(0.000504)	(0.000618)
80°F≤T<90°F	0.00248***	0.00232***	0.00216***	0.00202***	0.00187***
	(0.000366)	(0.000399)	(0.000333)	(0.000344)	(0.000288)
City-sector FE	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y
City-year trends	Y	Y	Y	Y	Y
Sector-year trends	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y
Observations	132444	132444	132444	132444	132444
R-squared	0.017	0.017	0.016	0.033	0.034
Number of city-sectors	11154	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 7: Heterogeneous effects by firm size

	(1)	(2)	(3)	(4)	(5)	(6)
	log(1+Number of entry)			log(1+Number of exit)		
	Large	Medium	Small	Large	Medium	Small
T≥90°F	0.00183	-0.00166	-0.00381***	0.00232***	0.00311**	0.00859***
	(0.00137)	(0.00116)	(0.00114)	(0.000941)	(0.00121)	(0.00114)
80°F≤T<90°F	0.000482	-0.000418	-0.000581	0.00131***	0.00510***	0.00630***
	(0.000577)	(0.000631)	(0.000563)	(0.000385)	(0.000539)	(0.000613)
City-sector FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
City-year trends	N	N	N	N	N	N
Sector-year trends	N	N	N	N	N	N
Weather Controls	N	N	N	N	N	N
Observations	132444	132444	132444	132444	132444	132444
R-squared	0.012	0.023	0.029	0.023	0.057	0.060
Number of city-sectors	11154	11154	11154	11154	11154	11154

	(7)	(8)	(9)	(10)	(11)	(12)
	log(1+Number of entry)			log(1+Number of exit)		
	Large	Medium	Small	Large	Medium	Small
T≥90°F	0.00157	-0.00159	-0.00350***	0.00272***	0.00329**	0.00840***
	(0.00146)	(0.00134)	(0.00102)	(0.000903)	(0.00127)	(0.00122)
80°F≤T<90°F	0.000461	-0.000425	-0.000911**	0.00149***	0.00529***	0.00655***
	(0.000533)	(0.000615)	(0.000404)	(0.000359)	(0.000573)	(0.000616)
City-Industry FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
City-year trends	Y	Y	Y	Y	Y	Y
Sector-year trends	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Observations	132444	132444	132444	132444	132444	132444
R-squared	0.016	0.027	0.035	0.026	0.061	0.066
Number of city-sectors	11154	11154	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 8: Selection effect: extensive margin

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(1+Number of entry)				log(1+Number of exit)			
	Above median	Below median	Above median	Below median	Above median	Below median	Above median	Below median
$T \geq 90°F$	-0.00136***	-0.00242***	-0.00142***	-0.00251***	0.00103	0.00580***	0.00104	0.00588***
	(0.000444)	(0.000524)	(0.000432)	(0.000512)	(0.000879)	(0.000843)	(0.000939)	(0.000813)
$80°F \leq T < 90°F$	-0.000556***	-0.00126***	-0.000549***	-0.00124***	-0.00246***	0.00153***	-0.00248***	0.00145***
	(9.52e-05)	(0.000123)	(9.66e-05)	(0.000113)	(0.000358)	(0.000324)	(0.000343)	(0.000333)
City-sector FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
City-year trends	N	N	Y	Y	Y	Y	Y	Y
Sector-year trends	N	N	Y	Y	N	N	Y	Y
Weather Controls	N	N	Y	Y	N	N	Y	Y
Observations	132444	132444	132444	132444	132444	132444	132444	132444
R-squared	0.053	0.085	0.059	0.092	0.190	0.217	0.196	0.221
Number of city-industries	11154	11154	11154	11154	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals ($T \geq 90°F$, $80°F \leq T < 90°F$, $70°F \leq T < 80°F$, $60°F \leq T < 70°F$, $40°F \leq T < 50°F$, $30°F \leq T < 40°F$, $20°F \leq T < 30°F$, $10°F \leq T < 20°F$, and $T < 10°F$) are included, with the fifth group $50°F \leq T < 60°F$ being excluded as the base group. Above median means that the firm's revenue/labor value is greater than the median of the city-sector-year. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 9: Heterogeneous effects by labor intensity

	(1)	(2)
	log(1+Number of entry)	log(1+Number of exit)
T≥ 90°F	-0.00144	0.00936***
	(0.00132)	(0.00154)
1(High labor intensity)*(T≥ 90°F)	-0.00479**	0.00539**
	(0.00214)	(0.00262)
80°F≤T<90°F	0.00136	0.00732***
	(0.000714)	(0.000715)
1(High labor intensity)*(80°F≤T<90°F)	-0.00360***	0.00224***
	(0.000774)	(0.000337)
City-sector FE	Y	Y
Year FE	Y	Y
City-year trends	Y	Y
Sector-year trends	Y	Y
Weather Controls	Y	Y
Observations	132444	132444
R-squared	0.019	0.084
Number of city-sectors	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. "High labor intensity" is defined as sectors that have a higher-than-median labor/capital ratio in the city-year cell. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 10: Heterogeneous effects by sector sensitivity to high temperatures

	(1)	(2)
	log(1+Number of entry)	log(1+Number of exit)
T≥ 90°F	-0.00215***	0.00569***
	(0.000442)	(0.00113)
1(Sensitive sector)*(T≥ 90°F)	-0.00270**	0.00399**
	(0.00104)	(0.00142)
80°F≤T<90°F	0.00144	0.00613***
	(0.00124)	(0.00115)
1(Sensitive sector)*(80°F≤T<90°F)	-0.00110***	0.00325***
	(0.000276)	(0.000437)
City-sector FE	Y	Y
Year FE	Y	Y
City-year trends	Y	Y
Sector-year trends	Y	Y
Weather Controls	Y	Y
Observations	132444	132444
R-squared	0.019	0.084
Number of city-sectors	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Sectors that are sensitive to high temperatures include the mining and smelting industries. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 11: Selection effects: intensive margin

	(1)	(2)	(3)	(4)	(5)	(6)
	log(labor)		log(capital)		log(revenue)	
	Above median	Below median	Above median	Below median	Above median	Below median
$T \geq 90°F$	0.00318***	-0.00178***	0.0137***	0.00352***	-0.000536*	-0.00169***
	(0.000353)	(0.000289)	(0.000483)	(0.000467)	(0.000291)	(0.000311)
$80°F \leq T < 90°F$	0.001456	-0.000579***	0.00364***	0.00115***	-0.000123	-0.000694***
	(0.00141)	(5.22e-05)	(9.88e-05)	(0.000132)	(0.000323)	(0.000101)
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Observations	1,418,636	1,359,216	1,445,689	1,359,502	1,449,086	1,364,352
R-squared	0.273	0.245	0.291	0.157	0.436	0.275
Number of firms	415,986	344,697	416,511	344,266	416,546	345,326

Notes: The sample covers about 430000 firms from 2001 to 2012. All the following temperature intervals ($T \geq$ 90°F, $80°F \leq T < 90°F$, $70°F \leq T < 80°F$, $60°F \leq T < 70°F$, $40°F \leq T < 50°F$, $30°F \leq T < 40°F$, $20°F \leq T < 30°F$, $10°F \leq T < 20°F$, and $T < 10°F$) are included, with the fifth group $50°F \leq T < 60°F$ being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 12: Effects on input use

	(1)	(2)	(3)	(4)	(5)	(6)
	log(labor)	log(capital)	log(labor/capital)	log(labor)	log(capital)	log(labor/capital)
$T \geq 90°F$	0.00496**	0.0165***	-0.0159***	0.00218***	0.0142***	-0.0123***
	(0.00245)	(0.00421)	(0.00223)	(0.000208)	(0.000298)	(0.000262)
$80°F \leq T < 90°F$	0.00131***	0.00134***	-0.00727***	0.000568***	0.00235***	-0.00164***
	(4.62e-05)	(6.15e-05)	(0.000382)	(9.35e-05)	(0.000136)	(0.000161)
Weather Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	N	N	N
Province-year FE	N	N	N	Y	Y	Y
Sector-year FE	N	N	N	Y	Y	Y
Observations	2,777,852	2,805,191	2,775,664	2,777,852	2,805,191	2,775,664
R-squared	0.192	0.211	0.072	0.450	0.488	0.329
Number of firms	430,230	430,151	430,112	430,230	430,151	430,112

Notes: The sample covers about 430000 firms from 2001 to 2012. All the following temperature intervals ($T \geq 90°F$, $80°F \leq T < 90°F$, $70°F \leq T < 80°F$, $60°F \leq T < 70°F$, $40°F \leq T < 50°F$, $30°F \leq T < 40°F$, $20°F \leq T < 30°F$, $10°F \leq T < 20°F$, and $T < 10°F$) are included, with the fifth group $50°F \leq T < 60°F$ being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table 13: Aggregate productivity effects

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted average of individual firms' productivity measure in a city-sector-year cell					
	TFP (OP)	TFP (LP)	TFP (GMM)	log(revenue/L)	log(output/L)	log(Solow residual)
T≥90°F	0.000215	0.000313	0.000115	-0.00215	0.000754	0.000662
	(0.00712)	(0.00747)	(0.00117)	(0.00235)	(0.00139)	(0.000575)
80°F≤T<90°F	0.000633	0.000119	0.000540	0.00023	-0.000469	0.000358
	(0.00115)	(0.000349)	(0.00226)	(0.000712)	(0.000505)	(0.000659)
City-sector FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Province-year FE	N	N	N	N	N	N
Sector-year FE	N	N	N	N	N	N
Weather Controls	N	N	N	N	N	N
Observations	55,219	55,219	55,219	89,732	89732	89732
R-squared	0. 003	0.003	0.003	0. 001	0.001	0.497
Number of city-sectors	9748	9748	9748	9748	9748	9748

	(7)	(8)	(9)	(10)	(11)	(12)
	Weighted average of individual firms' productivity measure in a city-sector-year cell					
	TFP (OP)	TFP (LP)	TFP (GMM)	log(revenue/L)	log(output/L)	log(Solow residual)
T≥90°F	0.000209	0.000351	0.000139	-0.00280	0.000567	0.000492
	(0.00711)	(0.00723)	(0.00119)	(0.00222)	(0.00144)	(0.00126)
80°F≤T<90°F	0.000644	0.000148	0.000502	0.000481	-0.000213	0.000964
	(0.00122)	(0.000338)	(0.00229)	(0.00115)	(0.00114)	(0.000499)
City-sector FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
Sector-year FE	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Observations	55,219	55,219	55,219	89,732	89732	89732
R-squared	0.042	0.045	0.045	0.049	0.052	0.599
Number of city-sectors	9748	9748	9748	9748	9748	9748

Notes: The sample covers 9748 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. TFP (OP (ACF), LP (ACF), GMM) only includes data during 2000-2007. TFP (OP and LP) are ACF corrected. TFP (GMM) is calculated using the method proposed in Yu (2015). Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table 14: Decomposition of the contribution of aggregate productivity by entry and exit

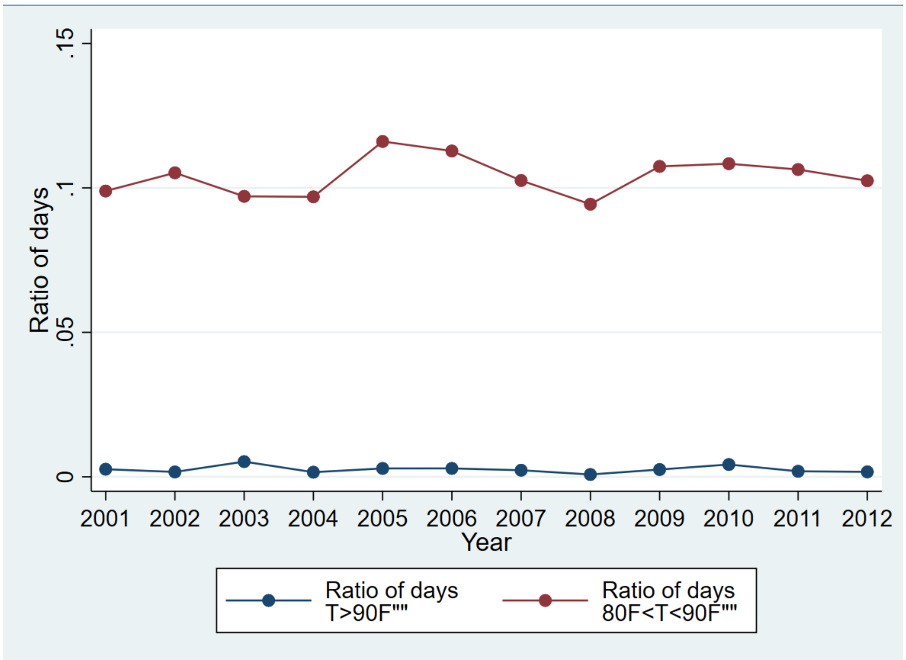
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
		TFP (OP)			TFP (LP)			TFP (GMM)	
	Entry	Exit	Incumbent	Entry	Exit	Incumbent	Entry	Exit	Incumbent
T≥90°F	0.00329***	0.00231	-0.00445***	0.00351***	0.00159	-0.00298***	-0.00298***	0.00255	-0.00336***
	(0.00095)	(0.00227)	(0.00103)	(0.000619)	(0.00146)	(0.000334)	(0.000257)	(0.00191)	(0.000673)
80°F≤T<90°F	-0.000322	0.00167	-0.00399***	-0.000335	-0.00145***	0.00112	0.000149	0.00157	-0.00162**
	(0.000226)	(0.00131)	(0.000908)	(0.000112)	(0.000319)	(0.00136)	(0.000220)	(0.00176)	(0.000503)
Observations	55,219	55,219	55,219	55,219	55,219	55,219	55,219	55,219	55,219
R-squared	0.012	0.012	0.014	0.016	0.016	0.022	0.014	0.012	0.021
Number of city-sectors	9748	9748	9748	9748	9748	9748	9748	9748	9748
	(10)	(11)	(12)	(13)	(14)	(15)	(16)	(17)	(18)
		log(Rev./L)			log(Ouput/L)			log(Solow residual)	
	Entry	Exit	Incumbent	Entry	Exit	Incumbent	Entry	Exit	Incumbent
T≥90°F	0.00633***	0.00298	-0.00932***	0.00631***	0.000966	-0.00487***	0.00199***	0.00132	-0.00466***
	(0.00105)	(0.00219)	(0.00265)	(0.000722)	(0.00170)	(0.00189)	(0.000379)	(0.000932)	(0.000981)
80°F≤T<90°F	-0.000349	0.000121	0.00421***	-0.000232	-0.00166***	0.00190***	0.000101	0.000645**	0.000149
	(0.000257)	(0.000724)	(0.000859)	(0.000169)	(0.000434)	(0.000595)	(8.25e-05)	(0.000309)	(0.000421)
City-sector FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y	Y	Y	Y
Sector-year trends	Y	Y	Y	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y	Y	Y	Y
Observations	99,779	99,779	99,779	99,779	99,779	99,779	99,779	99,779	99,779
R-squared	0.032	0.155	0.267	0.059	0.157	0.779	0.012	0.045	0.168
Number of city-sectors	11,191	11,191	11,191	11,191	11,191	11,191	11,191	11,191	11,191

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. TFP (OP, LP, GMM) only includes data during 2000-2007. TFP (OP and LP) are ACF corrected. TFP (GMM) is calculated using the method proposed in Yu (2015). Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Online Appendix For Publication

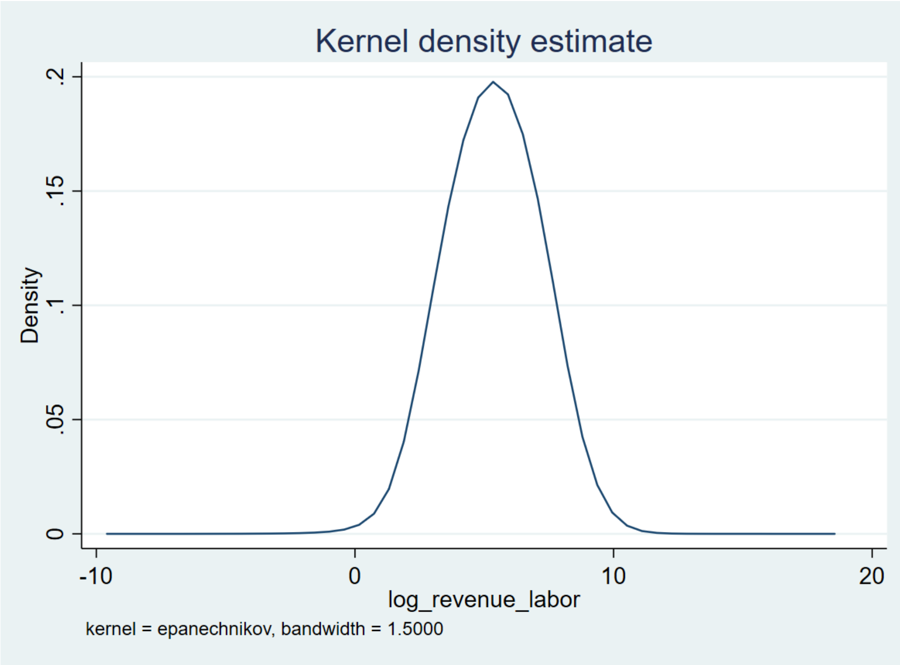
Appendix A Figures and Tables

Figure A1: Distribution of days of high temperature



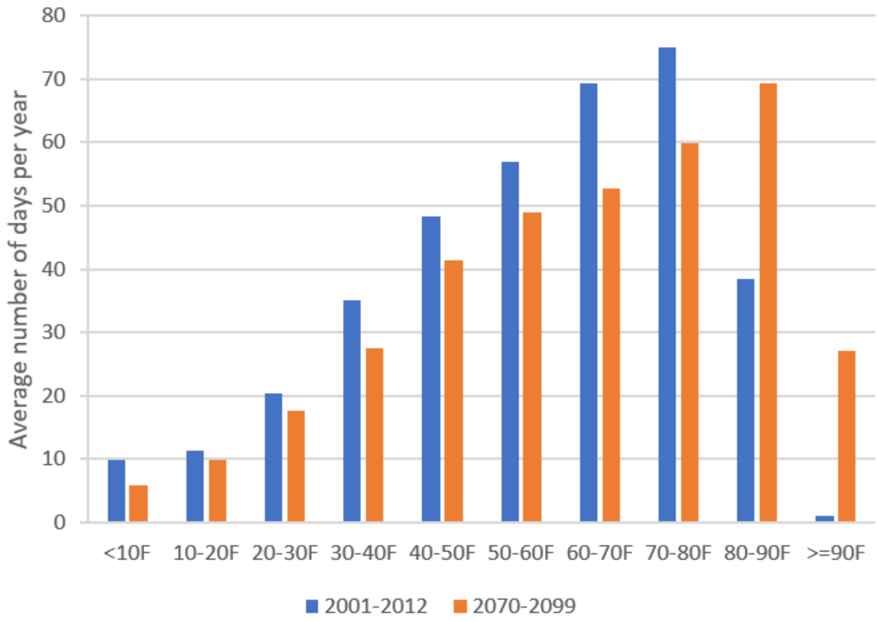
Notes: "Ratio of days" stands for the ratio of days in a certain temperature bin in a year.

Figure A2: Kernel density estimation of $\log(\psi z)$



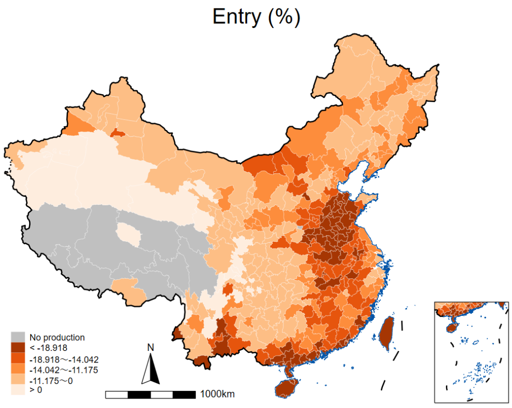
Notes: This figure shows the kernel density estimation of productivity $\log(\psi z)$*. The distribution resembles a normal distribution.*

Figure A3: Distribution of temperature, 2001-2012 and 2070-2099



Data sources: China National Meteorological Data Service Center (CMDC) and Hadley Centre Global Environment Model version 2 (HadGEM2-ES).

Figure A4: The predicted impacts of climate change on firm dynamics



(a) (b)

Notes: Figure A4 (a) shows the predicted impacts of climate change on entry. Figure A4 (b) shows the predicted impacts of climate change on exit. The effects are calculated using the measure of firm entry and firm exit in the quantitative model. All effects are measured by percentage points.

Table A1: Summary Statistics

Variable	Obs	Mean	Std. Dev.	Min	Max
log(1+entry)	138,060	2.002	1.740	0	9.355
log(1+entry, SOE)	138,060	0.076	0.267	0	4.796
log(1+entry, private)	138,060	1.940	1.728	0	9.290
log(1+entry, large)	138,060	0.811	1.148	0	7.447
1og(1+entry, medium)	138,060	1.268	1.446	0	8.327
log(1+entry, small)	138,060	1.452	1.548	0	8.793
log(1+exit)	138,060	1.316	1.539	0	8.789
log(1+exit, SOE)	138,060	0.022	0.178	0	4.654
log(1+exit, private)	138,060	1.171	1.485	0	8.709
log(1+exit, large)	138,060	0.239	0.624	0	7.447
log(1+exit, medium)	138,060	0.674	1.113	0	7.774
log(1+exit, small)	138,060	1.072	1.400	0	8.284
T<10°F	132,444	9.600	22.780	0	139
# days 10°F≤T<20°F	132,444	11.140	18.043	0	93
# days 20°F≤T<30°F	132,444	18.275	20.898	0	104
# days 40°F≤T<50°F	132,444	34.705	22.328	0	90
# days 50°F≤T<60°F	132,444	54.868	16.855	0	154
# days 60°F≤T<70°F	132,444	69.990	18.605	0	196
# days 70°F≤T<80°F	132,444	78.903	28.195	0	279
# days 80°F≤T<90°F	132,444	41.683	37.937	0	231
# days T≥90°F	132,444	1.077	3.040	0	32

Table A2: Using alternative temperature-city matching method on temperatures

	(1)	(2)	(3)	(4)	(5)	(6)
	log(1+Number of entry)			log(1+Number of exit)		
	Full sample	Above median	Below median	Full sample	Above median	Below median
T≥90°F	-0.00479***	-0.00215**	-0.00789***	0.00679***	0.00290**	0.00970***
	(0.00112)	(0.00110)	(0.00201)	(0.00138)	(0.00143)	(0.00226)
80°F≤T<90°F	-0.00198***	-0.000937***	-0.00244***	0.00382***	0.00154***	0.00450***
	(0.000544)	(0.000266)	(0.000527)	(0.000499)	(0.000322)	(0.000611)
City-sector FE	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
Sector-year FE	Y	Y	Y	Y	Y	Y
Economic Controls	N	N	N	N	N	N
Weather Controls	Y	Y	Y	Y	Y	Y
Observations	132444	132444	132444	132444	132444	132444
R-squared	0.022	0.017	0.029	0.042	0.038	0.055
Number of city-sectors	11154	11154	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A3: Using temperature bins of daily maximum and minimum

Panel A: Temperature bins of daily maximum						
	(1)	(2)	(3)	(4)	(5)	(6)
	log(1+Number of entry)			log(1+Number of exit)		
	Full sample	Above median	Below median	Full sample	Above median	Below median
T≥95°F	-0.00368***	-0.00155**	-0.00594***	0.00469***	0.00230**	0.00669***
	(0.000479)	(0.000731)	(0.00130)	(0.00131)	(0.00114)	(0.00114)
85°F≤T<95°F	-0.00159***	-0.000653***	-0.00216***	0.00252***	0.00104***	0.00437***
	(0.000666)	(0.000222)	(0.000514)	(0.000463)	(0.000215)	(0.000518)
Observations	132444	132444	132444	132444	132444	132444
R-squared	0.018	0.015	0.023	0.034	0.030	0.039
Number of city-sectors	11154	11154	11154	11154	11154	11154

Panel B: Temperature bins of daily minimum						
	(1)	(2)	(3)	(4)	(5)	(6)
	log(1+Number of entry)			log(1+Number of exit)		
	Full sample	Above median	Below median	Full sample	Above median	Below median
T≥85°F	-0.00290**	-0.00178**	-0.00677***	0.00375***	0.00250***	0.00599***
	(0.00141)	(0.00504)	(0.00226)	(0.000710)	(0.000608)	(0.000413)
75°F≤T<85°F	-0.00134***	-0.000663**	-0.00351***	0.00198***	-0.000225	0.00284***
	(0.000321)	(0.000321)	(0.000617)	(0.000544)	(0.000212)	(0.000521)
City-sector FE	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
Sector-year FE	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Observations	132444	132444	132444	132444	132444	132444
R-squared	0.022	0.017	0.029	0.042	0.038	0.055
Number of city-sectors	11154	11154	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. For daily maximum temperatures, all the following temperature intervals (T≥ 95°F, 85°F≤T<95°F, 75°F≤T<85°F, 65°F≤T<75°F, 45°F≤T<55°F, 35°F≤T<45°F, 25°F≤T<35°F, 15°F≤T<25°F, and T<15°F) are included, with the fifth group 55°F≤T<65°F being excluded as the base group. For daily minimum temperatures, all the following temperature intervals (T≥ 85°F, 75°F≤T<85°F, 65°F≤T<75°F, 55°F≤T<65°F, 35°F≤T<45°F, 25°F≤T<35°F, 15°F≤T<25°F, 5°F≤T<15°F, and T<5°F) are included, with the fifth group 45°F≤T<55°F being excluded as the base group. Panel A and B have the same controls and fixed effects. "Above median" indicates that firms in that city-sector-year cell have log(revenue/labor) higher than the sample median; "Below median" indicates that firms in that city-sector-year cell have log(revenue/labor) lower than the sample median. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A4: Using Celsius measure of temperatures

	(1)	(2)	(3)	(4)	(5)	(6)
	log(1+Number of entry)			log(1+Number of exit)		
	Full sample	Above median	Below median	Full sample	Above median	Below median
T≥32°C	-0.00346***	-0.00118***	-0.00556***	0.00469***	0.00198	0.00762***
	(0.000415)	(0.000315)	(0.00132)	(0.00131)	(0.00157)	(0.00132)
28°C≤T<32°C	-0.00163***	-0.000537***	-0.00338***	0.00252***	0.00132	0.00370***
	(0.000624)	(0.000163)	(0.000470)	(0.000463)	(0.00153)	(0.000445)
City-sector FE	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
Sector-year FE	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Observations	132444	132444	132444	132444	132444	132444
R-squared	0.018	0.015	0.023	0.034	0.030	0.039
Number of city-sectors	11154	11154	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 32°C, 28°C≤T<32°C, 24°C≤T<28°C, 20°C≤T<24°C, 16°C≤T<20°C, 8°C≤T<12°C, 4°C≤T<8°C, 0°C≤T<4°C, −4°C≤T<0°C, and T<−4°C) are included, with the sixth group 12°C≤T<16°C being excluded as the base group. "Above median" indicates that firms in that city-sector-year cell has log(revenue/labor) higher than the sample median; "Below median" indicates that firms in that city-sector-year cell have log(revenue/labor) lower than the sample median. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A5: Effects on agriculture and service sectors

	(1)	(2)	(3)	(4)
	log(1+Number of entry)		log(1+Number of exit)	
	Agriculture	Service	Agriculture	Service
T≥90°F	-0.00229**	-0.00379***	0.00256***	0.00319***
	(0.00114)	(0.000600)	(0.000506)	(0.000578)
80°F≤T<90°F	-0.00156***	-0.00152***	0.00129***	0.00195***
	(0.000442)	(0.000249)	(0.000338)	(0.000468)
City-sector FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
City-year trends	Y	Y	Y	Y
Sector-year trends	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Observations	17700	184860	17700	184860
R-squared	0.017	0.017	0.017	0.033
Number of city-sectors	1475	15405	1475	15405

Notes: The sample covers 1475 (agriculture) and 15405 (service) city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A6: Effects on firm dynamics for different size percentiles

Size percentile	Effects on entry	Standard error	Effects on exit	Standard error
Bottom 50%	-0.00381	0.00012	0.00859	0.00034
Bottom 40%	-0.00409	0.00015	0.00859	0.00136
Bottom 30%	-0.00459	0.00034	0.00859	0.00155
Bottom 20%	-0.00506	0.00042	0.00859	0.00117
Bottom 10%	-0.00585	0.00052	0.00859	0.00130

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals ($T \geq 90°F$, $80°F \leq T < 90°F$, $70°F \leq T < 80°F$, $60°F \leq T < 70°F$, $40°F \leq T < 50°F$, $30°F \leq T < 40°F$, $20°F \leq T < 30°F$, $10°F \leq T < 20°F$, and $T < 10°F$) are included, with the fifth group $50°F \leq T < 60°F$ being excluded as the base group. We only report the coefficient on $T \geq 90°F$. "Bottom 40%" indicates the effects on firms that belong to the bottom 40% in the size distribution, similar to the descriptions for other categories. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A7: Heterogeneous effects by ownership

	(1)	(2)	(3)	(4)
	log(1+Number of entry)		log(1+Number of exit)	
	SOE	Private	SOE	Private
T$\geq$ 90°F	0.000368	-0.00399***	-7.94e-05	0.00516***
	(0.000412)	(0.00131)	(0.000286)	(0.00154)
80°F$\leq$T$<$90°F	0.000125	-0.00109*	0.000625***	0.00623***
	(0.000196)	(0.000611)	(0.000121)	(0.000712)
City-sector FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
City-year trends	Y	Y	Y	Y
Sector-year trends	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Observations	132444	132444	132444	132444
R-squared	0.007	0.021	0.009	0.119
Number of city-sectors	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T$\geq$ 90°F, 80°F$\leq$T$<$90°F, 70°F$\leq$T$<$80°F, 60°F$\leq$T$<$70°F, 40°F$\leq$T$<$50°F, 30°F$\leq$T$<$40°F, 20°F$\leq$T$<$30°F, 10°F$\leq$T$<$20°F, and T$<$10°F) are included, with the fifth group 50°F$\leq$T$<$60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A8: Selection effects: More results

Panel A: Classifying firms according to output per worker

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(1+Number of entry)				log(1+Number of exit)			
	Above median	Below median	Above median	Below median	Above median	Below median	Above median	Below median
T≥ 90°F	-0.00156***	-0.00452***	-0.00113***	-0.00294***	0.00114*	0.00814***	0.00115	0.00790***
	(0.000431)	(0.000536)	(0.000414)	(0.000512)	(0.000877)	(0.000672)	(0.00137)	(0.000820)
80°F≤T<90°F	-0.000577***	-0.00144***	-0.000565***	-0.00115***	-0.00114	0.00168***	-0.00102	0.00352***
	(9.21e-05)	(0.000118)	(9.12e-05)	(0.000103)	(0.00355)	(0.000314)	(0.00142)	(0.000672)
City-sector FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
City-year trends	N	N	Y	Y	Y	Y	Y	Y
Sector-year trends	N	N	Y	Y	N	N	Y	Y
Weather Controls	N	N	Y	Y	N	N	Y	Y
Observations	132444	132444	132444	132444	132444	132444	132444	132444
R-squared	0.053	0.085	0.059	0.092	0.190	0.217	0.196	0.221
Number of city-sectors	11154	11154	11154	11154	11154	11154	11154	11154

Panel B: Classifying firms according to value added per worker

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(1+Number of entry)				log(1+Number of exit)			
	Above median	Below median	Above median	Below median	Above median	Below median	Above median	Below median
T≥ 90°F	-0.00105***	-0.00562***	-0.00118***	-0.00338***	0.00114	0.00669***	0.000886	0.00721***
	(0.000222)	(0.000514)	(0.000330)	(0.000492)	(0.00156)	(0.000776)	(0.000773)	(0.00132)
80°F≤T<90°F	-0.000806***	-0.00226***	-0.000645***	-0.00155***	0.000465	0.00221***	0.000486	0.00170***
	(7.63e-05)	(0.000118)	(7.34e-05)	(0.000225)	(0.000588)	(0.000445)	(0.00547)	(0.000225)
City-sector FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
City-year trends	N	N	Y	Y	Y	Y	Y	Y
Sector-year trends	N	N	Y	Y	N	N	Y	Y
Weather Controls	N	N	Y	Y	N	N	Y	Y
Observations	132444	132444	132444	132444	132444	132444	132444	132444
R-squared	0.053	0.085	0.059	0.092	0.190	0.217	0.196	0.221
Number of city-sectors	11154	11154	11154	11154	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A9: Heterogeneous effects by high tech industries

	(1)	(2)
	log(1+Number of entry)	log(1+Number of exit)
T≥ 90°F	-0.00334**	0.00866***
	(0.00132)	(0.00151)
1(High Tech)*(T≥ 90°F)	0.00811**	0.00535
	(0.00390)	(0.00441)
80°F≤T<90°F	-0.000365	0.00807***
	(0.000636)	(0.000722)
1(High Tech)*(80°F≤T<90°F)	0.00122	0.00242
	(0.00143)	(0.00135)
City-sector FE	Y	Y
Year FE	Y	Y
City-year trends	Y	Y
Sector-year trends	Y	Y
Weather Controls	Y	Y
Observations	132444	132444
R-squared	0.017	0.081
Number of city-sectors	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. High-technology industries include medicine manufacturing, electronic and telecommunication manufacturing, aviation and aerospace manufacturing, computer manufacturing, medical equipment manufacturing, and information chemicals manufacturing. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A10: Noon and night-time temperatures, and labor intensity

	(1)	(2)	(3)	(4)
	log(1+Number of entry)	log(1+Number of exit)	log(1+Number of entry)	log(1+Number of exit)
	Daily maximum (noon time temperatures)		Daily minimum (night time temperatures)	
T≥95°F	-0.00156	0.00968***		
	(0.00149)	(0.00155)		
1(High labor intensity)*(T≥95°F)	-0.00741***	0.00759**		
	(0.00142)	(0.00133)		
T≥85°F			-0.00100	0.00544***
			(0.00155)	(0.00116)
1(High labor intensity)*(T≥85°F)			-0.00296**	0.00430**
			(0.00110)	(0.00211)
85°F≤T<95°F	-0.00110	0.00815***		
	(0.000926)	(0.000632)		
1(High labor intensity)*(85°F≤T<95°F)	-0.00569***	0.00459***		
	(0.000634)	(0.000512)		
75°F≤T<85°F			-0.00103	0.00534***
			(0.000815)	(0.000490)
1(High labor intensity)*(75°F≤T<85°F)			-0.00262***	0.00211***
			(0.000667)	(0.000442)
City-sector FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
City-year trends	Y	Y	Y	Y
Sector-year trends	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	132444	132444	132444	132444
R-squared	0.019	0.084	0.019	0.084
Number of city-sectors	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 95°F, 85°F≤T<95°F, 75°F≤T<85°F, 65°F≤T<75°F, 45°F≤T<55°F, 35°F≤T<45°F, 25°F≤T<35°F, 15°F≤T<25°F, and T<15°F) are included, with the fifth group 55°F≤T<65°F being excluded as the base group. "High labor intensity" is defined as sectors that have a higher-than-median labor/capital ratio in the city-year cell. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A11: Disaggregated productivity effects

	(1)	(2)	(3)	(4)	(5)	(6)
	TFP, OP	TFP, LP	TFP, GMM	log(revenue/labor)	log(output/labor)	log(Solow residual)
$T \geq 90°F$	-0.00179***	-0.00598**	-0.00954***	-0.00635***	-0.00499**	-0.00337***
	(0.000341)	(0.00221)	(0.00111)	(0.00227)	(0.00231)	(0.000192)
$80°F \leq T < 90°F$	-0.000276***	0.00299***	-0.00947***	-0.00248***	-0.00296***	-0.00149***
	(0.0000363)	(0.000533)	(0.000199)	(0.000912)	(0.000713)	(2.33e-05)
Firm FE	Y	Y	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y	Y	Y
Sector-year FE	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Observations	1,504,341	1,504,341	1,504,341	2,783,995	2,530,523	2,769,609
R-squared	0.026	0.029	0.023	0.000	0.000	0.147
Number of firms	327,590	327,590	327,590	430,292	430,152	430,149

Notes: The sample covers about 430000 firms from 2001 to 2012. All the following temperature intervals ($T \geq 90°F$, $80°F \leq T < 90°F$, $70°F \leq T < 80°F$, $60°F \leq T < 70°F$, $40°F \leq T < 50°F$, $30°F \leq T < 40°F$, $20°F \leq T < 30°F$, $10°F \leq T < 20°F$, and $T < 10°F$) are included, with the fifth group $50°F \leq T < 60°F$ being excluded as the base group. TFP (OP, LP, GMM) only includes data during 2000-2007. TFP (OP and LP) are ACF corrected. TFP (GMM) is calculated using the method proposed in Yu (2015). Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A12: Firm-level exit

	(1)	(2)	(3)
		1(Exit)	
T≥90°F	0.00322***	0.00318***	0.00356***
	(0.000314)	(0.000329)	(0.00100)
80°F≤T<90°F	0.00177***	0.00147***	0.00158***
	(0.000662)	(0.000469)	(0.000573)
Firm FE	Y	Y	Y
Year FE	Y	N	N
Province-year FE	N	Y	Y
Sector-year FE	N	Y	Y
Economic Controls	N	N	Y
Weather Controls	Y	Y	Y
Observations	30560243	30560243	30560243
R-squared	0.008	0.019	0.019
Number of firms	4365749	4365749	4365749

Notes: The sample covers 4365749 firms from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Once the firm exits, it no longer exists in the regression sample. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A13: Effects on unweighted aggregate productivity

	(1)	(2)	(3)	(4)	(5)	(6)
	Unweighted average of individual firms' productivity measure in a city-sector-year cell					
	TFP (OP)	TFP (LP)	TFP (GMM)	log(revenue/L)	log(output/L)	log(Solow residual)
T≥ 90°F	0.000461	0.00239	-0.00281	-0.000307	-0.00132	0.000811
	(0.000694)	(0.00178)	(0.00233)	(0.000518)	(0.00120)	(0.00108)
80°F≤T<90°F	0.000556	0.000689	0.00192*	0.00747***	0.00589***	0.00494***
	(0.000894)	(0.00101)	(0.00101)	(0.000534)	(0.000690)	(0.000603)
City-sector FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Province-year FE	N	N	N	N	N	N
Sector-year FE	N	N	N	N	N	N
Weather Controls	N	N	N	N	N	N
Observations	55,219	55,219	55,219	89,732	89,732	89,732
R-squared	0.697	0.677	0.953	0.769	0.679	0.600

	(7)	(8)	(9)	(10)	(11)	(12)
	Unweighted average of individual firms' productivity measure in a city-sector-year cell					
	TFP (OP)	TFP (LP)	TFP (GMM)	log(revenue/L)	log(output/L)	log(Solow residual)
T≥ 90°F	0.000811	2.01e-06	0.00324	0.000995	-0.000341	0.00121
	(0.00108)	(0.000747)	(0.00224)	(0.00121)	(0.00144)	(0.00127)
80°F≤T<90°F	0.00166**	0.00284**	0.00149	0.00245***	0.00354***	0.00269***
	(0.00114)	(0.00126)	(0.00123)	(0.000645)	(0.000833)	(0.000736)
City-sector FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
Sector-year FE	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Observations	55,219	55,219	55,219	89,732	89,732	89,732
R-squared	0.717	0.704	0.956	0.799	0.715	0.644

Notes: The sample covers 55,219 (89,732) city-sector-year cells from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Once the firm exits, it no longer exists in the regression sample. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A14: (Long run) effects on city outcomes

	(1)	(2)	(3)	(4)
	GDP growth	log(Population)	log(Fiscal revenue)	log(Fiscal revenue)
T≥90°F	0.00656	-0.000174	0.000533	0.00156
	(0.0197)	(0.000272)	(0.00194)	(0.00142)
80°F≤T<90°F	-0.00215	-0.000275**	-5.11e-05	-0.00131
	(0.0102)	(0.000122)	(0.000533)	(0.000901)
City FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
City-year trends	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Observations	4,873	4,873	4,873	4,626
R-squared	0.567	0.999	0.991	0.981

Notes: The sample covers about 6800 city-year cells during 1990-2020. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, clustered at the city level, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A15: Long-term (accumulative) effects

	(1)	(2)	(3)	(4)
	log(1+No. of entry)	log(1+No. of exit)	log(1+No. of entry)	log(1+No. of exit)
	City-sector-year panel			
	Past 3 years		Past 5 years	
T≥90°F	-0.00134***	0.00167***	-0.000777***	0.00136***
	(0.000212)	(0.000413)	(0.000236)	(0.000344)
80°F≤T<90°F	-0.000457***	0.00149***	-0.000535***	0.000828***
	(0.000101)	(0.000223)	(0.000152)	(0.000212)
City-sector FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
City-year trends	Y	Y	Y	Y
Sector-year trends	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y
Firm FE	N/A	N/A	N/A	N/A
Observations	132444	132444	132444	132444
R-squared	0.017	0.081	0.017	0.081
Number of city-sectors	11154	11154	11154	11154

	(5)	(6)	(7)	(8)	(9)	(10)
	TFP (OP)	TFP (LP)	TFP (GMM)	TFP (OP)	TFP (LP)	TFP (GMM)
	Firm-year panel					
	Past 3 years			Past 5 years		
T≥90°F	-4.62e-05	-0.00224***	-0.000122	-1.32e-05	-0.00129***	-0.00199***
	(0.000159)	(0.000121)	(0.000474)	(0.000115)	(8.14e-05)	(0.000322)
80°F≤T<90°F	-0.000656***	-0.00135***	-0.00281***	-0.000298***	-0.000673***	-0.00197***
	(6.32e-05)	(5.46e-05)	(0.000154)	(3.56e-05)	(3.13e-05)	(0.000122)
City-sector FE	N	N	N	N	N	N
Year FE	Y	Y	Y	Y	Y	Y
City-year trends	N	N	N	N	N	N
Sector-year trends	N	N	N	N	N	N
Weather Controls	Y	Y	Y	Y	Y	Y
Firm FE	Y	Y	Y	Y	Y	Y
Observations	1,466,368	1,466,610	1,466,610	1,466,368	1,466,610	1,466,610
R-squared	0.466	0.707	0.310	0.466	0.707	0.310

Notes: The sample period for columns (1) through (4) is 2001-2012, and the sample period for columns (5) through (10) is 2001-2007 (due to limitations of data coverage). All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. The temperature intervals indicate the average annual number of days falling in each temperature bin over the past k years (k=3, 5). Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table A16: Using a longer sample period

	(1)	(2)	(1)	(2)	(1)	(2)
	log(1+Number of entry)			log(1+Number of exit)		
	Manufacturing	Agriculture	Service	Manufacturing	Agriculture	Service
$T \geq 90°F$	-0.00348***	-0.00424***	-0.00366***	0.00621***	0.00392***	0.00541***
	(0.00101)	(0.000641)	(0.000521)	(0.00112)	(0.000761)	(0.00112)
$80°F \leq T < 90°F$	-0.00178***	-0.00228***	-0.00168***	0.00241***	0.00164***	0.00218***
	(0.000323)	(0.000500)	(0.000414)	(0.000606)	(0.000361)	(0.000568)
City-sector FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
Sector-year FE	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Observations	345774	45725	477555	345774	45725	477555
R-squared	0.023	0.025	0.022	0.081	0.083	0.084
Number of city-sectors	11154	1475	15405	11154	1475	15405

Notes: The sample period is 1990-2020. All the following temperature intervals ($T \geq 90°F$, $80°F \leq T < 90°F$, $70°F \leq T < 80°F$, $60°F \leq T < 70°F$, $40°F \leq T < 50°F$, $30°F \leq T < 40°F$, $20°F \leq T < 30°F$, $10°F \leq T < 20°F$, and $T < 10°F$) are included, with the fifth group $50°F \leq T < 60°F$ being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table A17: Structural estimates - external calibration and estimation

Parameter	Calibration	
ϵ	1.2	
β	0.997	
γ	2	

Parameter	Estimates	S.E.
$\beta_{\psi 1}$	-0.00694	0.00224
$\beta_{\psi 2}$	-0.00306	0.00098
$\beta_{\psi 3}$	-0.00182	0.00143
$\beta_{\psi 4}$	-0.00219	0.00187
$\beta_{\psi 6}$	-0.00037	0.00232
$\beta_{\psi 7}$	-0.00012	0.00277
$\beta_{\psi 8}$	-0.00281	0.00115
$\beta_{\psi 9}$	-0.00281	0.00129
$\beta_{\psi 10}$	-0.00216	0.00168
σ	1.200	0.000

Table A18: Structural estimates - internal estimation

Parameter	Estimate	S.E.	Parameter	Estimate	S.E.	Parameter	Estimate	S.E.
$\beta_{\tau 1}$	0.00579	0.00231	$\beta_{f_e 1}$	0.00613	0.00119	τ_0	0.00521	0.00153
$\beta_{\tau 2}$	0.00273	0.00101	$\beta_{f_e 2}$	0.00299	0.00079	f_{e0}	0.00369	0.00137
$\beta_{\tau 3}$	-0.0005	0.00147	$\beta_{f_e 3}$	-0.0009	0.00187	λ_0	0.12037	0.04031
$\beta_{\tau 4}$	0.00033	0.00193	$\beta_{f_e 4}$	-0.0002	0.00198	λ_1	0.80001	0.23011
$\beta_{\tau 6}$	-0.0003	0.00239	$\beta_{f_e 6}$	0.00049	0.00209	λ_2	-0.0932	0.03175
$\beta_{\tau 7}$	0.0006	0.00285	$\beta_{f_e 7}$	0.00335	0.0022			
$\beta_{\tau 8}$	0.00355	0.00118	$\beta_{f_e 8}$	0.00513	0.00191			
$\beta_{\tau 9}$	0.00468	0.00133	$\beta_{f_e 9}$	0.0008	0.00221			
$\beta_{\tau 10}$	0.00412	0.00173	$\beta_{f_e 10}$	0.00433	0.00252			

Notes: We match the model-generated data to the following targeted reduced form estimates: (1) entry, whole sample; (2) exit, whole sample; (3) entry, below median performance; (4) entry, above median performance; (5) exit, below median performance; (6) exit, above median performance; (7) entry, large firms; (8) entry, medium firms; (9) entry, small firms; (10) exit, large firms; (11) exit, medium firms; (12) entry, small firms.

Table A19: Goodness of fit

	Data	Model
	Targeted Coefficients	
(1)	-0.00217	-0.00288
(2)	0.00919	0.00817
(3)	-0.00240	-0.00222
(4)	-0.00131	-0.00177
(5)	0.00567	0.00611
(6)	0.00154	0.00099
(7)	0.00181	0.00088
(8)	-0.00174	-0.00150
(9)	-0.00374	-0.00380
(10)	0.00278	0.00298
(11)	0.00323	0.00229
(12)	0.00832	0.00689
	Non-Targeted Coefficients	
(1)	-0.0190	-0.0133
(2)	0.0248	0.0112
(3)	-0.00675	-0.00331
(4)	-0.000817	-0.00119
(5)	0.00291	0.00360
(6)	0.000824	0.000325
(7)	-0.0133	-0.0163
(8)	0.0400	0.0201
(9)	-0.0406	-0.0280
(10)	-0.00199	-0.00177
(11)	0.00231	0.00165
(12)	-0.0133	-0.0122
(13)	-0.00525	-0.00319
(14)	0.0285	0.0199

Notes: Targeted coefficients: the coefficient on T$\geq$ 90°F for (1) entry, whole sample; (2) exit, whole sample; (3) entry, below median performance; (4) entry, above median performance; (5) exit, below median performance; (6) exit, above median performance; (7) entry, large firms; (8) entry, medium firms; (9) entry, small firms; (10) exit, large firms; (11) exit, medium firms; (12) exit, small firms. Non-targeted coefficients: the coefficient on T$\geq$ 90°F for (1) entry, Huabei; (2) entry, Northeast; (3) entry, Huadong; (4) entry, Huazhong; (5) entry, Huanan; (6) entry, Southwest; (7) entry, Northwest; (8) exit, Huabei; (9) exit, Northeast; (10) exit, Huadong; (11) exit, Huazhong; (12) exit, Huanan; (13) exit, Southwest; (14) exit, Northwest.

Table A20: Size-varying temperature damages and labor reallocation cost

Parameter	Estimates	S.E.
$\beta_{1,\tau_{size}}$	0.00202	0.00023
$\beta_{2,\tau_{size}}$	0.00024	2.95E-05
$\beta_{3,\tau_{size}}$	0.00083	3.61E-05
$\beta_{4,\tau_{size}}$	0.000213	4.20E-05
$\beta_{6,\tau_{size}}$	0.000134	4.12E-05
$\beta_{7,\tau_{size}}$	-0.00027	3.93E-05
$\beta_{8,\tau_{size}}$	0.00217	5.85E-05
$\beta_{9,\tau_{size}}$	-0.00071	7.91E-05
$\beta_{10,\tau_{size}}$	0.000229	6.18E-05
c^R	0.0564	0.0112

Online Appendix Not For Publication

Appendix B Data Compilation and Other Channels

B.1 Firm Data

The origin data set of the firm registration information consists of records of registration and deregistration of each firm. Each entry includes information on the registry capital, location, identity of the legal representative(s), ownership information, sectoral classification, and the year of exit (if any). Note that if the firm simply stops production or reallocates but does not deregister, then it is not deemed to have exited in our data set. However, we also merge the registration data set with the Annual Survey of Industrial Firms (ASIF) data set that has information on production, with a matching rate of 81%. 81% of the firms of the ASIF data set can be matched with the firm registration data set. If we take into account the fact that a firm may stop production and count this case as an exit, the new exit should be 2.24% larger, whereas all of the results on exit still hold.

Based on over 40 million registration records of the universe of Chinese firms, we aggregate the granular data into a city-sector-year panel data set. Specifically, we calculate entry and exit in each city-sector-year cell. Entry is defined and calculated as the number of firms that have been registered in a specific city, sector, and year. We discard observations whose registry capital is 0 or belongs to the top 0.1%. Similarly, exit is defined and calculated as the number of firms that have been deregistered in a specific city, sector, and year. Again, the measure of exit is subject to the issue of measurement error, but we can show that the magnitude of the error is small and does not alter our main results.

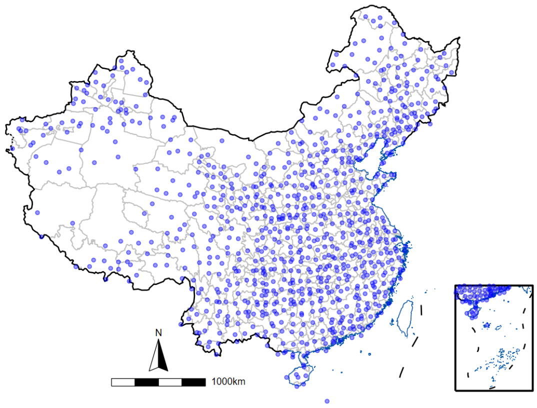
We also match the registration data set with a patent application data set, so that we can know which firm applies for which patent. In this way, we calculate the number of patent applications by firms that belong to a certain city-sector-year cell.

B.2 Temperature Data

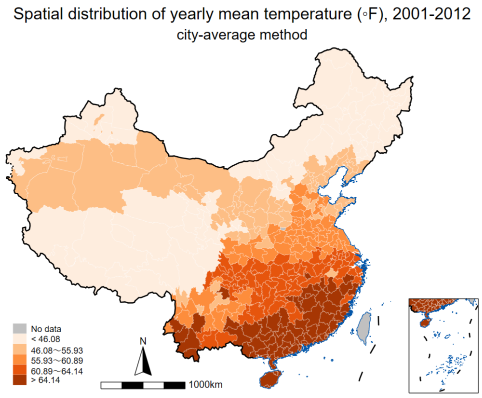
The weather data set provided by the CMDC has been widely used in the recent literature when studying weather/climate change in China (for example, Agarwal et al., 2021; Zivin et al., 2020). Figure B1 (a) displays the distribution of the weather stations. As far as we know, the distribution of the monitoring stations in this data set is finer than that of the gridded temperature products, which are typically at the $0.5°\times0.625°$ grid level. Since our main estimates are performed at the city level, we transform weather data from station to city level by calculating the mean values of weather variables from all the monitoring stations within each city.

As an alternative matching method, we interpolate the weather data from the stations into a $0.1°\times0.1°$ grid level using the inverse-distance weighting (IDW) method and extract the value of the weather measures based on the boundaries of each city from the gridded data. Interpolating the weather data from stations into the grid level enables us to match the weather data following the exact boundaries for each city, which can help ameliorate the concerns about potential measurement errors caused by the imprecise matching radius for some geographically large or small cities when using IDW method. Figure B1 (b) and (c) illustrate the spatial distribution of the yearly mean temperature from 2001 to 2012 for each matching method. The patterns obtained using the city-average and interpolating approaches exhibit substantial similarity. Additionally, Tables B1 through B3 demonstrate the robustness of our baseline estimates, as well as the results on selection effects, individual incumbent productivity effects, and aggregate productivity effects when employing the interpolating method.

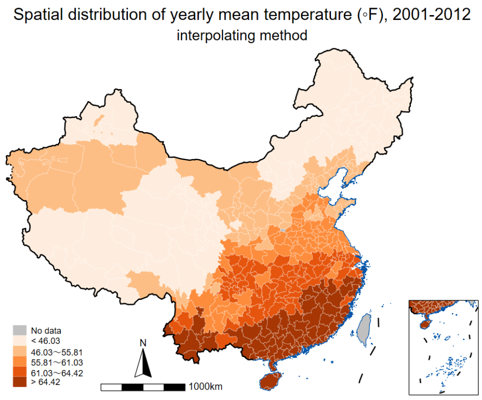
Figure B1: Map illustration of the temperature data



(a)



(b)



(c)

Notes: Figure B1 (a) shows the spatial distribution of weather stations. Figure B1 (b) shows the spatial distribution of yearly mean temperature, using the city-average method. Figure B1 (c) shows the spatial distribution of yearly mean temperature, using the interpolating method.

Table B1: Using an alternative temperature-city matching method

	(1)	(2)	(3)	(4)	(5)	(6)
	log(1+Number of entry)			log(1+Number of exit)		
	Full sample	Above median	Below median	Full sample	Above median	Below median
T≥90°F	-0.00479***	-0.00215**	-0.00789***	0.00679***	0.00290**	0.00970***
	(0.00112)	(0.00110)	(0.00201)	(0.00138)	(0.00143)	(0.00226)
80°F≤T<90°F	-0.00198***	-0.000937***	-0.00244***	0.00382***	0.00154***	0.00450***
	(0.000544)	(0.000266)	(0.000527)	(0.000499)	(0.000322)	(0.000611)
City-sector FE	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
Sector-year FE	Y	Y	Y	Y	Y	Y
Economic Controls	N	N	N	N	N	N
Weather Controls	Y	Y	Y	Y	Y	Y
Observations	132444	132444	132444	132444	132444	132444
R-squared	0.022	0.017	0.029	0.042	0.038	0.055
Number of city-sectors	11154	11154	11154	11154	11154	11154

Notes: The sample covers 11154 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B2: Incumbent productivity effects using alternative data

	(1)	(2)	(3)	(4)	(5)	(6)
	TFP, OP	TFP, LP	TFP, GMM	log(revenue/labor)	log(output/labor)	log(Solow residual)
T≥90°F	-0.00590***	-0.00303***	-0.00483***	-0.00248***	-0.00364***	-0.00556***
	(0.000462)	(0.000363)	(0.000543)	(0.000286)	(0.000301)	(0.000238)
80°F≤T<90°F	-0.00318***	-0.00263***	-0.00281***	-0.00249***	-0.00206***	-0.00262***
	(0.000189)	(0.000151)	(0.000215)	(0.000113)	(0.000122)	(9.64e-05)
Firm FE	Y	Y	Y	Y	Y	Y
Province-Year FE	Y	Y	Y	Y	Y	Y
Sector-year FE	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Observations	1,458,932	1,459,168	1,459,168	3,165,048	2,924,844	3,163,599
R-squared	0.573	0.768	0.918	0.478	0.551	0.556

Notes: The sample covers about 430000 firms from 2001 to 2012. In all columns firm, province-year, and sector-year fixed effects are included. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B3: Aggregate productivity effects using alternative data

	(1)	(2)	(3)	(4)	(5)	(6)
	Weighted average of individual firms' productivity measure in a city-sector-year cell					
	TFP (OP)	TFP (LP)	TFP (GMM)	log(revenue/L)	log(output/L)	log(Solow residual)
T≥90°F	0.000431	0.000446	0.000490	-0.00304	0.00112	0.00450
	(0.00652)	(0.00653)	(0.00202)	(0.00361)	(0.00198)	(0.00395)
80°F≤T<90°F	0.000532	0.000259	0.000602	0.00108	-0.00104	0.000216
	(0.00192)	(0.000441)	(0.00339)	(0.00235)	(0.00269)	(0.000357)
City-sector FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Province-year FE	Y	Y	Y	Y	Y	Y
Sector-year FE	Y	Y	Y	Y	Y	Y
Weather Controls	Y	Y	Y	Y	Y	Y
Observations	55,219	55,219	55,219	89,732	89732	89732
R-squared	0.043	0.048	0.048	0.054	0.079	0.612
Number of city-sectors	9748	9748	9748	9748	9748	9748

Notes: The sample covers 9748 city-sectors from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B4: Effects on intersectoral factor reallocation

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	Capital share				Labor share			
	Agricultural	Mining	Manufacturing	Service	Agricultural	Mining	Manufacturing	Service
T≥ 90°F	-0.000532	-0.000782	0.00271	-0.000777	0.000530	-0.000568	0.00156	-0.00163
	(0.000497)	(0.000851)	(0.00183)	(0.00200)	(0.000380)	(0.000547)	(0.00105)	(0.00114)
80°F≤T<90°F	-0.000193	0.000604	0.00107	-0.00134	0.000300	-1.27e-05	0.00116**	-0.00145**
	(0.000282)	(0.000516)	(0.000817)	(0.000885)	(0.000271)	(0.000316)	(0.000502)	(0.000564)
City FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Observations	2,634	2,634	2,634	2,634	2,634	2,634	2,634	2,634
R-squared	0.251	0.584	0.640	0.658	0.519	0.884	0.823	0.722

Notes: The sample covers 2,634 city-year observations from 2007 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, clustered at the city level, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B5: Effects on intercity capital flows

	(1)	(2)	(3)	(4)	(5)	(6)
	log(1+Capital)		log(1+Number)		1(Flow>0)	
Mean temperature difference	0.000491		0.000623		0.00168	
	(0.0126)		(0.00124)		(0.00244)	
Difference of T≥ 90°F		0.0163		-0.00690		0.0397
		(0.0126)		(0.00751)		(0.0350)
Difference of 80°F≤T<90°F		0.0122		0.0211		-0.00493
		(0.0147)		(0.0239)		(0.00303)
City dyad FE	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y
Observations	1,019,664	1,019,664	1,019,664	1,019,664	1,019,664	1,019,664
R-squared	0.065	0.065	0.062	0.051	0.051	0.051
Number of city dyads	84,972	84,972	84,972	84,972	84,972	84,972

Notes: The sample covers 84,972 city dyads from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, clustered at the city dyad level, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B6: Temperature and migration

	(1)	(2)
	Share of migrants, high skill	Share of migrants, low skill
T≥90°F	0.000189	-0.000604
	(0.000422)	(0.00175)
80°F≤T<90°F	-0.000536*	-0.00191
	(0.000313)	(0.00142)
Weather Controls	Y	Y
City FE	Y	Y
Year FE	Y	Y
Observations	959	959
R-squared	0.392	0.303
Number of cities	328	328

Notes: The sample covers 328 cities for 2000, 2005, and 2010. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B7: Effects on intercity migration flows

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
	log(High skill)	log(Low skill)	1(High skill>0)	1(Low skill>0)	log(High skill)	log(Low skill)	1(High skill>0)	1(Low skill>0)
Difference of T≥90°F	-0.00231	-0.00455	-0.000694	-0.000129				
	(0.00256)	(0.00379)	(0.00168)	(0.00151)				
Difference of 80°F≤T<90°F	-0.000564	-0.00104	-0.000347	-0.000112				
	(0.000510)	(0.000831)	(0.000357)	(0.000391)				
Mean temperature difference					-0.0168	-0.0209	-0.0125	-0.0169
					(0.0159)	(0.0235)	(0.0112)	(0.0115)
City dyad FE	Y	Y	Y	Y	Y	Y	Y	Y
Year FE	Y	Y	Y	Y	Y	Y	Y	Y
Controls	Y	Y	Y	Y	Y	Y	Y	Y
Observations	225,792	225,792	225,792	225,792	225,792	225,792	225,792	225,792
R-squared	0.816	0.877	0.648	0.715	0.816	0.877	0.648	0.715

Notes: The sample covers 225,792 city-dyad-year observations in 2005 to 2010. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, clustered at the city dyad level, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B8: The role of input-output linkages

	(1)	(2)	(3)	(4)
	Input share weighted		Output share weighted	
	log(1+Number of entry)	log(1+Number of exit)	log(1+Number of entry)	log(1+Number of exit)
$T \geq 90°F$	-0.00406***	0.00249***	-0.000612***	0.00443***
	(0.000394)	(0.000666)	(0.000233)	(0.00112)
$80°F \leq T < 90°F$	-0.00156***	0.00321***	-0.00166***	0.00266***
	(0.000355)	(0.000443)	(0.000442)	(0.000288)
City-Sector FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	134,976	134,976	134,976	134,976
R-squared	0.025	0.066	0.025	0.066

Notes: The sample covers 134,976 city-sector-year observations from 2001 to 2012. All the following temperature intervals ($T \geq 90°F$, $80°F \leq T < 90°F$, $70°F \leq T < 80°F$, $60°F \leq T < 70°F$, $40°F \leq T < 50°F$, $30°F \leq T < 40°F$, $20°F \leq T < 30°F$, $10°F \leq T < 20°F$, and $T < 10°F$) are included, with the fifth group $50°F \leq T < 60°F$ being excluded as the base group. Robust standard errors, two-way clustered at the city and sector levels, are presented in parentheses. *** $p<0.01$, ** $p<0.05$, * $p<0.1$.

Table B9: Effects on input dynamics

	(1)	(2)	(3)
	Δ log(L)	Δ log(K)	Δ log(L/K)
T≥90°F	0.000552	-0.0168	0.0181
	(0.00125)	(0.0108)	(0.0112)
80°F≤T<90°F	-0.000563	-0.00568	0.00535
	(0.000819)	(0.00685)	(0.00699)
Firm FE	Y	Y	Y
Year FE	Y	Y	Y
Controls	Y	Y	Y
Observations	2,105,854	2,096,467	2,090,860
R-squared	0.243	0.302	0.305

Notes: The sample covers about 941,091 firm-year observations from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and firm levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B10: Effects on innovation

	(1)	(2)	(3)	(4)
	log(1+RD)	log(1+Patent applications)		
	Firm-year panel		City-sector-year panel	
T≥90°F	0.00286	0.00331	0.00448	0.00499
	(0.00299)	(0.0155)	(0.00326)	(0.00442)
80°F≤T<90°F	0.00102	-2.48e-06	0.00324	0.00415
	(0.00195)	(7.32e-05)	(0.00325)	(0.00438)
City-sector FE	N	N	Y	Y
Province-year FE	Y	Y	Y	Y
Sector-year FE	Y	Y	N	Y
Weather Controls	N	Y	N	Y
Firm FE	Y	Y	N/A	N/A
Observations	3,234,001	3,234,001	132444	132444
R-squared	0.255	0.249	0.332	0.329

Notes: The sample period is 2001-2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and firm levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Table B11: Effects on productivity dynamics

	(1)	(2)	(3)	(4)
	ΔTFP (OP,ACF)	ΔTFP (LP,ACF)	ΔTFP (GMM)	ΔSolow residual
T≥90°F	-2.73e-05	-6.68e-05	0.000491	0.00514
	(0.00292)	(0.00299)	(0.00346)	(0.00316)
80°F≤T<90°F	-0.00211	-0.00245	-0.00154	3.40e-05
	(0.00176)	(0.00182)	(0.00203)	(0.00239)
Firm FE	Y	Y	Y	Y
Year FE	Y	Y	Y	Y
Controls	Y	Y	Y	Y
Observations	941,091	941,145	941,145	941,145
R-squared	0.201	0.226	0.188	0.247

Notes: The sample covers about 941,091 firm-year observations from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, two-way clustered at the city and firm levels, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

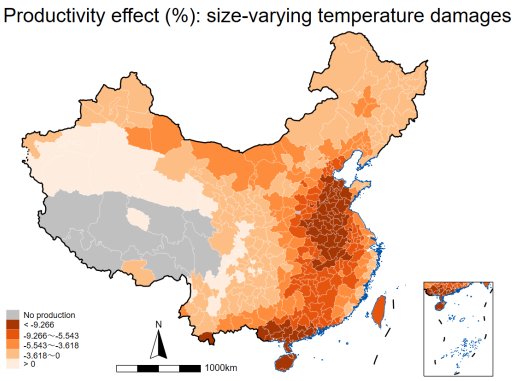
Table B12: Effects on local demand

	(1)	(2)	(3)
	log(Agricultural price index)	log(Manufacturing price index)	log(Service price index)
T≥90°F	0.000101	-0.000175	-3.71e-05
	(0.000202)	(0.000223)	(0.000161)
80°F≤T<90°F	-0.000125*	-3.50e-06	-6.43e-05
	(6.81e-05)	(7.20e-05)	(5.01e-05)
City FE	Y	Y	Y
Year FE	Y	Y	Y
Controls	Y	Y	Y
Observations	3,360	3,360	3,360
R-squared	0.985	0.985	0.993

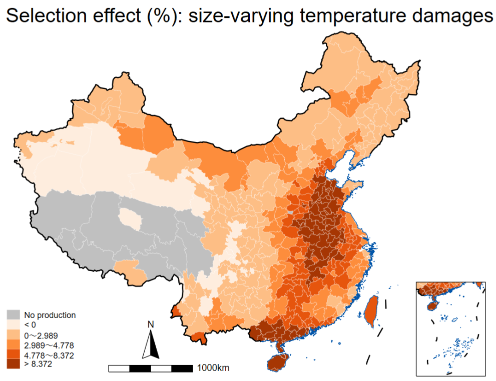
Notes: The sample covers 3,360 city-year observations from 2001 to 2012. All the following temperature intervals (T≥ 90°F, 80°F≤T<90°F, 70°F≤T<80°F, 60°F≤T<70°F, 40°F≤T<50°F, 30°F≤T<40°F, 20°F≤T<30°F, 10°F≤T<20°F, and T<10°F) are included, with the fifth group 50°F≤T<60°F being excluded as the base group. Robust standard errors, clustered at the city level, are presented in parentheses. *** p<0.01, ** p<0.05, * p<0.1.

Appendix C Figures for Model Extensions

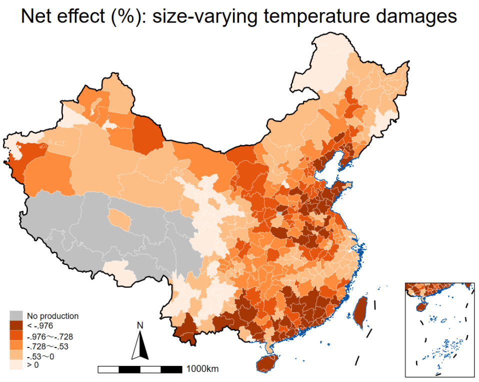
Figure C1: Counterfactual analysis based on size-varying temperature damages



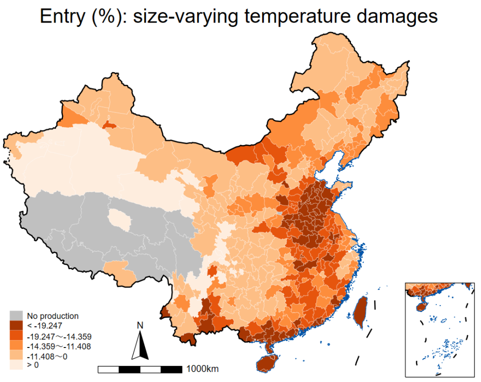
(a)



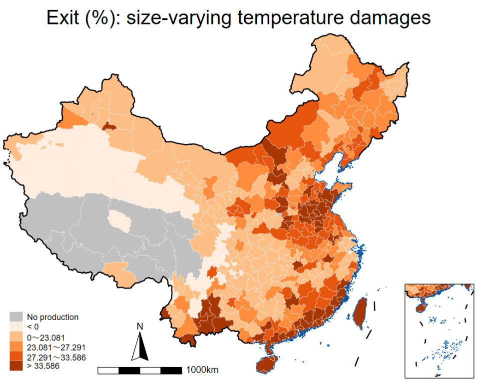
(b)



(c)



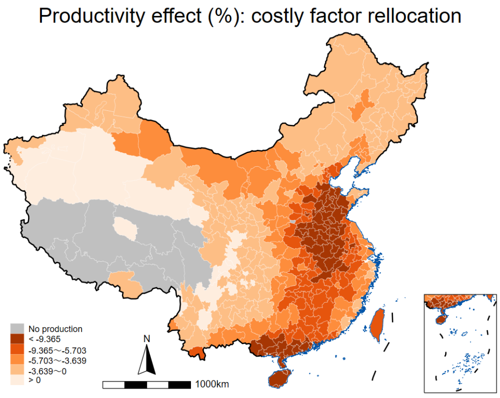
(d)



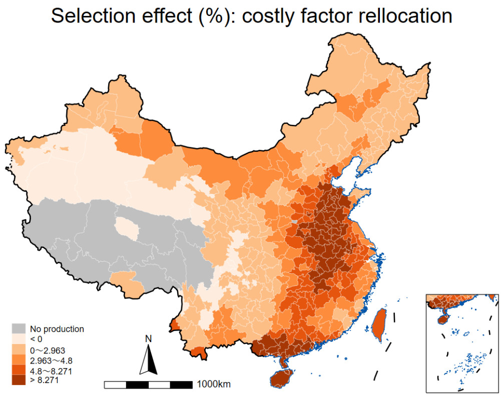
(e)

Notes: Figure C1 (a) shows the predicted impacts of climate change on aggregate productivity through the productivity effect. Figure C1 (b) shows the predicted impacts of climate change on aggregate productivity through the selection effect. Figure C1 (c) shows the combined effects of the productivity and selection effects. The productivity effect is obtained by calculating the change in mean productivity due to the direct and indirect productivity effects defined above. The selection effect is obtained by calculating the change in the mean of productivity distribution due to the change in productivity cutoff z^*. *The net effect is calculated by adding the productivity effect and the selection effect. All effects are measured in percentage points. Figure C1 (d) shows the predicted impacts of climate change on entry. Figure C1 (e) shows the predicted impacts of climate change on exit. The effects are calculated using the measure of firm entry and firm exit in the quantitative model. All effects are measured by percentage points.*

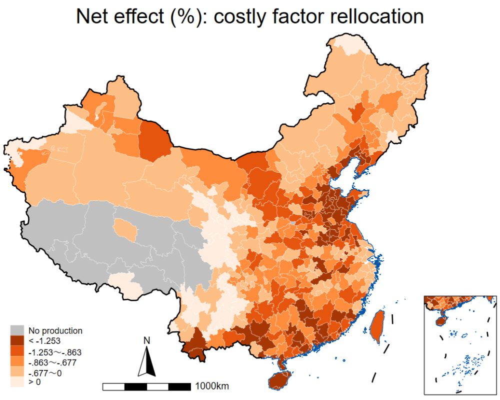
Figure C2: Counterfactual analysis based on costly factor reallocation



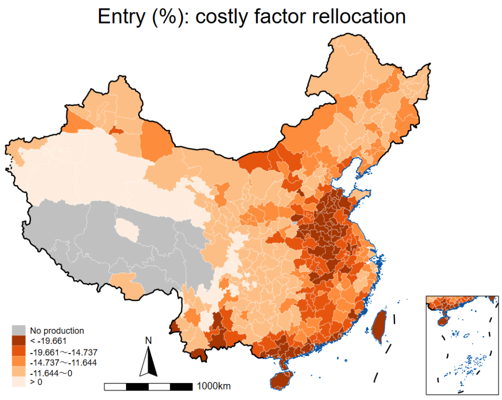
(a)



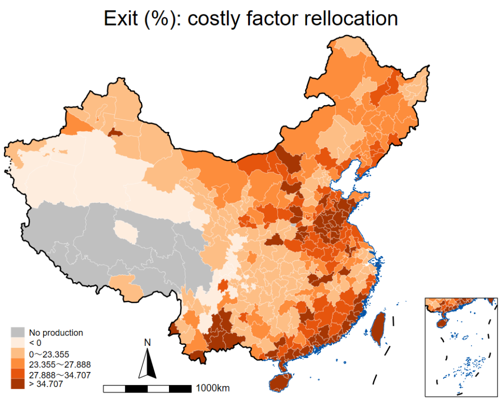
(b)



(c)



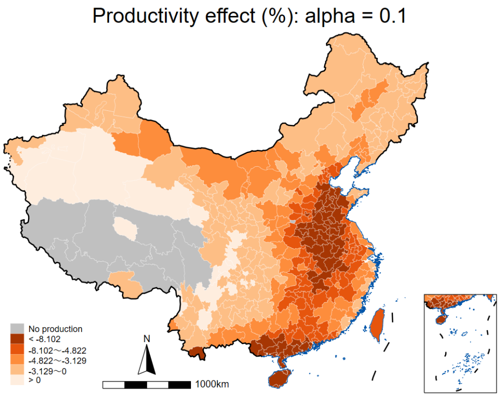
(d)



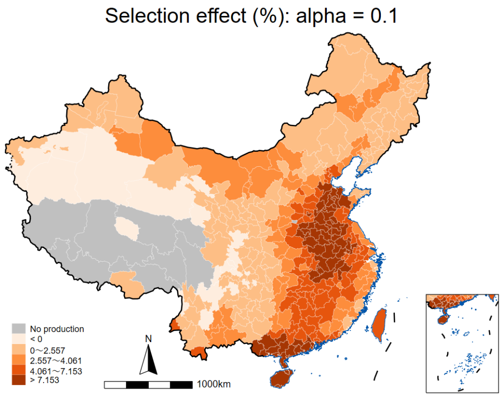
(e)

Notes: Figure C2 (a) shows the predicted impacts of climate change on aggregate productivity through the productivity effect. Figure C2 (b) shows the predicted impacts of climate change on aggregate productivity through the selection effect. Figure C2 (c) shows the combined effects of the productivity and selection effects. The productivity effect is obtained by calculating the change in mean productivity due to the direct and indirect productivity effects defined above. The selection effect is obtained by calculating the change in the mean of productivity distribution due to the change in productivity cutoff z^*. *The net effect is calculated by adding the productivity effect and the selection effect. All effects are measured in percentage points. Figure C2 (d) shows the predicted impacts of climate change on entry. Figure C2 (e) shows the predicted impacts of climate change on exit. The effects are calculated using the measure of firm entry and firm exit in the quantitative model. All effects are measured by percentage points.*

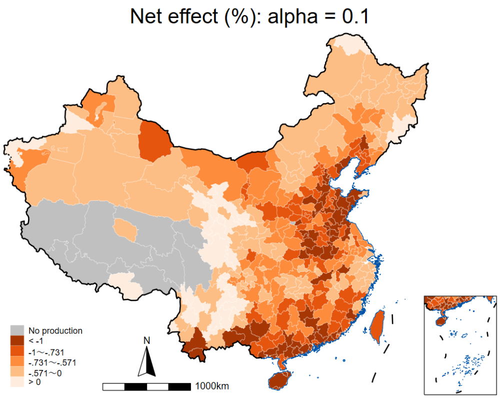
Figure C3: Counterfactual analysis based on long-run adaptation, $\alpha = 0.1$



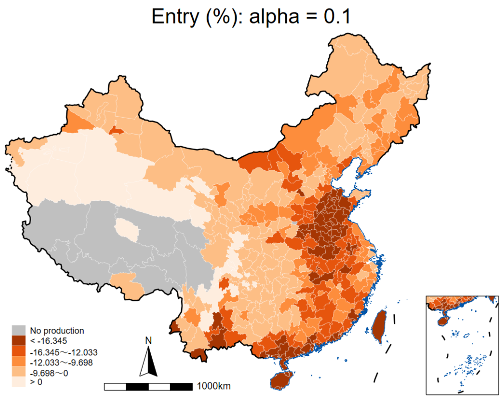
(a)



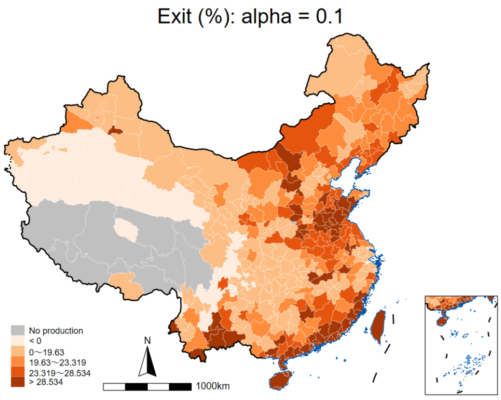
(b)



(c)



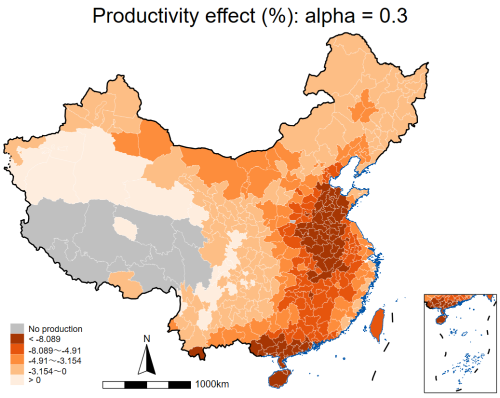
(d)



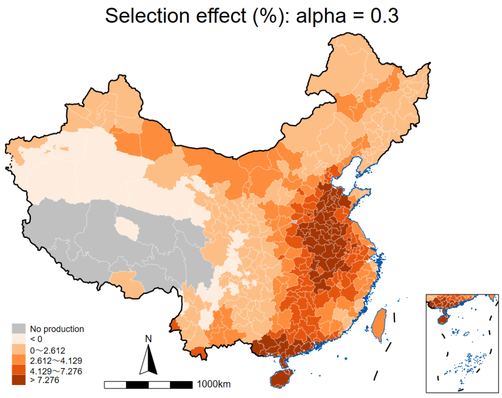
(e)

Notes: Figure C3 (a) shows the predicted impacts of climate change on aggregate productivity through the productivity effect. Figure C3 (b) shows the predicted impacts of climate change on aggregate productivity through the selection effect. Figure C3 (c) shows the combined effects of the productivity and selection effects. The productivity effect is obtained by calculating the change in mean productivity due to the direct and indirect productivity effects defined above. The selection effect is obtained by calculating the change in the mean of productivity distribution due to the change in productivity cutoff z^*. The net effect is calculated by adding the productivity effect and the selection effect. All effects are measured in percentage points. Figure C3 (d) shows the predicted impacts of climate change on entry. Figure C3 (e) shows the predicted impacts of climate change on exit. The effects are calculated using the measure of firm entry and firm exit in the quantitative model. All effects are measured by percentage points.

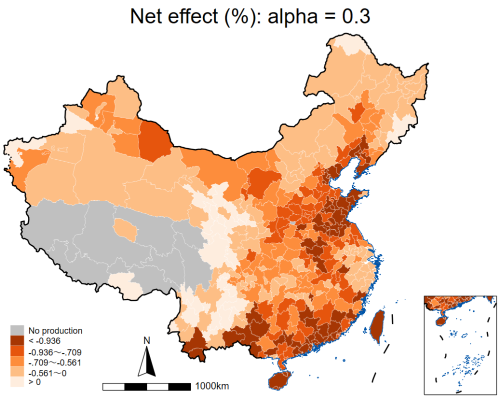
Figure C4: Counterfactual analysis based on long-run adaptation, $\alpha = 0.3$



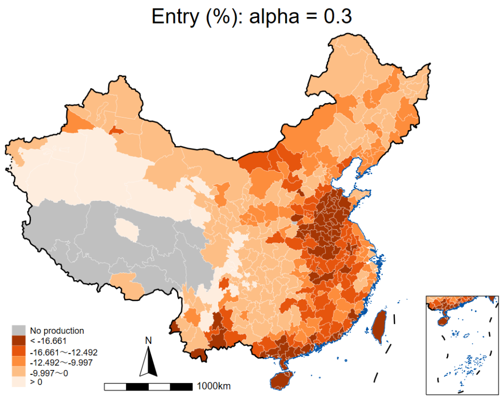
(a)



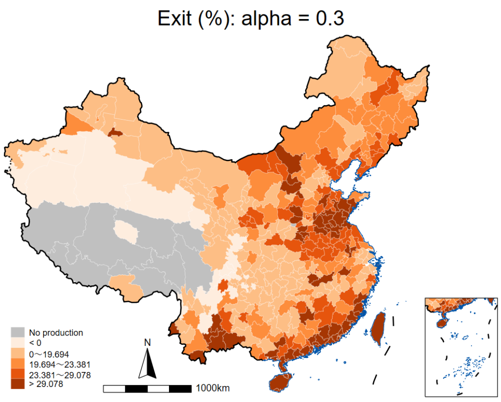
(b)



(c)



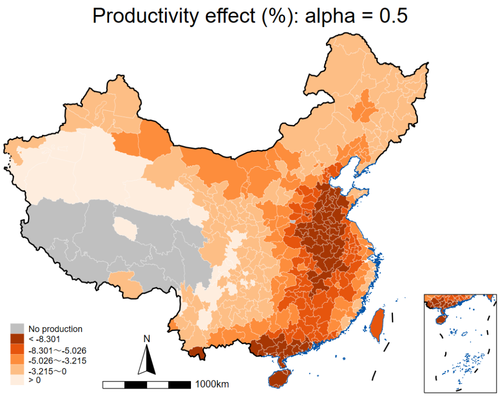
(d)



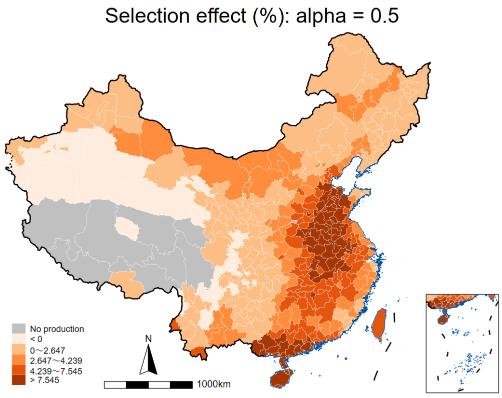
(e)

Notes: Figure C4 (a) shows the predicted impacts of climate change on aggregate productivity through the productivity effect. Figure C4 (b) shows the predicted impacts of climate change on aggregate productivity through the selection effect. Figure C4 (c) shows the combined effects of the productivity and selection effects. The productivity effect is obtained by calculating the change in mean productivity due to the direct and indirect productivity effects defined above. The selection effect is obtained by calculating the change in the mean of productivity distribution due to the change in productivity cutoff z^*. The net effect is calculated by adding the productivity effect and the selection effect. All effects are measured in percentage points. Figure C4 (d) shows the predicted impacts of climate change on entry. Figure C4 (e) shows the predicted impacts of climate change on exit. The effects are calculated using the measure of firm entry and firm exit in the quantitative model. All effects are measured by percentage points.

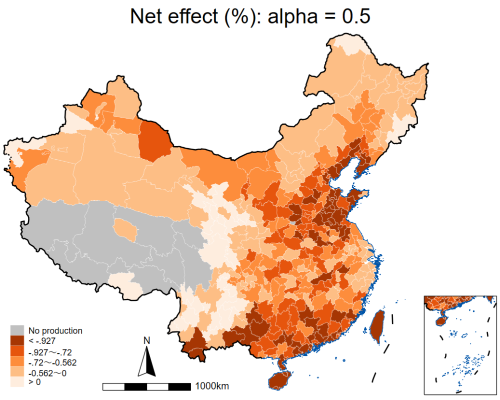
Figure C5: Counterfactual analysis based on long-run adaptation, $\alpha = 0.5$



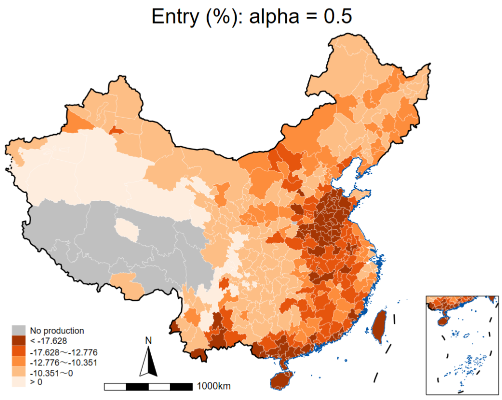
(a)



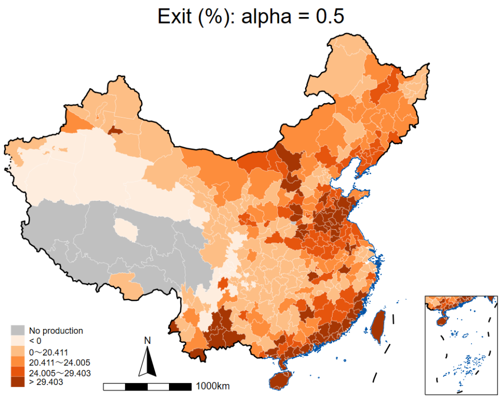
(b)



(c)



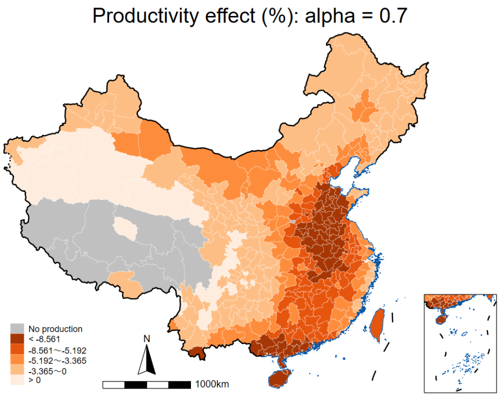
(d)



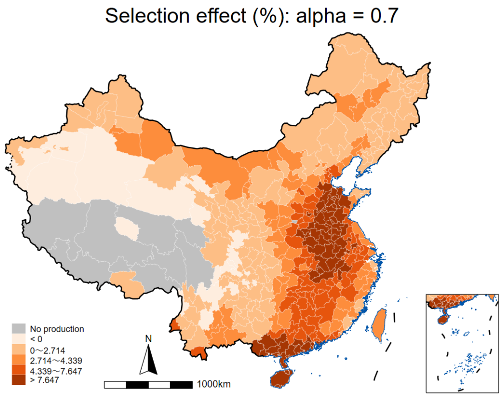
(e)

Notes: Figure C5 (a) shows the predicted impacts of climate change on aggregate productivity through the productivity effect. Figure C5 (b) shows the predicted impacts of climate change on aggregate productivity through the selection effect. Figure C5 (c) shows the combined effects of the productivity and selection effects. The productivity effect is obtained by calculating the change in mean productivity due to the direct and indirect productivity effects defined above. The selection effect is obtained by calculating the change in the mean of productivity distribution due to the change in productivity cutoff z^*. The net effect is calculated by adding the productivity effect and the selection effect. All effects are measured in percentage points. Figure C5 (d) shows the predicted impacts of climate change on entry. Figure C5 (e) shows the predicted impacts of climate change on exit. The effects are calculated using the measure of firm entry and firm exit in the quantitative model. All effects are measured by percentage points.

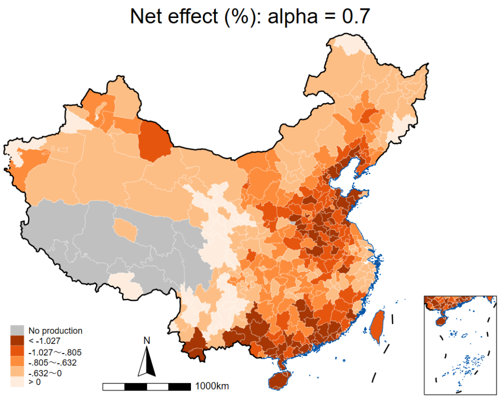
Figure C6: Counterfactual analysis based on long-run adaptation, $\alpha = 0.7$



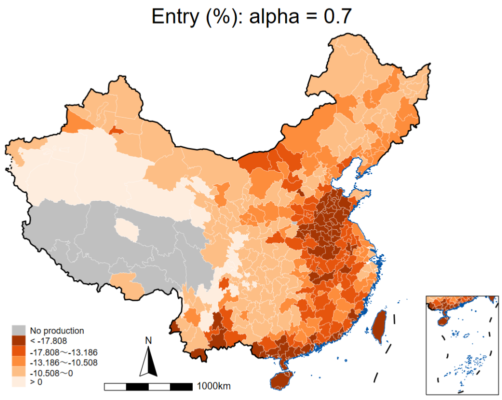
(a)



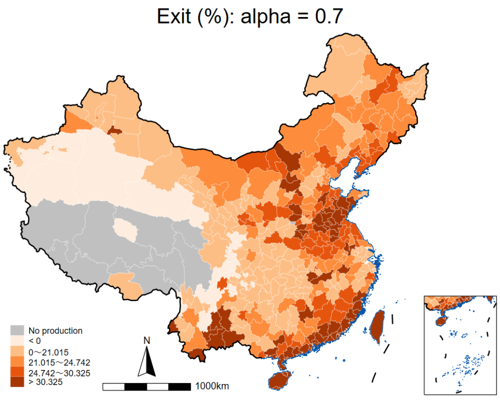
(b)



(c)



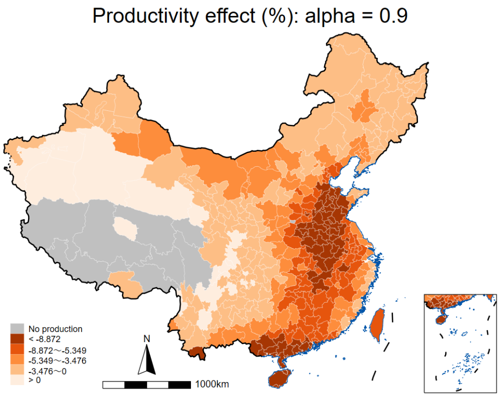
(d)



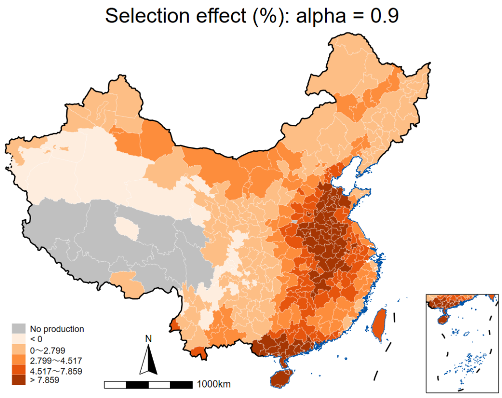
(e)

Notes: Figure C6 (a) shows the predicted impacts of climate change on aggregate productivity through the productivity effect. Figure C6 (b) shows the predicted impacts of climate change on aggregate productivity through the selection effect. Figure C6 (c) shows the combined effects of the productivity and selection effects. The productivity effect is obtained by calculating the change in mean productivity due to the direct and indirect productivity effects defined above. The selection effect is obtained by calculating the change in the mean of productivity distribution due to the change in productivity cutoff z^*. The net effect is calculated by adding the productivity effect and the selection effect. All effects are measured in percentage points. Figure C6 (d) shows the predicted impacts of climate change on entry. Figure C6 (e) shows the predicted impacts of climate change on exit. The effects are calculated using the measure of firm entry and firm exit in the quantitative model. All effects are measured by percentage points.

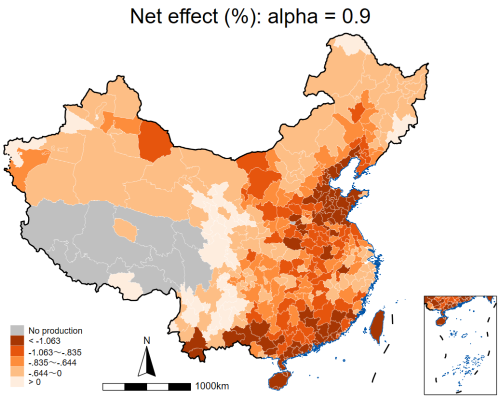
Figure C7: Counterfactual analysis based on long-run adaptation, $\alpha = 0.9$



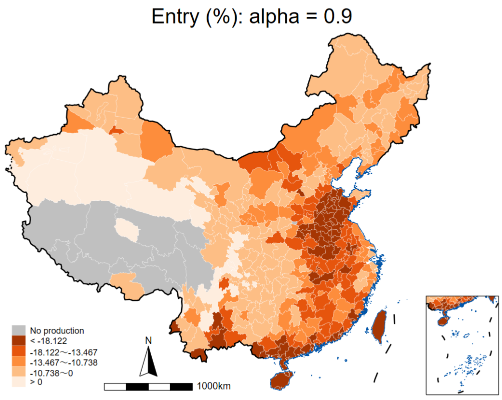
(a)



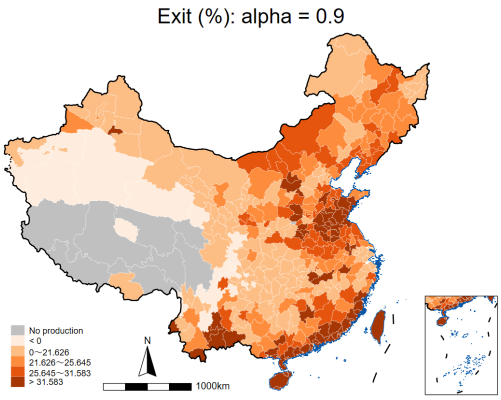
(b)



(c)



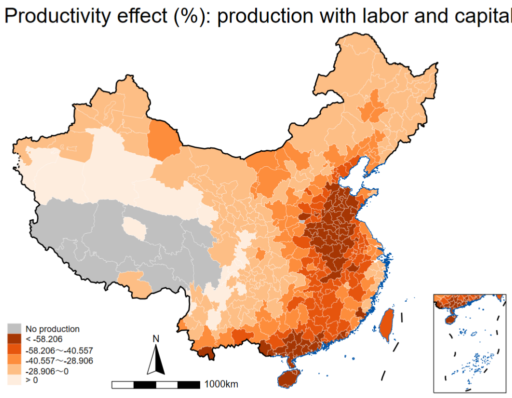
(d)



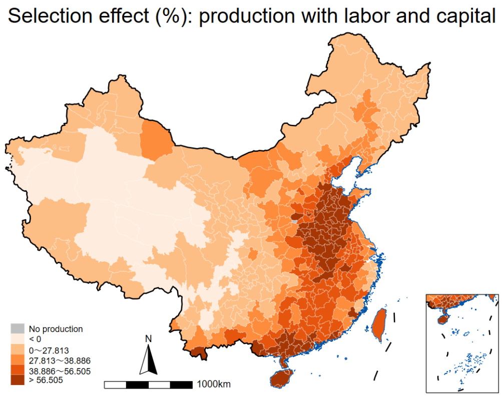
(e)

Notes: Figure C7 (a) shows the predicted impacts of climate change on aggregate productivity through the productivity effect. Figure C7 (b) shows the predicted impacts of climate change on aggregate productivity through the selection effect. Figure C7 (c) shows the combined effects of the productivity and selection effects. The productivity effect is obtained by calculating the change in mean productivity due to the direct and indirect productivity effects defined above. The selection effect is obtained by calculating the change in the mean of productivity distribution due to the change in productivity cutoff z^*. The net effect is calculated by adding the productivity effect and the selection effect. All effects are measured in percentage points. Figure C7 (d) shows the predicted impacts of climate change on entry. Figure C7 (e) shows the predicted impacts of climate change on exit. The effects are calculated using the measure of firm entry and firm exit in the quantitative model. All effects are measured by percentage points.

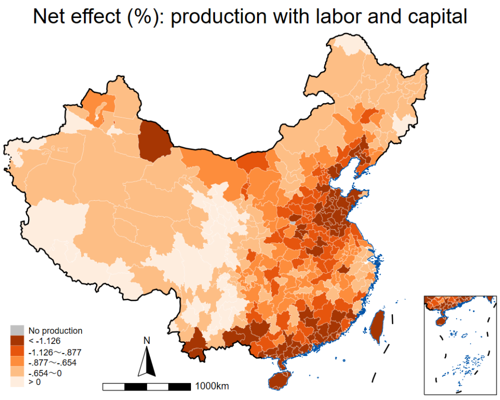
Figure C8: Counterfactual analysis based on production with labor and capital



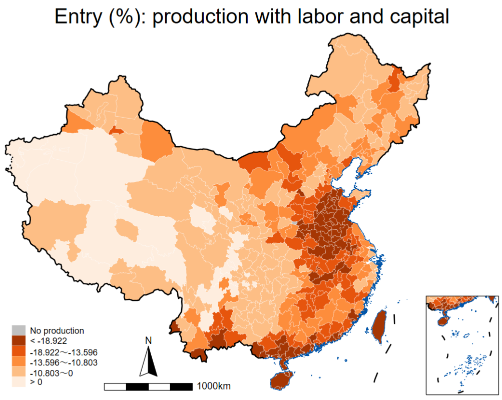
(a)



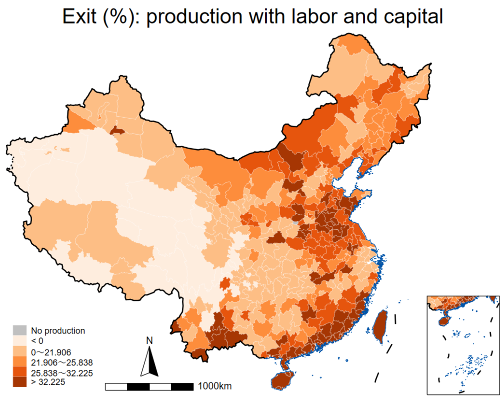
(b)



(c)



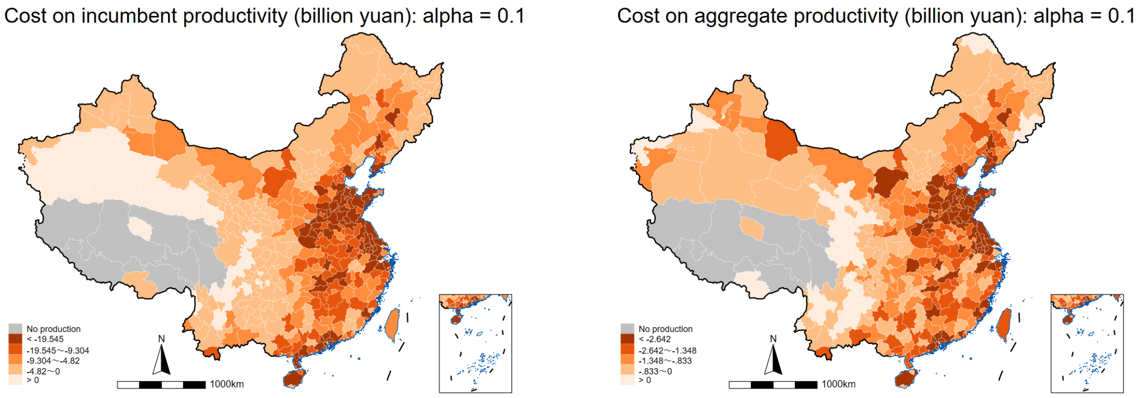
(d)



(e)

Notes: Figure C8 (a) shows the predicted impacts of climate change on aggregate productivity through the productivity effect. Figure C8 (b) shows the predicted impacts of climate change on aggregate productivity through the selection effect. Figure C8 (c) shows the combined effects of the productivity and selection effects. The productivity effect is obtained by calculating the change in mean productivity due to the direct and indirect productivity effects defined above. The selection effect is obtained by calculating the change in the mean of productivity distribution due to the change in productivity cutoff z^*. *The net effect is calculated by adding the productivity effect and the selection effect. All effects are measured in percentage points. Figure C8 (d) shows the predicted impacts of climate change on entry. Figure C8 (e) shows the predicted impacts of climate change on exit. The effects are calculated using the measure of firm entry and firm exit in the quantitative model. All effects are measured by percentage points.*

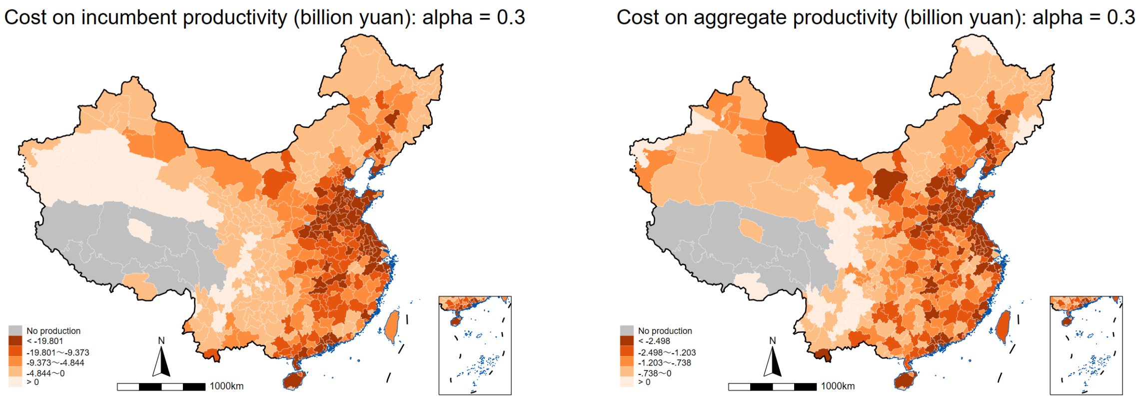
Figure C9: Damage of global warming, $\alpha = 0.1$



(a) (b)

Notes: Figure C9 (a) shows the damage of global warming on the value added of the manufacturing sector, using the individual incumbent productivity effects. Figure C9 (b) shows the damage of global warming on the value added of the manufacturing sector, using the aggregate productivity effects. The method of calculation is based on He et al. (2020).

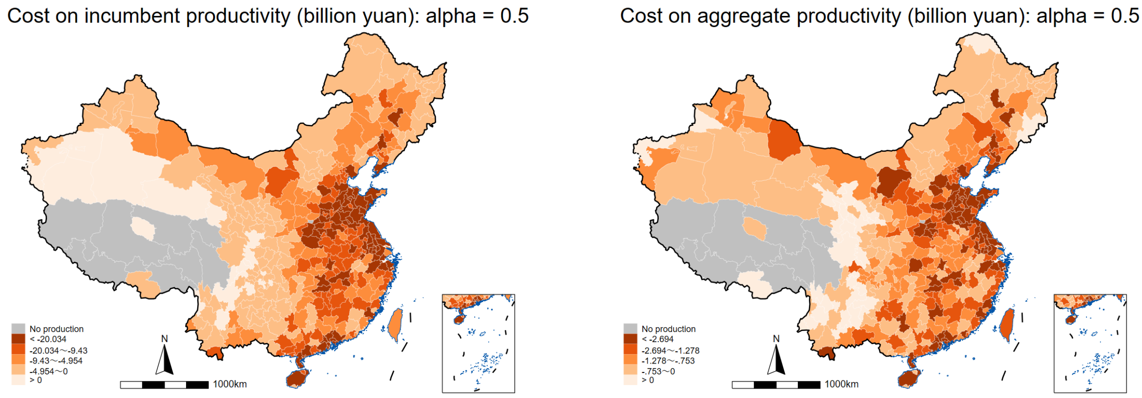
Figure C10: Damage of global warming, $\alpha = 0.3$



(a) (b)

Notes: Figure C10 (a) shows the damage of global warming on the value added of the manufacturing sector, using the individual incumbent productivity effects. Figure C10 (b) shows the damage of global warming on the value added of the manufacturing sector, using the aggregate productivity effects. The method of calculation is based on He et al. (2020).

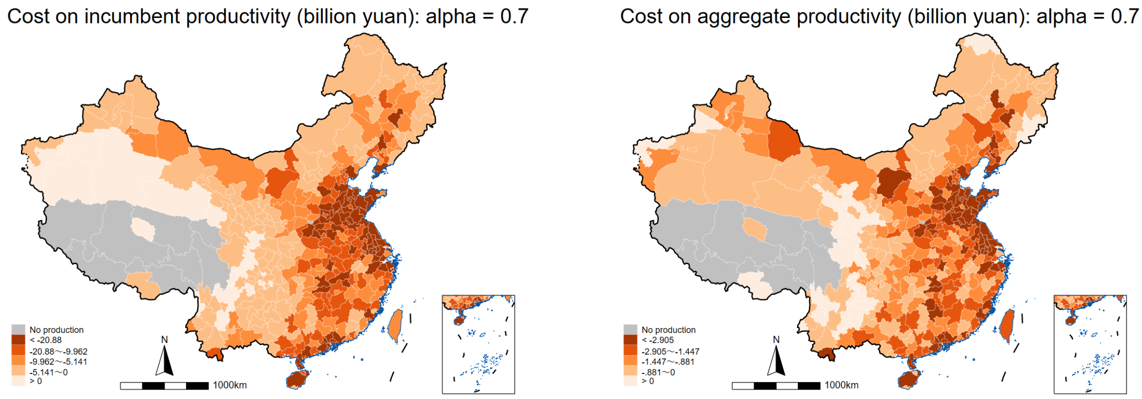
Figure C11: Damage of global warming, $\alpha = 0.5$



(a) (b)

Notes: Figure C11 (a) shows the damage of global warming on the value added of the manufacturing sector, using the individual incumbent productivity effects. Figure C11 (b) shows the damage of global warming on the value added of the manufacturing sector, using the aggregate productivity effects. The method of calculation is based on He et al. (2020).

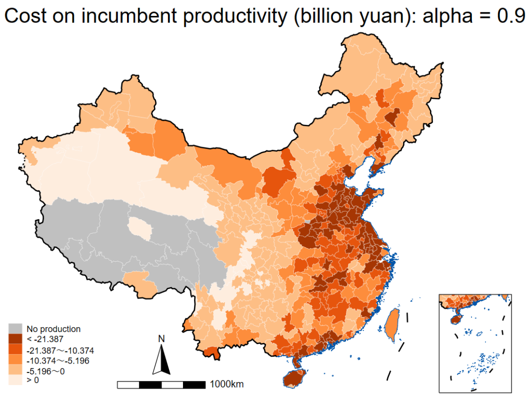
Figure C12: Damage of global warming, $\alpha = 0.7$



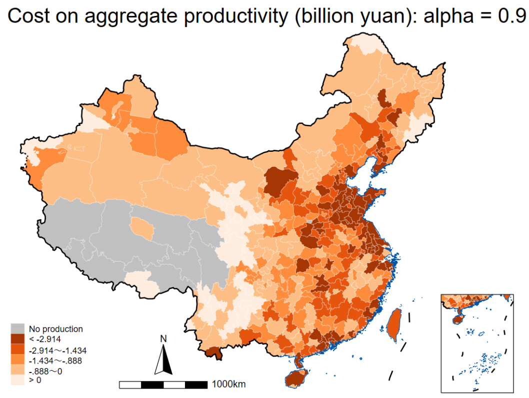
(a) (b)

Notes: Figure C12 (a) shows the damage of global warming on the value added of the manufacturing sector, using the individual incumbent productivity effects. Figure C12 (b) shows the damage of global warming on the value added of the manufacturing sector, using the aggregate productivity effects. The method of calculation is based on He et al. (2020).

Figure C13: Damage of global warming, $\alpha = 0.9$



(a)



(b)

Notes: Figure C13 (a) shows the damage of global warming on the value added of the manufacturing sector, using the individual incumbent productivity effects. Figure C13 (b) shows the damage of global warming on the value added of the manufacturing sector, using the aggregate productivity effects. The method of calculation is based on He et al. (2020).

Appendix D Manufacturing and Other Sectors

D.1 Within-China Comparison

In this paper, we focus mainly on the manufacturing sector of the Chinese economy. During our sample period, the manufacturing sector grew fast, while a large part of the productivity growth was created by the entry of high-productivity firms and the exit of low-productivity firms (Brandt et al., 2012). Thus, the firm dynamics in the manufacturing sector are important to study for a comprehensive understanding of the Chinese economy.

We also compare the manufacturing sector with the agriculture and service sectors in Table D1. We use three data sources: (A) National Tax Statistics Database (NTSD), using a sample period of 2007-2012; (B) China City Statistical Yearbooks, using a sample period of 2001-2012; and (C) Firm registration database, using a sample period of 2001-2012. We find that, on average manufacturing firms are larger, while the input structure is similar to that of agricultural and service firms. The manufacturing sector had the largest value-added share and, the second-largest employment and registry capital share (both close to the largest), during our sample period. Thus, the manufacturing sector plays an important role in the Chinese economy and has similarities and differences compared to the agriculture and service sectors. The uniqueness of the Chinese manufacturing sector renders it important to examine it, whereas the similarity of the manufacturing sector to the agriculture and service sectors makes it possible to extend the analysis of the manufacturing sector to the agriculture and service sectors.

D.2 Comparing China and the World

During our sample periods, the growth rate of value added of the Chinese manufacturing sector was about 10%, comparable to that of India and Malaysia, two other major developing countries. The share of value added of the Chinese manufacturing sector in GDP was 32%, comparable to that of Malaysia, and higher than that of India. The per capita value added of the Chinese manufacturing sector is 1986$, comparable to that of Malaysia and, higher than that of India. Therefore, although we focus on China in this paper, the analysis can be plausibly applicable to other developing countries.

Table D1: Comparison of manufacturing sector, agriculture sector, and service sector

	Firm-level Mean			Data Source
Variable	Agriculture	Manufacturing	Service	
log(L)	2.796	4.032	2.904	A
log(K)	6.996	7.770	6.892	A
log(Revenue/L)	4.902	5.466	6.003	A
log(L/K)	-3.806	-3.692	-3.872	A
	City-level Mean			Data Source
	Agriculture	Manufacturing	Service	
Employment share (%)	3.665	42.040	51.016	B
Value added share (%)	15.383	47.397	37.217	B
Registry capital share (%)	5.779	46.612	47.609	C

Notes: Data source: (A) National Tax Statistics Database (NTSD), using a sample period of 2007-2012; (B) China City Statistical Yearbooks, using a sample period of 2001-2012; (C) Firm registration database, using a sample period of 2001-2012.

Appendix E Proofs

Proof of Proposition 1: The productivity is lower under high temperatures for two causes. The first one is that high temperatures affect ψ; a higher level of temperatures implies a lower level of ψ. This is the direct productivity effect. The second one is that high temperatures affect l^R_{jf}. Given the first-order condition of the profit maximization problem: $\max_{l^P_{jf}, l^R_{jf}} \pi_f = p_{jf}y_{jf} - w(l^P_{jf} + l^R_{jf}) - \tau E(y_{jf}, l^R_{jf})$, a higher level of temperatures leads to a greater τ, which corresponds to a higher marginal return of using more l^R_{jf}. l^R_{jf} thus increases, following a standard comparative statics argument. Since l^R_{jf} is not used for production, the labor productivity, $\frac{p_{jf}y_{jf}}{l^P_{jf}+l^R_{jf}}$ decreases for any given l^P_{jf}. This is the indirect productivity effect. $\square$

Proof of Proposition 2: First, z^* is determined by a profit break-even condition: $\sum_{t=0}^{\infty}(\prod_{s=0}^{s=t} \frac{1}{R_s})\pi_f(\psi z^*) - wf_e = 0$. Higher temperatures lower the productivity of all surviving firms (ψ smaller and $\frac{p_{jf}y_{jf}}{l^P_{jf}+l^R_{jf}}$ lower) and increase the cost of operation ($\tau E(y_{jf}, l^R_{jf})$) larger, thus reducing the profit margin. A standard comparative statics argument indicates a higher z^*. $\square$

Proof of Proposition 3: Proposition 3 follows from the fact that z^* increases (Proposition 2), so that the measure of surviving firms, M, is smaller under higher temperatures. Since the supply of input, or labor, is fixed, firms on average must use more labor in equilibrium. In addition, since z^* increases, surviving firms have a higher productivity draw. As a result, they will use more labor l^P_{jf} in production. Finally, due to Proposition 1, l^R_{jf} increases under higher temperatures. $\square$

Proof of Proposition 4: Proposition 4 follows from the combination of Propositions 1 and 2. Proposition 1 suggests that all firms are subject to a reduction of productivity (ψ and $\frac{p_{jf}y_{jf}}{l^P_{jf}+l^R_{jf}}$). Proposition 2 suggests that the productivity cutoff for surviving firms, z^*, is higher. Thus, the change in aggregate productivity, or $\int_{z^*}^{\infty} \frac{p_{jf}y_{jf}}{l^P_{jf}+l^R_{jf}}(z)\mu(z)dz$ is uncertain. $\square$