Smart Prosperity Institute

CLEAN ECONOMY
WORKING PAPER SERIES

November 2020 / WP 20-11

Manufacturing Output and Extreme Temperature: Evidence from Canada

Philippe Kabore

Department of Economics,
University of Ottawa

Nicholas Rivers

Graduate School of Public and International Affairs
Institute of the Environment
University of Ottawa

Manufacturing Output and Extreme Temperature: Evidence from Canada[*†]

Philippe Kabore[‡] Nicholas Rivers[§]

Abstract

This paper analyzes the effects of extreme temperature on manufacturing output using a dataset covering the universe of manufacturing establishments in Canada from 2004 to 2012. Extreme temperature can affect manufacturing activity by affecting separately or jointly labour productivity and labour inputs. Using a panel fixed effects method, our results suggest a non linear relationship between outdoor extreme temperature and manufacturing output. Each day where outdoor mean temperatures are below -18°C or above 24°C reduces annual manufacturing output by 0.18% and 0.11%, respectively, relative to a day with mean temperature between 12 to 18°C. In a typical year, extreme temperatures, as measured by the number of days below -18°C or above 24°C, reduce annual manufacturing output by 2.2%, with extreme hot temperatures contributing the most to this impact. Given the predicted change in climate for the mid and end of century, we predict annual manufacturing output losses to range between 2.8 to 3.7% in mid-century and 3.7 to 7.2% in end of century.

Keywords: Climate change, Temperature, Manufacturing, Canada, Employment
JEL Classification: L60, Q56, Q54, O14, O44

[*]This project is funded by the Productivity Partnership as supported by the Social Science and Humanities Research Council of Canada and by the Canada Research Chairs program. We are thankful for help with accessing and interpreting the data from Statistics Canada. The views expressed in this paper are our own and do not reflect the view of either the Productivity Partnership or Statistics Canada.

[†]We are grateful to Catherine Deri Armstrong, Maya Papineau, Carolyn Fischer, Jason Garred, Werner Antweiler, Charles Mason, and Nouri Najjar for their valuable comments. We also thank the participants at the Canadian Resource and Environmental Economics Association PhD Workshop 2019, Canadian Economic Association 2019, and the University of Ottawa Economics department's Brown-Bag seminar.

[‡]Department of Economics, University of Ottawa

[§]Graduate School of Public and International Affairs and Institute of the Environment, University of Ottawa

1 Introduction

Climate change will affect the prevalence of extreme temperatures worldwide. Extreme temperatures can have a number of impacts on humans, including on behaviour, productivity, cognitive ability, mood, and health, and well-being. This paper aims to evaluate the effect of extreme temperatures on economic activity in Canada. We find that extreme temperatures – both cold and hot – reduce economic activity. We show that output losses from extreme temperatures are caused by both reductions in labour inputs as well as labour productivity. We estimate that extreme weather currently reduces Canadian manufacturing output by 2.2% per year, and that this impact will likely grow with future climate change.

Our study builds on a body of recent work that links economic activity to temperature and weather. Many studies focus on the agricultural sector (Deschênes & Greenstone (2007), Schlenker & Roberts (2009), Burke & Emerick (2016)) because of its direct link with atmospheric conditions. However, the agricultural sector in developed countries such as the United States and Canada represents only 1-2% of gross domestic product.[1] Little in known about how extreme temperatures affect other economic sectors, especially in developed countries. Our study is one of the first that aims to estimate the impact of extreme temperatures on economic activity in Canada. This type of research is critical for understanding potential economic impacts that may result from unabated climate change.

There is a growing body of evidence that relates short-term weather realizations to socio-economic impacts outside of the agricultural sector (for recent reviews, see (Auffhammer, 2018; Carleton & Hsiang, 2016). This research has uncovered links between extreme ambient temperatures and impacts on performance such as cognitive tasks, physical tasks, as well as overall workplace tasks and productivity. For example, an early study in the laboratory by Mackworth (1946) shows that higher ambient temperatures caused an increase in the number of transcription mistakes made by wireless operators, thus reducing productivity. The low

[1] https://www.ers.usda.gov/data-products/ag-and-food-statistics-charting-the-essentials/farming-and-farm-income/ and https://www.canada.ca/en/agriculture-agri-food/news/2017/11/canada_s_agriculturalsectorcontinuestoseeeconomicgrowth.html

performance is explained by a rapid increase of fatigue and discomfort during prolonged activities in hot environments (González-Alonso et al., 1999; Galloway & Maughan, 1997). These findings are also supported by a meta-analysis of Hancock et al. (2007) who find that thermal stressors (heat and cold stress) affect individual psychomotor and perceptual tasks.

Outside of the lab, studies also link cognitive performance to ambient temperatures. For example, Park (2017) links examination records for New York students with outside temperatures, and finds that extreme hot temperatures cause substantial declines in academic performance. Cook & Heyes (2020) uses a similar approach to find a strong negative impact of extreme cold weather on university student examination outcomes in Ottawa, Canada. Graff Zivin et al. (2018) show that short-run exposure to hot temperature leads to significant declines in math scores.

Other studies show that these impacts on cognitive performance are not limited to schooling outcomes, but also affect labour market outcomes, including labour productivity (Heal & Park, 2016). In a meta-analysis, Seppanen et al. (2006) find that the average individual work performance decreases by almost 2% per degree Celcius above the temperature of 25°C in a work office environment. These findings are supported by Somanathan et al. (2015) who find a decrease in labour productivity in garment manufacturing plants during days with mean temperature above 25°C.

Empirical studies have also shown that labour supply, as determined by the number of hours worked or absenteeism, is negatively affected by hot outdoor temperatures (Behrer & Park, 2017; Somanathan et al., 2015; Graff Zivin & Neidell, 2014). The negative effects are at least three times higher in industry sectors highly exposed to outside temperature than those less exposed to outside hot temperature.[2]

Like the present study, existing research has also estimated the link between ambient temperature and overall economic output, which captures the effect of temperature on both

[2] The literature does not provide a unique definition of extreme temperature. A maximum daily temperature of 85°C (30°C) and 95°C (32°C) is considered as hot day by respectively (Graff Zivin & Neidell, 2014; Behrer & Park, 2017) while Deschenes & Moretti (2009) consider a daily mean temperature above 80°F (26°C) as hot days and daily mean temperature below 30°F (-1°C) as cold days

labour supply and labour productivity (Zhang et al., 2018; Chen & Yang, 2019; Somanathan et al., 2015). These studies provide evidence that hot temperatures reduce industrial output in emerging countries. For example, annual manufacturing output in China is estimated to fall by 0.45% for each day with mean temperature above 32°C, and daily manufacturing output in India is estimated to fall by 3.1% when mean temperature is above 25°C. In contrast, Addoum et al. (2019) find no evidence that extreme temperatures affect industrial sales in US. At a more aggregate level, several studies find a negative impact of hot temperatures on economic activity at the country or sub-national level. For example, Dell et al. (2009) find that higher temperatures reduce gross domestic product in poor countries, Burke et al. (2015) find a global non-linear relationship between temperature and gross domestic product. These findings are in line with Newell et al. (2018); Deryugina & Hsiang (2017) who find a non-linear relationship between income and temperature in US counties.

Economists have developed techniques for using these estimated relationships to forecast future impacts of climate change (Carleton & Hsiang, 2016; Kolstad & Moore, 2019). Briefly, the approach is to use empirically estimated temperature-outcome relationships along with forecasts of future temperature outcomes in order to generate empirically-derived predictions of the impact of climate change on the outcome of interest. This approach is used by, for example, Deschênes & Greenstone (2007); Deryugina & Hsiang (2017); Zhang et al. (2018).

Our study estimates the impact of extreme temperatures on manufacturing output in Canada. Like prior studies, we use the estimated relationship to draw predictions about the impact of future climate change on this outcome. We conduct the empirical analysis in five steps. First, we estimate the causal effect of extreme temperature on manufacturing output using data from the universe of manufacturing establishments in Canada combined with local daily weather from 2004 to 2012.[3] We use a panel fixed effect method to identify a non linear causal effect of daily mean temperature on manufacturing output. We rely on the same identifying assumption as in prior literature, which is that after conditioning on

[3] As shown later in the data section, we transformed the daily data into an annual data by counting the number of days, within a given year, the mean temperature falls inside a predetermined temperature bins.

establishment, year-by-province, and year-by-industry fixed effects, remaining daily temperature variation is quasi-random (Chen & Yang, 2019; Zhang et al., 2018; Somanathan et al., 2015). Causal identification resides in the intuition that day-to-day variation in temperature is not correlated with unobserved determinants of manufacturing production.

We find that both extreme cold and hot temperatures negatively affect annual manufacturing output. In our preferred specification, an extra day with mean temperature below -18°C decreases establishment annual output by 0.18% while an extra day with mean temperature above 24°C lowers establishment output by 0.11% relative to a day with mean temperature between 12-18°C. On average, Canadian manufacturing establishments experience an annual loss of total output by 0.6% as a result of days with temperatures below -18°C and another 1.6% for days with mean temperatures above 24°C. In total, manufacturing establishments in Canada experience an output loss of 2.2% in a typical year due to extreme temperatures.

Second, to understand the factors driving the temperature-output relationship, we estimate the effects of extreme temperatures on manufacturing labour productivity and labor inputs. Our results show that both extreme hot and cold temperatures reduce labour inputs. An extra day with temperature below -18°C or above 24°C respectively reduces total employment by 0.14% and 0.14% relative to a day with mean temperature between 12-18°C. As well, extreme cold temperatures reduce labour productivity. An extra day with mean temperature between -18 and -12°C reduces labor productivity by 0.12% relative to a day with mean temperature between 12-18°C. Overall, we find that both hot and cold temperatures reduce overall manufacturing output.

Third, we divide our manufacturing sample into establishments operating in the warmest and coolest regions in order to understand potential adaptation to climate. Establishments operating in cold areas experience on average 15 cold days and 3 hot days in a typical year while those operating in hot areas face on average almost 0.2 cold days and 22 hot days within a year. Because they more regularly face hot (cold) temperatures, establishments in warm (cold) regions may be better adapted to hot (cold) temperatures. We estimate the temperature-output relationship separately in each region, and compare the marginal effect of an additional cold and hot day on manufacturing output across these regions. Our results suggest no difference in the temperature-output relationship in warm vs. cold regions, suggesting limited adaptation to climate differences.

Fourth, we analyze the heterogeneity in the response of manufacturing output to extreme temperatures across several dimensions, including facility size, and labour intensity.[4] Our result shows both small, medium, and large establishments are sensitive to extreme temperature. Both an extra cold or hot day reduce small/medium/large manufacturing output by respectively 0.17-0.22% and 0.08-0.11%. Our results also show that extreme temperatures affect both labour and capital intensive establishments. An extra cold or hot day reduces labour/capital intensive establishments' output by respectively 0.14% and 0.1% relative to a day with mean temperature between 12 to 18°C.

Finally, we predict the potential impact of climate change on Canadian manufacturing output using downscaled weather forecast from an ensemble of climate models for the mid (2050s) and end (2080s) of century along with our estimates of the temperature-output relationship. Following the climate impact calculation in empirical studies, we assume no additional adaptation with the potential of lowering the sensitivity of output to extreme temperatures. Using medium and high greenhouse gas scenarios for 2050s and 2080s, we find that the annual losses of manufacturing output due to extreme temperature would go from 2.2% today to 2.8-3.5% in mid-century and to 3.5-7.2% in end of century.

Our study provides several contributions to the literature. We provide the first evidence about the effect of extreme temperatures on establishment performance in Canada, as well as the first evidence of the potential economic impact of climate change in a cold environment. The paper highlights the importance of labor input as a main contributor to the temperature-output losses. We find no evidence that the manufacturing sector adapts

[4] In the appendix, we estimate the temperature-output relationship by ownership. We find no difference between foreign and Canadian owned establishments in the response to the extreme temperature.

to extreme temperatures. We also highlight the vulnerability establishments to extreme temperature regardless their size.

The remainder of this paper is organized as follows. In section 2, we present a conceptual framework to motivate our empirical approach. Section 3 describes the data and reports descriptive statistics. Section 4 presents the empirical strategy. Section 5 describes the results. Section 6 presents robustness checks. And finally section 7 concludes and discusses implications for policy.

2 Conceptual Framework

To illustrate the mechanisms that explain the temperature-output relationship, in this section we provide a simple conceptual framework. Our model is aimed at how temperatures affect the outputs and inputs of a representative manufacturing establishment. The establishment produces output using labour combined with other inputs. Using a basic production identity, we have the following equation:

$$Y \equiv Y/L \times L, \tag{1}$$

where Y is the total output, L is labour input, and Y/L is labour productivity. A weather shock can separately or jointly affect labor productivity or labor input which in return would determine manufacturing total output. In the empirical work that follows, we estimate impacts on log output, which can be decomposed based on (1) as follows:

$$lnY = ln(Y/L) + lnL. \tag{2}$$

Manufacturing output is either sold domestically, exported, or else added to the inventory:

$$Y \equiv D + X + I, \tag{3}$$

where D, X, and I respectively represent the manufacturing domestic sales, total export, and inventory. Any change in manufacturing output due to temperature shock can jointly or separately affect each component of the total sales.

We use this simple framework to answer several research questions related to how extreme temperatures affect manufacturing output:

1. Do extreme temperatures affect overall manufacturing output?

2. Do extreme temperatures affect manufacturing output through the labour input channel and/or through the labour productivity channel? (Equation (2))

3. Do output reductions from extreme temperatures affect domestic sales, exports, or inventories? (Equation (3))

3 Data

We use a confidential dataset that includes the universe of Canadian manufacturing establishments over the period 2004-2012.[5] This section describes the data and their sources and the process of matching annual manufacturing data to daily weather variables.

3.1 Manufacturing Data

The data in our analysis come from a longitudinal file collected by Statistics Canada and called Annual Survey of Manufacturing and Logging (ASML) which covers the period 2004-2012.[6] Each year, ASML collects establishment level information including total output,

[5]In this study, we are using interchangeably plant and establishment which refers to the physical unit where production is made. (According to North American Industry Classification System (NAICS), establishments in the manufacturing sector are often described as plants, factories, or mills and characteristically use power-driven machines and materials-handling equipment. Moreover, establishments that transform materials or substances into new products by hand or in the worker's home and those engaged in selling to the general public products made on the same premises from which they are sold, such as bakeries, candy stores, and custom tailors, may also be included in this sector. Manufacturing establishments may process materials or may contract with other establishments to process their materials for them. Both types of establishments are included in manufacturing).https://www.bls.gov/iag/tgs/iag31-33.htm

[6]Statistics Canada collects confidential data on manufacturing activities across Canada. This dataset contains the universe of establishments from 2000-2012. However, some changes happened in the data

total sales, total export, total employment, payroll, and etc.[7] The survey also provides information on whether manufacturing production activities were disrupted due to extreme weather or natural disasters.

The ASML has information on the industry sector in which establishments operate as well as some geographical information such as province and census-subdivision (CSD) for each establishment.[8] CSD is the smallest geographical unit at which we observe the manufacturing establishments due to confidentiality. Each CSD covers approximately 10,000 people, such that urban CSDs cover small geographical areas while rural CSDs can cover larger geographical areas as shown in figure 1. Importantly, ASML data contain a unique establishment identifier which allows us to follow each establishment over time.

Over the period 2004-2012, the initial dataset counts more than 72,000 establishments located in 10 provinces and 3 territories and 2846 CSDs.[9] A large number of manufacturing establishments operate in Ontario and Quebec and account for almost 65% of the total sample.[10] Using the raw data, nearly 2.2% of the establishments changed industry subsector, 0.6% move across provinces and more than 12% move across CSD.[11,12] In our study, we may

collection in 2003. From 2000 to 2003, Statistics Canada sent out a questionnaire to all establishments in Canada. Starting in 2004, ASML was redesigned to reduce respondent burden on very small establishments. In 2004, Statistics Canada decided to drop the bottom 10% of plants of each industry by geographical area from the survey. As a consequence, we observe a spike in the death or exit of firms in 2004 which in principle in not the case. In 2007, Statistics Canada realized that in some geographical areas the bottom 10% include both small, medium, and large establishments and decided to use Canada Revenue Agency information (administrative data) to fill that gap. Given the complexity of the business register, they were not successful at retracing back all the missing establishments. We keep the period 2004-2012 for our analysis as in Najjar & Cherniwchan (2018) and Yamazaki (2017). For more information on ASML data, see: http://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getInstanceList&Id=504733

[7]All monetary value are in current Canadian dollars.

[8]CSD is a general term for municipalities or areas treated as municipal equivalents for statistical purposes. More information on CSDs can be found at https://www.statcan.gc.ca/eng/statistical-programs/document/1105_D16_T9_V1

[9]Using the definition of CSD in 2012, we count 5250 CSD. The total number of CSD varies with the updating CSD definition.

[10]This result is in line with the table 36-10-0222-01 produced by Statistics Canada where Ontario and Quebec respectively represented 37.3% and 19.4% of Canada GDP in 2012.

[11]When an establishment operates in more than one industry, Statistics Canada assigns to the establishment the industry code corresponding to the sector where more than 50% of the establishment's revenue come from.

[12]According to experts at Statistics Canada, very small establishments are likely to easily move across CSDs because of the low fixed cost. We find that 86%, 12%, and 2% of movers across CSD are respectively small, medium, and large establishments.

have an issue of endogeneity if establishments are allowed to move across industry sectors. Assume an establishment that operates in two industries where one is sensitive to extreme temperature and the other not. In presence of extreme temperature, this establishment will maximize production from the less sensitive industry. We address this by assigning the first industry in which they started operating the first year we see them in our data. To avoid a self-selection bias in our result, we drop the establishments that move across provinces and CSDs.[13]

Finally, we clean the data by keeping positive values for the key variables of interest which include total output, total employment, and total sales. We retain observations that have annual total output values greater or equal to $1,000,000.[14] We also drop 1% of outliers, using Bacon-style dropping to detect outliers in multivariate data, to ensure that our result is not drawn by very small or large establishments.[15] We define the establishment size as follows: small establishments are those with total employees less then 50, medium establishments are those with total employees between 50 and 249 and large establishments are those to total employees greater or equal to 250.

Our final sample has 39,698 establishments. Table 1 panel A reports the manufacturing sector summary statistics.[16] A large number of establishments are small (76%), followed by medium establishments (20%), and large establishments (4%). The average annual manufacturing output is $19,800,000.

[13] In the appendix, we estimate 4 by keeping establishments that move across CSDs and removing establishments that moved across provinces and we find a similar effect of extreme temperatures on manufacturing output with higher magnitude (-0.22% versus 0.18% for one extra cold day and -0.14% versus 0.11% for one extra hot day).

[14] We estimate 4 using the full sample without restriction on total output, we find a similar trend as with the restricted sample.

[15] This is a typical approach in studies using self-reported manufacturing data (Fowlie et al., 2016)

[16] The manufacturing sector is divided into 21 subsectors based on the NAICS classification system, https://www.ic.gc.ca/app/scr/app/cis/summary-sommaire/31-33.

3.2 Weather Data

The daily weather data come from Environment Canada monitoring stations across Canada. Figure 1 presents the location of monitoring stations across Canada used in the study. Most of the monitoring stations are located in the south of the country, where many cities are located and also where a large proportion of manufacturing establishments are operating. Over the period 2004-2012, we count 1,101 valid monitoring stations.[17] The Environment Canada weather data covers 759 out of 1225 CSDs where manufacturing plants are operating, which corresponds to a coverage rate of 62% of the manufacturing establishments. For CSDs that have multiple weather stations, we take the daily average of all the stations within a CSD. In order to obtain weather data for all establishments, we assign the value of the closest CSD to CSD with no weather monitoring station.[18] The weather data also contain missing value dues to the fact that they are turned off or sometimes values are simply not recorded. We fill the missing observations using an inverse distance weighting measure of the 10 closest monitoring stations.

Environment Canada weather data provides daily information on mean, minimum, and maximum daily temperature, total rain, total snow, and total precipitation.[19] The wind speed and relative humidity data come from the National Aeronautics and Space Administration (NASA).[20] We derive these data from a gridded daily weather data using MERRA2 climate reanalysis.[21,22]. Table 1 panel *B* presents the summary statistics of the weighted weather data for our final sample.[23]

[17] A monitoring station is valid when it provides daily weather data covering the entire period of study.

[18] As a robustness check, we estimate 4 on the subset of establishments with a weather monitoring station in the CSD. The results are consistent with our main finding.

[19] Mean temperature is defined as the average of minimum and maximum temperature over 24 hours at a given location. See `https://climate.weather.gc.ca/glossary_e.html`

[20] We do not use the wind speed data from Environment Canada because of its large proportion of missing observations; Environment Canada only records the maximum wind gust greater or equal to 29 km/h

[21] MERRA-2 climate reanalysis data come from the file M2I3NPASM-5.12.4 with the grid 0.5 x 0.625 degree corresponding to almost 80 x 80 km on a map

[22] The literature shows that weather variables such as wind speed, total precipitation, and relative humidity could be a confounder to the temperature effects as in (Deschênes & Greenstone, 2007; Deryugina & Hsiang, 2017; Zhang et al., 2018).

[23] We compute a weight defined as the number of establishments in each CSD in order to account for the

3.3 Climate Change Prediction Data

In order to predict impacts from future climate change, we use climate projections from a climate adaptation conservation planning database for North America also called Adaptwest. This dataset contains downscaled climate predictions for North America with a resolution of 1km by 1km based on the Coupled Model Intercomparison Project phase 5 (CMIP5) database.[24] The data is an ensemble projection of 15 CMIP5 models that were chosen as representative. The database consists of 23 million grid cells and is designed to capture climate gradients, temperature inversions, and rain shadows in the landscape of North America. The CMIP5 accounts for 4 global climate model scenarios (RCP2.6, RCP4.5, RCP6, and RCP8.5). Each scenario corresponds to a certain level of greenhouse gas (GHG) emission with RCP2.6 the lowest level of GHG emission and RCP8.5 the highest level of GHG emission. We focus on the moderate (RCP4.5) and high (RCP8.5) GHG emission and consider the mid century (2050s) and the end of century (2080s) projections in order to study the potential changes in manufacturing output resulting from future climate changes. This dataset provides information on the expected temperature across CSDs in the mid and end of century.

3.4 Matching Weather and Manufacturing Data

ASML data are annual observations while the weather data are observed daily. To retain the variability of the daily information while collapsing the weather data into annual data, we discretize the daily data into exhaustive bins that count the number of days within a year that temperature falls within each bin. We create 9 temperature bins as follows: $]\infty : -18[$, $[-18 : -12[$,...,$[24 : \infty[$ with each bin 6°C wide before having access to the confidential manufacturing data.[25] By year and CSD, we count the number of days the temperature lays inside each bin. This approach is used in a number of similar studies such as Deschênes

representativeness of each CSD .

[24] https://adaptwest.databasin.org/pages/adaptwest-climatena

[25] We made a one-time choice of the temperature bins before seeing the manufacturing data.

& Greenstone (2007), Deryugina & Hsiang (2017), Zhang et al. (2018),and Addoum et al. (2019). We define T_{bct} as the number of days with temperature in bin b, at year t in the CSD c. We apply the same methodology to the other weather variables including relative humidity, wind speed, and total precipitation.

Figure 3 plots the weighted annual distribution of mean temperature across CSDs for observed establishments. The dark blue bars represent the daily mean temperature distribution over the period 2004-2012. The following bars represent the daily mean temperature distribution for mid and end of century projected under the scenarios RCP4.5 and RCP8.5. Under all the projected future climate scenarios, we observe a shift of daily mean temperature distribution to the right. Under the climate change scenarios, we observe that the number of days above 24°C will be 3 to 6 times higher than the current level in a typical year. Meanwhile the average number of days below -18°C is projected to decrease from 4 days annually to 1-2 days annually.

4 Empirical Approach

This section describes the reduced form approach used to estimate the effect of temperature on manufacturing output in Canada. Following other recent work outlined above, we use a panel fixed effects model for our analysis. We estimate the effect of extreme temperatures on manufacturing output by comparing the year-to-year within-establishment relationship between temperature and output. We control for province-by-time fixed effects and industry-by-time fixed effects. Equation (4) provides a standard formulation of the panel fixed effect method:

$$y_{icpdt} = \sum_{b} \beta_b T_{ct}^{b} + \sum_{w} \sum_{q} \theta_b W_{ct}^{qw} + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \tag{4}$$

where y_{icpdt} is the logarithm of the total output of establishment i operating in census subdivision c, province p, and industry d at time t. In addition to total output, we also estimate the effect of temperature on labor productivity, labor input, total sales, domestic sales, inventory, and exports, as motivated in section 2. T_{ct}^{b} is a count of the number of days in year t and census sub-division c that daily mean temperature falls within bin b. W_{ct}^{qw} is a count of the number of days in year t and census subdivision c that weather type w falls within bin q. The controlled weather variables (w) include relative humidity, total snow, total rain, and wind speed. For each of these weather variables, daily weather is discretized into 7 exhaustive bins (q=1..7). γ_i is the establishment fixed effect which captures all time invariant fixed characteristics of the establishment. ζ_{pt} is a province-by-year fixed effect. It accounts for annual shocks common to establishments within each province such as economic policy and energy prices. ψ_{dt} is the manufacturing sector-by-year fixed effect and it controls for annual shocks common to each manufacturing sector, such as input and output prices and technology change. Finally, ε_{icpdt} is the error term. The error term may be spatially correlated if there are common unobserved shocks that vary over space and may be serially correlated within a given establishment over time. We cluster the error terms at the census-subdivision level to address potential spatial and serial correlation in the error terms.

The coefficient of interest β_b is a semi-elasticity and is interpreted as the marginal effect of an extra day with temperature in bin b relative to a day with temperature in the reference bin (12 to 18°C) which is the omitted category. The causal interpretation comes from the assumption that year-to-year temperature fluctuations experienced by establishments are exogenous once fixed effects for establishment, province-by-year, and industry-by-year are conditioned on, as in Deryugina & Hsiang (2017), and Zhang et al. (2018).

5 Results

In this section, we first describe our main finding relating to the temperature-output relationship. We also make use of an alternative measure of temperature to study the relationship between temperature and output. Secondly, we discuss the mechanism through which temperature affects manufacturing output. We also analyze how changes in total output resulting from extreme temperatures affect domestic sales, exports, and inventories. We then indirectly analyze whether manufacturing establishments adapt to their local temperature through investments in adaptation infrastructure such as buildings, air conditioner or heating systems. Later, we provide evidence on the heterogeneity of the temperature effects across establishments of different size and labour intensity. We study how each industry sub-sectors are affected by the temperature-output relationship. Finally, we combine our estimates on the impact of extreme temperature on output with downscaled climate projections to predict the effect of future climate change on manufacturing output.

5.1 Main results

Table 2 presents the effects of temperatures on manufacturing annual output, based on estimating equation (4). Columns $A1 - A4$ test the robustness of our results to the inclusion of different sets of fixed effects. Column $A1$ includes only establishment and year fixed effect. The establishment fixed effects account for unobserved heterogeneity between establishments and the year fixed effects account for common shocks at the country level such as policy, technological, and price changes. In column $A2$, we replace year fixed effects with year-by-province fixed effect. This allows the shocks to be at the provincial level instead of country level. Since much economic policy is set at the provincial level, this specification may better account for confounders than the specification in column $A1$. In column $A3$, the year fixed effect is replaced by year-by-industry fixed effects, which control for shocks that are common within industry sub-sectors across the country. Unobserved changes in commodity prices, for example, have different effects on different sectors, and their confounding effect would be removed in this specification. In column $A4$, which is our preferred specification, the year fixed effect from column $A1$ is replaced by both year-by-industry fixed effects and year-by-province fixed effects, thus accounting for both sources of potential confounding described above.

Under the preferred specification, we find that both extreme cold and hot temperatures have a negative effect on manufacturing establishment output. Other specifications yield similar results for hot days, however, in specifications A1 and A3, the effect of cold temperatures is no longer statistically significantly different from zero. Each day in which the mean daily temperature is below -18°C reduces annual manufacturing output by 0.18% relative to a day with mean temperature between 12 to 18°C. Similarly, an extra day with mean temperature above 24°C causes annual manufacturing output to be reduced by 0.11% compared to a day with mean temperature between 12 to 18°C. In our data set, manufacturing establishments in Canada experience on average 4 cold days with mean temperatures below -18°C, and 14 hot days with temperature above 24°C. Given the number of cold and hot days in a typical year, annual manufacturing output in Canada is reduced on average by 2.2% as a result of extreme temperatures. This represents an annual output loss of $435,600 per establishment.

We provide two robustness checks in Table 2. In column B table 2, we run the analysis on a balanced sample of establishments–that is only the subset of establishments that are observed in every year of our data set. Restricting the sample to plants that always report ensures that our results are not driven by changing composition of establishments in the data. The results are very similar to our main specification, and confirm that the effect we observe is not related to plant entry and exit. In column C table 2, we run the model without the inclusion of other weather controls. We find that both cold or hot days reduce manufacturing annual output, suggesting that our main results are not affected strongly by the inclusion or exclusion of weather controls. The invariance of our results to weather controls provides some suggestive evidence that inclusion of other weather controls would not substantially impact the results.

We now analyze the mechanisms that give rise to the temperature-output relationship using equation 1, which decomposes total output into a total employment effect and a labour productivity effect.[26] Figure 5 shows that the manufacturing total employment response to

[26]Total employment is defined as the total number of employees for each manufacturing plant including both part and full-time employees. It also includes both production workers and salaries workers.

extreme temperature is almost similar to the one observed with manufacturing total output. Both an extra day below -18°C and above 24°C reduce manufacturing total employment by respectively 0.14% and 0.14% relative to a day with temperature between 12 to 18°C. The effect of hot days on total employment fully explains the drop of manufacturing output during hot days while the reduction of labour inputs during cold days only partially explains the temperature-output relationship observed during cold days. We also find that an extra day with temperature between -18 and -12°C reduces manufacturing labour productivity by 0.12% while labour productivity is not affected by hot days. Both total employment and labour productivity contribute to explain the drop of manufacturing output during cold days. These results suggest that the main driver behind the temperature-output relationship is manufacturing total employment adjustments.[27] Zhang et al. (2018) conducts a similar decomposition as we do here, but finds contradictory results. In that study, the output effect is mostly due to reduced productivity, and they observe relatively smaller impacts on factor inputs due to extreme temperatures.

Equation (3) decomposes manufacturing total output into domestic sales, exports, and inventories. We rerun equation 4 with different dependent variables reflecting the decomposition in equation (3). Figure 7 decomposes the effects of extreme temperatures on manufacturing output into these three demand components. We find that both cold and hot days reduce total sales by 0.23% and 0.14%, respectively – a similar magnitude to our estimates on total output. The losses in total sales are mainly driven by domestic sales which are also negatively affected by hot days as shown in Figure 7. We find no evidence that manufacturing total exports and inventory are affected by extreme temperatures.

Our analysis provides some evidences about the manufacturing activity disruption during extreme temperatures realization. We provide suggestive evidence that plants are affected through an adjustment of their total employment while the labour productivity is only

[27] In order to understand how the total employment is affected, we analyze the effect of extreme temperature on establishments' payroll. We find a reduction of establishments' payroll during both cold and hot temperatures. We do not find evidence that extreme temperature is causing establishments to close.

affected during cold days. One plausible explanation is that extreme temperatures affect primarily the demand for manufacturing goods, which results to a reduction of the total output. The establishments would then adjust the level of employment with respect to the drop in output.

5.2 Perceived temperature

In this section, we consider alternative measures of temperature, which adjust for relative humidity and wind speed, in order to estimate the effect of temperature on manufacturing total output. A combination of outside negative temperature and wind speed is called wind chill temperature, while a combination of outside positive temperature and relative humidity is called wet-bulb temperature. These measures usually differ from the outside temperature measure, and may better capture how humans perceive the extreme outdoor temperatures. These measures are also motivated by our finding that show that the temperature-output relationship is driven by change in labour inputs.

Using daily weather variables, we compute daily mean wind chill temperature and wet-bulb temperature following Equations (10) and (11) in the Appendix. We then define three bins for perceived temperatures, based on extreme weather risk thresholds suggested by Environment and Climate Change Canada: low, medium, and high. For example, the wind chill temperature is considered to be high risk when the wind chill adjusted temperature falls below -28°C. Full definitions are provided in the Appendix. For each year, we count the number of days the perceived temperature lies inside the defined bins and then estimate the perceived temperature effect on manufacturing output as follows:

$$y_{icpdt} = \sum_{b} \beta_b PT^b_{ct} + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \tag{5}$$

where PT^b is the perceived temperature in bin b in CSD c at time t.

Table 3 shows the results of estimating Equation (5). We find that high risk bin for both wind-chill temperature and wet-bulb temperature have a negative effect on manufacturing total output. An extra day of temperature in the high risk bin relative to the low risk bin, reduces manufacturing total output by 0.22% for wind-chill temperature and 0.14% for wet-bulb temperature. The magnitudes at which perceived temperatures affect manufacturing output are slightly higher than the ones found in our main result 2. This result supports our main finding in section 5.1 and highlights the importance of factors such as wind speed or relative humidity in studies analyzing the effects of extreme temperature on individuals.

5.3 Local adaptation

In this section, we analyze whether the temperature-output relationship depends on the local climate condition of establishments. We are testing the hypothesis that establishments operating in relatively hot areas would be less sensitive to hot temperature and vice-versa for those operating in relatively cold areas. It is assumed that establishments might adopt some types of adaptation to mitigate the effect of the extreme temperature they experience the most as in Chen & Yang (2019). In other words, establishments have an incentive to invest in adaptive equipment to mitigate the impact of their locational most frequent extreme temperature.

Using the distribution of the annual mean temperature by CSDs, we define coldest and hottest areas as those respectively below 30th centile and above the 70th centile.

Figure 13 presents the weighted temperature distribution for establishments operating below the 30th and above the 70th centile of temperature distribution. On average, establishments operating below the 30th centile experience 15 cold days per year and 3 hot days. Similarly, establishments operating above the 70th centile, on average, experience 1 cold days and 22 hot days per year. We then test whether establishments operating in coldest or hottest areas react differently to the temperature-output relationship.

We rerun equation (4) by interacting weather variables with a dummy for cold or hot areas as follows:

$$y_{icpdt} = \sum_b \beta_a T_{ct}^b + (\sum_b \beta_b T_{ct}^b + \sum_w \sum_q \theta_b W_{ct}^{qw}) \times climate + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \qquad (6)$$

where *climate* is a dummy variable taking the value of 1 for coldest or hottest areas and 0 otherwise. We also interact *climate* with both industry-year and province-year fixed effects.

Evidence of adaptation would be if establishments operating below the 30th(above the 70th centile) respond differently to cold(hot) temperature compared to those operating in other areas. We find no statistical difference between establishments operating in relatively cold/hot areas and the rest of establishments. This result suggests that there is no evidence of locational adaptation to the extreme temperature as shown in figure 15.

5.4 Heterogeneity

5.4.1 Establishment size

In this section, we study the effect of temperature on manufacturing output for small, medium, and large establishments. Our aim is to test the hypothesis that large establishments would have enough resources for adaptive investments compared to small or medium establishments. We rerun (4) by interacting weather variables with a dummy variable representing establishments' size as follows:

$$y_{icpdt} = \sum_b \beta_a T_{ct}^b + (\sum_b \beta_b T_{ct}^b + \sum_w \sum_q \theta_b W_{ct}^{qw}) \times size + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \qquad (7)$$

where *size* is a dummy variable taking the value of 1 for small, medium or large establishments and 0 otherwise. We also interact *size* with both industry-year and province-year fixed effects.

Figure 11 presents the effect of extreme temperature on manufacturing output by establishment size. We find that small establishments are the most affected by extreme cold temperature. Extreme hot temperature continue to adversely affect the manufacturing output regardless the establishment's size which may indicate the difficulty to adapt to extreme hot temperature despite the adaptive tools available as in Heyes & Saberian (2019).

5.4.2 Labour intensity

In this section, we study the effect of temperature on manufacturing establishments with different input structures. As shown in 5.1, total employment is the main factor explaining the temperature-output relationship. As a result, we may expect labour intensive establishments to be more affected by the temperature-output relationship compared to capital intensive establishments. We divide our sample into labour versus capital intensive establishments. We use two measures of labour intensity respectively defined as the share of labor in total output or as the share of total employment in total sales. An establishment is considered labor intensive when its share is above the median labour share in a given industry sector. We rerun (4) by interacting weather variables with a dummy variable representing labour intensity as follows:

$$y_{icpdt} = \sum_{b} \beta_a T_{ct}^{b} + (\sum_{b} \beta_b T_{ct}^{b} + \sum_{w} \sum_{q} \theta_b W_{ct}^{qw}) \times intensity + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \quad (8)$$

where *intensity* is a dummy variable taking the value of 1 when the establishment is labour intensive and 0 otherwise. We also interact *intensity* with both industry-year and province-year fixed effects.

We find no statistical difference between labour and capital intensive establishments regarding the impact of extreme temperature. However, using total employment over total sales as a measure of labour intensity, we find that relative to capital intensive establishments, an extra day with temperature between -18:-12°C or -12:-6°C reduces labor intensive manufacturing output by respectively 0.19% and 0.17% compared to a day with mean temperature between 12-18°C. We find no difference in the impact of extreme temperature between labour versus capital intensive establishments when using the other measure of labour intensity (labour/output).

5.5 Predicted impacts of climate change

Figure 3 shows the projected impacts of climate change on the distribution of temperatures that are likely to be experienced by manufacturing establishments in our sample. Climate change will increase the average temperature, and also shift the incidence of days with extreme temperatures. Climate models predict that the future holds more extremely hot days and less extremely cold days in places where manufacturing establishments are located. Under the moderate (RCP4.5) and the high (RCP8.5) scenarios of GHG emissions, the number of days with temperature greater or equal to 24°C would respectively increase from 14 days to 40 and 43 in the mid-century (2050s) for a typical manufacturing plant. At the end of century (2080s), climate change is expected to respectively increase the number of hot days experienced by a typical manufacturing plant to 43 and 80 under respectively medium and high scenarios of GHG emissions. These climate scenarios also predict a decrease in the number of days with mean temperature below -18°C from 4 to 1 in the mid and end of century.

To predict the impact of climate change on manufacturing output, we multiply the regression coefficient estimates from equation (4) by the predicted difference of the number of days between the mid/end of century projection and the current period (2004-2012) for each temperature bin.[28] The predicted difference between past and future is the difference in the height of the bars representing the number of day for each temperature bin as shown in Figure 3. We derive the standard error using the delta method. This methodology assumes that the determinants of manufacturing output are fixed over the time which include the

[28] Lemoine (2018) suggests that the reduced form estimates would recover the effects of climate change if establishments are myopic. Unlike the agricultural sectors, manufacturing establishments are limited in the adaptive tools to mitigate the effects of climate change. They might increase the proportion of capital stock in their production process since most of them already are using heating system and/or air conditioner. We also assume that establishments are operating under the optimal combination of labour inputs and capital stocks which limit their flexibility toward climate change.

baseline productivity and technology.

Table 4 presents the predicted effect of climate change on manufacturing establishment output for temperatures below -18 °C and above 24 °C. The predicted mid century effect suggests that extreme temperature would annually reduce the manufacturing output by almost 2.8 and 3.6% under medium and high GHG emission scenarios respectively. When we consider the predict effect for the end of century, the medium and high GHG emission scenarios respectively suggest a decrease of manufacturing output by 3.6 and almost 7.2% respectively.

6 Extensions

This section presents two extensions to our basic approach that are aimed at increasing confidence in our results.

6.1 Reduced activity due to extreme temperature or natural disasters

In this section, we use self-reported information from manufacturing establishments which captures whether an establishment has experienced reduced activity due to extreme weather or natural disasters. In the ASML questionnaire, establishments were asked if they experienced a reduction of their activity due to extreme temperature or natural disasters.[29,30]. We then estimate the impact of reduced activity due to extreme temperature or natural disasters on manufacturing output.

$$y_{icpdt} = \beta R_{it} + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \tag{9}$$

[29] This question has more than 21% missing values. The missing value is explained by both the non-response of some establishments and the use of tax file data to fill the information of some establishments.

[30] We may think that the non response indicate bias in our result, we then instrument the variable of interest using weather variables and estimate (9) We find that the negative effect of extreme temperature/natural disaster is now going up from 5% to 11% – table 6 in appendix

where R take the value of 1 when an establishment i experience a reduced activity due to extreme weather/natural disasters at time t and 0 otherwise.

Table 5 shows that manufacturing output is negatively affected by extreme weather/natural disasters realizations. Manufacturing total output is reduced by 5% for establishments that have experienced a reduction of their activity due to extreme weather/natural disasters. The result is in line with our main finding in 5.1 showing that manufacturing activity is adversely affected by extreme temperature.

6.2 Falsification test

In this section we report on a falsification test designed as a test of model specification to show that our results are not driven by spurious patterns. As in Fishman et al. (2019), we use a falsification test that consist to repeatedly and randomly "reshuffle" the weather data across time and location and estimate (4). For establishments in a given location, we allow them to randomly take the value of the temperature from a different year. Similarly for establishments observed at a given year, we allow them to randomly take the temperature of another location. We expect to see no relation between the randomly assigned temperature and manufacturing output. We repeat this process 1000 times, and report the coefficient estimates from these falsification tests, along with our real coefficients in figure 17.

Figure 17 plots the coefficient distribution for temperature below -18°C and above 24°C. When weather data are randomly assign across location and year, the temperature-output relationships are not statistically significant in 96.1% of cases for temperature below -18°C and in 94.3% of case for temperature above 24°C. The significant coefficient estimates from the falsification tests are strictly larger than those in our main finding 2. When the weather variables are randomly assign across location, we find that the coefficients estimates are not statistically significant in 94.7% and in 94% of cases for respectively temperature below -18°C and above 24°C. All the coefficients are centered around 0. Finally, we randomly assign weather variables across year and we find that in 95.2% and 93.3% of cases the estimates are not statistically significant. We also find that all the estimate coefficients from the falsification test are centered around 0. As expected, the random assignment weather variables across location or year are likely to lead to no significance effect of extreme temperature and are centered around 0 whenever significant. This result validate our empirical strategy in 4 and the data used in our study.

7 Summary and conclusion remarks

Our paper analyzes the effect of extreme temperature on manufacturing output in Canada. We find that extreme temperatures, as represented by mean temperature below -18°C and above 24°C, have a negative impact on manufacturing output. Our finding is robust to the use of alternative measures of temperature, fixed effects, controlling for other weather covariates, and sample. Overall, we find that the manufacturing sectors in Canada are vulnerable to extreme temperatures realizations in the short-term. Our estimates suggest that in a typical year, manufacturing output in Canada is reduced by almost 2.2% due to extreme temperatures.

The temperature-output relationship is mainly driven by the negative effect of temperature on manufacturing total employment. We also find that small establishments and labour intensive establishments are most sensitive to extreme cold temperatures. We study whether establishments adapt to their local temperatures by considering those operating in cooler versus hotter areas. We find no evidence that establishments operating in cold areas adapt to cold temperatures and those operating in hot areas adapt to hot temperatures.

Using downscaled climate change projections, we predict that the losses of manufacturing output in Canada would almost double in the mid century and quadrupled by the end of the century, as a result of an increase in the number of extremely hot days.

There are three main limitations in this study. First, our data are missing estimates of capital stock in manufacturing plants which prevents us from analyze the impact of temperature on total factor productivity (TFP). TFP, which represents the efficiency of employment of both labour and capital inputs to production, can be used to estimate welfare impacts of extreme weather shocks. Zhang et al. (2018) find some evidence that the capital stock is affected during extreme temperatures realization, which we cannot validate in our sample, given the missing information. The second limitation is the missing information on establishments' investments in equipment related to extreme temperatures. The investment variable would shed light on establishments' efforts to minimize the effect of extreme temperatures and therefore its efficiency. The final limitation comes from the predicted climate impact because establishments are likely to engage in variety of investments or actions in the long-run in response to the climate change. As the result, we may overestimate the effect of climate change on manufacturing output in the mid and end of century.

References

Addoum, J. M., Ng, D. T., & Ortiz-Bobea, A. (2019). Temperature shocks and establishment sales. *The Review of Financial Studies*, forthcoming.

Auffhammer, M. (2018). Quantifying economic damages from climate change. *Journal of Economic Perspectives*, *32*(4), 33–52.

Behrer, A. P., & Park, J. (2017). Will we adapt? Temperature, labor and adaptation to climate change. *Harvard Project on Climate Agreements Working Paper*, 16–81.

Burke, M., & Emerick, K. (2016). Adaptation to climate change: Evidence from US agriculture. *American Economic Journal: Economic Policy*, *8*(3), 106–40.

Burke, M., Hsiang, S. M., & Miguel, E. (2015). Global non-linear effect of temperature on economic production. *Nature*, *527*(7577), 235.

Carleton, T. A., & Hsiang, S. M. (2016). Social and economic impacts of climate. *Science*, *353*(6304), 1112–1127.

Chen, X., & Yang, L. (2019). Temperature and industrial output: firm-level evidence from China. *Journal of Environmental Economics and Management*, *95*, 257–274.

Cook, N., & Heyes, A. (2020). Brain freeze: Outdoor temperature and indoor cognitive productivity. *Journal of Environmental Economics and Management - Revise and Resubmit*.

Dell, M., Jones, B. F., & Olken, B. A. (2009). Temperature and income: Reconciling new cross-sectional and panel estimates. *American Economic Review*, *99*(2), 198–204.

Deryugina, T., & Hsiang, S. (2017). *The marginal product of climate* (Tech. Rep.). National Bureau of Economic Research.

Deschênes, O., & Greenstone, M. (2007). The economic impacts of climate change: Evidence from agricultural output and random fluctuations in weather. *American Economic Review*, *97*(1), 354–385.

Deschenes, O., & Moretti, E. (2009). Extreme weather events, mortality, and migration. *The Review of Economics and Statistics*, *91*(4), 659–681.

Fishman, R., Carrillo, P., & Russ, J. (2019). Long-term impacts of exposure to high temperatures on human capital and economic productivity. *Journal of Environmental Economics and Management*, *93*, 221–238.

Fowlie, M. L., Reguant, M., & Ryan, S. (2016). Measuring leakage risk. *Report for the California Air Resources Board*.

Galloway, S., & Maughan, R. J. (1997). Effects of ambient temperature on the capacity to perform prolonged cycle exercise in man. *Medicine and science in sports and exercise*, *29*(9), 1240–1249.

González-Alonso, J., Teller, C., Andersen, S. L., Jensen, F. B., Hyldig, T., & Nielsen, B. (1999). Influence of body temperature on the development of fatigue during prolonged exercise in the heat. *Journal of Applied Physiology*, *86*(3), 1032–1039.

Graff Zivin, J., Hsiang, S. M., & Neidell, M. (2018). Temperature and human capital in the short and long run. *Journal of the Association of Environmental and Resource Economists*, *5*(1), 77–105.

Graff Zivin, J., & Neidell, M. (2014). Temperature and the allocation of time: Implications for climate change. *Journal of Labor Economics*, *32*(1), 1–26.

Hancock, P. A., Ross, J. M., & Szalma, J. L. (2007). A meta-analysis of performance response under thermal stressors. *Human Factors*, *49*(5), 851–877.

Heal, G., & Park, J. (2016). Reflections-temperature stress and the direct impact of climate change: a review of an emerging literature. *Review of Environmental Economics and Policy*, *10*(2), 347–362.

Heyes, A., & Saberian, S. (2019). Temperature and decisions: evidence from 207,000 court cases. *American Economic Journal: Applied Economics*, *11*(2), 238–65.

Kolstad, C. D., & Moore, F. C. (2019). *Estimating the economic impacts of climate change using weather observations* (Tech. Rep.). National Bureau of Economic Research.

Lemoine, D. (2018). *Estimating the consequences of climate change from variation in weather* (Tech. Rep.). National Bureau of Economic Research.

Mackworth, N. H. (1946). Effects of heat on wireless operators. *British journal of industrial medicine*, *3*(3), 143–158.

Najjar, N., & Cherniwchan, J. (2018). Environmental regulations and the clean-up of manufacturing: Plant-level evidence from Canada. *University of Alberta School of Business Research Paper*(2018-701).

Newell, R., Prest, B., & Sexton, S. (2018). The gdp-temperature relationship: Implications for climate change damages. *Resources for the Future. 2018/07/05/.*.

Park, J. (2017). Hot temperature and high stakes exams: Evidence from new york city public schools. *URL: https://scholar. harvard. edu/files/jisungpark/files/papernycaejep. pdf*.

Schlenker, W., & Roberts, M. J. (2009). Nonlinear temperature effects indicate severe damages to US crop yields under climate change. *Proceedings of the National Academy of sciences*, *106*(37), 15594–15598.

Seppanen, O., Fisk, W. J., & Lei, Q. (2006). *Effect of temperature on task performance in office environment* (Tech. Rep.). Berkeley, Calif.: Lawrence Berkeley National Laboratory.

Somanathan, E., Somanathan, R., Sudarshan, A., Tewari, M., et al. (2015). The impact of temperature on productivity and labor supply: Evidence from Indian manufacturing. *Indian Statistical Institute: New Delhi, India*, 212–231.

Yamazaki, A. (2017). Jobs and climate policy: Evidence from British Columbia's revenue-neutral carbon tax. *Journal of Environmental Economics and Management*, *83*, 197–216.

Zhang, P., Deschenes, O., Meng, K., & Zhang, J. (2018). Temperature effects on productivity and factor reallocation: Evidence from a half million Chinese manufacturing plants. *Journal of Environmental Economics and Management*, *88*, 1–17.

8 Appendix

8.1 Tables and graphs

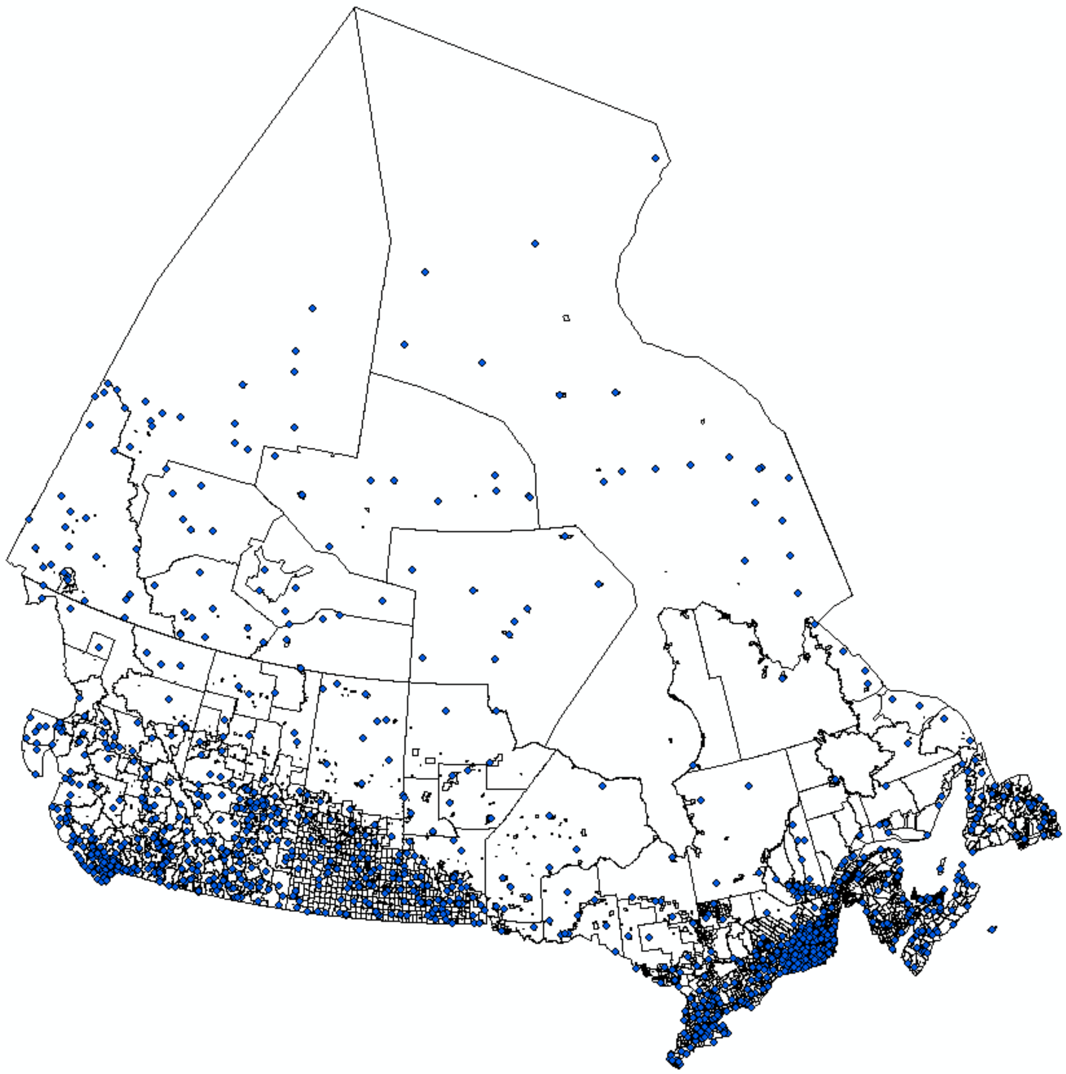


Figure 1: Dispersion of weather monitoring stations across Canada

Source: NAPS Canada. Each polygon represents the CSD borders. We observe large CSDs in the north of Canada because of its small population size while CSDs are smaller in the south of Canada with a high density of individuals. The blue dots are for the weather monitoring stations inside each CSD.

Table 1: Summary Statistics

	Panel A			
Manufacturing data			Period 2004-2012	
	total observations	total firms	mean	sd
Output	236007	39698	19,800,000	16,900,000
Total employment	236007	39698	54.6	152.3
Labor productivity	236007	39698	288,368	826,063
Small establishments	236007	39698	0.76	0.43
medium establishments	236007	39698	0.2	0.4
large establishment	236007	39698	0.04	0.18
	Panel B			
Weather data				
mean temperature (°C)	236007	39698	8.05	1.71
total rain (cm)	236007	39698	2.16	0.64
total snow (cm)	236007	39698	0.38	0.18
relative humidity (%)	236007	39698	0.7	0.04
wind speed (m/s)	236007	39698	6.06	0.54
	Panel C			
Predicted temperature	Mid century (2050s)		End century (2080s)	
	mean	sd	mean	sd
RCP 45 (°C)	10.69	1.7	11.37	1.69
RCP85 (°C)	11.57	1.69	13.76	1.66
total observation	236007	236007	236007	236007
total firms	39698	39698	39698	39698

Notes: The unit of observation is establishment-year. This sample represents establishments with output greater or equal $1 million CAD. All monetary units are in current CAD.

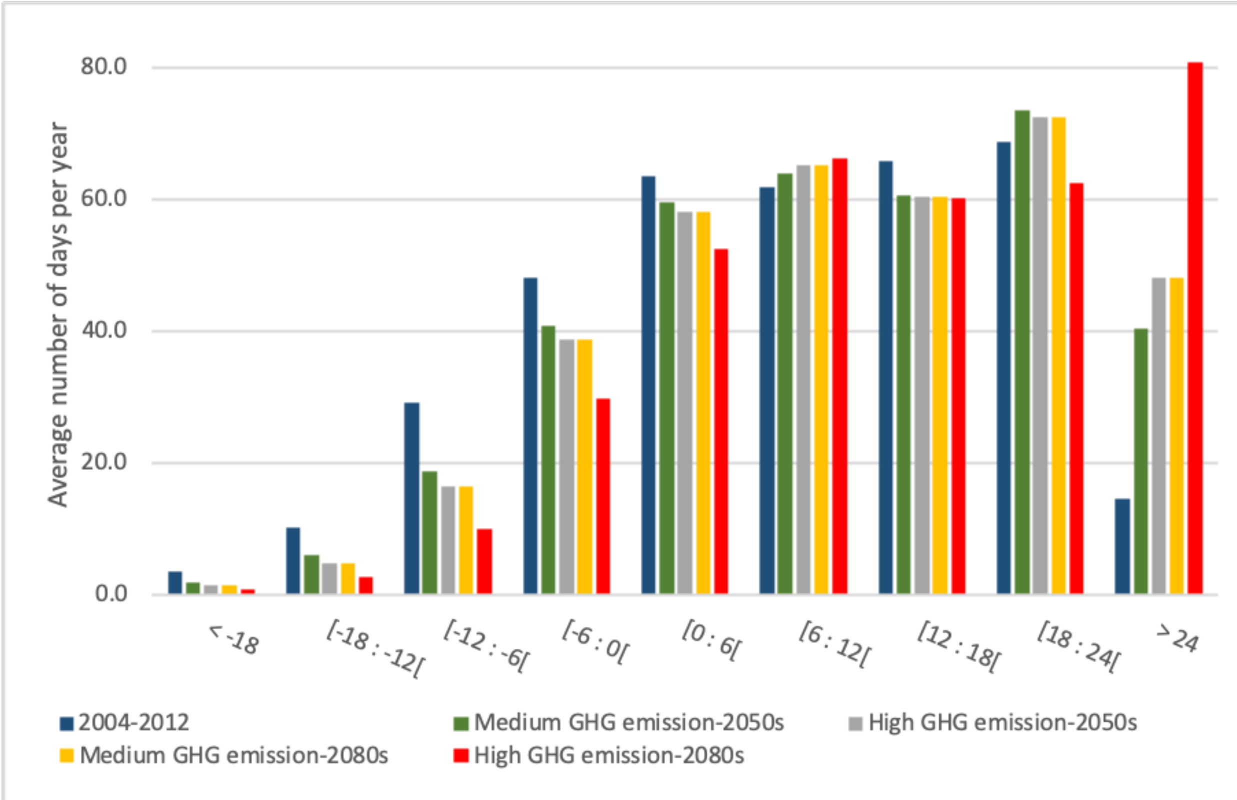


Figure 3: Current and predicted daily temperature distribution.

Notes: Each height represents the weighted average daily temperature across all establishments and year. The weight used is the number of establishments in each CSD. The blue bar represents the period 2004-2012. The green and yellow bars respectively represent the mid (2050s) and end of century (2080s) temperature projection for medium GHG emission scenario. Finally, the grey and red bars represent the mid and end of century temperature projection for high GHG emission scenario.

Table 2: Estimated effects of temperature of total output

	log (output)					
	A1	A2	A3	A4	B	C
< -18	0.02	-0.19**	0.02	-0.18**	-0.23***	-0.18**
	(0.07)	(0.07)	(0.06)	(0.07)	(0.09)	(0.07)
[-18 : -12[	-0.13**	-0.13*	-0.04	-0.11*	-0.15**	-0.09
	(0.06)	(0.06)	(0.05)	(0.06)	(0.08)	(0.06)
[18 : 24[	-0.04	-0.06*	-0.04	-0.05**	0	-0.05*
	(0.03)	(0.02)	(0.03)	(0.02)	(0.03)	(0.02)
>24	-0.08**	-0.12***	-0.05*	-0.11**	-0.16**	-0.12**
	(0.03)	(0.05)	(0.03)	(0.05)	(0.06)	(0.04)
Observations	236,007	236,007	236,007	236,007	112,635	236,007
Establishments FE	Yes	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	No	No	No	No	No
Year-province FE	No	Yes	No	Yes	Yes	Yes
Year-industry FE	No	No	Yes	Yes	Yes	Yes
Weather controls	Yes	Yes	Yes	Yes	Yes	No

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: This table presents the effetcs of daily extreme temperature on manufacturing total output. Column A1 controls for establishment and year FE. In column A2, we replace the year FE by year-province FE. In column A3, we replace the year FE by year-industry three-digit FE. Column A4 includes both establishment, year-province, and year-industry FE. Column B represents the estimations of balanced panel. Finally, column C represents the estimations without weather controls. Columns A1-A4 and B include weather controls which are total rain, total snow, relative humidity, and wind speed. For all estimations, the standard errors are clustered at the CSD levels. These coefficients are interpreted as the percentage change of an additional day at a given temperature relative to the reference bin [12:18[

.

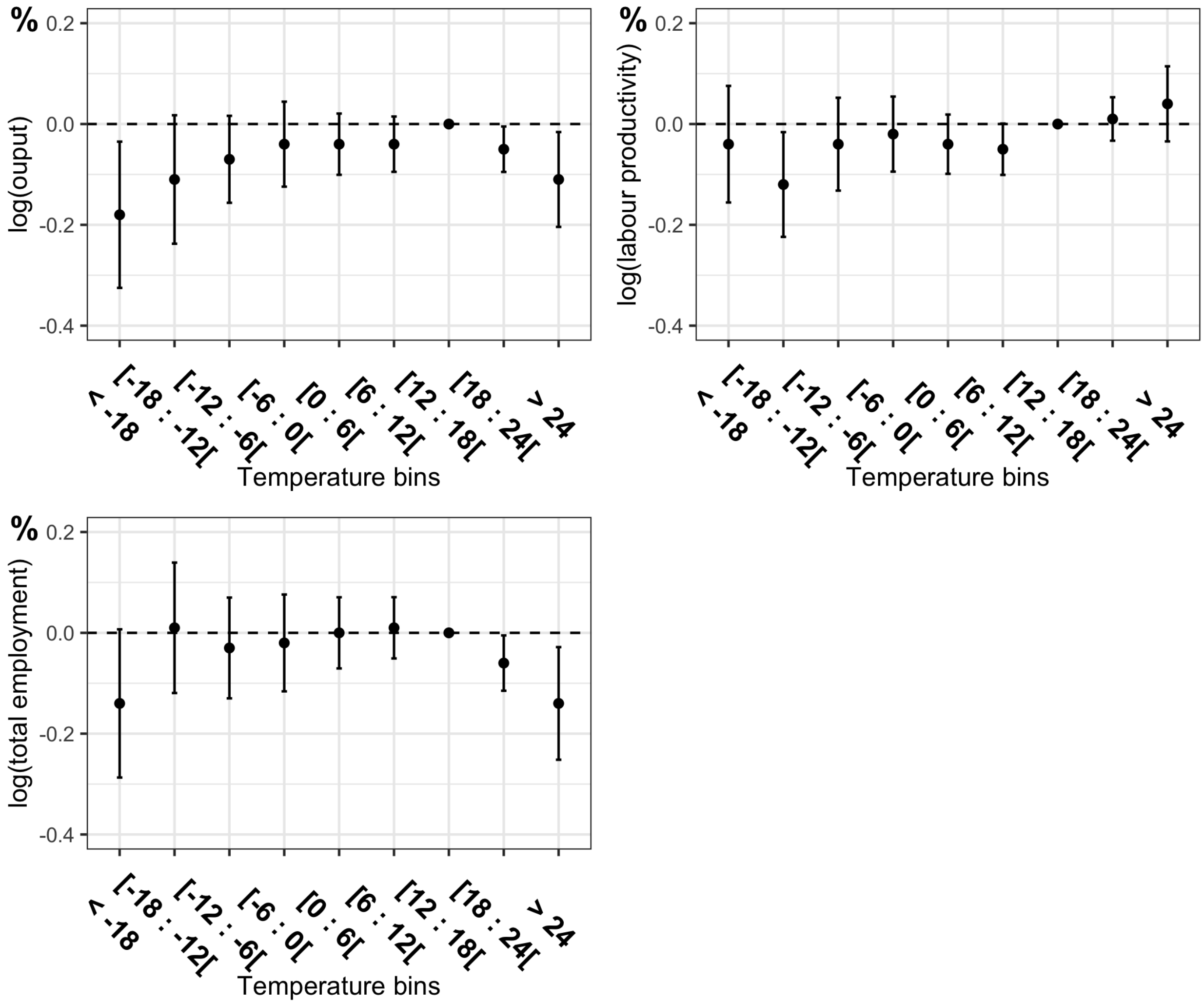


Figure 5: Estimated effects of extreme temperatures on manufacturing activity

Notes: These figures present the impact of daily mean temperature on manufacturing activity represented by total output, TFP, and total employment. All the specifications includes establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the CSD levels.

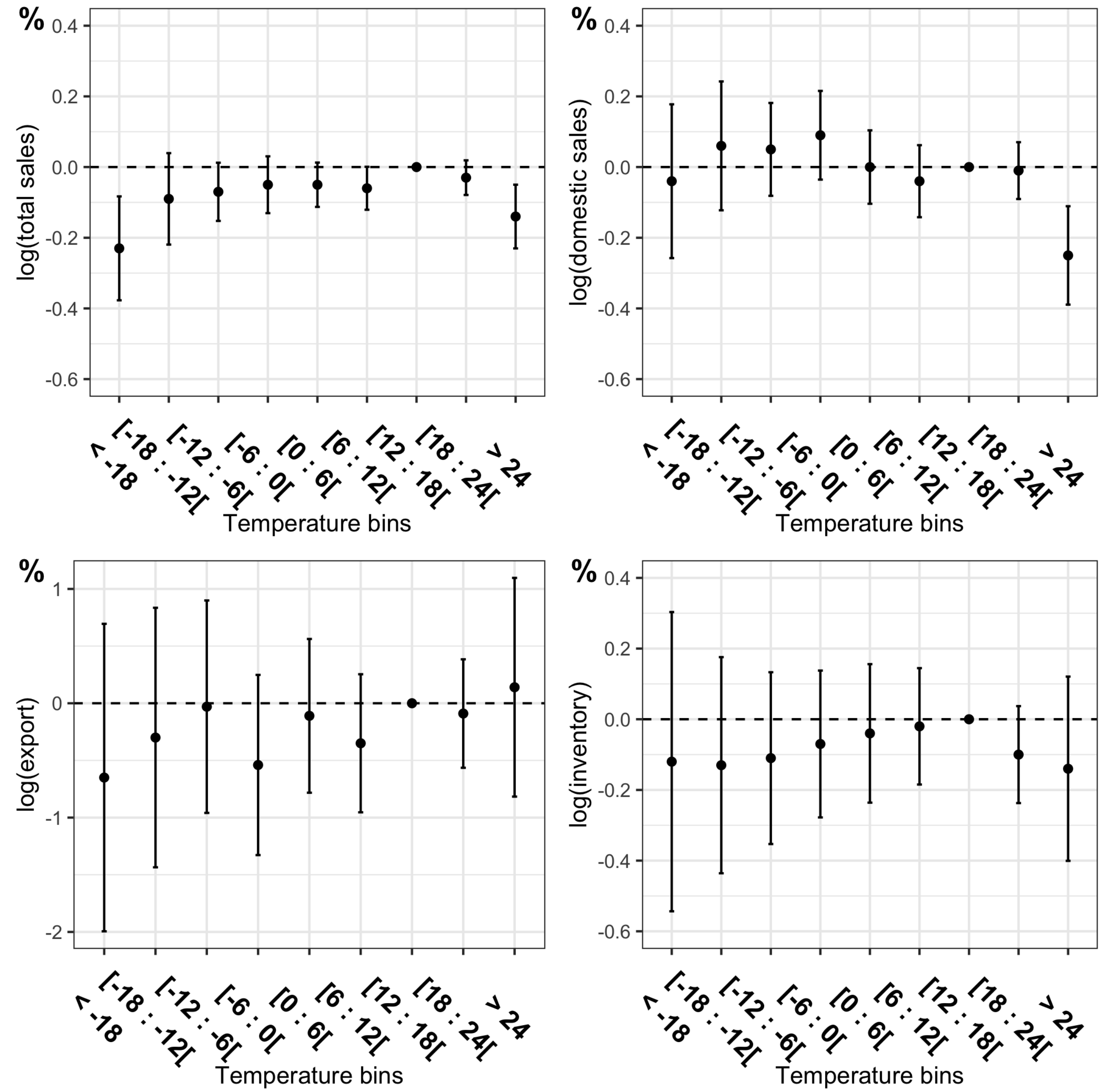


Figure 7: Estimated effect of extreme temperature on total sales and its components

Notes: These figures show the impact of daily mean temperature on manufacturing outcomes represented by total sales, domestic sales, export and inventory. All the specifications includes establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the CSD levels.

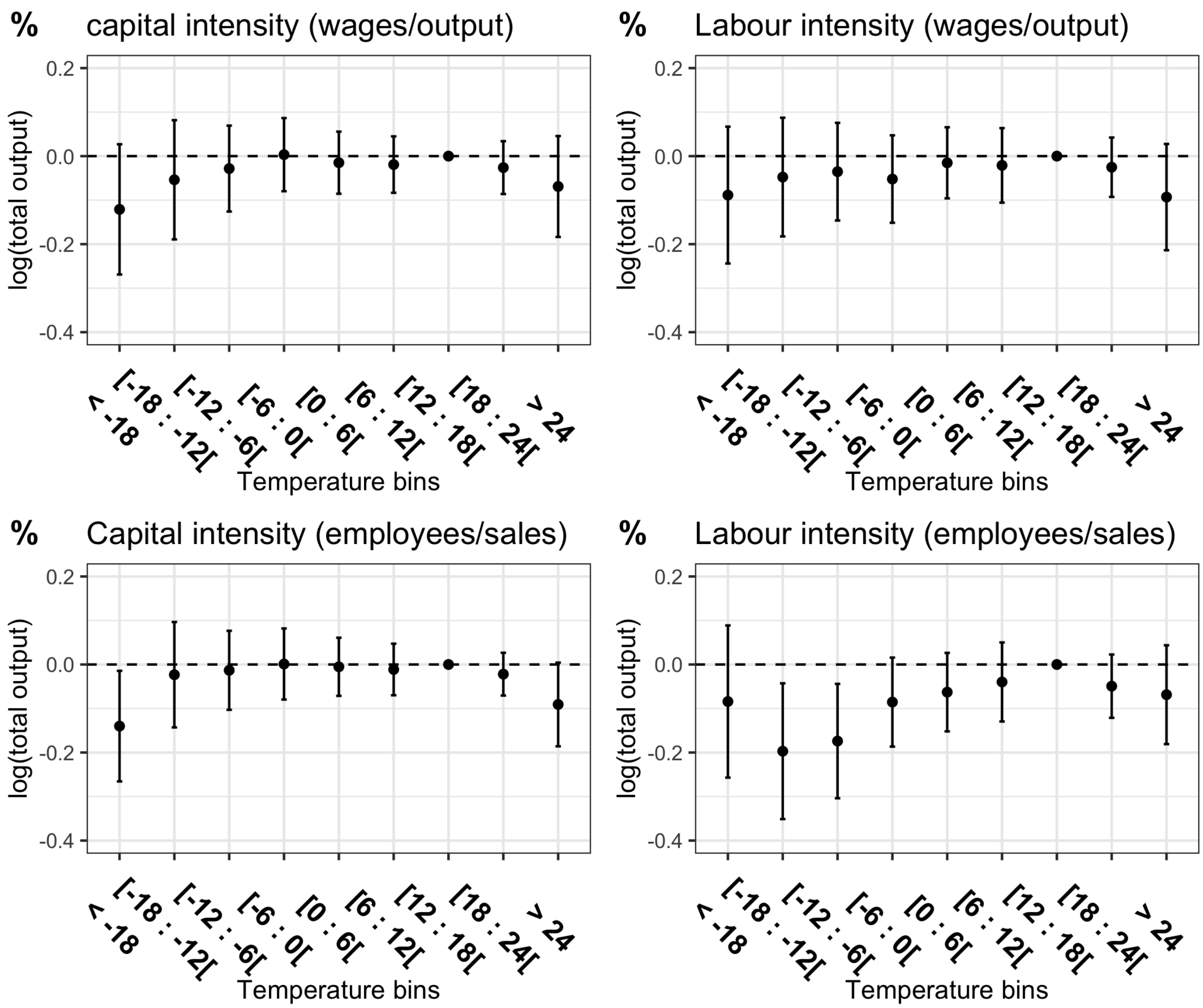


Figure 9: Estimated effect of extreme temperature on total output by manufacturing intensity

Notes: These figures present the effect of daily mean temperature on manufacturing output by type of manufacturing intensity. The top and bottom panels represent the marginal effect of extreme temperature on manufacturing output for labour intensive establishments versus capital intensive establishments. The top panel uses the first definition of labour intensity which is wage/output while the bottom panel uses another definition of labour intensity that is total employment/sale. All the specifications includes establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the CSD levels.

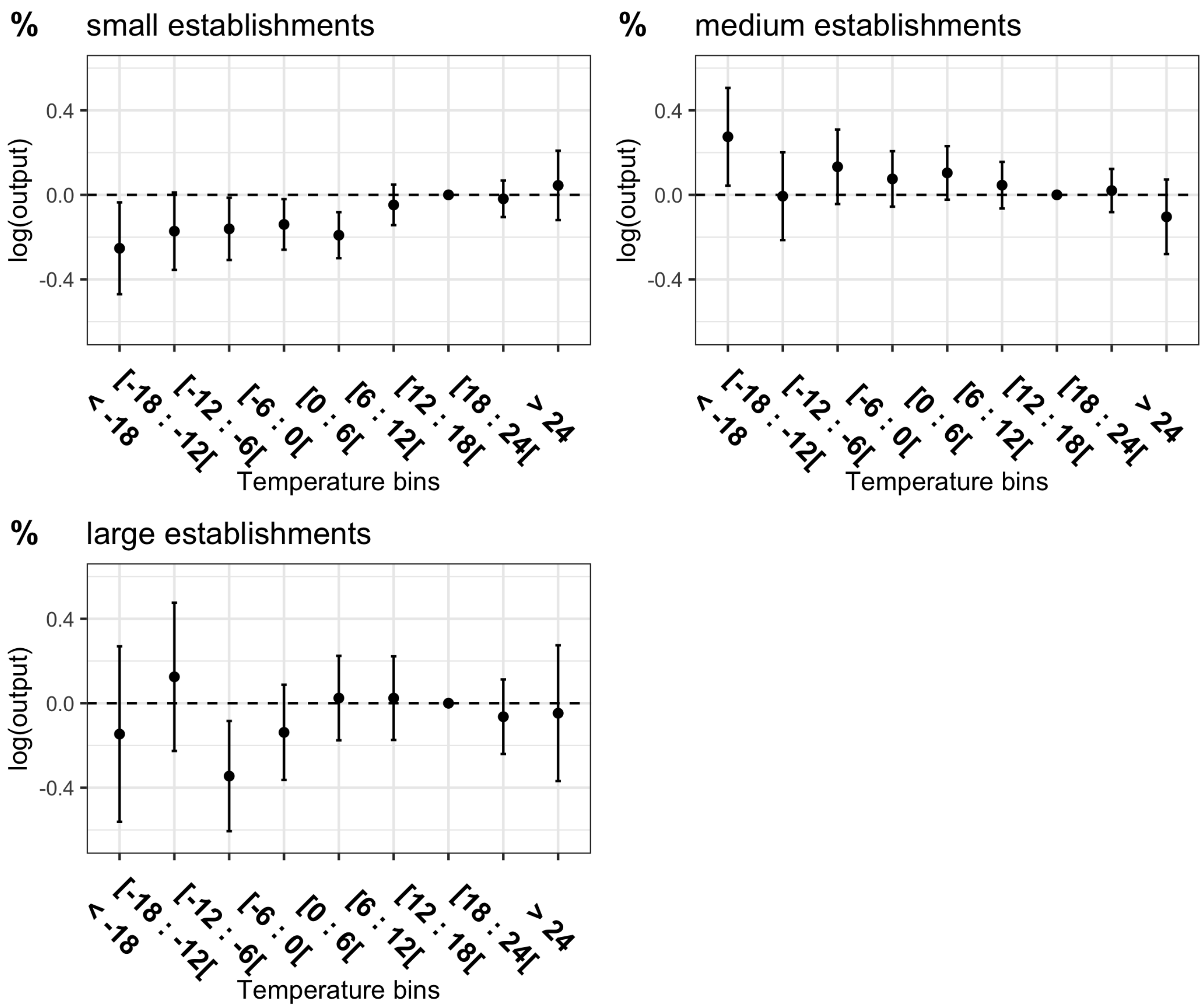


Figure 11: Estimated effect of extreme temperature on output by manufacturing size

Notes: These figures describe the marginal effect of extreme temperature on manufacturing output by establishments' size. They present the response of each type establishment's output to extreme temperature compared other establishments. All the specifications includes establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the CSD levels.

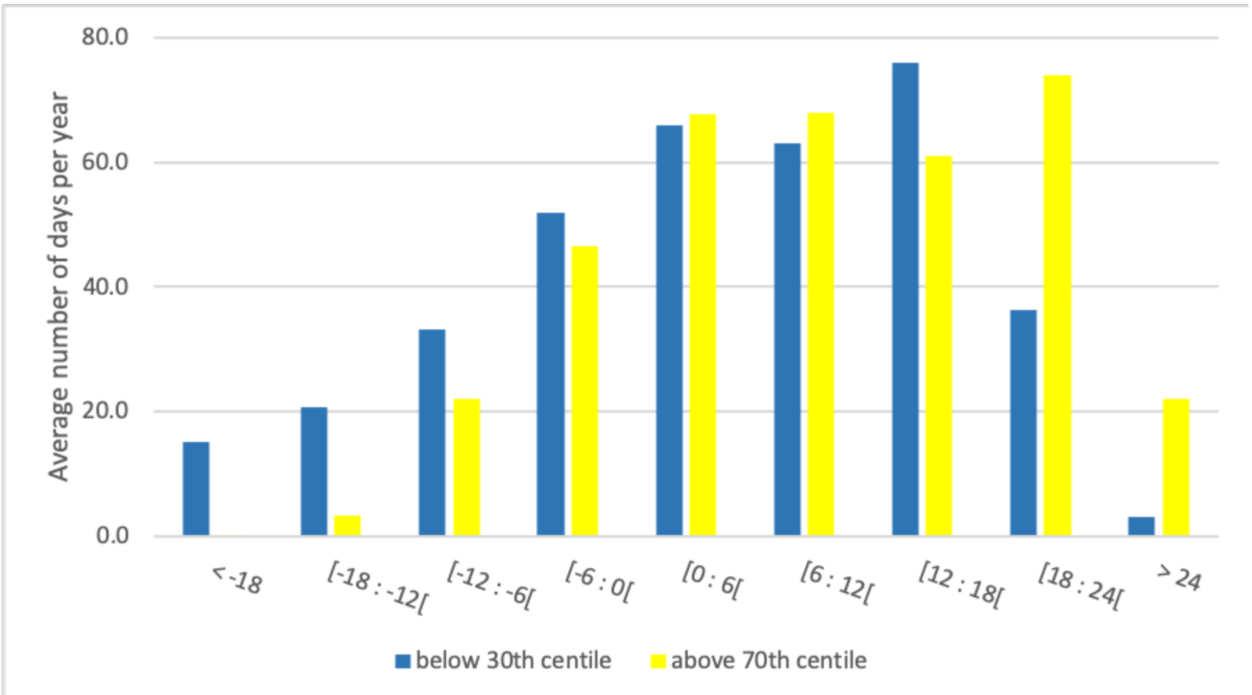


Figure 13: Daily temperature distribution in cooler and hotter CSDs.

Notes: Each height represents the weighted average daily temperature across all establishments and year. The weight used is the number of establishments in each CSD. The bar represents the average number of days per year over the period 2004-2012 for CSDs below the 30th centile (blue) and above the 70th centile (yellow) of mean temperature distribution.

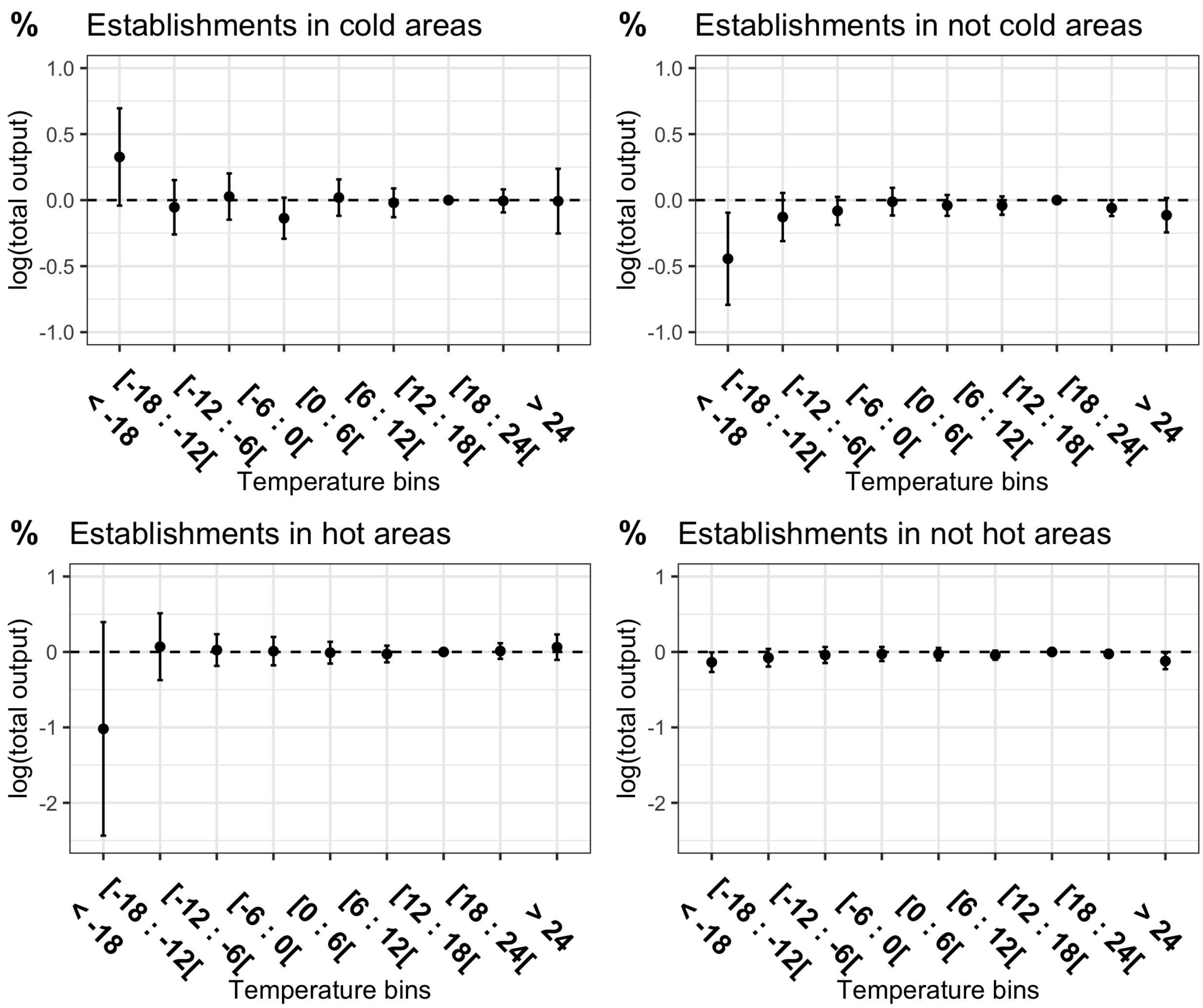


Figure 15: Estimated effect of extreme temperature on total output for establishments operating in cold and hot areas

Notes: These figures present the effect of daily mean temperature on manufacturing output. They represent the marginal effect of extreme temperature on output for establishments operating in respectively cold and hot areas compared to those operating in other areas. All the specifications includes establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the CSD levels.

Table 3: Estimated effect of wet-bulb and wind-chill temperature on total output

	wet buld	wind-chill
Medium risk	-0.07**	-0.01
	(0.03)	(0.03)
High risk	-0.15**	-0.22***
	(0.06)	(0.06)
Observations	236,007	236,007
Establishment FE	Yes	Yes
Year-province FE	Yes	Yes
Year-industry FE	Yes	Yes

$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

Notes: this table presents the efffects of wet-bulb and wind-chill temperatures on manufacturing output. All the specifications includes establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the CSD levels. The standard errors are clustered at the census-subdivision level.

Table 4: Predicted effects of climate change on manufacturing output by GHG emission scenarios

	Mid century (2050s)	End century (2080s)
Medium GHG emission (RCP45)	-2.8** (1.2)	-3.7** (1.6)
High GHG emission (RCP85)	-3.7** (1.6)	-7.3** (3.2)

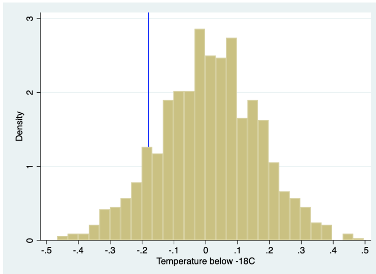
$^{***}p < 0.01$, $^{**}p < 0.05$, $^{*}p < 0.1$

This table presents the annual impact of climate change on manufacturing output in percentage change. We assume that the determinants of manufacturing output are fixed over the time which include the baseline productivity and technology. In parenthesis, we have the standard errors derived from the delta method.

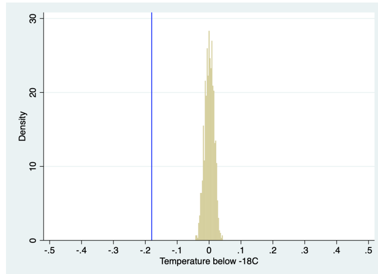
Table 5: Estimated effect of "reduced activity due to weather" on total output

	total output
Weather activity	-0.05***
	(0.018)
Observations	188,855
Establishment FE	Yes
Year-province FE	Yes
Year-industry FE	Yes

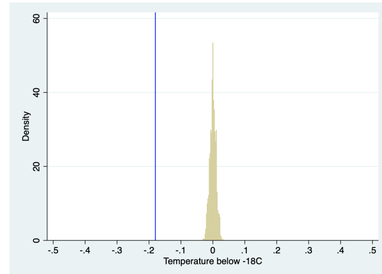
Notes: this table presents the efffects of reduced activity due to weather or natural disaster on manufacturing total output. The estimation includes establishment, year-province, and year-industry two-digit FE. The standard errors are clustered at the CSD levels.



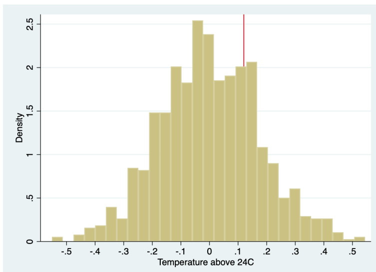
(a) Weather randomized across province and year



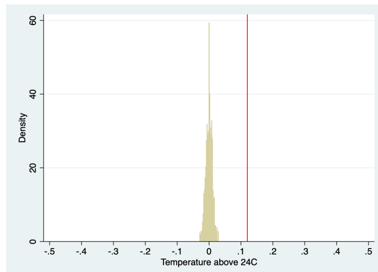
(b) Weather randomized across year



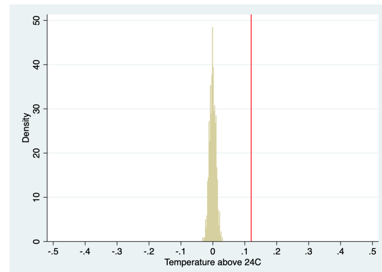
(c) Weather randomized across province



(d) Weather randomized across province and year



(e) Weather randomized across year



(f) Weather randomized across province

Figure 17: Estimated effect of extreme temperature on output by manufacturing output

Notes: These figures present the effect of random assigned temperature on manufacturing output. The blue line represents the true effect of temperature below -18°C while the red line represents the true effect of temperature above 24°C. All the specifications includes establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the CSD levels.

Appendix

Estimated impact of extreme temperature on manufacturing output using full sample

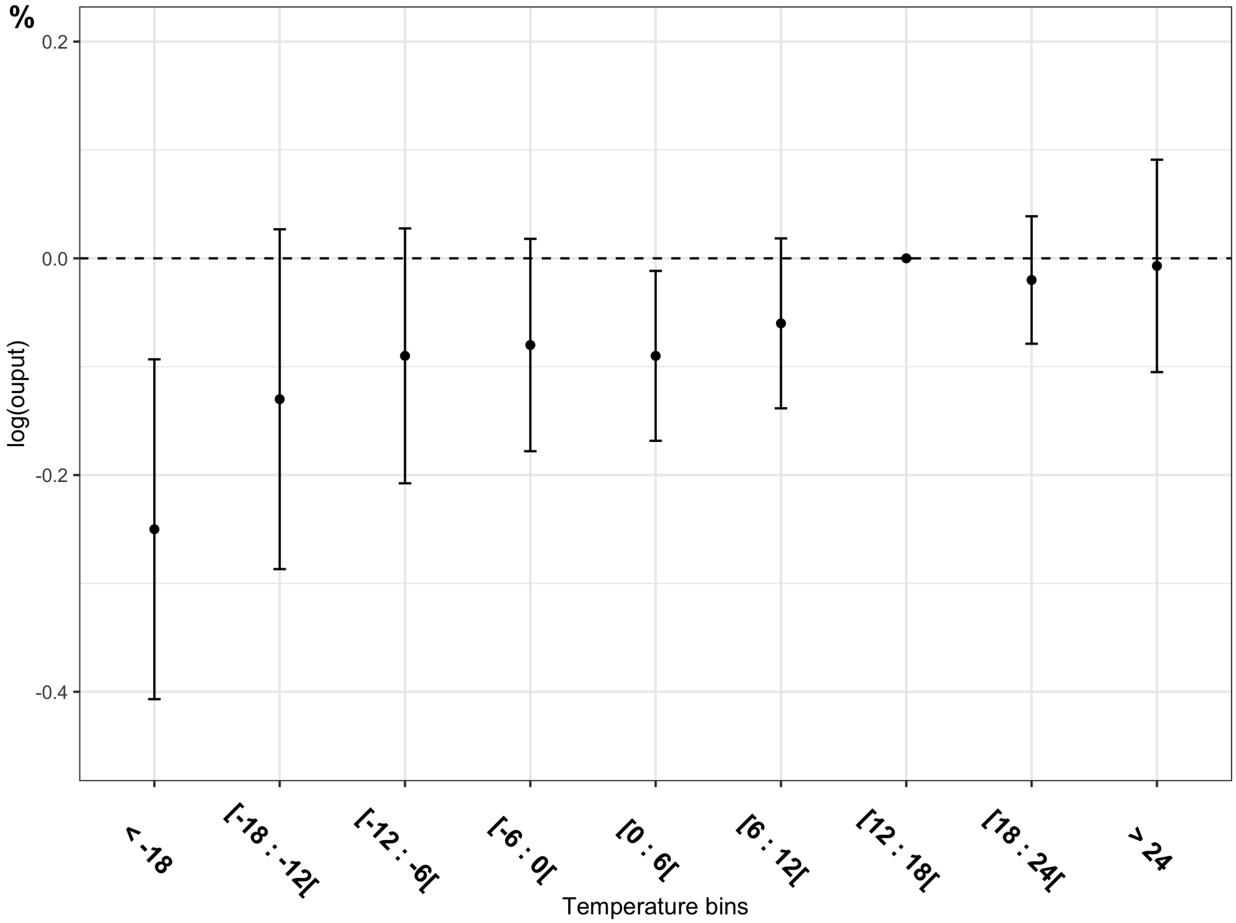


Figure 19: Estimated effect of extreme temperature on total output

Notes: This figure presents the effect of daily mean temperature on manufacturing output using the full sample. All the specifications includes establishment, year-province, and year-industry three-digit FE. We also control for weather variables such as total rain, total snow, relative humidity, and wind speed. The standard errors are clustered at the CSD levels.

Minimum and maximum temperatures

In the literature, other measures of temperature such as minimum or maximum temperature have been used as an alternative to mean temperature, to capture the exposure degree as in (Deschênes & Greenstone, 2007; Graff Zivin & Neidell, 2014). As a robustness test, we estimate the effect of maximum and minimum temperature of manufacturing output. The minimum temperature represents the lowest temperature faced in any given day while the maximum temperature captures the highest temperature experiences in any given day. For example, a day with minimum temperature between 18 to 24°C might represent a really hot day while a day with maximum temperature between -12 to -6 °C might indicate a very cold day. We estimate (4) by replacing mean temperature by respectively minimum and maximum temperature.

Figure 21 presents the effect of minimum and maximum temperatures on manufacturing output. We find a persistent negative impact of maximum temperature on manufacturing output during cold days while not having any impact during cold day. An extra day with maximum temperature less than -18°C or between -18 and -12°C reduces manufacturing output by respectively 0.13 and 0.17%. Using minimum temperature, we find that both cold and hot days have a negative impact on manufacturing output. An extra day with minimum temperature less than -18°C or greater than 18°C reduces manufacturing output by respectively 0.15 and 0.13% compared to a day with minimum temperature between 6-12°C. This result is consistent with our main finding showing that extreme temperatures have an adverse effect on manufacturing activity.

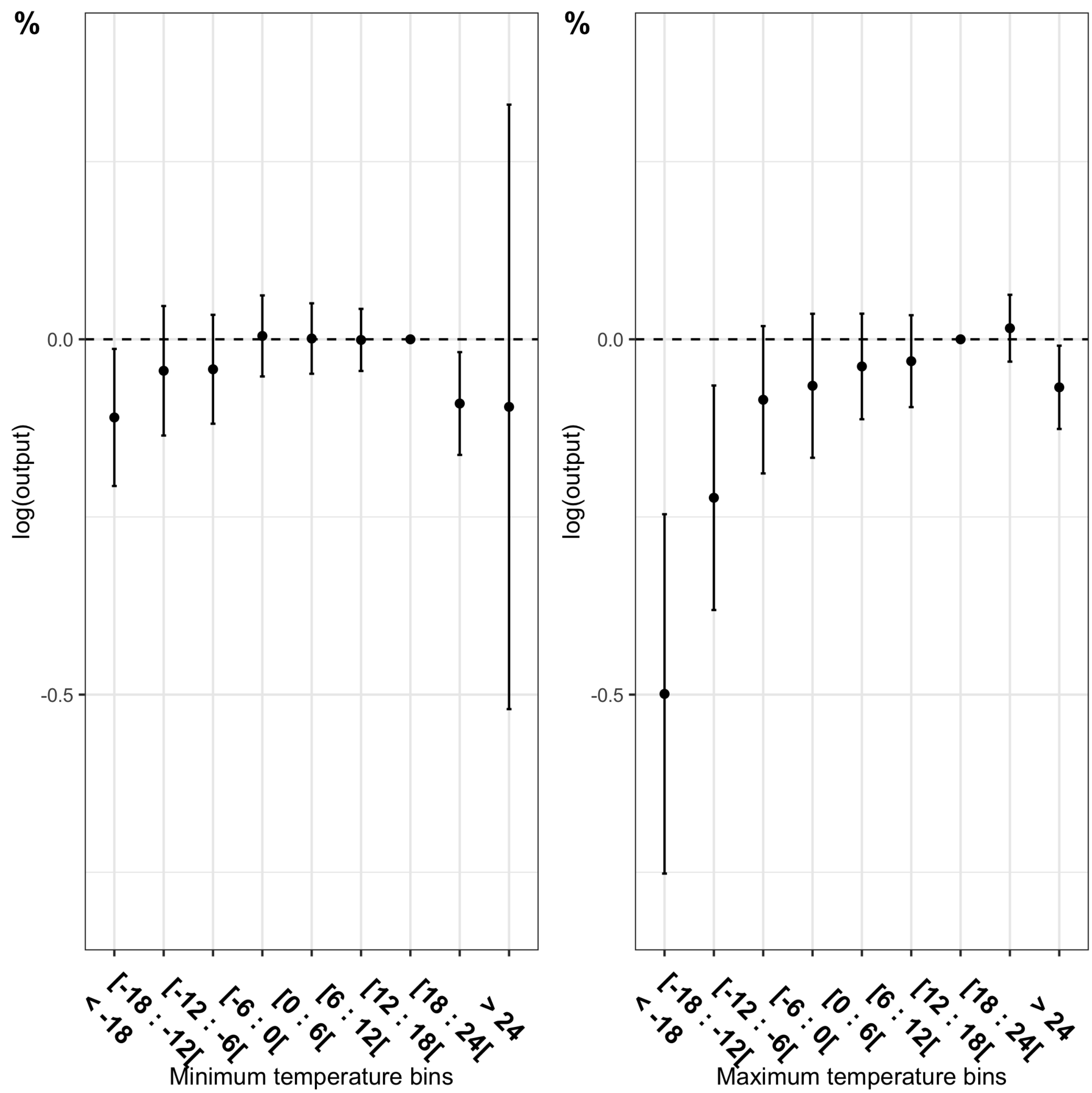


Figure 21: Estimated effect of extreme minimum/maximum temperature on total output

Notes: These figures present the effect of daily minimum/maximum temperature on manufacturing output. All the specifications includes establishment, year-province, and year-industry three-digit FE. We also controls for weather variables such as total precipitation, relative humidity, and wind speed. The standard errors are clustered at the CSD levels.

Wind chill temperature

Wind chill temperature is the combination of mean temperature and wind speed and represents the perceived temperature during cold days. We derive this variable following the index computed by Canada, United States, and United Kingdom experts as follows:[31]

$$windchill = 13.12 + 0.6215 * T - 11.37 * V^{0.16} + 0.3965 * T * V^{0.16} \tag{10}$$

Where T is the mean temperature in °C and $windkmh$ is the wind speed in kilometers per hours. When wind chill index is below 0, it has no effect. A wind chill index between 0 and -10 means a slight increase of discomfort. A day is called uncomfortable with moderate risk when the wind chill index is between -10 and -28. Finally, the wind chill index is qualified as high risk when its index is below -28.[32]

Wet-bulb temperature

Wet-buld temperature is a combination of temperature and relative humidity and represents the perceived temperature during hot days. It has been computed as follows:

$$\begin{aligned} Wetbuld = T * atan(0.151977 * (RH * 8.313659)^{1/2}) + atan(T + RH) \\ -atan(RH - 1.676331) + 0.00391838 * ((RH)^{3/2}) * atan(0.023101 * RH) - 4.686035 \end{aligned} \tag{11}$$

Where T is the mean temperature in °C, RH is for relative humidity in percentage. A wetbuld index lower than 24.5 means normal day for normal activities. For wetbuld index between 24.5 and 27.3, it is advised to use discretion for intense and prolonged activities. A wetbuld index between 27.3 and 29 implies a maximum of 2h activities outside. Finally, a wetbuld index above 29 means high discomfort and a maximum of 1h outside activities are advised.

[31] https://en.wikipedia.org/wiki/Wind_chill

[32] https://www.canada.ca/en/environment-climate-change/services/weather-health/wind-chill-cold-weather/wind-chill-index.html

Instrument for ”reduced activity due to extreme weather”

Table 6: Estimated effect of ”reduced activity due to weather” on total output

	total output
Weather-activity-hat	-0.11***
	(0.03)
Observations	235,623
Establishment FE	Yes
Year-province FE	Yes
Year-industry FE	Yes

Notes: We estimate the effect of reduced activities due to weather on manufacturing output by instrumenting the variable ”reduced activities” by weather variables”. We assume that the non response to this question by some establishments may indicate a bias. The estimation includes establishment, year-province, and year-industry three-digit FE. The standard errors are clustered at the CSD level. We find that manufacturing output decrease by 11% for establsihments that have experienced a reduced activities due to extreme weather/natural disasters.