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Manufacturing output and extreme temperature: Evidence from Canada

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Abstract. This paper analyzes the effects of extreme temperature on manufacturing output using a data set covering the universe of manufacturing establishments in Canada from 2004 to 2012. Extreme temperature can affect manufacturing activity directly through its impact on labour productivity and indirectly through a change in demand for products. 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 ° and 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 due to extreme temperature to range between 2.8% and 3.7% in mid-century and 3.7% and 7.2% in end of century.

Résumé. Ce papier analyse les effets des températures extrêmes sur la production manufacturières en utilisant une base de données couvrant l'ensemble des entreprises manufacturières au Canada sur la période 2004-2012. Les températures extrêmes peuvent affecter l'activité manufacturière, soit directement à travers leurs effets sur la productivité au travail, ou indirectement à par leurs effets sur la demande des produits. En utilisant une analyse de panel à effets fixes, nos résultats suggèrent une relation non-linéaire entre les températures extrêmes extérieures et la production manufacturière. Chaque jour avec des températures moyennes en dessous de −18 °C ou au dessus de 24 °C réduit la production manufacturière annuelle de 0.18 % et 0.11 %, respectivement, comparé à un jour avec une température moyenne se situant entre 12 ° et 18 °C. Au cours d'une année normale, les températures extrêmes, c'est-à-dire le nombre de jours en dessous de −18 °C ou au dessus de 24 °C, réduisent la production manufacturière annuelle de 2.2 %, avec les températures extrêmement chaudes contribuant le plus à cet impact. Compte tenu des changements climatiques prévus pour le milieu et la fin du siècle, nous prévoyons que les pertes annuelles de production manufacturière dues à des températures extrêmes se situeront dans une fourchette de 2.8 % à 3.7 % au milieu du siècle et de 3.7 % à 7.2 % à la fin du siècle.

JEL classification: L60, Q56, Q54, O14, O44

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Philippe Kabore was at the University of Ottawa when this research was conducted.
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, Nouri Najjar and the three anonymous referees for their valuable comments and suggestions. 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.

Canadian Journal of Economics / *Revue canadienne d'économique* 2023 56(1)
February 2023. / *Février 2023.*

22 / pp. 191–224 / DOI: 10.1111/caje.12633

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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, 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. Our results suggest that output losses from extreme temperatures are caused by a combination of impacts of temperature on consumer demand and on 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 and Greenstone 2007, Schlenker and Roberts 2009, Burke and 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% to 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 and Hsiang 2016). This research has uncovered links between extreme 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 temperatures caused an increase in the number of transcription mistakes made by wireless operators, thus reducing productivity. The low performance is explained by a rapid increase of fatigue and discomfort during prolonged activities in hot environments (González-Alonso et al. 1999, Galloway and 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 temperatures. For example, Park (2018) links examination records for New York students with outside temperatures, and finds that hot temperatures cause substantial declines in academic performance. Cook and Heyes (2020) uses a similar approach to find a strong negative impact of 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 and Park 2016). In a meta-analysis, Seppanen et al. (2006) find that the average individual work performance decreases by almost 2% per degree Celsius above the temperature of 25 °C in a work office environment. These findings are supported by Somanathan et al. (2021) who

1 See `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`.

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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 and Park 2017, Somanathan et al. 2021, Graff Zivin and Neidell 2014). There is also some evidence (in the Canadian context, which we study) that shirking increases when hot outdoor temperatures fall on a Friday or Monday (Shi and Skuterud 2015). 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 outdoor temperature and overall economic output, which captures the effect of temperature on both labour supply and labour productivity (Zhang et al. 2018, Chen and Yang 2019, Somanathan et al. 2021). 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. (2020) 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, and 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. (2021), Deryugina and 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 and Hsiang 2016, Kolstad and Moore 2020). 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 and Greenstone (2007), Deryugina and Hsiang (2017), Zhang et al. (2018).

Our study estimates the impact of extreme temperatures on manufacturing output in Canada.[3] 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.[4] We use a panel fixed effect method to identify a non linear causal effect of daily mean temperature on manufacturing output.

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

3 Manufacturing output is defined as the current value of goods produced within a year.

4 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, in which the mean temperature falls inside a predetermined temperature bins.

We rely on the same identifying assumption as in prior literature, which is that after conditioning on establishment, year-by-province and year-by-industry fixed effects, remaining daily temperature variation is quasi-random (Chen and Yang 2019, Zhang et al. 2018, Somanathan et al. 2021). 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 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 annual establishment output by 0.11% relative to a day with mean temperature between 12 °C and 18 °C.[5] On average during the 2004−2012 period, Canadian manufacturing establishments experience an annual loss of total output by 1% as a result of days with temperatures below −18 °C and another 1.2% 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 (relative to a hypothetical counterfactual with no extreme temperatures).

Second, to understand the factors driving the temperature−output relationship, we estimate the effects of extreme temperatures on annual manufacturing plant labour productivity, employment, domestic sales, and exports. The theoretical framework presented in section 2 postulates that direct impacts of extreme temperatures on labour productivity or consumer demand may indirectly affect plant output and employment in equilibrium. Empirically, we find that an extra day with mean temperature below −18 °C reduces labour productivity by 0.14% relative to a day with mean temperature between 12 °C and 18 °C. We do not find any evidence that hot temperatures affect labour productivity. In addition to impacts on labour productivity, we find that manufacturing plants respond to short-term hot and cold temperature shocks by reducing equilibrium employment at the plant. Based on our conceptual framework, we take this as evidence that extreme temperatures reduce local demand in addition to their effects on labour productivity. We find no impacts of extreme temperatures on exports or inventory additions but do find that extreme temperatures reduce domestic sales.

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 cooler areas experience on average 15 cold days (below −18 °C) and three hot days (above 24 °C) in a typical year, while those operating in warmer areas face on average 0.2 cold days and 22 hot days within a year. Because they more regularly face hot (cold) temperatures, establishments in warm (cool) regions may be better adapted to hot (cold) temperatures. We estimate the temperature−output relationship in warm, mild and cool regions across Canada. Our results do not provide evidence in favour of location-based adaptation—there are not statistically different relationships between temperature and output across climactic regions.

5 Daily mean temperature "above 24 °C" or "below −18 °C" refers to a 24-hour period. We use the daily mean temperature because many manufacturing plants operate 24/7. We do not have information on establishments operating the entire day or half of the day. We also analyze the output−temperature relationship using minimum and maximum temperature and we find a similar effect. In our data, on days where the daily mean temperature is above 24 °C, the average daily maximum temperature is 32 °C. On days where the daily mean temperature is below −18 °C, the average daily minimum is −28 °C.

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Fourth, we analyze the heterogeneity in the response of manufacturing output to extreme temperatures across several dimensions, including facility size and labour intensity. We find that small establishments are the most affected by the extreme temperatures. An extra day below −18 °C or above 24 °C reduces small-sized establishment output by respectively 0.22% and 0.08%. We find no evidence that hot temperatures have a negative effect on medium and large establishments (likely in part because we have fewer observations of large plants). Our results also show that labour-intensive establishments are more affected by the extreme temperature than capital-intensive establishments.

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-century (2050s) and end (2080s) of century along with our estimates of the temperature−output relationship. Like similar 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 the 2050s and the 2080s, we find that the annual losses of manufacturing output due to extreme temperature would go from 2.2% today to 2.8% to 3.7% in mid-century and to 3.7% to 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 new evidence of the potential economic impact of climate change in a cold environment. The paper highlights the importance of demand shifts as a main contributor to the temperature−output losses. We find no evidence that the manufacturing sector adapts 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

This section introduces a simple framework to help illustrate how extreme temperature realizations may affect annual manufacturing plant output, labour productivity, employment, domestic sales, exports and inventory additions—the variables we observe in our empirical analysis. We make the assumption that temperature shocks may directly affect labour productivity as well as potentially directly affect consumer demand. The existing literature reviewed in the prior section provides evidence to justify our assumption that extreme temperatures may affect labour productivity. There is also some evidence that weather may affect domestic demand for particular products (Li et al. 2017, Conlin et al. 2007, Agarwal et al. 2020, Busse et al. 2015), as well as evidence that extreme temperatures may reduce overall economic activity, which would also impact domestic demand (Burke et al. 2015, Dell et al. 2012).

We develop a model to show how these direct effects result in changes to equilibrium output as well as to labour demand. It is important to distinguish the time frame in which the shocks take place from the time frame in which we model equilibrium. The temperature shocks we model involve daily realizations of extreme hot or extreme cold temperature. In contrast, the establishment level outcomes we observe are at the annual level. In the model, we assume that the over the course of a year, the establishment takes account of

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the prices it faces and selects variable inputs accordingly. As a result, extreme temperature realizations can affect establishment input choices (and consumer demand) indirectly, as the market reaches equilibrium following a temperature shock, as well as directly and contemporaneously with the temperature shock.

Our empirical analysis is conducted at the level of manufacturing establishments, and so our theory focuses on a representative establishment. The representative establishment is assumed to take prices as given.

The representative establishment uses inputs of capital and effective labour to produce output. We treat capital as pre-determined and unaffected by temperature, consistent with the short-run focus of our empirical analysis, and denote it by $\overline{K}$.[6] Effective labour L is given by the number of employees N multiplied by their productivity A, such that $L = NA$. Given the short-term nature of temperature shocks that we analyze (daily variation in temperature), we assume that the number of employees in the establishment is not directly affected by temperature shocks.[7] However, although the number of employees is not directly affected by temperature shocks, the number of employees is endogenous and is chosen by the establishment in response to changes in prices or demand. Consistent with the empirical evidence summarized above, we treat labour productivity as a function of extreme temperature T, so that output is:

$$Y = Y(\overline{K}, L) = Y(\overline{K}, NA(T)) = Y(NA(T)).$$

We take the total derivative with respect to temperature to understand how extreme temperature affects output:

$$\frac{dY}{dT} = \frac{\partial Y}{\partial L}\frac{dL}{dN}\frac{dN}{dT} + \frac{\partial Y}{\partial L}\frac{dL}{dA}\frac{dA}{dT} = Y_L\left(A\frac{dN}{dT} + NA'\right) \tag{1}$$

where Y_L is the marginal product of effective labour and A' is the direct effect of extreme temperature on labour productivity (we assume that $A' < 0$, reflecting the evidence that extreme temperatures reduce productivity). This equation shows that changes in manufacturing plant output can be decomposed into an effect relating to changes in the number of employees, and an effect relating to changes in labour productivity.

Given these assumptions, and assuming constant returns to scale and a fixed wage rate and capital rental rate, the unit cost function for the firm can be expressed as:

$$C = C(A(T)).$$

Taking the derivative with respect to temperature yields:

$$\frac{dC}{dT} = \frac{\partial C}{\partial A}A'.$$

6 Zhang et al. (2018) provide some evidence that capital productivity may be affected by extreme temperatures. We treat capital productivity as fixed in our model because we do not observe capital productivity in the data and because adding capital productivity complicates the model without generating fundamental new insights. It is straightforward to modify the model such that capital productivity is affected by temperature, by treating the effective capital input as $K = \overline{K}B(T)$, where $\overline{K}$ is the fixed capital stock and $B(T)$ is the temperature-dependent capital productivity.

7 The data for this project include annual observations on the number of people employed by each manufacturing plant, and we assume that firms do not directly adjust employment levels in response to daily variation in weather experienced throughout the year.

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On the demand side, the establishment sells to a domestic consumer and also exports. The domestic consumer is exposed to the same temperature shocks as the manufacturing plant. Exports are consumed by a consumer that faces temperature shocks that are orthogonal to the domestic temperature and so we assume no direct response of exports to the domestic temperature shock. As a result, total firm sales S are given by:

$$S = D(P, T) + X(P),$$

where P is the price of the domestic good, D is domestic sales, and X is exports. The derivative of total sales with respect to temperature is given by:

$$\frac{dS}{dT} = \frac{\partial D}{\partial P}\frac{dP}{dT} + D' + \frac{\partial X}{\partial P}\frac{dP}{dT},$$

where D' is the direct effect of the temperature shock on demand. We lack evidence to sign D'. D' could be positive if extreme temperature events prompt consumers to purchase additional manufactured goods as adaptation investments—for example buying an air conditioner in response to a forecast or experienced hot day. D' could be negative if extreme temperatures reduce consumer incomes, as determined by Deryugina and Hsiang (2017) and Burke et al. (2015), among others. This expression shows that demand for the plant's output is a function of the equilibrium price as well as any direct impacts of temperature on demand.

The market clearance condition is $Y = S + I(P)$, where $I(P)$ is inventory additions (which we assume are a function by price and not directly affected by temperature), and the derivative of the market clearance condition is:

$$\frac{dY}{dT} = \frac{dS}{dT} + \frac{\partial I}{\partial P}\frac{\partial P}{\partial T}$$

Substituting the expressions above, we get:

$$Y_L\left(A\frac{dN}{dT} + NA'\right) = \frac{\partial D}{\partial P}\frac{dP}{dT} + D' + \frac{\partial X}{\partial P}\frac{dP}{dT} + \frac{\partial I}{\partial P}\frac{\partial P}{\partial T}$$

In equilibrium, $P = C$, so we can simplify to:

$$Y_L\left(A\frac{dN}{dT} + NA'\right) = \left(\frac{\partial D}{\partial P} + \frac{\partial X}{\partial P} + \frac{\partial I}{\partial P}\right)\frac{\partial C}{\partial A}A' + D'$$

We can now solve for $\frac{dN}{dT}$ to get:

$$\frac{dN}{dT} = \frac{1}{AY_L}\left[\left(\frac{\partial D}{\partial P} + \frac{\partial X}{\partial P} + \frac{\partial I}{\partial P}\right)\frac{\partial C}{\partial A} - NY_L\right]A' + \frac{1}{AY_L}D' \tag{2}$$

And we can substitute back into equation 1 to get:

$$\frac{dY}{dT} = \underbrace{\left[\left(\frac{\partial D}{\partial P} + \frac{\partial X}{\partial P} + \frac{\partial I}{\partial P}\right)\frac{\partial C}{\partial A}\right]A'}_{\text{Productivity shock}} + \underbrace{D'}_{\text{Demand shock}} \tag{3}$$

Equation (3) makes clear that equilibrium output can be affected through two channels in our simple model. First, a shock to productivity (A') affects unit costs, and as a result affects demand for output by the price-sensitive domestic and foreign consumers (the first term on the right hand side). Second, equilibrium output can be directly affected if temperature affects the demand from the domestic consumer (D', the second term on the

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right hand side). A similar logic applies to the equilibrium number workers at the plant in equation (2).

In our empirical analysis, we estimate the direct impact of temperature on productivity (A'), as well as the effect of temperature on output ($\frac{dY}{dT}$) and the number of employees ($\frac{dN}{dT}$). As is made clear from the preceding model, the output of the firm, as well as the number of employees in the firm, are equilibrium outcomes. Because we do not observe the demand shock D' directly in our data, we are not able to attribute changes in output or the number of employees to each of these channels, but the framework makes clear that equilibrium impacts on labour demand and output are a function of two potential shocks—to demand and productivity—which helps explain our empirical findings.

3. Data

We use a confidential data set that includes the universe of Canadian manufacturing establishments over the period 2004 to 2012. 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 to 2012.[8] Each year, ASML collects establishment level information including total output, total sales, total export, total employment, payroll, and etc.[9] 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 geographical information including the province and census subdivision (CSD) for

8 Statistics Canada collects confidential data on manufacturing activities across Canada. This data set contains the universe of establishments from 2000 to 2012. However, some changes happened in the data 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 to 2012 for our analysis as in Najjar and Cherniwchan (2018) and Yamazaki (2017). For more information on ASML data, see https://www23.statcan.gc.ca/imdb/p2SV.pl?Function=getInstanceList&Id=504733.

9 All monetary values are in current Canadian dollars. Total employment is defined as the sum of full time equivalent production workers and salaried employees (administrative/selling/operating staff). For example, if a firm hires two workers in 2012 where the first works half of year 2012 and the second works half of that year, then it would be counted as one employee in 2012. The ASML data do not contain information on short-term worker absences.

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each establishment. CSD is a general term for municipalities or areas treated as municipal equivalents for statistical purposes. 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 to 2012, the initial data set counts more than 72,000 establishments located in 10 provinces and 3 territories and 2168 CSDs. 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 have an issue of endogeneity if establishments are allowed to move across industry sectors. We address this by assigning each establishment to the first industry in which they started operating the first year we see them in our data. To avoid selection bias in our results, we drop 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 and at least one employee.[14] We define the establishment size as follows: small establishments are those with total employees less than 50, medium establishments are those with total employees between 50 and 249, and large establishments are those with total employees greater or equal to 250.

Our final sample has 39,684 establishments. Table 1 panel A reports the manufacturing sector summary statistics.[15] 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 per establishment.

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.

13 In the appendix, we estimate our main regression specification (equation (4)) without dropping establishments that move across CSDs/provinces (figure A1(d)).

14 We find a similar pattern when we estimate the main model (equation (4)) using the full sample without output and employment restriction (figure A1(c)). Finally, figure A1(b) presents similar result as in the main finding, when we restrict the sample to establishments with at least 10 employees and total output greater or equal to $1,000,000.

15 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.

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TABLE 1
Summary statistics

Panel A				
			Period 2004–2012	
Manufacturing data	Observations	Firms	Mean	SD
Output ($, in million)	235,683	39,684	19.8	169
Total employment	235,683	39,684	55	152
Labour productivity (in million)	235,653	39,684	0.39	0.78
Payroll ($, in million)	235,653	39,684	2.7	11
Total sales ($, in million)	232,904	39,476	19.8	170
Domestic sales ($, in million)	188,345	29,947	12.9	135
Export ($, in million)	106,136	15,614	14.4	138
Inventory ($, in million)	186,967	29,455	2.8	17
Small establishments	235,683	39,684	0.76	0.43
Medium establishments	235,683	39,684	0.2	0.4
Large establishments	235,683	39,684	0.04	0.19
Reduced activity (weather)	188,923	30,122	0.003	0.06
Panel B				
			Period 2004–2012	
Weather data	Observations	Firms	Mean	SD
Mean temperature (°C)	235,683	39,684	7.28	2.3
Total rain (cm)			2.26	0.89
Total snow (cm)			0.45	0.25
Relative humidity (%)			0.71	0.05
Wind speed (m/s)			5.78	0.9
Panel C				
	Mid-century (2050s)		End century (2080s)	
Predicted temperature	Mean	SD	Mean	SD
RCP45 (°C)	9.83	2.25	10.51	2.23
RCP85 (°C)	10.71	2.22	12.89	2.15

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.

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 to 2012, we count 1,101 valid monitoring stations.[16] The Environment Canada weather data covers 759 out of 2168 CSDs where manufacturing plants are operating, which corresponds to a coverage rate of 35% 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 CSDs with no weather monitoring station. 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.

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

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Environment Canada weather data provide daily information on mean, minimum and maximum daily temperature, total rain, total snow and total precipitation.[17] The wind speed and relative humidity data come from the National Aeronautics and Space Administration (NASA).[18] We derive these data from a gridded daily weather data using MERRA2 climate reanalysis.[19] The literature shows that weather variables such as wind speed, total rain, total snow, and relative humidity could be a confounder to the temperature effects (Deschênes and Greenstone 2007, Deryugina and Hsiang 2017, Zhang et al. 2018). Table 1 panel B presents the summary statistics of the weather data for our final sample.

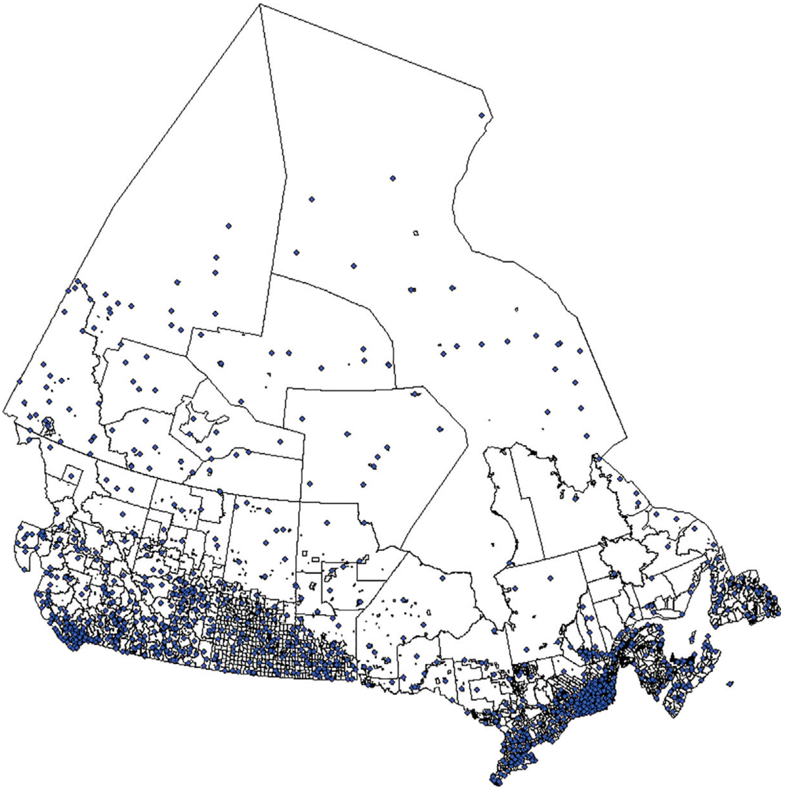

FIGURE 1 Dispersion of weather monitoring stations across Canada
NOTES: Each polygon represents the census subdivision (CSD) borders. We observe large CSDs in the north of Canada because of its small population size, while CSDs are smaller in the south of Canada with a high density of individuals. The blue dots are for the weather monitoring stations inside each CSD.
SOURCE: Environment Canada.

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

18 We do not use the wind speed data from Environment Canada because of its large proportion of missing observations; Environment Canada records only the maximum wind gust greater or equal to 29 km/h, and otherwise wind speed data are missing.

19 MERRA-2 climate reanalysis data come from the file M2I3NPASM-5.12.4 with the grid 0.5×0.625 degree corresponding to almost $80 \times 80\,\text{km}$.

3.3. Climate change prediction data

In order to predict impacts from future climate change, we use downscaled climate predictions for North America with a resolution of 1km by 1km based on the Coupled Model Intercomparison Project phase 5 (CMIP5) database.[20] The data reflect an average of 15 CMIP5 models that were chosen as representative. 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.

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 daily mean temperature falls within each bin. We create nine bins for daily (24-h) mean temperature as follows: $]\infty : -18[$, $[-18 : -12[, \dots, [24 : \infty[$ with each bin 6 °C wide.[21] By year and CSD, we count the number of days the temperature falls inside each bin. This approach is used in a number of similar studies such as Deschênes and Greenstone (2007), Deryugina and Hsiang (2017), Zhang et al. (2018), and Addoum et al. (2020). We define T^b_{ct} 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, total snow, and total rain.

Figure 2 plots the distribution of daily mean temperature across CSDs.[22] The dark blue bars represent the daily mean temperature distribution over the period 2004 to 2012. The following bars represent the daily mean temperature distribution for mid-century 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 for a typical manufacturing plant to 1-2 days annually.

20 The data are made available by Adaptwest at `https://www.adaptwest.databasin.org/pages/adaptwest-climatena`.

21 We made a one-time choice of the temperature bins before being provided with access to the manufacturing data.

22 For this figure, we weight each CSD by the number of manufacturing establishments it contains, so the temperature distribution reflects the exposure of manufacturing establishments in Canada.

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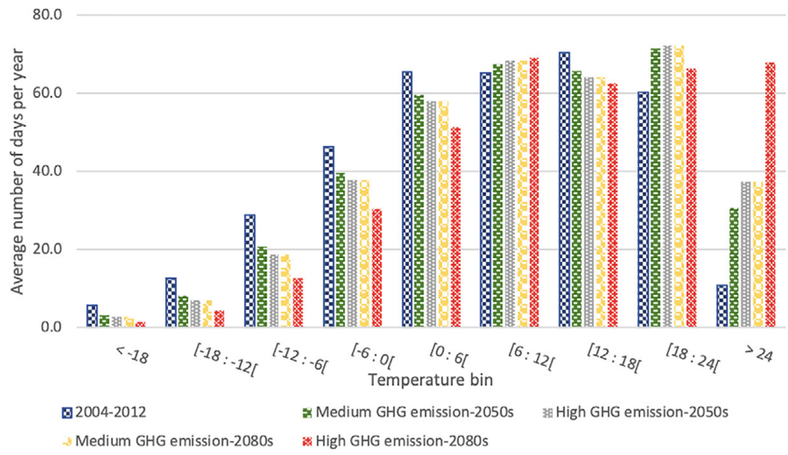

FIGURE 2 Current and predicted daily temperature distribution
NOTES: The height of each bar represents the weighted daily mean temperature across all establishments and years. The weight used is the number of establishments in each census subdivision. The blue bar represents the period 2004 to 2012. The green and yellow bars respectively represent the mid-century (2050s) and end of century (2080s) temperature projection for medium greenhouse gas (GHG) emission scenario. Finally, the grey and red bars represent the mid-century and end of century temperature projection for high GHG emission scenario.

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 inverse hyperbolic sine (IHS) of the total output of establishment i operating in census subdivision c, province p and industry d at time t.[23] In addition to total output, we also estimate the effect of temperature on labour productivity, labour input, total sales, domestic sales, exports and inventory, as motivated in section 2. T_{ct}^b is a count of the number of days in year t and census subdivision 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 seven 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

23 For all the continuous variables we apply the IHS transformation which accounts for 0 and negative values as explained in Bellemare and Wichman (2020). While we use the IHS transformation throughout the analysis, our results are virtually unchanged when we instead use a log transformation.

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to establishments within each province such as economic policy and energy prices. ψ_{dt} is the three-digit industry 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 follow Zhang et al. (2018) and cluster the error terms at establishment and CSD−year levels to address potential spatial and serial correlation in the error terms.[24] In estimating equation (4), we drop 1% of regression outliers using the approach proposed by Billor et al. (2000), Weber (2010). This is a typical approach in studies using self-reported manufacturing data (Fowlie et al. 2016, Ederington et al. 2005).

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 °C 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 and Hsiang (2017), Addoum et al. (2020), Zhang et al. (2018) and other similar papers.

5. Results

In this section, we first describe our main findings 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 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. 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). We report the coefficients for the "extreme" temperatures—the two coldest and hottest temperature bins. The full table with all temperature coefficients is in appendix table A1. This table presents the result in columns (A1) to (A4), which test the robustness of our results to the inclusion of different sets of fixed effects. Column (A1) includes only establishment and year fixed effects. 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

24 As an alternative approach to inference, we also implement a multi-way bootstrap as suggested in MacKinnon et al. (2019) in which we sample by province with replacement. This approach increases standard errors somewhat, such that our main coefficients are significant at $p < 0.1$ but no longer at $p < 0.05$ (table A4). Our main results use a two-way cluster as described in the text and consistent with other similar papers. In the appendix (table A3), we also report standard errors with coarser clusters. Coarser clusters increase the size of standard errors somewhat.

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TABLE 2
Estimated effects of temperature on total output

	ihs(total output) × 100					
Variables	(A1)	(A2)	(A3)	(A4)	(B)	(C)
< -18	0.013	−0.19**	0.01	−0.19**	−0.23***	−0.19**
	(0.064)	(0.079)	(0.057)	(0.076)	(0.089)	(0.074)
$[-18 : -12[$	−0.145**	−0.14**	−0.06	−0.11*	−0.16**	−0.1*
	(0.06)	(0.061)	(0.053)	(0.059)	(0.07)	(0.056)
$[18 : 24[$	−0.04	−0.06**	−0.04	−0.05*	0	−0.05*
	(0.027)	(0.027)	(0.025)	(0.026)	(0.032)	(0.026)
> 24	−0.072*	−0.12**	−0.05	−0.11**	−0.16***	−0.12**
	(0.041)	(0.055)	(0.037)	(0.051)	(0.063)	(0.051)
Observations	235,683	235,683	235,683	235,683	112,140	235,683
Establishment 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

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. $^{***}p < 0.001$, $^{**}p < 0.05$, $^{*}p < 0.1$. FE = Fixed effect.

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. Because 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 subsectors 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 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 0.19% relative to a day with mean temperature between 12 °C to 18 °C. Similarly, an extra day with mean temperature above 24 °C causes annual manufacturing output to be reduced by 0.11% compared with a day with mean temperature between 12 °C to 18 °C. In our data set, manufacturing establishments in Canada experience on average six cold days with mean temperatures below −18 °C and 11 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, relative to a hypothetical counterfactual where the establishment experiences no extreme temperatures. This represents an annual output loss of \$435,600 per establishment.

We visualize the relationship between manufacturing output and temperature using our preferred specification in the top-left panel of figure 3. The figure shows an inverted U-shaped relationship between temperature and output, where extreme hot and cold temperatures both depress manufacturing output compared with more moderate temperatures. This inverted-U relationship is similar to findings in other papers that analyze the

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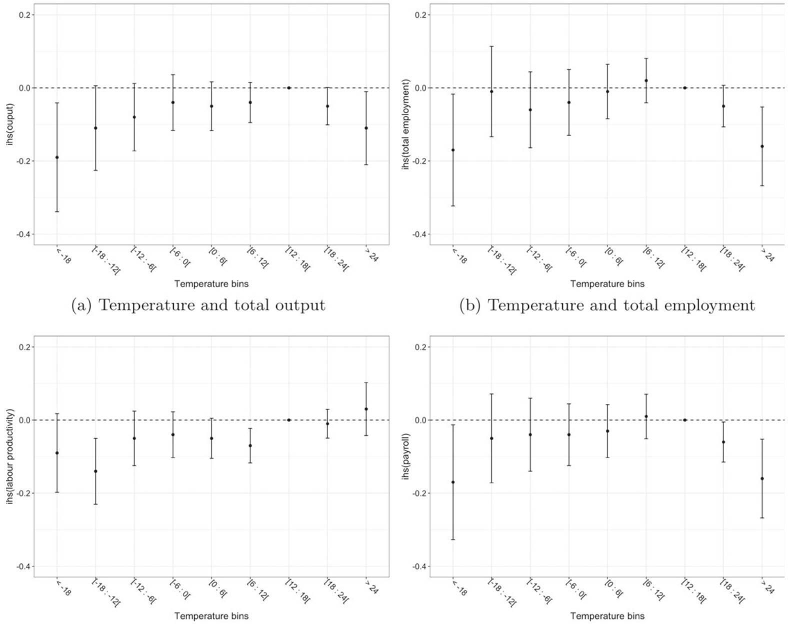

(a) Temperature and total output
(b) Temperature and total employment
(c) Temperature and labour productivity
(d) Temperature and payroll

FIGURE 3 Estimated effects of extreme temperatures on manufacturing activity
NOTES: The height of each bar represents the weighted daily mean temperature across all establishments and years. The weight used is the number of establishments in each census subdivision. The blue bar represents the period 2004 to 2012. The green and yellow bars respectively represent the mid-century (2050s) and end of century (2080s) temperature projection for medium greenhouse gas (GHG) emission scenario. Finally, the grey and red bars represent the mid-century and end of century temperature projection for high GHG emission scenario.

relationship in low-income and warmer countries, such as Zhang et al. (2018), who focus on Chinese manufacturing plants.

We provide two additional robustness checks in table 2. In column (B) of 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) of 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 by a similar magnitude as in the main specification, 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 suggestive evidence that inclusion of other weather controls would not substantially impact the results.

The conceptual framework presented in section 2 decomposes changes in manufacturing plant output into changes in employment and changes in labour productivity (equation 1). We create a labour productivity variable by dividing total output by number of employees, and conduct a similar regression as equation (4) with labour productivity and number of employees as dependent variables (we use our preferred specification, corresponding to column (A4) in table 2). We report the results as coefficient plots in figure 3. For labour productivity, the results suggest that cold temperatures worsen labour productivity, but that labour productivity is unaffected by hot temperatures. This result stands in contrast to the

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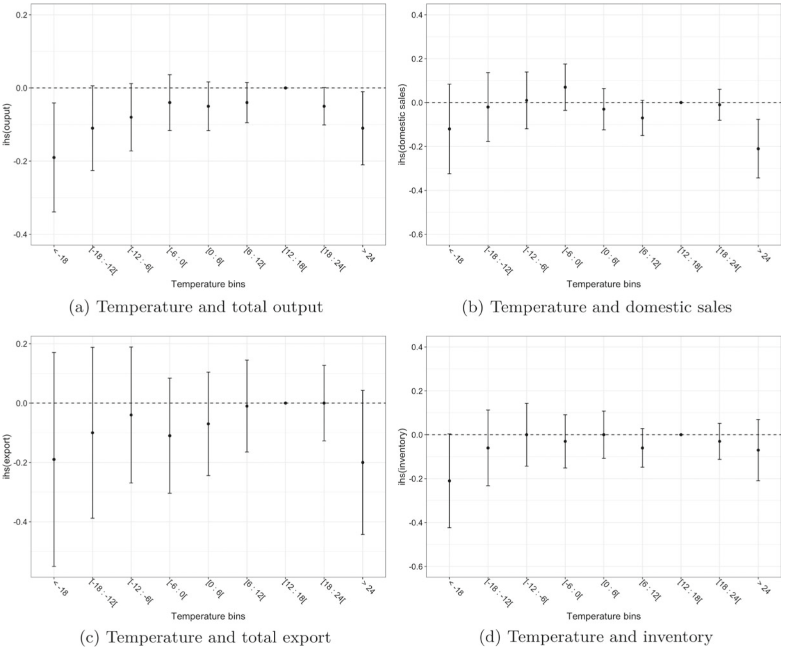
results in Zhang et al. (2018), who find that hot temperatures worsen labour productivity in Chinese plants. However, the results are consistent with Addoum et al. (2020), who find no impact of (hot) temperature on labour productivity in US firms. For employment, the results suggest that both hot and cold temperatures reduce manufacturing employment. The conceptual framework (equations (2) and (3)) shows that manufacturing plant employment and output are affected both by productivity shocks as well as by demand shocks. While we do not observe demand shocks directly, the results presented here suggest that for hot temperatures, (negative) demand shocks are the dominant channel impacting output and employment (because labour productivity effects appear muted). Figure 3 also shows the effect of extreme temperature on manufacturing payroll (i.e., total wage bill), as an alternative variable for measuring labour inputs. Unsurprisingly, we find that payroll is affected by extreme temperature similarly to the way employment is affected. Total annual payroll decreases by respectively 0.17% and 0.16% as a result of cold and hot days experienced during the year, again suggesting a decline in employment at manufacturing plants that face extreme temperatures.

Manufacturing total output can be decomposed into domestic sales, exports, and inventories. We re-run equation (4) with different dependent variables reflecting this decomposition. Figure 4 decomposes the effects of extreme temperatures on manufacturing output into these three demand components. We find that the reduction in total output resulting from extreme temperatures is explained mainly by the effects of cold and hot days on domestic sales. An extra day with temperature below −18 °C and above 24 °C decreases manufacturing domestic sales by respectively 0.12% and 0.21%. We also find some evidence



(a) Temperature and total output
(b) Temperature and domestic sales
(c) Temperature and total export
(d) Temperature and inventory

FIGURE 4 Estimated effect of extreme temperature on total sales and its components
NOTES: These figures present the impact of daily mean temperature on manufacturing output (a), domestic sales (b), total export (c) and inventory (d). The coefficients are multiplied by 100. All the specifications include establishment, year−province, and year−industry three-digit fixed effects. We also control for weather variables such as total rain, total snow, relative humidity and wind speed. The standard errors are clustered at the establishment and census subdivision−year levels.

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that manufacturing closing inventory is negatively affected by cold temperature. We find no evidence that manufacturing total exports are affected by extreme temperatures.

Overall, our analysis provides robust evidence that manufacturing output in Canada is susceptible to both extreme hot temperatures and extreme cold temperatures. We provide evidence that labour productivity is reduced on extreme cold days, which reduces manufacturing plant output. In contrast, our analysis suggests that labour productivity is unaffected as a result of hot weather. Instead, as suggested by our theoretical framework, hot weather appears to reduce manufacturing output and employment by affecting demand from domestic consumers.

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.

Using daily weather variables, we compute daily mean wind chill temperature and wet-bulb temperature following equations (A1) and (A2) 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:

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

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 the 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

TABLE 3

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

Variables	ihs(total output) × 100	
Medium risk (wet bulb)	−0.07**	–
	(0.03)	–
High risk (wet bulb)	−0.15***	–
	(0.05)	–
Medium risk (wind chill)	–	−0.03
	–	(0.03)
High risk (wind chill)	–	−0.22***
	–	(0.06)
Observations	235,683	

NOTES: This table presents the effects of wet-bulb and wind-chill temperatures on manufacturing output. All the specifications include establishment, year−province and year−industry three-digit fixed effects. The standard errors are clustered at the census subdivision (CSD) levels. The standard errors are clustered at the establishment and CSD−year levels. $^{***}p < 0.001$, $^{**}p < 0.05$, $^{*}p < 0.1$.

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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 in table 2. In particular, while we estimate that each day where mean daily temperature is below 24 °C reduces annual output by 0.19% in table 2, in table 3, we find that a high risk wind-chill day reduces annual output by −0.22%. The results are similarly comparable for high-risk wet-bulb temperature and mean daily temperatures above 24 °C. 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 economic effects of extreme temperatures.

5.3. Local adaptation

In this section, we analyze whether the temperature–output relationship depends on the local climate in which establishments are located. We test the hypothesis that establishments or consumers in relatively warm areas are less sensitive to hot temperature and vice-versa for those in relatively cool areas. For example, establishments might adopt some types of adaptation to mitigate the effect of the extreme temperature they experience the most as in Chen and Yang (2019), such as air conditioning or insulation. Alternatively, because our prior results point to the role of domestic consumer demand in affecting firm output, adaptation may occur on the consumer side. For example, Cook and Heyes (2020) find that people become acclimated to weather they most commonly face and are less impacted by temperature extremes they experience more regularly.

Using the distribution of the annual mean temperature by CSDs, we define coolest, mildest and warmest climates as those respectively below 30th centile, between 30 and 70 centile and above 70th centile of temperature annual temperature distribution. To better contrast the difference in temperature, figure 5 presents the temperature distribution for establishments operating in areas below the 30th and above the 70th centile of annual temperature distribution (we do not show the distribution of temperatures for the plants located in mild locations, between the 30th and 70th centiles). On average, establishments operating below

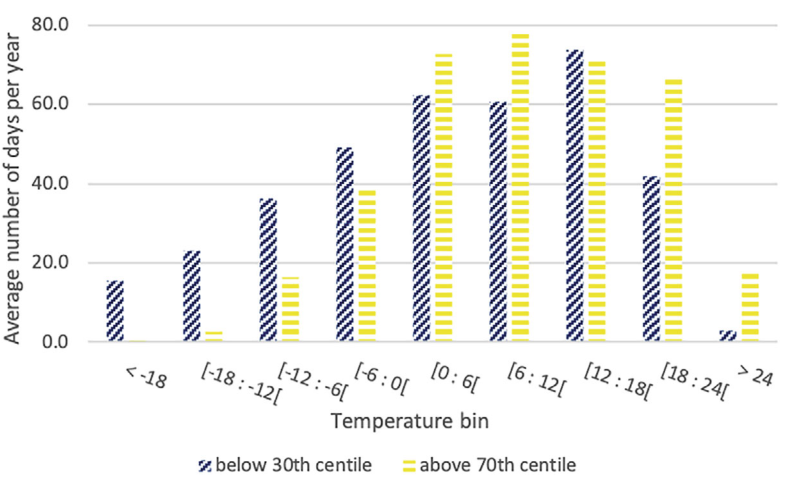

FIGURE 5 Daily temperature distribution in cooler and hotter CSDs
NOTES: Each height represents the weighted average daily temperature across all establishments and year. The weight used is the number of establishments in each census subdivision (CSD). The bar represents the average number of days per year over the period 2004 to 2012 for CSDs below the 30th centile (blue) and above the 70th centile (yellow) of mean temperature distribution.

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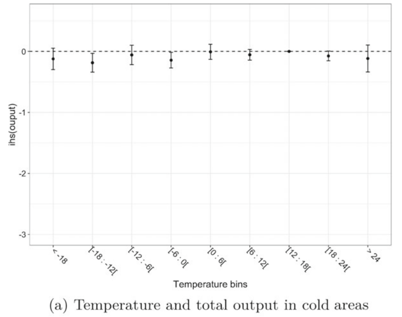
the 30th centile experience 15 cold days per year and three hot days. Similarly, establishments operating above the 70th centile, on average, experience one cold day and 18 hot days per year. We then test whether establishments operating in coolest or warmest areas react differently to extreme temperatures relative to establishments operating in areas with mild temperatures (between 30 and 70 centile of temperature annual temperature distribution).

We re-run equation (4) by interacting weather variables with warm/cool dummy variable as follows:

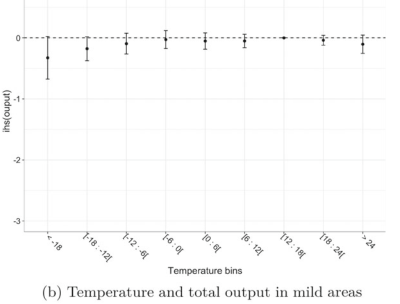
$$Y_{icpdt} = \left(\sum_{b} \beta_b T_{ct}^{b} + \sum_{w} \sum_{q} \theta_b W_{ct}^{qw} \right) \times adaptation + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \qquad (6)$$

where *adaptation* is a discrete variable that categorizes each region as (1) cool areas, (2) mild, or (3) warm. We also interact *adaptation* with both industry−year and province−year fixed effects.

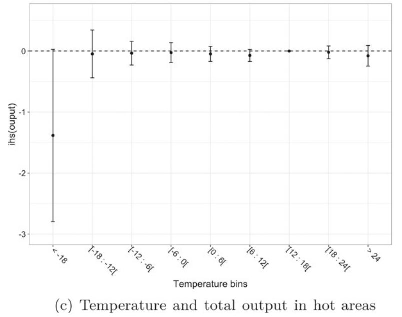
Evidence of adaptation would be if establishments operating in areas below the 30th centile of the temperature distribution (above the 70th centile) respond differently to cold (hot) temperature. As shown in figure 6, our results pertaining to local adaptation are inconclusive, but suggest limited adaptation to extreme temperatures. We do not find a statistically different response to extreme temperatures depending on the local climate (there is a large negative point estimate associated with extreme cold days in establishments operating in warmer climates, but with few instances of extreme cold in these regions the point estimate is very noisy). This may be in part because of our earlier finding that a key mechanism by which extreme temperatures impact plant output is not through productivity changes but as a result of local demand shifts.



(a) Temperature and total output in cold areas



(b) Temperature and total output in mild areas



(c) Temperature and total output in hot areas

FIGURE 6 Estimated effect of extreme temperature on total output
NOTES: These figures present the effect of extreme temperature on establishments output in cold, mild and hot areas relative to establishments in mild areas. The coefficients are multiplied by 100. All the specifications include establishment, year−province and year−industry three-digit fixed effects. We also control for weather variables such as total rain, total snow, relative humidity and wind speed. The standard errors are clustered at the establishment and census subdivision−year levels.

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5.4. Heterogeneity

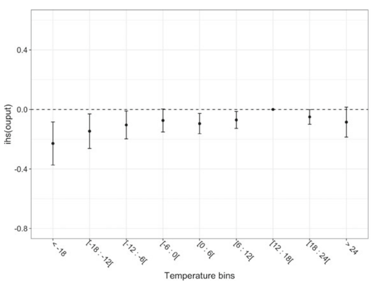
5.4.1. Establishment size

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 with small or medium establishments that the effect of temperature would be more muted. We re-run (4) by interacting weather variables with a discrete variable representing establishments' size as follows:

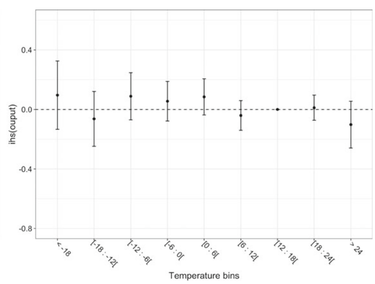
$$Y_{icpdt} = \left(\sum_b \beta_b T_{ct}^b + \sum_w \sum_q \theta_b W_{ct}^{qw} \right) \times size + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \tag{7}$$

where $size$ is a discrete variable that categorizes each establishment as: (1) small, with less than 50 employees, (2) medium, with 50 to 250 employments or (3) large, with more than 250 employees. We also interact $size$ with both industry–year and province–year fixed effects.

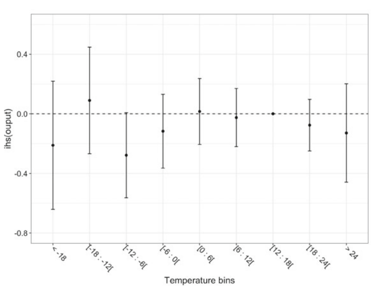
Figure 7 presents the effect of extreme temperature on small, medium, and large manufacturing output. We find a persistent negative effects of cold and hot temperature on small establishments output. An extra day with temperature below −18 °C to 6 °C to 12 °C decreases small establishments output by 0.07% to 0.23%. Similarly, an extra day with temperature above 24 °C or between 18 °C to 24 °C reduces small establishments output by 0.05% to 0.07%. Estimates for the effect of extreme temperatures on medium and large establishments are much noisier, owing to the much smaller number of establishments of this size. With imprecise estimates, it is difficult to determine whether larger establishments



(a) Temperature and total output for small establishments



(b) Temperature and total output for medium establishments



(c) Temperature and total output for large establishments

FIGURE 7 Estimated effect of extreme temperature on total output
NOTES: These figures present the effect of extreme temperature on small, medium, and large establishments output relative to medium establishments output. The coefficients are multiplied by 100. All the specifications include establishment, year–province and year–industry three-digit fixed effects. We also control for weather variables such as total rain, total snow, relative humidity and wind speed. The standard errors are clustered at the establishment and census subdivision–year levels.

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are differentially affected by extreme weather compared with smaller ones, but our results suggest there is no statistically significant differences in the response to extreme temperature by establishment size.

5.4.2. Labour intensity

In this section, we study the effect of temperature on manufacturing establishments with different input structures. In the conceptual framework presented in section 2, impacts on labour productivity reflect a key determinant of how manufacturing plants respond to temperature shocks. As a result, we may expect labour intensive establishments to be more affected by extreme temperature compared with 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 total wage in total output and the number of employee per output. An establishment is considered labour intensive when its share is above the median labour share in a given industry sector. We re-run (4) by interacting weather variables with a dummy variable representing labour intensity as follows:

$$\begin{aligned} y_{icpdt} = {} & \sum_b \beta_a T_{ct}^b + \left(\sum_b \beta_b T_{ct}^b + \sum_w \sum_q \theta_b W_{ct}^{qw} \right) \times labourintensity \\ & + \gamma_i + \zeta_{pt} + \psi_{dt} + \varepsilon_{icpdt}, \end{aligned} \tag{8}$$

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

Using the definition of labour intensity, as total employees over total sales (labour intensity 2), we find that labour intensive establishments suffer the most from cold and hot temperature compared with capital intensive establishments. An extra day with temperature below −18 °C or above 24 °C decreases labour intensive manufacturing output by respectively 0.31% and 0.14% as in table 4. However, when we use another measure of labour intensity (total wages divided total output or labour intensity 1), we find no statistically significant difference between labour and capital intensive establishments (although the coefficients still point to more labour intensive establishments being more negatively affected by extreme temperatures).

5.5. Predicted impacts of climate change

Figure 2 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 future climate change on manufacturing output, we multiply the regression coefficient estimates from equation (4), which capture how annual output is affected by a change in daily weather, by the predicted difference of the number of days

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TABLE 4
Estimated effects of temperature on total output by manufacturing intensity

Variables	ihs(total output) × 100	
	(A)	(B)
< -18	−0.14*	−0.01
	(0.08)	(0.07)
$< -18 \times$ labour intensity 1	−0.020	–
	(0.06)	–
$< -18 \times$ labour intensity 2	–	−0.31***
	–	(0.03)
$[-18 : -12[$	−0.11*	−0.0004
	(0.06)	(0.06)
$[-18 : -12[\times$ labour intensity 1	0.12**	–
	(0.05)	–
$[-18 : -12[\times$ labour intensity 2		−0.20**
		(0.07)
$[18 : 24[$	−0.02	−0.020
	(0.03)	(0.03)
$[18 : 24[\times$ labour intensity 1	−0.04	–
	(0.03)	–
$[18 : 24[\times$ labour intensity 2		−0.05
		(0.03)
> 24	−0.08	−0.06
	(0.05)	(0.06)
$> 24 \times$ labour intensity 1	−0.05	–
	(0.05)	–
$> 24 \times$ labour intensity 2	–	−0.14***
	–	(0.06)
Observations	235,672	232,891

NOTES: The coefficients are multiplied by 100. All the specifications include establishment, year−province and year−industry three-digit fixed effects. We also control for weather variables such as total rain, total snow, relative humidity and wind speed. The standard errors are clustered at the establishment and census subdivision−year levels. $^{***}p < 0.001$, $^{**}p < 0.05$, $^{*}p < 0.1$.

between the mid-century/end of century projection and the current period (2004−2012) for each temperature bin. We derive the standard error using the delta method. Lemoine (2018) shows that using reduced form estimates of weather−output in combination with climate projections as we do here would recover the effects of climate change if establishments are myopic (i.e., do not change production in response to anticipated weather). This methodology assumes that the determinants of manufacturing output are fixed over the time which include the baseline productivity and technology. While this is a strong assumption, it is consistent with the limited adaptation we found in tests of section 5.3.

Table 5 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

TABLE 5
Predicted effects of climate change on manufacturing output by greenhouse gas (GHG) emission scenarios

Variables	Mid-century (2050s)	End century (2080s)
Medium GHG emission (RCP45)	−2.8** (1.3)	−3.7** (1.7)
High GHG emission (RCP85)	−3.7** (1.7)	−7.3** (3.4)

NOTES: This table presents the annual impact of climate change on manufacturing output in percentage change relative to current temperature. We assume that the determinants of manufacturing output are fixed over the time which include the baseline productivity and technology. In parenthesis, we show the standard errors derived from the delta method. $^{***}p < 0.001$, $^{**}p < 0.05$, $^{*}p < 0.1$. GHG = Greenhouse gass suggests that extreme temperature would annually reduce the manufacturing output by 2.8% and 3.7% under medium and high GHG emission scenarios, respectively, relative to today's climate. When we consider the predicted effect for the end of century, the medium and high GHG emission scenarios respectively suggest a decrease of manufacturing output by 3.7% and 7.3% as a result of extreme temperatures.

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. While this is not a perfect parallel to the impact we estimate in the paper, it provides a useful check on how sensitive manufacturing output is to local shocks. In the ASML questionnaire, establishments were asked if they experienced a reduction of their activity due to extreme weather or natural disasters.[25] We then estimate the impact of reduced activity due to extreme temperature or natural disasters on manufacturing output:

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

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

Table 6 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. While not perfectly comparable to our main result, the result is in line with our main finding in 5.1 showing that manufacturing activity is adversely affected by extreme temperature. In terms of numerical magnitudes, our preferred model suggests that firm output would be reduced by 5% as a result of 26 days of extreme cold weather (daily mean below 18 °C) or 45 days of extreme hot weather (daily mean above 25 °C).

TABLE 6
Estimated effect of "reduced activity due to weather" on total output

Variables	ihs(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 effects of reduced activity due to weather or natural disaster on manufacturing total output. The estimation includes establishment, year−province and year−industry three-digit fixed effects (FEs). The standard errors are clustered at the establishment and census subdivision−year levels. $^{***}p < 0.001$, $^{**}p < 0.05$, $^{*}p < 0.1$.

25 This question has more than 21% missing values. Missing values are explained by both the non-response of some establishments and the use of tax file data to fill information of some establishments.

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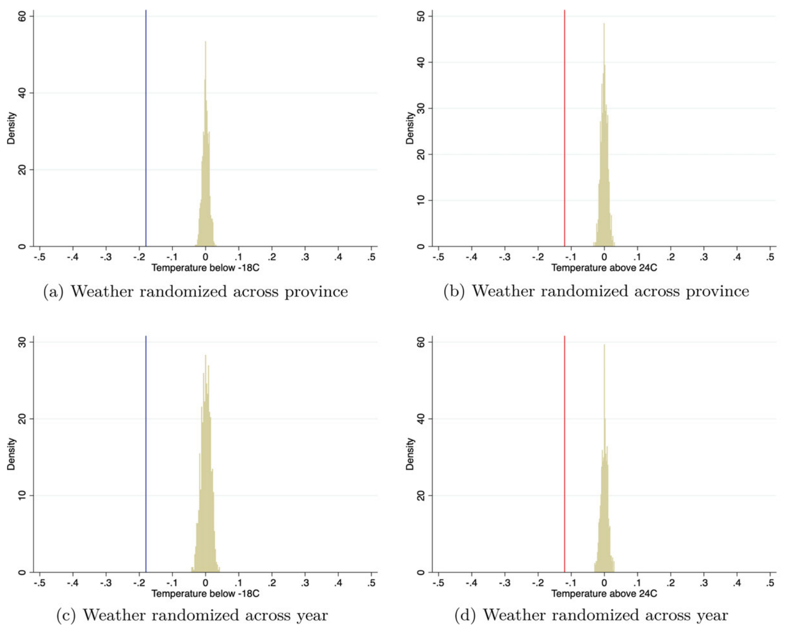
6.2. Falsification test

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 consists of repeatedly and randomly "reshuffling" the weather data across time and location and estimating equation (4) with the reshuffled data. We take two approaches to reshuffling the data. The first consists to randomly assign the temperature of another year to the current year within the same location. Similarly, the second consists to randomly assign the temperature of another location to a given location in a given year. We expect to see no relation between the randomly assigned temperature and manufacturing output. We repeat this process 1,000 times, and report the coefficient estimates from these falsification tests, along with our real coefficients in figure 8.

Figure 8 plots the coefficient distribution for temperature below −18 °C and above 24 °C. 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 centred around 0. We also 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 find that all the estimate coefficients from the falsification test are centred 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 centred around 0 whenever significant. This result validate our empirical strategy in 4 and the data used in our study.



(a) Weather randomized across province (b) Weather randomized across province

(c) Weather randomized across year (d) Weather randomized across year

FIGURE 8 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 preferred estimate of temperature below −18 °C, while the red line represents the preferred estimate of temperature above 24 °C. All the specifications include establishment, year−province and year−industry three-digit fixed effects. We also control for weather variables such as total rain, total snow, relative humidity and wind speed. The standard errors are clustered at the establishment and census subdivision−year levels.

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7. Summary and concluding remarks

This 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, controlling for other weather covariates, and establishments' fixed effects. 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 driven mainly by the negative effect of temperature on manufacturing sales. We find some evidence that labour intensive establishments are the most exposed to the temperature−output relationship compared with capital intensive establishments. Our findings also show that cold day has an extra negative effect on small and large establishments compared with medium establishments. We study whether establishments adapt to their local temperatures by considering those operating in cool and warm areas versus mild 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 quadruple 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 potential for adaptation. 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-century and end of century.

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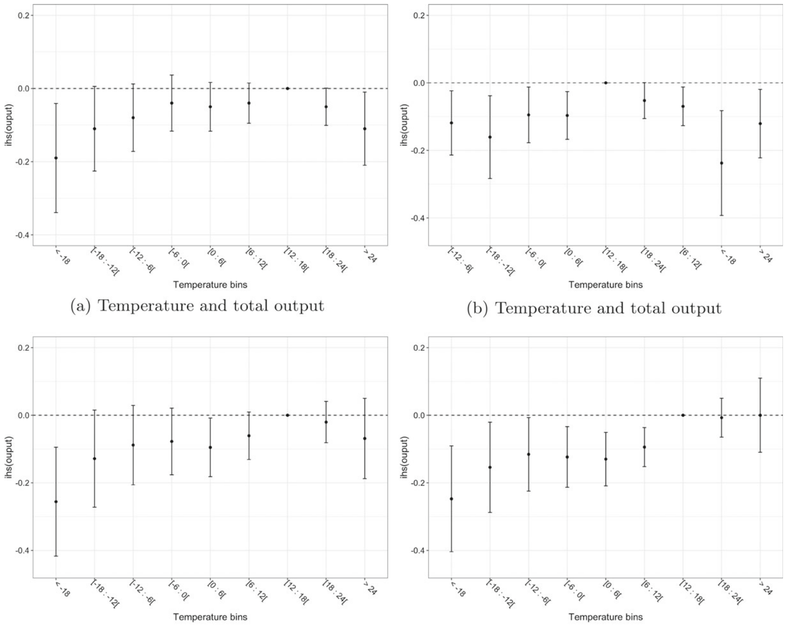
Appendix A1: Estimated effect of extreme temperature on manufacturing output using full sample



(a) Temperature and total output

(b) Temperature and total output

(c) Temperature and total output

(d) Temperature and total output

FIGURE A1 Estimated effect of extreme temperature on total output

NOTES: Panel a represents the main sample used in our analysis. Panel b is the main sample restricted to establishments with at least 10 employees. Panel c includes all observations without output and employment restrictions but excludes movers across industry, census subdivision and province. Finally, panel d represents all observations including movers. The coefficients are multiplied by 100. All the specifications include establishment, year–province and year–industry three-digit fixed effect. We also control for weather variables such as total rain, total snow, relative humidity and wind speed. The standard errors are clustered at the establishment and census subdivision–year levels.

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Appendix A2: Extreme temperature and manufacturing output – All bins

TABLE A1

Estimated effects of temperature of total output

	ihs(total output) × 100					
Variables	(A1)	(A2)	(A3)	(A4)	(B)	(C)
< -18	0.013	−0.19**	0.01	−0.19**	−0.23***	−0.19**
	(0.06)	(0.08)	(0.06)	(0.08)	(0.09)	(0.07)
$[-18 : -12[$	−0.145**	−0.14**	−0.06	−0.11*	−0.16**	−0.10*
	(0.06)	(0.06)	(0.05)	(0.06)	(0.07)	(0.06)
$[-12 : -6[$	−0.12***	−0.07	−0.08**	−0.08	−0.14**	−0.06
	(0.04)	(0.05)	(0.04)	(0.05)	(0.05)	(0.05)
$[-6 : 0[$	−0.12**	−0.05	−0.07	−0.04	−0.09**	−0.03
	(0.05)	(0.04)	(0.04)	(0.04)	(0.05)	(0.04)
$[0 : 6[$	−0.15***	−0.02	−0.11***	−0.05	−0.07*	−0.04
	(0.03)	(0.04)	(0.03)	(0.03)	(0.04)	(0.03)
$[6 : 12[$	−0.16***	−0.04	−0.11***	−0.04	−0.03	−0.04
	(0.04)	(0.03)	(0.04)	(0.03)	(0.04)	(0.03)
$[18 : 24[$	−0.04	−0.06**	−0.04	−0.05*	0	−0.05*
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
> 24	−0.070*	−0.12**	−0.05	−0.11**	−0.16***	−0.12**
	(0.04)	(0.05)	(0.04)	(0.05)	(0.06)	(0.05)
Observations	235,683	235,683	235,683	235,683	112,140	235,683
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

NOTES: This table presents the effects of daily extreme temperature on manufacturing total output. Column (A1) controls for establishment and year fixed effect (FEs). 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) to (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 establishments and census subdivision−year levels. These coefficients are interpreted as the percentage change of an additional day at a given temperature relative to the reference temperature bin [12:18[. $^{***}p < 0.001$, $^{**}p < 0.05$,$^{*}p < 0.1$.

Appendix A3: Temperature and relative humidity

Table A2 shows the result of interacting the temperature bins with an indicator for above-median humidity. We find no difference in the effect of extreme (hot) temperature, depending on whether it is humid or not.

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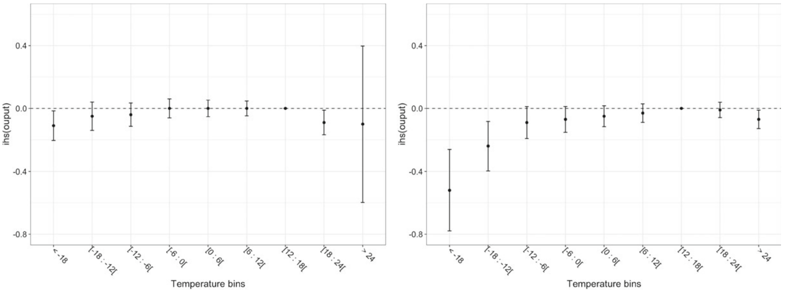
TABLE A2
Estimated effects of combined temperature-humidity of total output

Variables	ihs(total output) × 100
< -18	-0.176^{**}
	(0.084)
$[-18 : -12[$	-0.113
	(0.069)
$[-12 : -6[$	-0.08
	(0.056)
$[-6 : 0[$	-0.014
	(0.045)
$[0 : 6[$	-0.047
	(0.043)
$[6 : 12[$	-0.025
	(0.037)
$[18 : 24[$	-0.065^{*}
	(0.034)
> 24	-0.140^{**}
	(0.06)
$< -18 \times$ humidity	0.035
	(0.065)
$[-18 : -12[\times$ humidity	-0.023
	(0.072)
$[-12 : -6[\times$ humidity	0.033
	(0.055)
$[-6 : 0[\times$ humidity	-0.095^{**}
	(0.039)
$[0 : 6[\times$ humidity	0.038
	(0.036)
$[6 : 12[\times$ humidity	-0.019
	(0.044)
$[18 : 24[\times$ humidity	0.03
	(0.036)
$> 24 \times$ humidity	-0.015
	(0.052)
Observations	235,673

NOTES: This table presents the effects of daily extreme temperature and combined daily extreme temperature and relative humidity on manufacturing total output. We include weather controls which are total rain, total snow and wind speed. This specification includes establishment, year−province and year−industry three-digit fixed effects (FEs). The standard errors are clustered at the establishments and census subdivision−year levels. These coefficients are interpreted as the percentage change of an additional day at a given temperature relative to the reference temperature bin [12:18[. $^{***}p < 0.001$, $^{**}p < 0.05$,$^{*}p < 0.1$.

Appendix A4: 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 and Greenstone 2007, Graff Zivin and 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 °C to 24 °C might represent a really hot day, while a day with maximum temperature between −12 °C to −6 °C might indicate



(a) Minimum temperature and total output (b) Maximum temperature and total output

FIGURE A2 Estimated effect of extreme minimum/maximum temperature on total output
NOTES: These figures present the effect of daily minimum/maximum temperature on manufacturing output. The coefficients are multiplied by 100. All the specifications include establishment, year−province and year−industry three-digit fixed effect. We also control for weather variables such as total rain, total snow, relative humidity and wind speed. The standard errors are clustered at the establishment and census subdivision−year levels.

a very cold day. We estimate (4) by replacing mean temperature by respectively minimum and maximum temperature.

Figure A2 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 °C and −12 °C reduces manufacturing output by respectively 0.52% and 0.24%. 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 between 18 °C and 24 °C reduces manufacturing output by respectively 0.11% and 0.1% compared with a day with minimum temperature between 12 °C to 18 °C. This result is consistent with our main finding showing that extreme temperatures have an adverse effect on manufacturing activity.

Appendix A5: 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:[26]

$$windchill = 13.12 + 0.6215 * T - 11.37 * V^{0.16} + 0.3965 * T * V^{0.16} \tag{A1}$$

Where T is the mean temperature in degrees Celsius and $windkmh$ is the wind speed in kilometres 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.[27]

26 See https://en.wikipedia.org/wiki/Wind_chill.

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

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Appendix A6: Wet-bulb temperature

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

$$\begin{aligned} Wetbulb = {} & T * atan(0.151977 * (RH * 8.313659)^{1/2}) \\ & + atan(T + RH) - atan(RH - 1.676331) + 0.00391838 * ((RH)^{3/2}) \\ & * atan(0.023101 * RH) - 4.686035 \end{aligned} \tag{A2}$$

Where T is the mean temperature in degrees Celsius, RH is for relative humidity in percentage. A wet-bulb index lower than 24.5 means normal day for normal activities. For wet-bulb index between 24.5 and 27.3, it is advised to use discretion for intense and prolonged activities. A wet-bulb index between 27.3 and 29 implies a maximum of two-hour activities outside. Finally, a wet-bulb index above 29 means high discomfort and a maximum of one-hour outside activities are advised.

Appendix A7: Alternative standard errors

We re-run our preferred estimation with various approaches to two-way clustering. We report these results in table A3 below. In column (a), we report the main results of our preferred regression of output on temperature, where we cluster the error terms at the establishment and census subdivisions×year level. In column (b) , we implement a two way cluster at the establishment and province×year level. This approach allows for correlation of observations within a province in a year, as well as allowing for serial correlation of observations within an establishment. Standard errors increase slightly compared with our main specification,

TABLE A3
Estimated effects of temperature on total output

	ihs(total output) × 100		
Variables	(a)	(b)	(c)
< -18	−0.19**	−0.19**	−0.19*
	(0.076)	(0.079)	(0.086)
$[-18 : -12[$	−0.11*	−0.11*	−0.11*
	(0.059)	(0.061)	(0.059)
$[-12 : -6[$	−0.08	−0.08*	−0.08
	(0.047)	(0.041)	(0.051)
$[-6 : 0[$	−0.04	−0.04	−0.04
	(0.039)	(0.043)	(0.046)
$[0 : 6[$	−0.05	−0.05	−0.05
	(0.034)	(0.033)	(0.034)
$[6 : 12[$	−0.04	−0.04	−0.04
	(0.028)	(0.026)	(0.028)
$[18 : 24[$	−0.05*	−0.05**	−0.05
	(0.026)	(0.022)	(0.032)
> 24	−0.11**	−0.11*	−0.11
	(0.051)	(0.064)	(0.073)
Observations		235,683	

NOTES: These coefficients are interpreted as the percentage change of an additional day at a given temperature relative to the reference temperature bin [12:18[. Column (a) reports standard errors clustered by establishment and census subdivision×year; column (b) reports standard errors clustered by establishment and province×year; column (c) reports standard errors clustered by establishment and year. $^{***}p < 0.001$, $^{**}p < 0.05$,$^{*}p < 0.1$.

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but we still reject hypotheses of no impact of temperature on output for both hot and cold temperatures. Finally, in column (c), we cluster the error terms at the establishment and year level. Note that our data contain only nine years, and so standard errors using this approach are likely to be incorrect (MacKinnon et al. 2019). We report here for completeness only. Standard errors using this approach are somewhat larger, and the point estimate on the coefficient for the effect of hot temperatures on output is no longer statistically significant at conventional levels.

Appendix A8: Multi-way bootstrap

TABLE A4

Estimated effects of temperature on total output using multi way bootstrap

Variables	ihs(total output) × 100
< -18	−0.19*
	[0.08]
[−18 : −12[	−0.11*
	[0.08]
[−12 : −6[	−0.08
	[0.07]
[−6 : 0[	−0.04
	[0.43]
[0 : 6[	−0.05
	[0.26]
[6 : 12[	−0.04
	[0.34]
[18 : 24[	−0.05*
	[0.09]
> 24	−0.11*
	[0.08]
Observations	235,683

NOTES: These coefficients are interpreted as the percentage change of an additional day at a given temperature relative to the reference temperature bin [12:18[. In brackets, we report the p-value attached to each coefficient. $^{***}p < 0.001$, $^{**}p < 0.05$,$^{*}p < 0.1$.

Supporting information

The data and code that support the findings of this study are available in the Canadian Journal of Economics Dataverse at `https://doi.org/10.5683/SP3/8WSIZA`.

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