Stretching the Duck: How Rising Temperatures will Change the Level and Shape of Future Electricity Consumption

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ABSTRACT

This paper examines how rising temperatures due to climate change will affect electricity consumption patterns through mid- and end-century. We extend recent literature in two important ways. First, we directly incorporate adaptation in the form of increased air conditioner penetration, resulting in heightened responsiveness to hot temperatures. Second, we go beyond average effects to consider how higher temperatures will change the intraday and seasonal shape of consumption. This is found to be of greater importance in colder countries, where the average effect is dampened by reductions in heating demand from warmer winters. Seasonal peaks are projected to shift from winter to summer and the diurnal range of hourly consumption expands, exacerbating an increasing need for flexibility coming from the supply side due to a growing share of renewable energy.

Keywords: Climate change, electricity demand, air conditioning, adaptation

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1. INTRODUCTION

Climate change will affect many social and economic outcomes. However, the magnitude, and in some cases the sign, of these effects is the subject of considerable debate. Thus, the need for more evidence-based empirical estimates of the potential effects of climate change is important to improve adaptation capacity as well as for understanding its costs.[1] This paper examines the effect of rising temperatures due to climate change on one such outcome: future electricity consumption.

We consider how rising temperatures by mid- and end-century will alter both the level and timing of electricity consumption across Canada. While several studies have looked at the relationship between climate change and overall energy consumption (Isaac and van Vuuren, 2009; Davis and Gertler, 2015; De Cian and Wing, 2017; Wenz et al., 2017), a less explored area of the literature is how climate change will affect the intraday shape of consumption. The latter is of particular importance in electricity where supply must equal demand in every hour and storage is costly. Our study fills this void.

1. Previous literature has explored the effect of climate change on mortality (Barreca et al., 2016; Heutel et al., 2017), economic growth (Dell et al., 2012), economic production (Burke et al., 2015) and human capital (Graff Zivin et al., 2018), to name a few. In terms of future energy demand, several studies have examined the nonlinear effect higher temperatures are expected to have on electricity demand (Auffhammer and Aroonruengsawat, 2011; Auffhammer et al., 2017; Davis and Gertler, 2015;Wenz et al., 2017). Kahn (2016) offers a review of the climate change adaptation literature.

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Our results suggest a large increase across all provinces in ramping requirements—the range between minimum and maximum hourly consumption within a day—increasing the need for flexibility in future electricity systems. This finding from the demand side echoes a similar need coming from the supply side, where an increasing share of variable energy renewable resources is placing a greater importance on flexibility to meet larger ramping requirements.

We find significant heterogeneity in temperature sensitivity across provinces and, correspondingly, regional differences in projected electricity consumption. This is most notable in projected changes to peak demand—the maximum hourly demand within a year. The largest increase is predicted to occur in Ontario, a province that is currently summer-peaking, where we project peak demand to increase by 38%. In winter-peaking provinces, such as Quebec, which rely predominantly on electric heating, we project declines in peak demand despite growth in summer demand. In most provinces, however, we project a seasonal shift from winter-peaking to summer-peaking electricity grids, turning Canada into a summer-peaking country by end-century.

We find a relatively small increase of 4% in the overall level of electricity consumption across Canada, with rising summer demand offset by a reduction in winter demand. This result includes the effect of adaptation in the form of more air conditioner penetration and at the most extreme temperature scenario. This stands in contrast to much larger projected increases in future electricity demand from studies in warmer climates (Isaac and van Vuuren, 2009; Akpinar-Ferrand and Singh, 2010; Davis and Gertler, 2015). This result highlights the mitigating effect of a warming climate in a cold country such as Canada, whereby increases in summer cooling demand are largely offset by decreased electric heating demand from warmer winters.

Our empirical analysis consists of two parts. First, we estimate the relationship between temperature changes and electricity consumption to create *temperature response functions*, i.e. the marginal effect of temperature on electricity consumption. We then combine our estimated temperature response functions with projections of future temperature from an ensemble of global climate models under various emissions scenarios to project changes to the level and timing of future electricity consumption by mid- and end-century.

To estimate the causal relationship between temperature and electricity consumption, we draw on public and private data sources to construct an original dataset of hourly observations of electricity consumption for every Canadian province over the period 2001–2015.[2] We find temperature response functions characterized by a familiar U-shaped relationship: at colder temperatures, rising temperature leads to decreased electricity consumption due to less need for heating; whereas at warmer temperatures, rising temperature increases demand for cooling services and thus electricity. However, these estimates represent only the short run response, i.e. the assumption that future behaviour and technology matches that of today—an unsatisfactory result for long run projections.

To incorporate one potential dimension of adaptation, we exploit the significant heterogeneity in temperature responsiveness across provinces. These differences correspond to key observed differences in underlying ways electricity is used across provinces—differences in air conditioner and electric heat penetration, and residential share of total consumption. Re-estimating temperature response functions based on these key observables, allows for the estimation of future temperature responsiveness at various counterfactual levels that reflect potential adaptation in the form of air conditioner uptake. We then inform our adaptation-inclusive scenarios by estimating a model of air

2. We thank representatives from multiple balancing authorities and grid operators for their willingness to provide the data. To the best of our knowledge, no other hourly multi-year panel dataset of Canadian electricity consumption is readily available.

conditioner adoption using household-level microdata. We find by end-century, under most emission scenarios, residential air conditioner penetration reaches well above 90% in most provinces.

Combining our model of air conditioner adoption with the above temperature response functions delivers long run adaptation-inclusive demand projections—in effect, at higher levels of air conditioner penetration, electricity demand becomes more responsive (i.e. increases more) at hotter temperatures. Our results show a warmer climate leads to an increase in summer demand, an increase in peak hour demand in summer peaking regions and a shift to summer-peaking more generally, an expansion of the minimum to maximum intraday range of demand, and an overall—albeit small for Canada as a while—increase in average demand.

It is important to note that our results throughout this paper take the form of *ceteris paribus* projections. That is, we estimate the impact of changes in temperature on electricity consumption and on air conditioner adoption, holding all else equal. Of course, over the long time horizons we consider, many other variables will affect electricity demand, and changing temperatures will affect many other variables in addition to electricity demand. Our results should therefore be taken as the *marginal* effect of changing temperature on electricity consumption holding other factors constant, not as unconditional predictions of future electricity demand.

Our paper contributes to a new and growing literature, building on three recent studies that explore the effect of climate change on electricity demand. First, in terms of regional heterogeneity, our paper finds similar results as Wenz et al. (2017): rising temperatures do not significantly increase electricity consumption in a cold country, such as Canada. However, whereas Wenz et al. (2017) focus on regional heterogeneity driven by large climatic differences between southern and northern European countries, our paper finds differences in projected electricity consumption changes within Canada, despite relatively similar climatic conditions across provinces. Instead, we find heterogeneity driven by large variation in temperature-sensitive uses of electricity. Our finding emphasizes the importance of understanding underlying drivers of temperature-sensitive demand.

Second, Auffhammer et al. (2017) emphasize the importance of looking beyond average effects in difficult-to-store electricity, projecting changes in both average and peak demand. We extend this by using hourly granularity to estimate changes in the intraday shape of demand. This aspect is particularly important for electricity systems already grappling with large swings in intraday supply from a growing share of renewable resources. Considerable attention has been paid to the electricity "duck curve", so-named due to the shape of intraday net demand characterized by a midday belly of low net demand when solar is generating at its fullest, followed by a steep ramp in the late afternoon having the appearance of a duck's neck (CAISO, 2016).[3] Our results provide evidence of the need for even more flexibility to manage greater intraday variance coming from the demand side as well.

Third, we develop a tractable method to incorporate both the intensive and extensive margin of adaptation (in one dimension only—air conditioner adoption) into future projections of temperature-induced demand changes. Similar to Davis and Gertler (2015) we model the adoption of air conditioners in response to changes in temperature using household-level microdata, which can be used to project future air condition penetration in a warming climate. However, whereas Davis and Gertler (2015) use this information to project future consumption by assigning a temperature response function from a region with currently high air conditioner penetration levels, we estimate temperature response directly as a function of air conditioner levels and other temperature-sensitive observables. This innovation allows us to use the projected air conditioner penetration levels directly, while maintaining region-specific characteristics, to project future electricity consumption changes with adaptation.

3. Net demand is defined as metered demand net of renewable generation.

In a recent paper, Auffhammer (2018) exploits significant cross-sectional variation at the household level to estimate the relationship between temperature sensitivity and extant climate conditions. In doing so, this approach provides a reduced form method to incorporate adaptation by making temperature response a function of prevailing climate. This is a promising straightforward approach with the requirement of significant cross-sectional data. Our method is comparable and both papers seek the same thing: the effect of changing climate on electricity consumption, incorporating elements of adaptation. Our method unpacks the relationship by decomposing the change into its components: the direct effect of temperature on consumption and the indirect effect of temperature altering the stock of temperature-sensitive durables, such as air conditioners, and the corresponding effect of higher levels of air conditioner penetration on consumption. Thus our method offers different insights as to the channels driving the changes.

2. CONCEPTUAL FRAMEWORK

We motivate the empirical analysis with a simple representation of electricity demand that responds to temperature and other factors:

$$y = f(T, D(T), X) \tag{1}$$

The first element is the direct effect temperature T has on electricity demand y. The second term allows temperature to affect demand indirectly via $D(T)$. We can think of D as a vector of durables whose stock is both influenced by temperature and in turn alters the temperature sensitivity of demand.[4] As a concrete example, one can imagine the stock of air conditioners in a region to be an element of D. Higher temperatures directly affect the stock of air conditioners, and in turn the higher stock increases the temperature sensitivity of demand as a result of more air conditioners turning on during heat waves.[5] Conversely, one can also imagine a different element of D that has the opposite effect. For example, the stock of energy efficiency, such as better home insulation, is likely affected by changes in temperature, and a higher stock dampens the temperature sensitivity of demand. Lastly, X captures other variables that affect demand independently of temperature.

To see how temperature changes affect demand, we differentiate Eq.(1) with respect to T:

$$\frac{dy}{dT} = \underbrace{f_T}_{\substack{\text{Direct effect}\\ \text{or}\\ \text{Intensive margin}}} + \underbrace{f_D \frac{dD}{dT}}_{\substack{\text{Indirect effect}\\ \text{or}\\ \text{Extensive margin}}} \tag{2}$$

Equation (2) demonstrates the components of demand response to temperature. The first term, f_T, is the **direct effect** of changing temperature *holding the stock of D constant*, i.e. $\frac{\partial f(T, \bar{D})}{\partial T}$.[6] The second term is the **indirect effect**. It is the product of temperature changing the stock of durables through $\frac{dD}{dT}$ and, in turn, the change in durables affecting demand through f_D.[7] Since we can

4. We use the label *durables* as we focus on the role of air conditioners and electric heating, however, D encompasses a broader set of factors, including societal norms and behaviours that influence temperature sensitivity.

5. More precisely, higher *expectations* of future temperatures are likely to drive decisions regarding durables stock. We ignore differences in timescale here, but address them in the empirical work that follows.

6. This is what Davis and Gertler (2015) call the intensive margin, or what Burke and Emerick (2016) and Graff Zivin et al. (2018) call the short-run response.

7. The change in stock leads Davis and Gertler (2015) to refer to this channel as the extensive margin.

imagine the timescale at which the stock of durables changes to be long, or slow-acting, we can consider the sum of the direct and indirect effects to be the long-run response. In our empirical strategy, we estimate all three objects in Equation (2) to create an adaptation-inclusive temperature response function.

3. DATA

3.1 Electricity demand

The analysis is made possible due to a rich new dataset of hourly electricity consumption for each of Canada's ten provinces. The dataset was constructed in part from publicly available data in provinces with competitive electricity markets, but in most cases from the collection of private data directly from the respective provincial utilities and/or balancing authorities. For each province, the data consist of a time series of hourly system-wide consumption over the period 2001–2015.[8] Thus, for most provinces there are roughly 131,000 observations. Hourly consumption varies significantly across provinces and by season, reflecting large population differences and seasonal electricity uses that differ by province. As this is total system-wide consumption, it also represents a mix of residential, commercial and industrial demand. Summary statistics are listed in Table A1 of the Appendix.

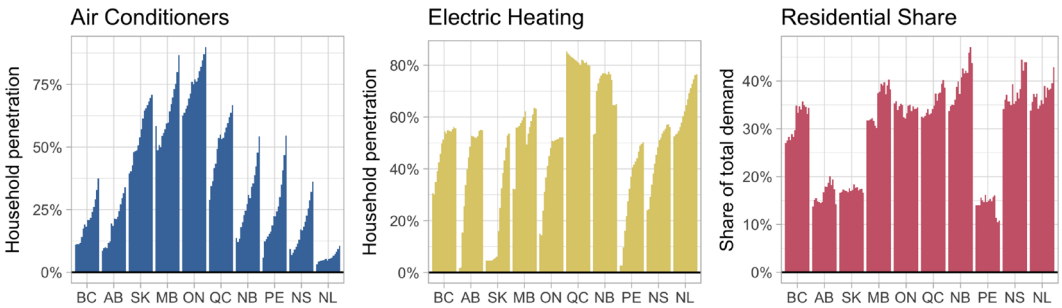
3.2 Temperature-sensitive demand drivers

We use data on temperature-sensitive demand drivers from two sources. First, we collect data on air conditioner penetration, electric heat penetration and residential shares of total electricity demand from Natural Resource Canada's Comprehensive Energy Use Database (CEUD). The CEUD data is an annual province-level panel from 2001 to 2015 with significant cross-sectional and temporal variation (see Figure 1). Residential air conditioner penetration has grown in all provinces in the years 2001–2015, however, there remain large differences across provinces (greater than 80% in ON vs less than 10% in NL). Residential electric heat varies across provinces, but stands out in QC—a province with large (and relatively cheap) hydro-electric resources. Residential shares are roughly bi-modal, with most provinces having roughly one-third of their total demand attributed to the residential sector, whereas AB, SK and PE have significantly lower residential shares. In the cases of AB and SK this is due to large electricity-intensive industrial sectors, whereas PE has a large commercial sector relative to residential.

Second, for the estimation of a model of air conditioner adoption, we collect household level microdata from Statistics Canada's Household and the Environment Survey (HES). The HES data come in several waves (we use the 2006, 2007, 2009, 2011 and 2013 waves of the HES) and contain information on air conditioner ownership, income, household demographic variables, ownership or rental status, and household age and size. The data are provided at the Census Subdivision (city) level, which we can then match to temperature data at the same level.

8. For PE, NS, NL and QC, the data are only available for 2007 onwards.

Figure 1: Observable temperature-sensitive demand drivers



Notes: Each bar represents an annual value for the years 2001–2015. Data from Natural Resource Canada's Comprehensive Energy Use Database (CEUD).

3.3 Historical temperature

We collect data from all active weather stations in each province from Environment Canada to calculate population-weighted hourly temperatures for each province for each hour of the 15 year period corresponding to the demand data. Details of our approach to collecting and aggregating the historical temperature data are provided in Appendix C. We then merge the hourly temperature data with our electricity demand data. Table A1 summarizes mean seasonal temperatures across the provinces. Mean summer temperatures range from 10.2 to 15.2°C, whereas mean winter temperatures show wider variation: from -9.8° in Manitoba (central Canada) to +4.0° in the west coast province of British Columbia.

3.4 Projected temperature

We obtain forecasts of future temperatures based on statistically downscaled global climate model outputs from the Pacific Climate Impacts Organization at the University of Victoria.[9] For our main results, we use an ensemble of projections from 12 global climate models under from CMIP5—the Coupled Model Intercomparison Project Phase 5.[10]

The data include temperature projections for mid-century (2041-2060) and end-century (2081-2100) at a roughly 10km gridded spatial granularity. We then geo-match the individual coordinates to 2016 Canadian census population data to produce population-weighted projections at the province level. We repeat this process for two *Representative Concentration Pathway* scenarios, representing alternative assumptions regarding mitigation efforts.[11] RCP 8.5 represents a relatively unchecked pathway for emissions, where little to no mitigation of greenhouse gas emissions are taken, and correspondingly large temperature increases (roughly 5.5°C by end-century for the national average). RCP 4.5 can be considered the moderate emission scenario, with end-of-century temperature increases of roughly 3°C across Canada.

9. Source: https://pacificclimate.org/data/statistically-downscaled-climate-scenarioshttps://pacificclimate.org/data/statistically-downscaled-climate-scenarios

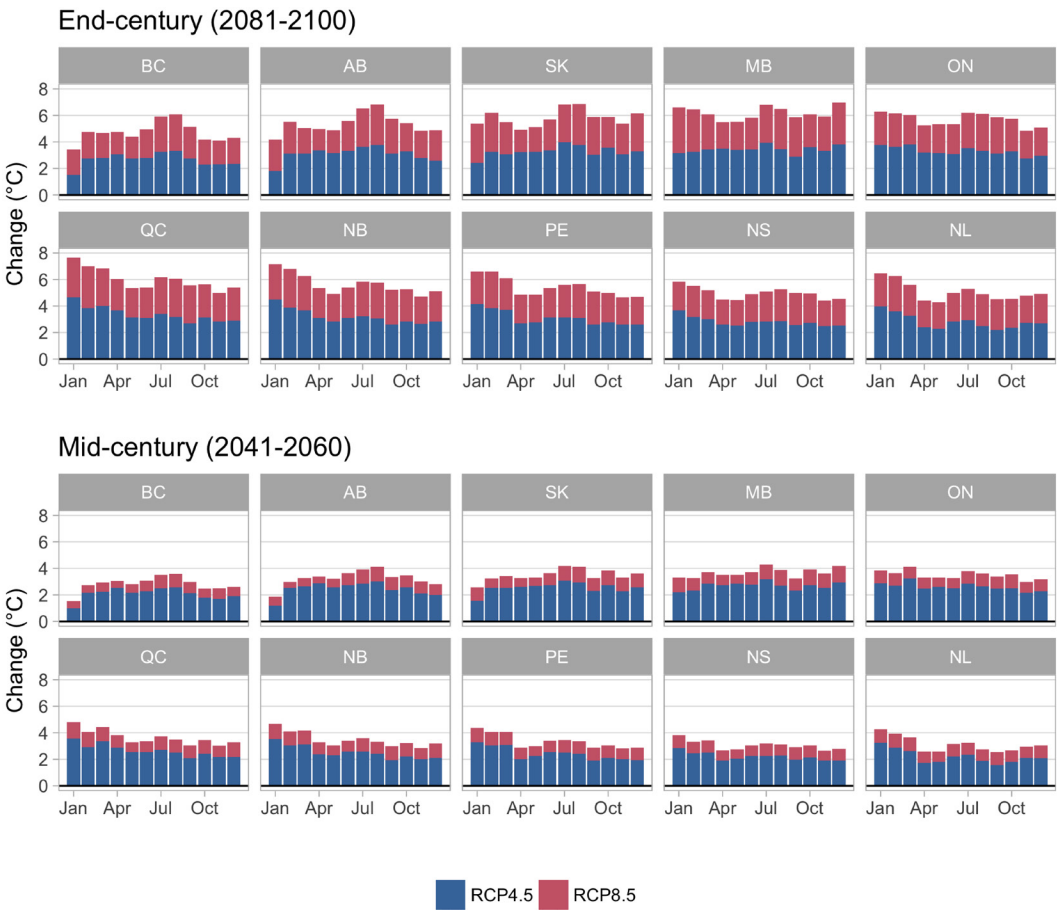
10. We take the simple average of projection from the following generalized circulation models (GCMs): ACCESS1.0, CanESM2, CCSM4, CNRM-CM5, CSIRO-Mk3-6.0, GFDL-ESM2G, HadGEM2-CC, HadGEM2-LR, INM-CM4, MPI-ESM-LR, MRI-CGCM3, MIROC5. We use both the RCP8.5 (high emissions) and RCP4.5 (medium emissions) scenarios for our analysis.

11. For the main results in Section 5 we use RCP 8.5, but include results from RCP 4.5 in the Appendix. For a thorough overview of representative concentration pathways, see Van Vuuren et al. (2011).

Figure 2 plots the mid- and end-century projected changes to mean temperature from the ensemble model for both the RCP4.5 and 8.5 scenarios. The projected temperature changes differ significantly by month and province.

We incorporate changes to the potential variance of hourly temperature in the following manner. In addition to projected changes to mean temperature, we also collect projected changes to minimum and maximum temperatures, by month, at the same spatial aggregation as described above (we plot changes to mean, min and max temperatures in the Appendix, Figures A2 and A3). We then interpolate hourly projected changes using the expected changes in minimum, maximum and mean temperatures.[12] We find that, for most provinces, the variance of intraday temperature decreases in winter months, with minimum temperatures rising more than maximum temperatures, while expanding slightly in summer months.

Figure 2: Projected temperature changes



Notes: Projected population-weighted temperature changes (°C) by province and month between 1981-2000 baseline and two periods: mid-century (2041-2060) and end-century (2081-2100). Based on the CMIP5 ensemble RCP8.5 (high emissions) and RCP4.5 (medium emissions) scenarios.

12. The interpolation procedure is described in detail in Appendix B.

4. ESTIMATING TEMPERATURE RESPONSE FUNCTIONS

Our strategy to create temperature response functions (TRFs) involves three steps. We provide a brief roadmap of the empirical strategy here, with more detail on each step below.

In Step 1, we exploit hourly temperature and consumption data to estimate a high resolution fixed effects model that delivers the short run effect, or intensive margin, of temperature on electricity consumption. This method allows for province-specific (unobserved) drivers of demand.

In the next two steps, we incorporate the extensive margin, or long-run effect. Davis and Gertler (2015) do so by applying a temperature response function estimated in the manner above from a region with currently high air conditioner penetration to regions whose air conditioner penetration is currently low and expected to rise. Instead, our method attempts to directly estimate TRFs that are themselves functions of observable drivers of demand, such as air conditioner penetration, electric heating share, and residential share of total demand, that can be flexibly changed to incorporate adaptation.

This involves, in Step 2, re-estimating temperature response functions by conditioning on selected key observable drivers of demand rather than unobserved regional differences. We note that this method exposes us to potential omitted variable bias moreso than the well-identified intensive margin in Step 1. While we cannot exclude this possibility entirely, we address this issue more fully below by demonstrating the strong fit between TRFs estimated using the two methods when evaluated at historical levels of key observables.

Finally, in Step 3, we estimate a model of air conditioner adoption that can be used to inform the long run temperature response at higher levels of air conditioner penetration. Having estimated TRFs as functions of air conditioner penetration in Step 2, we can thus plug in our projected air conditioner levels rather than relying on using a TRF from another region with currently high levels of air conditioning. The combination of Steps 2 and 3 can be viewed as a tractable alternative to the method of Davis and Gertler (2015) which allows for more flexible inclusion of adaptation while maintaining other province-specific characteristics.

Step 1: Short run temperature response

We estimate the relationship between temperature and electricity consumption using our hourly dataset of historical temperatures and electricity consumption by province. Referring to Eq.2 of the conceptual framework, we estimate the first term f_T, using a fixed effects approach on the rich hourly data. Specifically, we run ten separate regressions—one for each province—regressing hourly electricity consumption on temperature variables and a rich set of datetime fixed effects:

$$\log(y_t^p) = \sum_b \beta_b^p T_{tb}^p + \gamma^p \theta_t + \varepsilon_t^p \tag{3}$$

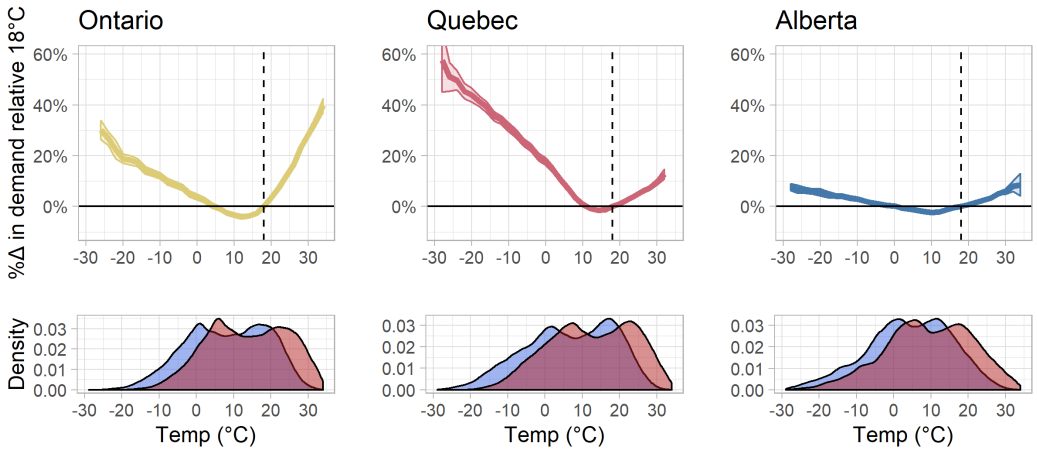
Temperature enters semi-parametrically, with T_{tb}^p representing the share of population in province p for which temperature at date-time t falls in the temperature bin b. Bins are defined in 2°C increments from -45°C to +39°C, the full range of hourly temperatures in Canada from 2001–2015.[13]

A large number of unobserved factors in addition to temperature influence electricity consumption in any given period. In order to identify the effect of temperature on electricity consump-

13. An alternative specification is to use the concept of heating (cooling) degree hours, which count the number of degrees below (above) an arbitrary threshold, typically 18°C. While common in the electricity literature, the semi-parametric specification allows for a more flexible non-linear response.

tion, we employ a fixed effects strategy that controls for unobserved factors that vary predictably over time. Specifically, θ_t contains hour-of-day, day-of-week, day-of-year, statutory holiday, and year fixed effects (dummy variables). Hour-of-day dummy variables absorb systematic differences in electricity consumption that occur within a day. This is important, as temperature also varies across the day. Day-of-year dummy variables soak up any variation in electricity consumption that occurs over the year, such as seasonal variation in consumption. Year dummy variables pick up changes in consumption that occur from one year to the next, for example due to changes in population or in the quality of housing stock. Day-of-week and statutory holiday dummy variables pick up variation in electricity consumption that occurs across days of the week or on holiday days. Successful identification of the effect of temperature on short-run electricity consumption requires that unobserved shocks to electricity consumption are not correlated with temperature after conditioning on the fixed effects described above. Because of the high resolution of fixed effects covering key drivers of electricity demand that we include in our specification, as well as year fixed effects making our identification based on within-year variation, we believe that this specification should successfully identify the short-run effect of temperature on consumption.[14]

Figure 3: Temperature response functions and end-century (RCP8.5) temperature changes for 3 major provinces



Notes: The temperature response function represents the coefficients of a regression of log(demand) on 2°C temperature bins and fixed date effect controls, relative to the 17-19°C bin. In other words, the percentage change in electricity consumption as temperatures differ from 17-19°C. The shaded region represents the 95% confidence interval with Newey-West heteroskedasticity and autocorrelation consistent standard errors calculated using a 168 hour (1 week) lag. The bottom panels show the density of historical (blue) and projected (red) hourly temperatures for end-century (RCP8.5).

We show estimation results graphically for three large provinces with distinct temperature response functions in Figure 3.[15] The interpretation of the value of the function is the percentage change in electricity consumption for a given hourly temperature relative to the omitted 17-19°C bin. Ontario, with the highest share of household air conditioner penetration of all provinces in Canada, has the steepest "right-side" temperature response function slope—consumption increases

14. Smith (2016) and Rivers (2016) use similar methods involving high resolution fixed effects to examine the causal effect of daylight saving time on traffic fatalities (Smith) and electricity demand (Rivers). Auffhammer et al. (2017) and Wenz et al. (2017) use similar methods for their identification of short run temperature response functions.

15. Short run temperature response functions for all provinces are shown in the Appendix, Figure A1.

sharply at hot temperatures as a result of cooling demand. Whereas Quebec, with its steep "left-side" slope is the province with the highest share of households using electric heat as their primary heating source and thus heating degree sensitivity—consumption increases sharply as temperature drops *below* a nadir level of roughly 14°C. Alberta, with the highest industrial share of electricity demand of any province (and thus low share of residential demand), has a rather flat temperature response function, reflecting weak temperature sensitivity. The bottom panels in Figure 3 show historical and projected future hourly temperatures (RCP8.5 scenario) for each region at end-century.

Step 2: Re-estimating temperature response based on observables

The prior section used high resolution fixed effects estimated separately by province to allow us to cleanly identify the causal effect of changes in temperature on short-run electricity demand. However, while the fixed effects are useful for identification, they also prevent us from understanding structural reasons why temperature responses might differ. In this section, we instead estimate a single temperature response equation based on key observable temperature-sensitive characteristics that differ across space (province) and time (year).[16] This allows us to understand what drives differences in temperature responsiveness across provinces and time. Accordingly, this allows for flexible counterfactual scenarios that include adaptive behaviour in response to higher temperatures, such as increased air conditioner penetration, that in turn affect temperature sensitivity in the long run.

To clarify this approach, we show how our empirical strategy aligns with our conceptual framework with the following illustration. Consider a version of Equation (3), but as a single regression, rather than ten separate provincial regressions, and including key observables D and their interaction with temperature. For the sake of building intuition, we simplify the temperature notation by dropping the semi-parametric binned temperature notation and revert to a generic T purely for exposition:

$$\log(y_{tp}) = \beta_1 T_{tp} + \beta_2 D_{tp} + \beta_3 T_{tp} D_{tp} + \gamma\theta_t + \eta_p + \varepsilon_t \tag{4}$$

Differentiating Equation (4) with respect to T gives the marginal effect of temperature on demand. Rearranging highlights the equivalency of this empirically-estimable equation to our conceptual framework:

$$\begin{aligned}\frac{\partial \log y}{\partial T} &= \beta_1 + \beta_2 \frac{\partial D}{\partial T} + \beta_3 D(T) + \beta_3 T \frac{\partial D}{\partial T} \\ &= \underbrace{\beta_1 + \beta_3 D(T)}_{f_T(T,D)} + \underbrace{(\beta_2 + \beta_3 T)}_{f_D(T,D)} \frac{\partial D}{\partial T}\end{aligned} \tag{5}$$

Thus, our challenge is to estimate the above β's to estimate temperature response for a given level of observable characteristics (D). To do so, we regress electricity demand on temperature and observables as per Eq.4, replacing the generic temperature notation with heating and cooling degree variables:

16. Another way to think of our previous estimation method is as a single regression whereby province dummies are interacted with temperature bins and fixed effects. In this section's specification, we instead interact temperature variables with the vector of observables, thus any differences in temperature responsiveness are explained by differences in observables rather than unobserved provincial heterogeneity.

$$\log(y_{tp}) = \beta_{11}CD_{tp} + \beta_{12}HD_{tp} + \beta_2 D_{tp} + \beta_{31}CD_{tp}D_{tp} + \beta_{32}HD_{tp}D_{tp} + \gamma\theta_t + \eta_p + \varepsilon_t \quad (6)$$

where CD_{tp} and HD_{tp} are cooling and heating degrees, i.e. the number of degrees actual temperature is above or below, respectively, a neutral temperature baseline.[17] This is a slightly less flexible specification than temperature bins, but still allows for different trends on either side of the neutral temperature baseline. It also greatly simplifies the regression and delivers easily interpretable coefficients.

This regression specification requires taking a stand on the elements of the temperature-sensitive durables vector, *D*. We include air conditioner and electric heating penetration levels and residential share of electricity demand, which we observe for each province-year. We again control for time fixed effects as well as province fixed effects that are, importantly, no longer interacted with temperature. Thus, the heterogeneous effect of temperature on demand across provinces comes only through differences in the observable characterized represented by *D*.

We estimate multiple variants of Equation (6), with results listed in Table 1. The first specification is the most straightforward: we include cooling and heating degrees, elements of *D* (air conditioner penetration, electric heating penetration and residential share) and the interaction between the temperature variables and observables. The second model augments the first by interacting residential share with air conditioner and electric heat penetration. This allows the potential for greater effect of durables at higher shares of temperature-sensitive residential demand. Newey-West heteroskedasticity and auto-correlation consistent standard errors are calculated with a 168 hour (one week) lag, as per the short run estimates.

Table 1: Regression estimates of demand on observables

	Dependent variable:	
	log(load)	
	(1)	(2)
Cooling degrees (cd)	0.006*** (0.002)	0.020*** (0.003)
Heating degrees (hd)	–0.008*** (0.001)	–0.008*** (0.001)
cd × AC	0.029*** (0.002)	–0.007 (0.007)
cd × Res Share	–0.024*** (0.007)	–0.072*** (0.012)
cd × AC × Res Share		0.115*** (0.025)
hd × Electric Heat	0.019*** (0.001)	0.019*** (0.002)
hd × Res Share	0.030*** (0.003)	0.027*** (0.007)
hd × Electric Heat × Res Share		0.005 (0.011)
Observations	1,171,966	1,171,966
Adjusted R^2	0.996	0.996

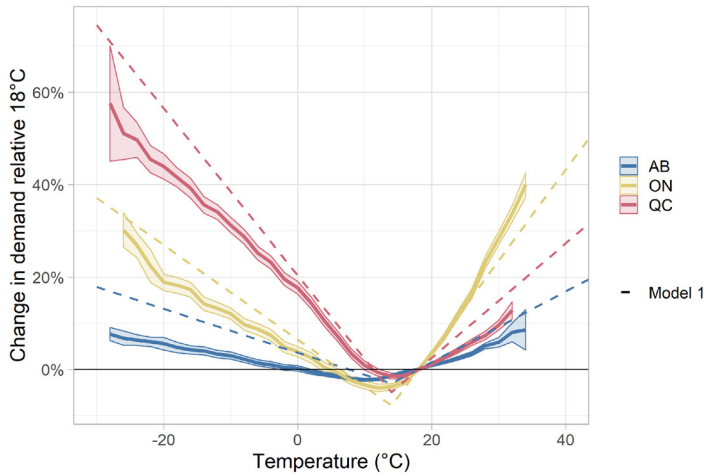
Notes: Newey-West HAC standard errors in parentheses. * p<0.1; ** p<0.05; *** p<0.01

Looking at Column 1, the sign of the coefficients is as expected: the sensitivity of demand to cooling degrees (temperature above 14°C) increases with greater air conditioner penetration (as seen by the significantly positive coefficient on $cd \times AC$). Similarly, the sensitivity of demand to heating degrees (temperature below 14°C) increases with greater electric heating penetration (as seen by the coefficient on $hd \times ElectricHeat$). In Column 2, the interaction term between air conditioner penetration and cooling degrees is rendered insignificant, but the effect is observed via the strongly positive triple interaction term with residential share. Cooling demand is increasingly sensitive to air conditioner penetration at higher levels of residential share.

17. We use 14°C as our neutral temperature baseline as this is the observed average nadir of demand from the previously estimated short-run temperature response functions across Canada.

Using these estimates, we can calculate temperature response functions holding the stock of durables constant at historical averages. Figure 4 plots the predicted temperature response functions for three provinces, holding the elements of *D* at historical average levels, as compared to the short run temperature response functions estimated separately by province. This figure highlights the strong explanatory power of this rather small set of observables in explaining the heterogeneity across province-specific temperature sensitivity.

Figure 4: Comparison of short run and predicted temperature response functions evaluated at historical averages



Notes: Temperature response functions show the estimated effect of temperature on electricity demand relative to 18°C. The short run estimates are shown by the solid lines with 95% confidence intervals (shaded). The predicted temperature response functions evaluated at historical average levels of air conditioner penetration, electric heating penetration and residential share of demand are shown by dashed lines (confidence intervals omitted on the latter for figure clarity).

A key concern with this method is the possibility of omitted variable bias.[18] We cannot exclude this possibility entirely, however, we address this issue in several ways. First, we demonstrate the strong fit of the predicted temperature response functions at historical observables levels with the province-specific short run temperature response functions previously estimated. This is shown graphically in Figure 4.

Second, we take a statistical approach. Our goal is to determine whether the selected observables in *D* sufficiently explain the underlying unobservable heterogeneity driving differences in short run temperature response functions when estimated separately by province. Thus, we take a straightforward approach to determining the appropriateness of the selected observables by regressing the slopes of the short run temperature response functions (a linear proxy for the estimated sensitivity to heating and cooling degrees) on the selected observables and examining the degree to which the fitted results explain the variation in the data, i.e. the R-squared.

18. The problem of *selection on observables* is not uncommon in empirical research. Oster (2017) proposes a method to investigate the likelihood of bias due to selection on observables by generalizing the approach previously suggested by Altonji et al. (2005). This involves estimating a *coefficient of proportionality*, δ, to determine how explanatory the unobservables would have to be to render the coefficients of interest insignificant. However, this approach is not entirely appropriate for our context. In the Oster (2017) *selection on observables* problem, the concern is whether controls have been appropriately selected such that the coefficient of interest on the treatment variable is robustly estimated. In our case, the selected observables are themselves the variables of interest, not simply controls.

The explanatory power of this small set of observables—air conditioner penetration, electric heat penetration and residential share of demand—is strong, showing an R-squared of 77-85% depending on specification. Despite only 10 observations (one for each province) the adjusted R-squared remains relatively strong despite only three observable variables used to explain the provincial heterogeneity. The full goodness-of-fit regression results and added-variable residual plots are shown in the Appendix.

Step 3: Modelling air conditioner adoption

The last part of obtaining the long run response involves estimating $\frac{\partial D}{\partial T}$—the change in durables in response to changing temperature. We focus solely on the effect of higher temperatures on air conditioner penetration; we do not estimate temperature driven changes to electric heating penetration or residential share of electricity since we consider these variables to be largely driven by policy and economic factors rather than temperature.[19]

We estimate a model of air conditioner adoption using household level microdata from Statistics Canada's Household and the Environment Survey (HES) on air conditioner penetration, in a similar approach as Davis and Gertler (2015). Specifically, we use cross-sectional variation in temperature to identify the effect of climate variables on air conditioner penetration, while conditioning on other variables. We use several waves of the HES public use microdata files, extracting data on air conditioner ownership, income, household demographic variables, and household size.[20] We obtain the Census Subdivision (city) for each household in the survey, and use historical weather data from Environment Canada to obtain measures of the climate in each Census Subdivision. We estimate:

$$AC_{ict} = \delta_0 + \delta_1 \tilde{T}_c + H_i \theta + \psi_t + \nu_{ict} \tag{7}$$

where AC_{ict} is a binary variable that takes on a value of one if the household owns an air conditioner and zero otherwise, H_i is a vector of observed household covariates,[21] and ψ_t is a time fixed effect to account for changes in household air conditioner penetration over time that are common across regions. The variable $\tilde{T}_c$ captures the exposure of city c to hot temperatures. We measure the climate of cities using several different variables: (1) the highest monthly mean temperature observed between 2000 and 2005, (2) the highest daily maximum temperature observed between 2000 and 2005, (3) the mean temperature in July and August observed between 2000 and 2005, and (4) the average of the maximum daily July and August temperature observed between 2000 and 2005.[22] We estimate the model using both linear probability, with and without sampling weights provided by Statistics Canada, as well as probit models. We also estimate a model that includes province fixed effects, such that the identification of the effect of climate on air conditioner penetration is identified

19. We include, however, the mechanical effect that increased air conditioner penetration would have on residential share, all else equal, and modify residential share accordingly. Specifically, the modified residential share is equal to the old residential share * $(1 - AC_{old} * Avg\_AC\_per\_HH) / (1 - AC_{new} * Avg\_AC\_per\_HH)$.

20. We use the 2006, 2007, 2009, 2011, and 2013 waves of the HES.

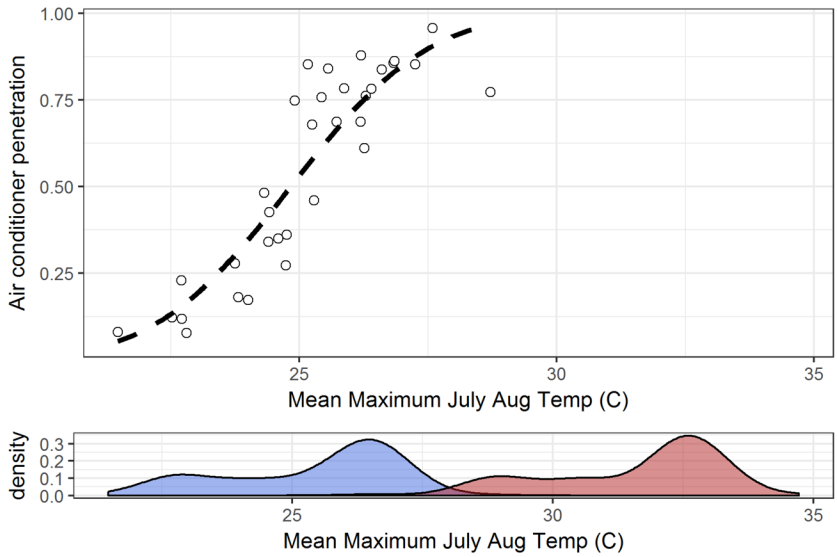
21. Household covariates include a binary variable that indicates whether the house is owned or rented, a categorical variable that captures the level of education, a variable that captures the dwelling type (apartment or home) of the dwelling, a variable that captures the number of people living in the household, indicator variables for the presence of individuals aged 0-17, 18-64, and 65-plus in the household, and a categorical variable capturing household income.

22. We focus on the years 2000 to 2005 because we were able to assemble a complete set of weather observations over this period for all cities in our sample, without any entry or exit of weather monitoring stations.

on within-province variation in climate. This helps to purge the data of any province-specific factors (e.g., regulations, norms) that drive air conditioner penetration.

We highlight the empirical relationship between residential air conditioner penetration and climate in Figure 5. The top panel summarizes air conditioner penetration in each of the 33 cities contained in the Households and the Environment Public Use file, as well as the average daily maximum July-August temperature observed between 2000 and 2005 in each city. There is a clear positive relationship between these two variables, which is summarized by a probit fit without any covariates (regression results for probit and OLS estimates including covariates are listed in the Appendix). The bottom panel shows the current exposure to hot summer weather weighted by population, as well as the projected exposure to different climates at the end-of-century under an RCP8.5 scenario. The cross-sectional relationship between current climate and air conditioner penetration suggests that future warming will induce substantial increases in air conditioner penetration.

Figure 5: Air conditioner penetration as a function of climate



Notes: Top panel shows air conditioner penetration for a cross-section of individual census metropolitan areas (weighted average of the 2006-2013 HES waves) plotted against a measure of hot summer temperature (average maximum July–August temperature for 2000-2005). Bottom panel shows the distribution of mean maximum July-August temperatures historically (blue) and projected end-century in the RCP8.5 scenario (red).

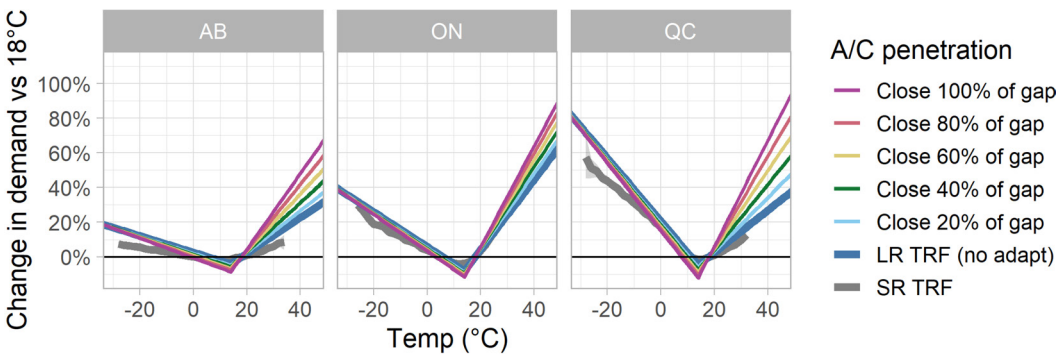
Motivated by the relationship in Figure 5, we estimate the relationship between climate and air conditioner penetration using the household-level data as described above (results shown in the Appendix). We find that for each 1 degree Celcius increase in the maximum daily July-August temperature, the penetration of residential air conditioners increases by 16.8 percentage points. Using alternative definition for the hot temperature variable $\tilde{T}$ also delivers positive and highly statistically significant relationship between the prevalence of warm weather and the penetration of air conditioners. We include several robustness checks as well as a probit model specification in the Appendix. We use our probit air conditioner adoption model to estimate projected air conditioner ownership under different future climates. Under the RCP8.5 scenario, we estimate an air conditioner penetration that increases nation-wide from about 55% today to above 99% in 2100.

Putting it all together: Long run temperature response functions

The above method of estimating temperature response response functions based on observable characteristics allows us to run scenarios of future adaptation, whereby higher levels of air conditioner penetration increase temperature sensitivity to warmer temperatures. This increased sensitivity is reflected in steepening right-side slopes of the temperature response functions. Figure 6 plots how temperature response functions for AB, ON and QC change as air conditioner penetrations increase from historical levels towards 100%.

Our multi-part method to incorporate adaptation extends the work by Davis and Gertler (2015) who estimate $\frac{\partial D}{\partial T}$ for air conditioners in Mexico. In that case, future air conditioner penetration is estimated based on projected temperature and income changes, however, the effect of changing durables on demand is not estimated. Instead, Davis and Gertler (2015) apply temperature response functions from a region with currently high air conditioner penetrations, similar to their future projections. By modelling temperature response functions as functions of the observable characteristics themselves rather than having to rely on using a comparable region's temperature response, our method allows for greater scenario analysis flexibility and the ability to retain unobservable characteristics of each province.

Figure 6: Temperature sensitivity at various levels of air conditioner penetration



Notes: The thick grey lines represent temperature response functions estimated separately by province. Thick blue lines represent temperature response functions estimated conditional on observables, rather than province-specific, evaluated at historic average levels. Their overlap highlights the strong explanatory power of these 3 key observables. The remaining lines represent counterfactual temperature response functions at increasing levels of air conditioner penetration, whereby the gap closes between historical and full (100%) penetration.

5. PROJECTING FUTURE ELECTRICITY CONSUMPTION

Combining our estimated temperature response functions with climate model temperature projections, we project temperature-driven changes to future electricity consumption.[23] We present results both without and with adaptation in the form of increased air conditioner penetration.[24]

23. To project demand based on out-of-sample temperature projections (i.e. higher than previously observed), we include a linear trend term above 18°C in the specifications using temperature bins. We choose 18° by visual inspection based on where a clear linear trend is established, slightly to the right of the low demand nadir of 14°. Robustness checks to alternative thresholds, and even the inclusion of a multi-point spline, do not alter the demand projections significantly. The temperature response functions conditioned on cooling degrees do not require this modification.

24. The main results are for end-century under the RCP8.5 emissions scenario. Projections using alternative RCP scenarios and for mid-century are listed in the Appendix.

Previous literature estimating the effect of climate change on energy demand has focussed on projections of annual or seasonal demand (De Cian and Wing, 2017; Davis and Gertler, 2015). Given the instantaneous nature of electricity, and relative lack of storability, considering peak demand is also important. Accordingly, Auffhammer et al. (2017) and Wenz et al. (2017) consider the implications of climate change on both aggregate and peak electricity demand. We go one step further, exploring how the intraday shape of electricity consumption will change in the future. Intraday shape is important due to, again, electricity's relative lack of storability. A steeper "ramp", i.e. the change in consumption from the lowest demand hour to the highest within a day, imposes higher system costs, requiring more flexibility to manage.

5.1 Average demand

Figure 7 shows projected changes to annual and seasonal electricity consumption in the RCP8.5 scenario for the end of century. For the country as a whole, the estimated change in annual electricity consumption is small and stands in contrast to previous studies in warmer countries showing large increases. Using the short run temperature response, annual consumption is projected to fall by 1.8%. When adaptation is incorporated, whereby air conditioner penetration reaches nearly 100% nationally, annual Canadian electricity consumption still only increases by 3.9%.[25] This result speaks to the beneficial effect (from an energy use perspective) of a warmer winter reducing heating demand and nearly offsetting the entirety of the incremental summer cooling demand.

In the summer months, average demand increases across all provinces since temperature in these months is mostly located on the upward sloping portion of the temperature response functions where higher temperature increases electricity consumption. The effect is largest in Ontario where the sensitivity to cooling degrees is steepest. British Columbia, despite its flatter sensitivity to cooling degrees, also shows a significant increase. This is due to its warmer climate, meaning fewer hours are located in the domain of heating demand, where higher temperature decreases consumption.

In the winter months, we project average demand to fall across Canada. The effect is largest in Quebec, New Brunswick and Newfoundland & Labrador, the three provinces where electric heating is the dominant heating method and correspondingly steepest left-side slope of their temperature response functions.

5.2 Peak demand

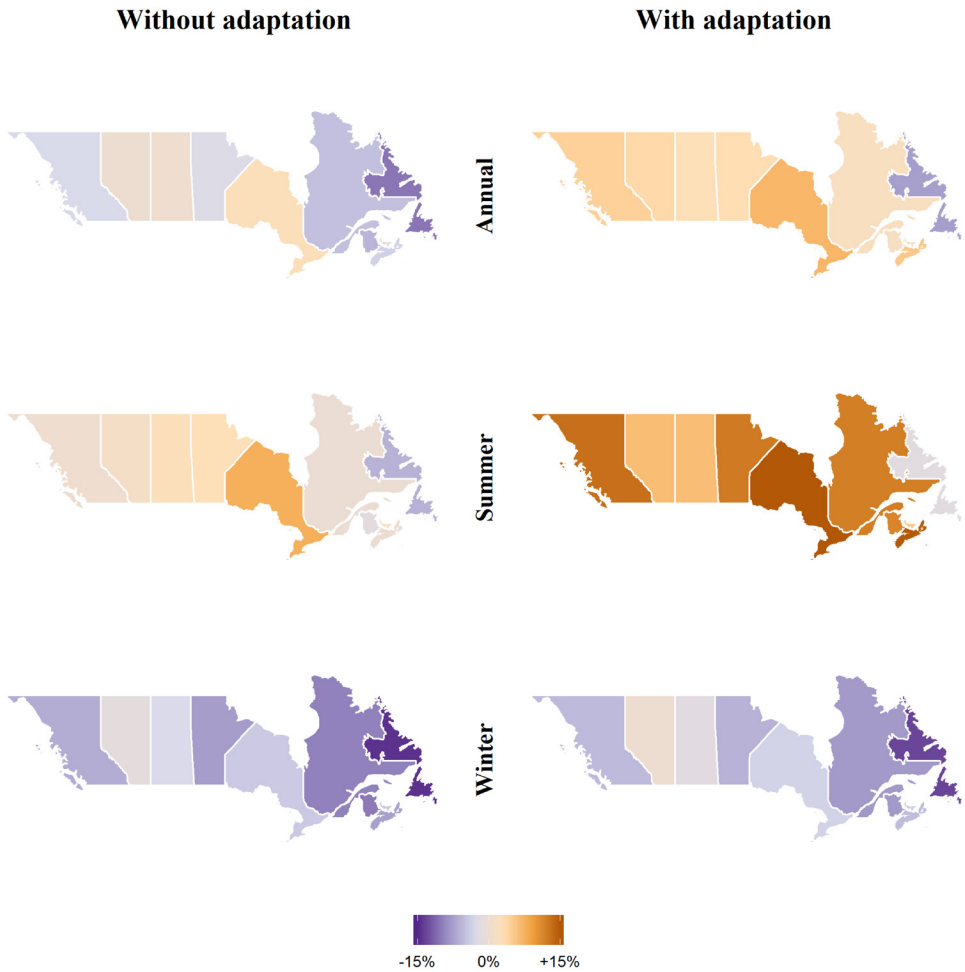
The importance of peak demand relates to the generation capacity requirements of the electricity system. Lack of storability means that the system must have sufficient capacity (or capability to generate) during the highest demand periods. The impact on the electricity system therefore depends not simply on how much demand increases, but when. An increase during non-peak period has no effect on peak capacity requirements.

Most provinces in Canada are currently winter peaking. As such, rising temperature reduces peak capacity demands in most provinces using only short run responses (Figure 8, left panel). Peak demand increases, however, for the two summer-peaking provinces of Saskatchewan and Ontario, and slightly for Alberta, which switches to summer-peaking even without including the effect of increased air conditioning.

When we incorporate adaptation in the form of greater air conditioner penetration, the increase in summer-peaking provinces is amplified (Figure 8, right panel). Ontario's peak demand

25. For full results see Tables 3 and 4 in the Appendix.

Figure 7: Annual and seasonal demand change (RCP8.5, End-century)



Notes: Maps show the percentage change in annual and seasonal total electricity consumption by province at end-century under the high emission (RCP8.5) scenario. The left column uses the short run temperature response. The right column incorporates adaptation from increased air conditioner adoption to provide a long run response.

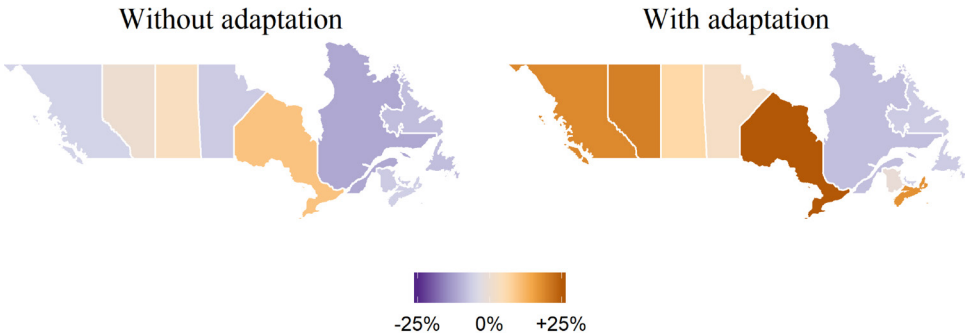
increases by 38% (vs 10% using only short run responsiveness) implying roughly 10GW of new generating capacity will be needed in that province solely due to temperature.[26] Furthermore, many provinces see their seasonal peak flipping from winter to summer leading to peak demand increases. BC, AB, MB and NS all go from winter peaking to summer peaking electricity systems (Figure 9). Alberta, in particular, sees a large increase (19.6%) in peak demand due to a significant increase in air conditioner adoption and relatively high hourly temperatures in the peak of summer.

5.3 Intraday demand

Having considered changes to average and peak demand, we investigate the effect of rising temperatures on the intraday shape of electricity consumption. Figure 10 shows the change in the intraday consumption profile for the province of Ontario. This figure shows average hourly consumption over the summer period for each hour of the day. Consumption increases across all hours, but

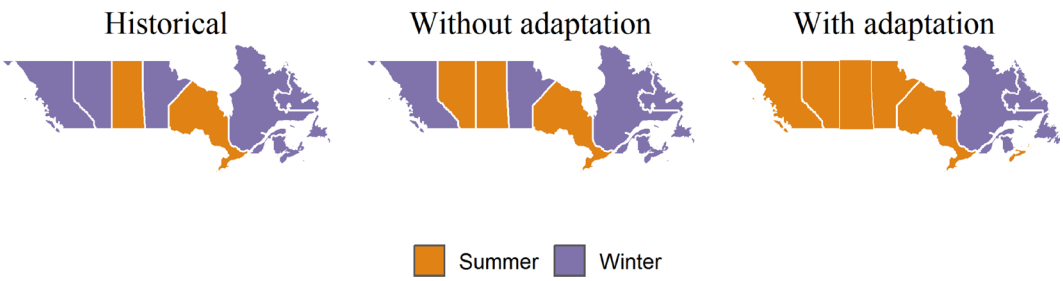
26. For full results see Tables A4 and A5 in the Appendix.

Figure 8: Peak demand change (RCP8.5, End-century)



Notes: Maps show the percentage change in peak hour demand by province at end-century under the high emission (RCP8.5) scenario. The left column uses the short run temperature response. The right column incorporates adaptation from increased air conditioner adoption to provide a long run response.

Figure 9: Seasonal peak hour demand (RCP8.5, End-century)



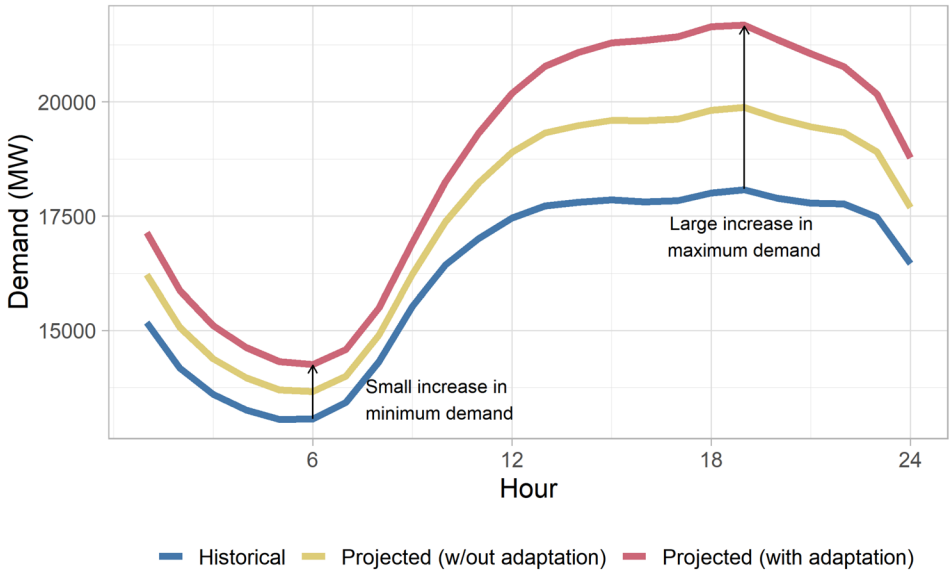
Notes: Maps show the period during which the annual hourly peak occurs, by province at end-century under the high emission (RCP8.5) scenario. The first column shows the historical peak, with only two provinces (SK and ON) having summer peaks. The second column uses the short run temperature response. The third column incorporates adaptation from increased air conditioner adoption to provide a long run response.

the increase is clearly larger in the peak demand hours of the afternoon as compared to the morning hours. As a result, there is a significant increase in the intraday "ramp", i.e. the difference between the minimum and maximum demand within a day. This finding is more pronounced at higher levels of air conditioner penetration. The max-min difference for an average summer day in Ontario rises from roughly 5,000MW (historical) to 6,200MW (without adaptation) and finally to 7,400MW (with increased air conditioning).

Figure 11 plots the change in the diurnal range of demand for all provinces for each month of the year. Unlike the effect on average or peak demand, the effect on intraday ramp requirements is consistent across all provinces, with all provinces projected to see a substantial increase in diurnal range of demand in the summer months. For some provinces, the diurnal range increases by as much as 100%, i.e. a doubling. In winter, most provinces see a slight decrease with the intraday shape getting flatter. Without adaptation, the largest increases are in the shoulder months, namely May and October.

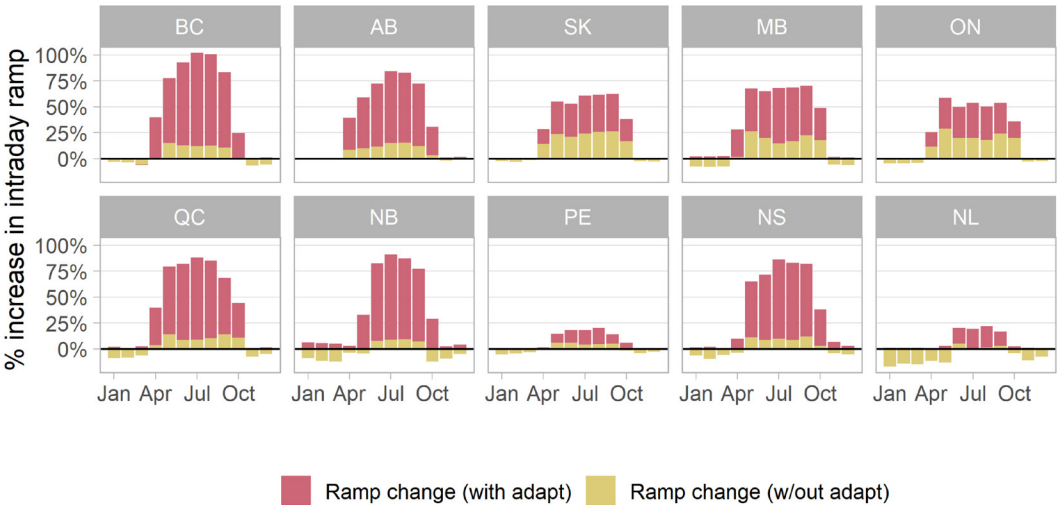
This challenge of an increased ramping requirement echoes a similar need arising from the supply side due to an increased share of renewable energy, notably solar. In California, for example, a large and growing share of solar generation has reduced net load during the sunny middle-of-the-day hours while increasing the ramping requirement into the evening peak as solar wanes (CAISO, 2019). Our finding, coming from the demand side, highlights the potential for higher temperatures to increase this flexibility challenge.

Figure 10: Intraday shape of summer demand in Ontario, historical and projected (End-century, RCP8.5)



Notes: Historical and projected end-of-century intraday demand using RCP8.5 temperature projections and authors' estimated temperature response functions, with and without adaptation.

Figure 11: Percentage change in min-to-max intraday demand (End-century, RCP8.5)



Notes: Plots show the percentage change in minimum to maximum intraday demand as a result of rising temperatures across all Canadian provinces, with and without adaptation. Forecast period 2081-2100. RCP8.5 (high emissions) scenario.

6. CONCLUSION

This paper finds that for a colder country, such as Canada, rising temperature due to climate change is unlikely to result in large increases in overall electricity use. In the absence of adaptation, we find a small (1.8%) decrease in national electricity consumption in the high emissions (RCP8.5) scenario. Incorporating an increase in air conditioner adoption as a result of higher temperatures,

annual demand increases by 3.9%. Given Canada's colder climate, it is perhaps not surprising to see a much smaller effect as compared to other results in the literature that have focussed on warmer climates.

In terms of peak demand, the results are mixed across the provinces. Summer-peaking provinces see peak demand increases, both with and without more air conditioning, whereas provinces with significant electric heating see peak demand decline even at higher air conditioner levels. In most provinces, however, the annual peak hourly demand shifts from winter to summer. It is ambitious to estimate costs as a result of end-of-century demand changes, but as a rough estimate we can use current values for peaking capacity. At $1,000 per kilowatt, the aggregate increase in peak demand across Canada would require an investment of roughly $13 billion (USD).

An important aspect of projected consumption changes due to higher temperature is the effect on the shape of intraday demand. We find that "ramping" requirements—the ability to swing from low to high demand within a day—are expected to increase substantially across all provinces. This finding, coming from the demand side, adds to the growing need for more flexibility on electricity grids coming from changes on the supply side of the market, where the cost of variable renewable energy is falling and their share is growing.[27] The so-called "duck curve" in California summarizes this issue: more solar generation in the middle of the day leads to a steep ramp in net demand in the afternoon (CAISO, 2016). In short, we find higher temperatures have the potential to "stretch the duck". While we do not place a cost estimate on this effect, it speaks to the increasing value of flexibility—be it in the form of storage, peaking capacity or load-shifting—to better manage an increasing variable supply and wider-ranging demand on future electricity systems.

In sum, our paper adds to the growing literature quantifying the effects of higher temperatures arising from climate change on important economic variables, in this case electricity consumption. We provide a method to incorporate adaptation by estimating temperature response functions as functions of key temperature-sensitive observables coupled with a model of air conditioner adoption at the household level. Our finding regarding intraday demand emphasizes the value and importance of capacity and flexibility, as well as the importance of understanding more than average effects when it comes to difficult-to-store electricity.

REFERENCES

Akpinar-Ferrand, E. and A. Singh (2010). "Modeling increased demand of energy for air conditioners and consequent CO2 emissions to minimize health risks due to climate change in India." *Environmental Science and Policy* 13(8): 702–712. ISSN 1462-9011. https://doi.org/10.1016/j.envsci.2010.09.009.

Altonji, J., T. Elder, and C. Taber (2005). "Selection on observed and unobserved variables: Assessing the effectiveness of Catholic schools." *Journal of Political Economy* 113(1): 151–184. https://doi.org/10.1086/426036.

Auffhammer, M. (2018). "Climate Adaptive Response Estimation: Short And Long Run Impacts Of Climate Change On Residential Electricity and Natural Gas Consumption Using Big Data." National Bureau of Economic Research Working Paper 24397. https://doi.org/10.3386/w24397.

Auffhammer, M. and A. Aroonruengsawat (2011). "Simulating the impacts of climate change, prices and population on California's residential electricity consumption." *Climatic change* 109(1): 191–210. https://doi.org/10.1007/s10584-011-0299-y.

27. On the demand side, recent analysis from the California Energy Commission (CEC, 2018) has shown that electric vehicle charging is expected to be concentrated when drivers return home from work, exacerbating the problem of meeting net demand as solar fades in the afternoon. Our finding highlights another potential issue: higher temperatures increasing ramping requirements, exacerbating both the EV charging and duck curve issues.

Auffhammer, M., P. Baylis, and C.H. Hausman (2017). "Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States." *Proceedings of the National Academy of Sciences* 114(8): 1886–1891. https://doi.org/10.1073/pnas. 1613193114.

Barreca, A., K. Clay, O. Deschenes, M. Greenstone, and J.S. Shapiro (2016). "Adapting to climate change: The remarkable decline in the US temperature-mortality relationship over the twentieth century." *Journal of Political Economy* 124(1): 105–159. https://doi.org/10.1086/684582.

Burke, M. and K. Emerick (2016). "Adaptation to Climate Change: Evidence from US Agriculture." *American Economic Journal: Economic Policy* 8(3): 106–40. https://doi.org/10.1257/pol.20130025.

Burke, M., S.M. Hsiang, and E. Miguel (2015). "Global non-linear effect of temperature on economic production." *Nature* 527(7577): 235–239. https://doi.org/10.1038/nature15725.

CAISO (2016). "What the duck curve tells us about managing a green grid." Available at https: //www.caiso.com/documents/flexibleresourceshelprenewables_fastfacts.pdf.

CAISO (2019). "Monthly renewables performance report." Available at http://www.caiso.com/ Documents/MonthlyRenewablesPerformanceReport-May2019.html.

CEC (2018). "Staff Report -California Plug-In Electric Vehicle Infrastructure Projections." Technical report California Energy Commission.

Davis, L.W. and P.J. Gertler (2015). "Contribution of air conditioning adoption to future energy use under global warming." *Proceedings of the National Academy of Sciences* 112(19): 5962–5967. https://doi.org/10.1073/pnas.1423558112.

De Cian, E. and I.S. Wing (2017). "Global Energy Consumption in a Warming Climate." *Environmental and Resource Economics* ISSN 1573-1502. https://doi.org/10.1007/s10640-017-0198-4.

Dell, M., B.F. Jones, and B.A. Olken (2012). "Temperature shocks and economic growth: Evidence from the last half century." *American Economic Journal: Macroeconomics* 4(3): 66–95. https://doi.org/10.1257/mac.4.3.66.

Graff Zivin, J., S. Hsiang, and M. Neidell (2018). "Temperature and Human Capital in the Short and Long Run." *Journal of the Association of Environmental and Resource Economists* 5(1): 77–105. https://doi.org/10.1086/694177.

Heutel, G., N.H. Miller, and D. Molitor (2017). "Adaptation and the Mortality Effects of Temperature Across US Climate Regions." National Bureau of Economic Research Working Paper 23271. https://doi.org/10.3386/w23271.

Isaac, M. and D.P. van Vuuren (2009). "Modeling global residential sector energy demand for heating and air conditioning in the context of climate change." *Energy Policy* 37(2): 507–521. ISSN 0301-4215. https://doi.org/10.1016/j.enpol.2008.09.051.

Kahn, M.E. (2016). "The climate change adaptation literature." *Review of Environmental Economics and Policy* 10(1): 166–178. https://doi.org/10.1093/reep/rev023.

Oster, E. (2017). "Unobservable selection and coefficient stability: Theory and evidence." *Journal of Business and Economic Statistics* : 1–18.

Rivers, N. (2016). "Does daylight savings time save energy? Evidence from Ontario." *Environmental and Resource Economics* : 1–27. https://doi.org/10.2139/ssrn.2772048.

Smith, A.C. (2016). "Spring forward at your own risk: Daylight saving time and fatal vehicle crashes." *American Economic Journal: Applied Economics* 8(2): 65–91. https://doi.org/10.1257/app.20140100.

Van Vuuren, D.P., J. Edmonds, M. Kainuma, K. Riahi, A. Thomson, K. Hibbard, G. C. Hurtt, T. Kram, V. Krey, J.-F. Lamarque, et al. (2011). "The representative concentration pathways: an overview." *Climatic change* 109(1-2): 5. https://doi.org/10.1007/s10584-011-0148-z.

Wenz, L., A. Levermann, and M. Auffhammer (2017). "North–south polarization of European electricity consumption under future warming." *Proceedings of the National Academy of Sciences* 114(38): E7910–E7918. https://doi.org/10.1073/pnas.1704339114.

APPENDIX A

Summary Statistics

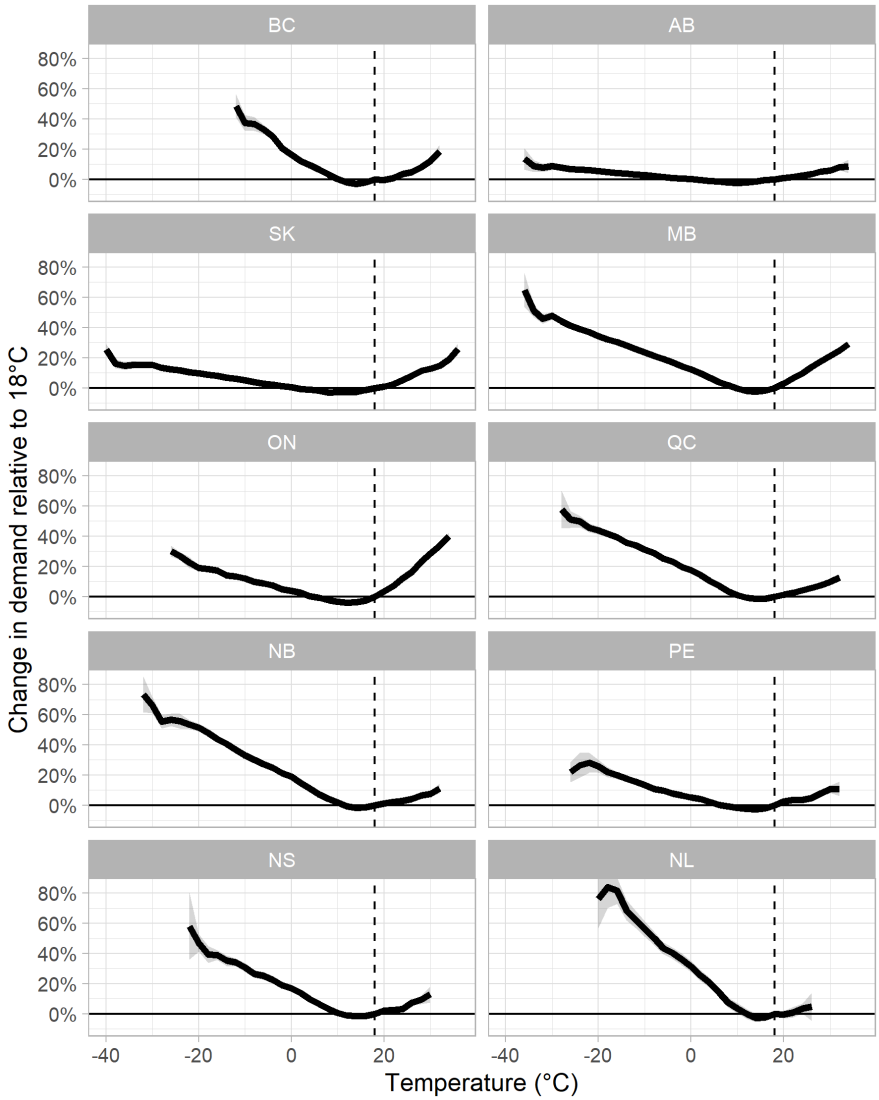
Table A1: Summary Statistics

	Average Demand (aMW)		Peak Demand (MW)		Mean Temp (°C)	
	Summer	*Winter*	*Summer*	*Winter*	*Summer*	*Winter*
BC	6254	7687	9061	11039	13.9	4.0
AB	7711	8296	10520	11229	11.1	–5.9
SK	2297	2623	4654	3682	11.7	–9.6
MB	2138	2948	3464	4366	13.3	–9.8
ON	16211	17440	27005	24979	15.2	–2.0
QC	18014	25203	29411	39266	14.3	–4.7
NB	1385	1966	2543	3326	13.1	–3.7
PE	135	150	208	265	12.8	–2.6
NS	1198	1510	1806	2192	13.1	–0.5
NL	614	936	1271	1523	10.2	–2.1

Notes: Summary statistics are for 2001–2015 (2007–2015 for PE, NS, NL and QC). Summer refers to April–October, winter refers to November–March. An average MW, or "aMW", is the total MWh of seasonal demand divided by the number of hours in the season. Temperature data are population-weighted averages of stations within each province.

Temperature response functions

Figure A1: Temperature response functions for each province



Notes: Temperature response functions estimate the percentage change in demand relative to 18°C. Shaded areas represent 95% confidence intervals using Newey-West HAC standard errors.

Projected changes to mean, min and max temperature

Figure A2: Projected temperature changes under RCP 8.5

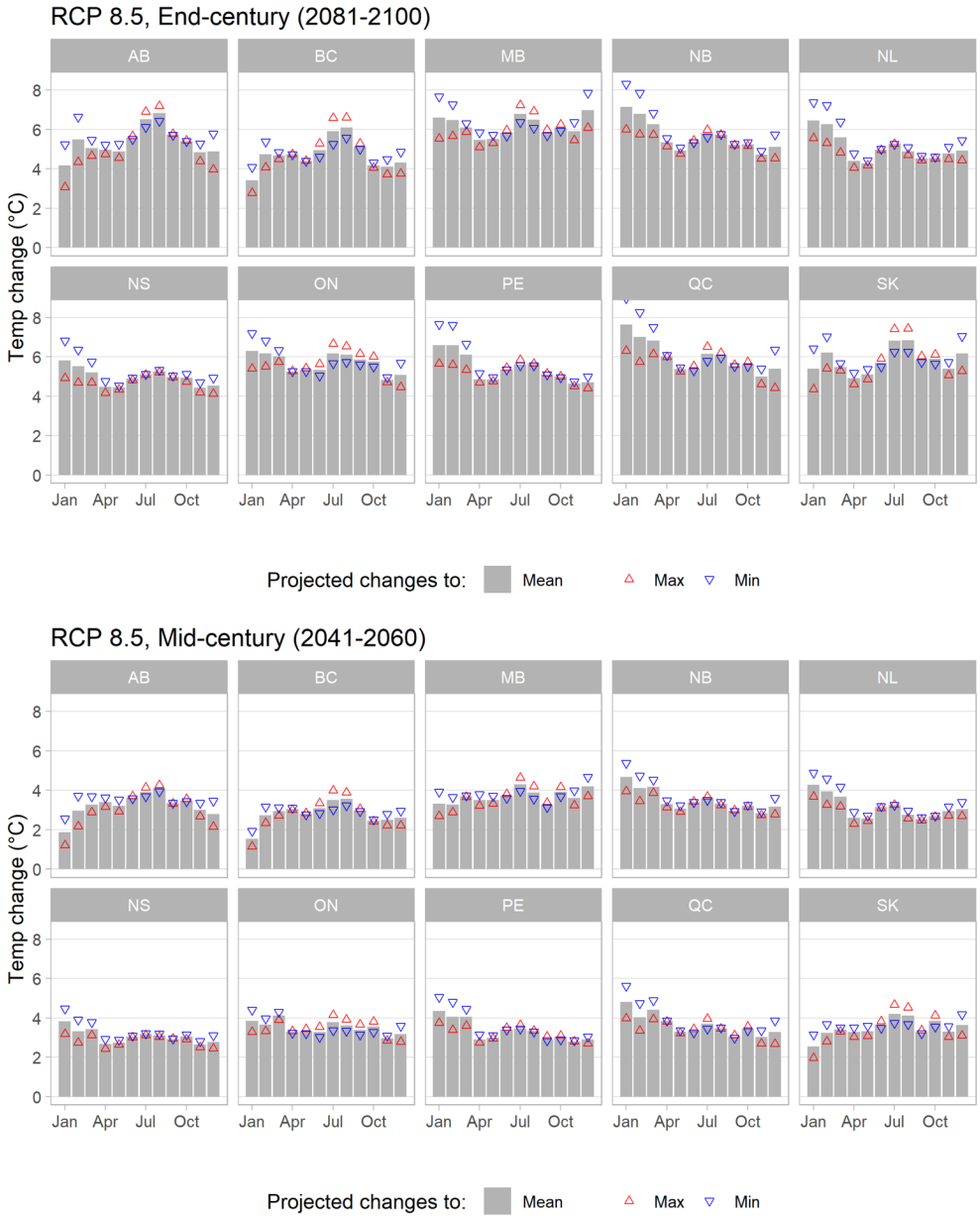
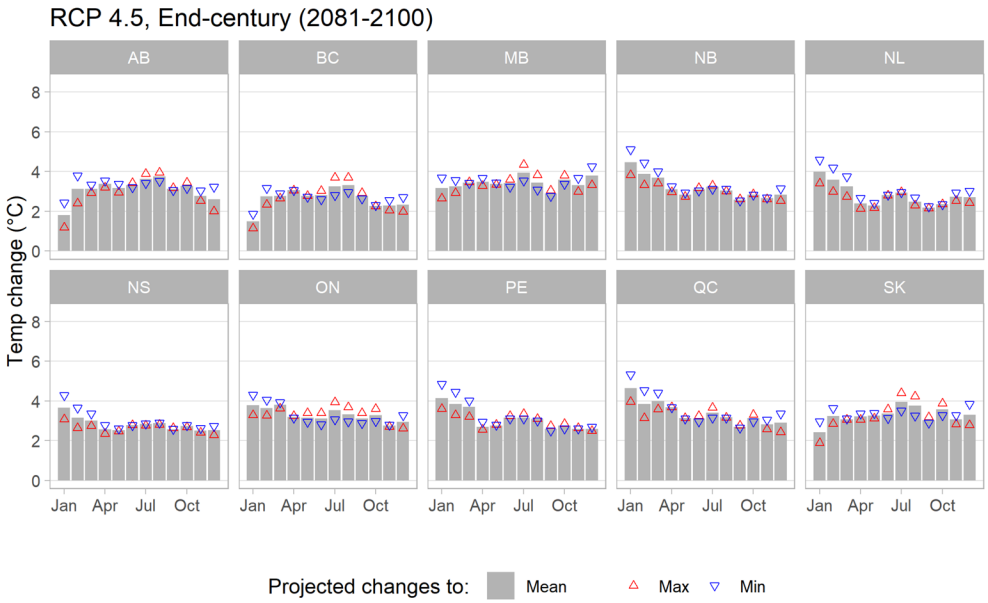
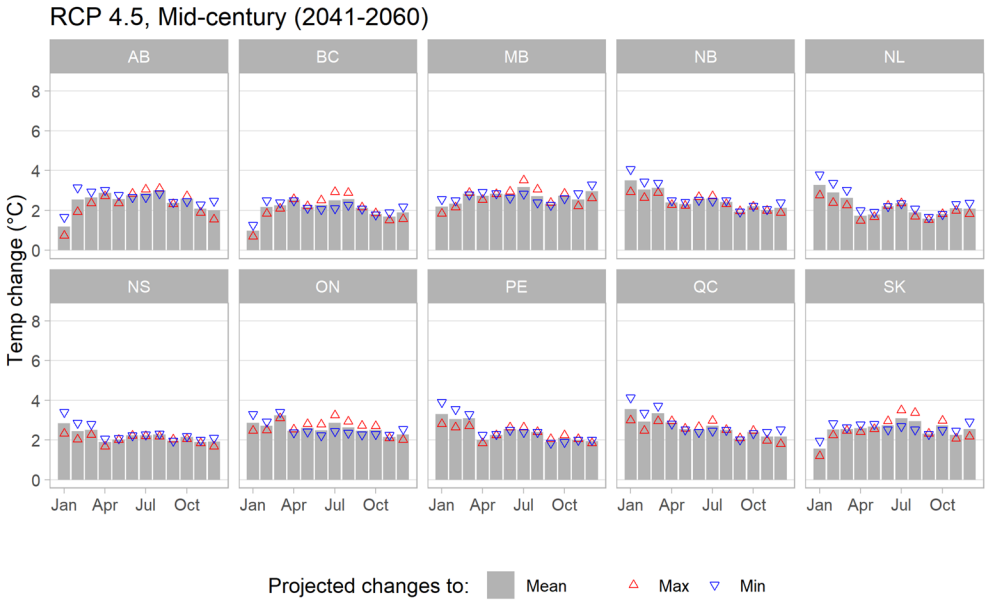


Figure A3: Projected temperature changes under RCP 4.5





Change in average demand tables

Table A2: Change in average demand, high emission scenario (RCP8.5)

	End-of-century projection					
	Without Adaptation (Δ%)			*With Adaptation (Δ%)*		
	Summer	Winter	Annual	Summer	Winter	Annual
BC	0.3	–6.5	–2.9	13.1	–5.5	4.4
AB	1.2	–1.3	0.1	6.5	0.0	3.7
SK	2.5	–2.7	0.2	6.4	–1.7	2.7
MB	2.9	–7.8	–2.4	12.2	–6.1	3.2
ON	7.7	–4.3	2.5	15.1	–3.5	7.0
QC	–0.3	–9.7	–5.0	11.9	–8.1	1.9
NB	–1.5	–10.1	–5.9	11.4	–8.0	1.6
PE	1.7	–4.5	–1.1	5.8	–3.7	1.6
NS	–0.1	–7.5	–3.6	14.8	–5.3	5.3
NL	–6.1	–14.4	–10.4	–1.6	–13.2	–7.6
CAN	**2.5**	**–6.6**	**–1.8**	**11.9**	**–5.3**	**3.9**
	Mid-century projection					
	Without Adaptation (Δ%)			*With Adaptation (Δ%)*		
	Summer	Winter	Annual	Summer	Winter	Annual
BC	–0.3	–3.8	–1.9	6.8	–2.9	2.3
AB	0.6	–0.7	0.0	4.1	0.6	2.6
SK	1.2	–1.5	0.0	4.1	–0.5	2.1
MB	1.3	–4.4	–1.5	8.3	–2.5	3.0
ON	4.2	–2.8	1.2	9.8	–2.0	4.7
QC	–0.6	–5.9	–3.3	8.4	–4.1	2.2
NB	–1.3	–6.4	–3.9	7.5	–4.3	1.5
PE	0.8	–2.9	–0.8	3.7	–2.1	1.1
NS	–0.4	–4.7	–2.4	9.8	–2.5	4.0
NL	–4.0	–9.0	–6.6	–1.3	–7.9	–4.7
CAN	**1.1**	**–4.0**	**–1.3**	**7.8**	**–2.7**	**2.9**

Notes: Summer refers to April–October, winter refers to November–March.

Table A3: Change in average demand, medium emission scenario (RCP4.5)

	End-of-century projection					
	Without Adaptation (Δ%)			*With Adaptation (Δ%)*		
	Summer	Winter	Annual	Summer	Winter	Annual
BC	–0.3	–3.6	–1.9	8.6	–2.3	3.5
AB	0.5	–0.7	0.0	4.3	0.8	2.8
SK	1.1	–1.4	0.0	4.0	–0.3	2.1
MB	1.1	–4.1	–1.5	8.1	–2.1	3.0
ON	3.9	–2.6	1.0	9.5	–1.8	4.6
QC	–0.6	–5.5	–3.1	8.4	–3.6	2.4
NB	–1.3	–5.9	–3.6	8.0	–3.5	2.2
PE	0.7	–2.7	–0.8	3.8	–1.9	1.3
NS	–0.4	–4.4	–2.3	10.3	–1.9	4.5
NL	–3.6	–8.2	–6.0	–0.6	–6.8	–3.8
CAN	**1.0**	**–3.8**	**–1.3**	**7.9**	**–2.3**	**3.1**
	Mid-century projection					
	Without Adaptation (Δ%)			*With Adaptation (Δ%)*		
	Summer	Winter	Annual	Summer	Winter	Annual
BC	–0.4	–2.8	–1.5	5.7	–1.7	2.2
AB	0.4	–0.6	0.0	3.5	0.9	2.4
SK	0.8	–1.1	0.0	3.4	0.0	1.9
MB	0.8	–3.1	–1.1	7.1	–1.1	3.0
ON	3.0	–2.1	0.8	8.1	–1.3	4.0
QC	–0.6	–4.3	–2.4	7.4	–2.3	2.6
NB	–1.1	–4.7	–2.9	6.6	–2.4	2.1
PE	0.5	–2.2	–0.7	3.0	–1.3	1.1
NS	–0.4	–3.4	–1.8	8.5	–1.2	3.9
NL	–2.8	–6.5	–4.7	–0.5	–5.3	–3.0
CAN	**0.7**	**–2.9**	**–1.0**	**6.6**	**–1.5**	**2.8**

Notes: Summer refers to April–October, winter refers to November–March.

Change in peak demand tables

Table A4: Change in peak hour demand, high emission scenario (RCP8.5)

	End-of-century projection									
	Historical		*Without Adaptation*				*With Adaptation*			
	Peak	MW	Peak	MW	ΔMW	Δ%	Peak	MW	ΔMW	Δ%
BC	Winter	11039	Winter	10404	–635	–5.8	Summer	13072	2033	18.4
AB	Winter	11229	Summer	11223	–6	–0.1	Summer	13432	2203	19.6
SK	Summer	4654	Summer	4813	159	3.4	Summer	4941	288	6.2
MB	Winter	4366	Winter	4066	–300	–6.9	Summer	4463	97	2.2
ON	Summer	27005	Summer	29623	2618	9.7	Summer	37365	10360	38.4
QC	Winter	39266	Winter	34732	–4534	–11.5	Winter	35944	–3322	–8.5
NB	Winter	3326	Winter	3094	–232	–7.0	Winter	3293	–33	–1.0
PE	Winter	265	Winter	247	–18	–7.0	Winter	248	–17	–6.3
NS	Winter	2192	Winter	2054	–138	–6.3	Summer	2569	377	17.2
NL	Winter	1523	Winter	1392	–131	–8.6	Winter	1420	–103	–6.7
	Mid-century projection									
	Historical		*Without Adaptation*				*With Adaptation*			
	Peak	MW	Peak	MW	ΔMW	Δ%	Peak	MW	ΔMW	Δ%
BC	Winter	11039	Winter	10703	–336	–3.0	Summer	11423	384	3.5
AB	Winter	11229	Winter	11162	–67	–0.6	Summer	12802	1573	14.0
SK	Summer	4654	Summer	4725	71	1.5	Summer	4783	129	2.8
MB	Winter	4366	Winter	4221	–145	–3.3	Winter	4321	–45	–1.0
ON	Summer	27005	Summer	28573	1568	5.8	Summer	35321	8316	30.8
QC	Winter	39266	Winter	36430	–2836	–7.2	Winter	37660	–1606	–4.1
NB	Winter	3326	Winter	3308	–18	–0.5	Winter	3507	181	5.5
PE	Winter	265	Winter	251	–14	–5.4	Winter	252	–13	–4.7
NS	Winter	2192	Winter	2112	–80	–3.6	Summer	2396	204	9.3
NL	Winter	1523	Winter	1459	–64	–4.2	Winter	1486	–37	–2.5

Notes: Timing of seasonal peak listed in "Peak" columns. Summer refers to Apr–Oct. Winter refers to Nov–Mar.

Table A5: Change in peak hour demand, medium emission scenario (RCP4.5)

	End-of-century projection									
	Historical		*Without Adaptation*				With Adaptation			
	Peak	MW	Peak	MW	ΔMW	Δ%	Peak	MW	ΔMW	Δ%
BC	Winter	11039	Winter	10757	–282	–2.6	Summer	12389	1350	12.2
AB	Winter	11229	Winter	11162	–67	–0.6	Summer	12980	1751	15.6
SK	Summer	4654	Summer	4708	55	1.2	Summer	4758	105	2.2
MB	Winter	4366	Winter	4221	–145	–3.3	Winter	4327	–39	–0.9
ON	Summer	27005	Summer	28483	1478	5.5	Summer	35287	8282	30.7
QC	Winter	39266	Winter	36430	–2836	–7.2	Winter	37728	–1538	–3.9
NB	Winter	3326	Winter	3308	–18	–0.5	Winter	3525	199	6.0
PE	Winter	265	Winter	251	–14	–5.4	Winter	253	–12	–4.6
NS	Winter	2192	Winter	2147	–45	–2.1	Summer	2458	266	12.1
NL	Winter	1523	Winter	1459	–64	–4.2	Winter	1491	–32	–2.1

	Mid-century projection									
	Historical		*Without Adaptation*				*With Adaptation*			
	Peak	MW	Peak	MW	ΔMW	Δ%	Peak	MW	ΔMW	Δ%
BC	Winter	11039	Winter	10918	–121	–1.1	Summer	11221	182	1.6
AB	Winter	11229	Winter	11162	–67	–0.6	Summer	12652	1423	12.7
SK	Summer	4654	Summer	4676	23	0.5	Summer	4705	52	1.1
MB	Winter	4366	Winter	4280	–86	–2.0	Winter	4373	7	0.2
ON	Summer	27005	Summer	28177	1172	4.3	Summer	34604	7599	28.1
QC	Winter	39266	Winter	36969	–2297	–5.9	Winter	38444	–822	–2.1
NB	Winter	3326	Winter	3308	–18	–0.5	Winter	3514	188	5.7
PE	Winter	265	Winter	256	–9	–3.4	Winter	258	–7	–2.7
NS	Winter	2192	Winter	2147	–45	–2.1	Summer	2356	164	7.5
NL	Winter	1523	Winter	1459	–64	–4.2	Winter	1487	–36	–2.4

Notes: Timing of seasonal peak listed in "Peak" columns. Summer refers to Apr–Oct. Winter refers to Nov–Mar.

Testing goodness-of-fit of selected observables

Table A6 summarises the right-side and left-side slopes for each province's short run temperature response functions by re-estimating them using only cooling and heating degrees (with a baseline of 14°C) rather than temperature bins. These are presented alongside mean values for the key observables.

Table A6: Temperature response function slope coefficients and observable averages

	RHS slope (CD)	LHS slope (HD)	AC	Electric Heat	Res Share
BC	0.008	0.015	0.211	0.488	0.320
AB	0.005	0.002	0.202	0.424	0.167
SK	0.010	0.004	0.571	0.230	0.173
MB	0.015	0.011	0.635	0.563	0.358
ON	0.019	0.008	0.761	0.435	0.342
QC	0.008	0.014	0.524	0.818	0.356
NB	0.007	0.016	0.301	0.718	0.402
PE	0.009	0.008	0.261	0.341	0.142
NS	0.008	0.014	0.184	0.465	0.384
NL	0.007	0.024	0.061	0.646	0.374

Notes: The RHS slope and LHS slope refer to the right- and left-side slope coefficients for the short run temperature response functions, i.e. the change in log(demand) for a 1°C change in temperature when above and below 14°C, respectively. AC and Electric Heat are the mean penetration of air conditioners and electric heating systems per household by province over the 2001-2015 period. Res Share represents the share of total demand attributed to the residential sector.

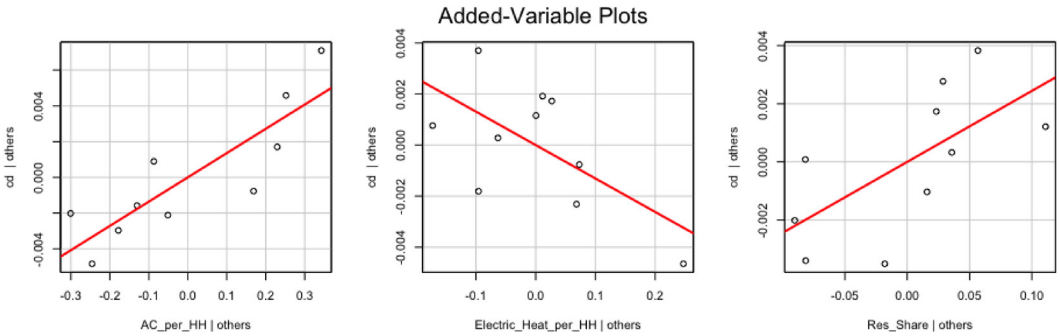
Table A7 presents the results of regressions to determine the explanatory power of the observables in explaining the provincial heterogeneity in slopes of short run temperature response functions. Specifically, we regress, separately, the left- and right-side slopes of the short run temperature response functions against provincial mean values of the observables, along with variants that interact residential shares with air conditioner and electric heat penetration. The explanatory power of these three observables is strong, showing an R-squared of 77-85% depending on specification. Despite only 10 observations (one for each province) the adjusted R-squared remains relatively strong despite only three observable variables used to explain the provincial heterogeneity. Figure A4 presents added-variable residual plots (for specification (i) in Table A7) to demonstrate the relationship between the RHS slope of the temperature response functions and the three observable variables.

Table A7: Testing for the explanatory power of observables

	Dependent variable:					
	Cooling Degree Slope			Heating Degree Slope		
	(1)	(2)	(3)	(4)	(5)	(6)
AC	0.014***	–0.013	–0.013	–0.012*	0.019	0.020
	(0.003)	(0.015)	(0.031)	(0.005)	(0.026)	(0.053)
Electric Heat	–0.013*	–0.018**	–0.019	0.006	0.011	0.013
	(0.007)	(0.006)	(0.051)	(0.010)	(0.011)	(0.087)
Res Share	0.024*	0.005	0.003	0.042*	0.066*	0.068
	(0.012)	(0.015)	(0.072)	(0.018)	(0.026)	(0.124)
AC × Res Share		0.079	0.082		–0.096	–0.099
		(0.045)	(0.091)		(0.078)	(0.156)
Electric Heat × Res Share			0.005			–0.005
			(0.134)			(0.232)
Observations	10	10	10	10	10	10
R^2	0.807	0.880	0.880	0.794	0.841	0.841
Adjusted R^2	0.711	0.784	0.731	0.691	0.714	0.643
df	6	5	4	6	5	4

Notes: Standard errors clustered by year-month. * p<0.1; ** p<0.05; *** p<0.01

Figure A4: Added-value plot for Model 1 (above)



Robustness checks for air conditioner regression

Table A8 shows the results from estimating a linear probability version of Eq.7. The table reports the results from four separate regressions, each using an alternative definition of the hot temperature variable $\tilde{T}$ in each city, as described above. In each case, the table shows that there is

a positive and highly statistically significant relationship between the prevalence of warm weather and the penetration of air conditioners. We focus on column (4), because it provides the best fit and is a natural way to describe the relationship between air conditioner penetration and the climate. In this column, we regress air conditioner penetration on the average July and August daily maximum temperature, as well as other covariates as described above. The table shows that for each 1 degree Celsius increase in the maximum daily July-August temperature, the penetration of residential air conditioners increases by 16.8 percentage points. Air conditioner penetration is clearly quite sensitive to the prevalence of warm summer temperatures.

Table A8: Linear probability model for air conditioner penetration with alternative climatic variables

	Dependent variable:			
	ac			
	(1)	(2)	(3)	(4)
highestMonthlyMean	0.145***			
	(0.001)			
highestTemp		0.111***		
		(0.001)		
meanJulyAug			0.142***	
			(0.001)	
meanmaxJulyAug				0.168***
				(0.001)
Household weights	No	No	No	No
Observations	33,591	33,591	33,591	33,591
R^2	0.304	0.280	0.253	0.325
Adjusted R^2	0.304	0.279	0.253	0.325
Residual Std. Error (df = 33575)	0.413	0.421	0.428	0.407
F Statistic (df = 15; 33575)	978.756***	869.343***	758.589***	1,077.589***

Note: * p<0.1; ** p<0.05; *** p<0.01

In Table A9, we provide some robustness checks for this main result. In column (1), we estimate the same model, but this time using sampling weights provided by Statistics Canada to ensure the sample is representative. Not surprisingly, the results are not substantially affected. In column (2), we estimate a probit model rather than a linear probability model. The key coefficient remains positive and highly statistically significant, and the average marginal effect remains very close to the estimate using the linear probability model: a one degree increase in the mean daily maximum July-August temperature is projected to increase air conditioner penetration by 14.9 percentage points. In column (3), we estimate a linear probability model with province fixed effects. In this case, the effect of climate on air conditioner penetration is identified from within-province variation in temperature, which eliminates any province-specific unobserved variables, such as building regulations or norms. The effect of climate is somewhat smaller in this specification, but remains significant and relatively close to the original specification. We use column (2) of Table A9 to project future air conditioner demand, conditional on climate.

Table A9: Alternative functional forms for air conditioner penetration

	Dependent variable:		
	ac		
	OLS (1)	*probit* (2)	*OLS* (3)
meanmaxJulyAug	0.162***	0.527***	0.115***
	(0.001)	(0.006)	(0.002)
Average marginal effect	—	0.149 (0.001)	—
Household weights	Yes	No	No
Province FEs	No	No	Yes
Observations	33,591	33,591	33,591
R^2	0.306		0.365
Adjusted R^2	0.306		0.365
Log Likelihood		–16,811.600	
Akaike Inf. Crit.		33,655.200	
Residual Std. Error	12.434 (df = 33575)		0.395 (df = 33567)
F Statistic	986.617*** (df = 15; 33575)		839.626*** (df = 23; 33567)

Note: * p<0.1; ** p<0.05; *** p<0.01

APPENDIX B

Interpolation procedure for hourly temperature projections

A limitation of our temperature projection data is that they lack hourly granularity. Instead, the data provide projected values for monthly mean, minimum and maximum temperature. To interpolate projected hourly temperature changes, we use the known values of projected mean, minimum and maximum temperature, and impose a quadratic form to the distribution of temperature changes between the lowest and highest original temperatures.

Specifically, we rank-order temperatures in each month from lowest to highest, and assume that temperature changes take the form of $y = a + bx + cx^2$, where x is the rank-order of the historical hourly temperature observation and y is the projected change in temperature. We know the value of a, this is the projected change in minimum temperature. We also know the value of y evaluated at the highest temperature (N), this is the projected change in maximum temperature. We also know that the mean temperature change, in other words the integral of this function over the range of lowest to highest temperatures divided by the number of hours, must equal the projected change in mean temperature. Thus we have a problem with three unknowns (a,b,c) and 3 constraints:

$$a = \Delta T_{min} \tag{A1}$$

$$a + bN + cN^2 = \Delta T_{max} \tag{A2}$$

$$\frac{1}{N}\int_1^N a + bx + cx^2 = \Delta T_{mean} \tag{A3}$$

Integrating the 3rd constraint and solving this system of equations produces a function to calculate the projected change for every hour of a given period (month containing N hours), based on the projected values of ΔT_{min}, ΔT_{max}, and ΔT_{mean}:

$$\Delta T_x = \Delta T_{min} - \frac{2x}{N}(\Delta T_{max} - \Delta T_{min}) + \frac{6x}{N}(\Delta T_{mean} - \Delta T_{min}) +$$

$$+\frac{3x^2}{N^2}(\Delta T_{max} - \Delta T_{min}) - \frac{6x^2}{N^2}(\Delta T_{mean} - \Delta T_{min}) \quad \text{(A4)}$$

where x is the rank-order of hourly historical temperature in the period.[28]

APPENDIX C

Historical temperature data

This section describes our approach to construction of a provincial temperature time series. We first obtain hourly temperature for all weather stations that record hourly temperature and that are active throughout 2000 to 2015 in each province. We retain only those weather stations for which fewer than 50% of observations in this period are missing. We impute missing observations for each remaining weather station using a regression-based approach, using non-missing observations from all other active weather stations in the province as predictors.

Weather stations are weighted according to population weights. We obtain population in each Census Sub-division from the 2011 Census of Population. For each Census Sub-division, we find the nearest weather station (to the centroid of the Census Sub-division) and assign the temperature at that station to the Census Sub-division. Population weights are then based on the share of total provincial population represented by each temperature monitoring station.

Our regressions involve two transformations of the raw temperature data: discretizing the temperature data into bins, and converting the temperature data into deviations from a base temperature and expressing as heating degree or cooling degree hours. In each case, we apply the transformations at each weather station separately, and apply the weights to the transformed data subsequently.

28. This solution uses the simplifying approximation that at high values of N, the terms $N-1$ and N^2-1 are approximately N and N^2, respectively. Given for most months, N is equal to 720 or 744, this is a reasonable approximation.