Energy Policy 106 (2017) 1–11

Contents lists available at ScienceDirect

Energy Policy

journal homepage: www.elsevier.com/locate/enpol

The effect of climate change on electricity expenditures in Massachusetts

Karina D. Véliz[a,b,*], Robert K. Kaufmann[c], Cutler J. Cleveland[c], Anne M.K. Stoner[d]

[a] School of Industrial Engineering, Universidad Diego Portales, Santiago, Chile
[b] Center for Climate and Resilience Research, Universidad de Chile, Santiago, Chile
[c] Department of Earth and Environment, Center for Energy and Environmental Studies, Boston University, Boston, MA 02466, USA
[d] Climate Science Center, Texas Tech University, Lubbock, TX 79409, USA

ARTICLE INFO

Keywords:
Climate change
Adaptation
Electricity expenditures
Electricity price
Electricity consumption

ABSTRACT

Climate change affects consumer expenditures by altering the consumption of and price for electricity. Previous analyses focus solely on the former, which implicitly assumes that climate-induced changes in consumption do not affect price. But this assumption is untenable because a shift in demand alters quantity and price at equilibrium. Here we present the first empirical estimates for the effect of climate change on electricity prices. Translated through the merit order dispatch of existing capacity for generating electricity, climate-induced changes in daily and monthly patterns of electricity consumption cause non-linear changes in electricity prices. A 2 °C increase in global mean temperature increases the prices for and consumption of electricity in Massachusetts USA, such that the average household's annual expenditures on electricity increase by about 12%. Commercial customers incur a 9% increase. These increases are caused largely by higher prices for electricity, whose impacts on expenditures are 1.3 and 3.6 fold larger than changes in residential and commercial consumption, respectively. This suggests that previous empirical studies understate the effects of climate change on electricity expenditures and that policy may be needed to ensure that the market generates investments in peaking capacity to satisfy climate-driven changes in summer-time consumption.

1. Introduction

The effect of energy production and use on climate is studied extensively. Only recently do studies examine the reverse, the effect of climate change on energy production and use. These empirical studies focus on the impact of climate change on electricity consumption (Dell et al., 2014; Amato et al., 2005; Mansur et al., 2008; Mirasgedis et al., 2007; Pilli-Sihvola et al., 2010; Rosenthal and Gruenspecht, 1995; Ruth and Lin, 2006; Sailor, 2001; Véliz, 2014) and assume that changes in consumption do not affect price. This assumption biases previous studies because a shift in demand alters the market equilibrium for quantity and price, and the magnitude of these effects depends on the price elasticities of both demand and supply. To evaluate this bias, one study computes the effect of climate change on electricity expenditures assuming an exogenous increase in electricity price (Deschênes and Greenstone, 2011). Here, we present the first empirical estimates for the effect of climate-induced changes in electricity consumption on electricity prices and measure their effects on expenditures in the US state of Massachusetts.

Massachusetts is a good case study because the state's wholesale market was restructured so that hourly electricity prices correspond to the marginal cost of supply (Joskow, 2008). Conversely, hourly consumption does not depend on price because neither residential nor commercial customers are charged the real-time price of their consumption. Econometrically, this allows us to identify the supply equation independently of the hourly relation between price and consumption in the demand equation.

In Massachusetts, real-time hourly locational marginal prices are the sum of 1) the marginal cost of providing the last block of electricity (real-time energy component), 2) the congestion cost of providing electricity to a specific zone (real-time congestion component), and 3) the electricity lost by moving it from the point of production to consumption (real-time marginal loss component). As such, locational marginal price reflects the zonal supply-demand equilibrium.

On the supply side, electricity is generated by dispatching capacity in merit order, from the least to most expensive marginal operating cost. Peaking units have operating costs that are several times greater than base and intermediate load generating units and therefore operate only during hours of very high consumption (often the hottest and most humid). This generates a non-linear relation between hourly prices and hourly consumption (Karakstani and Bunn, 2008; Kaufmann and Vaid, 2016). To illustrate, the all-time highest equilibrium quantity in the

* Corresponding author at: School of Industrial Engineering, Universidad Diego Portales, Av. Ejército 441, Santiago, Chile.
E-mail address: karina.veliz@udp.cl (K.D. Véliz).

http://dx.doi.org/10.1016/j.enpol.2017.03.016
Received 8 June 2016; Received in revised form 4 March 2017; Accepted 7 March 2017
Available online 20 March 2017
0301-4215/

Northeastern interconnected system occurs on August 2, 2006, when a 50% increase in the quantity of electricity consumed, relative to its off peak level, raised the hourly price by 400% relative to the lowest off peak price within the same day (temperature reached 37 °C; relative humidity reached 65%, WeatherSpark (2014) and Weather Underground (2014)).

Climate models forecast that global mean temperature will increase 2 °C (relative to the 1976–2005 climatology) between 2044 and 2070, depending on the general circulation model used, (Table A.1). Higher temperatures and more frequent heat waves in summer and less frequent cold episodes in winter (Beniston and Stephenson, 2004; Fischer et al., 2012) change monthly use such that summer-time consumption of electricity rises while winter-time consumption declines. We expect that winter-time reductions will be smaller than the summer-time increases because Massachusetts consumers generate a large portion of their space heating with natural gas or distillate oil.

Furthermore, climate models forecast that night-time temperatures will warm relative to day-time temperatures (Hartmann et al., 2013; Vose et al., 2005). This effect is particularly noticeable in winter, when the night-time minimum temperature in the Northern Hemisphere increases 0.099 °C per decade faster than the day-time maximum temperature. The resultant reduction in the diurnal temperature range (DTR) changes the daily pattern such that summer night-time consumption rises faster than day-time consumption.

Our paper quantifies the effect of climate change on electricity expenditures in Massachusetts. To do so, we simulate the electricity bill for a typical residential and commercial consumer. Bills are computed using hourly forecasts of consumption and price. We choose the 2044–2070 time frame based on the period by which the 2 °C will be achieved. We find that a 2 °C increase in global mean temperature increases electricity expenditures by the average Massachusetts residential and commercial customer by about 12% and 9% respectively. Most of these increases are caused by higher prices for electricity. These results suggests that previous analyses understate the impact of climate change on electricity expenditures.

These results, and the methods used to obtain them, are described in five sections. The Section 2 “Methodology” describes the data and methodology used to generate forecasts for electricity consumption, electricity prices, and electricity expenditures. The Section 3 “Results” present the empirical results related to these consumption, price, and expenditure forecasts. These results are described in the Section 4 “Discussion”. Finally, conclusions and policy relevance and implications of this study are discussed in the Section 5 “Conclusions and Policy Implications”.

2. Data and methodology

2.1. Data

To forecast electricity consumption, we compile observations for monthly cooling and heating degree hours and monthly observations for electricity consumption, electricity price, income, and employment. We construct monthly cooling and heating degree hours using hourly wet and dry bulb temperature, respectively. Observed temperature is obtained from the Weather Service of Amesbury, Massachusetts, and is measured at Boston Logan International Airport. We use this station because measurements from weather stations located in Western and Central Massachusetts are not available. Even if these measurements were available, their proximity to Logan airport suggests that their weather measurements share the same stochastic trend, which is the basis for the cointegrating relation between monthly electricity consumption and weather-related variables.

Monthly observations of electricity sales (in GWh) to (and revenues from) the residential, commercial, and industrial sectors are obtained from Form EIA-826 Monthly Electric Utility Sales and Revenue Survey (U.S. EIA, 2016). We compute the average monthly electricity price for sectors by dividing monthly revenues by monthly electricity sales. Prices are deflated with the Consumer Price Index All Urban Consumers (base year 2009). The same data are used to deflate observations for quarterly state personal income (in millions of dollars) for Massachusetts, which are obtained from the U.S. Bureau of Economic Analysis. Monthly observations for state personal income are created by using the same value for all months in a quarter. Data from the U.S. Bureau of Labor Statistics are used to measure monthly employment (thousands of employees) by the commercial and industrial sectors in Massachusetts.

Forecasts for monthly dry bulb temperature are compiled from simulations generated by nine circulation models that are run for the World Climate Research Programme's (WCRP's) Coupled Model Intercomparison Project Phase 5 (CMIP5) multimodel dataset (Online Appendix Section 1). The models are simulated using the highest representative concentration pathway (RCP 8.5) defined by the IPCC for its fifth Assessment Report. The 2 °C rise in global temperature relative to the 1976–2005 climatology occurs between 2044 and 2070, depending on the climate model used (Table A.1). To calculate a state-level value for monthly temperature forecasts, we weight the downscaled temperature forecasts by the share of population in each climatic zone. These population values are compiled from county data (U.S. Census Bureau).

To analyze the relation between electricity prices and electricity consumption, we compile hourly observations for real-time locational marginal price and electricity consumption (January 1, 2004 – December 31, 2012) for the three load zones in Massachusetts; Northeast Massachusetts and Boston (NE/Boston 4008), Western and Central Massachusetts (WCMA 4007), and Southeastern Massachusetts (SEMA 4006). We deflate electricity prices using the Consumer Price Index for 2009. Summary statistics show that consumption and prices vary greatly across space and time (Table A.9).

Finally, to calculate changes in electricity expenditures by representative consumers, we compile information about current monthly charges for basic service, transition energy, and delivery that are paid by residential and commercial consumers in 2013, which are obtained from the Department of Public Utilities of Massachusetts.

2.2. Methodology

We estimate the effect of climate change on electricity consumption, prices, and expenditures in three steps (Fig. 1). First, we use statistical models to translate the monthly changes in temperature that are forecast by climate models into monthly changes in electricity consumption, and translate these monthly changes into hourly rates of electricity consumption using Monte Carlo techniques. Second, we translate hourly rates of electricity consumption into hourly prices

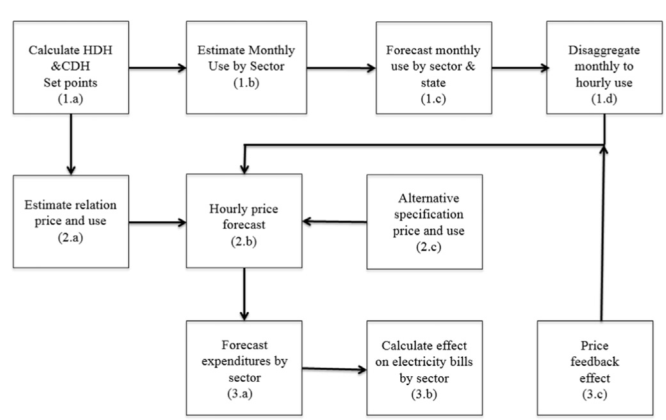

Fig. 1. General methodology.

using a statistical model that quantifies the relationship between hourly prices for and consumption of electricity. Third, we use the hourly forecasts for price and consumption to compute the effect of climate driven changes in temperature on electricity expenditures in Massachusetts. Linking these three steps requires considerable translational code that is described in the online appendix.

2.2.1. Forecasting electricity consumption

2.2.1.1. Measures for weather-related consumption. The effect of temperature on weather-related electricity consumption is represented as follows:

$$CDH_{y,m} = \sum_{h=1}^{N_m} I_{+}(T_{y,m,h} - j) \quad / \quad 24 \tag{1}$$

$I_{+}=1$ if $T_{y,m,h} \quad > j$, and zero otherwise.

$$HDH_{y,m} = \sum_{h=1}^{N_m} I_{+}(j - T_{y,m,h}) / \quad 24 \tag{2}$$

$I_{+}=1$ if $j > T_{y,m,h}$, and zero otherwise.

in which N_m is the number of hours in any given month, $T_{y,m,h}$ corresponds to temperature for hour h in month m of year y, CDH is cooling degree hours, HDH is heating degree hours, and j is the set point j={50 °F, 55 °F, 60 °F, 65 °F, 70 °F, 75 °F}. CDH and HDH are divided by 24 so that the quotients are comparable to standard measures of CDD and HDD computed from daily temperatures.

The set point j is chosen based on the electricity consumption model that generates the most accurate out-of-sample forecasts, as described by Kaufmann et al. (2013). For the residential sector, j is a dry bulb temperature of 65 °F for CDH and HDH. For the commercial sector, j is a wet bulb temperature of 50 °F for CDH and a dry bulb temperature of 50 °F for HDH. The set points for the commercial sector are increased by 5 °F between 11 p.m. and 4 a.m. for CDH and lowered by 5 °F between 11 p.m. and 4 a.m. for HDH. These “set backs” proxy changes in night-time thermostat setting that are designed to reduce energy use.

2.2.1.2. Monthly electricity use by sector. To evaluate the relation among weather, socioeconomic variables, and electricity consumption, we test whether these variables are stationary/nonstationary (Table A.2) using the MHEGY procedure (Beaulieu and Miron, 1993) and test whether they cointegrate (Engle and Granger, 1987; Dickey and Fuller, 1979) by analyzing the residual $\mu_{i,y,m}$ from the following statistical model:

$$\ln E_{i,y,m} = \phi_0 + \phi_1 CDH_{y,m} \quad + \phi_2 HDH_{y,m} + \phi_4 \ln I_{i,y,m} + \mu_{i,y,m} \tag{3}$$

in which $E_{i,y,m}$ is the time series for monthly electricity consumption by end-use sector i, with i={residential, commercial, industrial}, and $I_{i,y,m}$ is state personal income for the residential sector and employment for commercial and industrial consumers.

Test statistics indicate that the regression residual from Eq. (3) for electricity consumption by the residential sector is stationary (i.e. variables cointegrate), but the regression residuals from the equation for consumption by the commercial and industrial sectors contain a unit root (Table A.3). Based on these differences, residential electricity consumption is estimated using a cointegration/error correction model while the equations for commercial and industrial consumption are estimated with ordinary least squares (OLS).

The long-run cointegrating relation between residential consumption, weather, and income is estimated with dynamic ordinary least squares (DOLS) (Stock and Watson, 1993) as follows:

$$\begin{aligned}\ln \quad E_{y,m} &= \beta_0 + \beta_1 CDH_{y,m} + \beta_2 HDH_{y,m} + \beta_3 \quad \ln I_{y,m} \\ &+ \sum\nolimits_{i=-K}^{K} \varphi_i \Delta CDH_{y,m-i} \\ &+ \sum\nolimits_{i=-K}^{K} \lambda_i \Delta HDH_{y,m-i} + \sum\nolimits_{i=-K}^{K} \psi_i \Delta I_{y,m-i} + \eta_{y,m}\end{aligned} \tag{4}$$

in which Δ is the first difference operator (e.g. $CDH_{y,m}$-$CDH_{y,m-1}$). DOLS is used because OLS estimates of cointegrating relations contain small sample bias and their limiting distribution is non-normal with a non-zero mean (Stock, 1987). The number of lags and leads (K) is chosen using the Schwartz Bayesian criterion (Schwarz, 1978). DOLS results indicate that there is a statistically meaningful relation ($p < 0.01$) between electricity consumption and income, cooling degree hours, and heating degree hours (Table A.4). Furthermore, disequilibrium in the cointegrating relation generates adjustment towards the equilibrium value for consumption, as indicated by the results of an error correction model (Online Appendix Section 2).

Monthly consumption of electricity by the commercial and industrial sector is estimated as follows:

$$\begin{aligned}\ln E_{i,y,m} &= \pi_{0,i} + \pi_{1,i} CDH_{y,m} + \pi_{2,i} HDH_{y,m} + \pi_{3,i} \quad \ln Empl_{i,y,m} \\ &+ \pi_{4,i} \quad \ln P_{i,y,m} + \zeta_y + \mu_{i,y,m}\end{aligned} \tag{5}$$

in which $Empl_{i,y,m}$ is the number of people employed by end-use sector i, $P_{i,y,m}$ is monthly electricity price by end-use sector i, ζ_y are dummies for years 2004–2012 to control for patterns across years, and $\mu_{i,y,m}$ is the regression residual.

Regression coefficients associated with all independent variables are positive and statistically significant as indicated by *t*-tests that are calculated using robust standard errors (Newey and West, 1987) (Table A.5). We recognize that this interpretation is undermined by the lack of cointegration. We argue that the lack of cointegration is likely caused by the omission of a relevant variable, rather than the lack of a relation among the variables in the regression, given the strong theoretical rationale for there to be such a relation and empirical results that indicate these variables cointegrate when Eq. (5) is estimated using data from other states (Véliz, 2014).

2.2.1.3. Monthly electricity consumption forecast. We forecast monthly values for electricity consumption using the values for cooling and heating degree-days that are generated by the climate models (Online Appendix Section 3). To generate consistent estimates for changes in monthly consumption, we compare these values with those simulated by climate models for a base case scenario that uses the climatology of the period 1976–2010. This base period is chosen because it is the last thirty years of the historical CMIP5 GCM simulations and is the closest representation of the current climate. It is also the base period that is being used in the upcoming fourth U.S. National Climate Assessment.

We sum sectoral estimates for the change in monthly electricity consumption to compute a weighted change in total monthly consumption for Massachusetts (δ_m) for both day- and night-time (Table 1; Online Appendix Sections 4 & 5). Without statistical evidence for the effect of climate on the industrial sector (NREL, 2004), we assume that this sector is unaffected by a changing climate. If climate change increases residential and commercial electricity consumption, industry's share of Massachusetts electricity consumption will shrink.

2.2.1.4. Downscaling monthly forecasts to hourly values. We downscale monthly forecasts for day- and night-time electricity consumption into hourly values such that the monthly average of these hourly changes equals the change in the monthly value (Online Appendix Section 6). To account for changes in DTR, Monte Carlo techniques are used to downscale day- and night-time temperatures as

Table 1
Degree days forecasts and monthly electricity consumption forecasts.

Set point model:	$CDD_{65\,°F}$		$HDD_{65\,°F}$		$CDD_{50\,°F}$		$HDD_{50\,°F}$		Residential		Commercial		Total
	1976–2005	2 °C	1976–2005	2 °C	1976–2005	2 °C	1976–2005	2 °C	1976–2005	Δ% 2 °C $\delta_{m,r}$	1976–2005	Δ% 2 °C $\delta_{m,c}$	Δ% 2 °C δ_m
Jan	0	0	1164	975	0	0	699	510	1947	−8.1	2264	−4.1	−4.7
Feb	0	0	1037	715	0	0	613	291	1833	−12.5	2224	−7.0	−7.4
Mar	0	0	799	411	0	103	334	49	1631	−16.5	2095	−1.7	−6.5
Apr	0	0	541	290	0	162	91	3	1429	−11.6	1992	5.5	−1.6
May	0	6	255	51	210	420	0	0	1245	−6.8	2161	9.9	2.0
Jun	18	174	1	0	467	624	0	0	1168	21.3	2410	7.4	10.7
Jul	127	283	0	0	592	748	0	0	1314	37.6	2535	7.3	16.4
Aug	137	377	0	0	602	842	0	0	1431	46.5	2541	11.5	21.3
Sep	125	368	0	0	575	818	0	0	1443	55.4	2521	11.7	24.5
Oct	0	138	348	57	117	546	0	0	1405	21.0	2068	21.9	17.0
Nov	0	0	689	432	0	74	239	56	1537	−8.1	2063	−0.7	−3.1
Dec	0	0	1018	781	0	0	553	316	1839	−11.6	2215	−5.2	−6.3
Total	406	1346	5852	3712	2562	4338	2529	1225	1947	−8.1	2264	−4.1	4.6

Notes: $CDD_{65\,°F}$/$HDD_{65\,°F}$ and $CDD_{50\,°F}$/$HDD_{50\,°F}$ are computed for monthly electricity consumption models calibrated with dry and wet bulb temperature, respectively. Residential and commercial electricity consumption is measured in GWh. Residential electricity consumption forecasts are computed with forecasts for $CDD_{65\,°F}$ and $HDD_{65\,°F}$ for the period 1976–2005 and holding state personal income constant. Commercial electricity consumption forecasts are computed with forecasts for $CDD_{50\,°F}$ and $HDD_{50\,°F}$ and holding electricity price and employment constant. $\delta_{m,r}$ and $\delta_{m,c}$ correspond to the estimated changes in monthly consumption for the residential and commercial sectors, respectively. $\delta_{m,r}$ and $\delta_{m,c}$ changes are weighted by the share of monthly average consumption between 1990 and 2010 for the residential (35%), commercial (44%), and industrial (21%) end-use sectors. δ_m is the weighted percentage change in total monthly consumption.

follows,

$$E'^{day}_{m,h} = E^{day}_{m,h} \bullet \theta^{day}_{m} \tag{6}$$

in which $E^{day}_{m,h}$ is the electricity consumption for day-time hour h of any given month m and θ^{day}_{m} is a normally distributed parameter, $\theta^{day}_{m} \sim \mathcal{N}(\mu^{day}_{m}, \sigma^2_m)$, with μ^{day}_{m} equal to the expected value of the ratio between the projected and the current electricity consumption for each month ($\overline{E}'^{day}_{m}/\overline{E}^{day}_{m}$) (Table A.8). To create the hourly values for electricity consumption in the base case $\theta^{day}_{m}=1$. Without explicit information for the standard deviation associated with climate-induced changes in consumption, we assume that the variance is small ($\sigma^2_m=0.1$). This assumption is conservative because simulations indicate that there is a positive relation between variance (σ^2_m) and the change in electricity expenditures.

A parallel procedure is used to generate hourly values for consumption during night-time hours in the climate change scenario $E'^{night}_{m,h}$ and the base case scenario $E^{night}_{m,h}$. The entire process is repeated to generate one hundred experimental data sets for changes in hourly day- and night-time consumption. Finally, we disaggregate these hourly consumption changes by zone and sector (Online Appendix Section 5). Fig. A.1 in the Appendix shows an example of this downscaling procedure.

2.2.2. Electricity price forecast

2.2.2.1. Estimate the relation between price and consumption. Forecasts for hourly electricity prices are generated using statistical models of the relation between the hourly price for and consumption of electricity during the 2004–2012 sample for each load zone z as follows:

$$P_{h,z} = \beta_0 + \beta_{1,z}E_{h,z} + \beta_{2,z}E^2_{h,z} + \beta_{3,z}E^3_{h,z} + \zeta_{year} + \eta_{month} + \gamma_{dow} + \mu_{h,z} \tag{7}$$

in which $P_{h,z}$ is the real-time locational marginal price for electricity in zone z at hour h, (2009 dollars per MWh), $E_{h,z}$ is the hourly electricity consumption (or hourly load) in zone z, (GWh), and $\mu_{h,z}$ is the stochastic error term. The model includes dummies for individual years 2004–2012 (ζ_{year}), months (η_{month}), and days of the week (γ_{dow}) to control for patterns across these time scales. To assess the degree to which the relation between price and consumption is sensitive to year-to-year changes, Eq. (7) is estimated with subsamples that include a single year from the sample period (Table 3). Eq. (7) is estimated using OLS because all variables are stationary.

Statistical estimates for Eq. (7) are used to generate hourly estimates of price (and price changes $P'_{h,z}$) for each of the one hundred experimental data sets for hourly consumption. We average each set of 8760 annual hourly price forecasts and average this annual value across the one hundred experimental data sets to generate a single price change (Table 1). The 90% confidence interval is computed as the average value $\pm 1.645\times$the standard deviation. These values correspond to the 5th and 95th percentiles associated with price changes.

2.2.2.2. Price effect of consumption beyond individual load zones. Eq. (7) embodies an unstated assumption; Locational marginal price is determined by conditions solely within the load zone. But ISO-NE dispatches capacity based on consumption across its service area, which includes NE/Boston, WCMA, SEMA, Connecticut, Maine, New Hampshire, Rhode Island and Vermont. We assess the effect of system-wide consumption on electricity prices within load zones by expanding Eq. (7) as follows:

$$\begin{aligned} P_{h,z} = {} & \beta_0 + \beta_{1,z}E_{h,z} + \beta_{2,z}E^2_{h,z} + \beta_{3,z}E^3_{h,z} + \gamma_{1,z}E_{h,ISO-z} + \gamma_{2,z}E^2_{h,ISO-z} \\ & + \gamma_{3,z}E^3_{h,ISO-z} + \zeta_{year} + \eta_{month} + \gamma_{dow} + \mu_{h,z} \end{aligned} \tag{8}$$

in which $E_{h,ISO-z}$ is the consumption in the New England interconnected system minus consumption in zone z. Eq. (8) is estimated with observations from 2004 to 2012 for each load zone z. We use Eq. (8) in conjunction with the one hundred sets of hourly consumption data to generate one hundred sets of hourly estimates of price changes. For this exercise we hold $E_{h,ISO-z}$ constant at its sample value.

2.2.3. Electricity expenditure forecast

2.2.3.1. Change in electricity expenditure forecast for residential consumers. For residential consumers, climate change affects total electricity expenditures by altering consumption and the basic service charge. For 2012 and the median year with global mean temperature (GMT) increase of 2 °C ($year_{2\,°C}$), we multiply simulated values for hourly consumption and price and sum their hourly products over the

Table 2
Price change forecast and hourly price estimation.

	NEBoston	WCMA	SEMA
$\Delta\hat{P}$	28.8% (28.4, 29.2)	26.1% (25.8, 26.4)	21.4% (21.2, 21.7)
$\hat{P}$	61.5	62.5	61.4
mean $\hat{P}'$	79.3	78.9	74.6
sd $\hat{P}'$	0.14	0.11	0.10
$\Delta\hat{E}$	5.5% (5.5, 5.6)	5.3% (5.3, 5.4)	5.7% (5.7, 5.8)
Dependent variable:	Hourly electricity price		
E	218.786***	214.724***	203.166***
	(34.661)	(48.293)	(44.748)
E^2	−68.739***	−100.433***	−97.693***
	(11.482)	(23.512)	(24.590)
E^3	7.966***	18.296***	18.542***
	(1.230)	(3.709)	(4.310)
constant	−181.779***	−110.400***	−87.412***
	(33.755)	(32.006)	(25.852)
year==2005	22.795***	21.680***	21.037***
	(0.465)	(0.416)	(0.405)
year==2006	4.175***	4.651***	3.573***
	(0.47)	(0.339)	(0.32)
year==2007	5.230***	9.221***	9.488***
	(0.318)	(0.307)	(0.309)
year==2008	18.408***	22.728***	23.703***
	(0.4)	(0.384)	(0.39)
year==2009	−17.573***	−12.547***	−13.104***
	(0.289)	(0.272)	(0.287)
year==2010	−14.531***	−9.134***	−10.030***
	(0.339)	(0.311)	(0.337)
year==2011	−16.892***	−11.337***	−12.790***
	(0.318)	(0.306)	(0.321)
year==2012	−26.645***	−21.133***	−23.665***
	(0.316)	(0.312)	(0.327)
month==2	−7.599***	−7.260***	−7.807***
	(0.441)	(0.434)	(0.45)
month==3	−8.482***	−7.377***	−9.705***
	(0.418)	(0.405)	(0.433)
month==4	−2.588***	−0.904**	−4.408***
	(0.439)	(0.419)	(0.442)
month==5	0.692	1.271***	−2.864***
	(0.648)	(0.475)	(0.462)
month==6	−11.070***	−9.065***	−13.138***
	(0.499)	(0.483)	(0.465)
month==7	−19.427***	−14.376***	−22.580***
	(0.601)	(0.589)	(0.586)
month==8	−17.012***	−13.207***	−22.141***
	(0.524)	(0.467)	(0.486)
month==9	−9.591***	−6.398***	−12.021***
	(0.458)	(0.447)	(0.451)
month==10	−2.236***	−0.052	−4.977***
	(0.484)	(0.477)	(0.484)
month==11	−5.146***	−3.565***	−7.081***
	(0.446)	(0.435)	(0.452)
month==12	−1.203**	−0.835*	−2.977***
	(0.489)	(0.48)	(0.497)
dayofweek==1	−3.635***	−4.777***	−1.451***
	(0.327)	(0.299)	(0.293)
dayofweek==2	−5.080***	−7.485***	−3.050***
	(0.4)	(0.309)	(0.3)
dayofweek==3	−4.416***	−6.467***	−2.032***
	(0.362)	(0.327)	(0.328)
dayofweek==4	−4.848***	−6.623***	−2.389***
	(0.295)	(0.284)	(0.274)
dayofweek==5	−4.312***	−5.681***	−2.167***
	(0.293)	(0.278)	(0.272)
dayofweek==6	0.929***	0.507*	0.856***
	(0.277)	(0.278)	(0.273)
observations	78,903	78,903	78,903
adjusted R-squared	0.447	0.519	0.502

Notes: Numbers in brackets for $\Delta\hat{E}$ and $\Delta\hat{P}$ show 90% confidence intervals, which are the 5th and 95th percentiles associated with demand and price changes, respectively. E, E^2, and E^3 correspond to the linear, quadratic, and cubic hourly electricity demand terms. *** $p < 0.01$, ** $p < 0.05$, * $p < 0.1$. Robust standard errors in parentheses. All specifications include year, month and day of the week fixed effects (Equation (A.15)). Electricity price is measured in \$/MWh. Sensitivity of electricity prices to electricity consumption can be computed by taking the first derivative of the cubic function for price at the average increase in consumption ($\Delta\hat{E}$).

year for each experimental data set. Values for 2012 and $\text{year}_{2\,°\text{C}}$ are interpolated to generate annual values for intervening years. The net present value (NPV) of these annual values for the change in residential electricity expenditures due to climate change are calculated as follows:

$$NPV_{r,z} = \sum_{y=2012}^{\text{year}2°C} \frac{\sum_{h=1}^{8760}\left(\left(\hat{P}^{bs,r'}_{y,h,z} + \hat{P}^{ds,r}_{z}\right) \times \hat{E}^{r'}_{y,h,z}\right) - \sum_{h=1}^{8760}\left(\left(\hat{P}^{bs,r}_{y,h,z} + \hat{P}^{ds,r}_{z}\right) \times \hat{E}^{r}_{y,h,z}\right)}{(1+r)^{y-2012}} \tag{9}$$

in which $\hat{P}^{bs,r'}_{y,h,z}$ is the basic service charge (2009 dollars per kWh) for the climate change scenario, $\hat{P}^{bs,r}_{y,h,z}$ is the basic service charge for the baseline scenario, $\hat{E}^{r'}_{y,h,z}$ and $\hat{E}^{r}_{y,h,z}$ are the hourly residential consumption forecasts for the climate change and baseline scenario (kWh), respectively, and $\hat{P}^{ds,r}_{y,h,z}$ is the delivery service charge (2009 dollars per kWh). The annual discount rate *r* is assumed to be 3% (Deschênes and Greenstone, 2011). Eq. (9) is computed one hundred times, once for each set of hourly estimates for changes in consumption and price. We repeat this process nine times, with forecasts derived from the nine CGM models, to finally compute the average across NPVs.

The basic service charge $\hat{P}^{bs,r}_{y,h,z}$ reflects the wholesale price of electricity. $\hat{P}^{bs,r}_{y,h,z}$ changes in proportion to hourly changes in locational marginal price (Eqs. (7) or (8)) that are simulated in the climate change scenario to compute the effect of climate change on the basic service charge $\hat{P}^{bs,r'}_{y,h,z}$.

The costs of distributing and transmitting of electricity from the wholesale market to the final consumer is measured by the delivery service charge, which is computed as $\hat{P}^{ds,r}_{z} = \alpha^{ds,r} \times \overline{\hat{P}^{bs,r}_{y,h,z}}$. $\alpha^{ds,r}$ corresponds to the delivery service charge divided by the basic service charge paid by a residential customer with rate R-1 and 600 kWh of monthly consumption ($\alpha^{ds,r}$=0.75) (Table A.11) (Department of Public Utilities, 2014). $\overline{\hat{P}^{bs,r}_{y,h,z}}$ is computed as the average of $\hat{P}^{bs,r}_{y,h,z}$ in 2012.

Table 3
Price change forecast and hourly price regressions by year.

	2004	2005	2006	2007	2008	2009	2010	2011	2012
Dependent variable:		Hourly electricity price in NEBoston							
$\Delta\hat{P}$	22.4%	34.2%	42.8%	14.0%	18.6%	13.8%	33.6%	36.0%	36.9%
$\Delta\hat{P}$ lower bound	21.6%	33.0%	40.4%	13.6%	18.0%	13.4%	32.3%	34.6%	35.7%
$\Delta\hat{P}$ upper bound	23.2%	35.5%	45.2%	14.4%	19.1%	14.2%	34.8%	37.3%	38.0%
$\hat{P}$	61.5	89.2	68.2	71.2	83.7	44.0	51.8	47.1	36.2
mean $\hat{P}'$	75.3	119.7	97.4	81.2	99.2	50.1	69.2	64.1	49.5
sd $\hat{P}'$	0.3	0.7	1.0	0.2	0.3	0.1	0.4	0.4	0.2
$\Delta\hat{E}$	5.3%	5.7%	5.6%	5.4%	5.4%	5.3%	5.7%	5.6%	5.7%
$\Delta\hat{E}$ lower bound	5.1%	5.5%	5.4%	5.3%	5.2%	5.2%	5.5%	5.4%	5.5%
$\Delta\hat{E}$ upper bound	5.4%	5.8%	5.8%	5.6%	5.6%	5.5%	5.9%	5.8%	5.9%
E	227.33***	418.95***	669.59***	62.91**	125.22***	5.58	109.17***	181.37***	45.16*
	(54.39)	(107.82)	(139.65)	(29.04)	(28.40)	(25.20)	(26.40)	(57.17)	(23.50)
E^2	−73.22***	−130.91***	−213.07***	−12.63	−35.71***	0.45	−36.40***	−61.53***	−16.11**
	(19.67)	(36.16)	(46.33)	(9.43)	(9.04)	(8.48)	(8.63)	(18.85)	(7.82)
E^3	8.66***	14.52***	22.98***	1.55	4.47***	0.38	4.69***	7.49***	2.60***
	(2.32)	(3.93)	(4.98)	(1.00)	(0.94)	(0.93)	(0.91)	(2.01)	(0.84)
adj R-squared	0.37	0.47	0.29	0.55	0.50	0.55	0.48	0.47	0.46
Dependent variable:		Hourly electricity price in WCMA							
$\Delta\hat{P}$	29.2%	16.0%	42.6%	12.6%	18.4%	17.1%	33.4%	38.7%	39.0%
$\Delta\hat{P}$ lower bound	28.1%	15.6%	40.5%	12.3%	17.8%	16.6%	32.1%	37.3%	37.8%
$\Delta\hat{P}$ upper bound	30.3%	16.5%	44.8%	13.0%	18.9%	17.7%	34.6%	40.1%	40.3%
$\hat{P}$	62.6	88.5	67.5	73.4	84.6	44.8	52.7	48.0	37.1
mean $\hat{P}'$	80.8	102.7	96.3	82.6	100.2	52.5	70.3	66.5	51.6
sd $\hat{P}'$	0.4	0.2	0.9	0.2	0.3	0.2	0.4	0.4	0.3
$\Delta\hat{E}$	5.1%	5.5%	5.4%	5.3%	5.2%	5.2%	5.5%	5.4%	5.5%
$\Delta\hat{E}$ lower bound	5.0%	5.3%	5.2%	5.1%	5.0%	5.0%	5.3%	5.2%	5.3%
$\Delta\hat{E}$ upper bound	5.3%	5.7%	5.6%	5.4%	5.4%	5.3%	5.7%	5.5%	5.7%
E	520.36***	138.08***	882.90***	24.214	121.35***	57.708	157.81***	252.31***	97.05**
	(116.29)	(29.38)	(229.08)	(30.42)	(45.40)	(38.14)	(31.48)	(63.40)	(48.70)
E^2	−244.22***	−43.47***	−409.49***	3.35	−53.31**	−27.27	−80.85***	−136.35***	−52.68**
	(58.26)	(13.24)	(109.50)	(14.13)	(21.42)	(19.27)	(15.32)	(32.78)	(24.13)
E^3	40.12***	6.96***	64.63***	0.54	11.46***	6.43**	15.91***	26.17***	11.78***
	(9.51)	(1.93)	(16.99)	(2.14)	(3.30)	(3.17)	(2.42)	(5.49)	(3.87)
adj R-squared	0.41	0.60	0.45	0.57	0.53	0.57	0.53	0.49	0.43
Dependent variable:		Hourly electricity price in SEMA							
$\Delta\hat{P}$	13.5%	10.5%	34.2%	9.3%	16.7%	10.7%	26.5%	30.1%	32.3%
$\Delta\hat{P}$ lower bound	13.1%	10.3%	32.1%	9.1%	16.1%	10.4%	25.5%	28.8%	31.2%
$\Delta\hat{P}$ upper bound	14.0%	10.7%	36.4%	9.5%	17.2%	11.0%	27.5%	31.3%	33.4%
$\hat{P}$	60.7	85.9	65.7	72.2	85.4	44.5	52.4	47.4	36.7
mean $\hat{P}'$	68.9	94.9	88.2	78.9	99.6	49.3	66.2	61.7	48.5
sd $\hat{P}'$	0.2	0.1	0.9	0.1	0.3	0.1	0.3	0.4	0.2
$\Delta\hat{E}$	5.5%	5.9%	5.8%	5.6%	5.6%	5.5%	5.9%	5.8%	6.0%
$\Delta\hat{E}$ lower bound	5.3%	5.7%	5.6%	5.5%	5.5%	5.4%	5.7%	5.6%	5.8%
$\Delta\hat{E}$ upper bound	5.6%	6.0%	5.9%	5.8%	5.8%	5.7%	6.1%	6.0%	6.2%
E	101.95**	80.39***	676.64***	30.66	226.59***	6.965	88.86***	230.12***	75.79**
	(40.55)	(25.15)	(153.82)	(21.36)	(29.74)	(23.97)	(21.82)	(74.13)	(34.09)
E^2	−41.24*	−13.81	−347.96***	7.36	−104.08***	5.87	−46.08***	−125.39***	−38.92**
	(24.33)	(13.28)	(83.91)	(11.39)	(16.09)	(13.70)	(12.05)	(41.46)	(18.92)
E^3	8.47*	1.72	60.58***	−1.19	19.84***	0.06	10.75***	24.81***	9.26***
	(4.76)	(2.25)	(14.63)	(1.95)	(2.8)	(2.51)	(2.12)	(7.42)	(3.33)
adj R-squared	0.36	0.56	0.46	0.55	0.53	0.55	0.5	0.44	0.46

Notes: $\Delta\hat{E}$ lower bound and $\Delta\hat{E}$ upper bound show 90% confidence intervals, which are the 5th and 95th percentiles associated with electricity consumption changes. $\Delta\hat{P}$ lower bound and $\Delta\hat{P}$ upper bound are the analogous values for price changes. Robust standards errors in parenthesis. *** $p < 0.001$, ** $p < 0.05$, * $p < 0.1$. All specifications include month and day of week fixed effects. Electricity price is measured in $/MWh.

The effect of climate change on the delivery charge $\hat{P}_z^{ds,r}$ is unknown therefore it is held constant over the forecast period. This assumption is conservative because climate change will increase consumption, which will increase the infrastructure that is needed to transmit electricity, which will likely increase distribution charges. Finally, the changes are averaged across individual residential and commercial

Table 4
Expenditure change forecast for residential consumers of electricity.

	Δ Price and Consumption		Δ Consumption only		Δ Price only	
	cost 2 °C	NPV	cost 2 °C	NPV	cost 2 °C	NPV
NEBoston[a]	317 [314; 319]	2754 [2732; 2776]	99 [98; 99]	956 [950; 962]	137 [135; 139]	1329 [1312; 1346]
WCMA[a]	207 [205; 208]	1802 [1789; 1815]	67 [66; 67]	645 [641; 650]	88 [87; 89]	855 [845; 865]
SEMA[a]	158 [157; 160]	1395 [1385; 1405]	61 [61; 61]	590 [586; 594]	61 [61; 62]	595 [587; 602]
MA[b]	682 [677; 687]	5952 [5906; 5996]	226 [225; 228]	2191 [2177; 2205]	286 [283; 290]	2779 [2745; 2813]
MA/N[b]	256 [254; 258]	2236 [2219; 2253]	85 [85; 86]	823 [818; 828]	108 [106; 109]	1044 [1031; 1057]
Annualized MA/N_r[b]		95 [94; 95]		35 [35; 35]		44 [44; 45]

[a] Figures are measured in million 2009 dollars.
[b] Figures are measured in 2009 dollars. Cost estimates for residential consumers are computed for the following 2 °C scenarios: i) change in demand only; ii) change in price only; iii) change in both demand and price. The change in price in scenarios ii and iii are due to changes in the basic service charge. All present value calculations use a 3% discount rate (Deschênes and Greenstone, 2011).

consumers based on the ratio between expenditures added across zones and the number of residential consumers in Massachusetts (Table 4) (U.S. Energy Information Administration, 2011a). We compute the 90% confidence intervals for the expenditure forecasts using the 5th and 95th percentiles of the one hundred estimates for expenditure changes.

To separate the effects of climate-driven changes in price from the effects of climate driven changes in consumption (Table 4), we recompute Eq. (9) under the following assumptions: 1) climate change alters electricity prices ($\hat{P}^{bs,r\prime}_{y,h,z} \neq \hat{P}^{bs,r}_{y,h,z}$) but residential electricity consumption is unaffected ($\hat{E}^{r\prime}_{y,h,z} = \hat{E}^{r}_{y,h,z}$) and 2) climate change does not affect electricity prices ($\hat{P}^{bs,r\prime}_{y,h,z} = \hat{P}^{bs,r}_{y,h,z}$) but it does alter residential consumption ($\hat{E}^{r\prime}_{y,h,z} \neq \hat{E}^{r}_{y,h,z}$).

2.2.3.2. Change in electricity expenditure forecast for commercial consumers. Climate change affects total expenditures for electricity by commercial customers by altering consumption, the basic service charge, and the transition energy charge. These alterations change the net present value of electricity expenditures by commercial customers as follows:

$$NPV_{c,z} = \sum\nolimits_{y=2012}^{year2^{\circ}C} \frac{\sum_{h=1}^{8760}\left(\left(\hat{P}^{bs,c\prime}_{y,h,z} + \hat{P}^{tp,c\prime}_{y,h,z} + \hat{P}^{to,c\prime}_{y,h,z} + \hat{P}^{ds,c}_{z}\right) \times \hat{E}^{c\prime}_{y,h,z}\right) - \sum_{h=1}^{8760}\left(\left(\hat{P}^{bs,c}_{y,h,z} + \hat{P}^{tp,c}_{y,h,z} + \hat{P}^{toc}_{y,h,z} + \hat{P}^{ds,c}_{z}\right) \times \hat{E}^{c}_{y,h,z}\right)}{(1+r)^{y-2012}} \tag{10}$$

in which $\hat{P}^{bs,c\prime}_{y,h,z}$ and $\hat{P}^{bs,c}_{y,h,z}$ are the basic service charges to commercial consumers (2009 dollars per kWh) with and without climate change, $\hat{P}^{tp,c\prime}_{y,h,z}$ and $\hat{P}^{to,c\prime}_{y,h,z}$ are the transition energy peak and transition energy off-peak charges (2009 dollars per kWh) for the climate change scenario, ($\hat{P}^{tp,c}_{y,h,z}$ and $\hat{P}^{to,c}_{y,h,z}$ are the corresponding values for the base case), $\hat{E}^{c\prime}_{y,h,z}$ and $\hat{E}^{c}_{y,h,z}$ are hourly rates of commercial consumption in the climate change and baseline scenario, and $\hat{P}^{ds,c}_{z}$ is the delivery service charge for commercial consumers. As done with Eqs. (9) and (10) is computed one hundred times, once for each set of estimates for hourly estimates for changes in electricity consumption. Here we also repeat this process nine times to finally compute the average across NPVs.

The effect of climate change on the basic service charge for commercial consumers is simulated by changing $\hat{P}^{bs,c}_{y,h,z}$ in proportion to hourly changes in locational marginal price (Eqs. (7) or (8)) for the climate change scenario. The transition energy peak charge reflects the difference between the basic service charge and the price paid to suppliers during the peak period. We compute $\hat{P}^{tp,c}_{y,h,z}$ such that it equals $\alpha^{tp,c} \times \hat{P}^{bs,c}_{y,h,z}$ when h is within the peak period (from 9 a.m. to 6 p.m. from June through September, and from 8 a.m. to 9 p.m. from October through May), and zero otherwise. $\alpha^{tp,c}$ corresponds to the amount of the bill paid for transition energy peak divided by the amount of the bill paid for basic service by a commercial customer with rate G-3, 600 kW of power, 150,000 kWh of monthly consumption, and 55% of the consumption within the peak period ($\alpha^{tp,c}$=0. 08) (Table A.12) (Department of Public Utilities, 2014). We compute the transition peak energy charge for the climate scenario by assuming that $\hat{P}^{tp,c}_{y,h,z}$ increases in proportion to changes in locational marginal price.

The transition energy off-peak charge reflects the difference between the basic service charge and the price paid to suppliers during the off-peak period. $\hat{P}^{to,c}_{y,h,z}$ equals $\alpha^{to,c} \times \hat{P}^{bs,c}_{y,h,z}$ when h is within the off-peak period (all hours not included in the peak period) and zero otherwise. $\alpha^{to,c}$ corresponds to the amount of the bill paid for transition off-peak energy divided by the amount of the bill paid for basic service by a commercial customer with 45% of the consumption within the off-peak period ($\alpha^{to,c}$=0. 03) (Table A.12) (Department of Public Utilities, 2014). We compute the transition off-peak energy charge for the climate scenario by assuming that $\hat{P}^{to,c}_{y,h,z}$ changes in proportion to changes in locational marginal price. We assume that $\hat{P}^{ds,c}_{z}$ will not be affected by climate change. We compute $\hat{P}^{ds,c}_{z} = \alpha^{ds,c} \times \overline{\hat{P}^{bs,c}_{y,h,z}}$. $\alpha^{ds,c}$ corresponds to the amount of the bill paid for delivery service divided by the amount of the bill paid for basic service ($\alpha^{ds,c}$=0.36) (Department of Public Utilities, 2014) (Table A.12). Finally, changes in expenditures are allocated among commercial consumers based on the ratio of expenditures (summed across zones) to the number of commercial consumers in Massachusetts (N_c) (U.S. Energy Information Administration, 2011b). We decompose the changes shown in Table 5 between price and quantity using the same procedure described for residential consumers.

2.2.3.3. Sensitivity to real-time pricing information. As climate-induced increases in consumption raise electricity prices, these higher prices may dampen the initial increase in consumption. This reduction would lead to smaller changes in electricity prices and expenditures. To assess this mechanism for adaptation, we simulate scenarios in which real time information about electricity prices is available to consumers. This price information feeds back on hourly electricity consumption $E'^{feedback}_{h,z}$ via short-run (hourly) own-price elasticities of demand (average of 0.102, 0.124, 0.113, 0.105 and 0.096) (Ito, 2014; Faruqui and Sergici, 2011) as follows:

$$E'^{feedback}_{h,z} = E'_{h,z} + E'_{h,z}\eta \quad (P'_{h,z} - P_{h,z}) \tag{11}$$

in which $E'_{h,z}$ is the forecast for zone z at hour h, $P'_{h,z}$ is the hourly electricity price forecast in zone z at hour h, and $P_{h,z}$ is hourly electricity price. These feedbacks, $P'^{feedback}_{h,z}$, with $E'^{feedback}_{h,z}$ are used with Eq. (11) to generate hourly residential (commercial) consumption, $E^{r\prime feedback}_{h,z}$ ($E^{c\prime feedback}_{h,z}$). Finally, the net present value of

Table 5
Expenditure change forecast for commercial consumers of electricity.

	Δ Price and Consumption		Δ Consumption only		Δ Price only	
	cost 2 °C	NPV	cost 2 °C	NPV	cost 2 °C	NPV
NEBoston[a]	242 [240; 245]	2394 [2369; 2418]	44 [44; 45]	450 [444; 456]	172 [170; 174]	1781 [1759; 1804]
WCMA[a]	158 [157; 160]	1560 [1545; 1574]	30 [30; 31]	309 [304; 313]	111 [109; 112]	1144 [1131; 1157]
SEMA[a]	113 [111; 114]	1115 [1104; 1126]	26 [26; 27]	266 [262; 270]	75 [74; 76]	779 [769; 789]
MA[a]	513 [508; 518]	5069 [5018; 5117]	101 [99; 102]	1024 [1010; 1039]	358 [353; 362]	3705 [3659; 3750]
MA/N[b]	1367 [1353; 1380]	13,499 [13,364; 13,628]	268 [265; 272]	2728 [2690; 2767]	952 [941; 964]	9866 [9745; 9986]
Annualized MA/N_r[b]		569 [564; 575]		115 [113; 117]		416 [411; 421]

[a] Figures are measured in million 2009 dollars.
[b] Figures are measured in 2009 dollars. Cost estimates for residential consumers are computed for the following 2 °C scenarios: i) change in demand only; ii) change in price only; iii) change in both demand and price. The change in price in scenarios ii and iii are due to changes in the basic service charge, transition energy peak charge, and transition energy off-peak charge. All present value calculations use a 3% discount rate (Deschênes and Greenstone, 2011).

electricity expenditures by residential (commercial) consumers is calculated using Eqs. (9) and (10), and $E_{h,z}^{r\prime feedback}$ ($E_{h,z}^{c\prime feedback}$) and $P_{h,z}^{\prime feedback}$.

3. Results

3.1. Electricity consumption

Consistent with the results described by Auffhammer et al. (2017) the load duration curve (Fig. 2) indicates that warmer summer temperatures raise summer-time consumption by about 15% whereas winter-time consumption declines by about 6%. Consistent with the

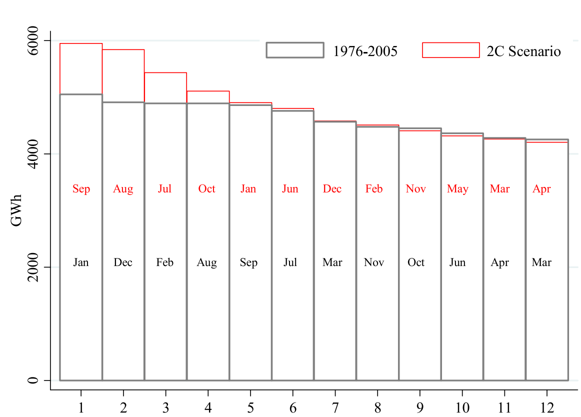

Fig. 2. Impact of climate change on the load duration curve constructed with monthly values. Source: Own construction based on results shown in Table 1.

expected reduction in DTR (Hartmann et al., 2013; Vose et al., 2005), electricity consumption during summer nights increases 16.6% whereas summer day-time consumption increases 16.2%.

3.2. Electricity prices

Statistical results for Eq. (7) indicate that electricity prices increase non-linearly with consumption. For all sample periods (Tables 2 and 3), the regression coefficients associated with the linear ($\beta_{1,z}$>0), squared ($\beta_{2,z}$<0), and cubed ($\beta_{3,z}$>0) values of hourly electricity consumption are statistically different from zero ($p < 0.01$) and Eq. (7) is able to account for 29–60% of the hourly variation in electricity prices. Consistent with merit order dispatch, the turning points are imaginary, which implies that prices always increase with consumption, albeit slowly at intermediate rates of consumption (Kaufmann and Vaid, 2016).

When translated through Eq. (7), changes in consumption increase the average annual price of electricity for the three Massachusetts load zones 21.4–28.8% (Table 2). The largest price increase occurs in NEBoston (4008) because consumption increases by the largest amount and because prices are more sensitive to electricity consumption. These results are robust to the sample used to estimate Eq. (7) (Table 3). For the three zones, the results indicate that price increases with consumption, with the exception of years 2007 and 2009 for the SEMA zone.

These results change little if we account for the effects of consumption beyond the load zone (Eq. (8)). The price change is relatively unaffected in load zones with higher levels of demand (e.g. NEBoston and WCMA) (Table A.10). Conversely, prices decline in the SEMA zone, which consumes the smallest quantity of electricity. Here, local prices are dominated by consumption increases beyond the load zone, which are eliminated by holding use beyond the SEMA load zone constant.

3.3. Electricity expenditures

The change in climate that is associated with the high emission scenario increases the net present value of electricity expenditures by residential and commercial customers by $5952 million (90% confidence interval $5906–$5996) and $5069 million (90% confidence interval $5018–$5117) (2009 dollars) respectively between 2013 and the median year with GMT increase of 2 °C (Tables 2, 3). These increases represent a $2236 (90% confidence interval $2219–$2253) and a $13,499 (90% confidence interval $13,364–$13,628) increase in the bill for an average residential and commercial customer. That translates into an annualized extra-cost of $95 (90% confidence interval $94–$95) and $569 (90% confidence interval $564–$575) per customer, which represents a 12.04% (90% confidence interval 11.95–12.13) and 9.34% (90% confidence interval 9.25–9.43) increase in their $785 and $6096 annual bill for electricity, respectively.

These increases are caused mainly by higher prices. If we ignore the effect of climate change on electricity prices (like previous analyses), the NPV of expenditures by residential and commercial customers increase by $2191 (90% confidence interval $2177–$2205) and $1024 (90% confidence interval $1010–$1039) million respectively. These increases represent an annualized extra-cost of $35 (90% confidence interval $35–$35) and $115 (90% confidence interval $113-$117) per customer. Conversely, eliminating the effect of climate change on electricity consumption, but retaining its effect on electricity prices, higher prices increase the NPV of expenditures by residential and commercial customers $2779 (90% confidence interval $2745–$2813) and $3705 (90% confidence interval $3659–$3750) million respectively. This represents an annualized extra-cost of $44 (90% confidence interval $44–$45) and $416 (90% confidence interval $411–$421) per customer.

4. Discussion

Climate change will affect both electricity consumption and price. Here, we present the first empirical estimates for the effect of climate change on electricity prices and quantify its effect on expenditures. We conclude that previous empirical studies understate the effects of climate change on electricity expenditures because our results indicate that higher consumption increases electricity prices and the total bill. This bias is especially strong because higher prices have a greater effect on expenditures than climate-related increases in consumption.

Our results carry several *caveats*. The annualized increase in electricity bills represents the effect of future changes in climate on the electric system as currently configured. But on-going and future changes in the stock of generating capacity and adaptation to climate change by producers and consumers will dampen or exacerbate the actual effect on expenditures.

The types of and price for fuels used to generate base-load and peak will change over the forecast horizon. In Massachusetts, economic incentives are increasing the fraction of electricity generated by renewable resources (from 2.6% to 5.2% during the 2004–2012 sample period) and this will likely dampen the effect of climate change on electricity prices because generation by renewable sources dampens summer-time increases in locational marginal price (CAISO, 2013; NREL, 2004; Kaufmann and Vaid, 2016). Conversely, fuel switching may have little effect on electricity prices and, therefore, on electricity expenditures. During the 2004–2012 sample period, the percentage of electricity generated in Massachusetts using coal and refined petroleum products declined from 39% to 7% while the percentage generated by natural gas rose from 45% to 70%. During that same period, the price of natural gas and coal to electric utilities in Massachusetts varied over a wide range (decreased by 42% for natural gas and increased by 9% for coal – FERC (2007), U.S. Energy Information Administration (2012)). Despite these changes, the sample period used to estimate the relation between hourly consumption and price has little impact on estimates for the effect of climate change on electricity prices (Table 3). Nonetheless, quantifying the sensitivity of climate-driven electricity expenditures estimates to changes in the generation technology and fuel price is a priority for future research.

The degree to which adaptation to climate change will reduce the effect of climate change on electricity prices and expenditures is uncertain. Price increases and total expenditures may be smaller if higher prices induce consumers to reduce consumption. We assess this mechanism for adaptation by recalculating the climate-induced changes in consumption with short-run (hourly) own-price elasticities of demand (Eq. (11)). The degree to which these price feedbacks reduce consumption depends on whether consumers have real-time information about electricity prices and whether they use this information to optimize electricity consumption (Eq. (11)). If residential (and commercial) consumers have complete or partial access to real time information about electricity prices, electricity expenditures rise 5.0 (2.9) percent and 8.5 (6.1) respectively, instead of the 12 (9) percent increase in the base-case, which implicitly assumes that consumers do not react to climate induced increases in electricity prices (Tables A.13–A.16).

Conversely, consumers may adapt to a warming climate by using more air conditioning (Sailor and Pavlova, 2003). This cost is not included in our statistical models; they implicitly assume the increase in summer-time use is consumed by operating the existing stock of air conditioners at higher utilization rates. If we allow the existing stock of air conditioners to grow by assuming that new 12,000 BTU, 1100 W window air conditioning units that operate for twelve hours per day consume all of the May-Sept increase in electricity consumption, which is simulated by the climate-induced monthly forecast, one in every three households will require a new unit. These new air conditioners, whose cost per unit is assumed to be \$300, would cost Massachusetts households an additional \$259 million (in 2009 dollars).

Higher electricity prices are likely to spur demand-side management, which seeks to reduce consumption during periods of peak demand. Programs to shave the peak in Massachusetts could reduce electricity expenditures 17% by 2019 (Faruqui and Sergici, 2011). These savings could be larger given the changes in the load duration curve shown in Fig. 2. But as described previously, capturing these savings would require consumers to have an advanced metering infrastructure that communicates real-time prices to all electricity consumers, as opposed to bills that communicate monthly use and an average price per kWh (Sailor and Pavlova, 2003; U.S. FERC, 2009).

On the supply side, adaptation to the increase skew of the load curve in Fig. 2 is likely to reduce the price effect relative to the current configuration of the electrical system. But the size of this reduction is uncertain. Increases in peak summer-time consumption relative to the base period imply investments in new peaking capacity. But this new capacity will operate for only a small fraction of the year. Under these conditions, the fixed costs of this new capacity will be recovered during relatively short operating periods, which translates into higher marginal generating costs.

Furthermore, the increased skew of the load duration curve in Fig. 2 implies that the transmission grid will be upgraded to carry higher loads during the summer-time peak. Such upgrades will reduce congestion costs relative to those embodied in locational marginal price. But their net effect on electricity expenditures is uncertain because the cost of upgrading the electricity grid will raise the delivery service charge, which we assume to remain constant.

5. Conclusion and policy implications

To summarize, our most important result is that climate change in Massachusetts alters the load duration curve, which raises prices. The size of this price rise will depend on the degree to which policy makers can create an environment that prompts generators, the distribution system, and electricity consumers to adapt. Adaptation can be enhanced by policies aimed at electricity supply and consumption. On the supply side, higher prices can be damped if policy creates a more certain environment for investment in new peaking capacity. On the demand size, higher prices can be damped if policy favors energy conservation measures that reduce and/or reschedule the electricity used for cooling.

The uncertainty about the effects of climate change on consumption and prices is especially important in Massachusetts, where the restructuring of electricity markets changes the way that investments are made in new capacity. The risks of investments no longer are bourn by rate-payers; private investors now weigh the costs and benefits. These costs and benefits are defined by market signals under the ‘energy-only’ design. But analysis indicates that this approach contains several market failures (e.g. Bidwell and Henney, 2004). Many of these failures pose challenges to generation adequacy, which may cause capacity to fall short of the level needed to satisfy demand.

To date, investment decisions regarding new capacity focus on socioeconomic variables, such as consumption, as influenced by population and economic growth, and the relative costs of competing technologies for generating electricity, as influenced by capital and operating costs. But this analysis adds a new variable to investment decisions; climate change will increase consumption and alter the load duration curve. The former has been well documented and has important implications for the construction of new base-load. But the skew in the load curve, and the resultant increase in prices described here imply that peaking capacity must increase faster than base-load.

But the investment in new generating capacity that is stimulated by the ‘energy-only’ market design is biased in the opposite direction, in favor of base-load. Risk aversion may limit the provision of peaking plants (Bidwell and Henney, 2004). The volatility of revenue flows for peaking units is much greater than the volatility of revenue flows for base-load units (Olsina et al., 2014). Under these conditions, scarcity rents are highly uncertain. This uncertainty reduces investment by risk averse investors, which leads to less peaking capacity than needed (Olsina et al., 2014).

To deal with the increased uncertainty about the need for investment in peaking plants, policy makers who wish to dampen the price increases that are associated with the increased skew of the load duration curve may need to look beyond the 'energy-only' market design and consider some form of capacity remuneration mechanisms (CRM's). CRMs aim to reduce the uncertainty associated with the revenue stream from electricity generating capacity, which enhances market incentives to invest in new capacity. Because climate-induced price increases are caused by increased summer-time peaks, as opposed to a general increase in consumption, our analysis suggests that CRM's focus on ways to enhance timely investment in peak capacity. For example, Olsina et al. (2014) describe CRM's that replace annual realizations of the stochastic revenue stream earned by each generating unit during scarcity in an 'energy only' market design with it's certainty risk neutral equivalent. This change would reduce financial risk while preserving the efficiency of the energy-only market design. This is not the only possible approach, but specific suggestions for the design of CRM's that would enhance investment in peak load capacity for Massachusetts is beyond the scope of this analysis.

Generation adequacy also is limited by market failures on the supply side. Bidwell and Henney (2004) argue that electricity demand is inelastic because most consumers do not have real-time information about electricity prices and even if they do, they are generally not interested in responding to price signals. As described by our adaptation scenario, higher prices due to summer-time increases in consumption can be damped only if consumers pay real-time prices, have real-time information about those prices, and have non-trivial short-run elasticities.

Rather than rely on heroic assumptions, policy makers may be able to dampen some of the increase in summer-time electricity prices if climate induced increases in cooling are satisfied by new efficient equipment and/or the electricity used for cooling can be shifted away from the hottest part of the day. To do so, policy makers may need to change the focus of incentives for utilities to reduce electricity sales. Currently, the State of Massachusetts compensates utilities for reduced sales of electricity when those reductions can be attributed to specific energy conservation measures. The measures that qualify for such compensation include a wide variety of end-uses, such as lighting, pumps and fans, and HVAC equipment.

But this analysis suggests that the effectiveness of dampening the effect of climate change on electricity consumption and prices by reducing consumption is not equal across eligible energy conservation measures. Lighting replacements, and retrofitting heating systems, pumps, and motors probably will have little effect on climate-induced increases in electricity prices for Massachusetts ratepayers. Instead, policy makers may want to alter incentives in ways that utilities favor investment in new energy efficiency cooling systems, including variable speed drives, or technologies that shift the cooling load, such as ice storage. These suggestions are specific to the analysis of Massachusetts that is presented here. The effects of climate change on the level and temporal distribution of electricity consumption (and prices) will vary among states and therefore, so too would the energy conservation measures that will be most effective.

Appendix A. Supporting information

Supplementary data associated with this article can be found in the online version at doi:10.1016/j.enpol.2017.03.016.

References

Amato, A.D., Ruth, M., Kirshen, P., Horwitz, J., 2005. Regional energy demand responses to climate change: methodology and application to the commonwealth of Massachusetts. Clim. Change 71, 175–201.

Auffhammer, M., Baylis, P., Hausman, C.H., 2017. Climate change is projected to have severe impacts on the frequency and intensity of peak electricity demand across the United States. PNAS 114 (8).

Beaulieu, J.J., Miron, J.A., 1993. Seasonal unit roots in aggregate U.S. data. J. Econom. 55, 305–328.

Beniston, M., Stephenson, D.B., 2004. Extreme climatic events and their evolution under changing climatic conditions. Glob. Planet. Change 44, 1–9.

Bidwell, M., Henney, A., 2004. Will the new electricity trading arrangements ensure generation adequacy? Electr. J. 17 (7), 15–38.

California Independent System Operator - CAISO, 2013. What the duck curve tells us about managing a green grid. 916.351.4400.

Dell, M., Jones, B.F., Olken, B.A., 2014. What do we learn from the weather? The new climate–economy literature. J. Econ. Lit. 52 (3), 740–798.

Department of Public Utilities, 2014. The Commonwealth of Massachusetts January 2014 Retail Rate Filing of Massachusetts Electric Company and Nantucket Electric Company d/b/a National Grid; D.P.U. 14.

Deschênes, O., Greenstone, M., 2011. Climate change, mortality, and adaptation: evidence from annual fluctuations in weather in the U.S. Am. Econ. J.: Appl. Econ. 3, 152–185.

Dickey, D.A., Fuller, W.A., 1979. Distribution of the estimators for autoregressive time series with a unit root. J. Am. Stat. Assoc. 74 (366), 427–431.

Engle, R.F., Granger, C.W.J., 1987. Co-integration and error correction: representation, estimation, and testing. Econometrica 55 (2), 251–276.

Faruqui, A., Sergici, S., 2011. Dynamic pricing of electricity in the Mid-Atlantic region: econometric results from the Baltimore gas and electric company experiment. J. Regul. Econ. 40, 82–109.

Fischer, E.M., Rajczak, J., Schär, C., 2012. Changes in European summer temperature variability revisited. Geophys. Res. Lett. 39 (L19702).

Hartmann, D.L., Klein Tank, A.M.G., Rusticucci, M., Alexander, L.V., Brönnimann, S., Charabi, Y., Dentener, F.J., Dlugokencky, E.J., Easterling, D.R., Kaplan, A., Soden, B.J., Thorne, P.W., Wild, M., Zhai, P.M., 2013. Observations: atmosphere and surface. In: Stocker, T.F., Qin, D., Plattner, G.-K., Tignor, M., Allen, S.K., Boschung, J., Nauels, A., Xia, Y., Bex, V., Midgley, P.M. (Eds.), Climate Change 2013: The Physical Science Basis. Contribution of Working Group I to the Fifth Assessment Report of the Intergovernmental Panel on Climate Change. Cambridge University Press, Cambridge, United Kingdom and New York, NY, USA.

Ito, K., 2014. Do consumers respond to marginal or average price? Evidence from nonlinear electricity pricing. Am. Econ. Rev. 104 (2), 537–563.

Joskow, P., 2008. Lessons learned from electricity market liberalization, The Energy Journal, Special Issue. The Future of Electricity: Papers in Honor of David Newbery.

Karakstani, N.V., Bunn, D.W., 2008. Forecasting electricity prices: the impact of fundamentals and time-varying coefficients. Int. J. Forecast. 24, 764–785.

Kaufmann, R., Vaid, Devina, 2016. Lower electricity prices and greenhouse gas emissions due to rooftop solar: empirical results for Massachusetts. Energy Policy 93, 345–352.

Kaufmann, R., et al., 2013. Revisiting the weather effect on energy consumption: implications for the impact of climate change. Energy Policy 62, 1377–1384.

Mansur, E., Mendelsohn, R., Morrison, W., 2008. Climate change adaptation: a study of fuel choice and consumption in the US energy sector. J. Environ. Econ. Manag. 55, 175–193.

Mirasgedis, S., et al., 2007. Modeling framework for estimating impacts of climate change on electricity demand at regional level: case of Greece. Energy Convers. Manag. 48, 1737–1750.

National Renewable Energy Laboratory – NREL, 2004. Advanced Inverter Functions to Support High Levels of Distributed Solar. Policy and Regulatory Considerations. NREL/BR-6A20-62612.

Newey, W., West, K., 1987. A simple positive semi-definite, heteroskedasticity and autocorrelation consistent covariance matrix. Econometrica 55 (3), 703–708.

Olsina, F., Pringles, R., Larisson, C., Garcés, F., 2014. Reliability payments to generation capacity in electricity markets. Energy Policy 73, 211–224.

Pilli-Sihvola, K., Aatola, P., Ollikainen, M., Tuomenvirta, H., 2010. Climate change and electricity consumption-witnessing increasing or decreasing use and costs? Energy Policy 38, 2409–2419.

Rosenthal, D.H., Gruenspecht, H.K., 1995. Effects of global warming on energy use for space heating and cooling in the United States. Energy 16 (2), 77–96.

Ruth, M., Lin, A.C., 2006. Regional energy demand and adaptations to climate change: methodology and application to the state of Maryland, USA. Energy Policy 34, 2820–2833.

Sailor, D.J., 2001. Relating residential and commercial sector electricity loads to climate: evaluating state level sensitivities and vulnerabilities. Energy 26, 645–657.

Sailor, D.J., Pavlova, A.A., 2003. Air conditioning market saturation and long-term response of residential cooling energy demand to climate change. Energy 28, 941–951.

Schwarz, G., 1978. Estimating the dimension of a model. Ann. Stat. 6 (2), 461–464.

Stock, J.H., 1987. Asymptotic properties of least squares estimators co-integrating vectors. Econometrica 55 (5), 1035–1056.

Stock, J.H., Watson, M.W., 1993. A simple estimator of cointegrating vectors in higher order integrated systems. Econometrica 61 (4), 783–820.

U.S. Energy Information Administration Survey Form EIA-923. Monthly Utility Fuel Receipts and Fuel Quality Data from 2008 to 2012.

U.S. Energy Information Administration, 2011a. Table 5A. Residential Average Monthly

Bill by Census Division, and State 2010.
U.S. Energy Information Administration , 2011b. Table 5B. Commercial Average Monthly Bill by Census Division, and State 2010.
U.S. Energy Information Administration, 2016. Form EIA-826 Monthly Electric Utility Sales and Revenue Survey.
U.S. Federal Energy Regulatory Commission, 2009. A National Assessment of Demand Response Potential. Table A-3: Potential Peak Demand Reduction by State (2019).
U.S. Federal Energy Regulatory Commission Survey Form FERC-423. Monthly Utility Fuel Receipts and Fuel Quality Data from 2004 to 2007.
Véliz, K., 2014. The Impact of Climate Change on the U.S. Power Sector: Price and Quantity Effects (Doctoral dissertation). Boston University, Boston, Massachusetts.
Vose, R., Easterling, D., Gleason, B., 2005. Maximum and minimum temperature trends for the globe: an update through 2004. Geophys. Res. Lett. 32, L23822.
WeatherSpark Historical. Weather for 2006 in Boston, Massachusetts, USA. ⟨http://weatherspark.com/history/29794/2006/Boston-Massachusetts-United-States⟩ (acceded October 1, 2014).
Weather Underground Weather History for Boston, MA. ⟨http://www.wunderground.com/history/airport/KBOS/2006/8/2/DailyHistory.html?Req_city=NA&req_state=NA&req_statename=NA⟩ (acceded October 1, 2014).