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Summary

This paper combines an econometric analysis of the response of energy demand to temperature and humidity exposure with future scenarios of climate change and socioeconomic development to characterize climate impacts on energy demand at different spatial scales. Globally, future climate change is expected to have a moderate impact on energy demand, in the order of 7-17% around 2050, depending on the degree of warming, because of compensating effects across regions, fuels, and sectors. Climate-induced changes in energy demand are relatively larger in tropical regions. Almost all continents see unequivocal increases in final energy demand, driven by the commercial and industrial sectors. In Europe the reduction in the use of residential energy prevails, driving an overall reduction in aggregate final energy use. Total final energy goes up in almost all emerging G20 economies located in the tropics, whereas temperate G20 countries outside Europe can either increase or decrease total final energy use depending on the geographic incidence of changes in the frequency of hot and cold days. We find that climate change has a regressive impact on energy demand, with the incidence of increased energy demand overwhelmingly falling on low- and middle-income countries, raising the question whether climate change could exacerbate energy poverty.

Keywords: Panel Data, Climate Change, Adaptation, Energy

JEL Classification: N5, O13, Q1, Q54

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Global Energy Demand in a Warming Climate

Abstract

This paper combines an econometric analysis of the response of energy demand to temperature and humidity exposure with future scenarios of climate change and socioeconomic development to characterize climate impacts on energy demand at different spatial scales. Globally, future climate change is expected to have a moderate impact on energy demand, in the order of 7-17% around 2050, depending on the degree of warming, because of compensating effects across regions, fuels, and sectors. Climate-induced changes in energy demand are relatively larger in tropical regions. Almost all continents see unequivocal increases in final energy demand, driven by the commercial and industrial sectors. In Europe the reduction in the use of residential energy prevails, driving an overall reduction in aggregate final energy use. Total final energy goes up in almost all emerging G20 economies located in the tropics, whereas temperate G20 countries outside Europe can either increase or decrease total final energy use depending on the geographic incidence of changes in the frequency of hot and cold days. We find that climate change has a regressive impact on energy demand, with the incidence of increased energy demand overwhelmingly falling on low- and middle-income countries, raising the question whether climate change could exacerbate energy poverty.

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1 Introduction

How climate change will impact the way we use energy is an important topic in environmental economics. Demand for energy is directly affected by changes in weather and climatic conditions. In addition to being the major source of greenhouse gases (GHGs) that drive climate warming, energy is a necessary input to the production of space conditioning services, which in turn are a critical margin of adaptation to high and low temperatures. Relative to the current climate, global warming will trigger more frequent high temperature extremes—increasing demands for cooling services and the energy necessary to produce them, while simultaneously decreasing the frequency of low temperature extremes—reducing the demand for heating and its associated energy use. As the world warms, the central question is whether, and if so by what margin, the former effect might outweigh the latter. The answer is complicated by the fact that shifts in energy consumption will be driven by the way in which the climate interacts with changing socioeconomic conditions. Countries' final energy consumption will depend on their economies' overall size and sectoral composition, the way in which these characteristics jointly impact on the mix of fuels, and, ultimately, the manner in which sectors' demands for individual fuels respond to future meteorological exposures.

A large and growing literature attempts to project future energy use and associated GHG emissions, principally for the purpose of analyzing the economic and environmental consequences of climate change mitigation policies. Much of this research is at the global scale, employing integrated assessment models (IAMs) sophisticated numerical simulations that divide the world into large regional economies encompassing substantial sectoral and technological detail (e.g. Bruckner et al, 2014; Clarke et al, 2014; Calvin et al, 2013; Riahi et al, 2017). Yet, application of this analytical machinery to quantify the impacts of climate change on energy demand is still limited (Ciscar and Dowling, 2014). The key missing elements are (i) the heterogeneous responsiveness of the demand for different fuels to meteorology in their constituent regions and sectors, and (ii) the manner in which these responses interact with geographically and temporally changing fields of temperature. Characterizing these elements is the focus of this paper.

Regarding (i), energy demand has been extensively investigated. However, empirical assessments at broad geographic scales are comparatively rare (see De Cian, Lanzi and Roson, 2013 for a recent exception). The geographic coverage of regional studies is patchy and tends to overrepresent industrialized countries. The literature's coverage of combinations of sectors and fuels is also limited, emphasizing electricity and, less commonly, natural gas, while prioritizing the residential sector over other parts of the economy

(Auffhammer and Mansur, 2014; Schaeffer, 2012). This omission is potentially significant given engineering and economic evidence of non-residential sectors' differential responses to weather variations—albeit mostly from the U.S. and Europe (e.g., Schaeffer, 2012; Howell and Rogner, 2014; Considine, 2000; Ruth and Lin, 2006; Bazilian et al, 2012; Wilbanks et al, 2012).

Turning to (ii), the precise manner in which empirical studies articulate the response of energy demand to meteorology directly affects how their results can be combined with projections of future meteorology to characterize climate change impacts. Energy consumption tends to be recorded on an annual (e.g., Deschenes and Greenstone, 2013) or monthly basis (e.g., Aroonruengsawat and Auffhammer, 2011; Auffhammer and Aroonruengsawat, 2011), with higher temporal frequency data being comparatively rare, with the exception of load on electricity grids (e.g., Scapin et al, 2015). Temperature is the meteorological driver that has been most widely considered, with other potentially relevant variables (e.g., humidity) receiving less attention (Barreca, 2012). Empirical studies have estimated elasticities of energy demand with respect to temperatures that are either averaged on an annual (Bigano et al, 2006) or seasonal basis (e.g., De Cian, Lanzi and Roson, 2013), accumulated heating and cooling degree days (e.g., Isaac and Van Vuuren, 2009; Ruth and Lin, 2006; Eskeland and Mideksa, 2010), and, more recently, temporal exposure to different intervals of temperature (e.g., Aroonruengsawat and Auffhammer, 2011; Auffhammer and Aroonruengsawat, 2011; Deschenes and Greenstone, 2013). The last approach, which we adopt here, is particularly attractive because of its ability to capture potential nonlinearity in the responses of demand to temperature extremes.

A critical issue in using such estimates to construct impact projections is consistent aggregation of current and future meteorological data across spatial and temporal scales. Earth system models (ESMs)—the principal tool for projecting future climates—simulate meteorological variables on time steps of hours to months at geographic scales of hundreds of kilometers. Averaging ESM outputs over space and time is inevitable, but often has the unpleasant side-effect of shrinking the tails of the distribution of meteorological drivers of energy demand, leading to underestimation of the large impacts that can arise from convolving nonlinear demand responses with extreme weather exposures. This is a particular problem where energy consumption data are coarse (e.g., country-year observations) and the observational units have a large latitudinal extent that encompasses different climatic regimes across which impacts on energy demand may switch sign. Effectively capturing the impacts of future extremes thus requires an empirical strategy that anticipates the challenges that attend the projection of future impacts. Key desiderata include assembling high spatial and temporal resolution datasets of historical meteorological observations and future climate simulations, processing the weather observations in such a way that they are able to be matched to the energy data with a minimum of aggregation for estimation purposes, and applying the identical data transformations to ESM outputs.

Here we develop a flexible methodology to characterize geographic variations in climate change impacts on energy demand across the globe. Our first step is to econometrically disentangle the short- and long-run responses of per-capita energy consumption to variations in exposure to hot and cold, dry and humid days. The resulting long-run semi-elasticities capture the nonlinear effect of the climate on energy use indicative of adaptation responses by final consumers along the intensive as well as the extensive margins. Second, we combine these estimates with ESM temperature projections and consistent scenarios of population and GDP growth to elucidate the potential climate change impacts on final energy consumption at the sectoral, regional, and global levels. Our temperature projections are simulations of two representative concentration pathway scenarios (RCPs— Van Vuuren, 2012) indicative of a high-warming no-policy scenario and moderate-warming mitigation policy scenario. These are augmented with a shared socioeconomic pathway scenario (SSP— Kriegler et al, 2012; Van Vuuren, 2014) that assumes a future world in which there is conventional economic development, slow population growth, international convergence, and rapid increase in final energy consumption. Comprehensive assessment of energy futures under different climate and socioeconomic assumptions is left to future work.

The rest of the paper is organized as follows. Section 2 provides the background and develops the theoretical framework that is used to motivate the empirical model of energy demand response to weather and that constitutes the foundation of the paper. Section 3 describes the results and uses the estimated elasticities to per capita income and the semi-elasticities to temperature exposure to calculate future baseline and climate-induced energy demand. Section 4 presents a number of robustness tests and compare our results to the existing literature. Section 5 concludes the paper by summarizing the main findings.

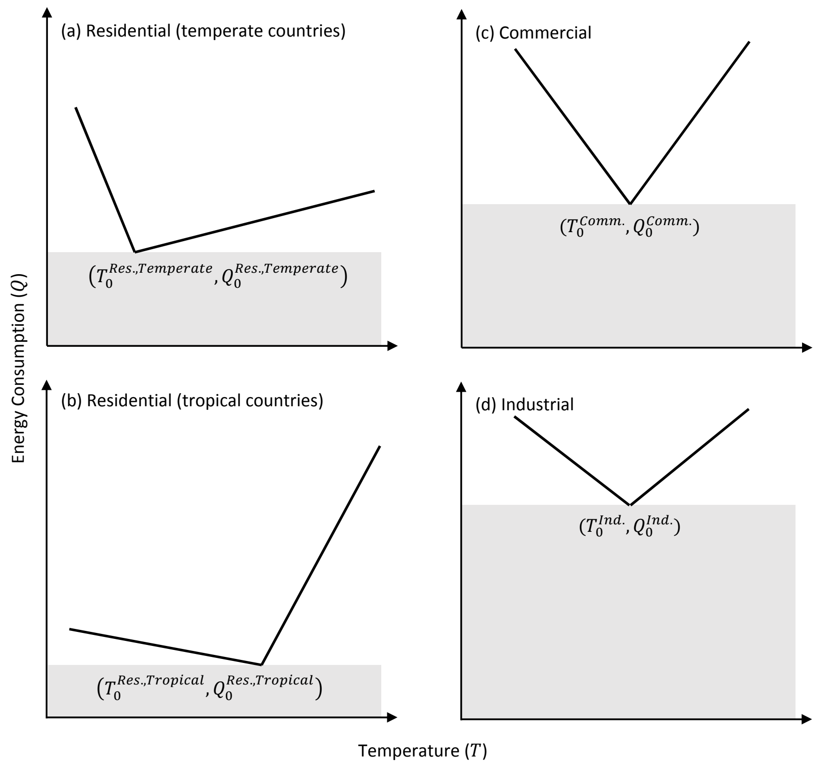

Figure 1: Temperature dependence of energy demand: stylized facts

2 Methods

2.1 Modeling the long-run demand for energy

We model the final demand for three energy commodities (electricity, petroleum,[1] and natural gas) in five economic sectors (residential, commercial, industrial, agriculture, transportation—see Table A1), characterizing the response of consumption to temperature and humidity. As shown schematically in Fig. 1, the response of energy demand (Q) to temperature (T) differs by region and economic sector. Energy demand responses are thought to exhibit generalized V-shape, with a nadir at the so-called "balance point" (T_0, Q_0) and the slope of each segment capturing the marginal effect on demand of additional exposure to heat or cold (see variously Engle et al, 1986; Aroonruengsawat and Auffhammer, 2011; Auffhammer and Aroonruengsawat, 2011; Deschenes and Greenstone, 2013). These attributes vary according to the prevailing climate

[1] This is a composite of refinery gas, ethane, LPG, aviation gasoline, motor gasoline, jet fuels, kerosene, gasoline and diesel, fuel oil, naphtha, white spirit, lubricants, bitumen, paraffin waxes, petroleum coke and other oil products. The last category encompasses products which can be obtained by distillation of crude oil but are normally used outside the refining industry, and exclude finished products classified as refinery feedstocks.

and the extent to which the energy using activity is exposed to weather. The height of the gray area (Q_0) indicates non-weather responsive energy consumption, which is highest (lowest) in the parts of the economy that are least (most) exposed to weather—typically the industrial (residential) sector. The decrease in average year-round temperatures with latitude suggests that residential balance point temperatures in the tropics exceed those in temperate regions ($T_0^{\text{Res, Tropical}} > T_0^{\text{Res, Temperate}}$). Responses are also likely to be asymmetric, with tropical regions' use of energy for cooling (heating) varying elastically (inelastically) with high (low) temperatures, and temperate regions exhibiting the opposite pattern. Given such potential heterogeneity, our challenge is to develop an empirical model that is parsimonious yet capable of identifying differences in asymmetric demand responses across regions, sectors and fuels from limited data.

The customary empirical framework for estimating the short-run response of energy demand to weather is static cross section-time series regressions. Elasticities estimated by these models are likely to underestimate energy consumption changes as an adaptation to climatic shifts because they capture adjustments along the intensive margin, namely, changes in energy consumption that are conditional on the stock of energy-using durable goods. Over the long time horizon on which the climatic changes occur, the key additional influence on energy demand will be movements along the extensive margin—i.e., adjustments in the quantity and energy efficiency of the capital stock (Auffhammer and Mansur, 2014). There is particular concern that the diffusion of air conditioning (AC) equipment throughout the developing world will amplify electricity demand responses to higher summer temperatures, and, further, that warming will itself accelerate the accumulation of AC capital stocks beyond the levels of penetration determined solely by economic forces such as income growth and the cost and efficiency of AC units, endogenizing the amplification of demand. Modeling such extensive-margin adjustments typically necessitates information on stocks of energy-using durables (Sailor and Pavlova, 2003; McNeil and Letschert, 2008; Mansur et al, 2008; Davis and Gertler, 2015), but at the global scale such data are not available. Our workaround is to statistically capture the effects of unobserved extensive margin adjustments by employing an error correction modeling (ECM) framework that distinguishes the short-run effects of weather shocks from the long-run responses to climate (Masish and Masish, 1996; De Cian, Lanzi and Roson, 2013). While ECMs are a standard tool for understanding non-stationarity, endogeneity and causality in the relationship between energy use and income (Stern, 2000; Masish and Masish, 1996; Chontanawat et al, 2008), to our knowledge, only Beenstock et al (1999) and De Cian, Lanzi and Roson (2013) use them to study the relationship between energy and weather. The latter findings that contemporaneous temperature shocks tend to have persistent effects is what motivates our approach.

Importantly, the ECM is the solution to the two-stage optimization problem of achieving a target level of thermal regulation in the face of weather fluctuations. In the spirit of Hunt and Ryan (2015)[2], consider a model of an economy in which each sector is a representative agent who derives utility (U) from the consumption of three types of commodities: a composite good (z), a generic energy service (v), and a weather sensitive "thermal regulation" service (r).[3] Thermal regulation generates utility by shielding the agent from exogenous weather exposures ($\mathcal{E}$). It is provided by combining quantities W_f of $f = \{1, \ldots, F\}$ distinct fuels with the sector's stock of durable goods (X) to produce the appropriate amount of thermal regulation service conditional on $\mathcal{E}$ (e.g., heating, cooling and humidification):

$$r = \mathcal{R}[W_1, \ldots, W_F, X; \mathcal{E}]$$

By contrast, generic energy services are a function of non-weather sensitive fuel consumption (N_f) and the durables stock:

$$v = \mathcal{V}[N_1, \ldots, N_F, X]$$

The agent's first-stage problem is at the intensive margin:

$$\max_{w_f, n_f, z} \left\{ U[r, v, z] \middle| Y \geq \sum_f p_f (W_f + N_f) + z \right\}$$

where Y and p_f denote the agent's income and the relative prices of fuels. The solution is the optimal unconditional demands for weather responsive and non-weather responsive energy

$$W_f^* = \mathcal{W}_f[p_1, \ldots, p_F, X, Y; \mathcal{E}] \quad \text{and} \quad N_f^* = \mathcal{N}_f[p_1, \ldots, p_F, X, Y; \mathcal{E}]$$

which in turn determine the latent utility-maximizing quantities of thermal regulation and generic energy services, r^* and v^*.

[2]We assert that per capita GDP causes energy use, which in our context is supported by the use of a sectoral approach, as in Medlock and Soligo (2001). Aggregate per capita GDP can be considered an exogenous driver of the sectoral demand of a specific fuel, as the sectoral demand of a specific fuel is unlikely to have a significant effect on aggregate GDP.

[3]The character of r varies by sector: in residential and commercial sectors it is primarily the maintenance of physiologically comfortable indoor temperature and humidity through the use of space conditioning, in agriculture it encompasses the shielding of crops from extreme heat by pumping irrigation water, or from extreme cold by using sprinklers, heaters or foggers, while in industry it is optimization of temperature-sensitive production processes.

Complete reversibility in the production of r and v allows the agent's demands for energy to shift smoothly in response to weather shocks. However, short-run fixity of durable stocks constrains the agent's ability to adjust instantaneously, causing actual energy use to depart from its target equilibrium level. We model this process assuming that the agent follows a separable two-stage decision process: first determining static optimal energy service demands, and then determining the speed of adjustment of energy service flows to their equilibrium levels.[4] We model the second stage using a dynamic adjustment cost framework (e.g., Fanelli, 2006). We let t index time periods, $\mathbf{b} = [r, v]'$ denote the vector of energy services (with optimal target values $\mathbf{b}^*$), and assume that the agent selects a sequence of future service flows that minimizes expected discounted adjustment costs, conditional on the information available at each time step. Adjustment costs are represented by the quadratic loss function

$$\min_{\mathbf{b}_{t+\tau}} \mathscr{L} = \mathbb{E}_t \sum_{\tau=0}^{\infty} \rho^\tau \left[(\mathbf{b}_{t+\tau} - \mathbf{b}^*_{t+\tau})' \mathbf{\Lambda}_0 (\mathbf{b}_{t+\tau} - \mathbf{b}^*_{t+\tau}) + (\mathbf{b}_{t+\tau} - \mathbf{b}_{t+\tau-1})' \mathbf{\Lambda}_1 (\mathbf{b}_{t+\tau} - \mathbf{b}_{t+\tau-1}) \right] \quad (1)$$

where $\rho \in (0, 1)$ is a time-invariant discount factor, and $\mathbf{\Lambda}_0$ and $\mathbf{\Lambda}_1$ are positive definite matrices. Eq. (1) is a rational expectations model whose first term is the cost of missing the target level of energy services and whose second term is the cost of adjusting the level of services from one period to the next. Using Δ to indicate first differences, the first-order necessary conditions are the Euler equations,

$$\Delta \mathbf{b}_t = \rho \mathbb{E}_t \Delta \mathbf{b}_{t+1} - \mathbf{\Lambda}(\mathbf{b}_t - \mathbf{b}^*_t)$$

where $\mathbf{\Lambda} = \mathbf{\Lambda}_0^{-1} \mathbf{\Lambda}_1$. Because $\mathbb{E}_t \mathbf{b}_{t+1} = \mathbf{b}^*_t$ and $\mathbb{E}_t \mathbf{b}_t = \mathbf{b}_t$, the first-order condition implies the partial adjustment rule

$$\mathbf{b}_t - \mathbf{b}_{t-1} = -(\rho + \mathbf{\Lambda})(\mathbf{b}_t - \mathbf{b}^*_t)$$

whose error-correcting form is the solution to the second stage problem:

$$\Delta \mathbf{b}_t = (\rho + \mathbf{\Lambda}) \Delta \mathbf{b}^*_t - (\rho + \mathbf{\Lambda})(\mathbf{b}_t - \mathbf{b}^*_t) \quad (2)$$

The first- and second-stage solutions may be straightforwardly connected by expressing the optimal quantities of energy services and energy use as stochastic linear functions:

[4] The separability assumption allows the adjustment trajectory to be specified independently from the target level of the control variable.

$$r_t^* = \vartheta^{0,R} + \vartheta^{E,R}\mathcal{E}_t + \vartheta^{X,R}X_t + \mathbf{W}_t^*\boldsymbol{\vartheta}^{W,R} + e_t^R \tag{3a}$$

$$v_t^* = \vartheta^{0,V} + \vartheta^{E,V}\mathcal{E}_t + \vartheta^{X,V}X_t + \mathbf{N}_t^*\boldsymbol{\vartheta}^{N,V} + e_t^V \tag{3b}$$

$$W_{f,t}^* = \varpi_f^{0,W} + \varpi_f^{E,W}\mathcal{E}_t + \varpi_f^{X,W}X_t + \mathbf{p}_t\boldsymbol{\varpi}_f^{P,W} + \varpi_f^{Y,W}Y_t + e_t^W \tag{4a}$$

$$N_{f,t}^* = \varpi_f^{0,N} + \varpi_f^{E,W}\mathcal{E}_t + \varpi_f^{X,N}X_t + \mathbf{p}_t\boldsymbol{\varpi}_f^{P,N} + \varpi_f^{X,Y}Y_t + e_t^N \tag{4b}$$

where the vectors $\boldsymbol{\vartheta}$ and $\boldsymbol{\varpi}$ are parameters, and $\mathbf{e}$ denotes random disturbances. Eqs. (2), (3) and (4) suggest that the demands for a particular fuel (f') also have an error-correcting form:[5]

$$\begin{aligned}\Delta W_{f',t}^* = {} & \omega_{f'}^{0,W} + \omega_{f'}^{E,W}\Delta\mathcal{E}_t + \omega_{f'}^{X,W}\Delta X_t + \Delta\mathbf{p}_t\boldsymbol{\omega}_{f'}^{P,W} + \omega_{f'}^{Y,W}\Delta Y_t \\ & + \chi_{f'}^W\left\{W_{f',t-1}^* - \psi_{f'}^{E,W}\mathcal{E}_{t-1} - \psi_{f'}^{X,W}X_{t-1} - \mathbf{p}_{t-1}\boldsymbol{\psi}_{f'}^{P,W} - \psi_{f'}^{Y,W}Y_{t-1}\right\} + \nu_{f',t}^W \qquad (5a)\\ \Delta N_{f',t}^* = {} & \omega_{f'}^{0,N} + \omega_{f'}^{E,N}\Delta\mathcal{E}_t + \omega_{f'}^{X,N}\Delta X_t + \Delta\mathbf{p}_t\boldsymbol{\omega}_{f'}^{P,N} + \omega_{f'}^{Y,N}\Delta Y_t \\ & + \chi_{f'}^N\left\{N_{f',t-1}^* - \psi_{f'}^{E,N}\mathcal{E}_{t-1} - \psi_{f'}^{X,N}X_{t-1} - \mathbf{p}_{t-1}\boldsymbol{\psi}_{f'}^{P,N} - \psi_{f'}^{Y,N}Y_{t-1}\right\} + \nu_{f',t}^N \qquad (5b)\end{aligned}$$

parameterized by the vectors of coefficients $\boldsymbol{\omega}$, $\boldsymbol{\psi}$ and $\boldsymbol{\chi}$, and errors $\boldsymbol{\nu}$. Sparsity of data on the components of energy demand W_f and N_f makes it impossible to directly estimate the system of equations (5). However, the total consumption of each fuel, $Q_f = W_f + N_f$, is readily available. Suppressing fuel subscripts, we model inter-period adjustment in Q as the sum of (5a) and (5b), yielding the specification we take to the data:

$$\begin{aligned}\Delta Q_t = {} & \omega^0 + \omega^E\Delta\mathcal{E}_t + \omega^X\Delta X_t + \Delta\mathbf{p}_t\boldsymbol{\omega}^P + \omega^Y\Delta Y_t \\ & + \chi\left\{Q_{t-1} - \psi^E\mathcal{E}_{t-1} - \psi^X X_{t-1} - \mathbf{p}_{t-1}\boldsymbol{\psi}^P - \psi^Y Y_{t-1}\right\} + \nu_t \qquad (6)\end{aligned}$$

We recast the dependent variable as the interannual difference in the logarithm of fuel $\times$ sector (s) $\times$

[5] We first substitute (3) into (2) and rearrange the result to obtain the interperiod adjustment in the demands for f':

$$\begin{aligned}\Delta W_{f',t}^* = {} & \xi_{f'}^{0,W} + \xi_{f'}^{E,W}\Delta\mathcal{E}_t + \xi_{f'}^{X,W}\Delta X_t + \Delta\mathbf{W}_{\neg f',t}^*\boldsymbol{\xi}_{f'}^{W,W} \\ & + \sigma_{f'}^W\left\{W_{f',t-1}^* - \zeta_{f'}^{E,W}\mathcal{E}_{t-1} - \zeta_{f'}^{X,W}X_{t-1} - \mathbf{W}_{\neg f',t-1}^*\boldsymbol{\zeta}_{f'}^{W,W}\right\} + \mu_{f',t}^W \\ \Delta N_{f',t}^* = {} & \xi_{f'}^{0,N} + \xi_{f'}^{E,N}\Delta\mathcal{E}_t + \xi_{f'}^{X,N}\Delta X_t + \Delta\mathbf{N}_{\neg f',t}^*\boldsymbol{\xi}_{f'}^{N,N} \\ & + \sigma_{f'}^N\left\{N_{f',t-1}^* - \zeta_{f'}^{E,N}\mathcal{E}_{t-1} - \zeta_{f'}^{X,N}X_{t-1} - \mathbf{N}_{\neg f',t-1}^*\boldsymbol{\zeta}_{f'}^{N,N}\right\} + \mu_{f',t}^N\end{aligned}$$

whose coefficients $\boldsymbol{\xi}$ and $\boldsymbol{\zeta}$ are functions of the parameters ρ, $\boldsymbol{\Lambda}$, $\boldsymbol{\vartheta}$, $\boldsymbol{\varpi}$, and the error terms $\boldsymbol{\mu}$ are functions of the parameters and the disturbances. We simplify the foregoing expression by using (4) to eliminate the right-hand side quantities of non-focal fuels ($\neg f'$), yielding (5).

country (i) $\times$ year (t) demand for final energy per person, q. The covariates of interest are the exposure over each calendar year (measured in days) to J intervals of average daily temperature and K intervals of average daily specific humidity.[6] These country-specific variables are derived from global gridded meteorological reanalysis data in two steps. First, for the j^{th} temperature interval with support $\langle \underline{T}_j, \overline{T}_j \rangle$, and the k^{th} humidity interval with support $\langle \underline{H}_k, \overline{H}_k \rangle$, year t exposure at the c^{th} grid cell is the accumulated count of days whose average temperature and humidity (T_c and H_c) fall into the appropriate ranges:

$$\varepsilon^T_{j,c,t} = \mathcal{C}\left[T_c \in \langle \underline{T}_j, \overline{T}_j \rangle\right] \quad \text{and} \quad \varepsilon^H_{k,c,t} = \mathcal{C}\left[H_c \in \langle \underline{H}_k, \overline{H}_k \rangle\right] \tag{7}$$

were $\mathcal{C}$ is the count operator. For each country, i, exposures are computed as the population-weighted sum of exposures over the county's constituent grid cells $c \in i$:

$$\mathcal{E}^T_{j,i,t} = \sum_{c \in i} w_{c,i,t} \varepsilon^T_{j,c,t} \quad \text{and} \quad \mathcal{E}^H_{k,i,t} = \sum_{c \in i} w_{c,i,t} \varepsilon^H_{k,c,t} \tag{8}$$

where the weights, $w_{c,i,t} = pop_{c,t}/Pop_{i,t}$, are the ratio of the grid cell to national population. Statistical controls include log per capita GDP (y), log real prices of electricity, natural gas, and petroleum (p_f), and the log of the aggregate capital stock per capita (x). The result is our benchmark specification, the cross section-time series error-correction model:

$$\begin{aligned}\Delta q_{i,t} = \alpha_i + &\left[\sum_{j=1}^{J} \beta^T_j \Delta \mathcal{E}^T_{j,i,t} + \sum_{k=1}^{K} \beta^H_k \Delta \mathcal{E}^H_{k,i,t} + \sum_f \beta^P_f \Delta p_{f,i,t} + \beta^Y \Delta y_{i,t} + \beta^X \Delta x_{i,t}\right] \\ &+ \theta \left\{ q_{i,t-1} - \sum_{j=1}^{J} \gamma^T_j \mathcal{E}^T_{j,i,t-1} - \sum_{k=1}^{K} \gamma^H_k \mathcal{E}^H_{k,i,t-1} - \sum_f \gamma^P_f p_{f,i,t-1} - \gamma^Y y_{i,t-1} - \gamma^X x_{i,t-1} \right\} + \nu_{i,t} \end{aligned} \tag{9}$$

where α is a fixed effect that captures the influence of unobserved time-invariant country-specific factors on the average growth rate of energy demand, and ν is a random disturbance term.

Eq. (9) partitions the influence of the covariates into short- and long-run effects, captured by the terms in square and curly braces, respectively. The former are identified from the contemporaneous co-variation between the interannual differences of energy consumption and the regressors. The latter are identified from the co-variation between lagged energy consumption and the prior levels of the covariates. The error-

[6]Relative humidity is a better indicator of the demand for cooling to counteract heat stress because it accounts for the attenuation of evaporative cooling through perspiration. Notwithstanding this, we use specific humidity because it is less correlated with temperature.

correction speed of adjustment parameter, θ, measures countries' common rate of adjustment toward the long-run equilibrium. The parameter vectors $\boldsymbol{\beta}^T$ and $\boldsymbol{\beta}^H$ identify the disequilibrium demand response to meteorology in the short run, while $\boldsymbol{\gamma}^T$ and $\boldsymbol{\gamma}^H$ capture the feedback effect of the divergence between observed energy consumption and long-term equilibrium energy use predicted by the covariates. The individual coefficient estimates are semi-elasticities that indicate the percentage by which demand shifts relative to its conditional mean level due to additional time spent in a given interval, which are the distinct marginal effects of each exposure range (e.g., the average annual impact of an additional day with 10-15 °C versus 25-30 °C temperatures). Collectively, the elements of $\boldsymbol{\gamma}^T$ and $\boldsymbol{\gamma}^H$ flexibly capture temperature and humidity long-run effects as a piecewise linear spline, whose shape is determined by the covariation between observed demand and meteorology within each interval, as well as by the distribution of observations across intervals over the historical period of the sample. The advantage of this formulation is its ability to capture potential nonlinearity in the demand responses to weather (cf Fig. 1) and more precisely resolve the effects of extreme heat and humidity relative to alternative specifications such as seasonally averaged temperatures or degree-days.

2.2 Data and empirical approach

Our dataset is an unbalanced panel of countries, depending on the fuel $\times$ sector combination, over the period 1970-2014, stratified by climatic regime into tropical or temperate groups according to the Koeppen-Geiger classification (Table A2). Our dependent variable is final energy consumption from the ENERDATA database (Table 1). Of the 219 exajoules (EJ) consumed by our sample of countries in 2010,[7] countries in temperate regions accounted for 77% of the total. In both temperate and tropical regions demand is concentrated in the transportation and industry, with residences coming in a close third in temperate countries and a distant third in the tropics. In both regions petroleum (used overwhelmingly by transportation) makes up around half of total consumption, while electricity accounts for roughly a quarter of tropical counties' use and more than a third temperate countries' use. Aside from transportation's use of petroleum, tropical countries' industrial sectors' use of all fuels, and temperate countries' industrial, commercial and residential sectors' electricity consumption, as well as residences' use of natural gas, are particularly important.

Meteorological covariates are calculated from 3-hourly fields of surface temperature and specific humid-

[7]Global total final energy consumption in 2010 was 376 EJ. Our smaller total reflects countries excluded because of missing data.

	Elec-tricity	Natural Gas	Petrol-eum	*Total*	Elec-tricity	Natural Gas	Petrol-eum	*Total*	Elec-tricity	Natural Gas	Petrol-eum	*Total*
	Tropical				Temperate				World			
Agriculture	0.8	0	1.5	*2.3*	0.9	0.3	3.2	*4.4*	1.6	0.3	4.7	*6.6*
Industrial	4.5	6.8	4.6	*15.9*	21.6	12.9	8	*42.5*	26.1	19.7	12.7	*58.5*
Residential	3.5	2	3	*8.5*	14	15.9	5.4	*35.3*	17.5	18	8.4	*43.9*
Commercial	2.6	0.3	0.7	*3.6*	14.1	7.4	3.2	*24.7*	16.7	7.7	3.9	*28.3*
Transportation	0.1	0.6	19.4	*20.1*	0.8	0.6	60	*61.4*	0.9	1.2	79.4	*81.5*
Total	*11.5*	*9.7*	*29.2*	*50.4*	*51.4*	*37.1*	*79.8*	*168.3*	*62.8*	*46.9*	*109.1*	*218.8*

Table 1: 2010 final energy consumption in our country sample (EJ)

ity on a 0.25° grid from the Global Land Data Assimilation System (GLDAS) dataset (Rodell et al, 2004). We first temporally aggregate the raw temperature and humidity fields to construct gridded daily averages, which we bin into 14 temperature ranges and 10 specific humidity ranges over the course of each year. The resulting annual counts of daily exposures are then spatially aggregated to the country level using geospatially referenced population for the year 2000 from the Global Rural-Urban Mapping Project (GRUMPv1) database.[8] Our statistical controls are countries' annual real PPP GDP per capita from the Penn World Table (Heston et al, 2013), real energy prices from the ENERDATA database,[9] and real capital stocks from Berlemann and Wesselhoft (2014) expressed in per capita terms, all in logarithms and lagged one period to guard against potential endogeneity. Descriptive statistics are summarized in the Appendix (Table A2).

Multiple data issues posed a tradeoff between identifying weather impacts and obtaining well-controlled empirical estimates. Small sample sizes precluded identification of the per capita energy demand responses to all but a few of the 14 temperature intervals. Given the collinearity between the fixed effects and moderate temperature and humidity intervals, our remedy was to drop these middle bins and aggregate adjacent extreme bins to focus the analysis on the effects of exposure to extreme hot and cold days ($T < 12.5$°C and $T > 27.5$°C). Gaps in ENERDATA's energy price series further reduced our sample sizes (especially in developing countries), and collinearity between country GDP and capital stock series prevented the use of both variables as independent controls. We pursued a general-to-specific modeling strategy, first dropping the capital stock variable and estimating eq. (9) with temperature, humidity, the full vector of energy prices and GDP per capita as our base specification (M1), then excluding cross-price terms (M2), excluding humidity terms (M3), and finally excluding both cross price and humidity terms (M4).[10] For each fuel × sector ×

[8] As dynamic population maps were not available, we assume identical weights for all years in our sample, $\overline{w}_{c,i,\text{Current}}$.

[9] As fuel price series for the agriculture and commercial sectors were not available, industrial fuel prices were used. The transportation sector includes the price of gasoline only.

[10] The combination of 4 models, 3 fuels, 5 sectors and 2 regions yields 120 regressions. There were insufficient observations of natural gas use by agriculture in the tropics generally, and residential use of electricity, natural gas and petroleum in the tropics

region combination, our preferred long-run elasticity values are taken from the least restrictive specification yielding estimates that are significant at the 10% level[11].

Collinearity of our capital stocks with GDP created an insurmountable obstacle to identifying the impact on the average set-point energy consumption in Fig. 1 of capital deepening—or unpacking the effect of the latter into the influences of increasing quantity or changing characteristics of energy-using durables. Both influences are subsumed within eq. (9)'s error-correcting speed of adjustment parameter and the long-run income elasticity. Nevertheless, we are able to elucidate the net impact of increases in the capital stock per person on the *marginal* response of energy demand to weather, by interacting the log capital stock per person with bins of temperature. The result is the extensive margin specification:

$$\begin{aligned}\Delta q_{i,t} = \alpha_i &+ \left[\sum_{j=1}^{J}\left(\beta_j^{XT}\Delta(\mathcal{E}_{j,i,t}^{T}x_{i,t}) + \beta_j^{TT}\Delta\mathcal{E}_{j,i,t}^{T}\right) + \sum_{k=1}^{J}\beta_k^{H}\Delta\mathcal{E}_{k,i,t}^{H} + \sum_{f}\beta_f^{P}\Delta p_{f,i,t} + \beta^{Y}\Delta y_{i,t}\right] \\ &+ \theta\left\{q_{i,t-1} - \sum_{j=1}^{J}\left(\gamma_j^{XT}(\mathcal{E}_{j,i,t-1}^{T}x_{i,t-1}) + \gamma_j^{TT}\mathcal{E}_{j,i,t-1}^{T}\right) - \sum_{k=1}^{J}\gamma_k^{H}\mathcal{E}_{k,i,t-1}^{H} - \sum_{f}\gamma_f^{P}p_{f,i,t-1} - \gamma^{Y}y_{i,t-1}\right\} + \nu_{i,t}\end{aligned} \tag{10}$$

which facilitates decomposition of the previously-estimated temperature elasticities into baseline responses (γ^{TT}) and the modulating effects of capital (γ^{XT}):

$$\gamma_j^{T} = \gamma_j^{TT} + \gamma_j^{XT}x \tag{11}$$

Capital's net influence is captured by the parameter γ^{XT}. Positive values suggest that the positive influence of a larger stock of energy-using durables outweighs the negative influence of the diffusion of energy efficiency improvements embodied therein, amplifying the response of energy consumption to exposure in a given temperature interval. Negative values indicate that the reverse is true, yielding an attenuating effect on demand. The direction and magnitude of the overall impact of temperature depends on the per-capita capital stock. Note that if γ^{TT} and γ^{XT} have different signs a given change in temperate exposure can lower energy demand in some locations while simultaneously raising it in others with larger or smaller ratios of capital per person.

when all prices are included. We end up with 29 fuel $\times$ sector $\times$ region combinations for specifications M2 and M4, and 26 such combinations for specifications M1 and M3. Results for the 110 regressions estimated are available upon request.

[11]If there are no estimates significant at 10% but there are estimates significant at 15% level, we use them

2.3 Climate change impact projections

The second phase of our analysis combines econometrically estimated long-run elasticities with scenarios of climate change and global socioeconomic development to characterize future impacts on energy demand, circa 2050. Projected changes in meteorology are simulated by runs of the CMCC-CM earth system model (Scoccimarro et al, 2011) under two a representative scenarios of moderate and high warming (RCP 4.5 and RCP 8.5, with radiative forcing of 4.5 W/m^{-2} and 8.5 W/m^{-2}, respectively, by century's end)[12]. ESM projections of climate are subject to considerable uncertainty, particularly in the vertical structure of water vapor which will influence sensible temperature and the demands for heating and cooling (Flato et al, 2013). Accordingly, we restrict our attention to temperature as the climatic predictor of energy consumption changes. Although ESM simulations exhibit skill relative to broad patterns of surface temperatures in the current climate, individual ESMs exhibit biases that tend to increase with spatial and temporal resolution. For this reason making direct comparisons between ESM simulations of future climate and historical reanalysis datasets such as GLDAS is not appropriate. Our solution is to employ the "delta" method, which consists of applying eq. (7) to CMCC-CM gridded model output to construct annualized PDFs of temperature exposures over the current and projection periods 2006-2015 and 2046-2055, denoted as $\widetilde{\varepsilon}^{T}_{j,c,\text{Current}}$ and $\widetilde{\varepsilon}^{T}_{j,c,\text{Future}}$, respectively. These two fields of temperature exposure can be validly compared for the purpose of constructing impact projections (Fig. 2). Relative to the 2006-2015 climate, circa 2050 the majority of grid cells will experience increased (decreased) frequency of hot days $> 27.5°$C (cold days $< 0°$C). The geographic incidence of these changes in uneven, with increased frequency of hot days in the tropics and areas such as southern Europe, as well as decreased frequency of cold days concentrated at high latitudes. In countries with large latitudinal extents (e.g., the U.S., China, Australia, and Brazil) increasing heat exposures and declining cold exposures are localized in different sub-national zones.

Our climate change impact metric is the change in per capita energy demand at the level of each grid-cell, c, which we calculate by combining the fitted long-run climatic estimates in (9) with our synthetic historical and future exposure series:

$$\phi^{\text{Climate}}_{c,f,s} = \exp\left\{ \sum_{j=1}^{J} \widehat{\gamma}^{T}_{j,f,s} \left(\widetilde{\varepsilon}^{T}_{j,c,\text{Future}} - \widetilde{\varepsilon}^{T}_{j,c,\text{Current}} \right) \right\} \tag{12}$$

[12]Relative to other ESMs participating in the Coupled Model Intercomparison Project Phase 5 (CMIP5), CMCC-CM generally exhibits less warming in the tropics and more cold days in the mid-latitudes (Bas van Ruijven, personal communication).

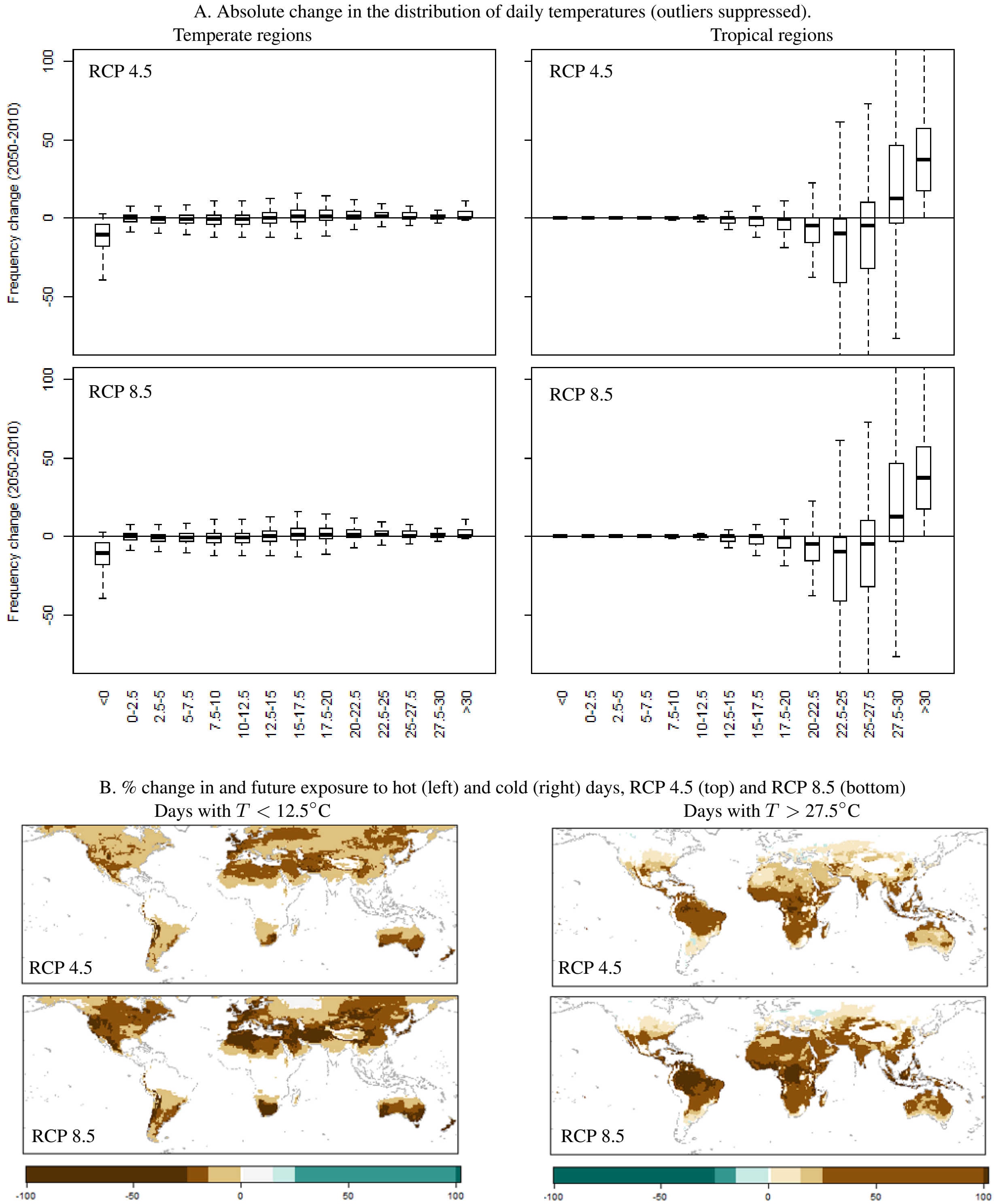

Figure 2: CMCC-CM simulated changes in future temperature exposure for different warming scenarios, 2046-2055 relative to 2006-2015.

The index ϕ^{Climate} can be interpreted as the ratio of per-capita fuel $\times$ sector energy consumption in a future climate relative energy use under the current climate. It is straightforward to use this kind of metric to quantify the effects that climatic shifts would have on *today's* economy. For example, using current energy consumption ($\widetilde{Q}_{i,f,s,\text{Current}}$) as the base, and assuming that sub-national per capita energy demand is uniformly distributed and equal to the national average, the net impact on contemporary country-level final energy demand, i, is found by aggregating across grid cells, fuels and sectors:

$$\Phi_{i,\text{Current}} = \frac{\sum_f \sum_s \left\{ \sum_{c \in i} \overline{w}_{c,i,\text{Current}} \phi^{\text{Climate}}_{c,f,s} \right\} \widetilde{Q}_{i,f,s,\text{Current}}}{\sum_f \sum_s \widetilde{Q}_{i,f,s,\text{Current}}} \tag{13}$$

The caveat is that the future global energy system is likely to differ substantially from the present, due especially to the growth of population and GDP anticipated in developing countries over the coming decades. The broader implication is that assessments should account for the character of vulnerable human systems in the *future* periods when climatic changes arise (Kriegler et al, 2012). Here the latter correspond to gridded fields of population and "business as usual" (BaU) fuel $\times$ sector per-capita energy demand circa 2050, which we construct using the Shared Socioeconomic Pathways. Using SSP5,[13] we obtain gridded and national population distributions, $pop_{c,\text{Future}}$ and $Pop_{i,\text{Future}}$ from Jones et al (2015), as well as the logarithms of countries current and future average per-capita GDP, $\widetilde{y}_{i,\text{Current}}$ and $\widetilde{y}_{i,\text{Future}}$. Combining the latter with our estimated long-run income elasticities ($\widehat{\gamma}^{Y}_{f,s}$), we enable economic growth to scale the country-level per capita energy demands

$$\phi^{\text{Economy}}_{i,f,s} = \exp \left\{ \widehat{\gamma}^{Y}_{f,s} \left(\widetilde{y}_{i,\text{Future}} - \widetilde{y}_{i,\text{Current}} \right) \right\} \tag{14}$$

yielding future country-level energy consumption in the absence of climate change:

$$Q_{i,f,s,\text{BaU}} = \phi^{\text{Economy}}_{i,f,s} \widetilde{Q}_{i,f,s,\text{Current}} \tag{15}$$

Using future population to calculate grid-cell level weights, $\overline{w}_{c,i,\text{Future}} = pop_{c,\text{Future}} / Pop_{i,\text{Future}}$, our ana-

[13] SSP5 evisages a future with conventional economic development, slow population growth, rapid growth in aggregate productivity and international convergence of GDP, and rapid increases in final energy consumption mostly through fossil fuels (O'Neill et al, 2014).

logue of (13) that accounts for future expansion in energy consumption is:

$$\Phi_{i,\text{Future}} = \frac{\sum_f \sum_s \left\{ \sum_{c \in i} \overline{w}_{c,i,\text{Future}} \phi^{\text{Climate}}_{c,f,s} \right\} \widetilde{Q}_{i,f,s,\text{BaU}}}{\sum_f \sum_s \widetilde{Q}_{i,f,s,\text{BaU}}} \tag{16}$$

The corresponding changes in energy use at the grid cell-level are summarized by the fuel, sector, and fuel $\times$ sector margins of (16):

$$\varphi^{\text{Fuel}}_{c,f,\text{BaU}} = \frac{\sum_s \delta_{i,c} \phi^{\text{Climate}}_{c,f,s} \widetilde{Q}_{i,f,s,\text{BaU}}}{\sum_s \delta_{i,c} \widetilde{Q}_{i,f,s,\text{BaU}}} \tag{17a}$$

$$\varphi^{\text{Sector}}_{c,s,\text{BaU}} = \frac{\sum_f \delta_{i,c} \phi^{\text{Climate}}_{c,f,s} \widetilde{Q}_{i,f,s,\text{BaU}}}{\sum_f \delta_{i,c} \widetilde{Q}_{i,f,s,\text{BaU}}} \tag{17b}$$

$$\varphi^{\text{Total}}_{c,\text{BaU}} = \frac{\sum_f \sum_s \delta_{i,c} \phi^{\text{Climate}}_{c,f,s} \widetilde{Q}_{i,f,s,\text{BaU}}}{\sum_f \sum_s \delta_{i,c} \widetilde{Q}_{i,f,s,\text{BaU}}} \tag{17c}$$

where the indicator variable, $\delta_{c,i} = 1 \cdot (\overline{w}_{c,i,\text{Future}} > 0)$, takes a value of unity if cell c lies within country i's administrative boundary, and zero otherwise.

Lastly, it is not straightforward to use our extensive margin specification (10) to construct detailed projections of climate change impacts on either the current or future energy system. The obstacle is absence of data on capital stocks at the grid cell level for the current period, and particularly for future periods consistent with the SSP scenarios. There is the potential to calculate an analogue of eq. (12) to assess the-present day impacts of future climate change,

$$\phi^{\text{Extensive Margin}}_{\text{Elec., Residential},c} = \exp\left\{ \sum_{j=1}^{J} \left(\widehat{\gamma}^{TT}_{j,\text{Elec., Residential}} + \widehat{\gamma}^{XT}_{j,\text{Elec., Residential}} \widetilde{x}_c \right) \left(\widetilde{\varepsilon}^{T}_{j,c,\text{Future}} - \widetilde{\varepsilon}^{T}_{j,c,\text{Current}} \right) \right\} \tag{18}$$

using a spatially downscaled capital stock proxy, $\widetilde{x}$, e.g., derived from the Global Exposure Database (De Bono and Mora, 2014). However, such an assessment is beyond the scope of the present study.

3 Results

3.1 Empirical energy demand responses to temperature and income

Table 2 summarizes our empirical estimates. Our preferred specification (9), shown in panel A, generates estimates for 12 fuel $\times$ sector combinations, the no cross-price effects model yielded a further 6 estimates,

			Response to cold days ($T < 12.5°$C)	Response to hot days ($T > 27.5°$C)	Log real GDP per capita elasticity	Error-Correcting Speed of Adjustment	Time to Equilibrium (years)
					Temperate regions		
Agriculture	Electricity	M4		0.008	0.645	-0.107	9.4
	Natural gas	M1	-0.0195^{+}		1.320	-0.188	5.3
	Petroleum						
Industrial	Electricity	M2		0.009	0.363	-0.175	5.7
	Natural gas	M2		0.033		-0.216	4.6
	Petroleum	M2			-1.089	-0.068	14.6
Residential	Electricity	M3		0.0146^{+}	0.366	-0.194	20.7
	Natural gas	M1	0.023		1.433	-0.117	8.5
	Petroleum	M4	0.0207^{+}			-0.056	17.9
Commercial	Electricity	M1	-0.006	0.047	0.864	-0.150	6.7
	Natural gas	M1			0.970	-0.240	4.2
	Petroleum	M3	0.012		-0.795	-0.257	3.9
Transportation	Electricity	M1	-0.003^{+}		0.260	-0.173	5.8
	Natural gas						
	Petroleum	M1			0.821	-0.235	4.3
					Tropical regions		
Agriculture	Electricity	M1	-0.008^{+}		-0.701	-0.939	1.1
	Natural gas						
	Petroleum	M1	0.066			-0.217	4.6
Industrial	Electricity	M1	-0.028	0.008^{+}	0.478	-0.157	6.4
	Natural gas	M2		0.010		-0.150	6.6
	Petroleum	M2		0.005		-0.206	4.8
Residential	Electricity	M2			1.287	-0.092	10.9
	Natural gas						
	Petroleum						
Commercial	Electricity	M1		0.008	0.702	-0.218	4.6
	Natural gas	M1					
	Petroleum	M3	-0.014	-0.017		-0.239	4.2
Transportation	Electricity	M3		-0.011	1.93	-0.192	5.2
	Natural gas						
	Petroleum	M1	-0.009	0.004^{+}	0.678	-0.206	4.8

All estimates significant at the 10% level, except where indicated: + $p<0.15$

Table 2: Long-run semi-elasticities of energy demand with respect to temperature exposures and income: preferred specification

the no-humidity model 4 more, and the model omitting both cross-price effects and humidity model, two estimates. Weather significantly influences energy consumption in less than 40% of fuel $\times$ sector $\times$ region combinations. Temperature semi-elasticities indicate that fuel demands tend to increase with hot days, an effect whose magnitude ranges in from 0.004 to 0.047 with larger values skewed toward temperate regions, and varies among fuels and sectors. These values generally exceed short-run elasticities estimated on aggregate data (e.g., Deschenes and Greenstone, 2013), and, for some fuel $\times$ sector combinations, attain magnitudes similar to those estimated by micro studies (Davis and Gertler, 2015; Auffhammer and Aroonruengsawat, 2011). Responses to hot and cold days are asymmetric (cf Fig. 1). Either the heating or the cooling response is significant—but not both—in most fuel $\times$ sector combinations (exceptions are electricity in commerce and industry, as well as petroleum in commerce and transportation).

Several weather elasticities are negative, mostly for low temperatures and especially in the tropics, suggesting that with high average temperatures, only extreme cold exposures induce changes in thermal regulation services large enough to permit identification of energy demand responses. While the aggregate nature of our data preclude our ability to pinpoint the precise mechanisms at work, we note that tropical countries predominantly represent developing economies with unreliable electricity distribution systems and consequent extensive use of distributed petroleum-fired generators to satisfy final electricity demand. Thus, while the declines in commercial and transportation electricity use seen in temperate countries are likely due to reduced AC usage during spring and fall, in tropical countries declines in commercial petroleum use may reflect a similar seasonal phenomenon, via the channel of reduced autoproducer electricity supplies. Declines in (non-autoproducer) electricity consumption by industry and agriculture in the tropics could reflect reduced AC use for occupational health and safety in heavy industries (particularly those with high temperature processes), as well as reduced irrigation water conveyance during the growing season or post-harvest refrigeration or processing of crops.

Other patterns of elasticity values are more challenging to explain, and we speculate may reflect fuel switching associated with seasonal variations in sectors' economic activity. In the agriculture-intensive developing economies that are concentrated in the tropics, increased demand for transport of harvested agricultural products during the relatively hot growing season accounts for the estimated increase (decrease) in transportation sector petroleum use in response to hot (cold) days. This also helps explain the increase in agricultural petroleum use with cold days as reflecting the switch from growing season use of off-farm (e.g., transport sector) motive power to on-farm alternatives related to out-of-season field operations. And while in tropical countries increased exposure to hot days is associated with switching between petroleum and electricity in the commercial and transportation sectors, the underlying drivers remain opaque.

The table also summarizes our long-run income elasticities, which are positive except for electricity use by agriculture in tropical countries and petroleum use by commerce in temperate countries. In line with expectations, demand in most fuel $\times$ sector $\times$ region combinations exhibit income responses that are relatively inelastic (absolute magnitude in the range 0.2-1). Natural gas in agricultural and residential sectors in temperate countries, and electricity in residential and transportation sectors in the tropics, increase elastically, while industrial petroleum use in temperate countries declines elastically. Comparing magnitudes across climates more broadly, elasticities of electricity use by residential, industrial and transportation sectors tend to be larger in the tropics, whereas those for commerce and agriculture tend to be larger in temperate regions. These values fall within the general range of estimates from previous aggregate analyses.

The effects of humidity and other covariates are reported in the online Appendix. Exposure to high humidity days increases industrial and commercial electricity use, and agricultural petroleum use in temperate regions, as well as residential and agricultural natural gas use in the tropics. Exposure to low humidity days increases use of electricity and natural gas in agriculture. The latter result likely indicates the correlation between low humidity and drought conditions that increase demands for irrigation, which in some countries is a major source of agricultural electricity consumption (Maddigan et al, 1982; Shah et al, 2008). Temperate countries are generally more sensitive to high humidity levels, reflecting the fact that their climates tend to be less humid than the tropics. While own-price elasticities are significant and with the expected negative sign in temperate countries, in the tropics energy prices are rarely significant, reflecting the patchiness of price data for developing countries, whose energy markets cover a smaller fraction of total final consumption and tend to be distorted. Long-run demand responses to temperature are uniformly larger in magnitude than their short-run counterparts.

Lastly, Table 2 records the error-correcting speed of adjustment coefficients and the implied length of time for energy demand to re-equilibrate after a shock. The coefficients, which are uniformly significant and less than unity, suggest that sectoral agents close anywhere from 7% to 94% of the disequilibrium gap between q and q^* in a year, confirming that energy consumption adjustments to contemporaneous weather shocks exert persistent effects on demand. The degree of persistence varies substantially. For agricultural electricity use in the tropics, full adjustment to a shock is practically instantaneous, taking about a year. But at the other extreme, residential energy use in temperate countries re-equilibrates very gradually, adjusting fully only after two decades. Across fuels and sectors it takes 7 years on average to fully adjust, but countries in the tropics adjust faster (5 years, as opposed to 8.6 years in temperate countries), consistent with the fact that they tend to be poorer economies with smaller (and thus more easily adjusted) stocks of energy-using capital.

Table 3 summarizes our long-run results at the extensive margin. Where γ^{TT} and γ^{XT} were both significant their estimates were always opposite in sign. Regarding the latter parameter, in temperate countries, capital deepening attenuates the demand response to cold days and amplifies the response to hot days. In the tropics the signs of the interaction estimates are mixed, especially for demand responses to cold days, while responses to hot days are more strongly weighted toward amplification. The implication is that the aforementioned temperature elasticities reflect the average of heterogeneous country responses that differ in sign and magnitude. Temperate-zone elasticities of heating (cooling) energy use are positive and significant for small to moderate (moderate to large) values of capital stock per person. Similar responses in tropical countries are not cleanly delineated by temperature: positive for low to moderate levels of capital stock per person and negative otherwise (demands for petroleum in agriculture and natural gas in commerce with low temperatures, as well as natural gas and petroleum in industry with high temperatures), and vice versa (demands for electricity in agriculture and industry with low temperatures, as well as for petroleum and electricity in agriculture and commerce with high temperatures). The biggest difference from Table 2 is that income elasticities are now only significant for a few fuel $\times$ sector combinations, mostly in the temperate zone. Notwithstanding this, the error-correcting speed of adjustment coefficients and associated equilibrium adjustment periods change only slightly in most cases, giving us confidence in the consistency of our intensive- and extensive-margin results.

Our finding of an amplified temperate-zone residential electricity response to heat vindicates our motivating concern about the consequences of AC penetration as poor countries develop. Already, our temperate-zone results encompass China (cf Auffhammer, 2014), and although we do not identify similar historical responses in the tropics, countries such as Brazil and India following similar development trajectories in the future is likely to portend substantial climate-driven increases in electricity consumption. It is this issue to which we now turn.

			Response to cold days ($T < 12.5°C$)					Response to hot days ($T > 27.5°C$)					Log real GDP per capita elasticity	Error-Correcting Speed of Adjustment	Time to Equilibrium (years)
			Base	Inter-action	@ %-iles of 2010 K per capita 50%	5%	95%	Base	Inter-action	@ %-iles of 2010 K per capita 50%	5%	95%			
			Temperate regions												
Agriculture	Electricity	M1	0.104	-0.006									1.172+	-0.127	7.9
	Natural gas	M2						-1.070	0.072	0.171		0.286		-0.208	4.8
	Petroleum														
Industrial	Electricity														
	Natural gas														
	Petroleum	M1	0.129	-0.007			0.025							-0.073	13.8
Residential	Electricity	M1	0.058	-0.003	0.006	0.012		-0.559	0.034	0.026	-0.039	0.080	0.998	-0.092	10.9
	Natural gas														
	Petroleum	M2	0.270+	-0.015										-0.049	20.4
Commercial	Electricity														
	Natural gas														
	Petroleum	M1	0.127	-0.006+	0.018	0.030				0.069				-0.271	3.7
Transportation	Electricity	M2	0.049	-0.003									1.071	-0.145	6.9
	Natural gas														
	Petroleum														
			Tropical regions												
Agriculture	Electricity	M2	-0.169	0.011			0.020	-0.233	0.015		-0.035	0.032		-0.307	3.3
	Natural gas														
	Petroleum	M1	1.510	-0.092	0.109	0.302	-0.103	-1.957	0.119	-0.139	-0.390	0.135		-0.194	5.2
Industrial	Electricity	M3	-0.880	0.053	-0.081	-0.191	0.040							-0.133	7.5
	Natural gas	M3						1.895	-0.116		0.373	-0.136		-0.294	3.4
	Petroleum	M3						0.626	-0.038	0.047	0.127	-0.040		-0.295	3.4
Residential	Electricity														
	Natural gas														
	Petroleum														
Commercial	Electricity	M1						-1.365	0.086	-0.051	-0.232	0.147		-0.219	4.6
	Natural gas	M1	3.064	-0.188	0.196	0.591	-0.237							-0.466	2.1
	Petroleum	M1						-1.354	0.083	-0.097	-0.270	0.093		-0.472	2.1
Transportation	Electricity	M1						-0.422	0.026		-0.086	0.026		-0.524	1.9
	Natural gas														
	Petroleum	M1						-0.020	0.002	0.004		0.007	0.698	-0.366	2.7

All estimates significant at the 10% level, except where indicated: + $p<0.15$

Table 3: Long-run semi-elasticities of energy demand with respect to temperature exposures and income: extensive margin specification

	Tropical				Temperate				World			
	Electricity	Natural Gas	Petroleum	*Total*	Electricity	Natural Gas	Petroleum	*Total*	Electricity	Natural Gas	Petroleum	*Total*
					2050 Energy Consumption (EJ)							
Agriculture	0.2	0	1.8	*2*	2.8	1.3	3.9	*8*	3.1	1.3	5.7	*10.1*
Industrial	13.6	10.7	6.4	*30.7*	41.8	16.8	2.9	*61.5*	55.4	27.5	9.4	*92.3*
Residential	51.7	2.5	3.8	*58*	26.7	108.8	6.7	*142.2*	78.4	111.3	10.6	*200.3*
Commercial	11.4	0.4	0.9	*12.7*	46.1	24.5	1.9	*72.5*	57.5	24.9	2.8	*85.2*
Transportation	5.5	0.7	85	*91.2*	1.2	0.6	196.8	*198.6*	6.7	1.3	281.8	*289.8*
Total	*82.4*	*14.3*	*97.9*	*194.6*	*118.6*	*152*	*212.2*	*482.8*	*201.1*	*166.3*	*310.3*	*677.7*
					Energy Consumption Growth Factor (2010 = 1.0)							
Agriculture	0	1	1	*1*	3	4	1	*2*	2	4	1	*2*
Industrial	3	2	1	*2*	2	1	0	*1*	2	1	1	*2*
Residential	15	1	1	*7*	2	7	1	*4*	4	6	1	*5*
Commercial	4	1	1	*4*	3	3	1	*3*	3	3	1	*3*
Transportation	55	1	4	*5*	2	1	3	*3*	7	1	4	*4*
Total	*7*	*1*	*3*	*4*	*2*	*4*	*3*	*3*	*3*	*4*	*3*	*3*

Table 4: Global weather-sensitive final energy consumption circa 2050 and change relative to 2010

3.2 The 2050 baseline: energy consumption and vulnerability to climate change

Using eqs. (14) and (15), we combine our preferred estimates with projected per capita GDP growth and gridded population from SSP5 to calculate BaU energy consumption circa 2050. The results, summarized in Table 4, indicate that in the absence of climate change global energy consumption will reach 677.7 EJ, a three-fold increase over 2010. This figure is in general agreement with IAM simulations of final energy under the SSP scenarios, falling just short of the lower end of the 709-895 EJ multimodel ensmble range (Riahi et al, 2017). Mirroring the range of our income elasticities, there is substantial heterogeneity in the extent of change in energy consumption across regions, sectors and fuels. We project a fourfold increase in final energy in tropical (generally emerging) economies, and a threefold increase in temperate (mostly advanced) economies, which shifts developing countries' share of global energy use from the current 23% to 29% by mid-century. Electricity accounts for the bulk of the expansion in energy use in the tropics, with rapid increases outside of agriculture, concentrated in the transportation and residential sectors. In temperate regions increases in energy consumption are driven by natural gas. Compared with the current energy system, the global final energy mix is slightly more skewed toward electricity and natural gas at the expense of petroleum, and toward the transportation and residential sectors at the expense of agriculture and industry.

Fig. 3 highlights the consequences of the spatial intersection between these patterns of energy use and

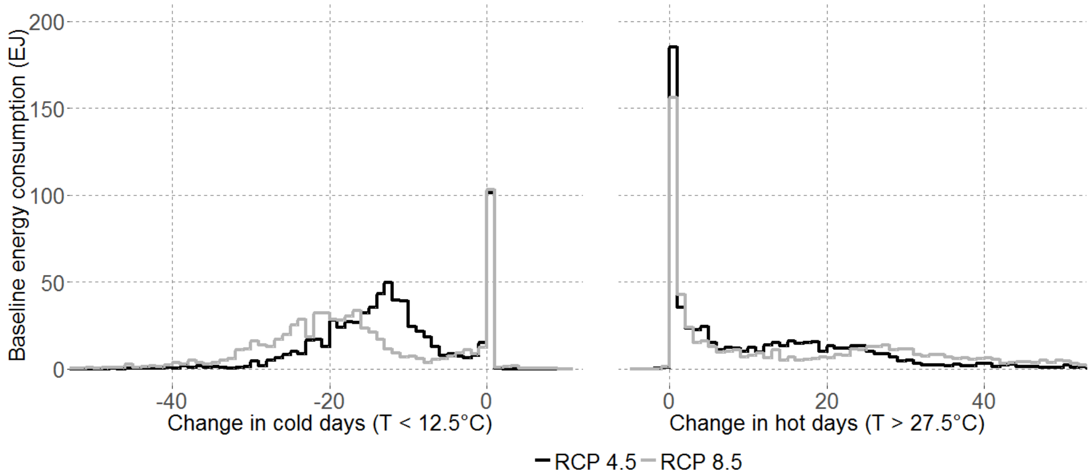

Figure 3: Exposure of business as usual energy demand to temperature changes

the climatic changes illustrated in Fig. 2.B. More than half BaU final energy consumption (65%) is projected to occur in areas that will be exposed to either slight declines in cold temperatures or slight increases in high temperatures (fewer than $\pm$ 5 extreme days). The largest absolute increases in hot days are concentrated in Southeast Asia, Latin America and Sub-Saharan Africa, regions where per capita and total final energy use are projected to still be small and whose frequency of hot days is already high in the current climate. The upshot is that the PDF of final energy's vulnerability exhibits a long upper tail, with relatively small quantities of total consumption exposed to a wide range of increases in heat. By comparison the lower tail is more compact, with a concentration of advanced, high energy consuming economies at high latitudes experiencing moderate reductions in cold temperature exposures. This pattern is accentuated under rapid warming, with more widespread areas—and concomitantly larger quantities of total energy consumption—experiencing bigger absolute increases in hot days, and, especially, declines in cold days, increasing the variance of the vulnerability distribution.

3.3 Future energy consumption impacts

The stratification of our econometric estimates means that a key determinant of the direction of climate change impact is distance from the equator, with the implication that tropical (temperate) responses disproportionately drive changes in the energy consumed by developing (advanced) countries (cf Fig. 2). Fig.

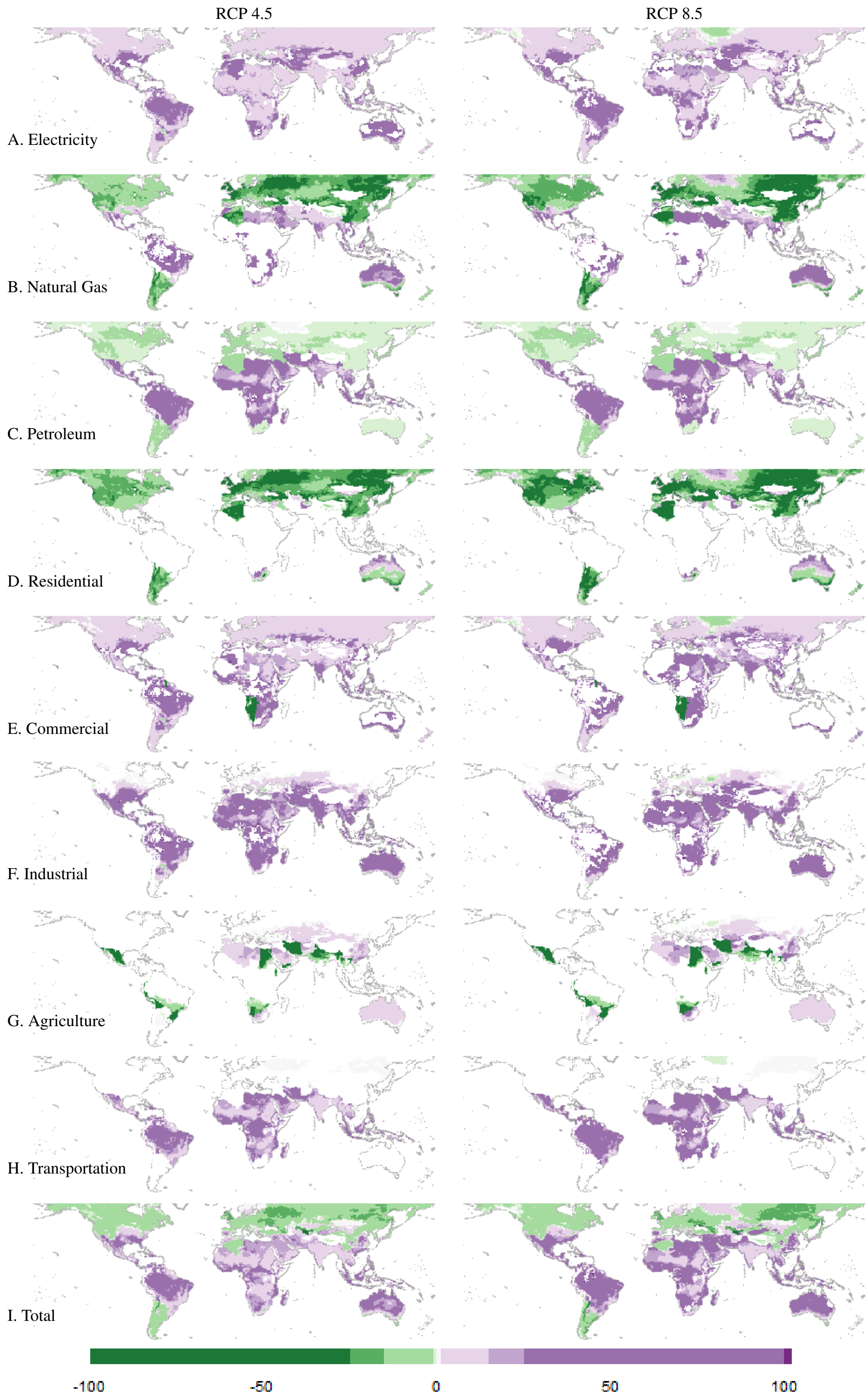

Figure 4: CMCC-CM simulated impacts on final energy demand circa 2050

4 shows the changes in demand at the grid-cell level for our three fuels (panels A-C), five sectors (panels D-H), and total final energy (panel I) calculated using eqs. (15) and (17).

Changes in the frequency of extreme days in Fig. 2 interact with the elasticities in Table 2 to affect the demand for petroleum and natural gas negatively in temperate regions (driven by residential and commercial sector responses) and positively in tropical regions. Impacts on natural gas use increase with latitude, whereas the strongest effects on petroleum use are largely in the tropics. Demand for electricity increases almost everywhere as the commercial and industrial sectors worldwide and the residential sector in temperate regions demand more energy to adapt to more frequent warm days.[14] Use of additional energy for cooling prevails in the commercial and industrial sectors globally, and in the transport sector in the tropics, while lower heating energy use prevails in the residential sector in temperate regions.[15] Agricultural adaptation is mixed, with no significant impacts in the tropics or high latitudes, and substantial reductions in overall energy use in the sub-tropics that transition to modest increases in demand use at mid-latitudes.

The ultimate effect on the total consumption of energy use is the superposition of the above impacts according to the intersectoral distribution of baseline uses of each type of energy. The upshot is amplification of demand concentrated in tropical and mid-latitude zones (Sub-Saharan Africa, Central and Latin America, South- and South-East Asia and Oceania) coexisting with mixed but predominantly negative demand impacts in temperate regions (especially in the northern hemisphere). In the mid latitudes, higher consumption is prevalent where the effects of more frequent high temperature exposures on cooling demand is large enough to outweigh the effects of less frequent low temperature exposures on the demand for heating demand (e.g., southern U.S. and Europe, Australia). More rapid warming accentuates the magnitudes of both kinds of changes, but the broad geographic patterns of their net effects persist across warming scenarios.

Aggregating the grid-cell level impacts in Fig 4 yields numerous insights. The first is the differential incidence of cooling-driven increases in energy consumption—and associated sectoral expenditures—relative to heating-driven savings. These are summarized by Fig. 5, which calculates their distribution across populations at the average income levels that correspond to the terciles of the SSP5 country per-capita GDP projections—low income: $<$\$10,000, middle income: \$10,000 - \$26,000 and high income: $>$ \$26,000. With both moderate and rapid warming more than 65% of the world's projected 8.5 billion people expe-

[14]The tropics are also influenced by the negative response of transportation, but that sector's baseline electricity use and its responsiveness to high temperature exposures are both too small to compensate for the increases described in the text.

[15]For some nations, the change in total commercial energy use is the opposite of others at the same latitude (e.g., Namibia's consumption declines, in contrast to similarly situated countries.). This phenomenon arises from the mix of fuels—Namibia's commercial sector overwhelmingly uses petroleum, whose demand falls with the decline cold days in southern Africa.

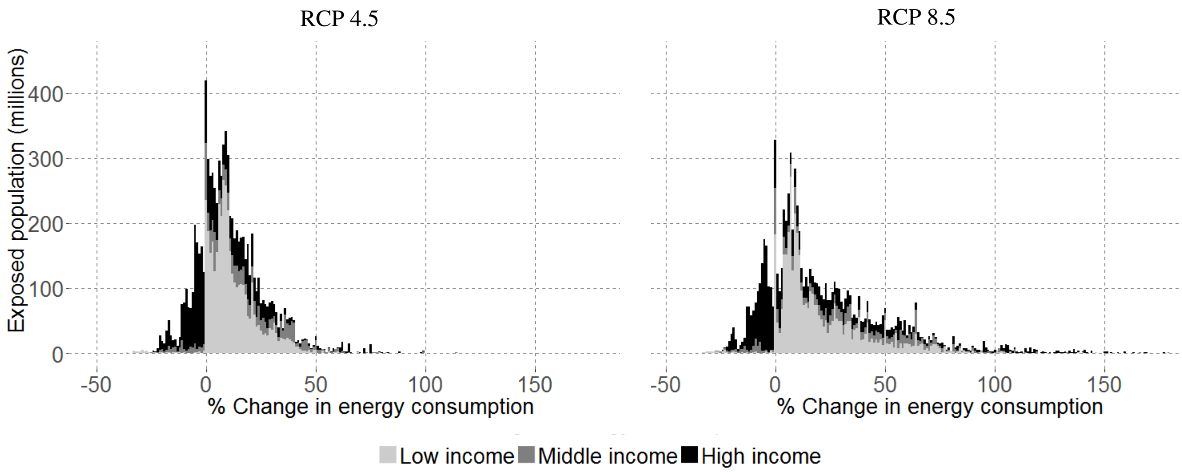

Figure 5: Incidence of climate change impacts on energy demand relative to future baseline

rience changes in weather-sensitive energy consumption in excess of $\pm5\%$ due to only to climate change, with the majority of those affected seeing increases. At the global level these impacts are regressive. The incidence of increased energy consumption rests overwhelmingly on populations in low- and middle-income countries (around 96% and 85%, respectively), while populations of high-income countries are split evenly between energy consumption increases and declines. Where warming scenarios diverge is in the upper tail of the impact distribution. Declines of more than 25% are virtually non-existent in either scenario. With moderate warming, 16% of the world's population experiences a $> 25\%$ increase in demand due to climate change, a fraction which more than doubles with vigorous warming. Moreover, in both cases around 40% of individuals experiencing such large increases live in poor countries.

A second insight is the impacts on energy use across countries and geopolitical regions. This is shown in Fig. 6, which summarizes our sectoral and total results for the 20 largest economies that account for about 80% of global energy consumption. Aside from Europe, Russia, South Korea, Canada and Argentina, impacts are positive and increase with the rate of warming. There are ubiquitous increases in industrial and commercial energy consumption, which are substantial, and in transportation fuel use, which is smaller, especially in high-latitude advanced countries. Residential energy declines in temperate countries, driven by reductions in natural gas and petroleum consumption with contracting demand for heating. The lone exception, South Africa, experiences an increase in hot days that is large enough to compensate for the relatively small positive response of electricity use for cooling. The absence of impact in tropical (developing) countries reflects our lack of identification of weather responses.

The sign and magnitude of economy-wide impacts reflect the balance between increased commercial,

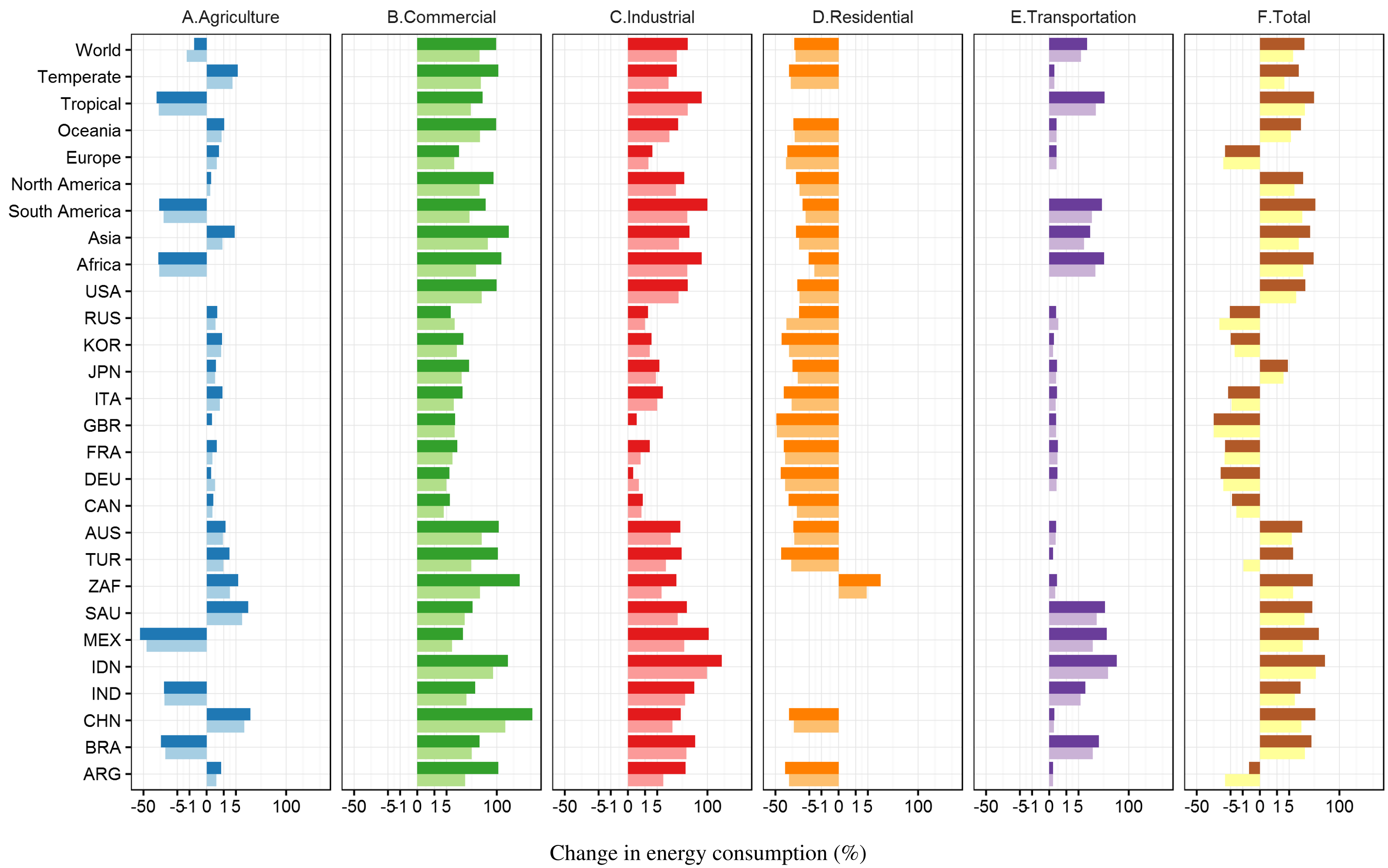

Figure 6: Sectoral and aggregate energy demand responses of G20 nations and world regions to different warming scenarios (RCP 4.5 light colors, RCP 8.5 dark colors) circa 2050. Percentage changes relative to the future baseline.

industrial and transportation sector demands, and declining residential demand, which is fundamentally determined by the intersectoral distribution of baseline energy use. As portended by Figs. 4 and 5, the flip in the direction of climate's effect with latitude translates into a divide along income lines. Large developing economies (with the exception of Argentina) see significant increases in total energy consumption, while advanced economies (excepting Australia, Japan, and United States) see modest energy savings. Further aggregation reveals that every continent but Europe will face increased consumption of, and likely larger expenditures on, energy. Collectively, tropical and temperate countries both experience a modest rise in demand under both mild and vigorous warming scenarios, under which global energy consumption increases by 7% and 17%, respectively. The increase in final energy demand is mostly driven by the higher frequency of hot days (+19%), whereas fewer cold days mostly in temperate regions results in a reduction in energy demand (-3%), see Table A6.

Finally, we illustrate what these effects mean, in terms of the changes in the absolute quantities of the different kinds energy being consumed. Table 5 compares the impacts, in physical units of consumption, of climatic changes circa 2050 on today's energy system (panel A, following eq. (13)) under future socioeconomic conditions (panel B, which has been the focus of this section). Accounting for the growth in the size of, and the intersectoral and interfuel shifts in, the global energy economy results in an almost threefold increase in impacts' absolute magnitude. Consistent with our results thus far, most of that increase comes from developing countries in the tropics, concentrated in transportation and industry, while temperate countries see large commercial demand increases that are substantially offset by residential declines. Overall, climate change increases future global demand by 119 EJ, amplifying the effect of BaU economic expansion (from the current 219 EJ to 678 EJ in 2050) by an additional 26%. A comparison with Table 1 helps to put these numbers in context. Occurrence of vigorous climate change today would increase total energy consumption by 20% globally, 12% in temperate countries but 40% in tropical countries. However, if we express future changes from the BaU scenario as fractions of current demands, these numbers rise dramatically, to 50% globally, 30% in temperate countries, and 124% in countries in the tropics!

	RCP 4.5				RCP 8.5			
	Elec-tricity	Natural Gas	Petrol-eum	*Total*	Elec-tricity	Natural Gas	Petrol-eum	*Total*
	A. Current energy system							
	World							
Agriculture	0.12	0	-0.38	*-0.26*	0.19	0	-0.45	*-0.26*
Industrial	4.41	6.2	0.97	*11.58*	8.08	11.64	1.64	*21.36*
Residential	1.63	-4.96	-1.57	*-4.9*	2.61	-5.82	-2.05	*-5.26*
Commercial	10.08	0	-0.78	*9.3*	19.74	0	-1.03	*18.71*
Transportation	0.02	0	4.36	*4.38*	0.02	0	7.38	*7.4*
Total	*16.26*	*1.24*	*2.6*	*20.1*	*30.64*	*5.82*	*5.49*	*41.95*
	Temperate							
Agriculture	0.07	0	0	*0.07*	0.12	0	0	*0.12*
Industrial	1.81	3.3	0	*5.11*	2.91	6.19	0	*9.1*
Residential	1.63	-4.96	-1.57	*-4.9*	2.61	-5.82	-2.05	*-5.26*
Commercial	9.18	0	-0.54	*8.64*	18.11	0	-0.74	*17.37*
Transportation	0.03	0	0	*0.03*	0.04	0	0	*0.04*
Total	*12.72*	*-1.66*	*-2.11*	*8.95*	*23.79*	*0.37*	*-2.79*	*21.37*
	Tropical							
Agriculture	0.05	0	-0.38	*-0.33*	0.07	0	-0.45	*-0.38*
Industrial	2.6	2.9	0.97	*6.47*	5.17	5.46	1.64	*12.27*
Residential	0	0	0	*0*	0	0	0	*0*
Commercial	0.9	0	-0.23	*0.67*	1.63	0	-0.29	*1.34*
Transportation	-0.01	0	4.36	*4.35*	-0.02	0	7.38	*7.36*
Total	*3.54*	*2.9*	*4.72*	*11.16*	*6.85*	*5.46*	*8.28*	*20.59*
	B. Energy system circa 2050							
	World							
Agriculture	0.3	0	-0.46	*-0.16*	0.5	0	-0.55	*-0.05*
Industrial	11.53	8.56	1.27	*21.36*	20.98	15.89	2.16	*39.03*
Residential	3.34	-32.63	-1.97	*-31.26*	5.37	-37.4	-2.56	*-34.59*
Commercial	41.18	0	-0.66	*40.52*	84.1	0	-0.86	*83.24*
Transportation	-1.15	0	19.56	*18.41*	-1.66	0	32.56	*30.9*
Total	*55.2*	*-24.07*	*17.74*	*48.87*	*109.29*	*-21.51*	*30.75*	*118.53*
	Temperate							
Agriculture	0.28	0	0	*0.28*	0.48	0	0	*0.48*
Industrial	3.77	4.45	0	*8.22*	6.07	8.2	0	*14.27*
Residential	3.34	-32.63	-1.97	*-31.26*	5.37	-37.4	-2.56	*-34.59*
Commercial	36.99	0	-0.33	*36.66*	76.59	0	-0.44	*76.15*
Transportation	0.05	0	0	*0.05*	0.06	0	0	*0.06*
Total	*44.43*	*-28.18*	*-2.3*	*13.95*	*88.57*	*-29.2*	*-3*	*56.37*
	Tropical							
Agriculture	0.02	0	-0.46	*-0.44*	0.03	0	-0.55	*-0.52*
Industrial	7.75	4.12	1.27	*13.14*	14.91	7.69	2.16	*24.76*
Residential	0	0	0	*0*	0	0	0	*0*
Commercial	4.19	0	-0.34	*3.85*	7.51	0	-0.42	*7.09*
Transportation	-1.2	0	19.56	*18.36*	-1.72	0	32.56	*30.84*
Total	*10.76*	*4.12*	*20.03*	*34.91*	*20.73*	*7.69*	*33.75*	*62.17*

Table 5: Sectoral and aggregate energy demand responses (EJ) for world regions for different warming scenarios circa 2050.

4 Discussion

4.1 Robustness of empirical estimates

Our projections of the energy system impacts of climate change impacts depend fundamentally on the quality of the underlying empirical estimates of demand responses to weather shocks and income. The fairly rapid adjustment of fuel demands to their long-run equilibrium levels in section 3.1 calls into question the advantage of eqs. (9) and (10) over their static counterparts, namely,

$$q_{i,t} = {}^{*}\alpha_i + g(t) + \sum_{j=1}^{J} {}^{*}\gamma_j^T \mathcal{E}_{j,i,t}^T + \sum_{k=1}^{K} {}^{*}\gamma_k^H \mathcal{E}_{k,i,t}^H + \sum_f \gamma_f^P p_{f,i,t} + {}^{*}\gamma^Y y_{i,t} + {}^{*}\lambda_{i,t} \tag{19}$$

$$q_{i,t} = {}^{*}\alpha_i + g(t) + \sum_{j=1}^{J} \left({}^{*}\gamma_j^{TT} + {}^{*}\gamma_j^{XT} x_{i,t}\right) \mathcal{E}_{j,i,t}^T + \sum_{k=1}^{K} {}^{*}\gamma_k^H \mathcal{E}_{k,i,t}^H + \sum_f \gamma_f^P p_{f,i,t} + {}^{*}\gamma^Y y_{i,t} + {}^{*}\lambda_{i,t} \tag{20}$$

in which $g(t)$ represents a function of time (a time trend or year effects). Estimates generated by these specifications are summarized in Tables A3 and A4. To facilitate comparison, we also estimate the short-run analogue of (19), a first-difference specification in which demand responses to weather and income are identified from interannual co-variation:

$$\Delta q_{i,t} = {}^{**}\alpha_i + \sum_{j=1}^{J} {}^{**}\gamma_j^T \Delta\mathcal{E}_{j,i,t}^T + \sum_{k=1}^{K} {}^{**}\gamma_k^H \Delta\mathcal{E}_{k,i,t}^H + \sum_f {}^{**}\gamma_f^P \Delta p_{f,i,t} + {}^{**}\gamma^Y \Delta y_{i,t} + {}^{**}\lambda_{i,t} \tag{21}$$

Our static and first-difference regression estimates are broadly similar to Table 2, with almost identical patterns of significance among elasticities. The first-difference model's temperature elasticities are smaller in magnitude—which not surprising since they are identified from interannual weather variation, while the income elasticities understate our preferred estimates for some fuel $\times$ sector combinations and exceed them for others, but are of similar overall size. The main difference is that the latter are uniformly positive. Similar patterns obtain in the static model, both in terms of the GDP elasticity (with the exception of agricultural electricity use), and the temperature elasticities, which tend to be somewhat smaller and more heavily weighted toward positive responses—especially to exposures to cold days in tropical countries.

These differences affect our estimates of adverse warming impact in opposite directions. On one hand, income elasticities that are bigger magnitude and more uniformly positive tend to increase the baseline quantity of energy consumption, and the associated absolute magnitude of changes. On the other, smaller temperature elasticities translate into reduced impacts in percentage terms. Additionally, more positive demand responses to low temperature exposures—especially in the tropics where cold days decline markedly—mean that warming will generate larger offsetting energy savings and net adverse impacts of smaller magnitude.

Turning to our static extensive margin specification, baseline and interaction elasticities to hot and cold days are significant for several additional fuel $\times$ sector combinations, but many of these are only at the 15% level, while some significant combinations in Table 3 become insignificant, particularly for heating responses. The remaining elasticities are almost all of the same sign as our previous estimates (exceptions are capital interaction effects of residential petroleum use in temperate countries and agricultural electricity use in the tropics), but, once again, generally smaller in magnitude—as expected. As well, income elasticities are significant for a larger number of combinations, and they are uniformly positive.

A final sensitivity check addresses the choice of variable used to weight our grid-cell level temperature and humidity exposures in agriculture. Instead of population we use average annual harvested area for all crops circa the year 2000 obtained from the MIRCA2000 database (Portmann et al, 2010). The resulting long-run elasticities, summarized in Table A5, are similar in sign and magnitude to our preferred estimates. Exceptions are the significance of the natural gas' response to hot days in temperate countries, and the lack of significance of petroleum' response to cold days in tropical countries, elasticity values which are both small.

4.2 Comparison with Previous Studies

Our analysis shows that climate change can be expected to increase global demand for energy, but the magnitude of change crucially depends on the interaction with changes in socioeconomic conditions. The impact of climate change remains of secondary importance relative to the prevailing role of economic growth. Whereas economic expansion increases energy demand in tropical regions up to a factor of 4, a change in climate contributes with a factor of 1.3 (e.g., relative to the future baseline). Similar conclusions are pointed out by one of the few studies at global scale, (Isaac and Van Vuuren, 2009), in the specific context of residential energy demand for heating and cooling. The study finds that future residential energy use will be driven by the growing demand for cooling services associated with the economic expansion of tropical countries. The global demand for AC could expand by a factor 20 in 2050, even assuming a constant climate. The key role of economic growth and affluence has also been highlighted by the studies focusing on the adoption of AC equipment (Sailor and Pavlova, 2003; McNeil and Letschert, 2008; Davis and Gertler, 2015). We do not look at specific energy services, such as cooling and heating. Yet, our aggregate framework points at similar implications, namely the response of energy demand to temperature depends on the level of affluence.

Similarly to Isaac and van Vuuren (2009), global aggregate changes in energy consumptions are the result of compensating changes across regions, fuels, and sectors. Consider for example our global results under high warming (+17%). The total aggregate increase in energy consumption is the result of two compensating effects across sectors, a 17% reduction in the residential sector and a 7%, 11%, 42% and 98% increase in the agriculture, transportation, industrial, and commercial sectors, respectively. Climate-induced changes in energy demand are disproportionally larger in tropical regions, where the overall percentage increase in total final energy consumption (32%) is greater than the one estimated for the globe (17%). Climate impacts lead to a geographic and seasonal re-distribution of energy consumption towards tropical regions and towards summer months, as most of the increase will be due to higher electricity use for cooling. As a consequence, global warming may amplify inequality because hot, low and middle income countries will face the largest increase in energy use. On the potential negative effect of global warming on inequality, previous studies looking at the macroeconomy have come to similar conclusions (Burke et al, 2015).

Our estimated elasticities are generally larger than previous studies focusing on short-run elasticities using aggregate data (Deschenes and Greenstone, 2013). On the one hand, long-run elasticities can be larger because they implicitly account for the extensive margin. On the other hand, they can be smaller due to efficiency improvements in energy-using durables or to the implementation of more stringent regulations. Some of our estimates coefficients come close to what found in microstudies (Davis and Gertler, 2015; Auffhammer and Aroonruengsawat, 2011).

Our results point at a strong net reduction in residential energy demand at the global level, as well as in most countries, driven by the prevailing heating effect, which depends on the interaction between the estimated response and the predicted change in exposure to cold and hot days. It is important to note that our projections look at 2050, whereas by the end of the century a different picture could emerge. Isaac and van Vuuren (2009) also suggest that during the first half of the century the decline in heating energy demand is larger than the increase in cooling energy demand, whereas during the second half of the century the pattern is reversed.

The analysis of the heterogeneous response across sectors adds broader empirical evidence on sectoral heterogeneity that was previously confined to specific countries or regions, such as the Maryland State (Ruth and Lin, 2006) and Massachusetts (Amato et al, 2005). Previous regional and global studies focusing on residential energy use miss this heterogeneity and tend to find a prevailing negative impact (De Cian, Lanzi and Roson, 2013; Pilli-Sihvola et al, 2010; Mima and Criqui, 2015). The aggregate implications on energy markets, trade, and emissions can be much more important than previously thought because adjustments outside the residential sectors are also relevant. The sectoral dimension of our work points at commercial and industrial activities as two sectors where climate change could significantly expand the use of energy in all countries.

Adjusting energy demand is an ubiquitous form of adaptation across different sectors of the economy. Focusing on the specific impacts on energy use we find that both rich and poor countries will be affected by climate change, though in a different way. More energy for adaptation will be needed in the commercial, industrial, and transportation sectors across all continents. This result differs from what found in studies looking at the aggregate response of the economy (Burke et al, 2015), which find only weak, suggestive evidence of adaptation. Our analysis does not look at the general equilibrium effects of energy-based adaptation and therefore cannot inform on the implications for the aggregate economy. Energy use is a small percentage of aggregate GDP, but the induced changes in prices can lead to important general equilibrium effects, a research topic that is left for future research.

5 Conclusion

This paper develops a flexible methodology to characterize geographic variations, sectoral and fuel heterogeneity in climate change impacts on global energy demand, while taking into account how vulnerable human and energy systems will change in future periods when climate changes generate impacts.

We use cross section-time series regressions to estimate short-run and long-run elasticities of energy demand with respect to different temperature and humidity intervals, controlling for other confounding factors. Long-run elasticities are subsequently combined with scenarios of climate change and socioeconomic development to project the future baseline energy consumptions as well as the additional changes induced by climate change circa 2050. We map the spatial distribution of future percentage change in energy demand for the three fuels (electricity, natural gas, petroleum), five sectors (residential, agriculture, industry, commercial, transportation), and in total. Future percentage and absolute changes (EJ) in energy demand due to socioeconomic development and changes in climatic conditions are calculated globally, for different world regions, and at the country-level.

As foreshadowed by the engineering and economic literature, our estimated response of energy demand to exposure to heat and cold is asymmetric with either the heating or the cooling response being significant in most fuel $\times$ sector combinations (exceptions are electricity in commerce and industry, as well as petroleum in commerce and transportation). Electricity mostly satisfies the needs to cope with hot days across all sectors, while natural gas and petroleum can also be used in industrial and commercial activities through the use of distributed-petroleum and gas fired generators. The use of petroleum in the transportation sector is also sensitive to weather variations. Energy consumption is relatively inelastic in most fuel $\times$ sector $\times$ region combinations. Prices also influence the demand for the different fuels especially in temperate regions, whereas we do not find evidence of price effects in tropical regions.

Maps of grid-cell level shocks show that the majority of grid-cells in the tropics will experience higher energy demand, driven by the increase in electricity in the commercial sector, by natural gas and electricity in industry, petroleum in transportation. In temperate regions the impact of climate shocks varies across sectors and fuels. Higher demand is prevalent where the effects of more frequent high temperature exposures on cooling demand is large enough to outweigh the effects of less frequent low temperature exposures on the demand for heating demand (e.g., southern U.S. and Europe, Australia). More rapid warming accentuates the magnitudes of both kinds of changes, but the broad geographic patterns of their net effects persist across warming scenarios.

Global energy demand will increase by 7% and 17% under moderate (RCP4.5) and more significant (RCP8.5) warming, respectively, driven by tropical regions (18% and 32%, respectively). Almost all continents will see unequivocal increases in final energy demand with the exception of Europe. When aggregated to the country level, total final energy goes up in almost all emerging G20 economies located in the tropics, whereas temperate G20 countries outside Europe can either increase (United States, Japan, Australia, South Africa, Turkey) or decrease (Argentina, Canada, South Korea and Russia) total final energy use, depending on the geographic incidence of climate change.

Varying energy demand is an important form of adaptation that allows achieving desired levels of thermal performance. The estimates presented in the paper should be interpreted as potential changes, or potential adaptation, because barriers to energy access or to expanding energy use have not been considered. Our incidence analysis indeed suggests that globally climate change impacts are regressive, and more energy is expected to be overwhelmingly needed in low- and middle income countries, raising the question whether climate change will further exacerbate poverty. Moreoever, energy use is an enabling condition for adaptation across various sectors. Accounting for the implications of energy consumption on emissions, and more generally for the interactions between mitigation, impacts, and adaptation in an Integrated Assessment Modeling (IAM) framework remains an area calling for more research where the methodology developed in this paper could contribute to. The results presented in this paper come at the right moment when the socioeconomic scenarios for climate impact analysis have been finalized (Riahi et al, 2017). The SSP-consistent climate shocks developed in this paper could be used in the new SSP-RCP scenario framework to analyze the macroeconomic implications of climate-induced energy demand propagating through changes in prices and international trade. Models accounting for income distribution could be used to elaborate on the distributional implications of our results. The objective of this paper is to establish a methodology, focusing on two key missing elements in the impact literature, namely the heterogeneity in demand response across sectors, fuels, and regions, and the way in which those responses interact with geographically and temporally varying temperature data. Future climate impacts are illustrated using one specific ESM and socioeconomic scenario. Incorporating additional GDP/temperature scenarios from the SSP-RCP scenarios as well as from additional ESMs is left for future research.

Our analysis is not without caveats. Energy demand data are available at the country-level. To calculate future projected energy demands at grid-cell level we assume a uniform distribution of per capita energy demand, which is set equal to the national average reported by energy statistics. We attempt to include in our assessment the energy demand that could come from changes in energy-using durable goods, but the extensive margin is only indirectly modeled (by using long-term elasticities) or imperfectly quantified (by capital stock proxies). Recent studies using high quality micro data (Davis and Gertler, 2015) show that the explicitly modelling the extensive margin can lead to much higher impacts on future residential electricity demand, more than five times larger compared to considering only the intensive margin. Our results also suggest that a larger stock of capital could amplify the demand response to hot days. Finally, we have used global statistics on energy demand by sector and we cannot explicitly associate the estimated changes in energy consumption to specific end-use services, although it is reasonable to assume that, for example, the increase in electricity demand in response to greater exposure to heat can be associated with higher demand for cooling. What will happen to energy prices and energy efficiency in 2050 is difficult to project. Our analysis does not explicitly illustrates the effect of price-based adaptation nor it discusses alternative energy efficiency scenarios. If we are to speculate, however, the fact that developing countries' energy markets have covered a smaller fraction of total final consumption, been more distorted and slower to develop, suggests that if expansions in demand are accompanied by substantial increases in the depth and scope of markets, then price-based adaptations can potentially lower the long-run impacts we project. Further, increases in energy prices that might result from the implementation of mitigation policies could further promote adaptation as well as improvements in efficiency, though they could also exacerbate the regressivity of impacts.

6 References

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Appendix

Agriculture	ISIC 01-03: Agriculture/forestry includes deliveries to users classified as agriculture, hunting and forestry by the ISIC, and energy consumed by such users whether for traction (excluding agricultural highway use), power or heating (agricultural and domestic).
Commercial	ISIC 33; 36-39; 45-47; 53; 55; 56; 58-66; 68-75; 77-82; 84 (excl. 8422); 85-88; 90-96; 99.
Industry	ISIC 241, 2431: Iron and steel; 20-21: Chemical and petrochemicals excl. petrochemical feedstocks; 242, 2432: Non-ferrous metal basic industries; 23: Non-metallic minerals; 29-30: Transport equipment; 25-28: Machinery, fabricated metal products, machinery and equipment other than transport equipment; 07, 08, 099: Mining (excl. fuels) and quarrying; 10-12: food and tobacco; 17-18: Paper, pulp and print; 16: Wood and wood products (other than pulp and paper); 41-43: Construction; 13-15: Textile and leather; 22, 31-32: Manufacturing n.e.c.
Residential	ISIC 97-98: Heat pumps operated within the residential sector where heat is not sold are not considered a transformation process and are included here.
Transportation	ISIC 49-51: Consumption in transport covers all transport activity (in mobile engines) regardless of the economic sector to which it contributes.

Table A1: Sector definitions

Variable	Mean	Std. Dev.	Min.	Max.	N. Obs
	Tropical countries				
Population ('000)	24430.68	90846.318	44.843	1259695	4972
Real GDP per capita (2005 \$)	9837.146	20129.606	126.444	208519.694	4657
Total final energy (ktoe)	34458.28	28896.342	2637.3	144905.703	264
Electricity (ktoe) Agriculture	173.76	943.075	0	14946.9	2361
Electricity (ktoe) Industrial	539.245	2046.403	0	34892.102	4938
Electricity (ktoe) Residential	374.267	1190.863	0	19319.699	4736
Electricity (ktoe) Commercial	328.994	979.936	0	12376.7	4112
Electricity (ktoe) Transportation	7.4124	63.4874	0 1440	5032	
Petroleum (ktoe) Agriculture	384.218	1090.939	0	10137	2537
Petroleum (ktoe) Industrial	792.652	2135.38	0	22321.9	4959
Petroleum (ktoe) Residential	505.095	1858.905	0	25628.699	4869
Petroleum (ktoe) Commercial	202.645	503.901	0	4009.3	2425
Petroleum (ktoe) Transportation	2368.638	6787.855	0	75339.1	4938
Natural gas (ktoe) Agriculture	25.954	82.476	0	670.5	309
Natural gas (ktoe) Industrial	629.325	2436.445	0	32946.699	5039
Natural gas (ktoe) Residential	778.176	3689.99	0	37642.801	1057
Natural gas (ktoe) Commercial	168.221	595.958	0	5445.7	792
Natural gas (ktoe) Transportation	26.1844	244.1962	0	6501.5	5034
Electricity price (2005\$/ktoe) Residential	1274.646	857.184	0	6138.309	754
Electricity price (2005\$/ktoe) Industrial	1136.988	982.700	0	14433.322	735
Natural gas price (2005\$/ktoe) Residential	304.924	286.67	23.571	1000.811	85
Natural gas price (2005\$/ktoe) Industrial	154.907	209.946	0	945.932	171
Petroleum price (2005\$/ktoe) Residential	516.632	304.74	64.671	992.892	43
Petroleum price (2005\$/ktoe) Industrial	480.161	271.26	10.928	2365.357	349
Premium gasoline price (2005\$/ktoe)	846.1022	446.5406	5.078	3910.637	1638
$T < 12.5°$C (population-weighted)	12.65	33.189	0	204.695	4759
$T > 27.5°$C (population-weighted)	64.406	72.73	0	332	4759
$\overline{H} < 4$ g/Kg (population-weighted)	10.458	25.629	0	199.982	4759
$\overline{H} > 14$ g/Kg (population-weighted)	191.901	114.322	0	366	4759
$T < 12.5°$C (cropland-weighted)	12.889	38.689	0	291.37	5073
$T > 27.5°$C (cropland-weighted)	63.362	71.141	0	332	5073
$T > 4$ g/Kg (cropland-weighted)	15.54	36.32	0	246.757	5073
$T > 14$ g/Kg (cropland-weighted)	177.224	123.702	0	366	5073
	Temperate countries				
Population ('000)	37339.019	138334.377	53	1364002.431	3168
Real GDP per capita (2005 \$)	15510.819	11547.56	431.082	72680.162	3015
Total final energy (ktoe)	45183.796	108088.769	417	713541.188	1891
Electricity (ktoe) Agriculture	251.218	763.200	0	8833.700	2510
Electricity (ktoe) Industrial	5217.512	16283.794	0	269110.5	2801
Electricity (ktoe) Residential	3370.816	11785.393	0	124331.203	2757
Electricity (ktoe) Commercial	3024.977	11598.494	0	130601.602	2757
Electricity (ktoe) Transportation	200.1858	555.6779	0	5762.5	2808
Petroleum (ktoe) Agriculture	1234.566	2762.615	0	24388.4	2466
Petroleum (ktoe) Industrial	3734.612	9006.767	0	98447.602	2801
Petroleum (ktoe) Residential	2543.193	6494.826	0	73395.203	2757
Petroleum (ktoe) Commercial	1715.746	4824.729	0	49770.699	2460
Petroleum (ktoe) Transportation	17078.38	63994.43	0	606586	2801
Natural gas (ktoe) Agriculture	106.033	376.517	0	3243.3	1916
Natural gas (ktoe) Industrial	4503.701	16132.07	0	177350.906	2841
Natural gas (ktoe) Residential	5495.63	16625.305	0	122087.797	2211
Natural gas (ktoe) Commercial	2614.686	9503.416	0	79013.5	2192
Natural gas (ktoe) Transportation	59.3338	507.5102	0	13399.8	2929
Electricity price (2005\$/ktoe) Residential	1502.164	770.033	81.821	3732.609	1506
Electricity price (2005\$/ktoe) Industrial	1031.863	561.905	83.562	12662.016	1433
Natural gas price (2005\$/ktoe) Residential	528.682	302.261	3.429	1635.434	1097
Natural gas price (2005\$/ktoe) Industrial	312.815	191.476	17.024	1821.825	1110
Petroleum price (2005\$/ktoe) Residential	780.008	354.645	32.831	1911.774	1043
Petroleum price (2005\$/ktoe) Industrial	609.193	273.064	0.001	1495.268	942
Premium gasoline price (2005\$/ktoe)	1367.345	534.5048	21.931	3150.702	1659
$T < 12.5°$C (population-weighted)	187.781	67.232	0	362.61	3193
$T > 27.5°$C (population-weighted)	9.611	22.23	0	169.825	3193
$\overline{H} < 4$ g/Kg (population-weighted)	71.008	51.734	0	264.811	3193
$\overline{H} > 14$ g/Kg (population-weighted)	15.979	26.439	0	127.867	3193
$T < 12.5°$C (cropland-weighted)	195.657	76.835	0	356.535	3238
$T > 27.5°$C (cropland-weighted)	12.76	28.898	0	165.623	3238
$\overline{H} < 4$ g/Kg (cropland-weighted)	84.686	59.963	0	270.921	3238
$\overline{H} > 14$ g/Kg (cropland-weighted)	11.221	19.403	0	112.169	3238

Table A2: Descriptive statistics of the dataset.

		First difference specification			Static specification			Preferred specification		
		Heating response to days with $T < 12.5^{\circ}$C	Cooling response to days with $T > 27.5^{\circ}$C	Log real GDP per capita elasticity	Heating response to days with $T < 12.5^{\circ}$C	Cooling response to days with $T > 27.5^{\circ}$C	Log real GDP per capita elasticity	Heating response to days with $T < 12.5^{\circ}$C	Cooling response to days with $T > 27.5^{\circ}$C	Log real GDP per capita elasticity
					Temperate					
Agriculture	Electricity		0.0005	0.4978		0.0129	-0.4475		0.0085	0.6447
	Natural gas	0.0018		1.6591	0.0023		1.3856	-0.0195		1.3202
	Petroleum									
Commercial	Electricity	0.0003	0.0011	0.4912	0.0005	0.0103	0.4584	-0.0062	0.0467	0.8645
	Natural gas			1.0362			0.6083			0.9696
	Petroleum	0.0015		0.825	0.0037		1.524	0.0118		-0.7947
Industrial	Electricity		0.0002	0.8672		0.0033	0.5393		0.0089	0.3628
	Natural gas		-0.0002			0.014			0.0334	
	Petroleum			1.0714			0.2398			-1.0886
Residential	Electricity		0.0015	0.1159		0.0103	0.3763		0.0146	0.3665
	Natural gas	0.0022		0.6917	0.0017		0.9625	0.023		1.4331
	Petroleum	0.0013			0.0045			0.0207		
Transportation	Electricity	-0.0001		0.3575	0.0005		0.1215	-0.0026		0.2597
	Natural gas	0.0006			0.0065			-0.0599		
	Petroleum			0.7362			0.904			0.8211
					Tropical					
Agriculture	Electricity	-0.0054		-0.0248	-0.0119		0.5416	-0.0079		-0.7014
	Natural gas									
	Petroleum	0.0003			0.0085			0.0662		
Commercial	Electricity		-0.0003	0.1897		0.0021	0.4146		0.0083	0.7028
	Natural gas	0.0043			0.0022			-0.0301		
	Petroleum	-0.0008	-0.0046		-0.0311	-0.0115		-0.0143	-0.0171	
Industrial	Electricity	-0.0024	0.0006	0.4962	-0.0053	-0.0015	0.4639	-0.0284	0.0082	0.4782
	Natural gas		0.0017			0.015			0.0105	
	Petroleum		0.0005			0.0022			0.005	
Residential	Electricity			0.2564			0.5179			1.2873
	Natural gas									
	Petroleum									
Transportation	Electricity		-0.0004	1.0083		-0.0004	0.2198		-0.0107	1.9303
	Natural gas		-0.0025	0.6178		0.0044	0.5916			
	Petroleum	0.0006	-0.0001	0.5605	-0.0011	0.0019	0.5457	-0.0092	0.0041	0.6778

Table A3: Long-run estimated semi-elasticities of energy demand to temperature bins. Robustness analysis to first-difference and static specifications. Elasticities statistically significant at 10% and 15% significance level.

			Response to cold days ($T < 12.5°C$)					Response to hot days ($T > 27.5°C$)					Log real GDP per capita elasticity
			Base	Inter-action	@ %-iles of 2010 K per capita			Base	Inter-action	@ %-iles of 2010 K per capita			
					50%	5%	95%			50%	5%	95%	
			Temperate regions										
Agriculture	Electricity	M1	0.105	-0.006	0.003	0.014	-0.007					0.022+	
Agriculture	Natural gas	M1						-3.977+	0.229+			0.320	2.141
Agriculture	Petroleum												
Industrial	Electricity	M2	0.017	-0.001		0.002	-0.001	0.040	-0.002	-0.002+	0.003	-0.006	0.754
Industrial	Natural gas	M1						-0.579	0.036	0.045		0.102	
Industrial	Petroleum												
Residential	Electricity	M1					0.002+	-0.184	0.012	0.020		0.038	0.207+
Residential	Natural gas	M1						-0.317+	0.020+				
Residential	Petroleum	M1	-0.118	0.007		-0.016	0.008						0.788+
Commercial	Electricity	M1	-0.030+	0.002+			0.003+	-0.307	0.019	0.017+		0.047	
Commercial	Natural gas												
Commercial	Petroleum	M4											
Transportation	Electricity	M1	0.025	-0.001		0.003	-0.002+						
Transportation	Natural gas	M1						0.449	-0.025		0.072		
Transportation	Petroleum	M1						0.071	-0.004		0.008	-0.007+	0.968
			Temperate regions										
Agriculture	Electricity	M1	-0.186	0.011	-0.023	-0.045		0.689	-0.042	0.044	0.133	-0.053+	
Agriculture	Natural gas												
Agriculture	Petroleum	M1						-0.668	0.041	-0.044	-0.130	0.051	0.753
Industrial	Electricity	M1						0.289	-0.018	0.020	0.057	-0.021	0.227
Industrial	Natural gas	M1	0.394	-0.024	0.032	0.082		0.754	-0.046		0.145	-0.059	
Industrial	Petroleum	M1											
Residential	Electricity												
Residential	Natural gas												
Residential	Petroleum												
Commercial	Electricity	M1						-0.783	0.048	-0.049+	-0.150	0.062	1.111
Commercial	Natural gas	M1						4.034	-0.248	0.258	0.778		
Commercial	Petroleum	M1						-0.953	0.059	-0.060+	-0.183	0.075	
Transportation	Electricity	M1						-0.143	0.009	-0.013+	-0.031		
Transportation	Natural gas												
Transportation	Petroleum	M1						-0.018	0.001	0.002		0.005+	0.650

All estimates significant at the 10% level, except where indicated: + p<0.15

Table A4: Static semi-elasticities of energy demand with respect to temperature exposures and income: extensive margin specification

	Heating response to days with $T < 12.5$°C	Cooling response to days with $T > 27.5$°C	Log real GDP per capita elasticity
	Temperate regions		
Electricity		0.0528	0.6388
Natural gas		0.0673	1.6604
Petroleum			
	Tropical regions		
Electricity	-0.0599		-0.8430
Natural gas			
Petroleum			

Table A5: Long-run estimated semi-elasticities of energy demand to temperature in the agricultural sector, country temperature exposures weighted by harvested area. Elasticities statistically significant at 10% and 15% significance level.

	RCP 4.5	RCP 8.5
A. Current energy system		
World		
Impacts due to cold days	*-1.6%*	*-1.1%*
Impacts due to hot days	*10.5%*	*19.3%*
Total impacts	*9.2%*	*19.2%*
Temperate		
Impacts due to cold days	*-3.3%*	*-3.9%*
Impacts due to hot days	*8.3%*	*15.7%*
Total impacts	*5.3%*	*12.7%*
Tropical		
Impacts due to cold days	*4.0%*	*8.4%*
Impacts due to hot days	*17.8%*	*31.6%*
Total impacts	*22.1%*	*40.9%*
B. Future energy system circa 2050		
World		
Impacts due to cold days	*-3.4%*	*-3.1%*
Impacts due to hot days	*10.2%*	*19.3%*
Total impacts	*7.2%*	*17.5%*
Temperate		
Impacts due to cold days	*-6.3%*	*-7.0%*
Impacts due to hot days	*8.7%*	*17.2%*
Total impacts	*2.9%*	*11.7%*
Tropical		
Impacts due to cold days	*3.7%*	*6.8%*
Impacts due to hot days	*14.0%*	*24.4%*
Total impacts	*17.9%*	*31.9%*

Table A6: Aggregate energy demand responses (%) to cold and hot days for different warming scenarios.

Regression summary tables are available in the online Appendix.

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