Climate Change Impacts on Energy: Empirical Estimates

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Energy Sector Impacts

	Intensive Margin	Extensive Margin
Demand	• Effect of temperature change on energy use	• Effect of temperature change on adoption of air conditioning
Supply	• Effect of precipitation change on hydro generation, thermoelectric cooling • Effect of changes in frequency and intensity of heatwaves and storms on energy supply and transmission infrastructure • Effect of changes in wind speed on wind power production	• Effect of water availability on adoption of dry cooling technology

Let i, t index observational units and time over some historical period.

Of interest is the relationship (F) between impact endpoints ($Y_{i,t}$) and a vector of meteorological variables ($\boldsymbol{M}_{i,t}$).

To estimate this statistically we need to control for time-invariant individual heterogeneity (μ_i), unspecified exogenous influences affecting all units (τ_t), and confounding factors ($\boldsymbol{Z}_{i,t}$).

$$Y_{i,t} = \mu_i + \tau_t + F\left[\boldsymbol{M}_{i,t}\right] + \boldsymbol{Z}_{i,t}\boldsymbol{\gamma} + \varepsilon_{i,t}$$

Challenges for IAM Integration

- Focal areas
  - Bulk of empirical estimates at the intensive margin and on the demand side—of these most focus on electricity
  - Far fewer credible estimates on the supply side, almost none at the extensive margin
- Geographic coverage
  - Patchy, with a substantial and growing number of national/regional studies, focused on developed countries
  - Very few studies with global scope
- Potential remedies
  - Apply $\widehat{F}$ estimated at regional/national scales more broadly (with attendant thorny translational research challenges)
  - Develop global-scale empirical estimates designed explicitly to be incorporated within IAMs

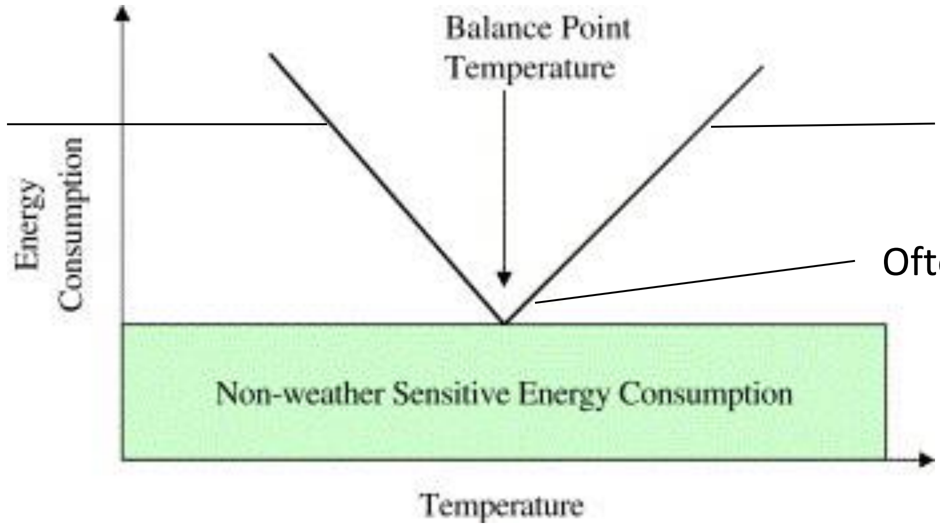
Energy Demand at the Intensive Margin (I): Engineering and Economic Conceptions of $\hat{F}$

Engineering (Ruth & Chen, 2006)

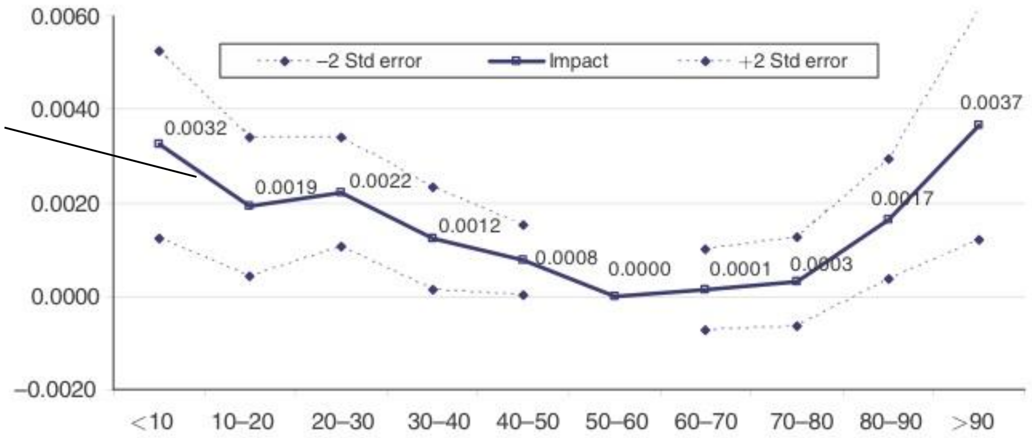
Heating Degree Days

Cooling Degree Days

Often assumed to be 65 °F



Envelope of response statistically estimated from the co-variation between energy demand and weather across space and time



Estimated impact of a day in 9 daily mean temperature (F) bins on log annual residential energy consumption, relative to a day in the 50°–60° F Bin

Y = log residential energy use (Q), $\boldsymbol{M}$ = vector of days of exposure to k temperature ranges ("bins", DT^k), i = US states, t = years

Economic (Deschenes & Greenstone, 2011)

$$\log Q_{i,t} = \mu_i + \tau_t + \Sigma_k \beta^k DT_{i,t}^k + \boldsymbol{Z}_{i,t}\boldsymbol{\gamma} + \varepsilon_{i,t}$$

Energy Demand at the Intensive Margin (II): Geographic Coverage

- Majority of demand-side estimates focus on the demand side, and on electric power
- Several studies at regional scales
- DeCian et al (2012) offers comprehensive estimates of demand impacts for the globe and different fuels, and is widely used by IAMs
  - LR temperature semi-elasticities of electricity demand generally +ve in spring and summer
  - Other elasticities –ve, in line with expected higher temperatures in cooler seasons
- i = countries, t = years, Y = log annual energy use (Q) from IEA Energy Balances, $\boldsymbol{M}$ = vector of average temperatures varying over s seasons (T^s) from CRU

$$\log Q_{i,t} = \mu_i + \tau_t + \Sigma_s \beta^s T^s_{i,t} + \boldsymbol{Z}_{i,t}\boldsymbol{\gamma} + \varepsilon_{i,t}$$

		Electricity	Gas	Oil
Short-run				
Summer	Cold	–0.39	–0.95	
	Mild	0.037	–0.95	
	Hot	0.92	–0.95	
Winter	Cold		–0.18	
	Mild		–0.18	
	Hot		–0.18	
Spring	Cold	–0.16		–0.70
	Mild	–0.29		–0.70
	Hot	0.61		–0.70
Fall	Cold			–0.025
	Mild			–0.02
	Hot			–0.025
Long run				
Summer	Cold	–3.33		
	Mild	2.08		
	Hot	1.80		
Winter	Cold	–0.88	–2.60	–3.45
	Mild	–0.88	–2.60	–3.45
	Hot	–0.88	–2.60	–3.45
Spring	Cold	5.42		
	Mild	–0.79		
	Hot	5.42		
Fall	Cold			–3.361
	Mild			–3.36
	Hot			–3.36

Energy Demand at the Intensive Margin (III): Sectoral Heterogeneity and Humidity Impacts

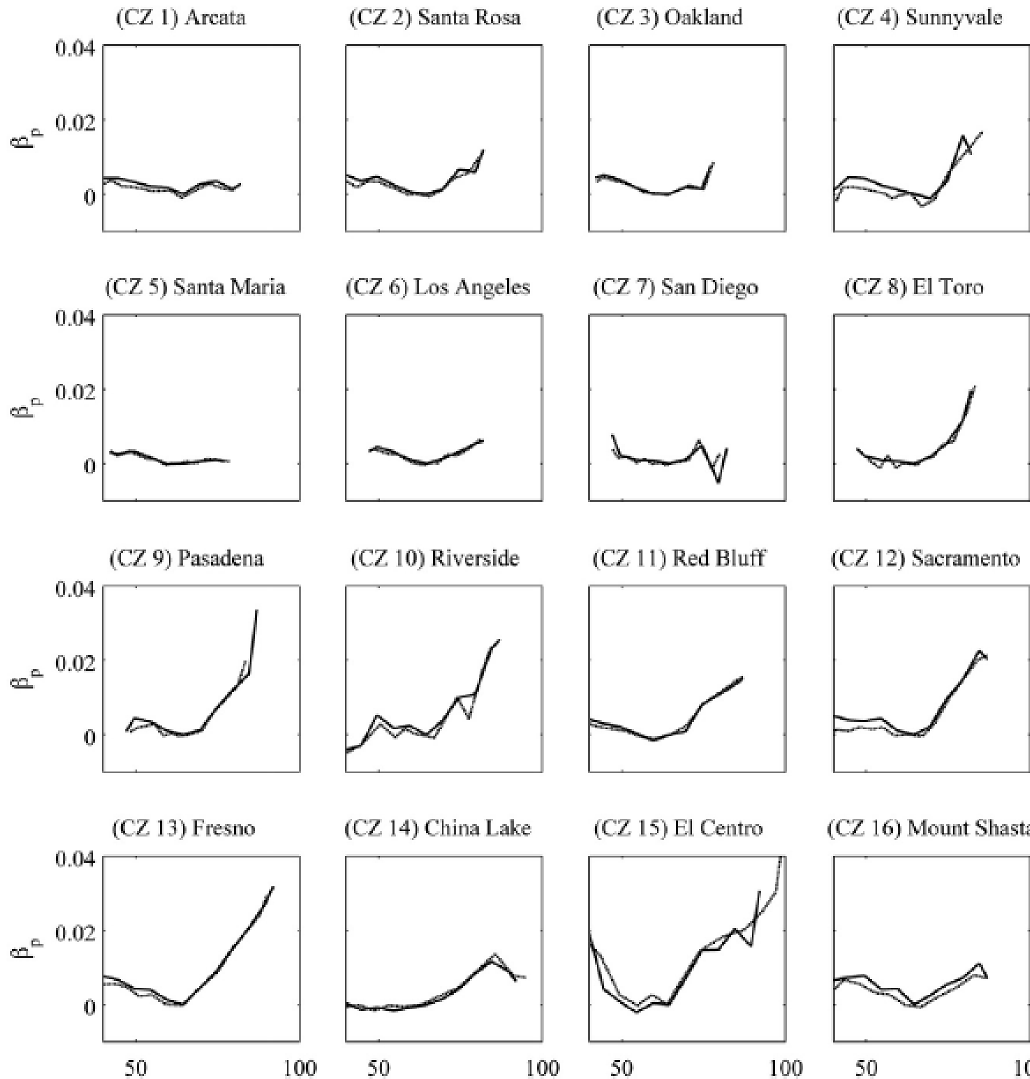
	Log Long-Run Electricity Demand (GWh)							
	Residential		Agriculture		Commercial		Industrial	
Temperature (°C)								
< 2.5	0.0009	(2.84)**	0.0009	(1.09)	0.0014	(3.26)**	0.0005	(1.08)
2.5-5	0.0009	(2.88)**	0.0016	(1.87)**	0.0013	(3.05)**	0.0014	(3.21)**
5-7.5	0.0006	(1.24)	0.0017	(2.14)**			0.0016	(3.17)**
7.5-10	0.0007	(2.03)**	0.0028	(2.87)**	0.0013	(1.87)**	0.0012	(3.04)**
10-12.5	0.0004	(1.74)**						
17.5-20			0.0023	(2.28)*				
25-27.5			0.0011	(1.47)*				
> 27.5	0.0004	(2.65)**	0.0003	-0.46				
Relative humidity (%)								
70-90	0.0005	(2.17)*	-0.0012	(1.60)*	0.0005	(1.15)	-0.0003	(0.74)
> 90	0.0010	(2.45)*	-0.0026	(2.03)*	0.0027	(1.66)**	-0.0004	(0.50)
R-sq.	0.12		0.09		0.10		0.09	
Obs.	3,972		2,504		3,598		3,982	

t-statistics in parentheses, ** p < 0.05, * p < 0.1

De Cian & Sue Wing (in prep., a): Y = log sectoral electricity demand (Q) from IEA Energy Balances, $\boldsymbol{M}$ = vector of days of population-weighted exposure to k temperature ranges, m humidity ranges (DT^k, DH^m) from GLDAS, i = countries, t = years, j = broad sectors

$$\log Q_{i,j,t} = \mu_{i,j} + \tau_{t,j} + \Sigma_k \beta_j^k DT_{i,t}^k + \Sigma_m \eta_j^m DH_{i,t}^m + \boldsymbol{Z}_{i,t}\boldsymbol{\gamma_j} + \varepsilon_{i,j,t}$$

Energy Demand at the Intensive Margin (IV): Fine-Scale Spatial Heterogeneity in $\hat{F}$



Log electricity demand response to temperature estimated for different California cities (Auffhammer & Aroonruengsawat, 2011)

Energy Supply at the Intensive Margin: Climate and Hydropower

	Log Hydropower Generation (MTOE)							
	(1)		(2)		(3)		(4)	
Months w/. 24-month SPI < -1.5			-0.012	(0.0035)**	-0.012	(0.0035)**	-0.012	(0.0035)**
Months w/. 24-month SPI > 1.5			0.000	(0.0052)	0.001	(0.0050)	0.001	(0.0050)
Months w/. 6-month SPI < -1.5			-0.011	(0.0044)**	-0.013	(0.0043)**	-0.013	(0.0043)**
Months w/. 6-month SPI > 1.5			-0.001	(0.0055)	-0.001	(0.0053)	-0.001	(0.0053)
Log annual runoff, small sized units	0.019	(0.0081)**	0.016	(0.0078)**	0.018	(0.0076)**	0.018	(0.0076)**
Log annual runoff, medium sized units	0.015	(0.0062)**	0.012	(0.0057)**	0.013	(0.0055)**	0.013	(0.0054)**
Log annual runoff, large sized units	-0.003	(0.0131)	-0.004	(0.0123)	-0.003	(0.0125)		
Log avg. spring temperature	-2.534	(0.6569)**	-2.128	(0.6321)**	-1.565	(0.5719)**	-1.560	(0.5687)**
Log avg. summer temperature	-1.486	(0.6437)**	-1.283	(0.6427)**	-1.363	(0.6431)**	-1.359	(0.6367)**
Log avg. fall & winter temperature	0.056	(0.0612)	0.038	(0.0567)				
Days w/. mean temperature > 27.5 °C	0.001	(0.0006)**	0.001	(0.0007)**	0.002	(0.0006)**	0.002	(0.0007)**
R-sq.	0.42		0.43		0.42		0.42	
Obs.	2,375		2,375		2,465		2,465	

Robust std. errors in parentheses, ** p < 0.05, * p < 0.1

De Cian & Sue Wing (in prep., b): Y = log hydro generation (G) from IEA Energy Balances, $\boldsymbol{M}$ = capacity-weighted months with SPI in u bins, annual runoff at v dam volumes, w temperature bins (MS^u, R^v, T^w) at 37,000 dam sites from GLDAS, i = countries, t = years

$$\log G_{i,t} = \mu_i + \tau_t + \Sigma_u \lambda^u MS^u + \Sigma_v \theta^v R_{i,t}^v + \Sigma_v \xi^w \log T_{i,t}^w + \boldsymbol{Z}_{i,t}\boldsymbol{\gamma_j} + \varepsilon_{i,j,t}$$

Adaptation

- Difficult to empirically distinguish from impacts
  - Inferences from historical observations captured by $\boldsymbol{Z\gamma}$ term in regressions
- Fisher-Vanden et al (2013) categorize adaptation into 3 types
  - I. Passive market adjustments
  - II. Deliberate shielding investments (reducing exposure to impacts)
  - III. Deliberate coping investments (reducing adverse consequences of residual impact exposure)
- In IAM projections, estimates I have discussed here are synonymous with Type I adaptations
  - Comparatively easily implemented within IAMs as secular shifts in demand/productivity
  - BUT, actual adaptation in say a CGE model will be the income and substitution effects that are triggered by the imposition of such a shock
- Extensive margin is much more interesting—and challenging to operationalize
  - Induced shifts in the quantity and energy-using characteristics of investment, and residential and industrial capital stocks
  - Several challenges
    - Obtaining historical data on investments/capital stocks with sufficient granularity to statistically discern the effects of weather
    - Investments are undertaken for all kinds of reasons, so also require a sufficiently rich set of statistical controls for potential confounding effects