Climate Change and US Electric Power

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Abstract

There has been intense recent interest in the vulnerability of the US electric power sector to the potentially adverse impacts of global warming. In this paper I use a three-phased approach to investigate the consequences of climate-driven temperature increases on electricity supply and demand within US states. Reduced-form long-run responses of electricity demand to temperature are estimated based on monthly data for the US using a dynamic econometric model. The resulting climate response functions are then applied to projections of temperature taken from a global climate model simulation for the year 2050 to construct vectors of shocks to electricity demand. Finally, the economic effects of these shocks are simulated within an interregional computable general equilibrium model that incorporates detailed information on power markets and generation technologies. My estimated temperature responses substantially exceed similar published estimates. I find that by 2050, projected climate change amplifies states' electricity demand by as much as 16%, with large increases concentrated in states that already have high summer temperatures. These demand shocks have only a slight effect on electricity prices, but are regressive in their incidence, and induce an expansion of generation that increases US carbon emissions by more than 6%.

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1 Introduction

The influence of weather on electricity markets has been extensively researched. However, in the past weather variables have typically been used as statistical controls that enable more precise estimates of price and income elasticities of demand (e.g. Maddala et al., 1997; Alberini and Filippini, 2011). Only recently has there been interest in the magnitude character of responses in their own right, spurred by concern over the energy market impacts of anthropogenic climate change on heating and cooling demands (Asadoorian et al., 2008; Auffhammer and Aroonruengsawat, 2011; Deschênes and Greenstone, 2011; Franco and Sanstad, 2008; Rosenthal et al., 1995; Sailor and Muñoz, 1997).

To construct assessments of the electricity market impacts of a changing climate it is necessary to move beyond existing estimates that rely on spatially and temporally aggregated measurements of electricity use—and particularly weather. The potential for seasonal temperature shifts to have offsetting impacts on the number of heating and cooling degree days within each month can lead to aggregation bias in the standard interpolation methods that are used to construct degree days from monthly average temperatures (see, variously Thom, 1954, 1966; Thevenard, 2011). Recent papers by Deschênes and Greenstone (2011) and Auffhammer and Aroonruengsawat (2011) circumvent this problem by using binned daily temperature data to identify differences in the marginal effect of exposure to particular temperature regimes.[1] But despite the enormous potential of this approach, precise estimates of the climate response of electricity demand over space and time remain elusive. Deschênes and Greenstone's results aggregate across fuels and time, yielding the static weather response of the US residential sector's total annual energy use. Auffhammer and Aroonruengsawat go further to investigate individuals' electricity demand using billing data on an approximately monthly cycle, but the geographic domain of their analysis is limited to the state of California. Moreover, in neither of these studies are the data series of demand both of sufficiently high frequency and length to empirically disentangle long-run responses to climate from short-run responses to weather.

This study overcomes these obstacles to provide an empirical characterization of the long-run impact of temperature on electricity use by different sectors for the entire US. Its principal in-

[1] This was first done by Engle et al. (1986), who employed a more complicated smooth regression approach.

novation is to couple a 20-year dataset of monthly electricity use by three economic sectors in 48 US states with spatially averaged observations of daily temperature in a dynamic estimation framework. Its second novel feature is to project the climate-induced shocks to states' monthly electricity demands by applying the empirically-derived climate responses to the geographically heterogeneous patterns of change in decadally-averaged daily temperatures generated by a global climate model (GCM) simulation. Finally, it assesses the implications of climate impacts by imposing the shocks on a spatially disaggregated numerical simulation of the US economy.

My key findings are that dynamic model estimates of the long-run effect of temperature on electricity demand are substantially larger than their static counterparts commonly cited in the empirical climate impacts literature. Applying these larger responses to the output of a CGM simulation of climate change in the year 2050 yields changes in electricity demand that are larger in the residential sector relative to commercial and industrial consumers, are overwhelmingly positive, ranging from 1%-14% with an average of just over 7%, and are concentrated in the Southwest and South Central portions of the US. Simulations of the economic effects of these secular shifts in demand generate ex-post realized changes in electricity use of as much as 16%, which result in climate impacts are regressive in their incidence, and induce expansion of fossil-fueled power generation that increases aggregate emissions of carbon dioxide (CO_2) by more than 6%.

The rest of the paper is organized as follows. Section 2 outlines the analytical approach, econometric modeling, and data. Section 3 presents and discusses the results. Section 4 concludes with a discussion of caveats and future research.

2 Approach

2.1 Econometric Model and Data

My starting point is a static empirical model of electricity demand in the vein of recent panel data studies which utilize responses to weather shocks to identify the impact of climate change (Deschênes and Greenstone, 2011; Auffhammer and Aroonruengsawat, 2011). The objective is to model monthly electricity use, $Q_{j,s,t}$, in the residential, commercial industrial sectors (indexed by j) of each state (indexed by s) and time (indexed by t) as a function of temperature. The basic

specification is the linear panel regression:

$$\log Q_{j,s,t} = \boldsymbol{\alpha}_{j,s} + \boldsymbol{\theta}_{j,y} + \sum_k \psi_j^k N_{s,t}^k + \boldsymbol{X}_{j,s,t}\boldsymbol{\beta}_j + u_{j,s,t} \tag{1}$$

in which $\boldsymbol{\alpha}$ and $\boldsymbol{\theta}$ are vectors of state fixed effects and year effects that capture unobserved geographic heterogeneity and temporally varying shocks that affect all states, N^k is the count of each month's days with average temperature in each of k bins, $\boldsymbol{X}$ is a vector of statistical controls (enumerated below), $\boldsymbol{\beta}$ is a vector of estimated parameters, and u is a random disturbance term. The coefficients of interest are the ψ_j^ks, which represent the semi-elasticities of sectoral electricity demand to an additional day in each of the temperature bins.

The ability of eq. (1) to capture the kind of *climatic* shocks to temperature expected to manifest themselves on decadal time-scales is called into question by recent empirical studies that use monthly data in an explicitly dynamic framework (Myers et al., 2009; Jorgensen and Joutz, 2012). Myers et al. estimate demand responses to heating and cooling degree days which have very different magnitudes at monthly and annual lag lengths. Jorgensen and Joutz find that short-run electricity demand responses are almost entirely weather-driven, with the marginal effects of contemporaneous heating degree days being significantly larger than that of their 30-year moving average. These results suggest the need to explicitly account for the divergence between short- and long-run responses by incorporating dynamics into the standard model. I proceed by recasting (1) according to the autoregressive distributed lag dynamic panel specification

$$\log Q_{j,s,t} = \boldsymbol{\alpha}_{j,s} + \boldsymbol{\theta}_{j,y} + \sum_{\ell=1}^{\mathcal{L}} \lambda_{j,\ell} \log Q_{j,s,t-\ell} + \sum_{\ell=0}^{\mathcal{M}} \left(\sum_k \psi_{j,\ell}^k N_{s,t-\ell}^k + \boldsymbol{X}_{j,s,t-\ell}\boldsymbol{\beta}_j \right) + v_{j,s,t}. \tag{2}$$

This model cannot be estimated consistently as the coefficients on the lags dependent variables are biased due to correlation with the fixed effects. The standard remedy is to re-parameterize (2) as an error correction model (ECM), which can be estimated consistently using maximum likelihood:

$$\begin{aligned}\Delta \log Q_{j,s,t} = \boldsymbol{\alpha}_{j,s} + \sum_{\ell=1}^{\mathcal{L}-1} \widetilde{\lambda}_{j,\ell} \Delta \log Q_{j,s,t-\ell} + \sum_{\ell=0}^{\mathcal{M}} \left(\sum_k \widetilde{\psi}_j^k \Delta N_{s,t}^k + \Delta \boldsymbol{X}_{j,s,t}\widetilde{\boldsymbol{\beta}}_j \right) \\ + \omega_j \left[\log Q_{j,s,t-1} - \sum_k \overline{\psi}_j^k N_{s,t}^k - \boldsymbol{X}_{j,s,t}\overline{\boldsymbol{\beta}}_j \right] + v_{j,s,t}. \end{aligned} \tag{3}$$

I am interested in the expression in square brackets, which is the long-run effect of the covariates on electricity demand. The parameter $\omega_j = -\left(1 - \sum_{\ell=1}^{\mathcal{L}} \lambda_{j,\ell}\right)$ is the error-correcting speed of adjustment, which is anticipated to be negative and significant. The coefficients $\widetilde{\psi}_j^k$ and $\widetilde{\boldsymbol{\beta}}_j$ indicate the short-run effects of temperature and other variables, while $\overline{\psi}_j^k = \psi_j^k \Big/ \left(1 - \sum_{\ell=1}^{\mathcal{L}} \lambda_{j,\ell}\right)$ and $\overline{\boldsymbol{\beta}}_j = \boldsymbol{\beta}_j \Big/ \left(1 - \sum_{\ell=1}^{\mathcal{L}} \lambda_{j,\ell}\right)$ are the corresponding long-run effects.

My data are drawn from several sources. Monthly electricity data were taken from Energy Information Administration (EIA) Form 826 files which tabulate sales and revenue for residential, commercial and industrial consumers in each state for the period 1990-2010. Temperature data for the same period were taken from the North America Land Data Assimilation System (NLDAS) daily maximum and minimum air temperature series, which we aggregated to state level. To capture consumers' own-price response I proxy for the unobserved price of electricity using real monthly average revenue in each of the three sectors, calculated from the Form 826 data. To capture consumers' cross-price response I use monthly natural gas prices by sector from EIA. To capture the separate elasticities of electricity demand with respect to the intensity of economic activity and the scale of the population, I use the Bureau of Economic Analysis (BEA) state quarterly personal income and annual population from the for the residential sector, and, for commercial and industrial sectors, quarterly compensation and monthly employment from the Bureau of Labor Statistics Quarterly Census of Employment and Wages.

My electricity demand climate response function is constructed from the fitted values of eq. (3). I make use of the monthly frequency distributions of normal temperatures under current and future climates in each state ($\overline{N}_C^k$ and $\overline{N}_F^k$) and apply the estimated long-run temperature semi-elasticities to the difference between the values in each monthly bin. Summing over bins and exponentiating yields the ratio of future to current electricity use in each month (cf Auffhammer and Aroonruengsawat, 2011):

$$\Psi_{j,s} = \exp\left[\sum_k \overline{\psi}_j^k \left(\overline{N}_{F,s}^k - \overline{N}_{C,s}^k\right)\right]. \tag{4}$$

To calculate $\overline{N}_C^k$ and $\overline{N}_F^k$ I use simulated daily surface temperatures for the years 1991-2000 and 2046-2055 from run 1 of the Geophysical Fluid Dynamics Laboratory (GFDL) CM 2.1 climate model (Delworth et al., 2006) forced with the SRES A2 (high) emissions pathway. Bias-corrected

model output mapped to a $2^\circ \times 2^\circ$ grid by Brekke and Barsugli (2013) was spatially interpolated to a GIS shapefile of US states, averaged over the two decadal periods representing current and future climate, and the results aggregated by temperature bin and month.

2.2 Simulating the Economic Impacts of Climate-Induced Electricity Demand Shocks

There is a burgeoning literature that employs numerical models of the economy to simulate the market implications of climate change impacts. However, these studies' most finely geographic unit of analysis is single large countries—and, most often, countries aggregated up to the level of world regions—which is arguably far coarser than the scale at which climate impacts will manifest themselves.[2] It is therefore not surprising that model-based investigations of climate impacts have tended to find only modest economic consequences—the larger spatial domain of analysis, the more likely it is that there will be impacts of opposite sign, whose shocks will tend to cancel out (cf the negative impact of climate change on US electricity demand found by Bosello et al.'s (2007) country-level analysis). The concern is that if the disparate sub-national impacts are resolved and allowed to simultaneously affect interconnected markets, then the general equilibrium effects can be substantially different.

To assess the impact of the climate's effect on the demand for electric power, I construct a multi-sector inter-regional computable general equilibrium (ICGE) model of the US economy which incorporates detailed information on the structure of electric power markets and generation technologies. The model's key feature is that it simulates the supply-demand equilibrium of the economy at the same geographic scale as my estimates of demand shocks. The model resolves the production and use of ten commodities at the state level. There are five energy commodities (Crude Oil & Gas, Refined Petroleum, Coal, Natural Gas and Electricity) and an equal number of non-energy goods (Agriculture, Transportation, Manufacturing, Energy-intensive goods and Services), each of which is produced by an individual sector within each state.

Production in each sector is represented by a nested constant elasticity of substitution (CES) production function whose structure and parameterization is based on Goulder (1995). These hierarchical structures, shown schematically in Figure 1, are differentiated by sector. Given my focus on electricity markets, I pay special attention to electric power production and upstream

[2]See Fisher-Vanden et al. (2011) for a review of model-based impact studies.

fossil fuel supply sectors. Non-energy industries in panel A use Goulder's basic structure. In the fossil fuel supply sectors in panel B, primary "fixed-factor" energy resources available within each state substitute for other inputs at the top level of the nesting hierarchy. Similarly, in the refined petroleum sector in panel C crude oil feedstocks substitute for intermediate and factor inputs at the top level.

The centerpiece of the model is the "bottom-up" representation of electric power production in panel D, which draws on Sue Wing (2006, 2008). Electric sector output is a CES function of transmission and distribution services and energy. The former is produced from labor, capital and non-energy materials. The latter is a CES function of three classes of load, each of which is a CES aggregation of the outputs of 17 discrete generation technologies, summarized in Table 2 panel A.[3] In turn, fossil and primary electricity generation are modeled as CES functions of labor, capital and fuel inputs. In the case of non-fossil technologies, the latter is modeled as a state- and technology- specific fixed-factor energy resource.[4]

On the demand side, the model groups the households in each state into nine income classes, each of which is represented by an archetypal consumer with CES preferences denominated over consumption of the ten commodities. Each representative agent is endowed with quantities of labor, capital and natural resources, which are rented out to the sectors in exchange for factor income that is used to finance expenditures on goods. Factors are immobile across states. Within each state, capital and labor are homogeneous and perfectly mobile across sectors, with households' endowments constituting an aggregate pool of supply that is allocated among sectors to equalize marginal productivity. Natural resources are sector- and technology-specific. The sluggish nature of electric generation technology capacity adjustments is captured by modeling generation capacity (i.e., inputs of capital) as a specific factor which is supplied by a "capacity transformation" sub-sector, a constant elasticity of transformation (CET) function which demands intersectorally mobile capital and transforms it into the 17 categories of technology-specific capital (Sue Wing, 2006). The model also resolves government activity at three levels (local, state and federal) which play the role of producer-consumers, collect taxing revenue from firms and households to finance

[3]Note that the same oil- and gas-fired generation technologies can satisfy electricity demand across different load classes.

[4]The resource represents the availability of insolation for solar power, stream flow or hydrostatic head for hydro power, surface wind velocity for windpower, hot dry rock for geothermal power, etc.

the purchase of commodities used to produce government goods.

Commodity demands by industries, households and government in each state are satisfied by domestic supply as well as imports from other states and international sources following the Armington (1969) specification of trade, illustrated in panel E of Figure 1. In each sector and state, output is allocated among own-state uses, exports to other states and international exports to the rest of the world according to a nested CET function. Interstate exports of each commodity supply a common national pool that satisfies each state's demand for domestic imports. A CES function is used to combine the latter with each state's international imports of the good to generate an import composite that substitutes for own-state uses in the production of an Armington aggregate composite. This composite output supplies the state's intermediate and final demands for the commodity in question. Interstate electric power markets are modeled in a slightly different fashion, with each state's electricity output feeding into one or more power pools defined by the North American Electric Reliability Corporation (NERC) regions (shown in panel B of Table 2), which are in turn connected by bulk power trade at the national level and supplying their constituent states' electricity demands.

Numerical calibration of the model's "top-down" input-output structure is based on IMPLAN state social accounting matrices for the year 2007 (Minnesota IMPLAN Group, 2008), based on the framework developed by Rausch and Rutherford (2008). Bottom-up technology detail is introduced into the electric power sector via the column disaggregation procedure developed by Sue Wing (2008), and using data on fossil fuel prices from EIA, the costs and input proportions of individual generation technologies from the supplement to the DOE/EIA 2012 Annual Energy Outlook, and year-2007 generation by technology, state and NERC region calculated from plant-level information in EIA's Form 906 data files.

The ICGE model is specified algebraically as a static equilibrium simulation, numerically calibrated and formulated as a large-scale mixed complementarity problem using the MPSGE subsystem (Rutherford, 1999) for GAMS (Brooke et al., 1998), and solved using the PATH solver (Dirkse and Ferris, 1995; Ferris and Munson, 2000). To perform an assessment of climate impacts I simulate projected baseline and counterfactual equilibiria of the US economy in the year 2050. Future expansion of income and output are captured by scaling up states' endowments of labor and capital at the historical rates of growth of real compensation and gross operating surplus, and the

decoupling of energy supply and use from GDP growth is modeled by scaling down the coefficients on energy in the model's cost and demand functions at the historical rates of decline in the energy intensity of sectors within each state.

3 Results

3.1 Econometric Estimates

The results of the static econometric model are presented in Table 3. The fit of the model to the data is quite good. Own-price demand responses are of the expected sign, inelastic, and similar in magnitude to previous estimates (e.g., Alberini and Filippini, 2011). Cross-price demand responses with respect to natural gas are positive, significant only in winter months and for residential and commercial sales, and highly inelastic. The residual sector does not exhibit a significant response to income, but the elasticity with respect to population is positive and significant. The commercial and industrial sectors exhibit positive and significant responses to both the average ware and employment, with the latter being dominant.

Electricity demand's response to temperature is for the most part precisely estimated, exhibiting the asymmetric "V"-shaped pattern found by Engle et al. (1986) and Deschênes and Greenstone (2011) with the nadir in the mild zone of 50-60 °F and an overall magnitude similar to their estimates. The magnitude of the residential response exceeds that for the commercial sector, which in turn exceeds that for industrial consumers, and all of the responses are generally small.

The dynamic model's long-run estimates are given in Table 4. To conserve degrees of freedom we estimate the simplest autoregressive model with a single one-month lag. In the long-run, own-price responses fall short of the corresponding static estimates while cross-price responses exceed them. Larger too are the long-run residential sector population and income elasticities, as well as commercial sector wage elasticity. Long-run labor elasticities are larger in the commercial sector and smaller in industry. Moreover, the error-correction parameters suggest that consumers respond rapidly: 99% of the adjustment to long-run equilibrium occurs within 3 years in the commercial and industrial sectors, and within 9 months in the residential sector.

The big difference between the models is in the temperature response. While the patterns of semi-elasticities over the span of temperature bins remain the same, the magnitudes the of long-

run marginal effects are between two and five times bigger! As well, the intersectoral differences in the magnitudes of the estimates diminish sharply, as indicated by Figure 2. This result suggests that existing static estimates may substantially underestimate the impact of climate on energy demand.

3.2 Robustness Tests

To be added...

3.3 Climate Shocks to Electricity Demand

Figure 3 shows the changes in monthly electricity demand that results when the GFDL CM 2.1 climate model's simulated change in decadal average daily temperatures from current climate to the year 2050 under the SRES A2 scenario is applied to our estimated long-run marginal temperature responses in eq. (4). As anticipated by the shape of the sectoral climate response functions in Figure 2, electricity demand simultaneously increases during the summer months while declining in the spring and fall. The largest positive responses occur in the residential sector, and are concentrated in the Southwest and West South Central portions of the country (New Mexico, Colorado, Missouri, Nebraska, Nevada). Commercial and particularly industrial consumption see much smaller increases concentrated in the South, but enjoy larger reductions in demand during the winter months.

The bottom-line impact on states' average annual electricity demand is calculated as the inner product of the monthly shocks reported above and the average monthly electricity sales by sector and state over the 1990-2010 sample period. The result, shown in Figure 4, is that the overwhelming majority of the responses take the form of increases in demand, with only a handful of high-latitude states exhibiting reductions, and then only in the commercial and industrial sectors. As before, these are largest in the residential sector and smallest in industry, and are concentrated in the South and South Central regions. The overall shock to electricity demand is positive, ranging from a 1% rise in North Dakota to a 14% rise in Mississippi, with a mean increase of 7.6%. The detailed state by sector annualized demand changes are applied as shift parameters to the the ICGE model's cost and demand functions in order to simulate the year-2050 counterfactual

equilibrium. The difference between these ex-ante shocks and the ex-post equilibrium demands generated by the concomitant price and substitution adjustments in the economy is a measure of passive market adaptation to climate change. (See Fisher-Vanden et al. (2011) for a taxonomy of adaptation responses.)

3.4 Simulation Results

Rarely do empirical studies of climate change impacts project economic conditions in the future years when the effects of climate change manifest themselves. The consequences of this are not well understood. On one hand, it imparts a downward bias to estimates of the level of climate-related damage or adaptation costs, because the economy that actually faces exposure to future climate risk will be bigger in size relative to today. But on the flip side, a larger economy will likely entail greater substitution possibilities which enable more elastic adjustment to climate shocks, reducing adaptation costs. The current assessment accounts for both influences.

Relative to the 2007 benchmark year, in 2050 the US economy's real output expands by a factor of three and its primary energy use increases by 51%. As shown in Table 5, this is accompanied by a substantial expansion in electricity supply in warmer regions—increases of two-thirds in the Southeast, a doubling in Florida and the Southwest, and a tripling in Texas—but modest increases elsewhere in the country. Growth in electricity use over the period exhibits a pattern that is similar but has a smaller regional amplitude, while bulk power prices increase only slightly in real terms, indicating that generation keeps pace with demand.

Imposing climate-induced electricity demand shocks onto these trends results in an 8% increase in aggregate electricity generation and use whose effects are concentrated in the South and are substantially smaller in the Northeast and Midwest. Interestingly, the ex-post increase in aggregate electricity use is slightly larger than the shock, but this masks considerable regional heterogeneity in substitution and market responses: increases in electricity generation and use outstrip the shock in the West, Southwest and Atlantic/East Central regions, but elsewhere fall short of the ex-ante stimulus to demand. The response of bulk power prices to the increase in heating and cooling demands is very slight, suggesting that the shock is small enough that existing substitution possibilities allow adjustments to be made cheaply.

Panel B summarizes the adjustments on the supply side. My assumptions used to construct the baseline equilibrium result in a marked expansion of renewable and oil generation, a somewhat smaller increase in natural gas, and modest growth in coal, hydro and nuclear. Despite the apparently large growth in oil-fired and renewable electricity, their levels of supply remain the smallest of the technology groupings. The demand shock's largest impact is on the supply of fossil electricity (principally oil, and, to a lesser extent, coal), especially in the Southwest and Atlantic regions. Nuclear power expansion exhibits the same geographic pattern, but its response is two-thirds as large, while hydro and renewables see their largest increases in the Southeast and Atlantic regions.

The impacts on states' economies are shown in Figure 5. In panel A, the ex-post change in electricity use computed by the ICGE model generally increases in magnitude with the ex-ante demand shock. However, the South Central and Southwestern states that are most affected by the climate's impact tend to see a 1-2 percentage point amplification of demand. The consequences for households' welfare are summarized in panels B and C, which plot the percentage change in households groups' real expenditure on electricity and all commodities with the simulated change in state electricity use. Almost without exception, spending on electricity rises by more than the average level of the shocks, a result which reflects the fact that electricity prices remain stable while the shock to residential demand exceeds that of other sectors (cf Figures 3 and 4). The percentage changes in electricity expenditure diverge only slightly across income levels, with the growth of expenditure exhibiting small increases with household income in the most affected states.

The most interesting result is the welfare impact of changes in households' demand for *non*-electricity goods. Substitution toward electricity to satisfy the rise in demand for space conditioning comes at the cost of reduced consumption of other goods, spending on which declines. Because electricity's baseline fraction of household expenditure is generally small (8%-16%), declines with progressively higher income, and is largest in states that in today's climate experience high summer temperatures. This suggests that substitution will induce the largest reductions in non-energy expenditure in low-income households and in the South-Central and Southwestern states, which is exactly what we see in panel C. Similar to recent findings for greenhouse gas (GHG) mitigation (e.g., Hassett et al., 2009; Grainger and Kolstad, 2010), the incidence of climate's impact on electricity is regressive along two dimensions, with the costs falling dispro-

portionately on households in the model's two lowest income categories, and in relatively poor Southern states. Interestingly, middle-income households remain essentially unaffected, while those in the two highest income categories also experience expenditure declines, albeit of a much smaller magnitude. In contrast to the effects of climate mitigation, households' burdens emanate overwhelmingly from declines in the budget shares of non-energy goods which account for the bulk of expenditures.[5]

I close by examining the environmental implications of the expansion in generation necessary to satisfy increased demand for electricity. The fact that fossil power generation tends to respond in a more elastic manner suggests that rising temperatures will induce increases in GHG emissions, thus raising the specter of a positive feedback between the impacts of climate change and the adaptation measures that facilitate adjustment to these shocks. Figure 6 shows that the climate shock stimulates increases in states' emissions of CO_2. While there are small changes in the emissions from the industrial and transportation sectors, the lion's share of the growth emanates from the electricity generation. The most affected South-Central and Southwestern states see emissions rise in excess of 10%, while aggregate emissions expand by 6.5%.

3.5 Sensitivity Analysis

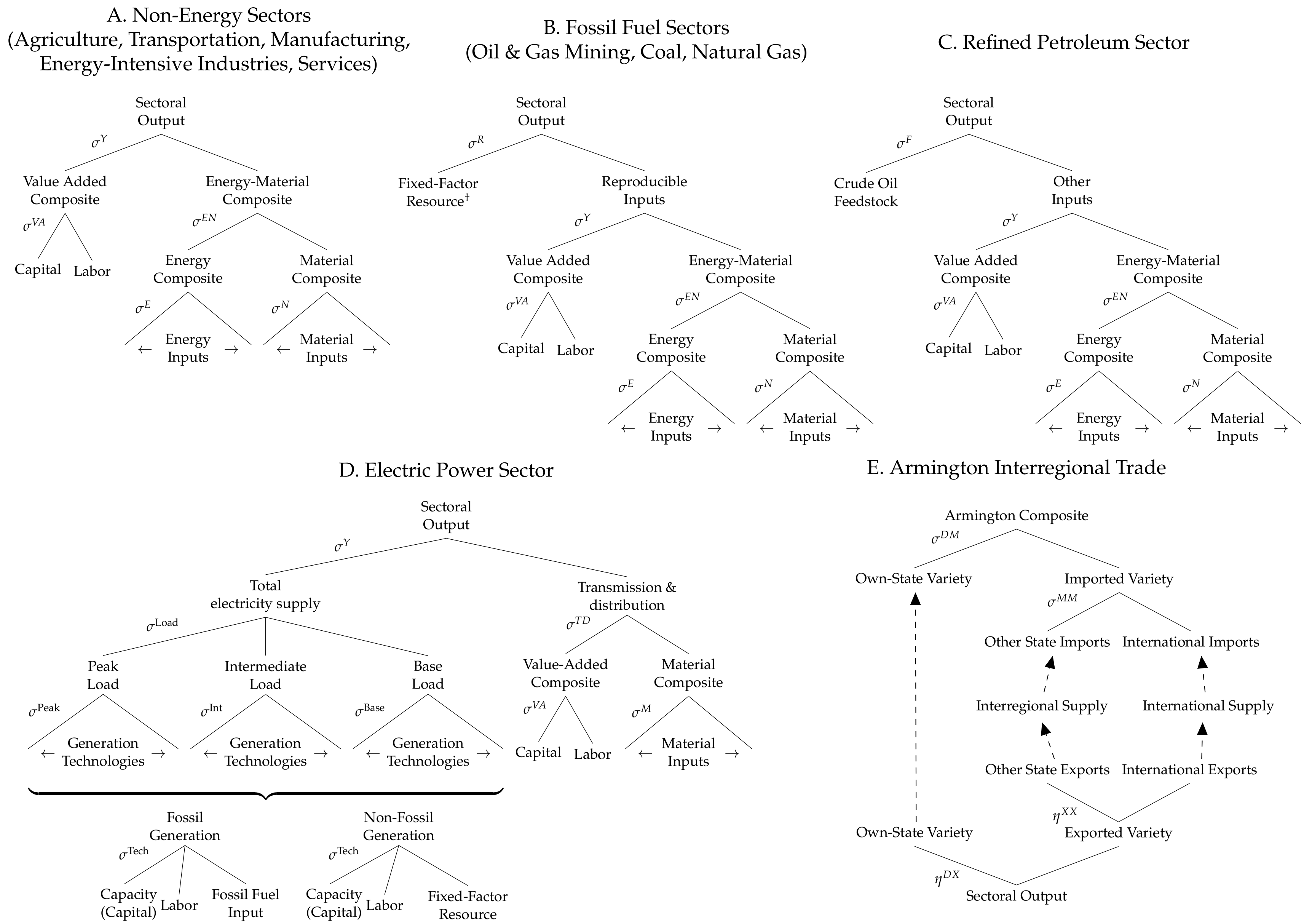
To be added...

4 Conclusion

To be added...

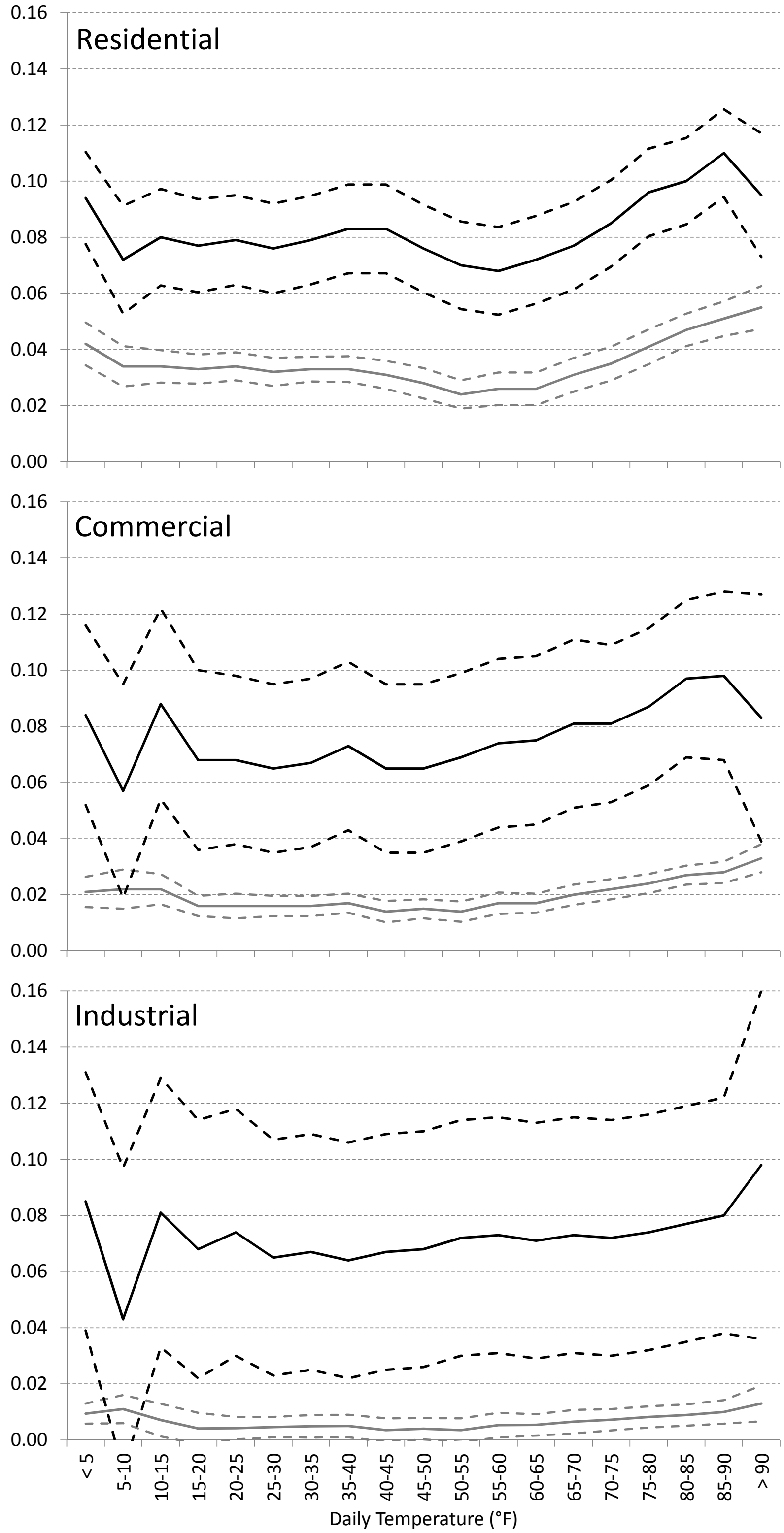
[5]Services alone make up 65-75% of baseline consumer spending. The changes in consumer prices of non-energy commodities simulated by the model are very small (on the order of 0.01%) and in many instances negative. These coincide with an order of magnitude larger percentage reductions in the quantities of these goods consumed, particularly by the lowest income households.

Figure 1: Sectoral Nesting Structure



σs and ηs represent elasticity of substitution parameters, whose values are summarized in an appendix, below.

Figure 2: Temperature Semi-Elasticities (log kWh Response)



Grey: static model; Black: dynamic model long-run component; Dashed lines: 95% confindence intervals

Figure 3: % Change in Monthly Electricity Demand by State,
2046-55 Relative to 1991-2000 (GFDL CM 2.1 simulation of SRES A2 Scenario)

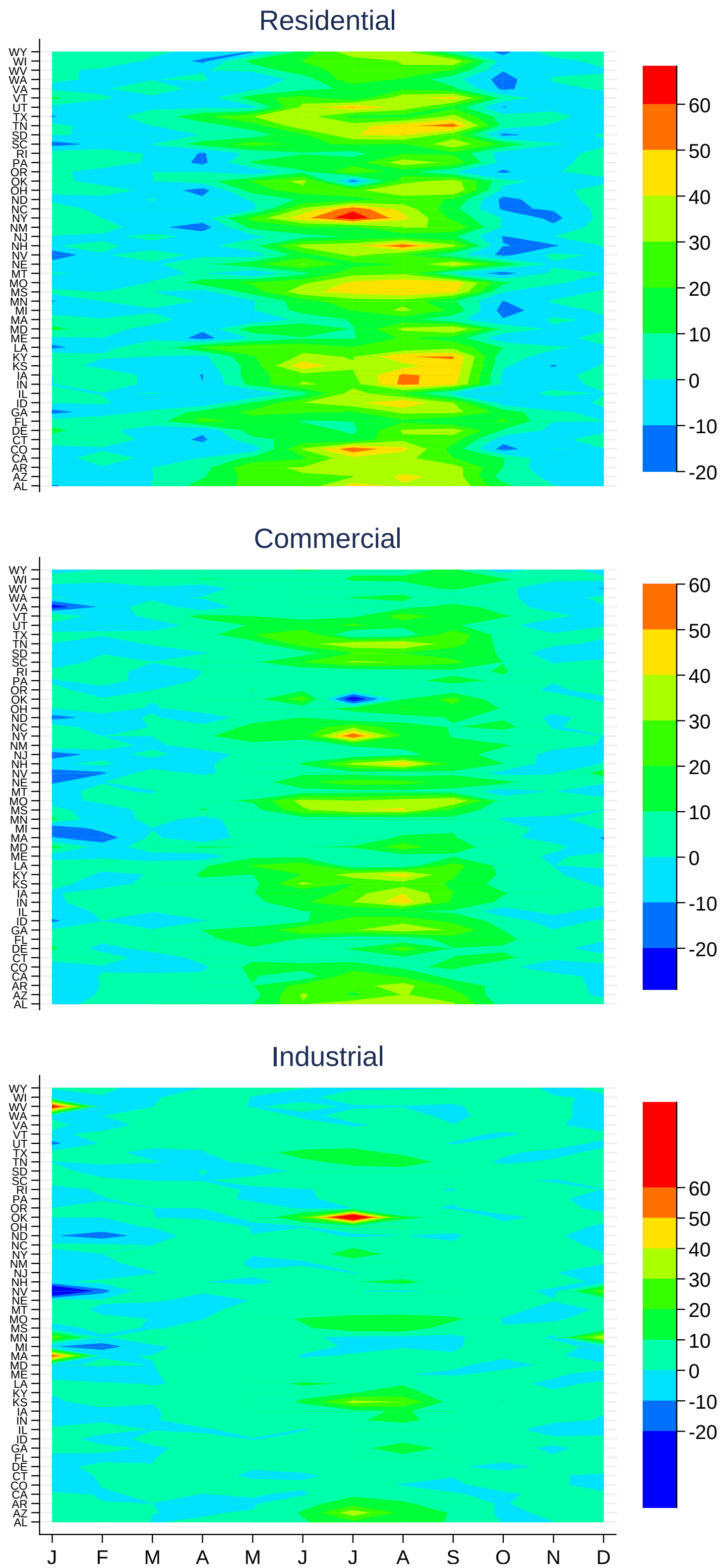


Figure 4: % Change in Total Electricity Demand, 2046-55 Relative to 1991-2000 (GFDL CM 2.1 simulation of SRES A2 Scenario)

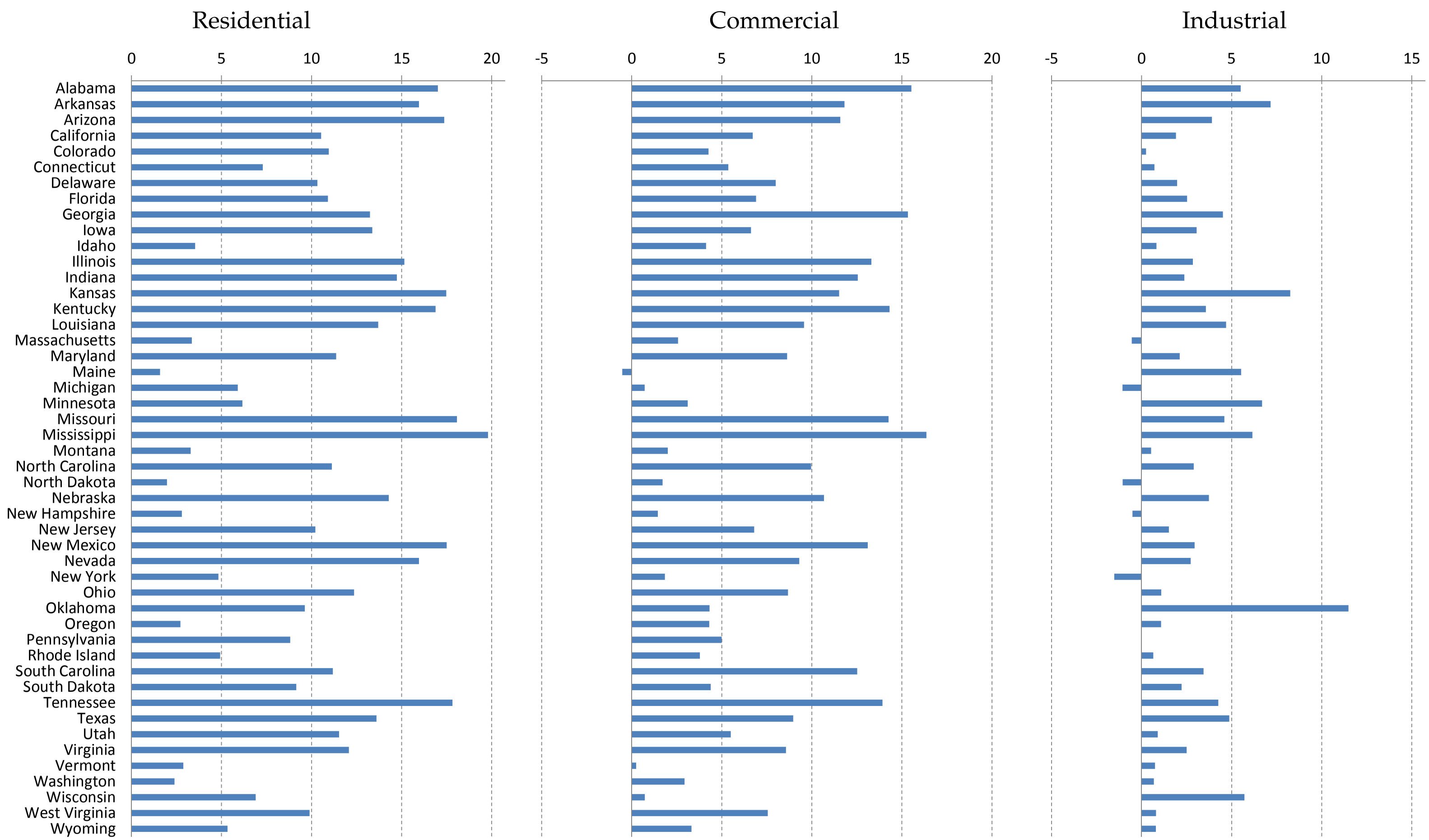


Figure 5: Simulated State-Level Impacts of Electricity Demand Shocks

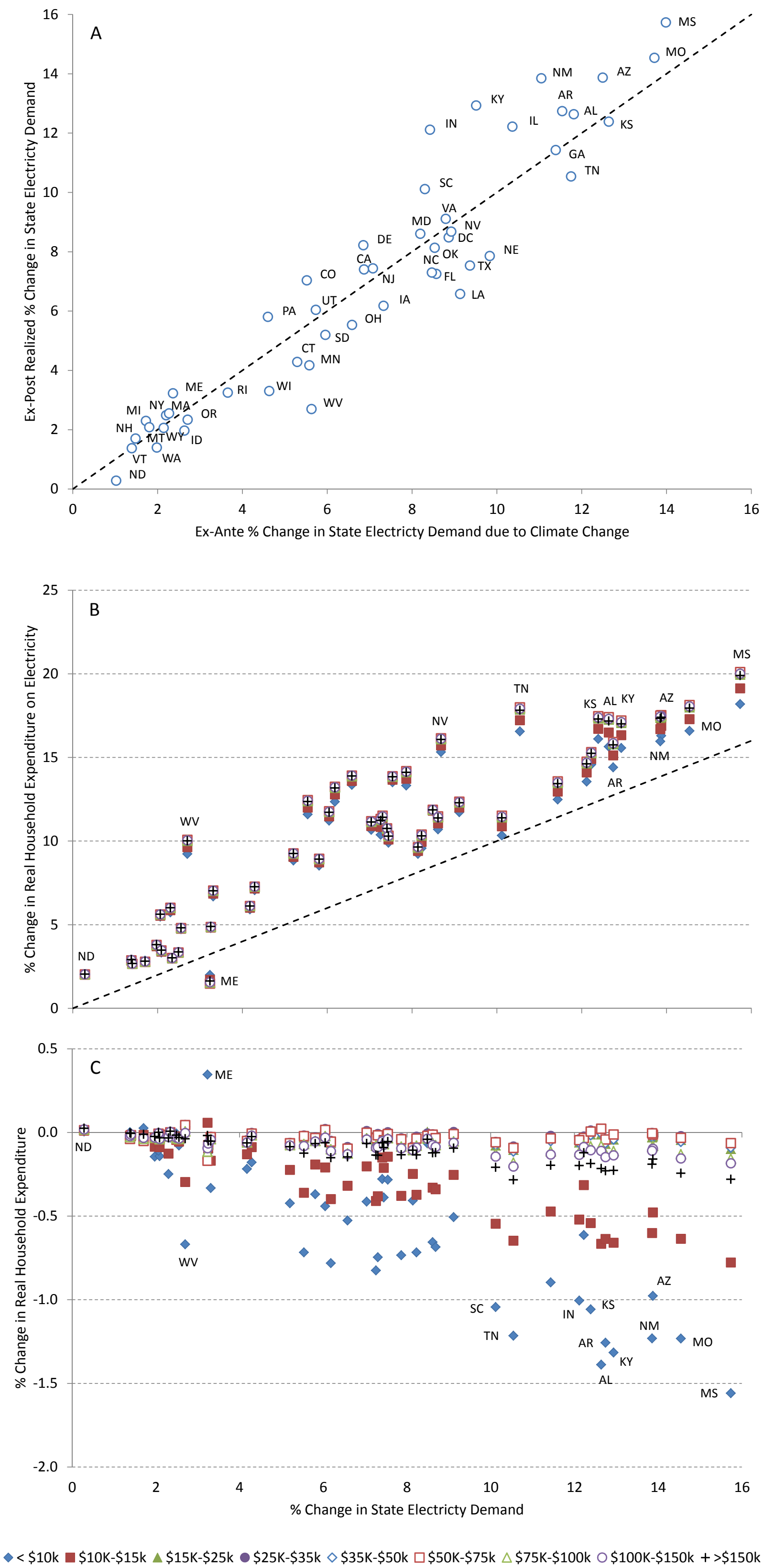


Figure 6: % Change in Sectoral CO_2 Emissions due to Electricity Demand Shocks

Table 1: Descriptive Statistics of the Dataset

	Mean	Std. Dev.	Min.	Max.
Montly Electricity Sales (kWh)				
Residential	1971066	2037506	0	16700000
Commercial	1747998	1850517	0	12600000
Industrial	1668253	1573469	0	10300000
Monthly Electricity Price (1982-84 $/kWh)				
Residential	0.051	0.013	0.027	0.114
Commercial	0.045	0.011	0.021	0.089
Industrial	0.032	0.010	0.011	0.078
Monthly Natural Gas Price (1982-84 $/MMBTU)				
Residential	10.42	5.11	0.00	58.38
Commercial	8.01	3.86	0.00	59.38
Industrial	6.95	2.91	0.00	59.38
Quarterly Personal Income Per Capita ('000 1982-84 $)	0.016	0.003	0.010	0.026
Monthly Real Avg. Wage Per Worker (1982-84 $)				
Commercial	4296.04	848.40	2441.24	18089.89
Industrial	5438.58	834.48	1908.83	8308.90
Annual Population	5569791	6180379	0	37300000
Monthly Employment				
Commercial	1786992	1941543	0	12500000
Industrial	473052	493794	0	3334621
Days with a Given Temperature				
$< 5\,^\circ$ F	0.197	1.256	0	21
5-10° F	0.179	0.794	0	10
10-15° F	0.327	1.174	0	15
15-20° F	0.575	1.640	0	16
20-25° F	0.948	2.242	0	16
25-30° F	1.417	2.828	0	19
30-35° F	1.836	3.177	0	23
35-40° F	2.103	3.250	0	22
40-45° F	2.312	3.307	0	25
45-50° F	2.409	3.304	0	24
50-55° F	2.397	3.203	0	23
55-60° F	2.420	3.187	0	22
60-65° F	2.545	3.401	0	21
65-70° F	2.741	3.921	0	24
70-75° F	2.705	4.364	0	28
75-80° F	2.210	4.483	0	28
80-85° F	1.534	4.525	0	31
85-90° F	0.352	2.004	0	29
$> 90°$ F	0.019	0.347	0	15

Number of observations: 12,086 (252 year-months $\times$ 48 states)

Table 2: Electric Power Detail in the CGE Model

A. Electric Power Technologies by Load Class

Technology	Base Load	Intermediate Load	Peak Load
Steam turbine	1. Coal, 2. Oil, 3. Gas		
Internal combustion			4. Oil, 5. Gas
Gas turbine		6. Oil, 7. Gas	6. Oil, 7. Gas
Combustion turbine		8. Oil, 9. Gas	8. Oil, 9. Gas
Combined cycle		10. Oil, 11. Gas	10. Oil, 11. Gas
Primary electricity	12. Hydro, 13. Nuclear, 14. Geothermal	15. Biomass	16. Wind, 17. Solar

B. North American Electric Reliability Corporation Regions and Constituent States*

SERC Reliability Corporation (SERC)	AL, AR, FL, GA, IL, KY, LA, MO, MS, NC, SC, TN, TX, VA
Western Electricity Coordinating Council (WECC)	AZ, CA, CO, ID, MT, NM, NV, OR, SD, TX, UT, WA, WY
Midwest Reliability Organization (MRO)	IA, MI, MN, MT, ND, NE, SD, WI
Southwest Power Pool (SPP)	AR, KS, LA, MO, NM, OK, TX
Northeast Power Coordinating Council (NPCC)	CT, MA, ME, NH, NY, RI, VT
Texas Reliability Entity (TRE)	TX
Florida Reliability Coordinating Council (FRCC)	FL
ReliabilityFirst Corporation (RFC)	DC, DE, IL, IN, KS, KY, MD, MI, NJ, OH, PA, TN, VA, WI, WV

*Alaska and Hawaii are modeled as autarkic regions that generate their own electric power.

Table 3: Static Fixed-Effects Electricity Demand Regressions

	Residential		Commercial		Industrial	
Log Elec Price	-0.34*	(0.054)	-0.19*	(0.063)	-0.44*	(0.088)
Log Gas Price × Winter	0.10*	(0.011)	0.023*	(0.0060)	-0.0065	(0.0060)
Log Per Capita Income	0.00095	(0.068)				
Log Avg Wage			0.29*	(0.11)	0.19+	(0.11)
Log Population	0.80*	(0.067)				
Log Labor			0.40*	(0.14)	0.69*	(0.11)
< 5 ° F	0.042*	(0.0038)	0.021*	(0.0027)	0.0094*	(0.0018)
5-10° F	0.034*	(0.0036)	0.022*	(0.0035)	0.011*	(0.0025)
10-15° F	0.034*	(0.0029)	0.022*	(0.0027)	0.0071*	(0.0029)
15-20° F	0.033*	(0.0026)	0.016*	(0.0018)	0.0041	(0.0028)
20-25° F	0.034*	(0.0025)	0.016*	(0.0022)	0.0042*	(0.0020)
25-30° F	0.032*	(0.0025)	0.016*	(0.0018)	0.0046*	(0.0018)
30-35° F	0.033*	(0.0022)	0.016*	(0.0018)	0.0049*	(0.0020)
35-40° F	0.033*	(0.0023)	0.017*	(0.0017)	0.0050*	(0.0020)
40-45° F	0.031*	(0.0025)	0.014*	(0.0019)	0.0035+	(0.0021)
45-50° F	0.028*	(0.0027)	0.015*	(0.0017)	0.0040*	(0.0019)
50-55° F	0.024*	(0.0025)	0.014*	(0.0018)	0.0035	(0.0021)
55-60° F	0.026*	(0.0029)	0.017*	(0.0019)	0.0053*	(0.0022)
60-65° F	0.026*	(0.0029)	0.017*	(0.0017)	0.0054*	(0.0019)
65-70° F	0.031*	(0.0030)	0.020*	(0.0018)	0.0065*	(0.0021)
70-75° F	0.035*	(0.0030)	0.022*	(0.0018)	0.0072*	(0.0019)
75-80° F	0.041*	(0.0031)	0.024*	(0.0017)	0.0082*	(0.0019)
80-85° F	0.047*	(0.0029)	0.027*	(0.0017)	0.0089*	(0.0019)
85-90° F	0.051*	(0.0031)	0.028*	(0.0019)	0.010*	(0.0021)
> 90° F	0.055*	(0.0038)	0.033*	(0.0025)	0.013*	(0.0032)
R-sq		0.77		0.79		0.30
F		1655.0		608.9		97.7
AIC		-17436.0		-16824.0		-11160.4
BIC		-17117.9		-16505.9		-10842.3
N		12086		12075		12075

$+$ p<.1 $*$ p<.05

Table 4: Dynamic Fixed-Effects Regressions: Long-Run Electricity Demand Impacts

	Residential		Commercial		Industrial	
Log Elec Price	-0.25*	(0.021)	-0.25*	(0.041)	-0.36*	(0.042)
Log Gas Price × Winter	0.18*	(0.0064)	0.18*	(0.015)	0.063*	(0.020)
Log Per Capita Income	0.47*	(0.030)				
Log Avg Wage			0.58*	(0.084)	0.026	(0.085)
Log Population	0.99*	(0.035)				
Log Labor			1.12*	(0.058)	0.50*	(0.050)
< 5 ° F	0.094*	(0.0082)	0.084*	(0.016)	0.085*	(0.023)
5-10° F	0.072*	(0.0096)	0.057*	(0.019)	0.043	(0.027)
10-15° F	0.080*	(0.0086)	0.088*	(0.017)	0.081*	(0.024)
15-20° F	0.077*	(0.0083)	0.068*	(0.016)	0.068*	(0.023)
20-25° F	0.079*	(0.0080)	0.068*	(0.015)	0.074*	(0.022)
25-30° F	0.076*	(0.0080)	0.065*	(0.015)	0.065*	(0.021)
30-35° F	0.079*	(0.0079)	0.067*	(0.015)	0.067*	(0.021)
35-40° F	0.083*	(0.0079)	0.073*	(0.015)	0.064*	(0.021)
40-45° F	0.083*	(0.0079)	0.065*	(0.015)	0.067*	(0.021)
45-50° F	0.076*	(0.0078)	0.065*	(0.015)	0.068*	(0.021)
50-55° F	0.070*	(0.0078)	0.069*	(0.015)	0.072*	(0.021)
55-60° F	0.068*	(0.0078)	0.074*	(0.015)	0.073*	(0.021)
60-65° F	0.072*	(0.0078)	0.075*	(0.015)	0.071*	(0.021)
65-70° F	0.077*	(0.0078)	0.081*	(0.015)	0.073*	(0.021)
70-75° F	0.085*	(0.0077)	0.081*	(0.014)	0.072*	(0.021)
75-80° F	0.096*	(0.0078)	0.087*	(0.014)	0.074*	(0.021)
80-85° F	0.10*	(0.0077)	0.097*	(0.014)	0.077*	(0.021)
85-90° F	0.11*	(0.0078)	0.098*	(0.015)	0.080*	(0.021)
> 90° F	0.095*	(0.011)	0.083*	(0.022)	0.098*	(0.031)
Error correction	-0.42*	(0.0072)	-0.14*	(0.0047)	-0.12*	(0.0044)

$+$ p<.1 $*$ p<.05

Table 5: Market Impacts of Electricity Demand Shocks

A. Electricity Supply, Use and Prices

	Demand	Supply			Use			Real Power Prices		
	Shock (%)	2050 Baseline (TWh)	% Chg. from 2007	% Chg. due to Shock	2050 Baseline (TWh)	% Chg. from 2007	% Chg. due to Shock	2050 Baseline ($/kWh)	% Chg. from 2007	% Chg. due to Shock
SERC	10.4	1851	66	8.9	1978	71	9.0	0.07	18	0.4
WECC	6.1	1127	52	7.3	1220	65	7.2	0.10	5	0.3
MRO	6.1	264	25	4.9	285	26	4.9	0.09	12	0.1
SPP	10.4	421	94	11.7	417	107	11.5	0.10	9	0.2
NPCC	2.6	350	27	2.5	348	15	2.5	0.13	-5	0.1
TRE	9.4	1018	203	7.3	849	159	7.7	0.09	-2	0.3
FRCC	8.6	424	102	7.3	540	124	7.5	0.05	11	0.5
RFC	6.3	1101	8	7.9	1201	23	7.8	0.10	7	0.3
US	7.6	6579	59	7.8	6861	64	7.8	0.09	2	0.1

B. Generation

	Coal			Oil			Natural gas		
	2050 Baseline (TWh)	% Chg. from 2007	% Chg. due to Shock	2050 Baseline (TWh)	% Chg. from 2007	% Chg. due to Shock	2050 Baseline (TWh)	% Chg. from 2007	% Chg. due to Shock
SERC	871	40	8.9	34	245	12.9	208	38	7.5
WECC	329	47	9.7	5	76	13.0	314	35	7.1
MRO	161	11	5.4	4	194	6.5	11	-14	5.0
SPP	207	79	12.8	4	325	13.9	153	122	11.2
NPCC	43	5	2.2	35	151	4.1	91	-9	2.8
TRE	303	148	7.4	7	590	12.2	374	122	7.3
FRCC	116	81	7.1	44	129	7.9	170	79	7.0
RFC	665	-2	9.2	18	179	10.9	90	16	8.4
US	2700	34	8.8	162	146	8.5	1415	56	7.4

	Nuclear			Hydro			Renewables		
	2050 Baseline (TWh)	% Chg. from 2007	% Chg. due to Shock	2050 Baseline (TWh)	% Chg. from 2007	% Chg. due to Shock	2050 Baseline (TWh)	% Chg. from 2007	% Chg. due to Shock
SERC	450	53	4.5	29	43	6.2	82	286	5.0
WECC	96	36	4.5	224	32	4.1	72	93	4.1
MRO	40	11	5.1	9	23	3.2	13	44	4.7
SPP	30	35	8.5	7	68	3.9	17	229	5.5
NPCC	88	11	2.3	35	14	2.7	25	136	2.2
TRE	62	84	1.5	2	82	2.0	33	287	1.7
FRCC	46	67	2.9	0	65	3.4	20	403	2.9
RFC	295	22	6.8	7	8	7.3	39	336	6.9
US	1108	37	4.8	315	30	4.2	302	187	4.3

Appendix

Table A.1: Dynamic Fixed-Effects Regressions: Short-Run Electricity Demand Impacts

	Residential		Commercial		Industrial	
Log Elec Price	-0.35*	(0.018)	-0.26*	(0.011)	-0.27*	(0.010)
Log Gas Price $\times$ Winter	0.0034	(0.0024)	-0.0016	(0.0017)	-0.013*	(0.0022)
Log Per Capita Income	-0.85*	(0.096)				
Log Avg Wage			-0.12*	(0.016)	0.072*	(0.023)
Log Population	1.98*	(0.30)				
Log Labor			0.030	(0.041)	0.20*	(0.040)
$< 5\,°$ F	0.012*	(0.0020)	0.015*	(0.0014)	0.0037*	(0.0016)
5-10° F	0.016*	(0.0024)	0.018*	(0.0017)	0.0075*	(0.0020)
10-15° F	0.012*	(0.0021)	0.013*	(0.0015)	0.0024	(0.0017)
15-20° F	0.012*	(0.0020)	0.014*	(0.0013)	0.0035*	(0.0016)
20-25° F	0.012*	(0.0019)	0.014*	(0.0012)	0.0027+	(0.0015)
25-30° F	0.012*	(0.0018)	0.013*	(0.0012)	0.0037*	(0.0015)
30-35° F	0.010*	(0.0018)	0.013*	(0.0012)	0.0031*	(0.0015)
35-40° F	0.0095*	(0.0018)	0.012*	(0.0012)	0.0033*	(0.0015)
40-45° F	0.0072*	(0.0018)	0.012*	(0.0012)	0.0026+	(0.0015)
45-50° F	0.0069*	(0.0018)	0.012*	(0.0012)	0.0027+	(0.0015)
50-55° F	0.0057*	(0.0018)	0.011*	(0.0012)	0.0024+	(0.0015)
55-60° F	0.0074*	(0.0018)	0.012*	(0.0012)	0.0035*	(0.0015)
60-65° F	0.0070*	(0.0018)	0.013*	(0.0012)	0.0038*	(0.0015)
65-70° F	0.0086*	(0.0018)	0.014*	(0.0012)	0.0044*	(0.0015)
70-75° F	0.010*	(0.0018)	0.016*	(0.0012)	0.0053*	(0.0014)
75-80° F	0.012*	(0.0018)	0.018*	(0.0012)	0.0058*	(0.0014)
80-85° F	0.014*	(0.0017)	0.019*	(0.0011)	0.0063*	(0.0014)
85-90° F	0.013*	(0.0018)	0.019*	(0.0012)	0.0066*	(0.0015)
$> 90°$ F	0.022*	(0.0030)	0.024*	(0.0022)	0.0056*	(0.0025)

$+$ p<.1 $*$ p<.05

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