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Hourly Electricity Loads: Temperature Elasticities and Climate Change

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I. Introduction

The role of climate change-driven effects on electrical energy demand and production is the focus of this modeling effort. The research requires detailed, disaggregated models that can link hypothesized climate change perturbations to specific demand effects in the residential and commercial sectors. This requires consideration of load shape forecasting and creation of detailed (one-hour) short-term forecasts. The end-use and load shape forecasts are employed to explore general relationships between climate and energy use on a regional scale.

II. Literature Review

In general, aggregate analyses have found that commercial and residential usage is more sensitive to temperature increases than industrial usage; this paper thus focuses on the former. Studies by Scott et al. (1994), Morris et al. (1996), and Sailor and Muñoz (1997) concluded that climate warming would produce an increase in cooling requirements of a few percentage points, and a similar decrease in heating requirements. Darmstadter (1993) notes that these offsetting effects imply a relatively small net impact on forecasted annual energy consumption. In another study, Baxter and Calandri (1992) forecast annual demand due to a 1.9^{o}C warming by 2010, finding that a temperature increase of 1.9^{o}C would increase California's annual electricity requirements by 2.6%. More relevant than the level of increase, however, is how any changes are distributed throughout the year. In particular, the greatest increases are likely to occur during weekdays in the air conditioning season, precisely at those times that tropospheric ozone violations occur. Baxter and Calandri's analysis used a two-stage process to distribute projected annual demand over individual hours of a summer peak day, finding that their assumed 1.9^{o}C warming would increase peak summer electricity demands by 3.7%. Our paper aims to continue in this vein, relating peak hourly electricity demand directly to hourly weather readings.

Liu et al. (1996) report that utility experience across the United States shows variations in weekday demands to be most strongly associated with temperature. Wind, humidity, and cloud cover are additional factors considered in many short-term models. Hobbs et al. (1998) estimates that 80% or more of the variation in demand is associated with weather. For the systems in our study, peak electric demands in the summer can easily vary by 25% or more due to day-to-day changes in temperature.

III. Data

We collected hourly demand figures for the Baltimore Gas & Electric Company (BGE) load region within the Pennsylvania, New Jersey, and Maryland Interconnection (PJM) from January 1st, 1998 through April 30th, 2001.[3] BGE has been operating for over 180 years, currently serving more than 1.1 million electric customers and 580,000 gas customers with 1,200 miles of transmission lines and more than 21,000 miles of overhead and underground distribution lines. The load region covers about 2,300 square miles including Baltimore City and all or part of 10 central Maryland counties. Prior to July 1st, 2000, BGE was a traditional vertically integrated utility, generating and delivering electricity. In July 2000, generation was transferred to two competitive affiliates by Constellation Energy Group, the BGE holding company formed a year earlier.

Our electricity demand data set consists of peak loads for hours 1 to 24 on each of the 1,216 days from January 1st, 1998 to April 30th, 2001. The highest average loads (above 4,000 MW) occur in the evening, between 7pm and 10pm. The lowest average hourly loads (below 3,000 MW) are found in the early morning, from 3am to 6am. Load variability is lowest during the early morning, with a standard deviation around 450 MW. Variablility is highest in the late afternon between 3pm and 6pm, when the standard deviation ranges as high as 700 MW.

Weather and temperature data were initially obtained from the NOAA data web site, http://www.ncdc.noaa.gov/. The weather station at Baltimore/Washington International Airport, WBAN #724060 (call sign KBWI), was the collection site in the BGE study region. The sample of 29,184 hourly temperature readings had 868 missing observations, usually around holidays when no staff was available to record observations. To improve the quality of our data set, we purchased the complete series from WeatherBank, a private weather forecasting and data storehouse, maintaining in-house archives of hourly and daily weather reports from locations across the globe. These data are filtered through a proprietary set of routines designed to screen out corrupted or missing data.[4]

As we are primarily interested in more extreme weather conditions we focus here on the month of July in the sample period. For July, the highest temperatures (above 84°F) are from 1pm-4pm, and the coolest temperatures (below 69°F) from 3am-5am. Warming begins between 5am and 6am, with morning temperatures rising faster than evening temperatures fall.

Electricity consumption models typically use transformations of the dry bulb temperature known as degree day measures. These represent the impact of temperature fluctuations on electricity load for heating or cooling needs, depending on the season. The current temperature minus 72°F gives cooling degree measures. For temperatures

[3] The source for our historical weather data is the PJM web-site http://www.pjm.com/market_system_data/system/historical.html.

below 72°F, the CDD is zero. Hourly patterns for degree day statistics are similar to those for the raw temperature data.

Figure 1 plots the average of the hourly load curve with the average of hourly degree days for July 1998. The graph is meant to demonstrate the importance of time of day and cooling degree effects. A single trough characterizes the July load curve graphs. This is shown in the early morning (4am to 6am), coincident with the lowest cooling degree day needs. Loads and cooling degree day needs increase dramatically between 7am and 11am. Cooling degree day needs begin falling after 3pm, but the load curve persists near its peak until the evening; after 10pm load declines dramatically. There is a fair amount of variation in cooling degree averages across the three years in our sample: Summer 1998 and 1999 were much warmer than Summer 2000.

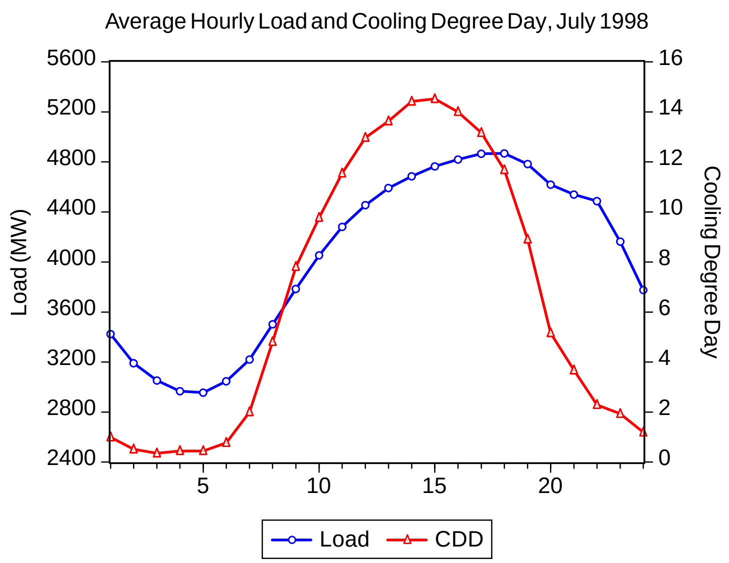

Figure 1 – The Relationship Between Hourly Loads and Cooling Degree

[4] From the WeatherBank website at http://www.WeatherBank.com

IV. Models

We specify hourly load models of electricity consumption for the Baltimore Gas and Electric region within PJM using the seasonal sub-samples of data from January 1st, 1998 through April 30th, 2001. The individual hourly models were estimated using ordinary least squares. MetrixND 3.0 (2001) and EViews 4.1 are the software used for estimating the models and developing the simulations.

Electricity loads are dependent on recent time of day and previous hour load effects, seasonal and daily weather patterns, weekday versus weekend effects, and holidays. These latter two effects are known as “trading day” variation effects and are modeled using 0-1 dummy variables. Dagum (1978) demonstrated that accounting for holidays and trading-day variation significantly improves modeling and seasonal adjustment techniques. Similarly, Pack (1990), and Joutz and Trost (1992) showed that incorporating these factors in univariate models can significantly improve forecasting performance.

We followed the simple standard seasonal time series modeling approach described by Diebold (2001) and Abraham and Ledolter (1983) .The general model for each summer hour **h** is specified as follows:

$$
\begin{aligned}
Log\left(Load_{ht}\right) = {} & \beta_0 + \sum_{i=1}^{6}\beta_i Day_{iht} + \beta_7 Holiday_{ht} + \sum_{j=1}^{3}\delta_j Month_{jht} \\
& + \sum_{j=1}^{4}\alpha_j Month_{jht}\cdot CDD_{jht} + \sum_{j=1}^{4}\gamma_j Month_{jht}\cdot CDD_{jht}^{2} + \phi(L) Log\left(Load_{ht}\right) + e_{ht}
\end{aligned}
$$

Time subscripts are denoted using **h** and **t**, where **h** gives the hour and **t** the day of the observation. A white noise random disturbance term, $\mathbf{e_{ht}}$, is added onto the end of the equation. Dummy variables are used for capturing effects of the day of the week and summer months. The hourly models are normalized on Mondays in June; the remaining six days of the week are captured by the six dummy variables for Day. The Month dummy variables capture the level effects for July, August and September (June’s level effect being captured by the intercept). There is also a Holiday dummy variable to capture the demand effects of national holidays.

The general model allows for separate monthly temperature sensitivities by interacting degree day measures with dummy variables for each summer month. As cooling demand may cause loads to rise faster than linearly with increasing temperature, we have included squared cooling degree day terms in the model.

Hourly loads are autocorrelated, with the lagged polynomial operator, $\phi(L) = (L+L^2+L^3+L^{24})$ capturing the effects of the previous three hours and for the same hour one day previous.

Hourly Electricity Loads

The general model has 23 parameters to estimate. We tested 52 hypotheses for hours 1 through 24 (a total of 1,248 hypotheses in all). These tests focused on the deterministic variables, on the temperature sensitivities, and both jointly in an attempt to derive more parsimonious models.[5] The best performer, which includes the deterministic effects of Day, Holiday and Month, was our "asymmetric" model. The description "asymmetric" indicates that this model allows for "start and end of season" effects, that is a difference in temperature sensitivities between June/September and July/August.

The residuals appear normally distributed in spite of a large Jarque-Bera statistic: the departure from normality can be attributed to two outliers. Both of these outliers are underpredictions occurring after August heat waves, the first on August 14, 1999 and the second on August 30, 1999. The former was the more extreme of the two: after three days with temperatures in the 90's, the high on August 14 was only 75°F. On this date, the model underpredicts demand by nearly eight standard deviations. This can be explained by the saturation effect that buildings experience during heat waves. After several days of high temperatures (90°F and above) buildings will become "saturated" and will retain heat even after outside temperatures have fallen. Thus, air conditioning will be required above what could be expected considering temperature alone.

V. Elasticity Estimates

We computed elasticity estimates of the impact of a 1°F change in the cooling degree days on electricity loads for each hour. The elasticity is a scale-free measure that permits comparisons of estimates across utilities and regions. Our hypothesis is that a summertime temperature increase will have a net positive effect on electricity consumption. We expect the level effects to be positive, while the quadratic effects could be positive or negative. The cooling degree day elasticity for hour **h** in month **j** is defined as

$$\eta_{hj} = \left(\alpha_{hj} + 2\gamma_{hj} MCDD_{hj}\right) \cdot MCDD_{hj},$$

where MCDD is the monthly mean of the cooling degree days for hour **h**.

As described above, we chose an asymmetric model to capture the "beginning and end of season" effect, that is, the different responsiveness of cooling degree day coefficients for June/September versus July/August. On net, all the hourly elasticities are positive. We found that the portion of the elasticity associated with the CDD level term was statistically significant at 5% in 21of 24 hours for the June/September pair and 18 of the 24 hours for the July/August pair. The portion of the elasticity associated with the quadratic term was negative and significant in 14 of the June and September measures and 13 of the July and August measures. An important point to take from

[5] Details of this process and the outcomes are available upon request in the full version of this paper.

this is that ignoring the quadratic terms in the model specification would bias the elasticity estimates upward. We have two possible explanations for the negative value. First, there is a limit on the total load that can be supplied by the existing capital stock. Second, the utilities find ways to reduce the load response during very warm weather, such as utility control of residential air conditioning.[6]

The highest elasticities occur during the warmest portion of the day, from 8am to 6pm. A surprising result is that the elasticity estimates appear larger in most hours for June and September than in July and August. This may be due to the two reasons mentioned above, along with the greater volatility in temperature in the middle of the summer season.

The average cooling degree values for June and September (between the hours of 9am and 6pm) range from 4 to 7.7 with a standard deviation from 5 to 6.9. The July and August values show a similar range in standard deviation (5.5 to 6.9), with the cooling degree day averages falling between 7.8 and 12.15. In addition, the July and August values appear to approximate a normal distribution: the Jarque-Bera test cannot be rejected at 10%. The test is rejected, however, for every hour in the June and September sample. There appear to be flatter tails in the June/September CDD distributions; that is, more observations close to zero, while maximum average values are close to those in July and August. Thus, even though hourly loads are on average larger in July and August, they appear to be relatively more temperature-sensitive in June and September.

The hourly elasticity estimates and corresponding electricity loads are presented in Figure 2 using a bar and line graph. During the night, between 10pm and 5am, the elasticity is significant, with values around 0.5%-1.0%. This may reflect the demand for comfort while sleeping: air conditioning demand is responsive on hot nights, so there is some cooling demand even in the trough load period. In the morning (7am and 11am) the elasticity averages about 1.5%: temperatures and loads are rising as businesses open and people begin their daily activities. The load sensitivity is marginal for the next three hours as the temperature peaks, and demand approaches its peak. Between 2pm and 6pm, the elasticity is greater than 1%. Between 6pm and 9pm the elasticity appears to be zero. This counter-intuitive result may be explained by offsetting effects: residential demand for electricity is increasing while businesses are closing. In addition, though the level of the temperature may by high, it is falling rather than rising.

[6] Programs such as this are offered as customer incentives by BGE: http://www.bge.com/CDA/files/rPG81-82.doc

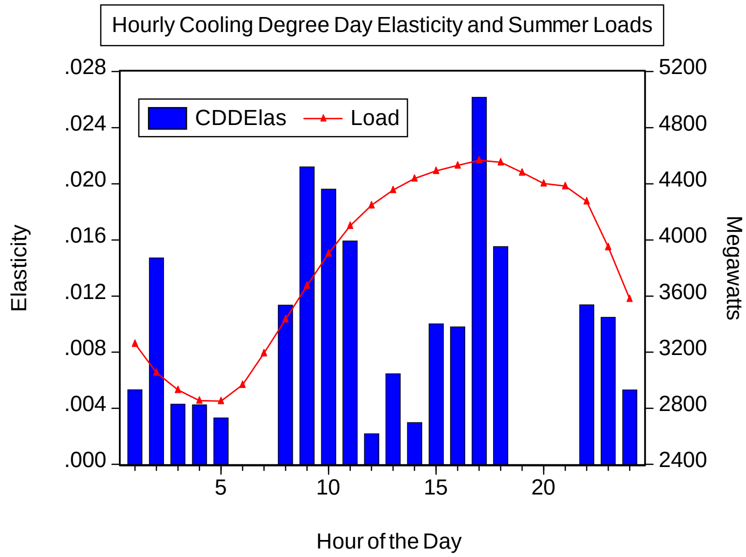

Figure 2 – CDD Elasticity and Level in July Hourly Load

VI. Simulation

We simulated the impact of higher summer temperatures, following the global warming scenarios of the Intergovernmental Panel on Climate Change[7]. Assuming a doubling of atmospheric CO_2 concentrations over the next 70 years, the IPCC's 19 global temperature simulations show an average warming of 3.24°F, with a standard deviation of 0.72°F. Our simulation is based on a more conservative 2°F increase. To investigate demand when peak loads are near maximum capacity, we performed our simulation on July 1999, this being the hottest single month in our data[8].

The hourly models are fit up through June 30; daily forecasts are then made for July, adjusting the cooling degree day variables for a 2°F increase. We compare the historical degree day series to two simulations: the unconditional simulation using actual degree day values, and the conditional simulation using the adjusted degree day series. Another important comparison is the relative difference between the two simulations: Figure 3 shows the ratio of these two at the noon hour during the month of July 1999.

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[7] The full text for these publications is available on-line at http://www.grida.no/climate/ipcc_tar
[8] Average temperature for July 1999 was 80°F compared to 77°F for July 1998. Considering cooling needs between these two months, CDDs were 35.8% higher in July 1999.

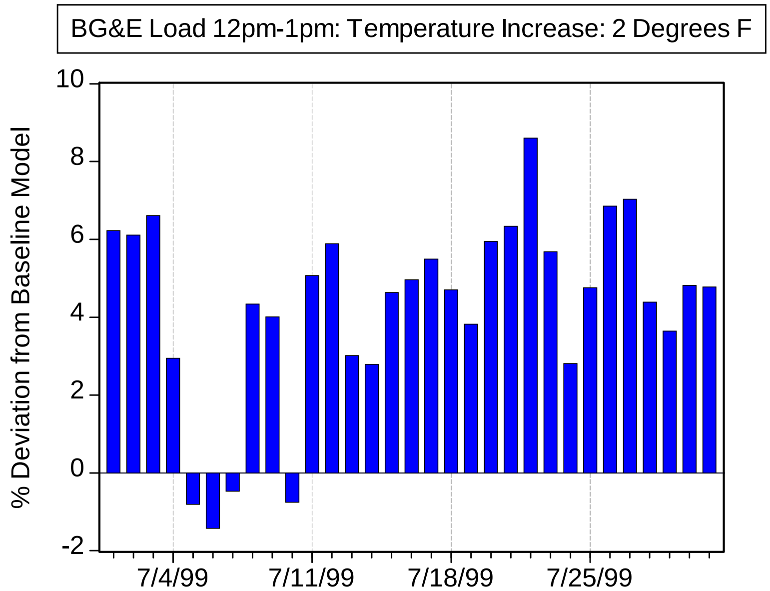

Figure 3 – Ratio of Simulation Temperature Forecast to Baseline Forecast

The results of the simulation show an increase in forecasted load throughout July, with the exception of July 5, 6, 7, and 10. For these dates the model predicts a fall in load from the early morning to early evening: July 5 from 5am to 7pm, July 6 from 3am to 7pm, July 7 from midnight to 6pm, and July 10 from 3am to 3pm. This fall in forecast load is small, however, averaging –1.2% among the negative predictions compared to a +4.2% change for the positive predictions. The overall result is a predicted 3.8% increase in electricity demand due to the 2°F rise in temperatures. These counter-intuitive results may be due to an interaction among trading day variables: the 4th of July holiday fell on a Sunday in 1999; the predicted fall in demand is for the following Monday, Tuesday, Wednesday and Saturday.

VII. Summary

This paper models the impact of climate change on electricity consumption behavior. Demand data were drawn from an hourly database of electricity loads for the Baltimore Gas and Electric service area within the Pennsylvania-New Jersey-Maryland Interconnection (PJM). A standard set of hourly forecasting models was estimated, accounting for autoregressive components, seasonal cooling degree temperature effects, and trading day variation for holidays and weekends. Short-run elasticities were calculated for the cooling degree day effects. A simulation over a particularly hot month (July 1999), considers the impact of a 2°F increase in the daily temperature on hourly peak loads. The result is an average demand increase of 3.8% over those forecasts using actual temperature data. This outcome is similar to results reported for California by Baxter and Calandri (1992).

In future research, we will compare the temperature sensitivity and simulation results from these models with those from a panel data model and an artificial neural network. In addition, we will compare our results for the PJM models with other publicly available hourly load models. Proposed additions include expanding the model to include other weather variables, such as humidity, cloud cover and wind speed.

References

Abraham, Bovas and Johannes Ledolter. Statistical Methods in Forecasting, Wiley Series in Probability and Mathematical Statistics, John Wiley and Sons, New York, (1983).

Baxter, Lester W., and Kevin Calandri. "Global warming and electricity demand; A study of California." *Energy Policy* March (1992): 233-244.

Dagum, E.B. "Modeling, Forecasting, and Seasonally Adjusting Economic Time Series with the X-11 ARIMA Method." *The Statistician* 27 No. 3,4 (1978): 203-216.

Darmstadter, Joel. "Climate change impacts on the energy sector and possible adjustments in the region." *Climatic Change* 24 (1993): 117-129.

Diebold, Francis X. Elements of Forecasting, second edition, Southwestern Publishing, Cincinnati, OH, (2001).

Hobbs, Benjamin F., et al. "Artificial neural networks for short-term energy forecasting: Accuracy and economic value." *Neurocomputing* 23 (1998): 71-84.

Joutz, F. and Robert Trost, "Using Stochastic Simulation to Test the Effect of Seasonal Adjustment on Forecast Standard Errors of Motor Gasoline Demand." *International Journal of Forecasting* 8 (1992): 219-231.

Morris III, Samuel C., Gary A, Goldstein, Ajay Sanghi, and Douglas Hill. "Energy Demand and Supply in Metropolitan New York with Global Climate Change." *Annals New York Academy of Sciences* 1998: 139-150.

Pack, D.J. "In Defense of ARIMA Modeling." *International Journal of Forecasting* 6 (1990): 211-218.

Sailor, David J., and J. Ricardo Muñoz. "Sensitivity of electricity and natural gas consumption to climate in the U.S.A. – Methodology and results for eight states." *Energy* 22, No. 10 (1997): 987-998.

Scott, Michael J., Laura E. Wrench, and Donald L. Hadley. "Effects of Climate Change on Commercial Building Energy Demand." *Energy Sources* 16 (1994): 317-332.