CSEM WP 136

Is Real-Time Pricing Green?: The Environmental Impacts of Electricity Demand Variance

Stephen P. Holland and Erin T. Mansur

August 2004

This paper is part of the Center for the Study of Energy Markets (CSEM) Working Paper Series. CSEM is a program of the University of California Energy Institute, a multi-campus research unit of the University of California located on the Berkeley campus.

2547 Channing Way
Berkeley, California 94720-5180
www.ucei.org

Is Real-Time Pricing Green?: The Environmental Impacts of Electricity Demand Variance

Stephen P. Holland and Erin T. Mansur*

August 11, 2004

Abstract

Economists have long advocated for electricity pricing that accurately reflects time-varying production costs. In particular, real-time pricing (RTP) would improve the efficiency of electricity consumption and investment and would lessen the potential harm from market power. Conventional wisdom has claimed that RTP has an additional benefit, namely, reduced emissions from reduced peak demand. We argue that RTP will reduce variance of electricity load and estimate the short-run impacts of a reduction in variance on emissions of SO_2, NO_x, and CO_2. According to our estimates, a reduction in within-day load variance would decrease emissions of some pollutants in some NERC regions (FRCC in Florida, MAAC in the Mid-Atlantic, and MAIN in the Illinois area). However, a reduction in within-day variance would actually *increase* emissions of all three pollutants in the Eastern Mid-West (ECAR) and the Southeast (SERC) and of two of three pollutants in Texas (ERCOT), the Great Plains (MAPP), and the West (WSCC). The effects are relatively small as the elasticity greatest in magnitude is 0.042. We further analyze reductions in across-day variance and find similar results. The results are also robust to alternate measures of within-day variance and to a nonparametric specification of the model. To understand our results, we note that changes in emissions are similar to changes in generation from power plants using fossil fuels. Furthermore, we observe that emissions reductions occur in regions with more hydroelectric capacity than oil-fired capacity. This supports the hypothesis that the environmental benefits of RTP come from reducing peak demand, but only if peak capacity is oil fired rather than hydroelectric.

**Holland:* Department of Economics, University of North Carolina, Greensboro, NC 27402-6165. Email: sphollan@uncg.edu. *Mansur:* School of Management and School of Forestry and Environmental Studies, Yale University, P.O. Box 208200, New Haven, CT 06520-8200. Email: erin.mansur@yale.edu.
We would like to thank Severin Borenstein, Jim Bushnell, Kevin Forbes, Jun Ishii, Nat Keohane, Al Klevorick, Frank Wolak, and seminar participants at the University of California Energy Institute and Yale University for comments. Thanks also to Meredith Fowlie and Nalin Sahni for excellent research assistance.

1 Introduction

Economists have long advocated for electricity pricing that accurately reflects time-varying production costs.[1] In particular, they have argued that real-time pricing of electricity (RTP) would improve the efficiency of electricity consumption and investment and would lessen the potential harm from market power.[2] However, these recommendations have met serious political opposition despite advances in real-time metering and in technology for responding to real-time prices.[3] Recently some environmental groups have supported real-time pricing for its potential to reduce pollution.[4] Indeed, the conventional wisdom seems to be that RTP will yield environmental benefits by reducing peak demand.[5] This paper estimates the short-run impacts of real-time pricing on the emissions of sulfur dioxide (SO_2), nitrogen oxides, (NO_x), and carbon dioxide (CO_2).[6]

RTP may affect pollution by changing the distribution of electricity load. The demand for electricity varies throughout the day due to hourly changes in, for example, temperature and economic activity. If the retail prices do not vary, customers conserve less than would be efficient during peak periods, but conserve more than would be efficient during off-peak periods. For example, during a peak period (*e.g.,* on a hot afternoon in Texas), the wholesale price of electricity is higher than the flat retail price. If customers faced

[1] See, for example, the peak-load pricing literature pioneered by Steiner (1957) and Boiteaux (1960). More recently, time-varying pricing under regulation has been discussed by Borenstein, Jaske and Rosenfeld (2002), and Borenstein and Holland (forthcoming) study real-time pricing in competitive electricity markets.

[2] Real-time pricing can be defined for the purposes of this paper as prices that vary hour by hour (or half hour by half hour). See Borenstein, Jaske, and Rosenfeld (2002) for further discussion of constructing discrete prices from continuously varying electricity load.

[3] Currently RTP is offered in just a few small pilot programs in the U.S., primarily in Georgia and New York. Time-of-Use pricing is more widely available but does not reflect hour-by-hour variation in production costs.

[4] An environmental group in California has proposed a real-time pricing scheme to remove the need for construction of additional generation capacity in the city of San Francisco. Another environmental group, Environmental Defense (2001) argued for RTP in California citing its environmental benefits.

[5] Hirst and Kirby (2001), Swofford (2001), Kiesling (2002), Smith and Kiesling (2003), and Nevada Power (2003) claim environmental benefits in their arguments for RTP.

[6] Since the work by Lipsey and Lancaster (1956) on the theory of the second best, economists have known that correcting for one market failure might perturb another. Optimal regulation may include a set of policies that allow for real-time pricing and also tax pollution directly. However, the aim of this paper is not normative: we do not argue that RTP need be "green" for implementation. Rather, we address a positive question in order to clarify the likely environmental implications of RTP.

the higher real-time price, each would use less electricity, and the system load would be smaller. Conversely, in an off-peak period (*e.g.,* late at night), the wholesale price is lower than the flat retail price, and the system load would be greater under RTP. Since real-time pricing decreases load in the peak periods and increases load off-peak, real-time pricing would decrease the variance of load.[7]

Decreasing the variance of load can increase or decrease pollution. Firms generally use generating units in order of their marginal costs.[8] Since fuel costs are a large component of marginal costs, low-cost generating units of a given fuel type generally are newer, use fuel more efficiently, and pollute less per megawatt-hour (MWh). In this case, decreasing the variance of load then causes the more efficient, cleaner units to generate more and the less efficient, dirtier units to generate less, thereby reducing total emissions.[9] On the other hand, real-time pricing may increase pollution. This occurs, for example, if base-load generation is met by coal-fired units while peak load generation is met by more expensive, but cleaner, gas-fired units.

These different effects imply that the environmental impact of real-time pricing will be heavily dependent upon the relative cleanliness of the production technologies available in each region. For example, if a region has peak load generation with low emissions rates, *e.g.,* hydro or gas-fired, a reduction in load variance may increase emissions. However, in a region with dirty peak capacity (*e.g.,* oil-fired), a reduction in load variance may decrease emissions. For this reason, we estimate the effects separately for various regions of the U.S.

We divide the issue of measuring the environmental consequences of real-time pricing into two questions: (*i*) How will RTP change demand and the market equilibrium? and (*ii*) How will these equilibrium changes affect firms' choices of production and pollution? The answer to the first question depends on the relevant own- and cross-price elasticities

[7] RTP may also change the average daily load depending on the relative demand elasticities. In this paper, we focus on changes in the variance of load holding average load constant.

[8] "Generating units" typically consist of boilers, turbines, and generators. A power plant may have several units.

[9] In addition to changing the technology used to generate electricity at different times of day, RTP can reduce emissions by reducing the frequency of restarting units and ramping their production up and down.

of demand.[10] While beyond the scope of this paper, Holland and Mansur (2004) simulate the effect of real-time pricing on load.

This paper analyzes the second question (namely, the effect of the distribution of load on emissions) by exploiting exogenous variation in load. Daily changes in temperature and economic activity lead to differences in the hourly demand for electricity and to significant variation in the distribution of load across days. This variation also leads to variation in emissions for a variety of pollutants. By estimating the relationship between the load distribution and emissions, we can analyze the environmental impacts of policies that reduce load variation such as real-time pricing.

One advantage of dividing the question into two steps is that the results of analyzing the environmental impacts of altering load variance have applicability beyond real-time pricing. In fact, the results are applicable to any policy, such as demand-side management or critical peak pricing, which would lead to a change in load variance.

This paper directly estimates the environmental effects of a reduction in load variance for various U.S. electricity regions. Section 2 describes the environmental impacts of real-time pricing. Section 3 compares generation technologies in the various regions. Section 4 presents the empirical model and Section 5 describes the data. In Section 6, we discuss the empirical results for the parametric approach. Section 7 tests the robustness of these findings using a nonparametric model. The empirical results are analyzed in Section 8 using the production technologies in each region. Section 9 concludes.

2 A Theory of the Environmental Impacts of Real-Time Pricing

To understand the effects of RTP on emissions, we sketch a simple model of real-time pricing in electricity markets.[11] For each period t, wholesale demand, $D_t(p_t, \overline{p}, \alpha)$, depends

[10] Demand elasticities have been estimated for various industries and retail pricing programs; see, for example, Patrick and Wolak (2001), Train and Mehrez (1994), Herriges *et al.* (1993), Taylor and Schwartz (1990), and Caves and Christensen (1980). Demand response varies greatly across industries and customer classes.

[11] This model follows Borenstein and Holland (forthcoming) and is described in more detail there.

on the wholesale price, p_t, the flat (time-invariant) retail price, $\overline{p}$, and the proportion of customers who are on RTP, α. In each period, given the market supply curve, $S_t(p_t)$, equilibrium in the wholesale market is determined by $S_t(p_t) = D_t(p_t, \overline{p}, \alpha)$. This wholesale market equilibrium is illustrated in Figure 1 for two time periods, peak or high demand (h) and off-peak or low demand (l).

Increasing the proportion of customers on RTP rotates the wholesale demand around the flat retail price, $\bar{p}$. For real-time prices below the flat price, increasing the proportion of customers on RTP increases wholesale demand since more customers face the lower real-time price. For high real-time prices, *i.e.,* prices above the flat rate, $p_t > \bar{p}$, increasing customers on RTP decreases demand, since more customers face the higher real-time prices. These demand rotations can be illustrated in Figure 1. If no customers were on RTP, the high demand would be perfectly inelastic through q_h. With some customers on RTP, the wholesale demand is elastic (rotates around $\bar{p}$) and the equilibrium quantity q_h' is less than q_h. Similarly in the low demand period, putting some customers on RTP makes demand elastic and increases the equilibrium quantity from q_l to q_l'.

By rotating the wholesale demand in each period, an increase in the proportion of customers on RTP changes the distribution of electricity loads across the day. Since peak loads are decreasing and off-peak loads are increasing, the effect on average load is ambiguous and depends on the relative slopes of supply and demand. The effect on the variance of load, however, is not ambiguous: if peak loads decrease and off-peak loads increase, then variance must decrease.[12]

The effects on average load and load variance can be illustrated with Figure 1. As illustrated, the increase in off-peak load, $q_l' - q_l$, is larger than the decrease in peak load, $q_h - q_h'$, so the average load increases in this example. Since $q_h'/q_l' < q_h/q_l$, the load variance has decreased in this Figure.[13]

The effect of RTP on emissions can also be illustrated in Figure 1. With RTP, $q_l' - q_l$

[12] Demand variance would likely decrease even if all of the real-time prices in a given day were below the flat rate. To see this, note that the loads would be bounded above by $S_t(\bar{p})$ and that the smallest load would increase. However, counter examples can be constructed.

[13] In the analysis below, we use a similar ratio of the maximum load to the minimum load as one measure of load variance.

additional electricity is generated off-peak, but $q_h - q_h'$ less power is generated on peak. However, the supply curve implies nothing about the *emissions* from generating the additional electricity off-peak relative to generating it on peak. Since emissions rates vary substantially across power plants, emissions may increase or decrease.

3 Comparisons of Technologies

The preceding theory suggests that the environmental effects of RTP adoption will depend on the technologies available in each region. In this section, we first analyze the effects of different technologies for one region. Then, we describe the relative differences in technology across U.S. electricity regions.

The different technologies for one region are illustrated in Figures 2 and 3. Figure 2 shows the market supply curve for the Mid-Atlantic region, where the PJM wholesale electricity market operates. Firms in PJM use a mix of fuel sources and technologies to produce electricity. *Fossil* fuel sources are coal, natural gas, and oil. Non-fossil power sources are nuclear and hydropower. By marginal production cost, fuel sources are generally ordered hydroelectric, nuclear, coal, natural gas, and oil. In this market, when quantity supplied is less than 30,000 MWh the marginal unit is coal. Above 30,000 MWh, the marginal unit is usually natural gas or oil.

Figure 3 shows the SO_2 emissions rates for each of the fossil fuel sources in PJM. The fossil-fired units are ordered by marginal cost along the horizontal axis, and their SO_2 emissions rates (expressed in pounds per MWh) are plotted. The base-load coal-fired units have an average SO_2 emissions rate of 20.3 with a range from 1.2 to 44.6 lbs/MWh.[14] Note that emissions rates are generally increasing in marginal cost for the coal-fired units.[15] Peak demand is met with many types of fuels. Note that the emissions rates vary dramatically both within and between fuel types. The more expensive units within each fuel type generally have higher emissions rates. However, the variation in emissions rates between fuel

[14] The corresponding SO_2 emission factors (lbs/mmBTU) for these primarily coal-fired units average 1.9 and range from 0.1 to 4.3. Cost data are from the PROSYM model (Kahn, 2000). Emissions data are from the EPA Continuous Emissions Monitoring System (CEMS).

[15] The correlation between units' marginal costs and the SO_2 emissions rates is 0.08.

types is much more dramatic since coal- and oil-fired generation generally has much higher emissions rates than the gas-fired generation. Gas fired units only have trace elements of SO_2 (unless the unit uses some oil, say for starting up). The emissions rates of the oil-fired plants are high on average and have a large variance, *e.g.,* SO_2 emissions rates average 7.0 but can range as high as 47.8 lbs/MWh for oil-fired units.

The NO_x emissions rates for the coal units average 5.8 and range from 2.6 to 18.9 lbs/MWh.[16] The NO_x emissions rates exhibit less variance across production technologies than the SO_2 emissions, but the gas-fired units have much lower NO_x emissions than the coal-fired units (NO_x emissions from gas-fired units average 0.9 and range from 0.2 to 3.1 lbs/MWh). NO_x emissions from oil-fired units are higher than the gas-fired units, but not necessarily higher than the coal-fired units (they average 3.5 and range from 0.2 to 16.3 lbs/MWh).

The distribution of CO_2 emissions rates are similar. Coal CO_2 emissions rates have a mean of 2198 lbs/MWh (with a range of 1798 to 3383). Natural gas plants' average is 1423 lbs/MWh (with a range of 1137 to 1903). Oil plants average 1790 lbs/MWh (with a range of 384 to 2990). These rates are increasing in marginal cost within a fuel type, but exhibit substantial variance across fuel types. Since emissions rates are not monotonic in marginal costs, a reduction in the load variance can increase or decrease pollution.

We expect the environmental impact of a reduction in load variance to be sensitive to the production technologies available in a each region. The North American Electric Reliability Council (NERC) defined regions in order to ensure a reliable, adequate, and secure electric system. Figure 4 illustrates the NERC regions. The regions are defined as:

[16] The corresponding NO_x emission factors (lbs/mmBTU) for these primarily coal-fired units average 0.5 and range from 0.3 to 1.7.

NERC Region	Description
ECAR	Eastern Mid-West
ERCOT	Texas
FRCC	Florida
MAAC	Mid-Atlantic
MAIN	Illinois, Wisconsin, and Missouri
MAPP	Great Plains
NPCC	Northeast
SERC	Southeast
SPP	Kansas and Oklahoma
WSCC[17]	West

Table 1 describes the fuel shares of installed capacity and generation for each of the ten NERC regions. Because coal and nuclear power tend to have low marginal costs, their shares of generation are larger than their shares of capacity. Conversely, since oil and gas have high marginal costs, their shares of capacity are higher than their shares of generation.

The share of hydroelectric capacity tends to be greater than its share of generation. This does not suggest that hydropower has high marginal costs (marginal production costs of hydroelectricity are typically low) but rather that there are two types of hydropower. First, run-of-river dams generate based on the natural flows of the river. Second, storage reservoirs (predominantly in the West) capture seasonal run-off and use this fixed stock of water to generate power throughout the year. The marginal opportunity cost of these units thus includes the scarcity cost of the exhaustible stock. These units are also valuable for their ability to start and ramp quickly and cheaply.

Coal is the dominant fuel source in many regions and has the largest share of generation in all of the regions except WSCC and NPCC. Of the other fuels, capacity is dominated by: natural gas in ERCOT; hydroelectric in WSCC; nuclear in MAAC, MAIN, and SERC; and oil in FRCC and NPCC. As noted above, coal is typically the dirtiest of the fossil fuels though some oil-fired units emit similar levels of some pollutants. Gas-fired generation has effectively no SO_2 emissions and much lower NO_x emissions rates than coal. Nuclear and hydroelectric do not emit SO_2, NO_x, or CO_2.

[17] After our sample, the WSCC merged with another organization (Southwest Regional Transmission Association) to form the Western Electricity Coordinating Council (WECC).

ECAR depends almost exclusively on coal-fired generation and has higher emissions rates than other regions. Approximately 80% of ECAR capacity is coal fired whereas less than 50% of the capacity is so in most of the other regions. This reliance on coal in ECAR is shown more dramatically in the generation shares. About 90% of the electricity generated in ECAR in 2000 was from coal. At the other extreme, WSCC is the least reliant on fossil fuels with approximately 40% of its generation from hydroelectric and nuclear power plants. In the WSCC, only 22% of the capacity and 32% of the utility generation in 2000 was coal fired.

4 Estimating Pollution Implications of Demand Variance

As described above the environmental impact of a reduction in load variance can be positive or negative depending on the underlying production technologies. These environmental effects could be estimated by a production cost model.[18] However, a production cost model would not capture the effects of nonconvexities in costs, and the estimates potentially could be misleading.[19] Even a dynamic production cost model that adequately modeled nonconvexities would not capture actual firm behavior given regional constraints on production. For these reasons, we follow an alternate econometric approach. In this section, we present an empirical model to directly test this environmental impact using exogenous variation in load variance.

Our test to determine the expected short run environmental impacts of a reduction in load variance examines the relationship between the distribution of load and emissions. The resulting equation, which will be estimated separately for each region, is of the form:

$$\begin{aligned} \ln(E_t) &= -\beta \cdot \ln(VAR_t) + \gamma_1[\ln(MEAN_t)] + \gamma_2[\ln(MEAN_t)]^2 \\ &\quad + \sum_{s=1}^{S*12} \delta_s TEMP_{st} + \phi_t + \epsilon_t, \end{aligned} \tag{1}$$

[18]See Holland and Mansur (2004) for production cost simulation of the environmental effects of RTP in PJM.

[19]Nonconvexities in costs include start up costs, no load costs, ramping rate constraints, and minimum up time constraints.

where E_t is the pollution emitted in the region on day t; VAR_t is a measure of the variance of the region's load on day t;[20] $MEAN_t$ is the region's mean daily load on day t; and $TEMP_{st}$ is a function of the temperature for one of the S states bordering the region. The parameters β, γ_1, γ_2, δ_s, and ϕ_t are estimated with ϕ_t being modeled as month-year fixed effects. The error term, ϵ_t, models the idiosyncratic shock.

The variable VAR_t, measuring the *within-day variance* of load, describes the load shape on day t. This parameter could be defined in many ways. We report results primarily for the coefficient of variation of hourly load, but explore the robustness of our results to five other possible measures of variance.[21] This functional form allows β to be interpreted as the elasticity of pollution with respect to a reduction in the variance measure.

The variable $MEAN_t$, measuring the *mean daily load*, measures the nonlinear relationship between pollution and production across days. To capture this, the equation is estimated using logarithms and higher order terms. The elasticity of pollution with respect to mean daily load is therefore $\gamma_1 + 2\gamma_2 \ln(MEAN_t)$. Below we use this elasticity to simulate the environmental effects of a reduction in *across-day variance*.

The estimating equation controls for other factors that explain daily emissions for a region. The production decisions (and therefore pollution levels) depend on outside opportunities. To control for imports and exports, the equation includes measures of temperature in nearby states. For each neighboring state, daily mean, minimum, and maximum temperature variables enter as quadratic functions with coefficients allowed to differ for cooling degree days (when temperature measure is above 65°F) and for heating degree days (when temperature measure is below 65°F). For each month in the sample, a month-year fixed effect captures differences in costs and abatement technologies across the different time periods. Finally, the error term is tested and corrected for heteroskedasticity and first-order autocorrelation.

[20] We include the negative sign for consistency with later simulations. The β is interpreted as the effect on emissions of a reduction of within-day variance.

[21] Coefficient of variation is the ratio of standard deviation to mean. The other measures include the relative mean deviation, the standard deviation of logarithms, and the Gini coefficient as in Atkinson (1970). In addition, we analyze the max/min ratio (daily maximum to minimum ratio of load) and the inverse load factor (daily maximum to mean ratio of load).

We define the level of analysis at a NERC region. Alternatively, we could have examined the relationship at the utility level, which historically were self contained. However, now substantial trading occurs among utilities. We could attempt to control for all of these outside opportunities, though such an approach would likely be subject to an omitted variables bias. For this reason, we analyze at the NERC level where there is substantial transmission and communication. Further aggregation to the interconnection level (all of the U.S. but the WSCC and ERCOT are one interconnection) would understate the importance of transmission congestion across regions.

To address potential concerns about the functional forms of both VAR_t and $MEAN_t$, we also include a nonparametric analysis, which is independent of the specific functional forms. Instead of aggregating the hourly data to the daily level, we determine whether each hour is a high or low demand hour on a high or low demand day. Using deciles, this defines a ten by ten matrix of bins into which each hour is sorted. For example, if the rows are based on the decile of mean daily load and the columns are based on the decile of the hourly load *for that type of day*, then the upper left bin would contain the low demand hours on low demand days and the upper right bin would contain the high demand hours on low demand days. Specifically, for each hour τ, we let the dummy variable BIN_{τ}^{dh} equal one if hour τ occurs on a day which is in the dth decile of mean daily load and in the hth decile of hourly load on dth decile days.

For hour τ, the model estimated is:

$$\frac{E_\tau}{q_\tau} = \sum_{d=1}^{10} \sum_{h=1}^{10} \beta_{dh} \cdot BIN_{dh}(q_\tau) + \sum_{s=1}^{S*12} \delta_s TEMP_{st} + \phi_t + \epsilon_t, \tag{2}$$

where q_τ is the hourly load. We define the *system emissions rate* as $\frac{E_\tau}{q_\tau}$. As above, the temperature variables control for imports and exports and the month-year fixed effects control for changes in relative costs. With the systems emissions rate as the dependent variable, we can simulate the effect of RTP by analyzing how the emissions rate changes by moving an hour from a high-load hour to a low-load hour for a given decile of average load.

5 Data

This analysis requires data on load, temperatures, and emissions. The load data are from the Federal Energy Regulatory Commission (FERC) Form 714. For each of more than 200 U.S. electric utilities, the 714 data report hourly load over the time period of our sample: January 1, 1997 to December 31, 2000. We aggregate these utility data to the NERC region level.[22]

Table 2 shows summary statistics (the average and the standard deviation) of each region's mean and maximum daily load. The largest regions are the WSCC (the Western U.S.) and SERC, which is located in the Southeast. On average, the load in the WSCC is the largest in the country. It averages 87 GW (a gigawatt is 1000 MW) compared to SERC with 75 GW. The across-day variance is greatest in the Southeast (the standard deviation of the mean daily load in SERC is 10.7 GW versus WSCC's 7.6 GW).[23] Load in these two regions is more than four times that in some of the smallest regions: MAPP (13.8 GW), SPP (20.2 GW), and FRCC (20.5 GW). The regions with the most variation across days, normalized by mean, are SPP (Kansas and Oklahoma) and ERCOT (Texas). The coefficient of variation of mean daily load for SPP, ERCOT, and WSCC are 0.194, 0.193, and 0.088, respectively. Note that the coefficient for SPP is 2.2 times that of the coefficient for WSCC.

Table 2 also summarizes the coefficient of variation that captures within-day load variation. The regions with the greatest variation are FRCC (Florida with an average coefficient of variation of 0.2) and NPCC (the Northeast) while ECAR and MAIN are those with the smallest within-day variation. The differences between these regions are not quite as substantial as in the across-day variation measures: the FRCC coefficient of variation is approximately 1.8 times that of ECAR.

The National Oceanic and Atmospheric Administration provides temperature data on daily mean, minimum, and maximum temperature for hundreds of weather stations nationally. We calculate statewide daily averages of each of these variables. Table 2

[22] Our aggregation data are consistent with NERC monthly load data.

[23] The maximum daily loads have similar relative magnitudes.

reports the summary statistics for the daily mean temperature in each region.[24] The hottest regions on average are FRCC, ERCOT, and SERC while MAPP and NPCC are the coldest. The regions with the most temperature variation are MAPP, MAIN, and SPP while FRCC and ERCOT have the least.[25]

Pollution data are from the Environmental Protection Agency's Continuous Emissions Monitoring System (EPA's CEMS). For almost all of the fossil power plants in the U.S., the CEMS data report hourly emissions of SO_2, NO_x, and CO_2.[26] By region, Table 3 summarizes the pollution data. A daily system emissions rate is calculated as the ratio of mean daily pollution to mean daily load. ECAR is clearly the dirtiest region with the highest emissions per MWh of SO_2 and NO_x, and second highest levels of CO_2 (MAPP has the largest system CO_2 rate). On the other hand, WSCC is the cleanest region in all pollutants. The WSCC SO_2 system emissions rate is less than a tenth that of ECAR and even a third of the next cleanest region, ERCOT. To a lesser extent, this is also seen in the system emissions rates for NO_x and CO_2. Each region's rates vary substantially day to day. The coefficient of variation for the SO_2 system emissions rate is 0.24 for MAIN, which is 3.4 that of the neighboring region of MAPP.

To understand the differences in system emissions rates, we also compare the share of load met by fossil fuel generation across regions.[27] The CEMS data report hourly gross generation at each unit.[28] Table 3 presents summary statistics on the daily gross generation as a share of total load. In the dirtiest region, ECAR, the average ratio is 0.98 while the cleanest region, WSCC, has an average ratio of 0.36. The other regions have average ratios ranging from 0.51 to 0.96.[29]

[24] We report statistics on the unweighted average daily temperatures for states in each region.

[25] Regions with high temperature variation are not necessarily those regions with high within-day or across-day load variation.

[26] All units over 25 megawatts and new units under 25 megawatts that use fuel with a sulfur content greater than .05% by weight are required to measure and report emissions under the Acid Rain Program. CEMS data are highly accurate and comprehensive for most types of fossil units (Joskow and Kahn, 2002).

[27] The remainder of load is met by nuclear, hydroelectric, and imports (net of exports).

[28] Gross generation differs from net generation because of the discrepancy between electricity generated by a unit and the amount of electricity sold onto the grid. This discrepancy arises from internal power usage for water pumps, conveyor belts, *etc.* Informal data on gross to net ratios suggest an average ratio of 1.05 to 1.1.

[29] These ratios can exceed one since a region may export electricity and since electricity is used internally at power plants.

To visualize the unconditional correlations in the pollution and load data, we use kernel regressions to estimate a smooth relationship between emissions and demand in each region. Figure 5 graphs kernel regression estimates for hourly pounds of SO_2 on hourly load for each of the ten regions. For some of the regions, there appears to be a general linear relationship between pollution and generation suggesting little impact of variance on pollution. However, for regions like ERCOT, SPP, and WSCC, the concave shape of the kernel estimates imply that reducing the likelihood of both extreme high and low demand hours will result in higher pollution. However, simply analyzing the shape of these estimates may be misleading since the kernel regressions do not control for covariates.[30]

6 Results of Parametric Estimation

To estimate the effect of a change in load variance on emissions, Equation 1 is estimated separately for each NERC region and for each of the three pollutants. Before presenting results for all the regressions, we first present the estimation results in detail for SO_2 emissions in ECAR. We then present the regression results for one measure of within-day variance and discuss their robustness to other measures of within-day variance. Next we use the regression results to simulate changes in across-day variance. Finally we analyze changes in gross fossil generation.

6.1 SO_2 Emissions in ECAR

Table 4 presents all the coefficients from the regression where the dependent variable is the log of SO_2 emissions in ECAR. Equation 1 is estimated using generalized least squares to account for an AR(1) error structure using the Prais-Winsten method. Robust standard errors using the White correction are reported.[31]

[30] Our nonparametric analysis below does control for covariates. The kernel regressions here could be adjusted to account for these other factors. However, these graphs are intended to display the unconditional correlations.

[31] Breusch-Godfrey LM test rejects no serial correlation ($\chi^2 = 534$). A Cook-Weisberg test rejects homoskedasticity ($\chi^2 = 51$). Both are significant at the one percent level.

The coefficient on the measure of variation reduction is 0.025 and is significant at the one percent level. This implies that a ten percent reduction in the coefficient of variation (*e.g.,* reducing the average coefficient of variation from its sample mean of 0.11 to 0.10) would result in an increase in SO_2 of 0.25 percent.

The log of mean daily load enters in a polynomial specification: the linear term has a coefficient of 11.7 and the squared term's coefficient is -0.49 (both are significant at the one percent level). Since the log of mean daily load ranges from 10.68 to 11.31, we can calculate the range of elasticities of SO_2 emissions with respect to mean daily load. This implies that the elasticity is positive throughout the range and decreases from 1.3 to 0.7 as mean daily load increases. These elasticities imply that emissions are increasing in mean daily load but the percentage change is decreasing. In regressions for other regions and other pollutants, this elasticity is always positive but may be increasing or decreasing across the relevant range.[32]

The month-year fixed effects are defined relative to January 1997. The fixed effects during winter of 1997-1998 are significant and positive. The emissions fall fairly continuously throughout the rest of the sample (conditional on temperature and load). Overall, SO_2 emissions fall by approximately 17 percent (see Figure 6). This could result from improvements in operation or from switching to lower sulfur coal in order to comply with the Clean Air Act.[33]

Figure 6 also graphs the fixed effects from similar regressions on NO_x and CO_2 emissions in ECAR. There is also a drop in NO_x emissions in later years, but CO_2 emissions remain fairly constant over the sample. In other regions, the fixed effects capture different phenomena. For example, in WSCC, there are strong seasonal effects likely driven by hydroelectricity availability. Thus, the fixed effects control for important unexplained variation.

The temperature variables include quadratic functions of the mean, minimum and

[32] RTP might be expected to reduce the across-day variation as well as the within-day variation. We simulate the effect of decreasing the variance of mean daily load below.

[33] While flue-gas desulfurization (i.e., scrubbers) also reduce emissions, very few plants installed this technology during our sample.

maximum temperatures in each of six states surrounding the ECAR region: IL, NC, PA, TN, VA, and WI. The coefficients are allowed to differ for heating and cooling days—based on whether the temperature is below or above 65 degrees. The temperature variables control for electricity demand outside ECAR and the availability of imports. The weather variables are highly correlated and only two of the 72 coefficients are significant at the five percent level. However, a Wald test of the joint significance of the weather variables is significant ($F(72, 1330) = 1.67$, ($Prob > F = 0.001$)). For all regions and pollutants, the temperature variables are jointly significant at the 6% level.

6.2 Within-Day Variation

Within-day variation is measured by the coefficient of variation. Table 5 presents the coefficient estimates and standard errors for the negative logarithm of the coefficient of variation for all three pollutants in all ten regions.[34] Each coefficient is from a regression described in Equation 1 where the dependent variable is the log of SO_2 pounds emitted in column (i), the log of NO_x pounds emitted in column (ii), and the log of CO_2 tons emitted in column (iii).[35] As above, these coefficient estimates are conditional on mean daily load, fixed effects, and temperature. Also, the coefficients are estimated using GLS accounting for a heteroskedastic, AR(1) error structure.

The estimates for SO_2 vary across all regions. For four of the ten regions—ECAR, ERCOT, SERC, and WSCC—the coefficient estimates are positive and significant at the five percent level. In these regions, we estimate that a reduction in within-day load variance would increase SO_2 emissions. In one region, MAIN, the negative coefficient indicates that a reduction in within-day load variance would decrease SO_2 emissions. The coefficient estimates in the other five regions are not significant. Note that even in the regions with statistically significant effects, the estimates are quite small. The largest effect, in WSCC, implies that a 10% reduction in the coefficient of variation would imply only a 0.4% increase in SO_2 emissions.

[34] As described above, we use the negative of the logarithm to be consistent with later simulations. The coefficients are interpreted as the effect on emissions of a reduction of within-day variance.

[35] Column (iv) will be discussed below.

The estimates for NO_x are similar to the SO_2 estimates, but are slightly more negative. Two regions, ERCOT and WSCC, have a positive coefficient for SO_2 but have insignificant coefficients for NO_x. One region, MAAC, has an insignificant coefficient for SO_2 but a negative coefficient for NO_x. Only one region, MAPP, has a more positive coefficient for NO_x than for SO_2, and it is significantly positive for NO_x. In summary, for NO_x three of the regions (FRCC, MAAC, and MAIN) have negative effects and three (ECAR, MAPP, and SERC) have positive effects. These estimates are generally more negative than the SO_2 estimates for which four coefficients were positive and only one coefficient was negative.

The CO_2 estimates are similar to the SO_2 estimates. Five regions, the same four plus MAPP, have positive coefficients, and two regions, MAAC and MAIN, have negative coefficients. The coefficients are generally more negative than the SO_2 coefficients (MAPP again is the exception) but are more precisely estimated. As with SO_2 and NO_x, the estimated elasticity with the largest magnitude is -0.04.

These coefficient estimates show positive effects for all three pollutants in two regions, ECAR and SERC, and for two pollutants in three regions, ERCOT, MAPP, and WSCC. For these five regions, the estimates imply that a reduction in within-day variance, for example, from RTP adoption, would increase emissions. However, this effect is not universal. Three regions had negative coefficient estimates including MAIN for which estimates are negative for all three pollutants. These regions would expect to see a reduction in emissions from a reduction in within-day variation for at least one pollutant. Finally, two regions show no effect. In SPP, the coefficients are not significant despite being very precisely estimated. This implies that there would be no effect on emissions from a reduction in within-day variation. In NPCC, the coefficients are not significant but are less precisely estimated.

6.3 Other Measures of Within-Day Variation

Table 5 reports the regression results using the coefficient of variation as the within-day measure of variance. Since these results could be specific to the coefficient of variation, we explore five other measures of within-day variance: the max/min ratio, inverse load factor, relative mean deviation, standard deviation of logarithms, and Gini coefficient.

These six measures do capture different aspects of within-day variance since they are not perfectly correlated. Calculating the correlations of these six measures for the ten regions shows that all but one of the 150 possible correlations are positive and the average correlation is 0.72. The smallest correlation (-0.01) is between the Gini coefficient and the inverse load factor in FRCC. In general, the Gini coefficient is less correlated with the other measures (an average correlation of 0.46) while the standard deviation of logarithms is correlated the most with the other measures (an average correlation of 0.82).

Despite the imperfect correlations, the coefficient estimates on the measures of variance are very robust to the different measures. We estimate Equation 1 for each of the six measures of variance for each of the three pollutants for each of the ten regions. The SO_2 results are particularly robust. For nine of the ten regions, the coefficients on the measure of variance agree in sign and significance for all six measures of variance. In the remaining region, WSCC, four of the six estimates are positive and significant while the other two estimates are positive but not significant. For NO_x, in eight of the ten regions, all the coefficients had either the same sign or the same significance.[36] For CO_2, in nine of the ten regions, all the coefficients had either the same sign or the same significance.[37] Note that no region has coefficients on any of the measures of variance that are significant but of opposite sign.

6.4 Across-Day Variation

We now return to the coefficients on the log of mean daily load. As described above, these coefficients can be used to compute the elasticity of emissions with respect to mean daily load. This elasticity is linear in the log of mean daily load. The elasticities are positive if emissions are increasing in load and unity if emissions are proportional to load.

[36] In MAAC, four coefficients are negative and significant but one coefficient (on the inverse load factor) is positive but insignificant. In MAPP, four coefficients are positive and significant but one coefficient (on the inverse load factor) is negative but insignificant.

[37] In MAPP, four coefficients are positive and significant but one coefficient (on the inverse load factor) is negative but insignificant.

The elasticities are increasing (decreasing) in mean daily load if larger mean loads have proportionally more (fewer) emissions.

Table 6 presents the elasticities over the observed ranges of mean daily load for each of the three pollutants (and for fossil generation) for each region. The estimated elasticities are all positive indicating that emissions, as expected, are increasing in system load. Most of the elasticities are decreasing in system load, indicating that a change in system load has a much larger proportional effect on small load days than at large load days.[38] For example, in the WSCC, a percent increase in system load on the lowest-load day leads to a 1.4% change in SO_2 emissions, whereas a percent increase on the highest-load day leads to a small increase in SO_2 emissions (0.04%).

Although these elasticities are suggestive of the effect of a reduction in load variation across days, they show only the proportional effect. To describe the effect of a reduction in load variation across days, we use the elasticities to simulate the change in emissions from a marginal change in the extremes of the load distribution. Specifically, we use the elasticities to calculate the percentage change in emissions from shifting one percent of the average load from the highest-load day to the lowest-load day. The results of this simulation, which can be interpreted as elasticities, are presented in Table 7.[39]

For a given pollutant, the simulations do not have the same effect across all regions. However, for several regions, the impacts are consistent across pollutants. In ECAR, MAPP, and SERC, this reduction in across-day load variance leads to statistically significant increases in all three pollutants. In the WSCC, the reduction leads to significant increases in SO_2 and NO_x, but not in CO_2. Recall that these regions also show positive effects from a reduction in within-day variance.

In other regions, the reduction in across-day variance can decrease emissions. NPCC and MAAC have reductions in emissions of all three pollutants while MAIN and SPP

[38] The estimated elasticities decrease significantly in load in ECAR, FRCC, MAPP, SERC, and WSCC for all pollutants and in NPCC for some pollutants. Elasticities only increase significantly for some pollutants in MAAC and SPP. We determine significance based on the significance of the coefficient on the log of daily demand squared in Equation 1.

[39] The standard errors are calculated from the covariance matrix of the parameter estimates using the delta method.

have reductions in two of the three pollutants. Finally, the results for ERCOT and FRCC are mixed: FRCC has a negative effect in SO_2 but positive effects in NO_x and CO_2, and ERCOT has a negative effect in NO_x but a positive effect in CO_2.

One final point can be noted about the simulation results. Since the results can be interpreted as elasticities, we can compare them across regions as above. In addition, we can compare the results to the elasticities measuring changes in emissions from within-day variation. A rough comparison of the within-day elasticities with the across-day elasticities indicates that the latter are often much larger. This suggests that a marginal change in across-day variation will have a larger effect than a marginal change in within-day variation. We will make this comparison more precise in the non-parametric analysis below.

6.5 Variance Effects on Fossil Generation

To understand the effects on emissions described above, we analyze the effects of changes in within- and across-day variation on gross fossil generation. We estimate an equation similar to Equation 1 where the dependent variable is now the log of gross fossil generation in MWh—instead of emissions.[40] The independent variables are identical to those in the regressions reported in columns (i) to (iii) of Tables 5 and 7. The proportion of load met by fossil generation varies by region. Load not met by fossil generation is served by imports or other fuel sources such as nuclear, hydropower, renewables, or small peaking units.[41]

Column (iv) of Table 5 reports the estimates of the coefficients on the coefficient of variation for the regressions with gross fossil generation as the dependent variable. We find statistically significant effects (positive or negative) on fossil generation in five of the ten regions: positive coefficients in ECAR, MAPP, and WSCC and negative coefficients in MAAC and MAIN. Several coefficients deserve note. First, the ERCOT coefficient is not statistically significant despite being very precisely estimated. This is reassuring since ERCOT is not interconnected with other regions and thus has limited imports. Since

[40] These regressions analyze the gross fossil generation and cannot be used to analyze changes in the gross to net ratio separately from changes in net fossil generation.

[41] Certain small peaking units under 25 MW are not regulated under the Clean Air Act and thus do not appear in the CEMS data on gross fossil generation. Transmission line losses and internal plant usage might also account for some of the discrepancy between gross generation and load.

Texas has quite limited hydroelectric resources and since nuclear power cannot respond to within-day load variation, fossil generation must follow load directly.[42] Second, the positive coefficient for WSCC likely reflects the significant hydro capacity in the West. Decreasing within-day load variance thus would decrease the demand for peak-shaving hydroelectricity. Finally, the four regions with significant effects in the East are closely interconnected and neighboring regions have coefficients with opposite signs. Thus, as the coefficients of variation are correlated across regions, the decreased fossil generation in ECAR likely is offset by the increased fossil generation in either MAAC or MAIN.[43]

In summary, we find that reducing within-day variance results in more gross fossil production in ECAR, in MAPP, weakly in SERC, and in WSCC. Note that these are the regions where we estimate increases in emissions.[44] In two regions, MAAC and MAIN, higher within-day variance is associated with less gross fossil production. These are the regions where reductions in emissions are seen.[45] Although two regions, ERCOT and FRCC, show some environmental effects but have no change in fossil generation, the majority of the environmental effects from changes in within-day variance seem to be driven by changes in fossil generation.

We now turn to the across-day variance effects on fossil generation. Column (iv) of Table 6 reports the elasticity ranges for fossil generation with respect to mean daily load. If fossil generation were a fixed proportion of load, then these elasticities would be unity. Since most (seven of ten) of these elasticities are decreasing, fossil generation accounts for a smaller proportion of load on the highest-load day than on the lowest-load day in most regions.

Column (iv) of Table 7 reports the simulated effects of the percentage change in gross

[42] Since the electrical grid must be balanced at all times, generation must equal load. If fossil generation is positively correlated with the coefficient of variation, then either imports or hydropower must be negatively correlated with the coefficient of variation since nuclear power cannot respond to within-day changes in load.

[43] The correlations among these coefficients of variation are high: corr(ECAR, MAAC)=0.78, corr(ECAR, MAIN)=0.87, and corr(MAIN, MAPP)=0.87.

[44] For these regions, the point estimates for all the pollutants are positive, and ten of the twelve are significantly positive.

[45] For these regions, the point estimates for all the pollutants are negative, and five of the six are significantly negative.

fossil generation of shifting one percent of the average load from the highest-load day to the lowest-load day. Five of the effects are positive and four of the effects are negative. The most important thing to note about these effects is that they coincide closely with the environmental effects. Thus, as with the within-day environmental effects, the across-day environmental effect seem to be driven largely by changes in the fossil generation.

7 Robustness using Nonparametric Model

Since the estimates of Section 6 depend on specific functional forms, we test the robustness of these results using the nonparametric model described in Section 4. We estimate Equation 2 and correct the standard errors for serial correlation and heteroskedasticity.[46] With ten regions, three pollutants (plus generation), and 100 bins each, there are thousands of coefficients. Instead of presenting all of these coefficients, we simulate the impacts of real-time pricing.

Figure 7 depicts the coefficients for ECAR SO_2 emissions rates. All of the other covariates have been demeaned and the regression does not include a constant. Therefore, each coefficient equals the average emissions rate for the hours in a given bin. Consistent with the sample mean in Table 3, the average of the emissions rate coefficients is 14.9 lbs per MWh. The rates range from 13.6 to 15.5 lbs per MWh. The lowest rate occurs when demand is in the bin with the highest decile of mean daily load and the highest decile of hourly demand for that type of day. The greatest emissions rate occurs in the highest decile of mean daily load but in the lowest decile bin of hourly demand for that type of day. Generally in ECAR, the SO_2 emissions rate decreases with hourly demand. Across regions and pollutants, we find substantially different patterns.

We simulate a reduction in within-day variance by comparing the various coefficient estimates of emissions rates. For each mean daily load decile, we move one MWh from the lowest decile of hourly load to the second lowest decile, and also move one MWh from the

[46] As this section attempts to estimate the impacts of real-time pricing using a nonparametric approach, we use a nonparametric technique to correct for serial correlation and heteroskedasticity as well. We use the Newey-West method assuming a six hour lag structure.

highest hourly load decile to the second highest decile. Then, we average these impacts over the ten mean daily load deciles. Therefore, the coefficients represent the average change in emissions given one fewer MWh in the first and tenth deciles of hourly load *and* one more MWh in the second and ninth hourly load deciles.[47] Table 8 reports the findings of this simulation.[48]

We compare the within-day effects of the parametric method (Table 5) with those of the nonparametric method (Table 8). About half (24 of 40) of the parametric estimations are significant across the ten regions and four dependent variables (SO_2, NO_x, CO_2, and gross fossil generation). The nonparametric simulations support these findings qualitatively in 17, or 71%, of these regressions. However, of the 34 significant effects that the nonparametric simulations predict, only half of them are also predicted by the parametric models.

Next, we use the nonparametric estimates to simulate the impact of reducing across-day variation. For each hourly load decile, we move one MWh from the lowest decile of mean daily load to the second lowest decile, and we move one MWh from the highest mean daily load decile to the second highest decile. Then, we average these impacts over the ten hourly load deciles. Table 9 reports the findings of this simulation.

For the across-day effects, the parametric models predict significant effects in 35 of the 40 models. Of these 35 effects, the nonparametric simulations are qualitatively similar in 21, or 60%. The nonparametric simulations are significant in only 27 regressions. Therefore, 78% of these regressions are supported by the parametric models.

We conclude that the nonparametric model supports our findings in Section 6. For most regions and pollutants, the parametric and nonparametric simulations are qualitatively similar. There were a total of 80 tests. In 38, both the parametric and nonparametric results agree in sign and significance. Seven of the tests were insignificant using both methods. For 26 tests, one method found significant results while the other did not. Finally, nine tests reached opposing significant conclusions.

[47] This is equivalent to calculating a change in the weighted average emissions rates by giving less weight to extreme events.

[48] The standard errors in Tables 8 and 9 are estimated using the delta method.

Furthermore, we find that the across-day variance effects are larger than the within-day effects. The manner in which we simulate RTP using the nonparametric coefficients allows us to compare the outcomes in Tables 8 and 9. We note that the impact of reducing across-day variance is about twice as large as the impact of reducing within-day variance. For example, in ECAR, moving one MWh from both the lowest and highest deciles towards the median results in an average increase of 0.45 pounds of SO_2 per hour when reducing across-day variance, but an average increase of only 0.11 pounds per hour when reducing within-day variance.

8 Discussion of the Environmental Impacts

The results of Section 6 imply that a reduction in within- or across-day load variance, whether through RTP or some other means, would have different environmental impacts in different regions. In particular, we found that the results were correlated with changes in fossil generation, *i.e.,* emissions tended to increase in a region if fossil generation in that region also increased with a reduction in load variance. In this section, we attempt to understand these changes in emissions and fossil generation by analyzing the production technologies and capacities in each region.

To understand the differences in how load variance affects the mix of fossil and non-fossil generation (and thus emissions) across regions, recall the capacity shares from Table 1. On days with more within-day variation, firms are likely to use technologies that ramp up and down quickly rather than slower base-load technologies. The peaking units are either fossil fired—typically burning either natural gas or oil—or are hydroelectric plants. Table 10 reports the shares of peaking capacity, which we define as hydroelectric, oil, and natural gas generation.

If hydro generation is a significant share of peak capacity, then a reduction in load variance will reduce peak hydro and may increase dirtier base-load fossil generation. On net this would increase emissions. Oil-fired peaking units have relatively high emissions rates (see Figure 3). In regions where oil-fired generation is a significant share of peak capacity, a reduction in within-day variance may reduce emissions if base-load generation is relatively clean.[49]

The regions with hydro shares larger than oil shares are ECAR, ERCOT, MAPP, SERC, SPP, and WSCC. In all of these regions except SPP, we find that a reduction in within-day variance leads to an increase in emissions (see Table 5). We find no effect in SPP. For most pollutants in these regions, the results are consistent with the hypothesis that reducing load variance leads to less peak hydro and, therefore, more emissions.

The regions with large oil shares, relative to hydro shares, are FRCC, MAAC, MAIN, and NPCC. These relatively large oil shares would suggest that a reduction in within-day variance should reduce emissions. This is consistent with our results for all of these regions except NPCC in which we find no effect.

The relative capacity shares of hydroelectricity and oil-fired generation help understand the different effects that we estimate for the various regions. Note, however, that the hydro effect has an interesting implication for the environmental impacts of a reduction in load variance. Since hydropower has low marginal cost and quick ramping rates, it can be used either as base load or to adjust to rapid changes in load. A reduction in load variance would imply that less hydropower is needed to follow load and can be used instead for base load. This suggests that the adverse environmental effects estimated here for some regions may be mitigated by using peak hydropower to offset dirty fossil base-load generation.

Understanding the implications of reducing across-day variance is less straightforward. For this measure of variance, most regions with relatively large hydro shares are predicted to see an increase in emissions. However, in SPP we predict a reduction in emissions and in ERCOT the effects are mixed. We estimate that most regions with relatively large oil shares will see a reduction in emissions if across-day variance is reduced. However, FRCC has mixed results.

[49] Natural gas typically has lower emissions rates than oil though is dirtier than hydroelectric.

9 Conclusion

Economists have advocated for real-time pricing in an attempt to improve the efficiency of investment and the allocation of electricity. Conventional wisdom, previously untested, has claimed that RTP has an additional benefit, namely, reduced emissions from reduced peak demand. This paper analyzes the environmental impacts of real-time pricing by estimating the effect of load variation on emissions of SO_2, NO_x, and CO_2. We argue that RTP will reduce load variance and estimate the effect of changes in load variation on emissions in all NERC regions. We find that the environmental impacts of a reduction in load variance are different for different regions. In particular, contrary to the conventional wisdom, RTP may actually increase emissions in some regions.

We estimate a reduction in within-day load variance would decrease emissions of some pollutants in three of the ten regions (FRCC, MAAC, and MAIN). However, a reduction in within-day load variance would actually *increase* emissions in most of the rest of the US. In fact, for ECAR and SERC, emissions of all three pollutants would increase and for ERCOT, MAPP, and WSCC, emissions would increase for two of the three pollutants.

We further argue that RTP will reduce the across-day variance of load and analyze the effect of a reduction in across-day load variance on emissions. Similar to our results for within-day variance we find that a reduction in across-day load variance would lead to a reduction in emissions in some regions (MAAC, MAIN, NPCC and SPP) but would lead to an increase in emissions in other regions (ECAR, MAPP, SERC, and WSCC). The final two regions show mixed effects: increases for some pollutants and decreases for others.

Our results are robust to alternate empirical specifications. We measure within-day variance using five other measures of variance and find very similar results. We also test a nonparametric specification of the model and find similar results. The stability of our results does not support the conventional wisdom that RTP will reduce emissions and even suggests that RTP will increase emissions in many regions.

To understand the different effects across regions, we test the effects of a reduction in load variance on fossil generation and compare the generation technologies in the various regions. We find that changes in emissions are similar to changes in fossil generation. In particular, if a reduction in load variance leads to an increase (*decrease*) in fossil generation, then it also leads to an increase (*decrease*) in emissions for most pollutants.

Since changes in emissions are driven by changes in fossil generation, we compare the generation technologies across the regions. We find that the results are consistent with the relative shares of hydroelectric and oil-fired capacity. In particular, a reduction in within-day load variance leads to an increase in emissions only for regions with more hydroelectric capacity than oil-fired capacity. This supports the hypothesis that the environmental benefits of RTP come from reducing peak demand, but only if peak capacity is oil fired rather than hydroelectric.

Several points should be noted in interpreting our results. First, SO_2 and NO_x are regulated in many regions by cap-and-trade programs. If the total amount of emissions is capped, then emissions cannot increase following a policy shift. However, our results reflect the demand for emissions. For example, if our coefficient estimate is positive (*i.e.,* an "increase in emissions") we are predicting that RTP would lead to an increase in demand for emissions permits and that the permit price would increase.

Second, hydroelectric power sometimes can be used either as baseload or as peakload. If an increase in emissions arises because of decreased demand for peak hydropower, then that hydropower can be used to offset off-peak emissions. In this case, actual emissions may not increase as much as our estimates predict.

Third, our estimates hold average load constant. If the average load increases or decreases substantially with RTP adoption, the environmental effects may be quite different. Holland and Mansur (2004) calculate an increase in average load from RTP adoption in one region. However, other regions may show decreases in average load depending on the relevant demand and supply elasticities.

Fourth, our estimates are not applicable to long-run questions of investment. Reduced investment may benefit the environment if the siting of new power plants causes environmental damage. Since investment under regulation is based on peak capacity requirements and RTP reduces the peak load, RTP may reduce investment in regulated markets. In competitive wholesale markets, investment is based on profit opportunities. Borenstein and Holland (forthcoming) show that investment could theoretically increase with RTP adoption in competitive markets. Thus the long-run environmental benefits of RTP adoption are unclear. Finally, our results are not in any way specific to RTP and apply equally to any regulatory program or market mechanism that affects the variance of the electricity load.

References

[1] Atkinson, Anthony B. "On the Measurement of Inequality," *Journal of Economic Theory*, **2**(3):244-263, 1970.

[2] Boiteaux, Marcel. "La tarification des demandes en point: application de la théorie de la vente au coût marginal." *Revue Général de l'Electricité*, August 1949, **58**, 321-40, translated as "Peak Load Pricing," *Journal of Business*, **33**:157-179, 1960.

[3] Borenstein, Severin and Stephen P. Holland. "On the Efficiency of Competitive Electricity Markets With Time-Invariant Retail Prices," *RAND Journal of Economics*, forthcoming.

[4] Borenstein, Severin, Michael Jaske, and Arthur Rosenfeld. *Dynamic Pricing, Advanced Metering, and Demand Response in Electricity Markets,* October 2002. Available at www.ucei.org/PDF/csemwp105.pdf.

[5] Caves, Douglas and Laurits R. Christensen, "Econometric Analysis of Residential Time-of-Use Electricity Pricing Experiments," *Journal of Econometrics*, 14:287-306, 1980.

[6] Environmental Defense. "Environmental Defense Decries CPUC Inaction On Real Time Pricing." http://www.environmentaldefense.org/pressrelease.cfm?ContentID=61, August 3, 2001.

[7] Herriges, J. A., S. M. Baladi, D. W. Caves, and B. F. Neenan, "The Response of Industrial Customers to Electric Rates Based Upon Dynamic Marginal Costs," *Review of Economics and Statistics*, 75(3): 446-454, 1993.

[8] Hirst, Eric and Brendan Kirby. "Retail-Load Participation in Competitive Wholesale Electricity Markets," Edison Electric Institute, www.ehirst.com/PDF/PRDReport.pdf, January, 2001.

[9] Holland, Stephen P. and Erin T. Mansur, "The Political Economy and Environmental Effects of Real-Time Pricing Adoption in Competitive Electricity Markets," mimeo, 2004.

[10] Joskow, Paul L. and Edward Kahn. "A Quantitative Analysis of Pricing Behavior In California's Wholesale Electricity Market During Summer 2000," *Energy Journal* **23**(4): 1-35, 2002.

[11] Kahn, Edward P. 2000. *Workpapers in Public Utilities Commission of Ohio, Case No. 99-EL-ETP.*

[12] Kiesling, Lynne. "Green Market for Electricity," Reason Public Policy Institute, www.rppi.org/greenmarket.html, August 13, 2002.

[13] Lipsey, R.G. and Kelvin Lancaster, "The General Theory of Second Best," *The Review of Economic Studies*, **24**: 11-32, 1956.

[14] Nevada Power. "Reducing Peak Power Demands To Benefit Environment, Consumers," http://www.eei.org/industry_issues/environment/voluntary_efforts/electric_customer_stories/nevada_power.htm, Edison Electric Institute, July 10, 2003.

[15] Patrick, Robert and Frank Wolak, "Real-Time Pricing and Demand Side Participation in Restructured Electricity Markets," mimeo, 2001.

[16] Smith, Vernon L. and Lynne Kiesling. "Demand, Not Supply" *Wall Street Journal,* New York, N.Y.: pg. A 10. August 20, 2003.

[17] Steiner, Peter O. "Peak Loads and Efficient Pricing." *Quarterly Journal of Economics*, **72**(1):585-610, 1957.

[18] Swofford, Gary. "Prepared Witness Testimony: The House Committee on Energy and Commerce," http://energycommerce.house.gov/107/hearings/06222001Hearing265/Swofford437.htm, June 22, 2001.

[19] Taylor, Thomas N. and Peter M. Schwarz, "The Long-Run Effects of a Time-of-Use Demand Charge," *RAND Journal of Economics*, 21(3):431-445, 1990.

[20] Train, Kenneth and Gil Mehrez, "Optional Time-of-Use Prices for Electricity: Econometric Analysis of Surplus and Pareto Impacts," *RAND Journal of Economics*, 25(2):263-283, 1994.

Tables and Figures

Table 1

Shares of Installed Capacity and Generation by Fuel Type

Panel A: Installed Capacity (MW)

		Shares				
NERC	Total	Coal	Gas	Hydro	Nuclear	Oil
ECAR	123,381	79%	9%	3%	7%	1%
ERCOT	72,583	24%	67%	1%	7%	0%
FRCC	43,880	29%	26%	0%	4%	38%
MAAC	64,512	44%	17%	4%	21%	13%
MAIN	64,238	54%	17%	2%	23%	3%
MAPP	36,244	63%	10%	10%	8%	5%
NPCC	67,841	13%	32%	14%	15%	23%
SERC	195,989	47%	21%	10%	18%	2%
SPP	47,440	48%	41%	5%	3%	2%
WSCC	144,046	22%	30%	36%	7%	1%

Panel B: Net Generation (GWh)

		Shares				
NERC	Total	Coal	Gas	Hydro	Nuclear	Oil
ECAR	590,666	87%	3%	0%	8%	1%
ERCOT	313,659	35%	51%	0%	12%	1%
FRCC	181,322	36%	23%	0%	18%	19%
MAAC	264,901	45%	9%	1%	40%	3%
MAIN	294,155	56%	3%	1%	39%	0%
MAPP	178,980	76%	1%	9%	12%	0%
NPCC	254,617	17%	25%	13%	26%	13%
SERC	861,033	55%	10%	2%	29%	1%
SPP	186,976	68%	23%	2%	5%	0%
WSCC	667,187	32%	23%	28%	11%	1%

Notes:

a) Source: EPA eGRID for 2000 (http://www.epa.gov/cleanenergy/egrid/index.htm).
b) Shares are of total capacity or total generation for utilities and non-utilities. Renewables are the missing share.
c) Net generation equals electricity produced excluding that which is used internally at power plants.
d) GWh are gigawatt-hours, or 1000 MWh.

Table 2

Summary Statistics of Quantity Demanded (MWh) and Mean Temperature (in degrees Fahrenheit) by Region

Region	Mean Daily Load	Max Daily Load	Coefficient of Variation	Mean Daily Temperature
ECAR	59,578 [6,481]	67,500 [8,201]	0.111 [0.030]	52.6 [17.2]
ERCOT	30,648 [5,913]	36,593 [8,451]	0.137 [0.042]	68.1 [14.1]
FRCC	20,556 [3,355]	25,899 [4,623]	0.199 [0.033]	72.6 [9.5]
MAAC	28,844 [3,881]	33,590 [5,029]	0.136 [0.032]	55.2 [16.2]
MAIN	26,510 [3,473]	30,366 [4,605]	0.119 [0.032]	52.1 [18.5]
MAPP	13,815 [1,713]	15,833 [2,174]	0.124 [0.028]	46.9 [20.5]
NPCC	24,244 [3,041]	28,600 [3,728]	0.153 [0.024]	47.6 [17.3]
SERC	75,240 [10,710]	87,992 [14,908]	0.126 [0.039]	62.7 [14.6]
SPP	20,237 [3,927]	23,642 [5,542]	0.125 [0.041]	58.6 [18.3]
WSCC	86,759 [7,611]	100,396 [9,737]	0.121 [0.022]	53.3 [14.4]

Notes:

a) For each variable, the table displays the sample mean with standard deviation in brackets.
b) The sample period is from January 1997 to December 2000, except MAPP does not include 2000. All days of daylight savings transitions are dropped.
c) Sources: Load data are from FERC Form 714. Temperature data are from NOAA.

Table 3

Pollution Summary Statistics by Region

Region	SO_2 Rate	NO_X Rate	CO_2 Rate	Fossil Share	Sample Size
ECAR	14.871 [1.149]	5.793 [0.701]	1.040 [0.039]	0.984 [0.033]	1,453
ERCOT	3.957 [0.681]	2.422 [0.227]	0.694 [0.028]	0.791 [0.044]	1,453
FRCC	6.082 [1.292]	2.766 [0.344]	0.556 [0.044]	0.590 [0.044]	1,453
MAAC	8.748 [1.183]	2.384 [0.431]	0.514 [0.058]	0.509 [0.051]	1,453
MAIN	9.106 [2.147]	3.783 [0.586]	0.754 [0.051]	0.678 [0.042]	1,453
MAPP	8.753 [0.614]	5.301 [0.438]	1.154 [0.073]	0.958 [0.067]	1,089
NPCC	4.974 [0.871]	1.525 [0.294]	0.471 [0.073]	0.594 [1.170]	1,453
SERC	9.338 [0.937]	4.223 [0.688]	0.758 [0.042]	0.740 [0.040]	1,453
SPP	5.513 [0.795]	3.753 [0.620]	0.899 [0.122]	0.908 [0.099]	1,453
WSCC	1.358 [0.179]	1.295 [0.107]	0.351 [0.033]	0.363 [0.043]	1,453

Notes:

a) For each variable, the table displays the sample mean with standard deviation in brackets.

b) Emissions rates are system-wide averages of total pollution (SO_2 and NO_X in lbs and CO_2 in tons) to total demand (in MWh).

c) The sample period is from January 1997 to December 2000, except MAPP does not include 2000. All days of daylight savings transitions are dropped.

d) Source: EPA Continuous Emissions Monitoring System.

Table 4

Parametric Estimation of SO_2 Emissions in ECAR
Dependent variable is log of daily sulfur dioxide emissions (in pounds)

Variable	Coef (s.e.)	Variable	Coef (s.e.)	Variable	Coef (s.e.)
constant	-52.750* (6.074)	MY199803	-0.018 (0.019)	MY199908	-0.058* (0.023)
- lncoefvar	0.025* (0.005)	MY199804	0.014 (0.019)	MY199909	-0.094* (0.024)
lndmd	11.689* (1.110)	MY199805	0.021 (0.022)	MY199910	-0.050* (0.022)
$lndmd^2$	-0.487* (0.051)	MY199806	0.007 (0.021)	MY199911	-0.066* (0.021)
MY199702	-0.031 (0.019)	MY199807	0.028 (0.022)	MY199912	-0.115* (0.022)
MY199703	-0.008 (0.019)	MY199808	0.003 (0.023)	MY200001	-0.132* (0.017)
MY199704	0.011 (0.018)	MY199809	-0.007 (0.023)	MY200002	-0.140* (0.019)
MY199705	0.000 (0.021)	MY199810	-0.005 (0.023)	MY200003	-0.163* (0.018)
MY199706	-0.033 (0.022)	MY199811	-0.048* (0.021)	MY200004	-0.145* (0.020)
MY199707	-0.024 (0.020)	MY199812	-0.044* (0.018)	MY200005	-0.163* (0.019)
MY199708	-0.021 (0.022)	MY199901	-0.051* (0.017)	MY200006	-0.179* (0.020)
MY199709	-0.004 (0.021)	MY199902	-0.073* (0.017)	MY200007	-0.177* (0.021)
MY199710	0.069* (0.021)	MY199903	-0.055* (0.018)	MY200008	-0.160* (0.022)
MY199711	0.042* (0.020)	MY199904	-0.039# (0.020)	MY200009	-0.186* (0.021)
MY199712	0.038# (0.020)	MY199905	-0.042* (0.019)	MY200010	-0.113* (0.019)
MY199801	0.038* (0.018)	MY199906	-0.060* (0.019)	MY200011	-0.147* (0.020)
MY199802	0.045* (0.018)	MY199907	-0.043* (0.021)	MY200012	-0.169* (0.020)

Notes:

a) Table presents GLS coefficients accounting for a common AR(1) error structure using the Prais-Winsten method.

b) Robust standard errors are in parentheses. We note significance at 5% level using (*) or at 10% level using (#).

c) The variables are: the log of the coefficient of variation (lncoefvar); a quadratic function of the log of daily demand (lndmd); month-year fixed effects, and temperature variables. For each neighboring state, daily mean (mn), min (mi), and max (ma) temperature variables enter as quadratic functions with coefficients allowed to differ for cooling degree days (when temperature measure is above 65°F) and for heating degree days (when temperature measure is below 65°F). We multiplied coefficients and standard errors by 10^6. State codes are IL (6), NC(7), PA (8), TN(9), VA(10), and WI(11).

d) Sample of 1453 includes daily observations from 1997 to 2000. All days of daylight savings transitions are dropped. AR(1) coefficient is 0.69, R^2 is 0.987, and joint F test of weather variables is $F(72, 1330) = 1.67$ (Prob > F = 0.0005).

(continued)

Table 4 *continued*

Variable	Coef (s.e.)	Variable	Coef (s.e.)	Variable	Coef (s.e.)
mn6heat	-0.472 (0.778)	mn8heat	1.652 (1.249)	mn10heat	-2.153 (2.353)
ma6heat	-0.930 (0.974)	ma8heat	-1.043 (1.309)	ma10heat	-1.380 (2.352)
mi6heat	0.268 (0.600)	mi8heat	-0.996 (0.768)	mi10heat	1.386 (1.438)
mn6heat2	0.002 (0.008)	mn8heat2	-0.014 (0.013)	mn10heat2	0.012 (0.023)
ma6heat2	0.014 (0.010)	ma8heat2	0.010 (0.013)	ma10heat2	0.013 (0.022)
mi6heat2	-0.005 (0.007)	mi8heat2	0.016# (0.010)	mi10heat2	-0.012 (0.017)
mn6cool2	0.015* (0.008)	mn8cool2	-0.019# (0.010)	mn10cool2	0.017 (0.014)
ma6cool2	-0.003 (0.007)	ma8cool2	0.014# (0.008)	ma10cool2	-0.009 (0.013)
mi6cool2	0.003 (0.014)	mi8cool2	0.012 (0.032)	mi10cool2	0.022 (0.028)
mn6cool	-1.409# (0.741)	mn8cool	1.947# (1.068)	mn10cool	-2.523 (1.788)
ma6cool	0.068 (0.788)	ma8cool	-1.256 (1.029)	ma10cool	0.037 (1.789)
mi6cool	-0.316 (1.036)	mi8cool	-0.785 (2.185)	mi10cool	-0.891 (2.044)
mn7heat	4.432# (2.541)	mn9heat	-1.488 (1.540)	mn11heat	-0.708 (0.696)
ma7heat	2.876 (2.848)	ma9heat	0.205 (1.590)	ma11heat	-0.755 (0.705)
mi7heat	-0.603 (1.589)	mi9heat	-0.025 (0.977)	mi11heat	0.441 (0.418)
mn7heat2	-0.039# (0.023)	mn9heat2	0.014 (0.016)	mn11heat2	0.008 (0.008)
ma7heat2	-0.028 (0.026)	ma9heat2	-0.002 (0.015)	ma11heat2	0.008 (0.008)
mi7heat2	0.004 (0.018)	mi9heat2	-0.002 (0.011)	mi11heat2	-0.005 (0.006)
mn7cool2	-0.014 (0.017)	mn9cool2	0.023* (0.011)	mn11cool2	-0.006 (0.008)
ma7cool2	0.001 (0.015)	ma9cool2	0.008 (0.009)	ma11cool2	-0.005 (0.006)
mi7cool2	-0.007 (0.027)	mi9cool2	-0.032 (0.021)	mi11cool2	0.025 (0.028)
mn7cool	2.885 (2.088)	mn9cool	-1.994 (1.237)	mn11cool	0.291 (0.726)
ma7cool	1.032 (2.140)	ma9cool	-0.423 (1.196)	ma11cool	0.056 (0.612)
mi7cool	0.225 (2.039)	mi9cool	1.913 (1.493)	mi11cool	-1.492 (1.892)

Table 5

Parametric Estimation of Regional Environmental Effects of Within-Day Variation

Dependent variable: Columns (i-iii) log of daily emissions in daily pounds of emissions, column (iv) log of daily gross fossil generation in MWh.
Independent variable: Negative log of the coefficient of variation (std. dev. over mean).

Region	(i) SO_2	(ii) NO_X	(iii) CO_2	(iv) Gen
ECAR	0.025*	0.020*	0.016*	0.021*
	(0.005)	(0.005)	(0.003)	(0.003)
ERCOT	0.036*	-0.008	0.009*	-0.002
	(0.008)	(0.005)	(0.003)	(0.003)
FRCC	0.028	-0.033*	0.013	-0.005
	(0.023)	(0.013)	(0.010)	(0.007)
MAAC	-0.009	-0.035*	-0.041*	-0.041*
	(0.014)	(0.017)	(0.015)	(0.016)
MAIN	-0.027*	-0.037*	-0.031*	-0.033*
	(0.010)	(0.010)	(0.006)	(0.006)
MAPP	0.012	0.022*	0.022*	0.030*
	(0.010)	(0.010)	(0.007)	(0.007)
NPCC	0.015	-0.047	-0.001	-0.010
	(0.019)	(0.036)	(0.013)	(0.032)
SERC	0.028*	0.015*	0.010*	0.008#
	(0.006)	(0.007)	(0.005)	(0.005)
SPP	0.001	-0.005	-0.001	0.001
	(0.014)	(0.010)	(0.007)	(0.007)
WSCC	0.042*	0.027	0.024*	0.025*
	(0.015)	(0.016)	(0.010)	(0.009)

Notes:

a) Table presents GLS coefficients accounting for a common AR(1) error structure using the Prais-Winsten method.
b) Robust standard errors are in parentheses. We note significance at 5% level using (*) or at 10% level using (#).
c) Regression includes month-year fixed effects, quadratic function of log of daily mean quantity demanded, and daily mean, minimum, and maximum temperatures for all states bordering each region.
d) Data are from January 1997 to December 2000 except MAPP does not include 2000. All days of daylight savings transitions are dropped.

Table 6

Parametric Estimation of Elasticity Range over Mean Daily Load

Region	(i) SO_2	(ii) NO_X	(iii) CO_2	(iv) Gen
ECAR	[1.279, 0.662]*	[1.400, 0.712]*	[1.093, 0.615]*	[1.146, 0.629]*
ERCOT	[0.520, 0.535]	[1.374, 1.291]	[0.970, 0.922]	[1.288, 1.098]*
FRCC	[2.313, 1.408]*	[1.996, 1.255]*	[1.590, 0.987]*	[1.680, 0.947]*
MAAC	[0.740, 0.776]	[0.692, 1.470]*	[0.642, 1.346]*	[0.672, 1.574]*
MAIN	[1.057, 1.069]	[1.146, 1.128]	[1.003, 0.948]	[1.027, 1.049]
MAPP	[0.823, 0.554]*	[0.960, 0.578]*	[0.826, 0.579]*	[0.908, 0.603]*
NPCC	[1.376, 1.225]	[1.339, 1.337]	[1.581, 1.195]*	[1.765, 1.306]*
SERC	[1.552, 0.481]*	[1.512, 0.606]*	[1.352, 0.637]*	[1.354, 0.736]*
SPP	[0.646, 0.763]	[1.085, 1.199]	[0.831, 1.031]*	[0.972, 1.088]
WSCC	[1.420, 0.042]*	[1.408, 0.491]*	[1.249, 0.552]*	[1.521, 0.707]*

Notes:

a) The elasticities are reported over the observed ranges of mean daily load.

b) Based on the significance of the coefficient on the log of daily demand squared, we note significant differences in the elasticities across the range at 5% level using (*) or at 10% level using (#).

Table 7

Parametric Simulation of Regional Environmental Effects of Across-Day Variation[Ψ]

Region	(i) SO_2	(ii) NO_X	(iii) CO_2	(iv) Gen
ECAR	0.256*	0.398*	0.467*	0.509*
	(0.031)	(0.037)	(0.022)	(0.022)
ERCOT	-0.040	-0.242*	0.046*	-0.052*
	(0.051)	(0.036)	(0.020)	(0.019)
FRCC	-0.710*	0.398*	0.252*	0.364*
	(0.095)	(0.037)	(0.039)	(0.036)
MAAC	-0.288*	-1.198*	-1.362*	-1.260*
	(0.085)	(0.099)	(0.119)	(0.113)
MAIN	-0.623*	-0.326*	-0.047	-0.132*
	(0.060)	(0.056)	(0.037)	(0.038)
MAPP	0.338*	0.414*	0.241*	0.298*
	(0.052)	(0.054)	(0.042)	(0.046)
NPCC	-0.638*	-3.383*	-0.370*	-0.795*
	(0.088)	(0.252)	(0.061)	(0.075)
SERC	0.908*	0.603*	0.570*	0.451*
	(0.042)	(0.048)	(0.031)	(0.030)
SPP	-0.112	-1.022*	-0.176*	0.042
	(0.069)	(0.097)	(0.054)	(0.050)
WSCC	1.016*	0.624*	-0.033	0.260*
	(0.070)	(0.075)	(0.074)	(0.052)

Notes:

Ψ: We simulate a reduction in across variation in the following manner. First we measure a one percent change in average load (*deltaload*). We then increase the minimum mean daily load by *deltaload* and decrease the maximum mean daily load by *deltaload*. The resulting change in pollution is normalized by the average daily pollution in that region. The estimates can be interpreted as elasticities. Standard errors are in parentheses and are computed using the delta method. We note significance at 5% level using (*) or at 10% level using (#).

Table 8

Non-Parametric Simulation of Regional Environmental Effects of Within-Day Variation

Region	(i) SO_2	(ii) NO_X	(iii) CO_2	(iv) Gen
ECAR	0.107*	0.082*	0.006*	0.011*
	(0.027)	(0.012)	(0.001)	(0.001)
ERCOT	0.060*	-0.017*	0.002#	0.007*
	(0.015)	(0.006)	(0.001)	(0.001)
FRCC	0.228*	0.078*	0.008*	0.013*
	(0.029)	(0.010)	(0.002)	(0.001)
MAAC	0.182*	0.036*	0.009*	0.012*
	(0.035)	(0.011)	(0.002)	(0.002)
MAIN	0.008	-0.028#	0.003	0.006*
	(0.037)	(0.015)	(0.002)	(0.002)
MAPP	0.031	0.050*	0.008*	0.012*
	(0.028)	(0.017)	(0.003)	(0.003)
NPCC	0.101*	0.015	-0.002	0.017*
	(0.023)	(0.014)	(0.002)	(0.002)
SERC	0.276*	0.128*	0.016*	0.019*
	(0.023)	(0.010)	(0.001)	(0.001)
SPP	0.059*	0.064*	0.003	0.005*
	(0.022)	(0.024)	(0.002)	(0.002)
WSCC	0.017*	0.019*	0.003*	0.008*
	(0.006)	(0.004)	(0.001)	(0.001)

Notes:

a) Table presents simulations based on OLS coefficients.
b) Standard errors, in parentheses, have been corrected for heteroskedasticity and serial correlation using the Newey-West method assuming a six-hour lag structure. We note significance at 5% level using (*) or at 10% level using (#).
c) Regression includes month-year fixed effects, quadratic function of log of daily mean quantity demanded, and daily mean, minimum, and maximum temperatures for all states bordering each region.
d) Data are from January 1997 to December 2000 except MAPP does not include 2000. All days of daylight savings transitions are dropped.

Table 9

Non-Parametric Simulation of Regional Environmental Effects of Across-Day Variation

Region	(i) SO_2	(ii) NO_X	(iii) CO_2	(iv) Gen
ECAR	0.447*	0.190*	0.020*	0.018*
	(0.051)	(0.021)	(0.002)	(0.002)
ERCOT	-0.044	-0.008	0.003	0.007#
	(0.027)	(0.014)	(0.003)	(0.003)
FRCC	0.213*	0.059*	0.014*	0.014*
	(0.062)	(0.022)	(0.003)	(0.003)
MAAC	0.158*	-0.035	-0.003	-0.012*
	(0.074)	(0.024)	(0.004)	(0.005)
MAIN	0.026	0.087*	0.010*	0.004
	(0.066)	(0.027)	(0.003)	(0.003)
MAPP	0.238*	0.159*	0.022*	0.021*
	(0.051)	(0.030)	(0.005)	(0.005)
NPCC	-0.054	-0.032#	-0.000	-0.002
	(0.043)	(0.016)	(0.003)	(0.003)
SERC	0.509*	0.173*	0.028*	0.024*
	(0.043)	(0.019)	(0.003)	(0.003)
SPP	-0.067	-0.145*	-0.005	-0.006
	(0.056)	(0.038)	(0.005)	(0.004)
WSCC	0.047*	0.042*	0.007*	0.006*
	(0.010)	(0.007)	(0.002)	(0.002)

Notes:

a) Table presents simulation based on OLS coefficients.
b) Standard errors, in parentheses, have been corrected for heteroskedasticity and serial correlation using the Newey-West method assuming a six hour lag structure. We note significance at 5% level using (*) or at 10% level using (#).
c) Regression includes month-year fixed effects, quadratic function of log of daily mean quantity demanded, and daily mean, minimum, and maximum temperatures for all states bordering each region.
d) Data are from January 1997 to December 2000 except MAPP does not include 2000. All days of daylight savings transitions are dropped.

Table 10

Peak Capacity Shares from Fossil Power Plants

	Share of Peak Capacity		
NERC	Hydro	Oil	Gas
ECAR	23%	8%	69%
ERCOT	1%	0%	99%
FRCC	0%	59%	41%
MAAC	12%	38%	50%
MAIN	9%	14%	77%
MAPP	40%	20%	40%
NPCC	20%	33%	46%
SERC	30%	6%	64%
SPP	10%	4%	85%
WSCC	54%	1%	45%

Notes:

a) Source: EPA eGRID for 2000 (http://www.epa.gov/cleanenergy/egrid/index.htm).
b) Peak includes oil, gas, and hydroelectric.

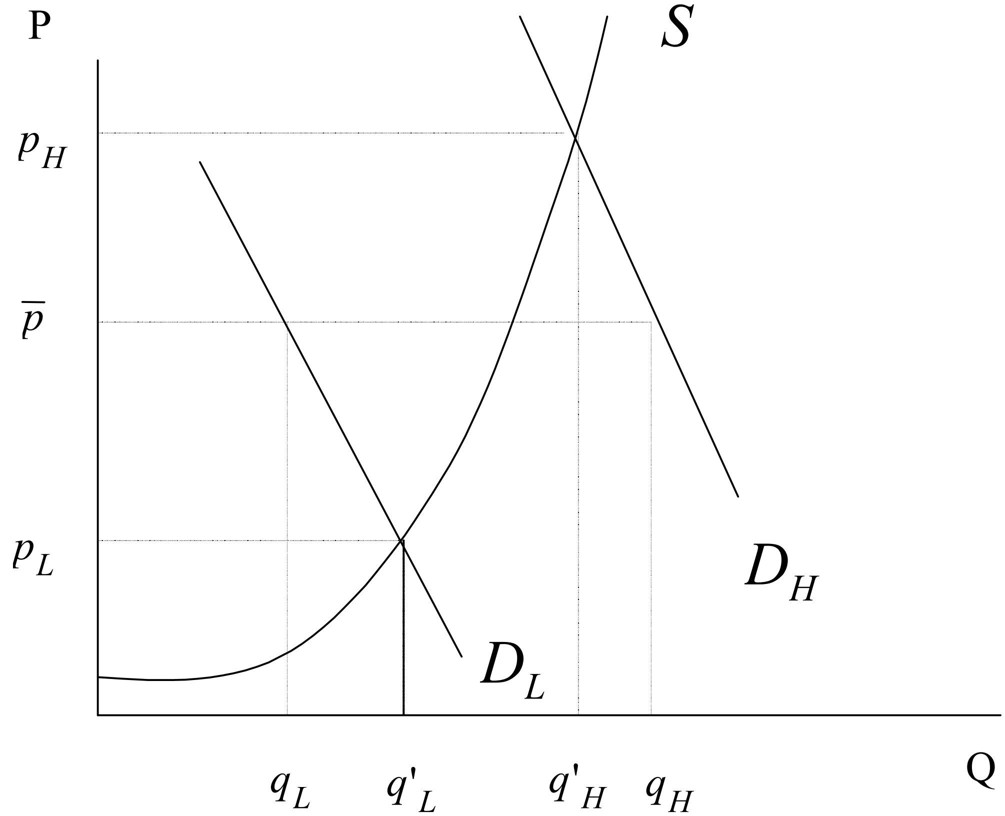


Figure 1: Example of switching from fixed retail price to real-time pricing for the high peak period (H) and low off-peak period (L) of demand.

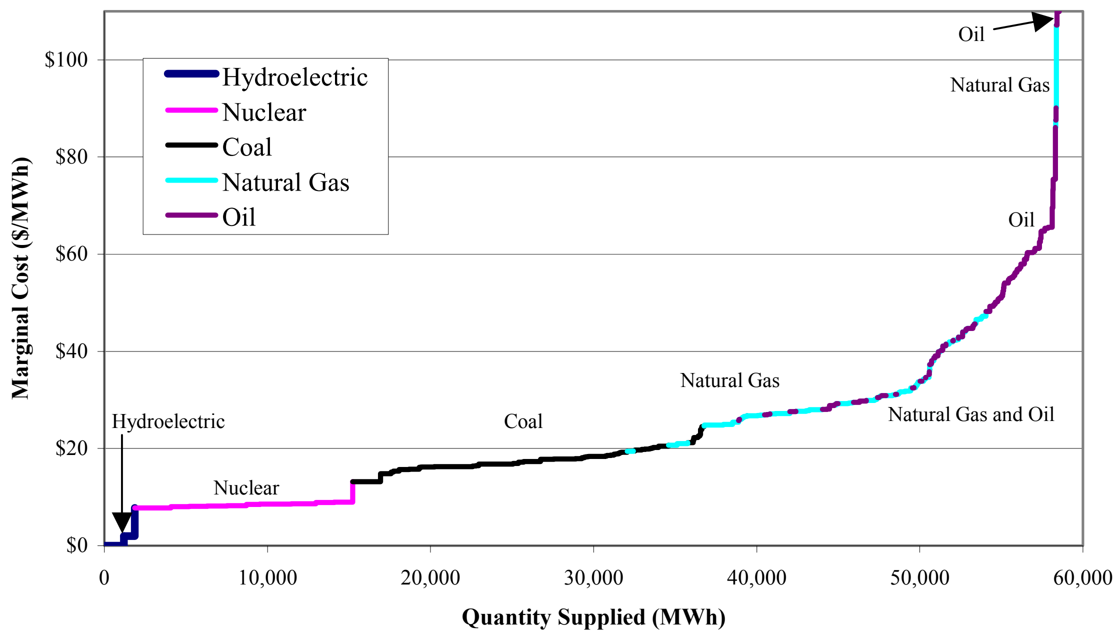


Figure 2: Supply curve for all PJM firms, April 1, 1999.

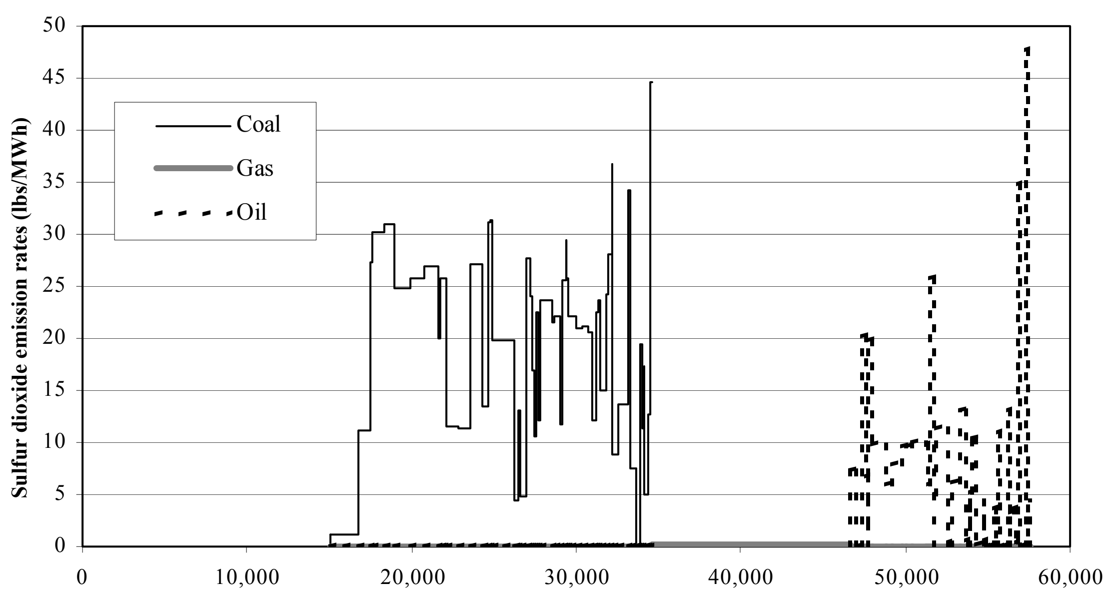
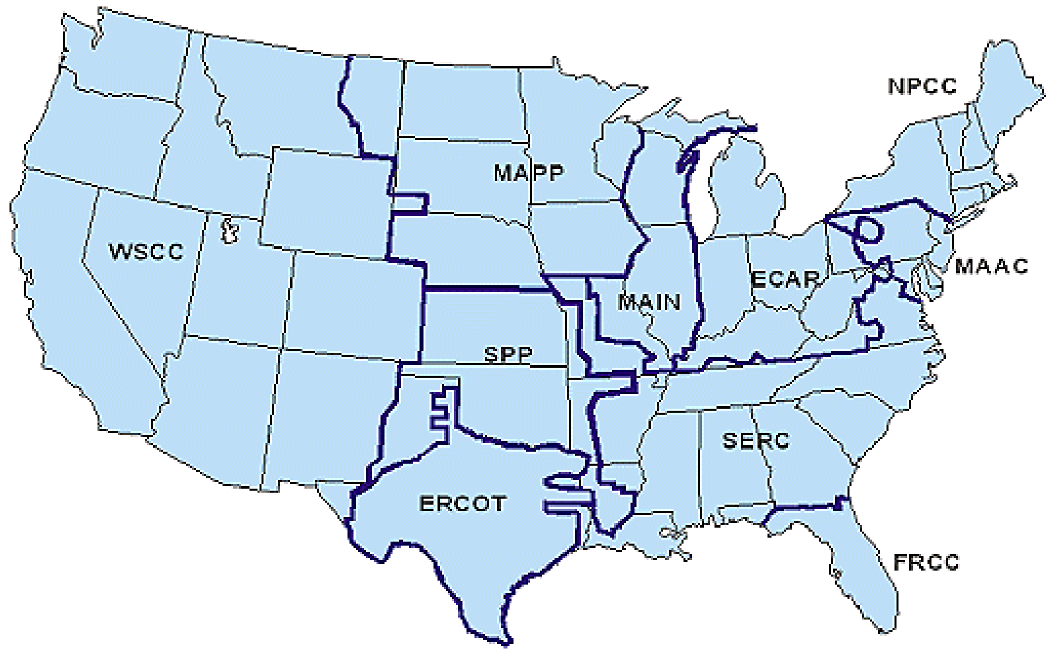


Figure 3: Example of sulfur dioxide emission rates varying along a supply curve. Source: EPA's CEMS.



North American Electric Reliability Council (NERC) Regions
ECAR = East Central Area Reliability Coordination Agreement
ERCOT = Electric Reliability Council of Texas
FRCC = Florida Reliability Coordinating Council
MAAC = Mid-Atlantic Area Council
MAIN = Mid-American Interpool Network
MAPP = Mid-Continent Area Power Pool
NPCC = Northeast Power Coordinating Council
SERC = Southeastern Electric Reliability Council
SPP = Southwest Power Pool
WSCC = Western Systems Coordinating Council

Figure 4. Map of NERC regions (source: www.nerc.com)

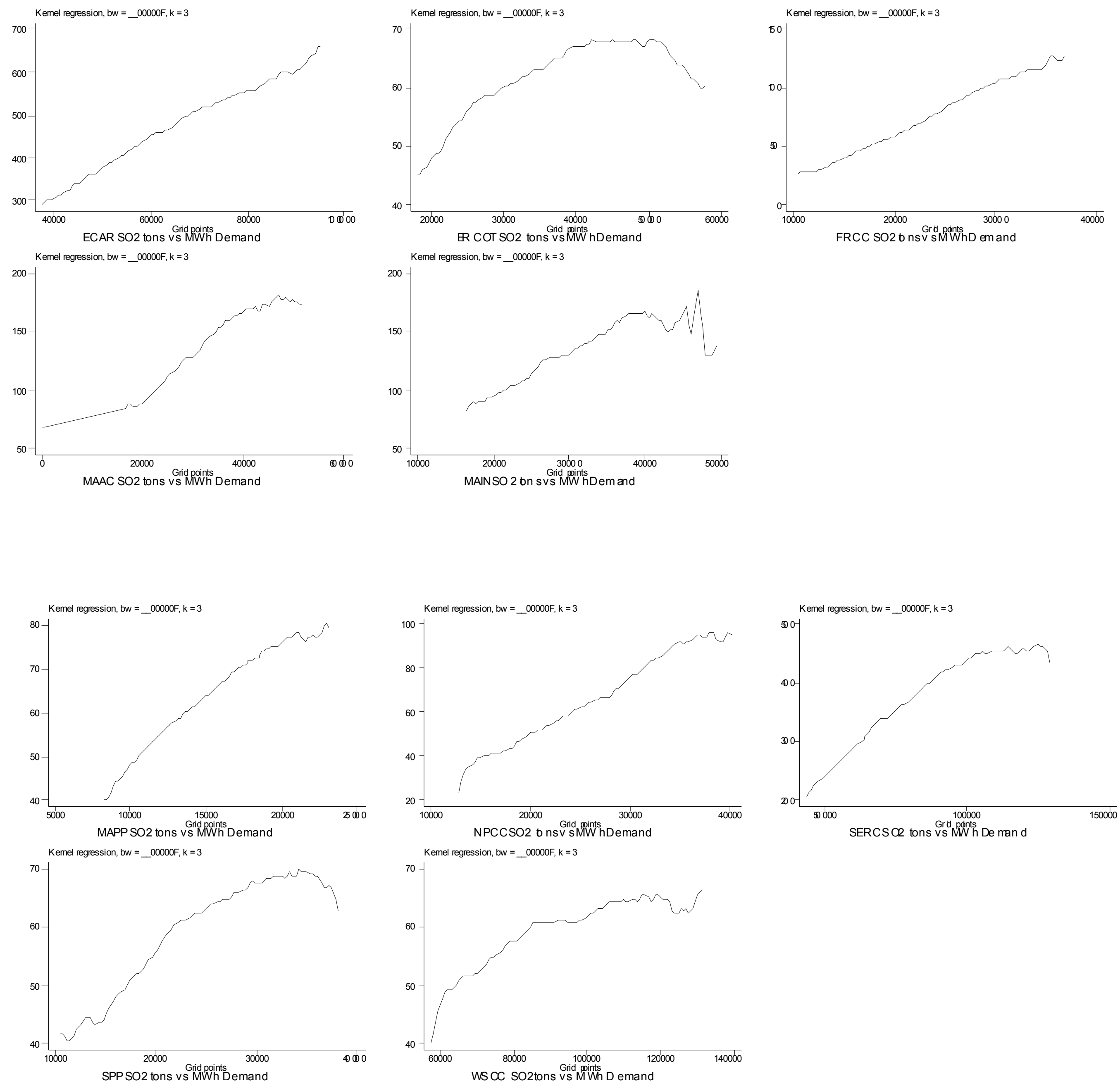


Figure 5. Kernel regressions of pounds of sulfur dioxide on MWh of electricity demanded.

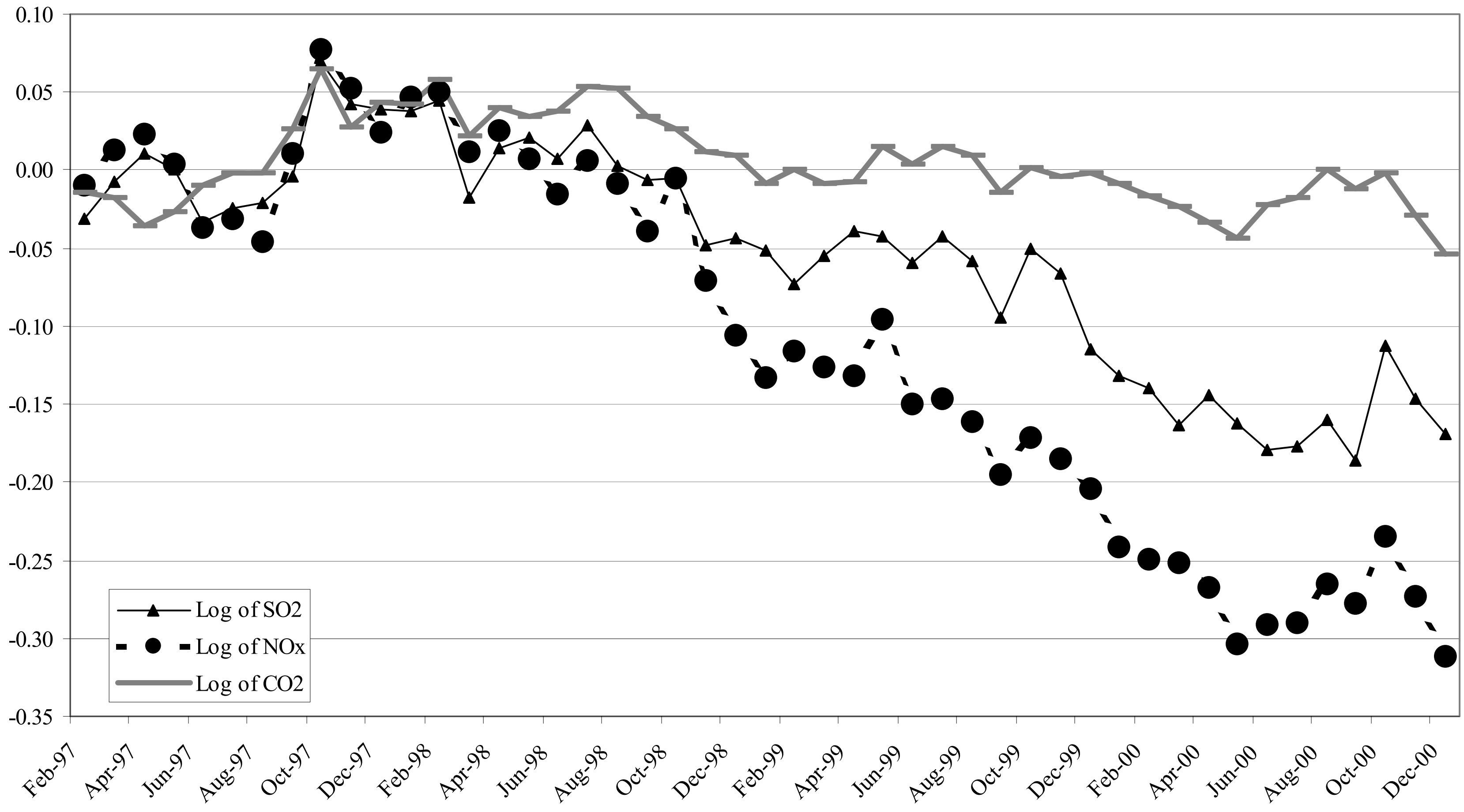


Figure 6. Month-year fixed effects for the ECAR region (Table 5 results).

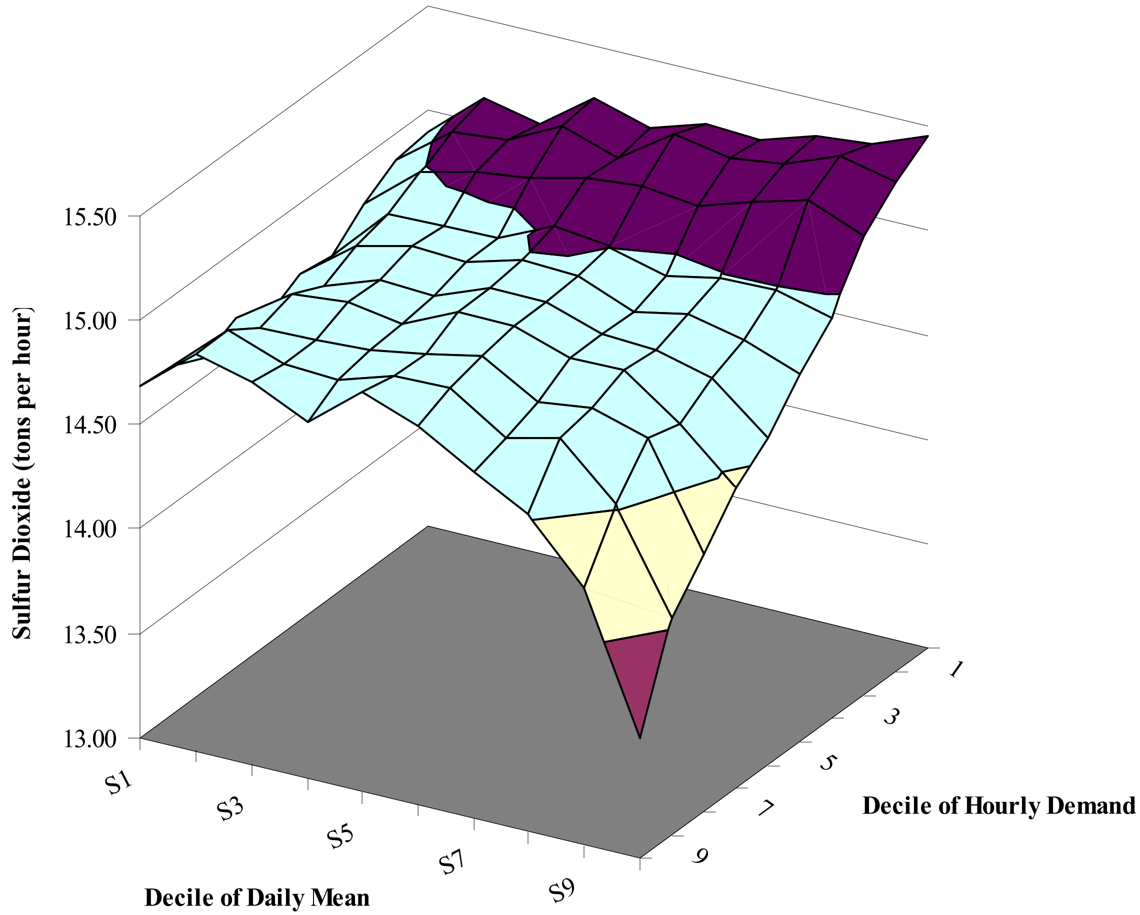


Figure 7. Plot of nonparametric estimation coefficients for ECAR SO_2 system emissions rate.