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

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

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## Abstract

Real-time pricing (RTP) of electricity would improve the efficiency of consumption and investment and would lessen the potential harm from market power. Conventional wisdom has claimed that RTP has an additional environmental benefit. 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<sub>2</sub>, NO<sub>x</sub>, and CO<sub>2</sub>. According to our estimates, a reduction in load variance, either within- or across-day, would decrease emissions in regions where peak demand is met with oil-fired capacity rather than hydroelectric capacity. These regions include the Mid-Atlantic and Illinois areas. However, reducing variance would increase emissions in regions with more hydroelectric capacity, such as the Eastern Mid-West, the Southeast, the Great Plains, and the West. The effects are relatively small.

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# 1 Introduction

Economists have long advocated for electricity pricing that accurately reflects time-varying production costs.<sup>1</sup> 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. However, these recommendations have met serious political opposition despite advances in real-time metering and in technology for responding to real-time prices.<sup>2</sup> Recently some environmental groups have supported real-time pricing for its potential to reduce pollution.<sup>3</sup> Indeed, the conventional wisdom seems to be that RTP will yield environmental benefits.<sup>4</sup>

RTP may impact the environment in several ways. In the short run, changes in generation will impact emissions, water discharge, nuclear waste production, and fossil fuel use. In the long run, RTP will impact investment decisions for generation and consumption. For any of these impacts, this paper is the first to examine whether RTP is green. We focus on the short run impacts on emissions of sulfur dioxide,  $\text{SO}_2$ , nitrogen oxides,  $\text{NO}_x$ , and carbon dioxide,  $\text{CO}_2$ , for various U.S. electricity regions.<sup>5</sup>

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<sup>1</sup>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 *et al.* (2002), and Borenstein and Holland (forthcoming) study real-time pricing, defined as prices that vary hour by hour, in competitive electricity markets.

<sup>2</sup>Currently RTP is offered in just a few U.S. pilot programs, e.g., Georgia and New York. Time-of-Use pricing is more widely available but does not reflect hour-by-hour variation in production costs.

<sup>3</sup>An environmental group in California has proposed a RTP 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.

<sup>4</sup>Hirst and Kirby (2001), Swofford (2001), Kiesling (2002), Smith and Kiesling (2003), and Nevada Power (2003) claim environmental benefits in their arguments for RTP.

<sup>5</sup>Some argue that anthropogenic emissions of  $\text{CO}_2$  may actually be beneficial. We make no assertions about the net benefits of  $\text{CO}_2$  emissions. RTP may impact other emissions not studied here, including particulate matter and mercury.

RTP may affect pollution by changing the distribution of electricity load.<sup>6</sup> 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 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, the effect on average load is ambiguous. However, real-time pricing would likely decrease the variance of load.<sup>7</sup>

Decreasing the variance of load can increase or decrease emissions. Firms use a mix of fuel sources to produce electricity including *fossil* fuel sources such as coal, natural gas, and oil, and non-fossil power sources, which have no emissions, like nuclear and hydropower. Firms generally use generating units in order of their marginal costs.<sup>8</sup> 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

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<sup>6</sup>See Borenstein and Holland (forthcoming) and Holland and Mansur (2004) for detailed theoretical models of RTP adoption.

<sup>7</sup>Given prices and elastic demand, variance must decrease with RTP adoption if average load is greater than all off-peak loads and less than all peak loads. Hypothetical examples can be constructed in which load variance increases.

<sup>8</sup>“Generating units” typically consist of boilers, turbines, and generators. A power plant may have several units.

emissions.<sup>9</sup> Similarly, if peak generation is oil fired, which typically has high emissions rates, reducing variance will reduce emissions. On the other hand, reducing variance may increase emissions. This occurs, for example, if base-load generation is met by coal-fired units while peak load generation is met by cleaner, gas-fired or hydro units. These different effects imply that the changes in emissions depend on the relative cleanliness of the available technologies. Therefore, we estimate the effects separately for various regions of the U.S.

This paper exploits exogenous variation in load to analyze the effect on emissions of changing the distribution of load. Daily changes in temperature and economic activity lead to variation in the distribution of load within and across days. This variation also leads to variation in emissions. By estimating this relationship, we can analyze the environmental impacts of real-time pricing.<sup>10</sup> Furthermore, the results are applicable to any policy, such as demand-side management or critical peak pricing, which would lead to a reduction in load variance.

Section 2 presents the empirical model. Section 3 compares generation technologies in the various regions and describes the data. In Section 4, we discuss the empirical results for the parametric approach. Section 5 tests the robustness of these findings using a nonparametric model. The empirical results are analyzed in Section 6 using the production technologies in each region. Section 7 concludes.

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<sup>9</sup>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 of ramping production up and down.

<sup>10</sup>The answer to how will RTP change demand and the market equilibrium depends on the relevant own- and cross-price elasticities of demand. 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. While beyond the scope of this paper, Holland and Mansur (2004) simulate the effect of real-time pricing on load.

## 2 Empirical Model

Exogenous changes in the distribution of load directly impact the generation decisions of firms, and these generation decisions affect emissions.<sup>11</sup> We examine the relationship between the distribution of load and emissions.<sup>12</sup> The equation that we estimate separately for each region is:

$$\ln(E_t) = -\beta \cdot \ln(VAR_t) + \gamma_1[\ln(MEAN_t)] + \gamma_2[\ln(MEAN_t)]^2 \quad (1)$$

$$+ \sum_{s=1}^{S*12} \delta_s TEMP_{st} + \sum_{m=1}^{48} \phi_m MOYR_{mt} + \epsilon_t,$$

where  $E_t$  is the pollution emitted in the region on day  $t$ ;  $VAR_t$  is a measure of the *within-day variance* of the region's load;  $MEAN_t$  is the region's *mean daily load*;  $TEMP_{st}$  is one of 12 functions of the temperature for one of the  $S$  states bordering the region; and  $MOYR_t$  is an indicator variable for each of the 48 months from January 1997 to December 2000. The error term,  $\epsilon_t$ , models the idiosyncratic shock.

The variable  $VAR_t$  describes the load distribution on day  $t$  and could be defined in many ways. We report results for the coefficient of variation of hourly load, but explore the robustness of our results to five other possible summary statistics of distribution.<sup>13</sup> The negative log-log functional form allows  $\beta$  to be interpreted as the elasticity of emissions with respect to a *reduction* in the variance measure.<sup>14</sup>

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<sup>11</sup>Electricity wholesale demand is extremely inelastic (see Borenstein, 2002). For identification, we treat it as exogenous to supply shocks.

<sup>12</sup>Our estimation can be interpreted as a reduced form of a two stage model.

<sup>13</sup>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).

<sup>14</sup>We assume this constant elasticity functional form. The nonparametric model discussed below allows us to test whether our results are robust to a general model specification.

The nonlinear relationship between emissions and production across days is captured by using logarithms and higher order terms of  $MEAN_t$ . The elasticity of emissions with respect to mean daily load is therefore  $\gamma_1 + 2\gamma_2 \ln(MEAN_t)$ . Below we use this elasticity to simulate the 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 opportunities outside the region. To control for unobserved imports and exports, the equation includes 12 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.<sup>15</sup>

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

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<sup>15</sup>Equation 1 is estimated using generalized least squares to account for an AR(1) error structure using the Prais-Winsten method. Robust standard errors use the White correction.

hours on low demand days and the upper right bin would contain the high demand hours on low demand days. Specifically, for each hour  $\tau$ , we let the dummy variable  $BIN_{\tau}^{dh}$  equal one if hour  $\tau$  occurs on a day which is in the  $d$ th decile of mean daily load and in the  $h$ th decile of hourly load on  $d$ th decile days.

For hour  $\tau$ , the model estimated is:

$$\frac{E_{\tau}}{q_{\tau}} = \sum_{d=1}^{10} \sum_{h=1}^{10} \beta_{dh} \cdot BIN_{dh}(q_{\tau}) + \sum_{s=1}^{S*12} \delta_s TEMP_{s\tau} + \sum_{m=1}^M \phi_m MOY R_{m\tau} + \epsilon_{\tau}, \quad (2)$$

where  $q_{\tau}$  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.

### 3 Data

The environmental impacts are likely to be sensitive to the production technologies in each of the ten NERC regions (see Figure 1 for regional definitions).<sup>16</sup> Table 1 describes the fuel shares of installed capacity and generation for each region. Because coal and nuclear power tend to have low marginal costs, their shares of generation are larger than their shares of capacity. Coal is the dominant fuel source in many regions and has the largest share of

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<sup>16</sup>The North American Electric Reliability Council (NERC) defined regions in order to ensure a reliable, adequate, and secure electric system. We could have examined the relationship at the utility level. However, substantial trading occurs among utilities. For this reason, we analyze at the NERC level where there is substantial transmission and communication. Further aggregation to the interconnection level would likely understate the importance of transmission congestion across regions.

generation in all of the regions except ERCOT and NPCC. Coal is typically the dirtiest of the fossil fuels.<sup>17</sup> Oil and gas have high marginal costs, and their shares of capacity are higher than their shares of generation. Gas-fired generation has effectively no SO<sub>2</sub> emissions and much lower NO<sub>x</sub> emissions rates than coal. Most oil-fired units are dirty and have similar emissions rates to coal-fired units. There are two types of hydropower. First, run-of-river dams generate based on the natural flows of the river and have low marginal costs. 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.

The load data are from the Federal Energy Regulatory Commission (FERC) Form 714.<sup>18</sup> Table 2 shows summary statistics (the average and the standard deviation) of each region's mean and maximum daily load. WSCC and SERC are the largest regions, with more than four times the average load of some of the smallest regions: MAPP, SPP, and FRCC. The regions with the most variation *across* days, normalized by mean, are SPP and ERCOT.<sup>19</sup> The table also summarizes the *within-day* load variation using the coefficient of variation. The regions with the greatest variation are FRCC and NPCC while ECAR and MAIN are those with the smallest within-day variation. The differences between these

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<sup>17</sup>For example in MAAC, the SO<sub>2</sub> emissions rates (in lbs per MWh) are 20.3, 0.0, and 7.0 for coal-, gas-, and oil-fired generation. NO<sub>x</sub> emissions rates are 5.8, 0.9, and 3.5 respectively, and CO<sub>2</sub> emissions rates are 2198, 1423, and 1790. These data are described in Holland and Mansur (2004).

<sup>18</sup>For each of more than 200 U.S. electric utilities, the 714 data report hourly load. We aggregate these utility data to the NERC region level. Our aggregation data are consistent with NERC monthly load data.

<sup>19</sup>The coefficient of variation of mean daily load for SPP, ERCOT, and WSCC are 0.194, 0.193, and 0.088, respectively. SPP's coefficient is 2.2 times that of WSCC.

regions are not quite as substantial as in the across-day variation measures.<sup>20</sup>

The National Oceanic and Atmospheric Administration (NOAA) provides temperature data on daily mean, minimum, and maximum temperature for hundreds of weather stations nationally. We calculate 12 statewide functions of temperature. Table 2 reports the summary statistics for the daily mean temperature in each region.<sup>21</sup> The hottest regions on average are FRCC, ERCOT, and SERC while MAPP and NPCC are the coldest. Regions with high temperature variation are not necessarily those regions with high within-day or across-day load variation.

Emissions 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<sub>2</sub>, NO<sub>x</sub>, and CO<sub>2</sub>.<sup>22</sup> By region, Table 3 summarizes the emissions data. A daily system emissions rate is calculated as the ratio of mean daily emissions to mean daily load. ECAR is clearly the dirtiest region with the highest emissions per MWh of SO<sub>2</sub> and NO<sub>x</sub>, and second highest levels of CO<sub>2</sub>. On the other hand, WSCC is the cleanest region in all pollutants.<sup>23</sup> Each region's rates vary substantially day to day.

To understand the differences in system emissions rates, we also compare the share of load met by fossil fuel generation across regions.<sup>24</sup> The CEMS data report hourly gross

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<sup>20</sup>The FRCC coefficient is approximately 1.8 times that of ECAR.

<sup>21</sup>We report statistics on the unweighted average daily temperatures for states in each region.

<sup>22</sup>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).

<sup>23</sup>The WSCC SO<sub>2</sub> 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<sub>x</sub> and CO<sub>2</sub>.

<sup>24</sup>The remainder of load is met by nuclear, hydroelectric, and imports (net of exports).

generation at each unit.<sup>25</sup> 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.<sup>26</sup>

To visualize the unconditional correlations in the emissions and load data, we use kernel regressions to estimate a smooth relationship between emissions and demand in each region. Figure 2 graphs kernel regression estimates for hourly pounds of SO<sub>2</sub> on hourly load for each of the ten regions. For some of the regions, there appears to be a general linear relationship between emissions and generation suggesting little impact of variance on emissions. 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 emissions. However, simply analyzing the shape of these estimates may be misleading since the kernel regressions do not control for covariates.

## 4 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.<sup>27</sup> Since there are hundreds of estimated coefficients, we first focus on those for within-day variance, *i.e.*,  $VAR_t$ . Next we simulate across-day variance using coefficients on  $MEAN_t$ . Finally we analyze changes in gross fossil generation.

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<sup>25</sup>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.

<sup>26</sup>These ratios can exceed one since a region may export electricity and since electricity is used internally at power plants.

<sup>27</sup>A detailed examination of the results for one equation, ECAR SO<sub>2</sub>, are presented in at web page: [http://www.som.yale.edu/faculty/etm7/papers/holland\\_mansur\\_rtp\\_pollution\\_append.pdf](http://www.som.yale.edu/faculty/etm7/papers/holland_mansur_rtp_pollution_append.pdf)

## 4.1 Within-Day Variation

Within-day variation is measured by the coefficient of variation. Table 4 presents the coefficient estimates and standard errors for the negative logarithm of the coefficient of variation for all three pollutants in all ten regions. The coefficients are the effect on emissions of a reduction in within-day variance. Each coefficient is from a regression described in Equation 1 where the dependent variable is the log of SO<sub>2</sub> pounds emitted in column (i), the log of NO<sub>x</sub> pounds emitted in column (ii), and the log of CO<sub>2</sub> tons emitted in column (iii). These coefficient estimates are conditional on mean daily load, fixed effects, and temperature.<sup>28</sup>

The estimates for SO<sub>2</sub> vary across the ten regions. For four 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<sub>2</sub> emissions. In one region, MAIN, the negative coefficient indicates that a reduction in within-day load variance would decrease SO<sub>2</sub> emissions. Note that 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<sub>2</sub> emissions.

The estimates for NO<sub>x</sub> and CO<sub>2</sub> are similar to the SO<sub>2</sub> estimates. For NO<sub>x</sub>, three of the regions have positive effects and three have negative effects. For CO<sub>2</sub>, five regions have positive coefficients, and two regions have negative coefficients. For both pollutants, the coefficients are generally more negative than the SO<sub>2</sub> coefficients but are still relatively small (the estimated elasticity with the largest magnitude is -0.04).

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<sup>28</sup>For all regions and pollutants, the temperature variables are jointly significant at the 6% level while the month-year indicator variables are jointly significant at the 1% level.

These coefficient estimates show positive effects for all three pollutants in two regions and for two pollutants in three regions. For these five regions (ECAR, ERCOT, MAPP, SERC, and WSCC), 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 (FRCC, MAAC, and MAIN) have negative coefficient estimates implying that a reduction in within-day variation will lead to a reduction in emissions. Finally, SPP and NPCC show no effect.<sup>29</sup> In Appendix A, we show that these results are robust to other measures of within-day variation.

## 4.2 Across-Day Variation

We now turn 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. The elasticities are unity if emissions are proportional to load.

Table 5 presents the elasticities over the observed ranges of mean daily load for each of the three pollutants 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.<sup>30</sup> For example, in the WSCC, a percent increase in system load on the lowest-load day leads to a 1.4% change in

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<sup>29</sup>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.

<sup>30</sup>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.

SO<sub>2</sub> emissions, whereas a percent increase on the highest-load day leads to a small increase in SO<sub>2</sub> 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 are presented in Table 6.<sup>31</sup>

As with the within-day variation, there are regional differences. In ECAR, MAPP, and SERC, the 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<sub>2</sub> and NO<sub>x</sub>, but not in CO<sub>2</sub>. 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 for all three pollutants (NPCC and MAAC) or for two pollutants (MAIN and SPP). For MAIN and MAAC, we also predict a reduction in emissions from reducing within-day variance. The results for ERCOT and FRCC are mixed.<sup>32</sup>

Since the simulation results describe a percent change in emissions from a one percent change in load, they can be compared with the within-day elasticities. We note that marginal changes in across-day variation have larger effects than marginal changes in

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<sup>31</sup>The standard errors are calculated from the covariance matrix of the parameter estimates using the delta method.

<sup>32</sup>FRCC has a negative effect in SO<sub>2</sub> but positive effects in NO<sub>x</sub> and CO<sub>2</sub>. ERCOT has a negative effect in NO<sub>x</sub> but a positive effect in CO<sub>2</sub>.

within-day variation. Here the largest elasticity in magnitude is -3.4 compared to the largest within-day elasticity of -0.04.

### 4.3 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.<sup>33</sup> The independent variables are identical to those in the regressions reported in columns (i) to (iii) of Tables 4 and 6.<sup>34</sup>

Column (iv) of Table 4 reports the estimates for the regressions with gross fossil generation as the dependent variable. Several coefficients deserve note. First, the ERCOT coefficient is not statistically significant despite being very precisely estimated. Since ERCOT is not interconnected with other regions and has limited hydroelectric resources, fossil generation must follow load directly.<sup>35</sup> 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

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<sup>33</sup>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.

<sup>34</sup>Load not met by fossil generation is served by imports or other fuel sources such as nuclear, hydropower, renewables, or small peaking units, which do not appear in the CEMS data. Transmission line losses and internal plant usage might also account for some of the discrepancy between gross generation and load.

<sup>35</sup>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.

across regions, the decreased fossil generation in ECAR likely is offset by the increased fossil generation in either MAAC or MAIN.<sup>36</sup>

We find statistically significant effects on fossil generation in five of the ten regions. Reducing within-day variance results in more gross fossil production in ECAR, MAPP, and WSCC, and weakly in SERC. Note that these are the regions where we estimate increases in emissions. 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. 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 5 reports the elasticity ranges for fossil generation with respect to mean daily load. 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 6 reports the simulated effects of the percentage change in gross 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

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<sup>36</sup>The correlations among these coefficients of variation are high:  $\text{corr}(\text{ECAR}, \text{MAAC})=0.78$ ,  $\text{corr}(\text{ECAR}, \text{MAIN})=0.87$ , and  $\text{corr}(\text{MAIN}, \text{MAPP})=0.87$ . These high correlations suggest exploring whether the effects in these four regions should be estimated jointly. We find that conditioning our estimates for each region on the load variance measures in each of the other three regions (plus NPCC for MAAC) does not change our results substantially. In particular, all of the coefficients for ECAR, MAIN, and MAPP agree in sign with those in Table 4 and they are all significant. However, the coefficients for MAAC are now insignificant.

environmental effects. Thus, as with the within-day environmental effects, the across-day environmental effect seem to be driven largely by changes in fossil generation.

## 5 Robustness using Nonparametric Model

Since the estimates of Section 4 depend on specific functional forms, we test the robustness of these results using the nonparametric model described in Section 2. We estimate Equation 2 and correct the standard errors for serial correlation and heteroskedasticity.<sup>37</sup> 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.<sup>38</sup>

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 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.<sup>39</sup> Table 7 reports the findings of this simulation.<sup>40</sup>

We compare the within-day effects of the parametric method (Table 4) with those of

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<sup>37</sup>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.

<sup>38</sup>See Appendix B for a depiction of one of the regressions.

<sup>39</sup>This is equivalent to calculating a change in the weighted average emissions rates by giving less weight to extreme events.

<sup>40</sup>The standard errors in Tables 7 and 8 are estimated using the delta method.

the nonparametric method (Table 7). About half (24 of 40) of the parametric estimations are significant across the ten regions and four dependent variables ( $\text{SO}_2$ ,  $\text{NO}_x$ ,  $\text{CO}_2$ , 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 8 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 4. For most regions and pollutants, the parametric and nonparametric simulations are qualitatively similar.<sup>41</sup> Furthermore, we find that the across-day variance effects are larger than the within-day effects.<sup>42</sup>

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<sup>41</sup>In 38 of 80 tests, both the parametric and nonparametric results agree in sign and significance. Seven 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.

<sup>42</sup>Comparing Tables 7 and 8, the impact of reducing across-day variance is about twice as large as the impact of reducing within-day variance.

## 6 Discussion

The results of Section 4 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 9 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. 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.<sup>43</sup>

The regions with hydro shares larger than oil shares are ECAR, ERCOT, MAPP,

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<sup>43</sup>Natural gas typically has lower emissions rates than oil though is dirtier than hydroelectric.

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 4). 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 to 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 production costs and quick ramping rates, it can be used to adjust to rapid changes in load. A reduction in load variance would imply that less hydropower is needed during the extreme peak loads and could potentially offset other emissions. This suggests that the adverse environmental effects estimated here for some regions might be partially mitigated by using peak hydropower to offset fossil generation.

To address this concern, we examine the relationship between emissions and the amount of load that is not met by hydropower. In so doing, we are assuming that reducing load variance will not impact the dispatch of hydropower.<sup>44</sup> Given data constraints, we use our

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<sup>44</sup>Run-of-river power cannot change and reservoir hydropower is dispatched during the set of hours with the highest prices. While reducing the variation of load will alter prices, it is unlikely to change the set of hours when prices are greatest.

measure of gross fossil generation as a proxy for load net of hydropower. This measure is imperfect as it does not account for net imports nor the conversion of gross to net generation. Furthermore, it is endogenous: an outage at a large fossil power plant will reduce emissions and gross fossil generation. Therefore, we instrument using our measures of the load distribution.<sup>45</sup> We find that our results are robust to this model, particularly in regions with little inter-regional trading.<sup>46</sup> We conclude that our findings are consistent with a model that accounts for the dynamic optimization of hydropower.

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.

## 7 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,

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<sup>45</sup>Specifically, we regress the log of daily emissions on the log of the coefficient of variation of gross fossil generation, the log of the mean daily gross fossil generation (and its square), and the other covariates as above. The coefficient of variation and the two measures of mean daily generation are endogenous so, in a first stage, we regress each of these variables on the coefficient of variation of load, the two mean daily load measures, and the other covariates. In order to address serial correlation, we assume a first order autocorrelation process as above and quasi-difference the data.

<sup>46</sup>The coefficients on the coefficient of variation for ERCOT, FRCC, NPCC, and SPP are nearly exactly the same as those in Table 4. Those for WSCC and SERC are slightly smaller in magnitude but are qualitatively similar. The Midwestern regions of ECAR, MAAC, MAIN, and MAPP are more integrated, as discussed in footnote 36, and the results are not robust in these regions. However, this part of the U.S. has very little hydroelectric power.

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  $\text{SO}_2$ ,  $\text{NO}_x$ , and  $\text{CO}_2$ . 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 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. 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).

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,  $\text{SO}_2$  and  $\text{NO}_x$  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, 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.

Third, 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. "The Trouble with Electricity Markets: Understanding California's Restructuring Disaster," *Journal of Economic Perspectives*, **16**, 2002.
- [4] Borenstein, Severin and Stephen P. Holland. "On the Efficiency of Competitive Electricity Markets With Time-Invariant Retail Prices," *RAND Journal of Economics*, forthcoming.
- [5] 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](http://www.ucei.org/PDF/csemwp105.pdf).
- [6] Caves, Douglas and Laurits R. Christensen, "Econometric Analysis of Residential Time-of-Use Electricity Pricing Experiments," *Journal of Econometrics*, **14**:287-306, 1980.
- [7] Environmental Defense. "Environmental Defense Decries CPUC Inaction On Real Time Pricing." <http://www.environmentaldefense.org/pressrelease.cfm?ContentID=61>, August 3, 2001.
- [8] 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.
- [9] Hirst, Eric and Brendan Kirby. "Retail-Load Participation in Competitive Wholesale Electricity Markets," Edison Electric Institute, [www.ehirst.com/PDF/PRDRReport.pdf](http://www.ehirst.com/PDF/PRDRReport.pdf), January, 2001.
- [10] Holland, Stephen P. and Erin T. Mansur, "The Political Economy and Environmental Effects of Real-Time Pricing Adoption in Competitive Electricity Markets," mimeo, 2004.
- [11] 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.
- [12] Kiesling, Lynne. "Green Market for Electricity," Reason Public Policy Institute, [www.rppi.org/greenmarket.html](http://www.rppi.org/greenmarket.html), August 13, 2002.

- [13] 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](http://www.eei.org/industry_issues/environment/voluntary_efforts/electric_customer_stories/nevada_power.htm), Edison Electric Institute, July 10, 2003.
- [14] Patrick, Robert and Frank Wolak, "Real-Time Pricing and Demand Side Participation in Restructured Electricity Markets," mimeo, 2001.
- [15] Smith, Vernon L. and Lynne Kiesling. "Demand, Not Supply" *Wall Street Journal*, New York, N.Y.: pg. A 10. August 20, 2003.
- [16] Steiner, Peter O. "Peak Loads and Efficient Pricing." *Quarterly Journal of Economics*, **72**(1):585-610, 1957.
- [17] Swofford, Gary. "Prepared Witness Testimony: The House Committee on Energy and Commerce," <http://energycommerce.house.gov/107/hearings/06222001Hearing265/Swofford437.htm>, June 22, 2001.
- [18] 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.
- [19] 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)

NERC	Total	Shares				
		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)

NERC	Total	Shares				
		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 Load (GW) and Mean Temperature (in degrees Fahrenheit) by Region

Region	Mean Daily Load	Max Daily Load	Coefficient of Variation	Mean Daily Temperature
ECAR	59.6 [6.5]	67.5 [8.2]	0.11 [0.03]	52.6 [17.2]
ERCOT	30.6 [5.9]	36.6 [8.5]	0.14 [0.04]	68.1 [14.1]
FRCC	20.6 [3.4]	25.9 [4.6]	0.20 [0.03]	72.6 [9.5]
MAAC	28.8 [3.9]	33.6 [5.0]	0.14 [0.03]	55.2 [16.2]
MAIN	26.5 [3.5]	30.4 [4.6]	0.12 [0.03]	52.1 [18.5]
MAPP	13.8 [1.7]	15.8 [2.2]	0.12 [0.03]	46.9 [20.5]
NPCC	24.2 [3.0]	28.6 [3.7]	0.15 [0.02]	47.6 [17.3]
SERC	75.2 [10.7]	88.0 [14.9]	0.13 [0.04]	62.7 [14.6]
SPP	20.2 [3.9]	23.6 [5.5]	0.13 [0.04]	58.6 [18.3]
WSCC	86.8 [7.6]	100.4 [9.7]	0.12 [0.02]	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 <sub>2</sub> Rate	NO <sub>x</sub> Rate	CO <sub>2</sub> Rate	Fossil Share	Sample Size
ECAR	14.87 [1.15]	5.79 [0.70]	1.04 [0.04]	0.98 [0.03]	1,453
ERCOT	3.96 [0.68]	2.42 [0.23]	0.69 [0.03]	0.79 [0.04]	1,453
FRCC	6.08 [1.29]	2.77 [0.34]	0.56 [0.04]	0.59 [0.04]	1,453
MAAC	8.75 [1.18]	2.38 [0.43]	0.51 [0.06]	0.51 [0.05]	1,453
MAIN	9.11 [2.15]	3.78 [0.59]	0.75 [0.05]	0.68 [0.04]	1,453
MAPP	8.75 [0.61]	5.30 [0.44]	1.15 [0.07]	0.96 [0.07]	1,089
NPCC	4.97 [0.87]	1.53 [0.29]	0.47 [0.07]	0.59 [1.17]	1,453
SERC	9.34 [0.94]	4.22 [0.69]	0.76 [0.04]	0.74 [0.04]	1,453
SPP	5.51 [0.80]	3.75 [0.62]	0.90 [0.12]	0.91 [0.10]	1,453
WSCC	1.36 [0.18]	1.30 [0.11]	0.35 [0.03]	0.36 [0.04]	1,453

*Notes:*

- For each variable, the table displays the sample mean with standard deviation in brackets.
- Emissions rates are system-wide averages of total pollution (SO<sub>2</sub> and NO<sub>x</sub> in lbs and CO<sub>2</sub> in tons) to total demand (in MWh).
- The sample period is from January 1997 to December 2000, except MAPP does not include 2000. All days of daylight savings transitions are dropped.
- Source: EPA CEMS.

**Table 4**

## 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 <sub>2</sub>	(ii) NO <sub>x</sub>	(iii) CO <sub>2</sub>	(iv) Gen
ECAR	0.025* (0.005)	0.020* (0.005)	0.016* (0.003)	0.021* (0.003)
ERCOT	0.036* (0.008)	-0.008 (0.005)	0.009* (0.003)	-0.002 (0.003)
FRCC	0.028 (0.023)	-0.033* (0.013)	0.013 (0.010)	-0.005 (0.007)
MAAC	-0.009 (0.014)	-0.035* (0.017)	-0.041* (0.015)	-0.041* (0.016)
MAIN	-0.027* (0.010)	-0.037* (0.010)	-0.031* (0.006)	-0.033* (0.006)
MAPP	0.012 (0.010)	0.022* (0.010)	0.022* (0.007)	0.030* (0.007)
NPCC	0.015 (0.019)	-0.047 (0.036)	-0.001 (0.013)	-0.010 (0.032)
SERC	0.028* (0.006)	0.015* (0.007)	0.010* (0.005)	0.008 <sup>#</sup> (0.005)
SPP	0.001 (0.014)	-0.005 (0.010)	-0.001 (0.007)	0.001 (0.007)
WSCC	0.042* (0.015)	0.027 (0.016)	0.024* (0.010)	0.025* (0.009)

*Notes:*

- Table presents GLS coefficients accounting for a common AR(1) error structure using the Prais-Winsten method.
- Robust standard errors are in parentheses. We note significance at 5% level using (\*) or at 10% level using (<sup>#</sup>).
- 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.
- Data are from January 1997 to December 2000 except MAPP does not include 2000. All days of daylight savings transitions are dropped.

**Table 5**

## Parametric Estimation of Elasticity Range over Mean Daily Load

Region	(i) SO <sub>2</sub>	(ii) NO <sub>x</sub>	(iii) CO <sub>2</sub>	(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:*

- The elasticities are reported over the observed ranges of mean daily load.
- 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 6**Parametric Simulation of Regional Environmental Effects of Across-Day Variation<sup>Ψ</sup>

Region	(i) SO <sub>2</sub>	(ii) NO <sub>x</sub>	(iii) CO <sub>2</sub>	(iv) Gen
ECAR	0.256* (0.031)	0.398* (0.037)	0.467* (0.022)	0.509* (0.022)
ERCOT	-0.040 (0.051)	-0.242* (0.036)	0.046* (0.020)	-0.052* (0.019)
FRCC	-0.710* (0.095)	0.398* (0.037)	0.252* (0.039)	0.364* (0.036)
MAAC	-0.288* (0.085)	-1.198* (0.099)	-1.362* (0.119)	-1.260* (0.113)
MAIN	-0.623* (0.060)	-0.326* (0.056)	-0.047 (0.037)	-0.132* (0.038)
MAPP	0.338* (0.052)	0.414* (0.054)	0.241* (0.042)	0.298* (0.046)
NPCC	-0.638* (0.088)	-3.383* (0.252)	-0.370* (0.061)	-0.795* (0.075)
SERC	0.908* (0.042)	0.603* (0.048)	0.570* (0.031)	0.451* (0.030)
SPP	-0.112 (0.069)	-1.022* (0.097)	-0.176* (0.054)	0.042 (0.050)
WSCC	1.016* (0.070)	0.624* (0.075)	-0.033 (0.074)	0.260* (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 7**

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

Region	(i) SO <sub>2</sub>	(ii) NO <sub>x</sub>	(iii) CO <sub>2</sub>	(iv) Gen
ECAR	0.107* (0.027)	0.082* (0.012)	0.006* (0.001)	0.011* (0.001)
ERCOT	0.060* (0.015)	-0.017* (0.006)	0.002 <sup>#</sup> (0.001)	0.007* (0.001)
FRCC	0.228* (0.029)	0.078* (0.010)	0.008* (0.002)	0.013* (0.001)
MAAC	0.182* (0.035)	0.036* (0.011)	0.009* (0.002)	0.012* (0.002)
MAIN	0.008 (0.037)	-0.028 <sup>#</sup> (0.015)	0.003 (0.002)	0.006* (0.002)
MAPP	0.031 (0.028)	0.050* (0.017)	0.008* (0.003)	0.012* (0.003)
NPCC	0.101* (0.023)	0.015 (0.014)	-0.002 (0.002)	0.017* (0.002)
SERC	0.276* (0.023)	0.128* (0.010)	0.016* (0.001)	0.019* (0.001)
SPP	0.059* (0.022)	0.064* (0.024)	0.003 (0.002)	0.005* (0.002)
WSCC	0.017* (0.006)	0.019* (0.004)	0.003* (0.001)	0.008* (0.001)

*Notes:*

- Table presents simulations based on OLS coefficients.
- 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 (<sup>#</sup>).
- 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.
- Data are from January 1997 to December 2000 except MAPP does not include 2000. All days of daylight savings transitions are dropped.

**Table 8**

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

Region	(i) SO <sub>2</sub>	(ii) NO <sub>x</sub>	(iii) CO <sub>2</sub>	(iv) Gen
ECAR	0.447* (0.051)	0.190* (0.021)	0.020* (0.002)	0.018* (0.002)
ERCOT	-0.044 (0.027)	-0.008 (0.014)	0.003 (0.003)	0.007 <sup>#</sup> (0.003)
FRCC	0.213* (0.062)	0.059* (0.022)	0.014* (0.003)	0.014* (0.003)
MAAC	0.158* (0.074)	-0.035 (0.024)	-0.003 (0.004)	-0.012* (0.005)
MAIN	0.026 (0.066)	0.087* (0.027)	0.010* (0.003)	0.004 (0.003)
MAPP	0.238* (0.051)	0.159* (0.030)	0.022* (0.005)	0.021* (0.005)
NPCC	-0.054 (0.043)	-0.032 <sup>#</sup> (0.016)	-0.000 (0.003)	-0.002 (0.003)
SERC	0.509* (0.043)	0.173* (0.019)	0.028* (0.003)	0.024* (0.003)
SPP	-0.067 (0.056)	-0.145* (0.038)	-0.005 (0.005)	-0.006 (0.004)
WSCC	0.047* (0.010)	0.042* (0.007)	0.007* (0.002)	0.006* (0.002)

*Notes:*

- Table presents simulation based on OLS coefficients.
- 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 (<sup>#</sup>).
- 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.
- Data are from January 1997 to December 2000 except MAPP does not include 2000. All days of daylight savings transitions are dropped.

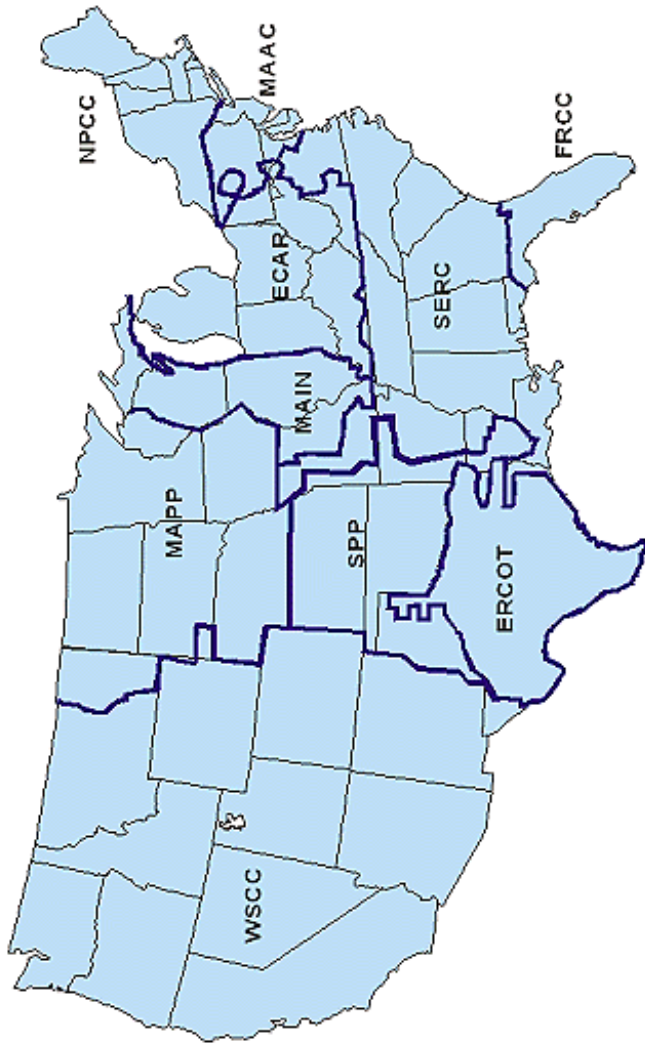
**Table 9**

## Peak Capacity Shares from Fossil Power Plants

NERC	Share of Peak Capacity		
	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:*

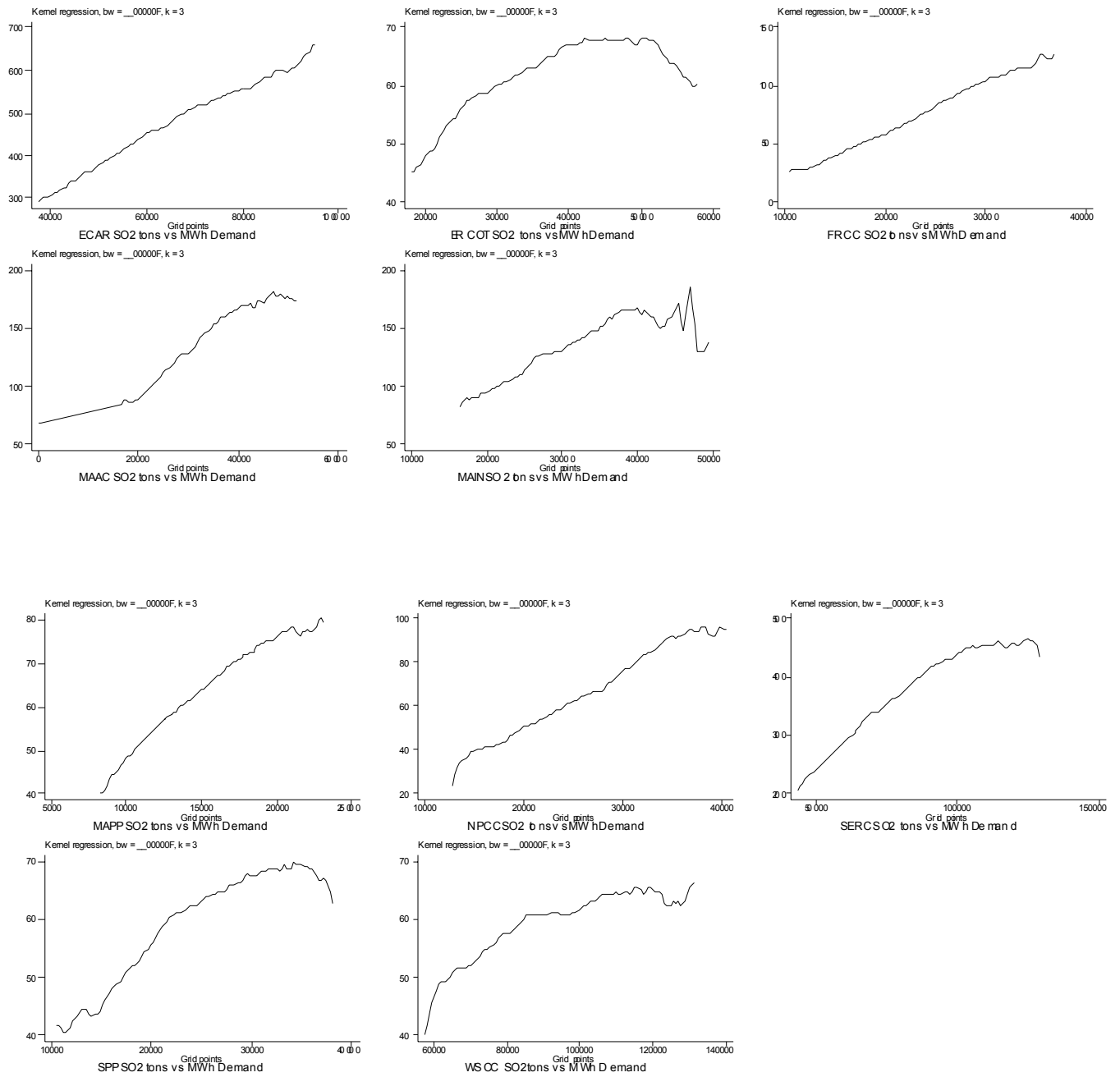
- a) Source: EPA eGRID for 2000 (<http://www.epa.gov/cleanenergy/egrid/index.htm>).
- b) Peak includes oil, gas, and hydroelectric.



*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 1. Map of NERC regions (source: [www.nerc.com](http://www.nerc.com))**



**Figure 2. Kernel regressions of pounds of sulfur dioxide on MWh of electricity demanded.**

# Appendices

## Appendix A

Table 4 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 distribution summary statistics 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<sub>2</sub> 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<sub>x</sub>, in eight of the ten regions, all the

coefficients had either the same sign or the same significance.<sup>47</sup> For CO<sub>2</sub>, in nine of the ten regions, all the coefficients had either the same sign or the same significance.<sup>48</sup> Note that no region has coefficients on any of the measures of variance that are significant but of opposite sign.

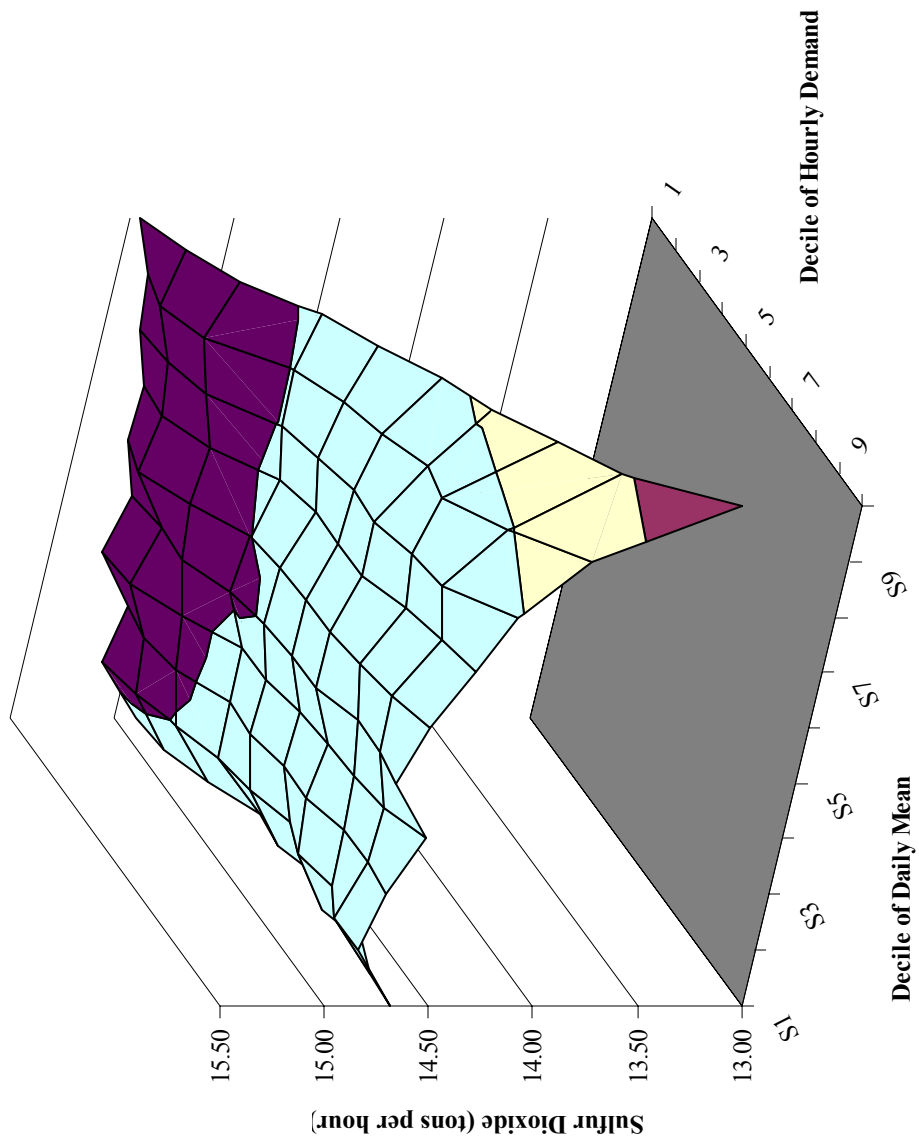
## Appendix B

Figure A1 depicts the coefficients for one of our estimates of Equation 2: SO<sub>2</sub> emissions rates in ECAR. 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<sub>2</sub> emissions rate decreases with hourly demand. Across regions and pollutants, we find substantially different patterns.

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<sup>47</sup>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.

<sup>48</sup>In MAPP, four coefficients are positive and significant but one coefficient (on the inverse load factor) is negative but insignificant.



**Figure A.1. Plot of nonparametric estimation coefficients for ECAR SO<sub>2</sub> system emissions rate.**