NBER WORKING PAPER SERIES

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Working Paper 13508
http://www.nber.org/papers/w13508

NATIONAL BUREAU OF ECONOMIC RESEARCH
1050 Massachusetts Avenue
Cambridge, MA 02138
October 2007

We would like to thank Severin Borenstein, Dallas Burtraw, Jim Bushnell, Judy Chevalier, Kevin Forbes, Jun Ishii, Nat Keohane, Al Klevorick, Robert Mendelsohn, V. Kerry Smith, Chris Timmins, Frank Wolak, an anonymous referee, and seminar participants at the University of California Energy Institute, Camp Resources, and Yale University for comments. Thanks also to Meredith Fowlie and Nalin Sahni for excellent research assistance. Holland thanks the University of California Energy Institute for generous research support during this project. The views expressed herein are those of the author(s) and do not necessarily reflect the views of the National Bureau of Economic Research.

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NBER Working Paper No. 13508
October 2007
JEL No. L51,L94,Q53

ABSTRACT

Real-time pricing (RTP) of electricity would improve allocative efficiency and limit wholesalers' market power. Conventional wisdom claims that RTP provides additional environmental benefits. This paper argues that RTP will reduce the variance, both within- and across-days, in the quantity of electricity demanded. We estimate the short-run impacts of this reduction on SO2, NOx, and CO2 emissions. Reducing variance decreases emissions in regions where peak demand is met more by oil-fired capacity than by hydropower, such as the Mid-Atlantic. However, reducing variance increases emissions in more US regions, namely those with more hydropower like 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.[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. However, these recommendations have met serious political opposition despite advances in real-time metering and in technology for responding to real-time prices.[2] Recently some environmental groups have supported real-time pricing for its potential to reduce pollution.[3] Indeed, the conventional wisdom seems to be that RTP will yield environmental benefits.[4]

RTP may affect the environment in several ways. In the short run, changes in generation will affect emissions, water discharge, nuclear waste production, and fossil fuel use. In the long run, RTP will affect 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, SO_2, nitrogen oxides, NO_x, and carbon dioxide, CO_2, for various U.S. electricity regions.[5]

RTP may affect emissions by changing the distribution of electricity load.[6] 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.[7]

Decreasing the variance of load can increase or decrease emissions. Firms use different power sources to produce electricity including *fossil* fuel sources (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.[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] 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.[10] 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.

In using historic data, our retrospective analysis will not capture adaptation to RTP by generators, consumers, and entrepreneurs. Furthermore, RTP may induce a change in the locational distribution of load. Finally, investment in generation, transmission, and consumption technology will likely be affected by RTP. Our analysis only addresses the short-run effects of reducing load variance and does not capture all of the ways in which RTP may or may not be green.

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.

2 Empirical Model

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

$$\begin{aligned} \ln(E_t) &= -\beta \cdot \ln(VAR_t) + \gamma_1[\ln(MEAN_t)] + \gamma_2[\ln(MEAN_t)]^2 \\ &\quad + \sum_{s=1}^{S*12} \delta_s TEMP_{st} + \sum_{m=1}^{48} \phi_m MOYR_{mt} + \epsilon_t, \end{aligned} \tag{1}$$

where E_t is emissions in the region on day t; VAR_t measures *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, ϵ_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 variation.[13] The negative log-log functional form allows β to be interpreted as the elasticity of emissions with respect to a *reduction* in the variance measure.[14]

The nonlinear relationship between emissions and generation 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.[15]

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.

We define the dependent variable, *system emissions rate*, as $\frac{E_\tau}{q_\tau}$, where q_τ is the hourly load. For hour τ, the model estimated is:

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

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 a MWh from a high-load hour to a low-load hour for a given decile of average load.

3 Data

As is common in electricity modeling, our level of analysis is a North American Electric Reliability Council (NERC) region (see Figure 1 for the ten regional definitions).[16] The council initially defined the regions in order to ensure a reliable, adequate, and secure system, and there is substantial transmission and communication within each region. For example, during our sample period, only seven percent of local demand was met by generation from other NERC regions.[17] We could have defined a coarser level (such as interconnection) or finer level (such as utility or control area) of analysis. We argue that NERC regions are the appropriate level of aggregation because of the trading that occurs within NERC regions and because of the transmission constraints between NERC regions.[18]

The environmental impacts are likely to be sensitive to the production technologies in each of the ten NERC regions. 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 generation in all of the regions except ERCOT and NPCC. Coal is typically the dirtiest of the fossil fuels.[19] 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_2 emissions and much lower NO_x 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.[20] 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. We compare variation *across* days by normalizing the standard deviation of mean daily load. The regions with the most variation across days are SPP and ERCOT.[21]

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 regions are not quite as substantial as in the across-day variation measures.[22]

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.[23] 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_2, NO_x, and CO_2.[24] 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_2 and NO_x, and second highest levels of CO_2. On the other hand, WSCC is the cleanest region in all pollutants.[25] 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.[26] The CEMS data report hourly gross generation at each unit.[27] 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.[28]

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_2 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.[29] 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.

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. 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). These coefficient estimates are conditional on mean daily load, fixed effects, and temperature.[30] The coefficients are the effect on emissions of a reduction in within-day variance; for example, a positive coefficient suggests that RTP would increase emissions.

The estimates for SO_2 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_2 emissions. In one region, MAIN, the negative coefficient indicates that a reduction in within-day load variance would decrease SO_2 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_2 emissions.[31]

The estimates for NO_x and CO_2 are similar to the SO_2 estimates. For NO_x, three of the regions have positive effects and three have negative effects. For CO_2, five regions have positive coefficients, and two regions have negative coefficients. For both pollutants, the coefficients are generally more negative than the SO_2 coefficients but are still relatively small (the estimated elasticity with the largest magnitude is -0.04).

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.[32] 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.[33] For example, in the WSCC, a percent increase in system load on the lowest-load day leads to a 1.4% increase in SO_2 emissions, whereas a percent increase on the highest-load day leads to a small increase in SO_2 emissions (0.04%).[34]

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.[35]

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_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 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.[36]

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 within-day variation. Here the largest elasticity in magnitude is -3.4 compared to the largest within-day elasticity of -0.04. This suggests that the largest environmental effects are likely to come from policies that reduce variance across days rather than within days.

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.[37] The independent variables are identical to those in the regressions reported in columns (i) to (iii) of Tables 4 and 6.[38]

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.[39] 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.[40]

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 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 evaluate the constraints of the parametric model using the nonparametric model described in Section 2. We estimate Equation 2 and correct the standard errors for serial correlation and heteroskedasticity.[41] 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.[42]

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.[43] Table 7 reports the findings of this simulation.[44]

We compare the within-day effects of the parametric method (Table 4) with those of the nonparametric method (Table 7). The primary difference between the two estimators is that the nonparametric estimator puts more weight on the tails of the distribution. 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.[45] These differences suggest that the environmental effects of RTP may depend on how it affects the entire load distribution.

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.[46] Furthermore, we find that the across-day variance effects are larger than the within-day effects.[47]

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.[48]

The regions with hydro shares larger than oil shares are ECAR, ERCOT, MAPP, SERC, SPP, and WSCC. In all of these regions (except SPP with no effect) we find that a reduction in within-day variance leads to an increase in emissions (see Table 4). 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 affect the dispatch of hydropower.[49] Given data constraints, we use our 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.[50] We find that our results are robust to this model, particularly in regions with little inter-regional trading.[51] 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, has claimed that RTP has an additional benefit, namely, reduced emissions from reduced peak demand. This paper analyzes the short-run environmental impacts of real-time pricing by estimating the effect of load variation on emissions of SO_2, NO_x, and CO_2. 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. These findings do 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. 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 (2006) 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, this paper does not capture ways that generators, retailers, and consumers may adapt to RTP. For example, generators (and load serving entities) may adapt by changing the types of retail contracts offered. In addition, our estimates do not capture the environmental effects 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. For competitive markets, Borenstein and Holland (2005) show that investment could theoretically increase with RTP adoption. Thus the long-run environmental benefits of RTP adoption are unclear. Finally, our results are not specific to RTP and apply equally to regulatory programs or market mechanisms affecting the variance of the electricity load in the short-run.

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Notes

[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 *et al.* (2002), and Borenstein and Holland (2005) study real-time pricing, defined as prices that vary hour by hour, in competitive electricity markets.

[2]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.

[3]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.

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

[5]Some argue that anthropogenic emissions of CO_2 may actually be beneficial. We make no assertions about the net benefits of CO_2 emissions. RTP may affect other emissions not studied here, including particulate matter and mercury.

[6]See Borenstein and Holland (2005) and Holland and Mansur (2006) for detailed theoretical models of RTP adoption.

[7]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.

[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 of ramping production up and down.

[10] 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 (2002), 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 (2006) simulate the effect of real-time pricing on load.

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

[12] Our estimation can be interpreted as a "reduced form" of a two stage model. Namely, emissions are a function of generation, which is likely endogenous. We could instrument generation with load distribution variables. However, to simulate RTP, we would need to perturb the instruments and measure the effect in each of the two steps. Instead, we estimate the indirect effect of load distribution on emissions.

[13] 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).

[14]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.

[15]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.

[16]The Department of Energy's National Energy Modeling System (Energy Information Administration, 2003) uses 15 NERC regions and subregions, and Resources for the Future's Haiku model (Paul and Burtraw, 2002) uses 13 NERC regions and subregions.

[17]Platts reports energy trading data between the 150 control areas. Over 80 percent of all the energy traded occurred within NERC regions.

[18]If we separately analyze California, the results differ from the results for the WSCC. A large share of California's demand for energy is met by imports over the AC network (about 22 percent) and direct DC lines to Los Angeles from coal plants in neighboring states (another 20 percent) (California Energy Commission, 2006). Therefore, ignoring importers' emissions could yield spurious results. Without developing a detailed model of transmission constraints, we argue that the WSCC coefficients approximate how emissions would change with RTP adoption in California.

[19]For example in MAAC, the SO_2 emissions rates (in lbs per MWh) are 20.3, 0.0, and 7.0 for coal-, gas-, and oil-fired generation. NO_x emissions rates are 5.8, 0.9, and 3.5 respectively,

and CO_2 emissions rates are 2198, 1423, and 1790. These data are described in Holland and Mansur (2006).

[20]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.

[21]The coefficient of variation of mean daily load for SPP and ERCOT are 0.194 and 0.193, respectively. In contrast, the coefficient in the WSCC is only 0.088.

[22]With the exception of FRCC at 0.20, the coefficients are similar across regions (averaging 0.11 to 0.15). FRCC likely has greater within-day variation because of residential customers' demand for air conditioning (over 50 percent of FRCC load is residential whereas it is approximately 33 percent in other regions).

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

[24]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).

[25]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.

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

[27]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.

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

[29]A detailed examination of the results for one equation, ECAR SO_2, are presented at: http://www.som.yale.edu/faculty/etm7/papers/holland_mansur_rtp_pollution_append.pdf

[30]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.

[31]As noted by a referee, these small effects may be an artifact of the SO_2 market, which has already dramtically reduced emissions.

[32]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.

[33]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.

[34]This is not surprising since peak loads in the WSCC tend to be met with hydropower.

[35]The standard errors are calculated from the covariance matrix of the parameter estimates

using the delta method.

[36]FRCC has a negative effect in SO_2 but positive effects in NO_x and CO_2. ERCOT has a negative effect in NO_x but a positive effect in CO_2.

[37]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.

[38]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.

[39]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.

[40]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. 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.

[41]As this section attempts to estimate the impacts of real-time pricing using a nonpara-

metric 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.

[42]See Appendix B for a depiction of one of the regressions.

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

[44]The standard errors in Tables 7 and 8 are estimated using the delta method.

[45]For example, the decreased emissions in MAIN are no longer significant with the nonparametric estimator.

[46]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.

[47]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.

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

[49]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.

[50]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.

[51] 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.

Tables and Figures

Table 1

Shares of Installed Capacity and Generation

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: Shares are of total capacity or total generation for utilities and non-utilities. Renewables are the missing share. Net generation is electricity produced for external sale. GWh are gigawatt-hours, or 1000 MWh. Source is EPA eGRID for 2000 (http://www.epa.gov/cleanenergy/egrid/index.htm).

Table 2

Summary Statistics of Load and Temperature

Region	Mean Daily Load	Max Daily Load	Coefficient of Variation	Mean Daily Temperature
ECAR	59.6	67.5	0.11	52.6
	[6.5]	[8.2]	[0.03]	[17.2]
ERCOT	30.6	36.6	0.14	68.1
	[5.9]	[8.5]	[0.04]	[14.1]
FRCC	20.6	25.9	0.20	72.6
	[3.4]	[4.6]	[0.03]	[9.5]
MAAC	28.8	33.6	0.14	55.2
	[3.9]	[5.0]	[0.03]	[16.2]
MAIN	26.5	30.4	0.12	52.1
	[3.5]	[4.6]	[0.03]	[18.5]
MAPP	13.8	15.8	0.12	46.9
	[1.7]	[2.2]	[0.03]	[20.5]
NPCC	24.2	28.6	0.15	47.6
	[3.0]	[3.7]	[0.02]	[17.3]
SERC	75.2	88.0	0.13	62.7
	[10.7]	[14.9]	[0.04]	[14.6]
SPP	20.2	23.6	0.13	58.6
	[3.9]	[5.5]	[0.04]	[18.3]
WSCC	86.8	100.4	0.12	53.3
	[7.6]	[9.7]	[0.02]	[14.4]

Notes: Table displays the sample mean with standard deviation in brackets. Load data (in GW) are from FERC Form 714. Temperature data (in degrees Fahrenheit) are from NOAA.

Table 3

Summary Statistics of Emissions and Generation

Region	SO_2 Rate	NO_X Rate	CO_2 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: Table displays the sample mean with standard deviation in brackets. 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). The sample period is from January 1997 to December 2000, except MAPP does not include 2000. Days of daylight savings transitions are dropped. Source is EPA CEMS.

Table 4

Parametric Estimation of Within-Day Effects

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: 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 (#). 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.

Table 5

Parametric Estimation of Across-Day Elasticity Ranges

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: 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 Across-Day Effects

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: We simulate a reduction in across-day 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 Within-Day Effects

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: 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 (#). 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.

Table 8

Non-Parametric Simulation of Across-Day Effects

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)

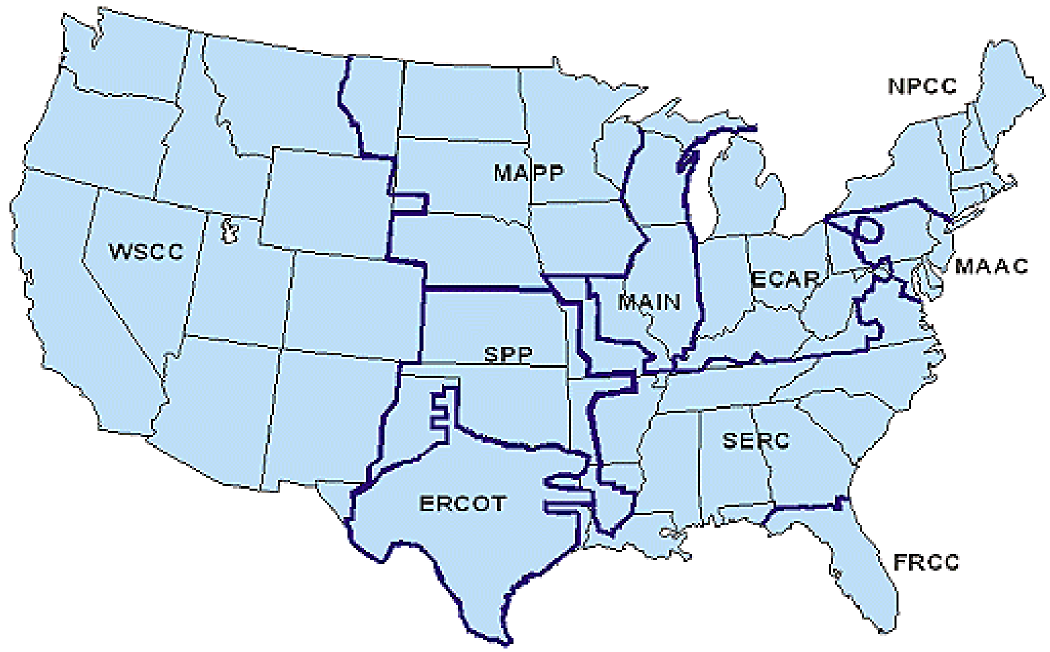
Notes: Table presents simulation based on OLS coefficients. Standard errors, in parentheses, have been corrected for heteroskedasticity and serial correlation using the Newey-West method assuming a six hour lag structure. We note significance at 5% level using (*) or at 10% level using (#). Regression 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.

Table 9

Peak Capacity Shares of 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: Peak includes oil, gas, and hydroelectric. The data are from the EPA eGRID for 2000 (http://www.epa.gov/cleanenergy/egrid/index.htm).



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)

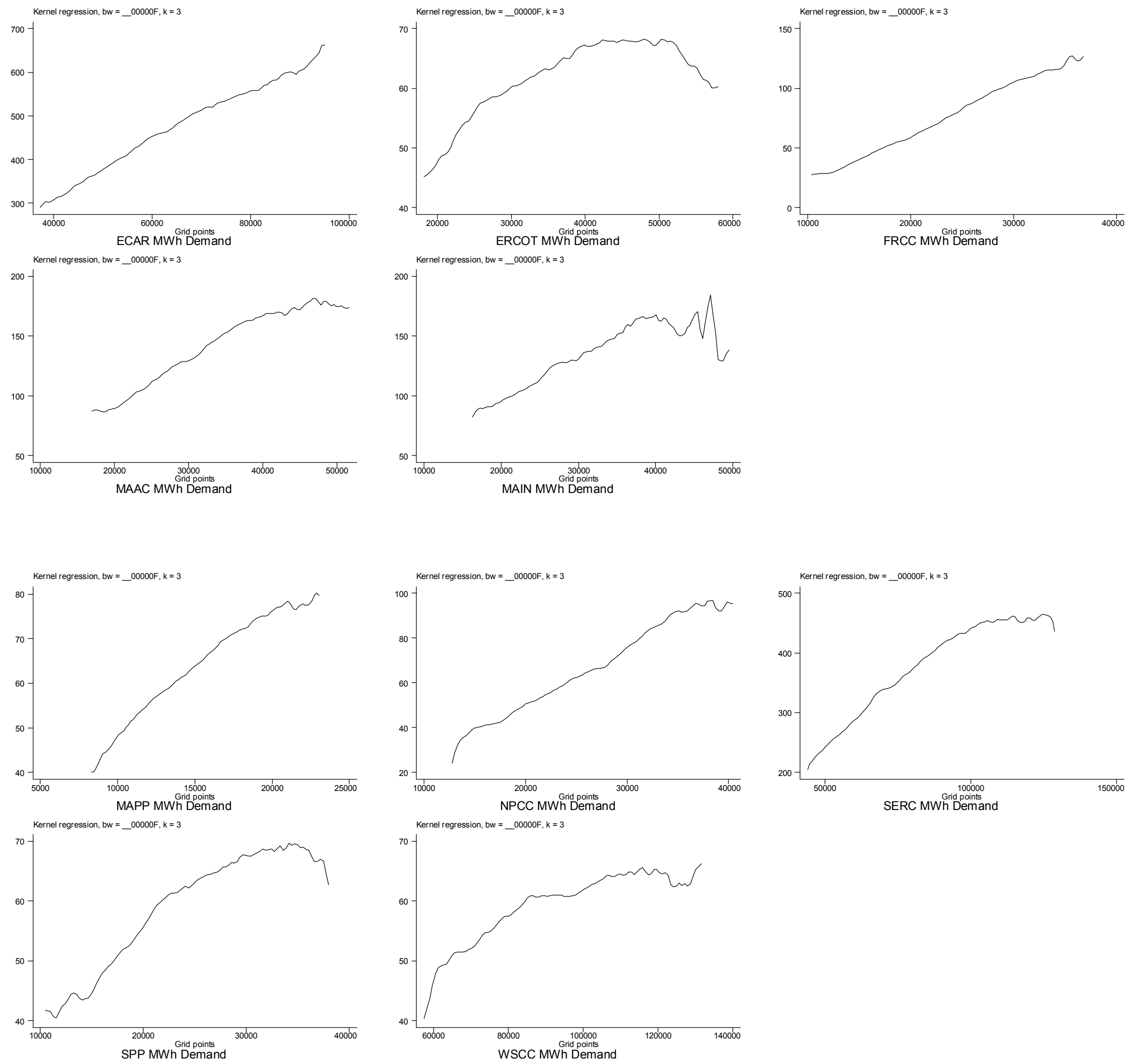


Figure 2. Kernel regressions of pounds of sulfur dioxide on MWh of electricity demanded.

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_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.[52] For CO_2, in nine of the ten regions, all the coefficients had either the same sign or the same significance.[53] 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_2 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_2 emissions rate decreases with hourly demand. Across regions and pollutants, we find substantially different patterns.

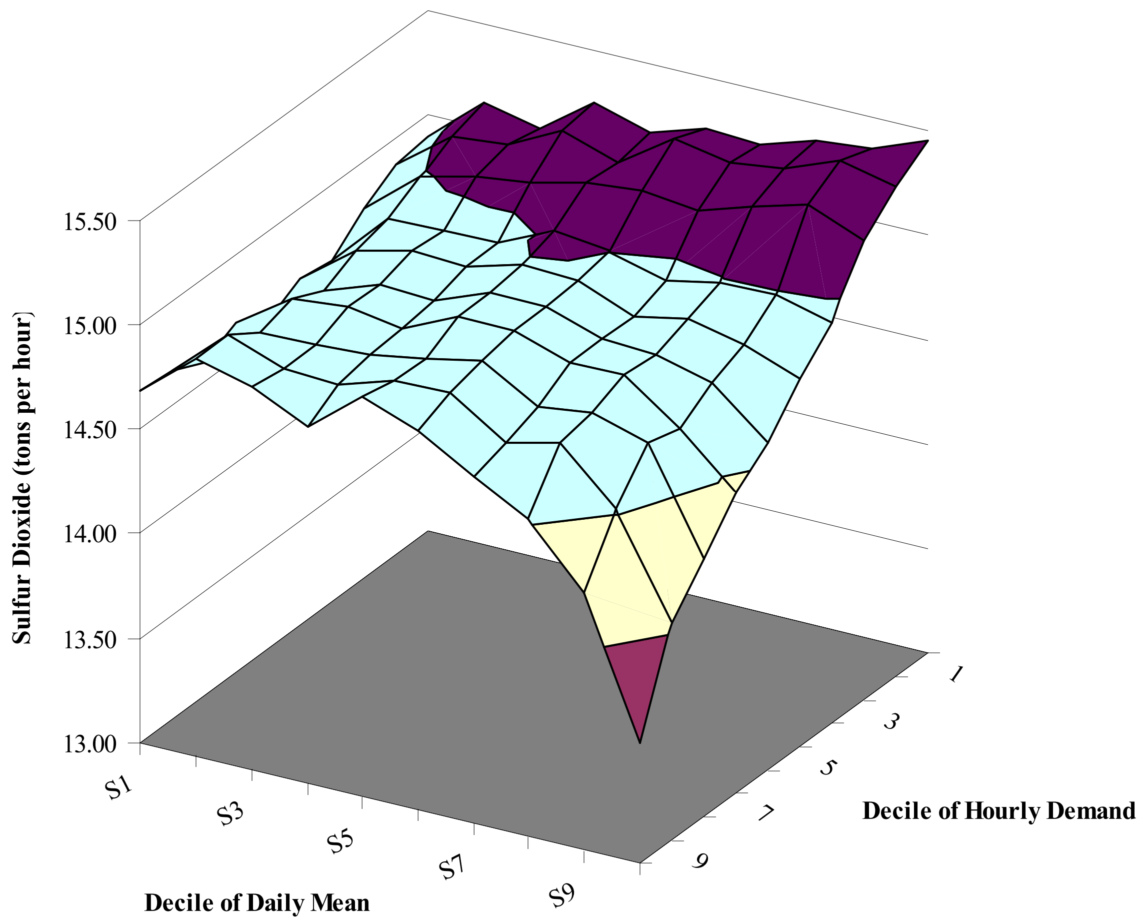


Figure A1. Plot of nonparametric estimation coefficients for ECAR SO_2 system emissions rate.