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"Electricity Sector Demand for Natural Gas in the United States"

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Abstract

We examine determinants of the natural gas share in power generation for the NERC regions in the US. Our results indicate that plant and grid-level fuel-switching, technology in generation, installed capacity and weather all affect the natural gas share of energy input into power generation. Furthermore, we argue that fuel-switching is likely an important demand-side factor in establishing a long run relationship between the prices of petroleum products and natural gas. We estimate two specifications – a translog specification for expenditure share and a double logarithmic transformation of gas-fired capacity utilization – because our analysis calls into question the validity of the translog specification for analyzing fuel shares in the power generation sector.

1. Introduction

Natural gas has risen from around 12% of energy used to generate electricity in the United States in the early 1990s to around 21% in 2008. Over the same period, oil products' share has fallen from about 4% to about 1%. Although these trends need not imply a long run substitution of gas for oil products in power generation, in this paper we present evidence of such substitution in the various North America Electric Reliability Council (NERC)[2] regions of the United States during the period January 1992-December 2006. Specifically, we show that changes in the relative price of natural gas to oil products, controlling for the improvements in heat rates (or thermal efficiencies) of natural gas plants that have resulted from the development of combined cycle gas turbines (CCGTs), have influenced demand for the fuels as inputs to electricity generation.

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[2] A map of the NERC regions and subregions used in the analysis is included in the appendix as Figure 1.

An implication of our results is that, as long as both natural gas and oil products continue to be used to generate electricity, fuel prices have to adjust to keep both fuels competitive at the margin. In particular, changes in the relative heat rates of plants that burn natural gas and oil products should shift the long-term relative prices of natural gas and oil products. This paper therefore provides direct microeconomic evidence complementing the analysis of aggregate time series data presented by Hartley, Medlock and Rosthal (2008), which showed that substitution between natural gas and oil products in electricity generation has maintained a link between their prices in recent decades.

There are several reasons why substitutability between natural gas and oil products can be relatively high in the electricity sector. To begin, some individual electricity-generating plants can substitute fuel oil for natural gas at relatively low cost. More importantly, however, so-called grid-level switching occurs when changes in relative fuel prices alter the relative position of different types of plants in the dispatch order (or supply stack) and hence the length of time that different plants are operated.[3] As natural gas plants are used less often, the demand for natural gas will decline while oil product demand increases.

While we focus on oil products as the key competing fuel for natural gas, we also consider competition with coal. We find some evidence that coal prices affect natural gas demand in some NERC regions, but the analysis suggests coal may be a complement to natural gas rather than a substitute. The absence of coal prices at the regional level, however, may introduce a bias to these results.

We do not examine potential substitutability (or complementarity) between natural gas and non-fossil fuel sources of electricity (such as nuclear, hydroelectricity or wind). As we explain later, this is partly the result of data limitations, but technological factors also severely limit the ability of generators to substitute between natural gas and many of these alternative non-fossil sources of energy.

[3] For combined-cycle plants, the competing oil-based fuel will likely be residual fuel oil, while for simple cycle gas turbines, the competing oil-based fuel will likely be distillate.

2. Previous Literature

In an influential early study, Hudson and Jorgenson (1974) examined electric utilities as part of a wider study of the role of energy in U.S. industry. They focused mainly on linkages between nine key industry sectors and the relationship of those industries to macroeconomic factors and economic growth. They estimated a system of equations, assuming a translog structure for the price possibility frontier[4] for each sector with factor inputs of capital, labor, materials and energy composite goods. The industries producing the energy composite input for each sector were also modeled using translog price possibility frontiers with five inputs or outputs of coal, crude oil and wellhead natural gas grouped together, refined petroleum products, electricity and marketed natural gas. Hudson and Jorgenson contrasted their approach with the then prevailing input-output, or Leontief, approach for analyzing interactions between the energy sector and the rest of the economy. They emphasized that the translog price possibility frontier allows energy inputs to adjust in response to variations in relative fuel costs while the Leontief approach assumed fixed energy input-output coefficients. Much of the subsequent literature examining fuel consumption in the electricity industry has followed the Hudson and Jorgenson translog approach.[5]

Atkinson and Halvorsen (1976) also estimated a translog functional form in a study of interfuel substitution in U.S. electricity generation using a sample of multiple-fuel plants for a single year (1972). However, they focused on a profit function rather than a price possibility frontier. Atkinson and Halvorsen note that the tiered structure for production assumed by Hudson and Jorgenson is tantamount to assuming fuel inputs are weakly separable from other inputs. The more general specification estimated by Atkinson and Halvorsen allows separability to be tested, and in most cases it was

[4] The translog (transcendental logarithmic) production function assumes that the output of a firm or industry can be written as a quadratic function of the logarithms of the factor inputs. For example, if the output is Q and various input factors of production, denoted F_i, $i = 1,\ldots 4$ the production function is

$$\ln Q = a_0 + \sum_{i=1}^{4} a_i \ln F_i + \sum_{i=1}^{4}\sum_{j=1}^{4} a_{ij} \ln F_i \ln F_j$$

The price possibility frontier, the dual of the production possibilities frontier, depicts the input and output prices for which profits are constant and equal to zero. It implicitly assumes a competitive industry with free entry, which is of questionable relevance to regulated utilities in the United States at that time.

[5] One attractive feature of a translog specification is that it can be viewed as a second-order approximation to a more general function.

rejected. They also found evidence of substantial interfuel substitution. A methodological innovation of their paper that was carried over to subsequent studies is that they treated non-energy factors of production as fixed inputs and thus included them as control variables in the fuel demand equations.

Uri (1977) estimated a translog price possibility frontier for pooled annual data during 1952–74 in each of 10 census regions using a structure similar to Hudson and Jorgenson. He found that regions with the greatest proportion of installed multiple-use capacity had the most elastic demand, while lower elasticities were found in regions where a single fuel represented a high proportion of total fuel costs. Uri (1978) estimated essentially the same model as Uri (1977), but used monthly data covering a shorter time period (July 1972–December 1976) for 10 regions that consisted of slightly different groups of states than the census regions.

In a comment on Uri (1977), Hogarty (1979) noted that although Uri used census regions, firms or plants compete in power pools or NERC regions, and the geographical boundaries of the power pools are not shared with census regions. Hogarty also noted that environmental policies alter the desirability of different fuels, but these were not taken into account. Finally, Hogarty claimed that fuel switching at the plant level was quite uncommon (especially in the short run) and that running plants for different periods of time (that is, changing their order in the supply stack) was the primary manner through which substitution occurred.

Uri (1982) employed a constant elasticity of substitution (CES) production function, and a translog price possibility frontier to determine fuel shares in producing the aggregate energy commodity. The translog fuel shares model was estimated using pooled annual data from 1961–78 compiled by census region.[6]

Bopp and Costello (1990) followed Atkinson and Halvorsen (1976) by including generating plant capacities as regressors, meaning the factor demand curves can be interpreted as short run demands holding capital fixed. They estimated a short run cost curve that was assumed to be translog in the fuel prices and various “shift factors”:

[6] Perhaps as a result of nonstationarity of the fuel prices, Uri found that the error terms were strongly serially correlated with a first order correlation coefficient of 0.9762 (standard error of 0.0127).

$$\log C = a(0) + \sum_i a_i \log p_i + \frac{1}{2} a_q (\log q)^2 + \frac{1}{2} \sum_i \sum_j a_{ij} \log p_i \log p_j +$$
$$\sum_i a_{qi} \log q \log p_i + \frac{1}{2} a_A (\log A)^2 + \sum_i a_{Ai} \log A \log p_i$$

where C is short run fossil fuel generating costs, p_i are the coal, oil and gas prices to utilities deflated by the producer price index and q is total fossil fuel (coal, oil and gas) generation. The set of variables A represents the shift factors, which include the generating capacities of the different types of plants, total hydro and nuclear generation (taken as exogenous), and heating and cooling degree days (used to control for shifts in weather sensitive demands). Bopp and Costello also included the lagged short run cost as a shift factor motivated by contractual arrangements that could delay short run adjustments to fuel price changes. They then noted that Shephard's lemma implies that the derivative of C with respect to p_i yields the conditional demand for the ith input and hence concluded that the share of the ith input in costs satisfies

$$S_i = a_i + a_{qi} \log q + \sum_j a_{ij} \log p_j + a_{Ai} \log A .$$

Since the cost function is homogeneous of degree 1 in prices, and the factor shares add to 1, $\sum a_i = 1$ and $\sum_i a_{qi} = \sum_i a_{Ai} = \sum_i \sum_j a_{ij} = 0$. The restrictions imply that only two input demand equations need to be estimated. The third follows by summing the constraints.

Bopp and Costello estimated the model using monthly data during 1977-87 for four major census regions of the United States, with the southern region split into western and eastern zones to make a fifth region. They found that the fuel used to supply base load power in each region had the most inelastic demand. In addition, they demonstrated that when the price of the base load fuel changed, the largest substitution was toward the fuel most used for intermediate and peak loads in that region. They also estimated the same model at the national level, but found that the regional models performed better.

Ko and Dahl (2001) reviewed the electric fuel substitution literature, including some of the articles mentioned above. They noted that the early literature (including Atkinson and Halvorsen (1976) and Haimor (1981)), which had focused on cross-sectional data, found that the highest substitution elasticity existed between oil and coal. Ko and Dahl attributed this early trend to price controls in the natural gas market, and also noted that few studies had been published in the 1990s, when market structure would have changed substantially. They noted that a more recent paper, McDonnell (1991), indicated a greater substitutability between gas and coal. Additionally, they noted that studies using data from the 1970s through the early 1990s largely agreed that oil was the most own-price elastic fuel.

Ko and Dahl updated the literature, drawing on the increased availability of data from Federal Energy Regulatory Commission (FERC) Form 423 ("Monthly Report of Cost and Quality of Fuels for Electric Plants"). Specifically, they analyzed cross sectional data for 185 utilities in 1993 that burned at least two of coal, oil or natural gas. They divided utilities into four groups based on their use of different combinations of the three fuels (coal and oil, coal and gas, oil and gas, and all three). They found that for utilities that use all three fuels, the own-price elasticity is highest for oil, while cross-price elasticities indicate that coal is a substitute for both oil and natural gas, but oil and gas are not substitutes for one another. For utilities that use only two types of fuels, oil and natural gas appear more responsive to coal prices than coal to either oil or natural gas prices, but all fuels appear to be substitutes for one another.

Söderholm (2001) argued that short run interfuel substitution can occur due to physical modifications of existing generating capacity as well as via switching of inputs by dual-fired generators and grid-level changes in the dispatch order.[7] Using a translog cost function and annual data for six Western European countries in a panel model with fixed effects for each country, he estimated fuel input share equations for coal, oil, and gas. He expanded on the literature by including the effect of a load factor, defined as the total generation relative to peak demand, noting that an increased load factor indicates a higher percent of base load generation, decreasing the cost share of peaking fuels (oil and gas). Söderholm estimated one model in which the effect of the load factor was constrained to be zero, and one in which the load factor coefficient was unconstrained. From the estimates, he derived own- and cross-price elasticities of demand for each type of fuel. He found some positive own-price elasticities, which may reflect nonconcavity in

[7] Since plant modifications take some time, however, it is debatable whether they should be considered short run. Perhaps it would be more accurate to call them intermediate-run, since modifications probably can be made more quickly than building new plants.

the cost function or a violation of the assumption that the translog functional form adequately approximates the underlying technology. Nevertheless, the results indicated significant cross-price elasticities, especially between peaking fuels, while the own-price elasticity of base load fuel (coal) was low.

The above publications provide evidence of interfuel substitution. We are interested, however, in the more specific question of whether the substitution is strong enough to maintain a long-term link between natural gas and oil product prices, and furthermore, whether changes in the heat rates of gas-fired generators have altered that long-term relationship. These concerns require that we examine the substitutability between natural gas and oil products in the electricity industry over an extended period of time. Most of the above studies used a cross-section of plants in a given year rather than following a sample of plants over a number of years.

One complication with using time series data is that the real fuel prices and technology are unlikely to be stationary. Indeed, our hypothesis that changes in the heat rates of natural gas plants have altered the long-term relationship between natural gas and oil product prices posits a cointegrating relationship between nonstationary variables.

There also is a relatively recent literature examining cointegration of fuel prices in the context of the electricity industry. For example, a recent paper by Hartley, Medlock and Rosthal (2008) investigated cointegration of natural gas prices, oil product prices and electric plant heat rates at the aggregate level. Their results form a foundation for what is presented herein. Specifically, in this paper we examine the issue at a more microeconomic level using a panel data set of U.S. electricity-generating plants measured monthly over the period January 1992–December 2006. Our analysis thus draws on both the cross-sectional and time series literatures discussed above.

3. Real input costs

Our analysis is based on the hypothesis that an electricity generating firm chooses among alternative fuels to minimize costs. Furthermore, if we take capital and labor as fixed inputs in the short run, the variable cost of generating electricity, in dollars per megawatthour (*$/MWh*), is given as the heat rate (*Btu*/*MWh*) times the fuel price ($/*Btu*). As a result, the relative heat rate between two plants using different fuels is fundamental to the decision to choose among alternative fuels, and so is part of the relationship between the prices of various competing fuels such as natural gas and oil products.

Figure 2 depicts the capacity-weighted average heat rate for natural gas-fired generation capacity in each NERC region over the period 1992–2006. Figure 3 shows that the reduction in heat rates has been accompanied by a rapid expansion in high efficiency CCGT generation capacity. In addition, no such improvement in heat rates has occurred over the same time period for the oil-fired generation capacity (not pictured).

We allow the relative *cost* of generating electricity using either natural gas or oil to affect the demand for natural gas as a fuel input. Specifically, for each NERC region i in each period t, we form a capacity-weighted real cost of natural gas using the plant-specific heat rates and the average electricity price as deflator

$$NGRCost_{it} = \frac{\sum_{j=1}^{N_{it}} K_{ij} HR_{ij} P_{ijt}^{NG}}{P_{it}^{E} \sum_{j=1}^{N_{it}} K_{ij}} \tag{1}$$

where N_{it} equals the number of natural gas-fired plants on-line in region i in period t. The capacity of plant j is K_{ij} and its heat rate (obtained from the Environmental Protection Agency's (EPA's) NEEDS 2006 data) is HR_{ij} (see appendix 2 for more details). The natural gas price P_{ijt}^{NG} can differ for each plant in each region and period. We use the state-specific city gate price reported by the Energy Information Agency (EIA) for plants located in a given state.[8] This procedure allows electricity generation to adjust to persistent basis differentials between states with deviations from those differentials driving changes in demand. Similarly, the electricity price P_{it}^{E} for region i in period t is a weighted average of state electricity prices with the weights given by the proportion of overall generating capacity within the NERC region that is located in a given state.

The NERC region petroleum product costs were constructed similarly to natural gas costs except we used product prices reported at the Petroleum Administration

[8] The 0.3% of city gate prices that were missing as a result of confidentiality restrictions were imputed using a regression of the nonmissing values of the state city gate price on the average U.S. city gate price.

Defense District (PADD) level since state-specific prices were not available.[9] Real coal costs also were calculated in a similar manner using region-specific heat rates. However, the coal price data, which was obtained from the EIA, was an average delivered price to electric generators throughout the United States and was not differentiated by region.

Table 1 presents test statistics for the null hypotheses that the natural log of the real cost variable is nonstationary for each fuel and region. The real oil cost variable appears to be nonstationary in every region.

In the case of natural gas, the *p*-values for the test of nonstationarity suggest that the hypothesis certainly can be rejected in three and perhaps as many as nine regions (ERCOT, FRCC, MAAC, MAIN, MAPP, NPCCI, NPCCN, WECC, and WECCC). However, the test in the final column of Table 1 provides contrary evidence. Although the real oil cost variable appears nonstationary in all regions, a linear function of the real natural gas and real oil costs is stationary in every region. Specifically, we estimate a long run relationship between real natural gas and oil generation costs in each of the 13 NERC subregions by regressing the natural logarithm of the real natural gas cost on the natural logarithm of the real oil cost

$$\ln NGRCost_{it} = \beta_0 + \beta_1 \ln OilRCost_{it} + \omega_{it} \tag{2}$$

The test result in the final column of in Table 1 reveals that $\hat{\omega}_t$ is stationary in every NERC region, implying that natural gas costs and oil costs are cointegrated.

The graph of the real natural gas cost variables in Figure 4 shows that the trend is similar in all regions. In the regions where we can reject the hypothesis of nonstationarity, however, the variability is much higher, which could lead to a spurious rejection of the null hypothesis. We conclude that the evidence of stationary real gas costs in some regions results from some (stationary) high variance components in real gas costs that mask the nonstationary component that real gas costs share with real oil costs.

Finally, the real coal cost terms appear to be stationary in all but three subregions, ECAR, FRCC and WECC. Since the coal prices we have used do not vary by region, slight differences in the temporal variations in the coal heat rates across regions must be

[9] As with the calculation for natural gas prices, the 5% of observations (0.8% if we omit PADD 4) that were missing were interpolated using a regression of nonmissing values on the U.S. average price.

driving the result. However, the technology for generating electricity from coal has not changed much in recent years, making the apparent nonstationarity of the real coal cost in these three subregions difficult to explain.

4. Translog expenditure function model

We first estimate a translog model, similar to Bopp and Costello (1990) and other previous literature, for each NERC subregion. To calculate the expenditure share, we multiply the cost of each fuel (as calculated above) times the amount of that fuel consumed in each subregion in each month. The natural gas expenditure share was then calculated as the ratio of the real expenditure on natural gas to the real expenditure on all fossil fuels (gas, oil and coal).

We take total fossil fuel generation in the region (*FE*) as the output measure. We use fossil fuel generation rather than *total* electricity generation as the determining variable because dispatch of a substantial amount of the non-fossil fuel generating capacity is unresponsive to fuel price changes or even changes in the total system load. For example, wind generation and "run-of-river" hydroelectric generation is determined by natural factors independent of load or the cost of competing sources. Also, while nuclear plant output could in principle respond to short run demand or cost variations, it is expensive and technologically complicated to do so. Substitution between nuclear and fossil fuels occurs in the capacity planning phase. Once nuclear plants have been built, their low operating cost means they will be used as much as technically possible.[10]

Hydroelectric plants based on stored water are dispatched on an economic basis and would compete with gas-fired plants. The key determinant of the dispatch decision in those cases is the shadow value of the stored water (its marginal value in its next best alternative period of use), which is not easy to calculate. It would require data on factors such as reservoir capacities and storage levels, anticipated precipitation, local hydrological conditions, and anticipated future electricity prices. This is beyond the scope of our analysis, especially since such plants are not a major influence on gas demand in

[10] Recent increases in capacity utilization at nuclear plants have resulted from technical improvements and improved operational procedures, not from any response to relative fuel prices.

most NERC regions. Hence, we treat all non-fossil generation as exogenous and look at total demand net of such generation output.

The resulting translog expenditure function becomes (where we have suppressed t and subregion subscripts for simplicity and the index i represents the different fuel types):

$$\begin{aligned}\ln Exp = a + \sum_i b_i \ln RC_i + \sum_i c_i \ln\left(K_i \cdot HR_i\right) + d_1 \ln FE + d_2\left(\ln FE\right)^2 \\ + \frac{1}{2}\sum_i \sum_j e_{ij} \ln RC_i \ln RC_j + \frac{1}{2}\sum_i \sum_j f_{ij} \ln RC_i \ln\left(K_j \cdot HR_j\right) \\ + \frac{1}{2}\sum_i g_i \ln RC_i \ln FE + \frac{1}{2}\sum_i h_i \ln\left(K_i \cdot HR_i\right) \ln FE\end{aligned} \tag{3}$$

where the per unit real cost variables RC_i are defined as in equation (1). Also, the capacities of the different types of plant are adjusted for changes in heat rates since a decline in heat rates, other things equal, would reduce the demand for that fuel as an input. Using Shephard's lemma, we can calculate:

$$\frac{\partial \ln Exp}{\partial \ln RC_i} = \frac{RC_i}{Exp}\frac{\partial Exp}{\partial RC_i} = S_i$$

so that the resulting expenditure share function for natural gas in particular relates the expenditure share on natural gas to input costs per unit of fuel, capacities (weighted by heat rates) and total fossil fuel generation FE:

$$\begin{aligned}S_t^{NG} = \alpha_0 + \alpha_1 \ln RC_{NG,t} + \alpha_2 \ln RC_{oil,t} + \alpha_3 \ln RC_{coal,t} + \alpha_4 \ln HR_{NG,t} \cdot K_{NG,t} \\ + \alpha_5 \ln HR_{oil,t} \cdot K_{oil,t} + \alpha_6 \ln HR_{coal,t} \cdot K_{coal,t} + \alpha_7 \ln FE_t\end{aligned} \tag{4}$$

There are four primary differences between equation (4) and the specifications in previous models. First, while others have used cross-sectional or time series data, we use both in a panel approach. However, we also examine time series results for each NERC subregion, which allows us to compare how responsive different regions are to deviations in the long run cost relationship. Second, we account for technological changes in the electricity industry by using real per unit cost of each fuel adjusting for the efficiency of generation (heat rate). Third, since the petroleum product and natural gas costs are cointegrated, we use the cointegrating error term in place of logs of real natural gas and petroleum input costs. Specifically, we use

$$\hat{\omega}_t = \ln RC_{NG,t} - a_0 - a_1 \ln RC_{oil,t} \tag{5}$$

in place of the two terms $\ln RC_{NG,t}$ and $\ln RC_{oil,t}$. Equation (5) is estimated separately for each subregion using ordinary least squares (OLS). Because the natural gas and oil real cost terms are cointegrated, the resulting parameter estimates are superconsistent and the estimated error term, $\hat{\omega}_t$, can be used in subsequent regressions as if it were known. Moreover, the error term is interpreted as the deviation from the long run equilibrium between real oil and natural gas input costs. Deviations in the long run relationship ought to affect the electricity generation fuel mix in such a way that subsequent price adjustments tend to bring the relative costs of competing fuels back into line. Without accounting for cointegration, the translog specification would have integrated variables on the right hand side, potentially leading to mistakes in estimation and inference.

A further complication is that the contemporaneous error term, $\hat{\omega}_t$, will be correlated with the dependent variable since current fuel prices are used to construct the current natural gas expenditure share. Therefore, we use an instrumental variables estimator with the lagged value of the cointegrating residual as an instrument for $\hat{\omega}_t$.

We also assume (4) is a long run equilibrium relationship and include the lagged cost share as a regressor to allow for gradual adjustment. However, the coefficient on the lagged dependent variable is likely to be estimated inconsistently in the panel. We therefore use the twice-lagged dependent variable as an instrument for the once-lagged value in the panel estimation.

We also augment (4) by including the number of heating and cooling degree days in each subregion and month and a set of monthly dummies. A month that has a larger number of cooling degree days (*CDD*) will also typically have a higher demand for electricity to run air conditioning equipment. While ln*FE* will measure higher electricity demand in such months, more extensive use of air conditioning will also emphasize peaks in the load curve, compared to months with equivalent total electricity demand but less air conditioning. Since gas turbines are called upon to provide peak power, we expect a larger value of *CDD* to be associated with higher natural gas demand ($\alpha_{10} > 0$).

Months with a larger number of heating degree days (*HDD*) might also have an elevated demand for electricity for heating purposes. This effect is not likely to be large, however, since space heating is not a significant factor in electricity demand. On the other hand, natural gas is itself a major source of space heating services on cold days, thus making changes in *HDD* relevant to residential and commercial natural gas demand. Local natural gas prices therefore are likely to be driven higher in months when *HDD* is large. Such higher prices will be reflected in the cost differential term $\hat{\omega}_t$. However, electric generating companies might also hold natural gas contracts with interruptibility provisions that allow for quantitative reductions when natural gas demand is high. If so, a large *HDD* value would be associated with lower gas use regardless of any price effects.

The monthly indicator variables (*Month*) reflect many influences. A month with 31 days will see greater natural gas demand than a month with 30 (or 28) days, all else equal. The variable *Month* is also correlated with variations in weather. Hence, the effects of *CDD* and *HDD* should be interpreted as the marginal effects of *departures* of cooling or heating degree days from their normal monthly averages. The monthly indicator variables will also reflect seasonal regularities in natural gas price movements relative to oil. For example, seasonal effects in natural gas basis differentials will cause $\hat{\omega}_t$ to vary by season. Since the coefficient on $\hat{\omega}_t$ will reflect the effects of price fluctuations *holding the month fixed*, any response of natural gas demand to normal seasonal price fluctuations will be captured by the monthly indicator variables rather than $\hat{\omega}_t$. Finally, if generating facilities are taken off-line for maintenance at the same time each year, the monthly indicator variable will capture the resulting impact on natural gas demand.

With these modifications, the equation to be estimated (omitting the subscript *i* which represents the NERC subregion) becomes:

$$\begin{aligned} S_t^{NG} &= \alpha_0 + \alpha_1 S_{t-1}^{NG} + \alpha_2 \hat{\omega}_t + \alpha_3 \ln RC_{coal,t} + \alpha_4 \ln HR_{NG,t} \cdot K_{NG,t} + \alpha_5 \ln HR_{oil,t} \cdot K_{oil,t} \\ &\quad + \alpha_6 \ln HR_{coal,t} \cdot K_{coal,t} + \alpha_7 \ln FE_t + \alpha_8\, CDD_t + \alpha_9\, HDD_t + \sum_j \beta_j\, Month_t \end{aligned} \tag{6}$$

Equation (6) is estimated for the full panel and for each region using $\hat{\omega}_{t-1}$ as an instrument for $\hat{\omega}_t$. In the panel estimation, S_{t-1}^{NG} is also instrumented. The constant and the coefficients on the monthly indicator variables are allowed to vary by region. In particular, the panel estimation is a fixed effects estimator. The results are shown in Table 2. To save space, the constant terms, the estimated monthly effects and the regional fixed effects in the panel regression are omitted from the table.

The full panel estimation produces a negative coefficient on the cointegration error term, implying that a rise in unit real natural gas costs relative to oil costs reduces the share of gas in overall expenditure on fuels. This implies that, for the U.S. power generation system as a whole, natural gas and oil products are substitute fuels. The cointegration error terms also had statistically significant negative coefficients in five of the regions. In three of the remaining regions, the point estimate is negative but not statistically significant. The coefficient is unexpectedly positive in five regions, but positive and statistically significant in only one region (MAPP).

The positive coefficient on the real cost of coal in VACAR and MAPP suggests that coal and natural gas are substitutes in those regions. Furthermore, the negative coefficient on the coal capacity variable in several regions also hints at substitution between natural gas and coal. However, the negative coefficient on the real cost of coal in ERCOT, MAIN, NPCCI, SERC, and SPP suggests that natural gas and coal are complements rather than substitutes in those regions. The real coal cost is omitted from the panel regression since the variable is missing in California.

The coefficient on the lagged dependent variable in the full panel implies that the adjustment to an exogenous shock will be about 35% complete after three months, around 55% complete after six months and more than 70% complete after one year. The estimated speed of adjustment is slower, however, in most of the regions.

The natural gas heat rate weighted capacity was statistically significantly different from zero in the panel and in seven regions. However, in the MAIN region it was significant but with an unexpected negative sign. None of the oil or coal heat rate weighted capacity variables was significant for the panel as a whole, although at least one of the oil capacity variables was significantly different from zero in seven of the 13 regions. The coal capacity variable was also significant in seven regions.

The coefficient on total electricity generation from fossil fuels was significantly different from zero and positive for the panel as a whole, implying that a marginal increase in fossil fuel generation tends to increase the demand for natural gas. This was also true in eight of the regions, but in MAAC the coefficient on $\ln FE$ was negative and significantly different from zero.

Increased demand for air conditioning, as signaled by a higher value for *CDD*, raised the demand for natural gas relative to other fossil fuels in the panel as a whole and for eight of the 13 regions. By contrast, *HDD* was not significantly different from zero in the panel regression or in six of the regions. Furthermore, in four regions it was significantly positive while in the other three, it was significantly negative.

5. Plant-level switching

The translog results do not reveal a strong degree of substitution between natural gas and oil products in the generation of electricity. While higher natural gas costs reduce the natural gas expenditure share for the panel as a whole, the effect is statistically significantly negative in only five regions and is (weakly) significantly positive in one region. Yet there is substantial capability to switch fuels at the individual plant level in many areas from Florida to New York. The results showing little or no substitution between natural gas and oil products for the Florida (FRCC), Mid-Atlantic (MAAC), and, to a lesser extent, the Virginia and the Carolinas (VACAR) regions are thus somewhat surprising. We therefore investigate fuel switching at the plant level in more detail.

In our data set of all generating plants in the Lower 48 states that were available (although not necessarily generating) every month during January 1992-December 2006, 143 plants used natural gas in at least one month and a petroleum product in at least one month. Of these 143 plants, 131 used natural gas in at least one month and distillate in at least one month. Natural gas was used in at least one month and residual fuel oil in at least one month in 38 plants. Figure 5 gives the proportion of the flexible fuel plants in each NERC subregion. Almost 40% were in the FRCC, MAAC and VACAR regions, with another 25% in SERC and NPCCN (New York).

To investigate the responsiveness of fuel switching to relative costs, for flexible fuel plants *i* generating electricity in month *t* we estimated:

$$\begin{aligned} NGPct_{i,t} &= a_0 + a_1 NGPct_{i,t-1} + a_2 \hat{\omega}_{i,t} + b_1 CDD_{i,t} \\ &\quad + b_2 HDD_{i,t} + \sum_j c_j\, Month_{j,t} + \varepsilon_{i,t} \end{aligned} \tag{7}$$

where

$$NGPct_{i,t} = \frac{\text{NG Consumption}_{\text{i,t}}}{\text{NG Consumption}_{\text{i,t}} + \text{Oil Consumption}_{\text{i,t}}}$$

is the percentage of fuel input (measured in MMBtu) at plant *i* in month *t* that is natural gas and, as above,

$$\hat{\omega}_{i,t} = \ln RC_{i,t}^{NG} - \hat{\beta}_0 - \hat{\beta}_1 \ln RC_{i,t}^{Oil}$$

The cost variables, $RC_{i,t}^{NG}$ and $RC_{i,t}^{Oil}$ were calculated using facility specific heat rates and the petroleum product used at each facility.[11] The lagged dependent variable is included to allow for a slow response to changes in fuel prices. The latter could arise, for example, from hedges for delivered fuel volumes or fixed costs of changing the fuel source. Monthly dummy variables allow, for example, for systematic plant outages. Finally, we assume the error term includes a plant-specific component. For convenience, write the resulting random effects panel model, $y_{i,t} = x_{i,t}\beta + v_i + \varepsilon_{i,t}$. In our case, however, the dependent variable $y_{i,t}$ is always between zero and one:

$$\begin{aligned} y_{i,t}^o &= 0 && \text{if} \quad x_{i,t}\beta + v_i \le -\varepsilon_{i,t} \\ y_{i,t}^o &= x_{i,t}\beta + v_i + \varepsilon_{i,t} && \text{if} \quad -\varepsilon_{i,t} \le x_{i,t}\beta + v_i \le 1 - \varepsilon_{i,t} \\ y_{i,t}^o &= 1 && \text{if} \quad x_{i,t}\beta + v_i \ge 1 - \varepsilon_{i,t} \end{aligned}$$

We account for the censoring by using a panel data Tobit approach. The random effects model assumes that the panel-specific intercept, v_i, is normally distributed. After accounting for truncation, we obtain a joint distribution for the observed data as follows:

$$f\left(y_{i,1}^o, \dots, y_{i,T}^o \mid x_{i,1}, \dots, x_{i,T}\right) = \int_{-\infty}^{\infty} \frac{e^{-v_i^2/2\sigma_v^2}}{\sqrt{2\pi}\sigma_v} \left\{ \prod_{t=1}^{T} F\left(y_{i,t}^o, x_{i,t}\beta + v_i\right) \right\} dv_i$$

where the truncation implies

[11] Only the natural gas heat rate was given for most facilities that can use either natural gas or distillate, so the distillate and gas heat rates were assumed to be the same. For the minority of these facilities where different fuel heat rates were available, the appropriate heat rate was used to calculate real costs.

$$F\left(y_{i,t}^{o},\Delta_{i,t}\right)=\begin{cases}\left(\dfrac{1}{\sqrt{2\pi}\sigma_{\varepsilon}}\right)e^{-\left(y_{i,t}^{o}-\Delta_{i,t}\right)^{2}/\left(2\sigma_{\varepsilon}^{2}\right)} & \text{if } y_{i,t}^{o}\in\left(0,1\right)\\ \Phi\left(\dfrac{y_{i,t}^{o}-\Delta_{i,t}}{\sigma_{\varepsilon}}\right) & \text{if } y_{i,t}^{o}=0\\ 1-\Phi\left(\dfrac{y_{i,t}^{o}-\Delta_{i,t}}{\sigma_{\varepsilon}}\right) & \text{if } y_{i,t}^{o}=1\end{cases}$$

and $\Phi(\bullet)$ represents the standard normal cumulative distribution function.

We estimated the model on the full sample and two subsamples of plants that switched between natural gas and distillate, or natural gas and residual fuel oil. Plants using all three fuels were included in all panels. We used the appropriate real oil product cost in the cointegrating equation for each subsample. The error terms associated with both real oil product costs entered the equation for the full sample, but only the real residual fuel oil cost error term remained statistically significantly different from zero. Table 3 summarizes the results (omitting the constant and monthly effects to save space).

The strong and statistically significant negative coefficients on the error terms indicate that plants do tend to switch to oil products when natural gas costs increase relative to their long run relationship with petroleum product costs. Comparing the two subsamples, the response to an increase in natural gas costs is stronger for plants that can use residual fuel oil than for facilities that can use distillate as the substitute fuel. In addition, the coefficient on the real residual fuel oil cost is considerably larger than the coefficient on the real distillate cost in the full sample regression. Hence, these results suggest that residual fuel oil is a stronger substitute for natural gas.

The heating and cooling degree day variables also are estimated to have a significant effect on switching. Since monthly dummy variables are included in the analysis, the coefficients on *HDD* and *CDD* again should be interpreted as the marginal effect of departures of degree days from their monthly averages. While the effect of heating degree days varied by region in the translog specification presented in Table 2, in Table 3 heating degree days consistently reduce natural gas demand. Since the relative costs variable should already account for the effect of higher natural gas prices, this could indicate that electric generators are relinquishing natural gas purchased under interruptible contracts when temperatures are below average and gas demand for space heating is high. Once cost variations and monthly effects have been controlled for, cooling degree days have a statistically significant effect only for plants that switch between natural gas and distillate fuel. Since a high value for *CDD* relative to normal would increase the demand for peaking plant, plants that can switch between natural gas and distillate are more likely to be used to provide peak power.

6. Utilization rate of gas-fired capacity

The strong results at the individual plant level, coupled with the information that there are a substantial number of plants capable of switching between fuels in FRCC, MAAC and VACAR, raises doubts about the results obtained using the translog specification. In addition, some variables that the theory implies ought to be significant drop from the translog specification, while others have a sign that is opposite to what would be expected. We conclude that, on the whole, the results do not provide strong support for the empirical relevance of the translog functional form. In addition, while the translog specification has the benefit when estimating multiple share equations that all cost shares must sum to one, we are only interested in natural gas demand.

An alternative approach focuses on the utilization of available natural gas generating capacity. Specifically, we define the maximum level of natural gas consumption for the month by calculating how much natural gas would be consumed if all available natural gas capacity were run for all hours of any given month. The ratio of actual natural gas consumed to this theoretical maximum level (*NGGasUtil*) would then lie in the [0, 1] interval.[12] The natural log of the negative natural log of the utilization factor ($\ln(-\ln NGGasUtil_t)$) was then used as the dependent variable.[13] This functional form, hereafter referred to as a "double log" transformation, allows a nonlinear response to changes in the determinants of natural gas demand that we believe better captures the way a power system is operated than does the simple log-linear form produced by the translog specification. Since combined-cycle electricity generation, conventional gas-fired steam generation and gas turbines each have different heat rates, they are used to

[12] In practice, some natural gas is used to generate power in every NERC subregion in every month, so the ratio is bounded above zero, ensuring that the logarithm of the ratio remains finite.
[13] The sign change relative to the translog cost share model will also change the expected signs of the coefficients of each of the right hand side variables.

supply power at different points on the load curve and thus for different amounts of time during the month. As the utilization rate of gas-fired generation increases, the most efficient (and typically larger) plants are used first and the least efficient (and typically smaller) plants are dispatched last. Natural gas demand can rise rapidly as many of the more efficient plants are brought online, but then will level off as the remaining smaller plants are added more gradually. This type of response is illustrated in Figure 6.

The double log functional form also ensures that the amount of natural gas input is bounded by the physical constraints of the system. No matter what values the independent variables take, natural gas use cannot be predicted to lie outside the bounds of what is feasible.

A technical advantage of the double log transformation relative to simply taking the utilization rate *NGGasUtil* as the dependent variable is that the transformation allows for an error term with classical properties. If the dependent variable were constrained to lie in the unit interval, the error terms in the equation would need to be bounded.

It is also worth noting that this specification eliminates the potential endogeneity of the dependent variable that exists when modeling expenditure shares. This allows us to use $\hat{\omega}_t$ from (5) as a standard regressor. By construction, the estimated residual $\hat{\omega}_t$ from (5) will be positive when real natural gas costs are above their long run relationship with real oil costs. We would then expect the demand for natural gas to fall as oil-fired capacity is dispatched instead. Because ln(-ln*NGGasUtil*) decreases as *NGGasUtil* increases, we should find that $\hat{\omega}_t$ has a *positive* effect on the dependent variable.

Similarly, if coal-fired plants are substitutes for natural gas plants we would expect an increase in the real costs of coal to raise the demand for natural gas. Thus, $\ln RC_{coal,t}$ should have a negative effect on the dependent variable. As above, the real coal cost is omitted from the panel since the variable is missing in California.

Since the natural gas capacity has been incorporated into the dependent variable, it is no longer present as a regressor. The remaining oil and coal capacity variables are also dropped from (6).

Retaining the weather variables (*CDD* and *HDD*), monthly dummies and total electricity generated from fossil fuels (FE_t) as the output measure, the estimated equation for each NERC subregion becomes (omitting subscripts *i* denoting the region):

$$\ln\left(-\ln NGGasUtil_t\right) = b_0 + b_1\ddot{\omega}_t + b_2 \ln RC_{coal,t} + b_3 \ln FE_t + b_4 CDD + b_5 HDD + \sum_i Month_i + \varepsilon_t \quad (8)$$

Rather than include a lagged dependent variable in the regression, we now allow ε_t to be autocorrelated and, in the time series models for each region, to have a moving average structure.[14] Specifically, $\varepsilon_t = \rho\varepsilon_{t-1} + \theta(L)u_t$ where $\theta(L)$ denotes a polynomial in the lag operator and u_t is a white noise process. Autocorrelation could arise for several reasons, including slow adjustment to changes in factors that affect natural gas demand. Explicit supply contracts or hedges that extend beyond the period of observation, which is one month, often lead to a moving average error structure. In addition, any important influences on natural gas demand that have been omitted from the equation would appear in the error term, and these influences could themselves be autocorrelated. In the panel estimation, we allow the error term to be first order autocorrelated, but we ignore any possible moving average component.

In general, we would also expect natural gas consumption to increase as total electricity generation from fossil fuels increases as gas-fired plants would be part of the mix of plants called upon to meet peak demands. Hence, we would expect to find $b_3 < 0$.

As argued previously, we would also expect an increase in *CDD* to increase the demand for natural gas (so $b_4 < 0$) as the load curve becomes more peaked. Admittedly, however, the contrary results for plants that can switch between fuels raise doubts about this expectation. The sign of the coefficient on *HDD* is not clear even in theory.

The variable *CACrisis* was set to 1 for the months January through June of 2001 and for the WECCC and WECC subregions only and zero for all other months and regions. This period corresponded to the crisis in the Californian electricity system when

[14] We examined some other models for the error term, including second-order autoregressions and nonstationary specifications. However, allowing for first-order autoregressive and a more general moving average component appeared to be most satisfactory. We also examined models that included a lagged dependent variable as an alternative, or supplement to autoregressive and moving average structure in the error term, but again the model as written above proved most satisfactory.

there was non-price rationing and disruption in the demand for many different types of fuel including natural gas.[15]

The estimation results are presented in Table 4. As in previous tables, the standard errors are presented below the coefficient estimates. The corresponding entries in the final two columns are, however, *p*-values for the null hypothesis. In this case, the values reported are for the Box-Pierce Q-statistic testing for the absence of serial correlation. The statistics are distributed chi-squared with 6 and 12 degrees of freedom in the two cases. The regressions also included constants, monthly dummies and, in the panel regression, region-specific constants, monthly effects and autoregressive parameters. These have not been reported to save space.

The panel estimation was obtained using a Prais-Winsten regression allowing for contemporaneously correlated panel errors each with a panel-specific autoregressive of order one time series structure. The standard errors are panel-corrected. The R^2 in the Prais-Winsten regression was 0.8162 and the chi-square for the joint significance of the regressors was $\chi^2_{160} = 6120.83$. A Kalman filter was used to obtain the maximum likelihood time series estimates for each subregion. This requires all the variables in the regression to be stationary and the error terms after correcting for autoregressive and moving average terms to be white noise.

The results in Table 4 show a strong tendency for increases in the real costs of natural gas relative to oil to induce a substitution away from natural gas as a fuel to generate electricity. This is true for the full panel and all but one NERC subregion. However, the coefficient is statistically significantly different from zero in only six subregions: FRCC, MAAC, MAIN, NPCCN, SERC, and VACAR. These regions encompass the East Coast from Florida to New York and Pennsylvania and Illinois and parts of surrounding Midwestern states. Three additional regions (ECAR, MAPP and NPCCI encompassing the rest of the Midwest and New England) have positive and reasonably large responses to deviations in costs, although the coefficients are not statistically significantly different from zero. The coefficients in the remaining four regions (ERCOT, SPP, WECC, and WECCC) are so small relative to their estimated

[15] We also tested for the presence of this variable in the translog model for the WECCC and WECC subregions but did not find it statistically significantly different from zero.

standard errors that no meaning can be attached to the estimated values. It should be emphasized, however, that part of the estimated monthly effects could be a response of gas demand to seasonal and predictable relative price fluctuations, so the coefficients on $\hat{\omega}$ may not be the only response directly aimed at maintaining relativity between natural gas and oil prices (adjusting for variations in heat rates).

As Figure 5 shows, the six regions where the coefficient on $\hat{\omega}_t$ is statistically significantly different from zero in Table 4 contain a large proportion of the switching capacity. From this perspective, the results in Table 4 would appear preferable to the translog results in Table 2. In particular, the fact that FRCC and MAAC are not found to be very sensitive to cost differentials in Table 2 casts doubt upon the ability of the translog framework to adequately measure fuel substitution in the U.S. electricity generating industry.

Substitution between natural gas and oil products also can occur even if there are few plants that can switch fuel inputs. Firms can respond to a change in fuel prices by running plants for different periods of time during each day. The ability to substitute in this way varies from one region to the next. This could explain why regions such as MAIN exhibit a stronger response to $\hat{\omega}_t$ than do other regions such as NPCCN even though the former has a smaller fraction of dual-fired capacity.

The results in Table 4 show few strong relationships between the cost of coal and the demand for natural gas by electric generators. In New England and New York a higher cost of coal is estimated to raise the demand for natural gas, but in SERC the coefficient is unexpectedly positive, implying that coal-fired and gas-fired plants are complements in this region.

All regions are estimated to have a strong and statistically significant response to changes in the quantity of fossil fuel-powered electricity generation, with ERCOT being the most responsive. This suggests that natural gas plants provide significant marginal generating capacity in all subregions, which is not surprising given the growth of natural gas generating capacity in the late 1990s and early 2000s across the nation. These results regarding the effect of ln*FE* are much stronger in Table 4 than in Table 2, again suggesting that the alternative specification may be more appropriate than the translog.

All regions except NPCCI (New England) and VACAR (Virginia and the Carolinas) reveal a positive demand responsive to increased cooling degree days, *CDD*. A similar response was indicated in Table 2 and Table 3. An increase in heating degree days is now estimated to be statistically significant for the panel as a whole and for nine subregions. For the panel as a whole and for eight of the subregions, an increase in *HDD* is estimated to increase the demand for natural gas to generate electricity. Only in NPCCI (New England), where a pervasiveness of extreme cold and high population density is more likely to result in gas curtailments, is the effect reversed.

Finally, all subregions had significant autocorrelation in the error term. This may indicate a lagged adjustment of demand to changes in driving factors. In twelve of the thirteen subregions, the error terms also displayed a significant moving average structure, which could reflect the importance of multiple month contracts in these regions. The presence of significant autocorrelation and moving average terms may also, however, be an indication of some significant autocorrelated omitted variables.

In order to measure the *sensitivity* of natural gas demand to changes in each of the individual variables, we can calculate the elasticity based on the estimated coefficient. For a right hand side variable x measured in logarithmic form with estimated coefficient α the elasticity of response is

$$\frac{x}{y}\frac{dy}{dx} = -xe^{x^{\alpha}}\alpha x^{\alpha-1}e^{-x^{\alpha}} = -\alpha x^{\alpha}$$

Then, $\alpha < 0$ indicates a positive effect of variable x on the consumption of natural gas, but the elasticity decreases as x increases. When $\alpha > 0$, variable x has a negative effect on the consumption of natural gas that becomes more negative, but at a decreasing rate, as x increases.

As an example, consider the estimated equation for the NERC subregion MAIN:

$$\begin{aligned}\ln\left(-\ln NGGasUtil_t\right) = 16.2921 + 0.1285\omega_t - 0.9053\ln FE_t \\ - 0.0012CDD_t - 0.0002HDD_t + \sum_i \gamma_i Month_i + \varepsilon_t\end{aligned}$$

$$\varepsilon_t = 0.9875\varepsilon_{t-1} + u_t - 0.3980u_{t-1} - 0.2101u_{t-4} + 0.4302u_{t-10} - 0.1889u_{t-11} - 0.2595u_{t-12}$$

The interpretation in terms of elasticity implies that when fossil fuel generation increases by 1%, the fraction of potential natural gas output that is actually used increases by

$0.9053 FE_t^{-0.9053}$ percent, holding all other influences fixed. Likewise, cooling and, to a lesser extent, heating degree days also have positive effects on natural gas demand.

The magnitude of the consumption response to $\hat{\omega}$ varies greatly across regions with FRCC being the most sensitive to the deviations from the long run relationship. Using the cointegrating relationship that defines ω

$$\omega = \ln\left(\frac{RC_{NG,t}}{RC_{Oil,t}^{\beta_1}} e^{-\beta_0}\right)$$

the elasticity in this case becomes

$$-\alpha\left(\frac{RC_{NG,t}}{RC_{Oil,t}^{\beta_1}} e^{-\beta_0}\right)^{\alpha} = -0.1285\left(\frac{RC_{NG,t}}{RC_{Oil,t}^{0.75}} e^{-0.27}\right)^{0.1285}.$$

Figure 7 indicates the estimated response surface to variations in costs in the case of the MAIN subregion (taking into account also the estimated cointegrating relationship between costs for that region). The graph has been drawn only for the range of cost variations actually observed in the MAIN region over the sample period.

A decline in natural gas costs, holding oil costs fixed, increases the use of natural gas capacity at an increasing rate (Path A). On the other hand, an increase in oil costs holding natural gas costs fixed increases the use of natural gas capacity at a decreasing rate (Path B). Consequently, if prices move from a region of high natural gas and low oil costs to one of low natural gas and high oil costs, there would be an S-shaped response of natural gas capacity use (along the diagonal connecting IV to II). The use of natural gas capacity would rise quickly at first, then more slowly until we move toward the opposite corner of the region where natural gas capacity use increases more rapidly again. This may reflect the ability to substitute different types of natural gas-fired capacity for oil-fired capacity at different relative costs. It must be stressed, however, that since natural gas and oil prices tend to return to long run equilibrium where prices move together, most of the data lies in the vicinity of the other diagonal in Figure 7 (connecting I to III).

7. Concluding remarks

We found that positive deviations from the long run relationship between the cost of using natural gas versus petroleum products to generate electricity exert a significant negative effect on natural gas demand in power generation. Moreover, while the effect is generally larger in regions where a significant number of plants can switch fuel inputs, it is present in almost all NERC regions as a result of grid-level switching, or plants moving up or down the supply stack as fuel prices change.

The finding that the demand for natural gas as an input to electricity generation responds strongly to changes in its relative cost is important. It elucidates a significant demand-side factor that drives a long-run equilibrium relationship between natural gas and crude oil prices, albeit one that evolves with changes in generating technology. The equations estimated in this paper are not sufficient to determine the speed of adjustment of relative prices, however, since the price consequences of any increase in the demand for natural gas will also depend on the elasticity of the supply curve and the elasticity of demand in other sectors of the economy. In addition, the ability of plant or grid-level switching to facilitate price convergence depends on there being sufficient capacity of both fuel types. A lack of oil-fired capacity, for example, could result in a much weaker demand side enforcement of long run equilibrium, as the mechanism would not be in place to encourage use of the alternative fuel in response to relative price movements.

The estimated equations also imply that weather and other seasonal effects alter the demand for natural gas as an input to electricity generation independent of any response to departures of the relative prices of fuels from their long run equilibrium relationship. In every NERC region, an increase in overall electricity demand is also met at the margin by burning more natural gas.

Consistent with the findings of Söderholm (2001), our analysis also casts doubt upon the adequacy of the translog functional form for representing the cost function in electricity generation. In particular, we find evidence of an asymmetric response to variations in the relative prices of fuels that cannot be captured using the translog functional form. A decline in natural gas costs, holding oil costs fixed, increases the use of gas capacity at an increasing rate, whereas an increase in oil costs holding natural gas costs fixed increases the use of gas capacity at a decreasing rate.

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Appendix 1: Figures and Tables

Figure 1: NERC regions and subregions used in the study

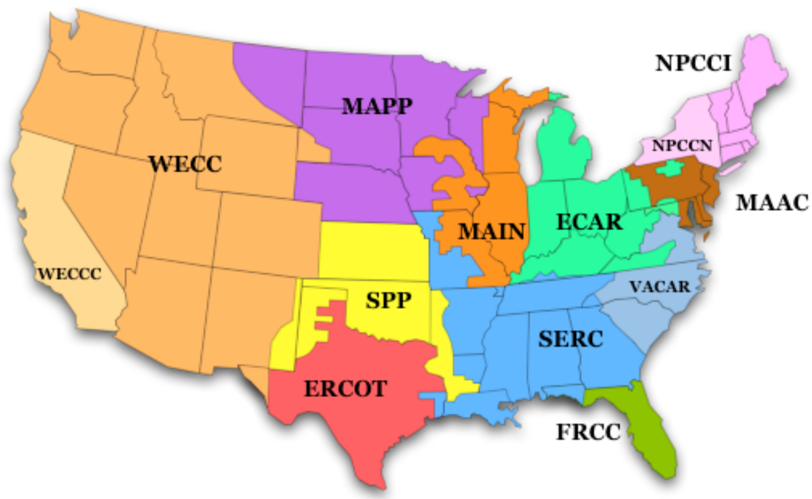

Figure 2: Capacity-weighted average natural gas heat rates (Btu/kWh)

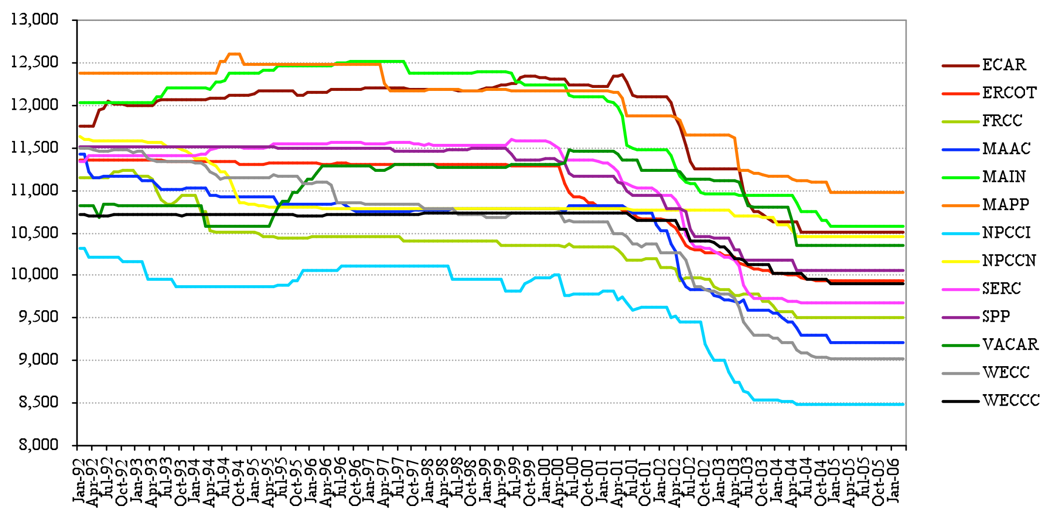

Figure 3: Combined cycle gas turbine capacity (MW)

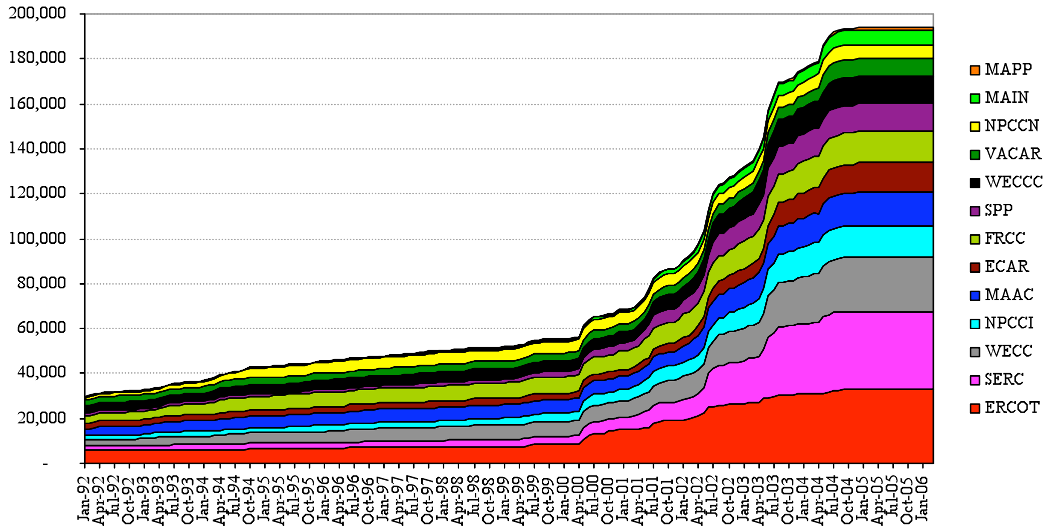

Figure 4: Real natural gas costs, Jan 1992-December 2006

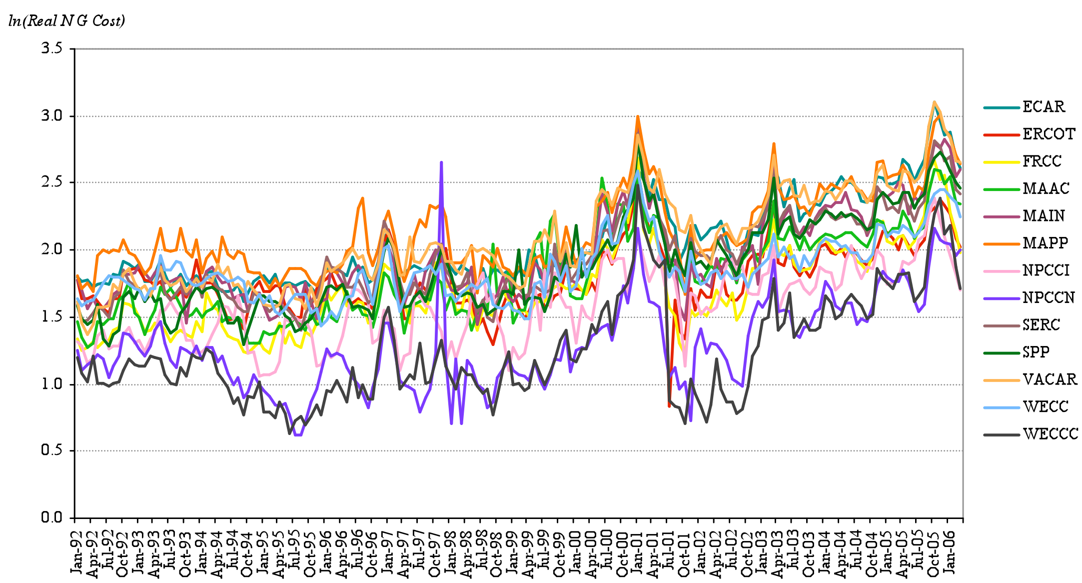

Figure 5: Proportion of dual-fired generation capacity in each NERC subregion

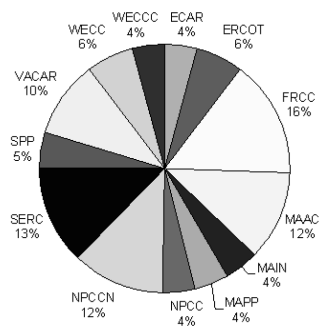

Figure 6: Response of *NGGasUtil* to changes in oil relative to natural gas prices

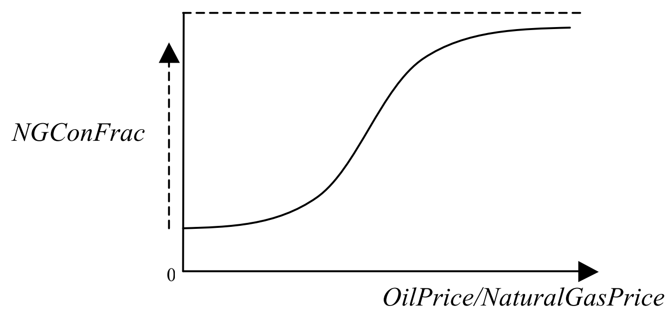

Figure 7: Estimated response of natural gas demand to cost variations

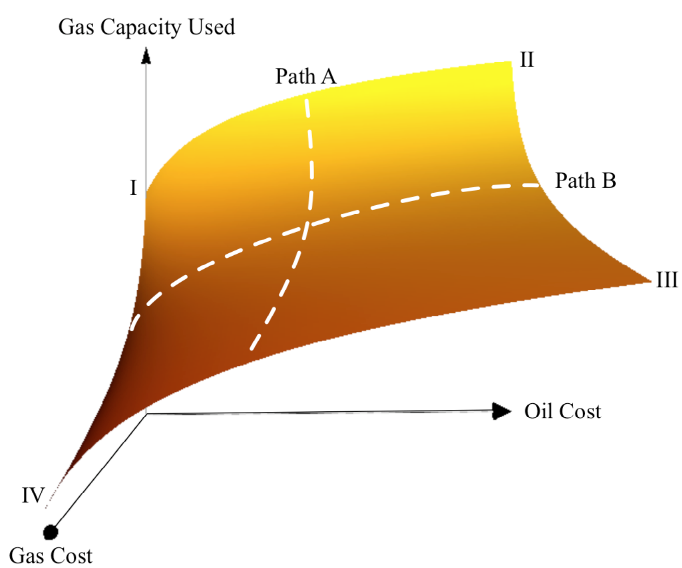

Table 1: Cointegration of the real input cost variables

NERC subregion	Test for *lnNGRCost* nonstationarity[a]	Test for *lnOilRCost* nonstationarity[a]	Test for *lnCoalRCost* nonstationarity[a]	β_0	β_1	Test for error nonstationarity[a]
ECAR	0.5116	0.8995	0.1825	-0.26	0.79	0.0000
ERCOT	0.0001	0.6377	0.0854	-0.41	0.57	0.0000
FRCC	0.0927	0.6454	0.5068	-0.18	0.77	0.0000
MAAC	0.0415	0.6899	0.0004	-0.14	0.63	0.0000
MAIN	0.0820	0.8085	0.0004	-0.37	0.75	0.0000
MAPP	0.0275	0.8039	0.0009	-0.27	0.65	0.0000
NPCCI	0.0001	0.6592	0.0196	-0.32	0.47	0.0000
NPCCN	0.0010	0.4922	0.0027	-0.11	0.90	0.0000
SERC	0.2687	0.7720	0.0023	-0.66	0.98	0.0005
SPP	0.2533	0.7725	0.0001	-0.92	0.93	0.0000
VACAR	0.2889	0.8804	0.0662	-0.16	0.74	0.0003
WECC	0.0865	0.8242	0.3429	-0.65	0.64	0.0000
WECCC	0.0154	0.7130	—[b]	-0.89	0.86	0.0001

[a] MacKinnon approximate p-value for the null hypothesis that the variable is nonstationary.

[b] There is no value for coal nonstationarity in WECCC because there is no non-cogeneration coal fired generation and therefore no relevant heat rate.

Table 2: Panel and NERC subregion translog results

NERC subregion	S_{t-1}^{NG}	$\hat{\omega}_t$	$\ln RC_{coal,t}$	*lnNGCap*	ln*RfoCap*	ln*DfoCap*	ln*CoalCap*	ln*FE*	*CDD*	*HDD*	Number of obs.	R^2 (overall)	R^2 (within)	R^2 (between)
Panel	0.8332*** (0.0120)	-0.0194** (0.0081)		0.0245*** (0.0032)				0.0121*** (0.0032)	0.0002*** (0.00004)		2327	0.9583	0.8724	0.985
ECAR	0.3760*** (0.0623)	0.0031 (0.0156)		0.0238*** (0.0052)	-0.20238*** (0.0913)		1.3782* (0.7788)		0.0004*** (0.00005)	0.00003* (0.00002)	179	0.8102		
ERCOT	0.4911*** (0.0775)	0.0042 (0.0337)	-0.1166*** (0.0436)			-0.0733*** (0.0237)	-0.8490** (0.3411)	0.2840*** (0.0420)			179	0.8235		
FRCC	0.7580*** (0.0538)	-0.0011 (0.0317)		0.1376*** (0.0271)			0.2011* (0.1156)	-0.1171* (0.0595)			179	0.9088		
MAAC	0.5690*** (0.0655)	0.0103 (0.0282)		0.0766*** (0.0192)	-0.3828** (0.1704)			-0.0354** (0.0165)	0.0006*** (0.0002)	-0.0001* (0.00006)	179	0.9097		
MAIN	0.3688*** (0.0541)	0.0100 (0.0235)	-0.1081* (0.0635)	-0.0255*** (0.0074)			-4.0203*** (1.4159)	0.0963*** (0.0220)	0.0008*** (0.00009)	0.00006* (0.00003)	179	0.7898		
MAPP	0.3872*** (0.0552)	0.0268** (0.0134)	0.1888*** (0.0389)	0.0614*** (0.0143)			3.1131* (1.8705)	0.0834** (0.3547)	0.0007*** (0.00008)		179	0.8942		
NPCCI	0.6488*** (0.0644)	-0.0342 (0.0700)	-0.2551** (0.1162)	0.1015*** (0.0224)		-0.7705** (0.3013)		0.0315*** (0.0113)		-0.0003*** (0.0001)	179	0.9301		
NPCCN	0.5994*** (0.0851)	-0.1590** (0.0808)					-1.489* (0.7838)			-0.00018** (0.00007)	179	0.7269		
SERC	0.4584*** (0.0638)	-0.0989*** (0.0279)	-0.5346*** (0.0927)				6.283*** (0.9194)		0.0002** (0.00008)	0.0001** (0.00004)	179	0.9056		
SPP	0.5962*** (0.0662)	-0.0931* (0.0473)	-0.2505*** (0.1090)			0.7988*** (0.1642)			0.0005*** (0.0001)	0.00009* (0.00005)	179	0.9003		
VACAR	0.3644*** (0.0638)	-0.0655* (0.0337)	0.2987*** (0.0801)	0.0477** (0.0191)	-0.6019** (0.2515)			0.0903*** (0.0323)	0.0011*** (0.0002)		179	0.8645		
WECC	0.9153*** (0.0312)	-0.0409 (0.0254)						0.1215*** (0.0368)			179	0.9626		
WECCC	0.3131*** (0.0734)	-0.0073** (0.0031)				0.0442** (0.0206)		0.0068*** (0.0010)	-0.00004** (0.00002)		179	0.5187		

*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level. Statistically insignificant variables are reported in grayed font.

Table 3: Plant-level panel Tobit results for switching plants

	All switching plants	Natural gas and distillate	Natural gas and residual
$NGPct_{t-1}$	0.6757*** (0.0086)	0.6641*** (0.0090)	0.6837*** (0.0127)
$\hat{\omega}_t^{Dfo}$		–0.0553*** (0.0122)	
$\hat{\omega}_t^{Rfo}$	-0.0888*** (0.0121)		-0.1456*** (0.0167)
CDD		0.00006* (0.00004)	
HDD	–0.00004*** (0.000014)	–0.00003** (0.00002)	–0.00013*** (0.00002)
σ_{υ}	0.2497*** (0.0152)	0.2311*** (0.0110)	0.1831*** (0.0219)
σ_{ε}	0.3129*** (0.0020)	0.3175*** (0.0022)	0.2543*** (0.0027)
observations	21961	20048	6384
left-censored	1752	1743	246
uncensored	12250	11203	4555
right-censored	7959	7102	1583
number of plants	143	131	38
$\ln L$	-8777.58	-8280.10	–1412.49
χ^2 (d.f.)	7357.5 (14)	6395.31 (15)	3713.8 (14)

*** significant at the 1% level, ** significant at the 5% level, and * significant at the 10% level

Table 4: Results for transformed utilization rate as the dependent variable

NERC subregion	$\hat{\omega}$	ln RC_{coal}	ln FE	CDD	HDD	CAcrisis	AR(1)	MA terms	Q-stat (6 lags)	Q-stat (12 lags)
Panel	0.1026^{***}		-0.4915^{***}	-0.0010^{***}	-0.0001^{***}	-0.1023^{**}	panel-specific			
	(0.0215)		(0.0270)	(0.00008)	(0.00004)	(0.0512)				
ECAR	0.0746		-0.5645^{***}	-0.0024^{***}	-0.0002^{***}		0.9708^{***}	$MA(1, 3, 4) = \underset{(0.0882)}{0.5179^{***}}, \underset{(0.0853)}{0.1435^{*}}, \underset{(0.0995)}{0.2268^{**}}$	2.6425	6.0717
	(0.0717)		(0.1902)	(0.0002)	(0.00007)		(0.0290)		(0.8522)	(0.9124)
ERCOT	0.0270		-1.0146^{***}	-0.0005^{***}			0.9912^{***}	$MA(1, 5, 6, 7, 9, 11) = \underset{(0.0755)}{-0.4108^{***}}, \underset{(0.0714)}{-0.1699^{**}}, \underset{(0.0812)}{-0.1544^{*}}, \underset{(0.0643)}{0.3001^{***}}, \underset{(0.0685)}{-0.2620^{***}}, \underset{(0.0745)}{0.3560^{***}}$	3.3254	11.038
	(0.0193)		(0.0484)	(0.00005)			(0.0134)		(0.7670)	(0.5257)
FRCC	0.2748^{***}		-0.3217^{***}	-0.0006^{***}	-0.0006^{***}		0.8501^{***}	$MA(1, 6, 10) = \underset{(0.0946)}{-0.1785^{*}}, \underset{(0.0734)}{0.2014^{***}}, \underset{(0.0793)}{0.2642^{***}}$	1.8184	6.2747
	(0.0778)		(0.0776)	(0.0002)	(0.0002)		(0.0552)		(0.9356)	(0.9016)
MAAC	0.1430^{**}		-0.2833^{***}	-0.0025^{***}			0.5831^{***}	$MA(4, 11) = \underset{(0.0808)}{0.2377^{***}}, \underset{(0.0734)}{0.1844^{**}}$	2.3865	8.8461
	(0.0617)		(0.0376)	(0.0004)			(0.0745)		(0.8809)	(0.7160)
MAIN	0.1285^{**}		-0.9053^{***}	-0.0012^{***}	-0.0002^{*}		0.9876^{***}	$MA(1,4,10,11,12) = \underset{(0.0836)}{-0.3979^{***}}, \underset{(0.0787)}{-0.2101^{***}}, \underset{(0.0930)}{0.4302^{***}}, \underset{(0.0895)}{-0.1889^{**}}, \underset{(0.0911)}{-0.2595^{***}}$	3.5171	5.4503
	(0.0550)		(0.0805)	(0.0003)	(0.00009)		(0.0180)		(0.7417)	(0.9412)
MAPP	0.0791		-0.4321^{***}	-0.0032^{***}	-0.0002^{**}		0.5624^{***}		4.445	9.656
	(0.0484)		(0.1411)	(0.0004)	(0.00008)		(0.0625)		(0.6167)	(0.6461)
NPCCI	0.0764	-0.9259^{**}	-0.6366^{***}		0.0007^{***}		0.7765^{***}	$MA(1, 2, 3, 4, 11) = \underset{(0.0831)}{0.1455^{*}}, \underset{(0.1101)}{0.2065^{*}}, \underset{(0.1095)}{-0.2960^{***}}, \underset{(0.0774)}{0.2895^{***}}, \underset{(0.0915)}{0.4763^{***}}$	1.938	5.4428
	(0.0925)	(0.3873)	(0.0540)		(0.0002)		(0.0639)		(0.9253)	(0.9415)
NPCCN	0.0831^{**}	-0.6983^{***}	-0.0964^{*}	-0.0007^{***}			0.8873^{***}	$MA(2, 5, 7, 8, 12) = \underset{(0.1205)}{-0.3108^{***}}, \underset{(0.0897)}{-0.1783^{**}}, \underset{(0.0862)}{0.1819^{***}}, \underset{(0.1055)}{-0.3987^{***}}, \underset{(0.0880)}{-0.2638^{***}}$	2.6722	6.5291
	(0.0411)	(0.1918)	(0.0577)	(0.0003)			(0.0440)		(0.8487)	(0.8871)
SERC	0.1706^{***}	0.5309^{**}	-0.6898^{***}	-0.0007^{***}	-0.0001^{**}		0.9614^{***}	$MA(2, 3, 8, 9, 11) = \underset{(0.0816)}{-0.2832^{***}}, \underset{(0.1257)}{0.2916^{**}}, \underset{(0.1055)}{-0.3261^{***}}, \underset{(0.0824)}{0.3054^{***}}, \underset{(0.1059)}{0.5181^{***}}$	2.6908	5.8804
	(0.0381)	(0.2454)	(0.0961)	(0.0002)	(0.00006)		(0.0256)		(0.8465)	(0.9220)
SPP	0.0014		-0.3693^{***}	-0.0014^{***}	-0.0002^{***}		0.9257^{***}	$MA(1, 2, 11) = \underset{(0.0963)}{-0.2338^{**}}, \underset{(0.0953)}{-0.2986^{***}}, \underset{(0.0907)}{0.2750^{***}}$	5.0311	8.2764
	(0.0471)		(0.1293)	(0.0002)	(0.00006)		(0.0479)		(0.5398)	(0.7632)
VACAR	0.2740^{***}		-0.6058^{***}		-0.0002^{*}		0.5439^{***}	$MA(3, 6, 10, 11) = \underset{(0.0778)}{0.2747^{***}}, \underset{(0.0806)}{0.2050^{**}}, \underset{(0.0734)}{0.3839^{***}}, \underset{(0.0798)}{0.1738^{**}}$	2.0659	6.5118
	(0.0993)		(0.1213)		(0.0001)		(0.0644)		(0.9135)	(0.8881)
WECC	-0.0625		-0.9791^{***}	-0.0006^{*}	-0.0002^{*}		0.8665^{***}	$MA(9) = \underset{(0.0857)}{0.1525^{*}}$	1.3687	3.9119
	(0.0698)		(0.1313)	(0.0003)	(0.0001)		(0.0400)		(0.9677)	(0.9850)
WECCC	0.0139		-0.4250^{***}	-0.0006^{***}		-0.1356^{***}	0.8952^{***}	$MA(12) = \underset{(0.0834)}{0.2222^{***}}$	2.8246	7.8857
	(0.0234)		(0.0081)	(0.00007)		(0.0277)	(0.0439)		(0.8305)	(0.7940)

*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level. Statistically insignificant variables are reported in grayed font.

Appendix 2: Data Description

Capacity-Weighted Heat Rates

The plant-level heat rates were taken from the EPA NEEDS 2006 data. The heat rates in the EPA data were matched to the facilities listed in the EIA Form-860 (Annual Electric Generator Report) in four steps.

- Step 1: For any plant where the facility ID and generator number matched exactly in the EIA and EPA datasets, the reported heat rate was matched to the EIA data.
- Step 2: For the remaining plants, a plant in the EIA database was matched to the plant in the EPA database with the same facility ID, year of first use, prime mover, and fuel type.
- Step 3: For the remaining plants, if the prime mover type, fuel type and year of initial use were known, the average heat rate of facilities with those same characteristics was used.
- Step 4: For the remaining plants, the average heat rate of all plants with same fuel type and prime mover was used.

The capacity weighted heat rates were calculated each month based on the capacity that was online during that month. Thus, if a plant began operations in a particular month it was included in that month's heat rate calculation. The formula used for calculating the capacity weighted heat rate (*CapWtHR*) is:

$$CapWtHR_t = \frac{\sum_i (Capacity_{i,t} * HeatRate_{i,t})}{\sum_i Capacity_{i,t}}$$

where i = any plant in the specified NERC region at time t.

Capacity-weighted heat rates are included for five groups – Coal, DFO, RFO, Total Oil, and Natural Gas. The RFO and DFO calculations were done separately by NERC subregion and then a weighted average of them was calculated based on the capacity of RFO and DFO in the region. The EIA database was used to perform the calculations once the heat rates were determined using the EPA data.

It is important to note that heat rates are not available for all facilities. Those that have no heat rate published in the EPA and EIA data were not used in the heat rate calculations. Specifically, plants powered by geothermal, hydro, or other nonfossil fuel sources are not included in the heat rate calculation.

The EIA database provides as many as six energy sources for any one generator. For the heat rate calculations only the primary energy source was considered.

Natural Gas Consumption

EIA Forms 906 and 920 spanning the years 1986-2006 report the total energy consumption of electricity generators by fuel type . Some modifications to the data were necessary in order to combine the data over the time period due to structural and formatting changes in the reports over the years.

Pre-2001 data include only the physical quantity of fuel consumed (bbl, mcf, tons), but neither the heat content of the fuel nor the total energy content of fuel consumed (MMBtu). The average heat content for each specific fuel type ('Reported AER Fuel Type') by state in 2001 was used for the heat content at each plant in that state using that fuel type. This was then used to calculate the total energy consumed for electricity generation by that plant.

1) Prior to 1997 FRCC was not a separate NERC Region and thus did not appear in the dataset. Based on the facility ID number, which remains constant over time, plants before 1997 were matched to facilities in later years to determine if they were in FRCC after its creation. Any plant located in Florida that appeared prior to 1997, but not after 1997, was assumed to be in FRCC. This allowed the construction of a longer time series for FRCC and SERC that was consistent throughout the time horizon.
2) The NERC region NPCC was separated into NPCCN (any plant in NPCC that is located in NY) and NPCCI (any plant in NPCC not in NY). Any plant in the NERC region SERC that was located in VA, SC or NC was placed in the subregion VACAR. Finally, California was separated from the rest of the WECC.
3) Facilities that reported negative electricity generation were included in the study, but their negative net generation was increased to zero, as their negative consumption can be seen as demand rather than supply.

Natural gas consumption (defined as MMBtu/month) was summed by month in each NERC region/subregion. The data were not adjusted for the number of days in the month.

Natural Gas Price

Natural gas prices for each NERC region were constructed as capacity-weighted averages of city gate prices reported by EIA:

$$NGPrice_{i,t} = \sum_j \alpha_{j,t} \, NGPrice_{j,t}$$

where:

$\alpha_{i,t}$ = Percent of natural gas capacity in NERC region i that is in state j at time t

$NGPrice_{j,t}$ = City gate price in state j at time t

In instances where the city gate price was missing, it was constructed using a regression analysis of the relationship between the average U.S. city gate price and the nonmissing values of the state city gate price.

Residual Fuel Oil and Distillate Prices

The NERC region petroleum product prices were constructed in much the same way as the natural gas price. However, since state-specific prices were unavailable, the PADD level product prices were used instead. The United States is divided into five PADD districts. The formula used to determine the NERC region prices is:

$$Price_{i,t} = \sum_j \alpha_{j,t} Price_{j,t}$$

where:

$\alpha_{i,t}$ = Percent of fuel-specific capacity in NERC region i that is in PADD j at time t

$Price_{j,t}$ = PADD j price at time t

Any missing values again were interpolated using a regression of nonmissing values on the U.S. average price.

Natural Gas Combined Cycle Capacity

Any generator with natural gas as the primary energy source and with prime mover marked CA, CT, CS, or CC in EIA Form 860 was classified as a natural gas combined cycle (NGCC) facility.

Heating and Cooling Degree Days

Heating and cooling degree days are population-weighted state-specific degree day averages where 2000 Census data on state population is used for the weightings within each state. The population weighted state level degree days were then aggregated in the same way that prices were, based on generating capacity shares. For example:

$$HDD_{i,t} = \sum_j \alpha_{j,t} HDD_{j,t}$$

where:

$\alpha_{i,t}$ = Percent of total capacity in NERC region i that is in state j at time t

$HDD_{j,t}$ = State j population weighted HDD at time t

CDD for the regions was calculated in the same way.

Generation Cost

Generation cost is defined the fuel component of the variable cost of producing electricity. It is a function of the price of the fuel as well as the technology employed (measured by the capacity-weighted heat rates (*Btu/kWh*)), and is calculated as follows:

$$Cost\left(\frac{\$}{kWh}\right) = \left(\frac{\$}{MMBtu}\right) * \left(\frac{Btu}{kWh}\right) * \left(\frac{1}{1000}\right)$$

The oil generation cost is similarly calculated as the capacity weighted average of residual fuel cost and distillate fuel cost.

Maximum Natural Gas Consumption

Maximum natural gas consumption is total amount of natural gas (MMBtu) that could be used in a given NERC subregion if all gas-fired facilities operated 24 hours per day for an entire month. It is calculated based on the natural gas capacity in the region, the total number of hours in the month, and the capacity-weighted heat rate of the plants:

$$NGmax_t = \frac{MWCap * hours * HeatRate}{1000}.$$

This theoretical maximum is then used to create the variable, *NG Consumption Fraction*, by dividing actual natural gas consumption by *NGmax*.

California Crisis Dummy Variable

A dummy variable was set equal to 1 for the months January to June 200 to allow for unusual behavior during the California energy crisis. The duration of the crisis period was indicated by an exceedingly large value of the cointegrating error term.