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Electricity Sector Demand for Natural Gas in the United States

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ABOUT THE POLICY REPORT

NATURAL GAS IN NORTH AMERICA:

MARKETS AND SECURITY

Predicted shortages in U.S. natural gas markets have prompted concern about the future of U.S. supply sources, both domestically and from abroad. The United States has a premier energy resource base, but it is a mature province that has reached peak production in many traditional producing regions. In recent years, environmental and land-use considerations have prompted the United States to remove significant acreage that was once available for exploration and energy development. Twenty years ago, nearly 75 percent of federal lands were available for private lease to oil and gas exploration companies. Since then, that share has fallen to 17 percent. At the same time, U.S. demand for natural gas is expected to grow close to 2.0 percent per year over the next two decades. With growth in domestic supplies of natural gas production in the lower 48 states expected to be constrained in the coming years, U.S. natural gas imports are expected to rise significantly in the next two decades, raising concerns about supply security and prompting questions about what is appropriate national natural gas policy.

The future development of the North American natural gas market will be highly influenced by U.S. policy choices and changes in international supply alternatives.

The Baker Institute Policy Report on *Natural Gas in North America: Markets and Security* brings together two research projects undertaken by the Baker Institute's Energy Forum. The first study focuses on the future development of the North American natural gas market and the factors that will influence supply security and pricing. This study considers, in particular, how access to domestic resources and the growth of international trade in liquefied natural gas will impact U.S. energy security. The second study examines the price relationship between oil and natural gas, with special attention given to natural gas demand in the industrial and power generation sectors – sectors in which natural gas can be displaced by competition from other fuels. This policy report is designed to help both market participants and policymakers understand the risks associated with various policy choices and market scenarios.

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The **Baker Institute Energy Forum** is a multifaceted center that promotes original, forward-looking discussion and research on the energy-related challenges facing our society in the 21st century. The mission of the Energy Forum is to promote the development of informed and realistic public policy choices in the energy area by educating policy makers and the public about important trends—both regional and global—that shape the nature of global energy markets and influence the quantity and security of vital supplies needed to fuel world economic growth and prosperity.

The forum is one of several major foreign policy programs at the James A. Baker III Institute for Public Policy at Rice University. The mission of the Baker Institute is to help bridge the gap between the theory and practice of public policy by drawing together experts from academia, government, the media, business, and nongovernmental organizations. By involving both policymakers and scholars, the institute seeks to improve the debate on selected public policy issues and make a difference in the formulation, implementation, and evaluation of public policy.

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I. Introduction

Combined cycle gas turbines (CCGTs) have made natural gas a more competitive fuel for generating electricity. As CCGTs gained in usage in the United States, natural gas has become an increasingly important fuel, rising from around 12% of energy used to generate electricity in the United States in the early 1990s to almost 17% in 2006. Over the same period, the oil share has fallen from around 4% to around 1.6%. Although these trends need not be linked, in this paper we present evidence of substitution between natural gas and oil products in the various North America Electric Reliability Council (NERC)[1] regions of the United States during the period January 1992-March 2006 that has served to maintain a link between natural gas and oil product prices. Furthermore, we show that improvements in the heat rates (or thermal efficiencies) of natural gas plants as a result of the development of CCGTs have influenced the relative demands for the two types of fuels.

More specifically, this study provides evidence that some generators and co-generation facilities consider the relative prices of oil products and natural gas adjusted for relative heat rates when choosing fuel inputs and which plants to operate. By doing so, we demonstrate that fuel switching between natural gas and oil products as inputs to electricity generation continues to link the prices of the two fuels. This paper therefore provides direct microeconomic evidence of our conclusion based on aggregate time series evidence, and presented in a related paper in this study, (Hartley, Medlock and Rosthal (2007)), that fuel choice in the electricity sector plays a key role in determining the relationship between natural gas and oil prices. So 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 produce a shift in the long-term relative prices of natural gas and oil products as we found in our time series analysis.

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[1] For reference, a map of the NERC regions is included in the appendix.

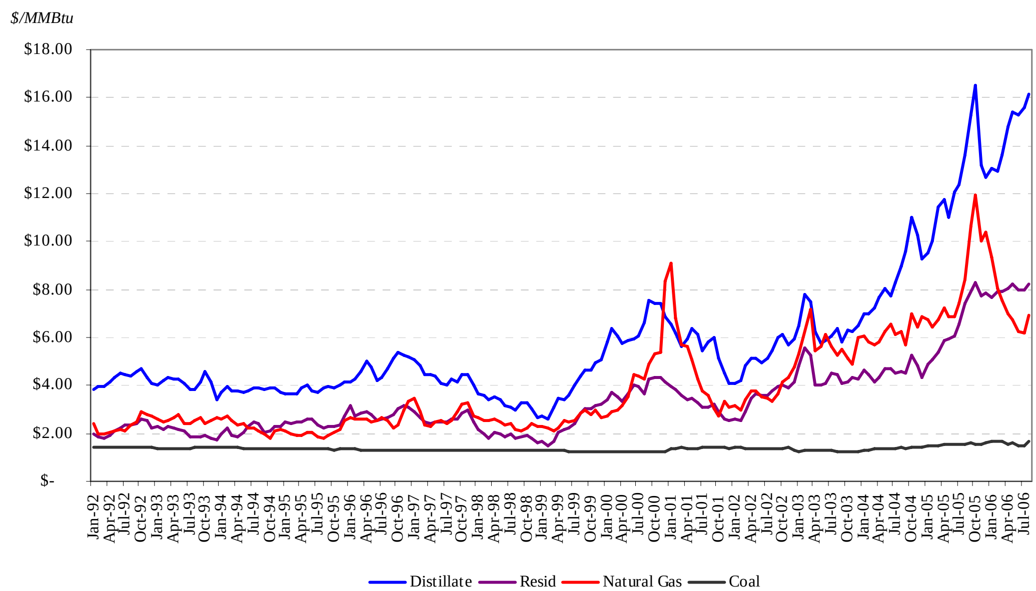
Electricity Sector Demand for Natural Gas

There are several reasons why substitutability between natural gas and oil products is higher in the electricity sector than in other industries. As we demonstrate later, some electricity-generating plants can substitute fuel oil for natural gas at relatively low cost. More importantly, however, the relative position of different types of plants in the dispatch order, the so-called supply stack, will change as fuel prices vary. When natural gas costs in power generation are high relative to oil costs, natural gas-fired generation will shift up in the supply stack, so that it will be dispatched later than cheaper oil-fired generation capacity. Accordingly, natural gas plants will be used for shorter periods of time within a day, greatly reducing the demand for natural gas and increasing the demand for oil products. For combined-cycle plants, the competing fuel will likely be residual fuel oil, while for gas turbines, the competing fuel will likely be diesel. Competition between natural gas and oil products in the electricity sector thus is likely to be critical for understanding future movements in natural gas prices.

There was a massive expansion in gas-fired power generating plants in the United States in the 1990s and in the earlier part of this decade. Around 52% of all new power stations built since 1995 have been gas-fired, but those plants have been larger than the average new plant (many of which were small wind generators) and represented 90% of new capacity added to the system. However, increasing demand for natural gas as an input into electricity generation, along with maturing domestic production and limitations on imports, has tended to raise natural gas prices in the United States. Generally speaking, higher prices have limited actual growth in consumption of natural gas in recent years. The result is that there is a tremendous latent capacity to burn natural gas. Thus, whenever natural gas prices fall, even temporarily for seasonal or other reasons, these lower prices trigger a rapid increase in consumption. For example, a heat wave in the summer of 2006 coupled with natural gas prices that were below parity with residual fuel oil prices spurred two weeks of withdrawals from natural gas storage to fuel an increase in utilization of natural gas peaking capacity. This was an unprecedented event for that time of the year.

Figure 1 plots the national average prices of natural gas, distillate, residual fuel oil and coal per million British thermal units (MMBtu).[2] It shows that natural gas prices have tended to fluctuate at levels close to residual fuel oil prices in energy-equivalent terms, but with some alternating periods of several months to a year where they are persistently above or below the residual fuel oil price. In some brief episodes, the natural gas price spikes substantially above the residual fuel oil price, and then appears to relate more closely to distillate prices, reflecting that the point of economic price competition has shifted to generating units burning diesel fuel. This substitution in end-use is a critical determinant in understanding the long and short run relationship between natural gas prices and crude oil prices.

Figure 1: Competing Fuel Prices



While we focus on oil products as the key competing fuel for natural gas, we also consider coal as a possible competitor. We find some evidence that it appears to be relevant in some NERC regions, but mainly as a complement to natural gas rather than a substitute for it. However, the information on coal may be less accurate since we only

[2] The conversion factors for energy content, obtained from the Energy Information Agency (EIA) Web site, were 1.03 MMBtu per thousand cubic foot for natural gas, 6.287 MMBtu per barrel for residual fuel oil, 5.838 MMBtu per barrel for distillate and 20.754 MMBtu per ton for coal.

had nationwide price data whereas we had regional gas and oil product prices. We also do not examine potential substitutability (or complementarity) between natural gas and nonfossil fuel sources of electricity (such as nuclear, hydroelectricity or wind). As we explain later, this is partly also the result of data limitations, but technological factors also severely limit the ability of generators to substitute between natural gas and these alternative nonfossil sources of energy.

II. Previous Literature

A number of previous studies have examined competition between fuels in the electricity sector. In an influential early study, Hudson and Jorgenson (1974) examined the electric utility sector as part of a wider study of the role of energy in U.S. industry. The main focus of this study was the linkages between nine key industry sectors and the relationship of those industries to macroeconomic factors and economic growth. The researchers estimated a system of equations, assigning a translog structure for the price possibility frontier[3] for each sector with capital, labor, materials and energy composite goods taken as factor inputs. 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 emphasized that the key contribution of their paper was methodological. They 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

[3] 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 the input factors of production are capital, labor, materials and energy, 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. In particular, it implicitly assumes a competitive industry with free entry, which is of questionable relevance to regulated utilities in the United States at that time.

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 Hudson and Jorgenson in assuming a translog functional form. Part of the attraction of the translog is that it can be viewed as a second-order approximation to a more general function.

Atkinson and Halvorsen (1976) also estimated a translog functional form in their study of interfuel substitution in U.S. electricity generation. However, they focused on a profit function rather than a price possibility frontier. They estimated their model on a sample of multiple-fuel plants for a single year (1972). Atkinson and Halvorsen note that Hudson and Jorgenson assumed a tiered structure for production with different fuels used as inputs into a composite energy commodity, which is then combined with other factors (capital, labor and materials in their specification) to produce final output. Atkinson and Halvorsen comment that this 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 rejected. Perhaps not surprisingly, they found evidence of substantial interfuel substitution in their sample of multiple-fuel plants. A methodological innovation of their paper that was carried over to subsequent studies is that they treated the nonenergy 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 model for pooled annual data during 1952–74 in each of 10 census regions assuming a production structure similar to Hudson and Jorgenson. Consistent with our results presented below, Uri found that regions with the greatest proportion of installed multiple-use capacity had the most elastic demand, while the lower elasticity estimates are found in regions where a single fuel represents a high proportion of total fuel costs. Uri (1978) estimated essentially the same model as Uri (1977) but using monthly data during the period July 1972–December 1976 for 10 regions consisting of slightly different groups of states than the census regions.

In a comment on Uri (1977), Hogarty (1979) notes that Uri inappropriately used census regions when he should instead have used power pools or NERC regions. Hogarty argued that competition occurs between firms or plants in the same power pool or NERC region, and the geographical boundaries of the power pools are not coterminous with census regions. Hogarty also noted that environmental policies alter the relative 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 in which substitution occurred.

Uri (1982) again separated the analysis into the production of electricity using capital, labor and an aggregate energy commodity as inputs and then the determination of the fuel mix given a demand for the aggregate energy commodity. In this case, however, he assumed that the top level process is governed by a constant elasticity of substitution (CES) production function, although he still used the translog price possibility frontier to determine fuel shares in aggregate energy input use. The translog fuel shares model was estimated using pooled annual data from 1961–78 compiled by census region. In the context of our results discussed later, an interesting result is that the error terms were strongly serially correlated with a first order correlation coefficient of 0.9762 (standard error of 0.0127). This could indicate problems with stationarity of the fuel prices.

Bopp and Costello (1990) followed Atkinson and Halvorsen (1976) in estimating a model that includes current capacities of different types of generating plants as regressors, so the factor demand curves can be interpreted as short run demands holding capital fixed. They base their estimation on a cost curve that is assumed to be translog in the fuel prices and various "shift factors" for the short run cost curve:

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

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 between peak and off-peak demand). They also include the lagged short run cost as a shift factor motivated by contracting and delivery arrangements that could delay short run adjustments to fuel price changes. Bopp and Costello then note that Shephard's lemma implies that the derivative of C with respect to p_i yields the demand for the ith input and hence conclude that the share of the ith input in costs satisfies an equation

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

Since the cost function is homogeneous of degree 1 in prices, and the factor shares have to 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 of the input demand equations need to be estimated. The third would then be determined by the adding up constraints.

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

Ko and Dahl (2001) review the electric fuel substitution literature, including some of the articles mentioned above. They note that few articles were published during the 1990s. They noted that the early literature (including Atkinson and Halvorsen (1976) and Haimor (1981)), which had focused on cross-sectional data, had 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. They noted that a more recent paper, McDonnell (1991), indicated a greater substitutability between gas and coal. Additionally, they noted that studies ranging 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 the Federal Energy Regulatory Commission 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 the fuels, 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 (in absolute value) 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 with one another.

Söderholm (2001) argues that there are three ways in which short run interfuel substitution can occur – 1) switching of input by dual-fired generators 2) changes in the dispatch order of plants, and 3) physical modifications of existing generating capacity (specifically from oil-fired to natural gas-fired).[4] Using a translog cost function, as in previous studies, Söderholm expands on the literature by including the effect of a load factor, which he defines as the total generation relative to peak demand. An increased load factor indicates a higher percent of total generation that is base load power, decreasing the cost share of peaking fuel (oil and gas). He estimates one model in which the effect of the load factor is constrained to be zero, and one in which the load factor coefficient is unconstrained. Using annual data for six Western European countries in a panel model with fixed effects for each country, Söderholm estimates fuel input share equations for coal, oil, and gas. From the estimates, he derives cross-price elasticities for the demands for each type of fuel. Söderholm finds that some of the own-price elasticities are positive, which may reflect nonconcavity in the cost function or a violation of the assumption that the translog functional form adequately approximates the underlying technology. Nevertheless, consistent with theory, the results indicate that there are significant cross-price elasticities, especially between peaking fuels, while baseload fuel (coal) demonstrates low own-price elasticity. As expected, the results also indicate that, even at the annual level, an increase in a country's load factor raises the share of coal in overall cost while reducing the shares of peaking fuels.

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[4] 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.

Bousquet and Ladoux (2004) look at interfuel substitution in the French industrial sector based on two alternative assumptions regarding the energy technology. One technology allows for one or more potential energy inputs to be excluded as an actual input exogenously. The other, flexible fuel technology assumes that a fuel that is not consumed in practice could have been consumed in principle, and that its absence is the result of an endogenous cost-minimizing choice of the firm. Bousquet and Ladoux use a translog cost function for both alternatives. In the case of the flexible fuel technology, they rely on the notion of virtual prices to find the corner solutions. Specifically, virtual prices are chosen so that a fuel that is not used would be at the margin of being used, and the approach uses a set of inequalities and equalities to define the fuel shares. Using maximum likelihood, they estimate a joint discrete (choice to use the fuel) and continuous (level of fuel use) model. They obtain two main conclusions. First, regardless of the technology, substitutability is higher among firms that have the option of using three fuels rather than just two fuels. This is illustrated by decreased (in absolute value) own-price elasticities when only two fuels are available. Second, the two models produce very different results with regard to the relative magnitudes of own- and cross-price elasticities. Specifically, when all three fuels are considered available, the fixed technology case results in higher demand responses to changes in own-prices and lower responses to changes in other fuel prices.

The above publications have all provided evidence of interfuel substitution in industry in general and in the electricity industry in particular. We are interested in a more specific question, however, than whether there is evidence of fuel substitution in generating electricity. We want to know if 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 some 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.

A complication with using a longer time series of 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 otherwise nonstationary variables.

There also is a relatively recent literature examining cointegration of fuel prices in the context of the electricity industry. Serletis and Herbert (1999), for example, test the existence of common trends in daily natural gas prices at Henry Hub and Transco Zone 6, the price of power in PJM,[5] and the price of residual fuel oil at New York Harbor during October 1996-November 1997. They find that the three fuel prices are nonstationary and cointegrated, and that Transco Zone 6 prices adjust significantly faster than do Henry Hub prices to deviations in their long run relationship. Similarly, Asche, Osmundsen and Sandsmark (2006), using data for the United Kingdom, report that the prices of crude oil, natural gas and electricity are cointegrated. Moreover, they find that there is a single market for primary energy in the United Kingdom in which price is determined exogenously by the global market for crude oil. In addition, they conclude that changes in regulatory structures and capacity constraints can make prices appear to be more or less cointegrated.

In a related paper in this study (Hartley, Medlock and Rosthal (2007)), we investigate cointegration of natural gas prices, oil product prices and electric plant heat rates at the aggregate level. 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–May 2006. Our analysis thus draws on both the cross-sectional and time series literatures discussed above.

[5] PJM Interconnection is a regional transmission organization that coordinates the movement of wholesale electricity in all or parts of Delaware, Illinois, Indiana, Kentucky, Maryland, Michigan, New Jersey, North Carolina, Ohio, Pennsylvania, Tennessee, Virginia, West Virginia, and the District of Columbia.

III. 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 (*$/MWh*), is given as (*Btu*/*MWh*) times ($/*Btu*), or heat rate times the fuel price. 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 naturally part of the relationship between various competing fuels such as natural gas prices and oil products.

As a preliminary to the formal statistical analysis, 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 2: Capacity-Weighted Average Natural Gas Heat Rates (Btu/kWh)

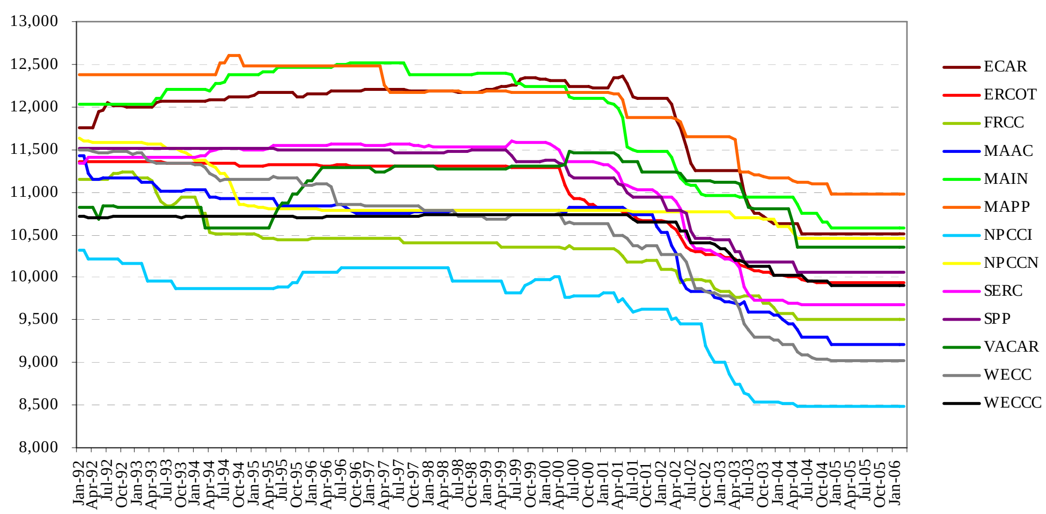
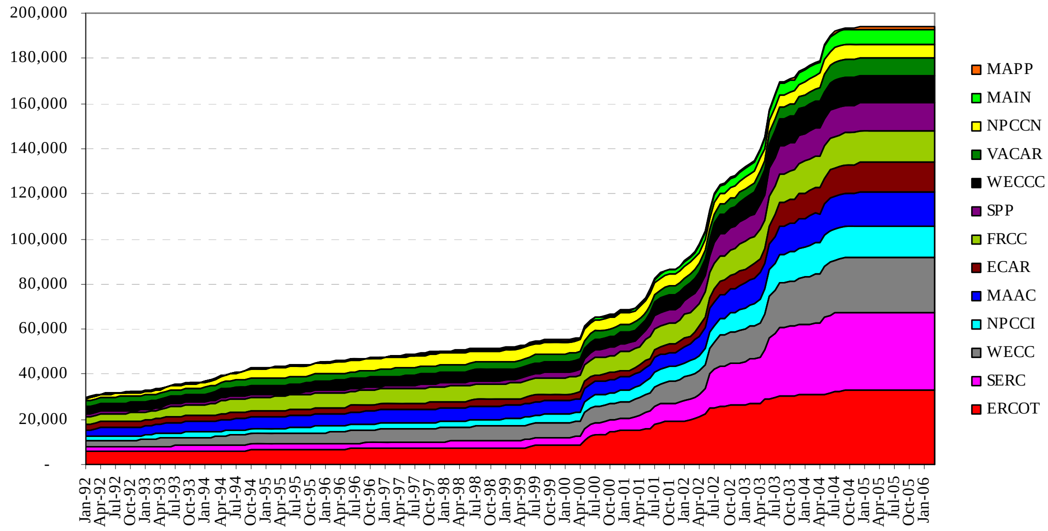


Figure 3 shows that the reduction in heat rates has been accompanied by a rapid expansion in high efficiency CCGT generation capacity. In addition, we find that no such improvement in heat rates has occurred over the same time period for the oil-fired generation capacity (not pictured).

Figure 3: Combined Cycle Gas Turbine Capacity (MW)



In our analysis, 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 to generating electricity. Specifically, for each NERC region *i* in each period *t*, we form a capacity-weighted real cost of natural gas using the average electricity price as deflator

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

where N_i equals the number of natural gas-fired plants on line in NERC region or subregion 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 2004 data) is HR_{ij} (see the appendix for more details). The formula above also allows for the possibility that the natural gas price P_{ijt}^{NG} is different 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.[6] This procedure allows electricity generation to adjust to persistent basis differentials between states with deviations from those differentials

[6] 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.

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 in much the same way as the natural gas costs. However, the same level of disaggregation was not available. Rather than using state-specific prices, the product prices are reported at the Petroleum Administration Defense District (PADD) level. The United States is divided into five PADD districts.[7] NERC region oil generation costs were then formed in a similar manner to the natural gas costs by multiplying product prices by plant heat rates in each region and then forming a weighted average of the results in each region using generating capacities as the weighting variable.

Finally, the real coal costs were again calculated in a similar manner using region-specific heat rates. However, the coal price data, which was obtained from the EIA, was not differentiated by region and was simply an average delivered price to electric generators throughout the United States.

Table 1 presents test statistics for the null hypotheses that the cost variable is nonstationary. There is evidence that the real natural gas cost variable is stationary in a few regions, especially ERCOT, NPCCI and NPCCN and, to a lesser extent, WECCC, WECC and MAPP. It may be the case in these regions that natural gas plants often determine the marginal cost of electricity. Thus, once we have corrected for heat rate changes, the ratio of the price of natural gas to the price of electricity would no longer appear to follow a trend**.** The graph of the real natural gas cost variables in Figure 4 shows, however, that the trend is similar in all regions. On the other hand, in the regions where we can reject the hypothesis of nonstationarity, the variability is much higher. This higher variability would make it much harder to detect any change in trend before and after 1999.

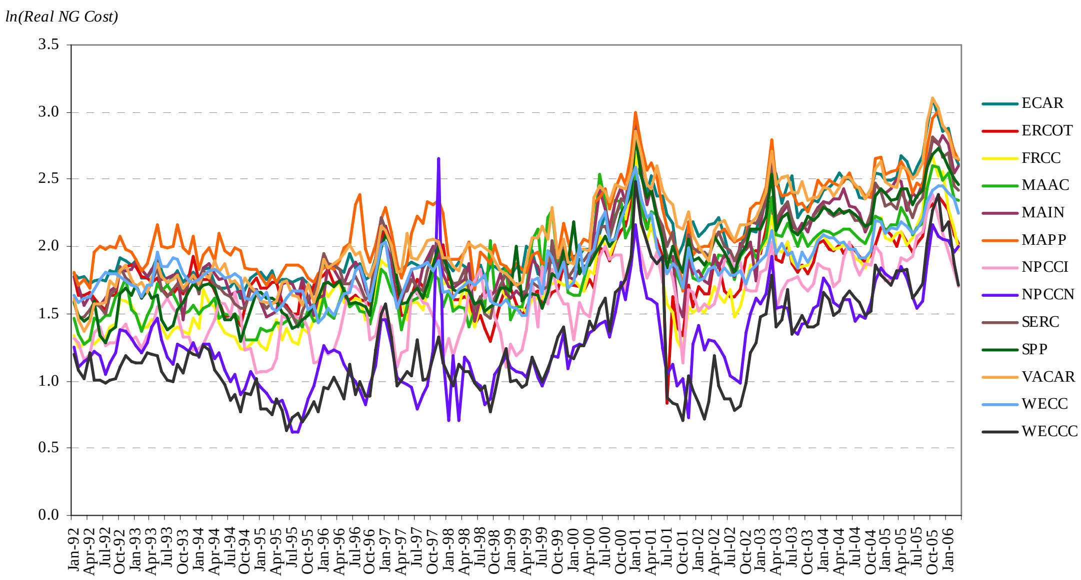
[7] As with the calculation for natural gas prices, the 5% of observations (0.8% if we omit PADD 4) that were missing were interpolated using a regression of nonmissing values on the U.S. average price.

Table 1: Cointegration of the Real Input Cost Variables

NERC subregion	Test for *NGRCost* nonstationarity[a]	Test for *OilRCost* nonstationarity[a]	Test for *CoalRCost* nonstationarity[a]	β_0	β_1	Test for error nonstationarit[a]
FRCC	0.081	0.708	0.332	0.050	0.896	0.000
VACAR	0.427	0.906	0.0096	-0.075	0.961	0.001
MAAC	0.138	0.885	0.0156	0.346	0.757	0.000
MAIN	0.168	0.859	0.0048	-0.212	0.893	0.000
MAPP	0.093	0.888	0.0138	-0.146	0.864	0.000
NPCCN	0.003	0.790	0.0062	-0.054	0.918	0.000
ECAR	0.587	0.913	0.0657	-0.22	0.973	0.000
SPP	0.298	0.778	0.0028	-0.923	1.102	0.000
SERC	0.222	0.849	0.0079	-0.523	0.967	0.000
WECC	0.091	0.818	0.2861	-0.070	0.724	0.000
WECCC	0.072	0.732	0.0386	-0.902	1.012	0.000
ERCOT	0.000	0.738	0.0247	0.050	0.741	0.000
NPCCI	0.003	0.637	0.0009	0.710	0.628	0.000

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

Figure 4: Real Natural Gas Costs, Jan 1992-May 2006



In addition, the evidence for stationarity of the real gas cost variable is less conclusive than might first appear to be the case. Certainly the *p*-values for the test of nonstationarity suggest the hypothesis can be rejected in three and perhaps five or six regions. On the other hand, contrary evidence is provided by the fact that the real oil cost variable appears nonstationary in all regions, while 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 logarithm of the real natural gas cost on the logarithm of the real oil cost

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

A test (also reported in Table 1) then reveals that $\hat{\omega}_t$ is stationary in every NERC region. Evidently, the real gas cost variable in each NERC subregion must contain a nonstationary component that cancels with a similar nonstationary component in oil costs. Hence, the real gas cost variable must be nonstationary in every NERC region. The apparent evidence to the contrary in some regions must result from some other (stationary) high variance components in real gas costs that mask the nonstationarity.

Finally, the real coal cost terms appear to be stationary in all but two subregions, FRCC and WECC. Since the coal prices do not vary by region, and the technology for generating electricity from coal has not changed much in recent years, nonstationarity of the real coal cost in just two subregions is difficult to explain.

IV. Translog Expenditure Function Model

For each NERC subregion, we first estimated a translog model, similar to Bopp and Costello (1990) and other previous literature in order to compare results. To calculate the expenditure share, we first multiplied the cost of each fuel as calculated above times the amount of that fuel consumed in each subregion in each month to obtain real expenditure on each fuel. 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 nonfossil fuel generating capacity is unresponsive to fuel price changes or even changes in the total system load. Wind generation and “run-of-river” hydroelectric generation is determined by natural factors independent of overall power demand or the cost of competing power sources. Also, while the output from nuclear plants could in principle be varied in response to short run demand or cost variations, it is expensive and technologically complicated to do so. Recent increases in capacity utilization at nuclear plants have resulted from technical improvements and improved operational procedures, and not from any response to relative fuel prices. Substitution between nuclear and fossil fuels occurs more at the level of decisions about the construction of new capacity. Once the nuclear plants have been built, their low operating cost means they will be used as much as technically possible.

Hydroelectric plants based on stored water (or pumped storage facilities), on the other hand, 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 (the marginal value of that same water 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 current analysis, especially since such plants are not a major influence on gas demand in many NERC regions. Hence, we treated all nonfossil generation as exogenous and looked at total demand net of such generation output.

The resulting translog model 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 log-linearly to input costs per unit of fuel, capacities (weighted by heat rates) and total fossil fuel generation FE:

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

There are four primary differences between our specification 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 price 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 prices are cointegrated, we use the cointegrating error term in place of real natural gas and petroleum input prices. 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 separate terms $RC_{NG,t}$ and $RC_{oil,t}$. 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 constructed and 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 prices adjusted for changes in heat rates. 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 since the current natural gas expenditure share is constructed using current fuel prices, the contemporaneous value of the error term, $\hat{\omega}_t$, will be correlated with the dependent variable by construction. Therefore, we use an instrumental variables estimator with the lagged value of the cointegrating residual as an instrument for $\hat{\omega}_t$. The fourth difference in our specification also arises from the time series component of our analysis. Specifically, we assume that the relationship (4) is a long run equilibrium relationship and we allow for a lagged adjustment to the long run equilibrium by including the lagged cost share as a regressor. 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 the specification (4) by including two weather variables, the number of heating and cooling degree days in each subregion and month, and a set of monthly dummies. The two weather variables are included for different reasons. A month that has a larger number of cooling degree days (*CDD*) will also 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 change the shape of the load curve, emphasizing peaks compared to months with equivalent total demand for electricity but less extreme temperatures. 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 be associated with an elevated demand for electricity for heating purposes. This effect is not likely to be large, however, since providing space heating is not a significant factor in electricity demand. The motivation for including *HDD* is therefore somewhat different from the motivation for including *CDD*. Natural gas is itself a major source of space heating services on cold days, thus making changes in *HDD* relevant to residential natural gas demand trends. 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 for heating purposes is high. If so, a large *HDD* value would be associated with lower gas use for generating power independently of any effects operating via higher prices. The two effects discussed here are offsetting in sign, so it is not clear *a priori* whether *HDD* would have a positive or negative coefficient, or even whether it would differ significantly from zero.

The monthly indicator variables (*Month*) reflect many influences on demand. For one, there are different numbers of days in each month, so *all else equal*, a month with 31 days should see greater natural gas demand than a month with 30 days. Second, 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. Third, the monthly indicator variables will also reflect seasonal regularities in natural gas price movements relative to oil. For example, since there are seasonal effects in natural gas price basis differentials, the cost differential term $\hat{\omega}_t$ will 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 $\hat{\omega}_t$. Last, 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 estimated equation (omitting the underscore *i* which represents the NERC subregion) then becomes:

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

Equations (6) for the full panel and for each subregion are estimated using $\hat{\omega}_{t-1}$ as an instrument for $\hat{\omega}_t$. In the panel estimation of (6), S_{t-1}^{NG} is also instrumented, while the constant term and the coefficients on the monthly indicator variables are allowed to vary by NERC subregion. In particular, the panel estimation is a fixed effects estimator. The results are shown in Table 2 in order of responsiveness to lagged deviations from the long run price relationship, $\hat{\omega}_t$. To save space, the constant terms, the estimated monthly effects and, in the panel regression, the regional fixed effects, have been 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 US power generation system as a whole, natural gas and oil products are substitute fuels.

Similarly, the negative coefficient on the coal cost variable for the panel as a whole and for four NERC subregions suggests that coal and natural gas are on the whole complements. This is feasible if coal and natural gas plants tend to be operated in different regions of the load curve. On the other hand, the positive coefficient on the real coal cost in the New York subregion (NCCN) suggests that coal and gas are substitutes in that region. The negative coefficient on the coal capacity variable in several subregions also hints at substitution between natural gas and coal.

The coefficient on the lagged dependent variable in the full panel implies that the adjustment to an exogenous shock will be about 40% complete after three months, around 60% complete after six months and more than 80% complete after one year. The estimated speed of adjustment is slower, however, in each of the subregions.

The cost share equation (6) also includes as regressors the logs of the heat rate weighted capacities for each type of fossil fuel. The natural gas capacity variable was statistically significantly different from zero in the panel and all but four subregions. However, in the SPP subregion it was significant but with an unexpected negative sign. None of the oil or coal capacity variables was significant for the panel as a whole, although one or other oil capacity variable was significantly different from zero in six of the 13 subregions. The coal capacity variable was significantly different from zero in only three subregions.

Table 2: Panel and NERC subregion translog results (in order of decreasing negative response to gas/oil cost difference)

NERC subregion	S_{t-1}^{NG}	$\hat{\omega}_t$	$RC_{coal,t}$	*lnNGCap*	ln*DfoCap*	ln*RfoCap*	ln*CoalCap*	ln*FE*	*CDD*	*HDD*	Number of obs.	R^2 (overall)	R^2 (within)	R^2 (between)
Panel	0.8793***	-0.0286***	-0.0372**	0.0200***				0.0067*	0.0002***		2184	0.9610	0.8499	0.9880
	(0.0160)	(0.0094)	(0.0172)	(0.0040)				(0.0037)	(0.00003)					
NPCCN	0.5395***	-0.1479**	0.1811**							-0.00018**	169	0.6889		
	(0.0860)	(0.0708)	(0.0901)							(0.00008)				
SERC	0.5934***	-0.0813***	-0.2210***		0.2608**			0.1058***		0.00009**	169	0.9076		
	(0.0616)	(0.0272)	(0.0638)		(0.1264)			(0.0301)		(0.00004)				
SPP	0.5822***	-0.0621*	-0.2668***	-0.1500**	0.8950**		-50.624***		0.0004***		169	0.9305		
	(0.0694)	(0.0359)	(0.0846)	(0.0733)	(0.4162)		(12.746)		(0.00009)					
NPCCI	0.6698***	-0.0613		0.1152***				0.0303***		-0.0002***	169	0.9069		
	(0.0693)	(0.0692)		(0.0267)				(0.0117)		(0.00007)				
WECC	0.8484***	-0.0577*		0.0215				0.1263***	0.00047***	0.00013**	169	0.9593		
	(0.0452)	(0.0299)		(0.0137)				(0.0409)	(0.00014)	(0.00005)				
VACAR	0.4176***	-0.0546*		0.0640**	0.8358		-0.4758***		0.0006***		169	0.8339		
	(0.0662)	(0.0312)		(0.0254)	(0.5128)		(0.1743)		(0.0001)					
ERCOT	0.5136***	-0.0413	-0.1796**	0.1782***	-0.3183***		-0.9734**	0.1098***	0.00016*		169	0.7837		
	(0.0904)	(0.0513)	(0.0700)	(0.0648)	(0.0843)		(0.4525)	(0.0314)	(0.00009)					
FRCC	0.7243***	-0.0299	-0.2735**	0.0637***							169	0.8743		
	(0.0548)	(0.0329)	(0.1252)	(0.0237)										
MAIN	0.4226***	-0.0237			-0.0931***			0.0688***	0.0007***		169	0.8171		
	(0.0538)	(0.0231)			(0.0337)			(0.0170)	(0.00008)					
MAPP	0.6187***	0.0060				-0.0076***			0.0004***		169	0.8745		
	(0.0468)	(0.0113)				(0.0013)			(0.00005)					
MAAC	0.5660***	0.0086		0.0663***		-0.5839**		-0.0336**	0.0005***		169	0.8756		
	(0.0721)	(0.0305)		(0.0215)		(0.2611)		(0.0156)	(0.0001)					
ECAR	0.5083***	0.0134		0.0184***					0.0003***		169	0.8020		
	(0.0582)	(0.0173)		(0.0035)					(0.00005)					
WECCC	0.2653***	0.0159*		0.0454***							169	0.3228		
	(0.0777)	(0.0096)		(0.0165)										

*** 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.

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 on five of the subregions, 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 subregions. By contrast, *HDD* was not significantly different from zero in the panel regression or all but four of the subregions. Furthermore, in two regions it was significantly positive while in the other two, it was significantly negative.

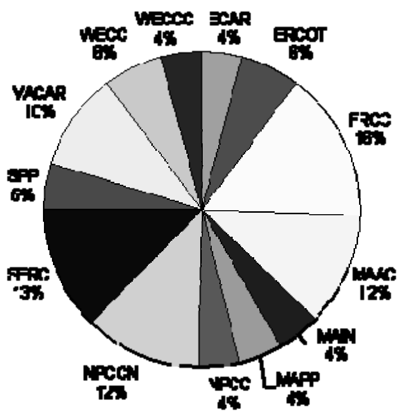
V. Plant-Level Switching

On the whole, the translog results do not reveal a strong degree of substitution between natural gas and oil products in the generation of electricity. For the panel as a whole, the expenditure share of natural gas does respond negatively to an increase in natural gas costs above their long run relationship with oil costs. However, this cost deviation variable is found to be statistically significantly negative in only five subregions and has a (weakly) significant positive sign in one region. Furthermore, it is well known that there is substantial capability to switch fuels within plants in many areas on the East Coast 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 investigated fuel switching at the plant level in more detail.

In the United States, approximately 18% of all generation is dual-fired, indicating either natural gas or a petroleum product can be used as the energy source. Seventy percent of all switching-capable facilities can run on either natural gas or distillate fuel. 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-November 2006, we identified 167 plants that used natural gas in at least one month and either distillate or residual fuel oil in at least one month. Of these 167 plants, 110 used natural gas in at least one month and distillate, but not residual fuel oil, in at least one month. Natural gas was used in at least one month and residual fuel oil, but not distillate, in at least one month in 43 plants. In the remaining 14 plants, each of natural gas, distillate and residual fuel oil was used in at least one month.

Figure 5 gives the proportion of these flexible fuel plants located in each NERC subregion. As noted above, almost 40% of these plants can be found in the FRCC, MAAC and VACAR regions, with another 25% in SERC and NPCCN (New York).

Figure 5: Proportion of Dual-Fired Generation Capacity in Each NERC Subregion



The model we estimate is:

$$NGPct_{i,t} = a_0 + a_1 NGPct_{i,t-1} + a_2 \ln\left(\frac{P_{it}^{NG}}{P_{it}^{E}}\right) + a_3 \ln\left(\frac{P_{it}^{oil}}{P_{it}^{E}}\right) + b_1 CDD_{i,t}$$
$$+ b_2 HDD_{i,t} + \sum_j c_j Month_{j,t} + \varepsilon_{i,t}$$

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. If plant *i* does not generate electricity during the month, it is omitted from the sample. The lagged dependent variable is included in the model to allow for a slow response to changes in fuel prices. The latter could arise, for example, if there are fixed costs associated with changing the fuel source. The price variables P^{NG}, P^{oil} and P^{E}, and the weather variables *CDD* and *HDD*, are defined as above. For notational convenience, we define the real fuel input prices (with electricity prices as deflator) $p_{it}^{NG} = P_{it}^{NG} / P_{it}^{E}$ and $p_{it}^{oil} = P_{it}^{oil} / P_{it}^{E}$. The heat rate variables were not included in the analysis since we have them by plant only and not by type of fuel.[8] Monthly dummy variables are included in order to account for systematic plant outage behavior. Finally, we assume the error term is a composite including 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:

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

Hence, we will have a censored dependent variable and must take that into account in the estimation procedure 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:

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

where the truncation implies

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

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

[8] If the available heat rates are used, they do not substantially alter the estimated coefficients or the conclusions of the analysis, although they do reduce the sample size.

We estimate three models. The first uses the full sample. The remaining two models use the subset of plants that switched between natural gas and distillate, or the subset that switched between natural gas and residual fuel oil. The 14 plants that used all three fuels are included only in the full sample. We use the appropriate real oil product price for each of the subsamples. We allowed both real oil product prices to enter the equation for the full sample, but only the real residual fuel oil price remained statistically significantly different from zero. The results of all three models are summarized in Table 3 (the constant term and monthly effects are also present in each model, but have been omitted to save space).

The strong and statistically significant negative coefficients on the real natural gas prices, and positive coefficients on the real oil product prices, indicate that plants do tend to switch to oil products in response to an increase in natural gas prices and vice versa. Comparing the two subsamples, the response to an increase in natural gas prices is stronger for plants that can burn residual fuel oil than for facilities that can burn distillate as the substitute fuel. In addition, the coefficient on the real residual fuel oil price is considerably larger than the coefficient on the real distillate price in the full sample regression. Hence, these results suggest that residual fuel oil appears to be a stronger substitute for natural gas overall. This result is necessarily a little tentative, however, because the residual fuel oil and distillate prices are themselves highly correlated.

The heating and cooling degree day variables also are estimated to have a significant effect on switching. However, the negative coefficients on these variables are inconsistent with the results in Table 2. In Table 2, cooling degree days generally had positive effects on the consumption of natural gas, while the effect of heating degree days appeared to vary by region.

Table 3: Plant-Level Panel Tobit Results for Switching Plants

	All switching plants	Natural gas and distillate	Natural gas and residual
$NGPct_{t-1}$	0.6635*** (0.0083)	0.7108*** (0.0112)	0.6317*** (0.0126)
$\ln p_t^{NG}$	–0.0590*** (0.0112)	–0.0560*** (0.0151)	–0.1055*** (0.0157)
$\ln p_t^{rfo}$	0.0715*** (0.0210)		0.0921*** (0.0174)
$\ln p_t^{dfo}$	0.0269 (0.0221)	0.1150*** (0.0178)	
CDD	–0.00015*** (0.000027)	–0.00015*** (0.000035)	–0.00003 (0.00004)
HDD	–0.00011*** (0.000014)	–0.00010*** (0.000018)	–0.00013*** (0.00002)
σ_υ	0.3262*** (0.0182)	0.3476*** (0.0237)	0.2669*** (0.0299)
σ_ε	0.3133*** (0.0020)	0.3465*** (0.0029)	0.2492*** (0.0026)
observations	26290	17558	7230
left-censored	2610	2271	346
uncensored	12885	7291	4921
right-censored	10795	7996	1963
number of plants	167	110	43
$\ln L$	–9604.41	–7198.39	–1376.54
χ^2 (d.f.)	8251.6 (17)	5412.6 (16)	3187.1 (16)

*** indicates significance at the 1% level, ** indicates significance at the 5% level, and * indicates significance at the 10% level. The chi-square tests the joint significance of the explanatory variables.

VI. An Alternative Specification for Gas Demand in Power Generation

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 at least some of the results in Table 2. In addition, some variables that the theory implies ought to be significant drop from the estimated equations in Table 2, 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, the translog specification loses one of its key advantages in our context where the focus is on the demand for natural gas as an input to electricity generation. Specifically, the translog functional form has added benefit when estimating multiple share equations because of the constraint that all cost shares must sum to one. However, for the purposes of this study, we are only interested in the natural gas share. Therefore, the cross-equation constraints arising from the translog function fail to provide any additional information.

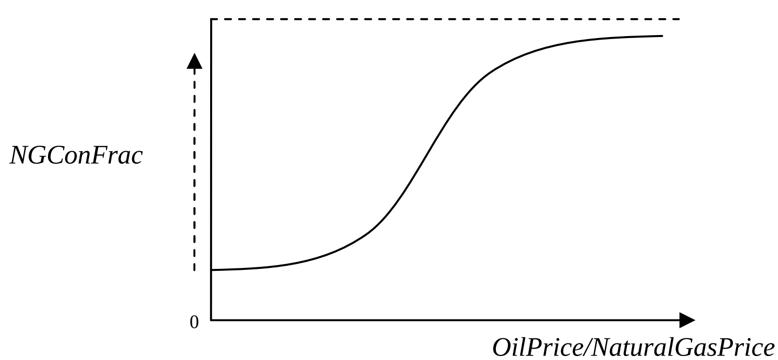
The apparent deficiencies of the translog functional form motivated the use of a different model that we believe better captures the way a power system operates than does the simple log-linear form produced by the translog specification. Primarily, we altered the dependent variable to focus explicitly on natural gas consumption, not as a share of costs but rather as a share of maximum potential consumption given the available capacity. The minimum natural gas usage in a month is obviously zero, while the maximum usage is limited by the total natural gas-fired generating capacity in the NERC subregion in a given month. Thus, we defined a 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 generate power to this theoretical maximum level (*NGConFrac*) would then be a number constrained to lie in the [0, 1] interval.[9]

[9] 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.

The dependent variable was then taken to be the double log of the capacity factor for natural gas plant usage in a month (ln(-ln$NGConFrac_t$)).[10] The double log functional form allows a nonlinear response to changes in the determinants of natural gas demand that reflects the way that the electricity system is operated in practice. Since combined-cycle electricity generation, conventional gas-fired steam generation and gas turbines each have different heat rates, they are used to supply power at different points on the load curve and thus for different amounts of time during the month. As total gas-fired generation increases, the most efficient plants are used first and the least efficient ones 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 the following 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 on the right hand side of the equation take, natural gas usage cannot be predicted to lie outside the bounds of what is feasible.

Figure 6: Response of *NGConFrac* to Changes in Oil Price for a Natural Gas Price



A technical advantage of the double log transformation is that it allows for an error term with classical properties as assumed by the statistical theory underlying the estimation of the equation and the hypothesis tests for statistical significance. If the

[10] The term ln*NGConFrac* will be negative and the logarithm of the negative logarithm will be well defined and can take any real value.

dependent variable were constrained to lie in the unit interval, for example, the error terms in the equation would need to be bounded.

Finally, with the expenditure share as a dependent variable as in (6), changes in the price of natural gas will alter the dependent variable by construction. We used instrumental variables to control for this potential endogeneity. With the new dependent variable, however, we avoid this problem and thus can use $\hat{\omega}_t$ from (5) as a standard regressor.

By construction, $\hat{\omega}_t$ will be positive when real natural gas costs are above their long run relationship with real oil costs. If this were the case, we would expect a reduction in the demand for natural gas as oil-fired capacity is dispatched more extensively. Because ln(-ln*NGConFrac*) decreases as *NGConFrac* increases we should find that $\hat{\omega}_t$ has a *positive* effect on the dependent variable.

Since the natural gas capacity has, in a sense, 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, monthly dummies and total electricity generated from fossil fuels as the output measure, the estimated equation for each NERC subregion becomes (omitting subscripts *i* denoting the region):[11]

$$\begin{aligned} \ln\left(-\ln NGConFrac_t\right) &= b_0 + b_1\hat{\omega}_t + b_2 \ln FE_t \\ &\quad + b_3 CDD + b_4 HDD + \sum_i Month_i + \varepsilon_t \end{aligned} \tag{7}$$

where $\hat{\omega}_t$ is the estimated residual from (5), FE_t is the total electricity generation from fossil fuels in region *i* and period *t*, cooling degree days (*CDD*) and heating degree days (*HDD*) are two weather variables, $Month$ is a set of monthly indicator variables and $\varepsilon_t = \rho\varepsilon_{t-1} + \theta(L)u_t$ is an error term that can be autocorrelated with a moving average

[11] In WECCC (California), the equation included an indicator variable set equal to 1 for the period January through June of 2001 and 0 elsewhere. This allowed for departures from the estimated relationship during the California electricity crisis of that year. The period was characterized by large deviations in ω_t and the use of natural gas to generate electricity that do not fit the estimated patterns for remaining time periods.

structure.[12] Specifically, the term θ(L) denotes a polynomial in the lag operator and leads to terms such as $u_t + \theta_1 u_{t-1} + \theta_3 u_{t-3} + \theta_6 u_{t-6}$ where the polynomial has nonzero coefficients corresponding to L, L^3 and L^6 only and u_t is a white noise process.

Autocorrelation could arise for a number of reasons, including slow adjustment to changes in factors that affect natural gas demand that continue to alter demand in subsequent periods, such as contracting behavior. In addition, any important influences on the demand for natural gas that have been omitted from the equation would appear in the error term, and these influences could themselves be autocorrelated over time. Explicit supply contracts or hedge or futures positions that cover a longer period than the period of observation, here one month, often lead to a moving average error structure. In the panel estimation, we allow the error term to be first order autocorrelated, but we ignore any possible moving average component. The latter are estimated only in the individual time series analyses for each NERC subregion.

In general, we would also expect natural gas consumption to increase as total electricity generation from fossil fuels (ln*FE*) increases as gas-fired plants would be part of the mix of plants called upon to meet peak demands. Obviously, we would expect gas demand for electricity generation to rise as ln*FE* rises, implying $b_2 < 0$.

As we argued previously, we would also expect an increase in *CDD* to increase the demand for natural gas (so $b_3 < 0$) 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.

[12] 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.

Table 4: Results for the Alternative Specification (in order of decreasing sensitivity to cost differences)

NERC subregion	$\hat{\omega}$	ln *FE*	*CDD*	*HDD*	CAcrisis	AR(1)	MA term	Q-statistic (6 lags)	Q-statistic (12 lags)
Panel	0.0858***	-0.3897***	-0.0012***	-0.00008**	-0.1299***	panel-			
	(0.0195)	(0.0222)	(0.00007)	(0.00003)	(0.0360)	specific			
FRCC	0.2997***	-0.3179***	-0.0006***	-0.0006***		0.9240***	$u_t - \underset{(0.0937)}{0.2878^{***}} u_{t-1}$	4.8774	15.684
	(0.0812)	(0.0773)	(0.0002)	(0.0002)		(0.0377)		(0.5596)	(0.2061)
VACAR	0.2179**	-0.1820*	-0.0019***			0.6251***	$u_t - \underset{(0.0888)}{0.2145^{**}} u_{t-5} + \underset{(0.0846)}{0.1994^{***}} u_{t-10}$	7.6000	14.080
	(0.0988)	(0.0953)	(0.0004)			(0.0628)		(0.2689)	(0.2957)
MAAC	0.1727**	-0.2320***	-0.0020***			0.6863***		3.5886	10.221
	(0.0719)	(0.0404)	(0.0004)			(0.0624)		(0.7321)	(0.5966)
MAIN	0.1358**	-0.5167***	-0.0020***	-0.0002***		0.9542***	$u_t - \underset{(0.0878)}{0.3617^{***}} u_{t-1}$	8.0131	16.225
	(0.0551)	(0.1251)	(0.0003)	(0.0001)		(0.0296)		(0.2371)	(0.1812)
MAPP	0.1079**		-0.0020***	-0.0001**		0.5049***		5.266	11.134
	(0.0505)		(0.0002)	(0.00004)		(0.0726)		(0.5102)	(0.5175)
NPCCN	0.0926***	-0.2003***	-0.0008**			0.8408***		1.7551	7.1401
	(0.0321)	(0.0665)	(0.0003)			(0.0456)		(0.9408)	(0.8482)
ECAR	0.0477	-0.5512***	-0.0017***			0.9613***	$u_t - \underset{(0.0980)}{0.4453^{***}} u_{t-1}$	8.2623	17.385
	(0.0750)	(0.2023)	(0.0002)			(0.0302)		(0.2195)	(0.1357)
SPP	0.0334	-0.6012***	-0.0013***	-0.0003***		0.9204***	$u_t + \underset{(0.0819)}{0.2492^{***}} u_{t-11} + \underset{(0.0898)}{0.4300^{***}} u_{t-13}$	3.5442	8.8185
	(0.0564)	(0.1287)	(0.0002)	(0.0001)		(0.0289)		(0.7381)	(0.7184)
SERC	0.0318	-0.5853***	-0.0007***	-0.0001*		0.9412***		7.8639	10.156
	(0.0520)	(0.0804)	(0.0002)	(0.00006)		(0.0285)		(0.2482)	(0.6023)
WECC	0.0125	-0.7045***	-0.0013***	-0.0002***		0.8908***		1.9780	12.204
	(0.0649)	(0.1078)	(0.0004)	(0.00009)		(0.0355)		(0.9217)	(0.4294)
WECCC	0.0109	-0.4172***	-0.0002***		-0.1027***	0.9558***	$u_t - \underset{(0.1052)}{0.1786^{*}} u_{t-1}$	2.9401	6.6784
	(0.0228)	(0.0080)	(0.00009)		(0.0251)	(0.0340)		(0.8163)	(0.8781)
NPCCI	0.0057	-0.4918***		0.0004***		0.9545***	$u_t - \underset{(0.1367)}{0.3331^{**}} u_{t-3} - \underset{(0.1029)}{0.2471^{**}} u_{t-6} - \underset{(0.0972)}{0.2291^{**}} u_{t-9} + \underset{(0.0837)}{0.2990^{***}} u_{t-11}$	7.2234	15.811
	(0.0830)	(0.0495)		(0.0001)		(0.0388)		(0.3007)	(0.2000)
ERCOT	0.0009	-0.4000***	-0.0007***	-0.0002***		0.9663***		7.2234	15.811
	(0.0320)	(0.0345)	(0.0001)	(0.00006)		(0.0262)		(0.3007)	(0.2000)

*** 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.

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 there was disruption in the demand for many different type of fuel including natural gas. 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.

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 absence of serial correlation. The statistics are distributed chi-squared with 6 and 12 degrees of freedom in the two cases.

The panel results were obtained using a Prais-Winsten regression allowing for contemporaneously correlated panel errors each with a panel-specific autoregressive of order 1 time series structure. The standard errors are panel-corrected. The R^2 in the Prais-Winsten regression was 0.7577 and the chi-square for the joint significance of the regressors was $\chi^2_{160} = 4353.02$.

The time series results for each subregion were obtained using maximum likelihood estimation obtained via a Kalman filter. 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 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 results in Table 4 show a strong tendency for increases in the relative real costs of natural gas and oil to induce a substitution away from natural gas as a fuel to generate electricity. This is true not only for the full panel results but also for all of the NERC subregions, although the coefficient is statistically significantly different from zero in only six of them: FRCC, VACAR, MAAC, MAIN, MAPP, and NPCCN. These regions encompass the East Coast from Florida to New York and Pennsylvania and Midwestern states inclusive of Illinois, Wisconsin, Iowa and Minnesota. Three additional regions (ECAR, SERC and SPP) 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 (WECC, WECCC, ERCOT and NPCCI) are so small relative to their estimated 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 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 respond to the cost differences by varying the position of plants on the supply stack, like the ability to switch fuel inputs in particular plants, varies from one region to the next. This could explain why some regions such as MAIN and MAPP exhibit stronger responses to $\hat{\omega}_t$ than do other regions such as SERC even though the former two regions have smaller fractions of dual-fired capacity.

All regions except MAPP are estimated to have a strong and statistically significant response to changes in the quantity of fossil fuel-powered electricity generation (ln*FE*), with WECC being the most responsive. This suggests that natural gas plants provide a significant component of marginal generating capacity in all subregions except MAPP. The results regarding the effect of ln*FE* are much stronger in Table 4 than in Table 2. This again suggests that the alternative specification may be more appropriate than the translog.

All regions except NPCCI (New England) are also responsive to cooling degree days. As in the translog results in Table 2, and unlike the results for the switching plants, the results in Table 4 show that an increased demand for air conditioning tends to raise the demand for natural gas. It is possible for the systemwide use of natural gas to increase even if its use in switching plants decreases if the nonswitching gas plants are used more intensively.

An increase in heating degree days is now estimated to be statistically significant for the panel as a whole and for eight subregions. For the panel as a whole and for seven of the subregions, an increase in *HDD* is estimated to increase the demand for natural gas to generate electricity. Only in NPCCI (New England) 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, but it could also indicate that significant omitted explanatory variables are themselves autocorrelated. In seven of the subregions, the error terms also displayed a significant moving average structure, which could reflect the importance of multiple month contracts in these regions, or perhaps omitted explanatory variables that are seasonal or correlated only over a few neighboring months.

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. These are constant in the translog specification (6) but in (7) they will vary. For illustrative purposes, suppose we have a right hand side variable *x* measured in logarithmic form with estimated coefficient α. The partial relationship, given as,

$$\ln(-\ln y) = \alpha \ln x$$

implies $y = e^{-x^{\alpha}}$ so the estimated elasticity of response becomes

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

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.

The weather variables are measured in levels rather than logs. In that case,

$$\ln(-\ln y) = \alpha x$$

implies $y = e^{-e^{\alpha x}}$ so the estimated elasticity of response becomes

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

For the indicator variables, it makes little sense to measure an elasticity of response since the variable can only be either 0 or 1. Instead, if

$$\ln(-\ln y) = k + \alpha D,$$

where k is a constant and D = 0 or 1, we measure the ratio of natural gas consumption between the two cases (D = 0 or 1) as

$$\frac{y_{D=1}}{y_{D=0}} = e^{e^{k}(1-e^{\alpha})}.$$

A positive value of α makes $y_{D=1}$ smaller than $y_{D=0}$ and vice versa.

As an example, consider the estimated equation for the NERC subregion MAIN (Middle America):

$$\ln\left(-\ln NGConFrac_t\right) = 10.0609 + 0.1358\omega_t - 0.5167\ln FE_t$$
$$-0.0020CDD_t - 0.0002HDD_t + \sum_i \gamma_i Month_i + \varepsilon_t$$

$$\varepsilon_t = 0.9452\varepsilon_{t-1} + u_t - 0.3617u_{t-1}$$

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 $0.5617FE_t^{-0.5167}$ percent, holding all other influences fixed. Meanwhile, cooling and, to a lesser extent, heating degree days have positive effects on the consumption of natural gas.

Although they are not presented above, the coefficients on the monthly indicator variables imply that natural gas demand for electricity generation in MAIN is significantly higher in February through May and again in September through December than it is in January. Demand in June and August (but not July) is also estimated to be higher than in January, but the difference is not statistically significantly different from zero. These effects are difficult to interpret since they could represent any number of seasonal influences on electricity demand, fuel prices, average number of working days in a month and so forth. The main purpose of including the monthly variables is to ensure that the remaining estimated coefficients are not distorted because the associated variables also contain a seasonal component.

Finally, for $\hat{\omega}$ positive, natural gas cost is high relative to the long run relationship with the oil cost of production. Therefore, this variable ought to have a negative impact on natural gas consumption, or positive coefficient, as is the case with MAIN. The estimated equation for MAIN thus implies that substitution between natural gas- and oil-fired generation contributes to bringing natural gas and oil costs back into line when they deviate from their long run relationship.

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

$$\omega = \ln\left(\frac{NGRCost}{OilRCost^{\beta_1}} e^{-\beta_0} \right)$$

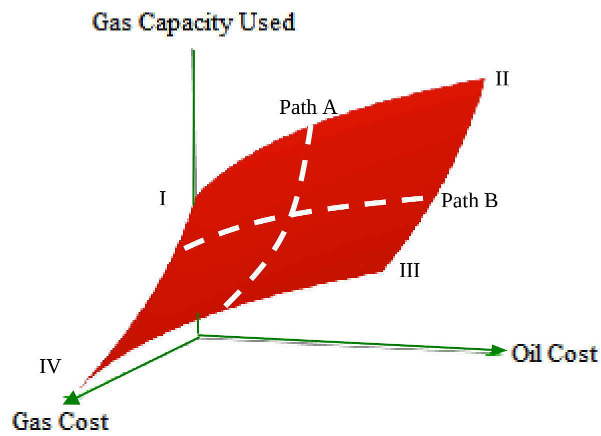
the elasticity in this case becomes

$$-\alpha\left(\frac{NGRCost}{OilRCost^{\beta_1}} e^{-\beta_0} \right)^{\alpha} = -0.1358\left(\frac{NGRCost}{OilRCost^{0.893}} e^{-0.212} \right)^{0.1358}.$$

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, leads to an increase in 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 leads to an increase in the use of natural gas capacity use at a decreasing rate (Path B). A consequence is that if prices moved 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 tend to 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 once 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 in practice most of the data lies in the vicinity of the other diagonal in Figure 7 (along the diagonal connecting I to III), which is precisely because natural gas and oil prices tend to return to a long run equilibrium, where prices move together.

Figure 7: Estimated Response of Natural Gas Demand to Cost Variations



VII. Concluding Remarks

As stated at the outset, a primary reason for analyzing natural gas demand in the power generation sector is to better understand the demand-side factors that drive a relationship between crude oil prices and natural gas prices. It is apparent that there is considerable influence coming from the power generation sector. We found that positive deviations from the long run relationship between the cost of using natural gas to generate electricity relative to the cost of using petroleum products exert a significant negative effect on natural gas demand in power generation. Moreover, while the effect is generally larger in regions with a significant number of plants can switch fuel inputs, it is present in all NERC regions as a result of movements of plants up or down the supply stack as fuel prices change. This is important as it establishes a force that drives crude oil prices and natural gas prices back to a long run equilibrium relationship, 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.

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 except MAPP, an increase in overall electricity demand is also met at the margin by burning more natural gas.

Another result of our analysis is that it casts doubt upon the adequacy of the translog functional form for representing the cost function in electricity generation. In this regard our results support the findings of Söderholm (2001), who also finds results that are inconsistent with the translog model. Our results suggest that there may be an asymmetric response to variations in the relative prices of fuels that cannot be captured using the translog functional form. Specifically, we found that 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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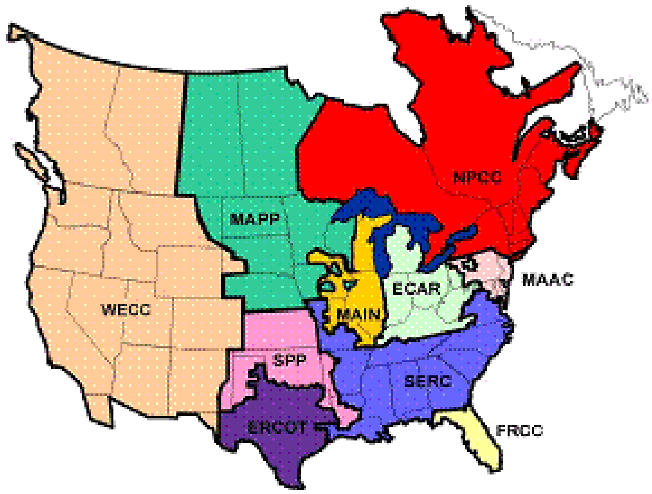
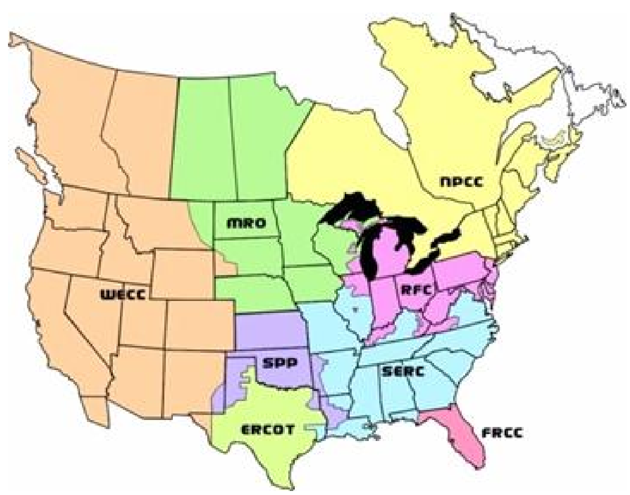
Appendix 1: North America Electric Reliability Council (NERC) Regions

Prior to Jan 1, 2006 (used for this study)



After Jan 1, 2006



Appendix 2: Description of the Electricity Data

Capacity-Weighted Heat Rates

The capacity-weighted heat rates were determined based on the heat rates at each facility as given in the EPA NEEDS 2004 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: A unique ID number was created for each generator at each facility. This ID number consisted of the facility ID and the generator number. These two components were available in both the EIA and EPA datasets and for any plant where there was an exact match of facility and generator number, the reported heat rate was matched to the EIA data.
- Step 2: The 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: The average heat rate of similar facilities (based on prime mover type and fuel type and year of initial use) was used for the facility.
- Step 4: The average heat rate of all plants with same fuel type and prime mover.

If matching was accomplished in Step 1, only the remaining plants in the database were subjected to Step 2. As plants were matched in each step, the number of remaining unmatched plants dwindled until the Step 4, which is the least precise metric.

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, those plants that are powered by geothermal, hydro, or other fuel sources that are not necessary for the electricity demand analysis 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. However, the formatting of the file allows the user to include secondary energy sources in the heat rate calculations (see “HR Capacity Layout.xls”).

Natural Gas Consumption

EIA Forms 906 and 920 spanning the years 1986-2006 (found in file “Generation Data.xls”) report the total energy consumed by fuel type for electricity generators. Some modifications to the raw 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.

1) Pre-2001 data include only the physical quantity of fuel consumed (bbl, mcf, tons), but do include neither the heat content of the fuel consumed nor the total energy content of fuel consumed (MMBtu). This problem was resolved by using the average heat content for each specific fuel type (‘Reported AER Fuel Type’) by state in 2001, and applying that heat content at each plant in that state that used that fuel type. This was then used to calculate the total energy consumed for electricity generation for that plant.
2) 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 that appeared prior to 1997, but not after 1997, and was located in Florida 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.

3) The data were organized by reported NERC region with the exception of the aforementioned FRCC/SERC modification and the subregions specified for the analysis, the subregionalization of NPCC into NPCCN (any plant in NPCC that is located in NY) and NPCCI (any plant in NPCC not in NY), the distinction of VACAR (a subregion of SERC located in VA, SC, NC), and the distinction of California from the rest of the WECC.
4) Facilities that reported negative fuel consumption or electricity generation were not included in the dataset to eliminate those facilities that are either purchasing electricity or selling their fuel supply.

After the above modifications were made to the dataset, 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 using state-specific city gate prices reported by EIA. The NERC region natural gas prices are a capacity-weighted city gate price, determined as in the following equation:

$$NGPrice_{i,t} = \sum_{j} \alpha_{j,t} NG\,\mathrm{Pr}\,ice_{j,t}$$

where:

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

$NG\,\mathrm{Pr}\,ice_{j,t}$ = City gate price in state *j* at time *t*

In some instances, data were missing. Thus, the missing state city gate price was constructed based on 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, the same level of disaggregation was not available. Rather than using state-specific prices, the product prices are reported at the PADD level. 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 total capacity in NERC region i that is in PADD j at time t

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

Any missing data was constructed in the same manner as described above for natural gas prices – missing values were interpolated using the regression of nonmissing values on the U.S. average price.

Natural Gas Combined Cycle Capacity

The capacity of natural gas combined cycle (NGCC) facilities is based on the prime mover characterization given in EIA Form 860, which results in any generator marked CA, CT, CS, or CC (see "HR Capacity Layout.xls" for descriptions) being characterized as an NGCC. In addition, only if natural gas is reported to be the primary energy source is the facility considered to be part of the total natural gas combined cycle capacity.

Natural Gas Steam and Gas Turbine Capacity

Any natural gas generator that is not considered combined cycle is included in the steam and gas turbine categorization for natural gas capacity.

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. Each state is assigned to only one NERC region, even if the state lies in more than one NERC region.

Generation Cost

Generation cost is defined here as 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 (heat rate), 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 capacity-weighted heat rates (*Btu/kWh*) are used as the technology measure. The oil generation cost is calculated as the capacity weighted average of residual fuel cost and distillate fuel cost.

Maximum Natural Gas Consumption

Maximum natural gas consumption is a measurement of the total amount of natural gas (MMBtu) that could theoretically 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*, which is a measure of the percentage of natural gas capacity that is actually used.

California Crisis Dummy Variable

A dummy variable was used to allow for the market peculiarities present at the time of the California energy crisis. This resulted in a dummy variable for the months January to June 2001. This period was indicated by an exceedingly large value of the cointegrating error term.