INTER FUEL SUBSTITUTION AND ENERGY TECHNOLOGY HETEROGENEITY IN U. S. MANUFACTURING

By

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ABSTRACT

This paper examines the causes of heterogeneity in energy technology across a large set of manufacturing plants. This paper explores how regional and intertemporal variation in energy prices, availability, and volatility influences a plant's energy technology adoption decision. Additionally, plant characteristics, such as size and energy intensity, are shown to greatly impact the energy technology adoption decision. A model of the energy technology adoption is developed and the parameters of the model are estimated using a large, plant-level dataset from the 1985 Manufacturing Energy Consumption Survey (MECS).

Keywords: energy, technology, heterogeneity, fuel switching

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I. INTRODUCTION

The energy requirements for many manufacturing processes may be met by using more than one type of fuel. [1] For instance, industrial boilers are designed to burn either coal, natural gas, distillate fuel oil, or residual fuel oil. [2] There are also boilers capable switching to other fuels in the short run without disrupting production. According to data from the 1985 Manufacturing Energy Consumption Survey (MECS), which asked approximately 8,500 plants about their energy consumption and energy technology, 18.9% of manufacturing plants possess the capability to switch to other fuels in the short run. The remaining plants rely primarily on single fuel technology; 38.8% on natural gas, 30.1% on electricity, and 11.4% on petroleum fuel oils.

The objective of this paper is to uncover the causes of this heterogeneity in energy technology by modeling the factors that enter into the plant level energy technology decision, and then estimate the model parameters using the 1985 MECS data. [3] There are several reasons for pursuing this line of research. The first is to explore one aspect of the manufacturing sector response to shocks in energy prices. [4] To understand how the manufacturing sector responds to an energy price shock, especially if the price shock primarily affects a single fuel, we must understand the factors that influence

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[1] Not all the energy requirements for production processes can economically be met with any fuel. For instance, in the production of aluminum from bauxite, the physical characteristics of electricity give it a clear advantage over other fuels. However, for many process heating applications and steam generation, different fuels can be used. In 1976, approximately 5,000 Annual Survey of Manufacturing plants were queried about their fuel consumption, and whether their energy needs could be met by consuming alternative fuels. These plants responded that only 14.4% of distillate fuel oil, 8.7% of residual fuel oil, 11.2% of natural gas, and 22.3% of coal consumed could not have been replaced by other fuels.

[2] According to Thermo-Electron Corporation (1976), steam production accounts for 45% of industrial energy use. The 1991 Manufacturing Energy Consumption Survey will provide estimates of the amount of total energy devoted to boilers, process heating, and facility heating and lighting.

[3] The literature on energy technology for manufacturing plants is scant since plant level-data on this subject is not widely available. One study, sponsored by the Energy Information Administration (1986), uses Dun and Bradstreet's Major Industrial Plant Database to examine the choice of fuels of plants that possess fuel switching technology. There have been numerous studies that examine fuel choice at a residential level, including Hartman (1984).

[4] Other responses that plants have to an increase in energy prices include producing less energy intensive products, closing down, or adopting more energy efficient technologies.

a plant's energy technology decision. [5] Once the plant level relationships are established, then the aggregate response across the underlying distribution of manufacturing plants can be computed. [6] For instance, if all manufacturing plants possessed fuel switching technologies, the aggregate price elasticities for a fuel would be much higher than if all plants possessed single fuel technologies. [7]

The second reason for examining the plant level energy technology adoption decision is the importance being placed on the production of greenhouse gases from the combustion of fossil fuels. In terms of the amount of carbon dioxide released per unit of energy, coal is the most carbon intensive while natural gas is the least. [8] One method for reducing carbon dioxide produced by the manufacturing sector is to invoke policies that would encourage plants to switch to less carbon intensive fuels, policies that influence the energy technology decision of plants.

This paper studies the factors that enter into a plant's energy technology adoption decision in an attempt to uncover the economic sources that generate heterogeneity in energy technology. The factors we examine can be divided into two groups: energy market conditions and plant characteristics. The first set of factors describe energy market conditions such as fuel prices, availability, and price volatility. Energy markets have undergone radical changes over the past two decades, including the supply constrictions of OPEC and the deregulation of natural gas. In addition to the

[5] Energy markets have witnessed their share of shocks in the 1970's and 1980's. Shocks in energy prices began as shocks to particular fuel types. Natural gas, the most widely used fuel in the industrial sector, underwent significant changes in deregulation with the passage of the 1978 Natural Gas Act. As a result of this legislation, natural gas prices increased closer to true market levels, alleviating previous supply shortages. The price volatility for petroleum based fuels arose as result of the creation and effectiveness of OPEC. The volatility of oil prices has continued with crude oil prices plummeting in 1986, closely followed by natural gas prices. In the first five months of 1986, the price of residual and distillate fuel oils dropped 44%. The impact this price change had on the fuel choice of the electric utility industry is examined in Department of Energy (1986).

[6] As one example, Stoker (1987) presents an example of the importance of the underlying distribution of agents when examining the relationship between income and consumption.

[7] Several studies have estimated inter-fuel elasticities for the industrial sector using aggregate data, including Hazilla and Kopp (1984) and Pindyck (1979).

[8] Numerous studies have emerged that estimate the impacts of carbon based taxes, such as Jorgenson, Slesnick and Wilcoxen (1991). See Hoeller et al (1990) for a review.

intertemporal shocks in energy markets, geography provides another source of energy price and supply variation. The geographic and intertemporal variation in energy market conditions provide natural experiments to examine how past and present price and supply conditions influence the 1985 distribution of energy technologies.

The second set of factors that contribute to the observed heterogeneity in energy technology is the heterogeneity in the characteristics of manufacturing plants. Fuels differ in their qualities, such as ease of use, cleanliness, and heating properties. The economies associated with each fuel will therefore vary by the energy application of each plant. For instance, plants that use energy intensive applications may prefer fuels that have the capability of reaching high, precisely controlled temperatures. Additionally, scale economies vary by fuel, as fuels like coal require storage facilities and pollution abatement equipment. There is tremendous variation across plants in both energy intensity and amount of energy consumed, so the distribution of energy technologies is in part attributable to the underlying distribution of energy characteristics of manufacturing plants.

This paper uses a putty-clay capital framework to model the energy technology adoption decision of plants. [9] Before the energy technology is adopted, a plant may choose from a host of technologies that differ by their input requirement sets. For instance, plants may purchase boilers, ovens, and heating equipment designed to consume a single fuel, or a combination of fuels. The "clay" nature of the model is that plants can change the fuels they consume if they undergo a fixed cost to change their capital. However, the fuel switching technology provides an interesting twist to the traditional putty-clay framework, since adopting this technology provides plants the ability to be more putty-putty than putty-clay. [10]

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[9] The model we develop is closely tied to Lambson (1990) in spirit. In Lambson's model, a plant purchases capital that favors particular factors, and the future prices of those factors are uncertain. The plant can only change its capital with a fixed cost. Abel (1983) examines the choice of energy intensity when future energy prices are uncertain.

[10] The energy technology decision is inherently dynamic with plant managers deciding each period whether to keep their present energy technology or undergo a fixed cost to change their energy technology. A class of empirical dynamic models with discrete choices is reviewed in Eckstein and Wolpin (1990). The papers reviewed estimate dynamic discrete choice models in which economic agents decide when to undertake an activity, such as replacing a bus engine (Rust (1988)) or to renew a patent (Pakes (1986)). Unfortunately, the estimation techniques reviewed by Eckstein and Wolpin require time series data, and the data available on energy technology is only cross sectional; the energy technology state of plants is observed in 1985

In response to the uncertainty over future energy market volatility, plants may adopt fuel switching technologies. In the event of changes in the relative prices of fuels, these technologies allow plants to purchase the cheapest fuel at a point in time. An additional benefit of fuel switching technology is that if there is a supply disruption, as was the case with natural gas in the mid 1970's, a plant can readily switch to a more abundant fuel. The last advantage of the fuel switching technology is that it provides a plant a credible threat to change to other fuels. If energy markets are imperfect, plants with the fuel switching technology can credibly bargain for lower fuel prices. [11]

To test the various hypotheses regarding the influences of energy market conditions and plant characteristics on the energy technology a plant possesses, a multinomial logit model of energy technology choice is estimated. Overall the results are encouraging. Many of the energy market variables have the expected influences on the plant's technology. For instance, plants in areas where natural gas is the least expensive are more likely to possess technologies that rely solely on natural gas. In areas in which natural gas prices are competitive with the prices of other fuels, plants are more likely to possess fuel switching technologies. Additionally, the severity of natural gas supply shocks of the 1970's appears to influence whether plants in 1985 have fuel switching capability.

In terms of plant characteristics, the amount of energy that plants consume greatly influences the technology choice, reflecting in part, the different economies associated with the consumption of different fuels. The energy intensity of the production process favors technologies that rely on natural gas and distillate fuel oil. After controlling for energy market conditions and plant characteristics, there remains large innate industry preferences towards particular energy technologies.

Section II of this paper describes the data and presents a series a stylized facts involving plant level energy technology distributions. A simple model of the energy technology decision, one that hopefully captures some of the more salient features of the decision process, is presented in

without knowing their previous or future state paths.

[11] According to Williams (1985), after the Natural Gas Policy Act of 1978, natural gas pipelines did price discriminate by charging customers with fuel switching capability lower prices than customers with single fuel technology. Using the 1985 MECS data, we find no significant natural gas price advantage of plants with fuel switching capability.

section III. Section IV presents estimates from the empirical model. The last section provides a few concluding remarks.

II. DATA AND STYLIZED FACTS

The goals of this section are to discuss the data sources, and then to present some plant level tabulations using these data. These tabulations provide insight into how to appropriately model the energy technology adoption decision by showing the energy consumption patterns of plants, and how these patterns vary by such characteristics as size and region.

The manufacturing plant-level energy data used in this study come from the 1985 Manufacturing Energy Consumption Survey (MECS). The MECS collects plant level energy consumption and production data on 20 different types of fuels from approximately 10,400 plants. In addition, the MECS also collects information on the degree which other fuels could have been consumed without disrupting production. This portion of the survey, the fuel switching component, asks plants about their ability to switch between the five most conventional fuels within 30 days without disrupting production. Of the 10,400 plants, 8,589 responded to questions concerning their ability to use other fuels. [12,13]

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[12] The plants that did respond to the switching portion of the survey accounted for 87, 92, 79, 91, and 93% of the total 1985 estimates of electricity, natural gas, distillate, residual, and coal and coke consumed.

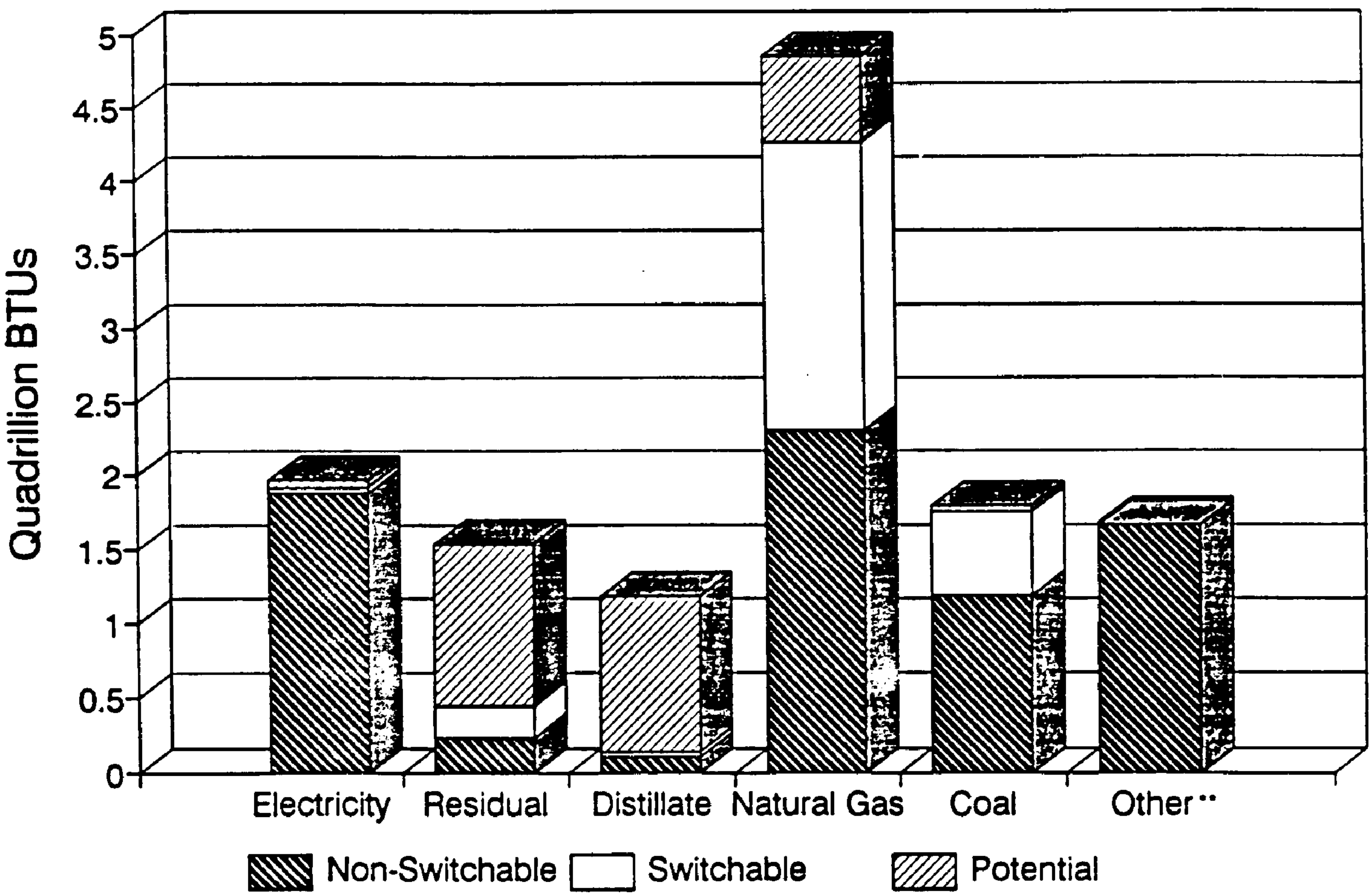
[13] The Petroleum Refining and Primary Metals industries are not included in this analysis. Petroleum refining plants use the fuels they create to provide their energy needs. For primary metals, steel and aluminum are the two largest components. In the production of aluminum, electricity, because of its physical properties, is used to transform bauxite into pure aluminum.
 In steel, there are two dominant steel making technologies that rely on different fuels. The last integrated steel plant was constructed in 1964, while every new steel making facility constructed since 1964 uses electric arc furnace technology. Integrated steel making facilities receive a majority of their energy requirements from coal, while electric arc facilities rely primarily on electricity. The decision to construct an integrated plant versus an electric arc plant depends on many factors including scale, scrap metal availability, and final product. In the case of steel, energy technology choice is not independent of the much larger production technology choice.

figure 1- total consumption

To meet its energy needs, the manufacturing sector relies on a variety of fuels. Figure 1 presents a summary of fuel use and fuel switching capability for the manufacturing sector. Each bar in figure 1 is composed of three segments representing non-switchable, switchable, and potential fuel use. The non-switchable regions represent the BTU amount, of fuel consumed that plants reported that they could not replace in the short run without disrupting production. The switchable portion of each segment represents the amount of fuel used that could have been replaced by other fuels without disrupting production. The sum of the switchable and non-switchable portions is the amount of the fuel consumed. The third segment of each bar in figure 1 represents the amount of each fuel that was not consumed, but could have been consumed had all plants with the ability to burn that fuel chose to do so. This amount is the potential use for each fuel.

Notice that although the use of energy is heavily concentrated with natural gas providing 41.7% of total energy requirements, the capability exists for there to be much less concentration since 45.9% of natural gas consumed could have been switched to other fuels. Distillate and residual fuel oils, provide only 5.8% of total energy needs, but they could provide up to 26.6%. These figures suggest that there are considerable and economically

FIGURE 1: 1985 MANUFACTURING FUEL CONSUMPTION AND SWITCHING CAPABILITY



** No fuel switching information was collected for Other iable substitution possibilities between fuels.

One of objective of this investigation is to determine the causes of the determinants of fuel technology choice at the plant level in order to help better understand aggregate distributions. However, the quantities in figure 1 do not describe the energy consumption patterns and fuel switching capability of individual plants. For instance, do the statistics in figure 1 suggest that all manufacturing plants consume a variety of fuels, or do individual plants consume only one type of fuel? Similarly, 30% of the energy derived from coal consumption could have been provided by other fuels. Does this imply that 100% of the plants that consumed coal could have reduced their coal consumption by 30%, or, at the other extreme, that 30% of the plants could have reduced their coal consumption by 100%? The answers to these questions are needed to accurately model the energy technology adoption decision at a plant level.

One of the first points to recognize about plant level energy consumption is that because of electricity's unique properties for lighting, electric motors, and computers, all plants consume electricity. Electricity can also be used for other conventional purposes, such as space heating. Unfortunately 1985 MECS and the LRD do not provide any information on how much electricity is used in applications that could rely on other fuels. [14]

The first two columns of table 1 present the weighted and unweighted distributions of the share of total plant energy requirements that electricity furnishes. [15] The unweighted distributions are based on plant counts while the weighted distributions are based on energy consumption. The first two columns reveal that nearly all manufacturing plants consume electricity, although the dependence on this energy type varies considerably across plants. The unweighted distribution shows that 54.6% of all plants receive less than half of their energy requirements from electricity, while the weighted distribution shows that these plants account for 91.8% of all energy consumed. These figures suggest that, on average, large energy consuming plants rely less on electricity than small energy consuming plants. For instance, 7.9% percent of manufacturing plants receive up to 10% of their energy requirements from

[14] According to a supplement to the 1975-1976 Annual Survey of Manufacturers, 50% of electricity consumed was reported to be non-substitutable with other energy sources. Howarth et al (1992) find that the industrial sector in Norway relies much more heavily on electricity than the U.S., as Norway possesses significant and relatively inexpensive hydro-electric capability.

[15] Only .1% of manufacturing plants respond that they have the capability of generating their own electricity.

electricity. This same group of plants, 7.9% of the total population, uses a disproportionate 47.9% of the total amount of energy consumed by the entire population.

TABLE 1
ENERGY CONSUMPTION DISTRIBUTIONS

	% Electricity		% Primary Fuel	
Share(%)	Unweighted	Weighted	Unweighted	Weighted
0	0.1	0.6	0.0	0.0
0-10	7.8	47.3	0.0	0.0
10-30	26.0	35.0	0.0	0.0
30-50	20.7	8.9	0.9	2.8
50-70	11.6	3.7	8.5	16.5
70-90	8.3	2.0	9.6	31.4
90-100	3.1	1.7	13.1	35.2
100	22.4	0.8	67.9	14.1

% Electricity is the plant's share of total energy that electricity provides.
% Primary Fuel is the share of non-electric energy met by a plant's primary fuel.

The electricity share figures demonstrate that many plants primarily rely on non-electric fuels to meet their energy needs. The next two columns in table 1 present the distribution of the share of non-electric energy requirements met by the primary fuel. Again, weighted and unweighted distributions are presented. An overwhelming majority of plants, 90.6%, obtain over 70% of their non-electric energy requirements from a single fuel, and these plants consume 80.7% of all energy.

Just as not all plants have the same reliance on a single fuel, not all plants have the capability of switching to other fuels. Figure 2 presents the distributions of the percent of each fuel that is switchable, where the unit of observation is plant-fuel. [16] Notice that the switching distributions are distinctly bimodal: if a plant has any capability to switch away from a fuel type, then it is likely that a plant can switch most of its consumption away to another fuel type. [17]

[16] Electricity is excluded from figure 2 since only 1.6% of electricity consumed is switchable.

[17] In most 2 digit industries, over 90% of the plants that have switching capability have natural gas as one of their primary fuel possibilities.

figure 2: switching distributions

The preceding tables and figures have shown that nearly all plants consume electricity, a majority of plants rely heavily on one other fuel source, and if plants possess any fuel switching capability, that capability is likely to be considerable. Based on these stylized facts, and in order to simplify the analysis in this and subsequent sections, each plant's energy technology is classified into one of six categories. The first step in classifying the energy technology of a plant is to determine the share of total energy met by electricity. Table 1 shows that 22.4% of all manufacturing plants rely entirely on electricity, and another 7.7% obtain at least 80% of their energy requirements from electricity. If a plant obtains 80% or more of its energy requirements from electricity, then its energy technology is classified as ELEC. [18]

For the remaining plants, 69.9% of the sample, the percent of non-electric fuels that can be switched to other fuels is calculated. If a plant can substitute over 50% of its non-electric fuels, then the plant is classified as SWITCH; otherwise, its energy technology is classified by the primary fuel source: DIST for distillate, RESID for residual, NAT GAS for natural gas, and COAL for coal.

Table 2 presents the distributions of energy technologies by 2-digit industry. These distributions demonstrate that although the distributions vary by industry, each industry displays the capability to use a variety of fuels, and each industry also has the ability to adopt fuel switching

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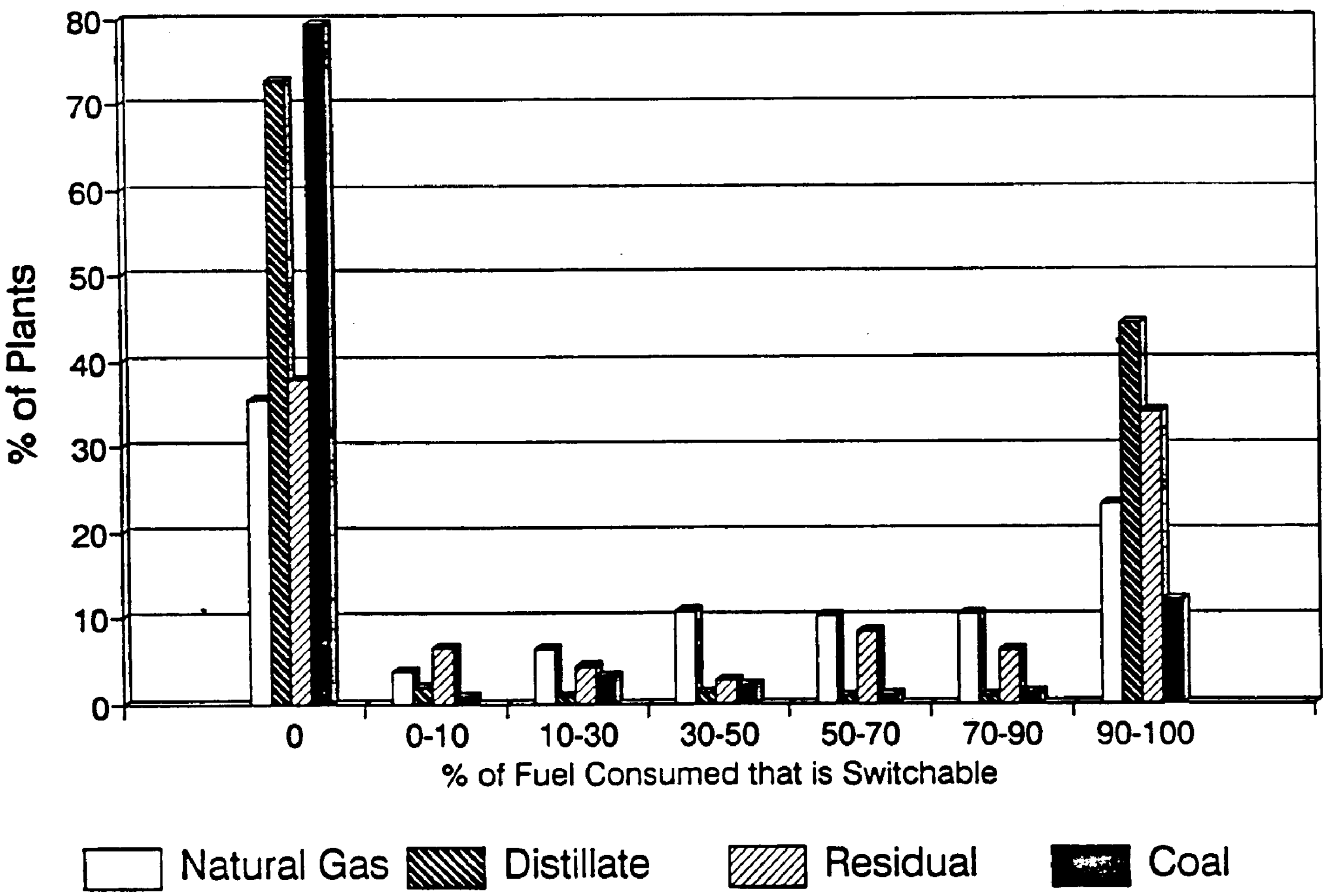
[18] An 80% cutoff is arbitrary. The estimates presented in the results section appear robust to using an 80%, 90% or 100% threshold.

FIGURE 2: PLANT LEVEL SWITCHING DISTRIBUTIONS BY FUEL TYPE



technologies. Although the energy technology distributions do vary by industry, there are strong trends that span industries. NAT GAS is the most popular technology in 11 out of 17 industries, and 38.8% of all manufacturing plants possess this technology. The second most popular technology is ELEC, with 30.1% of plants using this technology. ELEC is the most popular technology in 5 out of the 17 industries. Table 2 shows that nearly 19% of plants possess significant fuel switching capability, although the propensity to have this technology does vary considerably across industries. Plants in the food, textile, and paper industries are more likely to possess fuel switching capability than plants in the remaining industries. The inter-industry trends for COAL and RESID are more consistent in that the propensity to adopt either of these technologies never exceeds 3.8%. The remaining technology, DIST, displays tremendous variation, with the instrument industry rarely using this technology (.7%), while 34.7% of the plants in lumber employ DIST.

TABLE 2: ENERGY TECHNOLOGY DISTRIBUTIONS
BY 2-DIGIT INDUSTRY

Industry	ELEC	RESID	DIST	NAT GAS	COAL	SWITCH
Food	15.2	1.2	2.7	45.4	0.6	34.9
Textiles	21.9	3.8	11.2	19.5	1.7	42.0
Apparel	47.6	2.4	22.3	17.2	0.1	10.6
Lumber	39.6	1.9	34.7	19.3	0.0	4.5
Furniture	26.1	1.1	11.5	34.0	1.6	25.8
Paper	11.5	3.3	3.7	45.6	2.2	35.7
Printing	14.3	2.1	2.3	47.1	0.0	11.3
Chemicals	20.2	1.4	4.8	39.4	1.3	33.1
Rubber	27.3	3.6	3.1	41.1	0.2	24.7
Leather	28.8	2.0	19.5	27.7	2.4	19.5
Stone and Clay	16.1	0.2	31.3	28.2	1.2	23.0
Fabricated Metals	28.5	0.8	11.0	44.6	0.7	14.4
Machinery	23.6	0.2	10.8	45.9	0.4	19.2
Electronics	33.3	0.8	2.8	51.0	0.2	12.0
Transportation	34.8	0.5	4.2	40.9	1.0	18.6
Instruments	58.7	0.8	0.7	27.4	0.0	12.3
Miscellaneous	52.3	0.3	3.0	29.6	0.4	14.4
Total	30.1	1.3	10.3	38.8	0.6	18.9

Table 2 also demonstrates that there is considerable heterogeneity in energy technologies within and across industries. What is the source of this heterogeneity? As discussed in the introduction, many factors enter into the energy technology adoption decision. These factors include energy prices and availability in addition to plant level characteristics. As the economies associated with each fuel vary, so the energy technology a plant adopts is a function of plant characteristics, such as size and energy intensity. The distributions of these characteristics vary across industries, so these plant specific characteristics may explain some of the inter, as well as the intra, industry heterogeneity. The tables that follow present breakdowns of energy technology by plant level characteristics. Table 3, presents the cross tabulation between energy technology and size quintile, where size is defined as the quantity of BTUs consumed in a plant. [19] Of the cross tabulations that follow, the size table exhibits the most distinct patterns.

TABLE 3: ENERGY TECHNOLOGY DISTRIBUTIONS BY SIZE QUINTILE

Size Quintile	ELEC	RESID	DIST	NAT GAS	COAL	SWITCH
1	58.3	1.2	7.6	27.5	0.0	5.3
2	37.0	0.3	12.5	40.1	0.3	9.8
3	25.4	1.1	15.6	41.7	0.1	16.1
4	23.7	0.7	10.6	43.9	0.2	20.9
5	6.5	2.9	5.3	36.6	2.1	43.2
Total	30.1	1.3	10.3	38.8	0.6	18.9

Size Quintile 1 is the smallest, 5 is the largest.

The relationship between size and energy technology is most pronounced for ELEC and SWITCH, where SWITCH is sharply increasing with size and ELEC is sharply decreasing. The ELEC results could indicate that small energy consuming plants are not performing operations that involve the heating of raw materials. If a plant is primarily coal using, then there is a 75% chance the plant is in the largest quintile. The patterns for the three remaining technologies are not as distinct. NAT GAS and DIST are nonmonotonically related to size, as the propensity to solely rely on these fuels initially increases, then decreases with the last quintile. This final decrease is in part due to the tremendous increase in the likelihood of SWITCH in the largest quintile.

[19] When the size quintiles are determined within each 2-digit industry, the results are very similar except that the trends for ELEC and SWITCH are not as pronounced.

TABLE 4: ENERGY PRICE AND TECHNOLOGY DISTRIBUTIONS
BY CENSUS REGION

ENERGY TECHNOLOGY

REGION	ELEC	RESID	DIST	NAT GAS	COAL	SWITCH
1	41.0	5.5	18.9	19.4	0.1	15.1
2	35.9	2.9	18.1	23.5	0.5	19.1
3	13.6	0.1	3.0	56.8	0.8	25.6
4	27.4	0.1	2.2	52.6	1.1	16.7
5	35.6	1.6	14.4	27.1	0.7	20.7
6	25.9	0.1	9.8	32.3	1.2	30.7
7	28.4	0.0	6.5	46.4	0.1	18.6
8	7.2	0.1	25.2	44.9	0.3	22.5
9	44.1	0.9	8.2	39.0	0.0	7.8

MEAN 1985 ENERGY PRICES
(All figures are in dollars per million BTU.)

REGION	Electricity	Residual	Distillate	Natural Gas	Coal
1	25.14	4.15	8.05	6.62	2.32
2	25.79	4.32	7.84	5.91	1.76
3	19.22	4.37	7.66	5.23	1.87
4	18.12	3.60	6.77	4.65	1.46
5	18.36	4.12	7.27	5.20	1.90
6	16.53	3.96	6.63	4.50	1.82
7	19.08	4.08	6.29	3.39	1.71
8	17.50	4.17	6.71	4.72	1.31
9	20.74	4.94	6.87	5.20	2.22

Region: 1=New England, 2=Mid Atlantic, 3=East North Central, 4=West North Central, 5=South Atlantic, 6=East South Central, 7=West South Central, 8=Mountain, 9=Pacific

Table 4 presents how energy technology varies by Census region, and there is considerable variation across regions. Region affects the energy technology for several reasons. First, different industries are concentrated in different regions of the country. Second, energy prices and energy availability vary by region. The region with the lowest probability of using NAT GAS is New England, with only 19.4% of plants, which is 50% less than the national average. The distribution for SWITCH and ELEC are also varied, with only 7.8% of Pacific using SWITCH, and 7.2% of Mountain plants using ELEC.

Part of the regional variation in energy technologies can be attributed to regional variation in energy prices. Table 4 also presents average fuel prices, in dollars per million BTUs, by the nine Census regions for 1985, and there are quite pronounced regional price differentials.[20] One major cause for regional price differentials is transport costs. For instance, the 1985 price for natural gas in the West South Central region, where much of the domestic supply of natural gas is produced, is 49% lower than the average price paid in New England. Note that New England also has the lowest value of NAT GAS.

III. A MODEL OF ENERGY TECHNOLOGY ADOPTION

This section presents a putty-clay model of energy technology adoption where future energy prices are uncertain. The model explores the conditions in which plants would adopt fuel switching technology versus less expensive single fuel technologies. In this model, the fuel switching technology allows plants to consume the lowest cost fuel after prices are realized. In this case, the fuel switching technology protects plants from a price shock to a single fuel. Moreover, as discussed in the introduction, there are several other advantages that fuel switching technology provides for plants; protection against supply shocks, and the ability credibly negotiate lower prices in imperfect energy markets. [21]

In this model the objective for a risk neutral plant is to choose the energy technology that minimizes total expected energy related costs. These expected costs include two components; the variable cost of fuels and the fixed costs associated with each energy technology. Initially we examine the case where there are two fuel types, A and B, and three energy consuming technologies; T_A that consumes only A, T_B that consumes only energy B, and a fuel switching technology, T_S, that has the capability to consume either A or B. The fixed costs for T_A, T_B, and T_S are $K_A(()$, $K_B(()$, and $K_S(()$, respectively. These fixed costs include such things as storage facilities, pollution abatement equipment, personnel training, and the cost of new boilers. The cost for each technology is an increasing function of size, (.

To understand the energy technology adoption decision of plants, we must realize that these decisions are made in a dynamic world where plants make fixed cost decisions in the current period based on expectations of prices in future periods. In dynamic models where there are nonconvexities in adjusting

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[20] There are wide differences in per BTU prices across the fuels, as there are differing externalities associated with a BTU of electricity compared to a BTU of coal. Electricity is cleanest while coal is the dirtiest, and gelatinous residual fuel oil is harder to use than distillate fuel oil.

[21] What we mean by supply shocks is when the supply of a fuel is forcibly curtailed, such as the natural gas shortages of the 1970's.

the state variable, state dependence arises. In this paper we develop a one period model of energy technology adoption, where the plant initially possesses T_A. The plant in this model must decide whether to incur a fixed cost to change to either T_B or T_S. Which technology a plant decides to adopt depends on the initial condition, so we also examine the other initial condition possibilities; the plant initially possessing T_S, or a new plant that initially possesses no technology.

Whether or not a plant changes its energy technology depends upon whether the expected cost savings exceed the fixed cost of changing the technology. The variable costs associated with each technology depend upon the prices for the two fuel types, p_A and p_B. The prices are jointly distributed with density $h(p_A,p_B)$, $E(p_A)=\mu_A$, $E(p_B)=\mu_B$, $Var(p_A)=F_A^2$, $Var(p_B)=F_B^2$, and $Corr(p_A,p_B)=D$. We assume that energy does not have any short run substitution possibilities with the other inputs in production, allowing us to focus on the sub-problem of minimizing energy related costs. [22]

These costs include the variable costs associated with purchasing of fuels and the fixed costs of technology. The expected energy related costs, E(C), of the three energy technologies become

$$
\begin{aligned}
E(C_A) &= \gamma\mu_A \, , \\
E(C_B) &= \gamma\mu_B + K_B(\gamma) \, , \\
E(C_S) &= \gamma E(\min(p_A, p_B)) + K_S(\gamma) \, .
\end{aligned}
\tag{1}
$$

The expected costs for the two single fuel technologies are straightforward, as they include the expected price and any fixed costs. The expected energy price paid by a plant with the fuel switching technology, $E(\min(p_A,p_B))$, is a weighted sum of the conditional expectation of p_A when $p_A < p_B$ and the expected value of p_B when $p_B < p_A$.

$$
\begin{aligned}
E(\min(p_A, p_B)) = {} & E(p_A \mid p_A<p_B)\cdot \mathrm{Prob}(p_A<p_B) \\
& + E(p_B \mid p_B<p_A)\cdot \mathrm{Prob}(p_B<p_A)
\end{aligned}
\tag{2}
$$

Through some manipulation, (2) may be expressed as

---

[22] This strong separability is only assumed so we can derive closed form solutions on the expected profits for each of the three energy technologies. At a plant level, this may not be an unrealistic assumption. If there are short run substitution possibilities, then the expected advantages of the fuel switching technology will be overstated.

(3)
$$E(\min(p_A, p_B)) = \mu_A - E(p_A - p_B | p_A > p_B) \cdot \text{Prob}(p_A > p_B)$$
$$\text{or}$$
$$= \mu_B - E(p_B - p_A | p_B > p_A) \cdot \text{Prob}(p_B > p_A) \, .$$

Notice that the equations in (3) imply that in all cases in which $\text{Prob}(p_A > p_B)…0$ and $\text{Prob}(p_B > p_A)…0$, the expected fuel costs of the fuel switching technology will be less than $\min(\mu_A, \mu_B)$; $E(\min(p_A, p_B)) < \min(\mu_A, \mu_B)$.

In order to explore (3) further, we assume h($\cdot$) is a bivariate normal distribution. The properties of truncated normal distributions are well established, and this is the primary reason we chose the normal distribution in this analysis. Let $p_3 = p_A - p_B$ and $p_3 \text{-} N(\mu_3, F_3)$, where $\mu_3 = \mu_A - \mu_B$ and $F_3^2 = F_A^2 + F_B^2 - 2DF_AF_B$. Then,

(4)
$$E(p_A - p_B | p_A > p_B) \cdot \text{Prob}(p_A > p_B) = E(p_3 | p_3 > 0) \cdot \text{Prob}(p_3 > 0)$$
$$= \mu_3 (1 - \Phi(x)) + \sigma_3 \phi(x)$$

where $x = -\mu_3 / F_3$ and M and N are the cumulative and marginal standard normal distribution functions, respectively. Substituting (4) into (3), the expected energy related costs for the fuel switching technology becomes

(5)
$$E(C_s) = \gamma\left(\mu_A \Phi(x) + \mu_B (1 - \Phi(x)) - \sigma_3 \phi(x)\right) + K_s(\gamma)$$

There are three terms in which the mean fuel prices appear in (5). The first two terms are a weighted average of the two mean fuel prices, where each weight is the probability of that fuel being the cheaper of the two.

The third term, $-F_3N(x)$, represents a savings in expected variable cost from having the fuel switching technology. Notice that $F_3N(x)$ is a decreasing function of the absolute difference in the energy prices. As the difference in the two fuel prices increase, the value of having the option to switch between fuels decreases since the expected opportunities to exercise the option to switch fuels decrease. Empirically we will be able to test whether the probability of adopting T_S decreases as one of the fuel prices approaches extreme values.

Figure 3 illustrates the expected energy related costs of the three technologies over a range of μ_B and for a given value of μ_A. For simplicity and without loss of generality, we let $\mu_A = 0$. Two curves, $E(C_A)$ and $E(C_B)$, represent the expected costs of the two single fuel technologies: $E(C_A)$ is independent of μ_B, while $E(C_B)$ is a linear function of μ_B with slope (. Figure

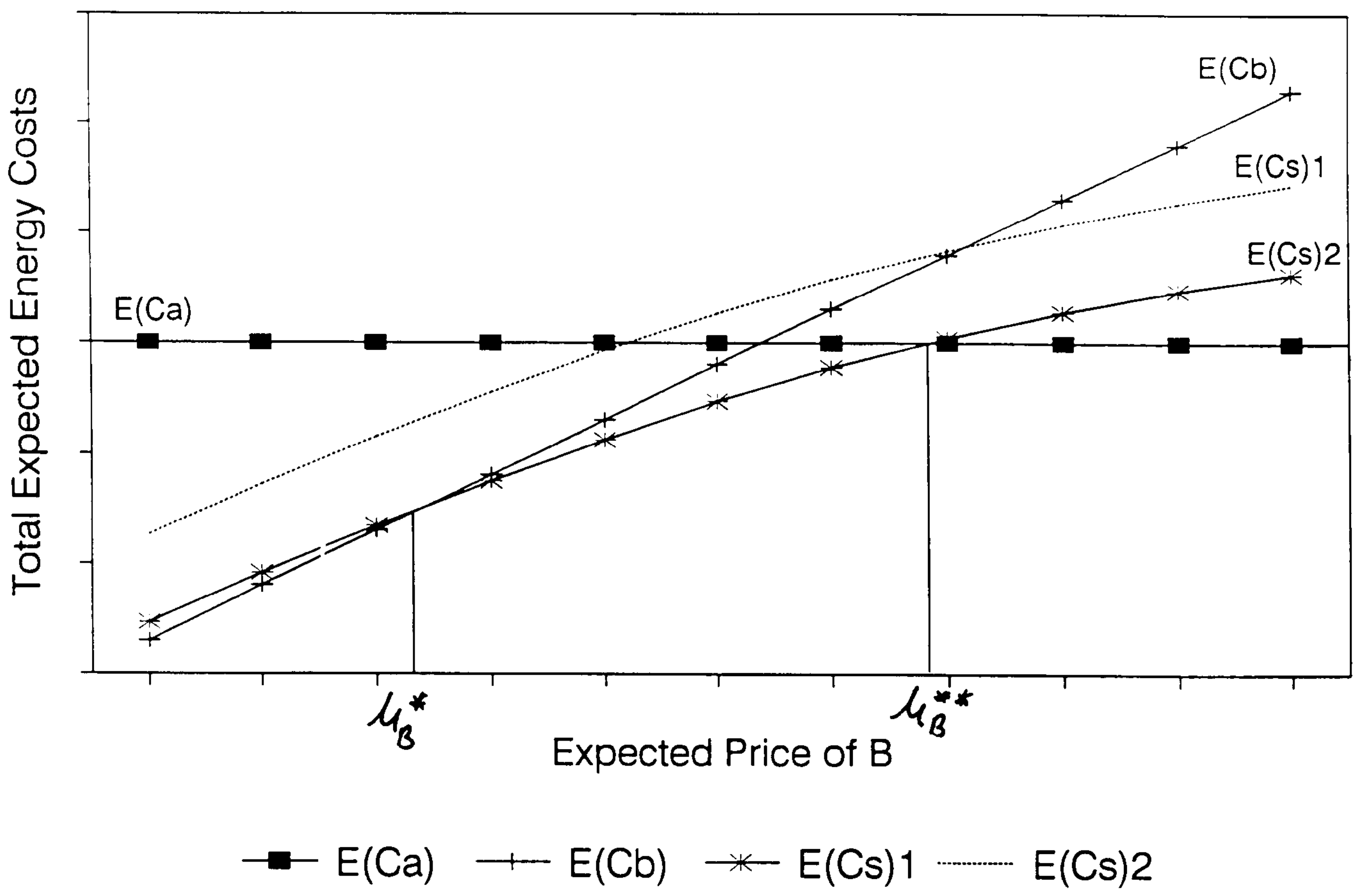
3 also contains two curves for the fuel switching technology, with the difference being that $E(C_S)_2$ is based on having a higher fixed cost than $E(C_S)_1$. As μ_B gets small, the difference in $E(C_S)$ and $E(C_B)$ approaches the difference in the fixed costs of the technologies, $K_S(()-K_B(()$. As μ_B gets large the difference in expected costs between T_S and T_A approaches $K_S(()$. In the limits of μ_B, $E(C_S)$ mimics the expected costs of the single fuel technologies, however with a parallel shift equal to the difference in fixed costs. The second derivative of $E(C_S)$ with respect to μ_B is negative, implying that $E(C_S)$ is concave, as shown in figure 3.

The plant chooses the energy technology with the smallest expected energy related costs. Note that for $E(C_S)_1$, there is a range (μ_B^*,μ_B^{**}) for which the fuel switching technology has the least expected cost. However, if the fixed cost associated with T_S is too large, as demonstrated by $E(C_S)_2$, then T_S will never be chosen. In this case the expected variable costs savings provided by the fuel switching technology never exceed the differential in fixed costs.

Figure 3 illustrates that as the absolute difference in the expected fuel prices increases, the less likely it is that the plant will adopt T_S. At some point μ_B^{**} it no longer is profitable for the plant to purchase T_S, but rather it is more profitable to remain with T_A.

The expected cost curves in figure 3 assume that the plant initially possesses T_A. However, if the initial conditions change, then the technology ranges also change. For instance, a new plant must pay a fixed cost for any technology. For the case of a new plant, $E(C_A)$ in figure 3 will shift upwards by $K_A(()$, resulting in an increase in μ_B^{**}. A new plant will therefore be more likely to adopt T_S than a plant that initially possesses T_A or T_B. The other

Figure 3: Expected Energy Costs by Technology



possible initial condition is that the plant initially possesses T_S. Under this scenario, the plant has no incentive to adopt any of the single fuel burning technologies, since doing so would entail a fixed cost and no possible reduction in fuel costs. [23]

Expected fuel prices and the initial conditions greatly influence the energy technology adoption decision for a plant. Additionally, (μ_B^*, μ_B^{**}) is a function of the remaining parameters of the model, variances, covariance, and size. Intuitively, variances and covariances affect the expected costs associated with the fuel switching technology since the fuel switching technology provides the plant with the option to buy the least costly fuel. As with standard option pricing, the value of the option depends not only on the expected prices, but also on the variances and covariances of the price series. This is also true for this special option.

In relation to figure 3, variance parameters affect the curvature of $E(C_S)_1$ and $E(C_S)_2$, but do not change their values in the limits. For instance, as the correlation between the two fuel prices increases, the expected fuel costs of the fuel switching technology always increases since the opportunities to exploit using a cheaper fuel decrease. Additionally, the expected costs increase at a decreasing rate.

(6)
$$\frac{\partial E(C_s)}{\partial \rho} = Y \frac{\partial \sigma_3}{\partial \rho} \phi(x) > 0$$

(7)
$$\frac{\partial^2 E(C_s)}{\partial \rho^2} = Y \frac{\phi(x)\, \sigma_A \sigma_B}{\sigma_3^3} \left(1 + \sigma_3^{-2}\right) < 0$$

The effect of increasing the correlation between the two prices is to make both $E(C_S)_1$ and $E(C_S)_2$ less concave: as D increases, μ_B^* increases and μ_B^{**} decreases.

The effect on expected cost is less clear when the variance of one of the prices is changed, as the derivative of the expected cost of the fuel switching technology with respect to one of the standard deviations is ambiguous.

[23] There may be incentive to change from T_S if the efficiency of the energy technologies increases over time.

(8)
$$\frac{\partial E(C_S)}{\partial \sigma_A} = \gamma \frac{\partial \sigma_3}{\partial \sigma_A} \phi(x) \; < 0 \text{ if } \sigma_A > \rho\sigma_B$$
$$> 0 \text{ if } \sigma_A < \rho\sigma_B$$

(9)
$$\frac{\partial^2 E(C_S)}{\partial \sigma_A^2} < 0$$

Although the first derivative is ambiguous, the second derivative is unambiguously negative.

The remaining parameter of the model, (, is size. There is considerable variation in (across plants, and the energy technology distribution varies considerably by size. We focus on plant size, in terms of the total amount of energy consumed, since economies do vary by fuel type. For instance, electricity, the most expensive fuel in terms of BTUs per dollar, requires no storage facilities, while the consumption of coal requires trained personnel, storage facilities, and pollution abatement costs.

At the point μ_B^*, $E(C_S)=E(C_B)$. To examine the effect of size on μ_B^*, we implicitly differentiate this equality to produce

(10)
$$\frac{\partial \mu_B^*}{\partial \gamma} = \frac{\left(-\mu_B \Phi(x) - \sigma_3 \phi(x)\right) + \partial(K_S(\gamma) - K_B(\gamma))/\partial\gamma}{\gamma \Phi(x)} \,.$$

An increase in (affects $E(C_S)$ and $E(C_B)$ through two channels. The first is by increasing the expected variable costs of the fuels, while the second is by increasing the fixed costs of the technologies. As the energy requirements for a plant increase, the expected variable cost savings from the switching technology increase proportionately. As demonstrated by (3), the expected marginal increase in the variable costs is less for a plant with T_S than a plant with T_B by $\mu_B M(x)+F_3 N(x)$. Notice that this expected price differential between the two technologies is the first quantity in the numerator.

The second component in the numerator of (10) is the marginal difference in the fixed costs of the two technologies. If these expected variable cost savings exceed the marginal difference of the fixed costs, then the plant will be more likely to purchase T_S. The fixed cost of the fuel switching technology, K_S((), will be at least as much K_B((). Let f(()=K_S(()-K_B((). It is reasonable to assume that f(() is an increasing function: the difference in fixed costs between T_S and T_B increases with the size of the furnace or oven. If there are scale economies in heating equipment, then f(() may be concave. If f(() is concave, then the sign of (10) is more likely to be negative as (increases.

A similar exercise is performed for the upper bound of $E(C_S)_1$.

(11)
$$\frac{\partial \mu_B^{**}}{\partial \gamma} = \frac{-\left[\mu_B(1-\Phi(x)) - \sigma_3\phi(x) + \partial K_S(\gamma)/\partial \gamma\right]}{\gamma(1-\Phi(x))}$$

Again the numerator has two components. The first is the difference in the expected variable costs between T_S and T_A, which is always negative. If the expected costs savings exceed the marginal fixed cost, then the plant will more likely purchase T_S.

This one period model is capable of producing heterogeneity in energy technology through several different mechanisms. The first is that plants may enter this model with different initial conditions; new plants may chose a different technology than existing plants. A second heterogeneity generating factor is the variance across plants in expectations of future energy prices. A portion of this variation is attributable to geographic factors. Third, due to the economies associated with each technology type, the energy technology depends upon size. Given the wide distribution of plant sizes in manufacturing (see Dunne, Roberts and Samuelson (1988)), heterogeneity may arise solely on account of the underlying size distribution.

Extensions

In the introduction, several other advantages of possessing fuel switching technology are suggested. For instance, if energy markets are not perfectly competitive, then the presence of the fuel switching technology makes the threat of going to an alternative fuel credible since the plant already has the capital capable of burning another fuel.

Another reason for plants to adopt fuel switching technology is as an insurance against supply shocks, especially in light of the natural gas shortages of the 1970's. By 1981 the shortages of natural gas abated and a glut had appeared. However, there is good reason for the natural gas supply shocks to affect the energy technology observed in 1985. In the model presented in this section, if the plant started with the fuel switching technology, then it has no incentive to adopt a single fuel system. With the fuel switching technology the plant may always purchase the least cost fuel.

However, plants do change their energy technologies for reasons other than to alter the fuel consumed, more recent technologies are more efficient.

The model presented here can be modified to address the supply shock scenario. We have assumed that the prices for the two fuel types are jointly normally distributed. To incorporate the supply shock, the normal distribution can be modified to include a non-zero probability of a near infinite price.

IV. ESTIMATION AND RESULTS

The appropriate estimation method depends on the hypotheses to be tested and the data used. The energy technology adoption decision is inherently dynamic, as plant managers decide each period whether to stay with their present technology, or adopt a new technology. Unfortunately, the data available on energy technology are cross-sectional; we observe the energy technology state of plants in 1985 without knowing their previous or future state paths.

In order to incorporate some of the dynamic aspects of the model, the cross-sectional energy technology data are merged with historical plant level investment and age data, in addition to historical energy supply and price data. These historical variables are included in the estimation to perform crude tests of the extent that past energy supply and price conditions have on the technology present in 1985. In addition to variables that describe past and present energy market conditions, the estimated model also includes plant specific variables such as measures of size, energy intensity, 2-digit industry dummies.

Estimation

The parameters of the model are estimated using a multinomial logit procedure.[24] The probability of adopting single fuel technology j is given by

$$P_j = \frac{\exp\left(\beta_j X_j\right)}{\sum_{k=1}^{N} \exp\left(\beta_k X_k\right)} \quad . \tag{12}$$

[24] Methods for estimating discrete choice models in which the error structure is more general have been posited by McFadden (1989) and Pakes and Pollard (1989).

Separate sets of $ß_j$'s are estimated for the RESID, DIST, NAT GAS, COAL, and SWITCH technologies.[25] For identification, the ß's for ELEC are set equal to 0.

The $ß_j$'s are estimated using the entire sample, which pools observations across all industries.[26] A disadvantage of pooling across industries is that the assumption of the $ß_j$'s being constant across industries is imposed. However, there is a benefit to pooling. The frequencies of COAL, RESID, and DIST technologies become sparse for many 2-digit industries, and therefore require the exclusion of many explanatory variables. Although pooling imposes cross industry parameter restrictions, it permits a much richer model specification. To reduce the cross industry restrictions, 2-digit industry dummies are included in the NAT GAS and SWITCH equations to capture some of the innate preferences particular industries may have towards particular technologies.[27]

Results

The energy technology adoption decision is a function of many variables. Some of these variables include plant specific characteristics, such as size, age, and energy intensity. Other variables include measures of energy market conditions, such as prices, natural gas availability, and the severity of previous natural gas shortages. The number of parameters estimated from (12) is 189.

For each of the five estimated equations, Appendix A provides detailed variable definitions, and a complete listing of the parameter estimates, standard errors, t-statistics, and mean values. Unfortunately, due to the nonlinearity of the model, visual examination of the parameter estimates does not readily convey the impact a variable has on the predicted probability of adopting a particular energy technology. To remedy this problem, a series of

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[25] SWITCH contains all plants that have significant fuel switching capability. As stated in the data section, over 90% of plants that have switching capability can use natural gas as a fuel. In earlier work, SWITCH was further broken down by the mix of fuels that plants could switch between. In estimation, the model had little predictive ability in selecting the specific switching technology, however, the model does have some predictive power in whether there is some switching capability.

[26] Recall that the Petroleum Refining (SIC 29) and Primary Metals (SIC 33) industries are not included in this analysis.

[27] A much simpler specification for equation 13 was also estimated by 2-digit industry. Across the 2-digit industry estimates, there were strong commonalities for the effects of size and prices.

graphs and tables present how the expected probability for each technology varies over the relevant range of the independent variables. These predicted probabilities are calculated, using (13), by varying the variable of interest while holding all other variables in system to their mean values. In most of the figures, the predicted probability for each technology is computed from the fifth percentile to the ninety-fifth percentile of the variable of interest.

The discussion of the results is divided by variables that describe plant characteristics and variables that describe energy market conditions.

Plant Characteristics

An influential variable in the model is the amount of energy consumed in a plant. The variable SIZE is defined as the total energy consumption for a plant, measured in BTUs. The logarithm of SIZE, along with the logarithm squared and cubed, are included in each of the five estimated choice equations. Additionally, the logarithm of SIZE is interacted with own price in each equation, allowing for price elasticities to vary by SIZE. Figure 4 presents the predicted probability for each technology over a logarithmic SIZE scale.[28] The numbers along the logarithmic SIZE scale are the percentiles of the SIZE distribution. We present the percentiles of the SIZE distribution instead of the value of the logarithms of SIZE to allow the reader to see how the predicted probabilities change for the distribution of plants as SIZE varies.

The predicted probabilities displayed in figure 4 vary tremendously by SIZE. Small energy consuming plants are much more likely to possess the ELEC or NAT GAS technologies. However, the propensity to possess ELEC quickly diminishes. As discussed in the data section, all plants rely on electricity to some extent. If a manufacturing plant does not require energy to generate steam or to heat raw materials, then the plant is likely to rely on electricity for machinery power and lighting. These plants will then likely be relatively small energy consumers. Additionally, the fixed costs associated with electricity are small, as storage facilities are not required.

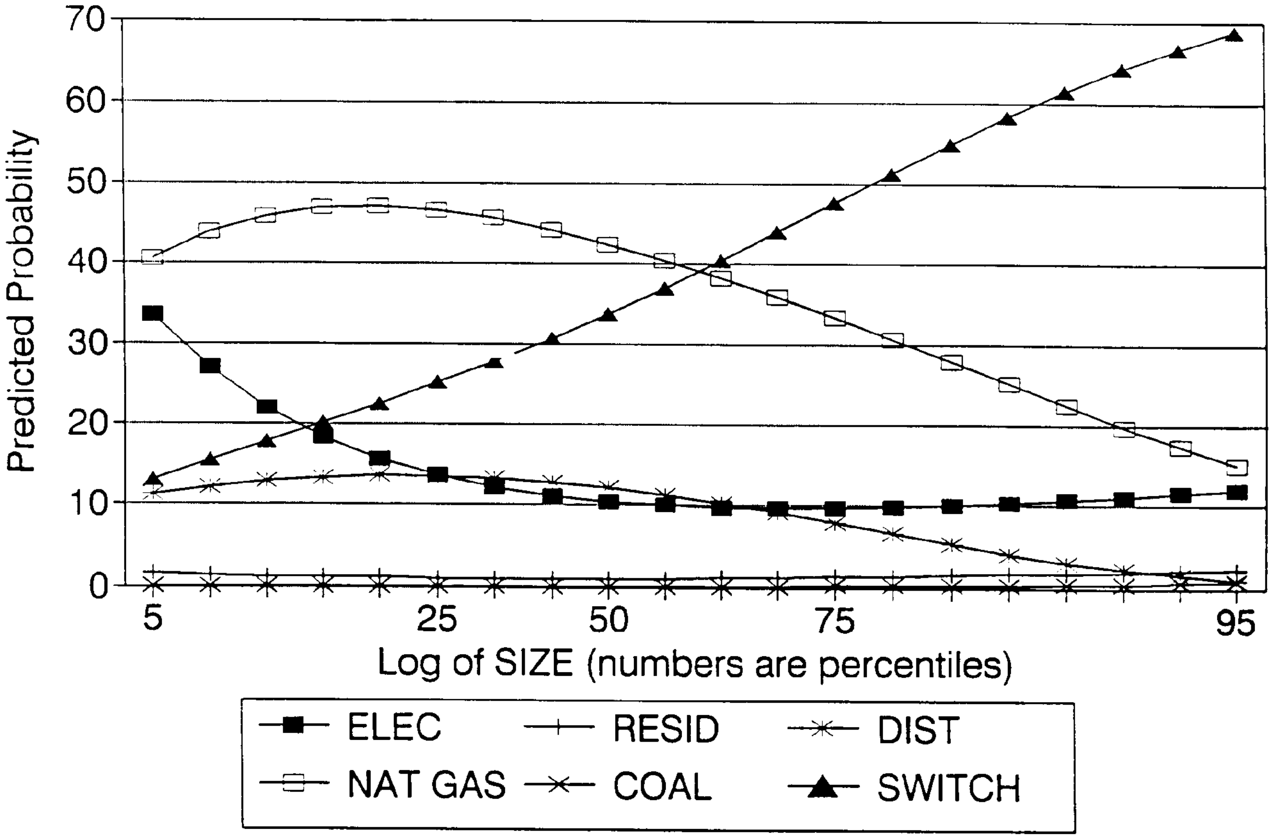
While the predicted probability of ELEC initially decreases, the predicted probability of NAT GAS increases. NAT GAS possesses the greatest predicted probability for over 50% of the sample, and is the second largest for most of the rest. However, even though NAT GAS has the highest predicted

[28] A logarithmic scale is used since the plant-level distribution of SIZE is very concentrated amongst small plants.

probability for most of the SIZE range, its predicted probability never exceeds 50%. After the 25th percentile of SIZE, the predicted probability of NAT GAS monotonically decreases.

The most striking results in figure 4 are those for SWITCH. The predicted probability of SWITCH is monotonically increasing over the 5th to

FIGURE 4: PREDICTED PROBABILITY OF ADOPTION AND LOG OF SIZE



95th percentile in SIZE. For the 95th percentile, the predicted probability of SWITCH approaches 70%, the largest predicted probability over the relevant range of SIZE. These results suggest that there are strong scale economies associated with fuel switching technologies.

The predicted probabilities of the other technologies tend to be nearly insignificant over large ranges of SIZE. The predicted probabilities for DIST hover between 10% and 15% for a large range of SIZE before declining as SIZE increases. An interesting phenomenon occurs for COAL. Beyond the 95th SIZE percentile, the predicted probability of COAL does rapidly increase. For the very largest plants in the sample, the predicted probability of COAL exceeds 60%, while the predicted probability of SWITCH diminishes to 30%. This result is consistent with large fixed and external costs associated with the burning of coal, such as storage facilities and pollution abatement equipment.

A second plant specific measure of energy consumption, INTENSITY, is computed as the ratio of SIZE to dollars value added. The correlation between SIZE and INTENSITY is .43, signifying that large energy consuming plants are not necessarily energy intensive plants. INTENSITY, its square and cube are included in each of the five equations. Figure 5 presents the predicted probabilities of the six energy technologies over the fifth to ninety-fifth percentile of INTENSITY. Again, like SIZE, the distribution of INTENSITY is heavily skewed, and figure 5 is presented using a logarithmic scale. The percentiles of the INTENSITY distribution are noted on the x-axis.

Although not as drastic as the SIZE results, the predicted probabilities do vary considerably over the range of INTENSITY. The largest changes in predicted probabilities occur after the 50th percentile, especially with ELEC. The ELEC results conform to the theory that ELEC plants are less likely to undertake process heating. Consequently, these plants will be relatively small energy consumers and will not be very energy intensive. The predicted probabilities in figure 5 suggest that natural gas and distillate fuel oil are desirable for energy intensive applications. This is due in part to the high temperature and desirable flame properties of natural gas.

SWITCH shows less covariation with INTENSITY than ELEC, DIST, or NAT GAS. However, there is a slight positive relationship, demonstrating that the greater reliance the production process is towards energy, the greater the likelihood that SWITCH will be installed. However, the relationship is weak with only an increase in 5% of the predicted probability. This is an interesting result. It demonstrates that plants with energy intensive applications are not more likely to insure against price or supply shocks by adopting fuel switching capability. Instead, the results seem to suggest that highly energy intensive applications may require special fuels, such natural gas and distillate fuel oil.

FIGURE 5: PREDICTED PROBABILITY OF ADOPTION AND ENERGY INTENSITY

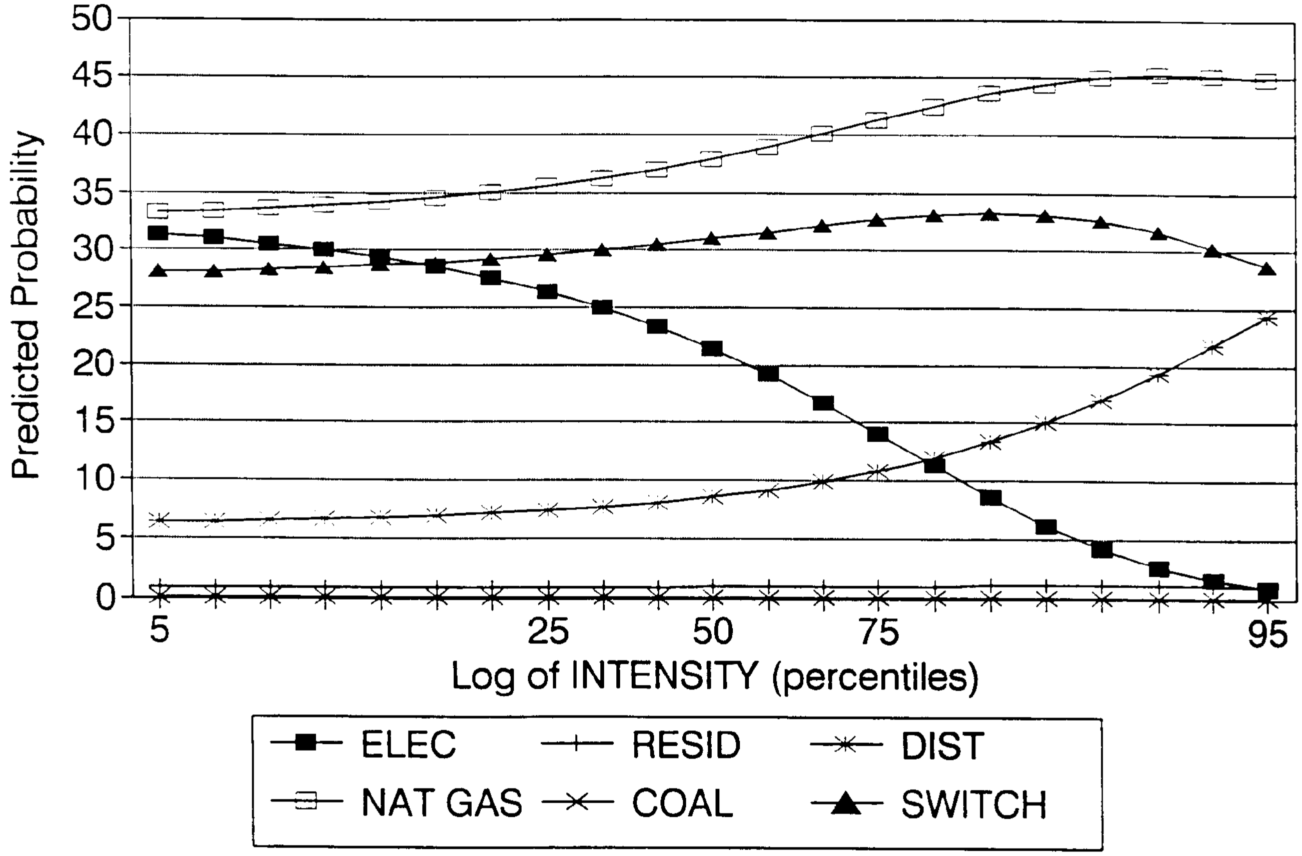


TABLE 5: PREDICTED PROBABILITY OF ADOPTION BY 2-DIGIT INDUSTRY

Industry	ELEC	RESID	DIST	NAT GAS	COAL	SWITCH
Food	5.8	0.6	6.8	44.2	0.14	2.5
Textiles	16.2	1.6	18.9	24.6	0.2	38.6
Apparel	18.0	1.8	21.0	27.1	0.2	32.0
Lumber	28.5	2.8	33.3	23.6	0.3	11.5
Furniture	9.8	1.0	11.5	35.3	0.1	42.3
Paper	6.7	0.7	7.8	48.8	0.1	36.0
Printing	8.5	0.8	10.0	51.5	0.1	29.1
Chemicals	8.7	0.8	10.1	42.5	0.1	37.8
Rubber	13.1	1.3	15.3	35.7	0.1	34.6
Leather	12.2	1.2	14.3	34.8	0.1	37.3
Stone and Clay	15.1	1.5	17.6	30.6	0.2	35.1
Fabricated Metals	12.0	1.2	14.0	45.5	0.1	27.1
Machinery	5.7	0.6	6.7	45.6	0.1	41.4
Electronics	8.7	0.9	10.2	57.4	0.1	22.7
Transportation	13.0	1.3	15.2	46.4	0.1	24.0
Instruments	12.8	1.3	15.0	37.9	0.1	32.9
Misc.	9.6	0.9	11.2	38.1	0.1	40.0
Total	10.5	1.0	12.3	42.8	0.1	33.2

The final plant characteristic that we control for is 2-digit industry. To capture some of the innate industry preference towards specific energy technologies, the SWITCH and NAT GAS equations contain dummy variables for 2-digit industries. [29] These dummy variables should capture the preference an industry has towards an energy technology, after controlling for size, energy intensity of the production process, and prices. [30]

Table 5 presents the predicted probabilities for an average manufacturing plant by 2-digit industry. Recall that table 2 displays a large amount of variation in energy technologies within and across industries. However, the distributions in table 2 do not control for factors that influence the energy technology of a given plant that also varies by industry. For instance, mean plant SIZE and INTENSITY vary tremendously by 2-digit industry, as shown in Appendix B. Table 5 shows the variation in industries that can be attributable to differences in the propensity to consume fuel by industry. The predicted probability for NAT GAS obtains a high of 40.8 for the Electronics industry, and a low of 14.1 for Lumber. Similar spreads exist for the other energy technologies. For SWITCH, a plant in the Food industry is most likely to adopt fuel switching capability while again Lumber is the least likely. [31]

Energy Market Characteristics

The other set of variables that are included in estimation capture energy market conditions. Specifically, the estimated model possesses variables that measure energy prices, availability, and variance. Just how these measures should be constructed and used in estimation is unclear. The appropriate price measures to include in the estimation depends upon the model of energy technology adoption. The energy technology adoption model is dynamic, where plants update their expectations regarding future energy prices

[29] In the unweighted sample, SWITCH and NAT GAS provide the largest number of observations, and that is why 2-digit industry dummies are included in the SWITCH and NAT GAS equations. Additionally, a dummy variable is not included for industry 21, Tobacco Products, due to the small number of observations.

[30] Recall that prices are based on heat content, and not on the other characteristics of the fuels, such as ease of use, temperature control, flame characteristics, or emissions.

[31] Part of the explanation for the low propensity for plants in Lumber to use natural gas is that lumber mills are often in rural areas without access to natural gas. Later in this section, a discussion follows that describes the control variables used for natural gas availability.

each period, and decide whether or not to replace their technology. Due to the fixed costs involved with changing technology, it is not always profitable to change a technology even though expectations of future prices may have altered. For this framework, current prices, and expectations or future prices are needed. Unfortunately, the energy technology data used in this study are cross-sectional, and we do not know when the energy technology was adopted, and therefore plant specific expected energy prices based on time of adoption can not be generated.

Several approaches to energy prices are used in this study. The first approach infers energy technology adoption dates by combining plant age and new machinery investment data. The second approach uses average energy prices for the 1982-1984 period. In the first approach, plant age and capital age information is used to place the energy technology adoption date within five year intervals. Actual energy prices, and forecasted energy prices (a second order autoregressive model with a linear time trend) based on these inferred technology adoption intervals are included in the model. However, these expected prices did not perform well in that they are not significant and have only marginal impacts on the predicted probabilities. The poor performance of these prices may have occurred for several reasons.

In the 1970's the price of natural gas was regulated. Due to the artificially low price, shortages of natural gas developed. Some trade literature suggests that those industrial firms that could purchase natural gas did so since natural gas prices were more favorable than prices from other fuels.[32] However, natural gas has not been available in all markets, so in the 1970's the price of natural gas was not the primary factor for plants not using natural gas. Hence, the expected energy prices based on plant age are not indicative of the true variables that entered into the decision. Another reason why the expected prices at the inferred adoption date may not have performed well is that the inferred adoption date is simply incorrect.

The second approach to prices, constructing an average of the 1982-84 prices, produced the best model fits. By 1982 natural gas prices increased closer to true market levels. Variables based on energy price forecasts and realized prices after 1985 were included in previous versions of the model. The inclusion of these future prices did not produce improved model fits. An

[32] The relative price of natural gas increased more than any other fuel between 1978 and 1985.

explanation is that relative energy prices have shown very little change at the state level before and after 1985. [33]

In the following results, the 1982-1984 average fuel prices are used. In each of the single fuel technologies two sets of prices are included: the price of the own fuel and the price of electricity. [34] For the SWITCH equation, natural gas and residual prices are used since plantz with fuel switching technology have the capability to use these two fuels most frequently. [35] In each of the equations, the log of prices, the square and cube are included. Additionally, the own price in each equation is interacted with SIZE.

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[33] The correlation between the ratio of natural gas to residual fuel prices in 1983 to 1987 is .95.

[34] Recall ELEC is the omitted equation in the multinomial logit system. To test whether the energy technology choice is a function of electricity prices, the price of electricity is included in each of the estimated equations. The predicted probabilities for the six energy technologies do not vary considerably over the range of electricity prices.

[35] All plants with significant switching potential are classified as SWITCH regardless of the types of fuels they may switch to and from. Over 90% of SWITCH plants have the capability of meeting a majority of their energy needs with natural gas. Models failed to distinguish between fuel specific categories.

natural gas prices

We focus first on natural gas prices since natural gas is the most widely used fuel in manufacturing, and fuel switching technologies often can use natural gas as a fuel source. Figure 6 presents the predicted probabilities over the range of natural gas prices, and some interesting patterns emerge. When natural gas is relatively inexpensive, as in states such as Louisiana, the predicted probability for NAT GAS reaches 63.2%. When natural gas prices increase from the lowest level to 31.5% higher, the predicted probability of NAT GAS falls to 43.3%. Almost all of this decrease is absorbed by SWITCH, whose predicted probability increases from 17.7% to 37.8%. The predicted probabilities for the other technologies remain relatively constant over this range.

Recall in the model section that the expected benefits of the switching technology diminish as the absolute difference in the energy prices increase. The predicted probabilities in figure 6 confirm this prediction. As the price of natural gas reaches either extreme, the predicted probability for SWITCH is low, since the expected opportunities to use the switching capability are small. When the price of natural gas is low plants are much more likely to adopt NAT GAS; conversely when prices of natural gas are high plants are much more likely to adopt ELEC or DIST.

Figure 6 displays the complex relationship between the predicted probability for each energy technology and the price of natural gas. The prices of residual fuel oil, distillate fuel oil, electricity, and coal, also enter the model. Table 6 summarizes the sensitivity of the predicted probability for each technology and changes in each of the fuel prices. The statistics presented in table 6 are the change in the predicted probability of technology j for a 1% increase in fuel price i. These elasticities, $>_{i,j}$, are computed as

(13) $$\xi_{j,i} = \frac{\partial P_j}{\partial \mathrm{Price}_i} \cdot \overline{\mathrm{Price}_i}$$

where P_j is defined in (13). The elasticities are computed for each technology-price combination.[36] Table 6 presents three sets of $>_{i,j}$, depending on whether they are computed at the 10th, 50th, or 90th percentile of SIZE. For example, a 1% increase in natural gas prices leads to the predicted

[36] The results for COAL are omitted since the expected probability of COAL is always less than 2%.

probability for NAT GAS to decrease by .25, for a plant in the 10th SIZE percentile.

TABLE 6: PREDICTED PROBABILITY PRICE ELASTICITIES
EVALUATED AT THE 10TH, 50TH, AND 90TH PERCENTILES OF SIZE

10th SIZE Percentile

	ELEC	RESID	DIST	NAT GAS	SWITCH
Electricity	.10	.01	-.42	.23	.08
Residual	-.12	-.05	-.07	-.25	.49
Distillate	.11	.01	-.44	.23	.09
Natural Gas	.57	.03	.34	-.02	-.55
P.P.	21.85	1.25	12.97	45.98	17.90

50th SIZE Percentile

	ELEC	RESID	DIST	NAT GAS	SWITCH
Electricity	.04	.01	-.40	.20	.14
Residual	-.05	-.04	-.06	-.22	.37
Distillate	.08	.01	-.68	.33	.26
Natural Gas	.28	.03	.33	-.01	-.43
P.P.	10.52	1.03	12.31	42.81	33.21

90th SIZE Percentile

	ELEC	RESID	DIST	NAT GAS	SWITCH
Electricity	.01	.01	-.09	.04	.04
Residual	.02	-.05	.01	.04	-.02
Distillate	.03	.01	-.28	.06	.18
Natural Gas	.18	.03	.05	-.01	-.02
P.P.	10.88	1.82	2.87	21.92	62.09

P.P.= Predicted Probability

The numbers in table 6 must be viewed with caution. Recall in figure 6 that the predicted probability of SWITCH is a non-monotonic function of the price of natural gas. The results in table 6 are computed at the means of all the variables in the model, except for SIZE. The statistics in table 6 do not convey any measures of concavity, convexity, or monotonicity in the relationships between prices and predicted probabilities.

Own price elasticities are negative, except for electricity. Over the range of electricity prices, the predicted probability of ELEC changes little. The own price elasticities for residual, distillate, and natural gas are negative, with DIST being the most price sensitive in each SIZE category. An interesting result is that the predicted probabilities for DIST, NAT GAS, and SWITCH, generally become less price sensitive from the 50th to the 90th SIZE percentile. Large energy consuming plants are much more likely to possess SWITCH, and as a result, the price of a single fuel is not as influential.

The analysis of energy market conditions and energy technology has so far focused on energy prices. However, other energy market conditions influence the energy technology choice of plants. For instance, whether or not plants chose NAT GAS does not only depend on prices, but also on whether natural gas is available, and whether the supply of natural gas in the past has been stable. In the estimated model, two controls for natural gas availability and supply stability are included.

Natural gas availability has increased during the past several decades, however, thre are remote areas that did not have access to natural gas in 1985. Using the 1975 Annual Survey of Manufactures data on natural gas usage, we compute how much of the manufacturing fuel requirements in each county is met by natural gas. A dummy variable, NAT75, is set equal to one if there is a significant of natural gas consumed in a county in 1975, otherwise NAT75 is 0. For the sample used in this study, 72.6% of plants are in counties in which natural gas was used in 1975. [37]

Table 7 presents how the predicted probabilities of the six energy technologies vary depending on the value of NAT75. This variable greatly influences the predicted probability of several of the technologies. The predicted value of NAT GAS more than doubles from 22.80 to 48.64. Absorbing most of this increase is DIST, whose predicted probability plummets from 40.55

[37] This variable, NAT75, is not the ideal measure for whether or not a plant can hook up to a natural gas pipeline. However, it appears to distinguish between urban and rural areas, where rural areas are less likely to have access to natural gas.

to a mere 7.03. The other large change in predicted probability occurs for SWITCH. This result is not surprising since fuel switching equipment often relies on natural gas as one of the fuel sources.

TABLE 7: NATURAL GAS AVAILABILITY IN 1975
AND PREDICTED PROBABILITY OF ADOPTION

	ELEC	RESID	DIST	NAT GAS	COAL	SWITCH
NAT75=0	11.19	2.69	40.55	22.80	.17	22.60
NAT75=1	9.21	.64	7.03	48.64	.09	34.39

Even in areas in which natural gas is generally available, shortages of natural gas have occurred. During the severe winters in the mid 1970's, natural gas shortages developed in many parts of the country, and the supply shortages vary in severity by region. Starrett (1976) presents average curtailment rates for 10 regions. We include this variable, CURTAIL, along with its square and cube, in each of the five estimated equations.[38] Figure 7 presents how the predicted probability for each technology varies over the relevant range of CURTAIL. There is generally a positive relationship between the degree of curtailments and the predicted probability of SWITCH. Corresponding to the increase in SWITCH, the predicted probability for NAT GAS declines dramatically.

The degree of curtailments in natural gas supplies is a measure of the variance in supply. In the model section we briefly explore the role of variances and covariances of prices on the expected energy related costs of the fuel switching technology. In estimation we include several measures of price variance, and these variance measures have little impact on the predicted probabilities. One measure of price variance is simply the standard deviation of a fuel price over time. The other measure included in estimation

[38] In a supplement to the 1976 Annual Survey of Manufacturers, 5,000 plants were asked how many production worker hours were lost as a result of natural gas supply disruptions. Unfortunately we do not have access to the micro data. However, the results are published for 21 states. For these 21 states we compute the ratio of production hours lost to total production hours, and included this variable in estimation. For the remaining states, we use a national average, as no other information is available. This variable has little impact on the predictive ability of the model.

is the variance of the error term from the price forecast equation. As with the prices, the question arises as to the appropriate definition of variance. That is, should variances based on data form the 1970's be used, or should we limit ourselves to the 1980's? An additional problem arises since the price data used in this study are annual, and this annual price data mask higher frequency volatility.

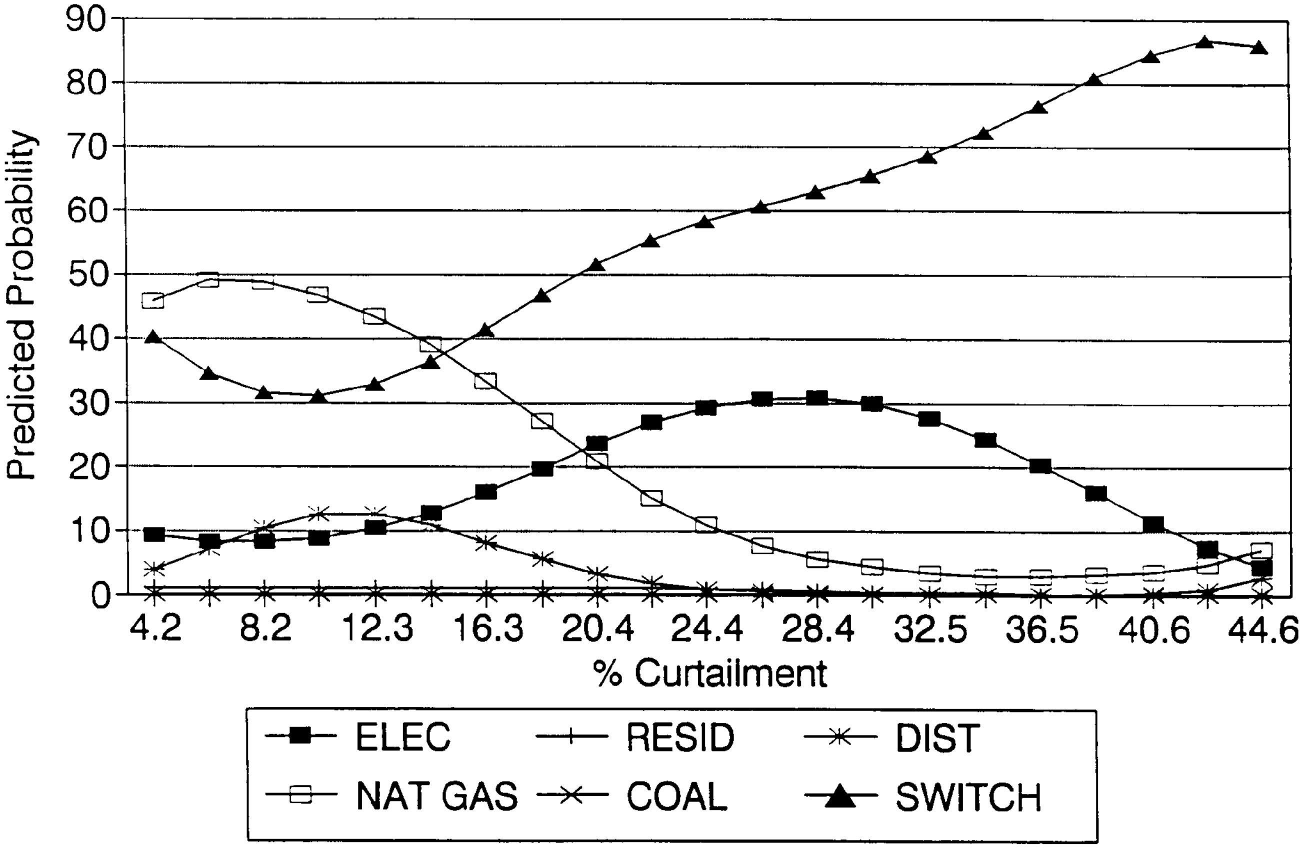
V. CONCLUSION

This paper is a first step in exploring how the manufacturing sector responds to energy price shocks by examining the factors that influence the energy technology choice of individual manufacturing plants. Using plant level data from the 1985 MECS and the LRD, this paper documents the heterogeneity in energy technologies across and within industries. The objective of this paper is not just to document the heterogeneity, but to explain how this heterogeneity has arisen by using basic economic concepts.

In order to test the impact of certain variables on the energy technology adoption decision, we estimate a multinomial logit model of technology choice. For simplicity, the variables that enter the model are classified into two categories; plant level characteristics and energy market conditions. Overall we find that both sets of variables greatly influence the energy technology adoption decision.

Because fuels differ in their attributes, the most economical energy technology for a plant depends on the amount of energy consumed and the production process. There is great variance in how much energy plants consume and the energy intensity of production. Our results show that large energy consuming plants are more likely to adopt fuel switching technologies, indicating the existence of strong scale economies for the fuel switching technology. Plants that partake in energy intensive applications are more likely to rely on natural gas and distillate fuel oil. Even after controlling for the amount of energy consumed and the energy intensity of the production process, we still find great innate industry preferences towards particular technologies.

FIGURE 7: PREDICTED PROBABILITY OF ADOPTION AND NATURAL GAS CURTAILMENTS



%Curtailment is based on the witnter of 1974/5 natural gas curtailments .

Besides the variables that describe the characteristics of manufacturing plants, the model also includes variables that describe energy market conditions that each plant faces. The natural experiment that enables us to identify the impacts of energy market conditions on the energy technology of a plant is that energy market conditions vary drastically by geographical region. The estimated model in this paper uses fuel prices and variables that capture natural gas availability.

The price results are interesting. As the price of natural gas increases, the predicted probability of relying solely on natural gas decreases. The relationship between natural gas prices and the predicted probability of adopting fuel switching technology confirms to the model of energy technology adoption. As the price of natural gas reaches either extreme, the predicted probability of adopting fuel switching technology decreases since the opportunities to exploit fuel switching capability decrease.

The price of natural gas is not the only factor in whether plants rely primarily on this energy source since not all communities have had access to natural gas, and some communities underwent severe natural gas shortages in the 1970's. Our results indicate that the severity of natural gas shortages of the 1970's is positively related to the predicted probability of possessing fuel switching technology in 1985.

The data used in this paper are cross sectional, and do not allow explicit modeling of the dynamic process of the energy technology decision of plants. However, our results indicate that a portion of the heterogeneity in energy technologies can be attributable to the heterogeneity in plant characteristics and geographical dispersion of energy prices and supplies.

APPENDIX A

VARIABLE DEFINITIONS, PARAMETER ESTIMATES, T-STATISTICS, AND MEAN VALUES

This appendix contains the parameter estimates for the multinomial logit model of energy technolgy choice:

$$P_j = \frac{\exp(\beta_j X_j)}{\sum_{k=1}^{N} \exp(\beta_k X_k)}$$

Seperate sets of ß's are estimated for the RESID, DIST, NAT GAS, COAL, and SWITCH technologies. In this appendix, we present a variable dictionary, followed by the parmeter estimates, t-statistics, and mean values for each of the estimated equations.

Variable Dictionary

AGE1	dummy variable whether the plant started between 1964 and 1974
AGE2	dummy variable whether the plant started between 1975 and 1981
AGE3	dummy variable whether the plant started after 1981
C	constant
CAP1	dummy variable whether the plant underwent significant investments after 1980
CAP2	dummy variable whether the plant underwent significant investments between 1975 and 1980
CURTAIL	percent of natural gas curtailed in the 1974/5 winter
CURT2	percent of worker hours lost due to natural gas curtailments
ECOAL	average square error for coal prices from an AR(2) model with a linear trend.
EDIST	average square error for distillate fuel oil prices from an AR(2) model with a linear trend.

ENATGAS	average square error for natural gas prices from an AR(2) model with a linear trend.
ERESID	average square error for residual fuel oil prices from an AR(2) model with a linear trend.
INDxx	dummy variable for 2-digit industry xx
INTENS	the ratio of total BTUs consumed in a plant to dollars value added
LSIZE	logarithm of total BTUs consumed in the plant
NAT75	dummy variable, =1 if the county had access to natural gas in 1975, =0 otherwise
PCOAL	state level 1982-84 average price of coal
PDIST	state level 1982-84 average price of distillate fuel oil
PELEC	state level 1982-84 average price of electricity
PNATGAS	state level 1982-84 average price of natural gas
PRESID	state level 1982-84 average price of residual fuel oil
STCOAL	standard deviation of coal prices for 1980-1987
STDIST	standard deviation of distillate fuel oil prices for 1980-1987
STNATGAS	standard deviation of natural gas prices for 1980-1987
STRESID	standard deviation of residual fuel oil prices for 1980-1987

Estimates from the RESID Equation

Variable	ß	T-stat	Mean
C	172.304	0.158	1.000
PRESID	-326.631	-0.153	1.531
PELEC	-168.393	-1.451	2.957
SIZE	-0.101	-0.091	-6.505
CURTAIL	0.112	0.453	12.529
INTENSITY	0.600	9.538	2.536
STRESID	-8.100	-0.460	26.330
ERESID	605.964	2.565	0.829
NAT75	-1.239	-3.721	0.726
CURT2	-0.280	-1.033	0.983
AGE1	0.550	1.972	0.235
AGE2	-1.328	-2.886	0.199
AGE3	-2.387	-4.189	0.251
CAP1	1.467	3.568	0.321
CAP2	1.883	4.435	0.224
PRESID^2	266.931	0.194	2.345
PELEC^2	53.375	1.258	8.742
SIZE^2	-0.007	-0.093	42.315
CURTAIL^2	-0.010	-0.602	156.977
INTENSITY^2	-0.021	-8.516	6.430
STRESID^2	0.275	0.410	693.244
ERESID^2	-577.632	-2.622	0.688
PRESID^3	-69.274	-0.235	3.591
PELEC^3	-5.625	-1.101	25.846
SIZE^3	0.000	0.070	-275.259
CURTAIL^3	0.000	0.515	1966.777
INTENSITY^3	0.000	7.350	16.305
STRESID^3	-0.003	-0.347	18252.788
ERESID^3	168.593	2.680	0.571
PRESID*SIZE	0.110	0.164	-9.962

Estimates from the DIST Equation

Variable	ß	T-stat	Mean
C	-8540.397	-3.235	1.000
PDIST	13211.935	3.363	2.024
PELEC	-316.982	-6.303	2.957
SIZE	0.199	0.176	-6.505
CURTAIL	0.880	8.616	12.529
INTENSITY	0.794	15.876	2.536
STDIST	-11.122	-3.394	13.172
EDIST	-84.366	-3.536	0.866
NAT75	-1.558	-11.664	0.726
CURT2	0.295	4.323	0.983
AGE1	0.399	2.733	0.235
AGE2	-0.192	-0.562	0.199
AGE3	0.083	0.225	0.251
CAP1	-0.295	-0.835	0.321
CAP2	0.949	2.816	0.224
PDIST^2	-6529.849	-3.375	4.097
PELEC^2	112.156	6.124	8.742
SIZE^2	-0.150	-1.436	42.315
CURTAIL^2	-0.057	-9.411	156.977
INTENSITY^2	-0.029	-11.319	6.430
STDIST^2	0.854	3.382	173.509
EDIST^2	84.395	3.278	0.751
PDIST^3	1074.693	3.386	8.293
PELEC^3	-13.242	-6.022	25.846
SIZE^3	-0.000	-0.083	-275.259
CURTAIL^3	0.001	9.686	1966.777
INTENSITY^3	0.000	10.508	16.305
STDIST^3	-0.021	-3.304	2285.517
EDIST^3	-25.285	-2.811	0.651
PDIST*SIZE	-1.037	-2.113	-13.167

Estimates from the NAT GAS Equation

Variable	ß	T-stat	Mean
C	-105.323	-3.004	1.000
PNATGAS	-37.187	-1.214	1.623
PELEC	148.435	4.401	2.957
SIZE	-0.706	-3.081	-6.505
CURTAIL	0.324	6.325	12.529
INTENSITY	0.607	15.395	2.536
STNATGAS	1.427	6.451	9.564
ENATGAS	-71.279	-7.919	0.464
NAT75	0.952	8.631	0.726
CURT2	-0.042	-0.938	0.983
AGE1	-0.227	-2.387	0.235
AGE2	-1.366	-6.700	0.199
AGE3	-1.132	-5.854	0.251
CAP1	0.445	2.422	0.321
CAP2	0.781	3.844	0.224
PNATGAS^2	29.273	1.477	2.635
PELEC^2	-56.134	-4.555	8.742
SIZE^2	0.025	0.759	42.315
CURTAIL^2	-0.027	-8.024	156.977
INTENSITY^2	-0.020	-12.590	6.430
STNATGAS^2	-0.124	-6.345	91.470
ENATGAS^2	125.685	7.093	0.216
PNATGAS^3	-7.648	-1.811	4.277
PELEC^3	6.883	4.629	25.846
SIZE^3	0.007	3.295	-275.259
CURTAIL^3	0.000	8.408	1966.777
INTENSITY^3	0.000	9.817	16.305
STNATGAS^3	0.003	5.940	874.812
ENATGAS^3	-66.795	-6.281	0.100
PNATGAS*SIZE	0.154	1.541	-10.559
IND22	-1.609	-5.875	0.021
IND23	-1.618	-7.842	0.045
IND24	-2.216	-12.391	0.066
IND25	-0.749	-3.417	0.027
IND26	-0.041	-0.172	0.027
IND27	-0.230	-1.532	0.116
IND28	-0.439	-2.192	0.040
IND30	-1.023	-5.844	0.052
IND31	-0.985	-2.937	0.009
IND32	-1.320	-7.427	0.059
IND34	-0.696	-4.776	0.115
IND35	0.045	0.316	0.164
IND36	-0.145	-0.879	0.064
IND37	-0.755	-3.399	0.024
IND38	-0.946	-4.680	0.035
IND39	-0.650	-3.603	0.052

Estimates from the COAL Equation

Variable	ß	T-stat	Mean
C	-20.343	-0.118	1.000
PCOAL	17.282	1.907	0.644
PELEC	29.138	0.153	2.957
SIZE	0.107	0.236	-6.505
CURTAIL	0.573	1.969	12.529
INTENSITY	0.613	10.539	2.536
STCOAL	0.040	0.036	6.596
ECOAL	-179.996	-1.741	0.169
NAT75	-0.506	-1.252	0.726
CURT2	-0.074	-0.334	0.983
AGE1	-2.202	-2.732	0.235
AGE2	-2.595	-3.061	0.199
AGE3	-1.327	-1.938	0.251
CAP1	0.818	1.347	0.321
CAP2	1.344	2.360	0.224
PCOAL^2	8.635	0.482	0.415
PELEC^2	-11.185	-0.160	8.742
SIZE^2	0.118	1.657	42.315
CURTAIL^2	-0.040	-2.158	156.977
INTENSITY^2	-0.020	-11.023	6.430
STCOAL^2	-0.027	-0.206	43.509
ECOAL^2	887.404	1.671	0.028
PCOAL^3	-28.669	-1.658	0.267
PELEC^3	1.278	0.151	25.846
SIZE^3	0.009	1.563	-275.259
CURTAIL^3	0.001	2.025	1966.777
INTENSITY^3	0.000	9.443	16.305
STCOAL^3	0.002	0.404	286.993
ECOAL^3	-1277.619	-1.540	0.005
PCOAL*SIZE	1.199	2.002	-4.189

Estimates from the SWITCH Equation

Variable	ß	T-stat	Mean
C	100.675	0.926	1.000
PNATGAS	109.011	2.644	1.623
PRESID	-232.952	-1.093	1.531
SIZE	-0.318	-1.091	-6.505
CURTAIL	0.017	0.239	12.529
INTENSITY	0.572	14.117	2.536
STNATGAS	0.052	0.170	9.564
STRESID	-11.254	-2.377	26.330
ENATGAS	-43.451	-3.754	0.464
ERESID	64.493	2.217	0.829
NAT75	0.614	5.040	0.726
CURT2	-0.133	-1.975	0.983
AGE1	-0.205	-1.857	0.235
AGE2	-1.137	-5.346	0.199
AGE3	-1.044	-5.021	0.251
CAP1	0.580	2.979	0.321
CAP2	0.999	4.795	0.224
PNATGAS^2	-53.534	-2.049	2.635
PRESID^2	194.028	1.369	2.345
SIZE^2	0.022	0.600	42.315
CURTAIL^2	-0.005	-1.131	156.977
INTENSITY^2	-0.020	-12.090	6.430
STNATGAS^2	0.002	0.068	91.470
STRESID^2	0.454	2.546	693.244
ENATGAS^2	72.809	3.252	0.216
ERESID^2	-95.490	-2.740	0.688
PNATGAS^3	8.196	1.501	4.277
PRESID^3	-50.923	-1.628	3.591
SIZE^3	0.005	2.272	-275.259
CURTAIL^3	0.000	1.847	1966.777
INTENSITY^3	0.000	9.603	16.305
STNATGAS^3	-0.000	-0.231	874.812
STRESID^3	-0.006	-2.725	18252.788
ENATGAS^3	-36.764	-2.759	0.100
ERESID^3	45.154	3.230	0.571
PNATGAS*SIZE	0.718	5.741	-10.559
PRESID*SIZE	-0.556	-3.865	-9.962
IND22	-1.119	-4.495	0.021
IND23	-1.411	-5.887	0.045
IND24	-2.896	-10.925	0.066
IND25	-0.529	-2.207	0.027
IND26	-0.305	-1.199	0.027
IND27	-0.759	-4.153	0.116
IND28	-0.515	-2.388	0.040

Estimates from the SWITCH Equation (Continued)

Variable	ß	T-stat	Mean
IND30	-1.015	-5.285	0.052
IND31	-0.877	-2.294	0.009
IND32	-1.146	-5.888	0.059
IND34	-1.176	-6.837	0.115
IND35	-0.012	-0.075	0.164
IND36	-1.036	-4.914	0.064
IND37	-1.373	-5.184	0.024
IND38	-1.048	-4.136	0.035
IND39	-0.564	-2.622	0.052

APPENDIX B

PLANT LEVEL MEANS OF SIZE AND INTENSITY
BY 2-DIGIT INDUSTRY

Industry	SIZE	INTENSITY
Food	5.88	3.30
Textiles	5.88	5.42
Apparel	0.26	0.85
Lumber	0.65	3.01
Furniture	0.68	1.31
Paper	22.80	6.70
Printing	0.28	0.86
Chemicals	32.80	6.73
Rubber	2.01	2.82
Leather	1.30	2.11
Stone and Clay	9.19	8.57
Fabricated Metals	1.22	2.43
Machinery	0.61	1.13
Electronics	1.35	1.18
Transportation	21.94	1.36
Instruments	1.17	0.67
Miscellaneous	2.46	0.94

SIZE=mean plant size in 10's of millions of BTUs
INTENSITY= thousands of BTUs per 1985 dollar value added.

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