**The Impact of Energy Prices on Technology Choice in the
United States Steel Industry**

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In the last thirty years U.S. steel producers have replaced their aging open hearth steel furnaces with basic oxygen or large electric arc furnaces. This choice of technology leads to the opportunity to substitute electricity for fossil fuels as a heat source. We extend earlier research to investigate whether or not energy prices affect this type of technology adoption as predicted by economic theory. The econometric model uses the "seemingly unrelated Tobit" method to capture the effects of the industry's experience with both technologies, technical change, and potential cost reductions, as well as energy prices, on adoption. When we include the prices of electricity and coking coal as explanatory variables, the four energy price coefficients have the signs predicted by the law of demand. The two price coefficients have a statistically significant effect on adoption of basic oxygen furnaces. The inclusion of energy prices leads to significantly more efficient estimates of the other coefficients in the model.

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1. Introduction

Throughout the past four decades, U.S. steel producers had the opportunity to replace their open hearth furnaces (OHFs) with basic oxygen furnaces (BOFs) or large electric furnaces (LEFs). Both technologies reduced steel producers' costs. The decision to install these technologies can be viewed, on one hand, as a choice between two alternative processes with different advantages and disadvantages in productivity or, on the other hand, as largely an issue of fuel choice. Whether the firm replaces the open hearth furnace, a technology based on fossil fuel, with another fossil-based technology (the BOF) or an electric-based one (the LEF) has important implications for the fuel consumption patterns of the industry.

Here we extend earlier research to see if energy prices had any effect on technology adoption in basic steel manufacturing in the United States. Other studies tend to focus on the way market structure issues such as firm size affect adoption¹. The usual issue is whether or not U.S. steel producers were technological laggards, meaning either that U.S. producers generally lagged behind the rest of the world or that the largest U.S. producers lagged behind their smaller competitors in modernizing their plants.

Our purpose is to identify the role energy prices play in technology adoption. Our results suggest steel producers respond to energy prices as the law of demand predicts. They delay adoption of basic oxygen or electric furnaces in the face of higher coal or electricity prices. Higher prices lead to slight delays in adoption. The models with energy price effects suggest that firms are prone to adopt new technologies that have high rates of productivity and have been demonstrated successfully. The addition of energy prices to the original model also leads to important changes in the original parameter estimates, suggesting an important role for energy prices as an omitted variable in the previous analyses.

We present an econometric model that captures the influences on innovation that theoretical research has identified. Since the model's equations have censored dependent variables and may have correlated disturbances, a "seemingly unrelated Tobit" approach estimates its coefficients.

2. The Model

Specification and Data

We assume that firms will be more likely to innovate the more certain they are that the innovation will lower their costs. In Karlson (1986), we see that innovation depends on previous successful experience with the technology, which makes innovation less of a gamble; on the current potential cost reduction the technology offers, which increases the adopter's current profits; on the rate of technical progress, which affects the potential for larger future profits from innovating later; and on differences in the current costs and knowledge of firms.

Our model builds on Karlson's (1984, 1986) specification. We capture previous successful experience with variables EXP_O and EXP_E , or the fractions of BOF and LEF capacity, respectively, installed up to time t that are still operating at time t . Our measures of technology-specific potential cost reductions include Karlson's indices of state-of-the-art technology at time of adoption, TEC_O and TEC_E . We include linear and quadratic terms for these variables in our equation to test for a critical level of technology that must be present before firms will adopt.

We add energy prices as additional sources of variation in the cost savings associated with each technology. The BOF is a converter technology that derives all its heat from a charge of molten pig iron. We expect higher coking coal prices to slow the rate at which firms install BOFs, because innovation will not reduce their costs as much. The electric arc furnace is a refining technology that uses large amounts of electricity to melt scrap metal and burn off impurities. We expect higher electricity prices to slow the rate at which firms install LEFs, again because innovation will not reduce costs as much. Our model contains the real prices of coke, $RPCOKE$, and electricity, $RPELEC$, that firms confront immediately before adoption.

The pace of technical progress influences innovation. Firms are likely to delay adoption of technologies that are improving rapidly (Kamien and Schwartz 1972; Balcer and Lippmann 1984.) Our ΔTEC variables proxy for the rate of technical change. Since the technologies compete with each other, we use the rates of technical progress of both BOF and LEF, ΔTEC_O and ΔTEC_E , as explanatory variables in each adoption equation.

Differences in the current costs and knowledge of firms depend on the equipment present at each plant a firm operates and on the firm's ability. We count the number of blast furnaces (BLF) and we calculate the average steel furnace size (FSZ) at each plant. More blast furnaces may lead to more rapid adoption of BOFs. To the extent that there are scale economies in steel furnaces, plants with larger furnaces have lower costs. Innovation is relatively less attractive at such plants. We capture differences among firms by their annual capacity (SIZE) and by whether they are multiplant firms. Scherer and Ross (1990) note that firm size may either help or hinder innovation. Larger firms may be able to maintain more diversified research programs, but they may also be less able to respond rapidly to changing economic conditions. Multiplant firms may be more likely to experiment with new technologies, because they will not risk their entire output when they convert single plants. The knowledge a firm obtains from conversion may be better than that reported in trade journals.

We use the number of years since adoption of a technology (Y_j , where j represents type of technology) as the dependent variable. It is 1980 minus the calendar year in which a plant receives either new technology. There is a series for BOFs (Y_O) and for

LEFs (Y_E). Earlier adopters have larger values of Y_j . While the model is for a cross-section study of adopters, the different adoption dates in Y_j give a time-series character to the study.

We describe the independent variables in Table 1. For a justification of the specification we use, see Karlson (1986). If a plant innovates at year t , we regress Y_j on the independent variables for $t-1$. We use the independent variables for 1979 with all censored Y_j .

We investigate adoption of the competing inventions at 57 steel plants operated by 28 companies in 1980. We list the firms and plants in Table 2. The unit of observation is the plant because firms make their conversion decisions on a plant-by-plant basis. Oxygen converters were installed in 20 sample plants by 1980. LEFs were installed in 22 plants by 1980. Eight plants used both technologies by 1980. Twenty-three plants never received BOFs or LEFs.

We report results for 1980 to capture the effect of changing energy prices. Real energy prices remained stable for many years prior to the price shocks of the 1970s. The 1980 results will show how steel producers reacted to those shocks.

By contrast, Karlson (1986) studied innovation in 1974 and 1980 to capture changes in the steel business. Domestic steel production reached its peak in 1973. The industry faced depressed business conditions, increased foreign competition, and domestic entry by new steel producers thereafter. There were a number of mergers and plant closings among the major producers. Improvements have been made in BOF and LEF technology.

Energy prices increased rapidly after 1974. We saw little change in real energy prices before 1974. We therefore estimate the expanded model only against 1980 data.

Estimation

Since the dependent variable is truncated at zero at plants that did not innovate, we estimate parameters by a seemingly unrelated Tobit technique. The single-equation Tobit estimator is well known. Fair (1977) has presented a procedure for its computation; Chow (1983) has observed that the Fair procedure is an application of the Dempster, Laird, and Rubin (1977) EM algorithm. Better estimates of the parameters and the imputed residuals associated with censored observations are calculated until the estimator converges to the maximum-likelihood solution. We use Karlson's extension to the two-equation case of Fair's procedure². The approach is similar to one offered by Huang, Sloan, and Adamache (1987).

Table 1: Definitions of Independent Variables

EXP_j: The ratio of surviving capacity of type j (j = O, B, E), at year t, to all installations of all types (OHF, BOF, LEF) of capacity, surviving or abandoned, which were built between 1951 and year t.

TEC: The ratio of the maximum capacity of a process in some year to the maximum capacity in 1967:

$$TEC_{jt} = \frac{HEAT_{jt} \text{ RATE}_{jt}}{HEAT_{j67} \text{ RATE}_{j67}}$$

where HEAT_{jt} is the largest heat size for furnace j at time t, and RATE_{jt} is the maximum operating rate in heats per year. The 1967 state-of-the-art electric furnace would produce 500,000 tons of raw steel per year, while the oxygen furnace would produce about 2 million tons.

ΔTEC: A five-year moving average of the increase in TEC.

Firm-Specific Variables

SIZE: The rated capacity of the firm, in thousands of tons of raw steel per year, as reported in the *AISI Directory of Steel Plants* and in Deily (1981).

MULT: A binary variable that takes value 1 for all firms operating more than one plant and 0 otherwise.

Plant-Specific Variables

BLF: The number of blast furnaces at a mill site as reported in the *AISI Directory*.

FSZ: The heat size of each furnace at a plant site as reported in the *AISI Directory*. The independent variable is a simple average of those heat sizes.

RPCOKE: The dollar price of a million Btu of metallurgical coal in each plant's home state. The Energy Information Administration (1983) reports prices for 1970-1980. Its appendix explains how to compute the prices. We apply its method to expenditure data as reported in *Minerals Yearbook* to obtain dollar prices for years before 1970.

RPELEC: The dollar price of a million Btu of electricity as a unit value. The Edison Electric Institute *Historical Statistics* and *Statistical Yearbooks* provide reports on revenues and kilowatt-hour sales of electricity to large industrial users in each state from 1960 on. We divide revenues by sales and apply a conversion factor to obtain dollars per million Btu. For the 1950s, we use a national unit value that we calculate from revenues reported and sales reported in *Historical Statistics*.

Table 2: Process Adoption Patterns of the Firms Included in the Study

	Adopt Both	Adopt BOF	Adopt LEF	Adopt Neither
Integrated Producers				
Bethlehem	4	2	2	
Ford	1			
Inland	1			
Kaiser		1		
Lone Star				1
McLouth	1			
Republic	3	2		
Sharon	1			
U.S. Steel	1	5	2	3
Nonintegrated Producers				
Atlantic			1	1
Auburn				1
Border				1
Cascade				1
Chaparral			1	
Continental			1	
Florida			1	4
Georgetown			1	1
Keystone			1	
Laclede			1	
Lukens			1	
Mississippi				1
Northwest (Seattle)				1
Northwestern (Sterling)			1	
Nucor				3
Oregon				1
Raritan River			1	
Ross				1
Wittman				1

3. Empirical Results

We report parameter estimates for the 1980 sample in Table 3³. The first two columns, which do not include energy price effects, were first reported in Karlson (1984). The final two columns are new results that include energy price effects. The log-likelihood of the model increases significantly when we include energy prices. The test statistic given by twice the difference in log-likelihood equals 140.176. It is an asymptotically distributed χ^2 , and its value leads us to reject the null hypothesis that the price coefficients jointly equal zero with more than 99.5% confidence.

The price coefficients have the expected signs. The values suggest steel firms substitute among energy sources when they choose technologies. Higher coke prices suggest later adoption of basic oxygen furnaces and earlier adoption of electric furnaces, *ceteris paribus*. Higher electricity prices lead to later adoption of LEFs and earlier adoption of BOFs.

The relatively small values of the price coefficients suggest that price changes, even large ones associated with supply shocks or stiff energy taxes, do not have much effect on adoption decisions, *ceteris paribus*. For example, a one-dollar increase in the real price of a million Btu of coking coal leads to a six-month delay in adoption of basic oxygen and moves forward the adoption of an electric furnace by three days. In 1979, a one-dollar increase in the coke price is approximately a 50% increase.

A 50% increase in the real price of a million Btu of electricity would raise the 1979 average price from 8 to 12 dollars. That price increase would delay adoption of an LEF by 12 days and advance the adoption of a BOF by three months, *ceteris paribus*.

Our results suggest that extreme changes in energy prices, including energy taxes, do not have a substantial effect on the pace of innovation in steel. The greatest inducement to earlier adoption of either technology is a more productive furnace. When we add energy prices to the model, the coefficients on technology and technical progress change. The results suggest that demonstration projects that are capable of producing steel on a large scale will be adopted more rapidly.

The most striking changes appear in the relationships between technologies and adoption. Our results suggest steel firms will be more likely to adopt extremely productive new technologies. The relationship between TEC_j and Y_j is positive for all sample values of TEC_j : firms adopt more productive furnaces earlier. We estimate critical furnace sizes, which we define as the value of TEC_j at which $\delta Y_j / \delta TEC_j$ equals zero. These sizes give the largest values of years since adoption, *ceteris paribus*.

Table 3: Estimated Coefficients (approximate standard errors)

	Without Energy Prices		With Energy Prices	
	Oxygen	Electric	Oxygen	Electric
Constant	20.90 ^a (2.02)	21.06 ^a (0.87)	27.92 ^a (0.14)	21.16 ^a (1.38)
EXP _O	-30.38 ^a (-13.94)	10.56 (6.6)	-39.05 ^a (-1.01)	11.83 ^a (4.89)
EXP _E	-94.56 (-53.42)	9.07 (20.61)	-115.81 ^a (-3.6)	12.47 (15.76)
TEC _O	40.4 (27.86)	-32.15 ^a (-12.09)	55.39 ^a (1.85)	-34.56 ^a (-8.69)
TEC _O ²	-24.89 (-14.22)	8.18 (6.34)	-28.45 ^a (-0.89)	9.06 (4.65)
TEC _E	7.90 ^a (3.83)	8.27 ^a (1.59)	-7.47 ^a (-0.22)	8.26 ^a (2.56)
TEC _E ²	-2.62 ^a (-1.11)	-5.05 ^a (-0.85)	1.58 ^a (0.06)	-3.03 ^a (-0.64)
ΔTEC _O	5.84 (12.43)	29.37 ^a (4.06)	-4.75 ^a (-0.77)	29.46 ^a (2.79)
ΔTEC _E	6.14 (4.32)	0.044 (2.2)	18.63 ^a (0.3)	0.23 (2.49)
BLF	0.039 (0.06)	-5.6×10 ⁻³ (-0.06)	-0.01 ^a (4.2×10 ⁻³)	3.39×10 ⁻⁴ (0.037)
FSZ	1.3×10 ⁻³ (2.0×10 ⁻³)	5.2×10 ⁻⁴ (-9.6×10 ⁻⁴)	-6.49×10 ⁻⁵ (-9.9×10 ⁻⁵)	5.53×10 ⁻⁴ (6.7×10 ⁻⁴)
SIZE	3.7×10 ⁻⁶ (1.4×10 ⁻⁵)	1.6×10 ⁻⁶ (1.1×10 ⁻⁵)	1.46×10 ⁻⁶ (8.2×10 ⁻⁷)	3.16×10 ⁻⁶ (8.3×10 ⁻⁶)
MULT	0.02 (0.29)	0.12 (0.22)	0.07 ^a (0.018)	0.12 (0.15)
RPCOAL			-0.49 ^a (-0.1)	0.007 (0.055)
RPELEC			0.06 ^a (0.01)	-0.008 (-0.12)
ASE of noncensored observations	0.398	0.295	0.019	0.213
Log-likelihood		-16.084		54.005

^aCoefficient is at least twice its approximate standard error.

When we add price effects to the model, we see a marked increase in critical furnace sizes. In the oxygen furnace equation without price effects, the critical value of TEC_O , 1.623, implies a furnace with a capacity of about 300 tons per heat. Such furnaces are significantly larger than the critical furnace size proposed by Dilley and McBride (1967), which was 200 tons per heat. But by 1980 the surviving basic oxygen capacity is in very large furnaces. When we add energy prices to the model, the critical value of TEC_O rises to 1.95, implying a furnace with capacity of about 400 tons per heat. The largest BOFs in the United States have a capacity of 360 tons per heat (*Iron and Steelmaker* 1989). Viewed from 1980, the model suggests that in the presence of higher energy prices, steel producers would delay adopting any BOFs, even the largest ones available.

The critical electric furnace size also increases. In the model without energy prices, critical TEC_E is 1.63, which is a furnace of about 250 tons per heat at 1979 operating rates. Critical TEC_E is 2.73, which is a furnace of about 400 tons per heat, in the model with energy prices. Only one U.S. company operates 400-ton electric furnaces (*Iron and Steelmaker* 1988).

Since the technologies compete with each other, we expect to see $\delta Y_E / \delta TEC_O < 0$ and $\delta Y_O / \delta TEC_E < 0$: firms will delay adopting one technology if the other is more productive. The results confirm our expectations; for the parameter estimates in equations without and with price effects, the derivatives are negative for all relevant values of TEC_O and TEC_E .

Taken together, the results suggest that small improvements in technology lead to large increases in adoption rates. Firms adopt more rapidly, *ceteris paribus*, when technology levels exceed the critical levels. At the critical levels ($TEC_O = 1.95$ and $TEC_E = 2.73$) there is no partial effect of technology on adoption. We would see adoptions of oxygen furnaces six months sooner, *ceteris paribus*, if TEC_O were 1.96 or if TEC_E were 2.90. A 1% increase in BOF size or operating rate has the same effect as a one-dollar reduction in the coke price. A 6% increase in electric furnace size or operating rate speeds adoption more than a four-dollar reduction in the electricity price.

The relationships between progress on and adoption of a technology are generally consistent with Balcer and Lippmann's (1984) hypothesis. Positive coefficients imply that firms adopt after a slowdown in technical progress, either with the furnace the firm chose or the competing one. Technical progress diminished after 1967 for BOFs and after 1969 for LEFs.

The relationship between ΔTEC_O and Y_O is the exception. The negative coefficient implies BOF adoption during a period of rapid technical progress. Karlson (1986) reported such a relationship in 1974 but not 1980. His interpretation was that "early adoption of a (too small) basic oxygen converter may have been a mistake." The "mistake" appears in the 1980 results that have energy prices in the model. We conjecture that the changing parameter estimates Karlson obtained earlier reflect energy price changes that his model did not include.

Addition of energy prices strengthens the demonstration effects we observe. Variables EXP_O and EXP_E in the oxygen process equation have negative coefficients. Smaller values of Y_O (later adopters) are associated with larger values of EXP_j (more successful trials of the process). The extremely large negative coefficients on experience suggest that a firm contemplating installing either technology for the first time in 1979 would not adopt basic oxygen. The success rate for LEFs rises from 12.4% in 1974 to 15.6% in 1980. That increase leads to adoptions of basic oxygen three years later, *ceteris*

paribus, in the model without energy prices. In the model with energy prices, we expect adoption of basic oxygen almost four years later in 1980 than it would take place in 1974.

A demonstration project that raised the success rate of oxygen furnaces by two percentage points would lead to adoption of oxygen furnaces six months sooner, *ceteris paribus*. A demonstration project that raised the success rate of electric furnaces by less than half a percentage point would delay adoption of oxygen furnaces by six months, *ceteris paribus*.

The positive coefficient on EXP_O in the electric furnace equation may indicate an adverse demonstration effect, since EXP_O decreases between 1974 and 1980. The positive coefficient on EXP_E has a large standard error.

The plant-specific variables, which are the number of blast furnaces (BLF) and steel furnace size (FSZ) at a plant, both have small influences on adoption. The negative coefficients on FSZ in the oxygen process equation with price effects suggest that smaller open hearth furnaces were replaced first, as Dilley and McBride (1967) and Oster (1982) show. Smaller furnaces do not lead to a dramatic increase in the pace of adoption. If two plants are otherwise identical but one has furnaces smaller by 100 tons per heat than the other, the oxygen process is installed one week earlier at the site with smaller furnaces. Large electric furnaces would be installed a few days later at sites with more blast furnaces, or earlier at sites with larger existing furnaces.

The company-specific coefficients (on SIZE and MULT) are so small that their effects are trivial. If two companies differ in capacity by 20 million tons (U.S. Steel compared to Bethlehem, or Bethlehem compared to Inland), *ceteris paribus* the larger firm adopts either BOF or LEF a few days earlier than their smaller rivals. Multiplant firms innovate slightly later than single-plant firms, *ceteris paribus*. The difference in adoption dates between a plant that is a company's only plant and an identical one operated by a multiplant firm never exceeds two months.

4. Conclusions

This paper examines the impact of energy prices on the adoption decision of two technologies that have fundamentally different energy use: coal coke and electricity. From the energy modeling perspective this is a fuel choice decision with important implications for energy use in the industry. Our results show that even in industries where energy use is a major component of costs, the role that energy prices take in the decision regarding a major process change is not as large as that of other technical variables, particularly performance and firm experience. The model that describes the role of these technical variables is significantly improved, which suggests an important statistical role for energy prices as an omitted variable in the original model.

It is most interesting to note that the statistically significant results of energy price on adoption come in the BOF equation. While it represents a different process from the open hearth furnace, the BOF is not a major process shift, involving different fuel and materials inputs. The firm decision process therefore considers input prices along with other productivity related variables in its adoption decision. LEF represents a major process change from the open hearth. Electricity and scrap are the major inputs and the overall engineering of the furnace is quite different. Viewed from this perspective the results presented here support the notion that energy prices may impact technology choice, but will have much less (if any impact) if the choice involves a major change in the production process.

The implications for other types of industrial energy modeling and government policy are far reaching. For example, in factor demand modeling of the steel industry the

role of factor biased technical change is demonstrated by this analysis to be significant. In this case the technical change, adoption of LEF, uses electricity and saves fossil fuel. The statistical record of shifts between these two energy types is ascribed to technology choice and change, not energy prices. Presumably the energy demand elasticities would be estimated more accurately when this factor biased energy-using technology is taken into account. Similarly, developers of government energy and technology policy might well look at the relative importance of technology R&D and demonstration vs. energy price oriented policies.

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1. For surveys of the academic literature, see Karlson (1986) and Papajohn (1990).
2. Details of this procedure are available on request.
3. In the discussion that follows Dempster, Laird, and Rubin's paper (1977, p.27), Murray observes that multiple stationary values of the likelihood function arise in estimates of parameters of simple multivariate normal distributions. A similar problem was encountered in performing these estimations. In practice, the behavior of the estimating algorithm is sensitive to starting values. With some starting values, divergence occurred. Flat spots on the likelihood function were also encountered. Reported parameters are obtained from runs with the highest computed log-likelihood value. Fitted values of Y_j are negative when Y_j is censored, as is required of Tobit estimators.

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