Energy Intensity, Electricity Consumption, and Advanced Manufacturing Technology Usage

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Abstract

This paper reports on the relationship between the usage of advanced manufacturing technologies (AMTs) and energy consumption patterns in manufacturing plants. Using data from the Survey of Manufacturing Technology and the 1987 Census of Manufactures, we model the energy intensity and the electricity intensity of plants as functions of AMT usage and plant age. The main findings are that plants which utilize AMTs are less energy intensive than plants not using AMTs but consume proportionately more electricity as a fuel source. Additionally, older plants are generally more energy intensive and rely on fossil fuels to a greater extent than younger plants.

Keywords: Energy intensity, technology

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I. Introduction

Over the course of the last 20 years, there has been significant growth in the use of advance manufacturing technologies (AMTs), such as computer-aided design and manufacturing, computer numerically-controlled machines, and information networks, in manufacturing plants. The adoption of such innovations by manufacturing facilities can be viewed essentially as embodied technical change. In this case, it is the capital factor, including both hardware and software, that incorporates the advances in technology. Technical change has two principle effects on plant-level production -- shifting the production function, e.g. movements from one isoquant to another, and changing the input mix, e.g. movements along an isoquant. This research reports on how AMTs influence factor input choice, and, in particular, the effect they have on plant-level energy intensity and fuel choice.

Most economic studies of energy and technology use aggregate or industry-level data and model technology as a time trend (for a review, see Berndt (1990).) These studies focus on disembodied technical change and attempt to measure whether technical change is energy using. This paper takes a different approach. Here, establishment-level variations in energy and electricity intensity are modeled as arising from differences in identifiable plant characteristics and factor prices. Olley and Pakes (1992) and Bailey, et al. (1992) show the importance of plant-level heterogeneity in models of productivity growth. Dunne and Roberts (1993) examine plant-level labor demand models. In a similar vein, we investigate the determinants of plant-level energy demand focusing on the role AMTs and plant age.[1]

This paper focuses on three main issues. First, are plants that employ advanced technologies, such as computer-aided design, robotics, and computers, relatively more or less energy intensive than plants relying on traditional technologies? The relationship between AMTs and energy intensity is an

[1]An exception is Doms (1992) which examines plant-level models of fuel switching.

ambiguous one. On the one hand, technological increases imply that more recent vintages of capital are likely to embody greater labor and energy efficiencies than older vintages. This acts to reduce overall input usage per unit output. On the other hand, newer vintages of capital, which consume energy, may also be viewed as labor substitutes (robotics is an example.) This latter case represents capital deepening and changes the input mix.[2]

The second goal of the paper is to test whether energy intensity varies systematically with the vintage of the manufacturing facility. In this case, the energy efficiency of older plants is compared to that of younger plants. Finally, the paper investigates the difference in energy mix across plants of differing ages and technologies. In the last twenty years, there has been a steady decline in overall energy intensity in U.S. manufacturing industries. At the same time, however, electricity's share of total energy consumption rose sharply.[3] A potential explanation for this increased electricity share is the adoption of electricity consuming innovations.[4]

A unique aspect of this study is that it employs plant-level data on both technology usage and energy consumption. The data come from two surveys. The 1988 Survey of Manufacturing Technology (SMT) documents the use of a wide set of computer, robotics, and information technologies in approximately 10,500 manufacturing plants. Although the SMT does not contain information on energy usage, we have combined the SMT with data on electricity, fuel consumption, and output collected from the 1987 Census of Manufactures (CM) to

[2]Preliminary evidence from the 1990 Survey of Manufacturing Technology indicates that a prime reason for purchasing AMTs is to lower labor costs. Roughly, two-thirds of the plants surveyed listed this as an important consideration in the decision to adopt AMTs.

[3]Ross (1991) shows that overall energy intensity, BTU's consumed over total output, declines by roughly a third between 1972 to 1985. However, as percent of total energy consumed, electricity has increased markedly.

[4]The relationship between technical change, productivity growth and electricity intensity has been examined in detail in Rosenberg (1983), Schurr (1983), and NRC (1986). These sources point out that many of the innovations that have occurred in the twentieth century are electricity using.

examine the relationship between energy and AMTs.

The main findings of this paper are fourfold. First, plants which utilize higher numbers of advanced technology are less energy intensive and rely more heavily on electricity as a fuel source. Second, plants utilizing computer automated design/computer automated manufacturing and flexible manufacturing systems based technologies consume less energy per unit of output, but consume a higher proportion of electricity. Third, plants constructed during the period of high energy prices, 1973-1983, are generally more energy efficient than plants built during other periods. Finally, plants over 30 years old are the most energy intensive and rely most heavily on non-electricity based fuels for energy.

The paper proceeds along the following lines. In the next section a simple empirical model of energy intensity is discussed. The third section of the paper describes the construction of the dataset. The fourth section summarizes the results from the energy and electricity intensity regressions and the fifth section provides concluding comments.

II. Energy Consumption and Technology

Two basic approaches have been taken to examine the relationship between energy and technology. One approach is to look at case studies of energy saving technology innovations (e.g., Ayres (1991), Joyce (1991).) This involves the analysis of individual production processes from an engineering perspective. A second approach models production functions and examines the role of technology in shifting production functions (e.g., Berndt and Wood (1975), and Berndt and Field (1984).)[5] These economic models typically do not explicitly account for shifts in production functions due to specific innovations, but allow general shifts in production relations over time.

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[5]For a review of the literature on energy and technical change see Berndt (1990). Jorgenson (1984) finds that strong evidence that technical change is energy using in most two-digit sectors.

This paper takes a hybrid approach. In the spirit of the case studies, the paper examines the relationship between the use of particular innovations and the energy intensity of manufacturing plants. This involves plant-level analysis focusing on specific technologies. In the spirit of the production studies, we econometrically estimate energy factor demand equations using a large set of plants across a range of industries.

The main focus of this paper is to explore the relationship between AMTs and energy consumption patterns in U.S. manufacturing plants. The effects of increased automation through the adoption of AMTs is hypothesized to impact the overall energy consumption at manufacturing plants in several ways. First, while these advanced technologies are not primarily designed to reduce the energy required to produce a good, AMTs may indirectly reduce overall energy intensity by having energy efficiency spillovers. For example, computers used in factories may reduce energy waste through the monitoring of production runs, the reduction of production errors, and the coordination of orders to productions. Similarly, one would expect the use of computer automated design/computer automated manufacturing (CAD/CAM) to reduce the amount of machining required to fabricate parts through more precise specifications. In the above cases, the usage of such advanced technologies may improve overall efficiency, thereby lowering energy input usage per unit of output.

Alternatively, these advanced technologies have a direct effect on energy intensity. These technologies are all energy using and employing these technologies will tend to increase energy consumption at manufacturing plants. One goal of this paper is to test whether the indirect energy savings of these advanced technologies exceed the direct energy requirements. This is an important issue for several reasons. First, these advanced manufacturing technologies are becoming more prevalent and the diffusion of these technologies will impact future energy demand patterns. Second, these advanced technologies tend to be heavily reliant on electricity. The increased application of these technologies may act to decrease overall energy demand while at the same time increasing electricity demand.

This work may also shed light on the energy-capital complement vs. substitute debate (see Solow (1987) for a review). Part of this debate centers on the characteristics of the capital being discussed. If new capital replaces older, more energy intensive capital, then energy and capital should appear as substitutes. However, if energy-using capital substitutes for another factor such as labor, then energy and capital would appear as complements. Therefore, part of the debate centers on the characteristics of the capital in question. It is an empirical question whether AMTs are complements or substitutes for energy.

Besides the effect of AMTs on energy usage, this paper examines whether older plants are more or less energy intensive than their younger counterparts. One might expect plant age to influence energy efficiency and energy mix through several mechanisms. The first is a technology effect. Older plants did not have initial access to recent energy-saving technologies as did younger plants. These technologies include specific innovations such as variable speed motors, heat exchangers and heat pumps. Therefore, if older plants are locked into old technologies then they may be more energy intensive than newer plants.

The second impact age has on energy intensity is presented in models by Abel (1983), Lambson (1989), and Doms (1992), which demonstrate the importance of expected relative prices in the choice of technology. During the period 1973-1981, the relative price of energy increased dramatically. The models above state that if expected energy prices are high, then firms will choose less energy intensive methods of production. Thus, one might hypothesize that plants constructed during the period of high expected energy prices may have chosen less energy intensive production facilities. Finally, if plant survival is an indicator of plant efficiency (see Jovanovic (1982)), then old plants (plants which survive for a long time) may in fact be generally more efficient than young plants (unproven operations.)[6]

An Empirical Model of Energy Intensity

To incorporate these facets of technology into an empirical model of energy consumption we derive an energy factor demand equation from a cost minimization model. Suppose each plant's short-run variable cost function has the following form:

$$VC(\mathbf{p},y,K,z,t) = y \cdot AVC(\mathbf{p},K,z,t), \qquad \textbf{(1)}$$

where VC() is a variable cost function, p is a vector of input prices, y is output, z is a vector of plant characteristics expected to affect costs, K represents the fixed factor capital, t incorporates measures of a plant's technology, and AVC() is an average variable cost function. The above expression equates total variable cost to output times average variable cost and implies a constant returns to scale (CRTS) technology.[7] Differentiating (1) with respect to the ith input price, p_i, and applying Sheppard's lemma yields

$$\frac{\partial C}{\partial \mathbf{p}_i} = y \cdot \frac{\partial AC}{\partial \mathbf{p}_i}(\mathbf{p},K,z,t) = x_i^*. \qquad \textbf{(2)}$$

[6]Empirical studies of plant growth and failure find that new firms have higher failure rates than older firms, see Dunne, Roberts and Samuelson (1989), and Evans (1987). These differential failure rates are interpreted as reflecting differences in plant-level efficiencies.

[7]The appropriateness of the CRTS assumption was examined through estimation of the underlying production function. We estimated the Cobb-Douglas KLE model for a value-added production function. The estimated parameters for the capital, labor, and energy factors summed to .98. This indicates a slightly decreasing returns to scale technology but close to CRTS. Bailey, Hulten and Campbell (1992) find CRTS technology in a broad range of industries using similar plant-level data.

where x_i^* is the cost-minimizing quantity of the ith factor. This is the standard expression for the ith factor demand equation in a unit variable cost framework. In this paper, we focus on the factor demand equation for energy and re-express it in intensity form as

$$\frac{x_E^*}{Y} = \frac{\partial AC}{\partial p_E}(\tilde{p}, K, \tilde{z}, t) . \qquad (3)$$

This says that energy consumption per unit of output is a function of input prices, the capital stock, plant characteristics, and technology. To estimate (3) we must first specify a functional form for the AVC function. In this paper, we will utilize a double-logarithmic form:

$$\ln(\frac{x_E^*}{Y}) = \sum_{i=1}^{j} \beta_i \ln p_i + \sum_{i=1}^{k} \theta_k \ln k + \sum_{i=1}^{l} \alpha_i z_i + \sum_{i=1}^{m} \gamma_i t_i . \qquad (4)$$

The dependent variable is measured as thousands of BTUs consumed divided by value-added measured in dollars.

The first set of independent variables represents factor prices at the plant. This vector includes the plant-level wage rate and state-level measures of energy prices. Ideally, we would like to have plant-level measures of energy prices, however, these are unavailable. Instead, we model differences in energy prices as geographically based and include state-specific dummy variables in the model. This provides maximum flexibility but sacrifices interpretation.[8] The next term in the model is a plant specific

[8]We also used state-level energy prices (electricity and natural gas) instead of the state dummies to control for differences in regional energy prices. The results reported below are insensitive to the choice of state dummies or state prices.

measure of the fixed factor capital. This also controls for differences in energy intensity across differences in plant size. The vector z contains a set of a production process variables that control for the four-digit SIC industry the plant operates in, and whether the plant primarily machines, assembles, or fabricates its products. The four-digit industry dummies also control for any differences in industry specific energy price variation.

The technology term will be modeled with two sets of variables. First, a set of plant age variables will be included to model the overall vintage of the plant. Second, a set of variables will be included to measure advanced technology usage in manufacturing plants. In terms of our hypotheses, both advanced technology and plant age could have either a positive or negative effect on plant-level energy consumption patterns. Finally, an additive i.i.d. error is appended, and the parameter vectors are estimated using ordinary least squares.

In addition to the above model, we also estimate an equation which specifies the electricity share, the number of BTUs of electricity consumed divided by total BTUs consumed at the plant, as a function of the same independent variables. Given that the advanced technologies considered in this study are all electricity consuming, the relationship between advanced technology usage and electricity share should be positive. With respect to plant age, one might expect that older vintage plants may rely on older technologies (fossil fuel using) and thus utilize electricity to a lesser extent.

III. Data

The data used in this analysis come from the merging of two Census Bureau plant-level data sets - the 1988 Survey of Manufacturing Technology (SMT) and the 1987 Census of Manufactures (CM). The SMT sampled plants operating in five two-digit SIC industries: Metals Fabrication (SIC 34), Non-Electrical Machinery (SIC 35), Electrical Machinery (SIC 36), Transportation

Equipment (SIC 37), and Scientific Instruments (SIC 38) industries.[9] These industries were chosen because they are the most likely users of the AMTs studied here. It should be noted that these are not heavily energy consuming industries. The most energy intensive of the five industries is Metals Fabrication.[10]

The SMT documents the usage of seventeen different AMTs in 10,500 U.S. manufacturing plants at the beginning of 1988. A list of these seventeen technologies is provided in Table 1. For the most part, these technologies are computer-based and represent recent multi-use innovations, such as computers, automated sensors, and numerically controlled machinery. For each of the seventeen technologies, the SMT asks plants whether they use a particular technology. There is, however, no information on the intensity of use.

The data on individual technology usage are aggregated to construct two indexes of AMT usage at the plant. The first index is based on the number of technologies used. We create a set of four indicator variables based on the following technology usage groups: plants utilizing none of the 17 technologies, plants utilizing one or two technologies, plants utilizing three to five technologies, and plants utilizing six or more technologies. This grouping provides a roughly even distribution of plants across the four categories with 20% of the plants using no AMTs, and a little less than 30% of the plants using six or more technologies. The second measure of technology indicates usage by technology group. The five main technology groups are: (1) Design and Engineering, (2) Flexible Machining and Assembly, (3) Automated Material Handling, (4) Communication and Control, and (5) Automated Sensors. The make-up of these groups is given in Table 1. An individual dummy variable

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[9] The sampling frame for the SMT was manufacturing plants with 20 or more employees, and operating in major industry groups 34 through 38.

[10] Collectively, these 5 industry groups account for only about 11.4% of total BTU consumption in manufacturing industries but produce 44% of the value-added in manufacturing.

is created for each of the five groups indicating whether or not a plant currently uses a technology from that group.

The SMT provides us with our index of capital vintage, plant age. The age data are categorical: zero to less than five years old, six to 15 years old, 16-30 years old, and older than 30 years. The SMT also contains data on the type of production activity occurring at the plant. Four different categories are provided: Fabrication and Machining; Assembly; Fabrication, Machining and Assembly; and Other Activity. A set of three categorical variables are constructed to control for the type of production activity. In general, assembly plants should require less energy than plants engaged in fabrication and machining.

In addition to the SMT, the estimated models draw variables from the 1987 Census of Manufactures (CM). The CM provides plant level data on location (state of operation), average annual production worker wage rate (WAGE), the gross book value of capital (K), value added (VA), and data on energy consumption. Specifically, the CM supplies the number of kilowatt hours of purchased electricity (Kwh) and the cost of fuels (CF). To construct a BTU index for the plant, the quantity of electricity and cost of fuels is converted to BTUs. The conversion of electricity is straight forward. The number of BTUs provided by electricity is simply the number of kilowatt hours of electricity times 3,412 BTUs per kWh. To convert the cost of fuels to BTUs we construct four-digit SIC conversion factors based from the 1988 Manufacturing Energy Consumption Survey (MECS.) The MECS has both data on cost of fuels and number of BTUs consumed for a sample of plants in manufacturing. We utilize these data to construct a conversion factor ($CONFACT_j$) for each four-digit SIC industry which converts a dollar of fuel cost into BTUs consumed.[11] The measure of energy intensity for plant i in industry j is constructed as

[11] In addition to a four-digit conversion factor, we also constructed industry by region conversion factors. The energy variables constructed were quite similar under both approaches.

(5)

$$EI_i = \ln\left(\frac{3412 * kWh_i + CONFACT_j \cdot CF_i}{VA_i}\right)$$

where the units are thousands of BTUs per dollar value-added. Additionally, electricity share of energy is constructed as the number of BTUs of electricity purchased divided by the total number of BTUs consumed at the plant.

The final merged dataset contains information on 6,370 plants. This is considerably less than the total possible sample of 10,500 plants. The reduction in sample occurs for three reasons. First, roughly 500 plants in the SMT are not found in the CM. Second, and most importantly, close to 3,500 plants contain imputed or missing data values in either the SMT or the CM. In general, the problem is of imputation in the CM generated by unit non-response.[12] Finally, a small number of plants with extreme outliers in their data are also removed from the datasets.

IV. Empirical Results

As discussed in the previous section, plant-level energy intensity and energy mix depend upon many factors, including the production process a plant employs, factor prices, and the state of technology. In this section, we econometrically estimate the impacts these variables have on the energy intensity and the energy mix of a manufacturing establishment. All regressions include controls for 4-digit industries (152 industry dummy variables), geography (48 State dummies), the plant wage rate, the plant's gross book value of capital, a set of production process dummies (the omitted

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[12]The SMT has a response rate of approximately 93% while the CM has a lower response rate for two reasons. Unit non-response is higher in the CM averaging 15-20% of the universe. Additionally, not all plants are sent forms. A large number of establishments data are imputed directly from the administrative records data. When either of these occur, the observation is dropped from the analysis.

group is the "other process" category), and a set of age dummies (the omitted group being the youngest plant - 0-4 years old.) Two regressions are run for each dependent variable. The MODEL I regression contains technology measures that controls for the number of technologies used. The omitted group in these regressions are plants utilizing zero technologies. The MODEL II regression includes technology measures that differentiate by type of technology. All regressions are estimated using ordinary least squares.

Energy Intensity

Table 2 provides the results from the energy intensity regressions. The second column presents the estimates from the MODEL I specification while the third column presents the results from the MODEL II specification. Examining the first column, the wage variable has a negative effect on energy intensity indicating as wages rise energy per unit output falls. The coefficient of the capital variable signifies that larger plants are more energy intensive than smaller plants. A one-percent increase in the capital variable increases energy-intensity by .058 percent. The next three variables are the dummy variables for the production process. As expected, plants engaged in some type of assembly work are much less energy intensive than plants performing fabrication and machining or doing some other production activity (the omitted group.) Plants which are primarily assembly oriented are 47.4% less energy intensive than plants engaged in other activities and 38.5% less energy intensive than plants performing fabrication and machining. This indicates that even after controlling for four-digit industry plant-level differences in production processes exist, and they have big effects on plant-level energy intensity.

Examining the age variables, two results are present. The first finding provides support for the hypothesis that plants built during the energy price shock periods should be less energy intensive. Plants built between 1972 and 1983 use 10% less energy per unit output than the youngest group and 21% less than the oldest group. This is broadly consistent with models of hysteresis suggested by Abel (1983), Lambson (1991), and Doms (1992.) Alternatively, the oldest plants consume the most energy per unit output of any age group. They are roughly 12% more energy intensive than the base group.

With respect to the AMT variables, a clear pattern emerges. The technology parameters are all statistically significant at the .05 level, and are monotonically declining. Thus, plants utilizing increasing amounts of AMT's are less energy intensive than plants using no AMT's. Plants using three to five AMTs consume 11% less energy per unit output than plants utilizing no AMTs, and plants with six or more AMTs are 20.2% less energy intensive. This is consistent with the view that advanced technologies improve net energy efficiency in manufacturing plants. Finally, statistical tests on the joint significance of the industry dummies and state dummies indicate that in both cases the null hypothesis of no effect would be rejected at the .01 level.[13]

The third column of Table 2 includes the technology measures for type of technology used. The results are the same as in column 2 for all the identical variables in the model. The technology type parameters show that design and engineering and the flexible manufacturing systems technologies lower the energy intensity of plants. The other three parameter estimates are not significantly different from zero.

<u>Electricity Share</u>

[13]The models were also estimated seperately for each two-digit industry. In general, the AMT results are quite similar to the pooled results for industries 34, 35, 36 and 37. In industry 38, the least energy intensive of the five two-digit industries, there is no effect of technology on energy intensity. Additionally, the age results are similar, but the quantitative effects are muted for the 5-15 year old age class. These results are available from the authors by request.

Besides energy intensity, we also examine how AMTs and plant age influence the energy mix of plants.[14] Our hypotheses are: (1) plants using more AMTs would be more electricity intensive, and (2) older plants would rely more heavily on direct fossil fuel sources as opposed to electricity. Table 3 reports the results for the electricity share equations. The wage variable and the process dummy variables do not have strong effects on the electricity share. The capital variable is positive and statistically significant at the 5% level. This indicates larger plants consume proportionately more electricity as fuel source.

Examining the age and technology variables, three results are present. First, older plants rely less on electricity than younger plants. Plants over 30 years old consume 15.8% less electricity as a proportion of total energy consumption. This supports the hypothesis that older plants are tied to older non-electricity based technologies. Second, as the number of technologies increases, the electricity share parameters monotonically increase. For plants using three to five AMTs the electricity share is 7.3% higher and for plants using six or more AMTs it is 15.5% higher. This is expected since all the technologies are electricity consuming. Finally, plants utilizing design and engineering and flexible machining and assembly innovations consume proportionately more electricity than plants not using these innovations.

Unobserved Productivity Heterogeneity

In this section, we consider the possibility that the technology effects may pick up the effects of unobserved plant-level productivity differences that are correlated with technology use. Suppose that plants are heterogenous in terms of their overall productivity. Some plants are more efficient, as measured by inputs per unit output, than other plants. One can think of this

[14] The electricity share model is run in double-log form. As an alternative the model was estimated using a tobit estimator with the dependent variable defined on the zero-one interval. The results from these tobit regressions are very similar to the OLS runs.

heterogeneity arising from differences in managerial abilities. Now, suppose that plants with good managers have a tendency to use advanced technologies. If this were the case, then the observed inverse relationship between energy intensity and AMT usage may be due to this unobserved managerial component.

To explore this possibility, we model differences in plant-level efficiency by the inclusion of firm effects. The firm effects will capture systematic differences in energy intensity due to firm-specific efficiency differences (e.g., managerial skills.)[15] The cost of this approach is a substantial reduction in sample size (n=2,600.) This reduction occurs because only firms with two or more plants can be included in the analysis. Another difference is that the technology dummy variables are redefined. The omitted group is plants using 3 or less AMTs. The three dummies included in the regression represent plants using 4 to 6 technologies, plants using 7 to 9 technologies and plants using 10 or more technologies, respectively. This reordering assigns roughly 25% of plants into each of the 4 technology categories.

Table 4 reports the results for the energy intensity and electricity share equations. The main results for the technology variables still hold. Plants utilizing higher numbers of AMTs are less energy intensive (column 2) and depend more upon electricity (column 3.) Thus, the inclusion of controls for unobserved productivity differences does not substantially affect the technology parameters. Some differences do emerge. In particular, the age results are somewhat muted in the energy intensity regressions. There does not appear strong differences in energy intensity across plants of differing ages.[16] However, in the electricity equation, older plants rely less upon

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[15]This is similar to the approach taken in Dunne and Roberts (1993) when estimating labor demand models in a cross-section. Olley and Pakes (1992) utilize panel information on plants and thus can control for plant-level differences in unobserved productivity differences.

[16]The change in the age parameters may be due, in large part, to the change in sample. The sample of 2600 plants contains primarily old plants. Thus, there is not as much variation in age in this sample as in the preceding sample.

electricity as a fuel source than younger plants. Overall, these results are broadly consistent with the findings above and indicate that the AMT-energy relationship is not simply an artifact of unobserved productivity differences.

V. Summary

This paper utilizes a unique plant-level data set to assess the role that advanced technology and other plant-level characteristics play in the consumption of energy in manufacturing plants. In general, the results indicate that differences in plant-level energy demand are systematically related to identifiable plant characteristics. Even after controlling for industry effects, and plant-level differences in production process, age and technology affect energy and electricity intensity in a statistically and quantitatively important manner.

Specifically, this paper documents that plants using AMTs are less energy intensive but more electricity intensive. With respect to plant age, plants built during the energy price shocks period, plants 5-15 years old, are the least energy intensive of the age groups. The oldest plants, plants greater than 30 years old, are more energy intensive and receive a higher proportion of their energy from direct fossil fuel sources (natural gas, oil, and coal) than from electricity. Finally, the production process dummies (assembly, fabrication and machining, assembly/fabrication and machining) illustrate how within industry producer heterogeneity can lead to substantial differences in the underlying production structure.

Table 1: Description of Technologies

Technology[1]	Description
Computer Aided Design(CAD):(1)	Use of computers for drawing and designing parts or products for analysis and testing of designed parts and products.
CAD Controlled Machines:(1)	Use of CAD output for controlling machines used to manufacture the part or product.
Digital CAD:(1)	Use of digital representation of CAD output for controlling machines used to manufacture the part or product.
Flexible Manufacturing Systems/Cell:(2)	Two or more machines with automated material handling capabilities controlled by computers or programmable controllers, capable of single path acceptance of raw materials and delivery of finished prod.
Numerically Controlled Machines/Computer Controlled Machines:(2)	NC machines are controlled by numerical commands punched on paper or plastic mylar tape while CNC Machines are controlled through an internal computer.
Materials Working Lasers:(2)	Laser technology used for welding, cutting, treating, scribing, and marking.
Pick/Place Robots:(2)	A simple robot with 1-3 degrees of freedom, which transfer items from place to place.
Other Robots:(2)	A reprogrammable, multifunctioned manipulator designed to move materials, parts, tools or specialized devices through variable programmed motions.
Automatic Storage/ Retrieval Systems:(3)	Computer controlled equipment providing for the automatic handling and storage of materials, parts, and finished products.
Automatic Guided Vehicle Systems:(3)	Vehicles equipped with automatic guidance devices programmed to follow a path that interfaces with work stations for automated or manual loading of materials, parts, tools, or products.
Technical Data Network:(4)	Use of local area network (LAN) technology to exchange technical data within design and engineering departments.

(Continued)

Table 1. Description of Individual Technologies (Continued).

Technology	Description
Factory Network:(4)	Use of LAN technology to exchange information between different points on the factory floor
Intercompany Computer Network:(4)	Intercompany computer network linking plant to subcontractors, suppliers, and/or customers.
Programmable Controllers:(4)	A solid state industrial control device that has programmable memory for storage of instructions, which performs functions equivalent to a relay panel or wired solid state logic control system.
Computers Used on Factory Floor:(4)	Exclude computers used solely for data acquisitions or monitoring. Include computers that may be dedicated to control, but which are capable of being reprogrammed for other functions.
Automated Sensors Used on Inputs:(5)	Automated equipment used to perform tests and inspections on incoming or in process materials.
Automated Sensors Used on Final Product:(5)	Automated equipment used to perform tests and inspections on final products.

Source: Manufacturing Technology 1988.
[1]The technology group is given in the parenthesis: (1) Design and Engineering, (2) Flexible Machining and Assembly, (3) Automated Material Handling, (4) Communication and Control, and (5) Automated Sensors.

Table 2: Energy Intensity Regressions

Variables:	Model I	Model II
4-digit Industry Dummies	Yes	Yes
State Dummies	Yes	Yes
Log of Capital	0.058(.008)	0.059(.008)
Log of Wage	-.105(.033)	-.095(.033)
Fabrication/Machining	-.089(.055)	-.080(.055)
Assembly	-.474(.055)	-.468(.055)
Fabrication/Machining & Assembly	-.265(.050)	-.253(.050)
5-15 years old	-.100(.037)	-.101(.037)
16-30 years old	-.035(.037)	-.034(.037)
Over 30 years old	0.118(.040)	0.120(.039)
1 or 2 AMTs	-.092(.032)	
3 to 5 AMTs	-.137(.033)	
6 or more AMTs	-.209(.037)	
Computer Automated Engineering		-.141(.023)
Flexible Manufacturing Systems		-.068(.025)
Automated Material Handling		-.007(.038)
Automated Sensors		-.013(.027)
Communication and Control		-.001(.024)
Mean of Log(Energy Intensity)	.564	.564
N	6370	6370
Adjusted R^2	.304	.306

Table 3: Electricity Share Regressions

Variables:	Model I	Model II
4-digit Industry Dummies	Yes	Yes
State Dummies	Yes	Yes
Log of Capital	0.034(.007)	0.035(.007)
Log of Wage	-.005(.021)	-.008(.021)
Fabrication/Machining	0.049(.035)	0.042(.036)
Assembly	0.023(.035)	0.019(.035)
Fabrication/Machining & Assembly	0.045(.032)	0.036(.032)
5-15 years old	0.021(.024)	0.022(.024)
16-30 years old	-.040(.024)	-.042(.024)
Over 30 years old	-.157(.025)	-.158(.025)
1 or 2 AMTs	0.040(.020)	
3 to 5 AMTs	0.073(.021)	
6 or more AMTs	0.155(.024)	
Computer Automated Engineering		0.059(.015)
Flexible Manufacturing Systems		0.055(.016)
Automated Material Handling		0.003(.024)
Automated Sensors		0.018(.018)
Communication and Control		0.018(.016)
Mean of Log(Electricity Share)	-.672	-.672
N	6370	6370
Adjusted R^2	.236	.236

Table 4: Energy Regressions with Firm Effects

Variables:	Energy Intensity	Electricity Share
552 Firm Dummies	Yes	Yes
Two-digit Industry Dummies	Yes	Yes
State Dummies	Yes	Yes
Log of Capital	0.100(.017)	0.014(.009)
Log of Wage	-.029(.069)	-.077(.038)
Fabrication/Machining	-.337(.103)	0.297(.056)
Assembly	-.768(.097)	0.192(.052)
Fabrication/Machining & Assembly	-.507(.092)	0.209(.050)
5-15 years old	-.126(.083)	-.009(.045)
16-30 years old	-.071(.083)	-.102(.045)
Over 30 years old	.094(.086)	-.208(.047)
1 or 2 AMTs	-.016(.048)	.061(.026)
3 to 5 AMTs	-.138(.055)	.125(.030)
6 or more AMTs	-.270(.064)	.170(.035)
Mean of Log(Electricity Share)	.606	-.619
N	2600	2600
Adjusted R^2	.386	.365

Table 5. Within Industry Regressions: Age and Technology Parameters

	Energy Intensity				
Variable	SIC 34	SIC 35	SIC 36	SIC 37	SIC 38
5-15 yrs.	-.077 (.068)	-.203 (.074)	-.057 (.070)	-.144 (.104)	-.049 (.096)
16-30 yrs.	-.042 (.091)	-.118 (.075)	-.005 (.072)	-.055 (.104)	.058 (.101)
>30 yrs.	.165 (.092)	.035 (.078)	.216 (.080)	-.087 (.110)	.201 (.111)
1-2 AMTs	-.128 (.059)	-.141 (.067)	-.081 (.070)	-.163 (.085)	.086 (.092)
3-4-5 AMTs	-.140 (.063)	-.173 (.068)	-.158 (.073)	-.181 (.093)	.023 (.096)
>= 6 AMTs	-.254 (.073)	-.274 (.078)	-.133 (.080)	-.193 (.106)	-.113 (.111)
Mean Y	.948	.586	.366	.577	.112
n	1571	1685	1447	864	802
Adj. R^2	.283	.240	.303	.247	.197
	Electricity Share				
	SIC 34	SIC 35	SIC 36	SIC 37	SIC 38
5-15 yrs.	-.024 (.059)	.017 (.048)	-.003 (.040)	.045 (.073)	.053 (.062)
16-30 yrs.	-.095 (.059)	-.058 (.049)	-.039 (.041)	.013 (.073)	-.002 (.065)
> 30 yrs.	-.216 (.059)	-.179 (.051)	-.157 (.046)	-.048 (.077)	-.188 (.071)
1-2 AMTs	.077 (.038)	.038 (.044)	.002 (.040)	.038 (.060)	-.005 (.059)
3-4-5 AMTs	.143 (.040)	.039 (.045)	.025 (.041)	.081 (.065)	.000 (.062)
>= 6 AMTs	.191 (.047)	.208 (.051)	.085 (.046)	.049 (.074)	.031 (.072)
Mean Y	-.773	-.703	-.549	-.723	-.574
n	1571	1686	1448	864	802
Adj. R^2	.218	.228	.332	.229	.237

Note: All models include the same variables as those reported in Table 3.

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