Impact of Strategic Energy Management Practices on Energy Efficiency: Evidence from Plant-Level Data[1]

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ABSTRACT

This paper estimates the effects of strategic energy management practices on plants' energy efficiency using plant-level energy and production data from the Census of Manufactures together with detailed Energy-Management data from the Manufacturing Energy Consumption Survey (MECS). After documenting considerable variation in plants' energy consumption both across and within industries, we explore whether four types of strategic energy management practices lead to improvements in energy efficiency. We find that designating an energy manager and undergoing an energy audit result in energy efficiency improvements in our 2006 - 2010 study period. Plants adopting an energy manager experienced a 6.9% reduction in energy consumption per dollar of output. Undertaking an energy audit resulted in a 6.4 % reduction in energy consumption per dollar of output. We also examine the effect of energy retrofits and computerized energy monitoring systems, finding noisy and mostly statistically insignificant short-run effects on energy efficiency.

Introduction

It is well known that there is substantial heterogeneity across industries in the amount of energy used to make different products. This is easily quantified using published data, such as energy intensity measured by total energy costs divided by total value added. It is also "well known" by businesses that there are substantial differences in energy use *within industries by plants that make the same products*. Measuring these differences and explaining them is more difficult, since plant-level energy and production data are rarely public. This paper leverages access to non-public plant-level data collected by the Census Bureau on energy and strategic energy management (SEM) practices to quantify and explain differences in within industry plant-level energy consumption. We use this data to shed light on the effectiveness of various energy initiatives in achieving energy reductions. For example, does designating an energy manager result in energy savings? Do energy audits lead plants to become more energy efficient? Answers to these questions are of interest to industry leaders wishing to adopt new practices that will lead to tangible energy savings.

Despite considerable industry interest in identifying best practices to reduce energy consumption, there exists surprisingly limited research examining whether they achieve their intended purpose. Existing research relies on case studies or small surveys, which may or may

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not be reflective of the manufacturing sector as a whole and are often unable to observe the inputs, output or value added of the plant. Using non-public, plant-level data allows us to overcome challenges that have hindered previous attempts to answer these questions. First, data from Census allows us to observe energy consumption, gross output, materials and value added for every manufacturing plant in the United States across multiple years. For a sub-sample of nearly 4,000 plants, we are also able to observe whether the plant has undertaken a variety of SEM practices. We are able to observe plants' output, value added, inputs and energy consumption both before and after the adoption of the energy initiatives.

The data allows us not only to measure differences in energy consumption for plants within the same industry, but also to attribute observed differences in within-industry energy consumption to particular energy initiatives. There are of course many reasons why plants, even those that produce the same good, may differ in their energy consumption. Production processes and the specific configurations of individual plants vary widely, as does access to fuels, not to mention differences in gross output. Our detailed input data allows us to control for differences in these specifications. However, even after controlling for these differences, we continue to see large variation in energy consumption. We then ask what practices plant managers might adopt that could increase energy efficiency relative to other plants in their industry. We ask whether appointing an energy manager, undergoing an energy audit, undergoing energy retrofits and computer monitoring of energy consumption results in efficiency improvements. We generate our estimates of these effects by comparing the energy efficiency of plants before and after the adoption of these energy initiatives.

We find that designating an energy manager results in average energy savings of 6.4% with a 90% confidence interval ranging from 1.0% to 11.8%. We also show that undergoing an energy audit results in a 6.9% average energy saving with a 90% confidence interval ranging from 0.9% to 12.8%. Estimates of the effect of energy retrogrades and adoption of computerized energy monitoring are noisier. These results provide perhaps the best available estimates of the effect of SEM Practices on energy efficiency. The remainder of the paper is organized as follows. We first define our measure of energy-intensity and provide industry and plant-level measures of energy efficiency. We examine the variation of energy intensity within different industries for any systematic patterns and also compare energy and labor intensities. Given that dispersion is common and sometimes quite large, the bigger question is what specific activities might influence some plants to be more efficient than others, in particular different types of SEM. We present the results of an analysis of 4 types of energy management on plant-level efficiency. We conclude with some thoughts about future research.

Within and between industry differences in energy

Figure 1 plots the ratio of energy cost per dollar of value added to cumulative value added at the 6-digit NAICS sector level. The average ratio of energy cost to value added is less than 5% and almost 90% of value added has an energy intensity of under 10%. What is less understood is that even within otherwise narrowly defined industry sectors, in this case a 6-digit NAICS code, there is substantial plant-level heterogeneity that results in large dispersion in the plant-level measure of energy intensity. This paper documents this dispersion using non-public, plan-level manufacturing microdata from the U.S. Census Bureau.

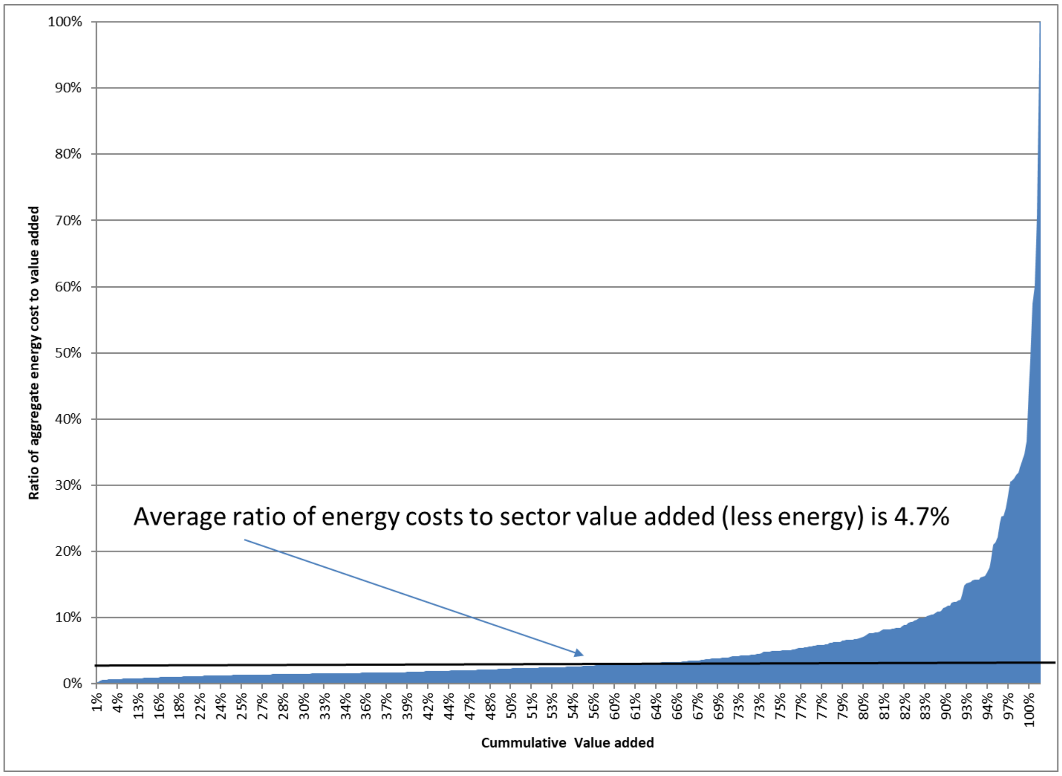

Figure 1 Distribution of the ratio of energy costs to value added by cumulative industry value added (source: 2007 Economic Census)

Evidence from other micro data studies

In a study of a group of 27 energy and carbon intensive, trade exposed 6-digit manufacturing sectors (Boyd, Kuzmenko et al. 2011) compare the publicly available industry average energy intensity, measured by thousand Btu per dollar value of shipments from the 2002 Manufacturing Energy Consumption Survey to corresponding microdata, including computing four moments of plant-level energy intensity distribution and kernel density plots[2]. The four moments from this study are shown in table 1. The log normalized kernel density plots (log difference between plant energy intensity and industry average intensity, 1.0 = industry average) reveals large within industry heterogeneity (see figure 2). In most of the industries the kernel plots reveal differences in intensity that often exceed 50%; some sectors exhibit a very flat distribution while others exhibit a highly peaked mode, which is not always at the mean. Using the first two moments, a coefficient of variation (C.V.) can be computed as a simple, comparable cross industry measure of within sector heterogeneity. Figure 3 plots the industry C.V. against the mean intensity. A log-log regression suggests a downward sloping relationship between the size of within industry dispersion and the magnitude of intensity. The log correlation coefficient between the C.V. and mean intensity is -0.45 and the slope of the log-log regression is -0.28 (p=0.023, R^2=0.21).

Another study by (Boyd 2016) examines within sector energy variability with a meta-analysis of 24 case studies. These case studies include regression models that explain plant-level energy use with physical production, weather, and other industry specific factors. The sectors

[2] This study also examines fuel and electricity separately, as well as intensity of co2 emission, but we focus on the total energy results.

are at the 6-digit NAICS level or lower and methods include OLS, SFA, kernel density approaches. The meta-analysis characterizes the industry specific efficiency distribution by the percent difference between the 50th and the 75th percentile; i.e. one "half" of the inter-quartile range. Figure 4 suggests a relationship between industry dispersion and energy intensity. The slope of the regression line is -0.44 ($p=0.05$, $R^2=0.18$).

Table 1 Four moments of total Energy Intensity -plant-level micro data (source: Boyd, Kuzmenko et al. 2011)

NAICS Code	Industry Name	Mean	Standard Deviation	Skewness	Kurtosis
311221	Wet Corn Milling	25.828	14.46	0.80	4.03
321219	Reconstituted Wood Product	22.154	16.20	1.76	8.28
322110	Pulp Mills	22.573	11.19	1.02	3.90
322121	Paper Mills, except Newsprint	22.027	15.24	2.51	13.54
322122	Newsprint Mills	52.049	22.25	-0.23	2.51
322130	Paperboard Mills	32.275	11.79	1.33	9.75
325110	Petrochemicals	21.222	20.60	1.22	3.33
325181	Alkalies and Chlorine	120.307	208.41	3.82	17.49
325188	Other Basic Inorganic Chemicals	21.711	32.20	4.28	26.90
325192	Cyclic Crudes and Intermediates	12.779	7.32	0.43	2.31
325199	Other Basic Organic Chemicals	16.557	19.79	2.28	8.53
325211	Plastics Materials and Resins	9.297	13.81	7.08	68.68
325212	Synthetic Rubber	8.515	8.43	1.04	2.78
325222	Noncellulosic Organic Fibers	12.520	8.64	1.36	4.59
325311	Nitrogenous Fertilizers	49.250	38.48	0.36	1.68
327211	Flat Glass	28.788	9.73	0.84	4.27
327212	Other Pressed and Blown Glass	20.304	11.86	1.51	4.95
327310	Cements	73.991	30.76	0.27	5.01
327410	Lime	168.794	323.26	5.47	34.39
327992	Ground or Treated Earth	23.542	23.54	1.07	2.97
327993	Mineral Wool	20.581	13.30	0.48	2.78
331111	Iron and Steel Mills	20.952	14.23	0.55	2.91
331210	Iron and Steel Pipe and Tube	4.424	3.53	2.33	11.14
331312	Primary Aluminum	89.457	49.01	0.15	2.61
331419	Primary Nonferrous Metal	20.810	22.55	1.09	3.41
331511	Iron Foundries	14.110	6.58	1.08	6.63
335991	Carbon and Graphite Product	13.268	10.54	0.66	2.00

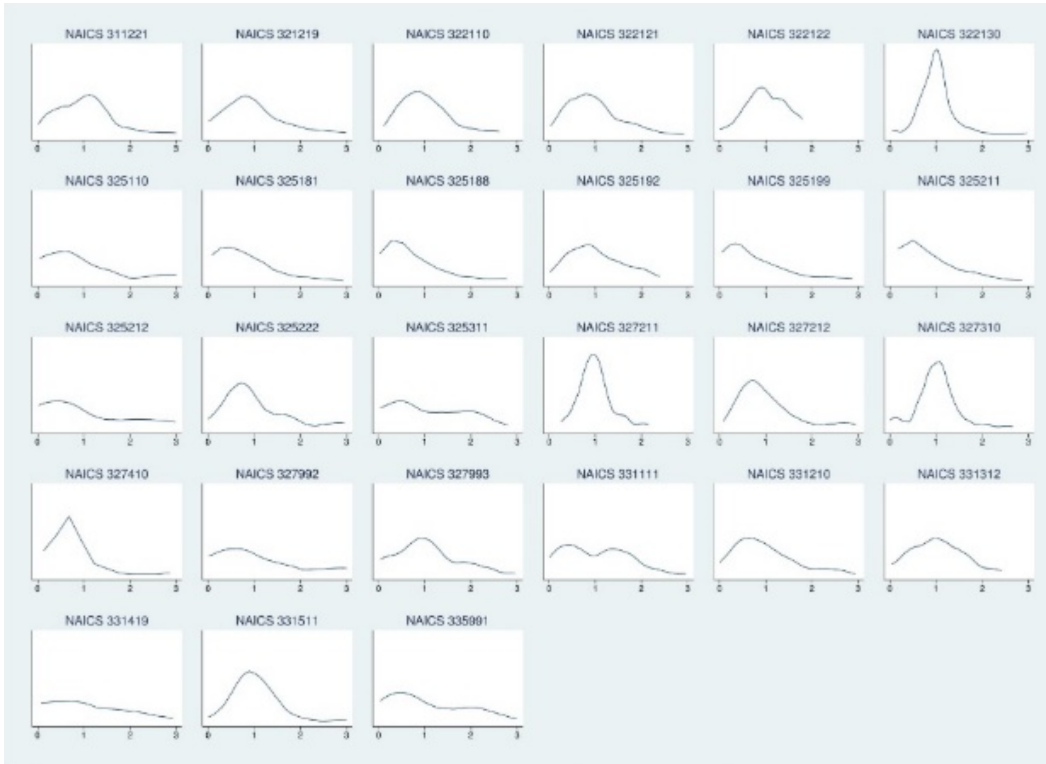

Figure 2 Kernel density of plant-level energy intensity, thousand Btu per dollar value of shipments, Log difference from industry mean (source: (Boyd, Kuzmenko et al. 2011)

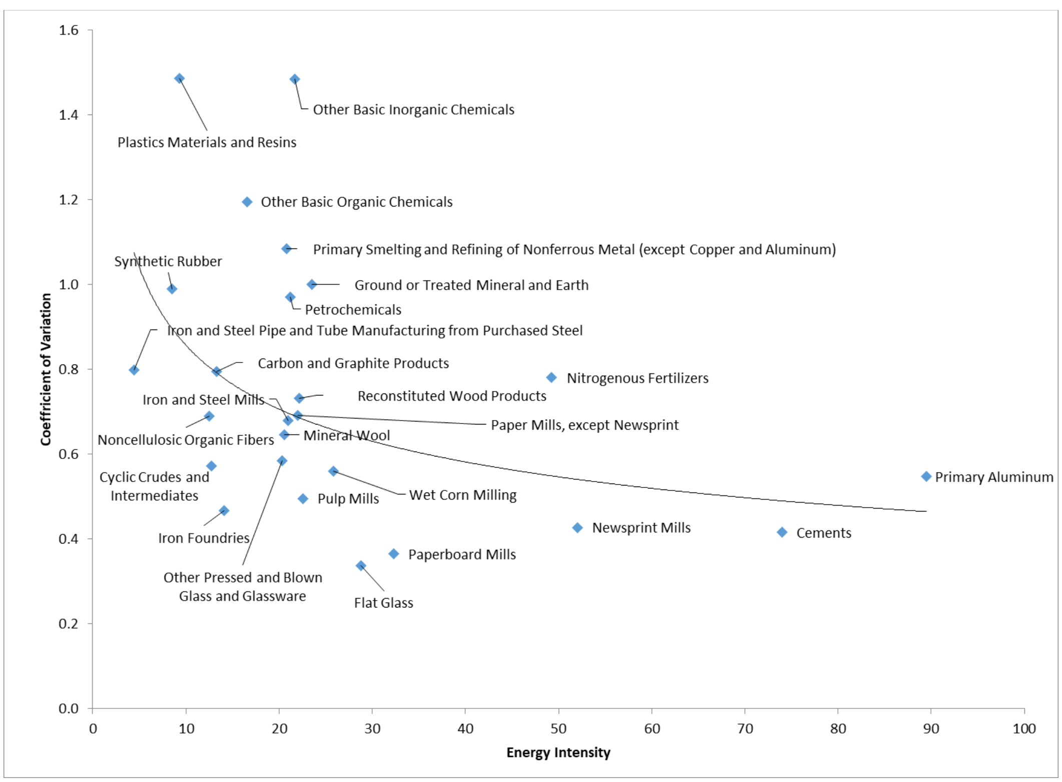

Figure 3 Industry Energy intensity coefficient of variation vs mean (source: authors' calculations based on table 1)

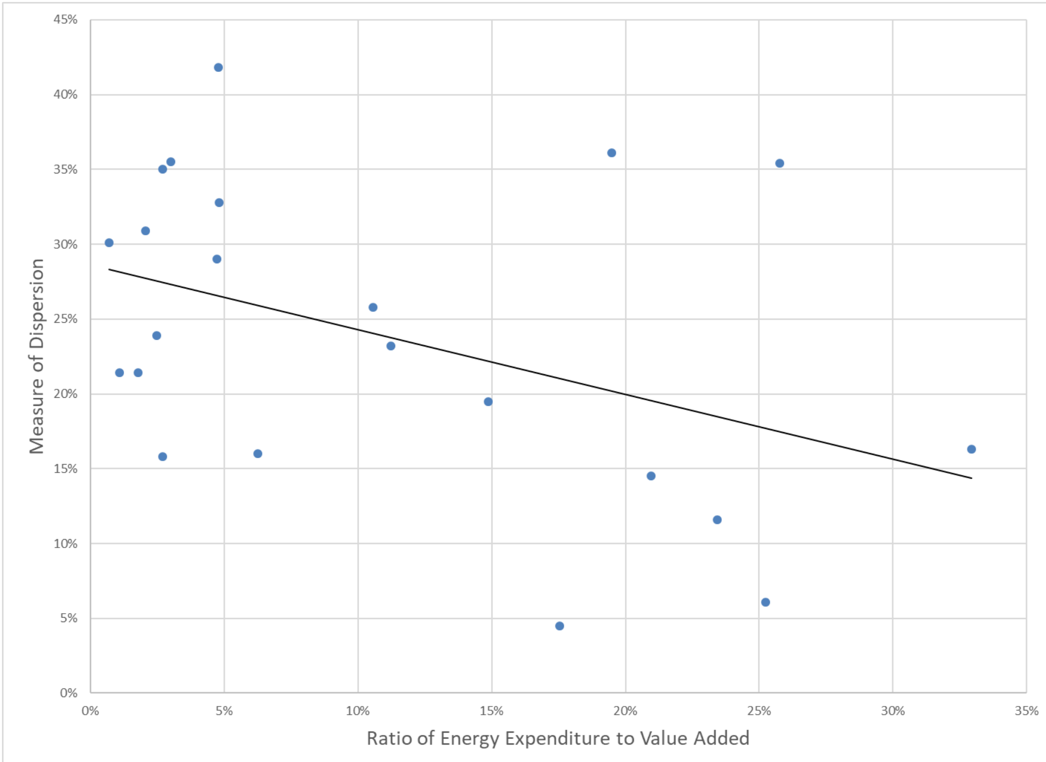

Figure 4 Relationship between the efficiency dispersion for 24 case studies and industry average cost: source (Boyd 2016)

Relationship between dispersion and industry energy costs

Consider the relationship between "energy efficiency," represented by the plant-level dispersion of energy intensity, and the "importance" of energy to an industry, represented by the industry energy costs. How this might the magnitude of energy costs (industry average cost of energy per dollar value added) impact the plant-level dispersion of energy intensity (energy use in Btu per dollar value added). Intuition suggests that as energy becomes more "important", i.e. a larger share of cost, then more managerial attention may be given to controlling those costs, lowering dispersion. To investigate this, we explore the within industry variation in energy intensity for 316 six-digit NAICS codes. First we compute, for each of the 316 six-digit NAICS industries, three measure of plant-level dispersion as the absolute difference between:

- 90th and 10th percentile of log plant energy intensity P90-P10
- 90th and 50th percentile of log plant energy intensity P90-P50
- 50th and 10th percentile of log plant energy intensity P50-P10

Since the ratio of energy intensity is easier to interpret, taking the exponent of the differences above gives.

- Overall dispersion ratio (OR) = $e^{(P90-P10)}$
- Inefficiency dispersion ratio (IR) = $e^{(P90-P50)}$
- Efficiency Dispersion ratio (ER) = $e^{(P50-P10)}$

OR is the full range of intensity dispersion, similar to what is used in other productivity dispersion analyses, for example (Syverson 2011). IR is the spread between the most energy intensive plants and the median and ER is the spread between the least intensive and the median; this represents the top and bottom of the overall dispersion. The terms "inefficiency" and "efficiency" dispersion are used very loosely here and are only intended to qualitatively describe the upper and lower half of the energy intensity distribution, not be a formal definition of (in)efficiency, per se. If overall dispersion is fairly symmetric then the ratio, IR/ER, will be close to unity.

OR, IR and ER are plotted on a log scale against the industry ratio of energy cost to value added (figures 5, 6, and 7 respectively). The first observation is that dispersion is very large; industry sector cross sectional average OR, IR and ER are 8.4, 3.2, and 2.7 respectively, with substantial variation around those cross sectional means. Contrary to other studies above, OR is upward sloping with the industry cost share. This would have major implications for climate policy suggesting that energy intensive industry in the U.S. is highly inefficient, even compared to peer establishments in the U.S. within a "narrowly defined" 6-digit NAICS. The pattern is quite different when we look at the upper and lower halves of this distribution. IR, (difference between the 90th and 50th) is *downward sloping*, while ER (difference between 50th and 10th) is *upward sloping*. The latter is the dominant effect that drives the overall result. The average asymmetry is 1.4.

The notion that market competition in energy intensive industry doesn't "tolerate" high levels of inefficiency may seem to be supported by the downward slope of IR with respect to average energy cost shares, but reconciling the upward slope of OR and ER with the prior studies is problematic. One possibility is that 6-digit NAICS isn't sufficiently narrow when it comes to energy using processes. NAICS are defined by product output, not a production process. Several examples come to mind where the major energy use in an energy intensive NAICS in concentrated in a few large plants. Ammonia production in *Nitrogenous Fertilizer*; clinker production in *Cement*; ethylene production in *Plastics Material and Resin*; steel production in blast and electric arc furnaces and in *Iron and steel mills and ferroalloy* are just a few examples. Downstream plants in these industries may purchase these primary products and then only perform the final stages of manufacture. In principle, use of value added would ameliorate this, but in practice the energy intensity of upstream (intermediate) product manufacturing in fully integrated plants may dwarf the value added difference. If this is the case, then including downstream, non-energy intensive plants in the NAICS classification where energy use is dominated by a small number of plants would increase the ER in those sectors.

Comparison of energy intensity and TFP dispersion

In light of the productivity dispersion literature reviewed by Syverson (2011), we should ask, *"Is energy special?"* Past research has shown that both labor productivity has wide, persistent, within-industry dispersion. If *"energy is just another input"* then we would expect energy to have similar dispersion as labor. To examine this, we compare the dispersion of plant-level energy intensity to the plant-level dispersion of labor. For the *nth* plant in industry *i* the energy input intensity $\left(\frac{E}{VA}\right)_{n,i}$, is standardized to the industry level mean and standard deviation $\frac{\left(\frac{E}{VA}\right)_{n,i} - \mu_i}{\sigma_i}$. A similar analysis if done for labor input intensity $\left(\frac{L}{VA}\right)_{n,i}$. These standardized intensities are plotted below. Energy intensity has a wider distribution than labor productivity dispersion measurements documented in previous research. It has a leftward skew compared to labor intensity, suggesting that energy does exhibit a different pattern of dispersion from another ubiquitous input.

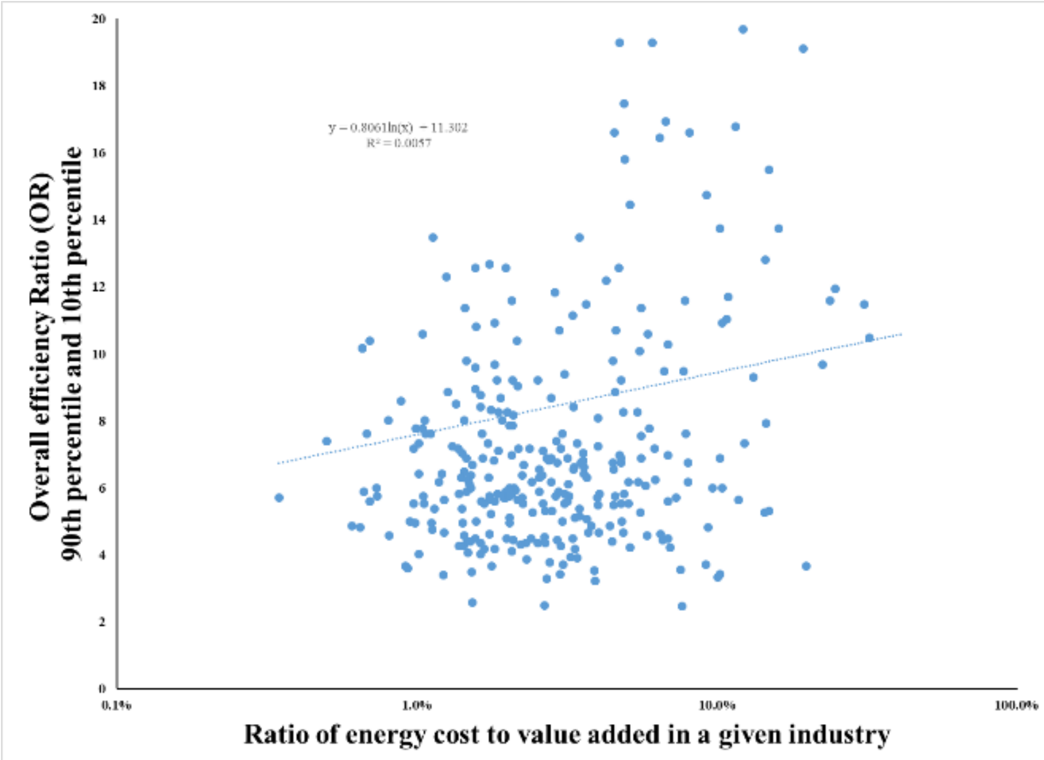

Figure 5 OR Plotted Against Industry Avearage Cost Share

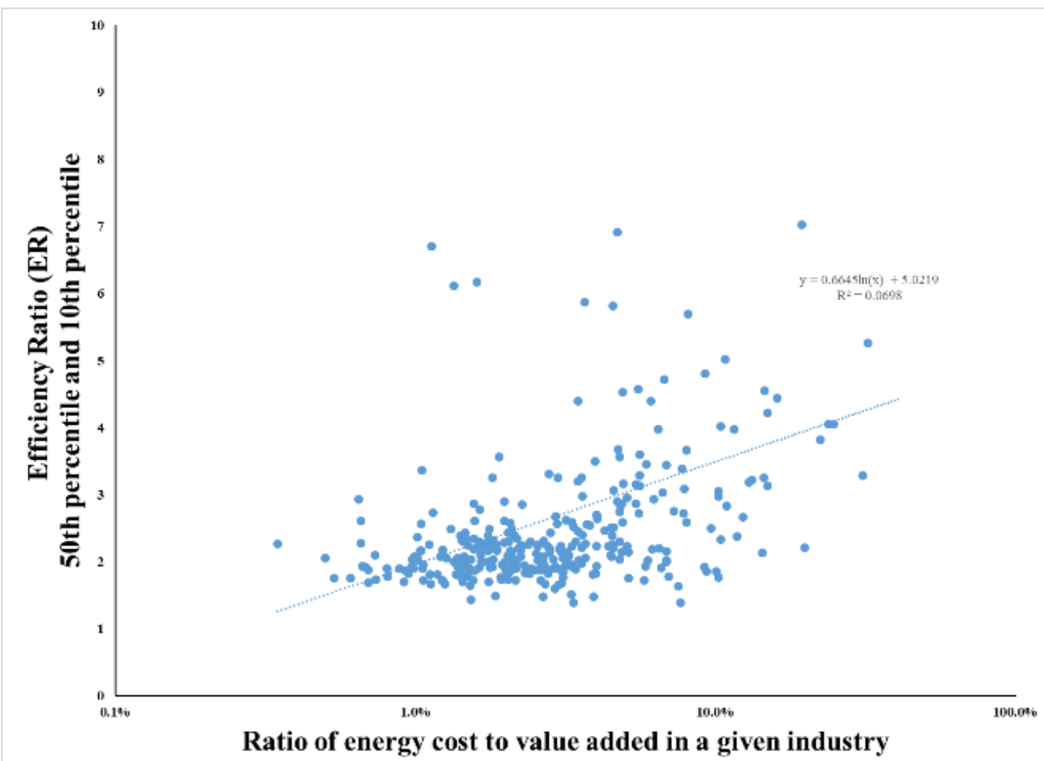

Figure 6 ER Plotted Against Industry Avearage Cost Share

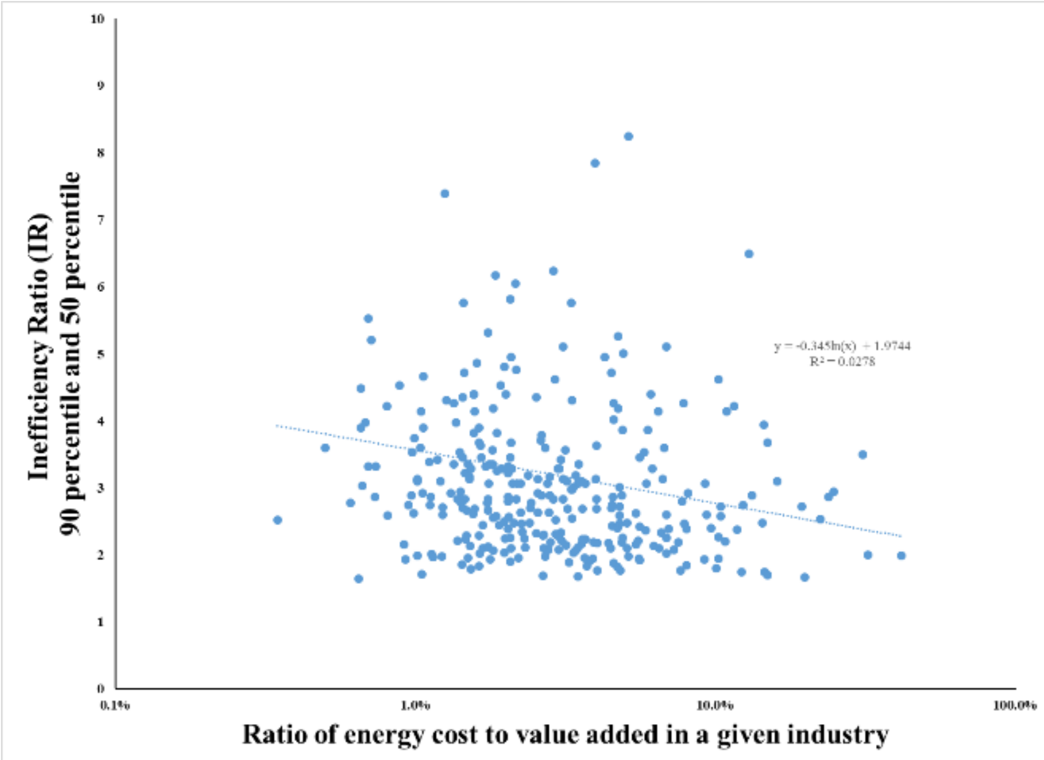

Figure 7 IR Plotted Against Industry Avearage Cost Share

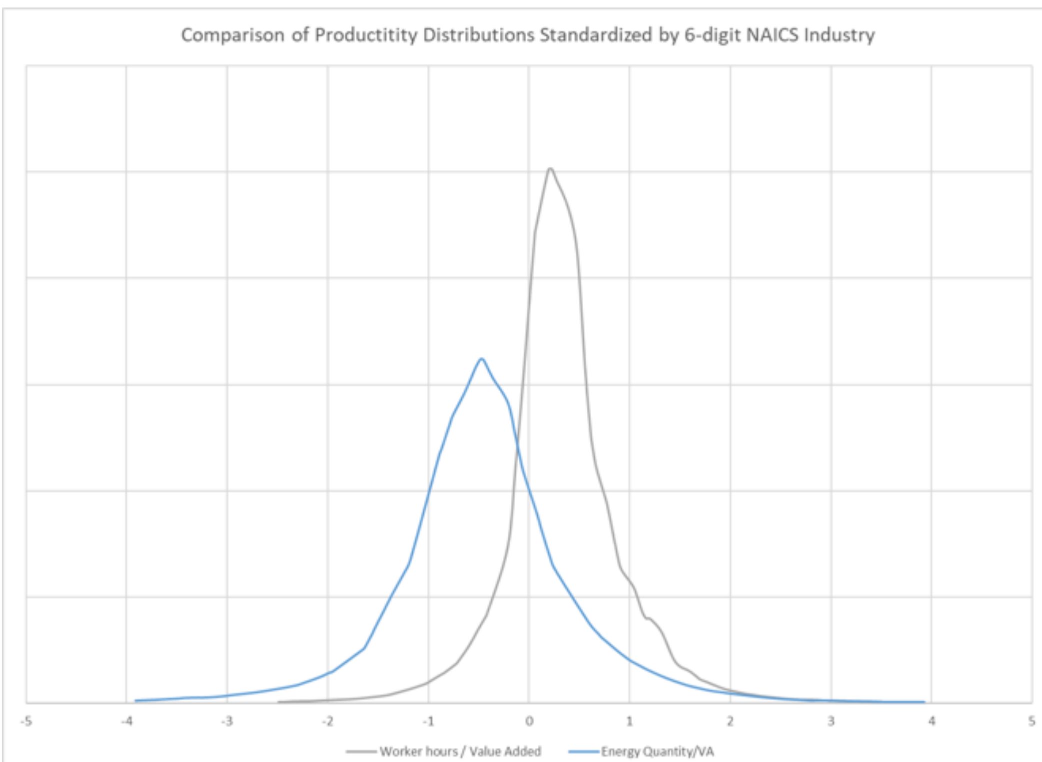

Figure 8 Kernel Denstiy of 6-digit NAICS energy
and labor intensity (standardised residuals)

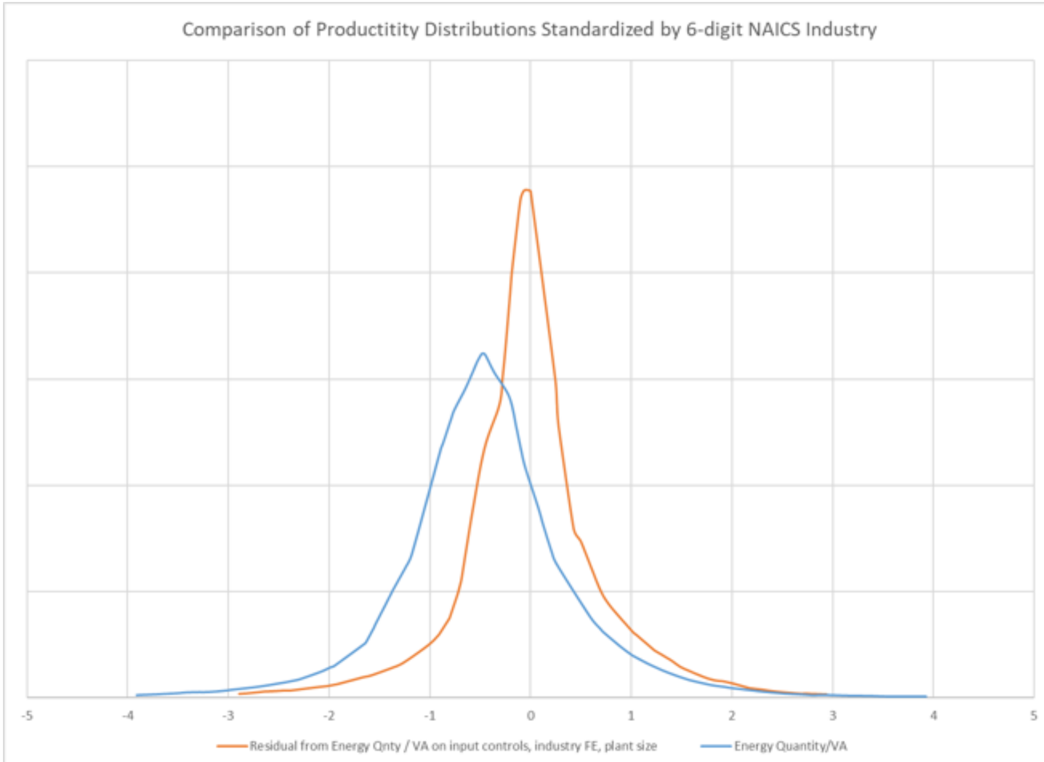

Figure 9 Kernel Density of 6-digit NAICS energy intensity and energy intensity with plant-level controls (standardized residuals)

The plots above suggest a systematic, industry level pattern of the overall level of energy intensity dispersion, so we regress energy intensity on a set of industry and plant-level controls, including industry fixed effects, plant size (TVS) and energy prices. These controls, as expected, reduce the dispersion *but also eliminate the skewness*.

Impact of Strategic Energy Management Practices on Efficiency

If there is a high degree of dispersion of efficiency are there ways that inefficiency can be eliminated? SEM approaches have been promoted by the U.S. Environmental Protection Agency's Energy Star program and ISO 50001 standard, as well as by state regulatory commissions to incentivize utilities to implement demand reduction programs. The cost effectiveness of specific programs has been the subject of scrutiny and the literature on measurement and verification (M&V) is extensive, but will not be reviewed here. We take a different approach and follow the literature on how management practices impact productivity generally and energy specifically. (Bloom, Genakos et al. 2010, Boyd and Curtis 2014) use survey data of non-energy management practices to statistically examine the impact of those practices on energy intensity in the UK and US, respectively. Results are mixed; in the UK "good management" is associated with lower energy intensity but not in the US. While some management practices in the US appear to support energy efficiency others are detrimental. Using plant-level data from the MECS the impact of specific management practices is investigated.

SEM Data Description

The MECS is a survey performed every four years of approximately 4,000 manufacturing plants. The survey oversamples large plants in energy-intensive industries and is designed to collect detailed information on energy consumption in the manufacturing sector. Unlike the Census of Manufactures, the MECS requests data on all types of fuels consumed in the plant and includes both the quantity of these fuels consumed as well as the price paid for the fuel. We use data from the 2006 and 2010 MECS surveys and create measures of the total MMBtu purchased and consumed by each plant.[3] We merge this data to plant-level data from the Annual Survey of Manufactures which contains further information on non-energy inputs (labor, capital, materials) as well as gross output. We use two outcome variables in the below regressions. The first is the logged value of energy per dollar of value added, where value added is the difference between gross output and the value of non-energy materials. The second outcome variable is simple the logged value of total MMBtu consumption. We limit our sample to plants that are surveyed in both 2006 and 2010. Our measures of SEM practices are mostly binary. Plants report if they have an energy manager or not, if they underwent an audit within the past year or not, if they use computers to monitor and control their major energy-using equipment. The only non-binary SEM variable is our retrofit measure. Plants are asked whether they installed or retrofitted equipment in seven different systems.[4] Our measure of retrofit is the percent of systems that plants reported as having retrofitted. Plants retrofitting all seven systems would receive a retrofit measure in our data of 1. Plants not retrofitting any systems would receive a measure of 0. Defining the variable this way allows all of our SEM measures to have a 0-1 range.

Econometric Model

To estimate the effect of SEM practices on plant's energy consumption, we consider the following model.

$$ln(E/VA)_{it} = \beta_1 SEM_{it} + X'_{it}\beta + \delta_i + \gamma_t + \varepsilon_{it}$$

Our outcome variable is the logged value of energy consumption per dollar of value added, for plant I in year t. The variable SEM is the strategic energy management practice of interest and β_1 captures the effect of that management practice on our energy outcome. We include a vector of controls, represented by X'_{it}. This specific controls we use vary across our specifications but includes logged gross output, logged materials, logged production worker hours and logged capital. Including gross output allows us to control for economies of scale in energy consumption. Larger plants tend to have higher productivity and our results show they are more productive with their energy consumption as well. Including measures of the plant's non-energy inputs allows us to control for differences in input ratios that may drive energy intensity. For example, plants that have chosen to automate and replace workers with machines are likely to use more energy to create a dollar of value-added.

The final two terms of the model are critical to understanding how we arrive at the main SEM results of the paper. The term δ_i represents a set of plant fixed effects. By including a

[3] To obtain a plant's total Mbtu we convert each fuel quantity to its Mbtu equivalent using standard conversion rates.
[4] These systems are steam systems, compressed air systems, heating systems, cooling systems, machine drive, HVAC and lighting. See https://www.eia.gov/survey/form/eia_846/form_a.pdf for the full list retrofit questions.

separate dummy variable for every plant in our data, we are controlling for any time-invariant difference between plants including, but not limited to, differences in industry and geographic location. By including δ_i we are estimating β_1 by measuring how much the energy intensity of a plant *changes* when they change their SEM practice, controlling for changes that may have occurred to other plant inputs and the gross output of the plant. The term γ_t is a dummy variable equal to one if the year is 2010. This controls for overall trends in energy intensity that are common across all plants.

Discussion and Interpretation of Results

Tables 2 through 5 are all formatted similarly with each table exploring the effect of a particular SEM practice. Each column reports results from a unique regression. Columns 1-3 report regression results where logged energy per value added is the outcome variable while columns 4 and 5 use logged energy as the outcome. By taking the log of the outcome variable we can interpret the coefficient estimates as percent changes. Our most basic specification is column 1 estimates the econometric model above but does not include any controls. The Energy manager coefficient is -0.04 with a standard error of 0.037. The coefficient of -0.04 implies that plants that hired an energy manager between 2006 and 2010 experienced a 4% reduction in energy per dollar of value added. As we add in controls this effect becomes larger and more precisely estimated. The energy manager coefficient in column 3, which includes the full set of controls shows that plants appointing an energy manager experienced a 6.5% reduction in energy per dollar of value added. The coefficients on the controls generally point in the expected direction. The coefficient on gross output shows that plants do experience economies of scale in energy, whereby plants experiencing output growth see reductions in energy per dollar of value added. The coefficient on labor is positive suggesting that plants do substitute between energy consuming capital and labor.

Coefficients in columns 4 and 5 now use logged energy as the outcome variable. Results for the energy manager coefficient (and other SEM categories in later tables) are very similar. The energy manager coefficient of -0.064 in column 5 can interpreted to mean that plants hiring an energy manager experienced a 6.4% reduction in total energy consumption holding constant output, materials, production hours and capital.

Tables 3, 4 and 5 are the same format but now explore the effect of energy audits, retrofits and computer monitoring. Our estimates on these measures may not fully capture their effect on energy outcomes because they are only able to capture the effect of these practices on energy consumption in the year in which the SEM practice was adopted. To better understand this, we consider the results in table 3. The Energy Audit coefficient is telling us how much energy intensity changed between 2006 and 2010 for plants that underwent an energy audit in 2010. Any changes in energy consumption that are attributable to the 2010 audit that occurred after 2010 will not be picked up in our estimates. As such, this and the coefficients on retrofits and computer monitoring will likely underestimate the effect of these practices. Nonetheless, the coefficients on energy audit show sizable effects of energy audits on contemporaneous energy outcomes. Results in tables 4 and 5 show limited effects of retrofits and computer monitoring on energy outcomes. The lack of an effect for retrofits may seem surprising, but perhaps should not be given that we might not expect energy reductions from retrofits to occur in the year in which the retrofits were made, but rather in later years after they are fully in place. Table 5 also shows limited effect of computer monitoring on energy consumption, though again it is possible that energy reductions from computer monitoring do not occur simultaneously with computer installation but rather in later years that we do not observe.

Table 2 Effect of Energy Managers (all variables in natural logs)

	Energy/VA	Energy/VA	Energy/VA	Energy	Energy
Energy Manager	-0.04	-0.067**	-0.065*	-0.077**	-0.064*
	(0.037)	(0.034)	(0.034)	(0.034)	(0.033)
Gross Output		-0.744***	-0.807***		0.236***
		(0.038)	(0.042)		(0.047)
Materials					-0.016
					(0.032)
Production Hours			0.147***		0.149***
			(0.05)		(0.05)
Capital			0.061		0.063
			(0.042)		(0.041)
R-sq	0.951	0.961	0.961	0.973	0.974

Table 3 Effect of Energy Audits (all variables in natural logs)

	Energy/VA	Energy/VA	Energy/VA	Energy	Energy
Energy Audit	-0.068*	-0.070**	-0.067*	-0.073**	-0.069*
	(0.04)	(0.036)	(0.036)	(0.036)	(0.036)
Gross Output		-0.742***	-0.804***		0.239***
		(0.037)	(0.042)		(0.047)
Materials					-0.017
					(0.032)
Production Hours			0.147***		0.149***
			(0.05)		(0.05)
Capital			0.062		0.063
			(0.042)		(0.041)
R-sq	0.951	0.961	0.961	0.973	0.974

Table 4 Effect of Retrofits (all variables in natural logs)

	Energy/VA	Energy/VA	Energy/VA	Energy	Energy
Retrofits	-0.125**	-0.039	-0.04	-0.004	-0.038
	(0.062)	(0.056)	(0.056)	(0.056)	(0.056)
Gross Output		-0.740***	-0.803***		0.239***
		(0.038)	(0.042)		(0.047)
Materials					-0.015
					(0.031)
Production Hours			0.148***		0.150***
			(0.05)		(0.05)
Capital			0.064		0.065
			(0.043)		(0.042)
R-sq	0.951	0.961	0.961	0.973	0.974

Table 5 Effects of Computer Monitoring (all variables in natural logs)

	Energy/VA	Energy/VA	Energy/VA	Energy	Energy
Computer Monitoring	0.003	0.013	0.006	0.014	0.004
	(0.059)	(0.053)	(0.053)	(0.054)	(0.053)
Gross Output		-0.742***	-0.805***		0.238***
		(0.037)	(0.042)		(0.047)
Materials					-0.016
					(0.031)
Production Hours			0.148***		0.150***
			(0.051)		(0.051)
Capital			0.063		0.065
			(0.042)		(0.042)
R-sq	0.951	0.961	0.961	0.973	0.974

Summary

It is well known that there is substantial heterogeneity across industries in the amount of energy used to make a product. This is easily measured using published data such as total energy costs divided by value added, but measuring and understanding differences in within industry requires plant-level data. These data allow us to compute three measures of within industry dispersion of energy intensity, OD, ID, and ED. We find that OD, overall dispersion, averaged across industries is 250%, with values of OR that can exceed 500% (upper decile) of the 316 sectors analyzed. When we standardize the within industry measures of dispersion we find energy intensity does differ from past measures of TFP.

We then directly analyze the effect of Strategic Energy Management practices on plant's energy efficiency. We find that plants appointing an energy manager experience energy savings of 6.4% with a 90% confidence interval ranging from 1.0% to 11.8%. Plants that undertook an energy audit saw 6.9% average energy savings with a 90% confidence interval ranging from 0.9% to 12.8%. It is worth noting that this estimate is *not identified savings but realized savings.* It is also worth noting that *this estimate is likely a lower bound* since plant that undertake an audit the same year as the survey will not yet have realized any savings. Due to measurement and timing issues, estimates of the effect of energy retrogrades and adoption of computerized energy monitoring are noisier. In particular, one model estimate finds large and significant savings from retrofits, but other models find no savings. We encourage future research exploring these and other energy efficiency initiatives in the industrial sector.

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