New Benchmarking Tools for Industrial Manufacturing: An Industry Collaboration to produce ENERGY STAR Energy Performance Indicators (EPIs)

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ABSTRACT

Industry-wide statistical benchmarking is a key element of the ENERGY STAR approach to advanced Strategic Energy Management. Benchmarking answers the question of where a plant would rank against its peers on the basis of energy performance. ENERGY STAR has been conducting benchmarking using the ENERGY STAR Energy Performance Indicator (EPI) for over fifteen years, and has analyzed two dozen industries. Given the differences among sectors, a tailored, collaborative approach between researchers and industry is necessary. Recently, EPIs were developed for six new industries: integrated steel, engine and transmission manufacturing, iron and aluminum casting, and commercial bakeries. The nature of energy use in these industries led to a new methodology that is utilized to provide an improved measure of efficiency. This new methodology considers processes within the plant to measure electric and fuel specific measures of efficiency. These methods can be used broadly across other industries in the future. For two sectors, we develop a simple way to capture the impact of a complex array of products on the underlying energy efficiency. In addition to the new methodologies, the EPI for integrated steel is the first of its kind to use a complete sample of facilities in both the US and Canada. Finally, these six new studies empirically showcase the diverse positions of different industries. For example, integrated steel manufacturing shows a normalized energy consumption distribution of 4.25% difference between an "average" and an "efficient" facility while other industries exhibit a much wider range, from 16% to 29%. The new methodologies and the empirical insights on the difference between simple energy intensity and the normalized EPI contribute to advancing Strategic Energy Management in these important industries.

Introduction

ENERGY STAR was introduced by EPA in 1992 as a voluntary, market-based partnership to reduce air pollution and greenhouse gas emissions associated with energy use through increased energy efficiency (U.S. Environmental Protection Agency 2015). This government program enables industrial and commercial businesses as well as consumers to make informed decisions that save energy, reduce costs, and protect the environment. For businesses, a key step in improving energy efficiency is to institutionalize a strategic approach to energy management. Drawing from management standards for quality and environmental performance, EPA developed the *ENERGY STAR Guidelines for Energy Management* that identify the components of successful energy management (U.S. Environmental Protection Agency 2003). These include:

- Commitment from a senior corporate executive to manage energy across all businesses and facilities operated by the company;
- Appointment of a corporate energy director to coordinate and direct the energy program and multi-disciplinary energy team;
- Establishment and promotion of an energy policy;
- Development of a system for assessing performance of the energy management efforts, including tracking energy use as well as benchmarking energy in facilities, operations, and subunits therein;
- Conduct of assessments to determine areas for improvement;
- Setting of goals at the corporate, facility, and subunit levels;
- Establishment of an action plan across all operations and facilities, as well as monitoring implementation and promoting the value to all employees; and,
- Pursuit of recognition and rewards to promote the success of the program.

Of the major steps in energy management program development, benchmarking energy performance by comparing current energy performance to a baseline or a similar entity is critical. In manufacturing, it may take the form of detailed comparisons of specific production lines or pieces of equipment, or it may be performed at a broader system level by gauging the performance of a single manufacturing plant with respect to its industry. Regardless of the application, benchmarking enables companies to determine whether better energy performance could be expected. It empowers them to set goals and evaluate their reasonableness.

(Boyd, Dutrow et al. 2008) describe the evolution of a statistically based plant energy performance indicator for the purpose of benchmarking manufacturing energy use for ENERGY STAR. (Boyd 2016) describes the basic approach used in developing such an indicator, including the concept of normalization and how variables are chosen to be included in the analysis. To date, ENERGY STAR has developed statistical indicators for a wide range of industries (U.S. Environmental Protection Agency 2015).

This paper expands on prior work (for overview see Boyd (2016)) by developing a new method that provides an aggregate measure of total energy efficiency from separate data on electricity and fuels. This paper also introduces a way to handle complex product differentiation in a simple way. The empirical results also inform the nature of efficiency in these specific six additional industries and illustrate how the distribution of a *normalized measure of efficiency* can be very different from a *simple energy intensity*. Specifically, this report describes a new statistical approach employed in developing performance-based energy indicators that produces an overall efficiency score in addition to separate efficiency scores for electricity and fuel utilization within the facilities. This is important since the statistical drivers for the different energy forms may be quite different. The utilization of production labor and product value variables have been able to distinguish energy usage per product type in the absence of quantities of different types of products, providing a better efficiency estimate for industries such as metal casting that have a diverse range of products. Finally, the differences between energy efficiency distributions for each industry is examined and explored on the basis of total energy consumption.

Methodology

The paper introduces a non-parametric approach to creating a total energy efficiency measure that accounts for the possibility that different factors influence electricity and fuels and that the energy-specific efficiencies may have different variances and be correlated. We also illustrate that, in the presence of very diverse products that have different energy intensities, the product diversity impact on energy efficiency can be easily captured with two simple ratios.

Modeling Electricity and Fuel Use Separately

There are instances in which modeling energy use from all sources together is the most appropriate approach, particularly when there are substantial opportunities to meet production energy requirements by switching between fuels and electricity, or when there is onsite electricity generation from combined heat and power (CHP) where typically more fuel is used and less electricity purchased. This would result in a plant appearing very fuel inefficient and very electric efficient; examples of the converse are possible. However, when certain products are inherently more (or less) electric or fuel intensive, then it may be appropriate to represent the electricity and fuel use separately since those production differences can more readily be accounted for in the analysis. Separating the energy forms may also improve the ability to measure weather effects, since higher cooling degree days (CDD) will be associated with higher cooling loads and electricity use; conversely, heating degree days (HDD) will be associated with heating loads and fuel use.[1]

The value of separately modeling electricity and fuel was quite high in the large commercial bakery sector: since some products are frozen, the process would be more electric intensive due to the electric load from freezers. There is also a sub-category of frozen products that are not baked, which would be both more electric intensive and less fuel intensive. To capture these product mix effects, a separate analysis of the two energy forms was needed. In addition, there are few, if any, applications of CHP in this industry, so this particular reason to model total energy is not a concern. Industry-provided data allowed for separate electric and thermal analyses in the third version of the draft model.

Engine and transmission manufacturing saw similar benefits for splitting the analysis of electricity and fuels. The production process in the powertrain industry almost exclusively uses electricity, and, therefore, energy from fuels should not be included in determining the efficiency of production. Fuels were found to be used for space heating and, thus, were dependent on the size of the facility and the weather. By modeling these separately, the effects can be captured more accurately providing a better breakdown of efficiency in the manufacturing process.

The analysis of each energy form follows the same general approach as would be taken for a total energy analysis, resulting in an individual measure of energy efficiency performance. Since the percentile rankings of these individual measures of efficiency are based on a probability distribution, each with its own variance, the Energy Performance Score (EPS) of the total energy use would also be derived from these separate variances. If electric efficiency was independent of (unrelated to) fuel efficiency, then the relevant variance for the sum of electricity use and fuel use would be the sum of the underlying variances, but this is unlikely to be the case. The energy management of the firm (plant) might make a particular location more (or less) efficient in both cases, making the efficiencies correlated. Either the joint distribution would need to be explicitly modeled, or another way to obtain the efficiency distribution for total energy would be necessary. In the case of the commercial baking EPI, the latter was chosen.

[1] There are exceptions to this pattern, e.g., electricity used in the heating system, fuels driving adsorption chillers, etc.

Equations 1-4 detail the common equations used to determine electric and fuel efficiency values individually, i.e., computing electric and fuel specific normalized energy efficiency. However, the EPS for total energy cannot be computed as a simple (or weighted) average of the electricity and fuel specific efficiency scores; the underlying distribution can be quite different. We employ a non-parametric approach to obtain the aggregate efficiency distributions from the individual models. Equations 5-7 discuss how to take those electricity and fuel efficiency values and combine them into one overall efficiency measure for the facilities.

Following Boyd (2016), the general form of the basic EPI equation is

$$E = f(Y, X;\ \theta) + \varepsilon \tag{1}$$

or, in this case

$$\ln(E) = a + \sum_{j=1}^{n} b_j \, ln(y_j) + \sum_{j=1}^{m} c_j \, x_j + \varepsilon \tag{2}$$

where Y includes various production-related measures, X is a vector of plant characteristics like weather and product mix, and the vector of parameters to be estimated is $\theta = (a, b_*, c_*, \sigma^2)$.

We compute the estimate of efficiency, $\hat{\epsilon}_{i,t}$, for every plant, i, and year, t, from the parameter estimates, $\hat{a}, \widehat{b_*}, \widehat{c_*}, \widehat{\sigma^2}$, using the following equation

$$\ln(E) - \hat{a} + \sum_{j=1}^{n} \widehat{b_j} \ln(y_j) + \sum_{j=1}^{m} \widehat{c_j} \, x_j = \hat{\epsilon}_{i,t} \tag{3}$$

For models using ordinary least squares (OLS) estimates, such as is the case for these industries, we have estimated the variance of the error term of equation (1), and we can compute the probability that the difference between actual energy use and predicted average energy use is no greater than this computed difference under the assumption that the efficiency, $\mathcal{E}$, is normally distributed with zero mean and variance σ^2, i.e., $\varepsilon \sim N(0, \sigma^2)$

$$\text{EPS} = \left(1 - \Pr\left(\varepsilon \le \hat{\epsilon}_{i,t}\right)\right) \cdot 100 \tag{4}$$

One minus this probability, multiplied by 100, is the EPS, and is the *percentile ranking of the energy efficiency of the plant.*[2]

However, the EPI has two types of energy, so it is necessary to have $\hat{\epsilon}_{i,t,e}$ and $\hat{\epsilon}_{i,t,f}$, where *e* and *f* represent electricity and fuels. The sum of two normally distributed variables is not necessarily normal, unless they are uncorrelated. To get the EPS for total energy is necessary to compute the analog of $\hat{\epsilon}_{i,t,e}$, $\hat{\epsilon}_{i,t,f}$, and the corresponding probability distribution for *the sum of electricity and fuels*, instead of the individual components. To do this, we need to account for the fact that the equations are estimated in log form, convert the predicted values for the energy use into levels, convert them to common units so they can be added together, and have a method to compute the probability in equation (4) that is the basis for the EPS.

While it is true that the predicted value of the natural log of energy use, $\widehat{\ln(E)}$, is

$$\widehat{\ln(E)} = \hat{a} + \sum_{j=1}^{n} \widehat{b_j} \ln(y_j) + \sum_{j=1}^{m} \widehat{c_j} \, x_j \tag{5}$$

we need the predicted *level of energy use* to add electricity and fuel together. For an OLS, the estimate of the predicted level of energy use, i.e., the expected value of E, is not the exponential of $\widehat{\ln(E)}$, but is

$$\widehat{E} = e^{\left(\widehat{\ln(E)} + \frac{\sigma^2}{2}\right)} \tag{6}$$

σ^2 is the OLS error variance estimated from (2).

[2] By ENERGY STAR convention, the EPS is 100 for the lowest value of energy intensity, representing highest efficiency. In statistics, the lowest (left-most value of the density and distribution) is zero and the largest (right-most value) is 100%. To create the EPS we use the simple transformation.

For notational simplicity, we denote $E_{i,t}$, $\widehat{E_{i,t}}$, $F_{i,t}$, and $\widehat{F_{i,t}}$ to be the actual and predicted pairs for electricity use and fuel use, respectively, for each plant and year. We can compute the estimates of plant level total energy efficiency by adding actual electricity and fuel use and subtracting the predicted levels from equation (6) above.

$$(E_{i,t} \cdot C + F_{i,t}) - (\widehat{E_{i,t}} \cdot C + \widehat{F_{i,t}}) = \widehat{\epsilon_{i,t}} \qquad (7)$$

C is the unit conversion of electricity to source MMBtu, since the model estimate for electric efficiency is in units other than source MMBtu.

To allow for the possibility that the distribution of $\epsilon_{i,t}$ from equation (7) is not a simple normal distribution, we estimate the distribution non-parametrically via a kernel density. Kernel density estimation is a flexible approach to computing the density function, similar in concept to a "smoothed histogram." The support points for the non-parametric estimate for the density of the plant level efficiencies, $\epsilon_{i,t}$, are then used to compute the cumulative distribution function via numerical integration over the support points. An example is shown in Figure 1 (Boyd and Lee 2016). The kernel density (blue) of energy efficiency and associated distribution (orange) of a set of empirical efficiency estimates are obviously not a normal distribution. The cumulative distribution can be converted to a lookup table for the percentile corresponding to any value of $\epsilon_{i,t}$ and then used in the ENERGY STAR EPI spreadsheet tools.

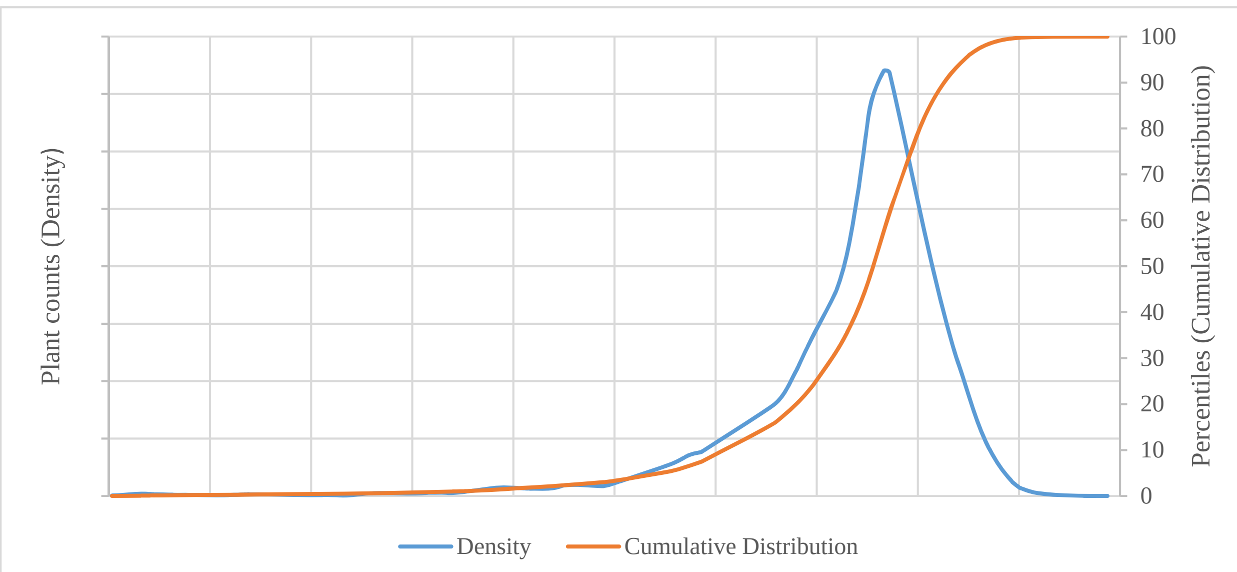

Figure 1. Example of a kernel density and associated cumulative distribution estimate for energy efficiency in metal based durables. *Source:* Boyd and Lee 2016.

Providing separate efficiency scores for electricity and fuels can give a more detailed picture to facility energy managers. If a plant received an average overall score but a lower electricity score, then the focus for improvements would be on the electricity processes within the plant. This efficiency breakdown can clarify the best way to improve overall efficiency, given the limited budgets of many industrial energy programs.

Using Labor and Sales Values to Determine Energy Consumption

When working with industry partners, there were many discussions about capturing the energy use associated with manufacturing more complex products, especially in the metal casting sectors. Certain products utilize more input materials per unit of final product, and hence more energy, while often requiring additional post-production processes as well. Below is a specific example from the aluminum casting sector that utilized data from the Census Bureau. Census data used in the EPI is the weight of the product, not the weight of the material that is melted and cast. Some diversity of the types of products is included in the EPI, but the range of product diversity and complexity would not be captured in any list of product types as the list would be far too long. Instead, the value of the product and the labor used to produce it is a statistical proxy for the product complexity. If higher value products with higher labor intensity are associated with complex molds, more metal melted, and more energy in finishing, then there will be a statistical relationship between the energy use and both higher value and labor intensity. The statistical analysis confirms this relationship. When these statistical result were incorporate into the draft EPI for testing, the analysis of individual plant data, conducted by the North American Die Casting Association (NADCA), also confirms this. The test data are shown in Figure 2. The curve is based on seven actual plants' data compiled by NADCA. While the plants are all aluminum die-cast plants, they help illustrate how the differences in average price per pound (higher value added) and labor hours per pound (more labor intensive) products can have higher energy requirements, but similar EPI scores. When the price and labor intensity are nearly the same, the comparison is easy: the plant with an intensity of 9 scores higher than the one with a 17. How do plants with very different price and labor intensity compare? Figure 2 shows there is only a two point difference between the EPI scores of plants with a simple energy intensity of 35 MMBtu/final product and 19 MMBtu/final product. Comparing the two facilities based on energy intensity alone would not showcase the true efficiency of either plant given the product differences. The EPI accounts for these differences in products in terms of value and labor intensity per pound and associates that with higher energy requirements, thereby not penalizing the more energy-intensive plant and allowing for an efficiency comparison between facilities producing two different products within the same industry. Incorporating labor and price into the efficiency model helps account for broad differences in energy consumption per product and the wide variety of products across the industry that are likely more complex to cast, have more finishing requirements, and associated energy use. This relationship has been found in other industries and will be explored when developing future EPI tools.

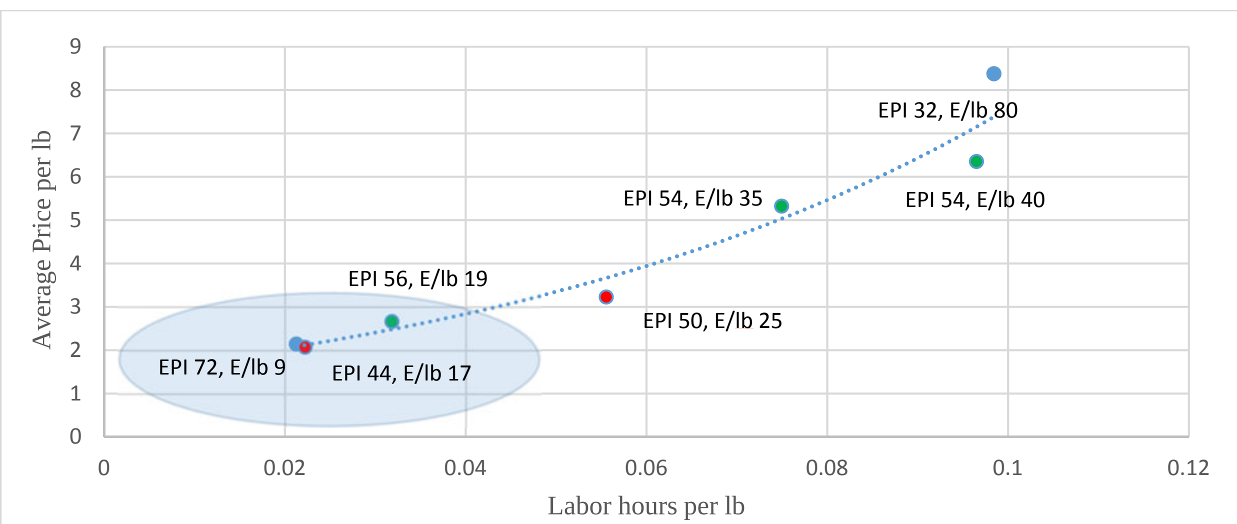

Figure 2. Aluminum die casting plants with diverse energy, labor, and value per pound.

Empirical Results

When examining the raw data on energy intensity, the range of performance is quite wide for all industries. The EPI analysis shows that this observation taken by itself could be misleading. The blue lines in Figures 3-6 below take the source energy intensity data from each industry and transform it into the distribution of plants that lie above or below the average energy intensity for each sector, represented as a percent difference.[3] The full range of intensity differs for each industry, but can often be twice as high or low as the average intensity. The red lines representing the EPI analyses tell a very different story. Most of those differences come from differences that are accounted for in the various analyses, including differences in product mixes, production labor, product values, or production processes. The range of actual efficiency, after these differences are accounted for, is narrower in every case. This is consistent with the results of a meta-analysis of EPI studies for other industries (Boyd 2016). While less energy intensive sectors have a relatively wide range of efficiency, energy intensive sectors exhibit a much narrower range when other factors that influence plant energy use have been considered. Integrated steel manufacturing, the most energy intensive sector detailed in this study, has the narrowest range by far, while the two powertrain studies have similar ranges as expected. The baking industry sees a similar efficiency distribution, but has more of a peak energy intensity distribution. In general, raw energy intensity distributions are platykurtic, exhibiting a broader range of possible values, and normalized energy efficiency scores are leptokurtic, showing a narrower distribution. These figures reinforce the value of the EPI normalization for comparing two facilities on an energy efficiency basis. The baking industry has the closest intensity and efficiency distributions, likely due to yield restrictions and small differences in energy usage per product type. However, the bi-modal nature of the simple energy intensity may reflect the importance of electricity use in products that a shipped frozen. This issue it handled by the new methodology that was developed.

Knowing this efficiency distribution for each industry can have practical effects on energy management and goal setting. Being aware of the range of energy efficiency within the industry can provide practical guidance when setting realistic energy improvement goals. For instance, a 5% reduction in overall energy could be a reasonable goal in the baking industry or powertrain manufacturing, dependent on the current efficiency of the facility, identified by calculating an EPI score. However, a 5% reduction for an integrated steel facility would prove to be much more difficult. The range of efficiencies is smaller in this industry and a 5% decrease in energy consumption reflects a significant shift in relative performance and may require more costly energy investments and provide less of a competitive advantage.

[3] Figures are not included for the iron and aluminum casting industries. At the time of this submission, those figures had not been cleared by the U.S. Census Bureau for distribution.

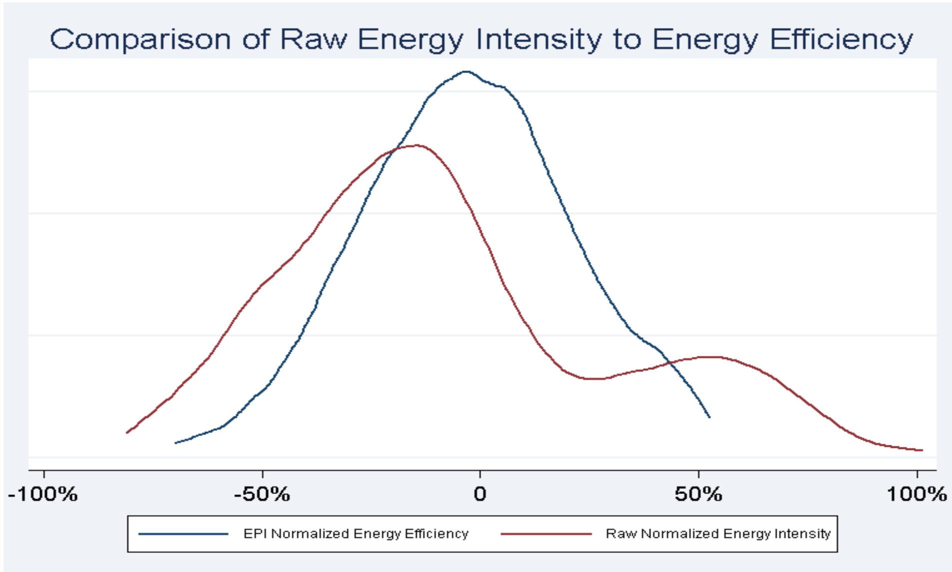

Figure 3. Comparing the distribution of intensity to efficiency in the baking industry. *Source:* authors' calculations.

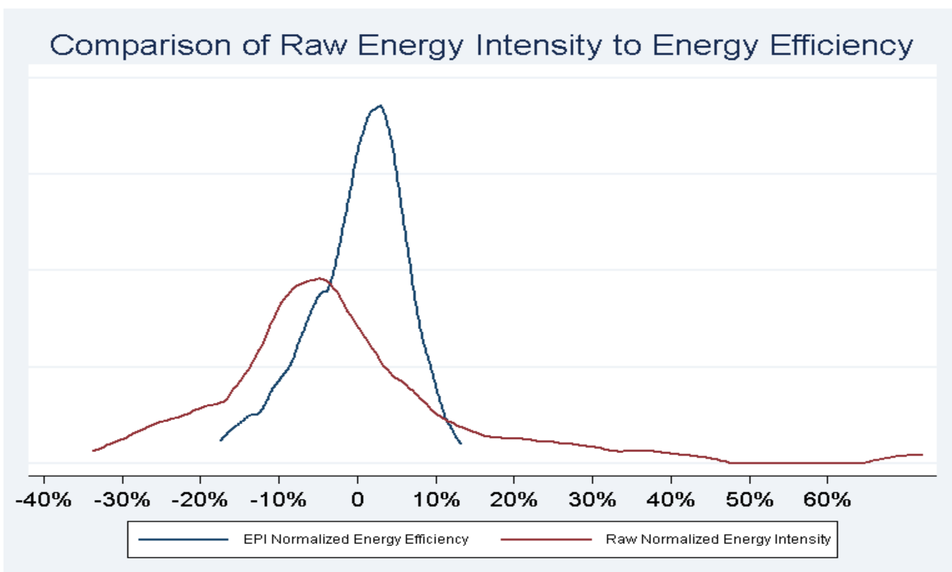

Figure 4. Comparing the distribution of intensity to efficiency in the integrated steel industry. *Source:* Boyd, Doolin et al. 2017.

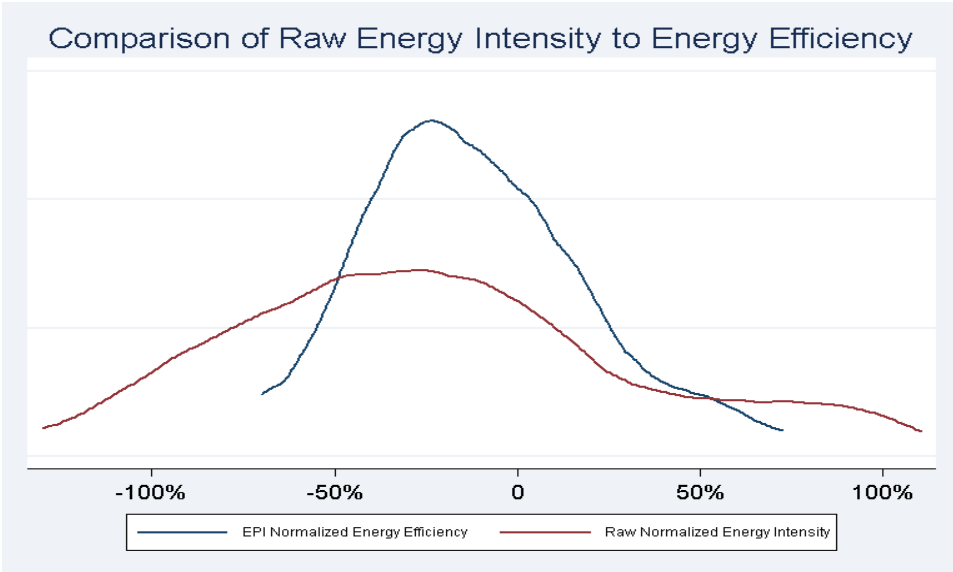

Figure 5. Comparing the distribution of intensity to efficiency in the engine manufacturing industry. *Source:* authors' calculations.

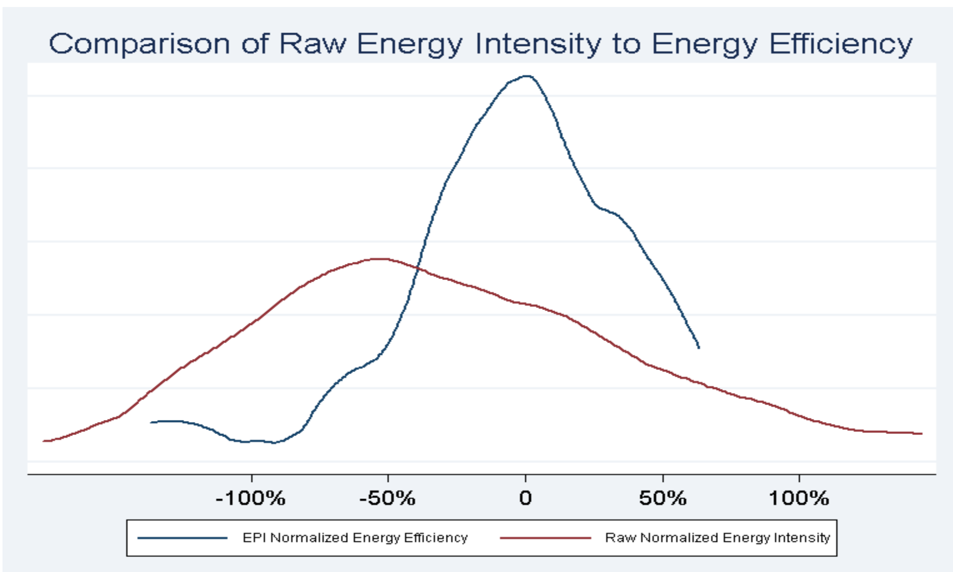

Figure 6. Comparing the distribution of intensity to efficiency in the transmission manufacturing industry. *Source:* authors' calculations.

Conclusion

This report provides an overview of the new methods of statistically benchmarking energy efficiency in the industrial sector and the corresponding efficiency distributions of six very different industries, with very different empirical implications. When the industry production processes are such that fuels and electricity are used for very different activities and with limited substitution opportunities, generating separate efficiency ratings for electricity and fuel consumption can provide a more accurate account of plant efficiency. There are also additional benefits provided to industrial energy managers in identifying areas of improvement within plants and more effectively utilizing company resources. We also find that utilizing production labor and product value can assist in benchmarking energy usage per product when there are diverse manufacturing processes and many product types; i.e. plants with very different energy per ton may, in fact, have similar normalized efficiency when labor and product value are taken into account. This connection between labor and cost data, data which are often easily obtainable, and energy intensity can be utilized in scenarios where there may be insufficient or missing data to capture the unique product level characteristics of plants.

Regarding the empirical results, we see that more energy-intensive sectors tend to have a narrower range of efficiency. Given the larger variable cost of energy in comparison to product value, more energy-intensive sectors generally are closer to each other regarding energy efficiency due to the competitive disadvantages that would result from ignoring energy efficiency projects. For these six industries, we find that the percent difference in energy performance from the 50th percentile (average) to the 75th percentile (efficient) of our normalized EPI distributions is as follows.

- Integrated Steel: 4.26%
- Bakeries: 15.84%
- Transmission: 23.31%
- Engine: 27.04%
- Iron casting: 21.65%
- Aluminum casting: 28.51%

Steel is the most energy intensive and has a very narrow quartile range, followed by bakeries. The remaining four metal-based durable goods industries cluster in a fairly similar range (20-30%).

Overall, the new methodology for producing EPIs can provide a more accurate breakdown of energy consumption efficiency. Established a link between labor, price, and energy allows the EPI to account for energy impacts of product differentiation in sectors where there a large number of different product types. Finally the results from these specific analyses can assist in setting energy reduction goals in these six new sectors and will allow for expansion of EPI development into other more diverse industries in the future.

References

Boyd, G., E. Dutrow and W. Tunnessen. 2008. "The Evolution of the ENERGY STAR Industrial Energy Performance Indicator for Benchmarking Plant Level Manufacturing Energy Use." *Journal of Cleaner Production* 16 (6): 709-715.

Boyd, G., and J. Lee. 2016. “Measuring Plant Level Energy Efficiency and Technical Change in the U.S. Metal-Based Durable Manufacturing Sector Using Stochastic Frontier Analysis.” *6th International Symposium on Energy Challenges & Mechanics (ISECM).* Inverness, Scotland, United Kingdom.

Boyd, G. 2016. "Comparing the Statistical Distributions of Energy Efficiency in Manufacturing: Meta-analysis of 24 Case Studies to Develop Industry-Specific Energy Performance Indicators (EPI)." *Energy Efficiency* 10 (1): 217-238.

Boyd, G., M. Doolin, E. Dutrow and S. Zhang (2017). "A New Benchmark of Energy Performance for Energy Management in U.S. and Canadian Integrated Steel Plants." Iron and Steel Technology (May): 53-61.

U.S. Environmental Protection Agency. 2003. *Guidelines for Energy Management*. Washington, DC, U.S. Environmental Protection Agency. www.energystar.gov/guidelines.

U.S. Environmental Protection Agency. 2015. “Reducing Greenhouse Gas Emissions by Advancing Industrial Energy Efficiency 2000—2015”. EPA Document Number 430-R-15-006. Washington, DC: US Environmental Protection Agency.