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Estimating the changes in the distribution of energy efficiency in the U.S. automobile assembly industry

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ABSTRACT

This paper describes the EPA's voluntary ENERGY STAR program and the results of the automobile manufacturing industry's efforts to advance energy management as measured by the updated ENERGY STAR Energy Performance Indicator (EPI). A stochastic single-factor input frontier estimation using the gamma error distribution is applied to separately estimate the distribution of the electricity and fossil fuel efficiency of assembly plants using data from 2003 to 2005 and then compared to model results from a prior analysis conducted for the 1997–2000 time period. This comparison provides an assessment of how the industry has changed over time. The frontier analysis shows a modest improvement (reduction) in "best practice" for electricity use and a larger one for fossil fuels. This is accompanied by a large reduction in the variance of fossil fuel efficiency distribution. The results provide evidence of a shift in the frontier, in addition to some "catching up" of poor performing plants over time.

1. Introduction

The environmental policy implications of lower energy use have led to the development of voluntary government programs for energy efficiency, particularly in the absence of, or supplement to, other types of climate policy. These programs arose in the early 1990s (Storey et al., 1997) and expanded in the US with the introduction of EPA ENERGY STAR for Industry (Environmental Protection Agency, 2013). In 2001, EPA created a new partnership as part of the ENERGY STAR buildings program (originally launched in 1999), the ENERGY STAR Focus on Energy Efficiency in Industry (hereafter "the Focus"). The initiative identified barriers to energy efficiency, developed approaches for removing these barriers, and facilitated a support group of energy professionals within the industry. EPA's goal was to cultivate energy management functions within companies. EPA approached senior executives to establish the business case for energy management, secure assignment of a responsible energy director for each corporation, and help the companies build the necessary internal supporting functions and networks. ENERGY STAR energy management tools such as program evaluation checklists, energy management guidelines, and information on forming energy management teams guided refinement of the energy management programs in participating companies. Voluntary programs like ENERGY STAR may require company commitments to specific energy reduction targets, or "energy management" generally. For example, a company joining ENERGY STAR as a Partner agrees to[1]

- Measure, track, and benchmark energy performance
- Develop and implement a plan to improve energy performance, adopting the ENERGY STAR strategy
- Educate your staff and the public about your partnership and achievements with ENERGY STAR.

Recently the International Standards Organization (ISO) has established requirements for "establishing, implementing, maintaining and improving an energy management system, whose purpose is to enable an organization to follow a systematic approach in achieving continual improvement of energy performance, including energy efficiency,

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[1] See http://www.energystar.gov/buildings/about-us/become-energy-star-partner/online-partnership-agreement for the complete process.

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energy use and consumption" as ISO 50001, which largely formalized the first two elements of the ENERGY STAR partner agreement (International Organization for Standardization, 2011).

The US based voluntary energy programs typically involve some type of government recognition for "good" performance. ENERGY STAR provides recognition for plants that reduce energy (ENERGY STAR Challenge for Industry) or that are in the upper quartile of performance (ENERGY STAR Certification). There is also a corporate level award for overall achievements (ENERGY STAR Partner of the Year). Similar DOE programs such as Superior Energy Performance (SEP) (Therkelsen et al., 2013), established in 2005, use the third party ISO 50001 certification as a core requirement and set various levels of performance to achieve formal recognition. International programs may have binding agreements for reductions in energy use or intensity in exchange for a variety of other incentives such as audits and assessments, financial assistance and incentives, exemption from regulation and taxes, in addition to government and public recognition (Price et al., 2003).

In addition to the management tools and facilitation of networking between the energy directors, ENERGY STAR developed industry specific tools, which include the Energy Performance Indicator (EPI), a stochastic frontier inter-plant energy benchmarking tool. Boyd et al. (2008) provide a discussion of the evolution of the EPI approach. Boyd and Tunnessen (2013) provide a summary of the industries, approaches, and results of the EPI benchmarking to date. The EPI is developed for and reviewed by knowledgeable representatives from companies that participate in the Focus. Since the motor vehicle industry focus and corresponding assembly plant EPI development began over ten years ago (Boyd, 2005a, 2005b), a second version of the EPI was prepared and made available to the public by EPA. Re-estimating the motor vehicle assembly EPI and comparing the two versions allow for the improvement in the industry to be quantified. This contributes to a greater understanding of how the industry has changed over time.[2]

This paper discusses the data and the underlying stochastic frontier analysis used to estimate version two of the ENERGY STAR EPI for motor vehicle assembly plants. The next sections discus the motivation behind measuring efficiency, the data and specification used in this version, and how the parameter estimates of the two models have changed over time; in particular the treatment of climate impacts from plant locations and from capacity utilization. The paper then computes several measures, based on the two models to illustrate how the distribution of energy efficiency has shifted over time.

2. Energy performance indicator

Efficiency is a measure of relative performance; but relative to what? Defining energy efficiency requires a choice of a reference point against which to compare energy use. The difference between the observed level and potential level of performance has been called the "efficiency gap." Jaffe and Stavins (1994) discuss a range of concepts from which to define "potential," including economic, technical, social and hypothetical. The first market failure they identify that leads to an efficiency gap is lack of information. It is the lack of information regarding economic potential for lower energy use that is the focus here. In other words, we are interested in *measuring economic potential based on* "observed best practice", which is by definition economically feasible. By providing this information, ENERGY STAR hopes to lower the barrier to more widespread adoption of economic potential for lower energy use. The reference point for economic potential (observed best practice) depends, in part, on the reason for measuring efficiency as well at the available information to create a reference. Generally, the *Ceteris Paribus* principle ("all other things being equal or held constant") is usually desired in creating the reference point, or benchmark. From a practical perspective there is a hierarchy of measures and methods by which one can "hold constant" things that influence the level of *energy use* that are not *energy efficiency*. The first is a measure of production activity. This is most commonly done by computing the ratio of energy use to production output, a measure of energy intensity. Energy intensity is a common metric that controls for changes in production and is commonly confused with energy efficiency, as in the statement "the plant's energy efficiency has improved based on the observation that the energy intensity has declined". This type of statement brings us to the second way that one may approach the ceteris paribus principle for measuring efficiency, comparing energy intensity a particular plant, firm, or industry to itself over time. This approach is a plant (firm, etc.)[3] specific *baseline* comparison, or *intra-plant* efficiency benchmark. ISO 50001 recommends developing such a baseline for measurement and tracking.[4] Baselines have the advantage of controlling for some plant specific conditions that do not change during the comparison period. The next level of this ceteris paribus principle is an *inter-plant* comparison that may include a variety of factors that influence energy use, but may not be viewed as efficiency. Factors may include difference in the types of product and materials used, as well as location specific conditions. Inter-plant comparisons within an industry also get us closer to the notion of an observed best-practice benchmark of economic energy efficiency, since by definition there is some group of plants that are the best performers.

To measure energy intensity you need a measure of energy in the numerator, and a measure of output for the denominator. Murray (1996) raises issues about both the numerator and dominator. For the numerator in our case we use total purchased energy, defined as the net Btu total of the fuels (Btu) and electricity (kWh). The choice of the denominator is a major issue for measuring intensity. Freeman et al. (1997) show that industry level trends in energy intensity based on value, both total and value added, can differ dramatically from those based on physical quantities. At the simplest level value, the value of output is simply price times physical quantity —so price movements account for these differences. Freeman et al. observe

> "For an industry producing a single, well-defined, homogeneous good, it is relatively easy to construct an accurate price index. Most industries, however, produce many poorly-defined, heterogeneous goods. For a variety of reasons, the more diverse the slate of products produced by an industry, the more difficult it becomes to construct an accurate price index. …the accuracy of industrial price indexes is of extreme importance to industrial energy analysts and policy makers who use value-based indicators of energy intensity."

Out of 450 Census 4-digit Standard Industrial Classifications (SIC) Freeman et al. analyze physical output data for only 14. This choice may be driven by the available data, but is in part based on the diverse types of production that may be included within the Census classifications. For physical production to be meaningful it needs to be at a high level of industry homogeneity. For example, the "Dairy" industry produces many products that could not be aggregated, but "Fluid Milk" might.

Freeman et al. employ a commonly used approach by comparing energy intensities over time within specific sectors, i.e. industry level intensity baselines. Companies commonly employ plant level energy intensity baselines to assess performance. EPA ENERGY STAR Challenge for industry[5] is also based on a plant level intensity baseline. Specifically, "The Challenge for Industry recognizes industrial sites that improve their energy efficiency by 10% within 5 years." A site with a 10%

[2] A similar analysis, but for the cement industry, is detailed in Boyd and Zhang (2012) and Boyd et al. (2011).

[3] Throughout the paper we will refer to the plant level as the unit of observation, but the concept may also apply to more aggregate levels like firms and industries, and disaggregate process units.

[4] ISO uses the term Energy Performance Indicator to refer to baselines. However, ISO uses the acronym EnPI, to differentiate it from the Energy Star EPI.

[5] EPA web site —http://www.energystar.gov/index.cfm?c=industry_challenge.industry_challenge.

improvement in energy efficiency is further defined as "Sites that achieve a 10 percent reduction in energy intensity within 5 years." The logic behind this approach is clear. Over a relatively short period of time production may vary (even trend up/down) but other plant conditions may not change, so the intensity baseline is a measure of efficiency *improvement*. The intensity baseline does achieve one type of relative performance (what the plant did 5 years ago) while "holding constant" production variation by normalizing energy use in the form of an intensity. Comparing a plant to itself over time can control for other plant specific characteristics that are unchanged over the time period, but still does not provide any information about the economic potential or the efficiency gap.

Comparing plants within an industry using a stochastic frontier is one approach to assessing a form of economic potential. By definition, at least one plant in the industry represents the observed "best practice". The frontier approach estimates the best practice levels of energy use, based on observed performance. The difference between estimated best practice and actual observed practice is the basis for an empirical efficiency distribution. In a seminal paper on measuring production efficiency, Farrell (1957) identifies two possible choices for information on this benchmark; "Although there are many possibilities, two at once suggest themselves —a theoretical function specified by engineers and an empirical function based on the best results observed in practice." Huntington (1994) discusses this same issue in the context of top-down and bottom up energy models.

The concept used here for the benchmark is the second approach suggested by Farrell, an empirical estimate of the best observable performance, or "best practice," and an empirical distribution of efficiency, based on the difference between estimated best practice and observed practice. The EPI is a stochastic frontier model of plant level energy use that enables comparison across facilities with different levels and types of production related activities that influence energy use. The stochastic frontier provides an econometric approach to estimating the "best", i.e. lowest, energy use within the industry; allowing a separation of an estimate of the frontier from an estimate of efficiency, i.e. how far each plant is relative to the frontier. Following Boyd (2008), this paper estimates an observed best practice, energy factor requirements function, which is equivalent to a sub-vector input distance function for energy, similar in concept to that proposed by Farrell, while controlling for output and other plant characteristics. For a complete review of the frontier approach see Murillo-Zamorano (2004).

Of course, observed best practice is only an estimate of economic potential to the extent that plant(s) in the sample achieve this level. On the one hand, the best observed performance may be taken as evidence of economic potential, since there must be a "best performer" in any industry. On the other hand, this analysis is of data at the whole plant level, so there may be plants that achieve "full" economic potential in only some energy service areas, but not all. This means that this analysis may not completely capture "full" economic potential at the detailed energy services level, but is based on the "best observed" realization of this concept of efficiency. However, the frontier approach is an improvement over statistical approaches based on average performance, e.g. OLS.

The difficulty with applying an industry level inter-plant benchmark is controlling for inter-plant differences other than production volume. While the things that differ between plants are numerous, the primary difference that has the most impact on energy fall into the following categories.

- Production level and mix
- Process inputs, e.g. vertical integration
- Size —Physical or productive capacity and utilization rates
- Climate (or other location specific factors).

These factors are all based on the technical or production aspects of energy use. The most obvious economic influence "missing" from the above list is input prices. The relative price of energy and the cost of capital are critical to economic decisions regarding the implementation of energy using (saving) technologies. Labor costs may also influence decisions on whether personnel are dedicated to the management of energy. This approach only examines production related factors in developing the inter-plant benchmark, i.e. takes a production function rather than cost function approach to defining efficiency. This does ignore differences between plants that arise from difference in the aforementioned prices. This is mitigated somewhat by considering plants located in the US (controlling for the larger global variation in prices that are often due to energy taxation) over short time periods when prices are relatively stable. This also avoids the more difficult question about what is the "correct" cost of capital. Plants may internally apply different costs of capital due to the financial conditions of the firm (i.e. those based on external capital markets) and the practices of internal capital budgeting, which may include capital rationing and setting hurdle rates. Jaffe and Stavins make several distinctions between different definitions of economic potential, one of which assumes that practices of capital budgeting do not bind the technology choices, i.e. decisions are based solely on market returns. However, observed practice likely include practices like capital rationing. From that perspective the benchmark developed here is *technically feasible* based on observed production practices, but include the possibility of rationing relative to industry specific practices and do not account for regional variability in energy prices. In this sense, these estimates may further depart from an estimate of "full" economic potential.

The next sections describe the history of the model development, the underlying data and stochastic frontier analysis, and estimates of the shift in the energy intensity distribution over time.

2.1. Stochastic frontier modeling of auto assembly plant data

Version one of the EPI auto assembly model; its background, motivation, data, and results, are described in Boyd (2005a, b). Companies in the *Focus* provided data for the years 1998–2000 to conduct the analysis for version one. The development process involved a period of testing and use that lead to eventual acceptance of the model by industry energy managers as a useful tool for benchmarking plant performance (Boyd et al., 2008). Based in part on this acceptance by the industry, EPA began using this model to measure and to recognize superior performance awarding the manufacturing plant ENERGY STAR to plants that are in the top quartile of energy efficiency.[6] Industry requested the EPA to update the analysis[7] so that the model would reflect more recent levels of energy efficiency and agreed to voluntarily provide the data[8] to perform the analysis. Data on energy use, production, capacity, and vehicle size, was received from 33 plants operating in the United States from six companies; Ford, General Motors, Honda, Nissan, Subaru, and Toyota. In the context of the four types of variables that one might consider as identified above, i.e. production level and mix, process inputs, e.g. vertical integration, physical or productive capacity and utilization rates, and climate (or other location specific factors) this study accounts for all four. Production is in terms of vehicles, and mix is accounted for by vehicle size (wheel base). Only data on body weld, paint and assembly are included in the data. Some plants do include stamping and other operations, while others do not. Those plants that do have stamping and parts fabrication have removed the energy related data for those process stages, making all plants consistent in that regard. Capacity utilization is also included in the analysis, as is climate. Based on the zip code location, the annual heating and cooling degree days (HDD and CDD

[6] Other criteria also apply. See http://www.energystar.gov/index.cfm?c=industry.bus_industry_plants for more information. For a list of plants that have received certification go to http://www.energystar.gov/buildings/about-us/find-energy-star-certified-buildings-and-plants/registry-energy-star-certified-buildings.

[7] 5th annual Motor Vehicle Assembly Energy Star Focus meeting, World Energy Engineering Congress, Washington DC, 2006.

[8] Data are collected directly from Energy Star Focus participant and are covered by a non-disclosure agreement with each participating company and Duke University.

Table 1
Summary statistics for 2005.

Variable	Mean	Std. Deviation	Lower decile	Upper decile
HDD	4764	1532	1937	7052
CDD	1413	507	703	2999
Wheel base (inches)	121	16.5	103	157
Production (vehicles per year)[a]	213,128	68,219	142,600	260,760
Capacity (vehicles per year)	223,806	45,271	169,090	256,200
kWh per vehicle	641	210	416	887
MMBTU per vehicle	4.63	2.3	2.52	7.36

[a] Two plants operate as separate entities under one roof. These plants are treated as two separate plants for purposes of measuring production and capacity for this and the previous analysis.

Table 2
Electricity energy model estimates.

Variable	Estimate	Standard error	t-Ratio
Constant	−91.8485	105.3997	−0.871
A_{2003}	23.92846	9.843368	2.431
A_{2004}	10.784	2.545143	4.237
WBASE	2.032419	0.401544	5.062
HDD	163.0618	36.33689	4.487
HDD^2	−15.1721	4.041763	−3.754
Util	−112.544	59.12416	−1.904
CDD	−223.899	170.7279	−1.311
CDD^2	86.61689	60.1926	1.439
AC	124.5492	108.496	1.148
Θ	0.00331	0.000819	4.041
P	0.65475	0.157012	4.17
σ_v	0.110233	2.295552	0.048

respectively) from an EPA ENERGY STAR database were merged with the industry provided data. Data for three years 2003–2005 were included in the analysis. Summary statistics for 2005 are shown in Table 1.

Boyd (2008) provides the background for use of stochastic frontier to estimate a directional distance function based, energy factor requirements equation, using the corn refining industry as an example. For purposes of this analysis, the same basic functional form and distributional assumptions used in Boyd (2005a) are followed. A parametric frontier model is chosen for this application over alternative non-parametric DEA approaches. The ENERGY STAR program encourages companies to use the EPI in an out-of-sample basis; distributing the results of this analysis in the form of a spreadsheet tool.[9] Since the data are confidential and cannot be included in such a spreadsheet, but parameter estimates can, the parametric form of efficiency analysis is chosen.

One difference between version one and the specification used in this paper is the annual fixed effects, to capture time varying shifts in the frontier from the earlier years relative to the last year, 2005. In the development of both versions of the model, linear and quadratic terms for utilization, HDD, and CDD were also tested. The logic for a possible non-linear impact of utilization on energy intensity is based on the fact that some energy is quasi-fixed and will be spread over more vehicles as utilization rises. Similarly, the impact of assembly plant heating and cooling loads from weather need not be linear. At some temperatures, the marginal impact of getting colder or warmer may a differential impact on the energy demand for the heating ventilation and air conditioning (HVAC) units. The specification in this paper takes a purely empirical approach to potential non-linearity. If the second order terms are insignificant they were dropped from the model and the most parsimonious version was selected. Slightly different approach for electricity and fuel use are employed regarding CDD. Only plants which provide air conditioning[10] for worker comfort are likely to have energy loads that are sensitive to summer temperatures, so a dummy variable to differentiate between such plants is used to capture this effect.

The preferred specification of the equation for electricity is

$$\frac{E_i}{Y_i} = A + A_{2003} + A_{2004} + \beta_1 WBASE_i + \beta_2 HDD_i + \beta_3 Util_i + \beta_4 Util_i^2 + \beta_5 CDD_i + \beta_6 CDD_i^2 + \beta_7 AC_i + u_i - v_i \tag{1}$$

where

E	total site electricity use in kWh;
Y	number of vehicles produced;
Util	plant utilization rate, defined as output/capacity;
HDD	thousand heating degree days for the plant location and year;
CDD	thousand cooling degree days for the plant location and year if the plant is air conditioned and zero otherwise;
AC	dummy variable equal to one if the plant is air conditioned and zero otherwise
WBASE	wheelbase of the largest vehicle produced; and
β	vector of parameters to be estimated.

The variable v_i is the statistical random error and is normally distributed as $N(0, \sigma_v^2)$. The variable u_i is the estimate of inefficiency. Note that in this form of the frontier, u_i is added to the RHS, reflecting the fact that actual energy use is expected to be higher than best practice. The efficiency term u_i is assumed to be distributed as a gamma distribution, summarized by the rate parameter, Θ, and shape parameter, P. The gamma distribution and density function are

$$f(u) = \left[\theta^P/\Gamma(P)\right] e^{-\theta u} u^{P-1}, u, P, \theta > 0$$
and
$$F(x) = \int_0^x f(u)du \tag{2}$$

respectively. This distribution provides a more flexible parameterization of the distribution than either exponential or half normal, which are commonly used for the estimation of stochastic frontier models. The gamma distribution is very flexible and can collapse to the exponential distribution ($P = 1$), Chi^2 ($\Theta = 2$), and other distributions with a one-sided skewness. Simulated maximum likelihood was used to estimate the parameters (Greene, 2003). The estimated parameters of the model are shown in Table 2. All parameters except for those variables associated with cooling, i.e. CDD and AC, are statistically significant at the 1% level or greater in a two-tailed test.[11] The small estimate of σ_v implies that the stochastic component is small and that most departures from the frontier are attributable to the inefficiency error term.

[9] See http://www.energystar.gov/buildings/tools-and-resources/automobile-assembly-plant-epi.
[10] The industry prefers the term "air tempering," since all plant "condition" the air to control humidity, but not all "temper," i.e. cool the air for comfort. Many plants located in "northern" climates do not provide cooling.
[11] The cooling degree variables are included in the model since controlling for those plants with air conditioning was felt to be important to industry reviewers who provided the data.

Table 3
Fuel energy model estimates.

Variable	Estimate	Standard Error	t-Ratio
Constant	−0.526	1.40	−0.37
WBASE	0.019	0.008	2.48
Util	−0.720	0.62	−1.15
HDD	0.439	0.14	3.07
θ	0.390	0.18	2.14
P	0.667	0.37	1.81
σ_v	0.676	0.21	3.28

The preferred specification of the equation for fossil fuel is

$$F/_{Y_i} = A + \beta_1 \mathrm{WBASE} + \beta_2 \mathrm{Util} + \beta_4 \mathrm{HDD} + u_i - v_i \tag{3}$$

where

F total site fossil fuel use in 10^6 Btu.

All other variables are defined with u and v distributed as described above. The parameter estimates of the model are shown in Table 3. Only the parameters for wheel base and HDD are statistically significant at the 1% level, or lower, in a two-tailed test. The size of σ_v is larger than for the electricity equation, which suggests that the fuel model is estimated with larger stochastic component, but most departures are still attributable to inefficiency.

The dummy variables are included to control for common industry effects for each year, presumably shifts that improve average efficiency over time. For electricity these estimates suggest that the frontier electricity use in 2003 and 2004 was higher by 24 and 11 kWh per vehicle, respectively. While the estimates appear to show a pattern of higher energy use in 2003 relative to 2004, the differences between the two years are not statistically significant. The non-linear relationship for HDD implies that increased HDD impacts electricity use positively, but at a diminishing rate as HDD approaches the upper quartile, where the quadratic reaches its maximum. While not significant, the non-linear relationship for CDD implies that warm temperatures only adds to the electricity loads in the plants located in the warmest of climates that provide cooling, since the quadratic function is fairly "flat" over most of the lower quartiles of the data.[12] For fuel use, initial estimates suggest that the frontier energy use in 2003 and 2004 was lower, not higher. These fixed effects were not significant and were dropped from the estimation. The second order variables for utilization and HDD were not significant and were dropped. The model estimates for the preferred specification are shown in Table 3.

Since this is an update of version one of the model estimated using 1998–2000 data it is useful to compare the two versions to see how much the coefficients had changed. The model based on the 1998–2000 data will be labeled version one and the model specified in this paper as version two. Table 4 compares the estimates of the two electricity models. While the estimates for wheel base and utilization are quite similar the climate variables appear very different. This is due in part to the correlation between HDD and CDD and the impact both of these variables have on electricity consumption in the quadratic specification. The slope of non-linear CDD function, evaluated at the median of the data, is 0.018 kWh/vehicle for every increase in degree day. The slope increases as CDD increases. Table 5 compares the estimates of the two fuel models. The utilization coefficients show the most change between the two versions. If we look at the slope of the curve evaluated at 100% utilization we find that every 1% increase in utilization decreases energy per vehicle by 0.02 MMBtu in version one and only 0.007 in version two. In version two the second order quadratic term was not significant, implying that the linear form with the smaller impact on energy (0.007 vs 0.02) better describes current industry conditions. This suggests that changes in energy practice have reduced the impact of utilization on energy use per vehicle. This may result from improvements in shut-down procedures and other changes in energy management.

[12] Some type of piece-wise linear function could also be used to capture this, but the quadratic form is more convenient.

Table 4
Comparison of electricity energy model estimates.

	Version one		Version two	
Variable	Estimate	Standard error	Estimate	Standard error
Constant	369.39	86.89	−91.84	105.39
A_{2003}			23.92	9.84
A_{2004}			10.78	2.54
WBASE	2.77	0.01	2.03	0.40
HDD	−48.41	26.26	163.06	36.33
HDD^2	4.79	2.60	−15.17	4.04
Util	−138.61	34.31	−112.54	59.12
CDD	−59.32	5.23	−223.89	170.72
CDD^2	41.91	0.99	86.61	60.19
AC			124.54	108.49
θ	0.0028	0.00006	0.00331	0.000819
P	0.5424	0.116	0.65475	0.157
σ_v	0.000004	0.00048	0.110233	2.295

2.2. Estimating the shift in the distribution of energy intensity

Measures of efficiency defined by versions one and two for both fuel and electricity are computed for each plant in the dataset used to develop version two (i.e. the 2003–2005 data). Denote $f_k^j(X_i)$ as the predicted best practice energy intensity for the *ith* plant with characteristics X, for model version j, and fuel type k. Efficiency is computed by first subtracting the predicted values from both versions of the models for each fuel type from actual energy use.

$$\frac{E_i}{Y_i} - f_k^j(X_i) = u_i - v_i.$$

Since we are interested in the estimate of efficiency, u_i, but can only observe $u_i - v_i$ the conditional JMLS estimator proposed by Jondrow et al. (1982) is used. Multiplying the JMLS estimate of efficiency by total vehicle production results in a plant level estimate of energy inefficiency.

Table 5
Fuel energy model estimates.

	Version one		Version two	
Variable	Estimate	Standard error	Estimate	Standard error
Constant	3.827	0.837	−0.526	1.40
WBASE	0.00322	0.000061	0.019	0.008
Util	−6.788	1.280	−0.720	0.62
$Util^2$	2.399	0.622		
HDD	−0.545	0.121	0.439	0.14
HDD^2	0.11	0.00131		
θ	0.268	0.00694	0.390	0.18
P	0.724	0.144	0.667	0.37
σ_v	0.000701	0.00698	0.676	0.21

Table 6
Average change in frontier energy use "best practice" implied by the difference between version one and version two.

	Electric (kwh/unit)	Fuel (MMBtu per unit)
Frontier per unit change	15.5	0.66
% frontier change	2%	12%
Reduction in frontier CO_2 emissions (10^6 lbs)	164	531

Table 7
Average change in inefficiency "best practice" implied by the difference between version two and version one.

	Electric (kwh/unit)	Fuel (MMBtu per unit)
Mean version one	194	2.70
Variance version one	69,184	10.1
Mean version two	198	1.71
Variance version two	59,761	4.4
Change in CO_2 emissions due to efficiency (10^6 lbs)	−42	809

If the estimate of best practice energy use is smaller using version two than when using version one then the shift in the frontier reflects an improvement in energy performance. The average change in the frontier based on subtracting version one from version two, for both energy types evaluated at every plant in the database, is shown in Table 6. Multiplying the average change in estimated best practice fuel and electricity intensity by the CO_2 emission factor for fuels (natural gas) and electricity (using national average emission rates), respectively, and then by the total production of all plants in this study yields an estimate of the carbon emission change that has resulted from the improvement in industry best practices and technology.

The model comparison can also provide information on whether a plant is keeping pace with these changes, catching up, or falling behind by comparing the estimated parameters of the gamma distributed efficiency term. Table 7 translates the parameters of the gamma distribution into a more familiar mean and variance. The mean inefficiency (amount by which the energy use of the typical plant fell short of best practice) rose slightly and the variance declined. The difference in the mean is very small but the reduction in the variance suggests that the wide range of performance has declined. A more dramatic story emerges for fuel use. Mean inefficiency is 1.0 MMBtu per vehicle lower and the variance is reduced by more than half. Computing the change in CO_2 in the same manner as the change in the frontier practices results in an estimate of the total CO_2 implication of the change in efficiency, which is slightly larger than the change in the frontier, 766 vs. 696 respectively. The total is 1462 million lbs of CO_2.

The difference between the results for fuels vs. electricity is likely a combination of efficiency improvements in each, but also some anecdotal evidence of substitution of fuel processes for electricity based processes. The main shift in energy processes is likely in paint booth technology, which is the dominant energy user in assembly plant (see Galitsky and Worrell, 2003). Some examples of this substitution are the shift from ovens to UV paint curing and the decline in the use of thermal oxidizers. These technology substitutions are not likely to be energy price driven, but are to meet environmental requirements for VOC emission control. An analysis of these process changes resulting in substitution between fuel and electricity is beyond the scope of this paper, but these types of technology trends mean that the fuel and electricity specific estimates are conditional on other drivers for underlying process change.

Another way to see how the distribution of energy intensity has changed over time is to use each model to simulate the range of performance for a hypothetical plant. Fig. 1 shows how each model would predict the simulated cumulative efficiency distribution, for a hypothetical plant producing 222,000 vehicles with a 120 in. wheel based per year, at a line speed of 65 vehicles per hour. This hypothetical plant is located in a climate that experiences an average of 3457 HDD and 1417 CDD per year. In other words, if all plants in the industry were identical, then this would be the distribution of total energy intensity. Plants to the right are less efficient when compared to the performance represented by the left most point on the curve. When we compare the cumulative distribution from version one of the EPI, with a base year of 2000, to that generated by version two, with the base year of 2005, we see that

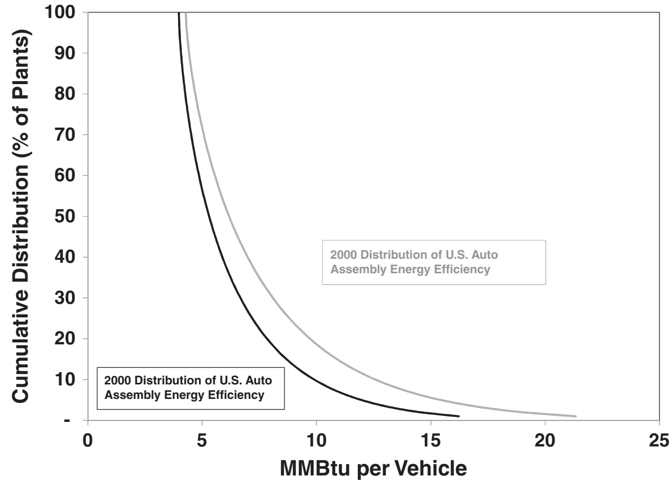

Fig. 1. Comparison of the distribution of total source energy intensity.[14]

the simulated distribution has shifted to the right.[13] The best practice (frontier), represented by the left-most portion of each curve, has shifted less than the middle of the distribution. This shows that while the best plants have only improved slightly, the new distribution is steeper and has a shorter tail. This implies that the "pack" has made progress in "catching up" with the industry leaders.

3. Conclusion

This paper describes the data and analysis to update the ENERGY STAR Auto Assembly Manufacturing Plant EPI from the base year of 2000 to a base year of 2005. Periodic update of any manufacturing plant EPI is needed to provide a useful management tool if the industry performance is changing over time. The update process provides an estimate how much "the industry" has improved, in aggregate or on average. There are two sources of improvement, the changes in the industry energy frontier, i.e. "best practices" and technology, and the changes in efficiency, i.e. whether plants are catching up or falling behind. The results suggest that changes in efficiency have slightly outpaced changes in the frontier. This effect is primarily manifesting itself in improvements in fossil fuel use; changes in efficiency of electricity use have been negligible. The combined effect when evaluated against the over 7 million vehicles produced in 2005 by the plants in our study implies in a reduction of 1462 million lbs of CO_2 attributable to changes in observed industry energy efficiency practices.

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[13] The vertical axis is essentially a percentile, but follows the ENERGY STAR convention of labeling the lowest energy use with the highest percentile (100). ENERGY STAR refers to this as the Energy Performance Score.

[14] Source energy is an aggregate that includes average power conversion and transmission losses for electricity, i.e. converts kWh to Btu using the US system average conversion and loss rate of 11,396 Btu/kWh.

References

Boyd, G., 2005a. A statistical model for measuring the efficiency gap between average and best practice energy use: the ENERGY STAR™ Industrial Energy Performance Indicator. J. Ind. Ecol. 9 (3).

Boyd, Gale A., 2005b. Development of a Performance-based Industrial Energy Efficiency Indicator for Automobile Assembly Plants. Argonne National Laboratory (ANL/DIS-05-3.).

Boyd, G., 2008. Estimating plant level manufacturing energy efficiency with stochastic frontier regression. Energy J. 29 (2), 23–44.

Boyd, G., Tunnessen, W., 2013. Plant energy benchmarking: a ten year retrospective of the ENERGY STAR Energy Performance Indicators (ES-EPI). Proc. ACEEE Summer Study on Energy Efficiency in IndustryNiagara Falls, NY.

Boyd, G., Zhang, G., 2012. Measuring improvement in energy efficiency of the US cement industry with the ENERGY STAR Energy Performance Indicator. Energy Efficiency 1–12.

Boyd, G., Dutrow, E., Tunnesen, W., 2008. The evolution of the ENERGY STAR Industrial Energy Performance Indicator for benchmarking plant level manufacturing energy use. J. Clean. Prod. 16 (6), 709–715.

Boyd, G., Dutrow, E., Tunnessen, W., Worrell, Ernst, 2011. Enabling the energy performance improvement of entire industries and measuring success. ACEEE Summer Study on Energy Efficiency in Industry. Energy Productivity in Industry: Partners and OpportunitiesNiagara Falls, NY.

Environmental Protection Agency, 2013. Celebrating a decade of ENERGY STAR buildings. report accessed at http://www.energystar.gov/buildings/tools-and-resources/celebrating-decade-energy-star-buildings (on 7/30/2013).

Farrell, M.J., 1957. The measurement of productive efficiency. J. R. Stat. Soc. Ser. A (Gen.) 120 (part 3), 253–281.

Freeman, S.L., Niefer, M.J., et al., 1997. Measuring industrial energy intensity: practical issues and problems. Energy Policy 25 (7–9), 703–714.

Galitsky, C., Worrell, E., 2003. Energy Efficiency Improvement and Cost Saving Opportunities for the Vehicle Assembly Industry: An ENERGY STAR®Guide for Energy and Plant Managers, LBNL-50939. Lawrence Berkeley National Laboratory, Berkeley, Calif.

Greene, W., 2003. Simulated likelihood estimation of the normal-gamma stochastic frontier function. J. Prod. Anal. 19 (2–3), 179–190.

Huntington, H., 1994. Been top down so long it looks like bottom up. Energy Policy 22 (10), 833–839.

International Organization for Standardization, 2011. ISO 50001:2011 energy management systems—requirements with guidance for use. http://www.iso.org/iso/iso_catalogue/catalogue_tc/catalogue_detail.htm?csnumber=51297 (Retrieved July 22, 2013.).

Jaffe, A.B., Stavins, R.N., 1994. The energy-efficiency gap: what does it mean? Energy Policy 22 (10), 804–810.

Jondrow, J., Materov, I., et al., 1982. On the estimation of technical inefficiency in the stochastic frontier production function model. J. Econ. 19 (2/3), 233–238.

Murillo-Zamorano, L., 2004. Economic efficiency and frontier techniques. J. Econ. Surv. 18 (1), 33–77.

Murray, G.P., 1996. What is energy efficiency?: concepts, indicators and methodological issues. Energy Policy 24 (5), 377–390.

Price, L., Worrell, E., et al., 2003. Voluntary agreements for increasing energy-efficiency in industry: case study of a pilot project with the steel industry in Shandong Province, China. Proc. Industrial Summer Study on Energy Efficiency in IndustryACEEE, Rye Brook, NY.

Storey, M., Boyd, G., Dowd, J., 1997. Voluntary agreements with industry. The Economics and Law of Voluntary Approaches, Special Issue of Fondazione Eri Enrico Mathei, Series 26.97 (Feb. 1997).

Therkelsen, P., Sabouni, R., et al., 2013. Assessing the costs and benefits of the superior energy performance program. Proc. ACEEE Summer Study on Energy Efficiency in Industry, Niagara Falls, NY.