Energy Efficiency, Technical Change and Price Responsiveness in Non-Energy Intensive Chemicals Manufacturing

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Introduction

The *chemical industry*, as defined by the North American Industry Classification System (NAICS) code 325, is a diverse collection of sectors ranging from commodity chemicals (e.g., ammonia, chlor-alkalies, ethaline) to consumer products (paint, pharmaceuticals, cosmetics, etc.). The former are the *up-stream* process industries that encompass some of the most energy-intensive, chemical conversions of feedstock into intermediate chemicals, which are used primarily by other industries. The consumer products uses and produces a wide range of downstream chemicals to make, package, and distribute final consumer goods. Of the more than 5 quaddrillion Btu (quads) of energy reported by the 2010 Manufacturing Energy Consumption Survey (MECS) that is used in NAICS 325, about 4.2 quads are used in the 13 energy-intensive 6-digit NAICS below. This 5 quads includes feedstocks as well as energy for heat and power[1].

- 325110 Petrochemicals
- 325120 Industrial Gases
- 325181 Alkalies and Chlorine
- 325182 Carbon Black
- 325188 Other Basic Inorganic Chemicals
- 325192 Cyclic Crudes and Intermediates
- 325193 Ethyl Alcohol
- 325199 Other Basic Organic Chemicals
- 325211 Plastics Materials and Resins
- 325212 Synthetic Rubber
- 325222 Noncellulosic Organic Fibers
- 325311 Nitrogenous Fertilizers
- 325312 Phosphatic Fertilizers

The remaining diverse, downstream chemical industry sectors use about 880 trillion Btu. While this is a much smaller amount of energy than is used by their energy-intensive, up-stream industry counterparts, it is still a substantial energy-consuming sector. This 880 trillion Btu is only slightly less than the energy consumption of the Food industry (NAICS 311), at 1,162 trillion Btu, or the energy consumption of all of Metal Based Durables (NAICS 332, 333, 334, 335, and 336), at 969 trillion Btu. On an end-use basis, electricity is only about 9% of the energy use in both the upstream and downstream chemicals. The upstream sector uses a wide range of fossil fuels for both feedstock, heat, and power, but the downstream industries' fuel use is dominated by natural gas; 82% of fossil fuel use is natural gas and Liquefied Petroleum Gas (LPG), and almost all use is for heat and power. We take advantage of this fact and make the simplifying assumption to treat all fuel use as if it were natural gas. We also define the fuel demand and associated efficiency estimate as only relative to heat and power. The same approach was used by (Boyd and Lee).

This report provides estimates of energy efficiency and energy price response in the non-energy-intensive chemical manufacturing sector. A companion report focuses on the upstream, energy-intensive part of the industry. Estimates of technical change in continuing plants and the relative

[1] All energy data are from the 2010 *MECS Table 1.2 First Use of Energy for All Purposes (Fuel and Nonfuel)*. These data are measured at end-use; i.e., electric generation losses are not included.

efficiency of new plants are also presented. A stochastic frontier regression analysis (SFA) is applied to repeated cross sections using plant-level data from the quinquennial Economic Census (EC) for the years 1992, 1997, 2002, 2007, and 2012. A Malmquist index is used to decompose aggregate technical change into efficiency and frontier (best practice) improvements. The relative efficiency of plants entering the industry is also measured. The methodology and data construction is comparable to (Boyd and Lee 2016 https://www.researchgate.net/publication/310752276) for metal based durables[2]. One notable difference is the possible endogeneity of plant level electricity prices, i.e., the possibility that large electricity users might have some market power or other mechanism to obtain lower electric rates. This would have tend to bias the cross-sectional estimates of the electric price elasticities. In the prior study by Boyd and Lee, tests for price endogeneity did not find this to be a significant concern for Metal-Based Durable (MBD). This is not the case for chemicals.

The report is organized as follows. First, we briefly discuss the approach used to deal with price endogeneity. We present the Ordinary Least Square (OLS) and SFA estimates using the plant-level prices. Then we introduce a control function approach to instrument plant-level prices with state-level prices. Next we present estimates of the SFA using the control function approach. Using the SFA estimates the Malmquist decomposition and the entering plant efficiency are computed.

Analysis of Plant-Level Electric prices

OLS estimates using plant-level electric prices[3] are presented in Table 1. All estimates include six-digit NAICS and state fixed effects. The variable are defined as follows.

- Lnpw natural log of production worker employees
- lnoe natural log of other (non-production worker) employees
- lntvs natural log of total value of shipments adjusted for inventory changes
- lnHDD natural log of heating degree days
- lnCDD natural log of cooling degree days
- geratio ratio of self-generated power less sales to the grid to total electric consumption
- lnngp natural log of state level natural gas prices
- lnep natural log of plant level electric prices

The variable geratio is included to control for plants with combined heat and power (CHP). This is not a widespread practice in this sector, but the small number of plants that have CHP use much less electricity and more fuel, as expected. Electricity own price elasticities, i.e., the elasticity of electricity demand relative to the price of electricity, ranges from -0.8 to -1.3. Fuel prices and weather variables are not significant in the electricity demand equation. The natural log of plant production activity variables (total value of shipments – *lntvs*, production worker hours – *lnpw*, and other employees – *lnoe*) are all significant and suggest slightly increasing returns to scale with respect to energy since the sum of the coefficients are greater than one[4]. For fuel use, the own-price elasticity is basically unity; ranging between -0.9 and -1.0. Production activity variables suggest constant returns; the sum is close to one in

[2] The reader is referred to that report for the details. They are not repeated here.
[3] Recall that the EC data do not include plant-level fuel prices. They only include plant-level electric prices.
[4] We did not test if this is significantly greater then unity.

all cases. There is a negative and significant coefficient for electric price on fuel use, implying complementarity. We will revisit this relationship result when price endogeneity is explored.

Concerns regarding the possible bias of the electricity price elasticity can be addressed using the state-level industrial customer electricity prices from the EIA State Energy Data System (SEDS) as an instrument. We employ a two-step procedure. The first step is a regression of the plant-level prices against the state-level prices from SEDS and all the other variables in our model. The second step is to use the residuals from stage one in our SFA model as a control function. A significant coefficient on these residuals is evidence of price endogeneity in the second-stage regression.

While the two-step process is done for each year in the repeated cross section SFA estimates, we also present results of the pooled data analysis (i.e., all five time periods). This pooled analysis illustrates how plant level prices are associated with our explanatory variables and is also empirically interesting. The results in Table 2 show that plant electric prices are correlated with state prices. Interestingly, the relationship between plant level electric prices is with both electric and natural gas prices, although the coefficient for electric prices is larger. The correlation between state and plant prices is not perfect, because the coefficient is significantly different from one. More importantly, the coefficient on *lntvs* and *lnpw* are both negative and significant. *Larger plants,* i.e., those with a higher value of shipments and employment, tend to have lower energy prices. This was exactly our hypothesis that some type of price endogeneity would bias our elasticities. The relationship between plant size, energy use, and prices can be complicated. Larger plants may tend to be more energy efficient. Low energy-intensity batch process plants can be small. Small plants have fewer personnel resources and often less availability of capital investment. Of course, small plants in a large company can have a lot of benefits from the company level.

Table 1 OLS Estimates with Plant prices

	Electricity				
	1992	1997	2002	2007	2012
lnoe	0.062***	0.046***	0.121***	0.067***	0.085***
lnpw	0.473***	0.391***	0.444***	0.423***	0.426***
lntvs	0.546***	0.628***	0.580***	0.616***	0.587***
lnngp	-0.016	0.064	-0.166*	0.01	0.058
lnHDD	-0.048	-0.04	0.017	0.016	-0.029
lnCDD	0.018	0.043	0.013	-0.043	-0.023
geratio	-0.737***	-1.143***	-0.821**	-0.816**	-0.759**
lnep	-0.880***	-0.936***	-0.765***	-0.792***	-1.322***
Constant	-0.135	-0.905*	-0.352	-0.138	-2.596***
	Fuels				
lnoe	0.080***	0.084***	0.162***	0.051*	0.154***
lnpw	0.397***	0.345***	0.369***	0.357***	0.371***
lntvs	0.470***	0.565***	0.524***	0.555***	0.529***
lnngp	-1.023***	-0.911***	-0.936***	-1.000***	-0.849***
lnHDD	0.028	0.025	0.078	-0.034	-0.007
lnCDD	0.025	0.004	-0.022	-0.053	-0.113
geratio	1.687***	2.105***	2.536***	1.541***	1.845***

lnep	-0.267***	-0.279***	-0.249***	-0.197***	-0.589***
constant	5.095***	3.758***	3.845***	5.726***	2.398**
legend: * p<0.05; ** p<0.01; *** p<0.001					
6-digit NAICS and State fixed effects					

To control for this endogeneity, we ran two different OLS regressions using the residuals and predicted values from the regression model similar to that shown in Table 2[5]. The first is the control-function estimate, where the residuals from the plant level energy price regression are included with plant energy prices (table 3). The second approach to treat endogenous prices is 2-stage least squares, using the predicted value from the plant-level energy price regressions instead of plant prices[6]. The coefficient on the control function residuals are significant in two out of five years for the electric equation and four out of five years for fuels. We take this as reasonable support for endogeneity. Own price elasticity of demand for electricity is lower; between -0.7 and -0.8. Cross price elasticity with respect to fuels is no longer significant except in 2002. It appears that most of the evidence of complementarity between fuels and electricity was an artifact of price endogeneity.

Table 2 Electric Price Control function estimates (pooled sample)

Variable	Coefficient
lnoe	0.0062**
lnpw	-0.0173***
lntvs	-0.0107***
lnstateep	0.7829***
lnngp	0.0539***
lnHDD	0.0162
lnCDD	0.0468***
geratio	0.0744*
constant|	-0.9902***
R^2	0.5039
legend: * p<0.05; ** p<0.01; *** p<0.001	6-digit NAICS, State and year fixed effects

[5] Actually we ran a separate control-function regression for each of the cross section time periods. Parameters of these five regressions are very similar to the results n Table 2.
[6] Results from the two-stage least square are not shown. They simply verify that you get the same estimates as obtained by the control function.

Table 3 Control function OLS estimates

	1992	1997	2002	2007	2012
			ELECTRICITY		
lnoe	0.064***	0.044***	0.120***	0.068***	0.086***
lnpw	0.477***	0.396***	0.445***	0.423***	0.434***
lntvs	0.546***	0.630***	0.581***	0.615***	0.611***
lnngp	-0.088	-0.006	-0.168*	0.009	0.046
lnHDD	-0.025	-0.017	0.022	0.012	0.029
lnCDD	0.005	0.02	0.013	-0.043	-0.007
geratio	-0.755***	-1.157***	-0.823**	-0.802**	-0.885***
lnep	-0.715***	-0.686***	-0.722***	-0.831***	-0.783***
Control Function Residuals	-0.207	-0.312**	-0.049	0.052	-0.665***
constant	0.29	-0.163	-0.27	-0.211	-2.073***
			FUELS		
lnoe	0.084***	0.083***	0.165***	0.048*	0.154***
lnpw	0.405***	0.350***	0.367***	0.356***	0.377***
lntvs	0.468***	0.567***	0.523***	0.556***	0.548***
lnngp	-1.182***	-1.005***	-0.932***	-0.996***	-0.859***
lnHDD	0.079	0.057	0.067	-0.018	0.038
lnCDD	-0.004	-0.027	-0.021	-0.053	-0.101
geratio	1.647***	2.086***	2.541***	1.491***	1.745***
lnep	0.098	0.056	-0.340*	-0.057	-0.165
Control Function Residuals	-0.461**	-0.419**	0.105	-0.188*	-0.523**
constant	6.040***	4.755***	3.670***	5.988***	2.809***

Frontier Efficiency Estimates

Because the two-stage least square estimate provides evidence of electric price endogeneity, we apply the same two-step procedure to the SFA estimates as well. Results for exponential and half-normal efficiency distributions for each five-year time step are shown in Tables 4 and 5 for electricity and fuels, respectively. As was the case for OLS, the control function shows evidence of price endogeneity, and the resulting electricity own price elasticities are lower and show no evidence of complementarity with fuel use. For electricity, the SFA converges for both distributions and all years, except for the half normal in 1997 . The performance for fuels is not quite as good. The SFA converges for both distributions in 1997, 2002, and 2012. Recall that λ is the ratio of efficiency variance (σ^2_u) to total variance $\sigma^2_u + \sigma^2_v$.

Average levels of efficiency are shown in Table 6. Average efficiency ranges from 0.58 to 0.76, with fuels being slightly less efficient on average. The non-parametric kernel density for the electricity and fuel efficiency estimates are given in Figures 1 and 2, respectively. One important point the kernel density shows is that few plants approach 100% efficiency. For example, the 99th percentile for fuel efficiency is 82% in 2012; for electricity it is 87%. So the size of the average efficiency needs to account for the fact that few plants are considered 100% efficient.

The changing average efficiency over time also reflects shifting overall distributions. For electricity, the years 1992, 1997, and 2007 are more similar. These shifting distributions also manifest themselves in the Malmquist decomposition estimates (Table 7). It should be noted that, at the plant level, total efficiency is the product of technical change and efficiency change, but this property is not preserved by the average over all the plants presented in the Table[7]. For electricity, we compute the Malmquist index for each five-year time step. The overall index and the index of technical change reflects efficiency progress in all years expect 2007. Changes in efficiency are more complex, mirroring the changing distributions in Figure 1. Taken over the 20-year period, electricity intensity improved at an overall annual rate of 1.2%, with efficiency and technical progress each contributing half. The failure of the fuel frontier to converge in 1992 and 2007 makes it harder to discern a pattern. Total annual rate of change for fuels was 0.3%, mostly from efficiency.

The Malmquist index reflects the changes observed in plants that continue to operate from the prior time period. Table 8 shows how new plants compare with existing plants. We find that new plants are statistically more efficient, with the exception of electricity use in 1997. The differences are small. Most years are about 1%. The largest improvement in new plants for both electricity and fuels occurred in 2002, 2.2% and 3.0% respectively.

[7] In the future it may be more appropriate to use geometric average for Malmquist results.

Table 4 SFA estimates - Electricity

Variable	Exponent 1992	Half 1992	Exponent 1997	Half 1997	Exponent 2002	Half 2002	Exponent 2007	Half 2007	Exponent 2012	Half 2012
lnoe	0.054**	0.064***	0.037**	0.042**	0.088***	0.092***	0.060***	0.065***	0.070***	0.078***
lnpw	0.471***	0.477***	0.393***	0.397***	0.405***	0.421***	0.395***	0.408***	0.424***	0.426***
lntvs	0.559***	0.546***	0.638***	0.631***	0.629***	0.610***	0.645***	0.627***	0.625***	0.618***
lnngp	-0.078	-0.088	-0.003	-0.006	-0.138*	-0.150*	-0.01	-0.007	-0.004	0.024
lnHDD	-0.035	-0.025	-0.022	-0.019	-0.003	0	0.008	0.007	0.02	0.021
lnCDD	0.001	0.005	0.018	0.02	0.003	0.007	-0.032	-0.035	-0.002	-0.004
geratio	-0.904	-0.755	-1.239***	-1.197***	-1.024**	-0.980**	-0.893*	-0.861*	-0.975***	-0.932***
lnep	-0.730***	-0.715***	-0.689***	-0.685***	-0.765***	-0.749***	-0.861***	-0.853***	-0.763***	-0.774***
Control Function Residuals	-0.184	-0.207	-0.274**	-0.299**	-0.017	-0.039	0.051	0.05	-0.573***	-0.620***
constant	-0.511	-0.129	-1.341**	-1.379**	-1.993***	-2.046***	-1.929***	-1.950***	-1.939***	-2.106***
σ_u	-2.204***	-13.03***	-2.212***	-1.381***	-1.187***	-0.140**	-1.602***	-0.519***	-1.516***	-0.546*
σ_v	-0.910***	-0.647***	-1.085***	-1.011***	-1.503***	-1.607***	-1.050***	-1.078***	-0.892***	-0.863***
Number of observatoins	5000	5000	4900	4900	4300	4300	4200	4200	3900	3900
# of iterations	6	49	7	9	6	11	6	10	6	12
λ	0.523	0.002	0.569	0.831	1.171	2.082	0.759	1.323	0.732	1.172

Table 5 SFA Estimates - Fuels

Variable	Exponent 1992	Half 1992	Exponent 1997	Half 1997	Exponent 2002	Half 2002	Exponent 2007	Half 2007	Exponent 2012	Half 2012
lnoe	0.084***	0.084***	0.082***	0.082***	0.157***	0.155***	0.048*	0.048*	0.159***	0.159***
lnpw	0.405***	0.405***	0.332***	0.344***	0.330***	0.346***	0.356***	0.356***	0.373***	0.373***
lntvs	0.468***	0.468***	0.574***	0.567***	0.533***	0.523***	0.556***	0.556***	0.544***	0.543***
lnngp	-1.182***	-1.182***	-1.004***	-1.005***	-0.851***	-0.867***	-0.996***	-0.996***	-0.853***	-0.856***
lnHDD	0.079	0.079	0.066	0.064	0.067	0.065	-0.018	-0.018	0.036	0.037
lnCDD	-0.004	-0.004	-0.031	-0.03	-0.021	-0.023	-0.053	-0.053	-0.104	-0.103
geratio	1.647***	1.647***	2.143***	2.116***	2.635***	2.583***	1.491***	1.491***	1.733***	1.731***
lnep	0.098	0.098	0.049	0.057	-0.352*	-0.349*	-0.057	-0.057	-0.185	-0.178
Control Function Residuals	-0.461**	-0.461**	-0.326*	-0.379*	0.085	0.077	-0.188*	-0.188*	-0.486**	-0.502**
constant|	4.895***	4.926***	3.105***	3.046***	1.128	1.059	4.550***	4.580***	3.188***	2.978***
σ_u	-6.902***	-12.78***	-1.366***	-0.418**	-0.774***	0.272**	-6.877***	-12.33***	-1.510***	-0.311
σ_v	-0.068*	-0.067*	-0.486***	-0.450***	-0.432***	-0.470***	0.100**	0.101***	0.151*	0.11
Number of observatoins	5000	5000	4900	4900	4300	4300	4200	4200	3900	3900
# of iterations	100	46	8	9	5	7	100	44	7	6
λ	0.033	0.002	0.644	1.016	0.843	1.45	0.031	0.002	0.436	0.81

Table 6 Efficiency Estimates from the exponential SF

Efficiency	Mean	variance
Electricity 1997	0.737	0.012
Electricity 2002	0.636	0.031
Electricity 2007	0.712	0.012
Electricity 2012	0.643	0.022
Fuels 1997	0.658	0.017
Fuels 2002	0.585	0.027
Fuels 2007	-	-
Fuels 2012	0.657	0.011

Table 7 Malmquist Decomposition of Aggregate Energy Intensity Change

	Overall	Efficiency	Technical change
		ELECTRICITY	
1997	1.031	1.01	1.018
2002	1.188	0.956	1.222
2007	0.966	1.306	0.79
2012	1.069	0.914	1.179
		FUELS	
1997	-	-	-
2002	1.067	0.931	1.151
2007	-	-	-
2012	0.993	1.321	0.822

Table 8 Efficiency Difference New vs Existing

	New plant	Existing Plant	Difference	t-test
		Electricity		
1997	0.7396	0.7375	0.2%	0.6963
2002	0.6582	0.6359	2.2%	4.202
2007	0.7199	0.7121	0.8%	2.3588
2012	0.6507	0.643	0.8%	1.5867
		Fuels		
1997	0.6666	0.6576	0.9%	2.4398
2002	0.6153	0.5848	3.1%	6.364
2007	-	-	-	-
2012	0.6674	0.6566	1.1%	3.3606

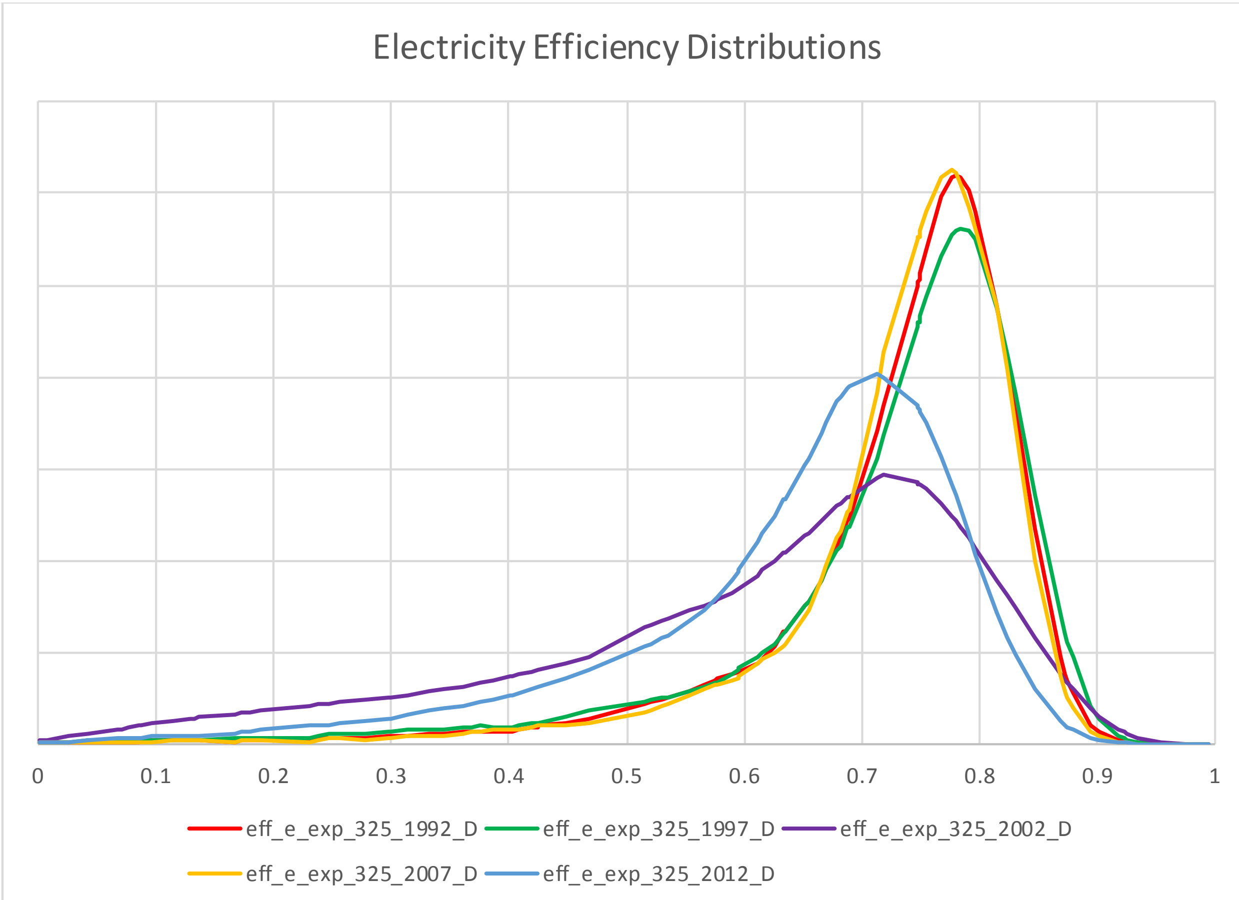

Figure 1 Electricity efficiency distribution using the exponential model estimates

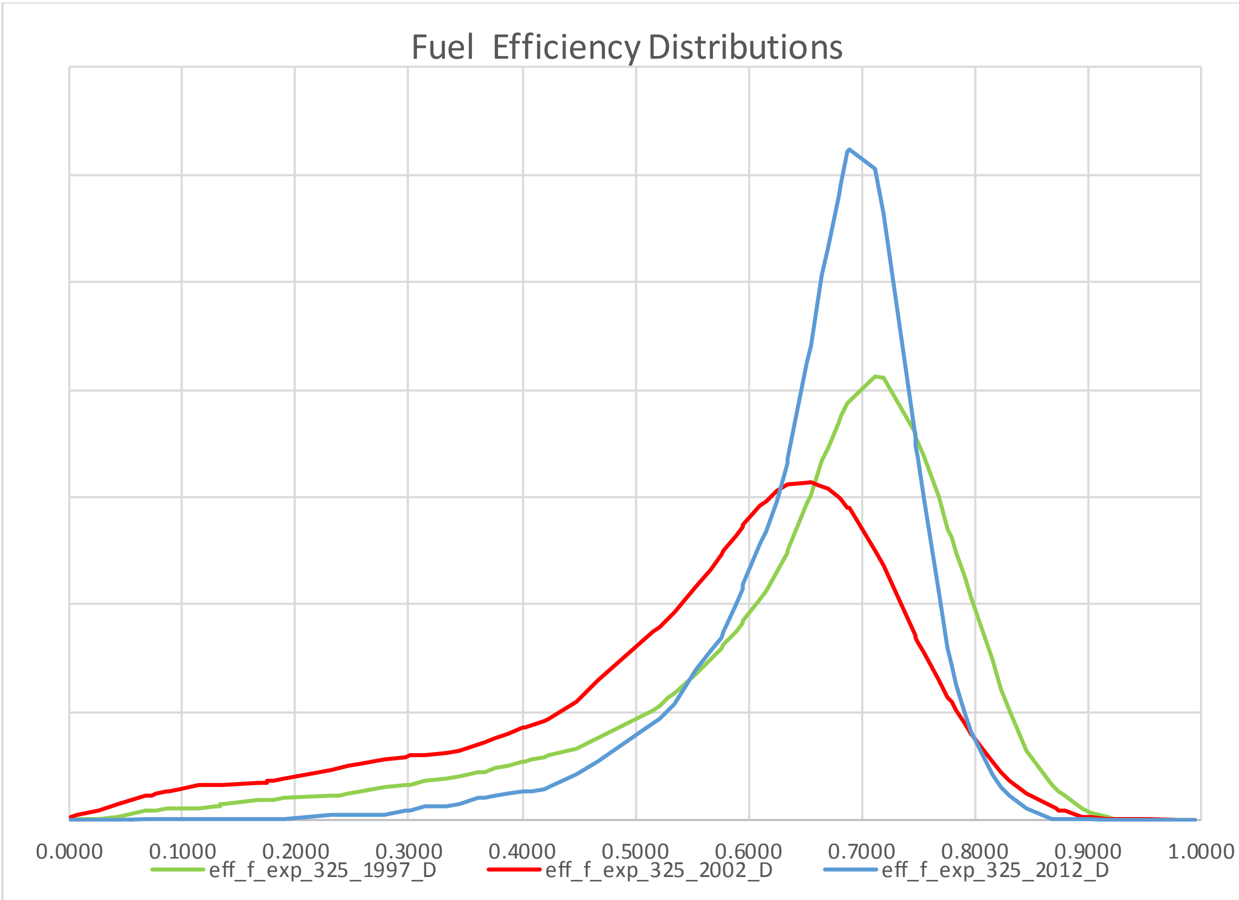

Figure 2 Fuel Efficiency Distribution using the exponential model estimates

References

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.