EMISSION SHADOW PRICE ESTIMATION BASED ON DISTANCE FUNCTION: A CASE OF THE CZECH ENERGY INDUSTRY

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Abstract

The main aims of the paper are to estimate shadow prices of classical airborne pollutants in the Czech energy sector and to analyze the main drivers of Marginal abatement cost development. We describe the theoretical concept of Input Distance Function based on Shephard (1970) theory of duality. We explain also the shadow pricing model that derives the shadow price from estimated Input Distance Function. Employing parameterized Input Distance Function, we estimate the shadow prices of SO_2, NO_x, PM, CO and VOC on firm level data from 9 firms producing heat and electricity over the period 2002-2007. The medians of our shadow prices estimates are 8374, 1198, 2805, 6051 and 8549 € per ton of PM, SO_2, NO_x, CO and VOC, respectively. We decompose shadow prices estimates and test the hypotheses that the marginal abatement cost decline over time; that marginal abatement cost rice with the declining emission level; and that marginal abatement cost rice with declining emission rate.

Key words: shadow prices, distance function, undesirable outputs, marginal abatement cost

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Introduction

Firms produce desirable outputs by using set of inputs and as by-products the firms can also produce undesirable outputs such as emissions of pollutants. The main aim of this paper is to estimate the shadow prices of classical air pollutants in the Czech energy sector. For the estimation, we employ the IDF in quadratic form. We will also try to decompose the emission shadow prices and analyze the factors that might affect them, such as emission level or emission concentrations. We will test the hypotheses that the marginal abatement costs (MACs) decline over time in our relative short period of six years; that MACs rice with the declining emission level; and that MACs rice with declining emission rate.

The original studies discussing the effects of undesirable outputs production have focused on the proper measurement of performance of firms producing the undesirable outputs. Pittman (1983) shows how to adjust the productivity indexes. He derives the shadow prices from survey data on abatement expenditures by producers and uses the data to the construction of an enhanced index of productivity factors. Färe R. , Grosskopf, Lovell, & Pasurka (1989) apply the linear programming approach, which allows that the technology can reflect the scarcity of freely disposable, undesirable outcomes which is regulated. By this, they don't have to estimate the prices of the undesirable outputs explicitly.

The studies following Pitman (1983) and Färe et al. (1989) findings focus already on other approach and aim. Since the nineties, the studies estimate the emission shadow prices rather based on the duality theories. Such shadow prices estimates consider not only the partial information about cost, but also the whole firm's behavior and the technology characterization. The shadow prices are estimated together with the estimation of producing technology and efficiency rate, which are specific for each firm taken into account. The main idea of this method is the estimation of distance function and thereafter the incorporation of Shephard (1970) duality theories. The input distance function (IDF) defines any technology and it is dual to the more familiar cost function. From incorporating of duality theories info the *IDF*, we obtain the revenue deflated shadow prices of all outputs. As Färe R. , Grosskopf, Lowell, & Yaisawarng (1993, p. 374) write: „*Throught the assumption that the observed price of one desirable output equals its shadow price, we may calculte shadow revenue and hence also absolute (undeflated) shadow prices of all other outputs. The absolute shadow prices of the undesirable outputs reflect the opportunity cost, in the terms of forgone revenue, of an incremental decrease in the ability to freely dispose of them.*" This means that we can interpret the shadow price as marginal abatement cost (MAC) and we will do so. Färe et al. (1993) inlustrate that this method can be used also in cases if firms face regulation of undesirable outputs and some outputs are non-marketable.

The paper is organized in the following manner. Section 1 provides the theoretical background to the shadow price estimation from IDF. Section 2 specifies the empirical model, describes the dataset and shows the empirical results. Section 3 goes over the MAC decomposition. Section 4 provides summary of results and concludes.

1. The theoretical model

We will follow Hailu & Veeman (2000) and Färe, Grosskopf, & Margaristis (2008) and define the technological set and the IDF.[1] Consider a technology that produces a vector of good outputs $y \in R_+^M$ and a vector of bad outputs $b \in R_+^B$ with a vector of inputs $x \in R_+^N$ Denoting *T* =[(x,y,b) : x can produce (y,b)] as the technology set, we define the IDF, which measures the maximum amount by which all of inputs can be proportionally reduce while maintaining the level of output. We can rewrite the technology set equivalenty via the output possibilities set, given by *P(x)* =[(y,b) : (x,y,b) $\in$ T] .

We define the IDF as follows:

$$\mathrm{ID(x, y,b)} = \sup[\lambda : (\mathrm{x}/\lambda, \mathrm{y,b}) \in \mathrm{P(x)}, \lambda \in R_+] , \qquad (1)$$

Table 1 shows the basic properties of the production technology and the IDF.

Table 1 Production technology and IDF's properties

Technology	Null-Jointness: if (y,b)∈P(x) and b=0, then y=0.	
	Free dispossibility of inputs: if $x' \geq x$ then $P(x') \supseteq P(x)$	
	Weak dispossibility of an output vector: (y,b)∈P(x) and 0≤θ≤1 imply (θy,θb)∈P(x)	
	Free disposability of good outputs: (y,b)∈P(x) and (y^0,b)≤(y,b) imply (y^0,b)∈P(x)	
IDF	Representation	$\mathrm{ID(x, y,b)} \geq 1$
	Monotonicity	$\partial \mathrm{ID(x, y,b)}/\partial \mathrm{x} \geq 0$
		$\partial \mathrm{ID(x, y,b)}/\partial y \leq 0$
		$\partial \mathrm{ID(x, y,b)}/\partial b \geq 0$
	Input homogeneity of degree +1	$\mathrm{ID}(\lambda \mathrm{x, y,b}) = \lambda ID(x,y,b), \lambda > 0$

Source: Färe, Grosskopf, & Margaristis (2008)

The technically efficient production is achieved if the *IDF* has a value of one. In other words, if the value of the function is bigger than one, the firm uses more inputs than it is optional to the given outputs. From the definition of the *IDF*, the degree of technical efficiency is defined as

$$TE = \frac{1}{ID(x, y, b)} . \qquad (2)$$

Thus, (1-TE) measures the proportion by which costs could be reduced by improving technical efficiency to optimum, without reducing output.

[1] For our purposes, we modify the notation slightly and we will distinguish the good output (*y*) and bad output (*b*).

1.1. The shadow-pricing model

Hailu & Veeman (2000) derive the output shadow prices from the *IDF* under the assumption of cost minimizing. The cost function is the solution to the minimization problem:

$$C(y,b,w) = \mathrm{Min}_x [w * x : ID(x,z,b) \geq 1, x \in R_+^N], \tag{3}$$

where $w \in \Re_+^N$ is the input price vector. Equation (3) is the duality between the cost and the *input distace function* due to Shephard (1970). We again apply the envelope theorem on the first order condition and the optimization problem in (3) yields output shadow price formulas:

$$\nabla_y C(y,b,w) = -C(y,b,w) * \nabla_y ID(x,y,b) \tag{4}$$

$$\nabla_b C(y,b,w) = -C(y,b,w) * \nabla_b ID(x,y,b) \tag{5}$$

The equations (4) and (5) are obtained from the first order condition for the solutions to (3) and from the fact that the Lagrangian multiplier ($\Lambda(y,b,w)$) is eaqual to the value of the optimized cost function in this case.

"*If we do not have input prices and cannot accurately estimate the cost of production, we can use the foolowing formula derived from"* (Hailu & Veeman, 2000, p. 260) (4) and (5) to calculate the absolute shadow price of output b in (6). We employ here the assumption that at least one of the good outputs (y_m) is sold on perfectly competitive market. This allows us to take the observed price (p_m) of such good output to be its absolute shadow price.

$$r_b = \left(\frac{\frac{\partial ID(x,y,b)}{\partial b_b}}{\frac{\partial ID(x,y,b)}{\partial y_m}} \right) * p_m, \qquad b=1,\ldots, B \tag{6}$$

2. The empirical model

Following Färe R. , Grosskopf, Noh, & Weber (2005) and Vardanyan & Noh (2006), we look for a function satisfying the translation property and that could provide a second-order approximation to a true, but unknown function. The quadratic IDF satisfies such condition:

$$\begin{aligned} &ID_{kt}(x_{kt}, y_{kt}, b_{kt}) = \\ &\alpha_0 + \sum_{n=1}^{N} \alpha_n x_{nkt} + \sum_{m=1}^{M} \beta_m y_{mkt} + \sum_{n=1}^{N} \gamma_b b_{bkt} + 1/2 \sum_{n=1}^{N} \sum_{n'=1}^{N} \alpha_{nn'} x_{nkt} x_{n'kt} \\ &+ 1/2 \sum_{m=1}^{M} \sum_{m'=1}^{M} \beta_{mm'} y_{mkt} y_{m'kt} + 1/2 \sum_{b=1}^{B} \sum_{b'=1}^{B} \gamma_{bb'} b_{bkt} b_{b'kt} \\ &+ \sum_{n=1}^{N} \sum_{m=1}^{M} \delta_{nm} x_{nkt} y_{mkt} + \sum_{n=1}^{N} \sum_{b=1}^{B} \eta_{nb} x_{nkt} b_{bkt} + \sum_{m=1}^{M} \sum_{b=1}^{B} \mu_{mb} y_{mkt} b_{bkt} \end{aligned} \tag{7}$$

We estimate the parameters of this function by minimizing the total distance between individual observations in the sample and the estimate of the optimal input set frontier solving the following linear programming problem:

$$\mathrm{Min}\sum_{k=1}^{K}\sum_{t=1}^{T}\left[ID_{kt}(x_{kt}, y_{kt}, b_{kt})-1\right]$$

s.t.

$$\begin{array}{llll}
\text{(i)} & \mathrm{ID}_{\mathrm{kt}}(x_{kt}, y_{kt}, b_{kt}) \geq 1 & \text{k=1,..., K t=1,...,T,} & \\
\text{(ii)} & \mathrm{ID}_{\mathrm{kt}}(x_{kt}, y_{kt}, b_{kt}) < 1 & \text{k=1,..., K t=1,...,T,} & \\
\text{(iii)} & \dfrac{\partial \mathrm{ID}_{\mathrm{kt}}(x_{kt}, y_{kt}, b_{kt})}{\partial y_m} \leq 0 & \text{k=1,..., K t=1,...,T m=1,..., M,} & \\
\text{(iv)} & \dfrac{\partial \mathrm{ID}_{\mathrm{kt}}(x_{kt}, y_{kt}, b_{kt})}{\partial b_b} \geq 0 & \text{k=1,..., K t=1,...,T b=1,..., B,} & (8) \\
\text{(v)} & \dfrac{\partial \mathrm{ID}_{\mathrm{kt}}(x_{kt}, y_{kt}, b_{kt})}{\partial x_n} \geq 0 & \text{k=1,..., K t=1,...,T n=1,..., N,} & \\
\text{(vi)} & \sum_{n=1}^{N}\alpha_n = 1 & & \\
 & \sum_{n=1}^{N}\alpha_{nn'} = 0 & \text{n'=1,..., N,} & \\
 & \sum_{n=1}^{N}\delta_{nm} = 0 & \text{m=1,..., M,} & \\
 & \sum_{n=1}^{N}\eta_{nb} = 0 & \text{b=1,..., B,} & \\
\text{(vii)} & \alpha_{nn'} = \alpha_{n'n}, n \neq n'; \beta_{mm'} = \beta_{m'm}, m \neq m'; \gamma_{bb'} = \gamma_{b'b}. & &
\end{array}$$

Where k and t are indexes of producer and year, respectively;k=1,…,K, t=1,…, T, K is number of producers and M is number of years. N, M and B are numbers of inputs, good and bad outputs, respectively. The restrictions in (8) are implemented in a way that satisfies all of the IDF properties in Table 1.

2.1. The data

The IDF is estimated using data on the Czech energy industry over the period 2002-2007. Our model has two good outputs (electricity and heat), five bad outputs (SO_2, PM, NOx, CO and VOC) and three types of production inputs, including total assets as capital input, number of employees and fuels consumption, i.e. M=2, B=5 and N=3. We have aggregated the fuels consumption from the single types of fuel into one aggregated fuel consumption. However, we still keep the information about the fuel types combusted in each firm. Our model contains nine firms producing electricity and heat with a total of 53 observations (due to one missing observation).

We collected the annual electricity (MWh) and heat (GJ) production of each generating firms in the sample from the Energy Regulatory Office year statistics.[2] The data about total assets and the number of employees are gathered by Creditinfo Czech Republic, s.r.o. Fuels consumptions (GJ) and emission data (tons) are gathered by the Czech Hydrometeorological Institute in the REZZO database[3]. Fuel consumptions and emission data are available even on generating unit level but the numbers of employees and information about total assets are available only on firm level data. Therefore we aggregate the fuel consumptions and emission data also on firm level. The power electricity price is obtained as a weighted average of daily market averages from the OTE's annual reports. In 2002 the electricity started to be traded on marked in the Czech Republic and since this year OTE has been reporting the electricity price.[4] Since the electricity price is created on the market, we assume that it is common for all firms. The capital input (in thousand CZK) and electricity price (CZK/MWh) are both deflated by the OECD consumer price index (2005=100).[5]

The IDF is sensitive to fuel mix and it is appropriate to estimate the IDF for a group of firm with approximately the same fuel mix. Therefore we split our dataset into two samples of data according the coal consumption. Sample A includes firms combusting hard coal and other fuels – there are 18 observations from 3 firms. Sample B includes firms, where brown coal is the main fuel and no hard coal is combusted – there are 35 observations from 6 firms. The summary statistics of the samples are compiled in Table 2.

Table 2 Dataset descriptive statistics - Sample A and B

	Sample A				Sample			
	Mean	Std. Dev.	Min	Max	Mean	Std.	Min	Max
Capital(mil.CZK)	92200	121000	8267	296000	2369	2550	247	8677
Labor	3095	2690	752	7677	259	126	84	444
Fuels (TJ)	142000	168000	8199	407000	7823	9523	703	28000
Electricity (TWh)	21000	28900	149	65400	483	719	12	2074

[2] Energy Regulatory Office (ERO) provides statistics about yearly electricity and heat production on its web pages http://www.eru.cz/dias-browse_articles.php?parentId=131&deep=off&type and http://www.eru.cz/dias-browse_articles.php?parentId=136&deep=off&type, respectively.

[3] REZZO - Register of Emissions and Air Polluters - is reporting system operated by the Czech Hydrometeorological Institute in accordance with Act No. 86/2002 Coll., Clean Air Act.

[4] In accordance with Act No. 458/2000 Coll., the electricity market in the Czech Republic was opened as of January 1, 2002. Before this date, the electricity prices were fully regulated and the price of power electricity was not available because the Czech Statistical Office reports only the final electricity price including the transmission costs. This is the main reason why our time series begins in year 2002 and not earlier.

[5] For the conversion between CZK 2005 and € 2005, the exchange rate 29.78 CZK/€ is used.

Heat (TJ)	11600	5556	348	21600	2536	2123	307	6090
PM (t)	1078	1323	17	3010	59.5	69.7	1.4	279.1
SO2 (t)	25233	26061	897	65621	2521.2	2515.8	340.7	10110.6
nox (t)	23835	27976	800	66075	1058.8	1262.3	64.5	4616.4
co (t)	1615	1748	56	4577	163.1	214.4	9.0	828.0
voc (t)	1498	1942	29	4585	83.1	98.0	0.5	319.7

Source: dataset

2.2. Empirical results

The IDF is estimated for each sample of data separately. 80 parameters are needed to be estimated in each sample. The parameter estimation for the IDF is carried out by minimizing the sum of deviation from unity – as described in (8) – subject to 223 and 410 constrains for sample A and B, respectively.

The estimated value of the IDF is very close to one in most cases, which implies very high technical efficiency. This could be partly caused by the relative small size of the data samples, but on the other hand we can find very similar results also in the literature (e.g. Hailu & Veeman (2000)). The firm averages of the IDF value together with emission rates (ER) for each pollutant are displayed in Table 3.

Table 3 Firm averages of IDF values and Emission Rates

Firm	Value of	ER PM	ER SO_2	ER NO_x	ER CO	ER VOC
1	1.058503	7.8	161.4	166.6	10.7	11.2
2	1.000039	7.1	264.0	131.6	21.3	10.1
3	1.000041	11.6	373.3	154.0	20.4	10.1
4	1.007060	6.7	322.1	194.6	17.8	6.9
5	1.004077	5.0	130.8	97.3	8.7	3.3
6	1.000040	7.2	386.9	132.5	12.4	12.1
7	1.000043	7.4	498.9	163.0	15.3	15.6
8	1.000043	5.1	656.3	124.5	49.9	13.4
9	1.000043	5.1	656.3	124.5	49.9	13.4

Source: own calculations

The emission shadow prices are derived from the IDF as described in (6). The shadow prices are in term of forgone output (electricity) and therefore are in negative terms. For better convenience, we present the result already as MAC in positive terms. The overall emission-weighted average (WA) of MACs is 5223, 1726, 2450, 4946 and 5921 € per ton of PM, SO_2, NO_x, CO and VOC with standard deviation 54150, 3274, 6704, 24502 and 25595, respectively. For comparison with other MAC estimations for the Czech Republic we use the median of the MACs, because neither Salnykov & Zelenyuk (2006) nor the estimates from GEM-E3 and GAINS model provide emission-weighted averages of MACs. The medians of our MACs are 8374, 1198, 2805, 6051 and 8549 € per ton of PM, SO_2, NO_x, CO and VOC, respectively. The estimated MACs vary across firms and also over. For sample A, the medians of MACs are 6256, 1491, 2210, 3092 and 10548 per ton of PM, SO_2, NO_x, CO and VOC, respectively. For sample B, the medians of MACs are 8670, 847, 3293, 7005 and 7398 per ton of PM, SO_2, NO_x, CO and VOC, respectively. Table 4 provides the summary statistics of the results.

Table 4 Summary statistics of MAC (€2005/t)

	PM	**SO_2**	**NO_x**	**CO**	**VOC**
WA	5223	1726	2450	4946	5921
Mean	26857	2087	5312	16014	18715
Median	8374	1198	2805	6051	8549
S.d.	54150	3274	6704	24502	25595
Min	36	80	4	10	42
Max	240764	20886	36903	122657	116223

Source: own calculation

3. Decomposition of MACs

In order to analyze the factors that might affect the MACs of pollution, we will test the hypotheses that the MACs decline over time; that MACs rice with declining emission level; and that MACs rice with declining emission rate. We run following five Fixed-effects models with robust standard errors for all pollutants (9 – 13)[6], where ER is Emission Rate and EL is Emission level[7]. We use the robust standard errors because of heterogeneity of the data. We have only 53 observations in our panel dataset – 9 firms over 6 years. Not all models fit the data properly and not all are significant.

Model 1 $\ln MAC_{it} = \alpha + \beta \ln ER_{it} + \delta \ln year_{it} + \mu_i + v_t$

Model 2 $\ln MAC_{it} = \alpha + \beta \ln ER_{it} + \mu_i + v_t$

Model 3 $\ln MAC_{it} = \alpha + \beta \ln EL_{it} + \delta \ln year_{it} + \mu_i + v_t$

Model 4 $\ln MAC_{it} = \alpha + \beta \ln EL_{it} + \mu_i + v_t$

Model 5 $\ln MAC_{it} = \alpha + \delta \ln year_{it} + \mu_i + v_t$

Table 5 provides results all the models for all pollutants. The asterisk in the right marks which of the pair of Model 1 and 2 or the pair of Model 3 and 4 is better based on the Log-likelihood, Schwarz, Akaike and Hannan-Quinn criteria.

Generally, all coefficients by $\ln ER_{it}$ are negative for all pollutants with exception of VOC, which is in accordance with the theory that MACs rice with declining emission rate.

[6] Due to high multicollinearity we don't report the model that includes both $lnER_{it}$ and $lnEL_{it}$.
[7] Emission Rate is defined as ton of pollutants per input (ton/PJ). Emission level means the absolute amount of emission produced by the firm.

Unfortunately, the results are significant only for NO_x and CO. By VOC, the β and γ are negative in model with time term (Models 1and 3) and positive in models without the time term (Models 2 and 4), but in all cases the coefficient are very close to zero and insignificant. The coefficients by $\ln EL_{it}$ are negative for all other pollutants with exception of SO_2. This also confirms the hypothesis that MACs rice with the declining emission level. But again, the results are significant only for NO_x and CO. The hypothesis that MACs decline over time, has the least support in the data. In the Model 5, the coefficients by time are positive by all pollutants with exception of VOC, they are significant for SO_2 and significant at 10% significance level. In other models, where time is included, the time coefficients are also positive with exception of Model 3 by PM and VOC models. These econometric models are not ideal. There is a problem of non-normality of residuals in all models and tests for differing group intercepts confirm the heterogeneity of the data which lead to different intercepts among the firms.

Table 5 Results with significant results

	Model	α		β		γ		δ		
PM	1	-84.8906	(2110.35)	-0.92889	(0.601855)	-		12.5185	(277.557)	
	2	10.299	(1.15257)	-0.93409	(0.608989)	-		-		*
	3	63.2481	(2162.19)	-		-0.83351	(0.608987)	-6.74556	(284.354)	
	4	11.945	(2.53854)	-		-0.82967	(0.616949)	-		*
	5	-681.512	(2198.89)	-		-		90.7579	(289.208)	
SO2	1	-2896.08	(1122.75)	-0.73469	(0.711176)	-		382.39	(147.356)	
	2	10.1031	(5.43116)	-0.53024	(0.942093)	-		-		*
	3	-2825.71	(1285.43)	-		0.27623	(0.532863)	372.287	(168.955)	*
	4	5.90042	(6.82548)	-		0.14346	(0.854566)	-		
	5	-2794.5	(1271.92)	-		-		368.473	(167.29)	
NOx	1	-1186.64	(1111.11)	-3.27965	(1.17058)	-		159.255	(145.861)	
	2	25.2681	(6.11488)	-3.49655	(1.23328)	-		-		
	3	-240.35	(1267.34)	-		-3.53826	(1.05396)	35.9967	(165.895)	
	4	33.9638	(8.10376)	-		-3.62553	(1.12842)	-		*
	5	-1914.5	(1206.37)	-1.10489	(1.43257)	-		252.847	(158.667)	
CO	1	-3585.5	(965.251)	-2.15888	(0.909945)	-		473.54	(127.016)	*
	2	14.7397	(3.13291)	-2.10811	(1.08498)	-		-		
	3	-3039.05	(1099.22)	-		-2.18128	(0.903957)	402.314	(144.494)	
	4	20.3564	(5.51889)	-		-2.29057	(1.0801)	-		
	5	-3436.76	(1429.61)	-				453.157	(188.029)	
VOC	1	3803.31	(2544.14)	-0.05324	(0.105309)	-		-499.06	(334.595)	*
	2	8.654	(0.149037	0.060848	(0.0720876	-		-		
	3	3846.31	(2589.66)	-		-0.07836	(0.145008)	-504.687	(340.542)	*
	4	8.5182	(0.439375	-		0.060985	(0.10243)	-		
	5	3753.89	(2475.46)	-		-		-492.575	(325.584)	

Source: own calculation; (Standard errors in parentheses)

4. Conclusions

We have applied the IDF in quadratic form on firm level data over the period 2002-2007. We have found that the distance function is sensitive also to structure of fuelmix. Most studies apply the distance function either on homogeneous firm level data (e.g. coal power plants) or on aggregated data (sectoral or country level). We have relative heterogeneous firm level data and therefore we have split our dataset into two samples according to fuelmix structure. The overall medians of our MACs are 8374, 1198, 2805, 6051 and 8549 € per ton of PM, SO_2, NO_x, CO and VOC, respectively. Our estimates are lower than the estimates for the Czech Republic at values of 5485 and 57805 € per ton of SO_x and NO_x in Salnykov & Zelenyuk (2006), respectively, but are higher than the estimates from the GEM-E3 model – 7764, 785, 1520 and 0 € per ton of PM, SO_2, NO_x and VOC in scenario S-CE (Pye, Holland, Van Regemorter, Wagner, & Watkiss, 2008). Our estimates are also within the range from the GAINS model estimates for the Czech Republic.

We cannot reject the hypotheses that MACs rice with declining emission level and that MACs rice with declining emission rate at least by NO_x and CO. By other pollutants the results also support the hypotheses but are no significant. The emission level and emission rate are correlated, therefore we cannot say if the MACs really decline also due to increasing the level of emission produced by the firm or if the MACs decline only due to increasing emission rates. The hypothesis that the MACs decline over time, we cannot confirm, because it has no support in the data. On the contrary, most results (although only insignificant) indicate that the MACs rice over time. We have short time series to make some conclusions about time trend of MACs, but the increasing MACs in time would be in accordance with Bauman, Lee, & Seely (2008) findings that production process innovations can increase MACs.

There are two ways for further research. Either to employ the IDF on aggregated – sectoral level data. This should allow working with longer time series, because the GDP could be a proxy for the desirable output and the problem with availability of market electricity price only since 2002 will fall away. Or the second – and more challenging – way is to acquire the unit level data about employees and capital and employ the IDF these data. This would bring another view on the MACs according the plant size and combusted fuel.

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