Shadow prices of air pollutants in Czech industries: A convex nonparametric least squares approach

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Abstract
The paper estimates the shadow prices of SO_2 emissions for 36 Czech industry sectors during the period 2000-2008. A convex nonparametric least squares quadratic optimization formulated by Mekaroonreung & Johnson (2012) is applied to measure technical efficiency and to jointly estimate the shadow prices of SO_2 emissions. The weighted average shadow price ranges between 360€ and 1,316€ per ton of SO_2 and it declines over time. These values are in line with other estimates of SO_2 shadow price and marginal abatement cost estimated for the Czech Republic. Since the estimated shadow prices of emissions can be interpreted as marginal abatement cost, the ExternE method is applied to compare them with the marginal environmental external costs that are attributable to SO_2 emissions released by the industry sector. We conclude that current regulation is far from the economic optimum, since the estimated SO_2 shadow prices are much lower than corresponding marginal damage costs: in some sectors the shadow prices are even one order of magnitude smaller than the external costs. Since current market-based instruments have internalised the external costs only partly, these instruments have been ineffective and economically sub-optimal.

Keywords: Shadow price; abatement cost; externality; nonparametric regression; SO_2
JEL Code: C14, Q53, Q58

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1 INTRODUCTION

The Czech Republic, with a 28% of GDP represented by industry, belongs among the most industrialized countries in the European Union (Eurostat, 20115). Although the air quality in the Czech Republic has significantly improved as a result of stricter air quality control during the transition period in 1990's and the implementation of environmental *acquis communitaire* of the European Union in the following decade (Ščasný & Máca, 2009), sustainable energy (Olabi, 2014) is far away and further airborne emission reduction (Ščasný et al. 2009) and energy savings are desirable. In reality, however, since the end of 1990's the rate of emission reduction has slowed down significantly (EEA, 2014). The aim of our paper is therefore to identify sectors with the highest economic potential for reduction of sulphurous emissions[1] in the Czech Republic, measured through the shadow price of SO_2 across the industry sectors. We also aim to compare the implicit price of SO_2 emissions with the magnitude of damage caused by these emissions and with the current level of market-based instruments which should internalise these external costs.

We contribute to the literature by estimating shadow prices of SO_2 emissions emitted by 36 industrial sectors in a post-transition European country, the Czech Republic, during the years 2000 to 2008, supplementing our previous study based on ODF method and aimed at the Czech power sector (Rečka & Ščasný, 2011). In this paper, we specifically follow the Mekaroonreung & Johnson (2012) study and apply Convex Nonparametric Least Squares quadratic optimization to analyse technical efficiency jointly with emission shadow price estimation. Then we apply the impact pathway analysis embedded in the ExternE method (Preiss, Friedrich, & Klotz, 2008) to quantify the environmental external costs attributable to SO_2 emissions. Lastly, the shadow prices (i.e. the marginal abatement costs) are compared with corresponding external costs to draw policy-relevant conclusions.

Our findings indicate a significant potential for SO_2 emission reduction in the sectors with high SO_2 emission production. The weighted average of estimated shadow prices is at the value of 834€ per ton of SO_2 and has a decreasing trend from more than 1100€ 2000 to less than 500€ in 2008. The rest of the paper is organized as follows: section 2 describes our method, i.e. the CNLS quadratic optimization problem applied for the inefficiency estimation, and how our approach derives the shadow prices and the external cost. Section 3 describes the data used, and Section 4 presents the results. The final section draws concluding remarks.

2 LITERATURE REVIEW

Färe et al. (1990) provided the first estimates of shadow prices of production factors based on a frontier approach. Färe and Grosskopf (1993) were then the first who applied Shephard's (1970) concept of weak disposability between desirable and undesirable outputs on distance function with the translog functional form in order to estimate the shadow price of four air pollutants released from pulp and paper mills in Michigan and Wisconsin, USA. Since translog or similar functional forms of the distance function are differentiable, this parametric approach was applied in many other studies, mostly in the USA and Asia (e.g. Bauman, Lee, & Seeley, 2008; Coggins & Swinton, 1996; Gupta, 2006; Hailu & Veeman, 2000; Kwon & Yun, 1999; John R. Swinton, 1998) thanks to the fact that functions are differentiable everywhere. On the other hand, if the functional form is misspecified, the parametric approach can yield biased estimates.

[1] Sulphurous emissions are measured as SO_X (mixture of SO_2/SO_3) and are expressed in SO_2 equivalents.

Alternatively, Boyd et al. (1996) used a nonparametric specification of directional distance function to estimate the marginal abatement cost (MAC) of SO_2 on a sample of 62 US power plants. Lee et al. (2002) extended the nonparametric direction distance function approach to control also for the inefficiency in production process. For these purposes, Lee et al. (2002) define an efficiency rule as $\sigma_g = \sigma_g(\lambda), \sigma_b = \sigma_b(\lambda)$, where σ_g and σ_b are called inefficiency factors and λ is a parameter relating σ_g to σ_b. The efficiency rule maps a point $(y, b) \in P(x)$ to corresponding (y^*, b^*) on the boundary $P(x)$ in a way that $\sigma_g(\lambda)y = y^*, \sigma_b(\lambda)b = b^*$, where y, b and x denotes the vectors of desirable outputs, undesirable outputs, and inputs, respectively. Furthermore they defined an efficiency path and iso-efficiency path as follows: $EP(y^*, b^*) = [(y, b) \in P(x): \sigma_g(\lambda)y = y^*, \sigma_b(\lambda)b = b^*$ and $IEP(y_0, b_0) = [(y, b) \in P(x): D\left(x, \sigma_g^0 y, \sigma_b^0 b\right) = 1]$, respectively. Following Kumbhakar et al. (n.d.), they estimate the direction distance function with the elements $\sigma_g y\ and\ \ \sigma_b b$, when the directional vector $g = (b, y)$ is calculated "*by utilizing the annual abatement schedules of pollutants and the production plans of good output as proxy variables for b and y, respectively*" (J.-D. Lee et al., 2002, p. 371). Using this nonparametric approach and controlling for inefficiency, the shadow price of SO_x, NO_x and TSP is estimated for the electric power industry in Korea during the period of 1990-1995 in a sample of 43 power plants. They found the average shadow prices "are approximately 10% lower than those calculated under the assumption of full efficiency"(J.-D. Lee et al., 2002, p. 365). Still this deterministic nonparametric approach cannot capture statistical noise – thus the data must be without error and the production model specified without omitting any inputs or outputs (Mekaroonreung & Johnson, 2012) – and is more sensitive to outliers than parametric methods.

More recent nonparametric approaches, such as Convex Nonparametric Least Squares, (CNLS) as developed by Kuosmanen & Johnson (2008), deal with the two above drawbacks, i.e. sensitivity to outliers and exclusion of statistical inference. Kuosmanen & Kortelainen (2012) introduce a two-stage Stochastic Non-parametric Envelopment method (StoNED) that combines a nonparametric data envelopment analysis with a stochastic frontier analysis to decompose statistical noise and inefficiency. Mekaroonreung & Johnson (2012) extend the StoNED method by applying CNLS quadratic optimization to estimate a frontier production function and the shadow prices for SO_2 and NO_x emitted by US coal power plants.

The studies that estimate the shadow price of emissions can be also differentiated according to level of data disaggregation or environmental domain that is examined. Regarding the former dimension, most of the studies are based on firm level data focusing on an individual sector (e.g. Färe et al., 1993; Färe, Grosskopf, Noh, & Weber, 2005; Mekaroonreung & Johnson 2012; Park & Lim 2009), whereas there are some studies that estimated the shadow price of emissions at country level (e.g. Wu, Chen, & Liou (2013) or Salnykov & Zelenyuk (2004)). To our knowledge, only Peng et al. (2012) have estimated the shadow prices of pollutants using sector-level data. Considering the latter dimension of studies, most of the literature has dealt with airborne pollution and GHG (e.g. Boyd et al., 1996; Färe et al., 2005; John R. Swinton, 1998), while water pollution and other environmental burdens have been analysed less often (e.g. Färe et al., 1993; Hailu & Veeman, 2000; Marklund, 2003).

Chyba! Nenalezen zdroj odkazů. provides a chronological overview of the shadow price estimates for air emissions.

Table 1 Chronological overview of emission shadow price estimates

Study	Model	Function	DATA Country	Data type	# obs.	Period	Sector	Shadow price estimates (€2005/t) CO2	SOx	NOx	PM
Färe et al. (1993)	ODF	translog	US[a]	firm	30	1976	pulp	-	9,956	-	68,075
Boyd et al. (1996)	DDF	nonparametric	US	firm	29	1989	power	-	475	-	-
Coggins & Swinton (1996)	ODF	translog	US[b]	firm	42	1990-92	power	-	357	-	-
John R. Swinton (1998)	ODF	translog	US[c]	firm	123	1990-92	power	-	254	-	-
Kwon & Yun (1999)	ODF	translog	Kor	firm	57	1990-95	power	5.2	426	201	21,211
Hailu & Veeman (2000)	IDF	translog	Can	sector	36	1959-94	pulp	-	-	-	-
J.-D. Lee et al. (2002)	DDF	nonparametric	Korea	firm	258	1990-95	power	-	3,791	21,219	62,334
Swinton (2002)	ODF	transcendental logarithmic	US[d]	firm	63	1990-98	power	-	177	-	-
Marklund (2003)	DDF	quadratic	Swe	firm	86	1983-90	pulp	-	-	-	-
Atkinson & Dorfman (2005)	IDF	Bayesian approach	US	firm		1980, 5, 90, 5	power	-	502[e]	-	-
Färe et al. (2005)	DDF	quadratic / stochastic	US	firm	418	1993&97	power	-	1,506/ 106	-	-
M. Lee (2005)	IDF	translog	US	firm	380	1977-86	power	-	451	-	344 (ash)
Maradan & Vassiliev (2005)	DDF	nonparametric	World	country	76	1985	econ.	2.1 - 9.6	-	-	-
Gupta (2006)	ODF	translog	India	plant		1990-2000	power	67.6; 48			
Salnykov & Zelenyuk (2004)	DDF	translog	PCC[f]	country	96	1995	econ.	115[g]	5,485[g]	57,805[g]	-
Murty, Kumar, & Dhavala (2006)	DDF	quadratic	Ind	firm	480[h]	1997-2004	power	-	51	182	130
Rezek & Campbell (2007)	ODF	Cobb-Douglas/RGME	US	plant	260	1998	power	17	278	883	
Bauman et al. (2008)	ODF	translog	Kor	sector	29	1970-98	power	-	225	-	-
Rečka & Ščasný (2011)	IDF	quadratic	CZE	firm	53	2002-2007	power	-	1,198[i]	2,805[i]	5,223[i]
Mekaroonreung & Johnson (2012)	StoNED		US	Boiler	3024	2000-2008	power		207[j]	763[j]	
This study	StoNED		CZE	sector	324	2000-2008	all	-	878 [i]	-	-

Notes: ODF – output distance function, IDF – input distance function, DDF – directional distance function, StoNED - Stochastic Non-parametric Envelopment method; [a]Michigan & Wisconsin; [b]Wisconsin; [c]Wisconsin, Illinois and Minnesota; [d]Florida; [e] in 1995; [f]Post-Communist countries; [g]estimates for the Czech Republic; [h]monthly data; [i]median; [j]avereages of the original year averages .

3 METHODS

Following Mekaroonreung & Johnson (2012) and Shephard (1970) we define the production possibility set. For each industry $i = 1, \dots, n$ let $x \in R_+^M$ is a vector of inputs, $y \in R_+^S$ is vector of good outputs and $b \in R_+^J$ is a vector of bad outputs. The basic characterization of the polluting production technology is the technology set T of all feasible input-output combination: $T = [(x, y, b) : x \text{ can produce } (y, b)\ ]$. T is convex and there are variable returns to scale.

The production technology satisfies the following assumption, orginaly proposed by Shephard (1970):

1. Free disposibility of inputs:
   if $(x, y, b) \in T$and $\acute{x} \geq x$, then $(\acute{x}, y, b) \in T$.

2. Free disposability of good outputs:
   if $(x, y, b) \in T$ and $y^0 \leq y$ then $(x, y^0, b) \in T$.

3. Weak disposibility between good and bad outputs: if $(x, y, b) \in T$ and $0 \leq \theta \leq 1$ then $(x, \theta y, \theta b) \in T$.

The variable returns to scale weakly disposable production possibility set T can then be rewritted as (Mekaroonreung & Johnson (2012)):

$$T = \left\{ (x, y, b) \in R_+^{M+S+J} | x \geq \sum_{i=1}^{n} (\lambda_i + \mu_i) x_i \,; y \leq \sum_{i=1}^{n} \lambda_i y_i \,;\ b \geq \sum_{i=1}^{n} \lambda_i b_i \,; \sum_{i=1}^{n} (\lambda_i + \mu_i) = 1,\ \ \lambda_i, \mu_i \geq 0 \right\} \quad (1)$$

where λ_i allows the convex combination of observed industries and μ_i allows to scale down both good outputs and bad ouputs while maintaining the level of inputs. Note that the inequality in bad output constrains implies a negative shadow price on additional pollution which satisfies the economic intuition incurring certain costs in production (Mekaroonreung & Johnson, 2012).

We apply the CNLS technique with composite disturbance term considering a single output production function with a multiplicative disturbance term:

$$y_i = f(x_i, b_i) \exp(\epsilon_i) \quad \forall i = 1, \dots, n \quad (2)$$

where $f(x_i, b_i)$ satisfies continuity, monotonicity, concavity and weak disposability; ϵ_i is disturbance term and the bad outputs are treated as independent variables, as in Cropper & Oates (1992).

Applying the log transformation to (2) we obtain (3):

$$\epsilon_i = \ln(y_i) - \ln\big(f(x_i, b_i)\big) \quad (3)$$

Following Mekaroonreung & Johnson (2012) we assume statistical noise in the data and therefore the disturbance term can be written as:

$$\epsilon_i = v_i - u_i \ \ \forall i = 1, \dots, n \quad (4)$$

where v_i is a random noise component.

Because – as Kuosmanen & Kortelainen (2012) point out – the composite disturbance term in (4) violates the Gauss-Markov properties that $E(\epsilon_i) = E(-u_i) = -\mu < 0$, the composite disturbance term is modified and the multiplicative disturbance production model $y_i = f(x_i, b_i)\exp(\epsilon_i)$ is written as in Mekaroonreung & Johnson (2012):

$$\ln(y_i) = \left[\ln\big(f(x_i, b_i)\big) - \mu\right] + [\epsilon_i + \mu] = \ln\big(g(x_i, b_i)\big) + \nu_i \;\; \forall i = 1, \dots, n \tag{5}$$

where $\nu_i = \epsilon_i + \mu$ is the modified composite disturbance term and $E(\nu_i) = E(\epsilon_i + \mu)$=0. The CNLS problem is then defined as follows:

$$\begin{aligned}
&\min_{\alpha,w,c,\nu} \sum_{i=1}^{n} \nu_i^2 \\
&\text{s.t.} \quad \nu_i = \ln(y_i) - \ln(\alpha_i + w_i'x_i - c_i'b_i) && \forall i = 1, \dots, n \\
&\quad \alpha_i + w_i'x_i - c_i'b_i \le \alpha_h + w_h'x_i - c_h'b_i && \forall i, h = 1, \dots, n \\
&\quad \alpha_i + w_i'x_h \ge 0 \;\; \forall i, h = 1, \dots, n \\
&\quad w_i, c_i \ge 0 \qquad \forall i = 1, \dots, n
\end{aligned} \tag{6}$$

where $w_i = (w_{i1}, \dots, w_{iM})$ and $c_i = (c_{i1}, \dots, c_{iJ})$ are marginal products of good output and bad output, respectively.

The technical efficiency and statistical noise components are separated using the estimated modified CNLS residuals $\hat{\nu}_i$ from (6) in the second stage of CNLS. Assuming technical efficiency is independent and identically distributed (i.i.d.) and has a half normal distribution and the statistical noise is i.i.d. and normally distributed, $u_i \sim |N(0, \sigma_u^2)|$ and $\nu_i \sim N(0, \sigma_u^2)$, the method of moments (Aigner, Lovell, & Schmidt, 1977) is applied as in Mekaroonreung & Johnson (2012):

$$\hat{\sigma}_u = \sqrt[3]{\frac{\widehat{M}_3}{\left(\frac{2}{\pi}\right)\left(1 - \frac{4}{\pi}\right)}} \text{ and } \hat{\sigma}_\nu = \sqrt{\widehat{M}_2 - \left(\frac{\pi - 2}{\pi}\right)\hat{\sigma}_u^2} \tag{7}$$

where $\widehat{M}_2 = \frac{1}{n}\sum_{i=1}^{n}\left(\hat{\nu}_i - \hat{E}(\nu_i)\right)^2$ and $\widehat{M}_3 = \sum_{i=1}^{n}\left(\hat{\nu}_i - \hat{E}(\nu_i)\right)^3$.

The average production function $g(x_i, b_i)$ is obtained from the CNLS problem (6) and it is multiplied by the expected technical efficiency to estimate the production function:

$$\begin{aligned}
\ln\big(\hat{g}(x_i, b_i)\big) = \left[\ln\left(\hat{f}(x_i, b_i)\right) - \hat{\mu}\right] = \ln\big(\hat{f}(x_i, b_i) - exp(-\hat{\mu})\big), \text{ thus} \\
\hat{f}(x_i, b_i) = \hat{g}(x_i, b_i)\exp(\hat{\mu})
\end{aligned} \tag{8}$$

where $\hat{\mu} = \hat{\sigma}_u\sqrt{\frac{2}{\pi}}$.

Jondrow et al. (1982) decomposition can be applied to estimate industry specific inefficiency based on $\hat{\sigma}_u$ and $\hat{\sigma}_\nu$:

$$\hat{E}(u_i|\hat{\epsilon}_i) = -\frac{\hat{\epsilon}_i\hat{\sigma}_u{}^2}{\hat{\sigma}_u{}^2 + \hat{\sigma}_\nu{}^2} + \frac{\hat{\sigma}_u{}^2\hat{\sigma}_\nu{}^2}{\hat{\sigma}_u{}^2 + \hat{\sigma}_\nu{}^2}\left[\frac{\phi\big(\hat{\epsilon}_i/\hat{\sigma}_\nu{}^2\big)}{1 - \Phi\big(\hat{\epsilon}_i/\hat{\sigma}_\nu{}^2\big)}\right] \tag{9}$$

where $\hat{\epsilon}_i = \hat{\nu}_i - \hat{\mu}$, ϕ is the standard normal density function and Φ is the standard normal cumulative distribution.

3.1 Shadow Price Of Emissions

Assuming profit-maximizing behaviour for all firms in each industry, the profit maximization problem for a production process with outputs and pollutants (i.e. bad outputs) is the following:

$$\pi(p_y, p_b, p_x) = \max_{y,b,x} p_y' y - p_b' b - p_x' \mathrm{x} \qquad (10)$$

s.t. $(F((x,b,y)) = 0)$

where $p_y = (p_{y_1}, \dots, p_{y_S})$,$p_b = (p_{b_1}, \dots, p_{b_J})$, $p_x = (p_{x_1}, \dots, p_{x_M})$ are the price vectors of outputs, pollutants and inputs, respectively. As in Mekaroonreung & Johnson (2012) $F(x,b,y)$ is the transformation function corresponding to a multi-output production function and since the shadow price of pollutants are our focus, the constrain $F(x,b,y) = 0$ is imposed in order to consider only the production possibility set. Applying the method of Lagrangian multipliers to (7) and following Färe et al. (1993), the relative shadow price of pollutants for industry i are estimated as follows:

$$p_{b_{ij}} = p_{y_i} \frac{\partial f(x_i, b_i)}{\partial b_{ij}} \qquad (11)$$

where $p_{y_i}$is price of and output of industry i. Since we use gross value added as a proxy of the industry's output, $p_{y_i} = 1$. By solving the CNLS problem (6) we estimate first the average weak disposability production function $\hat{g}(x_i, b_i)$ and second we calculate the estimated expected inefficiency components $\hat{\mu}$. The relative shadow price of pollutants for each industry is obtained as $\frac{\partial \hat{g}(x_i,b_i)}{\partial b_{ij}} \exp(\hat{\mu}) = \hat{c}_{ij} \exp(\hat{\mu})$, where the variable $\hat{c}_{ij} \in \hat{c}_i = (\hat{c}_{i1}, \dots, \hat{c}_{iJ})$ results from solving (6).

3.2 Externality

Emissions of air pollutants have adverse impacts on human health, biodiversity, crops, and building materials (Máca, Melichar, & Ščasný, 2012). We quantify these impacts using the ExternE method and the impact pathway analysis in particular (see, for instance, Preiss et al. (2008) or Weinzettel et al. (2012)). The ExternE Impact Pathway Approach consists of four steps: it starts with the emission of a pollutant at the location of the source into the environment. Then the dispersion and chemical transformation of pollutants in the different environmental media are modelled in the second step. Physical impacts, such as new cases of respiratory illness for example, are linked with changes in concentrations in the atmosphere by concentration-response functions. Introducing receptors and population data, the cumulative exposure of the receptors is calculated and total physical impacts are derived. In the last step, the physical impacts are monetised.

The marginal damage cost of SO_2 released in the Czech Republic under the Average Height of Release scenario[2] is estimated at the value of 7,235€ per ton of SO_2 (Preiss et al., 2008). This estimate includes damages associated with adverse impacts not only in the Czech Republic but also across the whole of Europe.

[2] Damage of airborne pollution is significantly influenced by height of stack releasing pollution

4 DATA

Our balance panel includes industry-level NACE tier 2 data for 36 sectors of the Czech economy for the period 2000 to 2008.[3] We use industry specific gross value added (GVA) in constant prices as a proxy for desirable output. Gross stock of fixed assets is expressed in constant prices, labour in full time equivalents of persons (L), and energy (E) in gigajoules constitute inputs, while SO_2 emissions in tons comprise the undesirable output. The whole data set is obtained from the Czech Statistical Office, all monetary values are expressed in Euros c.p. 2000. The GVA was selected as a variable for output because it is not dependent on intermediate inputs and, as a result, we can omit the intermediate inputs from our model and increase the degree of freedom of our CNLS problem.

5 RESULTS

Our results obtained from (11) support our hypothesis that the sectors with low production of SO_2 emission might have higher shadow prices of SO_2 than the sectors with a high volume of SO_2. On average, the highest shadow price of SO_2 – above 4,000€ per ton of SO_2 – is estimated for '*Motor vehicles*', '*Water*', and '*Rubber & Plastics*', while the lowest time-average of SO_2 shadow prices are estimated for '*Chemicals'* (219€) and '*Textile'*, '*Furniture'*, '*Other mining'*, '*Wood', and 'Food',* ranging from 539€ to 686€. In the remaining sectors, the average estimated shadow price of SO_2 varies between 757€ and 2,678€ per ton of SO_2.

In the *Electricity, gas & hot water sector* – which releases the highest volume of SO_2 emission – the average shadow price during the period 2000 to 2008 is 764€, and the shadow price have decreasing trend from more than 1000€ to 327€ in 2008. These results correspond to the previous estimates we obtained by using IDF method (Rečka & Ščasný, 2011); the median of shadow price of SO_2 was estimated at 1,491€ and 847€ for power plants with main fuel other than brown coal and brown coal power plants in the Czech Republic in the period 2002-2007, respectively.

[3] From the original 59 sectors we construct 9 years balanced panel data set. We exclude 23 sectors with negative values of GVA in some years or with negligible levels of SO_2 emissions.

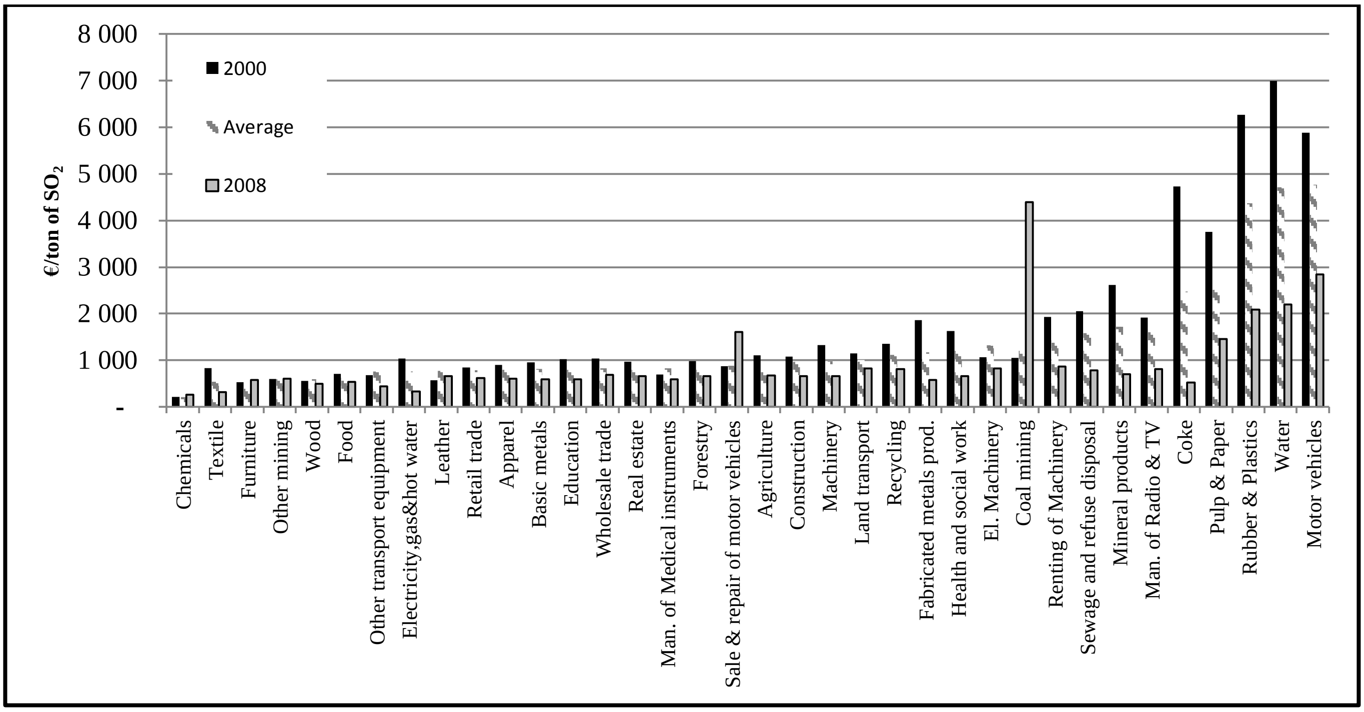

Figure 1 Shadow price of SO_2 emission in Czech industries (2000, 2008 and average)

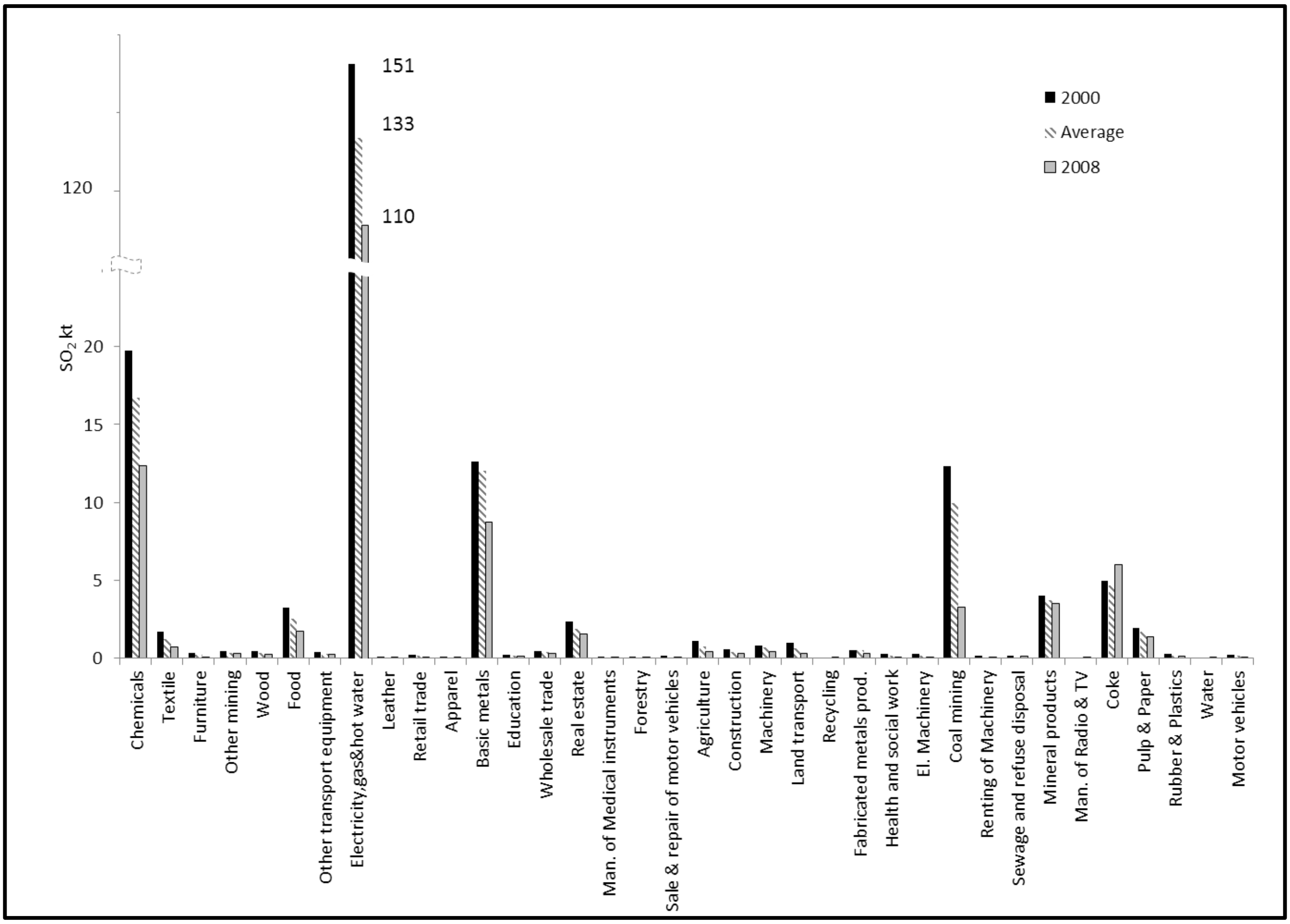

Figure 2. SO_2 emissions in Czech industries (2000, 2008 and average)

Although the shadow price of SO_2 significantly varies across the sectors, the shadow price decreases over time in all of them, except manufacture of *Other transport equipment* and *Retail trade* (Figure 1).

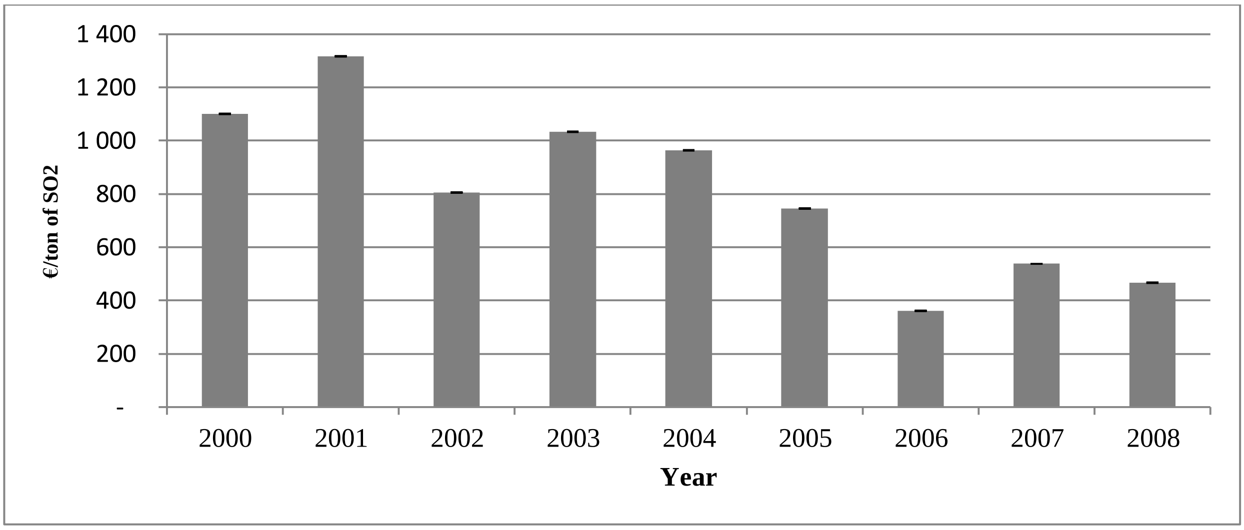

Figure 3. Weighted average of SO_2 shadow price

The average, weighted by industry SO_2 emission, shadow price of SO_2 decreases over time, especially from 2003, starting at above 1,000€ per ton of SO_2 in 2000 and reaching its minimum at 360€ in 2006 (Figure 3).The weighted average of SO_2 shadow price over the whole period is 834€. Our results are in line with the technology specific marginal abatement cost (MAC) as estimated for the Czech Republic by other approaches; for instance, the MACs of ton SO_2 derived from the GAINS database on the costs and technical potential of current and prospected abatement technologies (Ščasný, Pavel, & Rečka, 2008) are in the range of 430 to 4,000 €, and the implicit MACs derived from the computable general equilibrium GEM-E3 model (Pye er al. 2008) are between 545 and 785 € per ton of SO_2.[4]

We also found that the SO_2 shadow prices are in almost all sectors smaller than the magnitude of the external cost associated with SO_2 emissions, that is 7,235€ per each ton. The only three exceptions, '*Rubber & Plastics*','*Water'* and '*Motor vehicles'* sectors, for which we record a higher shadow price for SO_2 than the corresponding external cost in year 2001. However these three sectors release only a negligible amount of SO_2 emissions with very limited potential to reduce them (see Figure 2).

6 CONCLUSIONS

This paper estimates the shadow prices of SO_2 emissions for industrial sectors in the Czech Republic during the post-transition period 2000-2008. We rely on the CNLS quadratic optimization that allows the estimation of shadow prices jointly with analysis of technical efficiency and the capture of possible statistical noise in the data. We find the shadow price ranges between 200€ to 9,000€ per ton of SO_2, and sector averages vary between 219€ and 4,764€, with the mean of 764€ in the most polluting power sector. Our recent results for the power sector estimated by the StoNED method are comparable with

[4] All estimates are in €2005.

our previous estimates of the SO_2 shadow prices that we estimated on the firm-level data from power sector by following the non-parametric method based on the output distance function.

Our findings show a strong decreasing trend in the average magnitude of the shadow prices over time, especially during 2001-2006. We note that the Czech Republic became a full member of the European Union on May 1st, 2004, and from this time Czech firms can freely participate in the European economic market and hence import advanced technologies without paying duties.

We also conclude that current regulation is far from the economic optimum, since in many sectors the estimated SO_2 shadow prices are much lower than the marginal damage cost, that is 7,235€ per ton of SO_2. For example, the average SO_2 shadow prices in the two most emitting sectors – '*Electricity, gas & hot water'* and '*Chemical's* – are 769€, or 219€, respectively.

The magnitude of shadow prices of SO_2 emissions is also very far from the rates of SO_2 emission charges being currently enforced, having its rate below 40€ per ton (Máca et al., 2012). Considering the magnitude of the shadow prices, we also conclude that to date air quality regulation based on market-based instruments in the Czech Republic have been ineffective and economically sub-optimal. As shown by Máca et al. (2012), the level of internalization of the external costs associate with air quality pollutants and attributable to the power sector has remained rather low, up to 55% in the case of coal-fired power plants. As of 2016, a new pricing system for SO_2 discharges will be introduced in the Czech Republic, which proposes a gradual increase in the charge from actual 36 €/ton of SO_2 to 175 €/ ton after 2021. Despite this new regulation, the new level of emission charge rate is at least one order of magnitude lower than our estimate of shadow prices for SO_2 emissions.

Assuming full efficiency in this study – contrary to Lee (2002) – our estimates of shadow prices may be biased slightly upward. We are aware of the fact that the top-down approach, as followed in this analysis, can't fully reveal all aspects of the costs that in reality, all play their role. In particular, additional costs associated with abatement in industrial companies can be involved by other non-environmental regulations, such as requirements on higher safety standards. This analysis merely aims at estimation of the shadow prices of undesirable outputs, such as air emissions, and it cannot serve to examine the effect of all other possible factors on the abatement costs, cost effectiveness or on the emission reduction potential.

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