A Dynamic Analysis of Interfuel Substitution for Swedish Heating Plants*

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January 8, 2001

Abstract

This paper estimates a dynamic model of interfuel substitution for Swedish heating plants. We use the cost share linear logit model developed by Considine and Mount (1984). All estimated own-price elasticities are negative and all cross-price elasticities are positive. The estimated dynamic adjustment rate parameter is small, however increasing with the size of the plant and time, indicating fast adjustments in the fuel mix when changing relative fuel prices. The estimated model is used to illustrate the effects of two different policy changes.

*The authors acknowledge research grants from the Swedish National Energy Administration.

1 Introduction

The ultimate purpose of this paper is to estimate how the choice of fuel mix in the production of heat changes as the relative prices on various fuels changes. To accomplish this we specify and estimate dynamic conditional demand functions for various fuels using a panel-data set that describes the fuel mix for individual Swedish heating plants over the period 1990-1996. The methodology we use follow to a large extent the methodology suggested by Considine and Mount (1984), and Considine (1989a and 1989b, and 1990).[1] The methodology involves the estimation of a dynamic linear logit model where the dynamics implicitly are assumed to evolve from costs of adjustments for the various inputs. This paper differs from earlier studies in that we have a plant level panel data set, and that we allow the adjustment parameter depend on characteristics of the firm and time. Thus we are able to investigate how size and diversification in different combustion technologies affect the rate of dynamic fuel substitution due to price changes. In addition an attempt is made to cope with the problem that not all firms are using all inputs. To accomplish the latter we adopt a dummy variable approach suggested by Battese (1998), which essentially implies that we allow for different technologies depending on what inputs a firm is using.

The background to the empirical problem goes back to the beginning of 1997, when the Swedish government devised a program which objective was to stimulate an increase of the use of biofuels. This program is one part in a scheme which ultimate aim is to make the Swedish energy system "sustainable" in the sense that it should be based on renewable resources. The program includes subsidies to households and large-scale combustion plants, and comes amidst an overhaul of the whole energy taxation system.

[1] For recent applications of this model see e.g. Jones (1995) and Jones (1996).

Thus, given estimates of demand functions for fuels we are in a position to shed light on the possible impact on the choice of fuel mix due to a change in tax policy. The results can be used to shed light on the fuel mix per se, but also to investigate environmental impacts due to policy shifts (see Brännlund and Kriström, 1999), and to investigate how much and how fast different types of plants adjusts to new relative prices.

Traditionally most studies of the choice of fuel mix in energy transformation concerns electricity generation. In fact, we have only found one study, Brännlund and Kriström (1999), that explicitly investigates the economics of fuel choice in heat generation. In Brännlund and Kriström demand elasticities are estimated indirectly through the estimation of a production function, which in a second step is utilized in a cost minimization problem. The resulting elasticities have the expected signs and magnitudes, i..e. own-price elasticities are negative, and cross-price elasticities are positive. Concerning studies of fuel mix in electricity generation there are essentially two lines of research. One line follows an approach that explicitly takes into account the "discreteness" of fuel burning techniques, i.e., that a firm can make use of a few fixed coefficient fuel burning technologies. This line of research can be represented by Joskow and Mischkin (1977), who basically estimates the probability for choosing a specific burning technology, and hence fuel type. The model is a conditional logit model following McFadden (1973). the second line of research can be viewed as a "continuous" approach in that fuel demand is modelled as a continuous variable. A seminal paper in this area is Atkinson and Halvorsen (1976). They specify a translog profit function, and by applying Hotelling's lemma they get estimable demand functions for various fuels. The data they use are regional US data. A problem with their study is that all plants are not using all types of fuels. They circumvent this problem by estimating demand functions "pair-wise". In this paper we try to solve this problem by using the dummy variable approach described above. Since then a large number of studies concerning fuel substitution has been undertaken. Most of them adopt a cost function approach, and except for Kolstad et. al. (1986), and Pindyck (1980), they employ data for electricity generation in the US.[2]

The rest of the paper is structured as follows: In section 2 we outline the theory underlying our empirical model. Data and the choice of empirical model is discussed in section 3. The empirical results are commented upon in section 4, while simulations of two policy changes are presented in section 5. Finally, section 6 offers some concluding remarks and hints for future research in this area.

2 Model

The basic assumption underlying our model is that each heat generating firm is minimizing its costs, subject to a transformation function. The transformation (or production function) is a function describing maximal output for different combinations of input quantities. It is assumed that three different types of inputs are necessary to generate heat; primary energy (fuels), labor, and capital. Furthermore it is assumed that the production function is weakly separable in the different types of inputs. The production function for firm i in period t can thus, in general form, be written as:

$$y_{it} = f(h_{it}(\mathbf{x}), L_{it}, K_{it}), \ i = 1, ..., n, \text{ and } t = 1, ..., T, \tag{1}$$

where $\mathbf{x} = [x_{it1}, ..., x_{itK}]$ is a vector of K fuel inputs, $h_{it}(\mathbf{x})$ is the aggregate input of primary energy, L_{it} and K_{it} is labor and capital input respectively.

[2] Uri (1977), Lutton and LeBlanc (1984), Bopp and Costello (1990).

The assumption of separability implies that the marginal rate of technical substitution between fuel inputs is independent of labor and/or capital input. In addition we will assume that h_{it} is a homothetic function. Given these assumptions it can be shown (see Chambers, 1988) that the corresponding cost function is weakly separable in factor prices and output, i.e. (suppressing time and firm indexes)

$$c(\mathbf{p}, y) = C(g(\mathbf{p}), w, q, y), \tag{2}$$

where $\mathbf{p} = [p_1, ...p_K]$ is a vector of factor prices corresponding to $\mathbf{x}$, w and q are price of labor and capital respectively, and y is output.

The assumption of weak separability and homotheticity allows us to analyze a separate cost function corresponding to the input vector $\mathbf{x}$:

$$c_e = g(\mathbf{p}). \tag{3}$$

The cost function c_e have the usual properties, i.e. it's nondecreasing in $\mathbf{p}$, concave and continuous in $\mathbf{p}$, and homogenous of degree 1 in $\mathbf{p}$. Applying Shepard's lemma gives us the derived demand for the input vector $\mathbf{x}$:

$$x_k(\mathbf{p}) = \frac{\partial g(\mathbf{p})}{\partial w_k}, \; k = 1, ..., K. \tag{4}$$

Due to the properties of the cost function the demand functions in equation (4) are homogenous of degree 0 in $\mathbf{p}$, $x_k \geqslant 0$, the matrix of elements $\partial x_k / \partial w_l$ are negative semidefinite, and $\partial x_k / \partial w_l = \partial x_l / \partial w_k$ (symmetric) for $k \neq l$. Specification of a demand system for the input subvector $\mathbf{x}$ that satisfies these properties will thus be consistent with an underlying cost function which is the dual to a weakly separable homothetic production function. The usual approach in empirical applications is to specify an empirical cost function and derive the system of demand equations by applying Shepard's lemma as above. An often used functional form for the cost function is the translog cost function (Christensen, Jorgensen and Lau, 1975). A potential problem with the translog specification is that it is "well-behaved" for only a limited range of relative prices (see Caves and Christensen, 1980). Outside this specific range regularity conditions such as positive cost shares and negative own-price effects are not satisfied. This may be a particular problem if the model is intended for simulation purposes. A cost function that globally satisfies the regularity conditions is the Cobb-Douglas function. The trade-off for this virtue in the Cobb-Douglas case is that the elasticities of substitution between any pair of inputs equals one. Thus, traditionally the choice of functional form has been viewed as a choice between regularity and flexibility.

From above it should be clear that there are two possible routes to take. The first route is to specify a cost function, apply Shepard's lemma, and estimate the resulting demand functions together with the cost function. The second route is to specify demand functions that fulfill, or at least has the potential to fulfill, the neoclassical foundations. As, for example, Jones (1996), Jones (1995) and Considine and Mount (1984), we will follow the second route by using the linear logit model. The linear logit model has several advantages. One is that it more flexible than the Cobb-Douglas function, at the same time as it fulfill the regularity conditions (given appropriate parameter restrictions). Also, the linear logit model can be specified so that it explicitly captures dynamic effects by including lagged quantities, rather than lagged cost shares as in the case of a dynamic Translog specification. This quantity based adjustment process ensures the Le Chatelier principle, i.e. short run elasticities are always smaller than the long run elasticities. Several studies, see for example Jones (1995) and references therein, has performed a "horse race" between the translog specification and the linear logit model. In most cases the linear logit model outperforms the translog specification, especially when dynamic adjustment processes are introduced.

A static version of the linear logit model can be specified in terms of cost shares as follows (firm index suppressed):

$$S_{kt} = \frac{e^{\upsilon_{kt}}}{\sum_{l=1}^{K} e^{\upsilon_{lt}}}, \tag{5}$$

where

$$\upsilon_{kt} = \eta_k + \sum_{l=1}^{K} \gamma_{kl} \ln p_{lt}, \tag{6}$$

and $k, l = 1, ..., K$ is the index for inputs and K is the number of inputs. From equation (5) it should be clear that the cost shares will always be positive. By imposing the appropriate restrictions on the parameters in equation (6) symmetry and homogeneity will follow.

The model specified in equations (5) and (6) is static, which in this case means that input demand, due to price changes, instantaneously adjusts to long-run equilibrium. To introduce dynamics we will basically assume that there is some kind of adjustment cost that may create differences between short and long-run demand. For example, changing fuel mix may be costly due to technological constraints. Here we will follow Treadway (1974) by simply assuming that $y = f(x, \dot{x})$, where x is a vector of inputs, and $\dot{x}$ is the rate of change in x. As usual we have that $\partial f / \partial x \geq 0$, but in addition we have that $\partial f / \partial \dot{x}$ □ 0, implying adjustment costs. According to Treadway (1971), under certain assumptions about the adjustment process, the optimal path of input x can be written as:

$$\dot{x} = L [x - x^*], \tag{7}$$

where x^* is the long-run stationary equilibrium, and L is a matrix which elements measures the rate of adjustment to long run equilibrium. In general

L is a function of the discount rate and x^*. Assuming that $L_{kl} = 0$ for $k \neq l$ and that $L_{kk} = L$ for all k enables us to write a dynamic version of equation (6) as:

$$\upsilon_{kt} = \eta_k + \sum_{l=1}^{K} \gamma_{kl} \ln p_{lt} + \lambda \ln x_{kt-1}, \tag{8}$$

where λ measures dynamic rate of adjustment (see Considine and Mount, 1984, for a complete derivation).

3 Data and Empirical model

In our application we use a panel data set containing fuel input in Swedish heat generating combustion plants between 1990 and 1996 ($t = 1, ..., 7$) for 252 number of firms ($i = 1, ...252$). All major combustion plants in Sweden are included. The data set includes input values as well as input quantities for each individual fuel. Each observation unit in our data set is a firm that may have several combustion units. That means that an individual firm may use up to 16 different fuel types within a year, which neccesitates aggregation. Here we have aggregated fuels into four major fuel types: (*i*) wood fuel (x_1), (*ii*) non-gaseous fossil fuels (x_2), (*iii*) gaseous fossil fuels (x_3), and (*iv*) "other fuels" (x_4). Wood fuel consists of residues from forest cuttings. Non-gaseous fossil fuel is oil and coal, and gaseous fossil fuel is natural gas and propane. "Other fuels" include, for example, waste, peat, and industrial hot water. Firm specific prices, p_{kit}, for each fuel type are obtained by dividing the input value for each aggregate fuel type by the input quantity. Descriptive statistics for input quantities and input prices are provided in the appendix.

Given the level of aggregation we have a system of four dynamic cost-share equations, derived from equation (5) and (8). Imposing symmetry and homogeneity we can write the system as a stochastic normalized three-equation system, where we have normalized with the 4^{th} ("other fuels") cost share, i.e.,

$$
\begin{aligned}
\ln\left(\frac{S_1}{S_4}\right)_{it} &= \eta_{1i} + B_1^x d_1^x - B_1^S d_1^S \\
&- \left[\gamma_{12} S_2^* + \gamma_{13} S_3^* + \gamma_{14}\left(S_1^* + S_4^*\right)\right] \ln\left(\frac{p_1}{p_4}\right)_{it} \\
&+ \left(\gamma_{12} - \gamma_{24}\right) S_2^* \ln\left(\frac{p_2}{p_4}\right)_{it} + \left(\gamma_{13} - \gamma_{34}\right) S_3^* \ln\left(\frac{p_3}{p_4}\right)_{it} \\
&+ \lambda(\mathbf{z}, t) \ln\left(\frac{x_1}{x_4}\right)_{it-1} + \varphi_1 t + \varepsilon_{it}^1, \qquad (9)
\end{aligned}
$$

$$
\begin{aligned}
\ln\left(\frac{S_2}{S_4}\right)_{it} &= \eta_{2i} + B_2^x d_2^x - B_2^S d_2^S \\
&- \left[\gamma_{12} S_1^* + \gamma_{23} S_3^* + \gamma_{24}\left(S_2^* + S_4^*\right)\right] \ln\left(\frac{p_2}{p_4}\right)_{it} \\
&+ \left(\gamma_{12} - \gamma_{14}\right) S_1^* \ln\left(\frac{p_1}{p_4}\right)_{it} + \left(\gamma_{23} - \gamma_{34}\right) S_3^* \ln\left(\frac{p_3}{p_4}\right)_{it} \\
&+ \lambda(\mathbf{z},t) \ln\left(\frac{x_2}{x_4}\right)_{it-1} + \varphi_2 t + \varepsilon_{it}^2, \qquad (10)
\end{aligned}
$$

$$
\begin{aligned}
\ln\left(\frac{S_3}{S_4}\right)_{it} &= \eta_{3i} + B_3^x d_3^x - B_3^S d_3^S \\
&- \left[\gamma_{13} S_1^* + \gamma_{23} S_2^* + \gamma_{34}\left(S_3^* + S_4^*\right)\right] \ln\left(\frac{p_3}{p_4}\right)_{it} \\
&+ \left(\gamma_{13} - \gamma_{14}\right) S_1^* \ln\left(\frac{p_1}{p_4}\right)_{it} + \left(\gamma_{23} - \gamma_{24}\right) S_2^* \ln\left(\frac{p_2}{p_4}\right)_{it} \\
&+ \lambda(\mathbf{z},t) \ln\left(\frac{x_3}{x_4}\right)_{it-1} + \varphi_3 t + \varepsilon_{it}^3, \qquad (11)
\end{aligned}
$$

The equation system (9)-(11) needs some clarifications. First of all it should be noted that we allow for firm specific effects, represented by η_{ki} in each equation. Moreover, S_1^*, S_2^*, S_3^*, and S_4^* represents a specific set of cost shares for each observation that ensures that the property of symmetry is fulfilled.[3] Local symmetry is imposed by using time invariant means, $\bar{S}_{k,i}$, as specific cost shares, and can therefore easily be implemented when estimating the model. Global symmetry is imposed if the predicted shares, $\hat{S}_{k,it}$, are used in the estimation (Considine, 1990). When imposing global symmetry, parameter estimates are obtained through a two-step iterative estimation method. Below we present estimation results using the latter method. The error terms, ε_{it}^1, ε_{it}^2, and ε_{it}^3, are assumed to have white noise properties.

The parameter $\lambda(\mathbf{z}, t)$ measures rate of dynamic adjustment. Note that this parameter is common to all share equations, and it can be interpreted as the rate of adjustment in total fuel use. Allowing $\lambda(\mathbf{z}, t)$ to vary across equations makes the model much more complicated and probably difficult to estimate at all. However, without obvious complications, we can allow the adjustment parameter to vary across different types of firms. Therefore, the adjustment parameter is allowed to depend upon the vector $\mathbf{z}$, which contains firm characteristics and a time trend. To ensure that the time effect in $\lambda(\mathbf{z}, t)$ does not capture technological progress, we append a linear time trend to all three equations. This deterministic trend term serves as a proxy for efficiency gains or technical change in the Swedish heating sector. The main hypothesis we want to test here is whether the rate of adjustment or flexibility depends on firm size (total fuel use) and/or the number of different fuels used. Concerning the latter we would expect that firms that

[3] For a complete derivation of the restrictions neccessary for symmetri and homogeneity, see Considine and Mount (1984).

currently are using many different fuel types are more flexible, and hence have a smaller $\lambda(\mathbf{z}, t)$. Concerning firm size the effect is less obvious and is thus a purely empirical question. More specifically the unconstrained adjustment parameter is specified as:

$$\lambda(\mathbf{z}, t) = \delta_0 + \sum_{m=2}^{4} \delta_{1m} D_{1mit} + \sum_{n=1}^{4} \delta_{2n} D_{2nit} + \theta t, \tag{12}$$

where D_{1mit} is a set of dummy variables taking the value of one if the i^{th} firm in period t are using m number of fuel inputs, and zero otherwise, D_{2nit} equals one if firm i in period t belongs to "size class" n and equals zero otherwise. We have divided firms into four different size classes based on total fuel use.[4] Also, the adjustment parameter is possibly time dependent. Summary descriptives for dummies on fuel use and firm size are provided in the appendix.

The production of heat is characterized by switching between fuels and different fuel mixes. The estimation of (9)-(11) is complicated by the fact that the variables $\ln(x_k/x_4)_{it-1}$ and $\ln(S_k/S_4)_{it}$, are undefined for many observations, i.e. $x_{k,it-1}$ and/or $S_{k,it}$ are zero due to zero input in production of that particular fuel. One solution to this problem is to use only a subset of the data to estimate the system of share ratios, namely a subset of firms that are using strictly positive amounts of all inputs. A drawback with this approach is that not all information is used, and that the subset of plants may not be representative for the whole sector. In order to utilize the data set efficiently, but also to test the hypothesis implicit in equation (12), we will use an approach similar to the approach suggested by Battese (1998).[5] Each equation in the system is therefore modified to account for zero or undefined values in the variables $(x_k/x_4)_{it-1}$ and $(S_k/S_4)_{it}$. The use of this method

[4] Firms are divided into quartiles (total fuel use).

[5] For an application of this approach, see Brännlund and Kriström (1999).

allows us to use the full data set instead of a smaller subset. The dummy variables d_k^x and d_k^S equals one when $(x_k/x_4)_{it-1}$ and $(S_k/S_4)_{it}$ are undefined, and zero otherwise. If d_k^x and d_k^S equals one, then $(x_k/x_4)_{it-1}$ and $(S_k/S_4)_{it}$ are substituted with ones so that $\ln{(x_k/x_4)_{it-1}}$ and $\ln{(S_k/S_4)_{it}}$ equals zero.

Measured at sample means, $\overline{S}_k$, the short-run demand elasticities are calculated as:

$$E_{kk}^S = (\gamma_{kk} + 1)\,\overline{S}_k - 1, \tag{13}$$

and

$$E_{kl}^S = (\gamma_{kl} + 1)\,\overline{S}_l, \text{ when } k \neq l, \tag{14}$$

where γ_{kk} is

$$\begin{aligned}
\gamma_{11} &= -\frac{\left(\gamma_{12}\overline{S}_2 + \gamma_{13}\overline{S}_3 + \gamma_{14}\overline{S}_4\right)}{\overline{S}_1}, \\
\gamma_{22} &= -\frac{\left(\gamma_{12}\overline{S}_1 + \gamma_{23}\overline{S}_3 + \gamma_{24}\overline{S}_4\right)}{\overline{S}_2}, \\
\gamma_{33} &= -\frac{\left(\gamma_{13}\overline{S}_1 + \gamma_{23}\overline{S}_2 + \gamma_{34}\overline{S}_4\right)}{\overline{S}_3}, \\
\gamma_{44} &= -\frac{\left(\gamma_{14}\overline{S}_1 + \gamma_{24}\overline{S}_2 + \gamma_{34}\overline{S}_3\right)}{\overline{S}_4}.
\end{aligned}$$

The corresponding long-run demand elasticities are given by

$$E_{kl}^R = \frac{E_{kl}^S}{1 - \lambda(\mathbf{z}, t)}, \text{ for all } k, l. \tag{15}$$

From (15) it is clear that the value of the parameter $\lambda(\mathbf{z}, t)$ should be bounded between 0 and 1. If $\lambda(\mathbf{z}, t)$ is close to zero the adjustment process is fast, and slow if $\lambda(\mathbf{z}, t)$ is close to one. For details on the derivation of the elasticities see Considine and Mount (1984).

4 Results

The specification in equations (9) - (11) provides several natural specification tests. In our model specification the unrestricted model is the one that includes fixed effects, and all three sets of dummy variables. Thus, our first test is to decide whether fixed effects should be included or not. Conditional on the outcome of this test we will proceed with all other specification test. The final model specification is selected according to the following likelihood ratio test scheme:

1. Test no fixed effects against fixed effects. Unrestricted model includes fixed effects, Battese dummies, firm characteristics dummies, and the potential time effect (in $\lambda(\mathbf{z}, t)$).

2. Test if restrictions imposed by setting Battese dummies to zero are valid. Unrestricted model is determined in step 1.

3. Using the specification determined by step 1 and 2 we here test if the adjustment rate parameter is constant with respect to firm characteristics and time. Unrestricted model is determined in step 2.

4. If the test in step 3 can be rejected, we test if setting the parameters associated with the "number of fuels"-dummies to zero is a valid restriction. Unrestricted model is given by step 3.

5. Finally, we test if setting the "size class"-dummy parameters to zero is a valid restriction. Unrestricted model determined in step 4.

The time effect is tested with a simple t-test on the parameter θ. The test results are displayed in Table 1. The likelihood ratio test statistic, $-2\ln(L_R/L_U)$, is χ^2 distributed with degrees of freedom equal to the number of restrictions imposed. The model that the above described five step test scheme generates is chosen as the final model, and its estimated parameters are used when calculating short- and long-run elasticities. The final model parameter estimates are presented in Table 2. When conducting the tests and when estimating the final model, we use the two-step iterative procedure suggested by Considine (1990).[6] This estimation procedure generates parameter estimates that ensures global symmetry.

Table 1. Likelihood ratio tests - model selection.

Test	$\ln L_U$	$\ln L_R$	$-2\ln\left(\frac{L_R}{L_U}\right)$	restr.	crit. val.
(1)	-3978 (3)	-5293 (10)	2630^R	252	350*
(2)	-3978 (3)	-3996 (3)	36^R	6	14
(3)	-3978 (3)	-3997 (3)	38^R	9	19
(4)	-3978 (3)	-3981 (2)	6^A	4	11
(5)	-3981 (2)	-3994 (2)	26^R	4	11

Note: The test statistic is chi-squared. Degrees of freedom equals restrictions imposed. Number of iterations within parenthesis. $^R \longrightarrow$ not valid restriction. $^A \longrightarrow$ valid restriction.
*Critical value for 300 restrictions according to standard chi-square table.

From Table 1 we conclude that the model specification should include fixed effects, a non-constant adjustment rate, Battese dummies, and size dummies. Interestingly we cannot reject the hypothesis that the adjustment rate is independent of a firms diversification in terms of the number of fuels used. Parameter estimates using this specification is presented in Table 2 in the column labeled Model 1.

[6] See also Jones (1995) for an application of this estimation procedure.

Table 2. Model estimation (Iterative FIML).

Parameter	Model 1	Model 2
γ_{12}	-0.148 (-4.67)	-0.098 (-2.99)
γ_{13}	-0.263 (-2.09)	-0.233 (-1.91)
γ_{14}	-0.228 (-7.95)	-0.323 (-11.23)
γ_{23}	-0.344 (-11.56)	-0.235 (-7.27)
γ_{24}	-0.329 (-9.68)	-0.369 (-12.50)
γ_{34}	-0.101 (-4.28)	-0.359 (-16.73)
φ_1	0.011 (2.77)	0.007 (1.81)
φ_2	0.023 (3.26)	0.017 (2.40)
φ_3	0.039 (7.53)	0.028 (5.25)
λ(size1)	-0.138 (-2.14)	0.623E-07 (0.01)
λ(size2)	0.133 (2.05)	0.206 (2.95)
λ(size3)	0.243 (3.79)	0.231 (3.34)
λ(size4)	0.262 (4.10)	0.248 (3.56)
λ(time)	0.018 (5.70)	0.019 (6.62)
$\ln L$	-3981	-4097
Iterations	2	2

In Model 2 the restriction $\lambda(\text{size1}) \geq 0$ is imposed.

Asymptotic t-values within parenthesis.

Note that the Model 1 estimate of λ(size1) is significant and negative which, in terms of short- and long-run elasticities, is a violation of the Le Chatelier principle. Therefore, we restrict λ(size1) to be greater or equal to zero in Model 2. The parameter estimates in Table 2 are to a large extent significantly different from zero, and the estimates of the adjustment parameters indicates that adjustment is rather fast. Furthermore the dynamic adjustment rate seems to decrease with the size of the firm and over time. One conclusion is then that the fuel mix is more "static" for large firms than for small ones.

Short-run fuel demand elasticities, based on Model 2 parameter estimates, are displayed in Table 3.

Table 3. Short-run demand elasticities.

	x_1	x_2	x_3	x_4
p_1	-0.63	0.21	0.18	0.16
p_2	0.37	-0.45	0.31	0.26
p_3	0.09	0.09	-0.65	0.07
p_4	0.15	0.14	0.15	-0.51

Long-run fuel demand elasticities are shown in Table 4. The long-run elasticities are evaluated 1996 (i.e. at $t = 7$).

Table 4. Long-run demand elasticities.

	Size 1				Size 2			
	x_1	x_2	x_3	x_4	x_1	x_2	x_3	x_4
p_1	-0.73	0.24	0.20	0.18	-0.96	0.32	0.27	0.24
p_2	0.42	-0.53	0.36	0.30	0.56	-0.70	0.47	0.39
p_3	0.10	0.10	-0.75	0.09	0.14	0.14	-0.99	0.11
p_4	0.18	0.17	0.17	-0.58	0.24	0.22	0.22	-0.77
	Size 3				Size 4			
p_1	-0.99	0.33	0.28	0.25	-1.02	0.34	0.29	0.25
p_2	0.58	-0.73	0.49	0.40	0.59	-0.74	0.50	0.42
p_3	0.14	0.14	-1.03	0.12	0.14	0.14	-1.06	0.12
p_4	0.24	0.23	0.23	-0.80	0.25	0.23	0.24	-0.82

From Table 3 and 4 we conclude that all of the own-price elasticities have the expected signs and in the short-run they are all about the same magnitude. In the case of size class 1 firms, the long-run elasticities are slightly higher than the corresponding short-run elasticities, indicating fast adjustment for small firms. For firms in size class 2-4 the long-run elasticities are higher than for firms in size class 1. This implies that larger firms are relatively slow in adjusting their fuel mix. The demand for wood fuel and non-gaseous fossil fuels seem to be more sensitive to own-price changes compared to the demand for gaseous fossil fuels and "other fuels". Concerning cross-price elasticities we have that price changes of non-gaseous fossil fuels (oil and coal) induces the largest substitution effects, and that wood fuels and non-gaseous fossil fuels seems to be the fuels that are easiest to substitute for each other. Not surprisingly have gaseous fossil fuels the lowest cross-price elasticities. The latter is in line with the findings by for example Atkinson and Halvorsen (1976). Overall the magnitude of the elasticities are slightly higher in this study, compared to Brännlund and Kriström (1999). An interesting conclusion from a policy point of view is then that a subsidy of wood fuel will increase the use of wood fuel, and decrease the use of other fuels, especially oil and coal. Similarly we have that an increase of the CO_2 tax will induce a change in fuel mix towards less use of fossil fuels and more use of wood fuel. However, since the analysis show that $\lambda(\mathbf{z}, t) > 0$, the change will take some time. The estimates of $\lambda(\mathbf{z}, t)$ implies a mean adjustment period (in 1996) of 1.15 years for size 1 firms, and about 1.60 years for size 2-4 firms. In other words, for size 1 firms almost 90% and of the long-run response occurs in the same year as it occurs. For size 2-4 firms the first year long-run response is about 63%.

5 Simulation

In order to illustrate the substitution possibilities two simple policy changes will be evaluated. The policy changes will be considered as "marginal" changes, which allows us to approximate the short- and long-run quantity change for a given size class and for input k as:

$$\Delta x_k^n = \sum_{l=1}^{4} E_{kl}^{S,L} \Delta p_l, \tag{16}$$

where n denotes size class, and S and L indicates short-run and long-run respectively. Here Δ denotes the percentage change. Total long-run change in the heating sector, i.e. across size classes, is calculated as:

$$\Delta X_k = \sum_{n=1}^{4} w_k^n \Delta x_k^n, \tag{17}$$

where $w_k^n = x_k^n / X_k$ is the weight for size class n, and X_k is total use of input k across size classes (1996 size class mean values are used for x_k^n). Note that in the short-run (16) and (17) will be the same since $\Delta x_k^n = \Delta x_k = \Delta X_k$.

The first policy scenario considered involves an increase of the CO_2 tax by 50%. This implies that the average user price of non-gaseous fossil fuels increases by approximately 27%, and gaseous fuels by approximately 18%, compared to the price level in 1996.[7] All other prices remains unchanged. The CO_2 tax simulations are presented in Table 5.

Table 5. Percentage change in fuel mix due to a 50% increase of the CO_2 tax.

	Short-run	Long-run				
Change (%)	size 1-4	size1	size2	size3	size4	total
Δx_1	12	13	17	18	19	18
Δx_2	-11	-12	16	-17	-18	-17
Δx_3	-3	-4	5	-5	-5	-5
Δx_4	8	10	13	13	13	13

The second scenario can be viewed as a subsidy for producing wood fuel that induces a price decrease for the user of wood fuel by 26%. All other

[7] The change in prices are calculated as:

$$\Delta p_2 = \Delta p_{oil} \frac{x_{oil}}{x_2} + \Delta p_{coal} \frac{x_{coal}}{x_2}$$

$$\Delta p_3 = \Delta p_{nat.gas} \frac{x_{nat.gas}}{x_2} + \Delta p_{propane} \frac{x_{propane}}{x_2}$$

where

$$\Delta p_m = \frac{(p_m^0 + (\tau^1 - \tau^0)) - p_m^0}{p_m^0}$$

where $m =$ *oil, coal, natural gas, propane,* $\tau = CO_2$ tax, and a superscript 0 denotes before tax change, and 1 after tax change.

prices are unchanged. The results from the wood fuel subsidy simulations are presented in Table 6.

Table 6. Percentage change in fuel mix due to a subsidy of wood fuel.

	Short-run	Long-run				
Change (%)	size 1-4	size1	size2	size3	size4	total
Δx_1	16	19	25	26	27	26
Δx_2	-5	-6	-8	-9	-9	-9
Δx_3	-4	-5	-7	-7	-7	-7
Δx_4	-4	-5	-6	-6	-7	-7

In Table 5 it can be seen that a 50% increase of the CO_2 will lead to a substitution from fossil fuels to wood fuel. According to the results the short-run, or immediate, effect will be a 12% increase of wood fuel in the whole sector, whereas oil and coal will decrease by approximately the same number. The use of natural gas will also decrease, but to a lesser extent, while the use of "other fuels" (such as waste) will increase. The long-run increase of wood fuel will, according to the results in Table 5, be 18%, i.e. 50% larger than short-run effect. The results in Table 6 shows that the qualitative effect from a subsidy to wood fuel will be the same as an increase of the CO_2 tax, i.e. an increase in the use of wood fuel, and a decrease in the use of fossil fuels. The quantitative effects of the wood fuel subsidy differs from the effects of the CO_2 tax in the sense that all types of fossil fuels are decreasing by approximately the same amount (in percent). To conclude the simulations give by the hand that the use of wood fuel will increase and the use of fossil fuel decrease if the CO_2 tax is increased, and/or the use of wood fuel is subsidized. Finally, the two policy scenarios illustrates a fundamental result in environmental economics, namely that a policy aiming at reducing a specific type of emissions should be targeted as close to the emission source as possible. In the present case if the aim is to reduce CO_2 emissions, the simulation results show that a CO_2 tax will be more efficient than a wood fuel subsidy. The reason is that the tax will penalize the use of coal and oil more than the use of natural gas, compared to the case of a wood fuel subsidy. A wood fuel subsidy does not discriminate between different types of fossil fuels, which is inefficient from CO_2 point of view.

6 Concluding comments

The main purpose of this study is to estimate how the choice of fuel mix in the production of heat changes as the relative prices on various fuels changes. The methodology involves the estimation of a dynamic linear logit model where the dynamics implicitly are assumed to evolve from costs of adjustments for the various inputs. This paper differs from earlier studies in that we have a plant level panel data set, and that we allow the adjustment parameter depend on characteristics of the firm and time. Thus we are able to investigate how size and diversification in different combustion technologies affect the rate of dynamic fuel substitution due to price changes.

The main results from the empirical analysis is that fuel demand respond to price changes as we expect, i.e. a price increase of a fuel input decreases the demand for that input. Furthermore the results shows that the substitution possibilities, reflected by cross-price elasticities, varies between different pairs of fuels. The highest cross-price elasticities can be found between wood fuel and non-gaseous fossil fuels (oil and coal), reflecting a relatively large substitution possibility. Concerning the dynamic adjustment rate the results reveals that most adjustment takes place within one year, which indicates high flexibility in fuel mix changes for Swedish heating plants.

This type of model can be used to illustrate the effects of various policy changes. Here we have simulated the effect due to a change of the carbon dioxide tax, and an introduction of a wood fuel subsidy. The simulation results shows that a higher carbon dioxide tax will result in a change of the fuel mix in the sense that fossil fuels decrease and wood fuel increase, implying a reduction of carbon dioxide emissions. To conclude we have found that the linear-logit model may be a suitable model in this case, and that dynamics relatively easily can be incorporated in a consistent way.

The analysis presented here is of course contingent upon a number of assumptions, some more crucial than others. Here we will comment on three very crucial assumptions. The first one is that each firm act as price takers on all markets. This assumption is reasonable for some fuels such as oil, coal, and natural gas. However, for wood fuels there are reasons to believe that this assumption may be violated in practice. Large district heating plants are in many cases the only large-scale user of wood fuel within an area. This together with the fact that wood fuels are subject to relatively high transportation costs may indicate that this market is better described as a monopsony. The consequences here may be that the estimates are biased, since we do not consider that the price of wood fuel may be endogenous. A remedy to this problem may be to employ a "shadow cost function" approach in line with Atkinson and Kerkvliet (1989) and Bergman and Brännlund (1995). This, however, is not feasible with the data set used here, but will be a subject for future research. A second crucial assumption is that the rate of dynamic adjustment is equal across demand equations, which can be interpreted as a cost of adjustment in total fuel use. However, it is not difficult to imagine that the cost of adjustment is linked to individual fuels, due to differences in technological uncertainty as well as differences in uncertainty concerning future prices and taxes. Allowing for different rate of dynamic adjustment is not, using the framework presented here, feasible from an empirical point of view. A third crucial assumption is that the technology is separable, which in this particular case implies that the rate of technical substitution between any fuel and capital/labor is zero. This in turn implies that the choice of fuel mix is independent of the price of capital and the wage rate. Intuitively we find this as a fairly reasonable assumption. Ideally we would like to test the separability hypothesis along the lines in Atkinson and Halvorsen (1976). Unfortunately this is not feasible in this case due to lack of data concerning capital and labor.

Appendix

Table A1. Descriptive statistics on fuel inputs and prices

	1990	1991	1992	1993	1994	1995	1996
x_1	18 (48)	21 (56)	24 (60)	30 (72)	36 (94)	38 (97)	47 (131)
p_1	118 (28)	131 (45)	120 (37)	124 (53)	120 (54)	117 (53)	98 (26)
x_2	53 (152)	54 (182)	47 (168)	51 (181	53 (192)	47 (195)	75 (227)
p_2	187 (83)	200 (75)	197 (73)	214 (80	231 (101)	227 (82)	246 (85)
x_3	12 (87)	14 (98)	17 (108)	19 (121	20 (128)	20 (122)	24 (125)
p_3	184 (34)	225 (42)	216 (52)	202 (26	210 (27)	206 (29)	211 (31)
x_4	51 (129)	54 (137)	53 (142)	64 (152)	75 (184)	81 (223)	92 (314)
p_4	108 (43)	123 (53)	137 (71)	125 (55)	124 (57)	121 (58)	112 (67)
Nobs	215	214	218	207	206	199	159

Quantities (x_k) in GWh, and prices (p_k) in SEK/GWh.

Standard deviation within parenthesis.

Table A2. Mean values for dummy variables in $\lambda(\mathbf{z}, t)$.

	1990	1991	1992	1993	1994	1995	1996
D_{11}	0.25	0.24	0.22	0.18	0.14	0.16	0.10
D_{12}	0.38	0.41	0.43	0.43	0.44	0.42	0.40
D_{13}	0.12	0.10	0.10	0.10	0.11	0.11	0.10
D_{14}	0.23	0.23	0.23	0.27	0.29	0.29	0.33
D_{21}	0.25	0.27	0.25	0.24	0.26	0.29	0.16
D_{22}	0.27	0.25	0.27	0.26	0.25	0.23	0.20
D_{23}	0.25	0.24	0.25	0.24	0.23	0.24	0.33
D_{24}	0.23	0.24	0.23	0.25	0.26	0.24	0.31
Nobs	215	214	218	207	206	199	159

$D_{11} - D_{14}$ is one if number of fuel inputs are 1-4 respectively.

$D_{21} - D_{24}$ is one if a firm belongs to size class 1-4 respectively.

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