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E-mail addresses: Kurt.Kratena@wifo.ac.at, Michael.Wueger@wifo.ac.at
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THE ROLE OF TECHNOLOGY IN INTERFUEL SUBSTITUTION: A COMBINED CROSS-SECTION AND TIME SERIES APPROACH

Kurt Kratena
Michael Wueger
Austrian Institute of Economic Research
P.O. Box 91 , A-1103 Vienna, AUSTRIA
Tel.: +43 1 7982601 246
Fax: +43 1 7989386
e-mail: kurt.kratena@wifo.ac.at

Abstract:

This paper describes interfuel substitution for coal, oil, gas and electricity at a level of 12 activities. We use cross section data in each activity for appliance technologies (heating/cooling, steam generation, industrial processes, motors and lighting/computing) to estimate fuel input demand equations by appliance technology in a panel estimation with fixed effects for activities and a uniform effect of technical progress across appliance technologies. In a synthesis with the time series approach we estimate fuel input demand equations at the 'aggregate' level of activities as the weighted sum of appliance technologies by inserting parameters from the panel estimation. In this 'disaggregated' model the impact of prices and of technical progress in each activity can be decomposed into two effects: (i) changes in the share of appliance technologies and (ii) fuel switch within appliance technologies.

Key words: Interfuel substitution, appliance technologies, panel data estimation

JEL classification: Q41, O33, C33

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1. Introduction

The analysis of industrial energy demand plays an important role in applied economics since the first oil price shock in 1973 and recently due to the impact studies on Kyoto policies. The seminal studies for industrial energy demand in the setting of a K,L,E,M production or cost function using the translog cost function are Berndt, Wood (1975) and Hudson, Jorgenson (1976). Industrial energy demand is often treated as a two level decision process, where firms decide upon total energy demand first and then about the single fuel use as in Harvey, Marshall (1991). Models of interfuel substitution using so called ‘flexible functional forms’ like translog have therefore become an important line of research on industrial energy demand analysis also including power generation (for example: Atkinson, Halvorsen (1976), Ko, Dahl (2001), Magnus, Woodland (1987) and Urga, Walters (2003)).

Analysis of total energy demand was from the beginning puzzled with the role of technology in energy demand reaction patterns on price changes. Already Berndt, Wood (1975) intensively discussed their results of capital – energy complementarity and the introduction of different types of neutral or non-neutral technological change played an important role. Berndt et al., 1993 provide a literature overview on that and suggest different types of technical change as well as the concept of embodied technical change in a K,L,E,M translog cost function. The idea that technical change is embodied in capital goods can be successfully analysed in the concept of a cost function with (short run) variable and fixed factors. There are several studies treating the capital stock and/or a deterministic trend as these ‘quasi fixed’ factors in a K,L,E,M cost function (Morrison, 1989, 1990). The embodied nature of technical change leads to the distinction of short and long run reactions to price changes and that adjustment to price reactions takes time and is costly as it requires investment. On the other hand the option of adjustment by changing technologies opens up a wider range of reaction patterns. Both aspects have been discussed extensively in impact analysis of Kyoto policies, where the latter aspect has been dealt with under the notion of ‘induced technical change’ or ‘induced innovation’. Newell et al. (1999) emphasize the importance of regulation for induced innovation and Popp (2002) discusses the role of energy prices. If technical change is induced it can also be seen as endogenous, so that measures to reduce greenhouse gas emissions must take into account different channels, by which technological change might be induced (see also Ferrante, 1998 and van der Zwaan et al., 2002). The problem lies mainly in the information about the exact linkages between measures and induced technical change. Economic instruments that only aim at a change in *effective* energy prices (including emissions trading) might lead to high adjustment costs, if adjustment heavily depends on technological change. If on the other hand the design of the instruments also induces technological change, adjustment will be eased and become less costly. This argument not only holds for overall energy efficiency, but also for interfuel substitution. Recent studies on emissions trading (see for example: Boehringer, 2002 and Rose, Oladosu, 2002) have shown, that an important amount of emissions reduction stems from interfuel substitution between coal, oil, gas and electricity, as these fuels exhibit rather different CO_2 emission factors.[1] Therefore the question arises, if interfuel substitution also requires technological change brought about by investment and if this change can also be induced by instruments that at the same time change effective energy prices. Some recent studies analyse panel data sets of firms to get more insight into interfuel choice of firms as Bjorner, et.al. (2001) and Bousquet, Ladoux (2002). In the analysis of overall energy efficiency it is the specific energy use factor embodied in the capital stock that matters (as in Newell et al., 1999). In the case of interfuel substitution it is the flexibility of the applied capital stock to use different fuels that matters and determines the extent to which interfuel substitution is bound to investment in new capital stock.

In this paper we introduce a new notion of embodied or induced technological change in a model of interfuel substitution by dealing with appliance technologies. Although we do not deal explicitly with different types of capital stock, we know that the appliances are linked to different capital goods with different flexibility in fuel use. The paper is organized as follows: Section 2 describes three different models of interfuel substitution. The first one is a time series model for different industries with uniform technical change by industry. The second is a model of interfuel substitution for different appliance technologies, which can be estimated

[1] If we normalize the emission factor of coal as 100, the emission factor of oil products is 78 and of gas 55.

with cross section data by pooling over industries. This model starts from the hypothesis, that appliance technologies fully determine the flexibility for interfuel substitution at the industry level. Finally the third approach combines both methods into a consistent estimation method for time series data. The properties of the resulting model allow to split up reactions to price changes into changes in the structure of appliance technologies and 'pure' interfuel substitution effects. Two specifications of technical change can be formulated, namely a uniform rate by the technology in use or a uniform rate by industry. In section 3 we present empirical results from estimation for price elasticities in the three models and results of a simulation experiment on emissions trading with the combined model (model 3). In this experiment we attempt to show a decomposition of price reactions into technological change and 'pure' interfuel substitution. A final section draws some conclusions.

2. Models of Interfuel - Substitution

Technological change can be incorporated in different ways into models of interfuel substitution. The state of the art model of interfuel substitution starts from a flexible form of a cost function (Translog or Generalized Leontief) and derives factor demand functions applying Shephard's lemma. In the literature so far the Translog approach dominates. The models presented here all start from the same specification of factor (or input) demand function, but at different aggregates concerning industries and appliance technologies. These differences allow to test empirically the role of technology in interfuel substitution in a broad sense.

Model 1: A Time Series Approach for Different Industries

Starting point of our model is an extended Generalized Leontief (GL) function, as introduced by Morrison (1989, 1990). For s industries we face a cost function, where total variable costs for fossil energy and electricity, EC, depend on total energy demand ('output' of the bundle), EN, and prices p of fuels i,j. Fuel prices are also different by industries. The extension of the original GL function lies in the introduction of a deterministic trend *t* by fuel as a 'quasi fixed' factor:

$$(1) \qquad EC = EN\left[\sum_i \sum_j a_{ij}\left(p_i p_j\right)^{1/2} + \sum_i \delta_i p_i t^{1/2} + \sum_i \gamma \ p_i t\right]$$

Applying Shephard's lemma allows us to derive factor or input demand functions in terms of optimal input-output coefficients for the *i* fuels coal, oil products, gas and electricity.

$$(2) \qquad \frac{En_i}{EN} = \alpha_i + \sum_{ij} \alpha_{ij}\left(\frac{p_j}{p_i}\right)^{1/2} + \delta_i t^{1/2} + \gamma \ t$$

This model can be applied to data for 10 manufacturing industries, services (excluding transport) and households. Equation (2) can be further directly used to calculate own and cross price elasticities $\varepsilon_{ij} = \partial \log(En_i)/\partial \log p_j$. Concavity restrictions of the underlying cost function imply, that $\Sigma\ \varepsilon_{ij} > 0$ for $i \neq j$ and $\Sigma\ \varepsilon_{ij} = 0$ for all i and j as well as symmetry of the Hicksian cross price effects. These conditions guarantee negative own price elasticities and are introduced in the GL model by the symmetry restriction on the α_{ij} parameters: $\alpha_{ij} = \alpha_{ji}$. In the case of the GL function derivation of elasticities yields:

$$(3) \qquad \varepsilon_{ij} = -(\alpha_{ij}/2)\ (EN/En_i)\ (p_j/\ p_i)^{1/2}$$

The 'quasi fixed' factor *t* as a measure of technical change enters in two terms in equation (2). The first term $\delta_i t^{1/2}$ might capture different trends in technology in favour or against certain fuels whereas the second term γt, which is restricted to be the same for all fuels should measure 'pure' technological progress for all fuel applications. Therefore we expect γ to be negative. The driving force for technical change in this model is a deterministic trend, which cannot be influenced by policy.

Model 2: A Cross Section Approach for Different Appliance Technologies

The same GL function can now be used at the level of appliance technologies, where we make use of the following data set for fuel use for *s* industries and appliance technologies *k*:

	Appliances, *k*	TOTAL
Fuels, *i*	En_{ik}	En_i
TOTAL	En_k	EN

The fuel input coefficient from equation (2) En_i/EN in one industry can now be described as the weighted sum over appliances of the fuel input coefficients En_{ik}/EN_k with the weights $w_k = En_k/EN$:

$$\frac{En_i}{EN} = \sum_k w_k \frac{En_{ik}}{EN_k} \tag{4}$$

The appliance technologies *k* are: heating/cooling, steam generation, industrial processes, motors and lighting/computing. A different treatment of the role of technology can now be applied by specifying interfuel substitution for each appliance technology *k*, thereby postulating that the appliances are directly linked to some technologies embodied in the capital used and that this fully determines the flexibility of fuel use. The GL function for the coefficients En_{ik}/EN_k is the same as above in (2):

$$\frac{En_{ik}}{EN_k} = \alpha_{Sk} + \sum_{ij} \alpha_{ij,k} \left(\frac{p_j}{p_i}\right)^{1/2} + \delta_{ik} t^{1/2} + \gamma_k t \tag{5}$$

Here we start from the assumption that prices in each industry s are the same across appliance technologies.

The factor demand function (5) can then be specified by pooling over industries s and using the panel data set with fixed effects, which in matrix notation yields:

(6) $\boldsymbol{E}_s = \mathrm{i}\, \boldsymbol{A_S} + \Pi_S\, \boldsymbol{A}_{ij} + \mathrm{T_I}\, \boldsymbol{\Delta_i} + \mathrm{T_{II}}\, \boldsymbol{\Gamma} + \boldsymbol{\varepsilon_S}$

or

$$(7)\begin{bmatrix} E_1 \\ . \\ E_S \end{bmatrix} = \begin{bmatrix} i & 0 \\ . & . \\ 0 & i \end{bmatrix} \begin{bmatrix} \alpha_1 \\ . \\ \alpha_S \end{bmatrix} + \begin{bmatrix} \pi_{1i} & \pi_{1j} \\ . & . \\ \pi_{Si} & \pi_{Sj} \end{bmatrix} \begin{bmatrix} \alpha_{ij} \\ . \\ \alpha_{ij} \end{bmatrix} + \begin{bmatrix} T_I & 0 \\ . & . \\ 0 & T_I \end{bmatrix} \begin{bmatrix} \delta_i \\ . \\ \delta_i \end{bmatrix} + \begin{bmatrix} T_{II} & 0 \\ . & . \\ 0 & T_{II} \end{bmatrix} \begin{bmatrix} \gamma \\ . \\ \gamma \end{bmatrix} + \begin{bmatrix} \upsilon_1 \\ . \\ \upsilon_S \end{bmatrix}$$

In this specification $\boldsymbol{E}_s$ is the column vector of all t observations in all s industries for the coefficient En_{ik}/EN_k. The fixed effects are captured by the α_S vector, where i is the summation diagonal matrix. All variables from (2) are now in matrices Π, $\mathrm{T_I}$ and $\mathbf{T_{II}}$ and are multiplied by parameter (column) vectors A, Δ and Γ. Matrix Π contains all t observations in all s industries for all (ij) price variables $\pi = \left(\frac{p_j}{p_i}\right)^{½}$ and vector A contains the parameters for all fuels α_{ij}. The two technological change terms can be found in the two diagonal matrices T_I and T_{II} (as all t observations are identical in all s industries for the deterministic trend t). The corresponding parameter values are described in Δ (all parameters δ_i) and Γ (the parameter γ) and υ_s represents the vector of disturbances. The assumption that technical change is a uniform deterministic trend for each appliance technology k regardless of the industry might be seen as too restrictive. The alternative model without this deterministic trend can therefore also be tested:

(7a) $$\begin{bmatrix} E_1 \\ . \\ E_S \end{bmatrix} = \begin{bmatrix} i & 0 \\ . & . \\ 0 & i \end{bmatrix} \begin{bmatrix} \alpha_1 \\ . \\ \alpha_S \end{bmatrix} + \begin{bmatrix} \pi_{1i} & \pi_{1j} \\ . & . \\ \pi_{Si} & \pi_{Sj} \end{bmatrix} \begin{bmatrix} \alpha_{ij} \\ . \\ \alpha_{ij} \end{bmatrix} + \begin{bmatrix} \upsilon_1 \\ . \\ \upsilon_S \end{bmatrix}$$

From both specifications parameters of the fixed effects for each industry α_{Sk} as well as for each appliance technology $\alpha_{ij,k}$ can be estimated and used to derive own and cross price elasticities by appliance technology:

(8) $$\varepsilon_{ij,k} = -(\alpha_{ij,k}/2)\ (EN_k/En_{ik})\ (p_j/\ p_i)^{½}$$

Model 3: A Combined Cross Section and Time Series Model

Both models can now be combined in a consistent procedure starting from the definition in (4). In the literature we find different methods of combining cross section and time series models into a consistent framework. Most applications in this field deal with demand systems of private consumption combining cross section data sets from household surveys with aggregated data from national accounts. The problem can be approached from a theoretical point of view as well as from an applied econometric perspective. From a theoretical perspective the question of aggregation of individual utility or cost function arises, which can be dealt with in a concept of 'exact aggregation' as outlined in Jorgenson, Lau, Stoker (1980). There one also finds conditions for the consistent stochastic specification of time series and cross section data in such a model of 'exact aggregation'. The other approach combines variables or parameter estimates from both models as in Bardazzi, Barnabani (2001). They use cross section data from household surveys to derive an estimate of income elasticities of goods, which are then inserted in a time series estimation of an AIDS model. The methodology used here follows this latter approach as it is assumed that the definition in (4) describes the aggregation rule and that the GL cost and factor demand functions by appliance technologies can be aggregated in each industry. Re-inserting the results of (5) into this definition could yield two versions of the combined model according to the treatment of technical change.

The first model assumes that appliance technologies determine fuel demand, but that technical change can be captured by a deterministic trend by fuels and industry as in (2). The cross section estimates for $\bar{\alpha}_{ij,k}$ without deterministic trend as in (7a) are therefore combined with (2) and (4) to yield:

$$(9)\qquad \frac{En_i}{EN} = \alpha_i' + \beta_{1i}\left[\sum_k w_k \sum_{ij} \overline{\alpha}_{ij,k}\left(\frac{p_j}{p_i}\right)^{½}\right] + \delta_i t^{½} + \gamma t + \upsilon_i$$

The second more restrictive model assumes that appliance technologies determine short term fuel flexibility as well as technical change and use the deterministic trend by appliance technology as specified in (5), (6) and (7) to get:

$$(9a)\qquad \frac{En_i}{EN} = \alpha_i' + \beta_{1i}\left[\sum_k w_k \sum_{ij} \overline{\alpha}_{ij,k}\left(\frac{p_j}{p_i}\right)^{½}\right] + \beta_{2i}\left(\sum_k w_k \delta_{ik}' t^{½}\right) + \beta_{3i}\left(\sum_k w_k \gamma_k' t\right) + \upsilon_i$$

One could even imagine a more restrictive model, where the constant α_i' is substituted by the product of the fixed effect of panel data estimation α_{Sk} and the weights w_k. In this model we derive parameters β_{1i}, β_{2i} and β_{3i} to combine cross section and time series information in an efficient way. The prices parameter α_{ij} in (2) is now defined by the product of the parameter β_{1i} with the weighted sum of the cross section parameters $\Sigma w_k\, \bar{\alpha}_{ij,k}$:

$$(10)\qquad \alpha_{ij}' = \beta_{1i} \sum_k w_k \overline{\alpha}_{ij,k}$$

where the symmetry restriction on the α_{ij} parameters: $\alpha_{ij} = \alpha_{ji}$ can now be applied to this product. Own and cross price elasticities can now be written as:

$$(11) \qquad \varepsilon_{ij} = -(\beta_{1i} \sum_k w_k \overline{\alpha}_{ij,k} /2)\ (EN/En_i)\ (p_j/\ p_i)^{½}$$

Interfuel substitution is therefore not only determined by prices, but also by changes in the structure of the *k* energy appliances as well. This can be seen as another source of exogenous technical change. In a complete model one would additionally aim at endogenizing the weights of appliance technologies w_k, as that represents additional potential for adjustment, e. g. to price shocks. If appliances with high substitution potential become more important after a price shock, the aggregate substitution elasticity rises. A change in the structure of appliances has by itself an impact on fuel mix *at given prices* as not all fuels are represented in each technology. This is especially interesting for coal, which only is used in industrial processes and for electricity, where we have one appliance with no substitution potential (lighting/computing). Therefore an increase in the weight of lighting/computing has a direct positive impact on electricity demand.

3. Empirical Results

The three models lined out above have been estimated using time series data from Austrian energy balances (1976 – 2000) and cross section data from the survey on energy use in Austria (1993 – 2000). The sectoral classifications in both sources are identical and comprise 21 sectors with a disaggregated treatment of transport (which has not been included in our study), one (other) services sector, one household sector and a disaggregated treatment of manufacturing industries. The data sets have also been made consistent with each other by Statistics Austria, so that the aggregation condition of equation (4) above is fulfilled for the sample 1993 – 2000 using both data sets.[2] For the time series model the industries have been aggregated to the level consistent with National Account data, for the panel data estimation the full range of 21 sectors has been used. The estimation parameters of all three models are first of all used to derive own price elasticities and compare them with each other. Then the model is used to calculate a 'baseline' scenario up to 2010 using price forecasts from the most recent IEA World Energy Outlook. As a simulation experiment we then apply an emissions trading regime for manufacturing, where we use results from another study (Kletzan et al., 2002) for economic consequences of emissions trading. The changes in output by industry are implemented in our simulation via adjustment in the structure of processes (= appliance technologies) in each industry. That allows us to decompose the fuel demand reactions into a 'pure' interfuel substitution effect and a 'technological' effect.

3.1 Estimation Results

The time series model (equation (2)) has been estimated implying the concavity and symmetry restrictions of the GL function. According to (3) own price elasticities have been derived, that all fulfill the microeconomic condition of negativity (Table 1). We get the well known result from other studies that these elasticities are higher for coal and oil products and lower for gas and electricity (where availability of infrastructure and 'locking in' plays a role). We further find that coal input cannot be explained by this model in a statistical significant way in some sectors.

The cross section model is estimated in the two versions of (7) and (7a) with fixed effects for industries. Not all fuels are equally important for each appliance, so that we had to construct a balanced panel for each appliance in a first step. Lighting/computing is excluded as this appliance is a 'corner solution' (cf. Bousquet, Ladoux, 2002) to the problem of interfuel substitution with electricity as the only input. Table 2 shows the amount of heterogeneity of own price elasticities derived from estimated parameters across appliances. In general the

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[2] We gratefully acknowledge that Wolfgang Bittermann from Statistics Austria has made available these data for us in electronic form.

elasticities are very low for motors, where no short term fuel switch between oil products and electricity without investment is possible. The rather low elasticities for heating/cooling might reflect the low shares of these appliances in the overall energy use of industries. Fuel demand is only elastic in industrial processes, where multi-fuel structures dominate. It is interesting to note that even in steam generation, where multi-fuel structures also exist, the elasticities are much lower than in industrial processes. Furthermore we observe that there are only slight differences between the results of the two different specifications. The conclusion is that a model, where the main impact of technical change on each fuel is determined by the appliance technology does not perform significantly different from a model without this assumption.

Table 1: Own price elasticities, time series GL function

	Coal	Oil products	Gas	Electricity
Ferrous and Non-Ferrous Metals	– 0.02	– 1.66	– 0.60	– 0.13
Non-metallic Mineral Products	– 0.35	– 0.69	– 0.13	– 0.09
Chemicals	– 0.77	– 0.54	– 0.06	– 0.03
Machinery, Electronics, etc.	0.00	– 0.44	– 0.10	– 0.01
Transport Equipment	–	– 0.51	– 0.13	– 0.29
Food and Tobacco	– 1.98	– 0.24	0.00	– 0.02
Textiles, Clothing and Footwear	–	– 0.09	– 0.20	– 0.04
Wood	–	– 0.11	– 0.09	– 0.18
Paper, Pulp and Printing	– 0.53	– 1.18	– 0.07	– 0.09
Other Industries	– 1.44	– 1.11	– 0.22	– 0.03
Services	–	– 0.08	– 0.09	– 0.01
Households	–	– 0.06	– 0.15	– 0.06

Table 2: Own price elasticities, panel data estimation

GL function without deterministic trend

	Heating/cooling	Steam generation	Industrial processes	Motors
Coal	–	–	– 1,00	–
Oil products	– 0.09	– 0.16	– 0.40	– 0.01
Gas	– 0.03	– 0.05	– 0.01	–
Electricity	– 0.11	–	– 0.04	0.00

GL function with deterministic trend

	Heating/cooling	Steam generation	Industrial processes	Motors
Coal	–	–	– 1.23	–
Oil products	– 0.01	– 0.01	– 0.36	– 0.07
Gas	0.00	0.00	0.00	–
Electricity	– 0.12	–	– 0.07	0.00

The combined model has then been estimated using the paramter estimates ($\bar{\alpha}_{ij,k}$) from the panel data estimation in the two different specifications of (9) and (9a). For this purpose we needed first to arrive at a time series (1976 – 2000) of the weights of appliances (w_k). As this is not available we used the mean of the sample available (1993 – 2000) and inserted it into (9) and (9a). The parameters β_{1i}, β_{2i} and β_{3i} therefore also take account of changes in these weights and of other additional information of the time series data. The more flexible approach (9) in general yields higher own price elasticities than the alternative approach, where technical change is restricted to be determined by appliance technologies. Comparing the results for the elasticities in Table 3 and 4 with those of the time series model (Table 1) we observe in general lower values for these elasticities in the combined model. This is consistent with the hypothesis that the combined model *ceteris paribus*, i. e. without technical change concerning the structure of appliances, only measures 'pure' interfuel substitution.

Table 3: Own price elasticities, combined model (GL function)

Deterministic trend by fuels and industries

	Coal	Oil products	Gas	Electricity
Ferrous and Non-Ferrous Metals	– 0.07	– 0.45	– 0.07	– 0.02
Non-metallic Mineral Products	– 0.05	– 0.01	0.00	0.00
Chemicals	– 0.56	– 2.12	– 0.25	– 0.01
Machinery, Electronics, etc.	– 5.36	– 0.16	– 0.01	– 0.01
Transport Equipment	–	– 0.15	– 0.17	– 0.03
Food and Tobacco	– 0.24	– 0.15	– 0.09	0.00
Textiles, Clothing and Footwear	–	– 0.06	– 0.05	0.00
Wood	–	– 0.04	– 0.03	0.00
Paper, Pulp and Printing	– 0.30	– 0.59	– 0.28	– 0.01
Other Industries	– 3.39	– 0.30	– 0.15	– 0.04
Services	– 0.10	– 0.02	– 0.03	– 0.01
Households	– 0.02	– 0.02	– 0.04	– 0.01

In general the estimation results show that appliance technologies matter together with a deterministic trend for each fuel representing exogenous technical change. This exogenous technical change is not bound itself to the appliances in use. Therefore the role of appliance technologies can be limited to their influence on the elasticities directly, i. e. on the flexibility to react to price shocks. The next logical step of endogenizing technical change would be to explain the development of appliances within each industry. It is very probable that prices also play an important role at this stage of decision. This question cannot be analysed empirically at the industry level here due to the lack of data. From our estimation results we can only conclude that the role of technical change in interfuel substitution can be differentiated into an exogenous component and a component influenced by appliance technologies. An endogenous treatment of the use of these appliances can be seen as a promising path of future research towards endogenous or induced technical change in interfuel substitution.

Table 4: Own price elasticities, combined model (GL function)

Deterministic trend by appliance technologies

	Coal	Oil products	Gas	Electricity
Ferrous and Non-Ferrous Metals	– 0.22	– 0.71	– 0.06	– 0.11
Non-metallic Mineral Products	– 0.90	– 0.15	0.00	– 0.05
Chemicals	– 0.07	– 0.07	0.00	0.00
Machinery, Electronics, etc.	– 3.27	– 0.05	0.00	0.00
Transport Equipment	–	– 0.09	– 0.06	– 0.11
Food and Tobacco	– 0.28	– 0.03	0.00	0.00
Textiles, Clothing and Footwear	–	– 0.01	0.00	0.00
Wood	–	– 0.16	– 0.10	– 0.06
Paper, Pulp and Printing	– 0.46	– 0.14	– 0.01	– 0.02
Other Industries	– 0.75	– 0.03	0.00	– 0.01
Services	– 0.12	– 0.01	0.00	– 0.01
Households	– 0.02	– 0.01	0.00	– 0.02

3.2 A Simulation Experiment: Emission Trading

In this section we attempt to give another indication on the importance of technical change on the fuel demand reactions after a price shock. For this purpose we implement the results of another study on a domestic emissions trading system in Austria (Kletzan et al., 2002) in our model as a simulation experiment. Kletzan et al. (2002) derive results for a domestic emissions trading system in Austria, where emissions are reduced according to the Austrian Kyoto target by 13 percent compared to baseline until 2010. The models used in Kletzan et al. (2002) are a disaggregated macroeconometric model and an econometric energy model with a block for interfuel substitution identical to the specification in (2) in this study. Here we use the combined model of specification (9) for this simulation experiment. First of all we derive a baseline scenario until 2010 without climate policies and with a development of international energy prices as lined out in the most recent IEA World Energy Outlook. The permit prices resulting from the Kletzan et al. (2002) study are 13.9 € per ton of CO_2 in 2006 and 26.8 € in 2010. These permit prices are implemented as exogenous price shocks for coal, oil and gas in our model. Kletzan et al. (2002) also quantify the economic impact of the domestic emissions trading system. We use their results of output changes by industry for our simulation exercise. These impacts are rather small, we concentrate on the larger output changes in the following industries:

Ferrous and Non-ferrous Metals (–0.33%), Non-metallic Mineral Products (+0.1%), Chemicals (+0.52%), Machinery, Electronics, etc. (–0.1%), Food and Tobacco (–0.25%), Textiles, Clothing and Footwear (+0.24%), Paper, Pulp and Printing (–0.3%).

These output changes are translated into changes in the weights of appliance technologies by assuming that the price shocks generate a shift from energy intensive processes to more value added intensive processes. The output changes are therefore fully transformed into a decrease of an energy intensive appliance and/or an increase in a non-energy intensive appliance, which then changes the weights of all other appliances in a proportional way.

Table 5: Effects of emission trading (combined model), without changes in appliance technologies (w_k)

Difference from baseline in percent (2010)

	Coal	Oil products	Gas	Electricity
Ferrous and Non-Ferrous Metals	− 5.2	− 1.3	1.6	1.9
Non-metallic Mineral Products	− 1.8	0.2	0.1	0.1
Chemicals	− 55.6	22.3	−	0.8
Machinery, Electronics, etc.	−	− 2.9	0.6	0.4
Transport Equipment	−	0.2	− 1.1	0.2
Food and Tobacco	− 5.3	49.3	− 0.2	0.1
Textiles, Clothing and Footwear	−	18.6	− 0.3	−
Wood	−	1.5	− 0.3	−
Paper, Pulp and Printing	− 14.5	26.2	− 5.4	0.9
Other Industries	− 73.8	4.3	− 1.9	1.0
MANUFACTURING (total)	− 6.6	2.2	− 0.6	0.8

In order to decompose the overall fuel demand effects we first simulate the impact of the emissions trading system without allowing for changes in appliances. These results (Table 5) indicate a large decrease of coal and very small decreases for gas. Fuel demand is shifted to oil products and electricity, where demand increases.

Table 6 describes the changes in appliance technologies derived from the output changes towards less energy intensive processes. In general the resulting shifts in the structure of appliances is very small and much beyond the variance observed in the sample from 1993 to 2000. It must be emphasized again that a model that endogenously explains the structure of appliances would be superior to the simulation techniques implemented here. The impact of these changes in the structure of appliances has a direct impact for fuels, that dominate certain appliances (electricity) or are found just in one appliance (coal) and the indirect impact via the substitution parameters. These effects might be directed against each other: a decrease in industrial processes directly diminishes coal (and only coal), as this fuel is only used in industrial processes. On the oher hand the same decrease in industrial processes indirectly increases coal and decreases other fuels as the substitution elasticity in industrial processes is higher than in other appliances.

Table 6: Changes in appliance technologies (w_k), 'Baseline' vs. 'Simulation'

	Steam generation		Industrial processes		Motors	
	Baseline	Simulation	Baseline	Simulation	Baseline	Simulation
Ferrous and Non-Ferrous Metals	21.78	21.95	56.74	56.41	15.46	15.58
Non-metallic Mineral Products	0.95	0.95	79.31	79.23	11.90	11.99
Chemicals	41.94	41.59	17.78	17.63	37.71	38.24
Machinery, Electronics, etc.	2.72	2.72	43.09	43.08	7.94	7.94
Food and Tobacco	58.40	58.15	8.91	8.96	24.27	24.42
Textiles, Clothing and Footwear	38.81	38.67	4.02	4.00	32.78	33.02
Paper, Pulp and Printing	32.31	32.01	43.47	43.66	43.47	43.66

Table 7 now shows the results after these changes in appliances have been implemented. Although these changes are very small they have important repercussions on the fuel demand results. A decomposition of effects can also be carried out. Table 8 describes the difference between the two simulations, i. e. the impact of changes in appliances on fuel demand.

Table 7: Effects of emission trading (combined model), including changes in appliance technologies (w_k)

Difference from baseline in percent (2010)

	Coal	Oil products	Gas	Electricity
Ferrous and Non-Ferrous Metals	− 5.2	− 1.4	1.6	2.1
Non-metallic Mineral Products	− 1.8	0.2	0.1	0.1
Chemicals	− 57.6	− 22.8	− 0.5	0.7
Machinery, Electronics, etc.	−	− 2.9	0.6	0.4
Transport Equipment	−	0.2	− 1.1	0.2
Food and Tobacco	− 5.1	35.3	− 0.2	0.2
Textiles, Clothing and Footwear	−	16.0	− 0.3	−
Wood	−	1.5	− 0.3	−
Paper, Pulp and Printing	− 14.4	23.7	− 5.8	0.9
Other Industries	− 73.8	4.3	− 1.9	1.0
MANUFACTURING (total)	− 6.7	1.5	− 0.8	0.9

Table 8: Impact of appliance technologies (w_k) on fuel demand

Difference from baseline in percent (2010)

	Coal	Oil products	Gas	Electricity
Ferrous and Non-Ferrous Metals	− 0.1	− 0.1	0.1	0.1
Non-metallic Mineral Products	−	−	−	−
Chemicals	− 2.0	− 45.1	− 0.5	0.0
Machinery, Electronics, etc.	−	−	−	−
Transport Equipment	−	−	−	−
Food and Tobacco	0.2	− 14.0	0.0	0.0
Textiles, Clothing and Footwear	0.0	− 2.6	0.0	0.0
Wood	−	−	−	−
Paper, Pulp and Printing	0.1	− 2.5	− 0.5	0.0
Other Industries	−	−	−	−
MANUFACTURING (total)	− 0.1	− 0.8	− 0.2	0.0

4. Conclusions

We have introduced a new concept of endogenous technical change in a model of interfuel substitution via appliance technologies. Adjustment to price shocks can therefore be decomposed into fuel substitution within an appliance and changes in the structure of appliances. Endogenizing this latter adjustment is one major direction for future research. Although this endogenizing has not been carried out, the impact of appliances is an explicit treatment of the influence of technology on fuel demand. Besides that the estimation results show that there is still scope for further exogenous technical progress, captured here with a deterministic trend. There is no evidence that this exogenous technical change is also bound to appliances. A model incorporating this hypothesis does not perform better than a less restrictive model, that allows for a deterministic trend in each industry for each fuel. The model simulation revealed that also very small changes in the structure of appliances can have an important aggregate impact on interfuel substitution.

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