MODELLING FUEL DEMAND IN THE INDUSTRIAL SUB-SECTORS: A COINTEGRATING SYSTEM APPROACH

Paolo Agnolucci [a,*] and Vincenzo De Lipsis [a]

[a] UCL Institute for Sustainable Resources, Central House, 14 Upper Woburn Place, London, WC1H 0NN

[*] Corresponding author

Abstract

Heterogeneity is a theme acquiring considerable importance in the energy economic literature from both a modelling and policy-making perspective, which can now be addressed due to increasingly detailed data made available for relatively long period of time. Motivated by the goal of developing the new industrial energy consumption model adopted by the UK government Department of Business, Energy and Industrial Strategy (BEIS), we propose the first cointegration analysis that shows the applicability of a consistent system approach to the estimation of fuel demand elasticities with respect to relative own and cross-price prices and scale effects at a disaggregated industrial level. Our estimates not only show considerable heterogeneity across industrial subsectors but also show that fuel demand for the industrial sector as a whole is considerably more elastic than most estimated presented in the literature finding which has direct relevance for the policies aimed at influencing industrial fuel consumption through fuel switching.

Keywords: fuel demand; energy demand; elasticities; industrial subsectors, industrial sector; cointegration.

1 Introduction

A considerable amount of energy is used by the industrial sector across the world, yet econometric studies on industrial energy demand are surprisingly scarce, as argued in Bernstein and Madlener (2015). Following Pesaran et al. (1999), who advocated estimation of energy demand functions on a set of consumers that is as homogeneous as possible, the aim of this paper is to demonstrate the implementation of a cointegration approach to the estimation of fuel demand at a disaggregate level by making use of a standard dataset, collected by most national offices for statistics across the world (Eurostat 2018). Our choice to explicitly estimate the long-run equilibrium relationship between energy consumption and its main determinants enables us to investigate a number of key questions related to: 1) the impact on price and scale effects on demand for energy fuels; and 2) the level of heterogeneity across industrial subsectors which have been typically aggregated in other studies.

Our conclusions are important not only from a modelling perspective, in a way which we would expect to be replicated for other countries, but also, and probably more tangibly, for policy-making purposes. In fact, the elasticities we present in this paper are key for policies that rely on price signals, e.g. the EU ETS or the UK climate change levy, to achieve fuel substitution in a way which helps steering the economy towards decarbonisation. As a matter of fact, the analysis developed in this paper has been motivated by the very goal of developing the new industrial energy demand model adopted by the UK government Department of Business, Energy and Industrial Strategy (BEIS), as part of their wider Energy Demand Model.

The structure of the paper is as follows. After describing our methodological approach in Section 2, we discuss the data in Section 3, and in Section 4 we assess our results in relation to unit root tests, cointegration analysis and estimation of fuel demand equations. Section 5 concludes.

2. Methodological Approach

Our study starts with the implementation of unit root testing relying on standard ADF and the Zivot and Andrews (ZA) (1992)[1] tests, with the latter allowing for one break in the deterministic components at an unknown point in time. We selected the number of lags in the testing equations based on the modified Akaike information criterion of Ng and Perron (2001), as it is robust to the presence of negative MA components in the error term, and chose the deterministic terms by assessing the Akaike and the Bayesian information criteria in models that include an intercept only or an intercept and a linear trend. Implementation of unit root testing is important as the cointegrating Vector Autoregression (VAR) model briefly discussed below requires variables to be integrated of order one, which is indeed confirmed by the tests.

Estimation of fuel demand for gas and electricity is implemented through a Vector Autoregression (VAR) approach to model a system that describes the dynamics of fuel shares, prices and energy consumption. Considering that we have *n* different fuels and indicating by *d* the one that is dropped from estimation and used as *numeraire*, our starting point is the static relationship between fuel share and its determinants

$$w_{it} = \varphi_i + \sum_{\substack{j=1 \\ j \neq d}}^{n} \beta_{ij} \ln \frac{P_{jt}}{P_{dt}} + \delta_i \ln ec_t + \gamma_i T_i + \varepsilon_{it} \qquad (1)$$

where w_{it} indicates the logit transformation of the fuel *i* share, that is $\mathrm{w}_{it} = log\left(\frac{s_{it}}{1-s_{it}}\right)$, the share is defined as $s_{it} = \sum_i \frac{fc_{it}}{ec_t}$, with fc_{it} being the consumption level of fuel *i* and ec_t the level of energy consumption, φ_i is an intercept, P_{Jt} is the fuel *j* price and P_{dt} is the fuel *d* price, T_i is a deterministic time trend and ε_{it} is an error term representing the deviations from equilibrium. This specification is similar to the one deriving from a translog cost function, with the difference that we focus on the fuel share rather than the cost share, and we follow Smith et al. (1998) in using the level of energy consumption to capture the scale effect, instead of the industrial output used for example by Urga and Walters (2003). We include a deterministic time trend

[1] ZA henceforth.

as a proxy for changes in the preferences for a specific fuel, technological innovation, or any other factor influencing fuel shares beyond relative prices and energy consumption level. We choose the logit transformation of fuel shares as dependent variable for two reasons. First, with this transformation all estimated coefficients in each share equation can be interpreted as elasticities of fuel consumption with respect to the independent variables[2], and second, the estimated system can readily be employed to generate forecasts since the resulting fuel shares are by construction bounded between zero and one.

Static formulations of fuel demands have several limitations as they ignore the dynamics of the adjustment process in inter-fuel substitution, which in particular is related to the costs of switching between fuels and the necessary modifications in the energy-consuming stock. One way to tackle this issue is to implement joint models of energy-consuming stock and energy consumption, as in Dubin and McFadden (1984), although this is particularly challenging in the case of the industrial sector due to the variety of uses energy is consumed for. An alternative option is to insert the static model above within a framework that explicitly describes the dynamics towards the equilibrium level in response to changes in the driving factors. This is essentially the strategy followed by Urga and Walters (2003), who use an ARDL framework, and Pesaran et al. (1999), who embed an interfuel substitution system similar to (1) in a cointegrating VAR. We follow this latter strategy as it features all the typical advantages of a system approach to estimation, as well as providing the ability to rigorously identify the long-run equilibrium demand for fuel via the Johansen procedure to estimate cointegrating vectors.

Our fuel share demand model can be succinctly written in its VECM representation as

$$\Delta \mathbf{x}_t = \mathbf{\Phi_0} + \boldsymbol{\alpha}\boldsymbol{\beta}'\mathbf{x}_{t-1} + \sum_{j=1}^{p-1} \mathbf{\Phi}_j \Delta \mathbf{x}_{t-j} + \mathbf{u}_t \qquad (2)$$

where $\mathbf{x}_t$ is the vector of endogenous variables in the system, $\boldsymbol{\alpha}$ is the $m \times k$ matrix of adjustment coefficients, $\boldsymbol{\beta}$ is the $m \times k$ matrix of cointegrating vectors, both having as

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[2] Since $\frac{s_{it}}{1-s_{it}} = \frac{fc_{it}}{\sum_{j \neq i} fc_{jt}}$, we have that $\frac{d(w_{it})}{dlog(fc_{it})} = 1$, so that, for instance, $\delta_i = \frac{d(w_{it})}{dlog(ec_t)} = \frac{dlog(fc_{it})}{dlog(ec_t)}$.

many rows as the number of endogenous variables in the system and as many columns as the number of cointegrating relationships, $\mathbf{\Phi}_0$ is a $m \times 1$ vector of deterministic terms, and $\mathbf{u}_t$ is a $m \times 1$ vector of mean zero error terms.

Selection and estimation of the model specification is implemented in two steps. In the first step, we look for evidence of long-run relationships by testing for cointegration using the trace and the maximum eigenvalue tests of Johansen (1991). As to the deterministic terms in the cointegrating vector we estimate both a model with an intercept only and one with a restricted trend, following Johansen (1992), as we have no strong reason to prefer one specification to the other. We select one lag only in our VECMs given the limited size of the available sample, but also because this choice turns out to be enough to remove any residual autocorrelation. After establishing the evidence for two cointegrating relationships, in the second step we start by estimating models that are as general as possible, with two cointegrating vectors including fuels shares, relative fuel prices and energy consumption, and allowing for substitution to happen through cross-price elasticities and adjustment coefficients, i.e. a fuel share adjusting to the disequilibrium in the demand for another fuel as well as to that of its own demand. In determining the final specification, we impose only one assumption on the long-run relationship, that is a negative own-price elasticity in conformity with standard economic theory, but we leave unrestricted the cross-price elasticities as different signs might reflect complementarities as well as substitutability between fuels. As a consequence, if the own-price elasticity is not negative we simplify the model by imposing a zero coefficient on the level of energy consumption within the cointegrating relationship and, in case the sign issue persists, also on the price of the other fuel. As discussed in Section 5, this sign issue occurs only in two subsectors, in the case of Non-Ferrous Metals (NFM), where energy consumption is dropped from the cointegrating vector, and Food, Beverages and Tobacco (FBT), where cross-price elasticities have to be imposed equal to zero.

After estimating by Maximum Likelihood the VECMs including the cointegrating vectors, we implement likelihood ratio tests to assess the statistical significance of the variables on right-hand-side of the fuel share demand equation, their potential weak exogeneity, and the evidence for equality of cross-price elasticities in the two cointegrating vectors, restriction that is incorporated in the final model if accepted. We augment the model with pulse dummies when substantial isolated outliers remain in the residuals, and study the residuals of the estimated VECMs to verify the absence of serial correlation, of heteroscedasticity and of evident deviations from the normality assumption.

3. Data

Our dataset includes four sets of fuel prices and fuel consumptions, observed at an annual frequency between 1990 and 2014 for the eight industrial subsectors in the UK, which are listed in Table A1 of the Appendix. The total level of energy consumption, which is computed as the sum of fuel consumption from data in BEIS (2016a), takes into account fuels used for the production of heat. Fuel prices were obtained by converting prices indices from BEIS (2016b), which incorporate all relevant taxes (Climate Change Levy included), into price levels by using information on the 2000 average fuel price. We then added the price of the EU ETS allowances based on the carbon intensity of oil, coal and natural gas and the share of each industrial subsector covered by the EU ETS to compute a time series for each fuel price. All data were converted into indices, although this does not affect the value of the coefficients from the estimation, as we take the logarithms of all variables.

In all eight subsectors, there is a specific fuel share that has been very small in size and rather constant across time. We decide to exclude such fuel share from the model since its inclusion cannot add information that is relevant to fuel substitution and may instead complicate estimation of the system. As a consequence, coal was dropped in the majority of the subsectors, namely CHE, ENV, FBT, PPP and TEX, while oil was dropped in MIN, NFM and OTH. A key to the acronyms of the industrial subsectors modelled in this study can be found in Table A1 of the Appendix. Levels of consumption of the four fuels in the subsectors modelled in this study and the resulting total energy consumption can be seen in Figure A1 and Figure A2 of the Appendix, respectively. Figure A3 displays the log of the relative fuel prices that are used in the modelling. In the figure, one can notice the difference between the time plots for the prices in NFM, MIN and OTH, which are built using coal as numeraire, and that for all the other subsectors where oil is used as numeraire.

4. Estimation results

5.1 Results from unit root tests

Our unit root testing procedure points at the variables used in the modelling, i.e. fuel shares, relative fuel prices and energy consumption in UK industrial subsectors, being integrated of order 1, with some series characterized by evident structural breaks. More precisely, electricity shares appear to be integrated of order 1 based on ADF tests in all but two subsectors – NFM and OTH – see Table A2a of the Appendix, although one can conclude that electricity shares in these subsectors are integrated of order 1 only after allowing for the presence of one break in trend through the application of a ZA test – see Table A2d. Evidence of integration of order 1 in the gas shares seems less strong – with this variable appearing to be integrated at least of order 2 in four subsectors – see Table A2b – but again one can conclude that gas shares in these four subsectors are integrated of order 1 based on results from the application of a ZA test – see Table A2d. Also in the case of oil and coal shares, the ZA tests suggests integration of order 1 in the two cases where the series appear to be integrated at least of order 2 based on ADF tests – see Table A2c and see Table A2d. Similar results are obtained in the case of the other three variables, i.e. relative price of electricity and gas, and energy consumption, as one can see in Table A3 and Table A4. The outcome from the unit root tests implies that we can proceed to test for the existence of cointegration among the variables used in our study.

5.2 Results from cointegration analysis

Results from the cointegration tests, shown in Table A5 of the Appendix, points overall at the existence of two cointegrating vectors among our variables. More precisely, the maximum eigenvalue test suggests two cointegrating vectors in seven of the eight subsectors, while in four subsectors, namely CHE, ENV, FBT and PPP, this finding is also supported by the trace test. The trace test indicates one cointegrating vector in the

MIN subsectors, and more than two cointegrating vectors in the OTH and TEX sector[3]. In the case of NFM, both the trace and the maximum eigenvalue statistics suggest one cointegrating vectors. Agnolucci et al. (2017) report that cointegration evidence in the NFM subsector differ from the results for all the other subsectors, a finding they attributed to the fact that, contrary to other subsectors, there is no perfect match between the definition of the NFM subsector in the DUKES and ONS datasets – see Table A1 of the Appendix. Given the rather robust and consistent evidence we obtained from the other seven subsectors, we take the indication of one cointegrating vector in NFM as a likely spurious finding, and we estimate a VECM with two cointegrating vectors in all of the eight industrial subsectors.

The results from applying the Johansen approach to estimation of cointegrating relationships are displayed in Table 1. First of all, we stress how estimates for the NFM subsector are fairly similar to those for the other subsectors, with the exception of the coefficient on the gas price in the gas demand equation, therefore leading us to believe that our assumption of two cointegrating vectors also for this subsector is reasonable. Statistical significance of the coefficients in the cointegrating vectors is assessed by running Likelihood Ratio tests (see Table 2). We observe that estimates for the own-price elasticities (for both electricity and gas) are highly significant in all but the TEX subsector. Cross-price elasticities are not statistically significant in two subsectors, ENV and OTH. Energy consumption and the linear deterministic trend are always statistically significant. When considered jointly, all variables in the two cointegrating vectors are highly statistically significant in all subsectors, providing in this way a strong confirmation of the validity of our empirical model of the long-run fuel share demand. While the two fuel shares of electricity and gas are assumed endogenous by definition of demand function, it is interesting to explore whether the other variables can be treated as weakly exogenous in the VECM environment, that is whether it can be excluded that they also adjust to past departures from the long-run equilibrium. To verify such property we run a Likelihood Ratio test on the joint weak exogeneity of prices and energy consumption with respect to both cointegrating relationships. We reject such hypothesis at 5% significance level in all but the NFM

[3] The higher probability of size distortions of the trace test in finite samples is highlighted in Lütkepohl et al. (2001).

subsector, again an exception which we attribute to the imperfect match between the definition of the NFM subsector in the economic and the energy datasets (Table 2).

Table 3 displays the outcome from implementing standard diagnostic tests on the VECMs used to produce the cointegrating vectors in Table 1. Results confirm the overall validity of the selected models across subsectors. Indeed, residual autocorrelation, as measured by the LM test, is evident only in the case of the TEX subsector, although only at 5% significance level. Heteroscedasticity is never detected by the White test, while deviation from normality emerges only in the MIN subsector, probably due to remaining outliers not explicitly taken into account by the included pulse dummies.

	CHE		ENV		FBT		MIN		NFM		OTH		PPP		TEX	
	Ele	Gas	Ele	Gas	Ele	Gas	Ele	Gas	Ele	Gas	Ele	Gas	Ele	Gas	Ele	Gas
Electricity Price	-0.22	-0.47	-0.74	-0.08	-0.49		-0.44	0.48	-0.67	0.66	-1.90	0.14	-0.61	0.32	-0.22	-1.17
Gas Price	-0.47	-1.37	-0.08	-0.71		-0.67	-0.52	-1.68	0.66	-0.17	-0.13	-1.31	1.14	-1.61	-1.17	-2.40
Energy	-0.69	2.12	0.45	1.16			-0.84	1.87			-1.56	0.38	-1.50	1.82	-0.62	1.52
Trend							-0.01	0.05	0.05	-0.01					-0.03	-0.06
Constant	4.40	-16.62	-2.95	-9.22	-0.55	-0.08	5.94	-14.10	0.66	-1.90	15.75	-3.13	11.29	-13.82	2.63	-8.76

Table 1. Long-run elasticities from the cointegrating vectors of the VECMs. A key to the acronyms of the industrial subsectors can be seen in Table A1.

	CHE	ENV	FBT	MIN	NFM	OTH	PPP	TEX
Own price - electricity	4.80(*)	7.86(**)	7.88(*)	8.41(**)	7.05(**)	21.85(**)	9.31(**)	0.52
Own price - gas	32.32(**)	12.25(**)	5.58(*)	5.26(*)	22.69(**)	16.84(**)	13.37(**)	10.64(**)
Cross price	9.05(**)	0.08		13.30(**)	5.30(**)	1.63	16.65(**)	17.03(**)
Energy	52.57(**)	13.03(**)		16.60(**)		44.76(**)	13.23(**)	9.00(**)
Trend				9.80(**)	22.39(**)			8.14(**)
All	57.97(**)	34.28(**)	9.55(**)	56.42(**)	38.58(**)	82.00(**)	40.47(**)	50.91(**)
Exogeneity	37.23(**)	26.62(**)	17.72(**)	32.51(**)	4.84	38.92(**)	21.53(**)	34.73(**)

Table 2. Likelihood Ratio tests for significance of the coefficients in the cointegrating vectors. Significance level is indicated by: * (5%), ** (1%). A key to the acronyms of the industrial subsectors can be seen in Table A1.

	CHE	ENV	FBT	MIN	NFM	OTH	PPP	TEX
Serial Correlation	0.14	0.94	0.24	0.29	0.79	0.72	0.13	0.05
Hetero	0.49	0.55	0.69	0.36	0.86	0.56	0.47	0.63
Non-normality	0.96	0.84	0.68	0.00	0.96	0.87	0.89	0.79

Table 3. p-values of diagnostic tests for the VECMs used to estimate the cointegrating vectors . A key to the acronyms of the industrial subsectors can be seen in Table A1.

5. Conclusions

We estimated demand functions for different fuels by implementing the first cointegration analysis at a disaggregated level, and we showed that plausible and robust estimates of price elasticities can be obtained even from relatively short time series using a parsimonious but careful application of the system approach to cointegration analysis. As time goes by, we would expect to see the level of disaggregation pursued here being applied to other countries to start building evidence on fuel demand elasticities, which accounts for the peculiarities of firms belonging to different industrial subsectors to help policy maker assess the impact of energy, climate and industrial policies at the subsectoral level. Modelling a VECM for each of the eight industrial subsectors we obtained a surprisingly uniform and unequivocal evidence for the existence of two cointegrating relationships representing demand for electricity and gas fuel. Compared to previous empirical contributions our estimates present greater statistical significance, whether we consider the whole cointegrating vectors in general or the own-price elasticity in particular. As for the methodology we adopt, the validity and advantages of a system approach to estimation is confirmed by the steady rejection of the weak exogeneity hypothesis for energy prices and consumption across all subsectors.

Our results can be summarised in four points. First, the magnitude of electricity and gas own-price elasticity, that is -0.77 and -1.22 on average respectively, is markedly greater than the typical values reported in the existing empirical literature. There are two possible explanations for such outcome: previous studies may suffer from aggregation bias since they are based on coarser representations of the industrial sector; our estimation focuses on long-run fuel demand functions, which are expected to be more elastic as a result of substantial inter-fuel substitution costs. Second, we obtained that price considerations are more important in gas than in electricity consumption, confirming previous understanding in the field. Third, we found that demand for gas is positively related to total energy consumption while the opposite occurs for electricity demand, with this pattern being common to all subsectors, therefore showing the relevance of scale effects in the determination of fuel consumption level. Fourth, and presumably our most important finding, we uncovered substantial heterogeneity in the magnitude of own-price and cross-price elasticity of fuel demands across the eight industrial subsectors. While this heterogeneity is not new, the range of values we obtained is even wider than most previous results, providing a warning to those studies that aggregate data under the assumption of homogeneous coefficients across subsectors, like in panel data models. In particular from the sign of cross-price elasticities it turned out that there is no clear dominant evidence of substitutability over complementarity between fuels. This is likely the consequence of important differences in the ability of firms to respond to changes in prices, which is related to the specific characteristics of each subsector, and in particular to the different degree to which electricity and gas are used for different purposes across subsectors. This type of evidence clearly suggests a careful assessment of the likely performance and effectiveness of energy policies that aim at fostering certain fuel substitutions but that fail to account for these idiosyncratic features of each industrial subsector.

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Appendix

Sector Identifier	Description	DUKES energy data	ONS GVA data
		SIC 2007 code	SIC 2007 code
FBT	Food, Beverages and Tobacco	10-12	10-12
TEX	Textiles, Clothing, Leather and Footwear	13–15	13–15
PPP	Pulp, Paper, Printing and Publishing	17–18	17–18
CHE	Chemicals	20-21	20-21
MIN	Non-Metallic Mineral products	8, 23	8, 23
ENV	Engineering and Vehicles	25-30	25-30
NFM	Non-Ferrous Metals	24.4, (excluding 24.46), 24.53, 24.54	24.4-5
OTH	Other industries	16, 22, 31-33, 36-39	16, 22, 31-33, 36-39

Table A1. Matching between energy consumption and economic activity data for the industrial subsector assessed in our study.

	Levels			Differences		
	Test Statistic	Lags	tre/int	Test Statistic	Lags	tre/int
CHE	-2.03	0	trend	-4.17 (**)	0	constant
ENV	-1.18	2	constant	-3.15 (*)	0	constant
FBT	-2.29	0	trend	-4.78 (**)	0	constant
MIN	-3.63 (*)	0	trend	-4.75 (**)	0	constant
NFM	-1.72	0	trend	-1.40	2	constant
OTH	-1.97	0	trend	-1.13	2	trend
PPP	-3.01	0	trend	-5.34 (**)	0	constant
TEX	-2.79	0	trend	-6.16 (**)	0	constant

Table A2a. Results from unit root tests for electricity share. A key to the acronyms of the industrial subsectors can be seen in Table A1. Key: (**) and (*) indicate significance at the 99% and 95% significance level, respectively.

	Levels			Differences		
	Test Statistic	Lags	tre/int	Test Statistic	Lags	tre/int
CHE	-1.52	0	constant	0.43	3	trend
ENV	-1.22	0	constant	-3.45 (*)	0	constant
FBT	-1.76	0	constant	-2.86	2	trend
MIN	-2.28	0	constant	-2.26	2	constant
NFM	-1.64	0	constant	-2.39	2	constant
OTH	-1.49	1	trend	-2.76(+)	2	constant
PPP	-1.85	3	trend	-4.64 (**)	0	constant
TEX	-1.71	1	constant	-6.00 (**)	0	constant

Table A2b. Results from unit root tests for gas share. A key to the acronyms of the industrial subsectors can be seen in Table A1. Key: (**), (*) and (+) indicate significance at the 99%, 95% and 90% significance level, respectively.

	Levels			Differences		
	Test Statistic	Lags	tre/int	Test Statistic	Lags	tre/int
CHE	-1.34	1	trend	-6.56 (**)	0	trend
ENV	-1.39	2	constant	-3.61 (*)	0	constant
FBT	-1.08	0	constant	-1.89	2	constant
MIN (COAL)	-2.62	0	constant	-5.14 (**)	0	constant
NFM (COAL)	-0.89	2	constant	-2.37	2	constant
OTH (COAL)	-0.16	2	trend	-6.21 (**)	0	trend
PPP	-1.32	0	constant	-4.99 (**)	0	constant
TEX	-2.11	0	trend	-4.15 (**)	0	constant

Table A2c. Results from unit root tests for coal/oil share. A key to the acronyms of the industrial subsectors can be seen in Table A1. Key: (**) and (*) indicate significance at the 99% and 95%, respectively.

		Statistic	Lags	Break date	Statistic	Lags	Break date
ELE	NFM	-2.27	0	2012	-7.17$^{(**)}$	1	2003
	OTH	-4.23	2	2008	-8.21$^{(**)}$	1	2006
GAS	CHE	-4.48	0	1999	-10.88$^{(**)}$	1	2007
	FBT	-3.68	4	2012	-5.53$^{(*)}$	2	2010
	MIN	-6.14$^{(**)}$	4	2007	-6.41$^{(**)}$	0	2005
	NFM	-3.00	0	2003	-6.16$^{(**)}$	1	2003
OIL	FBT	-4.16	5	2012	-6.59$^{(**)}$	2	2000
COAL	NFM	-6.20$^{(**)}$	5	2008	-7.57$^{(**)}$	5	2005

Table A2d. Results from ZA unit root tests for shares appearing to be at least (I2) based on ADF unit root tests. Acronyms of the sectors assessed in this study can be seen in Table A1 in the appendix. Key: $^{(**)}$ and $^{(*)}$ in the superscripts indicates significance at the 99% and 95% significance level.

	Levels			Differences		
	Test Statistic	Lags	tre/int	Test Statistic	Lags	tre/int
CHE	-2.85	0	trend	-5.09$^{(**)}$	0	constant
ENV	-2.84	0	trend	-4.88$^{(**)}$	0	constant
FBT	-2.88	0	trend	-4.99$^{(**)}$	0	constant
MIN (COAL)	-3.41$^{(+)}$	0	trend	-6.67$^{(**)}$	0	constant
NFM (COAL)	-2.12	0	constant	-4.53$^{(**)}$	0	constant
OTH (COAL)	-2.22	0	constant	-2.04	2	constant
PPP	-2.91	0	trend	-5.16$^{(**)}$	0	constant
TEX	-2.85	0	trend	-4.80$^{(**)}$	0	constant

Table A3a. Results from unit root tests for relative electricity price. A key to the acronyms of the industrial subsectors can be seen in Table A1. Key: $^{(**)}$ and $^{(*)}$ indicate significance at the 99% and 95% significance level, respectively. Energy consumption in OTH is I(1) based on the ZA test – value of the statistics being -5.97 for the first difference of the series. Relative electricity price in OTH is I(1) based on the ZA test – value of the statistics being -6.16 for the first difference of the series.

	Levels			Differences		
	Test Statistic	Lags	tre/int	Test Statistic	Lags	tre/int
CHE	-1.96	2	trend	-5.50$^{(**)}$	0	constant
ENV	-1.97	2	trend	-5.45$^{(**)}$	0	constant
FBT	-1.97	2	trend	-5.49$^{(**)}$	0	constant
MIN (COAL)	-2.18	0	trend	-4.52$^{(**)}$	0	constant
NFM (COAL)	-2.12	0	trend	-5.37$^{(**)}$	0	constant
OTH (COAL)	-2.24	0	trend	-5.53$^{(**)}$	0	constant
PPP	-1.96	2	trend	-5.52$^{(**)}$	0	constant
TEX	-1.97	2	trend	-5.45$^{(**)}$	0	constant

Table A3b. Results from unit root tests for relative gas price. A key to the acronyms of the industrial subsectors can be seen in Table A1. Key: $^{(**)}$ and $^{(*)}$ indicate significance at the 99% and 95% significance level, respectively.

	Levels			Differences		
	Test Statistic	Lags	tre/int	Test Statistic	Lags	tre/int
CHE	-1.39	0	trend	-2.85$^{(+)}$	3	constant
ENV	-1.71	0	trend	-3.75$^{(*)}$	0	constant
FBT	-2.25	0	trend	-5.39$^{(**)}$	0	constant
MIN (COAL)	-3.21	0	trend	-5.62$^{(**)}$	0	constant
NFM (COAL)	-0.21	0	trend	-6.47$^{(**)}$	0	constant
OTH (COAL)	-1.70	0	trend	-1.94	2	constant
PPP	-1.69	0	trend	-3.68$^{(*)}$	0	constant
TEX	-2.40	0	trend	-5.72$^{(**)}$	0	constant

Table A4a. Results from unit root tests for energy consumption. A key to the acronyms of the industrial subsectors can be seen in Table A1. Key: $^{(**)}$ indicates significance at the 99% significance level. Energy consumption in OTH is I(1) based on the ZA test – value of the statistics being -5.97 for the first difference of the series.

	Trace				Max Eigenvalue			
	H_0	H_1	λ_{trace}	p-value	H_0	H_1	λ_{max}	p-value
CHE	r = 0	r ≥ 1	102.76	0.00$^{(**)}$	r = 0	r = 1	52.38	0.00$^{(**)}$
	r ≤ 1	r ≥ 2	50.38	0.03$^{(*)}$	r = 1	r = 2	26.43	0.07$^{(*)}$
	r ≤ 2	r ≥ 3	23.95	0.20	r = 2	r = 3	16.19	0.21
ENV	r = 0	r ≥ 1	86.28	0.00$^{(**)}$	r = 0	r = 1	41.20	0.01$^{(**)}$
	r ≤ 1	r ≥ 2	45.08	0.09$^{(+)}$	r = 1	r = 2	25.03	0.10$^{(+)}$
	r ≤ 2	r ≥ 3	20.05	0.42	r = 2	r = 3	14.08	0.36
FBT	r = 0	r ≥ 1	64.67	0.00$^{(**)}$	r = 0	r = 1	31.87	0.01$^{(**)}$
	r ≤ 1	r ≥ 2	32.80	0.02$^{(**)}$	r = 1	r = 2	21.21	0.05$^{(*)}$
	r ≤ 2	r ≥ 3	11.59	0.18	r = 2	r = 3	9.61	0.24
MIN	r = 0	r ≥ 1	98.85	0.01$^{(**)}$	r = 0	r = 1	40.28	0.03$^{(*)}$
	r ≤ 1	r ≥ 2	58.56	0.13	r = 1	r = 2	31.56	0.06$^{(+)}$
	r ≤ 2	r ≥ 3	27.00	0.68	r = 2	r = 3	13.55	0.76
NFM	r = 0	r ≥ 1	62.88	0.06$^{(+)}$	r = 0	r = 1	29.58	0.10$^{(+)}$
	r ≤ 1	r ≥ 2	33.29	0.32	r = 1	r = 2	19.15	0.30
	r ≤ 2	r ≥ 3	14.14	0.65	r = 2	r = 3	8.01	0.82
OTH	r = 0	r ≥ 1	115.24	0.00$^{(**)}$	r = 0	r = 1	50.34	0.00$^{(**)}$
	r ≤ 1	r ≥ 2	64.89	0.00$^{(**)}$	r = 1	r = 2	25.54	0.09$^{(+)}$
	r ≤ 2	r ≥ 3	39.35	0.00$^{(**)}$	r = 2	r = 3	17.17	0.16
PPP	r = 0	r ≥ 1	105.75	0.00$^{(**)}$	r = 0	r = 1	45.59	0.00$^{(**)}$
	r ≤ 1	r ≥ 2	60.16	0.00$^{(**)}$	r = 1	r = 2	34.14	0.01$^{(**)}$
	r ≤ 2	r ≥ 3	26.02	0.13	r = 2	r = 3	16.62	0.19
TEX	r = 0	r ≥ 1	122.39	0.00$^{(**)}$	r = 0	r = 1	48.12	0.00$^{(**)}$
	r ≤ 1	r ≥ 2	74.27	0.01$^{(**)}$	r = 1	r = 2	29.67	0.10$^{(+)}$
	r ≤ 2	r ≥ 3	44.60	0.03$^{(*)}$	r = 2	r = 3	19.14	0.30

Table A5. Results from the trace and max eigenvalue cointegration tests. Key: (**) in the superscripts indicates significance at the 1% level; (*) indicates significance at the 5% level; (+) indicates significance at the 10% level. A key to the acronyms of the industrial subsectors can be seen in Table A1.

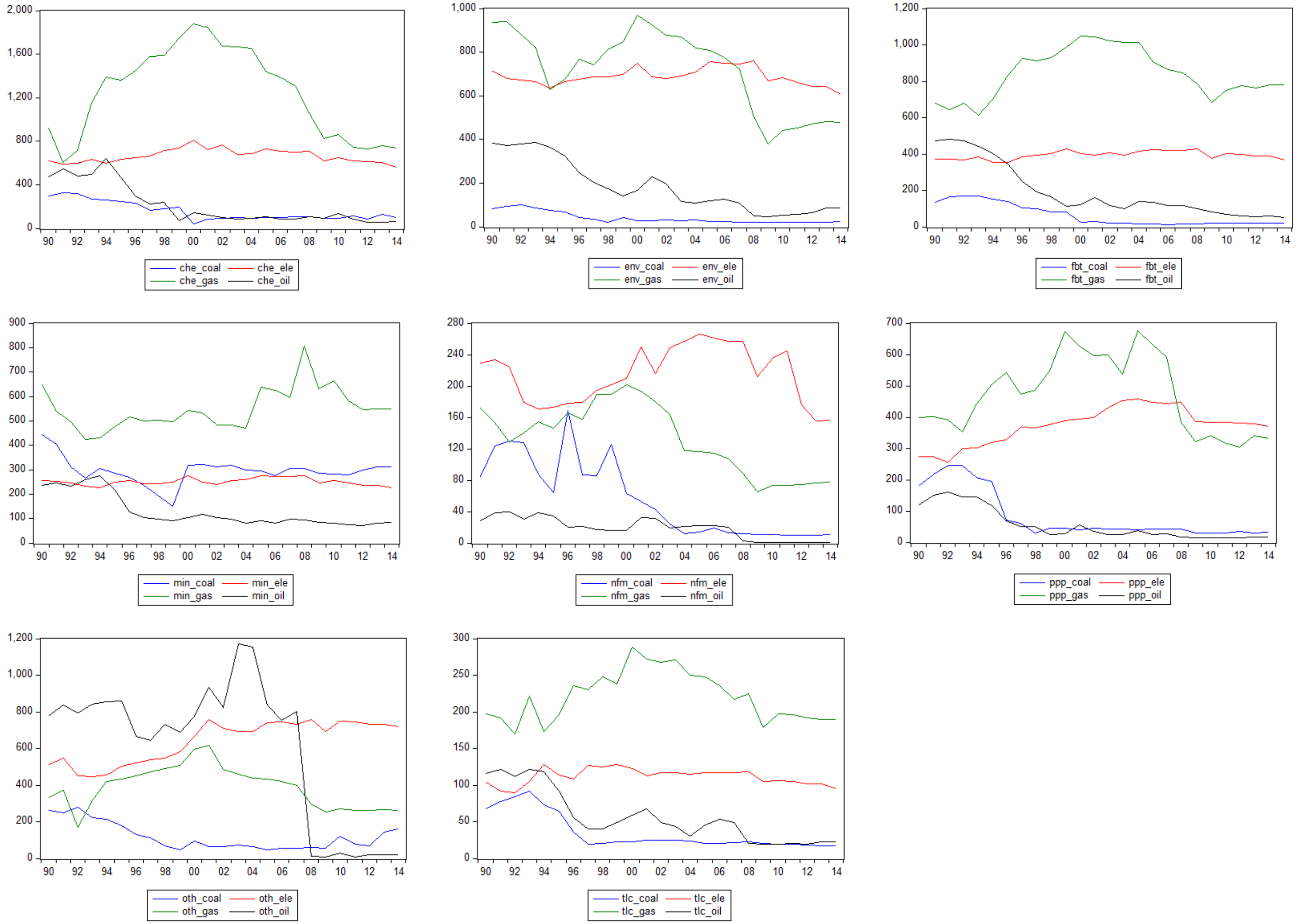

Figure A1 Consumption of coal, gas, electricity and oil, expressed in million therms, for each subsector. A key to the acronyms of the industrial subsectors can be seen in Table A1.

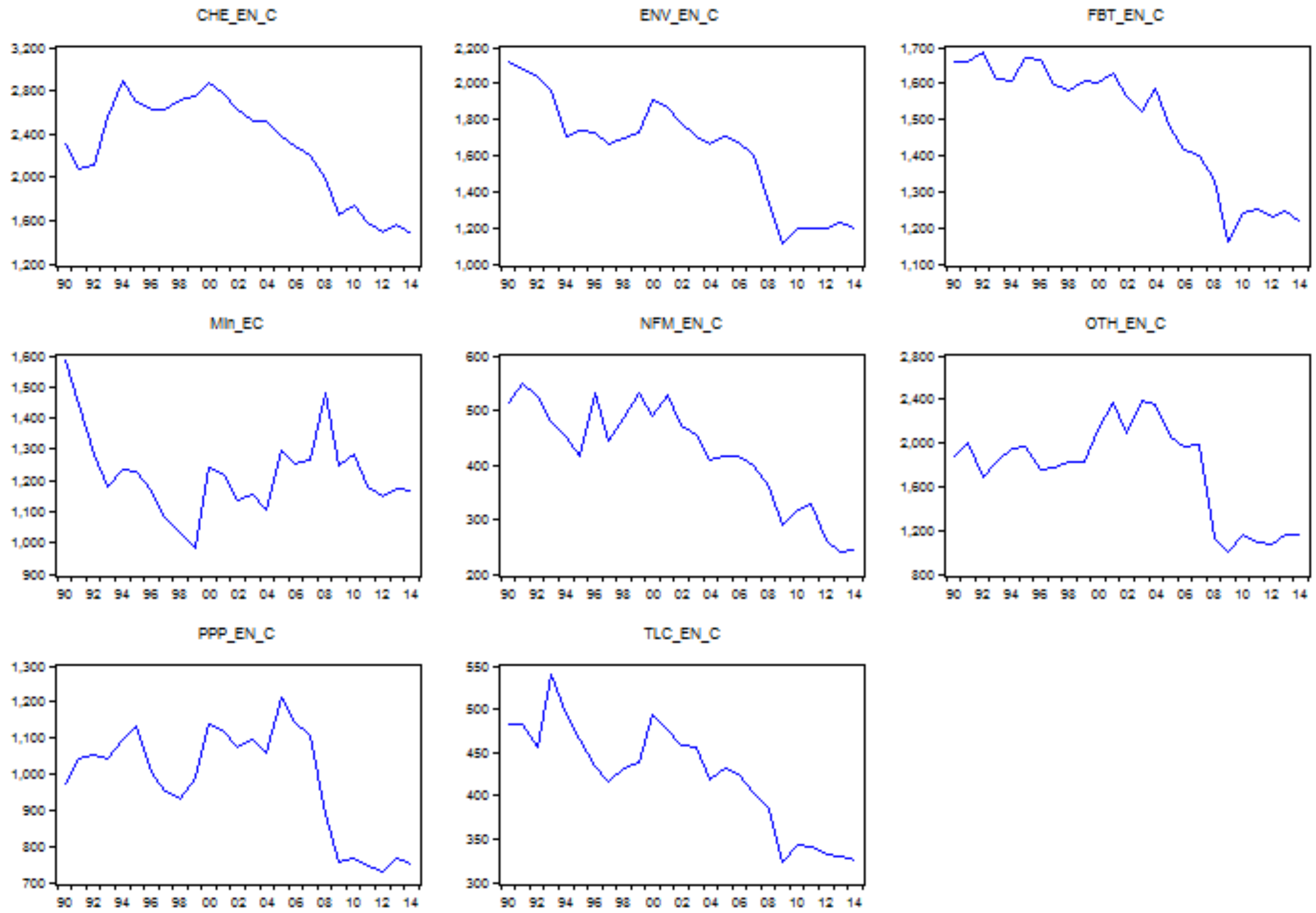

Figure A2. Energy consumption in million therms. A key to the acronyms of the industrial subsectors can be seen in Table A1.

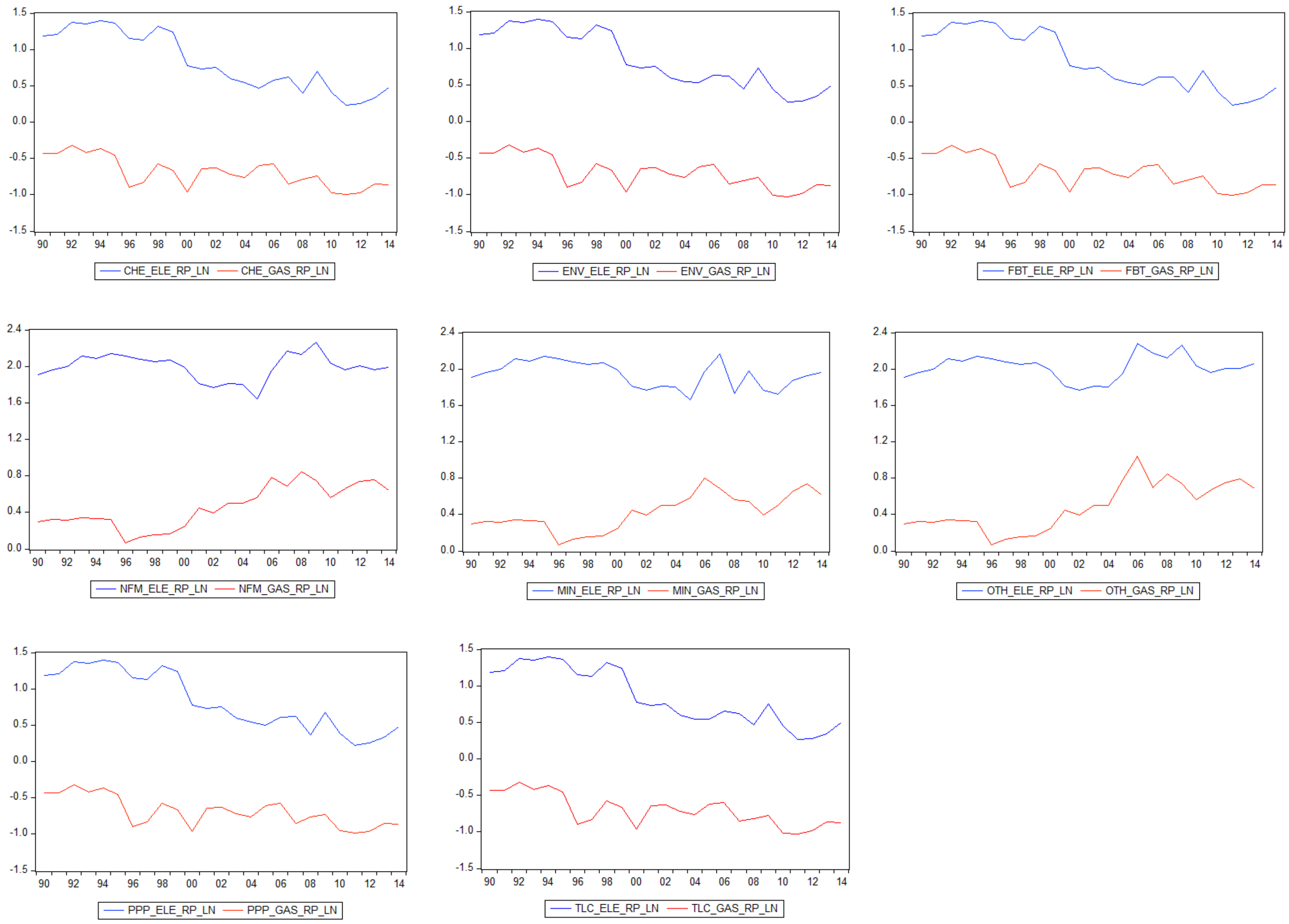

Figure A3. Relative fuel prices in each subsector. A key to the acronyms of the industrial subsectors can be seen in Table A1.