Modelling UK sub-sector industrial energy demand

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ABSTRACT

The importance of considering homogenous economic agents when estimating energy demand functions is recognized in the literature, but so far data availability problems have explained the prevalence of empirical analyses only at an aggregate level. Motivated by the goal of developing the new industrial module to be adopted by the UK government Department of Business, Energy and Industrial Strategy (BEIS) for their econometric Energy Demand Model, we propose the first cointegration analysis that provides evidence on energy demand elasticities with respect to economic activity and energy price at a disaggregated industrial level. While the average of our estimates are comparable to those of the existing literature on the industrial sector as a whole, we find that there is considerable heterogeneity in relation to the long-run impact of economic activity and energy price on energy consumption, as well as to the speed with which firms re-adjust their equilibrium demand of energy in response to economic shocks. Finally, we learn that long-run disequilibria are tackled through altering the level of energy consumption rather than economic activity, a conclusion that has important implications for policy analysis.

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1. Introduction

The amount of energy used in industrial sectors constitutes an important share of national energy balances. Despite decreasing in some OECD countries, industrial energy consumption has accounted for a surprisingly constant share of world energy consumption, fluctuating between 33% in 1971 and 27% in 2013 (IEA, 2016). While the 2007 special issue of Energy Economics devoted to modelling industrial energy demand (Greening et al., 2007) testifies the academic interest for this subject, econometric studies on industrial energy demand are surprisingly scarce, as argued in Bernstein and Madlener (2015). A somewhat plausible explanation for this lack of published studies could be related to the perception that the industrial sector is one of the hardest end-uses to analyse, model and forecast (Greening et al., 2007), a perception which might be imputed to aggregation problems, i.e. the high heterogeneity of industrial firms, lumpy and sunk nature of investments, lags between the time when investments are made and when their impact on energy consumption unfolds, and the diversity in the energy price faced by industrial firms.

Existing data and tools available in standard econometric toolkits, however, are able to tackle these issues to a reasonable extent. In the spirit of Pesaran et al. (1999), who advocated estimation of energy demand functions on a set of consumers that is as homogeneous as possible, the increasing availability of data disaggregated at two-digit SIC level for a sufficiently long time span should help overcome aggregation issues. The impact of the lumpy nature of energy investments can manifest itself as structural breaks in the coefficients of energy demand models but rigorous econometric tests, like the one adopted in this study, can easily be employed to ascertain and control for these changes. Modelling the impact of economic variables on energy-using stock while taking into account the lag between the time investments are made and when their impact on energy consumption unfolds is more problematic. The capital measurement framework and the dynamic factor demand model of Pindyck and Rotemberg (1983) can be used to take into account different vintages of capital and price-induced improvements in the energy efficiency of capital stock, as recently implemented in Steinbuks and Neuhoff (2014), but comprehensive data are rarely available.[1] Finally, the difference in energy price levels faced by industrial firms is also difficult to incorporate in econometric studies. In some cases data are available, e.g. Department for Business, Energy and Industrial Strategy (BEIS) (2016a) publishes data on fuel prices paid by firms of different sizes, but similarly disaggregated information on energy consumption and GVA is not accessible, therefore hindering any econometric analysis. Microeconometric approaches like the one

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[1] As an example, the EU KLEMS database used in Steinbuks and Neuhoff (2014) ends in 2009.

implemented in Bjørner and Jensen (2002) are however able to address this problem.

The aim of this paper is to estimate the industrial energy demand in the UK by examining its dynamics within the different subsectors. In this respect we make two substantial contributions to the existing literature. First of all, we highlight that our paper is the first cointegration study that provides evidence on energy demand elasticities at a disaggregated industrial level. Our review of the literature identifies only three studies estimating industrial energy demand at a comparable level of disaggregation, none of which takes into account the time series characteristics of the variables.[2] 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 energy price and economic activity of disequilibria in energy consumption; 2) the speed of the adjustment process originated by any disequilibrium; 3) the role of trends in the long-run energy consumption; 4) the structural stability of the estimated relationships.

Our second contribution consists in providing new evidence about the relative importance of economic activity and energy price in determining the energy consumption level. No general consensus could be found in the existing literature on the industrial sector of the economy, a problem that might be due to the fact that industrial sectors have rarely been subject to systematic investigation. A rare exception is the UK, but unfortunately estimated elasticities differ significantly among studies. In some cases, such as in Dimitropoulos et al. (2005) and Hunt et al. (2003), elasticities of economic activity is higher than that of energy price, whereas a more balanced view can be found in Agnolucci (2009) and Agnolucci (2010). Therefore, by looking at the dynamics of energy consumption at the subsectoral level we hope to cast new light on the current debate about the value of energy demand elasticities. Our conclusions are important not only from an academic perspective, but also, and probably more tangibly, for policy-making purposes as, for instance, a very low value of the elasticity with respect to price questions the very rationale of policies that rely on price signals, e.g. the EU ETS or the UK climate change levy, to achieve climate and energy goals. 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. In Section 2 we discuss the existing literature and assess its conclusions. Reflecting our two lines of contribution we mentioned above, we discuss two sets of studies, with the first focused on the estimation of industrial energy demand at the subsectoral level, and the other focused on the UK industrial sector as a whole. After setting out our methodological approach in Section 3, we provide details on the data we use in Section 4. In Section 5, after assessing the outcome from the unit root tests, we present our main results in terms of cointegration analysis and estimation of energy demand equations. These results are then discussed in Section 6, followed by a summary of our findings in Section 7.

2. Literature review

In the energy literature, consumption of energy in the industrial sector is posited to be positively related to economic activity and negatively related to relative energy price (when modelling energy demand) or relative fuel prices (when modelling demand for a specific fuel).[3] The

methodologies that have been applied to the study of energy and fuel consumption in the industrial sector include:

1) Time series analysis based on cointegration, e.g. Polemis (2007), sometimes allowing for time-varying parameters, e.g. Chang et al. (2014);
2) Panel cointegration studies focused on the time component, e.g. El-Shazly (2013), or the cross-section component of the panel, e.g. Bjørner and Jensen (2002);
3) Input factor and fuel substitution models based on translog and linear logit specifications, which are normally static models applied to one single (Kim and Heo, 2013) or several industrial subsectors (Frondel and Schmidt, 2002), although dynamic specifications can also be found (Christopoulos, 2000, Urga and Walters, 2003);
4) Approaches focusing on the asymmetric impact of economic variables, mainly implemented with regard to energy price, normally based on the decomposition methodology introduced by Dargay and Gately (1995) – see Adeyemi and Hunt (2007) and Adeyemi and Hunt (2014) for two recent applications of this methodology in the industrial sector;
5) Implementations of the Structural Time Series Model of Harvey (1989), an approach introduced in the energy literature through the Underlying Energy Demand Model (UEDM) of Hunt et al. (2003) – see Dilaver and Hunt (2011) and Adeyemi and Hunt (2014) for two recent applications in the industrial sector.

As noticed by Bernstein and Madlener (2015), disaggregated analyses of energy consumption of industrial subsectors have rarely been undertaken. In their literature review these authors cite five studies that use two-digit industrial data: Agnolucci (2009), Calogirou et al. (1997), Christopoulos (2000), Christopoulos and Tsionas (2002), and Floros and Vlachou (2005). All these papers, with the exception of Floros and Vlachou (2005), use two-digit industrial data to create a panel dataset, i.e. Agnolucci (2009) and Calogirou et al. (1997), or to build a series for the manufacturing sector as a whole, i.e. Christopoulos (2000), and Christopoulos and Tsionas (2002). In other words, four out of the five mentioned papers are not interested in producing estimates of elasticities at the two-digit industrial subsector level.

In addition to Floros and Vlachou (2005), we identified two other studies estimating energy price and economic activity elasticities in industrial subsectors. Bjørner and Jensen (2002) compute these elasticities by using a fixed effects static model estimated on data from 8 surveys of firms collected in Denmark between 1983 and 1997. Price elasticities vary between −0.69 and −0.21 with the average for the whole industry being −0.44. Statistically significant energy demand elasticities with respect to economic activity vary between 0.44 and 0.65, with the average for the whole industry being 0.54. Floros and Vlachou (2005) model consumption of energy and energy fuels in the Greek two-digit industrial subsectors by using a two-stage translog model, where the first stage assesses the substitution between energy, capital and labour, while the second stage captures the substitution between energy fuels. The model is estimated using time series data over the period 1982–1998. Price elasticities vary considerably between −1.13 and −0.02, with the upper bound decreasing to −0.04 when non-statistically significant elasticities are discarded.

Steinbuks and Neuhoff (2014) assess the impact of energy price on energy consumption by modelling price-induced and autonomous changes in the energy efficiency of capital stock. These authors analyse 5 industrial subsectors in 19 OECD countries over the period 1990–2005 by means of two models: a Vintage Capital model and a restricted version where the input efficiency of capital stock does not change, as in Pindyck and Rotemberg (1983). Their results indicate that higher energy prices decrease energy use through improved energy efficiency of capital stock and reduced demand for energy inputs. Price elasticities of energy demand obtained from the Vintage Capital model estimated for the UK industrial subsectors vary between −0.87 and −0.26,

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[2] Bernstein and Madlener (2015) undertake an analysis similar to ours but concentrating on electricity rather than energy demand.
[3] This simply implies that energy is assumed to be a normal good with respect to income and an ordinary good with respect to price.

Table 1
Energy demand elasticities with respect to price and economic activity estimated for the UK industrial sector.

Study	Model	Estimation period	Price	Economic activity
Hunt et al. (2003)	STSM with symmetric price	1971–1995	− 0.2	0.71
Dimitropoulos et al. (2005)	STSM with symmetric price	1967–1999	− 0.17	0.70
Agnolucci (2009)	Average from various panel estimators	1978–2004	− 0.64	0.52
Agnolucci (2010)	STSM with symmetric price	1973–2005	− 0.59	0.45
Agnolucci (2010)	STSM with asymmetric price	1973–2005	− 0.65/− 0.47/− 0.37[a]	0.48
Adeyemi and Hunt (2014)	STSM with asymmetric price	1962–2010	− 0.51[b]	0.49

Key: STSM = Structural Time Series Model.
[a] Elasticity with respect to price maxima, price recoveries and price cuts.
[b] Elasticity with respect to price maxima.

narrower than the range obtained from the model of Pindyck and Rotemberg (1983), i.e. between − 1.04 and − 0.25. The investment response to energy prices varies considerably across manufacturing industries, being higher in energy-intensive sectors, but unfortunately no results about the UK industrial subsectors are presented. Estimates from Bjørner and Jensen (2002), Floros and Vlachou (2005), and Steinbuks and Neuhoff (2014) are displayed for comparative purposes in Table A2a and A2b of the Appendix.

In our literature review we discovered that the same uncertainty as to the magnitude of the elasticities with respect to price and economic activity characterizes the UK industrial sector, as can be seen in Table 1). At one extreme, we have studies like Dimitropoulos et al. (2005) and Hunt et al. (2003), according to which energy price has a relatively modest direct impact on consumption. At the other extreme, Agnolucci (2009) and Agnolucci (2010) conclude that the effect of energy price is clearly stronger than that of economic activity. Adeyemi and Hunt (2014), more recently, obtain an estimate for the elasticity with respect to economic activity that is very similar to Agnolucci (2009) and Agnolucci (2010), but the contribution of energy price in explaining the highly variable pattern of energy consumption is, however, limited by the fact that Adeyemi and Hunt (2014) employ a model with energy price maxima only, based on the decomposition approach of Dargay and Gately (1995). This choice entails that the time series on price is mainly constant with only few step changes occurring in the periods when a new price maximum is reached.

3. Methodological approach

Our study starts with the implementation of a unit root testing procedure relying largely on the DF-GLS test of Elliott et al. (1996), given its higher size-adjusted power in finite samples, and the Zivot and Andrews (1992)[4] test, which allows for one break at an unknown point in time. The number of lags in the testing equations was selected by the modified Akaike information criterion of Ng and Perron (2001), which is robust to the presence of negative MA components in the error term. We choose the deterministic terms by considering both the Akaike and the Bayesian information criteria on 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 integrated of order one. In case of stationary variables, one could implement a VAR in levels or in case of non-stationary variables which do not appear to be cointegrated a VAR in first differences, i.e. without the component in levels in the equation below. In case of inconclusive results from unit root testing, implementation of the Bounds testing procedure of Pesaran et al. (2001) offers the advantage of being robust to variables being stationary or integrated of order one. As evidence from unit root testing on the variables used in this study point decisively at integration of order one, see results below, discussion of the methodology is focused on the cointegrating VAR.

Estimation of the energy demand function is implemented in two steps. In the first step we look for evidence of long-run relationships

by testing for cointegration, using a Vector Autoregression (VAR) approach to model a system that describes the dynamics of energy consumption, energy price and GVA (see Johansen, 1988 and Johansen, 1991). More formally, we estimate a standard Vector Error Correction model (VECM) of order p

$$\Delta \boldsymbol{x}_t = \boldsymbol{\Gamma}_0 + \boldsymbol{\Pi}\boldsymbol{x}_{t-1} + \sum_{i=1}^{p} \boldsymbol{\Gamma}_i \Delta \boldsymbol{x}_{t-i},$$

where $\boldsymbol{x}_t$ is a 3×1 vector containing the logarithms of energy consumption, GVA and energy price, $\boldsymbol{\Pi}$ and $\boldsymbol{\Gamma}_i$ are 3×3 coefficient matrices and $\boldsymbol{\Gamma}_0$ contains deterministic terms. In those cases where cointegration is found by the trace and maximum eigenvalue tests, one can then assess the exogeneity assumption for the variables in the system and their significance inside the cointegrating vector. To assess the robustness of the results from the trace and maximum eigenvalue cointegration tests we also run the Bounds Testing procedure of Pesaran et al. (2001), which is implemented within a ARDL model that results from applying the Akaike information criterion on the general specification corresponding to the VECM used in the trace and maximum eigenvalue tests. Additional lags are added until serial autocorrelation is removed from the residuals, as assessed by the LM statistic and the inspection of the correlogram. In those cases where cointegration is not found one would need to estimate a VAR in first differences (based on our results from unit root testing). This is not implemented in our study due to prevailing evidence for cointegration discussed below. In the second step of our methodology, we study the single equation Error Correction Model (ECM) explaining energy consumption conditional on the cointegrating vector estimated from the VECM. This allows us to analyse more in depth the fit of the model and the short-run dynamic specification, including the adjustment coefficients, as well as run the relevant diagnostic checks. A detailed discussion of the two steps included in our methodological approach can be found below.

Factors that might influence energy consumption include energy-saving technological innovation, the price of other production inputs and changes in the structural composition of the industrial subsectors. While a STSM can capture at least in part these factors through a stochastic trend component, we prefer to focus on identifying the long-run relationships between the variables, which is best accomplished by a cointegration analysis within a VAR framework. Moreover, we opt for a parsimonious specification, a choice justified by the limited time period spanned by the dataset and the inevitable loss of degrees of freedom which would be implied by a VAR with a high number of variables. Drawbacks and advantages of linear models like ours, which are the workhorse in the estimation of energy demand, are well known in the literature. They are normally preferred on the basis of better performance compared to more complex models, simplicity and limited data requirements (Amarawickrama and Hunt, 2008; Bernstein and Madlener, 2015; Bhattacharyya and Timilsina, 2010, and Pesaran et al., 1999).[5]

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[4] ZA henceforth.

[5] It is also worth mentioning that using a non-linear functional form would prevent us from implementing cointegration analysis based on Johansen (1988) and Johansen (1991) or the cointegration break analysis of Kejriwal and Perron (2010) discussed below.

We adopt Johansen's VAR approach to cointegration for two main reasons. Firstly, we do not want to impose the existence of only one cointegrating vector, but instead let the data provide evidence for this.[6] Secondly, we prefer to adopt an agnostic reduced form modelling strategy, rather than imposing weak exogeneity assumptions on energy price and GVA. By doing so we are able to investigate the validity of the exogeneity restrictions rather than imposing them.[7] A drawback of the Johansen method, compared to the bounds testing approach of Pesaran et al. (2001), is the need for all variables to be integrated of the same order, which leaves some uncertainty related to the degree of integration ascertained by any unit-root testing procedure. This does not seem to be a very compelling reason for discarding the VAR approach based on the results from our unit-root tests.

In the first step of our methodological approach, we test for cointegration by using the trace and maximum eigenvalue tests of Johansen (1991). Following Johansen (1992) determination of the cointegrating rank is based on the interpretation of the estimated cointegrating relations as well as their statistical properties. This implies that we require estimated coefficients in the cointegrating vector to conform to economic theory, i.e. a positive coefficient on economic activity and a negative one on energy price. With regard to the deterministic terms in the cointegrating vector we have no prior reason for preferring a cointegrating vector with a constrained trend to a vector where only the intercept is present. Again, we follow Johansen (1992) and estimate a model with a intercept only and one with a restricted trend as well. Bearing in mind the methodological advice on cointegration analysis in small samples from Lütkepohl (2005), and Lütkepohl and Krätzig (2004), we start testing for cointegration in the VECM with no lags and increment the lag order up to a maximum of two if a cointegrating vector with signs consistent with economic theory cannot be found in more parsimonious models.[8]

During the estimation of the cointegrating vector, we drop either energy price or economic activity if coefficients with signs consistent with economic theory cannot be found in models including up to two lags, and examine VARs with two variables. As discussed in Section 4, this occurred only in the case of one subsector. After estimating the cointegrating vector, we implement likelihood ratio tests to assess the exogeneity assumptions in the VECMs and the significance of each variable in the cointegrating vector. We also analyse the residuals of the estimated VECMs to verify the absence of serial correlation and heteroscedasticity. The stability of the long-run energy demand equation is investigated by implementing the procedure of Kejriwal and Perron (2010)[9] which allows for structural breaks at unknown points in time in the cointegrating relationship.[10] We consider a pure structural change model, i.e. case 1) in KP, where all coefficients are allowed to change across regimes. We deal with potentially endogenous regressors by adding one lead and one lag of the first-differences of the integrated variables in an equation comprising the cointegrating vector, as suggested by the dynamic OLS regression (DOLS) approach of Saikkonen (1991).[11] Considering the sample size, we decide to allow for one single break throughout the testing procedure.

As mentioned above, in the second step of our methodological approach we study the short-run dynamics, including the adjustment coefficients, by estimating energy demand equations for all subsectors as Error Correction Models (ECMs), conditional on the long-run relationship identified in the cointegrating VARs, and incorporating the structural break if detected by the KP test. We add impulse dummies in the short-run component of the model if extreme outliers emerge from visual inspection of the residuals. As simulation studies have shown that excessive model reduction in ECMs carries the risk of wrongly removing relevant variables, we adopt a conservative approach by dropping only those variables with a sign not consistent with economic theory and those with the expected sign but a p-value higher than 0.50.[12] Finally, as a validation check, we test the estimated ECMs for heteroscedasticity, serial correlation, functional misspecification and structural stability using a CUSUM test.

4. Data

Our dataset includes three variables, energy consumption, energy price and GVA, observed at an annual frequency between 1990 and 2014 for all the eight industrial subsectors, which are listed in Table A1 of the Appendix. Energy consumption, which is computed as the sum of fuel consumption from data in Department for Business, Energy and Industrial Strategy (BEIS) (2016a), takes into account energy used for the production of heat and, from 2000 onwards, the impact of energy efficiency policies. Energy price was obtained as a weighted average of fuel prices, taken from Department for Business and Energy and Industrial Strategy (BEIS) (2016b). Prices indices, which incorporate all relevant taxes (Climate Change Levy included), were converted 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 energy fuels and the share of each subsector covered by the EU ETS, and finally computed a time series for the energy price. Data on the Gross Value Added which are measured in chained volume measures (million pounds) and were obtained from ONS (2016). This data source enabled an almost perfect match with the taxonomy of the industrial sector used in Department for Business, Energy and Industrial Strategy (BEIS) (2016a), with the exception of the Non-Ferrous Metals subsector, as shown in Table A1 of the Appendix. 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.

Time patterns of the data can be seen in Fig. A1 of the Appendix. Visual inspection of the data hints at the possibility of our variables being integrated of order 1, whereas the likelihood of a structural break in the marginal distributions appears to vary considerably across subsectors and variables. In the case of energy price, the change in the pattern unfolding from 2005 onwards is apparent from the graphs. One can also appreciate that, with the exception of TEX, the industrial GVA was considerably affected by the financial crisis although economic activity quickly return to pre-crisis levels in the case of ENV, FBT and NFM subsectors. A key to the acronyms of the industrial subsectors modelled in this study can be found in Table A1 of the Appendix.

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[6] Given the variables used in this study, i.e. energy consumption, energy price and GVA, we interpret the existence of one cointegrating relationship as the demand for energy in that specific industrial subsector.

[7] Other advantages of Johansen's approach include higher estimation efficiency resulting from a full information maximum likelihood method, absence of bias that might be produced by neglecting either the short-run or the long-run components of the model, and the ease with which this framework allows to test for restrictions on the long-run equilibrium relationships. There is also some evidence of better finite sample properties (see e.g. Gonzalo, 1994).

[8] As discussed in Lütkepohl and Krätzig (2004), starting with a large order, and sequentially testing to remove not significant lags, has the problem of large Type I error. In addition, Lütkepohl (2005) clarifies that consistent order estimation may not be a relevant objective in small sample situations. In fact, the true data generating process may not admit a finite order VAR representation.

[9] KP henceforth.

[10] KP propose a more comprehensive framework, specifically devised to address stability in cointegration models, than the alternative of applying standard tests for unknown breaks combined with Hansen's (2000) fixed regressors bootstrap procedure, or the approach followed in Johansen et al. (2000), which only deals with structural breaks in the trend and intercept at a known point in time.

[11] Cfr. equation (9) in KP.

[12] While simplicity and parsimony of a model are usually associated with a good forecasting performance, Brüggemann (2004) finds that reduction of the short-run dynamics in a VECM can be detrimental not only for impulse response analysis but also for forecasting.

5. Estimation results

5.1. Results from unit root tests

Our unit root testing procedure points at GVA, energy consumption and energy prices of UK industrial subsectors being integrated of order 1, with some series characterized by evident structural breaks. This is consistent with what was obtained by Bernstein and Madlener (2015) for GVA, electricity prices and consumption in the German industrial subsectors. More precisely, the DF-GLS tests on energy consumption point at the variable being integrated of order 1 in all but one subsector – OTH - see Table A3a of the Appendix. First differences of energy consumption in this subsector, however, appear to be stationary based on the results from the ZA test. Based on our results from the DF-GLS test, energy price seems to be integrated of order 2, with few exceptions at the 10% significance level (see Table A3b), but application of the ZA test decisively points at the variable being integrated of order 1. GVA appears to be integrated of order 1 in five subsectors out of eight, based on the DF-GLS test, as shown in Table A3c. However, results from the ZA test lead us to conclude that GVA is integrated of order 1 in the remaining three subsectors. Results from the unit root tests imply that we can proceed to test existence of cointegration among the variables used in our study. As described above we do so by adopting the Johansen's approach to cointegration and the Bounds Testing procedure of Pesaran et al. (2001).

5.2. Results from cointegration analysis

Results from the cointegration tests, shown in Table A4 of the Appendix, points overall at the existence of one cointegrating vector in the estimated system. More precisely, at 10% significance level, the trace statistic suggests one cointegrating vector in seven of the eight subsectors, but in five subsectors, namely CHE, FBT, OTH, PPP and TEX, this finding is supported by both the trace and the maximum eigenvalue tests. Only the trace test indicates one cointegrating vector in the ENV and MIN subsectors, whereas in the case of NFM, the trace and the maximum eigenvalue statistics both suggest two cointegrating vectors.[13] Results from our application of the Bounds Testing procedure of Pesaran et al. (2001), as described above, are shown in Table A5, while the critical values can be found in Table A6 of the Appendix. After selecting the model specification using the strategy discussed above, we obtain evidence of cointegration in all but the ENV subsector.[14]

In summary, we can be sufficiently confident about the existence of one cointegrating relationship in all of our eight industrial subsectors. The exception of NFM, where apparently two cointegrating vectors emerge, might be caused by the fact that, contrary to the other subsectors, there is no perfect match between the definition of the subsector in the economic and the energy datasets – see Table A1 of the Appendix.[15] Given the consistent evidence from the other seven subsectors we take the indication of a second cointegrating vector in NFM as a likely spurious finding, and so decide to estimate a VECM with one cointegrating vector also for the this latter subsector.

Results from the cointegration tests imply that we can proceed with the estimation of the cointegrating VAR described in the equation above, according to the Johansen approach to cointegration, the results from which are displayed in Table 2. All eight cointegrated VARs turn out to be stable, with energy demand reducing the discrepancy from

Table 2

Estimated cointegrating vectors from the VECMs. The last column labelled "Exogeneity" displays the p-value of the Likelihoood Ratio test on the joint significance of the adjustment coefficients of the two equations describing energy price and economic activity. A key to the acronyms of the industrial subsectors can be seen in Table A1.

	y_t	p_t	Trend	Constant	Exogeneity
CHE	0.48	−0.32	−0.02	3.87	0.58
ENV	0.32	−0.30	−0.01	4.47	0.11
FBT	0.50	−0.17	−0.01	3.13	0.22
MIN	0.36			3.04	0.08
NFM	1.10	−0.52		1.50	0.93
OTH	1.42	−0.78		1.09	0.01
PPP	0.24	−0.34		4.83	n/a
TEX	0.12	−0.44		5.80	0.06

the long-run equilibrium of the previous period.[16] The values of the co-efficients for the NFM subsector are well within the range spanned by the other subsectors, therefore leading us to believe that our assumption of one cointegrating vector for this subsector is reasonable. The table also presents the value of the Likelihood Ratio test assessing the weak exogeneity of energy price and economic activity with respect to energy consumption. In all but two subsectors, OTH and PPP, the weak exogeneity assumption is accepted at the 5% significance level, and therefore incorporated in the model used to estimate the cointegrating vectors in the table. In the case of OTH, rejection of the weak exogeneity assumption is due to energy price appearing to adjust to the disequilibrium in the cointegrating relationship.[17] As this is unlikely to reflect actual market dynamics, due to energy consumption of OTH being only 2% of total energy consumption in the UK, the exogeneity assumption is imposed in the model used to estimate the cointegrating vector also for OTH. Statistical significance of the coefficients in the cointegrating vectors is assessed by running Likelihood Ratio tests (see Table 3). We observe that energy price is highly significant with very small p-values in all but one subsector. Economic activity is statistically significant at 5% only in the case of CHE and OTH, although significance can be acknowledged at 20% in 6 out of the 8 subsectors. When considered jointly, energy price and economic activity are strongly statistically significant in all subsectors, providing in this way confirmation on the existence of a long-run cointegrating relationship.[18]

Table 4 displays the outcome from implementing standard diagnostic tests on the VECMs used to produce the cointegrating vectors in Table 2. Results confirm the overall validity of the selected models across the eight subsectors. Residual autocorrelation, as measured by the LM test, is evident only in the case of the TEX subsector, whereas heteroscedaticity, as measured by the White test, can be found only in the MIN subsector. Further diagnostic tests are performed on the conditional ECMs describing the energy demand equation in each subsector, as discussed below.

5.3. Results from the conditional error correction models (ECMs)

Before estimating the ECMs, conditional on the cointegrating relationships identified in the VECMs, we investigate the stability of the long-run energy demand equation by implementing the procedure of

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[13] Results for the ENV and MIN sectors could be reflective of the findings of Toda (1994) according to which these tests are not very powerful for sample sizes that are typical for economic time series. Lütkepohi et al. (2001) concludes that the trace test performs better than the maximum eigenvalue tests when the power is low, which might explain our results in the ENV and MIN sectors.

[14] Cointegration is however detected by the bounds test also in the ENV sector when we include four lags in the ARDL model – test statistic being equal to 11.85.

[15] Limitations arising from data availability are not new in this field. Bernstein and Madlener (2015), for instance, highlight how this could be due to problems with data quality.

[16] Stability of the VAR in all subsectors is confirmed by the fact that all roots, apart from the two that are equal to 1, are within the unit circle.

[17] The p-value of the Likelihood Ratio statistic on GVA, conditional on the exogeneity of energy price, is 0.39.

[18] It is worth mentioning that it is possible to either drop a variable when the corresponding coefficient is not statistically significant, an approach implemented in Bernstein and Madlener (2015), or alternatively to keep that variable in the model, a choice taken in Bjørner and Jensen (2002) and Floros and Vlachou (2005). In our study, we adopt the latter approach and keep variables in the cointegrating vector, even if non statistically significant, given the unequivocal evidence on the existence of cointegration among the three variables, and also mindful of the fact that the lack of statistical significance could be simply due to the limited time span of the sample used in our study.

Table 3
P-values of the likelihood ratio tests for the coefficients in the cointegrating vectors shown in Table 2. A key to the acronyms of the industrial subsectors can be seen in Table A1.

	p_t	y_t	p_t and y_t	p_t, y_t and trend
CHE	0.004	0.049	0.010	0.005
ENV	0.005	0.480	0.001	0.003
FBT	0.000	0.134	0.000	0.000
MIN		0.157		
NFM	0.001	0.139	0.000	
OTH	0.002	0.044	0.004	
PPP	0.000	0.467	0.000	
TEX	0.001	0.200	0.001	

Table 4
Number of lags and p-values of diagnostic tests for the VECMs used to estimate the cointegrating vectors presented in Table 2. A key to the acronyms of the industrial subsectors can be seen in Table A1.

	Lags	Serial correlation	Heteroscedaticity
CHE	1	0.91	0.29
ENV	1	0.61	0.08
FBT	0	0.14	0.09
MIN	0	0.21	0.02
NFM	2	0.41	0.22
OTH	1	0.10	0.15
PPP	2	0.08	0.42
TEX	1	0.00	0.45

Table 5
Results from the KP test. A key to the acronyms of the industrial subsectors can be seen in Table A1.

	KP statistics	95% CV	Notes
CHE	4.82	10.88	qb = 2, trend, trimming = 0.20
ENV	8.99	10.88	qb = 2, trend, trimming = 0.20
FBT	15.35	10.88	qb = 2, trend, trimming = 0.20, break date: 2009
MIN	6.65	9.27	qb = 1, trimming = 0.15
NFM	8.34	12.27	qb = 2, trimming = 0.20
OTH	11.18	12.27	qb = 2, trimming = 0.20
PPP	9.39	12.27	qb = 2, trimming = 0.20
TLC	5.16	12.27	qb = 2, trimming = 0.20

Kejriwal and Perron (2010). Results, presented in Table 5, are overwhelmingly in favour of the stability of the equilibrium relationship, the only exception being the FBT subsector. Unfortunately, as the break is estimated to occur in 2009 this does not leave enough observations to identify the parameters associated with the second segment.

The coefficients capturing the short-run dynamics of energy consumption in the conditional ECMs are shown in Table 6. Economic activity is present in the short-run dynamics of two out of the eight economic subsectors, while energy price is never retained.[19] Based on visual examination of the residuals from the conditional ECMs we added impulse dummies to control for outliers in the energy consumption of all subsectors. In almost all cases a dummy is required to capture an abnormal observation in correspondence of the recent financial crisis. It is worth noting that in the majority of cases these impulse dummies imply an additional reduction in energy consumption around 2008–2009, beyond what is explained by the fall in economic activity, with the exception of NFM and MIN, where energy consumption appears to fall less than what could be expected from its relationship with GVA.[20]

Finally, we display in Table 7 the outcome from standard diagnostic tests. The magnitude of the *p*-values for the Breusch-Godfrey, Breusch-Pagan-Godfrey and the RESET tests overall confirms the validity of the estimated models. The test against autocorrelation rejects at 5% significance level only in the PPP subsector. This seems a reasonable result bearing in mind the parsimonious short-run dynamics represented in the ECMs.[21] To assess the possibility of structural breaks in the short-run coefficients we also performed the CUSUM test, which suggests no evident sign of parameter instability (see Fig. A2 of the Appendix).

6. Discussion

The estimated cointegrating vectors, adjustment coefficients and short-run dynamics enable us to draw a number of interesting insights into the dynamic features of the UK industrial energy consumption, in particular in terms of: the direction of causality in the long-run equilibrium relationship between the variables, the impact on energy consumption of changes in price and economic activity, the existence of long-run trends in the energy demand equations, and the speed with which energy demand corrects past discrepancies with respect to the long-run equilibrium.

First of all, based on the results from the Likelihood Ratio tests in Table 3, we can conclude that the impact of energy price is easier to identify from the data than the effect of economic activity. This result is clearly in contrast with the findings of Bernstein and Madlener (2015), who claim to estimate a statistically significant price and economic activity in two and five, respectively, of the analysed five subsectors.[22] Confirming our conclusions, all price elasticities for the UK industrial subsectors in Steinbuks and Neuhoff (2014) are statistically significant, while this occurs only for a third of the Greek subsectors assessed by Floros and Vlachou (2005). In Bjørner and Jensen (2002), on the contrary, the elasticity with respect to economic activity is statistical significant in all but one industrial subsector.

In terms of causality, it is striking how both economic activity and energy price appear to be weakly exogenous, given that the estimates indicate no adjustment of these two variables to the disequilibrium in the energy demand cointegrating equation in all but the PPP subsector. This is an important finding both in terms of modelling and policy implications, which is confirmed by the results of Likelihood Ratio tests on the adjustment coefficients of the price (α_p) and GVA equations (α_y) in Table 2. For modelling purposes, this may be interpreted as justifying a cointegration approach that assumes weak exogeneity of the right-hand side variables of the energy demand equation. As for policy implications, it shows that any event that produces a deviation from the long-run energy consumption equilibrium, like the introduction of energy efficiency policies, is likely to give rise to an adjustment in the level of energy consumption, rather than influencing economic activity or energy prices. Although we expected energy price to be weakly exogenous, given the limited size of energy consumed by any of the subsectors assessed in this study relative to the total size of the UK energy market, we had no clear expectation on the GVA, as firms might choose to alter their production in response to disequilibria in the long-run energy equilibrium condition. Our finding partially match those of Bernstein and Madlener (2015), given that they find evidence of energy price being exogenous, but they reject exogeneity of GVA in three of the five analysed subsectors.

We also notice substantial differences across subsectors in the estimated value of the long-run elasticities within the cointegrating equation. From a methodological point of view this can be taken as evidence against pooling under the assumption of homogeneity of slopes across subsectors, typical of panel data studies, a point advocated in Agnolucci (2009), and against conducting energy demand modelling

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[19] In the case of two sectors, FBT and MIN, there is no short-run dynamics as the VECM selected during the cointegration analysis had no lags.

[20] In one case, MIN, the positive coefficient is due to a spike in energy consumption.

[21] As 1 rejection out of the 24 tests we implemented corresponds to about 4%, this outcome could be simply explained by the size of the tests.

[22] Comparison is complicated by the fact that Bernstein and Madlener (2015) reports ordinary t-statistics for the coefficients of the cointegrating vector rather than likelihood ratio tests, which might explain their higher frequency of significant coefficients on economic activity, as the Wald (and t) test suffers from larger size distortions than the likelihood ratio test (see Haug, 2002).

Table 6
Estimated coefficients and t-stats (in square brackets) from conditional ECMs for the energy demand equations. Figures in parentheses in the Dummy 1 and Dummy 2 columns indicate the years characterized by a one-time shift in the intercept. A key to the acronyms of the industrial subsectors can be seen in Table A1.

	Δe_{t-1}	Δe_{t-2}	Δy_{t-1}	Constant	Dummy 1	Dummy 2	α_e	Adj R²
CHE	0.66 [3.99]		0.67 [1.83]	−0.01 [−0.58]	−0.15 [−2.41] (2014)		−1.01 [−5.07]	0.56
ENV				−0.01 [−1.28]	−0.15 [−3.24] (2009)	−0.10 [−2.11] (1994)	−0.42 [−3.31]	0.56
FBT				−0.01 [−2.11]	−0.07 [−2.82] (2009)		−0.86 [−5.11]	0.70
MIN				−0.03 [−2.29]	0.19 [3.07] (2008)	0.17 [2.87] (2000)	−0.32 [−3.20]	0.62
NFM	−0.18 [−0.99]	−0.13 [−0.78]		−0.06 [−3.31]	0.22 [2.53] (1996)	0.20 [1.99] (2010)	−0.39 [−2.83]	0.50
OTH				0.00 [0.12]	−0.51 [−5.40] (2008)		−0.29 [−2.01]	0.66
PPP	0.21 [1.39]		0.29 [0.64]	−0.01 [−0.68]	0.15 [2.72] (2005)	−0.13 [−2.12] (2008)	−0.34 [−2.73]	0.55
TLC	−0.09 [−0.68]			−0.03 [−3.46]	0.18 [4.33] (1993)	0.12 [2.82] (2000)	−0.36 [−3.17]	0.66

Table 7
P-value for the Serial correlation (Breusch-Godfrey), Heteroscedasticity (Breusch-Pagan-Godfrey) and the RESET tests. A key to the acronyms of the industrial subsectors can be seen in Table A1.

	Serial correlation	Heteroscedasticity	Reset
CHE	0.44	0.59	0.93
ENV	0.17	0.73	0.89
FBT	0.18	0.58	0.50
MIN	0.49	0.56	0.66
NFM	0.45	0.46	0.60
OTH	0.09	0.44	0.97
PPP	0.04	0.86	0.19
TLC	0.43	0.43	0.66

for the industrial sector as a whole. From a policy perspective, we observe that the NFM and OTH subsectors show a price elasticity of energy demand respectively of −0.52 and −0.78, which are markedly higher than the values in all the other subsectors, where elasticity ranges between −0.17 and −0.44. The values of the elasticities are overall fairly similar to the figures obtained by Bjørner and Jensen (2002), and Steinbuks and Neuhoff (2014), a similarity that is also found in the estimated elasticity for the industrial sector as a whole. Indeed, we obtain an average price elasticity of −0.41, which is virtually identical to the −0.44 in Bjørner and Jensen (2002) for the Danish industrial firms.[23] The average elasticity obtained by Steinbuks and Neuhoff (2014) for the three subsectors analysed in their study is −0.35, fairly close to our value of −0.28 for the same three subsectors. Our findings are also close to those of Bernstein and Madlener (2015), who estimated the price elasticity of electricity demand to be between −0.30 and −0.50.[24] An even greater heterogeneity is observed in the elasticity of energy demand with respect to economic activity, with values ranging from 0.12 to 1.42. Once we remove the OTH and the NFM subsectors, however, the values vary between 0.12 and 0.50. These estimates are very similar to those shown in Bjørner and Jensen (2002), with our average value across all eight subsectors being 0.57, which is very close to their 0.54. Our values are however smaller than those presented in Bernstein and Madlener (2015) for electricity, possibly suggesting a

shift towards electricity as the level of economic activity in the industrial sector grows over time.

As discussed above, the presence of significant time trends in the cointegrating vectors may account for factors that are not modelled explicitly, such as energy efficiency improvements or changes in the structure of the industrial subsectors occurring over time. As can be seen in Table 2 though, time trends are present only in three subsectors, i.e. ENV, CHE and FBT. Interestingly, in the last two subsectors a linear trend is estimated also for electricity consumption in Bernstein and Madlener (2015). Nevertheless, contrary to these authors, our trends are all negative, reflecting the likely impact of non-modelled drivers that produces a gradual decrease over time in the level of energy consumption. Presumably, this estimated negative trend captures increases in energy efficiency within the production process, or the impact of government policies aimed at encouraging energy-saving efforts.

From the value of α_e in Table 6 we can also appreciate the speed of adjustment to shocks that temporarily divert the dynamics of the variables from the equilibrium condition describing energy consumption in the long-run. Six of the eight subsectors have equilibrium adjustment coefficients falling between −0.29 and −0.42. However, in CHE and FBT the adjustment coefficient is considerably larger in absolute value, −1.01 and −0.86 respectively. This implies that, ignoring the short-run dynamics, 90% of the long-run disequilibrium generated by a shock will be absorbed in about one year in CHE and FBT, and in about six years in all other subsectors.[25] We can, therefore, conclude that the UK industrial subsectors are characterized by considerable heterogeneity not only in relation to the impact of changes in price and economic activity on energy consumption, but also in terms of the speed with which firms re-adjust their equilibrium consumption of energy as different shocks hit the economy. This finding suggests the existence of important structural differences which make the relative importance of disequilibrium costs against adjustments costs highly heterogenous for firms belonging to different industrial subsectors.

7. Conclusions

This is the first cointegration analysis that provides evidence on the UK energy demand elasticities at a disaggregated industrial level, following in this way the example of Bernstein and Madlener (2015), which employed a similar approach to estimate electricity demand for the German industrial subsectors. We performed a multivariate cointegration analysis of the UK industrial subsectors, using data between 1990 and 2014, with the aim to uncover the peculiarities of the energy demand function across the different subsectors, overcoming in this way the risks implied by an aggregate analysis (Pesaran et al., 1999).

The validity of our estimated long-run energy demand equation is substantiated by the outcome of the cointegrations tests, the plausibility of the coefficients values, and the results of the diagnostic checks and the stability tests. In particular, we performed a rigorous analysis of

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[23] One should bear in mind however that comparing our estimates to those from Bjørner and Jensen (2002)) and Steinbuks and Neuhoff (2014) is complicated by a number of factors. In the case of the former, this is due to the different econometric methodology, type of data used in the study, limited overlap of the time span covered by the datasets, and more importantly to the fact that the same industrial sector in two different countries might reasonably have different elasticities. Insights from the comparison of our results with those in Steinbuks and Neuhoff (2014) are influenced by the different econometric methodology and the limited variability of energy price in their sample, i.e. containing only one observation (2005) with a relatively high energy price.

[24] This is surprising as we would have expected electricity not only to command a price premium but also to be less amenable to be substituted in the production process, therefore having a smaller price elasticity, like for example found by Arnberg and Bjorner (2007) in the case of the Danish industrial companies. It is worth mentioning that results from Bernstein and Madlener (2015) are, according to the authors, in line with the previous literature and that in two cases, i.e. FBT and CHE sectors, Bernstein and Madlener (2015) impose a price elasticity equal to zero as the coefficients are not statistically significant.

[25] It is worth mentioning that in the case of CHE the adjustment coefficient implies a very slight overshooting as 101% of the past long-run disequilibrium is corrected.

the stability of the cointegration models and we found that, with one exception, there is no evidence of significant structural breaks in the estimated energy demand equations. Despite we have to admit that additional future observations will be needed for a more conclusive answer, we notice that the validity in terms of stable coefficients survives even throughout the period of the recent financial crisis. As time series for industrial subsectors at the two-digit SIC level with a length similar to the dataset used in this study are increasingly becoming available, we would expect to see this approach to be applied to other countries to start building evidence on energy demand elasticities which accounts for the peculiarities of firms belonging to different industrial subsectors. Considering the salience and visibility of energy, climate and industrial policies, building robust evidence on energy demand elasticities at the subsectoral level seems particular important for policy-makers, especially in light of the recent increase in energy prices and the effort to tackle CO_2 emissions.

The first clear conclusion that one can draw from our study is the existence of considerable heterogeneity in relation to the magnitude of the long-run impact on energy consumption of economic activity and energy price, with the former varying between 0.12 and 1.42 and the latter ranging between −0.78 and −0.17 across the eight different industrial subsectors. Considerable heterogeneity can also be observed in relation to the speed with which firms re-adjust their long-run equilibrium demand for energy in response to economic shocks. This is likely the consequence of important differences in the ability of firms to respond to changes in prices and economic activity, which is related to the specific structural characteristics of each subsector. Estimated adjustment coefficients between −1.01 and −0.29 imply that, depending on the specific subsector and ignoring the short-run dynamics for simplicity, it can take approximately from 1 to 6 years to absorb 90% of any shock to the energy demand equation. Heterogeneity of long-run elasticities and adjustment coefficients across industrial subsectors has interesting implications both in terms of modelling and policy-making. With regard to the former, our results advice against pooling under the assumption of homogeneity of coefficients across subsectors, typical of panel data studies, and specifically against modelling energy demand for the industrial sector as a whole. From a policy perspective, the markedly different values in the coefficients can be used by policy-makers to quantify the plausible effect of policies targeted at specific industrial subsectors, as well as the length of the time span that is required for policies to display its full impact.

A second conclusion emerging from our study is that any disequilibrium in the long-run energy demand seems to be tackled by adjusting the level of energy consumption rather than economic activity. In terms of policy implications, this suggests that policies affecting the long-run level of energy consumption, e.g. energy efficiency policies, are unlikely to influence the level of economic activity. Our work also casts some light on the presence of long-term trends in the evolution of energy consumption. Interestingly, the data suggested the inclusion of a linear trend in the long-run energy demand equation only for three of the eight subsectors assessed in our study. As linear trends are, however, all negative, they are likely to reflect the impact of energy efficiency measures or a change in the composition of the industrial subsectors away from energy intensive economic activities.

Finally, our contribution is helpful in reconciling the previous results for the UK industrial sector discussed in Dimitropoulos et al. (2005) and Hunt et al. (2003) with those in Agnolucci (2009, 2010), in relation to the impact of energy price and economic activity on energy consumption. The former set of studies estimated a relatively modest impact of price on energy consumption compared to the impact of economic activity, while the second set of studies reached a more balanced conclusion. Interestingly, 3 of these four studies implement a Structural Time Series Model, therefore casting doubts on the estimation methodology as a possible reason for the difference in the value of elasticities. Other possible reasons could be aggregation bias – as all four contributions estimate energy demand for the industrial sector as a whole – or the fact that the value of elasticities change considerably across time. Our study produce average elasticities with respect to economic activity and energy price across subsectors equal to 0.57 and −0.41, respectively. As the value of the elasticities in this study are fairly close to those presented in Agnolucci (2009, 2010), we produce further evidence suggesting that economic activity and energy price are similarly important in explaining observed energy consumption. We also notice that while estimates of elasticity with respect to economic activity are fairly similar in the four contributions above and in the recently published Adeyemi and Hunt (2014) (using a Structural Time Series Model estimated for the industrial sector as a whole), elasticity with respect to energy price in the two most recent articles (Agnolucci, 2009, 2010) and in this study is considerably higher, in absolute value, than the estimates in earlier contributions, such as Dimitropoulos et al. (2005) and Hunt et al. (2003). This hints at the possibility of price elasticities changing across time, an interesting line of enquiry which should be explored in future research. Finally, the fact that our results for the energy demand elasticities are comparable to those obtained by Bjørner and Jensen (2002) and Steinbuks and Neuhoff (2014) for the Danish and UK industrial subsectors, respectively, provides further support to the robustness of our estimates, which can therefore be adopted as plausible reference value for policy-making analysis on the UK industrial sector.

Acknowledgements

Appendix A. Supplementary data

Supplementary data to this article can be found online at http://dx.doi.org/10.1016/j.eneco.2017.08.027.

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