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INDUSTRIAL ENERGY INTENSITIES IN THE UK:

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Keywords:	panel unit root tests, structural breaks, energy intensity, stochastic convergence



Dear Professor Taylor,

I would like to thank you and the referees for the feedback we have received on our paper. We were very encouraged by the fact that referees found our work interesting and we thank them very much for spending their valuable time reading our article. We genuinely believe that we have accommodated all the points raised by you and the referees. Please find below the list of the specific comments and our responses to them. Our response is typed in red ink following the word "Reply:".

Best wishes,
The Authors

1. The article contains several typing errors and they have to be corrected. Reply: The article was sent again for proof-reading
2. The article says that long-term differences are either stochastic or deterministic. Does this imply anything in regard to the form of Equation 1 on page 6. If it does, then how should the equation be. Reply: The regression in the article wanted to be a general representation of the differences among the series and the benchmark. We have now a more detailed equation for the case where differences are deterministic and another for the case of stochastic differences – see section 4.
3. On page 6, the author(s) wrote: "The nature of the differences among the series can be assessed by testing for the presence of unit roots". Does this statement talk about time series of different sectors or a time series for one sector. Reply: both – it depends on whether one uses univariate unit root tests or panel tests. This is hopefully clarified in the text.
4. All in all, more clarification has to be given for the term "Long Term Differences". Does this term stand for a difference between a time series observation and a benchmark or for a difference between several time series. This comment is mainly about pages 1 and 6. Reply: if there is a difference between a set of series and their benchmark, then it seems to us that there is a difference among the series themselves as the benchmark is

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4 fixed. Apart from this, we clarified that differences are taken with respect to a benchmark
5 by repeating the definition of the variable for the unit root analysis ($y_{it}^d = Y_{it} - Y_{bt}$) on
6 page 6 (now page 11) and by defining more accurately long-term differences on page 1
7 (now page 2).
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11 5. What are GVA and ONS on page 8. It is sufficient to give the full term for each one
12 only on this page. **Reply:** The meaning of the acronyms has been added in the text
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16 6. What does ISIC on Table 1 stand for? **Reply:** We now understand that ISIC is used
17 only in the UK to indicate the NACE taxonomy. Table 1 has been edited
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21 7. What is the equation of the time series that is being tested by ADF? It would be better
22 to give this equation. **Reply:** This has been added to the text (see page 12).
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26 8. The article can be recommended for publication after considering the questions and
27 comments given above. **Reply:** We tried our best to accommodate the issues mentioned
28 above.
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32 1. The paper could be structured better. I would like to see a shorter introduction which
33 says briefly what the paper is going to do and what the reader will learn from the paper.
34 **Reply:** Section I has been shortened, i.e. cut to about half the original length. We added
35 an introductory paragraph. As suggested by the referee we mention what the paper is
36 going to do and the conclusions which can be drawn without going into details. Section II
37 should be a discussion of why differences in energy intensities are stochastic or
38 deterministic matters. Some of this is discussed on pp. 5-7, together with the
39 methodology. The motivation deserves its own section and could be expanded a bit.
40 **Reply:** Section II now contains only a discussion of the motivations of our study. This
41 discussion has been built from the contents of the pages mentioned above by the referee,
42 although it has been expanded. Section III should be a review of the existing literature
43 (which is currently in the introduction). The literature review should end by pointing out
44 the gaps and saying which of these gaps this paper addresses **Reply:** Section III has been
45 added to the manuscript. As required by the referee, the literature review has been
46 dropped from the introduction. It has been considerably expanded and now mentions the
47 gaps this article aims to fill. Section IV should be the methodology. **Reply:** done. Section
48 V should be the data description, Section VI the results of the univariate tests, Section
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4 **VII** the results of the panel tests. **Reply:** Section V, VI and VII have been structured in
5 the way suggested by the referee. Section VIII discusses our findings while section IX
6 presents the conclusions from our study. Section IX has been added to the paper while
7 Section VIII has been built from the Conclusion sections of the previous draft- - although
8 it has been considerably expanded.
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13 A disjoint in the paper is that the univariate tests w/o structural breaks are followed by the
14 panel tests w/o structural breaks followed by the univariate tests with structural breaks
15 followed by the panel tests with structural breaks. It would make more sense to have the
16 univariate tests w/o structural breaks followed by the univariate tests with structural
17 breaks followed by the panel tests without and with structural breaks. There would not
18 need to be much additional information to address this criticism. Instead, what is there
19 could be presented more logically. **Reply:** The reason for organising the paper in this
20 fashion was related to our intention to stress the effect of modelling breaks on the results.
21 However, we have now re-organised the paper in the way suggested by the referee.
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28 2. For the univariate tests reported in Table 2, what critical values (CVs) are being used?
29 Given the small sample sizes (26 or 34 observations) the CVs should be simulated. While
30 the Elliott, Rothenberg and Stock (1996) tests are supposed to have superior small
31 sample properties, I think the CVs given in their article are based on $N=50$. Were these
32 CVs used? **Reply:** Correct we used those CVs (ERS 1996 – Table 1), which are
33 simulated with $N=50, 100, 200$ and infinite. We now discuss this issue in the text and we
34 thank the referee to draw our attention to this. This is likely the cause explaining the
35 rejection occurring in M^{GLS} tests. However, while the point raised by the referee is a fair
36 point, we do not see much value in simulating CVs on the basis of the number of
37 observations in the sample. Considering the results from the tests (H_0 cannot be rejected
38 except in a couple of instances) and that simulating the CV would imply higher CVs
39 (because our sample is lower than those used in the simulations from which we take the
40 CV), simulating the CVs would further decrease the number of rejections in the table. As
41 we overall conclude that series do have a unit root on the basis of our results in Table 2,
42 simulating CVs is not likely to affect this conclusion. We argue this point of view in the
43 paper. We think this is a decent compromise between methodological rigour (as we
44 acknowledge the importance of this issue in the text) and practical constraints related to
45 time available on a research project (especially considering that the insights from
46 simulating CVs would be minimal). We would also like to point out that the meat of the
47 paper is on the modelling of structural breaks rather than the tests presented in Table 2. It
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4 seems to us that in the literature it is customary to report the results from these tests by
5 using tabulated rather than simulated CVs.
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10 3. At the beginning of the section on panel testing, it would be useful to say which panel
11 tests the authors intend to implement. This can be followed by a brief discussion of the
12 pros and cons of each test that they intend to implement. In discussing the tests,
13 it would be logical to start with the homogenous tests, proceed to the
14 heterogeneous tests and finally the test allowing for cross-sectional dependence.
15

16 **Reply:** We now mention upfront the tests we are going to implement. We discuss the
17 limitations of panel tests in the order suggested above and for each criticism we mention
18 which tests among those implemented in the paper are affected by the criticism.
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23 4. Given the stated advantages of the LM tests with structural breaks over the ADF-type
24 tests with structural breaks (as discussed on pp. 14-15), why do the ZA and LP tests at
25 all? Why not just present the results of the LM tests with one and two breaks? **Reply:** We
26 agree with the referee and the results from the ZA and LP tests have now been dropped.
27 We also refer a number of articles presenting only results from the LM test, as suggested
28 by the referee.
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33 5. The sample size seems too small, at least to do the univariate two break tests. With the
34 trimming region set equal to 0.15 (as usual) there is virtually no degrees of freedom.
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36 **Reply:** We are a bit puzzled by this remark. Trimming does not imply dropping
37 observations from the sample but simply assuming that no breaks occurred in the first and
38 last, say, 15% of observations. The regressions are run over the whole sample but the
39 dummies to simulate the breaks are inserted only for the time span $(0.15T, 0.85T)$ where
40 T is the whole timespan. The rationale of having a sample of say 100 observations,
41 throwing 15 observations away at each side and then using 70% of the observation to do
42 the modelling is somewhat unclear. How would the results from this procedure differ
43 from those using only a shorter sample (i.e. the central 70% of the longer sample) without
44 any trimming? We acknowledge that some articles in the literature are a bit unclear on
45 this. However ILT (2005: p413) (quoted in our paper) mentions that “the shift locations
46 are determined through a grid search over the time interval $[0.10T, 0.90T]$ ”. This
47 suggests to us that the breaks cannot occur on the first and last 10% observations of the
48 sample, as those locations are excluded from the grid search, but it does not suggest us
49 that those observations are thrown away from the sample. Similarly, ZA (1992) run an
50 empirical analysis using the test they propose. They use the database from Nelson and
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4 Plosser (1982). From Table 4 of NP (1982) we see that real GNP spans the period 1909-
5 1970. However, ZA (1992) when applying their test reports a T of 62 – see Table 6. If
6 they had discarded x% of the observations, the T of the sample would have been
7 consequently reduced. This can be taken as evidence that trimming refers to the sample
8 over which breaks are allowed to occur not to the sample used in the regression. We
9 believe that our argument is correct. However, should our understanding be wrong, we can
10 argue that our long sample goes from 1967 to 2007 and that we have dropped the first
11 and last 10%, therefore making it equal to the 1970-2004 used in the estimation. The
12 rationale of this is still unclear to us but then, should our understanding be wrong, we can
13 say that our procedure conforms to common practice in the literature.
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21 6. The selection of the model (model A or C [in the one break case] or AA or CC [in the
22 two break case] should be discussed in the text and not relegated to the Table. **Reply:**
23 This is now discussed in the text – see Section 6.
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26
27 7. What CVs are used for the ZA and LP tests? I can't find this discussed anywhere. You
28 need to simulate the CVs. This should be done for N=26 and N=34 and the simulated
29 CVs reported. **Reply:** Following advice from this referee - see point 4 above - the results
30 from the ZA and LP tests have now been dropped.
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35 8. In the univariate results, why is energy intensity in some sectors stationary and not in
36 others? Is there anything about the nature of particular industries and their energy use that
37 can be linked back to the finding of whether energy intensities are deterministic or
38 stochastic? **Reply:** The reasons why in some cases long-term differences appear to be
39 stochastic is now discussed in Section VIII.
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44 9. Problems with References Some references cited in the text are missing from the
45 references – eg. Hlouskova & Wagner (2006); Narayan & Smyth (2005); Wagner (2005)
46 Breitung & Pesaran (2005) listed in references as forthcoming Pesaran (2006) listed in
47 references as forthcoming Mehara (2007) in text but listed as (2006) forthcoming in
48 references Hooi & Smyth (2007) should be Lean & Smyth (2007) (Hooi is the given
49 name) **Reply:** references have been revised and in some cases dropped. In the case of
50 Breitung & Pesaran (2005), 2005 referred to the chapter, written originally in 2005, while
51 forthcoming referred to the collection of essays comprising the chapter. This collection
52 has been published only after we submitted our paper, i.e. at that time it was forthcoming.
53 We thank the referee for mentioning our mistake related to Hooi and Smyth (2007). We
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4 are actually a bit puzzled by this author – Applied Economics report that paper as
5 “**Authors:** Lean Hooi Hooi^{ab}; Russell Smyth^{ab}” which makes us think that Lean is a first
6 name. However, we follow the advice of the referee and Hooi and Smyth (2007) is now
7 referred as Lean and Smyth (2007)
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For Peer Review

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2 **1 Introduction**

3
4 Industrial energy consumption has been one of the main targets of policies aimed
5 at increasing energy efficiency or reducing carbon emissions. The EU Emission
6 Trading Scheme, for example, is focused exclusively on some of the most energy
7 intensive industrial subsectors (see Annex I of the 2003/87 EC Directive). Other
8 examples are provided by policy instruments, such as the Climate Change Levy and
9 the Climate Change Agreement in the UK, the Swedish and German environmental
10 tax reform, and the energy taxes and related energy efficiency agreements introduced
11 in the Netherlands and Denmark (Speck et al 2006). Despite concerns related to
12 industrial competitiveness, some other sources of CO₂ emissions have not been
13 regulated as much as the industrial sector (OECD 2006).

14

15 Energy consumption, like the consumption of any productive factors, is
16 determined by the final product and the used technology. It goes without saying that
17 the energy intensity, i.e. the ratio between energy consumption and economic activity,
18 of, say, the chemical sector will be different from that of, say, the construction sector.
19 The existence of different energy intensities across industrial subsectors is simply a
20 fact. This study assesses whether long-term differences among the energy intensities
21 of the British industrial subsectors are deterministic or stochastic. For each industrial
22 subsector we first determine the difference between its energy intensity and the
23 intensity of the industrial sector as a whole, and then we assess the nature of these
24 differences, which are called long-term differences, as they persist across time. From
25 a time series point of view these differences can be either deterministic, i.e. can be
26 approximated by an intercept and a time trend possibly subject to breaks, or they are
27 stochastic, i.e. they are unpredictable but persistent. In fact, the properties of long-
28 term differences are related to the properties of the innovation terms, i.e. the random
29 shocks to the series. If these are transitory, long-term differences will be

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8 1 deterministic. If random shocks are persistent, they accumulate across time and long-
9 2 term differences will be stochastic. After assessing the nature of the differences
10 3 among energy intensities of the British industrial subsectors, this article discusses the
11 4 policy implication of our analysis.
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17 6 A number of contributions to the energy literature can be found in this study. First
18 7 of all, as far as we know, no article in the literature has so far assessed the nature of
19 8 the differences among energy intensities of industrial subsectors by adopting the
20 9 approach discussed in this paper. By focusing on the properties of a time series
21 10 relative to a benchmark, we apply a methodology relatively common in a number of
22 11 economic fields which has been applied rarely to an energy dataset – see Lee et al
23 12 (2008) and Robinson (2007). In addition, as far as the authors of this article are
24 13 aware, the DF^{MAX} , the DF^{RMA} , the LM test with one and two breaks, and the CIPS
25 14 test have never been applied in the energy literature. We also discuss a number of
26 15 limitations of panel unit root tests. However, in this article we do not exhaustively
27 16 implement panel tests, as modelling structural breaks seems a more promising
28 17 avenue. From both univariate and panel tests, we can conclude that long-term
29 18 differences among the energy intensities of industrial subsectors are deterministic if
30 19 the testing procedure allows for breaks.
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43 21 This paper is structured as follows. Section 2 describes the motivation of this
44 22 study. Section 3 frames our contribution in the literature and surveys a number of
45 23 studies which have taken an approach similar to ours. Section 4 introduces our
46 24 methodology while Section 5 describes the dataset used in this study. Section 6
47 25 presents the results from univariate unit root tests with and without structural breaks.
48 26 After stressing the limitations of panel testing procedures, Section 7 applies a number
49 27 of tests so as to assess whether a panel approach confirms the results from the
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1 univariate tests described in the previous section. Finally, Section 8 discusses the
2 findings from our study while Section 9 draws some conclusions.

3 4 **2 Motivation of this study**

5
6 Energy intensity is a ratio which has received considerable attention in the
7 academic and policy making community. From a policy point of view, energy
8 intensity is related to energy efficiency, i.e. the focus of a number of policies adopted
9 in several countries (World Energy Council 2004) and a priority for the European
10 Commission and Member States (DTI 2006). Energy efficiency is the ratio between
11 energy services and energy consumption. As the former are difficult to measure, and
12 in some cases even to define, energy intensity is normally used in policy-making and
13 sets of indicators are regularly produced by a number of governments. These
14 indicators can be used to help raise public awareness; complement other inputs to
15 policy and program analyses; and increase the role of energy efficiency measure in
16 the market (US DoE 2006). Energy intensity is also particularly important in the
17 studies adopting the index decomposition approach - see Ang and Zhang (2000) for a
18 review. In some of these studies energy intensity is the left hand side variable which
19 is decomposed. When energy consumption or carbon emissions are decomposed,
20 energy intensity is strictly related to one of the right hand side variables, i.e. the
21 intensity effect.

22
23 This study has a number of aims and motivations. By using unit root tests, we
24 assess the long-term differences among the energy intensities of industrial subsectors
25 and draw conclusions on the frequency of the changes in these differences. In the
26 trend-cycle decomposition of Beveridge and Nelson (1981), if a time series has no
27 unit root, the trend reduces to a deterministic function of time while if it has a unit
28 root, the direction of the trend changes at every point in time. Applying unit root tests

1 enables us to assess whether changes in the differences occur either in every point in
2 time or never at all. Applying unit root tests allowing for structural breaks enable us
3 to assess whether changes occur in every point in time or at most occasionally, i.e. at
4 the occurrence of the breaks (Perron 2006).

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6 The nature of the long-term differences among the energy intensities of industrial
7 subsectors affects policy-making with regard to the timing and frequency of policy
8 interventions and with regard to the choice of policy instruments. Most of these
9 policy implications are similar to those normally discussed in the studies assessing the
10 stationarity of an economic time series – see for example Chen and Lee (2007) and
11 Narayan and Smyth (2007) – although some implications are specific to the studies
12 assessing the difference of a time series from a benchmark. From a policy point of
13 view, given the downward trend in energy intensity in the industrial sector (see the
14 Odyssee database and Figure 1 below), policy makers are likely to have a special
15 interest in the time pattern of energy intensities of a number of sectors or equivalently
16 in their long-term differences with a benchmark. This special interest could be
17 motivated by the fact that some sectors are considered energy inefficient, compared to
18 international benchmarks, or politically-sensitive.

19
20 If long-term differences among industrial sectors are stochastic, short-term
21 random difference accumulated across time, as a certain component of the shocks to
22 the series persists indefinitely. When policy makers have an interest in the series
23 following a certain time pattern, they will need to intervene any time a random shock
24 pushes the series in a direction opposite to that desired by policy makers. On the other
25 hand, when long-term differences are deterministic, the series reverts to its
26 deterministic components, as random shocks will naturally dissipate across time. In
27 this case, policy makers do not need to intervene at any single minor departure of the
28 series from the desired time pattern. In fact, if they want to affect the evolution of the

1 series, policy makers will need to implement prolonged policy measures able to affect
2 the deterministic components of the series. Only concerted and prolonged efforts will
3 have an effect on long-term differences. Unfortunately, policies determined by the
4 electoral cycle or any other short-term mechanism will have no lasting effect on the
5 value of the long-term differences.

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7 The nature of long-term differences is also important to assess the ability to
8 forecast future values on the basis of past behaviour. In fact, the use of univariate
9 time-series models for short-term forecasting is related to the persistency of shocks. If
10 shocks do not persist indefinitely, a time series will return to its path and it will be
11 possible to forecast future value based on its past behaviour. If a significant portion of
12 shocks persists indefinitely, the time series will present a stochastic trend and past
13 trend will not necessarily be useful to produce forecasts.

14
15 Finally, assessing the difference of a series from a benchmark allows us to
16 provide advice on the choice of policy instruments available to policy-makers. When
17 long-term differences are stochastic, policy mechanisms affecting economic actors in
18 a uniform fashion would seem a rather blunt instrument. Ideally, policy instruments
19 would need to take into account the evolution of the series and the peculiarity of the
20 subsectors. On the other hand, when long-term differences are deterministic, a
21 uniform policy instrument not subject to periodical reviews would seem suited to
22 meet the policy-makers' objectives. It goes without saying that periodical reviews of
23 these instruments can still be needed due to changes in the information set or in the
24 objectives of policy-makers.

25 26 27 **3 Literature Review** 28

1 From a conceptual point of view this paper is part of the branch of the economic
2 literature assessing the convergence of time series. This line of enquiry is employed
3 often, especially when assessing income per capita and prices of a certain good or a
4 basket of goods. In these cases empirical studies have been motivated by the desire to
5 verify theoretical propositions, i.e. respectively, the neoclassical growth models, the
6 law of one price and the Power Purchasing Parity (PPP). Empirical studies have,
7 however, assessed the existence of convergence of certain variables across sectors in
8 fields where theoretical expectations on their convergence were less strong than those
9 mentioned above. An example is provided by the employment rate across countries.
10 Blanchard and Katz (1992) and Decressin and Fatas (1995)) are two authoritative
11 studies in this field.

12
13 Three notions of convergence, namely β -, σ - and stochastic convergence, are
14 normally used in empirical studies - see, amongst others, Lee et al. (1997), for a
15 discussion. Another approach to the analysis of convergence of economic variables is
16 based on a Markov chain transition matrix and the speed to an ergodic distribution –
17 see Kakamu and Fukushige (2006) and Happich and van Lengerke (2007) for two
18 recent applications. Going back to the notions of convergence normally used in the
19 literature, β -convergence assesses the speed at which the variable of interest tends to
20 its steady-state value. The estimate of the speed of convergence is assessed through
21 time-series, panel, or cross-sectional regressions. The validity of the cross-sectional
22 approach has been seriously put in doubt by Evans (1997). Bianchi and Menegatti
23 (2007) discusses the potential pitfalls connected with the use of pooled and panel
24 estimators. Convergence may be unconditional or conditional to some variables;
25 steady-state growth rates can be common or member-specific (Lee et al. 1997).
26 Cuaresima et al (2008) and Galvati and Gomes (2007) are two examples of
27 empirical studies analyzing the issue of β -convergence

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1 Sigma convergence, which focuses on the behaviour of the variance, is
2 theoretically interesting if one believes that there is a common equilibrium and that
3 the speed of convergence to steady-state outputs is the same (Lee et al. 1997). Gil-
4 Pareja and Sosvilla-Riviero (2008) examines whether the law of one price holds in
5 the European Union car market over the period 1995-2005. In order to measure the
6 degree of price convergence, the coefficient of price variation of each car model
7 across the European markets is regressed on a time trend and a constant. Sigma
8 convergence occurs if cross-sectional dispersion decreases over time, i.e. coefficient
9 on the time trend is negative and statistically significant. The authors find clear
10 evidence of price convergence among the EU15 countries after 1999. In some
11 articles, the existence of sigma convergence is assessed on the basis of unit root tests,
12 i.e. with a methodology similar to the one employed in this article – see, among
13 others, Blot and Serranito (2006) and Koukomelis (2008).

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15 Finally, stochastic convergence focuses on the time series properties of the
16 variables and assesses whether a time series observed for different economic agents,
17 e.g. regions, countries or economic sectors, share a common trend. Stochastic
18 convergence is normally tested by analyzing cointegration among economic series or
19 the presence of unit roots. Jenkins and Madzaharova (2008) is a paper using
20 cointegration tests, both univariate and panel, to assess the presence of stochastic
21 convergence. In our study, the presence of stochastic convergence is investigated
22 through unit root tests. De Siano and D'Uva (2006) and Lima and Resende (2007) are
23 two examples of studies adopting this approach. Before surveying a number of
24 studies from the energy literature, it is worth mentioning that the use of the word
25 convergence, in any of three meanings described above, is not very common in the
26 energy literature. As some readers might be wrongly misled to believe that the levels
27 of energy intensities in different sectors become gradually similar, we prefer avoid
28 the use of the term convergence when discussing the results of our study, and report

1 our results by discussing the equivalent concept of long-term differences. In fact, two
2 series are stochastically convergent when the long-term differences are deterministic,
3 while they fail to be stochastically convergent when long-term differences are
4 stochastic.

5
6 In the energy literature researchers have been assessing convergence between
7 prices across markets, e.g. Robinson (2007), and prices of different products, e.g.
8 Lanza et al (2005), and between per-capita levels of CO₂ emissions (Lee et al 2008).
9 Robinson (2007) uses the concepts of β - and stochastic convergence to investigate the
10 degree to which the ambition to create a single European electricity market, as set out
11 in a number of legislative measures, has been practically achieved. In the case of
12 stochastic convergence, the author applies the methodology we discuss in the next
13 section. Stochastic-convergence, which is tested through an ADF test, is accepted in
14 six out of nine instances. Neumann et al (2006) assess the β -convergence of natural
15 gas prices in the European markets while allowing for time-varying parameters by
16 using the Kalman filter. The dataset used by the authors comprises daily day-ahead
17 prices observed over March 2000-February 2005 at three trading hubs, the British
18 National Balancing Point (NBP), the Belgian Zeebrugge and the Bunde-Ounde hub at
19 the German-Dutch border. In the case of the NBP and the Zeebrugge, there is a clear
20 trend towards convergence, arguably promoted by the interconnector between the
21 English and the Belgian markets. On the other end the β -coefficient for the pair
22 Zeebrugge–Bunde does not reveal any particular pattern of convergence.

23
24 Lee et al (2008) is very similar to our study with regard to the methodology and
25 the findings. The authors investigate whether the long-term differences among the per-
26 capita CO₂ emissions of 21 OECD countries during the 1960–2000 period are
27 stochastic or deterministic by using univariate tests assuming structural stability and
28 the suite of tests proposed by Sen (2003) which allows for a break in the intercept and

1 the slope. In the case of univariate tests the null of unit root is rejected only in about
2 15% of the cases. However, when using the F^{MAX} test, the unit root is rejected in 13
3 of the 21 countries assessed in the study. Unlike traditional unit root tests, when one
4 controls for breaks, the results provide evidence that relative per capita CO₂
5 emissions are stochastically convergent.

6
7 It is worth pointing out that the findings of Lee et al (2008), i.e. strong influence
8 of structural breaks on the assessment of convergence, are not uncommon in the
9 literature. In Drine and Rault (2006), the empirical validity of the PPP can be
10 confirmed only when employing a LM test allowing for breaks. A similar finding is
11 discussed in Cuntildeado and Gracia (2006) with regard to the convergence of per-
12 capita output of a number of East European countries towards the German and US
13 level. Other examples of this pattern can be found in Galvatildeo and Gomes (2007)
14 and Narayan (2006). However, it should be pointed out that employing unit root tests
15 allowing for structural breaks is no guarantee for an increase in the rejection rate of
16 the null hypothesis – see for example Lee (2006).

17
18 From the brief discussion above, we can conclude that the concept of convergence
19 has been rarely assessed in the energy literature with the exception of price series
20 observed in different markets or related to different products. This paper aims to fill
21 this gap in the literature by extending the convergence analysis to the energy intensity
22 of industrial subsectors. As far as we are aware, no analysis of the convergence of this
23 variable using the approach described below can be found in the literature. In
24 addition, we noticed that the modeling of structural breaks had quite an important
25 effect on the results from the studies assessing the convergence of economic
26 variables. We also discovered that the Lagrange-Multiplier unit root tests have never
27 been applied to an energy dataset. This paper fills this methodological gap in the

1 applied literature, which is a valuable undertaking if one bears in mind the superior
2 performance (see below) of Lagrange-Multiplier unit root tests.

3 4 5 **4 Methodological Approach** 6

7 This paper follows the approach of Carlino and Mills (1993) where a series $Y_{i,t}$ is
8 assessed relative to a benchmark Y_{bt} . The dependent variable of the study is therefore
9 $y_{it}^d = Y_{it} - Y_{bt}$ rather than the levels Y_{it} . If the logarithms of the data are used, y_{it}^d is
10 equal to the logarithm of the ratio between the series and the benchmark, which is
11 normally set to be the average across the series in the dataset. One can further assume
12 that the difference from the benchmark consists of a time invariant differential x_i ,
13 random short-run difference v_t , and the initial difference v_0 . Breaks in the
14 deterministic components can also be accommodated by the variable m_i . If the
15 trending long-term differences are found to be deterministic, differences between a
16 series and the benchmark can be written as

$$17$$

$$18 \quad y_{it}^d = x_i + v_0 + \rho_i y_{it-1}^d + \beta_i t + \delta_i m_i + v_t \quad (1).$$

19
20 where t indicates a linear trend t . However, in case of trending long-term stochastic
21 differences, (1) can be re-written as $y_{it}^d = x_i + v_0 + y_{it-1}^d + \delta_i m_i + v_t$, therefore
22 imposing the joint restriction $\rho = 1$ and $\beta = 0$ in (1). The nature of the differences
23 among the series Y_{it} and the benchmark Y_{bt} can be assessed by testing for the
24 presence of unit roots in y_{it}^d . This analysis can be undertaken for each time series in
25 the dataset separately or for the dataset as a whole by using panel tests. If there is a
26 unit root, long-term differences between y_{it} and the benchmark are stochastic, as
27 short-term random differences accumulate across time. If there is no unit root, short-

1 term random differences dissipate and long-term differences are deterministic. In the
 2 case of the ADF tests, the testing regression can be written as

$$\Delta y_{it}^d = \mu_i + \beta t + \rho_i y_{it-1}^d + \sum_{j=1}^k c_j \Delta y_{it-j}^d + \varepsilon_{it} .$$

5 Data Description

8 Annual data on energy consumption is taken from IEA (2005), which provides
 9 information for the sectors listed in the first column of Table 1 for the 1970-2004
 10 timespan. Data on the Gross Value Added (GVA) have been sourced from Office for
 11 National Statistics (ONS) (2006a) and ONS (2006b). As shown in the third and fourth
 12 columns of Table 1, GVA data are available at two different levels of detail¹. The
 13 more aggregate time series match the timespan of the energy data but require
 14 aggregation of the last five sectors in column 1. On the other hand, the most
 15 disaggregated GVA time series (matching the energy taxonomy with the exception of
 16 Iron and Steel and Non-Ferrous metals which need to be aggregated) requires
 17 dropping eight observations, i.e. the time period spanned by the sample becomes
 18 1978-2004. While using the longer sample is preferable for the power of the tests, one
 19 can also have concerns related to the difference among the sectors which need
 20 aggregation, i.e. the sectors in the last five rows of Table 1². For this reason, the
 21 differences among industrial sectors were assessed in both samples, i.e. by using the

¹ Energy and GVA data are available separately for the sectors Wood and Wood Products, and Paper, Pulp and Print. The decision to consider these two sectors together is related to the quality of the data on energy consumption in the Wood and Wood and Products. Energy Consumption decreases from 127 TTOE in 1991 to 21 TTOE in 1992 while GVA decreased from 2783 to 2751 million pounds. The breaks in the series disappear when the energy consumption from Wood and Wood Products is added to Paper, Pulp and Print due to the considerable higher consumption of the latter.

² In fact, as shown in Figure 1b, the Metal sector has by far the highest energy intensity, i.e. twice as big as the second highest sector. When the metal sector is aggregated to other three sectors in OTH₁, see Figure 1a, the energy intensity is similar to that of Food and Tobacco.

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8 1 taxonomy in column 3 for the longer sample and that in column 4 for the shorter
9 2 sample.

10 3
11 4 [INSERT TABLE 1]
12 5

13 6 The energy intensities can be observed in Figure 1. As can be seen, the
14 7 Construction, Wood, Pulp, Paper and Print, Food and Tobacco, Textiles, Machinery
15 8 and Transport Equipment have lower energy intensities than the average of the
16 9 industrial sector. The Chemical, Non-Mineral Metal and Metal sectors have the
17 10 highest energy intensities. Figure 2 displays the difference between the sectoral
18 11 energy intensities and the average of the industrial sector. The time series of some
19 12 sub-sectors presents a number of spikes mainly caused by sudden changes in the sub-
20 13 sectors³. In the Food and Tobacco sector, the increase between 1980 and 1990 is due
21 14 to energy intensity in the sector decreasing at a lower rate than in the other industrial
22 15 sectors. The increase in the textile sector at the end of the sample is caused by the fact
23 16 that a decrease in GVA is not matched by a corresponding change in energy
24 17 consumption. Similarly to the Food and Tobacco sector, the time series for the
25 18 Chemical sector in Figure 2 switches between two levels, namely the pre-1982 and
26 19 the post-1989 levels. Energy Intensity in this sector almost halves between 1982 and
27 20 1989 – see Figure 1. As this reduction exceeds the decrease in the industrial sector,
28 21 the time plot in Figure 2 presents a downward trend. Finally, the decrease in the time
29 22 series for the Non-Metallic Mineral sector observed in the first few years and in the
30 23 last 10 years of the sample is mainly due changes in energy consumption in the
31 24 sector.
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³ Those occurring in 1970-72 and 1984 in the textile sector and in 1989 and 2003 in the mining sector are all caused by sudden changes in energy consumption unmatched by changes of the GVA. A sudden decrease in the energy consumption is also the cause of the marked decrease in the construction sector in the last two years of the sample.

1 [INSERT FIGURE 1 AND FIGURE 2]

2
3 With regard to the subsectors aggregated together into the Other Industry sector in
4 the 1970-2004 sample (see Figure 2d), the Metallic, Transport Equipment and
5 Machinery sectors are relatively flat until 1995. A decrease in the Metallic sector can
6 be observed thereafter. In the Transport Equipment sector, the sudden increase in
7 1984 and the decrease in 1988 in the relative energy intensity are caused by sudden
8 changes in the energy consumption. Quite interestingly, the non specified industrial
9 sector (OTH₂) shows increasing energy intensity over the whole observation sample.

10
11 While gradual changes in the level or trend of long-term difference could be
12 explained by structural change in the sectors or by changes in the level or trends of
13 factors affecting the energy intensity (e.g. energy price), it is worth stressing that a
14 number of the sudden changes described above are likely to be caused by
15 measurement errors and other limitations in the dataset. While we bear this point in
16 mind, using a dataset published by international institutions seems more advisable
17 than embarking on a subjective data adjustment process guided by uncertain and
18 somewhat arbitrary criteria.

19 20 21 **6 Univariate Testing with and without Structural Breaks**

22
23 The presence of unit roots is tested by running the ADF, the PP test and a number
24 of other tests. As both the PP and ADF tests suffer from low power, especially when
25 the value of the parameter on the first autoregressive term is close to one or when the
26 series is trend-stationary (see among others, DeJong et al (1992) and Campbell and
27 Perron (1991)), two strategies have been followed in the literature to increase the
28 power of the tests. The first approach exploits the identical covariance structures of
29 forward- and backward-looking finite order stationary AR models; the other recurs to

1 a non-OLS estimator in order to estimate the deterministic components of the
 2 univariate process. Among the tests using the first approach, this paper implements
 3 the DF^{MAX} (Leybourne 1995). The DF^{RMA} (Shin and So 2001), the DF^{GLS} (Elliott,
 4 Rothenberg and Stock 1996) and the M tests (Ng and Perron 2001) are three types of
 5 tests using a non-OLS estimators to compute the deterministic components in the
 6 series.

7
 8 The results from the tests discussed above are shown in Table 2 for the 1970-2004
 9 and 1978-2004 samples⁴. Overall, the results estimated over the two samples point at
 10 the time series being integrated of order one. The long-term difference in the
 11 construction sector can be judged deterministic in the shorter sample according to the
 12 M^{GLS} tests in the model with intercept only. In the same sample, the differences can
 13 be judged deterministic also in the Machinery sectors according to the DF^{RMA} and
 14 DF^{MAX} tests, and in the Metal sector according to the DF^{RMA} with intercept and trend
 15 – see Table 2. It should be borne in mind that the statistical significance in the table is
 16 determined by using the critical values computed with a number of observations
 17 closest to our sample among those published in the literature. While in the case of
 18 DF^{MAX} test we were able to use a critical value based on 25 observations,
 19 asymptotical critical values needed to be used in the case of the \bar{M}^{GLS} tests. In the
 20 case of the ADF and PP tests we used critical values from MacKinnon (1996).
 21 However, as critical values simulated on the basis of the length of our sample would

⁴ In the case of the \bar{M}^{GLS} , i.e. MZ_{α} , MZ_t , MSB and MP_T in the table, GLS detrended data are used to construct the series on which the test is run and the autoregressive spectral density estimator S_{AR}^2 , as suggested in ERS (1996) and NP (2001). The Modified Akaike Information Criterion (MAIC) has been used to determine the lag in the estimation of S_{AR}^2 and in the unit root regressions. When using the MAIC, the maximum lag was set at $l/12$. The PP test was run for a bandwidth going from $l/10$ to $l/12$. The deterministic components in the ADF and DF^{GLS} tests were chosen according to the value of the Schwarz and Akaike Information Criterion (SC and AIC, respectively). The specification selected for the ADF test is also used for the PP, DF_{MAX} and the DF^{RMA} tests while that selected for the DF^{GLS} test is also used for the \bar{M}^{GLS} tests.

1 be higher than those we used in Table 2, our results should be considered optimistic,
2 in the sense that a lower number of rejections would likely have been obtained if
3 simulated critical values had been used. Our use of tabulated rather than simulated
4 critical values can be the cause of the reason why the null hypothesis for the
5 construction sector is rejected in the shorter sample according to the \bar{M}^{GLS} test.
6 Overall, from Table 2 we conclude that long-term differences are stochastic. As using
7 simulated critical values would not affect this conclusion, critical values are not
8 simulated.

9
10 [INSERT TABLE 2]

11
12 The results from unit root tests can be misleading when a structural break goes
13 unaccounted, the so-called Perron-effect (Perron 1989). Considering the breaks
14 discussed in Section 5 (see also Figure 2), it is therefore unclear if the failure to reject
15 the null hypothesis in the case is due to the processes being I(1) or to the presence of
16 structural breaks. Univariate tests allowing for structural breaks have found extensive
17 implementation in the energy literature. Most papers, see for example Lanne and
18 Liski (2004), implement ADF-based tests, like those from Zivot and Andrews (ZA)
19 (1997), and Lumsdaine and Papell (LP) (1997). However, both tests tend to select T_B -
20 1 as the breakpoint, where T_B is the real breakdate. In addition, when a break occurs
21 under the null hypothesis, the size of the tests markedly increases (Lee and Strazicich
22 2001). In order to account for these two problems Lee and Strazicich (LC) (2004) and
23 LC (2003) extend the Lagrange Multiplier procedure of Schmidt and Phillips (1997)
24 to DGPs with one and two structural breaks, respectively. The finite sample
25 properties of the LM-based tests are discussed in Lee (1997). While in the ADF-based
26 test no break is assumed under the null, as the critical values of the test would
27 otherwise depend on the location and magnitude of the break, the LM statistics are
28 invariant to these nuisance parameters (LC 2003). Unlike the ADF-based tests, LM

1 unit root tests will not spuriously reject the unit root hypothesis if there is a break
2 under the null. Following a number of articles in the applied literature, for example
3 Galvatiildeo and Gomes (2007) and Narayan (2006), this study implements the LM
4 tests only on the basis of the limitations discussed above for the ADF-based tests.
5

6 For the LM test with one break we ran the model allowing for a break in the
7 intercept (model A) and the model allowing for a break in the intercept and slope
8 (model C). Similarly, in the case of the LM test with two breaks, we ran the model
9 allowing for breaks in the intercept (model AA) and the model allowing for breaks in
10 the intercept and slope (model CC). Model selection was implemented on the basis of
11 the value of the information criteria. When the Akaike and the Schwarz information
12 criteria failed to agree on which model fits the data best, two models are reported.
13 Before discussing the results from the tests, it is worth mentioning that in the case of
14 the LM tests run on model CC, our samples implied running a regression with 35 and
15 27 to estimate a number of parameters going from a minimum of six to a maximum of
16 ten, depending on the number of lags of the differenced dependent variable added to
17 the regression. Although it would be preferable to have a higher number of
18 observations, we however notice that the estimation of a model with two breaks over
19 a sample spanning a time period similar to ours is not uncommon in the literature –
20 see for example Narayan (2005). In addition, despite the many limitations of panel
21 unit root testing described in the next section, we also implement a panel LM test
22 which can be considered an indirect way to validate the results from the tests
23 discussed in this section.
24

25 Results from the LM tests differ somewhat from those presented in Table 2. As
26 can be seen in Table 3, in 38% and 45% of the industrial sectors long-run differences
27 can be considered deterministic in the longer and in the shorter sample, respectively.
28 Comparing the results from the two samples, one can notice that breakpoints tend to
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1 be the same if the breakpoint in the longer sample falls in the time window where
2 breakpoints are allowed to occur in the shorter sample. When using the LM test
3 allowing for a break, only in two instances long-term differences among the
4 subsectors can be considered deterministic in the longer sample. In the shorter sample
5 however this occurs in about 55% of the cases. When using the LM test allowing for
6 two breaks, in 50% and 73% of the cases the long-term differences can be considered
7 deterministic in the longer and the shorter sample, respectively. With regard to
8 breakpoints, in six instances the LM with one and two breaks over the longer sample
9 select a common breakdate. In the shorter sample, the number of series sharing a
10 common breakdate rises to eight. It is fair to conclude that the application of
11 univariate tests allowing for structural breaks has reversed the conclusions of the
12 univariate and panel unit root tests discussed in Sections 4 and 5.

13
14 [INSERT Table 3 HERE]

15
16 Figure 3 shows the breakpoints selected by the models allowing for two breaks
17 displayed in Table 3. It can be seen that in both samples, breakdates can be grouped
18 into three clusters which in the case of the shorter sample go from 1983 to 1988, from
19 1990 to 1993 from 1997 to 1999. These breaks are likely to be caused by a
20 combination of changes in the economic conditions and energy price fluctuations.
21 The first group of breaks can be imputed to the recession affecting the British
22 industrial sector in the eighties – the real term GVA of the manufacturing sector went
23 back to its 1979 value only in 1987 (ONS 2007). It is also worth noting that the
24 energy price in the industrial sector has been rather unstable over the same time
25 period, reaching its peak in 1985 and crashing the following year (DTI 2005). Also
26 the breaks in the following group might be influenced by the milder and shorter
27 recession of the early nineties, i.e. the real term GVA of the manufacturing sector
28 went back to its 1990 value only in 1994. However, energy price were rather stable.

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1 Finally, the time period over which the last group of breaks occurred, 1997-1999, was
2 not really remarkable in terms of economic conditions, with the GVA growing at a
3 rate comparable to that observed in the previous couple of years (ONS 2007). The
4 trend in the energy price however changed suddenly in 1996 when the decreases
5 started in 1986 finally came to an end; prices stayed stable until 2003 before heading
6 upwards in 2004 (DTI 2005). It should also be borne in mind that breaks in the series
7 used in this study can be caused by limitations in the dataset. While there seems to be
8 some truth in this argument, as discussed in Section 5, it remains unclear how the data
9 should be adjusted. Overall, using official data seems preferable to embarking on a
10 somewhat arbitrary revision of the data. If breaks are due to the limitations of the
11 dataset, modelling structural breaks can be considered a convenient approach to take
12 into account limitations in the quality of data available to researchers.

13
14 [INSERT Figure 3 ABOUT HERE]

15 16 **7 Panel Testing**

17
18 We also assessed whether the results from univariate tests discussed above are
19 confirmed by panel unit root tests. In the energy literature, Chen and Lee (2007),
20 Narayan and Smyth (2007) and Tauchmann (2006) are few examples of papers
21 implementing panel unit root tests. In this article we implement the LLC test (Levin,
22 Lin and Chu (LLC) (2002)), the Breitung test (Breitung 2000), the Hadri test (Hadri
23 2000), the tests from Maddala and Wu (1999) and Choi (2001) (labelled Fisher and
24 Choi in the table below), the test from Im, Pesaran and Shin (IPS) (2003) and, finally,
25 the CIPS test of Pesaran (2007). As most of these tests have been already discussed in
26 a number of applied papers, rather than reviewing the tests it seems more useful to
27 discuss the limitations of panel unit root testing.

1 The first limitation is related to the alternative hypothesis. In the case of
2 homogenous tests, the alternative hypothesis is rather restrictive, i.e. all series are
3 stationary and have the same AR(1) coefficient. Among the tests in Table 4, the LLC,
4 the Hadri and the Breitung tests are affected by this criticism. In the case of
5 heterogeneous tests, under the alternative hypothesis some series are allowed to have
6 unit roots while others are allowed to be stationary and have different AR(1)
7 coefficients. While this makes heterogeneous tests more appealing, the less restrictive
8 alternative hypothesis makes the results from the tests inconclusive. When rejecting
9 the null hypothesis, one can simply conclude that a significant fraction of the cross
10 section units is stationary. The panel tests do not provide information on the size of
11 this fraction or the identity of the cross section units that are stationary (Breitung and
12 Pesaran 2005). Among the tests in Table 4, this criticism applies to the Fisher, Choi,
13 IPS, CIPS and ILT tests.

14
15 A limitation which applies to all tests in Table 4, with the exception of the ILT
16 test of Im, Lee and Tieslau (ILT) (2005) is related to the fact that time series are
17 assumed to be structurally stable. Only in the ILT test, breaks are allowed under the
18 null and the alternative hypothesis. Another test allowing for structural breaks, which
19 is not implemented in this study, is discussed in Carrion-i-Silvestre, Del Barrio-
20 Castro and Lopez-Bazo (2005). The panel LM statistic can be computed by
21 standardizing the average of the univariate LM statistics by their variance. Another
22 limitation which applies to all tests in Table 4, with the exception of the CIPS test,
23 and to all tests implemented so far in the energy literature with the partial exception
24 of Chen and Lee (2007), is related to the correlation among the series comprised in
25 the dataset, also known as cross-sectional dependence. Correlation can be tackled by
26 demeaning the data - see among others IPS (2003) – although this approach works
27 only when correlation is constant. The feasible generalised least squares (SUR)
28 method can be applied to more general types of correlation (O’Connell 1998)
29 although it can be used only for small N (less than 10) and large T (Breitung and

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8 1 Pesaran 2005), and only when cross-sectional correlation occurs between the
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10 2 stationary components (Wagner 2005). Another approach for dealing with cross-
11
12 3 sectional dependence assumes that correlation enters the model through common
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14 4 factors. After estimating the common factors, test statistics can be obtained by
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16 5 averaging Dickey-Fuller tests (heterogeneous tests) from defactored data or by
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18 6 pooling defactored time series (homogenous tests). This paper implements the CIFS
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20 7 test of Pesaran (2007), i.e. an extension of the IPS test to allow for the presence of
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22 8 one stationary factor. The CIPS statistic is obtained by averaging the t-statistics from
23
24 9 the cross-sectionally augmented DF regression. Other tests are presented in Bai and
25
26 10 Ng (2004), Moon and Perron (2004) and Phillips and Sul (2003).
27

28
29 12 We conclude this brief discussion of the limitations of panel unit root tests with a
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31 13 criticism that applies to all panel tests. This is related to the argument that panel unit
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33 14 root tests can be used to increase the power of univariate tests. However, as different
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35 15 null and alternative hypotheses are tested when running univariate and panel unit root
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37 16 tests, the power of the two procedures cannot be compared – see Maddala and Wu
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39 17 (1999). Bearing this rather lengthy list of limitations, we implement the panel unit
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41 18 root testing mainly to obtain confirmation of our results for the univariate LM tests
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43 19 discussed above. Confirmation of those results is beneficial especially in the case of
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45 20 the models allowing for two breaks in the short sample, where the estimation
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47 21 procedure could be negatively influenced by the relatively low number of
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49 22 observations available for the estimation.
50

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52 24 The table below summarises the results of the panel unit root tests computed in
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54 25 this study. The bandwidth lag in the Hadri, the LLC and in the tests based on the PP
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56 26 tests (Fisher Chi and Choi Z in the table) has been selected by using the Newey-West
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58 27 criterion.. Among the tests assuming structurally stable time series, only the Breitung
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60 28 test rejects the null hypotheses in the case of the model with intercept. The CIPS test

1 is not statistically significant in either of the samples used in this study. However, in
2 the shorter sample, the statistics fall very close to the 10% critical value. The
3 application of the panel LM test of ILT (2005) supports the results of the univariate
4 tests discussed in the previous section. The statistics in the table have been computed
5 on the basis of the observations in our sample, i.e. 35 and 28 respectively. Long-term
6 differences among the energy intensity are deterministic, regardless of the breaks in
7 the model. However, from the table it can be concluded that assuming breaks in the
8 intercept only tends to lower values of the test statistics compared to models with
9 breaks in the intercept and trend. Similarly, the value of the tests run on models with
10 two breaks is higher than the value of the tests from models with one break only.
11 Similarly to Costantini and Arbia (2008) and Lean and Smyth (2007), panel unit root
12 tests confirm the results obtained from univariate tests. Despite the limitations of
13 panel unit root testing procedure, we can therefore conclude that modelling breaks
14 has a very strong influence on our results and that the limited span of our sample and
15 the consequent few observations available in univariate LM tests with two breaks
16 does not produce different results from those we could observe when using a panel
17 procedures.

18 [INSERT TABLE 4]

19 20 **8 Discussion**

21
22 This paper has assessed whether long-term differences among energy intensities
23 of industrial subsectors are stochastic or deterministic. The spirit of our findings is
24 similar to Gaffeo et al (2005) where inference appears to be strongly dependent on the
25 type of tests used, so that conclusions reached at early stages of the testing procedure
26 can be discarded at subsequent stages. In the case of this paper, if the analysis had not
27 included tests allowing for breaks, we would have concluded that the long-term
28 differences of energy intensities among industrial sectors were stochastic. However,

1 after allowing for structural breaks, the opposite conclusion can be reached. With few
2 exceptions, long-term differences can be considered deterministic. The findings from
3 our paper are similar to those from Chen and Lee (2007), Lee et al (2008) and
4 Cuntildeado and Gracia (2006), as the modelling of structural breaks is found to be
5 the determining factor in judging the stationarity of the time series under analysis.
6

7 When applying the LM tests our results are rather sensitive to the number of
8 breaks allowed in the testing procedure, especially over the 1978-2004. In presence of
9 contrasting results from the tests allowing for one break and those with two breaks we
10 overall lean towards the latter. In fact, as discussed in Gadea et al (2004), the
11 inference on unit roots when the model is underparameterised (e.g. the time series has
12 two breaks but only one is modelled) will be biased toward the acceptance of the null
13 hypotheses. Although estimating model with redundant breaks reduces the power of
14 the tests, the loss of power is much more serious when the testing procedure does not
15 allow for a sufficient number of breaks. The lack of sufficient breaks in the testing
16 procedure could also be the cause of our failure to reject the null hypothesis in the
17 case of the Textile and Leather, and the Wood and Wood Product, and the Mining
18 and Quarrying sectors. With regard to the last sector, it is interesting to notice that its
19 long-term differences from the benchmark are stochastic in the longer sample but
20 deterministic in the shorter sample. Following Perron (1989), this can be taken as
21 evidence that an additional break takes place in the longer sample, probably around
22 1977 – Figure 2. From the figure one can also see that the time series for the Textile
23 and Leather, and the Wood and Wood Product sectors is rather irregular. This hints
24 at the possibility that if we had more observations, a tests allowing for a higher
25 number of breaks would probably reject the null hypothesis of unit root. A flexible
26 number of breaks can be modelled by a finite Markov chain of the type introduced by
27 Hamilton (1989). It is also interesting to notice that the long-term differences of the
28 residual sector, i.e. OTH_1 and OTH_2 in Table 1, cannot be considered deterministic in

1 either the short or the log sample. This could probably be due to the fact that the
2 residual sector comprises a number of subsectors which are very different from each
3 other. In fact when the subsectors comprised in the OTH₁ sectors are modelled
4 separately in the shorter sample, in three out of the four instances the long-term
5 differences can be considered deterministic.

6
7 Going back to the motivation of our study, our analysis discovered that the the
8 trend of long-term differences among the energy intensity of industrial subsectors
9 changes occasionally, i.e. only at the occurrence of structural breaks in the
10 deterministic component. This implies that the future movements of the long-term
11 differences can be predicted on the basis of past behaviour. However, this is true only
12 if one is ready to assume that the series will be structurally stable over the forecast
13 horizon. The frequency of the breaks, i.e. about one every fifteen years, makes this
14 assumption acceptable overall.

15
16 The policy implications of this study are related to the timing and frequency of
17 policy interventions and to the policy instruments which can be used. As long-term
18 differences among industrial sectors are mainly deterministic, short-term random
19 difference dissipates across time. For this reason, policy makers with an interest in the
20 series following a certain time pattern do not need to intervene at any single minor
21 departure of the series from the desired trend. As pointed out by Chen and Lee (2007)
22 and Narayan and Smyth (2007), in this case government should not be concerned
23 with short-term fluctuations when implementing energy policies. In fact, if they want
24 to affect the evolution of the series, policy makers will need to implement prolonged
25 policy measures able to affect the deterministic components.

26
27 In relation to the type of instruments which can be used by policy makers, we can
28 conclude that policies taking into account the evolution of the series and the

1 peculiarity of the economic actors cannot be justified on the basis of our analysis. In
2 fact, the presence of long-term deterministic differences among the series supports the
3 adoption of policy instruments which are applied across productive sectors without
4 frequent changes. Among the policies in the energy sector, energy and CO₂ taxes
5 applied to all industrial subsectors would be an example of this type of instrument.
6 While the analysis discussed in this paper does not consider the effects on the
7 competitiveness of the industrial sectors, we can conclude that it is not possible to
8 dismiss the introduction of these taxes on the basis of the peculiarity of some
9 industrial subsectors. In addition, if there is a relationship between the supposed
10 adverse effects of these taxes and the difference in energy intensities across sectors,
11 the importance of these effects is likely to reflect the deterministic nature of the series
12 assessed in this study and its long-term pattern. A final advice to policy-makers is
13 related to the caution needed when drawing conclusions from the use of a narrow set
14 of statistical methodologies. As discussed above, the results from tests allowing for
15 breaks are opposite to univariate and panel tests assuming structural stability. Policy
16 advice from the latter would be completely different from the conclusions drawn from
17 this article.

18
19 In this study, modelling breaks has turned out to be a rather important issue.
20 Breaks in the long-term differences can be due to time-varying and sector-specific
21 factors which are not directly taken into account in this study. Alternatively, structural
22 breaks can be caused by a change in the importance of subsectors comprised in the
23 industrial sectors assessed in this study, provided that these subsectors have different
24 energy intensities (e.g. pharmaceuticals and base chemicals in the chemical sector).
25 Estimated breakdates seems to have been influenced by changing economic
26 conditions, i.e. the recessions in the eighties and early nineties, and fluctuations in the
27 energy price, notably the 1986 crash and the level off of the price in 1996. It is also
28 possible that some of the breaks in the series are caused by limitations in the dataset,

1 as discussed in Section 5. If this argument is right, modelling structural breaks can be
2 considered a convenient approach to take into account limitations in the quality of
3 data available to researchers.

4 5 **9 Conclusions**

6
7 From our study we can conclude that long-term differences in the energy
8 intensities of the British industrial subsectors are deterministic, after allowing for
9 structural breaks in the series. The few cases where the null hypothesis of stochastic
10 long-term differences could not be rejected are probably due to our testing procedure
11 which cannot take into account more than two breaks in the series or to the fact that
12 some of the sectors assessed in this study comprise a number of subsectors with a
13 very different technological profile. The implication from our study is that the trend
14 of long-term differences changes only occasionally, i.e. only at the occurrence of
15 structural breaks in the deterministic components. For this reason, future movements
16 of the long-term differences can be predicted on the basis of past behaviour. From a
17 policy point of view, our analysis implies that policy makers do not need to intervene
18 at any single minor departure of the series from the desired trend. In addition, our
19 analysis supports the adoption of policy instruments which are applied across
20 productive sectors without frequent changes. Among the policies in the energy sector,
21 energy and CO₂ taxes applied to all industrial subsectors would be an example of this
22 type of instrument.

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25
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Industrial subsectors	NACE code	Acronym	
		1970-2004	1978-2004
Mining and Quarrying	13 and 14	MIN	MIN
Food and Tobacco	15 and 16	FT	FT
Textile and Leather	17, 18 and 19	TXT	TXT
Wood and Wood Products	20	WPP	WPP
Paper, Pulp, and Printing	21 and 22		
Chemical and Petrochemical Industry	24	CHE	CHE
Non-Metallic Minerals	26	NMM	NMM
Construction	45	CON	CON
Iron and Steel	27.1 + 27.31	OTH ₁	MET
Non-Ferrous Metals	27.2 + 27.32		TRA
Transport Equipment	34 + 35		MAC
Machinery	28, 29, 30, 31 and 32		OTH ₂
Non Specified Industry	25, 33, 36 and 37		

Table 1 Industrial sectors modelled in the 1970-2004 sample and in the 1978-2004 sample. In the first sample the Iron and Steel, the Non-Ferrous Metals, the Transport Equipment, the Machinery and the Non Specified Industry sectors are grouped together (acronym OTH₁). In the second sample, the Iron and Steel and the Non-Ferrous Metals are grouped together (acronym MET). In both samples, the Wood and Wood Products and the Paper, Pulp, and Printing are grouped together (acronym WPP).

1970-2004																
	MIN		FT		TXT		WPP		CHE		NMM		CON		OTH ₁	
ADF	-1.99/-2.43	I/T	-1.05/-1.83	I/T	-1.58	I	-1.11	T	-1.91	T	-2.15	I	0.06	T	-2.39	T
PP	-1.96/-2.43	I/T	-1.14/-1.97	I/T	-1.80	I	-1.26	T	-3.01	T	-2.42	I	1.44	T	-2.42	T
MZ_α	-10.69	T	-5.24	T	-5.84	T	-3.31	T	-4.67	T	0.07	I	-31.19	T	-8.03	T
MZ_t	-2.08	T	-1.62	T	-1.66	T	-1.17	T	-1.52	T	0.02	I	-3.45	T	-1.92	T
MSB	0.19	T	0.31	T	0.28	T	0.35	T	0.33	T	0.35	I	0.11	T	0.24	T
MP_T	9.58	T	17.38	T	15.51	T	25.14	T	19.45	T	12.76	I	5.58	T	11.57	T
DF^{GLS}	-2.58	T	-1.80	T	-1.90	T	-1.25	T	-1.56	T	-0.54	I	-1.29	T	-2.34	T
DF^{MAX}	-1.99/-2.43	I/T	-1.05/-1.63	I/T	-1.58	I	-1.11	T	-1.20	T	-1.56	I	0.06	T	-2.35	T
DF^{RMA}	-1.36/-1.45	I/T	-0.29/0.51	I/T	-0.05	I	0.86	T	1.00	T	0.52	I	1.67	T	-0.62	T

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1978-2004										
	CON		MET		TRA		MAC		OTH ₂	
ADF	1.19	T	0.19 /-0.01	I/T	-0.94 /-1.77	I/T	-2.54	I	-2.41	T
PP	1.52	T	0.71 /-2.25	I/T	-0.77 /-1.80	I/T	-2.57	I	-2.33	T
MZ_α	-21.39 (**)/ -0.76	I/T	-11.39	T	-6.33	T	-9.37	T	-7.22	T
MZ_t	-2.49 (*) / -0.39	I/T	-2.22	T	-1.58	T	-2.16	T	-1.87	T
MSB	0.12 (**)/ 0.22	I/T	0.20	T	0.25	T	0.23	T	0.26	T
MP_T	3.49(+) / 20.33	I/T	8.80	T	14.31	T	9.74	T	12.67	T
DF^{GLS}	0.14 / -0.49	I/T	-3.22 (*)	T	-2.23	T	-2.77	T	-2.39	T
DF^{MAX}	1.19	T	0.19/-0.01	I/T	-0.94/-0.35	I/T	-2.54 (*)	I	-2.08	T
DF^{RMA}	2.33	T	1.50/-4.44 (**)	I/T	-0.36/-0.27	I/T	-2.41 (*)	I	-0.29	T

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3 **Table 2** Results from the unit root tests listed in the first column of the tables over the 1970 -2004 and the 1978-2004
4 sample. In the case of the latter, the table shows only the sectors grouped under the OTH₁ acronym in the longer sample
5 and the Construction sector, i.e. the only sector presenting different results across samples. The list of sectors described
6 by the acronyms in the first row of the table can be seen in Table 1. Key: ADF = Augmented Dickey Fuller; PP = Phillips
7 Perron; MZ_α = Modified Z_α test; MZ_t = Modified Z_t test; MP_T = Modified Point Optimal test; MSB = Modified R₁
8 statistics. The symbols (+), (*) and (**) indicate statistical significance at the 10, 5 and 1% significance level. I and T
9 indicate the model selected by the information criteria, i.e. intercept only (I) or an intercept and trend (T). Both models
10 are reported when the information criteria were inconclusive on the choice of the model.

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1970-2004							
	LM – 1 break	Breakdate	Model	LM – 2 breaks	Breakdates	Model	
MIN	-3.87	1998	C	-4.02	1996	1998	CC
FT	-3.42	1990	C	-5.86 (**)	1979	1990	CC
TXT	-3.46	1983	C	-2.90	1977	1983	AA
WPP	-2.88 / - 3.14	1991 / 1979	A / C	- 3.06 / -4.56	1977 / 1977	1991 / 1990	AA / CC
CHE	-3.92 ⁽⁺⁾	1988	A	-5.54 (**)	1985	1988	AA
NMM	-2.77	1989	C	-5.68 (*)	1976	1987	CC
CON	-6.27 (*)	1998	C	-6.57 (**)	1991	1998	CC
OTH ₁	-2.86	1980	A	-3.03	1980	1983	AA

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[CONTINUE]

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1978-2004							
	LM – 1 break	Breakdate	Model	LM – 2 breaks	Breakdates	Model	
MIN	-3.43	1999	C	-5.73 ^(*)	1988	1999	CC
FT	-3.83 ^(*)	1990	A	-3.96 ⁽⁺⁾	1990	1998	AA
TXT	-2.43	1983	C	-2.86	1983	1997	AA
WPP	-3.44	1999	C	-3.10	1984	1991	AA
CHE	-3.29 ⁽⁺⁾	1988	A	-4.57 ^(**)	1985	1988	AA
NMM	-4.89 ⁽⁺⁾	1987	C	-6.10 ^(*)	1987	1993	CC
CON	-4.63 ⁽⁺⁾	1998	C	-6.93 ^(**)	1990	1998	CC
MET	-5.14 ^(**) / - 6.33 ^(**)	1991 / 1985	A / C	-6.62 ^(**)	1985	1991	CC
TRA	-2.62 / - 3.46	1995 / 1987	A / C	-5.75 ^(*)	1983	1999	CC
MAC	- 4.97 ⁽⁺⁾	1993	C	-5.43 ⁽⁺⁾	1993	1998	CC
OTH ₂	-2.46 / - 4.41	1985 / 1993	A / C	-2.96	1983	1988	AA

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3 **Table 3** Results for the LM test with one and two breaks. The symbols ⁽⁺⁾, ^(*) and ^(**) indicate statistical significance at
4 the 10, 5 and 1% significance level. The list of sectors described by the acronyms in the first column of each table can be
5 seen in Table 1. For each test the tables show the value the test statistic, the estimated breakdate and the model selected
6 by the two information criteria. The letters A and C indicate the model with a break in the intercept and with a break in
7 the intercept and trend, while the letters AA and CC indicate the model with two breaks in the intercept and with two
8 breaks in the intercept and trend, respectively. Two models are reported when the information criteria were inconclusive
9 on the choice of the model.

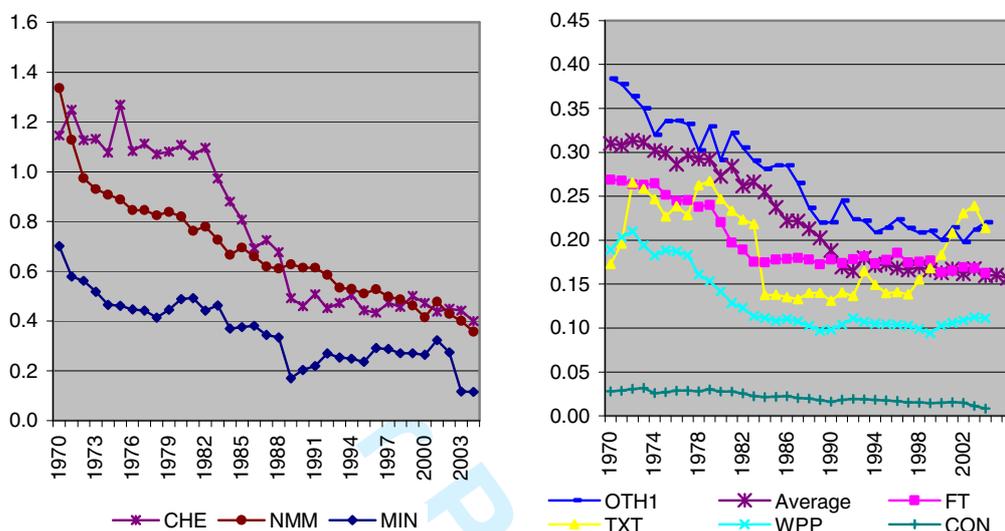
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	1970-2004		1978-2004	
	Intercept	Intercept and Trend	Intercept	Intercept and Trend
<i>Homogenous tests</i>				
LLC	2.39	2.53	2.52	0.19
Breitung	- 2.06 (*)	1.42	-2.73 (**)	0.36
Hadri Z	5.48 (**)	4.75 (**)	9.04 (**)	5.37 (**)
<i>Heterogeneous tests</i>				
PP Fisher Chi	9.87	12.40	9.77	16.57
PP Choi Z	1.46	1.53	3.18	1.21
ADF Fisher Chi	8.68	8.67	8.31	10.56
ADF Choi Z	1.50	1.46	3.30	2.71
IPS	1.35	1.46	2.99	2.27
ILT – 1 break	-2.06 (*)	7.42 (**)	-5.27 (**)	-11.79 (**)
ILT – 2 breaks	-4.73 (**)	-15.44 (**)	-8.61 (**)	-18.78 (**)
<i>Tests allowing for cross-section dependence</i>				
CIPS	- 1.20	- 1.82	-1.08	-2.68

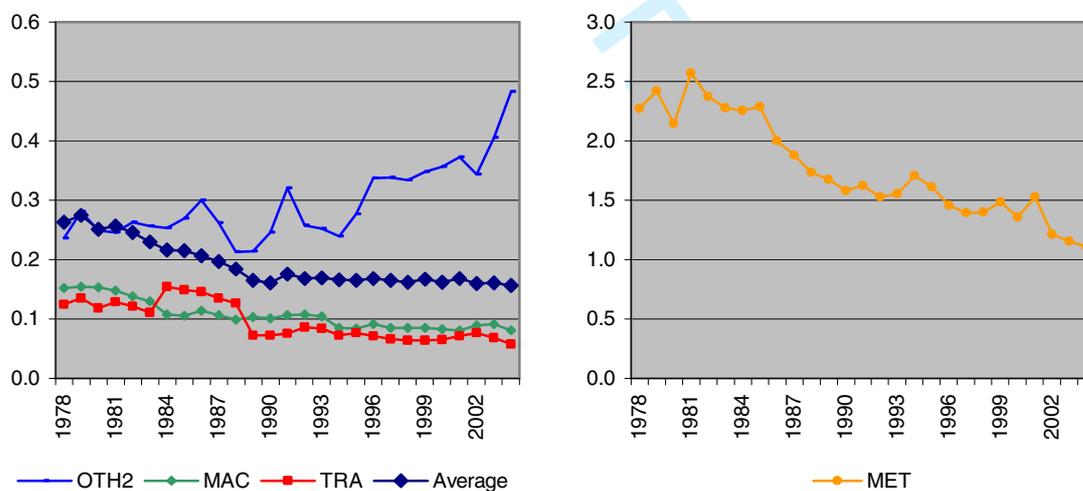
Table 4 Results from the panel tests for the two samples assessed in this study. The tests listed in the first column of the table are all unit root tests with the exception of the Hadri Z test which is a stationary test, i.e. the series is assumed stationary under the null hypothesis. The symbols (+), (*) and (**) indicate statistical significance at the 10, 5 and 1% significance level. The CIPS statistic for the model with intercept and trend over the longer period falls very close to the 10% critical value, i.e. -2.73.

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3 **Figure 1a** 1970 - 2004 Energy intensity of the industrial subsectors assessed in this study.
 4 The list of sectors described by the acronyms in the figure column can be seen in Table 1.
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7 **Figure 1b** 1978 - 2004 Energy intensity of the industrial subsectors. The list of sectors
 8 described by the acronyms in the figure column can be seen in Table 1.
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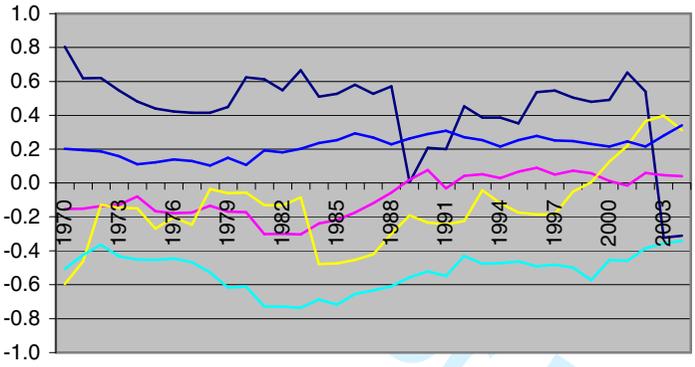


Figure 2a — MIN — FT — TXT — WPP — OTH

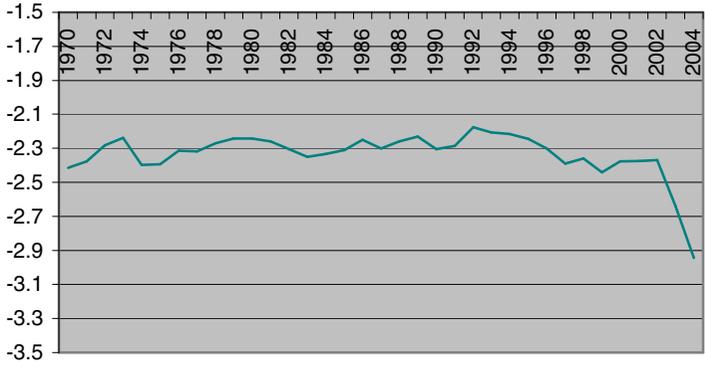


Figure 2b — CON

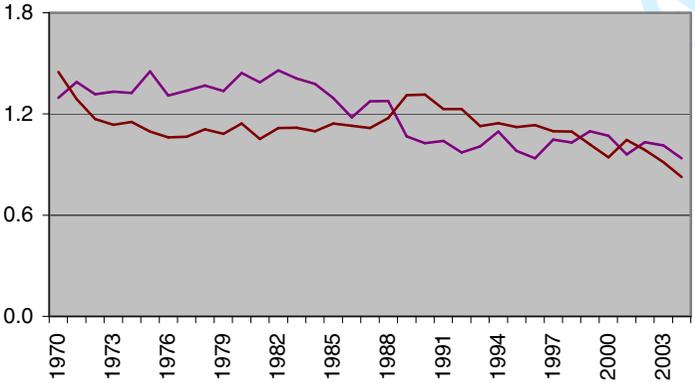


Figure 2c — CHE — NMM

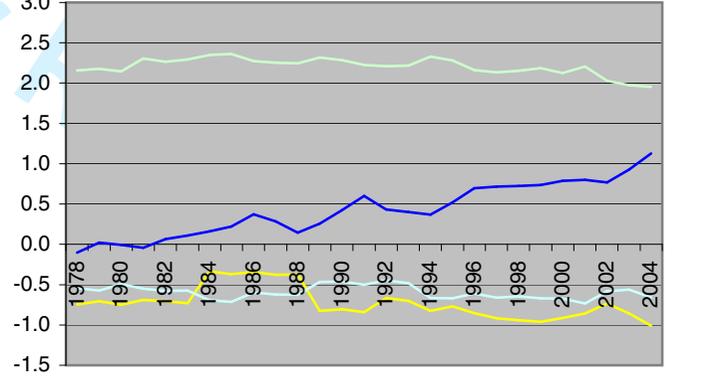


Figure 2d — TRA — OTH2 — MAC — MET

Figure 2 Difference between energy intensity in the subsectors assessed in this study and the energy intensity in the industrial sector as a whole. Figure 2a, Figure 2b and Figure 2c show the time series for the sector assessed over for the 1970-2004 sample while Figure 2d shows the time series from the additional sectors assessed over the 1978-2004 sample. The list of sectors described by the acronyms in the figure column can be seen in Table 1.

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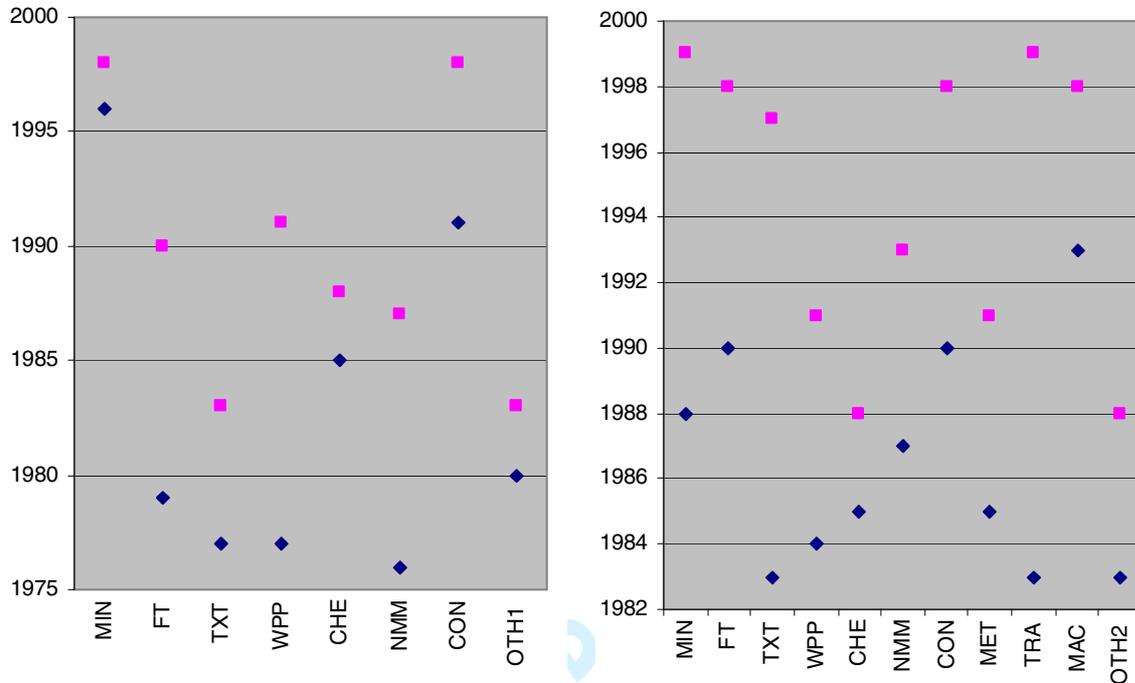


Figure 3 Breakdates estimates by the models allowing for two breaks presented in Table 3. The figures on the left presents the breakpoint estimated over the 1970-2004 sample while the figure on the right presents those estimated over the 1978-2004 sample. The list of sectors described by the acronyms in the figure column can be seen in Table 1.