1. Introduction

As a result of recent concerns relating to the harmful effects of climate change, policy makers have become increasingly interested in reducing greenhouse gas emissions using a variety of policy tools such as environmental taxation and the increased use of renewable energy. In addition, countries have been set targets for greenhouse gas emissions, such as through the Kyoto Protocol, whilst EU members, including the UK, have been set voluntary targets for the reduction in these emissions. Even before greenhouse gas emissions became an important issue, the UK was seeking to pass legislation in order to reduce the production of key pollutants such as sulphur dioxide (SO_2), which started with the Alkali Act of 1874. Evidence of the harmful effects of pollutants to the environment has led to increasing political efforts to reduce them and academic efforts to model how the pollutants relate to the economy. In the 1990s one of the main developments in understanding the link between the environment and economy was the Environmental Kuznets Curve (EKC), which suggested a non-linear relationship between income and pollutants.

Stern (2004, p.1420) asserts that “The EKC is an essentially empirical phenomenon, but most of the EKC literature is econometrically weak.” Researchers are increasingly employing more advanced econometric techniques to try and uncover any statistical shortcomings of the EKC. Single country studies have used time series econometrics, with various methodological developments taking the form of unit root testing and cointegration analysis. These developments have been necessary as in the absence of these tests there is the possibility of the ‘spurious’ regression problem arising from looking at variables with common trends. Recent studies generally look at the EKC over very short time spans; something which could be potentially problematic when using time-series models, such as cointegration, which perform better in large samples. Secondly, papers to date have only looked at symmetric cointegration.

This paper aims to look at re-specifying the EKC in an asymmetric framework to allow for a different speed of adjustment to the long-run relationship depending on whether emissions are above or below the EKC in the short-run. In addition further explanatory variables are added into this model, such as energy prices, to test the robustness of the results. Regulation on air pollution has become increasingly stringent, including international protocols such as the Oslo Protocol and the Kyoto Protocol. Such regulations may explain why actions are more likely if emissions are too high – as there may be penalties for industry and the threat of increased legislative action. Thus, in the presence of environmental regulation we may expect any short-run deviations in emissions to be corrected more quickly if they are too high, whereas if emissions are too low, there is no immediate pressure for them to rise back to their long-run levels.

This could essentially imply that emissions are 'sticky upwards' with respect to the long-run EKC. Two different environmental hypotheses are constructed and tested using the threshold autoregressive (TAR) and momentum threshold autoregressive (M-TAR) cointegration method of Enders and Siklos (2001), which as far as we know has not been used to analyse emissions in the current EKC literature.

Following the introduction, we discuss the related literature on the EKC, then the data and non-linear cointegration techniques are examined. We then discuss the results and finally offer some conclusions.

2. Literature Review

Empirical work into the Environmental Kuznets Curve (EKC) to date has produced mixed findings. Studies use a very wide variety of countries, pollutants, data sources and econometric techniques[1], each one coming up with a slightly different perspective on the acceptance or rejection of the EKC hypothesis, and what it means for the theory[2]. Perhaps the most important distinction between studies is the approach they use with regards to multiple- or single-country analysis and therefore the use of panel data or time series techniques. One of the reasons why time series aspects are appearing is that over the last few years there has been an increasing acceptance of the fact that not only with time series studies, but now with panel data there is the need for checking the order of integration and the cointegration of variables used in the models. This is due to the fact that 'large N, large T' datasets are becoming feasible and available.

2.1. Panel data Estimation

The original work in the area of the EKC came from Grossman and Krueger (1995) who employed a database for a range of cities from the Global Environmental Monitoring Systems (GEMS). They used panel data techniques, confirming the existence of the inverse-U relationship between air and water basin pollution and income per capita. As such, after this paper, the majority of work was to perform analysis in a panel data framework. For instance, Managi and Jena (2008) create an environmental productivity index to be used as a dependent variable, and use additional explanatory variables such as urbanisation and population density.

[1] These include cross-section, time series and panel methods. Here we focus on studies with a time dimension.

[2] The literature on the EKC is dominated by empirical studies, Harbaugh *et al*. (2002) point out there is little theoretical literature to guide the correct specification, so most studies follow the approach used by Grossman and Krueger (1995).

However, there have been several criticisms of panel data techniques in the context of the EKC mentioned in the literature, all of which would seem to be in favour of focussing on individual country analysis in a time series framework. In his survey Dinda (2004, p.449) points to the critical flaw in the panel approach, noting that "the basic assumption behind pooling the data of different countries in one panel is that economic development trajectory would be the same for all."

Another point about the use of panels is that, due to data limitations, researchers are generally restricted to a small time period over many countries. Since this period is generally from the early 1980s until the current day, Vincent (1997) notes that panel studies of the EKC may be little more than a statistical artefact. This is because over this data range, developing countries can generally be seen to have a positive relation between emissions and output and many developed countries may exhibit a negative relation, thus leading to an overall conclusion that the EKC holds over all countries.

2.2 Time Series Estimation

Some studies, noting the above criticisms of cross-country panels, go on to estimate a single-country panel regression by pooling data for regions within the country. While this circumvents some of the problems discussed, de Bruyn et al. (1998, p.173) argue that "the EKC, as estimated from panel data does not capture dynamic processes well enough to justify the claim that economic growth is de-linked from environmental pressure in individual countries". This argument suggests that using panel data even within countries may not be capable of measuring the EKC relation.

With this in mind, several studies have employed time series analysis of emissions in individual countries, deploying a range of unit root and cointegration techniques to examine a non-spurious long-run EKC relationship. Perman and Stern (2003) look at sulphur emissions for a large number of countries both at an individual level, and then at a panel level. Using the Engle-Granger (1987) method they find that a long-run cointegrating relationship only exists in 35 out of 74 countries. They also found that in more than one third of cases, the EKC hypothesis was rejected. However, their analysis was only performed on a relatively small dataset from 1960-1990. Other studies such as Markandya *et al*. (2006) and Lindmark (2002) also use long datasets stretching back to the nineteenth century, with the former using a similar dataset to the one used in this paper and the latter a Swedish dataset starting in 1870.

Other time series studies use the more recently developed Pesaran et al. (2001) Autoregressive Distributed Lag (ARDL) bounds testing approach to cointegration. This has benefits over other cointegration methods as it allows for a mixture of I(1) and I(0) variables to be included in the long-run cointegrating relation, as is often the case with CO_2 emissions. Ang (2007) looks for a quadratic EKC relationship in French CO_2 emissions over the period 1960-2000. The results give the correct signs, lending evidence towards the EKC hypothesis.

With the above mentioned advantages of single-country studies in mind, this paper aims to look at how the EKC is dynamically misspecified. The specification of the empirical model is subject to some discussion, and this can be seen to change dramatically across studies. Carson (2010) provides a survey of the EKC literature and suggests several possible sources of misspecification. Amongst other, he mentions omitted variables and the functional form as key factors which could lead to misspecification. Studies that have examined omitted variables include Soytas *et al* (2007), who added total labour force and energy use as additional explanatory variables.

Very few studies have looked to move away from the classic quadratic or cubic specification of the EKC. Galeotti et al. (2006) moves away from this specification of per capita income by imposing the inverse-U shape into the relationship through other bell-shaped distributions.

They do this for CO_2 emissions in OECD and non-OECD countries, finding that the bell-shape fits the OECD countries but not the non-OECD countries, where they find an increasing, or "slowly concave" pattern.

However, to the best of the authors' knowledge, no studies to date have looked for asymmetric behaviour in emissions with regards to disequilibrium from the long-run EKC. Time series studies, such as those mentioned above, all favour symmetric (linear) cointegration techniques. However, as mentioned in Section 1, there is substantial reason to believe that we may expect pressure from environmental agreements to cause a quicker adjustment back to the EKC when emissions are temporarily too high compared to when they are too low.

3. Materials and Methods

3.1 Data

This paper uses a long historical dataset, which yields benefits in terms of sample size. The vast majority of time series studies use less than 50 observations. We use historical CO_2 data from the Carbon Dioxide Information Analysis Centre (CDIAC) based in the Oak Ridge National Laboratory (ORNL). This is fossil-fuel CO_2 emissions measured in metric tonnes estimated from historical energy statistics and spans the period 1751-2007 for the United Kingdom. Holtz-Eakin and Selden's (1995) important work also used this dataset though it was truncated to a shorter dataset due to the data availability of the countries selected to form a panel. The SO_2 data is that of David Stern and is available over the period 1850-2002 for the UK. The data for real GDP is taken from Maddison and measured in 1990 international Geary-Khamis dollars (GK$). Population data is taken from the same source and is used to transform the variables into per capita terms. The real GDP and population variables run from 1830-2003 and 1820-2008 respectively. This data is also used by papers such as Markandya et al. (2006) to analyse European countries in a panel data context. The data for energy prices[3] comes from a series generated by Fouquet (2011), where this series is expressed in a form equivalent to their energy service, which requires that they are combined with the energy efficiency of the equipment used, the adjustment required to produce energy prices in this form is explained in Fouquet (2011).

In order to maximise the number of useable observations the largest common sample for the per capita CO_2 and SO_2 emissions with real GDP per capita are used. This means a sample from 1830 to 2003 for the CO_2 model and from 1850 to2002 for the SO_2 model. Charts of the data and the common sample descriptive statistics are shown in Figures 1 and 2. The clearest falls in both series occur in 1921, 1926 and from 1956 onwards. Markandya et al (2006) largely attribute these to regulation – 1926 being the year of the Smoke Abatement Act and 1956 onwards being the epoch of the Clean Air Acts. However, 1926 also saw the General Strike in the UK and the National Coal Strike took place in 1921. These broader economic events may have had a more significant impact than regulation in those particular years. This also explains the lack of a continuing downward trend after these years. The steeper fall in SO_2 emissions shows that these have been easier to reduce using new technologies applied to power stations, such as the use of 'Flue Gas desulphurisation' techniques, whereas with CO_2 the technology has been less effective.. In addition there has over recent years been a move away from the use of coal which emits large quantities of SO_2 to other fuels such as gas which emit far lower levels.

[3] We would like to thank Roger Fouquet for allowing us access to this dataset. Other energy prices in addition to gas prices could have been included but gave similar results to gas prices. Although Lindmark (2002) uses a price index which includes non CO_2 emitting energy carriers, as he adds it could also be concluded that the relative price for them could be insignificant. In addition to the results included here, other tests were conducted on energy prices without the trend, but the results are similar to the standard model.

Clearly the range of real GDP per capita is smaller for the common sample with SO_2 per capita emissions due to the removal of observations from the beginning and end of the dataset as compared with the CO_2 dataset. This range of values will be relevant when looking at the turning points of the EKC relation to see whether they lay within the observed dataset. The data will be transformed into natural logarithms for the econometric analysis; this is important as the real GDP variable in particular exhibits an exponential trend in levels.

3.2. Methodology

Enders and Siklos (2001) propose two methods to test for asymmetric cointegration which are based on the two-step cointegration procedure of Engle and Granger (1987). In this way the first stage is to estimate the long-run regression using ordinary least squares (OLS). To allow for the most flexible shape for the EKC, we will follow much of the literature by allowing polynomial terms for real GDP per capita up to and including the third order (cubic). This produces a relatively parsimonious model, which is of importance as the addition of variables to the cointegrating relation not only uses up degrees of freedom but also changes the appropriate response surface for the cointegration test statistic, making it harder to find significant cointegrating relationships. The basic model is written as follows:

$$e_t = \beta_0 + \beta_1 y_t + \beta_2 y_t^2 + \beta_3 y_t^3 + \mu_t \tag{1}$$

where e_t denotes emissions of CO_2 or SO_2 in metric tonnes (MT) per capita and y_t denotes real GDP per capita and both series are in natural logarithms. μ_t is the residual. We also consider energy prices as an explanatory variable which is discussed later in this section.

Having run the long-run regression, the second stage is to perform a unit root test on the residual series μ_t, with the null hypothesis of a unit root being equivalent to no cointegration.

The original test of Engle and Granger (1987) tests for symmetric cointegration by running the standard Dickey-Fuller (1979) test on the residuals of the regression as follows:

$$\Delta\mu_t = \rho\mu_{t-1} + \varepsilon_t \qquad (2)$$

The residual term of this regression ε_t, is assumed to be pure white noise with a zero mean and a constant variance. Enders and Siklos (2001) present two modifications to this simple model in order to test for asymmetries: a threshold autoregressive (TAR) model, and a momentum-threshold autoregressive (M-TAR) model. We can use these two models to test for two different hypotheses.

The first hypothesis is that the pressure of environmental agreements causes more attention to be given to emissions when they are temporarily above the EKC; $\mu_t \geq 0$, than when they are below the EKC; $\mu_t < 0$. In other words certain regulations or the existence of emissions penalties mean that there is more motivation to reduce emissions when they are too high in levels, but there is less urgency to increase emissions when they are too low. This notion can be tested with use of the TAR modification to the Engle-Granger (1987) test:

$$\Delta\mu_t = I_t\rho_1\mu_{t-1} + (1 - I_t)\rho_2\mu_{t-1} + \varepsilon_t \qquad (3)$$

Where I_t is the Heaviside indicator function, described as follows[4]:

$$I_t = \begin{cases} 1 \text{ if } \mu_t \geq 0 \\ 0 \text{ if } \mu_t < 0 \end{cases} \qquad (4)$$

A second hypothesis asks whether the pressure of environmental agreements means that deviations of emissions from the long-run EKC are corrected more quickly when emissions

[4] In fact, they suggest a threshold for μ_t of τ rather than 0. However, in this case we are only interested in what happens when we are either above or below the EKC, so we set it equal to 0, as in Enders and Siklos (2001).

are tending to increase relative to the EKC; $\Delta\mu_t \geq 0$, than when they decrease relative to the EKC; $\Delta\mu_t < 0$. Unlike the TAR framework it does not matter whether emissions are above or below the EKC, only the direction in which emissions are moving, in other words their momentum. This can be tested using the second modification of Enders and Siklos (2001):

$$\Delta\mu_t = M_t \rho_1 \mu_{t-1} + (1 - M_t)\rho_2 \mu_{t-1} + \varepsilon_t \tag{5}$$

Where M_t is the Heaviside indicator function, described as follows:

$$M_t = \begin{cases} 1 \text{ if } \Delta\mu_t \geq 0 \\ 0 \text{ if } \Delta\mu_t < 0 \end{cases} \tag{6}$$

So both of these specifications can test for the different ways in which we may expect emissions to be more ‘sticky upwards’, so as to meet environmental regulation.

If the residual series ε_t is not deemed to be white noise, then lags of the dependent variable may be added to Equations 3 and 5, according to an information criterion. The necessary and sufficient conditions for stationarity of μ_t are that $\rho_1 < 0, \rho_2 < 0$ and $(1+\rho_1)(1+\rho_2) < 1$, as stated by Petrucelli and Woolford (1984). Enders and Siklos (2001) propose to test the first two conditions jointly using the null hypothesis $H_0 : \rho_1 = \rho_2 = 0$. Since this F-statistic does not follow a standard distribution, it must be compared with the ϕ_μ tables for the TAR model and the ϕ_μ^* tables for the M-TAR model, which Enders and Siklos (2001) compute through Monte Carlo simulation. However, since this response surface changes with the number of observations, the number of variables in the long-run regression and the number of lagged dependent variables, the more complete tables of Wane, Gilbert and Dibooglu (2004) as cited in Wang and Thi (2010) have been used. Having established cointegration, to test for asymmetric cointegration, the F-statistic for the null hypothesis $H_0 : \rho_1 = \rho_2$ is calculated, which Enders and Siklos (2001) note can be compared to the standard F-distribution. We would have a priori expectations that $|\rho_1| > |\rho_2|$ for both the TAR and M-TAR frameworks.

If there is evidence to support the existence of a single cointegrating vector, then Engle and Granger (1987) show that there exists an error-correction model (ECM) representation. For the Enders and Siklos (2001) TAR model these can be written for e_t *and* y_t as follows:

$$\Delta e_t = \rho_{11} I_t \mu_{t-1} + \rho_{12}(1-I_t)\mu_{t-1} + \sum_{i=1}^{3} \alpha_{1i} \Delta y_{t-1}^{i} + \alpha_{14} \Delta e_{t-1} + v_{1t} \quad (7)$$

$$\Delta y_t = \rho_{21} I_t \mu_{t-1} + \rho_{22}(1-I_t)\mu_{t-1} + \sum_{i=1}^{3} \alpha_{2i} \Delta y_{t-1}^{i} + \alpha_{24} \Delta e_{t-1} + v_{2t} \quad (8)$$

where i denotes the power operator on emissions. Similarly for the M-TAR model the indicator function I_t can be replaced with M_t. The two further ECMs exist for the variables y_t^2 and y_t^3 though these have little useful economic interpretation, so the regressions are run but not reported (Results available from authors on request). Clearly for cointegration between these variables to be meaningful, some of the ρ terms should be statistically significant for a given pollutant. If none of the ρ terms were significant it would mean that no variables adjust in the short-run to correct for any disequilibrium from the long-run EKC. Furthermore some of the ρ terms should be negative so that if the error term is positive, one of the variables decreases rather than increases, thus ensuring that the system is dynamically stable.

In addition to the above approach, we have incorporated two further factors into the basic EKC model in Equation 1 to control for the effects of technological change on emissions and changes in energy prices. This also enables us to determine whether the asymmetric adjustment is due to technological changes, for instance there may only be government backed incentives for firms to invest in technologically advanced processes for reducing pollutants, when the authorities are trying to ensure targets for pollution emissions are met, that is when they are above the EKC. When below the EKC, there is little need to invest in the more technologically advanced products, so any asymmetry can be accounted for by technological progress[5]. We have also included energy prices as a further factor in the model, as other studies such as Lindmark (2002) suggest these may have a significant effect on emissions. This produces the following augmented model:

$$e_t = \gamma_0 + \gamma_1 y_t + \gamma_2 y_t^2 + \gamma_3 y_t^3 + \gamma_4 ep_t + \gamma_5 Trend + v_t \tag{9}$$

Where ep_t is the log of energy prices and *Trend* is a linear trend, which proxies technological change. In the models estimated here, we have used gas prices to represent energy prices, as this has been a popular source of energy throughout the data span used here, in contrast to coal, oil or wood, which have varied in popularity. However although over the entire data span gas has been a major source of energy, during some time periods, such as the 1990s, oil was the most popular source of energy. This fact may also suggest the potential for structural breaks as different sources of energy have varied in popularity over the data range. If this were the case then we need to account for this when performing unit root tests, which we discuss in the next section with reference to the structural break unit root test of Zivot and Andrews (1992.

4. Results and Discussion

4.1 Long-run EKC and cointegration results

Table 1 contains the summary statistics for all the variables, showing that CO_2 emissions are considerably higher on average than SO_2 emissions. Before performing any cointegration

[5] See Jaffe *et al*. (2002) for a review of some of the theoretical implications of technological change to environmental policy.

analysis, unit root tests were run to check the order of integration of the variables. First of all we run three basic tests with no structural breaks, namely the augmented Dickey-Fuller test, the GLS-detrended ADF test of Elliot, Rothenberg, and Stock (1996) – ERS and the Phillips-Perron (1988) test - PP. However given the above point that there could be reason to believe that there is a structural break in the time series we also run the structural break unit root test of Zivot and Andrews (1992) - ZA.

This is a test of the null hypotheses of a unit root process without a structural break (equation 6 in ZA) against the alternative of trend-stationarity with a structural break in the intercept and trend. We have chosen this test as it determines the breakpoint λ endogenously, unlike its predecessor Perron (1989) where the researcher must specify the break date. For maximal generality we allow for breaks in both the constant and trend, and therefore only consider the third model of ZA, and hence run the regression:

$$\Delta y_t = \mu + \theta DU_t(\lambda) + \beta t + \gamma DT_t^*(\lambda) + \alpha y_{t-1} + \sum_{j=1}^{k} \varphi_j \Delta y_{t-j} + \upsilon_t \qquad (10)$$

Here $DU_t(\lambda)$ denotes the dummy variable for the break in the constant term from the estimated breakpoint λ so $DU_t(\lambda) = 1$if $t > T(\lambda)$ 0 otherwise. DT_t^* is the variable for the break in the trend, namely $DT_t^* = t - T(\lambda)$ if $t > T\lambda$, 0 otherwise, As usual, the estimate of interest is α though we are also interested in the breakpoint if we can reject the null hypothesis and conclude trend stationarity with a structural break.

The results of these tests are reported in Tables 2a and 2b. Table 2a confirms that the variables are all I(1), meaning we can look for a long-run cointegrating vector amongst the variables. More notably perhaps, the evidence in Table 2b shows that we cannot reject the null hypothesis of a unit root without structural breaks, so there is not an issue of controlling for structural breaks in the following analysis.[6] The estimated break dates are reported in parentheses though they are not relevant following the non-rejection of the null hypothesis.

Table 3 presents the results of running the OLS regressions of Equation 1 for both CO_2 and SO_2 emissions and therefore shows the long-run EKC relations. Before analysing the results in terms of the acceptance or rejection of the EKC hypothesis, it is necessary first to look at the cointegrating behaviour of these variables, otherwise the above regressions can be deemed spurious. In tables 4 and 5 for the TAR and M-TAR tests, the ρ estimates are presented, along with the ϕ_μ or ϕ_μ^* statistics for cointegration, the standard F test for the null hypothesis $H_0 : \rho_1 = \rho_2$ to detect asymmetry and the Schwarz-Bayesian information criterion (SBC) of the regression..

The results for the asymmetric cointegration tests yield some interesting findings about dynamic misspecification in the EKC[7]. In all cases no lags are included in any of the tests as unit root tests on the ε_t residual series reveal that they are sufficiently white noise for all regressions. Firstly, it can be seen that the necessary and sufficient conditions for cointegration hold in all cases. The ρ terms have negative signs, which are significant due to the rejection of the null hypothesis $H_0 : \rho_1 = \rho_2 = 0$ in all cases and at every conventional significance level. In the basic model, equation 1, using the standard F-statistic for the restriction; $H_0 : \rho_1 = \rho_2$ shows that asymmetric cointegration is strongly significant in the TAR framework for both the CO_2 and SO_2 EKC relations. In the more powerful M-TAR

[6] We did not present the results of the Zivot Andrews (1992) test on the differences of the variables as there is no reason why the alternative hypothesis of trend-stationarity with a structural break is appropriate for the differences of these variables.

[7] The cointegration tests did not include a trend, as it was insignificant in all of them. It is only included in the long-run EKC model when testing the augmented model in equation (9).

framework, asymmetric cointegration is only detected in the case of per capita CO_2 emissions, but not for SO_2. Therefore the results show that the TAR adjustment process is more appropriate for SO_2. As for the CO_2 model we will follow Enders and Chumrusphonlert's (2004) advice in using the AIC or SBC to select the best adjustment mechanism. Looking at the reported SBC for each regression shows that indeed for the SO_2 model, the TAR model is more appropriate, and the M-TAR model is the most appropriate adjustment mechanism for the case of CO_2 (the appropriate minimum SBC is in bold.)

With respect to the ρ coefficients of the estimated models, we can see in both cases $|\rho_1| > |\rho_2|$. Therefore we can say that, in the basic specification, the hypothesis of stickiness of emissions holds for both CO_2 and SO_2 emissions, though they both follow slightly different adjustment processes, namely M-TAR and TAR respectively. These results point to a significant effect of environmental pressure when emissions are either rising, or above equilibrium. This may in part reflect the role of environmental regulation, with penalties from existing regulation. For the CO_2 result, the finding of an M-TAR model could be due to the emphasis placed on it in terms of reducing greenhouse gas emissions. As the political momentum has swung towards reducing CO_2 emissions, the emphasis has been on *increases* in CO_2, rather than its actual level, which drives the return to equilibrium.

Furthermore, we can see that the correction back to equilibrium is faster for CO_2 than SO_2. Comparing the TAR models of both CO_2 and SO_2, and the M-TAR models reveals this to be the case. For the selected M-TAR model for CO_2, we see that 62.11% of the deviation from equilibrium is corrected when emissions are rising, compared to only 21.57% when they are falling. Using the selected TAR model for SO_2, we can see that when emissions are temporarily above the long-run EKC, only 38.91% of the deviation is corrected in the next period, and only 15.34% is corrected when SO_2 emissions are below the EKC. This may also reflect the relative marginal abatement costs of SO2 and CO2, with CO2 being relatively easier to abate. The marginal abatement cost curves of each show that currently for the UK SO2 is significantly more expensive to abate (Rabl et al, 2005).

Having established M-TAR cointegration in the long-run relation for CO_2, and TAR cointegration in that of SO_2, it is now possible to analyse the estimation results and what they imply for the EKC hypothesis. For CO_2, one can see that in terms of the β coefficients described in the EKC relation in Equation 1, we have $\beta_0 < 0, \beta_1 > 0, \beta_2 < 0$ and $\beta_3 > 0$, which implies an N-shaped function. This pattern is the same as found for Turkish CO_2 emissions in the time series study by Akbostanci et al. (2009). The fitted values of CO_2 emissions for the observed values of real GDP are displayed in Figure 3. These results show that there is strong evidence in favour of the EKC hypothesis. The only turning point in the observed range of real GDP for CO_2 occurs at GK$7691 in 1990 international Geary-Khamis dollars. This shows that the inverted-U shape holds and, due to the cubic term, the curve seems to flatten-out towards the upper-end of the real GDP range.

For SO_2 emissions, the regression results are quite different, as shown in Figure 4. In this case we see the opposite signs to the CO_2 case, namely $\beta_0 > 0, \beta_1 < 0, \beta_2 > 0$ and $\beta_3 < 0$. This finding is similar to the result that Fodha and Zaghdoud (2010) find in Tunisian SO_2 data. These estimates indicate an inverse-N shape, so it is necessary to check the location of the turning points in order to see whether the EKC hypothesis is rejected or not. Once again, ignoring infeasible turning points shows that the EKC is again seen to be an inverse-U shape when looking at the estimated EKC at the observed levels of real GDP per capita. The main turning point here is located at GK$8167, whereas using the same datasets for both real GDP per capita and SO_2 emissions, Markandya et al. (2006) find the turning point in the UK to be GK$10,700. The graphs seem to indicate that a steeper inverted U shape for the EKC of SO_2

compared to CO_2. This is resulting from the observed sharp drop in SO_2 emissions explained in section 3.1, and this attribute of the data is translated directly into the fitted EKC for SO_2.These results are therefore strongly in favour of the EKC hypothesis in the UK for both CO_2 and SO_2 emissions with turning points of GK$7691 and GK$8167 respectively. Looking at the Maddison dataset we see that the turning point for CO2 occurred in 1954, whereas for SO2 this would have been 1958 or 1959.

The addition of energy prices and a time trend to the model has not affected the results in terms of the presence of cointegration and in the long-run equations the non-linear relationship remains significant and correctly signed, suggesting the relationship is reasonably robust. However the trend is significant indicating that technological change has contributed to the emissions of pollutants, in addition to the change in income, although the energy prices tend to be insignificant when the trend is included in the model. However the results differ for the tests on whether $\rho_1 = \rho_2$, as for the TAR model, the hypothesis is only rejected at the 10% level of significance for both carbon dioxide and sulphur dioxide. However we fail to reject the null of symmetry for the M-TAR models for both pollutants. The addition of the trend and energy prices appears to have explained part of the asymmetry in adjustment. These findings could seem to suggest that the mis-specification of the EKC model could be partially through the econometric technique used, but also through the omission of factors such as technological change.

4.2 Short-Run Error Correction Model Results

Having established asymmetric cointegrating relationships of different kinds of CO_2 and SO_2 emissions, we can now estimate the ECMs as described in Equations 7 and 8, using the appropriate TAR or M-TAR indicator functions. These results are reported in Tables 5 and 6 for CO_2 and SO_2 emissions respectively.

The ECM results for CO_2 and SO_2 emissions show some very similar findings. Firstly, any deviation away from the long-run EKC is corrected solely by movements in emissions, not by movements in real GDP per capita. This can be seen by the insignificance of the error correction parameter ρ_{21} in the ECM for y_t for both CO_2 and SO_2 emissions, though it is significant for CO_2 at the 10% level. This means that if emissions were above what is expected in long-run equilibrium, this error is corrected in the next period by a fall in emissions rather than a change in real GDP per capita. This is as expected because over the last two centuries there has been a policy of maximising economic growth regardless of effects on the environment, emissions have been reduced through legislation on the polluter.

Secondly, the results indicate that deviations from the long-run EKC for both CO_2 and SO_2 are corrected in the short-run by changes in emissions according to the hypotheses made in Section 4. In other words, since $|\rho_{11}| > |\rho_{12}|$ in both cases, for CO_2 emissions adjust more quickly to correct disequilibrium when they are rising, and for SO_2 emissions change to correct disequilibrium when they are above the EKC. This is consistent with the results in Table 4 for the long-run relation. It also must be noted that the estimates of ρ_{12} and ρ_{21} are insignificant in both cases which reiterates the point that there is very little tendency for emissions to change in order to restore equilibrium when emissions are below the EKC as there is no pressure from the environmental movement for politicians to intervene if emissions are too low. Adding the gas price and trend to the error correction models makes little difference overall to the results although gas prices have a positive effect on SO_2 emissions. However this measure of gas prices also takes into account the efficiency of the machinery which uses the gas, so this probably reflects the increased efficiency of the machinery rather than increases in gas prices affecting emissions positively. In the income equation, both the technological change and gas prices have a significantly positive effect.

5. Conclusion

This study uses threshold cointegration methods to study the EKC and the results shed some interesting light on how emissions behave when they are above equilibrium and showing signs of potentially violating environmental regulation. In the case of CO_2, we find that any temporary disequilibrium from the EKC relation is corrected quicker when per capita CO_2 emissions show momentum in an upwards direction than when they show momentum in a downwards direction (M-TAR adjustment.) For SO_2, a similar result is found in that any disequilibrium from the EKC relation is corrected quicker when per capita SO_2 emissions are above the EKC than when they are below the EKC (TAR adjustment.) Furthermore, the short-run error correction models reveal that disequilibrium is corrected solely by changes in per capita emissions, and not by movements in real GDP per capita, as expected since emissions have been reduced by legislation rather than a policy of reducing economic growth. This suggests mitigating CO_2 or greenhouse gas emissions and SO_2 emissions will rely more on legislation than reductions in economic growth.

With this in mind, the long-run results find strong evidence in favour of the EKC hypothesis with per capita CO_2 and SO_2 emissions having an inverse-U relation with real GDP per capita. The evidence suggests that the turning point for SO_2 occurred at a higher level of income than CO_2, at GK$8167 and GK$7691 respectively. The results also suggest that the asymmetry of the adjustment can be partially explained by technological change and energy prices. This suggests the EKC model needs to be estimated using an approach which accounts for asymmetric adjustment and also specified to incorporate technological change. Future studies need to concentrate on alternative measures of technological change, as the data becomes available.

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Figure 1: Graph of per capita CO_2 and SO_2 emissions for the UK from 1830.

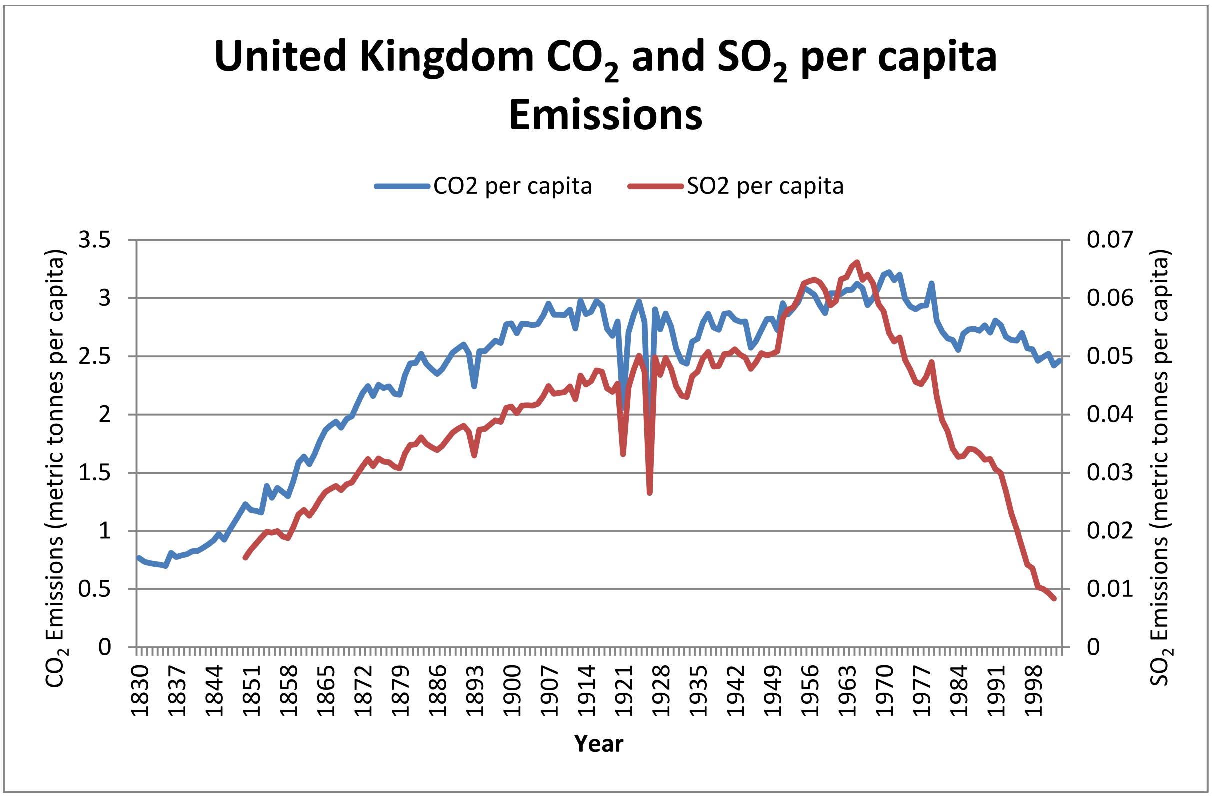

Figure 2: Graph of UK real GDP per capita in 1990 international Geary-Khamis dollars from 1830

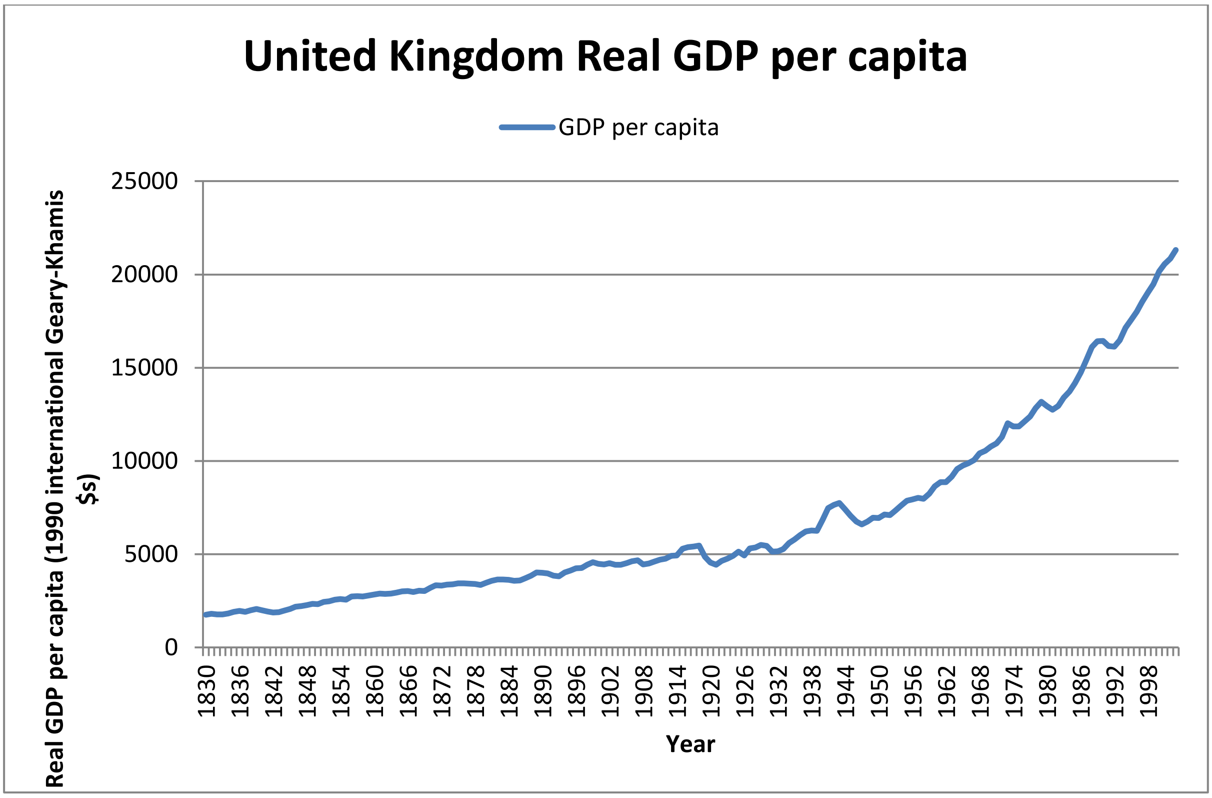

Figure 3: Graph of the fitted values of the estimated EKC results for CO_2

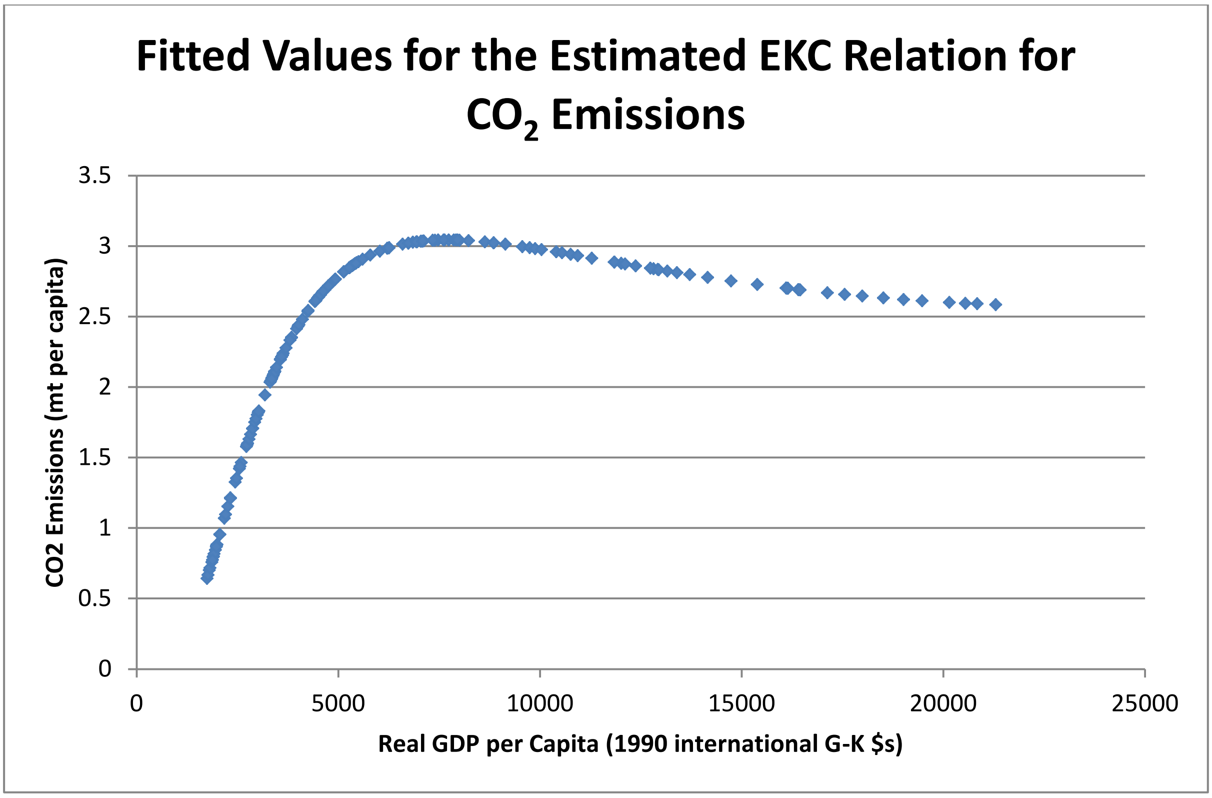

Figure 4: Graph of the fitted values of the estimated EKC results for SO_2

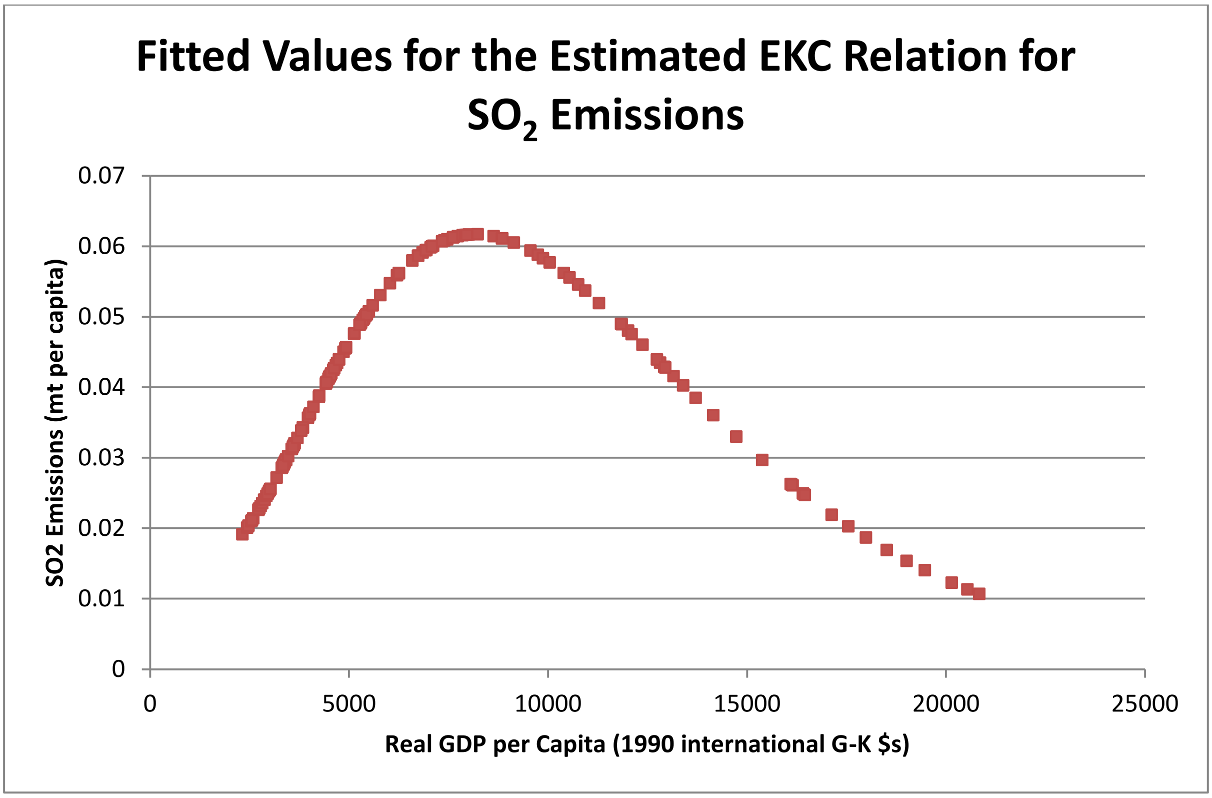

Table 1: Descriptive statistics for the common samples of per capita CO_2 and SO_2 emissions with real GDP per capita.

	CO_2 per capita	Real GDP per capita	Gas prices	SO_2 per capita	Real GDP per capita	Gas prices
Sample	[1830-2003 – 174 obs.]			[1850-2002 - 153 obs.]		
Mean	2.360	6733.099	909.723	0.0400	7259.7798	668.962
Median	2.640	4816.078	676.403	0.0415	5288.2658	594.225
Minimum	0.700	1749.368	4181.461	0.0084	2330.3778	1435.890
Maximum	3.224	21310.137	130.477	0.0662	20851.0396	132.630

Notes: All data is in levels

Table 2a Unit Root Tests

	CO_2 – Data Range: 1830-2003 (174 observations)														
	ADF					ERS					PP				
	C and t		C only			C and t		C only			C and t		C only		
e_t	-1.9561	*(4)*	-5.2326	***	*(4)*	0.1634	*(4)*	0.6440		*(4)*	-1.6406	-	-3.0377	**	-
y_t	-1.7524	*(1)*	0.7162		*(1)*	-1.9331	*(1)*	3.5538		*(1)*	-0.7214	-	1.3564		-
y_t^2	-1.1899	*(1)*	1.1866		*(1)*	-1.3541	*(1)*	3.7783		*(1)*	-0.0136	-	2.1984		-
y_t^3	-0.7006	*(1)*	1.6509		*(1)*	-0.8592	*(1)*	4.0009		*(1)*	0.6190	-	3.0764		-
ep_t	-3.209	*(0)*	-1.061		*(0)*	-1.507	*(0)*	2.580		*(0)*	-2.883	-	-1.097		-
Δe_t			-10.6139	***	*(3)*			-2.8269	***	*(4)*			-18.6032	***	-
Δy_t			-9.5558	***	*(0)*			-7.9071	***	*(0)*			-9.1186	***	-
Δy_t^2			-9.3367	***	*(0)*			-8.2786	***	*(0)*			-8.8349	***	-
Δy_t^3			-9.0852	***	*(0)*			-8.4999	***	*(0)*			-8.7043	***	-
Δep_t			-11.937	***	*(0)*			-3.722	***	*(1)*			-11.933	***	-
	SO_2 – Data Range: 1850-2002 (154 observations)														
	ADF					ERS					PP				
	C and t		C only			C and t		C only			C and t		C only		
e_t	2.5209	*(1)*	0.8104		*(1)*	1.4276	*(1)*	-0.2121		*(1)*	2.4682	-	0.3577		-
y_t	-1.5739	*(1)*	0.9094		*(1)*	-1.7175	*(1)*	3.3469		*(1)*	-0.4571	-	1.6767		-
y_t^2	-1.1782	*(1)*	1.2666		*(1)*	-1.2892	*(1)*	3.5136		*(1)*	0.0580	-	2.4035		-
y_t^3	-0.8264	*(1)*	1.6214		*(1)*	-0.9265	*(1)*	3.6817		*(1)*	0.5338	-	3.1654		-
ep_t	-2.515	*(1)*	-0.007		*(1)*	-2.518	*(1)*	1.353		*(1)*	-2.058	-	0.406		-
Δe_t			-3.1446	**	*(4)*			-1.1880		*(4)*			-14.6694	***	-
Δy_t			-8.9150	***	*(0)*			-5.7949	***	*(0)*			-8.5164	***	-
Δy_t^2			-8.7024	***	*(0)*			-6.2227	***	*(0)*			-8.2599	***	-
Δy_t^3			-8.4737	***	*(0)*			-6.6150	***	*(0)*			-8.1181	***	-
Δep_t			-8.247	***	*(0)*			-6.181	***	*(0)*			-8.256	***	-

Notes: Unit root test results for y_t, y_t^2 and y_t^3 are reported for both sample sizes as the test statistics are different. Lag length displayed in parentheses and is selected by the Schwarz-Bayesian information criterion, subject to a maximum lag length of 4 for annual data. As usual *** (**) denotes rejection of the null hypothesis at the 1% (5%) level .

Table 2b. Zivot-Andrews (1992) Unit Root Tests

CO_2	Level	
Variable	Break date	Statistic
e_t	(1859)	-3.024
y_t	(1919)	-4.782
y_t^2	(1919)	-4.599
y_t^3	(1919)	-4.157
ep_t	(1970)	-4.416
SO_2	Level	
e_t	(1972)	-1.041
y_t	(1919)	-5.322
y_t^2	(1919)	-4.742
y_t^3	(1919)	-4.157
ep_t	(1970)	-4.416

Notes: Critical values -5.57 (-5.08) at the 1% (5%) level of significance. Lag length determined using the Akaike Information criterion. Test includes intercept and trend.

Table 3: Estimated parameters of long-run EKC equation for both CO_2 and SO_2 emissions.

Parameter	CO_2 Emissions		SO_2 Emissions	
constant	-186.841***	-173.596***	300.288***	291.930***
	(12.969)	(8.828)	(8.752)	(8.827)
y_t	59.583***	53.687***	-114.156***	-113.605***
	(11.870)	(7.816)	(9.752)	(10.065)
y_t^2	-6.275***	-5.490***	14.140***	14.289***
	(10.802)	(6.835)	(10.646)	(11.106)
y_t^3	0.220***	0.187***	-0.578***	-0.589***
	(9.828)	(6.022)	(11.526)	(12.061)
ep		0.059		0.035
		(1.489)		(0.568)
trend		-0.004***		-0.007***
		(3.487)		(3.486)

Notes: t-statistics are in parentheses, see Table 2. Estimated parameters for equations (1) and (9).

Table 4. Results of TAR and M-TAR Enders-Siklos (E-S) test for cointegration on the standard EKC model

TAR	ρ_1	ρ_2	ϕ_μ	$F(\rho_1 = \rho_2)$	Lag	SBC
CO_2	-0.592*** (7.307)	-0.286*** (2.896)	30.893***	5.743***	0	-2.419
SO_2	-0.3891*** *(-5.1960)*	-0.1534* *(-1.7649)*	15.0567***	4.2193**	0	**-2.1944**
M-TAR						
CO2	*-0.621**** *(-7.933)*	*-0.216*** *(-2.142)*	33.763***	10.102***	0	**-2.443**
SO2	*-0.354**** *(-4.856)*	*-0.189*** *(-2.076)*	13.750**	1.982	0	-2.180

Notes: Results from the estimation of Equations 3 and 5 for CO_2 and SO_2 emissions*** (**)

(*) Indicates significance at the 1% (5%) (10%) level. T-statistics for ρ in parentheses

Critical values from Wane *et al.* (2004).

Table 5. Results of TAR and M-TAR Enders-Siklos (E-S) test for cointegration including gas prices and Trend.

TAR	ρ_1	ρ_2	ϕ_μ	$F(\rho_1 = \rho_2)$	Lag	SBC
CO_2	-0.598*** *(6.798)*	-0.3926*** *(4.125)*	31.614***	3.472*	0	**-2.449**
SO_2	-0.382*** *(4.903)*	-0.191** *(2.240)*	14.528***	2.885*	0	-2.197
M-TAR						
CO2	*-0.605**** *(7.224)*	*-0.359**** *(3.532)*	32.334***	2.406	0	-2.279
SO2	*-0.340**** *(-4.350)*	*-0.258**** *(-2.837)*	13.487**	0.465	0	**-2.218**

Notes: See Table 4, model includes *ep* and a trend.

Table 6. Results for the M-TAR error correction models for CO_2.

Parameter	Dependent Variable Δe_t			Dependent Variable Δy_t	
ρ_{11}	-0.557***	-0.554***	ρ_{21}	-0.066*	-0.027
	(6.254)	(5.638)		(1.876)	(0.737)
ρ_{12}	-0.081	-0.169	ρ_{22}	0.038	0.069
	(0.773)	(1.499)		(0.896)	(1.635)
α_{11}	-24.073	-16.559	α_{21}	0.501	-0.322
	(0.838)	(0.543)		(0.044)	(0.028)
α_{12}	2.942	2.014	α_{22}	-0.105	0.076
	(0.880)	(0.567)		(0.080)	(0.056)
α_{13}	-0.118	-0.080	α_{23}	0.008	-0.002
	(0.912)	(0.581)		(0.162)	(0.046)
α_{14}	-0.238***	-0.242***	α_{24}	-0.066**	-0.074**
	(3.057)	(3.020)		(2.154)	(2.463)
$\alpha_{15}(ep)$		0.048	$\alpha_{15}(ep)$		0.056*
		(0.077)			(1.918)
$\alpha_{16}(trend)$		-0.00002	$\alpha_{16}(trend)$		0.00001***
		(0.290)			(3.045)

Notes: See Table 2. The first column includes the parameters contained in equations 7, the fourth column the parameters from equation 8. *ep* are energy prices.

Table 7. Results for the TAR error correction models for SO_2

Parameter	Dependent Variable Δe_t			Dependent Variable Δy_t	
ρ_{11}	-0.342***	-0.285***	ρ_{21}	-0.009*	0.001
	(3.589)	(2.758)		(1.876)	(0.028)
ρ_{12}	-0.053	-0.134	ρ_{22}	-0.016	0.026
	(0.480)	(1.243)		(0.459)	(0.747)
α_{11}	-62.519	-67.328	α_{21}	-10.648	-11.848
	(1.013)	(1.110)		(0.554)	(0.650)
α_{12}	7.809	8.297	α_{22}	1.179	1.398
	(1.113)	(1.203)		(0.540)	(0.674)
α_{13}	-0.322	-0.338	α_{23}	-0.041	-0.053
	(1.211)	(1.294)		(0.497)	(0.673)
α_{14}	-0.199**	-0.215**	α_{24}	-0.074**	-0.071**
	(2.173)	(2.325)		(2.610)	(2.446)
$\alpha_{15}(ep)$		0.258*	$\alpha_{15}(ep)$		0.072**
		(2.216)			(2.044)
$\alpha_{16}(trend)$		-0.00001	$\alpha_{16}(trend)$		0.0001**
		(0025)			(2.857)

Notes: See Table 5.