Trends of U.S. Emissions of Nitrogen Oxides and Volatile Organic Compounds

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Abstract

Using an array of unit root and structural break tests we find that the trend behavior of two air pollutants, Nitrogen Oxides (NO_X) and Volatile Organic Compounds (VOCs), is substantially different. VOCs emissions are found to be trend-stationary with a break at the time the Clean Air Act of 1970 was passed whereas NO_X emissions are found to be difference-stationary. The presence and location of a trend break in the NO_X emissions depends on the test used, whether the break date is known or unknown in advance, the null hypothesis specification, and on data transformations.

Key Words: pollution emissions, government regulation, structural break, time-series, unit root.

JEL Classification: C22, C53, Q53.

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1. Introduction

It has been more than 35 years since the United States (U.S.) Environmental Protection Agency (EPA) was established and the Clean Air Act (CAA) of 1970 was passed. Time-series analysis of how government regulation has affected the U.S. air pollution trends since 1970 has generated a strong interest in the area of environmental economics (e.g. see Lee and List (2004), and McKitrick (2007)). Such assessments of environmental regulations are important because they can show the past outcomes and provide us with more insight into forming better policies in the future.

In the present paper we use time-series econometric techniques to study the long-term air pollution trends in the U.S., and to examine how government policies such as the CAA of 1970 affect them. Specifically, we concentrate on answering two questions. First, are the U.S. emissions of Nitrogen Oxides (NO_X) and Volatile Organic Compounds (VOCs) trend-stationary (TS) or difference-stationary (DS)? And second, was there a break in the trends of NO_X and VOCs emissions around the same time the CAA of 1970 was passed?

Whether emissions follow a TS or a DS process is important for two reasons. First, as has been noted by Lee and List (2004) and McKitrick (2007), the difference-stationarity of the pollution emissions has significant implications for the studies of the Environmental Kuznets Curve (EKC), which analyze the relationship between country's levels of pollution and income (e.g. see Selden and Song (1994) and Grossman and Krueger (1995), among others). The majority of the EKC studies assume that the pollution variables are TS. However, an EKC-type model that uses emissions series that is DS as the dependent variable runs the risks of spurious inferences if the independent variables, such as gross domestic product (GDP) or income, are also DS and difference-stationarity in the variables is not accounted for (McKitrick 2007).

Second, distinction between TS and DS processes is important for forecasting of the future emissions values as well as the accuracy of these forecasts. Forecasts of the emissions can provide economists and legislators with an understanding of what emissions will be in the future allowing them to make more informative decisions about the future national policies. There is more uncertainty in forecasts for a DS process compared to a TS process. The time series y_t is TS about the deterministic trend if it can be represented as:

$$y_t = a + bt + \varepsilon_t, \quad (1)$$

where $a + bt$ is a deterministic linear trend and ε_t is a stationary (i.e. integrated of order zero, I(0)) error term. If the time series y_t is DS then we can represent it as:

$$\Delta y_t = b + \varepsilon_t, \quad (2)$$

where ε_t is a stationary error term. DS series in (2) is also called an integrated of order one (I(1)) because its first-difference is stationary. Starting at y_0, through recursive substitution, we can re-write (2) as:

$$y_t = y_0 + bt + \sum_{i=1}^{t} \varepsilon_i, \quad (3)$$

where $y_0 + bt$ is a deterministic linear trend and $\sum_{i=1}^{t} \varepsilon_i$ is a stochastic trend. Mills (2003) compares forecasts for TS and DS processes. For TS processes the forecast errors are bounded no matter how far into the future forecasts are made, and, over long horizons, the only relevant information about the future series is its deterministic trend. As a result, neither current nor past events will alter long-term expectations about the TS series. In contrast, for DS processes defined by equation (3), the forecast error variance will increase without bound because it is an increasing function of time. Consequently, the long-term forecasts for the DS series will always be

influenced by historical events through the accumulation of the shocks. Figure 1 illustrates the above discussed differences between forecasts for TS and DS processes for the natural logarithm of per capita NO_X emissions.

Government policies are usually implemented to affect the direction of a specific activity. The policy shock is said to have a permanent effect if it has changed the trend of the data. Both TS and DS processes can have trend breaks. Therefore, identification of the break date in the emissions trend can show us whether implemented government policy at a certain time proved to be effective. If the break in the trend exists but its estimated date does not correspond to the specific policy, we can identify other events that could have contributed to this change. In addition, distinction between TS and DS data has impact on the methods used to determine if and when a trend break in the pollution emissions has occurred. As illustrated in Figure 1 (a) and (b), for a TS emissions it looks like there was a break in its trend whereas for a DS emissions it is not so clear.

Our analysis of the first question follows along the lines of Lee and List (2004). Using different time-series techniques we show that the previous results regarding trend-stationarity of the NO_X emissions are sensitive to the methods used. The techniques we employ in the second question to determine policy impact on the emissions trends have not been used in the environmental literature before and are valid for both TS and DS data.

We find that the trend behavior of NO_X and VOCs emissions is substantially different. VOCs emissions are found to be TS series with a break at the time the CAA of 1970 was passed whereas NO_X emissions are found to follow a DS process. Whether NO_X emissions is a DS series with a break in its trend at the time the CAA of 1970 was passed or without a break depends on the test used, whether the break date is known or unknown, and the null hypothesis

specification. In addition, we find that some of our results are sensitive to nonlinear transformations of the emissions series.

We proceed as follows. In Section 2 we briefly describe the previous time-series analyses of the U.S. air pollution. In Section 3 we present data and background information on the pollution regulation in the U.S. In Section 4 we perform unit-root tests to determine whether emissions series are TS or DS. In Section 5 we test for a trend break and its location in the emissions of the NO_X and VOCs, and see if the break date corresponds to the year the CAA of 1970 was passed. In Section 6 we illustrate how future emissions forecasts differ for TS and DS series with and without the trend breaks. We conclude by summarizing our findings.

2. Previous Time-Series Analyses of the U.S. Air Pollution

We start with a brief survey of three articles that used time-series techniques to analyze the effects of the environmental regulation on the U.S. air pollution.

Lee and List (2004) studied the stochastic nature of per capita U.S. emissions of NO_X over the period 1900-1994. They found that NO_x emissions series were DS but once the CAA of 1970 had been taken into account, emissions series could be described as being TS with a one-time break. The authors' main conclusion was that EPA mandates had permanently affected the path of NO_X emissions by changing its trend. Lee and List (2004) attributed all the changes in the emissions to the CAA of 1970 and calculated that U.S. had avoided about 48% of NO_X emissions due to this regulatory policy.

More recently Fomby and Lin (2006) examined total U.S. emissions of NO_X, VOCs and Sulfur Dioxide (SO_2) for the period 1940-1998 to determine if President Ronald Reagan's "Environmental Federalism" had any effect on the trends of these series. They utilized the

change point analysis developed by Bai (1997a; 1997b) to identify the potential break dates in the emissions. The estimated break dates were 1978 for NO_X, 1973 for SO_2 and 1969 for VOCs, implying that changes in the emissions had occurred prior to the Reagan presidency in 1981 and Reagan's devolution in 1987. The authors could not locate any additional changes in the emissions to confirm the effectiveness of Reagan's "Environmental Federalism" with certainty.

Lastly, McKitrick (2007) applied nonstructural vector autoregression (VAR) methodology to portfolio of five U.S. air pollutants (NO_X, carbon monoxide (CO), VOCs, SO_2, and particulate matter smaller than ten microns (PM10)). He found that the CAA of 1970 might have increased air pollution in the short-run, but it led to accelerated improvements in abatement technology which resulted in the substantial reduction of the emissions in the long-run. According to McKitrick's calculations, the CAA, by accelerating improvements in abatement technology, reduced total emissions as of 1998 by 55% compared to what they would have been. He also found that growth in GDP and per capita consumption had no effect on air pollution with the exception of CO, and that oil price increases led to small reductions in the emissions.

3. Data and Government Regulation Overview

Our dataset consists of annual observations for NO_X emissions for the period 1900-1998 and VOCs emissions for the period 1940-1998 and was obtained from EPA (1985; 2000).[1] This is the same data source that has been used in the previous time-series analyses of the U.S. air pollution emissions. For example, Lee and List (2004) obtained NO_X emissions data from EPA (1985;

[1] NO_X emissions estimates for the period 1900-1939 were obtained from EPA (1985) and for the period 1940-1998 from EPA (2000). VOCs emissions estimates for the period 1940-1998 were obtained from EPA (2000).

1995) whereas Fomby and Lin (2006) and McKitrick (2007) used EPA (2000). All emissions are measured in thousands of short tons, where one short ton is equivalent to 0.9072 of a metric ton.

There are two main reasons why we chose to concentrate on NO_X and VOCs emissions. First of all, both of these pollutants have been regulated by the EPA due to their adverse health and environmental effects. Second, the long time-series dataset available for NO_X and VOCs shows an obvious change in the trend function of these emissions around the year the CAA of 1970 was passed (see total NO_X and VOCs series in Figures 2 (a) and 3 (a)).

NO_X is formed when fuel is burned at high temperatures (combustion process) and its primary sources include motor vehicles, electric utilities, and other industrial, commercial and residential sources that burn fuels. NO_X by itself and in combination with other pollutants can lead to respiratory health problems, lung tissue damage, vegetation damage, reduction in crop yields, buildings and historical monuments deterioration, acceleration of eutrophication, global warming, biological mutation and others. VOCs are emitted as gases from certain solids or liquids such as paints, lacquers, paint strippers, cleaning supplies, pesticides, dry cleaning solvents, some petroleum fuels (gasoline and natural gas), and trees. VOCs can cause headaches, nausea, damage to liver, kidney, and central nervous system, cancer in animals and even cancer in humans. In addition, in the presence of sunlight, VOCs react with NO_X and form ozone (O_3), which has been regulated by the EPA on account of its own negative effects on health and the environment.

The official date of air pollution control in the U.S. is associated with the establishment of the EPA and the passage of the CAA in 1970. However, efforts to control air pollution began earlier than that. The original CAA was passed by Congress in 1963. It seems, though, that the prior activity was just preparation for the major action that took place in 1970. Under the CAA of

1970, National Ambient Air Quality Standards (NAAQS) were set for NO_X and for non-methane hydrocarbons. EPA calculates non-methane hydrocarbons as VOCs emissions and, at that time, it regulated hydrocarbons (VOCs) because they were a precursor to O_3. The emission standards were developed for new stationary sources (i.e. factories, power plants, refineries) for NO_X only and for mobile sources (i.e. trucks, cars, motor vehicles) for both NO_X and VOCs. A visual inspection of Figures 2 (a) and 3 (a) shows that prior to 1970 both NO_X and VOCs emissions were rising. Immediately after 1970, NO_X emissions started to decline but then increased and have been fluctuating around the same level since then. Even though we do not see a decline in total NO_X emissions, it is obvious they are not growing as fast as they used to prior to 1970. Starting from 1970 VOCs emissions have been steadily declining indicating a clear change in the direction of the trend.

Emissions estimates of NO_X and VOCs prior to 1985 are based on so called "top-down" methodology where national information was used to create national emission estimates. The EPA estimates emissions generally using three elements: (1) activity indicator of a process producing emissions of interest, which is measured by the consumption of fuel, the throughput of raw materials, or some other production indicator, (2) the emissions factor, which determines the amount of an individual pollutant emitted based on the activity of the process and, finally, (3) the control efficiency, which quantifies the amount of a pollutant not emitted due to the presence of control devices. Depending on a pollutant, other elements can be included such as in the case of SO_2, the sulfur content of the fuel. Emissions for the years after 1985 are produced using "bottom-up" methodology, according to which the EPA derives emissions at the plant or county level and then aggregates them to the national levels.[2]

[2] For more detailed description of the emissions calculations we advise to consult EPA (1998; 2001).

We point out two caveats associated with this dataset. First of all, there may be a concern about merging the data that is based on two different methodologies: "top-down" and "bottom-up". However, Zimmerman and Battye (1994) showed that using "bottom-up" or "top-down" methodologies yielded similar aggregate national SO_2 emissions estimates, but estimates for specific categories and for processes within those categories differed significantly. The second caveat is the use of the emissions estimates instead of measured ambient concentrations. Portney (1990), however, identifies an advantage of using emissions instead of concentrations. He argues that if many industrial plants located in the monitored areas shut down and new plants opened in unmonitored areas, the ambient concentrations would show a sharp decline although the total emissions may stay the same; which could result in misleading conclusions. This statement is especially pertinent to our analysis because we are investigating the national pollution trends and not pollution in specific areas. Another drawback of the concentrations dataset is the lack of long enough data sample.

Throughout our analysis, we use total national NO_X and VOCs emissions as well as the natural logarithms of total and per capita NO_X and VOCs emissions. Per capita transformation allows us to control for population growth and the use of natural logarithms reduces fluctuations in the data. Population data in thousands was obtained from the U.S. Census Bureau website at www.census.gov.

We briefly discuss why we chose to use both logged and levels data for total emissions. It is a common practice to analyze time-series data in natural logarithms. However, unless the series exhibits exponential growth, in which case log-transformation is preferred to reduce variance, there is no clear reason why logged data should be used instead of levels. It has been shown that unit root tests, which are used to determine whether series is DS or TS, are sensitive to the

nonlinear transformation of the data, such as when a variable is found to be DS in levels but TS in logarithms (e.g. see Granger and Hallman (1991) for details). Therefore, it will be interesting to compare results for the data in levels and logs.

To ease the notation we refer to total NO_X and VOCs emissions as *nox* and *voc*, to the natural logarithms of total NO_X and VOCs emissions as *lnox* and *lvoc*, and to the natural logarithms of per capita NO_X and VOCs emissions as *lpnox* and *lpvoc*. Figures 2 and 3 show emissions series used in the analysis. We can see that *nox*, *lnox*, *lpnox*, *voc*, *lvoc* and *lpvoc* are upward trending until 1970, the year CAA was passed, and then either decline or do not grow as fast. The first-differences of these six series also indicate a change in the mean of the data around the same time, however, it is not as obvious as a change in the trend.

4. Are the U.S. Emissions of Nitrogen Oxides and Volatile Organic Compounds Trend-Stationary or Difference-Stationary?

In this section we test *nox*, *lnox*, *lpnox*, *voc*, *lvoc* and *lpvoc* for a unit root. The unit root tests help us determine whether emissions are TS or DS.[3]

4.1. Unit Root Test with an Exogenous Break

When we apply the most commonly used Augmented Dickey-Fuller (ADF) test of Said and Dickey (1984) to our dataset we find that all six pollution series follow a DS process.[4] However, the ADF test is not the appropriate unit root test in our situation because it ignores the potential break in the emissions trends at the time the CAA of 1970 was passed. It is well-known that in the presence of a structural break, ADF unit root test is biased towards the non-rejection of a unit root (see Perron (1989) for discussion). As a result, we need to use a unit root test that allows for

[3] Implications of TS and DS processes were discussed in Section 1.
[4] The estimated ADF unit root test statistics are available upon request.

a structural change in the data. To do this, we utilize the Perron test (1989) that allows testing for a unit root in the presence of a one-time change in the intercept or slope (or both) of the trend function of the time series.

The Perron unit root test is carried out by estimating "the breaking slope and crash" model:

$$y_t = \mu + \theta DU_t + \beta t + \gamma DT_t + dD(TB)_t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t, \qquad (4)$$

where y_t is either *nox, lnox, lpnox, voc, lvoc* or *lpvoc*, μ is a constant, DU_t = 1 if $t > T_B$ and 0 otherwise, *t* is a time trend, $DT_t = t$ if $t > T_B$ and 0 otherwise, $D(TB)_t$ = 1 if $t = T_B + 1$ and 0 otherwise, Δy_{t-i} is the lagged first-difference terms of y_t (e.g. $\Delta y_{t-1} = y_{t-1} - y_{t-2}$), and the number of lagged first-difference terms *k* in (4) needs to be chosen so that e_t behaves like a white noise.[5] We set the break date to T_B =1969, which is associated with a passage of the CAA in 1970. To determine *k* we use sequential *t* rule used by Perron (1989).[6]

Under the null hypothesis, the series follows a unit root process with a one-time change in its level and drift implying that in equation (4) $\alpha = 1$, $\beta = 0, \gamma = 0$, $\theta \neq 0$ and $d \neq 0$. Under the alternative hypothesis, the series is TS with a one-time break in the intercept and slope of its trend function and hence, $\alpha < 1$, $\beta \neq 0, \theta \neq 0$, $\gamma \neq 0$, and $d = 0$. For trending data $\mu \neq 0$. Equation (4) is also known as an innovation outlier (IO) model that allows policy changes like the CAA of 1970 to take effect gradually. We estimate equation (4) by ordinary least-squares (OLS) and the Perron's unit root test is the *t*-statistic to test the null hypothesis that $\alpha = 1$ against an alternative that $|\alpha| < 1$ in equation (4).

[5] Visual inspection of the emissions series (see Figures 2 (a), (c) and (e) and 3 (a), (c) and (e)) suggests that there was a break in both intercept and slope.

[6] We set the maximum of *k* to the integer of ($T^{1/4}$), where T=99 for NO_X and T=59 for VOCs. k_{max}= 3 for NO_X series and k_{max}= 2 for VOCs series.

Table 1 reports Perron unit root test statistics. We do not report results for the other regression parameters because they have non-standard distributions (e.g. see Murray and Zivot (1998) and Vogelsang and Perron (1998) for discussion). From Table 1 we conclude that *nox*, *lnox* and *lpnox* are DS series with possibly a one-time break in the level and drift of their trend functions. This finding implies that both environmental policy in 1970 and all other non-policy shocks will have permanent effects on the NO_X emissions.[7] As a result, its long-term trend will be changing to reflect these shocks. In contrast, we reject a unit root in the *voc*, *lvoc* and *lpvoc* series at the 5% significance level. Rejection of the null hypothesis for these series indicates that only a one-time shift in the trend function is permanent and all other shocks will only have temporary effects. Based on a trend of VOCs series after 1970 (see Figure 3 (a), (c) and (e)), we should expect these emissions continue to decline.

Our results for *lpnox* differ from the results of Lee and List (2004). They concluded that *lpnox* series can be viewed as being TS with a one-time break at the time the CAA of 1970 was passed based on the Park and Sung (1994) Phillips-Perron (PP) type unit root test that allows for a one time break in the trend under the null and the alternative hypotheses. Since our sample includes four more observations, we re-estimate the test regression equation (4) using the same dataset as Lee and List (2004) and we cannot reject the null of a unit root in *lpnox* for the shorter sample, which contrasts with the results of Lee and List (2004).[8] The difference in the results can be explained by the use of different tests. We chose to use the Perron test because, based on Monte Carlo experiments presented in Jones (2007), it has better finite sample properties than

[7] Examples of non-policy shocks include surges in prices of fossil fuels that would foster development of more fuel-efficient technologies, exogenous technological advances that use less fuel and hence, emit less pollution, and any other random shocks that affect national economy because amount of pollution emitted is directly related to its growth.

[8] The estimated Perron unit root test statistic is -2.98 using the dataset of Lee and List (2004), which is greater than the 5% critical value of -4.18. We used k=1 in regression (4). We would like to thank Dr. Junsoo Lee and Dr. John A. List for providing us their dataset.

the Park and Sung PP test. In particular, the Park and Sung PP test shows substantial size distortion for processes calibrated to match the dynamics of the pollution data.

4.2. Unit Root Test with an Endogenous Break

The assumption that the trend break date is exogenous in the Perron test in Section 4.1 has been heavily criticized. Christiano (1992) and Zivot and Andrews (1992) argued that the choice of the break date is correlated with the data, which is a serious problem because the standard sampling theory used to interpret structural break tests assumes that the break date is chosen independently of the data sample.

To avoid the criticism of the Perron test we also tested for a unit root in the emissions utilizing the Zivot-Andrews (ZA) test that does not require a prior knowledge of the break date. For the ZA test, the null hypothesis is that the time series follows a unit root process with a drift and no structural change and the alternative is that the time series is a TS process with a one-time break in the trend function occurring at unknown point in time. The ZA unit root test is based on regression equation:

$$y_t = \mu + \theta DU_t(\lambda) + \beta t + \gamma DT_t^*(\lambda) + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t , \qquad (5)$$

where λ is the break fraction calculated as T_B / T , T_B is a break year, $DU_t(\lambda) = 1$ if $t > T\lambda$ and 0 otherwise, $DT^*_t(\lambda) = t - T\lambda$ if $t > T\lambda$ and 0 otherwise, and all other variables are defined as in equation (4). To compute the ZA unit root test statistic, we estimate regression equation (5) by OLS for each value of the break fraction λ that ranges from 0.1 to 0.9. For each regression, we compute the number of lagged first-differences *k* by using sequential *t* rule, and then compute the *t*-statistic for testing the null hypothesis that $\alpha = 1$ against an alternative that $|\alpha| < 1$. The ZA unit

root test statistic is the minimum *t*-statistic over all regressions with different $\lambda's$ and the estimated break year is the year corresponding to this minimum *t*-statistic.[9]

The results for the ZA unit root test are presented in Table 2. We do not report *t*-statistics for other regression parameters because, similar to the Perron test, they have non-standard distributions. We reject the unit root hypothesis in *voc*, *lvoc* and *lpvoc* at the 1%, 5% and 10% levels, respectively. We conclude that all three VOCs emissions series can be viewed as being TS with a one-time break in their trend functions. These findings support the unit root test results in Section 4.1 when we assumed the break date to be exogenous. We fail to reject a unit root hypothesis with a drift and no break in *nox*, *lnox* and *lpnox* series. The difference in the results for the NO_X emissions between the ZA and Perron tests is not surprising because of the null hypothesis specification in the two tests. The Perron test allows for a structural change both under the null and alternative hypotheses whereas the ZA test only allows for a break under the alternative. Another difference between the two tests is that the Perron test regression includes one-time dummy ($D(TB)_t$) whereas the ZA test does not. This discrepancy becomes relevant when we look at the break years estimated by the ZA test. The estimated break date for VOCs emissions is 1970, which is one year ahead of the previously assumed break in 1969 in the Perron test from Section 4.1. The exclusion of a one-time dummy in the ZA test is responsible for this one year difference (see Perron (1997; 2007) for discussion).

5. Was There a Break in the Emissions Trends in 1970?

In this section we consider our second question: Was there a break in the trends of NO_X and VOCs emissions and if there was a break, did it occur at the same time the CAA of 1970 was

[9] Similar to the Perron tests we set k_{max} =3 for NO_X emissions and k_{max} =2 for VOCs emissions.

passed? Results in Section 4 suggest that there was a break in the trend of VOCs emissions and that the estimated break date corresponds to the CAA of 1970. In contrast, results for NO_X emissions were mixed. In the previous section when we tested pollution emissions for a unit root and let the break date to be endogenous, we did not find a break in the trend of NO_X emissions. However, the ZA test that we used allows for a trend break only under the alternative of trend-stationarity and not under the null of a unit root. It is possible, though, for a series to be DS with a break. Therefore, we need to use a test which is specifically designed to locate trend breaks while being valid for both DS and TS series. The set of breakpoint tests that satisfies this criteria is due to Vogelsang (2001).[10]

5.1. Vogelsang Structural Break Tests

Following the framework by Vogelsang (2001), we estimate the regression equations:

$$y_t = \mu + \beta t + \delta DU_t + \gamma DT_t + u_t, \tag{6}$$

and

$$z_t = \mu t + \beta[\frac{1}{2}(t^2 + t)] + \delta DT_t + \gamma[\frac{1}{2}(DT_t^2 + DT_t)] + S_t, \tag{7}$$

where y_t is either *nox*, *lnox*, *lpnox*, *voc*, *lvoc* or *lpvoc*, $DU_t = 1$ if $t > T_B^{'}$ and 0 otherwise, and $DT_t = t - T_B^{'}$ if $t > T_B^{'}$ and 0 otherwise.[11] $T_B^{'}$ denotes the date of the break should it occur. Assumptions on the error term $\{u_t\}$ are the same as those assumed by Vogelsang (2001) and are provided in Appendix A. Regression equation (7) is obtained by partially summing equation (6), which implies that $z_t = \sum_{j=1}^{t} y_j$ and $S_t = \sum_{j=1}^{t} u_j$.

[10] As an alternative one can use recently developed Perron and Yabu (2005) tests that can detect a structural change in both DS and TS data. Authors claim that their tests are more powerful than Vogelsang (2001) tests.

[11] Visual inspection of the emissions series (see Figures 2 (a), (c) and (e) and 3 (a), (c) and (e)) suggests that there was a break in both intercept and slope.

We are interested in testing three null hypotheses in equations (6) and (7): (i) $\delta = 0$, (ii) $\gamma = 0$, and (iii) $\delta = \gamma = 0$ against the corresponding alternatives: (i) $\delta \neq 0$, (ii) $\gamma \neq 0$, and (iii) $\delta \neq \gamma \neq 0$. To test these hypotheses we use the Wald $T^{-1}W_T$ and partial sum PS_T test statistics, details of which are given in Appendix A.[12]

When the break date is assumed to be known, we use the $T^{-1}W_T$ and PS_T test statistics directly. Vogelsang (2001) shows that $T^{-1}W_T$ has power when the errors are I(1) (emissions are DS), but is conservative when the errors are I(0) (emissions are TS), whereas PS_T has power when the errors are I(0) but remains robust to I(1) errors. When the break date is unknown, Vogelsang (2001) uses the approach proposed by Andrews (1993) and Andrews and Ploberger (1994), which involves computing $T^{-1}W_T$ and PS_T for a range of possible breaks and then taking the supremum or some form of an average. Specifically, we use the mean (Mean), mean-exponential (Exp), and supremum (Sup) statistics that are defined in Appendix A. A nice feature of the Sup statistic is that it gives us an estimate of the break date.

Table 3 provides test results when the break date is unknown. When the break date is unknown we test only the joint null hypothesis of no change in the intercept and slope in the emissions trend function against the alternative that there was a change in both intercept and slope. We fail to reject the null hypothesis of no structural change for *nox*, *lnox* and *lpnox* series at the 5% significance level. However, we conclude that there was a change in both intercept and slope in the trend function of the *voc*, *lvoc* and *lpvoc* series. The Sup PS_T test statistic indicates that this change for *voc* occurred in 1968, for *lvoc* in 1971 and for *lpvoc* in 1969. The break date suggested by the Sup $T^{-1}W_T$ test is the same for all three VOCs series and is 1969.

[12] We would like to thank Dr. Tim Vogelsang for proving us the Gauss code to do Vogelsang (2001) tests.

Table 4 displays results when the break date is known. When the break date is known we test both joint and separate null hypotheses of no change in the intercept and slope. We set the break date to $T_B^{'}$ =1969. We detect a change in both intercept and slope for *voc*, *lvoc* and *lpvoc* series. Joint and separate null hypotheses are rejected at the same significance levels for all three VOCs series in all cases but one. For NO_X emissions, results vary for all series. When we use the PS_T test nothing definite can be concluded because we reject and do not reject different hypotheses for different series. When we use the $T^{-1}W_T$ test we get the same results for *lnox* and *lpnox* and different results for *nox*. For *nox* we reject the joint hypothesis and separate hypothesis of no change in the intercept at the 10% and 5% levels, respectively, and do not reject the separate hypothesis of no change in the slope. For *lnox* and *lpnox* we do not reject the joint hypothesis but reject both separate hypotheses of no change in the intercept and slope at the 10% and 5% levels, respectively.

Results from the Vogelsang tests reveal that there was a break in the trend function of VOCs series at the time the CAA of 1970 was passed. Our inability to detect a change in both intercept and slope in NO_X series when the break date is unknown supports the results of the ZA test where we could not reject the null hypothesis that these series follow a unit root process with a drift and no break. The Vogelsang tests are able to detect a change in the trend for both DS and TS series, suggesting that both total and per capita NO_X emissions series may simply be DS without a break. Nevertheless, when we assume the break date to be known we conclude that there was a trend break in the NO_X emissions based on a $T^{-1}W_T$ test. Recall, that $T^{-1}W_T$ test has a power when series is DS, and based on the unit root tests performed in Section 4 NO_X emissions is DS.

5.2. Additional Structural Break Tests for NO_X emissions

For a DS time series in levels, a change in its slope is equivalent to a change in the mean of its first-difference. In Section 5.1 we obtained mixed results about the change in the trend of the NO_X emissions. In this sub-section we perform additional structural break tests for the first-differences of NO_X emissions.[13] We utilize the procedure of Bai and Perron (1998; 2003) to determine whether or not there was a break and if there was a break when it occurred in the mean of the first-differenced NO_X emissions.[14] We point out one caveat associated with the Bai and Perron test. The test considers a change in the mean of first-differenced data and therefore, it only identifies the year the break occurred in the slope of the trend function of the data in levels and does not account for a possible change in the intercept. Instead it treats the change in the intercept, if it occurred, as an outlier.

Fomby and Lin (2006) also tested for the existence and the number of breaks in the emissions of NO_X, SO_2 and VOCs. They used the procedure by Bai (1997a; 1997b), which estimates breaks one at a time. In contrast, we use the procedure by Bai and Perron (1998; 2003), which estimates breaks simultaneously.

We test for a change in the mean of the first-differenced NO_X emissions and determine the location of the break(s) by calculating the Sup *F*-type tests that are based on the test regression:

$$y_t = z_t'\delta_j + u_t \quad \text{for } t = T_{j-1}+1,...,T_j,\ j = 1,...,m+1,\ T_0 = 0 \text{ and } T_{m+1} = T, \tag{8}$$

where y_t denotes either first-differences of *nox*, first-differences of *lnox* or first-differences of *lpnox*, z_t denotes a vector of ones, u_t is an error term that can be serially correlated and heteroskedastic, and *m* is the number of breaks.

[13] We consider only first-differences of NO_X emissions because in Section 4 we found that VOCs emissions series were TS with a one-time break at the time the CAA of 1970 was passed.
[14] We performed ADF unit root test for the first-differences of *nox*, *lnox* and *lpnox* and rejected the null of a unit root in all three series.

We use three tests, details of which are provided in Appendix B. The first test is the $\mathrm{Sup}F_T(\mathrm{k})$ test, which tests the null hypothesis of no break (m=0) against an alternative that there is a fixed number of breaks (m=k). To find if at least one break is present without having to pre-specify the exact number of breaks we employ Double Maximum tests. The last test we consider is the $\mathrm{Sup}F_T(\ell+1|\ell)$, which tests the null hypothesis that there is ℓ breaks against an alternative that there is $(\ell+1)$ breaks.

The results for the above tests are provided in Table 5. In addition, we estimate model (8) for each series using the number of breaks provided by the sequential procedure as suggested by Bai and Perron (2003).[15] The estimated coefficients and break dates with corresponding confidence intervals can be found in Table 6. Based on our estimations we can draw the following conclusions. We do not find a break in the first-differences of *nox* but find a break in the first-differences of *lnox* in 1923 at the 10% level but not at the 5% level. Double maximum tests suggest that at least one break is present in first-differences of *lpnox*. Using the sequential procedure we estimate that this break occurred in 1977, which may be related to the amendment to the CAA in 1977.[16] The last row in Table 6 shows 90% confidence intervals for the estimated break points. One cannot ignore the fact how large they are. Large confidence intervals are a known paradox in Bai and Perron break tests.

5.3. Summary of the Structural Break Tests

Based on the tests results in Sections 5.1 and 5.2, we can now answer the question we posed in the beginning: Was there a break in the NO_X and VOCs emissions around the same time the

[15] In our analysis we utilized the Gauss code of Bai and Perron that was available on Pierre Perron's website. We would like to thank them for allowing us to do this.

[16] We also did simple Chow Breakpoint tests and got similar results. We tested the null of no change in the mean of first-differenced *nox*, *lnox* and *lpnox* and imposed break in 1970. We could not reject the null of no structural change in 1970 in all three series.

CAA of 1970 was passed? Our analysis shows that there was definitely a break in the trend of VOCs emissions at that time. As for NO_X emissions, the break presence and its location depend on the test used, whether the break date is known or unknown, the null hypothesis specification, and on data transformations. When we use Vogelsang tests assuming break date is unknown we do not detect a change in the trend of the NO_X emissions. However, when we account for a CAA of 1970 (i.e. known break case) we find support for a trend break in the NO_X emissions based on the Vogelsang $T^{-1}W_T$ test. When we test for a mean shift in the first-differences of the NO_X emissions, we do not find a break in total emissions in levels but find one break in total emissions in logs and per capita emissions in logs. However, the break dates differ in each case and do not correspond to the CAA of 1970.

Structural break tests performed in this section imply that the CAA of 1970 has been effective in reducing VOCs emissions, however, its effectiveness with respect to NO_X emissions depends on whether we treat the break date to be known or unknown.

Fomby and Lin (2006) also found that the trend break in VOCs emissions occurred in 1969. However, their results for the NO_X emissions differ from ours. Fomby and Lin (2006) used total emissions of NO_X for the period 1940-1998 and found that the trend break occurred in 1978 in the first-differences of NO_X emissions in levels and in 1973 in the first-differences of NO_X emissions in logs.

6. Forecasting of the Future Emissions

Forecasts of the future pollution emissions differ for TS and DS series with and without the trend breaks. Based on our estimations and results of Lee and List (2004) we can fit the natural logarithm of per capita NO_X emissions with three different model specifications: (1) TS with a

trend break, (2) DS with a trend break, and (3) DS without a trend break. Figure 4 shows forecasted values of the natural logarithm of per capita NO_X emissions along with $\pm$ 1.96 standard deviations bands for the period 1999-2030 under three model specifications. We assume that the trend break occurred at the time the CAA of 1970 was passed. From Figure 4 we see that forecasted trend is downward sloping for both TS and DS emissions with a break but the magnitude of the slope is larger for a TS series compared to a DS series. When we assume emissions is simply DS without a trend break we see that its forecasted trend is upward sloping.

7. Conclusion

We have applied time-series econometric techniques to determine whether emissions of NO_X and VOCs are TS or DS and whether there was a break in the trends of these emissions around the same time the CAA of 1970 was passed. Our analysis revealed that the trend behavior of NO_X and VOCs emissions is substantially different. We found that VOCs emissions can be described as being TS series with a break at the time the CAA of 1970 was passed. This finding suggests that the environmental regulation in 1970 has changed VOCs emissions from increasing to decreasing. In addition, all other shocks will have only short-term effects, and thus, we should expect VOCs emissions continue to decline. Our analysis finds that NO_X emissions follow a DS process. Whether NO_X emissions is a DS series with a break in its trend at the time the CAA of 1970 was passed or without a break depends on the test used, whether the break date is known or unknown, and the null hypothesis specification. Based on a series of unit root and structural break tests, we conclude that the trend of NO_X emissions is changing and there is uncertainty in its future behavior.

One explanation for the different trend behavior of NO_X and VOCs emissions is the use of more stringent controls of VOCs compared to NO_X to reduce O_3 level in 1970s and 1980s. O_3 is not usually emitted directly into the air, but at ground-level is created by a chemical reaction between NO_X and VOCs in the presence of sunlight. Therefore, controls must be placed on either NO_X, VOCs or some combination of both to reduce O_3. In the first two decades of O_3 pollution mitigation in the U.S., VOCs were the primary target for emission reductions (NRC 2004). Helms et al. (1993) explain that NO_X controls were rarely contemplated to reduce O_3 at that time. Focus on VOCs emissions to mitigate O_3 levels could have contributed to a significant decline in VOCs emissions after 1970.

Appendix A: Vogelsang Structural Break Tests

Assumptions on the error term $\{u_t\}$

Following Vogelsang (2001) we use the following assumptions on the error term $\{u_t\}$:

$$(1-L\alpha_T)u_t = \upsilon_t, t = 2,3,...,T\ , \tag{A1}$$

$$u_1 = \sum_{i=0}^{[\kappa T]} \alpha_T^i \upsilon_{1-i}\ , \tag{A2}$$

$$\upsilon_t = d(L)e_t,\quad d(L) = \sum_{i=0}^{\infty} d_i L^i,\ \sum_{i=0}^{\infty} i\,|d_i| < \infty \ \text{ and } \ d(1)^2 > 0, \tag{A3}$$

where $\{e_t\}$ is a martingale difference sequence with $E(e_t^2 \mid e_{t-1}, e_{t-2}, ...) = 1$ and $\sup_t Ee_t^4 < \infty$, L is the lag operator, and $[x]$ denotes the integer part of x. When $\alpha_T = \alpha$ and $|\alpha| < 1$, then $\{u_t\}$ is I(0). When $\alpha_T = (1-\bar{\alpha}/T)$, $\{u_t\}$ is nearly I(1) process and a pure I(1) process when $\bar{\alpha} = 0$. Assumptions (A1)-(A3) are sufficient to obtain the main results. For more details see Vogelsang (2001).

$T^{-1}W_T$ and PS_T test statistics when the break date is known and unknown

When the break date is known we use test statistics $T^{-1}W_T$ and PS_T that are defined as:

$$T^{-1}W_T = T^{-1}(R\hat{\nu} - r)'[R(X_y'X_y)^{-1}R']^{-1}(R\hat{\nu} - r)/s_y^2, \tag{A4}$$

and

$$PS_T = T^{-1}(R\tilde{\nu} - r)'[R(X_z'X_z)^{-1}R']^{-1}(R\tilde{\nu} - r)/(s_z^2 \exp(bJ_T(m))), \tag{A5}$$

where X_y and X_z denote the (Tx4) matrices of the regressors in test equations (6) and (7), respectively. The (4x1) vector of the parameters in both regressions is denoted by letter ν[17]. We

[17] Note that ν is the same in both regressions (6) and (7).

define $\hat{v}$ and $\tilde{v}$ as the OLS estimates of v from the equations (6) and (7), respectively, and $s_y^2 = T^{-1}RSS_y$ and $s_z^2 = T^{-1}RSS_z$, where RSS_y denotes the OLS sum of squared residuals from the regression (6) and RSS_z – from the regression (7). The null hypothesis can be generally written as $H_0 : Rv = r$, where R is a (qx4) matrix of constants, r is a (qx1) vector of constants and q is the number of the restrictions tested.[18] Constant b is chosen so that the asymptotic critical values are the same for I(0) and I(1) errors. Lastly, $J_T(m)$ is a scaling factor that is defined as $(RSS_y - RSS_J)/RSS_J$, where RSS_J denotes the sum of squared residuals from the regression:

$$y_t = \mu + \beta t + \delta DU_t + \gamma DT_t + \sum_{i=2}^{m} c_i t^i + u_t, \tag{A6}$$

where $m = 9$ and the rest of the variables are defined as in equation (6).

When the break date is unknown, we use the mean (Mean), mean-exponential (Exp), and supremum (Sup) statistics that are defined as:

$$\text{Mean}h_T = [T^{-1} \sum_{T_B \in \Lambda} h_T(T_B)] \exp(-bJ_T(m)), \tag{A7}$$

$$\text{Exp}h_T = \log[T^{-1} \sum_{T_B \in \Lambda} \exp(\frac{1}{2} h_T(T_B))] \exp(-bJ_T(m)), \tag{A8}$$

$$\text{Sup}h_T = [Sup_{T_B \in \Lambda} h_T(T_B)] \exp(-bJ_T(m)), \tag{A9}$$

where T_B denotes the break date used to estimate the model and it may be different from the $T_B^{'}$ (true break), $h_T(T_B)$ denotes $T^{-1}W_T$ or PS_T where PS_T is computed using b=0. In a case of $T^{-1}W_T$, b always equals zero. Possible break dates are restricted to the set

[18] When q=1 (i.e. only one restriction), we can use the following t-statistic versions of the tests:

$T^{-1/2}t - W_T = T^{-1/2}(R\hat{v} - r)[R(X_y{}'X_y)^{-1}R's_y^2]^{-1/2}$,

$t - PS_T = T^{-1/2}(R\tilde{v} - r)[R(X_z{}'X_z)^{-1}R's_z^2]^{-1/2} \exp(-bJ_T(m))$.

$\Lambda = (T_B^*, T_B^* + 1, ..., T - T_B^*)$, where $\lambda^* = T_B^* / T$ remains fixed as $T \to \infty$. We define λ^* as the amount of trimming and use 1% trimming whenever dataset allows it. Lastly, $\log(.)$ is a natural logarithm and $J_T(m) = \inf_{T_B \in \Lambda} J_T(T_B, m)$, where $J_T(T_B, m)$ denotes $J_T(m)$ defined in regression with a break date T_B.

Critical Values and b's for Vogelsang $T^{-1}W_T$ and PS_T tests

Unknown Break		PS_T			$T^{-1}W_T$		
		Mean	*Exp*	*Sup*	*Mean*	*Exp*	*Sup*
$H_0 : \delta = \gamma = 0$	90%	1.597	0.969	3.970	1.471	0.923	3.838
	b	3.103	4.807	3.939			
	95%	2.125	1.388	5.321	1.885	1.312	5.168
	b	3.946	6.216	5.153			

Known Break		PS_T		$T^{-1}W_T$	
		$\lambda = 0.5$	$\lambda = 0.7$	$\lambda = 0.5$	$\lambda = 0.7$
$H_0 : \delta = \gamma = 0$	90%	2.641	1.826	2.689	1.975
	b	1.984	1.389		
	95%	3.633	2.555	3.769	2.818
	b	2.554	1.815		
$H_0 : \delta = 0$	90%	0.772	0.634	0.649	0.552
	b	0.406	0.270		
	95%	0.990	0.816	0.818	0.700
	b	0.486	0.320		
$H_0 : \gamma = 0$	90%	1.032	0.503	1.156	0.769
	b	0.770	0.317		
	95%	1.344	0.656	1.517	1.000
	b	1.058	0.469		

Note: Left tail critical values follow by symmetry around zero.

Source: Vogelsang (2001), Tables 3A, 3B, 3C, and 4.

Appendix B: Bai and Perron Tests

The $\mathrm{Sup}F_T(\mathrm{k})$ *Test.*

Following Bai and Perron (2003), we let $(T_1,...,T_k)$ denote a partition such that $T_i = [T\lambda_i], (i = 1,...,k)$, R denote a matrix where $(R\delta)' = (\delta_1' - \delta_2', ..., \delta_k' - \delta_{k+1}')$, and $\hat{V}(\hat{\delta})$ denote an estimate of the variance-covariance matrix of $\hat{\delta}$ that is robust to serial correlation and heteroskedasticity. Some minimum distance between each break is denoted by *h*, or $\varepsilon = h/T$. Each value of ε corresponds to different maximum number of breaks, *M*, allowed. For example, if $\varepsilon = 0.15$ then *M*=5 and if $\varepsilon = 0.20$ then *M*=3 and so on. We set *q*=1 and $\varepsilon = 0.15$.[19]

The $\mathrm{Sup}F_T(\mathrm{k})$ test is defined as:

$$\mathrm{Sup}F_T(\mathrm{k}) = \sup_{(\lambda_1,...,\lambda_k)\in\Lambda_{k,\varepsilon}} F_T(\lambda_1,...,\lambda_k;q) = F_T\left(\hat{\lambda}_1,...,\hat{\lambda}_k;q\right), \quad \text{(A10)}$$

where $F_T(\lambda_1,...,\lambda_k;q) = \frac{1}{T}\left(\frac{T-(k+1)q}{kq}\right)\hat{\delta}' R'(R\hat{V}(\hat{\delta})R')^{-1}R\hat{\delta}$,

$\Lambda_\varepsilon = \left\{(\lambda_1,...,\lambda_k); |\lambda_{i+1} - \lambda_i| \geq \varepsilon, \lambda_1 \geq \varepsilon, \lambda_k \leq 1-\varepsilon\right\}$, and $\hat{\lambda}_1,...,\hat{\lambda}_k$ are the estimates of the break fractions obtained by minimizing the sum of squared residuals in regression (8) by searching over partitions defined by the set Λ_ε (Perron 2007).

The Double Maximum Tests

The *UDmax* and *WDmax* and are defined as:

$$UDmaxF_T(M,q) = \max_{1\leq m\leq M} F_T\left(\hat{\lambda}_1,...,\hat{\lambda}_m;q\right), \quad \text{(A11)}$$

[19] We also tried setting ε =.20 and m=3, but this did not give us any different results.

$$WDmaxF_T(M,q) = \max_{1\le m\le M} \frac{c(q,\alpha,1)}{c(q,\alpha,m)} F_T\left(\hat{\lambda}_1,...,\hat{\lambda}_m;q\right), \quad \text{(A12)}$$

where $c(q,\alpha,m)$ is the asymptotic critical value of the test $F_T\left(\hat{\lambda}_1,...,\hat{\lambda}_m;q\right)$ for a significance level α and the rest of the terms are defined as in $\text{Sup}F_T(\text{k})$ Test.

The $\text{Sup}F_T(\ell+1|\ell)$ *Test.*

For each model with ℓ breaks, we first estimate the break points $\left(\hat{T}_1,...,\hat{T}_\ell\right)$ by globally minimizing the sum of squared residuals in regression (8) and then test each $(\ell+1)$ segment for the presence of an additional break. Simply put, the $\text{Sup}F_T(\ell+1|\ell)$ test procedure entails estimating $(\ell+1)$ tests of the null of no structural change versus the alternative hypothesis of a single change and is applied to each segment containing observations $\hat{T}_{i-1}$ to $\hat{T}_i\,(i=1,...,\ell+1)$. We reject the null of ℓ breaks if the overall minimal value of the sum of squared residuals over all segments that have additional break is sufficiently smaller than the sum of squared residuals from the ℓ breaks model (Bai and Perron 2003).

References

Andrews, D. W. K. “Tests for Parameter Instability and Structural Change With Unknown Change Point.” *Econometrica*, 61, 1993, 821–856.

Andrews, D. W. K., and W. Ploberger. “Optimal Tests When a Nuisance Parameter is Present Only Under the Alternative.” *Econometrica*, 62, 1994, 1383–1414.

Bai, J. “Estimation of a Change Point in Multiple Regression Models.” *Review of Economics and Statistics*, 79, 1997a, 551–563.

Bai, J. “Estimating Multiple Breaks One at a Time.” *Econometric Theory*, 13, 1997b, 315–52.

Bai, J., and P. Perron. “Estimating and Testing Linear Models with Multiple Structural Changes.” *Econometrica*, 66, 1998, 47–78.

Bai J., and P. Perron. “Computation and Analysis of Multiple Structural Change Models.” *Journal of Applied Econometrics*, 18, 2003, 1–22.

Bunzel, H., and T.J. Vogelsang. “Powerful Trend Function Tests That Are Robust to Strong Serial Correlation, With an Application to the Prebisch-Singer Hypothesis.” *Journal of Business and Economic Statistics*, 23, 2005, 381–394.

Christiano, L.J. “Searching for Breaks in GNP.” *Journal of Business and Economic Statistics*, 10(3), 1992, 237–250.

EPA (U.S. Environmental Protection Agency). *The Clean Air Act.* Washington, D.C.: U.S. Environmental Protection Agency, 1970.

EPA (U. S. Environmental Protection Agency). *Historic Emissions of Sulfur and Nitrogen Oxides in the United States from 1900 to 1980.* EPA paper EPA-600/7-85-009a and b. Research Triangle Park, NC: U. S. Environmental Protection Agency, 1985.

EPA (U. S. Environmental Protection Agency). *National Air Pollutant Emissions Trends, 1900-1994.* EPA paper EPA-454/R-95-011. Research Triangle Park, NC: U. S. Environmental Protection Agency, 1995.

EPA (U. S. Environmental Protection Agency). *National Air Pollutant Emissions Trends, Procedures Document, 1900-1996.* EPA paper EPA-454/R-98-008. Research Triangle Park, NC: U. S. Environmental Protection Agency, 1998.

EPA (U. S. Environmental Protection Agency). *National Air Pollutant Emissions Trends, 1900-1998.* EPA paper EPA-454/R-00-002. Research Triangle Park, NC: U. S. Environmental Protection Agency, 2000.

EPA (U. S. Environmental Protection Agency). *Procedures Document For National Emission Inventory, Criteria Air Pollutants 1985-1999*. EPA paper EPA-454/R-01-006. Research Triangle Park, NC: U. S. Environmental Protection Agency, 2001.

Fomby, T. B., and L. Lin. "A Change Point Analysis of the Impact of 'Environmental Federalism' on Aggregate Air Quality in the United States: 1940–98." *Economic Inquiry*, 44(1), 2006, 109–120.

Granger, C. W. J., and J. Hallman. "Nonlinear Transformations of Integrated Time Series." *Journal of Time Series Analysis*, 12(3), 1991, 207–224.

Greene, W.H. *Econometric Analysis, Fifth Edition.* Upper Saddle River: Prentice Hall, 2003.

Grossman, G.M., and A.B. Krueger. "Economic Growth and the Environment." *The Quarterly Journal of Economics*, 110(2), 1995, 353-377.

Hayashi, F. *Econometrics.* Princeton: Princeton University Press, 2000.

Helms, G. T., J. B. Vitas, and P. A. Nikbakht. "Regulatory Options under the U.S. Clean Air Act: The Federal View." *Water, Air and Soil Pollution*, 67, 1993, 207–216.

Jones, N. S. “A Monte Carlo Investigation of Unit Root Tests with Structural Change.” Working Paper, University of Washington, 2007.

Lave, L. B., and G. S. Omenn. *Clearing the Air: Reforming the Clean Air Act.* Washington, D.C.: Brookings Institution, 1981.

Lee, J., and J. A. List. “Examining Trends of Criteria Air Pollutants: Are the Effects of Governmental Intervention Transitory?” *Environmental and Resource Economics*, 29, 2004, 21–37.

Maddala, G.S., and I. Kim. *Unit Roots, Cointegration, and Structural Change.* Cambridge: Cambridge University Press, 1998.

McKitrick, R. “Why Did US Air Pollution Decline After 1970?” *Empirical Economics*, 33(3), 2007, 491–513.

Mills, T. C. *Modeling Trends and Cycles in Economic Time Series*. New York: Palgrave Macmillan, 2003.

Murray, C.J., and E. Zivot. “Inference on Unit Roots and Trend Breaks in Macroeconomic Time Series.” Working Paper, University of Washington, 1998.

NRC (National Research Council). *Air Quality Management in the United States*. Washington, D.C.: The National Academy Press, 2004.

Park, J. Y., and J. Sung. “Testing for Unit Roots in Models with Structural Change.” *Econometric Theory*, 10, 1994, 917–936.

Phillips, P. C. B., and P. Perron. “Testing for a Unit Root in Time Series Regression.” *Biometrika* 75, 1988, 335–346.

Perron, P. “The Great Crash, the Oil Price Shock, and the Unit Root Hypothesis.” *Econometrica*, 57, 1989, 1361–1401.

Perron, P. “Further Evidence on Breaking Trend Functions in Macroeconomic Variables.” *Journal of Econometrics,* 80(2), 1997, 355–385.

Perron, P. “Dealing with Structural Breaks,” in *Palgrave Handbook of Econometrics, Volume 1: Econometric Theory*, edited by K. Patterson and T.C. Mills. New York: Palgrave Macmillan, 2007, 278–352.

Perron, P., and T. Yabu. “Testing for Shifts in Trend with an Integrated or Stationary Noise Component.” Working Paper, Boston University, 2005.

Portney, P. R. “Air Pollution Policy,” in *Public Policies for Environmental Protection*, edited by P. R. Portney. Washington, DC: Resources for the Future, 1990, 27-96.

Said, S. E., and D. A. Dickey. “Testing for Unit Roots in Autoregressive-Moving Average Models of Unknown Order.” *Biometrika* 71, 1984, 599–608.

Selden, T., and D. Song. “Environmental Quality and Development: Is There a Kuznets Curve for Air Pollution Emissions?” *Journal of Environmental Economics and Management*, 27, 1994, 147-162.

Vogelsang, T.J. “Wald-Type Tests For Detecting Breaks in the Trend Function of a Dynamic Time Series.” *Econometric Theory*, 13: 1997, 818–849.

Vogelsang, T.J. “Trend Function Hypothesis Testing in the Presence of Serial Correlation.” *Econometrica* 66, 1998a, 123–148.

Vogelsang, T.J. “Testing for a Shift in Mean Without Having to Estimate Serial Correlation Parameters.” *Journal of Business and Economic Statistics*, 16, 1998b, 73–80.

Vogelsang, T. J. “Testing for a Shift in Trend When Serial Correlation is of Unknown Form.” Working Paper, Cornell University, 2001.

Vogelsang, T.J., and P. Perron. “Additional Tests for a Unit Root Allowing for a Break in the Trend Function at Unknown Time.” *International Economic Review*, 39(4), 1998, 1073–1100.

Zimmerman, D., and R. Battye. “Comparison of the 1985 NAPAP Emissions Inventory with the 1985 EPA Trends Estimate for Industrial SO2 Sources.” EPA paper EPA/600/SR-94/012. Research Triangle Park, NC: United States Environmental Protection Agency, 1994.

Zivot, E., and D. W. K. Andrews. “Further Evidence on the Great Crash, the Oil Price Shock, and the Unit Root Hypothesis.” *Journal of Business & Economic Statistics*, 10(3), 1992, 251–70.

Zivot, E. “Lectures on Structural Change.” Manuscript, University of Washington, 2003.

TABLE 1

Perron Unit Root Test

Variable	*k*	*t-statistic to test* $H_0: \alpha = 1$	*Conclusion*
nox	0	-1.67	Do Not Reject H_0
lnox	1	-3.03	Do Not Reject H_0
lpnox	1	-3.32	Do Not Reject H_0
voc	1	-5.47***	Reject H_0 at 1%
lvoc	1	-5.08***	Reject H_0 at 1%
lpvoc	1	-4.66**	Reject H_0 at 5%

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level.

Critical values at the 1%, 5%, and 10% levels are -4.90, -4.24, and -3.96 for $\lambda = T_B / T$ =0.5 and -4.75, -4.18, and -3.86 for $\lambda = T_B / T$ =0.7 (Perron 1989, Table VI.B).

Hypothesis testing example: For a break fraction λ =0.7 we reject the null hypothesis that the series follows a unit root with a one-time break in its level and drift at the 5% significance level if *t*-statistic < -4.18.

TABLE 2

Zivot-Andrews Unit Root Test

Variable	*k*	*Minimum t-statistic to test* H_0: $\alpha = 1$	*Estimated Break Year*	*Conclusion*
nox	0	-2.70	N/A	Do Not Reject H_0
lnox	1	-3.24	N/A	Do Not Reject H_0
lpnox	1	-3.54	N/A	Do Not Reject H_0
voc	2	-6.45***	1970	Reject H_0 at 1%
lvoc	2	-5.29**	1970	Reject H_0 at 5%
lpvoc	2	-4.91*	1970	Reject H_0 at 10%

*Significant at the 10% level; **significant at the 5% level; ***significant at the 1% level.

Critical values at the 1%, 5%, and 10% levels are -5.57, -5.08, and -4.82 (Zivot and Andrews 1992, Table 4).

Hypothesis testing example: We reject the null hypothesis that a series follows a unit root process with a drift and no break at the 5% significance level if the minimum *t*-statistic < -5.08.

TABLE 3

Vogelsang Tests when Break Date Is Unknown

Variable	PS_T				$T^{-1}W_T$			
	$H_0 : \delta = \gamma = 0$							
	Mean	*Exp*	*Sup*	$\hat{T}_B$	*Mean*	*Exp*	*Sup*	$\hat{T}_B$
nox	0.00	0.00	0.00	N/A	0.71	0.39	2.44	N/A
lnox	0.00	0.00	0.00	N/A	0.40	0.19	1.06	N/A
lpnox	0.06	0.01	0.09	N/A	0.36	0.16	1.07	N/A
voc	21.44**	29.77**	81.92**	1968	4.19**	5.36**	16.46**	1969
lvoc	13.72**	16.98**	52.14**	1971	4.21**	5.02**	14.86**	1969
lpvoc	6.65**	5.35**	18.11**	1969	3.39**	3.41**	11.46**	1969

*Significant at the 10% level; **significant at the 5% level.

Critical values for $T^{-1}W_T$ test, and critical values and corresponding *b* values for PS_T test are provided in Appendix A.

Hypothesis testing example: We reject the null hypothesis that there was no break in the intercept and slope in the trend function of a series at the 5% significance level if |Mean statistic| > 2.125 using PS_T test and if |Mean statistic| > 1.885 using $T^{-1}W_T$ test. Similar hypothesis testing procedure applies to Exp and Sup statistics.

TABLE 4

Vogelsang Tests when Break Date Is Known

Variable	PS_T			$T^{-1}W_T$		
	$H_0:\delta=\gamma=0$	$H_0:\delta=0$	$H_0:\gamma=0$	$H_0:\delta=\gamma=0$	$H_0:\delta=0$	$H_0:\gamma=0$
nox	0.07, 0.23	0.98**, 1.13*	-0.23, -0.37	2.41*	1.46**	-0.46
lnox	0.12, 0.20	0.53, 0.56	-0.57, -0.68*	1.06	0.61*	-1.03**
lpnox	0.47, 0.58	0.73, 0.75*	-0.85**, -0.91*	1.07	0.67*	-1.03**
voc	118**, 149*	1.80**, 1.85*	-11.56**, -13*	16.46**	0.77*	-4.02**
lvoc	85.7**, 118*	1.17**, 1.22*	-10.08**, -11.84*	14.86**	0.57	-3.84**
lpvoc	43.5**, 60.7*	1.47**, 1.54*	-7.33**, -8.68*	11.46**	0.72*	-3.34**

*Significant at the 10% level; **significant at the 5% level.

For PS_T test, the first value corresponds to 5% significance level and the second value to 10% significance level. The reason is the use of different *b's* for different significance levels. Critical values for $T^{-1}W_T$ test, and critical values and corresponding *b* values for PS_T test are provided in Appendix A. $\lambda' = T_B'/T = 0.7$ for NO_X emissions, and $\lambda' = T_B'/T = 0.5$ for VOCs emissions. Hypothesis testing example: For a break fraction $\lambda' = 0.7$ we reject the null hypothesis that there was no break in the intercept and slope in the trend function of a series at 5% significance level if |PS_T test statistic| > 2.555 and if |$T^{-1}W_T$ test statistic| > 2.818.

TABLE 5

Bai and Perron Multiple Structural Break Tests

	nox	*lnox*	*lpnox*
SupF_T(1)	6.36	7.21*	15.03**
SupF_T(2)	6.64*	11.21**	9.30**
SupF_T(3)	5.90*	10.03**	7.05**
SupF_T(4)	4.57*	8.89**	7.15**
SupF_T(5)	3.10	6.70**	5.34**
UDmax	6.64	11.21**	15.03**
WDmax at 5% level	8.50	15.29**	15.03**
SupF_T(2|1)	8.86**	8.21*	2.66
SupF_T(3|2)	4.54	3.55	2.71
SupF_T(4|3)	2.48	1.46	1.17
SupF_T(5|4)	N/A	N/A	N/A
Number of breaks selected	0	1 (at 10% only)	1

*Significant at the 10% level; **significant at the 5% level.

TABLE 6

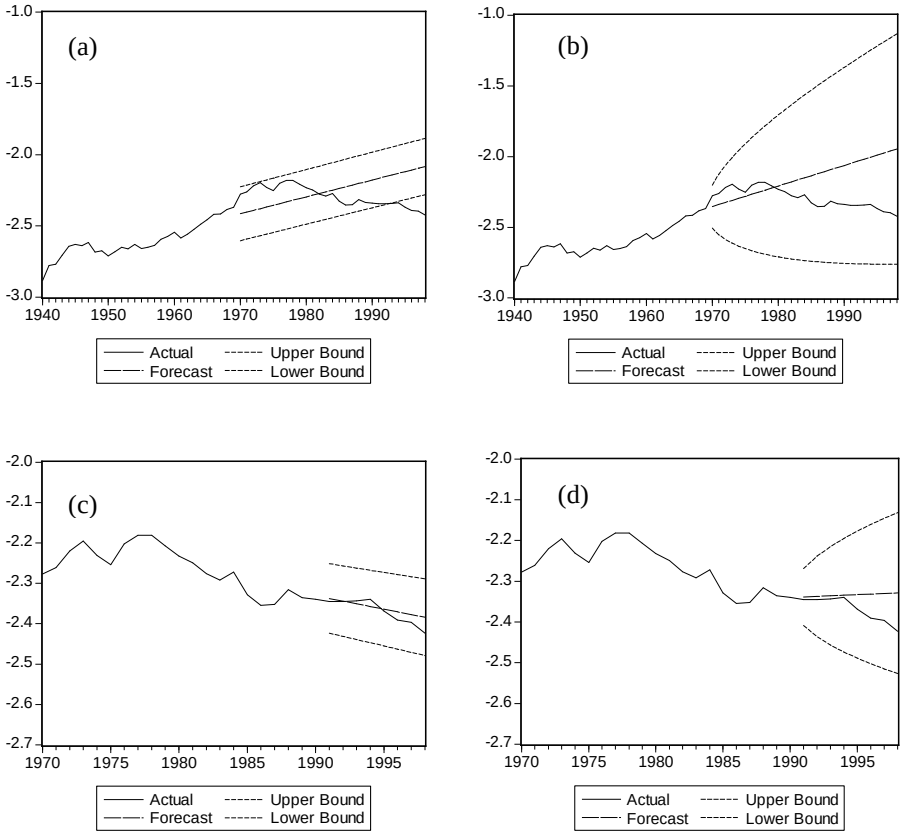
Estimated Coefficients and Break Dates for Model (8)

	nox	*lnox*	*lpnox*
$\hat{\delta}_1$	N/A	0.0455	0.0155
		(0.0096)	(0.0055)
$\hat{\delta}_2$	N/A	0.0159	-0.0115
		(0.0052)	(0.0042)
$\hat{T}_1$	N/A	1923	1977
90% C.I.	N/A	[1905, 1942]	[1975, 2004]

Standard errors are given in parentheses.

FIGURE 1

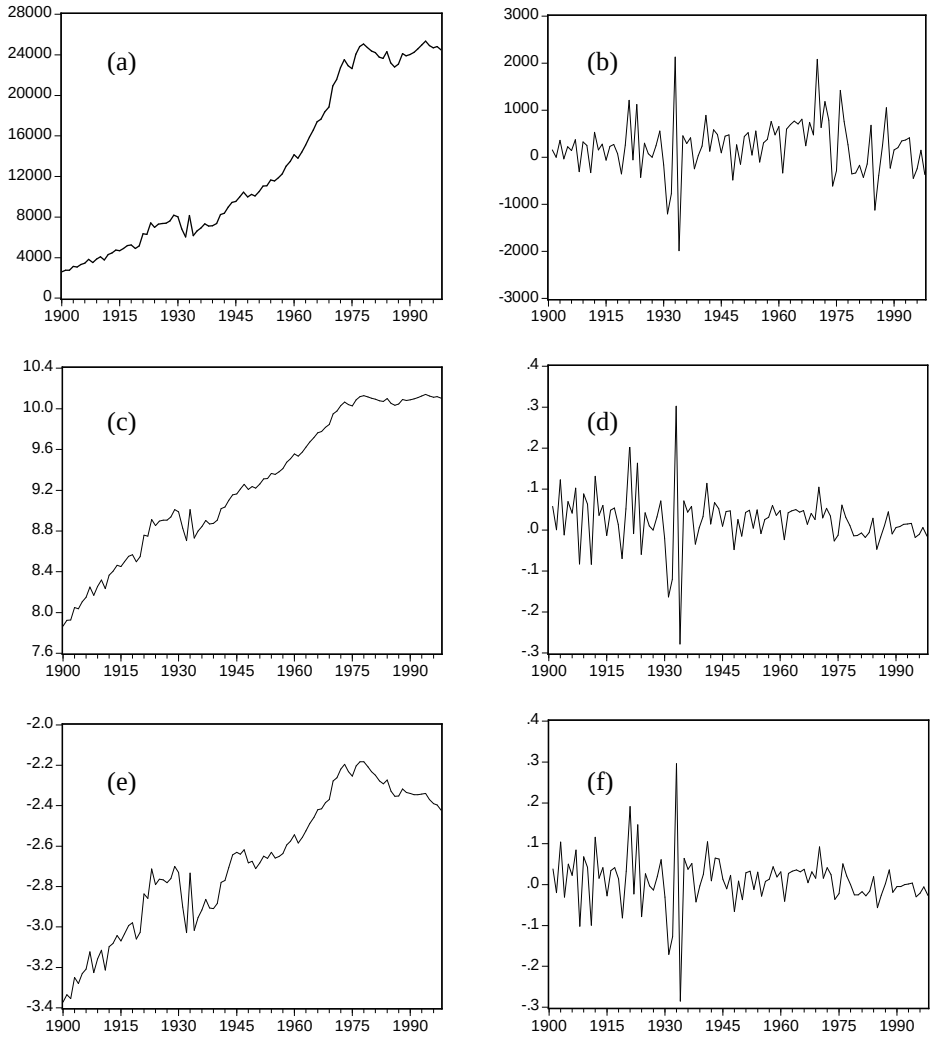
Difference between Forecasts for TS and DS Natural Logarithm of Per Capita NO_X Emissions



Notes : We estimated TS and DS models for per capita NO_X emissions in logs for the period 1900-1969 and then generated forecasts for the period 1970-1998. Panels (a) and (b) show actual values for the period 1940-1998 and forecasted values for the period 1970-1998 along with ± 1.96 standard deviations for TS and DS models, respectively. We also estimated TS and DS models for the period 1970-1990 and then generated forecasts for the period 1991-1998. Panels (c) and (d) show actual values for the period 1970-1998 and forecasted values for the period 1991-1998 along with ± 1.96 standard deviations for TS and DS models, respectively. In the above forecasts we ignored ARMA structure in the error terms.

FIGURE 2

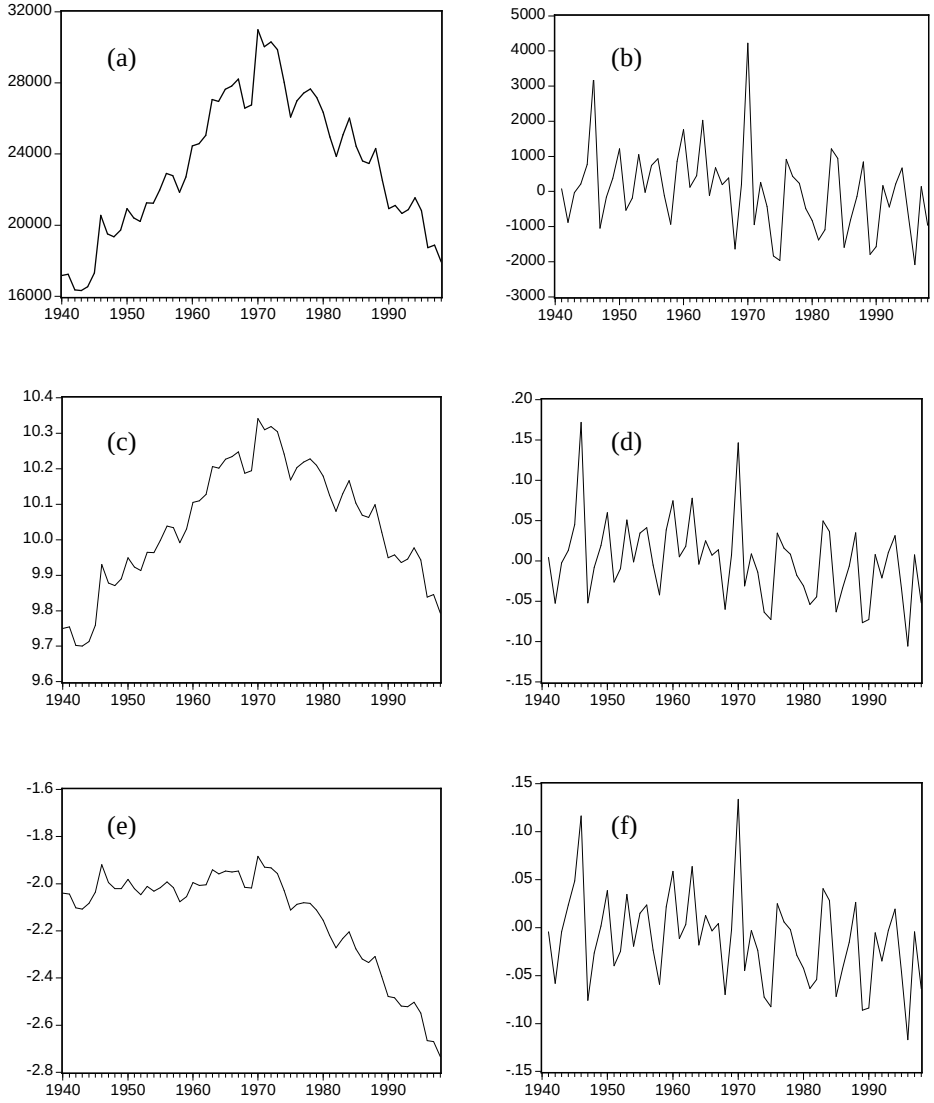
NO_X Emissions Series, 1900-1998



Notes : Panels (a), (b), (c), (d), (e), and (f) show total emissions in levels (in thousands of short tons), first-difference of total emissions in levels, total emissions in logs, first-difference of total emissions in logs, per capita emissions in logs, and first-difference of per capita emissions in logs, respectively.

FIGURE 3

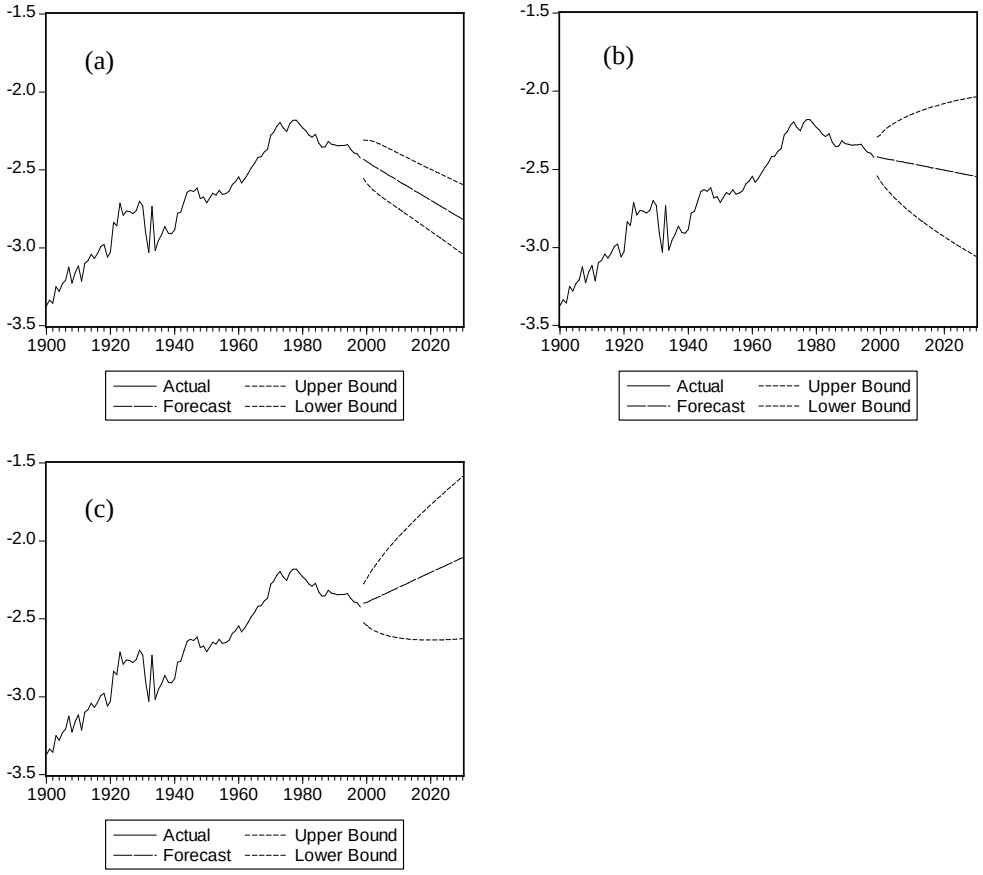
VOCs Emissions Series, 1940-1998



Notes: Panels (a), (b), (c), (d), (e), and (f) show total emissions in levels (in thousands of short tons), first-difference of total emissions in levels, total emissions in logs, first-difference of total emissions in logs, per capita emissions in logs, and first-difference of per capita emissions in logs, respectively.

FIGURE 4

Forecasts of the Natural Logarithm of Per Capita NO_X Emissions



Notes: Panel (a) shows actual values for the period 1900-1998 and forecasted values for the period 1999-2030 along with ± 1.96 standard deviations assuming emissions is TS with a trend break. Panel (b) shows actual values for the period 1900-1998 and forecasted values for the period 1999-2030 along with ± 1.96 standard deviations assuming emissions is DS with a trend break. Panel (c) shows actual values for the period 1900-1998 and forecasted values for the period 1999-2030 along with ± 1.96 standard deviations assuming emissions is DS without a break.