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

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ABSTRACT

Time-series analysis of how government regulation has affected the U.S. air pollution trends since 1970 has generated considerable interest in the area of environmental economics . Using recently developed structural break tests that are valid for difference-stationary (DS) and trend-stationary (TS) data and efficient unit root tests that allow for breaks we examine the trend behavior of two air pollutants, Nitrogen Oxides (NO_X) and Volatile Organic Compounds (VOC). We concentrate on answering two questions. First, was there a break in the trends of NO_X and VOCs emissions around the time the CAAA of 1970 were passed? And second, are the U.S. emissions of NO_X and VOC trend-stationary or difference-stationary. Existence of a reduction in the slope of the trend in pollution emissions around the timing of the CAAA of 1970 provides strong evidence of the effectiveness of the policy, and the distinction between DS and TS processes is important for assessing the potential long-term impact of environmental policy which relies on forecasting future emissions and evaluating the accuracy of these forecasts. We find that there was a break in the trend of both air pollutants at the time the Clean Air Act Amendments of 1970 were passed. The unit root tests show that NO_X are difference-stationary whereas VOC emissions are trend-stationary. (JEL C22, C53, Q53)

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I. INTRODUCTION

Time-series analysis of how government regulation has affected the U.S. air pollution trends since 1970 has generated considerable interest in the area of environmental economics as exemplified by the studies of Lee and List (2004) and McKitrick (2007). Such assessments of environmental regulations are important because they can show the past outcomes of policy on variables of interest and provide more insight into forming better future policies. In this paper we use recently developed time-series econometric techniques to study long-term air pollution trends in the U.S., and to examine how government policies such as the establishment of the Environmental Protection Agency (EPA) and the passage of the Clean Air Act Amendments (CAAA) in 1970 affect them. Our analysis focuses on two pollution series: emissions of Nitrogen Oxides (NO_X) and Volatile Organic Compounds (VOC). The natural logarithm of these series are illustrated in Figures 1 (a) and 2 (a). NO_X and VOC emissions exhibit different trending behavior and both series show a reduction in trend around the time of the CAAA in 1970. In addition to CAAA of 1970 the other major environmental policies include CAAA of 1977 and 1990. All pollution series except for per capita NO_X emissions show trend break around 1970 whereas for per capita NO_X emissions it is not clear whether the break occurred in 1970 or 1977. We concentrate on only one break because based on the data sample analyzed there does not appear to be any additional breaks. In our analysis of these series, we concentrate on answering two questions. First, was there a break in the trends of NO_X and VOCs emissions around the time the CAAA of 1970 were passed? And second, are the U.S. emissions of NO_X and VOC trend-stationary (TS) or difference-stationary (DS)?

Our first question is directly related to the effectiveness of the CAAA. The CAAA were implemented to permanently reduce certain pollution emissions. For trending data like pollution emissions, the CAAA are said to have a permanent effect if they permanently change the trend path of the data. Existence of a trend break (reduction in the slope of the trend) in pollution emissions around the timing of the CAAA of 1970 provides strong evidence of the effectiveness of the policy. Therefore, a natural test for the effectiveness of the CAAA is a test for a reduction in trend in pollution emissions. Unfortunately, the distributions of traditional statistical tests for shifts in trend, assuming the break date is known or is estimated, depend on whether the data is DS or TS. Pretesting the data to determine if it is DS or TS is complicated by the fact that unit root tests used to determine if a series is DS or TS also depend on the whether or not there has been a shift in trend and if the timing of the shift is known or estimated. To circumvent these problems, we employ recently developed tests for shifts in trend due to Perron and Yabu (2007) that can be used without knowing if the data are DS or TS. An advantage of these tests for the pollution data is that they allow the full impact of the break to be spread over several periods.

Regarding our second question, once we have established if there is a trend shift in pollution emissions, we then use the Perron (1989) and Perron and Rodríguez (2003) unit root tests to determine if the emissions are DS or TS. These tests allow for the possibility of a trend shift under both the null and the alternative, exhibit stable size and good power. Determining whether emissions follow a DS or a TS 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 a country's levels of pollution and income. The majority of the EKC studies assume that the pollution variables are TS. However, an EKC-type model that uses a DS emissions series in levels as the dependent variable runs the risk of spurious inference if the independent variables, such as gross domestic product or income, are also DS. Second, the distinction between DS and TS processes is important for assessing the potential long-term impact of environmental policy which relies on forecasting future emissions and evaluating the accuracy of these forecasts. For both DS and TS processes, long term forecasts are the extrapolated deterministic trend. However, forecast uncertainty for a DS process increases with the forecast horizon whereas it is bounded for a TS process. As a result, the long-term effects of a policy that changes the trend is much more certain when the data are TS than when they are DS.

Figure 3, which shows the natural logarithm of per capita NO_X emissions for two sub-periods of the data along with trend forecasts, illustrates the statistical difficulties associated with determining if a trend shift has occurred as well the implications for forecasting of assuming emissions are DS or TS. Panels (a) and (b) show trend forecasts and 95 percent confidence intervals estimated using data prior to 1970 under the assumption of TS and DS, respectively. Heuristically, statistical evidence for a trend break using traditional structural break tests occurs if actual emissions fall outside of the forecast confidence intervals. Assuming TS data provides evidence for a trend break in 1970 but assuming DS data does not. Panels (c) and (d) show trend forecasts and 95 percent confidence intervals assuming a trend shift occurred in 1970 estimated using data prior to 1991 under the assumption of TS and DS. The TS forecasts show a steeper decline than the DS forecasts and imply much more accuracy.

Our empirical results show that the trend behavior of NO_X and VOC emissions is substantially different. We find clear evidence of a trend shift in NO_X and VOC emissions at the time the CAAA of 1970 were passed. We find, however, that VOC emissions are TS whereas NO_X are DS.

The remainder of our paper is as follows. In Section II we present data and background information on the air pollution regulation in the U.S. In Section III we test for a trend break in the emissions of the NO_X and VOC under the assumption the break date corresponds to the year the CAAA of 1970 were passed, as well as when the break date is estimated from the data. In Section IV we perform unit-root tests allowing for possible trend breaks under the null and the alternative to determine whether emissions series are best described as TS or DS. In Section V we illustrate how future emissions forecasts differ for TS and DS series with the trend breaks. We conclude by summarizing our findings and providing suggestions for future research.

II. DATA AND GOVERNMENT REGULATION OVERVIEW

Our dataset consists of annual observations for NO_X emissions and VOC emissions for the period 1940-1998 and was obtained from EPA (2000). This is the same data source that has been used in some previous time-series analyses of the U.S. air pollution emissions. For example, Lee and List (2004) used NO_X emissions data from EPA (1985; 1995) whereas Fomby and Lin (2006) and McKitrick (2007) used data from EPA (2000). All emissions are measured in thousands of short tons, where one short ton is equivalent to 0.9072 of a metric ton.

We chose to concentrate on NO_X and VOC emissions for two reasons. First, both of these pollutants have been regulated by the EPA due to their adverse health and environmental effects. Second, as shown in Figures 1 (a) and 2 (a), the long time series available for NO_X and VOC show an apparent reduction in the long-term trend of these emissions around the year the CAAA of 1970 were passed.

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 other ill effects. VOC 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. VOC 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, VOC 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 CAAA of 1970 laid out a basic framework for current air pollution regulation. However, efforts to control air pollution began before 1970. The original Clean Air Act was passed in 1963, the Motor Vehicle Air Pollution Control Act in 1965 and the Air Quality Act in 1967. It seems, though, that the prior activity was just preparation for the major action that took place in 1970. Under the CAAA of 1970, National Ambient Air Quality Standards were set for NO_X and for non-methane hydrocarbons. EPA calculates non-methane hydrocarbons as VOC emissions and, at that time, it regulated VOC 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 VOC. Figures 1 (a) and 2 (a) show that prior to 1970 both NO_X and VOC 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 VOC emissions have been steadily declining indicating a clear change in the direction of the trend.

Emissions estimates of NO_X and VOC prior to 1985 are based on a so called "top-down" methodology, where national information was used to create national emission estimates. The EPA estimates emissions generally using three elements: (1) an 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 sulfur dioxide (SO_2), the sulfur content of the fuel. Emissions for the years after 1985 are produced using a "bottom-up" methodology, according to which the EPA derives emissions at the plant or county level and then aggregates them to the national levels.[1]

We point out two caveats associated with our dataset. First, 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, identified an advantage of using emissions instead of concentrations. He argued 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. Another

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

drawback of the concentrations dataset is the lack of long enough data sample especially prior to 1970.

Throughout our analysis, we use the natural logarithms of total and per capita NO_X and VOC emissions. The per capita transformation allows us to control for population growth and the use of natural logarithms reduces fluctuations in the data that increase with the level of the data. Population data in thousands was obtained from the U.S. Census Bureau Web site at www.census.gov. We refer to the natural logarithms of total NO_X and VOC emissions as *lnox* and *lvoc*, and to the natural logarithms of per capita NO_X and VOC emissions as *lpnox* and *lpvoc*.

III. WAS THERE A BREAK IN THE EMISSIONS TRENDS AT THE TIME CAAA OF 1970 WERE PASSED?

In this section we consider our first question: Was there a break in the trends of NO_X and VOC emissions and, if there was a break, did it occur at the same time the CAAA of 1970 were passed? We consider the cases of known and unknown break dates to allow for the possibility that pollution emissions may have started to abate before or after the passage of CAAA of 1970. As discussed in Perron (2007) and Perron and Yabu (2007), testing for a break in trend, whether the break date is known or unknown, is complicated when one has no prior knowledge about whether the data is DS or TS because the distributions of traditional tests (e.g., Chow tests) for structural change are different for DS and TS processes. One cannot easily remedy the problem by pretesting the data to see if it is DS or TS using unit root tests because the appropriate unit root tests should take into consideration the possibility that there is a break in trend. What is required are tests for a shift in trend, that allow the date of structural change to be known or unknown, which have the same distribution for both DS and TS series. The trend-shift tests of Perron and Yabu (2007) satisfy this requirement.[2]

Following the framework of Perron and Yabu (2007), we assume a data generating process for a scalar random variable y_t of the form:

$$y_t = \mu_0 + \mu_1 DU_t + \beta_0 t + \beta_1 DT_t + u_t\,, \tag{1}$$

$$u_t = \alpha u_{t-1} + v_t, \tag{2}$$

for $t = 1, \ldots, T$ with $v_t = d(L)e_t$, $d(L) = \sum_{i=0}^{\infty} d_i L^i$, $\sum_{i=0}^{\infty} i\,|\,d_i\,| < \infty$, $d(1) \neq 0$, $e_t \sim i.i.d.\ (0, \sigma^2)$, $DU_t = 1$ if $t > T_1$ and 0 otherwise, $DT_t = t - T_1$ if $t > T_1$ and 0 otherwise. T_1 denotes the date of the break should it occur, and $\lambda_1 = T_1 / T$ denotes the break fraction. For our empirical analysis y_t is either *lnox*, *lpnox*, *lvoc* or *lpvoc*. We assume that $-1 < \alpha \leq 1$. When $\alpha = 1$, u_t is an integrated process of order 1 and denoted $u_t \sim I(1)$, which implies that y_t is a DS process with a possibly broken trend; when $-1 < \alpha < 1$, u_t is an integrated process of order 0 and denoted $u_t \sim I(0)$, so that y_t is a TS process with a possibly broken trend. In addition, this model is in the class of innovation outlier (IO) models that allow the impact of the break to be spread over several periods depending on the dynamics of the error term.

Perron and Yabu (2007) considered three trend shift models. Model I only allows for a shift in intercept. Model II only allows for a shift in slope. Model III allows for both a shift in intercept and slope and is given in (1). We only consider Model III in our empirical analysis for the following reasons. Because the CAAA of 1970 applied to new sources, in the short run emissions could have increased because, for example, old plants were allowed to be in operation.

[2] The trend break tests of Vogelsang (2001) can also be used, but simulation results presented in Perron and Yabu (2007) show that the Vogelsang tests are less powerful. In an earlier version of the paper, we used the Vogelsang tests. See footnote 4 for a summary of the results.

However, as new plants were built to replace old plants emissions would decline. Allowance for both intercept and slope changes would capture this effect. This is the same conclusion that McKitrick (2007) found in his analysis.

We are interested in testing the null hypothesis of no structural change in the intercept and slope, $H_0: \mu_1 = \beta_1 = 0$ and use the Perron and Yabu (2007) Robust Feasible Quasi Generalized Least Squares (FGLS) Wald statistic, W_{RQF}.[3] The W_{RQF} is a Wald statistic based on least squares estimation of a Cochrane-Orcutt transformation of (1) using a modified estimate of α. The modified estimate is given by

$$\hat{\alpha}_s = \begin{cases} \hat{\alpha} \text{ if } T^{1/2} \,|\, \hat{\alpha} - 1 \,|> 1 \\ 1 \text{ if } T^{1/2} \,|\, \hat{\alpha} - 1 \,|\leq 1 \end{cases},$$

where $\hat{\alpha}$ is obtained by least squares estimation of (2) with u_t replaced by $\hat{u}_t$, the least squares residual from (1). The modified estimate $\hat{\alpha}_S$ converges at a sufficiently fast rate such that the asymptotic distribution of W_{RQF} under the null hypothesis of no structural change is the same for DS and TS processes. When the break date is assumed to be known, we use the W_{RQF} statistic directly to test the no structural change hypothesis $H_0: \mu_1 = \beta_1 = 0$. When the break date is treated as unknown, Perron and Yabu (2007) used the approach proposed by Andrews (1993) and Andrews and Ploberger (1994), which involves computing the fixed break test statistics for a range of possible breaks and then computing the supremum or some form of an average of the resulting statistics. We use the Exp statistic for the W_{RQF} test (*Exp*-W_{RQF}) because this statistic was shown to have approximately the same distribution for DS and TS processes. We also report the estimated break date computed by minimizing the sum of squared residuals from (1).

[3] Full technical details of the application of the W_{RQF} test to the NO_X and VOC series are given in Appendix A. We use the bias-corrected version of W_{RQF} that also accounts for autocorrelation in the data.

Perron and Zhu (2005) showed that such an estimate is consistent for the true break date (provided there is one) whether the errors are $I(0)$ or $I(1)$.

Table 1 provides test results for Model III when the break date is treated as known and is set to 1969, which corresponds to the year the CAAA of 1970 were passed. We reject the null hypothesis of no structural change at the 5% level for all four pollution series. The results clearly indicate structural change in the trend functions of both NO_X and VOC emissions.

So far we have assumed that the break in the trend of pollution series occurred at the time when the environmental policy was implemented. However, the change in the trend could have happened at some other time. We continue our analysis by testing for a structural break in the pollution series assuming the exact timing of the break date is unknown and report our results in Table 2. We reject the null of no structural change for all pollution series at the 5% significance level using the $Exp\text{-}W_{RQF}$ statistic. The estimated break dates correspond to the time the CAAA of 1970 were passed. Hence, our results obtained under the assumptions of a known and unknown break date are the same.[4]

Based on the above tests results, we can now answer our first question. Our analysis shows that there was definitely a break in the trend of VOC and NO_X emissions at the time the CAAA of 1970 were passed. We find a strong evidence that the CAAA of 1970 have been effective in permanently reducing VOC and NO_X emissions.[5]

[4] We also computed the Vogelsang (2001) structural breaks tests that are valid for TS and DS processes but are less powerful than the Perron-Yabu tests. Using the Vogelsang tests we found that there was a structural break in the VOC emissions at the time CAAA of 1970 were passed assuming both a known and an unknown break date. Our results differed for NO_X emissions. We did not find a structural change in NO_X emissions when the break date was assumed to be unknown. However, we found that there was a trend break in NO_X emissions when we imposed the break date in 1969. These results are reported in N.S. Jones Ph.D. dissertation and in the earlier versions of this paper and are available upon request.

[5] We note that Fomby and Lin (2006) also found that a trend break in VOC 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 for the first-differences of NO_X emissions in levels and in 1973 for the first-differences of NO_X emissions in logs.

Tables 3 and 4 present the estimated trend functions for the pollution series based on least squares estimation of (1) and the first difference of (1) using 1969 as the break date. The trend estimates are very similar under the assumptions of TS and DS, respectively. The estimates in Table 3 show that the trend reversal in VOC emissions is remarkable. The annual compound rates of growth go from 1.9 percent to -1.7 percent and from 0.3 percent to -2.7 percent for *lvoc* and *lpvoc*, respectively. The trend reduction in NO_X emissions is more modest but still substantial: from 2.8 percent to 0.4 percent and from 1.2 percent to -0.7% for *lnox* and *lpnox*, respectively. Long-run forecasts for these series under the assumption of TS and DS are the extrapolated trends after the break in 1969. Uncertainty about the trend forecasts, however, depends on whether the series are DS or TS. We answer this question in the next Section.

IV. ARE THE U.S. EMISSIONS OF NITROGEN OXIDES AND VOLATILE ORGANIC COMPOUNDS TREND-STATIONARY OR DIFFERENCE-STATIONARY?

In this section we address our second question: Are the U.S. emissions of NO_X and VOC TS or DS? To answer this question we need to test the VOC and NO_X series for the presence of a unit root. Given the results of the previous section, the appropriate unit root test should account for a break in trend, either at a known or an unknown date, and the break should be allowed under both the unit root null hypothesis and the trend stationary alternative. For the unit root tests, the DGP is still assumed to be (1) and (2). The null hypothesis is that y_t is DS ($\alpha = 1$) with a possible trend break at time T_1 (equivalently, break fraction λ_1). The alternative hypothesis is that y_t is TS ($-1 < \alpha < 1$) with a possible trend break.

<u>Unit Root Test with Known Break</u>

For the case of a known break date, Perron (1989) showed that traditional unit root tests, like the Augmented Dickey-Fuller (ADF) test, are inappropriate because they are not invariant to the magnitudes of the trend shift parameters and, as a result, are biased towards non-rejection of a unit root. Indeed, when we apply the ADF and the locally detrended generalized least squares version of the ADF test (ADF-GLS) advocated by Elliot *et al*. (1996), we find that all pollution series follow a DS process.[6] To remedy this problem, Perron (1989) proposed ADF-type and Perron and Rodríguez (2003) proposed ADF-GLS-type unit root tests that allow for a trend shift at a known date under the DS null and the TS alternative. We use these tests to determine if the pollution series are DS or TS under the assumption that a trend shift occurred at the timing of the CAAA of 1970.

The Perron (1989) test for Model III is carried out by estimating the test regression:

$$y_t = \mu + \theta DU_t + \beta t + \gamma DT_t + \pi D(TB)_t + \alpha y_{t-1} + \sum_{i=1}^{k} c_i \Delta y_{t-i} + e_t , \qquad (3)$$

where y_t is either *lnox*, *lpnox*, *lvoc* or *lpvoc*, DU_t and DT_t are as defined after equation (1), $D(TB)_t = 1$ if $t = T_1 + 1$ and 0 otherwise, and $\Delta = 1 - L$ is the first-difference operator. Equation (3) is an IO model that allows the policy change effects of the CAAA of 1970 to take effect gradually. Perron's unit root test is the *t*-statistic computed from (3) to test the null hypothesis that $\alpha = 1$ against an alternative that $|\alpha| < 1$.

For the Perron and Rodríguez (2003) test, the data are assumed to be generated from (1) and (2) with $\alpha = \alpha_T = 1 - c/T$ for $0 \leq c < \infty$. The DS null hypothesis is $H_0 : c = 0$ and the local TS alternative hypothesis is $H_0 : c > 0$. The Perron-Rodríguez test for Model III is based on a quasi-differenced transformation (local detrending) of (1) of the form

[6] These results are available upon request. Elliot *et al*. (1996) showed that the ADF-GLS test has substantially higher power than the ADF test for TS alternatives that are close to the DS null.

$$y_{\bar{c},t} = X_{\bar{c},t}(\lambda_1)'\theta + u_{\bar{c},t} \tag{4}$$

where

$$y_{\bar{c},t} = \begin{cases} y_1 & t=1 \\ y_t - \bar{\alpha}_T y_{t-1} & t = 2,\ldots,T \end{cases},$$

$$X_{\bar{c},t}(\lambda_1) = \begin{cases} X_1(\lambda_1) & t=1 \\ X_t(\lambda_1) - \bar{\alpha}_T X_{t-1}(\lambda_1) & t = 2,\ldots,T \end{cases},$$

with $\bar{\alpha}_T = 1 - \bar{c}/T$ and $X_t(\lambda_1) = (1, t, DU_t, DT_t)'$. The quasi-difference parameter $\bar{c}$ is chosen to be the value of *c* at which the infeasible point optimal test has asymptotic power approximately equal to 0.50.[7] Let $\hat{\theta}_{\bar{c}}$ be the least squares estimate of θ in (4) and let $\hat{u}_t$ denote the resulting residuals from (1). Then the Perron-Rodríguez test is the *t*-statistic for testing $\alpha = 1$ in the test regression

$$\hat{u}_t = \alpha \hat{u}_{t-1} + \sum_{j=1}^{k} c_j \Delta \hat{u}_{t-j} + e_t \tag{5}$$

The local detrending procedure increases the power of the Perron-Rodríguez over the Perron test. However, the local detrending assumes an additive outlier (AO) framework in which the policy change has an immediate impact.

For both tests, we set the break date to T_1=1969. The number of lagged first-difference terms *k* in (3) and (5) are chosen so that the regression error e_t behaves like white noise. To determine k we use sequential *t* rule used by Perron (1989) and the modified Akaike Information Criterion (MAIC) of Ng and Perron (2001). Both rules resulted in the same value of *k*.[8]

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[7] Perron and Rodríguez (2003) showed that $\bar{c}$ depends on λ_1 as well as the significance level of the test. Table 1 in Harris *et al.* (2007) give values of $\bar{c}$ and critical values of the Perron-Rodríguez test for a grid of λ_1 values between 0.15 and 0.85 and for 0.01, 0.05 and 0.10 significance levels, respectively.

[8] We set the maximum of *k* to the integer of ($T^{1/4}$), where *T*=59 for NO_X for VOC, thus, k_{max}= 2.

Tables 5 and 6 report the unit root test results. We conclude that *lnox* and *lpnox* are DS series with 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 have had permanent effects on the NO_X emissions.[9] As a result, the long-term trend in NO_X emissions will be constantly changing to reflect these shocks. In contrast, we reject a unit root in the *lvoc* and *lpvoc* series at the 5% significance level. Rejection of the null for these series indicates that the CAAA of 1970 represented the only permanent shock and all other shocks had only temporary effects.

Our results for *lpnox* differ from the results of Lee and List (2004). They concluded that the *lpnox* series can be viewed as being TS with a one-time break at the time the CAAA of 1970 were 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 the data for the period 1940-1998 whereas they used the data for the period 1900-1994, we re-estimated the test regressions (3) and (5) using the same dataset as Lee and List (2004). We could not reject the null of a unit root in *lpnox*, which contrasts with the results of Lee and List (2004).[10] The difference in the results can be explained by the use of different tests. We chose to use the Perron test for the IO model because, based on Monte Carlo experiments presented in Jones (2009), it has better finite sample properties than the Park and Sung PP test. In particular, the Park and Sung PP test shows substantial size distortion (false

[9] 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.

[10] 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 (3). The estimated Perron-Rodríguez unit root test statistic is -2.17 using $\overline{c}$ = -16.6 from Harris *et al*. (2007). This statistic is greater than the 5% critical value = -3.44 and thus, we do not reject the null of a unit root. We would like to thank Dr. Junsoo Lee and Dr. John A. List for providing us their dataset.

rejections of the unit root null hypothesis) for processes calibrated to match the dynamics of the pollution data.

<u>Unit Root Test with an Estimated Break</u>

As argued by Christiano (1992) and Zivot and Andrews (1992), in order for Perron's unit root tests to be valid the break date should be exogenous; i.e., it should be chosen independently of the data. This is the case for the CAAA of 1970. However, it may be possible that the break in trend due to the CAAA of 1970 occurred at some time before or after 1969. In this case, imposing an incorrect break at 1969 may lead to biases in Perron's unit root tests. That is, a TS series may be erroneously found to be DS if the break date is incorrectly specified. This has implications for the NO_X series because we do not reject the unit root hypothesis using the Perron test imposing the break date at 1969. Hence, it is of interest to consider Perron-type unit root tests for the NO_X series using an estimate of the break date.

Performing unit root tests with an estimated break date is complicated when it is unknown as to whether a trend break occurs or not. There are two cases to consider. First, if it is known that a break occurs, then Kim and Perron (2007) and Harris *et al.* (2007) showed that if the estimated break date converges to the true break date sufficiently fast then it can be treated as known for the Perron and Perron-Rodríguez unit root tests. Unfortunately, they showed that the break date estimated by minimizing the sum of squared residuals from (1) does not converge fast enough to be treated as known for these tests. Fortunately, they proposed estimators of the break date that do converge sufficiently fast. In particular, Harris *et al*. (2007) showed that the break date which minimizes the sum of squared residuals from (1) in first differences can be treated as the known break date for the unit root tests provided a break occurs. Second, if there is no break in trend and the break is estimated then the break point estimator converges to a random variable and the distributions of the Perron and Perron-Rodríguez tests based on treating the estimated break date as known are no longer valid. In this case, one has to use conservative critical values computed under the assumption that no break has occurred that are tailored to the way the break date is estimated as in Zivot and Andrews (1992), Perron (1997) and Perron and Rodríguez (2003).[11] While this approach guards against spurious rejection of the DS null hypothesis, it leads to tests that have poor power against TS alternatives (without breaks) because irrelevant trend break dummy variables are included in the test regressions.

To deal with these issues, we use a two-step method advocated by Perron (2007), Kim and Perron (2007), Harris *et al*. (2007) and Carrion-i-Silvestre *et al*. (2008). In the first step, we pre-test the pollution series of interest for structural change using $Exp\text{-}W_{RFS}$ which is valid whether the series is DS or TS. If this pre-test rejects, we proceed as if we know a break occurs and we evaluate the Perron/Perron-Rodríguez unit root test at the estimate of the break date that minimizes the sum of squared residuals from

$$\Delta y_t = \delta_0 + \delta_1 DU_t + \phi_0 D(TB)_t + u_t \quad , \tag{6}$$

which converges fast enough to be treated as a known break date in the unit root tests if a break exists. If the pre-test does not reject, we proceed as if we know a break does not occur and use the ADF-GLS test for a unit root that does not allow for a break. Harris *et al*. (2007), Kim and Perron (2007) and Carrion-i-Silvestre *et al*. (2008) showed that such a two step procedure leads to unit root tests with good size and power properties whether a break occurs or not.

Applying the two- step procedure to the pollution data leads to the following results. First, as we have already seen, Table 2 shows that the $Exp\text{-}W_{RFS}$ statistic rejects no structural change for all of the pollution series. It also shows that 1969 is the break date that minimizes the sum of

[11] One can also use the LM type tests of Lee and Strazicich (2003; 2004).

squared residuals from (6). Therefore, the unit root test results when the break date is estimated are the same as when the break date is assumed to be 1969.

V. FORECASTING OF THE FUTURE EMISSIONS

Forecasts of the future pollution emissions differ for TS and DS series with 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 two different model specifications: (1) TS with a trend break and (2) DS with a trend break. The former is the specification of Lee and List (2004) and the latter is our specification. Figure 4 (a) and (b) shows forecasted values of the natural logarithm of per capita NO_X emissions along with $\pm$ 1.96 standard deviations bands for the period 1999-2020 under two model specifications. We assume that the trend break occurred at the time the CAAA of 1970 were passed. From Figure 4 we see that forecasted trend is downward sloping for both TS and DS NO_X emissions with a break but the magnitude of the slope is larger and the forecast confidence bands are narrower for a TS series compared to a DS series. We also estimate the TS model with a trend break for the natural logarithm of per capita VOC emissions and Figure 4 (c) shows its forecasted values along with $\pm$ 1.96 standard deviations bands for the period 1999-2020. The forecasted trend of the VOC emissions is declining rapidly with a very narrow confidence band.

VI. CONCLUSION

We have applied state-of-the-art time-series econometric techniques to determine whether there was a break in the trends of NO_X and VOC emissions around the time the CAAA of 1970 were passed, and to determine whether these emissions are DS or TS. Our analysis revealed that the trend behavior of NO_X and VOC emissions is substantially different. We found that VOC emissions can be described as being TS series with a break at the time the CAAA of 1970 were passed. This finding suggests that the environmental regulation in 1970 has changed VOC emissions from increasing to decreasing. In addition, all other shocks will have only short-term effects, and thus, we should expect VOC emissions to continue to decline steadily. Our analysis finds that NO_X emissions is a DS series with a break in its deterministic trend at the time the CAAA of 1970 were passed. This implies that the upward drift in NO_X emissions has been permanently reduced but that the overall trend continues to change randomly and there is considerable uncertainty about the direction of its future behavior.

One explanation for the different trend behavior of NO_X and VOC emissions is the use of more stringent controls of VOC compared to NO_X to reduce O_3 level in 1970s and 1980s. O_3 is not emitted directly into the air, but at ground-level is created by a chemical reaction between NO_X and VOC in the presence of sunlight. Therefore, controls must be placed on either NO_X, VOC or some combination of both to reduce O_3. In the first two decades of O_3 pollution mitigation in the U.S., VOC 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 VOC emissions to mitigate O_3 levels could have contributed to a significant decline in VOC emissions after 1970.

For future research, we can consider the possibility of multiple breaks in the pollution series due to other major environmental policies such as CAAA of 1977 and 1990. Jones (2008) used the procedure of Bai and Perron (1998; 2003) to determine whether or not there was a break (or breaks) in the mean of the first-differenced natural logarithm of per capita NO_X emissions for the period 1900-1998 and found only one break in 1977. [12] However, there is a caveat associated with the Bai and Perron test. The test is appropriate for detecting break dates in stationary time series and only considers a change in the mean of first-differenced data. As a result, 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. This problem can be overcome by using an extension of the Perron and Yabu (2007) test in Kejriwal and Perron (2009) to allow for multiple breaks.

[12] Jones (2008) performed ADF unit root test for the first-difference of the natural logarithm of per capita NO_X emissions and rejected the null of a unit root.

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APPENDIX A

Perron and Yabu (2007) Structural Break Tests

Regression equation:

$y_t = x_t'\Psi + u_t$

$u_t = \alpha u_{t-1} + e_t$ (or $AR(p)$ error term)

$e_t \sim iid\left(0, \sigma^2\right)$

We consider Model III: Structural Change in both intercept and slope $H_0 : \mu_1 = \beta_1 = 0$

$x_t = \left(1, DU_t, t, DT_t\right)'$

$\Psi = \left(\mu_0, \mu_1, \beta_0, \beta_1\right)'$

where $DU_t = 1$ if $t > T_1$ and 0 otherwise, $DT_t = t - T_1$ if $t > T_1$ and 0 otherwise, T_1 is a break year, $\lambda_1 = \frac{T_1}{T}$ is a break fraction.

Procedure:

Step 1: Detrend the data by OLS to obtain residuals $\hat{u}_t$ (i.e. regress y_t on x_t).

Step 2: Estimate equation $\hat{u}_t = \alpha\hat{u}_{t-1} + \sum_{i=1}^{k}\zeta_i\Delta\hat{u}_{t-i} + e_{tk}$

Select k by BIC, set $k_{\max} = \left[0{,}12\left(\frac{T}{100}\right)^{\frac{1}{4}}\right]$. Get $\hat{\alpha}$ and $\hat{\tau}$.

If $k = 0$, then we have AR(1) errors

AR(1) errors case

Step 3: Use $\hat{\alpha}$ and $\hat{\tau}$ to get Roy and Fuller (2001) biased corrected estimates $\hat{\alpha}_M$

$$\hat{\alpha}_M = \hat{\alpha} + C\left(\hat{\tau}\right)\hat{\sigma}_\alpha$$

$$C\left(\hat{\tau}\right) = \begin{cases} -\hat{\tau} \text{ if } \hat{\tau} > \tau_{pct} \\ I_p T^{-1}\hat{\tau} - (1+r)[\hat{\tau} + c_2(\hat{\tau} + a)]^{-1} \text{ if } -a < \hat{\tau} \le \tau_{pct} \\ I_p T^{-1}\hat{\tau} - (1+r)\hat{\tau}^{-1} \text{ if } -c_1^{1/2} < \hat{\tau} \le -a \\ 0 \text{ if } \hat{\tau} \le -c_1^{1/2} \end{cases}$$

where $c_1 = (1+r)T$, r is the number parameters estimated in the trend function (i.e. 4), $c_2 = \left[(1+r)T - \tau_{pct}^2 \left(I_p + T \right) \right] \left[\tau_{pct} \left(a + \tau_{pct} \right) \left(I_p + T \right) \right]^{-1}$, $a = 10$, τ_{pct} is a percentile of the limit distribution of $\hat{\tau}$ when $\alpha = 1$. Use $\tau_{0.95}$ for a known break case and $\tau_{0.99}$ for an unknown break case from Perron (1989), and $I_p = \left[\left(p+1 \right) / 2 \right]$, p is order of AR errors.

<u>Step 4:</u> Apply truncation:

$$\hat{\alpha}_{MS} = \begin{cases} \hat{\alpha}_M & \text{if } \left| \hat{\alpha}_M - 1 \right| > T^{-\frac{1}{2}} \\ 1 & \text{if } \left| \hat{\alpha}_M - 1 \right| \leq T^{-\frac{1}{2}} \end{cases}$$

<u>Step 5:</u> Apply the quasi GLS procedure with $\hat{\alpha}_{MS}$ to obtain estimate of Ψ . Estimate regression equation $\left(1 - \hat{\alpha}_{MS} L\right) y_t = \left(1 - \hat{\alpha}_{MS} L\right) x_t{}' \Psi + \left(1 - \hat{\alpha}_{MS} L\right) u_t$ for $t = 2, \ldots, T$ together with $y_1 = x_1{}' \Psi + u_1$. Denote residuals $\hat{e}_t$. Denote the estimates by $\hat{\Psi}$. Compute Wald test as follows: $W_{RQF} = \left[R\hat{\Psi} - \gamma \right]' \left[s^2 R \left(X'X \right)^{-1} R' \right] \left[R\hat{\Psi} - \gamma \right]$ where $X = (1 - \hat{\alpha}_{MS} L) x_t$ and $s^2 = T^{-1} \sum_{t=1}^{T} \hat{e}_t^2$.

<u>Step 6:</u> when break date is unknown repeat steps 1-5 for all permissible break dates and construct $Exp - W_{RQF}$ test as follows:

$Exp - W_{RQF} = \log \left[T^{-1} \sum_{\Lambda} \exp \left(\frac{1}{2} W_{RQF} \left(\lambda_1' \right) \right) \right]$ where $\Lambda = \left\{ \lambda_1'; \varepsilon \leq \lambda_1' \leq 1 - \varepsilon \right\}$ for some $\varepsilon > 0$. Here T_1' (or λ_1') denotes a generic break date (or break fraction) used to construct particular value of the Wald test.

AR(p) errors case

Steps 3 and 4 are the same as for AR(1) errors.

<u>Step 5:</u> Apply the quasi GLS procedure with $\hat{\alpha}_{MS}$ to obtain estimate of Ψ . Estimate regression equation $\left(1 - \hat{\alpha}_{MS} L\right) y_t = \left(1 - \hat{\alpha}_{MS} L\right) x_t{}' \Psi + \left(1 - \hat{\alpha}_{MS} L\right) u_t$ for $t = 2, \ldots, T$ together with $y_1 = x_1{}' \Psi + u_1$. Denote the estimates by $\tilde{\Psi}$. The specific form of the Wald test depends on the model and whether errors are I(0) or I(1).

<u>Case I(0) errors:</u> The Wald test is computed as follows

$W_{RQF} = \left[R\tilde{\Psi} - \gamma \right]' \left[\hat{h}_\upsilon R \left(X'X \right)^{-1} R' \right] \left[R\tilde{\Psi} - \gamma \right]$ where $X = (1 - \hat{\alpha}_{MS} L) x_t$. The only difference from AR(1) errors is that s^2 is now replaced by $\hat{h}_\upsilon$, an estimate of (2π times) the spectral density function at frequency zero of $\upsilon_t = \left(1 - \alpha L\right) u_t$. Perron and Yabu suggest using one of the two proposed estimates of $\hat{h}_\upsilon$.

Type 1: $\hat{h}_{\upsilon} = T^{-1}\sum_{t=1}^{T}\hat{\upsilon}_t^2 + T^{-1}\sum_{j=1}^{T-1}\omega(j,m)\sum_{t=j+1}^{T}\hat{\upsilon}_t\hat{\upsilon}_{t-j}$, where $\hat{\upsilon}_t = (1-\hat{\alpha}_{MS}L)\hat{u}_t$

Type 2: Estimate regression $y_t - \hat{\alpha}_{MS}y_{t-1} = x_t{}'\Psi^* + \sum_{i=1}^{k} p_i\Delta y_{t-i} + e_{tk}$, denote residuals $\hat{e}_{tk}$ and compute $\hat{h}_{\upsilon} = (T-k)^{-1}\sum_{t=k+1}^{T}\hat{e}_{tk}^2$.

Case I(1) errors: Type 2 $\hat{h}_{\upsilon}$ is computed as follows. Now $\hat{\upsilon}_t = \Delta\hat{u}_t$. Estimate regression $\hat{\upsilon}_t = \sum_{i=1}^{k}\zeta_i\hat{\upsilon}_{t-i} + e_{tk}$. Denote the estimate by $\hat{\zeta}(L) = \left(1-\hat{\zeta}_1 L\cdots-\hat{\zeta}_k L^k\right)$ and $\hat{\sigma}_{ek}^2 = (T-k)^{-1}\sum_{t=k+1}^{T}\hat{e}_{tk}^2$, then $\hat{h}_{\upsilon} = \hat{\sigma}_{ek}^2/\hat{\zeta}(1)^2$.

Since Model III includes change in intercept the Wald test should be computed differently in this case.

$W_{RQF}^* = \left[R\tilde{\Psi}^* - \gamma\right]'\left[\hat{h}_{\upsilon}R\left(X'X\right)^{-1}R'\right]\left[R\tilde{\Psi}^* - \gamma\right]$ where $\tilde{\Psi}^* = (\tilde{\mu}_0, \tilde{\mu}_1^*, \tilde{\beta}_0, \tilde{\beta}_1)'$ and

$\tilde{\mu}_1^* = \hat{h}_{\upsilon}^{\frac{1}{2}}\hat{\zeta}(L)\tilde{\mu}_1(T_1)/\hat{\sigma}_{ek}$.

Following Perron and Yabu we use type 1 estimate of $\hat{h}_{\upsilon}$ for I(0) errors and type 2 for I(1) errors.

Step 6: With unknown break tests statistic needs to be evaluated for each break date candidate and the *Exp* functional is evaluated.

TABLE 1

Perron and Yabu (2007) Structural Break Test, Known break case, Model III, $T_1 = 1969$

y_t	W_{RQF}	k
lnox	23.20**	1
lpnox	17.59**	1
lvoc	441**	2
lpvoc	264**	2

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

Notes: 5% and 10% critical values for $\chi^2(2)$ distribution are 5.99 and 4.61, respectively. k represents a lag length correction for autocorrelation.

TABLE 2

Perron and Yabu (2007) Structural Break Test, Unknown break case, Model III

y_t	$Exp - W_{RQF}$	Estimated Break Year using regression (1) in levels	Estimated Break Year using regression (1) in first-differences
lnox	8.49**	1969	1969
lpnox	5.76**	1969	1969
lvoc	234**	1969	1969
lpvoc	110**	1969	1969

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

Notes: 5% and 10% critical values for $I(0)$ errors are 3.34 and 2.68 and for $I(1)$ errors are 3.55 and 2.96, respectively (Perron and Yabu, 2007, Table 1).

TABLE 3

Estimated OLS coefficients from regression $y_t = \mu_0 + \mu_1 DU_t + \beta_0 t + \beta_1 DT_t + e_t$ when $T_1 = 1969$

y_t	μ_0	μ_1	β_0	β_1
lnox	8.95	0.22	0.029	-0.025
lpnox	-2.80	0.24	0.012	-0.019
lvoc	9.69	0.09	0.019	-0.036
lpvoc	-2.06	0.11	0.003	-0.031

TABLE 4

Estimated OLS coefficients from regression $\Delta y_t = \delta_0 + \delta_1 DU_t + \phi_0 D(TB)_t + u_t$ when $T_1 = 1969$

y_t	δ_0	δ_1	ϕ_0
lnox	0.032	-0.027	0.099
lpnox	0.018	-0.023	0.097
lvoc	0.015	-0.034	0.166
lpvoc	0.001	-0.031	0.164

TABLE 5

Perron (1989) Unit Root Test

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

y_t	*k*	*t-statistic*
lnox	0	-3.93
lpnox	2	-3.06
lvoc	1	-5.08***
lpvoc	1	-4.66**

*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 $\lambda = T_1 / T = 0.5$

(Perron 1989, Table VI.B).

TABLE 6

Perron and Rodriguez (2003) Unit Root Test

Test regression: $\hat{u}_t = \alpha \hat{u}_{t-1} + \sum_{j=1}^{k} c_j \Delta \hat{u}_{t-j} + e_t$

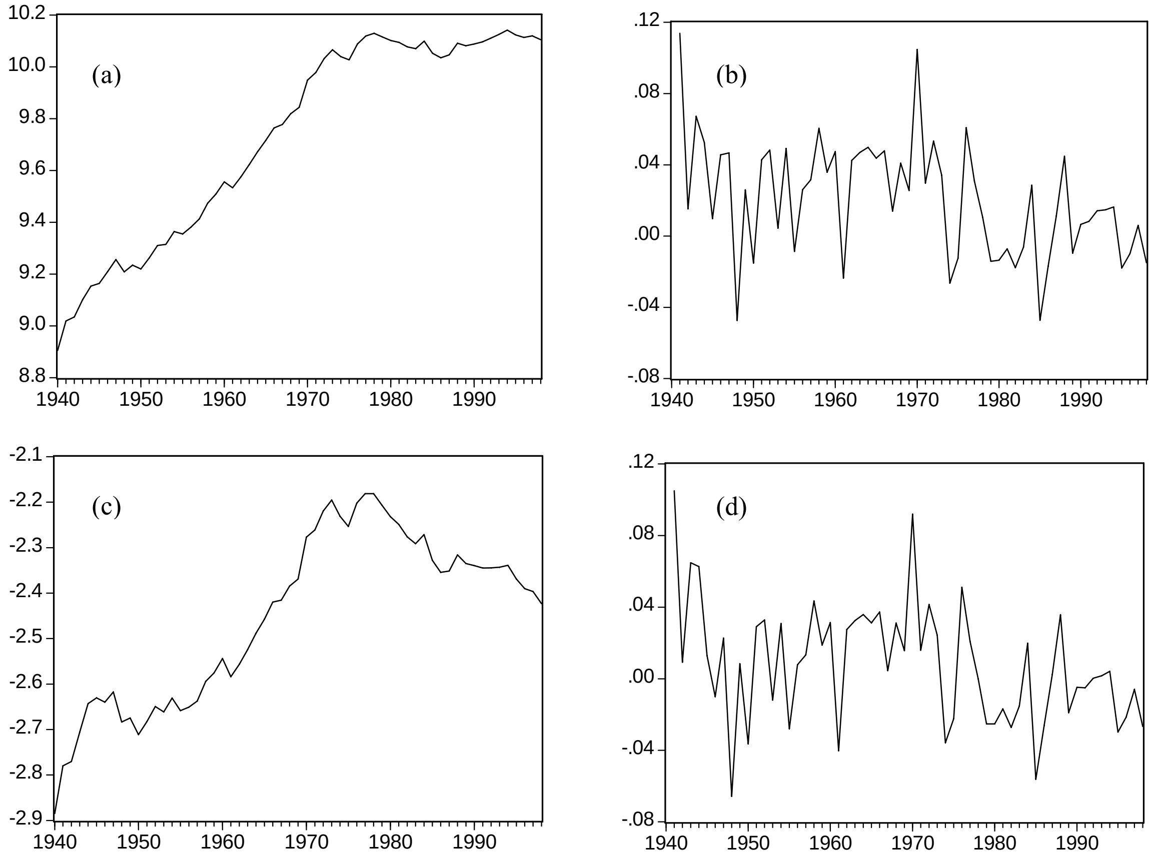
y_t	*k*	*ADF-GLS statistic*
lnox	1	-2.49
lpnox	1	-2.29
lvoc	2	-3.98**
lpvoc	2	-4.00**

**Significant at the 5% level.

Critical value at the 5% level is -3.55 and $\bar{c} = -18.2$ (Harris *et al*. 2007, Table 1).

FIGURE 1

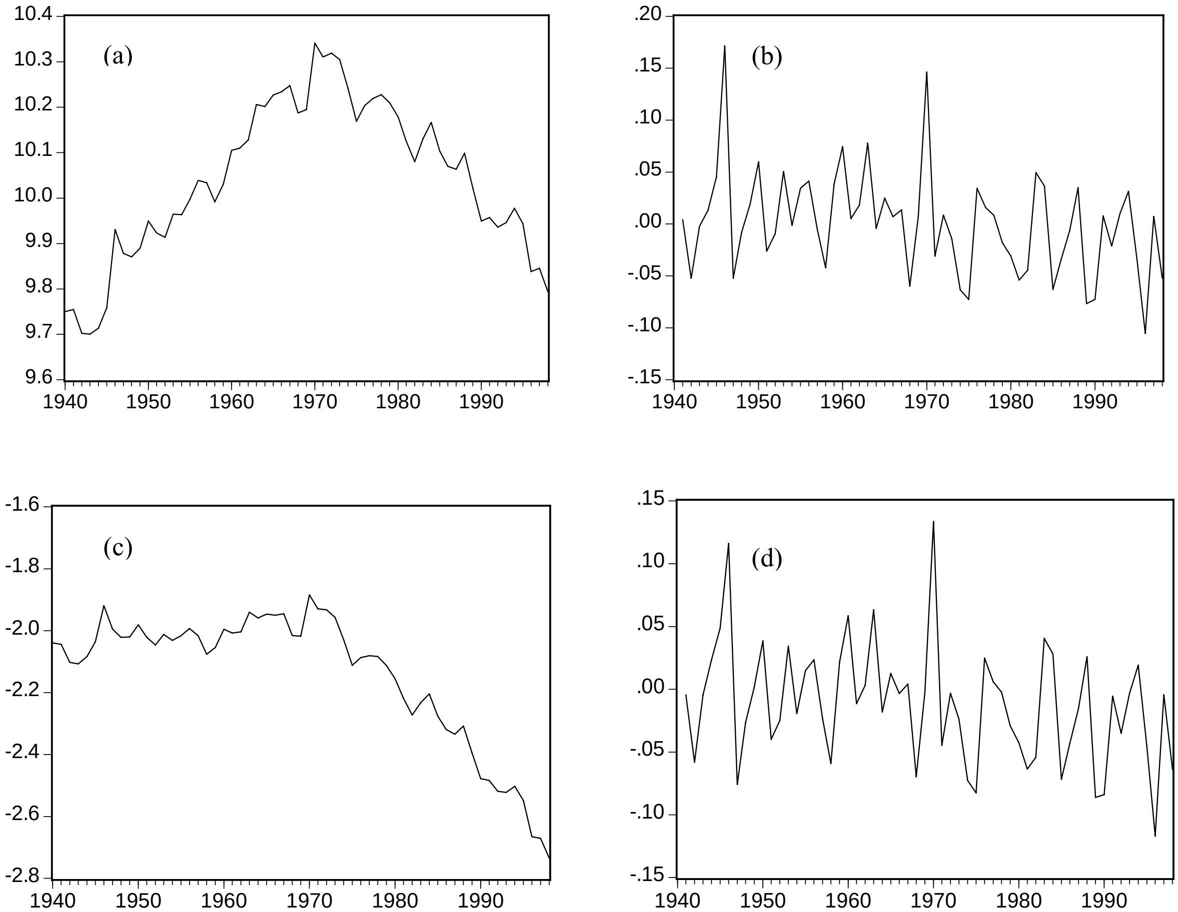
NO_X Emissions Series, 1940-1998



Panels (a), (b), (c), and (d) show 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 2

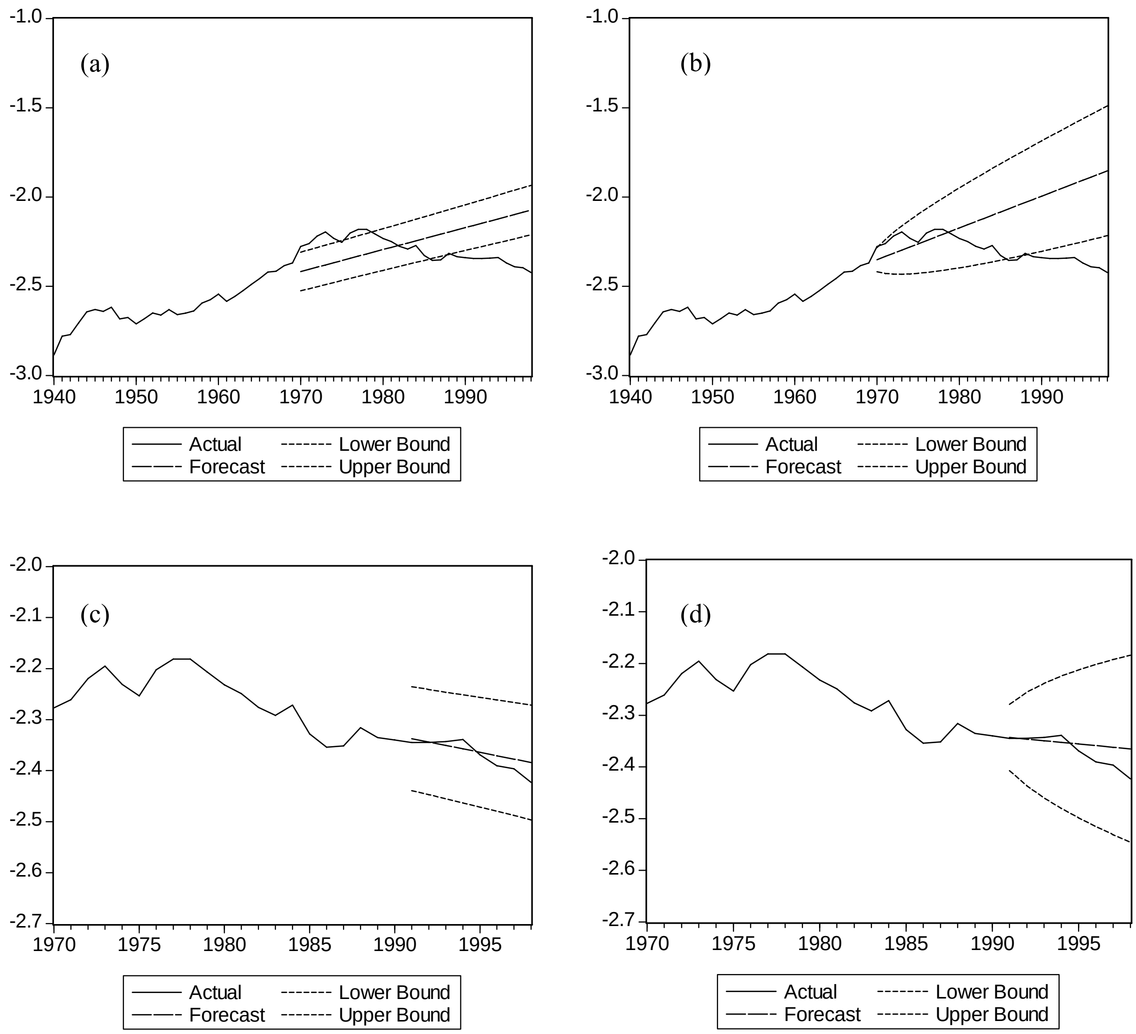
VOC Emissions Series, 1940-1998



Panels (a), (b), (c), and (d) show 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

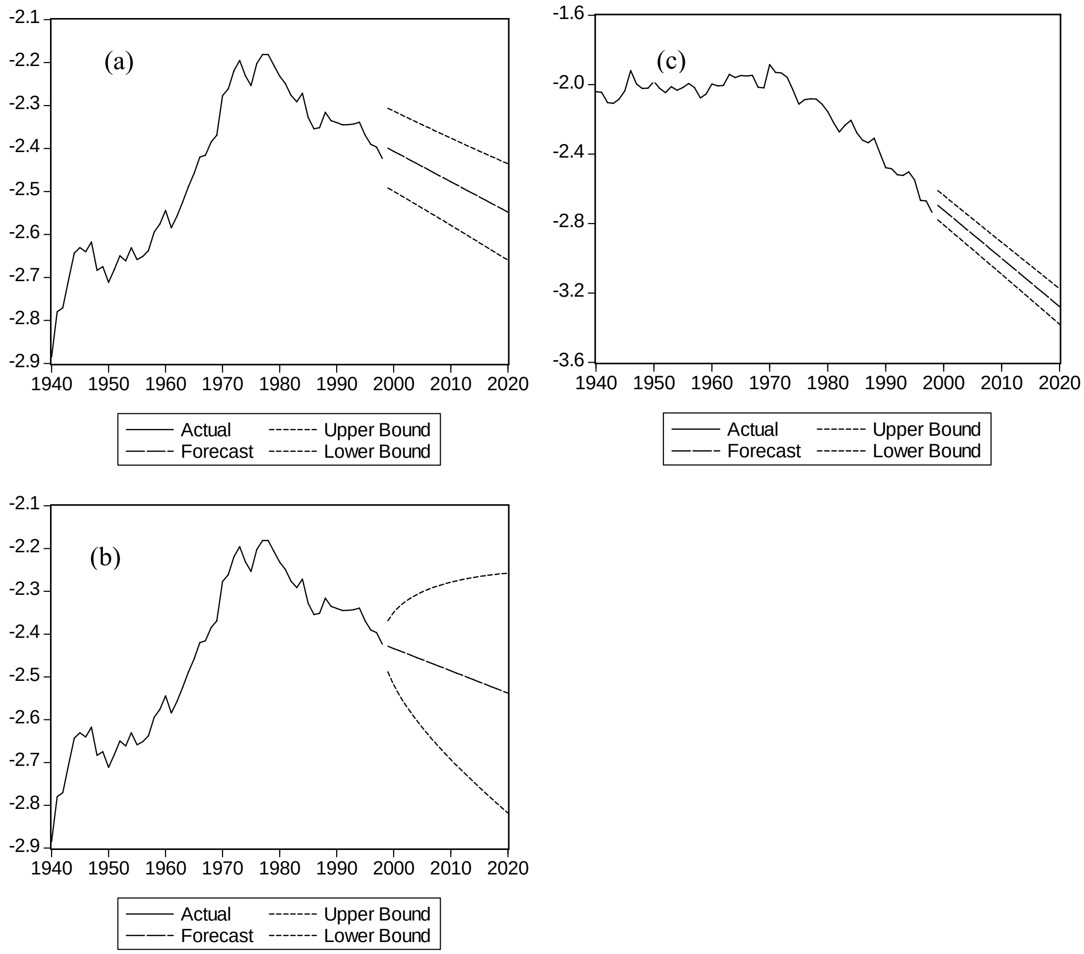
Difference between Forecasts for TS and DS Natural Logarithm of Per Capita NO_X Emissions



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 estimated TS model $y_t = a + bt + \varepsilon_t$ and DS model $\Delta y_t = b + \varepsilon_t$ for the period 1940-1969. 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. We estimated TS model $y_t = a + cDU_t + bt + dDT_t + \varepsilon_t$ and DS model $\Delta y_t = b + cDU_t + dD(TB)_t + \varepsilon_t$ for the period 1940-1990 assuming the break occurred in 1969. In the above forecasts we ignored ARMA structure in the error terms.

FIGURE 4

Forecasts of the TS and DS emissions series with a trend break



Panel (a) shows actual values for the period 1940-1998 and forecasted values for the period 1999-2020 along with ± 1.96 standard deviations assuming *lpnox* is TS with a break. Panel (b) shows actual values for the period 1940-1998 and forecasted values for the period 1999-2020 along with ± 1.96 standard deviations assuming *lpnox* is DS with a trend break. Panel (c) shows actual values for the period 1940-1998 and forecasted values for the period 1999-2020 along with ± 1.96 standard deviations assuming *lpvoc* is TS with a break. We estimated TS model $y_t = a + cDU_t + bt + dDT_t + \varepsilon_t$ and DS model $\Delta y_t = b + cDU_t + dD(TB)_t + \varepsilon_t$ for the period 1940-1998 assuming the break occurred in 1969.