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Regulatory effectiveness and the long-run policy horizon: The case of U.S. toxic chemical use

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ABSTRACT

This paper employs state-of-the-art time series analysis to examine the long-run economic and institutional drivers of toxic chemical use behavior in the U.S. Toxic chemicals are classified into *growth*, Environmental Kuznets Curve (*EKC*), and *kinked-growth* chemicals, according to their long-run use trend behavior. Cointegration analysis shows that while some toxic chemicals have been successfully reduced by regulatory efforts, a majority of the toxic chemicals used in commercial products share a long-run equilibrium with national accounts and industrial production, suggesting that toxic chemical use has been largely driven by changes in GDP, industrial production, and private R&D investments, rather than by government regulations. Estimated structural break results indicate that the 1986 Emergency Planning and Community Right-to-Know Act, which created the Toxic Release Inventory has had impact on the consumptive use of more poisonous industrial chemicals than command-and-control regulations.

1. Introduction

Unlike other major environmental laws, the Toxic Substances Control Act (TSCA), which underpins U.S. toxic chemical regulation has not been significantly amended since it was adopted by Congress in 1976. This may be beginning to change: a major spill of a chemical used to wash coal (three methylcyclohexane methanol) into West Virginia's Elk River in 2014 has renewed the debate over toxic chemical policy reform.[1] In light of this renewed attention on toxic chemical policy reform, this paper examines the determinants of long-run policy effectiveness since the advent of the Environmental Protection Agency (EPA), the chief regulator of toxic chemical use and emissions in the U.S.

Toward this effort, recently developed structural change and unit root tests, as well as cointegration analysis are employed to answer three questions: first, which of the enacted federal regulations have had a restraining effect on the industrial use of toxic chemicals? Second, what do the time series properties of the toxic chemical use data reveal about the potential effectiveness of policy interventions over the long-run? Relatedly, are there clusters of chemicals that share a common trend, which suggest shared economic and institutional drivers of long-run change?

In addition to answering these questions, this paper establishes the proper statistical methodology to evaluate policy impacts on variables of interest when data are vectors of single time series that can be either difference-stationary (DS or $I(1)$) or trend-stationary (TS or $I(0)$). The statistical methods

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[1] *Source*: http://online.wsj.com/articles/SB10001424052702304347904579312401864798652 (Retrieved December 1, 2014).

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that are applied in this paper can be used by researchers and analysts to conduct analyses on other time series and relate them to understanding long-run drivers of change.

Time series econometrics have been mainstay tools in macroeconomic growth and finance studies but are less widespread in other areas of applied economics. Yet, uncovering the temporal dynamics of data could be informative for policy making. Proper time series methods can aid in the optimal setting of regulatory policy by providing information about the temporal dynamics of the variables of interest, as well as examining causal effects of policy interventions.

Previous research has utilized time series techniques to confirm or deny the existence of the Environmental Kuznet Curve in OECD countries (e.g., Chang and Lee, 2008; Friedl and Getzner, 2003; Romero-Ávila, 2008; Friedl and Getzner, 2003) and examine the stochastic properties of natural resource stock, flows, and prices (Ahrens and Sharma, 1997; Berck and Roberts, 1996; Labson, 1995; Labson and Crompton, 1993; Lee et al., 2006; Alberola et al., 2008; McMillan et al., 2010).

By contrast, the dynamics of pollution data have seldom been investigated with time series analysis. That being said, a new line of research in pollution time series dynamics is emerging. Lee and List (2004), Fomby and Lin (2006), McKitrick (2007), and Sidneva and Zivot (2014) investigate the time series properties of the NO_x, SO_2, and/or VOCs emissions. These authors find evidence to suggest that the 1970 Clean Air Act and related amendments have had a permanent negative effect on air pollution. Moreover, Bulte et al. (2007) find strong evidence of converging emission rates for NO_x and SO_2 during the federal pollution control years (1970–1999) as opposed to the local or state control years (1929–1969). This study seeks to contribute to this emerging body of research.

A methodological issue that has hampered the ready use of time series analysis in empirical studies is the identification problem between the existence of unit roots and structural changes.[2] As is commonly known, analysis on data that contain a unit root (i.e., DS or *I*(1) data) could lead to spurious results. The existence of structural breaks or permanent shifts in the mean and/or slope of the data obscures both the size and power properties of conventional statistical tests on the existence of unit roots (e.g., Zivot and Andrews, 1992), where typically a structural break is allowed in the alternative but not in the null hypothesis. In effect, there is a bias toward not rejecting the null hypothesis of a false unit root when structural breaks are ignored (Amsler and Lee, 1995; Perron, 1989).

Similarly, the distributions of traditional statistical tests for structural breaks depend on whether the noise component of the data can be perceived as being trend-stationary (i.e., *I*(0) or unit root free) or difference-stationary. Differencing the data, as is commonly done, does not help because differenced data, which is equivalent to assuming a trend-stationary noise component, have very poor properties when the data in fact have a trend-stationary or unit root-free noise component (Perron and Yabu, 2009a; Vogelsang, 1998).

This paper's empirical strategy resolves this identification problem by employing recently developed methodologies to analyze the historical use time paths of 13 industrial toxic chemicals from 1900 to the present. The advanced time series methods enable (i) robust detection of multiple structural breaks in the mean and/or the slope of the trend function that have the same distribution whether the data are trend-stationary or difference-stationary, (ii) reliable inference regarding the presence of a unit root conditional on the presence/absence of breaks under both the null and the alternative hypotheses, and (iii) robust inference regarding the existence of cointegrating relationships (i.e., co-movements) allowing for the presence of structural breaks.

Government policies and other interventions are said to have a permanent effect if they impart a permanent structural shift (i.e., a reduction in the level and/or the slope) in the trend path of the data. Existence of a structural break in toxic chemical use around the timing of a government policy provides compelling evidence of the effectiveness of the policy but does not necessary establish causality, and comparing pre and post break trends quantifies this effectiveness. If no reduction in trend is found then it can be concluded a policy intervention did not permanently reduce toxic chemical use. Therefore, a natural test for the effectiveness of government policies is a test for a reduction in the trend in toxic chemical use around the time that a policy or program was implemented.

The distinction between *I*(0) and *I*(1) processes in trend behavior 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 (Sidneva and Zivot, 2014). For both processes, long-term forecasts are the extrapolated deterministic trend. However, forecast uncertainty for a *I*(1) process increases with the forecast horizon whereas it is bounded for a TS process.

A series that is *I*(0) with a broken trend suggests that a given policy intervention will likely be relatively effective because the series/variable will remain close to the new trend (that is induced by a given policy) rather than drift in a random walk fashion. By contrast, a series represented by a *I*(1) process with a broken trend suggests that the series/variable will likely drift in a random walk fashion, i.e., the overall trend will change randomly to reflect all shocks. The empirical implication is that the long-term effect of a policy that changes the trend is much more certain when the data are *I*(0) than when they are *I*(1).

In this paper, for the toxic chemical use series that follow a deterministic or *I*(1) process, cointegration analyses determine whether there is a long-run equilibrium relationship among chemicals that are regulated under the same laws and whether there are clusters of chemicals that share common trends, which could suggest common economic and institutional drivers. The cointegration analyses provide corroborating evidence as to whether the major umbrella federal environmental regulations that control a wide range of industrial toxic chemicals have had a comprehensive impact as purported by law on the *I*(1) toxic chemical series. Moreover, cointegrating relationships among these series and national accounts and industrial production suggest that the long-run trend behavior of toxic chemical use is linked to aggregate economic behavior.

This paper's empirical analysis permits a robust classification of the 13 industrial chemical use time series under investigation into three categories according to their trend

[2] I refer to structural changes also as structural breaks, change-points, structural shifts, and shifts in the mean and/or slope of the trend, depending upon the usage in the literature cited.

behavior over the long-run policy horizon (1900–2011): *growth*, Environmental Kuznet Curve (*EKC*), and *kinked-growth* chemicals. By and large, structural changes occurred around the time of economic booms and busts, World War II, environmental regulations, and industry developments. The 1986 Emergency Planning and Community Right-to-Know Act, which created the Toxic Release Inventory—an information disclosure policy—has had impact on the consumptive use of more poisonous industrial chemicals than command-and-control regulations.

While the *kinked-growth* chemical use time series exhibit stationarity, forecast uncertainty characterizes the trends of the *EKC* and the *growth* chemicals because these series contain a unit root, which suggests that the potential effect of policy interventions is less predictable given that changes in the trend are likely to correspond to random shocks rather than hold close to a new trend associated with a policy change.

Moreover, cointegration analysis shows that while some toxic chemicals have been successfully phased-out or reduced by regulatory efforts, a majority of the *EKC* and *growth* chemicals used in commercial products share a long-run equilibrium with national accounts and industrial production, suggesting that toxic chemical use in the U.S. has been driven by changes in U.S. GDP, industrial production, and private investments in R&D, rather than by government regulations.

The reminder of the paper is as follows. In Section 2, I present background information on toxic chemical use policy and efficacy in the U.S. In Section 3, data and empirical strategy and models are presented. I report results on the tests for structural breaks and classify the toxic chemicals into three categories of long-run use trend behavior in Section 4. In Section 5, results are presented on unit root tests that allow for possible trend breaks under the null and the alternative hypotheses to determine what the time series properties of toxic chemical use reveal about long-run policy effectiveness. Results on cointegration tests are reported to adjudicate on the long-run drivers of change in toxic chemical use in Section 6. Finally, Section 7 concludes with a discussion of the paper's findings and their policy implications.

2. Background: regulatory policy and efficacy

The virtues and vices of toxic chemicals have meant that they are highly controlled substances: these toxic chemicals are target substances in all major federal environmental legislations as well as the subjects of international agreements (e.g., Basel Convention on the Control of Transboundary Movements of Hazardous Wastes and their Disposal). Before the mid-1960s, there was very little policymaking addressing toxic chemical use at the federal level; whatever government intervention, if any, occurred at the state level (Ringquist, 1993). By and large, this was an era marked by rapid industrial development and commercialization; two world wars spurred the demand and the development of weaponry and commercial products that required toxic chemical inputs.

As the modern environmental movement gained political force (Anderson, 1994; Carson, 1962), the enactment of the 1969 National Environmental Policy Act and the subsequent establishment of the EPA in 1970 ushered in the environmental regulatory era. Since then toxic but economically important chemicals have been largely placed under the jurisdiction of command-and-control regulations (Revesz, 2001; Stavins, 2004).

Between 1970 and 1990, three out of the eight major federal statutes addressed the handling, use, and emissions of toxic chemicals: the Federal Insecticide, Fungicide, and Rodenticide Act (FIFRA) of 1972, the Toxic Substances Control Act (TSCA) of 1976, and the Emergency Planning and Community Right-to-Know Act (EPCRA) of 1986, which established the Toxics Release Inventory. The first two of the three laws were conventional command-and-control regulations that stipulate the use of the "best available technology economically achievable" (Revesz and Stavins, 2007). By contrast, the third legislation was the first time Congress passed an information disclosure regulation, whereby the emphasis is on increasing the transparency of chemical hazards present in local communities.

A challenge facing toxic chemical regulation in the U.S. and beyond is the rapid speed of technological development in toxic chemical-using sectors. It has been challenging for regulators to understand the toxicology of currently available toxic chemicals and their impact on human health and the environment before the next new chemical is on the market (GAO, 2007). Thus the EPA, the federal regulator of industrial chemical use and emissions has increasingly worked with the private sector to curb toxic chemical use through government or private sector sponsored voluntary programs, including voluntary agreements that are negotiated between regulators and private industry to reduce or phase-out industrial chemicals (Morgenstern and Pizer, 2007).

Three prominent government-sponsored voluntary programs that targeted the reductions of a wide range of toxic chemicals are the EPA's 33/55 Program, which was created in 1991, the 1996 Great Lakes Binational Toxic Strategy (GLBTS), and the 1998 High Production Volume (HPV) Challenge. Prominent industry-initiated voluntary programs include the 1996 voluntary agreement between the agriculture sector and the EPA to reduce arsenic acid in cotton production, the 2003 voluntary agreement between the pressure-treated wood industry and the EPA to ban CCA, which is a poisonous arsenic compound in residential uses, as well as the 1998 voluntary stewardship initiative by the chlor-alkali industry to reduce mercury use in chlorine production.

2.1. *Regulatory efficacy*

How effective have federal environmental regulations been in reducing toxic chemical use, all else equal? The general consensus is that command-and-control regulations have been overly prescriptive and burdensome on firms and regulators alike and often do not pass benefit–cost tests (Anderson, 1994; Revesz and Stavins, 2007; Hahn, 2000; Stavins, 2004). In particular, FIFRA has not prevented the proliferation of pesticides that are suspected of being unsafe, in part because the EPA has been overwhelmed by the burden of reviewing the data and assessing the risk (Anderson, 1994).

Similarly, the government's own evaluations of the TSCA find that the law places too much burden on the EPA to demonstrate that a chemical poses a risk to human health or

Table 1 – Commercial applications and environmental hazards of toxic chemicals.

Toxic chemicals	Commercial applications	Human carcinogen	Health benefits	National defense stockpile	EPA priority
Antimony	Ammunition; batteries; plastics			●	232
Arsenic	Electronics; pesticides; glass	●			1
Asbestos	Building materials; friction products	●			94
Beryllium	Electronics; nuclear; mirrors	●		●	43
Bromine	Pesticides; flame retardants; pharmaceuticals				153
Cadmium	Aircraft; batteries; wireless	●		●	7
Chromium	Aircraft; missiles	●		●	78
Cobalt	Aircraft; electronics; steel	●	●	●	52
Lead	Ammunition; batteries; wireless	●		●	2
Manganese	Batteries; steel; wireless		●	●	N/A
Mercury	Basic inorganic chemicals; electronics			●	3
Selenium	Electronics; pesticides; glass	●	●	●	146
Zinc	Batteries; steel; paint; preservatives		●	●	75

Source: Agency for Toxic Substances & Disease Registry, U.S. Department of Defense, USGS.

the environment before the EPA can promulgate formal rules to regulate its production or use (GAO, 1994, 2005, 2007). In fact, since the passage of the TSCA, the EPA has promulgated directives for only nine chemicals: five are "existing" chemicals or chemicals that have already been inventoried when TSCA was enacted (GAO, 2005), as well as four new chemicals that were discovered or developed since 1976.[3] These findings suggest that umbrella command-and-control regulations (namely, FIFRA and TSCA) have had minimal effect in reducing the industrial use of specific toxic chemicals.

By contrast, studies have shown that the Toxic Release Inventory (or the TRI as is commonly called), has been associated with declines in reported toxic releases and worker chemical exposure under certain conditions, such as when publicly traded firms use the disclosed information for their environmental management-related decision-making (Khanna et al., 1998; Konar and Cohen, 1997; Weil et al., 2006; Finger and Gamper-Rabindran, 2013).

Studies on the effectiveness of voluntary programs have generally been mixed. Government-sponsored and industry initiated voluntary programs have tended to yield modest or no impact on abating pollution (Gamper-Rabindran and Finger, 2012; Gamper-Rabindran, 2006; Morgenstern and Pizer, 2007; Vidovic and Khanna, 2007; Welch et al., 2000; Khanna and Damon, 1999). However, voluntary agreements negotiated between government and private industry that stipulate guidelines for compliance and sanctions for noncompliance in specific industries have fared considerably better than other types of voluntary programs in their efficacy (Glachant and Muizon, 2007; Glachant, 2007; Hsueh, 2013; Krarup and Millock, 2007). For example, Hsueh (2013) finds that two industry-initiated voluntary agreements to ban the use of poisonous arsenic compounds are associated with substantial declines in arsenic use.

[3] The five "existing" chemicals/chemical categories are polychlorinated biphenyls (PCB), fully halogenated chlorofluoroalkanes, dioxin, asbestos, and hexavalent chromium. The four "new" chemicals also regulated under TSCA are mixed mono and diamides of an organic acid, triethanolamine salts of a substituted organic acid, triethanolanime salt of tricarboxylic acid, and tricarboxylic acid.

3. Using time series analysis to uncover long-run effects

3.1. *Data and measures*

This paper analyzes the consumptive use time path of 13 elemental toxic chemicals that are naturally occurring or are byproducts of industrial processes and are key inputs in the manufacturing of commercial products: antimony, arsenic, asbestos, beryllium, bromine, cadmium, chromium, cobalt, lead, manganese, mercury, selenium, and zinc. There is considerable variation among these chemicals with respect to their commercial applications, status as human carcinogens, and relative priority to the EPA.

Table 1 documents each chemical's commercial applications, as well as whether each chemical is considered a human health hazard; in fact, for several chemicals, their use in small quantities garner health benefits. These chemicals are key inputs in the manufacturing of steel (cobalt, manganese), aircraft (cadmium, chromium, cobalt), ammunition (antimony, lead), electronics (arsenic, beryllium, mercury, selenium), batteries (cadmium, manganese, lead), pesticides (arsenic, bromine, selenium, zinc), among other commercial products. A majority of these toxic chemicals are a part of the National Defense Stockpile for military industrial and essential civilian use during a national emergency (USGS Minerals Information, 2012).

The last column of Table 1 indicates the EPA's priority rank for each of the chemicals with respect to their potential threat to human health. The range in priority rank is wide, from number 1 (arsenic) to 232 (antimony) on the EPA's priority list of hazardous substances. Exposure to arsenic (in its inorganic form), which is ranked number 1 on the EPA's list of highly hazardous substances, is lethal. Cadmium, which is ranked number 7 damages the kidneys, lungs, and bones. Antimony, which is very low on the EPA's priority list of hazardous substances is more benign but can cause problems for the

lungs, heart, and stomach when high levels are inhaled. By contrast, small doses of selenium, manganese, cobalt, and zinc can help maintain good health (ATSDR, 2015). For example, the World Health Organization recommends zinc supplements for the treatment of acute diarrhea.

Annual consumptive use data for these toxic chemicals, measured in metric tons, are available for the period 1900–2011 with the exception of beryllium (1935–2011), bromine (1900–2006), and mercury (1900–2000) from the United States Geological Survey (USGS).[4] The toxic chemical use data are available in the form of univariate time series and are a combination of published and calculated industrial use data. Use data are estimated by the USGS using the following equation for most years: Chemical Use = Production + Imports − Exports ± Stock Changes. Data for the other years come from published data from the USGS Mineral Facts and Problems and the Mineral Yearbook.

In the following time series analysis, the toxic chemical use series are in their natural logarithm form. For the sake of brevity, for the rest of the paper I refer to the natural logarithm of toxic chemical use either simply as toxic chemical use (or arsenic use, mercury use, and so on) or with the lower case 'l' preceding the names of toxic chemicals (e.g., *larsenic*, *lmercury*, *lantimony*) to denote that the natural logarithm is used in the analysis.

3.2. Advanced time series methodology

In this paper, time series behavior is modeled as

$$y_t = d_t + u_t = \mu_0 + \beta_0 t + \sum_{i=1}^{m} \mu_i DU_{it} + \sum_{i=1}^{m} \beta_i DT_{it} + u_t, \quad t = 1, \ldots, T \tag{1}$$

$$u_t = \rho u_{t-1} + v_t, \quad t = 2, \ldots, T, \;\; u_1 = v_1, \quad -1 < \rho \leq 1 \tag{2}$$

where d_t represents the deterministic trend (with possible multiple trend breaks) and u_t represents the stochastic deviation from the deterministic trend. I assume d_t are structurally determined by a number of casual factors or large shocks, such as industrial activity, population trends, technological changes, environmental policy changes or major business initiatives that can permanent change its level and direction.

Eqs. (1) and (2) represent a general model that allows for m possible structural changes or breaks ($m + 1$ regime) in both the intercept and the slope, i.e., a "mixed" model: $DU_{i,t} = I(t > T_i)$ are indicator variables that specify where there are changes in the intercept, with $i = 1, \ldots, m$. $DT_{it} = (t - T_i)I(t > T_i)$ are indicator variables that specify when there are changes in the slope. A break in the trend occurs at $T_i = [T\lambda_i]$ when $\beta_i \neq 0$.

For the noise component of the model, u_t, I focus on the AR(1) case (although a more generalized error structure could be utilized). The parameter ρ lies between −1 and 1, such that u_t can be stationary or have a unit root. If $-1 < \rho \leq 1$ and v_t is covariance stationary (i.e., v_t is an *iid* process with mean 0 and variance σ^2) then the stochastic innovation u_t are trend reverting and y_t is a trend-stationary (TS) process. If $\rho = 1$ and v_t is covariance stationary then u_t is unit root nonstationary and y_t is a difference-stationary (DS) process.

3.2.1. Test for structural breaks

To answer the first question posed in Section 1 and to classify the toxic chemicals by their long-run use trend behavior, I test for structural breaks in the 13 toxic chemical use data, one time series at a time. I employ Kejriwal and Perron (2010) (KP) sequential procedure for determining multiple breaks in the trend that are robust to stationarity/nonstationarity properties of the data. The KP procedure is an extension of Perron and Yabu's (2009a) robust quasi-feasible generalized least squares method to multiple breaks. Formally, the Wald statistics-based sequential test developed by KP assesses the null hypothesis of l change points against the alternative hypothesis of $(l + 1)$ changes in the intercept and slope, which corresponds to testing $H_0 : \mu_{m+1} = \beta_{m+1} = 0$ conditional on there being m breaks. KP shows that this sequential procedure consistently estimates the number of breaks (see Theorem 2 in Kejriwal and Perron, 2010).

The robust quasi-feasible GLS Wald statistics of interest, W_{RQF}, is based on the least square estimation of a Cochrane–Orcutt transformation of (1) using a modified estimate of ρ: $\hat{\rho}$ 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 the DS or TS processes.[5] In practice, when the break date is unknown (which is the assumption made in this paper), Perron and Yabu (2009a, 2009b) propose using the *Exp* functional over the set of permissible break dates. They show that when using *Exp* functional the asymptotic critical values (i.e., limit distributions) in the $I(1)$ and $I(0)$ cases are very close; as such using the larger of the two can be expected to provide tests with the correct size for both stationary and unit root errors.

Hence, the robust quasi-feasible GLS Wald statistics for multiple breaks is:

$$\exp - W^i_{RQF} = \log\left[(T_i - T_{i-1})^{-1} \sum_{\tau \in \Lambda_{i,t}} \exp\left(\frac{W_{RQF}(\lambda_{i-1}, \tau, \lambda_i)}{2}\right)\right] \tag{3}$$

Given $\exp - W^i_{RQF}$ for $i = 1, \ldots, l + 1$, the KP sequential test is defined by

$$F_T(l + 1|l) = \max_{1 \leq i \leq l+1} \{\exp - W^i_{RFQ}\} \tag{4}$$

[4] To the best of my knowledge, there is no other source of comprehensive data for the industrial use of toxic chemicals. Data are publically available on the USGS website (http://minerals.usgs.gov/ds/2005/140/). The USGS houses data on the production, trade, and commercial use of over 80 mineral commodities in the U.S.

[5] The super-efficient estimate of ρ is as follows: $\hat{\rho}_s = \begin{cases} \hat{\rho}, & if\ T^{\delta}|\hat{\rho} - 1| > d \\ 1, & if\ T^{\delta}|\hat{\rho} - 1| \leq d \end{cases}$ for $\delta \in (0,\ 1)$ and $d > 0$ where $\hat{\rho} = \frac{\sum_{t=2}^{T} \hat{u}_t \hat{u}_{t-1}}{\sum_{t=2}^{T} \hat{u}^2_{t-2}}$ and $\{\hat{u}_t\}$ are the OLS residuals from the regression of y_t on x_t. Perron and Yabu (2009b) show that: (i) $T^{1/2}(\hat{\rho}_s - \rho) \xrightarrow{d} N(0, 1 - \rho^2)$ when $|\rho| < 1$ and (ii) $T(\hat{\rho}_s - 1) \xrightarrow{d} 0$ when $\rho = 1$. The main point to note is that these results remain valid both under the null hypothesis as well as under the alternative hypothesis of a structural break.

One concludes in favor of a model with $(l+1)$ breaks if the maximum of the $\exp - W^{i}_{RQF}$ is sufficiently large. This process is repeated by increasing l sequentially until the test fails to reject the null hypothesis of no additional structural breaks. The estimated number of breaks is then obtained as the number of rejections.

For the model with m breaks, the break dates $T_1 < T_2 < T_3 \cdots < T_m$ in Eq. (1) are obtained as the global minimizers of the sum of squared residuals using an algorithm based on a dynamic programming approach first introduced in the structural change context by Bai and Perron (1998, 2003) (BP).[6]

Simulations conducted by KP point to the importance of the choice of the maximal value of the number of breaks in relation to the size of the sample available. While there is currently no consensus in the literature regarding the criteria for determining the minimum regime size—which ultimately dictates the maximum number of change points—a trimming parameter of 0.15 is the common practice. Kejriwal and Perron (2010) and Bai and Perron (2003) show that a trimming parameter of 0.15 should ensure reasonable degrees of freedom for calculating an initial error sum of squares in the KP method.

3.2.2. *Test for unit roots*

I administer Carrion-in-Silvestre et al.'s (2009) (CKP) GLS-based unit root test, which allows for multiple structural breaks under both the null and the alternative hypotheses to assess what the time series properties of the toxic chemical use series reveal about the potential effectiveness of policy interventions. Such a symmetric treatment of breaks alleviates the unit root tests from size and power problems that plague tests based on search procedures.

Formally, the multiple breaks "mixed" model presented in Eqs. (1) and (2) are the starting point. The GLS-detrended unit root test statistics is based on the use of the quasi-differenced variable $y^{\bar{\rho}}_t$ and $x^{\bar{\alpha}}_t(\lambda^0)$ defined by

$$\begin{aligned} y^{\bar{\alpha}}_1 &= y_1, \\ x^{\bar{\rho}}_1(\lambda^0) &= x_1(\lambda^0), \quad \text{and} \\ y^{\bar{\rho}}_t &= (1-\bar{\rho}L)y_t, \end{aligned} \tag{5}$$

where $x^{\bar{\rho}}_t(\lambda^0) = (1-\bar{\rho}L)x_t(\lambda^0)$ for $t = 2, \ldots, T$ with $\bar{\rho} = 1 + \bar{c}/T$ where $\bar{c}$ is a noncentrality parameter. λ^0 represents the collection of the m break fraction parameters: $\lambda^0 = (\lambda^0_1, \ldots, \lambda^0_m)'$. Once the data have been transformed, the parameters Ψ, associated with the deterministic components, can be estimated by minimizing the following objective function (the sum of squared quasi-differenced residuals):

$$S^*(\Psi, \bar{\rho}, \lambda^0) = \sum_{t=1}^{T} (y^{\bar{\rho}}_t - \Psi x^{\bar{\rho}}_t(\lambda^0))^2. \tag{6}$$

The minimum of this function is denoted by $S(\bar{\rho}, \lambda^0)$.

CKP considers M-class unit root tests, first described by Perron and Ng (1996) for both the known break date case and the unknown break date case. This paper is concerned only with the latter case because I want to retain as much generality as possible; importantly, it is rarely if ever possible to know the true break dates with certainty in empirical research.[7]

I employ the modified feasible point optimal test statistics to determine whether the 13 toxic chemical use series, allowing for structural breaks are $I(0)$ or $I(1)$ series.[8] The modified feasible point optimal test is defined by

$$MP^{GLS}_T(\lambda^0) = \frac{[c^{-2}T^{-2}\sum_{t=1}^{T}\tilde{y}^{-2}_{t-1} + (1-\bar{c})T^{-1}\tilde{y}^2_T]}{s(\lambda^0)^2} \tag{7}$$

The null hypothesis is that y_t is DS ($\alpha = 1$) with possible trend breaks at unknown times $T_1, \ldots, T_m$ (equivalently, break fractions $\lambda_1, \ldots, \lambda_m$). The alternative hypothesis is that y_t is TS ($-1 < \alpha < 1$) with trend breaks at unknown times $T_1, \ldots, T_m$.

Given the break dates are unknown, CKP estimates the break dates using a detrended GLS version of a BP type structural break test. They follow an iterative procedure similar to that of Perron and Qu (2006). The CKP test allows for a maximum of five breaks.[9]

Simulations by others, including KP have shown that the CKP unit root tests are superior to that of alternative methods, but that these tests exhibit important size distortions when no breaks occur.[10] The solution, as advised by CKP, Kim and Perron (2009), and Harris et al. (2009) is to perform a structural break pre-test (that is insensitive to the presence of a unit root). For toxic chemical use series with no breaks, I conduct the Elliott et al. (1996) ADF-GLS test to maximize power, size, and efficiency, as Sidneva and Zivot (2014) do in their evaluation of the trend behavior of NO_x and VOCs, respectively.

3.2.3. *Test for cointegration*

In the toxic chemical use series containing a unit root, I test for evidence of cointegrating relationships among DS chemicals regulated under the same laws and between chemical use and national accounts and industrial production, respectively. I apply the standard Johansen (1991, 1995) cointegration test for toxic chemical use series without structural breaks, and apply Juselius' (2006) cointegrated VAR methodology, which imposes the restriction that the cointegrating relations

[6] The Bai and Perron (1998, 2003) method is concerned with assessing deviations from stability in the classical linear regression model, where changes concern divergence from the intercept or the mean of the data. Breakpoint estimates are the global minimizers of the sum of squared residuals determined using an algorithm based on a dynamic programming approach. The BP method alone ignores the possible presence of unit roots.

[7] CKP shows that if the breaks are estimated by minimizing the sum of squared residuals from the appropriate GLS regression, the limit distributions of the unknown break date case are the same as in the known break date case, provided that breaks are present.

[8] Carrion-i-Silvestre et al. (2009) consider three other M-class unit root tests analyzed in Perron and Ng (1996), which I do not employ in this paper. That being said, all four tests are nearly efficient because the local power functions are nearly identical and very close to the Gaussian power envelop (Carrion-i-Silvestre et al., 2009).

[9] Carrion-i-Silvestre et al. (2009) have made publicly available the GAUSS code that extends the dynamic programming of algorithm of Bai and Perron (1998) to solve this problem. This paper's unit root analysis is conducted utilizing the authors' code.

[10] When no breaks occur, the asymptotic results do not hold because, under the null hypothesis of a unit root, the estimates of the break fractions have a nondegenerate limit distribution on the interval [0, 1] instead of converging to either zero or one.

contain a linear trend while allowing for structural breaks, for toxic chemical use containing structural breaks.

Formally, this paper's cointegration analysis is based on the VAR(p) model

$$Y_t = \Phi D_t + A_1 Y_{t-1} + \cdots + A_p Y_{t-p} + \epsilon_t, \quad (8)$$

where Y_t is a vector with the first element the log form of chemical use and the remaining elements chemical use of DS chemicals regulated under the same laws or the log form of national accounts or industrial production. D_t contains deterministic terms, namely level-shift dummy variables associated with the estimated break dates derived by the KP method (see Section 3.2.1). ε_t is the spherical error process, which satisfies $E(\varepsilon_t) = 0$, $E(\epsilon_t \epsilon_s') = 0$ for $t \neq s$, and $E(\epsilon_t \epsilon_s') = \Sigma$ for $t = s$. For all individual chemical use series, a VAR(2) process has been selected based on the Akaike information criterion (AIC) as the best fitting model.

For toxic chemical use series that exhibit clear upward or downward trends with breaks, I apply, Juselius's (2006) cointegrated VAR procedure; this imposes the restriction that the cointegrating relations contain a linear trend while allowing for breaks in the trend. The presence of intervention dummy variables in D_t influences the distribution of the Johansen rank and trace tests; as such, appropriate critical values described in Johansen et al. (2000) are used.[11] For individual chemical use that do not exhibit structural breaks I apply the standard Johansen (1995, 1991) cointegration test, which do not impose a deterministic trend nor breaks in the trend.

4. Which of the federal regulations have had an effect on the industrial use of toxic chemicals?

This section presents estimated structural breaks, along with estimated intercepts and slopes for each segment of the toxic chemical use series. Together, they enable the classification of the toxic chemicals into three categories of long-run trend behavior: *growth*, Environmental Kuznets Curve (*EKC*), and *kinked-growth* chemicals. The classification is then employed as an organizing framework to present and discuss the rest of the empirical results in subsequent sections.

Table 2 reports results for the Kejriwal and Perron (2010) multiple breaks tests for the mixed model; structural changes are assumed to be unknown a priori. The trimming parameter ε is set at 0.15 for all toxic chemical use series. Columns 2–4 report the $\exp - W_{RFQ}$ test statistics for one, two, and three breaks given the existence of zero, one, or two breaks. Statistical significance are based on critical values derived from the asymptotic distribution of $\exp - W_{RFQ}$ (see Table 1b in Kejriwal and Perron, 2010). The break dates for each of the estimated breaks are reported in column 6 of Table 2.

In order to determine the direction and to quantify the rate of change in each of the regimes demarcated by the estimated structural breaks, intercepts and slopes for each segment of the toxic chemical use series have been computed based on ordinary least squares (OLS) estimation of Eq. (1) assuming the number of breaks and the break dates as provided in Table 2. The estimated intercepts and slopes are presented in Table 3. While the coefficient estimates are consistent under the TS and DS processes, the OLS standard errors are only appropriate if the series are TS, so they are omitted here. We determine whether the series are TS or DS in the next section (Section 6).

Fig. 1 illustrates the chemical use time paths of antimony, beryllium, bromine, and lead, along with their respective linear fitted lines. As the individual plots show, the trend behavior of antimony use, beryllium use, bromine use, and lead use, respectively, is upward sloping, exhibiting no structural change according to the KP test (see Table 2). These four toxic chemicals are classified as *growth* chemicals, as they exhibit uninterrupted trend growth.

Amongst the *growth* chemicals, bromine use has grown the fastest with an estimated slope of 0.08, according to Table 3. This is not particularly surprising because bromine has wide-ranging commercial applications and is not considered a human carcinogen, unlike lead and beryllium.

By contrast, the long-run trends in lead use exhibit an estimated slope of 0.01. Lead's properties as a carcinogen have been well documented (see Table 1). Ranked right behind arsenic as the number 2 most hazardous substance by the EPA, lead has been banned in several commercial products, including paint and gasoline since the 1980s and 1990s, respectively (US EPA, 2015). The fact that lead is a key input in the manufacturing of ammunition and batteries likely explains why, while government policies could have had a restraining effect—as evidenced by a flatter slope or slower growth than the other *growth* chemicals—lead use is characterized by unbroken long-run growth trends; no interventions, government or otherwise, have had a permanent effect on altering lead's trend behavior.

Fig. 2 plots the consumptive use time path of arsenic, asbestos, cadmium, and mercury.

Similar to the plots in Fig. 1, a linear fitted line has been estimated for each chemical use time series; dotted vertical lines delineate the year of the estimated changepoints. A 95% confidence interval bounds each of the estimated breakdates. The long-run trends of arsenic use, asbestos use, cadmium use, and mercury use are inverted U-shaped: they each have risen to their respective peaks and have since fallen to levels that are near or below levels recorded in the early 1900s (with the exception of cadmium use). Given the inverted U-shapes of these toxic use series, the four chemicals are categorized as the "Environmental Kuznets Curve" or *EKC* chemicals.[12]

The first few decades of the 20th Century were a period of rapid growth in toxic chemical use for arsenic use, cadmium use, and asbestos use. Changepoints in these toxic chemical use series coincided with a period of much commercial development and technological change in the U.S. Rapid growth culminated in structural changes in 1922 and 1925, respectively, for arsenic use and cadmium use, at which points

[11] Since the estimated break fractions converge sufficiently fast, the break dates can be treated as known for the purpose of testing the cointegrating rank.

[12] It is beyond the scope of this paper to examine the precise relationship between these chemicals and national income. As such, this paper does not claim the existence of an inverted U-shaped relationship between these chemicals and national income.

Table 2 – Kejriwal and Perron's (2010) structural break test, mixed model.

y_t	$F(1\|0)$	$F(2\|1)$	$F(3\|2)$	# Breaks	Estimated break year	95% confidence interval
lantimony	−0.20			0		
larsenic	2.23**	38.07**	3.99**	3	1922	(1920, 1924)
					1945	(1944, 1947)
					1995	(1993, 1996)
lasbestos	4.80**	10.59**	107.74**	3	1915	(1914, 1917)
					1940	(1939, 1942)
					1976	(1975, 1977)
lberylllium	0.15			0		
lbromine	0.28			0		
lcadmium	2.88**	19.51**	49.83**	3	1925	(1923, 1926)
					1942	(1941, 1943)
					1986	(1984, 1987)
lchromium	68.80**	1.32		1	1965	(1964, 1966)
lcobalt	113.86**	−0.26		1	1959	(1958, 1960)
llead	0.80			0		
lmanganese	2.91**	1.47		1	1979	(1978, 1985)
lmercury	34.35**	13.43**	5.73**	3	1940	(1938, 1944)
					1961	(1958, 1962)
					1985	(1984, 1986)
lselenium	7.85**	55.06**	9.70**	3	1929	(1928, 1930)
					1950	(1945, 1952)
					1967	(1932, 1971)
lzinc	13.92**	1.64		1	1973	(1972, 1974)

Note: The KP test allows for a maximum of three breaks. 5% critical values for $F(1|0)$, $F(2|1)$, and $F(3|2)$ are 1.67, 2.22, and 2.56, respectively (see Table 1b in Kejriwal and Perron, 2010). The break dates are estimated by minimizing the sum of squared residuals in the R software using the *strucchange* package.

** Significant at the 5% level.

the upward sloping trend continued with a shift up in average use levels for both chemicals, albeit at a slower pace of growth (i.e., lower slopes in the trend) than in the previous periods. For asbestos use, there was a structural shift in 1915; this demarcated a flatter slope in the trend (from 0.38 in regime I to 0.22 in regime II).

For these three chemical use series, the second regime either demarcated the start or end of the Second World War (WWII). Asbestos use ramped up for the war efforts and remained there until the regulatory era (i.e.1970-present). A structural shift in 1945 at the end of WWII signaled a third regime for the arsenic use trend. Cadmium use trend growth reached its peak in 1942 and largely remained there until the mid-1980s.

By contrast, mercury use recorded its first estimated structural change in 1940, which coincided with the economic run-up associated with WWII. The second changepoint occurred in 1961, about a decade before the start of the regulatory era, although the federal government had already began to lay out broad environmental goals (Ringquist, 1993). The slope in regime III, which follows the 1961 structural break is slightly below zero.

The third structural break in the trend behavior of *lasbestos*, *lcadmium*, and *lmercury* occurred during the regulatory era

Table 3 – Intercepts and slopes coefficients for each segment of toxic chemical use data estimated by OLS from mixed model with multiple breaks.

y_t	Intercepts				Slopes			
Regimes	I	II	III	IV	I	II	III	IV
lantimony	8.84				0.02			
larsenic	7.69	8.69	9.18	24.65	0.05	0.03	0.01	−0.15
lasbestos	5.32	11.34	12.38	28.52	0.38	0.22	0.16	−0.19
lberyllium	4.08				0.02			
lbromine	5.72				0.08			
lcadmium	0.95	3.33	8.19	16.46	0.17	0.12	0.003	−0.09
lchromium	8.95	13.89			0.07	−0.007		
lcobalt	2.36	8.09			0.12	0.01		
llead	12.93				0.01			
lmanganese	12.11	13.09			0.03	0.004		
lmercury	6.44	6.90	8.91		0.01	0.009	−0.02	−0.15
lselenium	1.57	3.68	5.83		0.18	0.05	0.005	−0.004
lzinc	12.01	13.45			0.03	0.004		

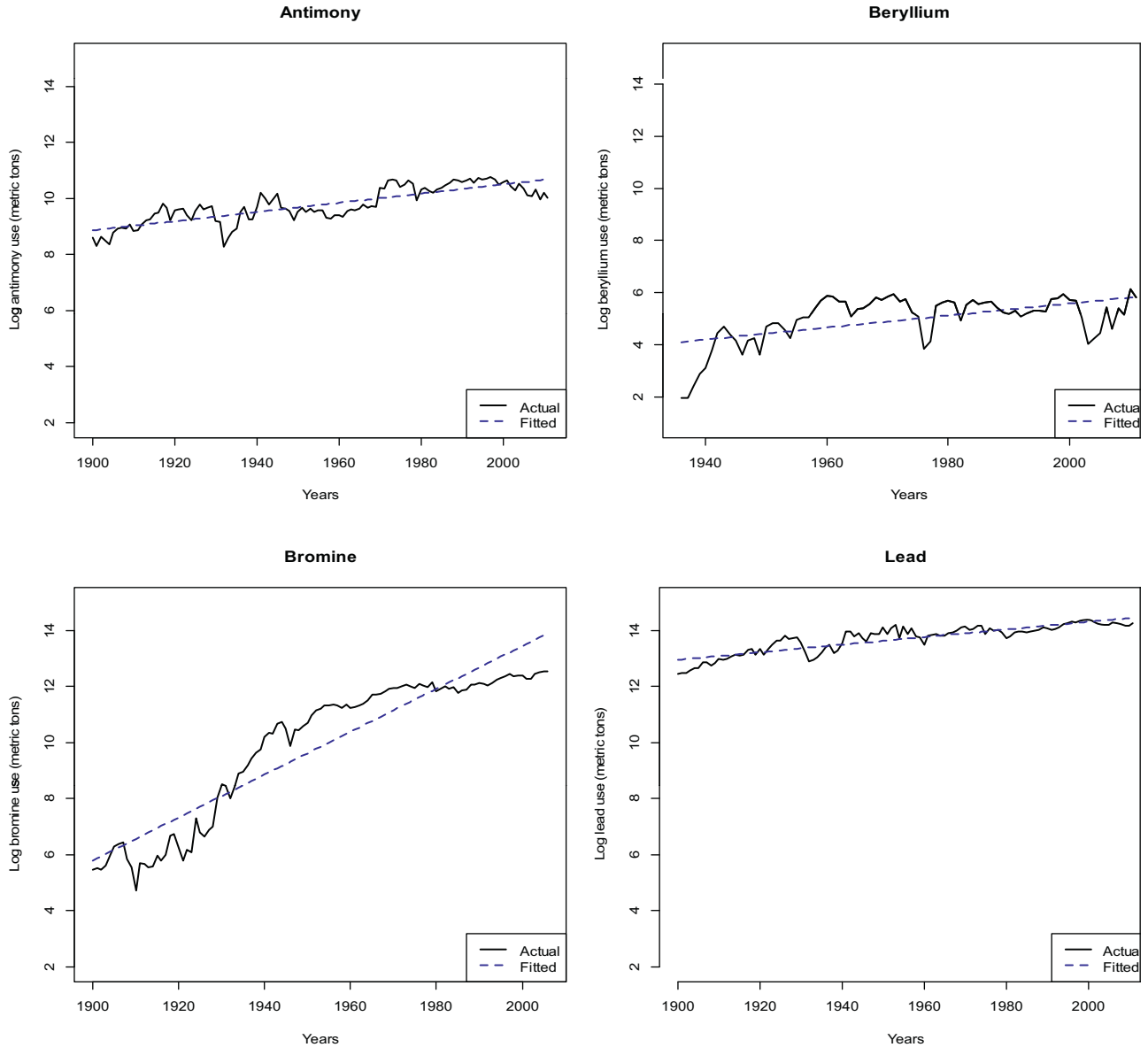


Fig. 1 – *Growth* chemicals.
Source: USGS.

around the time of the passage of two major federal environmental legislations. First, asbestos, which is one of only five existing chemicals that the federal government has promulgated specific rules experienced a structural break in 1976: this was the year the 1976 Toxics Substance Control Act was passed by Congress. A year later in 1977, the CPSC banned consumer products containing inhalable asbestos (such as artificial fireplace ash containing asbestos). 1977 lies within and represents the upper bound of the 95% confidence interval of the estimated break (see Table 2). Another regulatory ban on asbestos-containing products and new uses in 1986 may have helped to explain asbestos use's relatively steep decline (a slope of −0.19, as reported in Table 3) in the fourth and last regime.

Structural breaks in 1985 and 1986, respectively, for mercury use and cadmium use matched that of the passage of the Emergency Planning and Community Right-to-Know Act of 1986, which created the TRI. These changepoints established a fourth regime of downward sloping trends for mercury and cadmium use, respectively, which have not been reversed.

None of arsenic use's estimated structural breaks occurred during the same time as the enactment of environmental policies. Rather, an estimated break in the arsenic use trend occurred in 1995, two years after the agricultural industry—which is the second largest commercial user of arsenic—voluntarily banned the use of arsenic acid, a pesticide that had been commonly used in cotton production. The actual year, 1993, in which the arsenic acid voluntary ban went into effect is well within the 95% confidence region (1993–1996) of the estimated structural break.

Fig. 3 plots the toxic use time paths of chromium, cobalt, manganese, selenium, and zinc along with their estimated

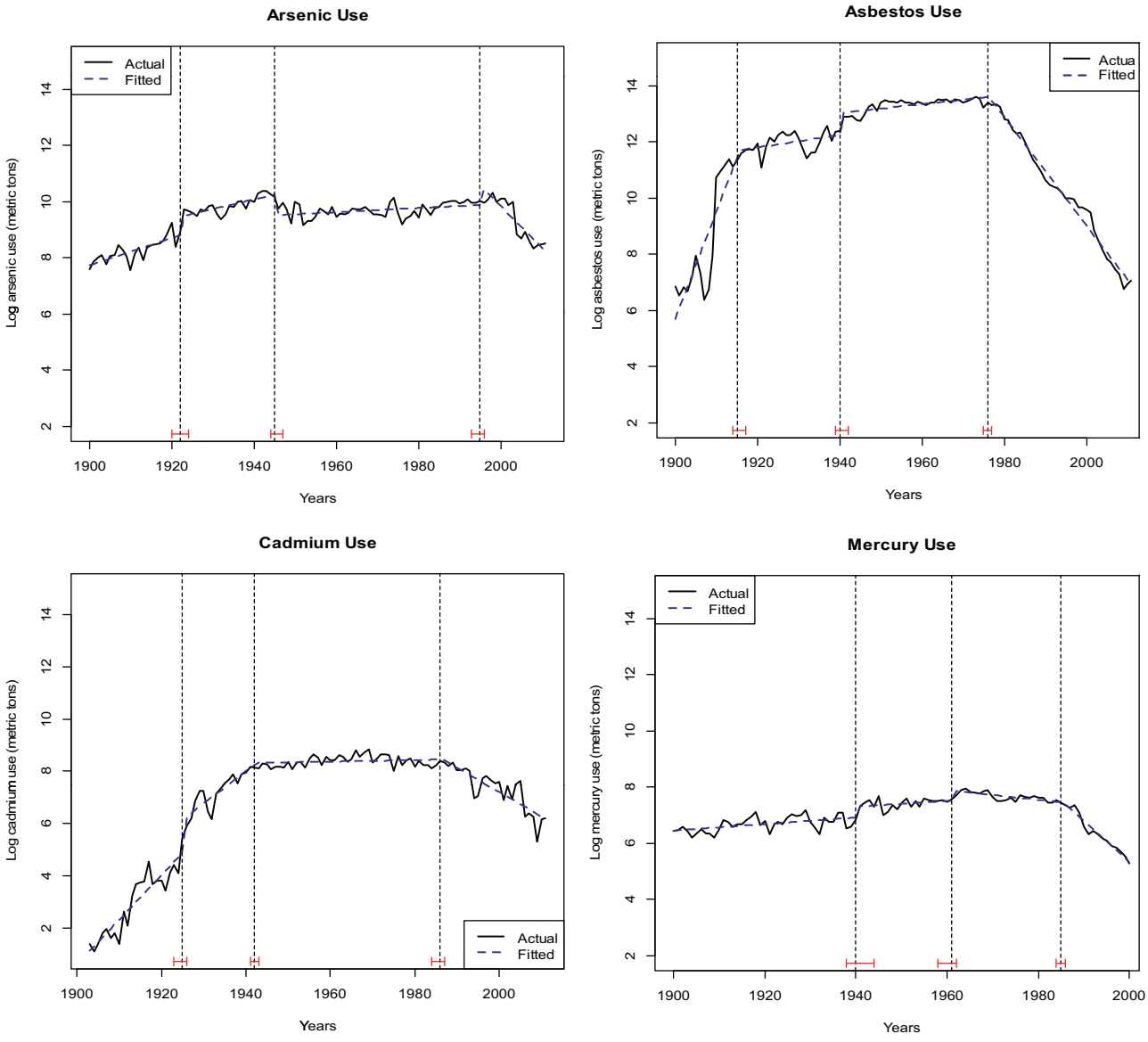


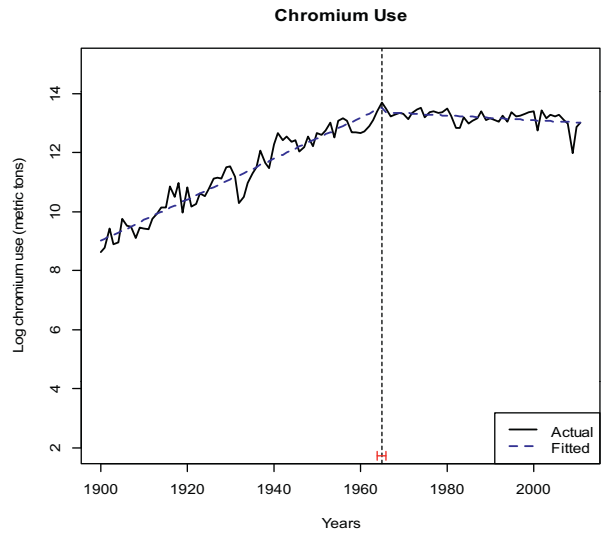
Fig. 2 – *EKC* chemicals.
***Source*: USGS.**

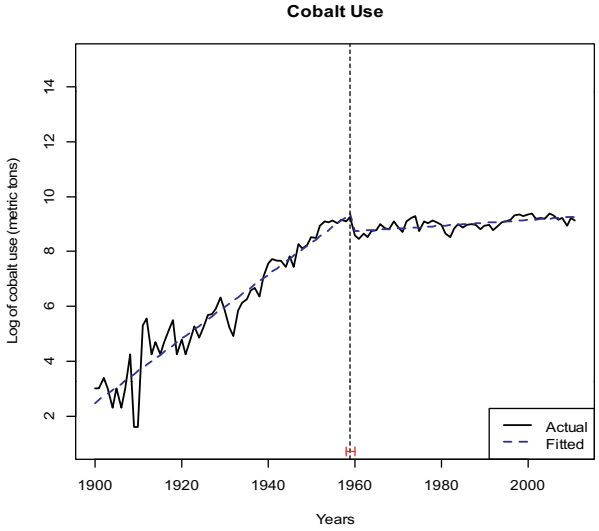
breaks. These five chemical use series share a common feature: a steady rise and then a kink-like turning point (delineated by a structural break), at which point the consumptive use of the said chemicals flattens out to a steady horizontal growth trend. As reported in Table 3, close to zero slopes are recorded for these chemicals in regime II and beyond. Unlike the other chemicals, apart from being listed as a target chemical by FIFRA or the TRI none of these five chemicals has been subjected to additional regulatory actions. These chemicals are categorized as the *kinked growth* chemicals.

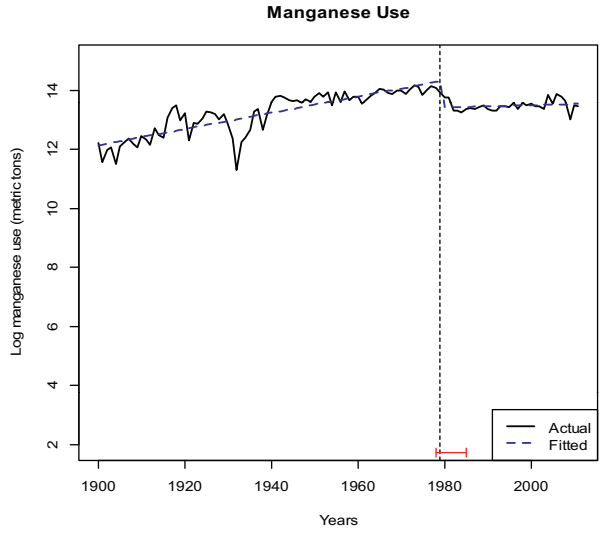
Four of the five *kinked growth* chemicals experienced a single structural break that demarcated two regimes: the first regime was an upward sloping trend and the second was a nearly flat trend exhibiting steady horizontal growth. The second regime coincided with the enactment of federal environmental regulations or the start of the regulatory era more generally, suggesting that federal regulatory policies on the whole likely have had a restraining effect on the trend behavior of these chemicals.

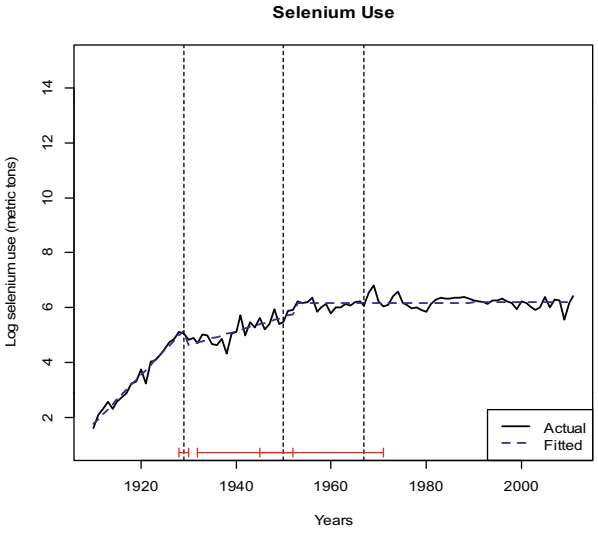
For zinc use, the estimated break in 1973 occurred a year after major amendments was made to the FIFRA, the federal government's chief law for regulating pesticides. The tight 95% confidence region around the changepoint suggests that FIFRA has had a moderating effect on the growth trends of zinc use. That being said, the healthful properties of zinc and its use in steel and shipbuilding have likely sustained its high consumptive use over the years.

The consumptive use of chromium and cobalt has remained high likely because both chemicals are deemed "strategic materials" by the federal government as part of the Defense Logistic Agency's strategic materials stockpile program. Moreover, neither chemicals ranks among the top 10 nor top 50 of EPA's priority list of hazardous substances (see Table 1).









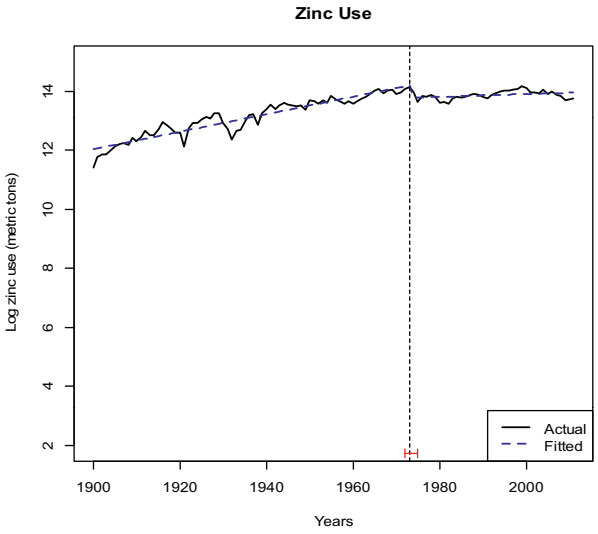


Fig. 3 – *Kinked growth* chemicals.
***Source*: USGS.**

lmanganese's single estimated break, which occurred in 1979 is not precisely estimated; its 95% confidence region spans eight years (1978–1985). Several notable events ensued in the in this period: two recessions (1980 and 1981–82) and the establishment of the TRI by the EPA.[13] It is not clear whether the estimated changepoint, which demarcated a structural shift to a zero slope in the trend was due to changes in regulation or to the slowing economy. The steady albeit flat growth of manganese use over the past two decades is likely explained by the fact that manganese is an essential input in steel and iron production, as there are no satisfactory substitutes (U.S. Geological Survey, 2015).

The only *kinked growth* chemical that experienced multiple structural breaks is selenium. The first estimated break in 1929 corresponded with the Great Depression (1929–1933); the slope between the first and second regimes declined from 0.18 to 0.05 (see Table 3). The second changepoint (1950) in *lselenium* preceded the founding of the EPA and the advent of major environmental legislations. The third break in *lselenium* occurred in 1967. This final break is imprecisely estimated—the 95% confidence interval spans 39 years (1932–1971). Several major events occurred in the political economy during these years, including the end of the Great Depression, WII buildup, and the establishment of the EPA. Identification of the break is made further difficult by the fact that selenium use time trends in regimes III and IV have close to zero slopes (see Table 3).

In summary, the Kejriwal and Perron (2010) sequential structural breaks tests indicate that only asbestos, cadmium, and mercury—they are classified as *EKC* chemicals—have had structural breaks in its long-run trends around the dates of the advent of the major federal legislations that controlled toxic chemical use. The 1976 TSCA has had a permanent effect on asbestos use, which is the only toxic chemical among the 13 examined in this paper that EPA has promulgated specific rules. The advent of the TRI coincided with estimated structural breaks in cadmium use and mercury use; these changepoints preceded downward sloping trends for mercury use and cadmium use, respectively, which have not been reversed. The mandatory ban on inhalable asbestos and the voluntary ban on arsenic acid matched structural breaks in asbestos use and arsenic use in 1977 and 1993, respectively.

Structural changes that occurred right before and/or near the start of the regulatory era for chromium use, cobalt use, and zinc use suggest that federal regulatory policies on the whole exerted a restraining effect on these *kinked growth* chemicals. By contrast, antimony, beryllium, bromine, and lead are *growth* chemicals that exhibited unbroken trends in long-run toxic use.

5. What do the time series properties reveal about potential policy effectiveness over the long-run?

In this section, I administer the Carrion-in-Silvestre, Kim, and Perron's unit root test, which allows for multiple breaks in the null and the alternative hypotheses to answer the question:

Table 4 – Unit root tests.

	No breaks Elliott et al. (1996)	Multiple breaks Carrion-i-Silvestre et al. (2009)
	ADF-GLS statistics[a,b]	MPT statistics[c]
EKC chemicals		
larsenic		6.92
lasbestos		6.47
lcadmium		6.67
lmercury		16.10**
Kinked growth chemicals		
lchromium		18.62**
lcobalt		21.69**
lmanganese		7.39**
lselenium		9.67**
lzinc		8.26**
Growth chemicals		
lantimony	−2.72*	
lberyllium	−1.63	
lbromine	−0.83	
llead	−2.08	

* Significant at the 10% level
** Significant at the 5% level.
[a] An intercept and three lags of the dependent variable is added to the test regression: $\Delta y_t = \mu + \beta t + \alpha y_{t-1} + \phi \Delta y_{t-1} + \gamma \Delta y_{t-2} + \theta \Delta y_{t-3} + e_t$.
[b] Critical values for 1%, 5%, and 10% levels for the ADF-GLS statistics are −3.46, −2.93, and −2.64, respectively.
[c] Critical values for 5% and 10% levels are reported in Tables 2A and 2B in Carrion-i-Silvestre et al. (2009) for the MPT test.

What do the time series properties of the toxic chemical use data reveal about potential long-run policy effectiveness, regardless of the existence (or not) of structural breaks?

Results for the CKP unit root test for toxic chemicals exhibiting one or more structural breaks are reported in Column 3 of Table 4. These results are based on the number of breaks determined by the KP sequential structural break tests, as reported in Table 1. CKP provide tables of critical values for $m = 1$ and $m = 2$ based on their derivation of the asymptotic distributions of (see Table 2A and Table 2C in Carrion-i-Silvestre et al., 2009).[14] When the number of estimated breaks are at least two, CKP's critical value for $m = 2$ is used to reject or accept the null hypothesis of a unit root.

While the trend behavior of the *EKC* chemicals appears to be on the phase-down (see Tables 2 and 3 and Fig. 3), I do not reject the null hypothesis at the 5% significance level that arsenic use, cadmium use, and asbestos use series are DS series with at least two breaks in the level and slope of their trends. The fact that these series contain a unit root implies that *all* shocks impose a permanent effect. For example, the creation of the Toxic Release Inventory had a permanent effect on cadmium use, and the 1993 voluntary ban of arsenic acid by the agriculture industry imposed a lasting effect on reducing arsenic use, but so did all other shocks, random and otherwise,

[13] U.S. expansions and contractions dates are from the NBER: http://www.nber.org/cycles.html (Retrieved December 1, 2014).

[14] Carrion-i-Silvestre et al. (2009) show that the asymptotic distributions of the test statistics depend on the number of breaks and the break location λ. For example, when $m = 2$, $\lambda_1 = 0.2$, and $\lambda_2 = 0.8$ the 5% and 10% critical values for MPT_T^{GLS} are 8.56 and 7.31, respectively.

on the industrial use of these chemicals. As a result, the long-term trends in arsenic use, cadmium use, and asbestos use will be constantly changing to reflect these shocks, which will make it increasingly challenging to predict their trend behaviors in response to policy interventions. The downward sloping trends of the *EKC* chemicals (with the exception of mercury) may not be assured in the long-run policy horizon.

By contrast, the time paths of the *kinked growth* chemicals, namely, chromium, cobalt, manganese, selenium, and zinc are all TS. Mercury use is the only *EKC* chemical that is TS. Rejection of the null hypothesis for these series indicates that the policy or non-policy shock that induced the structural break(s) in these toxic chemical use series represents the only permanent shocks and all other shocks had only temporary effects. This result implies that a forecast of long-run policy effectiveness will be more certain for the TS chemicals than for the DS chemicals. To be specific, the effectiveness of FIFRA and the TRI on zinc use and mercury use, respectively, were permanent shocks on their trend behaviors while all other shocks that did not induce a structural break have only temporary effects. This result suggests that the horizontal growth trends of the kinked growth chemicals will likely be projected forward into the foreseeable future undeterred by random shocks.

The ADF-GLS unit root test has been administered on the zero-break series, namely the *growth* chemicals; results are reported in Column 2 in Table 4. Amongst the toxic chemical use series without breaks, beryllium, bromine, and lead each contains a unit root. Antimony is the only break-free chemical use series without a unit root at the 10% significance level. Forecast uncertainly for beryllium, bromine, and lead use increases with the forecast horizon whereas it is more likely to be bounded for antimony.

6. Are there clusters of chemicals that share a common trend, which suggests common economic and institutional drivers?

As the previous section explicates, it is harder to predict the trend behaviors of DS than TS chemical use series. As such, a cointegration analysis is conducted on the industrial use of these *I*(1) toxic chemicals to adjudicate on the long-run drivers of change in their respective trend behaviors.[15] In particular, *larsenic*, *lasbestos*, *lcadmium*, *lantimony*, *lberyllium*, *lbromine*, and *llead* are analyzed for evidence of cointegrating relationships among chemicals regulated under the same laws and between individual chemical use series and national accounts and industrial production, respectively.

To test for evidence of cointegrating relationships among chemicals regulated under the same laws, I consider different combinations of DS *EKC* chemicals and DS *growth* chemicals separately and together.[16] Table 5 reports the results on the inference on cointegration rank for the *EKC* chemicals allowing for structural breaks, if any exist, in a restricted cointegrated VAR model. The trace statistics are reported for the null hypothesis that $r = 0$ (i.e., no cointegration relation exists), $r \leq 1$, $r \leq 2$, and so on up to $r \leq 5$. Critical values for the unrestricted and restricted Johansen cointegration tests come from Osterwald-Lenum (1992) and Johansen et al. (2000), respectively.

The null hypotheses of zero and one cointegration relationship among *larsenic*, *lasbestos*, and *lcadmium* are rejected at the 5% significant level, while the null hypothesis of two cointegration relationships cannot be rejected. Furthermore, all combinations of the *EKC* chemicals in pairs are cointegrated at the 5% significance level, as the null hypothesis that $r = 0$ is rejected.

For the *growth* chemicals, the Johansen cointegration test rejects $r = 0$ cointegration vector for *lantimony*, *lberyllium*, *lbromine*, and *llead* at the 5% significant level. This result indicates that at least one cointegrating relationship exists for the *growth* chemical use series when all the series are considered together. Results also show that *lberyllium* shares a cointegration vector with *lantimony*, *lbromine*, and *llead*, respectively, when separate pairs of the *growth* chemicals are tested for cointegration.

Table 5 also presents the results of the Johansen cointegration test on different combinations of the *EKC* and *growth* chemicals as co-moving series that share a long-run equilibrium. The Johansen cointegration test rejects $r \leq 4$ but cannot reject $r \leq 5$ cointegrating vectors at the 5% significance level; this result indicates that there exists five cointegrating relationships among all the *I*(1) toxic chemical use series.

When all possible pairs of the *EKC* and *growth* chemicals are tested for cointegration, all but four pairs (out of the 12 pairs) of toxic chemicals share at least one cointegration relationship. Together these results suggest that for the most part the different combinations of the seven DS toxic chemical series share a common trend or co-move together, which imply that they share common economic and institutional drivers in the long-run policy horizon.

Another conjecture is that toxic chemicals that are key ingredients in commercial products share a long-run equilibrium with macroeconomic factors. Empirical results, which are reported in Table 6, generally affirm the conjecture that toxic chemical use is cointegrated with industrial production and national accounts, respectively. Trace statistics are reported for the null hypothesis that $r = 0$, or no cointegration relation exists between each pair of the DS series and industrial production, real GDP, and the R&D investment series, respectively.

For the *EKC* chemicals, arsenic use, cadmium use, and asbestos use are each cointegrated with industrial production; asbestos and cadmium use are also cointegrated with real GDP. Cadmium use is cointegrated with all the R&D investment time series. Likewise, the industrial use of *growth* chemicals—antimony, beryllium, bromine, and lead—is cointegrated with industrial production and real GDP, respectively, at the 5% significance level or higher except for antimony, which is significant at the 10% level. The *growth* chemical use series are also respectively cointegrated with private sector R&D investments and with R&D investments by the electronics

[15] Antimony use is included in the cointegration analysis because the null hypothesis of a unit root is rejected at the 10% level rather than at a lower threshold level.

[16] Mercury use, which is classified as a *EKC* chemical, has been excluded from the cointegration tests because mercury use is stationary according to the CKP unit root test (see Table 4).

Table 5 – Johansen cointegration test for chemical use under the same laws.

y_t	Trace statistics[a]					
	$r = 0$	$r \leq 1$	$r \leq 2$	$r \leq 3$	$r \leq 4$	$r \leq 5$
EKC chemicals						
larsenic, lasbestos, lcadmium	64.95**	25.02**	2.21			
larsenic, lasbestos	21.19**	4.36				
larsenic, lcadmium	32.60**	4.69				
lasbestos, lcadmium	37.25**	3.22				
Growth chemicals						
lantimony lberyllium, lbromine, llead	54.00**	20.80	8.38	0.97		
lantimony, lberyllium	17.92**	0.54				
lantimony, lbromine	8.25	0.05				
lantimony, llead	8.83	1.45				
lberyllium, lbromine	25.89***	3.00				
lberyllium, llead	15.76**	0.32				
lbromine, llead	8.86	0.00				
EKC and growth chemicals						
larsenic, lasbestos, lcadmium, lantimony, lberyllium, lbromine, llead	246.37**	158.32**	101.82**	64.98**	39.64**	17.89
larsenic, lantimony	40.11**	10.35**				
larsenic, lberyllium	35.46**	3.94				
larsenic, lbromine	28.29**	6.10				
larsenic, llead	26.58**	10.82**				
lasbestos, lantimony	17.28	3.04				
lasbestos, lberyllium	18.60	1.36				
lasbestos, lbromine	6.90	2.75				
lasbestos, llead	23.20**	2.64				
lcadmium, lantimony	24.20**	6.82				
lcadmium, lberyllium	19.85	5.24				
lcadmium, lbromine	24.93**	9.6**				
lcadmium, llead	24.84**	4.64				

** Significant at the 5% level.
*** Significant at the 1% level.
[a] Critical values for unrestricted and restricted Johansen cointegration tests come from Osterwald-Lenum (1992) and Johansen et al. (2000), respectively.

sector. Finally, beryllium and bromine use, respectively, are cointegrated with R&D investments by the chemical sector.

Table 6 results suggest that by and large macroeconomic factors are drivers of long-run change in the trend behaviors of the toxic chemical use series that contain a unit root. Real GDP is by far the most important driver of long-run changes for all $I(1)$ toxic chemical use series. Evidence also indicates that industrial production, and to a lesser degree, real investments in R&D share a long-run equilibrium with toxic chemical use.

7. Discussion and conclusion

State-of-the-art time series econometric techniques that overcome thorny methodological issues have been applied to analyze long-term trends of the industrial use of 13 toxic chemicals that vary in their relative priority to the EPA (among other dimensions) and to determine how past environmental regulations have affected them. These chemicals are classified into *growth*, *EKC*, and *kinked-growth* chemicals according to their respective trend behaviors, as demarcated by estimated structural breaks. Nonstationary series are further analyzed for cointegration relationships with national accounts and industrial production to uncover links to aggregate economic behavior.

By and large, structural changes have occurred around the time of economic booms and busts, World War II, environmental regulations, and major industry developments. An analysis of the historical trends since 1900 reveals compelling evidence that while some toxic chemicals—such as asbestos, mercury, and cadmium—have been successfully reduced by regulatory efforts, a majority of the toxic chemicals used in commercial products shares a long-run equilibrium with national accounts and industrial production, suggesting that toxic chemical use in the U.S. has been driven by changes in U.S. GDP, industrial production, and private investments in research and development, rather than by government regulations.

The 1986 Emergency Planning and Community Right-to-Know Act, which created the Toxic Release Inventory—an information disclosure policy—has had impact on the consumptive use of more poisonous industrial chemicals than command-and-control regulations. Voluntary programs, which have been frequently utilized by policymakers to restrain toxic chemical use have not been effective in reducing toxic chemical use. One exception is an industry-initiated voluntary agreement in 1993 between the agriculture sector and the EPA to ban the use of arsenic acid in cotton production: the industrial use of arsenic, a substance that ranks number 1 on the EPA's list of priority chemicals has exhibited a

Table 6 – Johansen cointegration test for toxic chemical use and industrial production and national accounts.[a]

	Ind Prod	Real GDP	R&D	R&D Gov't	R&D private	R&D Chem	R&D Elec
EKC chemicals							
Larsenic	21.78**	14.51	12.83	11.83	18.67	10.64	12.88
Lasbestos	25.94**	52.97**	13.67	13.62	13.41	17.68	9.38
lcadmium	34.40**	34.00**	26.70**	23.56**	22.20**	25.67**	21.93**
Growth chemicals							
lantimony	10.47*	15.00**	8.14	7.00	11.34*	28.19***	9.08
lberylllium	15.10**	23.70***	17.16**	11.53	23.61***	21.78***	15.55**
lbromine	12.63**	13.26**	19.80**	10.04	12.19*	20.04**	11.62*
Llead	12.40**	12.32**	9.11	4.92	12.72**	24.21***	8.96

* Significant at the 10% level.
** Significant at the 5% level.
*** Significant at the 1% level.
[a] Trace statistics are reported for the null hypothesis that $r = 0$ or no cointegrating relation exists. Critical values for unrestricted and restricted Johansen cointegration tests come from Osterwald-Lenum (1992) and Johansen et al. (2000), respectively.

downward sloping trend since the structural break that was demarcated by this industry voluntary ban.

The toxic chemicals that are ranked among the most poisonous by the EPA—namely, arsenic, asbestos, cadmium, and mercury—what this paper classifies as *EKC* chemicals, have trended downward, as demarcated by the negative and permanent structural breaks in their time series trends. That being said, the direction of the future behavior of these DS toxic chemical use series (with the exception of mercury use) is likely to be subjected to considerable uncertainty because their overall trend behavior is stochastic, evidenced by the presence of a unit root.

Forecast uncertainty is also likely for beryllium, bromine, lead, and antimony, which this paper classifies as *growth* chemicals. The fact that these series contain a unit root suggests that the potential effect of policy interventions are less predictable given that changes in the trend are likely to correspond to random shocks rather than to hold close to a new trend associated with a policy change.

By contrast, the time paths of the *kinked growth* chemicals—chromium, cobalt, manganese, selenium, and zinc—are free of a unit root. This implies that these toxic chemicals are the most likely amongst the 13 toxic chemicals examined to be restrained by government interventions in the long-run policy horizon. Government policies notwithstanding, the commercial demand for and the health benefits of several of these chemicals, such as manganese and zinc, will likely to continue to drive the steady consumption of these chemicals.

Several policy implications for U.S. toxic chemical policy reform can be drawn from this paper's empirical findings. First, existing federal rules by and large have not had their intended effects. In fact, according to the paper's analysis, the TSCA, which is the main regulation addressing toxic chemical use has had an effect only on one of the 13 chemicals examined in this paper, namely asbestos. This is unsurprising since asbestos is the only toxic chemical among the 13 examined in which the EPA has promulgated rules under the TSCA. This result suggests that any reform on toxic chemical policy must address and strengthen the link between the TSCA (or a newly enacted legislation) and the consumptive use of targeted toxic chemicals. A step in this direction would include shifting more of the burden to the actual producers or users of the chemicals themselves for demonstrating the safety of their chemicals, which will expedite formal rulemaking by the EPA for regulating production or use (GAO, 2007).

Second, the fact that publicly initiated voluntary programs, such as the 1998 High Production Volume (HPV) Challenge have not had a permanent effect (i.e., no structural breaks) in reducing toxic chemical use does not necessarily imply that voluntary programs do not work nor that they should never be utilized as a policy tool alongside directives or market-based policies. In this study, the only voluntary program that corresponded to a structural change was the 1996 voluntary agreement between the agriculture sector and the EPA. This result is consistent with the findings in the voluntary program literature that voluntary programs that involve negotiated agreements between regulators and the private sector to reduce toxic chemical use, combined with government monitoring and sanctioning have the potential to reduce toxic chemical use by a substantial amount and could be a winning policy combination.

This combined with the fact that the TRI has had a permanent effect on the consumptive use of more toxic chemicals than command-and-control policies suggest that the government's role is broader, more collaborative, and more dynamic than conventionally accepted. The role of public agencies is not just to set and enforce technology standards, but to establish an information-rich context for private citizens, interest groups, and firms to solve environmental problems (Weil et al., 2006; Fung and O'Rourke, 2000).

Finally, an important lesson from this paper's analysis of the temporal dynamics of toxic chemical use is that a large part of what drives chemical use in the long-run policy horizon are macroeconomic factors, such as growth in real GDP and private investments in R&D. The demand for toxic chemical use will likely ebb and flow with the economy for the toxic chemical use series that are difference-stationary (namely, arsenic, asbestos, cadmium, antimony, beryllium, bromine, and lead) and forecasts of these chemicals will be less certain and more variable than the forecasts of the toxic chemicals that are trend-stationary (namely, mercury, chromium, cobalt, manganese, selenium, zinc).

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