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Assessing the accuracy of self-reported data: an evaluation of the toxics release inventory

Scott de Marchi · James T. Hamilton

Abstract Self-reported regulatory data are hard to verify. This article compares air emissions reported by plants in the Toxics Release Inventory with chemical concentration levels measured by EPA pollution monitors. We find that the large drops in air emissions reported by firms in the TRI are not always matched by similar reductions in measured concentrations from EPA monitors. When the first digits of the monitored chemical concentrations follow a monotonically decreasing distribution, we expect (via Benford's Law) a similar distribution of first digits for the TRI data. For lead and nitric acid the self-reported data do not follow the expected first digit pattern. This suggests that for these two heavily regulated chemicals plants are not reporting accurate estimates of their air emissions.

Keywords Toxics release inventory · Benford's law · Reporting accuracy · Information provision

JEL Classification K32, Q53

Information provision of self-reported data is increasingly used as a regulatory tool. Companies routinely provide the public with data on firm finances, product content, and political donations. Under the U.S. Environmental Protection Agency's Toxics Release Inventory (TRI) program, manufacturing facilities that handle threshold amounts of specific chemicals must report yearly their releases and transfers of these toxic substances. The data have become the yardstick by which regulators, investors, environmental organizations, and local community groups measure company environmental performance. For the 2000 reporting year, 23,484 facilities submitted 91,513 reports about the emissions and transfers of the approximately 650 chemicals tracked in the TRI. Between 1988 and 2000, the data reported

S. de Marchi
Department of Political Science, Duke University
e-mail: demarchi@duke.edu

J. T. Hamilton (✉)
Terry Sanford Institute of Public Policy, Box 90245, Duke University, Durham, NC 27708
e-mail: jayth@pps.duke.edu

to the EPA indicated that releases of the core TRI chemicals by manufacturing plants dropped by 48 percent, with part of the reduction attributed to scrutiny generated by public release of the data.[1] Persistent questions about the operation of the TRI program, however, are generated because the data are self-reported. This article investigates how one can assess the accuracy of pollution data reported by firms by analyzing a surprisingly informative source, the distribution of the first digits of reported pollution figures.

The operation of the TRI program relates to numerous current debates in law and policy implementation.[2] Researchers in many fields have focused on the increasing use of information provision as a regulatory instrument. Within the environmental policy area, information provision has been one of the policies considered in attempts to find alternatives to traditional reliance on command and control regulations. The detailed pollution data in the TRI have allowed analysts to examine how the distribution of pollution varies by demographic group and community and have sparked extensive debate over environmental equity. The impact of the TRI on firm releases of air toxics in particular relates to policy debates about self-regulation, self-reporting, and the effects of air toxic regulations.

Empirical research on TRI and toxics reduction generally focuses on one of three units of observation: firms, plants, or areas of exposure (i.e., geography). Research on firm level influences on pollution reduction has explored firm size, research and development expenditures, regulatory interactions, and the degree that firm products face demand by green consumers. Hamilton (1995a) finds that the initial release of TRI data did provide new information to investors and journalists, as evidenced by the negative stock market reactions to the release of the data and the number of pollution stories generated by the TRI figures. Studying the relationship between adverse stock market reactions to TRI information and pollution reductions, Konar and Cohen (1997) establish that firms with the largest adverse market reactions subsequently reduced their TRI releases more. Khanna, Quimio, and Bojilova (1998) find that negative stock market reactions to TRI information lead to a reduction in the release of toxics onsite but increase the waste shipped offsite. Khanna and Damon (1999) and Arora and Cason (1996) trace how firm-level benefits and costs influenced company choices about whether to join the EPA's voluntary 33/50 program, which targeted reductions in 17 TRI chemicals. Harford (1997) examines company-level decisions about voluntary pollution reduction.

Less research focuses on the relationship between plant-level characteristics and toxics reduction. Streitwieser (1994) combines detailed census production data on chemical plants with TRI information to find that *intra*-industry variations in toxics generation are as great as *inter*-industry variations; additionally, substantial differences exist across firms within an industry. Marakovits and Considine (1996) use engineering and risk models to explore how exposure to risks can be measured from steel plants emitting air toxics.

Finally, much of the current TRI research takes a geographic area as the unit of observation, so that analysts can explore how community characteristics influence pollution decisions and what types of exposures are faced by particular communities. Shapiro (2005) summarizes the research on community exposures and lays out hypotheses about how polluting firms react

[1] See U.S. EPA, 2002a.

[2] For research on information provision as a regulatory instrument, see Lyon and Maxwell, 1999; Sunstein, 1999; Maxwell, Lyon, and Hackett, 2000; Roe, 2000; Cohen, 2001; Fung, Graham, and Weil, 2002; Graham, 2002; Stephan, 2002. For debate about environmental policy instrument selection, see Esty, 1996; Farber, 2000; Schroeder, 2000; Karkkainen, 2001; Spence, 2001. Assessments of environmental justice analyses include Hamilton (1993, 1995b); Been (1994); Hamilton and Viscusi (1999); Viscusi and Hamilton (1999); Lazarus (2000); Cole and Foster (2001). Helland (1998) and Reitze and Schell (1999) focus on self-reporting in environmental regulation, while Levinson (1999) examines command and control regulation of air toxics.

to variations in neighborhoods, state toxic regulations, and production-related factors. The units of observation in these exposure studies include states (Terry and Yandle, 1997), zip code neighborhoods (Arora and Cason, 1999), and 1 square kilometer grids (Shapiro, 2005). Hamilton (1999) provides estimates of cancer risks generated by air carcinogens released by plants and finds that plants appear to take into account human health risks when making pollution reduction decisions. In general, the research on TRI exposure finds that there are large differences in community exposures to toxics, and that income, education, and voter turnout are associated at the community level with different levels of pollution exposure. Additionally, differences in exposure correlate with race, depending on the measures of risk used and the region of the country examined.

Unfortunately, less academic research has focused on the accuracy of the TRI information. The text of the law creating the TRI, the Emergency Planning and Community Right-to-Know Act of 1986 (EPCRA), explicitly states that plants need not engage in substantial effort to derive their TRI figures:

> In order to provide the information required under this section, the owner or operator of a facility may use readily available data (including monitoring data) collected pursuant to other provisions of law, or, where such data are not readily available, reasonable estimates of the amounts involved. Nothing in this section requires the monitoring or measurement of the quantities, concentration, or frequency of any toxic chemical released into the environment beyond that monitoring and measurement required under other provisions of law or regulation.[3]

EPA (1990a) and General Accounting Office (1991) studies estimate that nearly one-third of the facilities that were required to report toxic emissions under the TRI program did not file reports in its first years of operation (i.e., 1987 or 1988 emissions). Studying compliance with TRI reporting in Minnesota after substantial outreach efforts by regulators there, Brehm and Hamilton (1996) find that over one quarter of the plants eventually reporting for 1990 were plants that had originally failed to submit TRI forms. Though the efforts of Minnesota environmental regulators added a large number of plants to the reporting program, these facilities generally reported lower pollution levels and accounted for only a small percentage (6%) of the total releases and transfers in the 1990 Minnesota TRI data. Brehm and Hamilton conclude that ignorance of reporting requirements rather than strategic evasion helps explain noncompliance in the early years of the program.

Under EPCRA, the EPA can assess a civil penalty of up to $25,000 per violation of TRI reporting requirements. In ten years of enforcement operations (FY 1990–1999), the EPA brought 2,309 administrative actions against facilities under EPCRA.[4] Of the 17,560 environmental compliance inspections the EPA conducted in FY 2001, only 321 dealt with TRI reporting requirements. Since the legislation does not set a particular standard for accuracy and gives wide latitude for estimates, the EPA's TRI cases often focus on the failure of a plant

[3] U.S. Senate Committee on Environment and Public Works, 1990, p. 132.

[4] For historical enforcement figures see U.S. EPA, 2000. Data for FY 2001 enforcement are from U.S. EPA, 2002b. Cohen (1999) examines why firms comply with environmental regulations despite the fact that inspections are relatively infrequent and fines relatively low. The low penalties assessed for violating TRI reporting requirements are evident when one compares sanctions for violating EPCRA versus the Clean Air Act (CAA). In FY 2001 for EPA enforcement actions under ECPRA there were $15,000 in criminal penalties assessed, $12,957 in civil judicial penalties, and $3,515,780 in administrative penalties. Under the CAA in FY 2001 the EPA had $25,315,683 in criminal penalties, $55,015,441 in civil judicial penalties, and $4,006,848 in administrative penalties assessed. When the EPA found a facility in noncompliance with EPCRA reporting requirements it often focused on getting the plant into compliance through the filing of TRI reports rather than on assessing large fines. EPA's EPCRA enforcement policy (EPA, 2001a) notes that if the agency does discover a significant release estimation error in a facility's TRI report this can trigger a civil administrative complaint.

to file any form reporting releases and transfers of chemicals rather than on the accuracy of filed reports. Environmental groups have complained about the potential for firms to overestimate their reductions in emissions and have labeled some declines in reported TRI figures as "phantom" or "paper" reductions. The National Wildlife Federation (1990) surveyed 29 facilities about their toxic releases and transfers for 1987 and 1988 and determined that the largest reported decreases came from "changes in reporting requirements, analytical methods, and production volume, and not from source reduction, recycling, or pollution abatement."[5] An EPA (1993) study in which plants were surveyed about changes in their reported TRI figures for 1989 and 1990 found that at least half of the net change in TRI figures came from real changes in chemical releases, with the rest a mixture of real and paper changes. EPA analyses (1990b, 1998a, 1998b) in which site surveys are used to verify the accuracy of TRI reports consistently find that some plants have difficulties in determining whether their use of a chemical surpasses thresholds for reporting and that plants are more likely for air releases to have monitoring data on stack releases than on fugitive emissions (e.g., leaks).

Relying on industrial facilities to devise their own estimates of toxic releases and transfers offers regulators one obvious advantage—the government does not have to expend the resources necessary to generate plant-level figures for emissions of the more than 650 TRI chemicals. OMB estimates that each TRI chemical form filled out by facility employees takes 52.1 hours, which includes time to determine requirements, gather data, make calculations, and fill out the form.[6] Giving plants leeway to develop their own estimates of TRI emissions allows the EPA to avoid the substantial transaction costs involved in defining calculation procedures and implementing or supervising the onsite gathering of information. The public scrutiny of TRI figures, however, gives plants the incentive to develop "optimistic" assessments of their efforts to control or reduce pollution.

Our article offers two efficient ways to investigate the reliability of self-reported data, cross-checking the data with a source outside the control of firms and analyzing the self-reports for peculiar statistical patterns. Actual measures of ambient chemical concentrations for 12 TRI chemicals from the EPA's national system of pollution monitors provide a benchmark to compare with the self-reported data. We first use information on average concentrations for the subset of 5 TRI chemicals with sufficient data to compare the percentage change in average TRI emissions and in the average monitored concentration between the initial period of reporting for each chemical (1988–1990) and the latest period of reporting (1998–2000). For two of the chemicals, benzene and lead, we find that the large pollution reductions reported by firms in the TRI data are not fully supported by the chemical monitoring data tracked by the EPA.

We then exploit a statistical property called Benford's Law to examine the distributions of first digits in pollution figures. Benford (1938) determined that for some samples of numbers the distribution of first digits is monotonically decreasing, with 1s outnumbering 2s, which in turn outnumber 3s, and so on. Later work determined this result is scale invariant (e.g., one can scale the data by a constant and still observe the same distribution of first digits). If the monitored chemical concentration data follow Benford's Law, we would thus expect that the first digits of the self-reported pollution figures should follow the same monotonically declining pattern. For the first digits of the TRI reported emissions data for these chemicals, 1s should appear more frequently than 2s, which should appear more frequently than 3s. Yet for two of the most heavily regulated and hazardous chemicals in our

[5] See Poje and Horowitz, 1990, p. 1.

[6] See U.S. EPA, 2002a.

sample—lead and nitric acid—we find that self-reported TRI figures do not follow the expected patterns of first digits. Several factors could explain why Benford's Law might not hold for these two chemicals. Plants might underestimate their releases of lead and nitric acid because of the relatively high levels of regulatory scrutiny and health hazards involved. The relatively low levels of releases per facility for these chemicals, however, may also mean that companies are less likely to track their releases and thus more likely to "guess" about estimated quantities. If persons filling out the TRI forms choose simple benchmarks as estimates (e.g., 50 pounds?), this would be another reason why the first digit distribution will diverge from the Benford pattern.

Overall our results show how simple tests such as comparing monitor data with reported emissions and examining the distribution of first digits can provide environmental regulators with information about data quality. Auditors already use Benford's Law to look for accounting violations (Nigrini, 2000). An examination of stock prices on the NASDAQ that found dealers avoided odd-eighth quotes (i.e., prices ending in 1/8, 3/8, 5/8, or 7/8) set off antitrust litigation and government investigations into pricing collusion (Christie and Schultz, 1999). We cannot determine the motives behind the statistical anomalies we observe in the TRI; divergences between monitored concentrations and reported emission levels could have many explanations, including evasion or guesswork. Our results do, however, suggest tests that regulators can use to distinguish among chemicals as they decide which sets of self-reported data to trust and which to verify.

1. Methodology

In this article we propose two different types of tests that would allow regulators to assess the quality of self-reported data such as TRI pollution figures. The first set of tests concerns the correspondence between data reported in the TRI program and pollution figures collected by the EPA Ambient Air Monitoring Program. Under air quality monitoring programs the EPA collects information on ambient pollution concentrations from over 5,000 monitors across the country that are primarily operated by state and local environmental agencies.[7] Fortunately, there is an overlap of 12 chemicals between the set of pollutants monitored by the EPA and those tracked in the TRI. This overlap allows us to conduct a series of tests designed to see if the broad reductions reported in TRI pollution figures are accompanied by concomitant reductions in concentrations measured by the EPA monitors. If there are large reported reductions in the amounts of a given chemical emitted by facilities, we would expect decreases in ambient concentrations of the chemical if TRI facilities generate a significant portion of the chemical's releases.

[7] The monitors used in our study come from the State and Local Air Monitoring Stations (SLAMS) program and National Air Monitoring Stations (NAMS) program. The SLAMS network of more than 4,000 stations is used by states and localities to measure state pollution requirements, while the NAMS network of 1,080 stations is used to measure concentrations in urban and multi-source areas with high population densities. Monitor data were accessed at www.epa.gov/aqspubl1, while TRI data used in the study were from the EPA's Envirofacts database (www.epa.gov/enviro). We treat the monitoring and Envirofacts data as given. For example, though formal reporting of n-Hexane did not start until 1995 the TRI data in Envirofacts contain a few reported observations in prior years.

A second set of tests relies upon mathematical techniques developed in light of Benford's Law.[8] Physicist Frank Benford noticed in 1938 that among the sections of logarithm tables, pages with numbers starting with the numeral 1 were much more worn than those starting with 2, which in turn were more smudged than those starting with 3. He determined that for some samples of numbers the distribution of first digits follows a distribution such that that the probability of a number starting with the digit D is given by log (1 + 1/D). Thus the probability a number began with the first digit 1 would be .301, with a 2 would be .176, and so on. The probability declines to .046 for a number with 9 as the first digit. There is limited analytic guidance to determine *a priori* whether or not a given sample will follow Benford's distribution, since there is no characteristic of the number system that inexorably leads to Benford's Law.[9] Yet if the leading digits in a sample do follow this distribution, the result will be scale invariant. Benford's Law has been used in accounting and tax analyses to screen for potential fraud. If individuals are guessing or estimating numbers for a process that conforms to Benford's Law, they will in the aggregate tend to overestimate the prevalence of larger numbers for the first digits and underestimate the presence of 1s or 2s. Varian (1972) has proposed evaluating a model's predictions in part by determining if input data that follow Benford's Law generate predicted values that also follow Benford's Law. Dumas and Devine (2000) examine the application of Benford's Law to self-reported emissions data on criteria air pollutants in North Carolina for 1996–1998.

There is of course the question of determining whether or not an empirical distribution matches the theorized Benford distribution. Following Scott and Fasli (2001), we rely upon several tests to determine conformity, including a chi-square test, the Kolmogorov-Smirnov (KS) test, and a visual inspection of the histograms of first digits.[10] The Kolmogorov-Smirnov test, which relies upon the maximum absolute difference across the nine leading digits, is very sensitive to threshold and rounding effects. This can be a good feature of the test and is the reason why we include it, but one can also reject a match based on relatively few outliers. The chi-square test, on the other hand, provides good insight into the general fit over the entire range of the distribution, but is not very sensitive to threshold and rounding effects for a particular digit. Both tests are very brittle in the face of large sample sizes, and for that reason, visual inspection of the histograms of first digits is necessary to determine conformance to Benford's Law.[11]

[8] See Benford (1938) for the original work and Nigrini, 2000 for an overview and applications to accounting fraud. Browne, 1998 recounts the history of Benford's Law. For applications of Benford's Law in economic analysis, see Varian, 1972 and Helland and Nye, undated.

[9] Raimi (1976, 1985). For the scale invariance result, see Pinkham, 1961 and Hill, 1995. Dumas and Devine (2000) offer arguments for why air pollution emission data from facilities may be expected to generate a distribution that follows Benford's Law. They apply a number of digital frequency tests to criteria air pollutant emissions figures from plants in North Carolina to demonstrate the desirability of using digits tests to analyze self-reported data from firms.

[10] The essence of both the chi-square and KS tests is to determine if two distributions match; in other words, the null hypothesis is that the sample distribution (from either the EPA or the TRI) is indistinguishable from the theorized Benford's distribution. Thus, higher chi-square or Kolmogorov-Smirnov values indicate greater deviation from our expectation that Benford's Law holds for these data (see Table 2).

[11] In this context, "brittle" means that relying upon traditional significance tests can easily be swamped by the sample size. For example, for very large samples, comparing two distributions with chi-square tests at the .05 level will always determine that there is a difference between the distributions. Thus, arbitrary choices like which years or which value for distance is the threshold for inclusion in a sample can overdetermine whether or not significance is reached. For that reason, it is our belief that a visual inspection of the relevant histograms for conformance to Benford's law is a superior practice.

Table 1 Change in average TRI reported air emissions versus average ambient concentrations tracked in EPA Monitors, 1988–1990 to 1998–2000

Chemical	Data source	% Change
Benzene	EPA monitors	−56%
	TRI Reports	−84%
Ethylbenzene	EPA monitors	−72%
	TRI Reports	−35%
Lead	EPA monitors	−24%
	TRI Reports	−45%
Nitric Acid	EPA monitors	−20%
	TRI Reports	−13%
Toluene	EPA monitors	−67%
	TRI Reports	−61%

2. Results

A first test for irregularities in self-reported TRI data concerns whether TRI data exhibit reductions similar to those found in the EPA monitored data. As noted above, while the TRI covers approximately 650 toxic chemicals, there is a subset of twelve TRI pollutants whose levels are also tracked in EPA monitoring stations across the country. To determine whether or not the TRI releases match the EPA monitored data, we compare reported changes in average TRI releases per facility with changes in average ambient concentrations. Plants that meet reporting thresholds for a given chemical must file a form with the EPA that lists releases and transfers of the chemical. Using the latitude and longitude data in the EPA TRI and monitor data, we created a database for analysis that consisted of the TRI reporting facilities that had at least one air monitor within a 50 km radius.[12] In Table 1, for each chemical for the first year with at least 100 observations for TRI facilities and monitor data we calculated the average air emissions per plant based on the data in the TRI Form Rs. We defined air emissions as the sum of the reported stack emissions and fugitive emissions (e.g., leaks).[13] We also calculated

[12] We chose 50 km for this test because it captures the greatest diversity of facilities and facility locations, thereby representing the greatest possible canvas of facilities across the United States. If one were to use a smaller value for distance, urban facilities would be overrepresented, and the only two chemicals with sufficient observations would be lead and nitric acid. A more exacting test using 5km thresholds is provided in the next section on Benford's law.

[13] The TRI Form R (see EPA, 2001b) asks for the total release in pounds per year for "fugitive or non-point air emissions" and "stack or point air emissions." We sum these for each plant (i.e., for each TRI facility ID number) to get a total air release figure and use this number in our analyses. For annual releases of less than 1,000 pounds the TRI form allows a facility to enter in a range code indicator instead of a precise estimate, where the range codes are A = 1–10 pounds, B = 11–499 pounds, and C= 500–999 pounds. In the TRI data these figures are converted to the midpoint of the range, so that a facility listing C as its stack emissions would in the TRI data have a figure of 750 pounds. We use these midpoint figures in our analysis of changes in TRI releases over time. In our analysis of first digits this use of midpoints would result in excessive reports of 5, 2, and 7 (from the midpoints 5, 250, and 750). For plants that reported category responses we looked at the distribution of reported figures within that range and randomly picked a figure from the distribution. For a facility that reported a range code of B, we replaced the midpoint estimate with a figure picked from those TRI forms with reported figures between 11–499 and used that number for the first digit analysis. We also found that when we simply dropped the category data from the first digit analyses our results were similar. Another caveat is that in 1998 seven new industries were added to the TRI database. These industries are included in our analysis of TRI chemicals, though they do not appear to contribute significantly to the emissions of the 12 chemicals we analyze here.

the average ambient concentration for the monitors within 50 km of the TRI facilities.[14] We then calculated the percentage change in average TRI emissions and in the average monitored concentration between the initial period of reporting for each chemical (1988–1990) and the latest period of reporting (1998–2000).[15]

Table 1 shows that for 2 of 5 of the chemicals the TRI data report substantially better news about pollution reduction than the EPA monitoring program. For example, between the earliest and latest time periods the average air emissions of benzene reported in the TRI data dropped 84% while the average concentration of benzene in the monitors within 50 km of the TRI facilities dropped by 56%. Similarly, average TRI reports of lead air emissions declined by 45% while average concentrations measured by EPA monitors declined by only 24%.[16] Two other chemicals—nitric acid and toluene—were similar for both TRI reports and EPA monitors. Ethylbenzene, however, had *less* of an improvement on TRI reports than that measured by EPA monitors.

At least four explanations could account for these differences. In some cases, firms could be strategically overestimating their pollution reductions in TRI. Since reductions are greeted by regulators, investors, and environmentalists as good news, plants may have incentives to provide optimistic, and inaccurate, estimates of pollution reductions. Given the difficulties of determining whether the data are correct and lack of real regulatory penalties for misestimating releases, overestimating pollution reduction may be rational for TRI reporters. This, however, does not explain the case where TRI reductions do not rival those found in the monitoring data. As noted above, ethylbenzene actually displayed less improvement in the TRI program than on the EPA monitors. A second explanation might be that the TRI reports are accurate and that the monitors are simply not placed close enough to the participating TRI facilities, so there need not be an expected correspondence between emissions and concentrations.[17] A third possibility is that average TRI figures for some of these chemicals are

[14] For each monitor registering a concentration of one of our 12 chemicals we used the annual arithmetic mean concentration as the figure from that monitor. In Table 1 if a TRI facility has at least one monitor within a 50 km radius its data is included in the analysis once. If there are multiple monitors within a 50 km radius, the data from each monitor is included in the calculation of the national average concentration. For the first digit analysis we took the first figure in the annual arithmetic mean concentration reported for each monitor within a 50 km radius. If a monitor had more than one concentration estimate associated with it, we took the first concentration associated with the monitor since this is usually generated by the dominant monitoring technology used by the monitor. In Table 1 TRI averages were measured in pounds. Chemical concentrations were in measured in units of ppb C, except for lead (ug/m^3 SC) and nitric acid (ppm).

[15] We began with 1988 as the starting point for the early period (rather than 1987), as this is the first year the EPA views as reliable for TRI data. The results above are not sensitive to the particular thresholds chosen (e.g., one could choose 2 or 4 year spans for the two time periods), but it is worth nothing that benzene and ethylbenzene have very few observations. In the early period, benzene has 169 monitor observations and ethylbenzene has 279; lead, nitric acid, and toluene all have over 1000 observations. The remaining chemicals were excluded because they had only a handful (or 0) observations.

[16] Seven of the 12 chemicals did not have sufficient numbers of monitors/reporters in the early period (1988–1990) to be included in Table 1. Taking the base year as the first year with 100 monitors and TRI reports, one finds the following percentage changes (year 2000 vs base year) in average concentrations from monitors and average reported releases of TRI air emissions: 1, 2, 4-trimethylbenzene (1993) –37% for monitor data vs 118% for TRI data; cyclohexane (1993) 19% vs –59%; ethylene (1993) –39% vs 73%; *n*-hexane (1995) –40% vs -46%; o-xylene (1993) –45% vs –52%; and styrene (1991) –54% vs 52%. Thus for 3 of the 7 chemicals the TRI averages report more progress in pollution reduction than the monitor data. Note that the TRI total emissions in year 2000 used in Table 1 include figures from the seven industries that started reporting in 1998.

[17] We plan to use the latitudes and longitudes of the TRI facilities and EPA monitors and GIS software in future work to examine the relationship between the measured concentrations at a particular monitor and the reported TRI releases from a nearby facility. This will also allow us to control in part for the impacts of

driven by a relatively small number of plants with large emissions. This would mean there could be large changes in the TRI average emissions based on a relatively small number of plants; thus, average concentrations measured by a large number of monitors would tend to underreport the influence of large facilities. A fourth possibility is that sources other than industrial plants drive the ambient concentrations of the overlapping chemicals.[18]

The first test suggests that one cannot rely upon a straightforward comparison of measurements over time. The differences between the TRI reports and the EPA monitors are in many cases quite large, but there is no pattern across chemicals—for some, the TRI shows gains not mirrored by the monitors and vice versa. We thus need a better test to assess the reliability of the TRI program. Our second test improves our ability to determine the veracity of the TRI by examining whether or not the distribution of *first* digits of pollutant data conform to Benford's Law. This analysis requires two steps. First, we determine which of the 12 chemicals monitored by the EPA Ambient Air Monitoring program conform to a Benford distribution. We take the first digit of the annual average concentration reported at each monitor within a 5 km radius of a TRI facility reporting air emissions of the chemicals, create a distribution of the number of times each first digit appears in the data, and compare this distribution to the Benford distribution.[19] Second, we examine the corresponding distribution of the chemicals in the TRI data. We take the first digit of the total air emissions (stack and fugitive) reported by each plant with at least 1 air monitor within a 5 km radius and create a distribution of these first digits for each chemical. As noted above, one of the properties of Benford's Law is that resultant distributions of first digits are scale invariant; without this property, searching for this type of correspondence between concentrations and emissions would be merely suggestive.[20]

An example of the second test is provided in Figures 1 and 2. Figure 1 shows the Benford distribution. One way to think of this is in terms of the physical process behind the production of a chemical. Moving from a leading digit of 1 to 2 means doubling the amounts, moving from 1 to 3 requires tripling, and so on. As the magnitude of the leading digit increases, the probability of producing that amount should decrease, reflecting the ever-increasing difficulty of getting to the next higher digit.

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the surrounding community on monitored concentrations. For some chemicals, the release of pollutants by mobile sources (e.g., cars) can contribute significantly to local ambient chemical concentrations. Note that the locations of the monitors can change over time, so the areas monitored year to year can vary.

[18] The EPA list of air toxics from motor vehicle operation includes the following chemicals from the set of 12 overlapping chemicals: benzene, ethylbenzene, *n*-hexane, lead, styrene, and toluene. A report on toxic air contaminants in the California South Coast Air Basin estimated that 70 percent of total 1998 emissions of benzene would be from on road sources. See South Coast Air Quality Management District, 1997.

[19] The choice of 5 km as a threshold for the radius matters, insofar as for some chemicals a smaller (i.e., closer) threshold would not produce enough observations for analysis. It is also true that traditional tests of statistical significance are sensitive to these sample sizes. Despite these issues, visual inspections of the histograms for EPA and TRI data remain virtually unchanged at any given threshold.

[20] The EPA's Risk-Screening Environmental Indicators (RSEI) model translates TRI emissions into ambient concentrations for areas surrounding facilities; see EPA, 2002c. For an example of a simple equation translating emissions into ambient concentrations, see Georgia Department of Natural Resources, 1998. In this equation, the emission rate of the toxic chemical is multiplied by factors including wind velocity, effective stack height, and dispersion parameters relating to downwind distance and atmospheric stability. If one assumes for a given chemical that these factors are similar across the plants and monitors then the transformation from emission rate to concentration involves an order preserving scaling factor, meaning that if the first digits of the concentrations exhibit a Benford distribution then so too will the first digits of the emissions. For analysis that translates emissions data on 148 toxic chemicals into concentration estimates for more than 60,000 census tracts and discusses public health implications, see Woodruff et al., 1998.

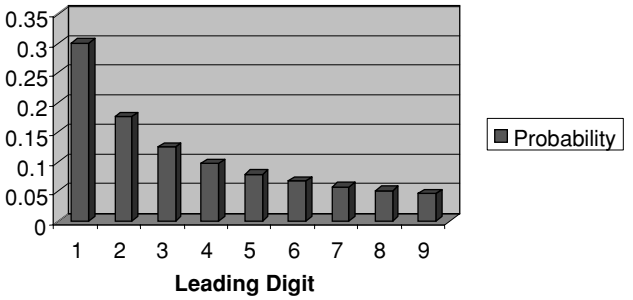


Fig. 1 Probability of leading digits for Benford's law

Figure 2 shows the *actual* distributions of first digits for three of the chemicals, comparing the EPA monitored data to the TRI data for all reports from 1988 through 2000. For styrene, there were 1,058 data points in the Benford analysis of the TRI data within 5 km, consisting of the 1,058 instances when in a given year between 1988 and 2000 there was a TRI report with an estimated air emission of styrene and an EPA monitor within 5 km of the TRI facility that tracked an ambient concentration of styrene. The first digits from the TRI air emission totals from a plant and the first digits from the ambient concentrations tracked in the monitors both generate distributions that look Benford upon visual examination for styrene. The same congruence of EPA monitor and TRI data appears in visual comparisons for benzene, ethylbenzene, *n*-hexane, propylene, and toluene. Figure 2 shows that the EPA monitor data for lead and nitric acid both appear to follow a Benford pattern in the distribution of first digits from the concentration figures. For the TRI air emission totals, however, the distribution of first digits diverges widely from the Benford pattern. For lead and nitric acid, 2s and 5s are overrepresented in the estimates provided by the TRI facilities.

If the congruence between plant emissions and monitor concentrations declines with distance, one would expect a closer match between the two datasets for monitors close by the facilities. Table 2 reports the results of three different ways of determining whether the first digits data follow a Benford distribution for monitors within 5 km of the TRI plants: a chi-square test, a Kolmogorov-Smirnov test, and a visual inspection of the histograms. For 9 of the 12 chemicals, the EPA monitor data visually conform to the shape of Benford's distribution and in all 12 cases the tests indicate no great deviation from the expected Benford distribution. Surprisingly (given the relatively large sample sizes), half of the chemicals are not significantly divergent from Benford's distribution at traditional significance levels.

The TRI data also visually match a Benford distribution for half of the chemicals, though only two cases are not divergent in terms of statistical significance. As a group, the TRI data fit less well to the hypothesized Benford distribution, but two chemicals stand out with much more dramatic deviations. As Figure 2 shows, lead and nitric acid are in a different class from the rest of the TRI chemicals, which is immediately obvious from the histograms.

Table 2 details the two (imperfect) statistical tests we use to compare the first digit distributions of the concentrations and air totals to the Benford distribution. The chi-square test sums the squared differences between the Benford distribution and the actual distribution of first digits, while the Kolmogorov-Smirnov (KS) test relies on the maximum difference for

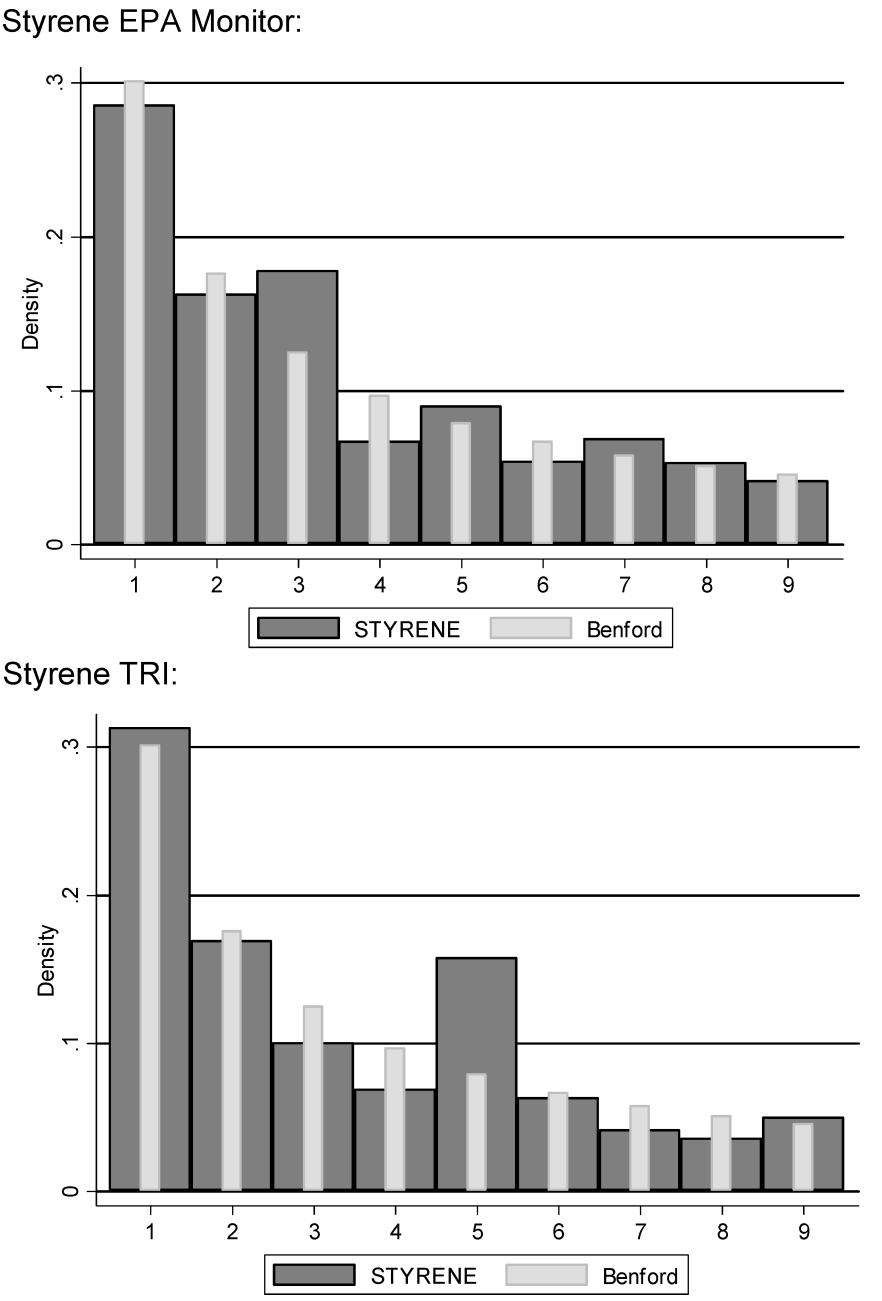


Fig. 2 Distribution of first digits from EPA monitor concentrations and TRI facility air emission totals
(*Continued on next page*.)

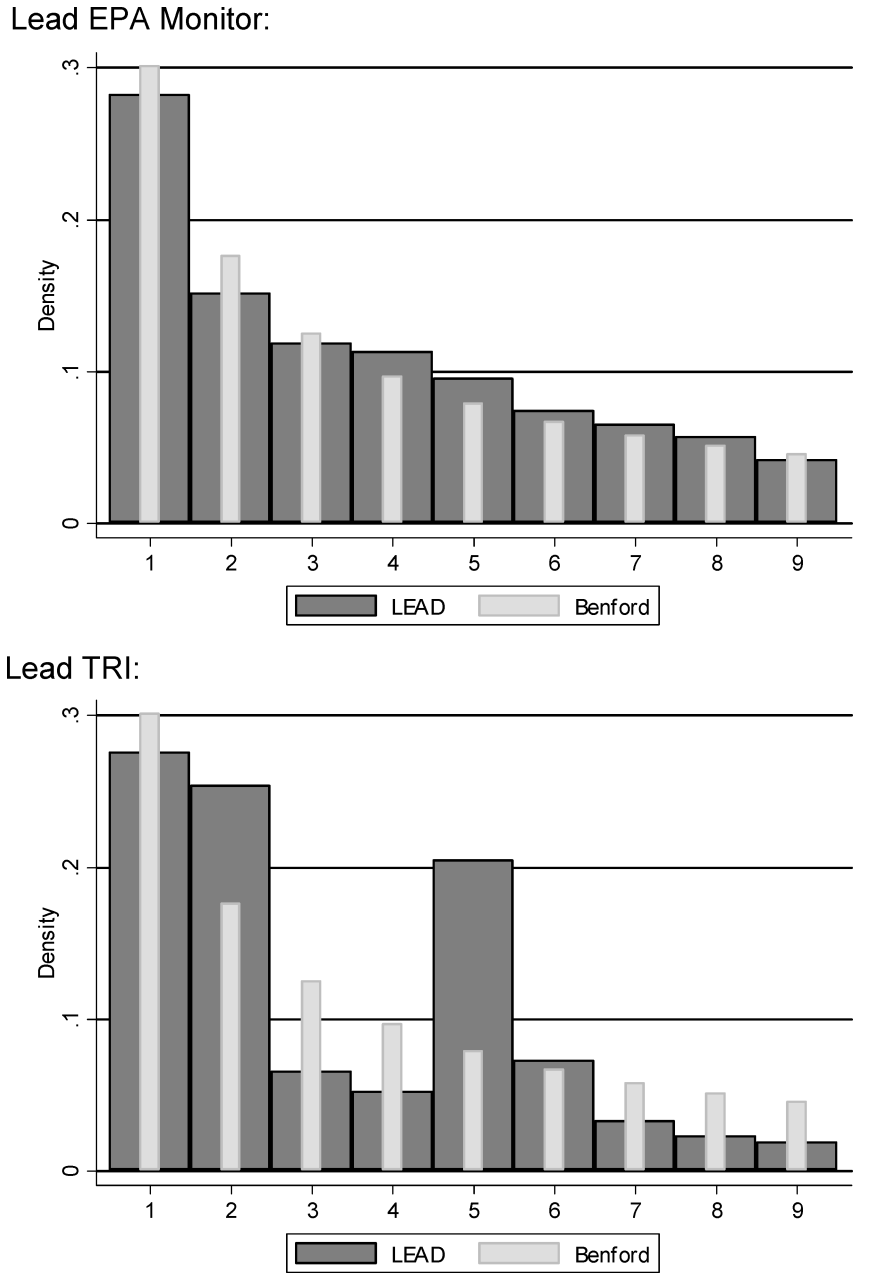


Fig. 2 (*Continued*).

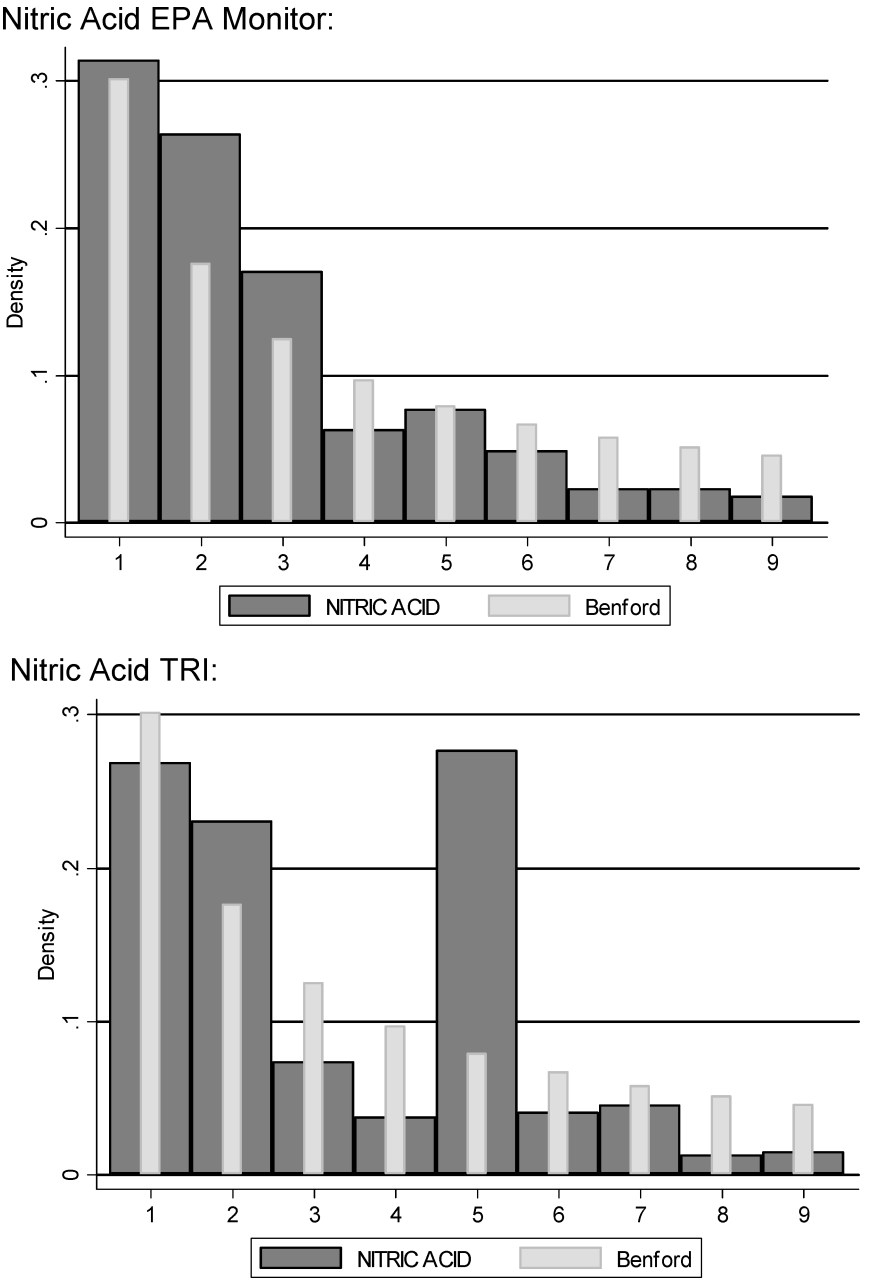


Fig. 2 (*Continued*).

Table 2 Comparing EPA monitor data to the Benford distribution at 5 km or less (1988–2000)

EPA data	N	Visual	Chi-square	KS
1, 2, 4-Trimethylbenzene	123	–	48	0.08*
Benzene	237	Yes	23	0.11
Cyclohexane	73	Yes	25	0.09*
Ethylbenzene	232	Yes	10*	0.04*
Ethylene	43	–	28	0.31
Lead	750	Yes	11*	0.04
N-Hexane	91	Yes	17	0.06*
Nitric acid	363	Yes	70	0.2
O-Xylene	72	Yes	13*	0.17
Propylene	80	Yes	9*	0.06*
Styrene	190	–	51	0.17
Toluene	186	Yes	16	0.06*

Given the size of the samples involved, traditional significance tests are inappropriate, but an *denotes no significant difference from the Benford distribution at the .05 level or better on the Chi-square test and .10 or better on the Kolmogorov-Smirnov test. Instead, one should compare the Chi-square and Kolmogorov-Smirnov test values between the EPA and TRI data. In general, most differences are slight, except for lead and nitric acid, where the TRI data are dramatically different (i.e., one—two orders of magnitude on the Chi-square tests, and double the Kolmogorov-Smirnov values).

any of the nine digits between the Benford and the observed distribution.[21] The large sample sizes involved mean that using the chi-square tests and traditional significance values we would reject our hypothesis that there is no difference between the concentration or the air total distribution and the Benford distribution for many of the chemicals at the .05 level. The relative size of the chi-square statistic for the TRI vs monitor data for lead (1,816 vs 11) and for nitric acid (2,524 vs 70) suggests that the TRI data diverge much more from the Benford distribution on this test.

Tables 2 and 3 suggest that while some chemicals conform to a Benford distribution in both the EPA and the TRI data, for lead and nitric acid the monitored data follow a Benford distribution and the TRI data do not. Such a finding indicates that some sort of intervening process distorts the TRI data, so that the distributional properties revealed in the monitored data do not hold. While one cannot ascertain from distributional tests what this intervening process is, it does raise a reasonable doubt about the validity of the TRI data. Note that lead was also one of the two chemicals in our first test where the reported reductions in the TRI were greater than the measured changes in ambient air concentrations.

Why are lead and nitric acid, of the twelve we have considered, especially problematic? An interesting partial answer is provided in Table 4. The first column lists the number of EPA enforcement cases in the EPA's civil enforcement case docket generated by each chemical. The second column lists the number of federal regulatory lists that contain the chemical. The third column is derived from information compiled by the Environmental Defense group on

[21] We are taking liberties by using the Kolmogorov-Smirnov test for non-continuous data. One could generate Benford distributions for the first two digits to more closely approximate the continuous case, but we have not done so here for purposes of exposition, following Scott and Fasli (2001).

Table 3 Comparing TRI data to the Benford distribution at 5 km or less (1988–2000)

TRI data	N	Visual	Chi-square	KS
1, 2, 4-Trimethylbenzene	773	–	121	0.07
Benzene	1234	Yes	68	0.07
Cyclohexane	263	–	78	0.16
Ethylbenzene	1858	Yes	145	0.05
Ethylene	226	Yes	26	0.06*
Lead	3770	No	1816	0.09
N-Hexane	406	Yes	20	0.07
Nitric acid	4253	No	2524	0.1
O-Xylene	106	–	43	0.15
Propylene	342	Yes	23	0.04*
Styrene	923	–	139	0.08
Toluene	4204	Yes	81	0.03

*See the note above for Table 2.

Table 4 Regulatory scrutiny and risks for TRI chemicals

chemical	# Cases, EPA civil enforcement docket	# federal regulatory lists	More hazardous than most chemicals in ranking system	Mean air releases (Pds), 2000 TRI
1, 2, 4- Trimethylbenzene	2	1	4 of 10	8250
Benzene	139	7	5 of 14	9113
Cyclohexane	3	3	4 of 11	9150
Ethylbenzene	22	6	3 of 10	6778
Ethylene	28	3	0 of 8	72577
Lead	458	8	11 of 11	789
N-Hexane	5	4	3 of 7	31788
Nitric Acid	26	6	6 of 9	2617
O-Xylene	82	3	2 of 10	5981
Propylene	4	2	1 of 10	39863
Styrene	43	5	6 of 10	25472
Toluene	114	7	2 of 10	16579

the number of hazard ranking systems in which the chemical is deemed to be more hazardous than most other chemicals.[22] The final column reports the average total air releases per facility in the 2000 TRI data for each chemical.

Table 4 indicates that lead generates the greatest amount of enforcement litigation among the 12 chemicals where EPA monitor data and TRI data overlap. Both lead and nitric acid

[22] Information on regulatory lists and hazard rankings came from www.scorecard.org. Counts of EPA actions involving a chemical came from the Lexis Environmental file entitled EPA Civil Enforcement Docket.

are on a relatively high number of federal regulatory lists. In terms of dangers to human health and the environment, lead is ranked as more dangerous than other chemicals on all the ranking systems evaluated by Environmental Defense. Nitric acid rates relatively highly on the hazard scales too. Lead and nitric acid stand out in two other respects—the average total stack and fugitive emissions for both are an order of magnitude lower than the releases for many of the other chemicals in the table. In the year 2000, for example, the mean air emissions for lead was 790 pounds and for nitric acid was 2,620 pounds. This compares to mean releases of 72,580 for ethylene and 16,580 for toluene.

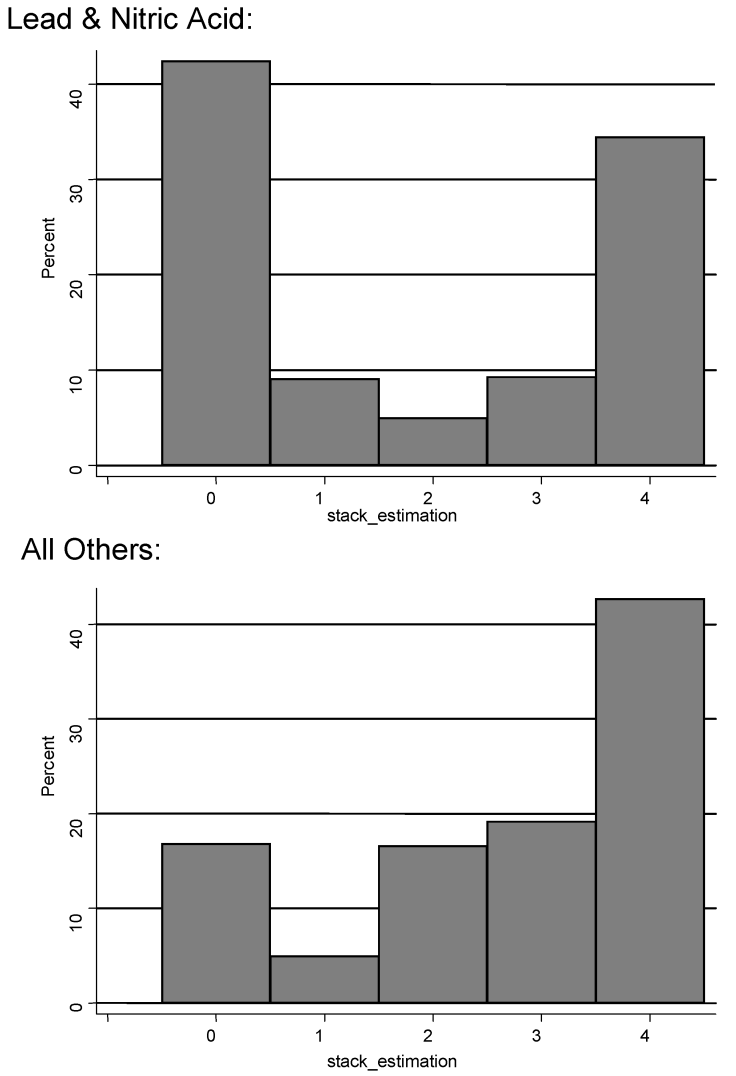
Table 4 suggests at least two reasons why lead and nitric acid estimates may diverge from Benford estimates. The relatively high levels of regulatory scrutiny and health hazards associated with lead and nitric acid may give plants an incentive to underestimate their releases. The relatively low levels of releases per plant may also mean that firms are less likely to track these releases and may be more likely to "guess" about estimated quantities. If their guesses focus on a few focal values (e.g., 50 pounds?), then this would be another reason why the first digits would fail to exhibit a Benford distribution.[23]

Figure 3 indicates that TRI facilities do approach the generation of air emission estimates differently for lead and nitric acid. For the other 10 chemicals, TRI facilities were much more likely in the forms to report (83% of the time) that they used a specific technique to generate their TRI estimates. Yet for lead and nitric acid, TRI facilities left the method of estimation question on the reporting form blank 43% of the time. The lower likelihood of answering the question was true both for facilities that used a range code to report estimated levels and for those plants that provided numerical estimates for lead and nitric acid. This suggests that firms were more likely to make guesses about their release of lead or nitric acid, rather than rely on monitoring data or mass balance calculations. The use of guesswork may come about because of the relatively small magnitude of the emissions, or because of the relatively high hazards and regulatory scrutiny associated with the chemicals.

The divergence between reported and monitored results thus raises questions about the quality of the TRI data for two chemicals, lead and nitric acid. The failure of self-reported data to follow the pattern of the underlying pollution data suggests that facilities are not accurately estimating their air releases in the TRI. While these aggregate tests cannot isolate which facilities are misestimating their air releases, they can set up a screen so that an agency concerned with data accuracy might investigate reported emissions for these two chemicals more intensively.[24] Section 4 develops the implications of our findings and their potential use in detecting anomalies in self-reported information.

[23] In the TRI samples in Table 3, for lead the top 5 reported stack emissions for those not using a range response answer were 2, 1, 50, 4, and 14 pounds. These responses accounted for nearly a quarter of the stack emissions reported. The frequent estimate of 50 pounds does suggest that some reporters chose a focal point in their responses, though whether they did this as a guess to avoid the transaction costs of measurement or as an estimate to underreport true emissions is not determined here. Note that if reporters are using rules of thumb that focus on changes in emissions (e.g., reduce TRI emissions by 5% from the previous year), the focal points will be evident in percentage changes rather than absolute numbers of pounds reported. For propylene, a chemical where the TRI reports track the Benford distribution more closely, the top 5 responses for stack emissions (12,000, 19,000, 30, 32,000, and 6,101 pounds) do not suggest the use of easily identifiable focal points in these reports. The top five most frequent figures reported for propylene stack emissions accounted for about 7 percent of reported responses, indicating the wider dispersion of estimates reported for this chemical.

[24] Other factors that regulators may consider in investigating data accuracy include the relative size of emissions per plant, likely hazards posed by a chemical, and the size of exposed populations. Regulators could also match individual monitors with TRI facilities and explore the divergences between the monitored chemical concentrations and the predicted values (controlling for plant and community characteristics) based on TRI emissions.



Description: Code for the principal method used to determine the amount of stack or point air emission releases reported. "1" indicates that the estimate was derived through monitoring data or measurements. "2" indicates that the estimate was derived through a mass balance calculation. "3" indicates that the estimate was based on published emission factors such as those relating to specific pieces of equipment. "4" indicates that the estimate was derived through some other form of engineering calculation or estimation technique. “0” indicates no method was reported.

Fig. 3 Basis of TRI data estimate

3. Conclusions

The principal agent relationship established by delegated decision-making inevitably gives the agent some power arising from hidden action or hidden information. When Congress through EPCRA and the EPA in the TRI delegated to facilities the responsibility to estimate and report their toxic releases and transfers, the flexibility inherent in self-reporting gave

plants leeway in devising their pollution estimates. Some facilities might choose to expend resources to develop accurate estimates, others might avoid transaction costs and simply make rough guesses, while others could use their freedom to develop excessively optimistic reports of pollution reduction. The EPA could discourage cursory or strategic estimates by expending significant resources to monitor emissions and inspect all facilities. Yet these agency efforts would erase the cost savings to the government of having facilities bear the responsibility of devising pollution estimates.

Benford's Law offers a way to conduct triage on self-reported regulatory data. If monitoring data establish that a sample should follow the first digit law, then one can expect the emissions data reported by plants to show a similar pattern. Our results suggest that for at least two of the twelve chemicals, lead and nitric acid, facilities may not be accurately reporting their TRI figures since the self-reported data fail to follow the Benford pattern evident in the monitoring data. This test does not allow an analyst to say which facilities reporting a 2 or a 5 as a first digit, for example, are inaccurate and which are reporting their best estimate. But the approach does allow the EPA to determine which classes of chemicals should be investigated more closely through plant inspections or monitoring. Applying the first digit law to self-reported data can provide a regulator with a first cut on which data to trust and which data to verify. The results also may be helpful in considering the desirability of lowering the reporting thresholds for the reporting of TRI chemicals. If plants are less likely to monitor smaller emissions, the data derived from reporting of small quantities may be less likely to be accurate than figures for chemicals released in larger quantities.

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