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DO STATES' DATA PROCESSING EFFORTS HELP MORE THAN THE INFORMATION DISCLOSURE ITSELF?

Hyunhoe Bae
Peter Wilcoxon
David Popp

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ABSTRACT

The Toxics Release Inventory (TRI) was expected to reduce health risks stemming from emissions of hazardous chemicals by increasing public pressure on polluters. However, it is a massive and complex dataset, requiring significant expertise to interpret in its raw form. State governments have attempted to mitigate the TRI's information processing burden on the public via two types of policies: (1) selection and dissemination of raw TRI data for plants within the state, and (2) data processing activities producing more refined reports and analysis. This study assesses the effectiveness of those policies. Our results show that state-level data dissemination efforts lowered the total number of pounds of chemicals released, but had little effect on health risks. State-level data processing efforts, in contrast, did lead to significant reductions in health risks. We conclude that simple dissemination of the data was ineffective (and even counterproductive in some instances), and that the states' data processing efforts have played a critical role in achieving the TRI's underlying goal.

Hyunhoe Bae
Syracuse University
The Maxwell School
411 Crouse-Hinds Hall
Syracuse, NY 13244-2130
hbae01@maxwell.syr.edu

Peter Wilcoxon
Syracuse University
The Maxwell School
411 Crouse-Hinds Hall
Syracuse, NY 13244-2130
wilcoxon@maxwell.syr.edu

David Popp
Associate Professor of Public Administration
Syracuse University
The Maxwell School
426 Eggers
Syracuse, NY 13244-1020
and NBER
dcpopp@maxwell.syr.edu

INTRODUCTION

The command-and-control approach has been the predominant form of US environmental regulation for the past three decades (Case, 2001; Esty, 2004). However, it has often generated high direct costs (Bui and Mayer, 2003) and more recent regulation has been moving toward market-based methods and other more indirect and flexible approaches.

One type of indirect and flexible strategy is compulsory information disclosure. The most salient example in environmental regulation is the Toxics Release Inventory (TRI). The TRI was established in 1986 by the Emergency Planning and Community Right-to-Know Act (EPCRA) which was part of the Superfund Amendments and Reauthorization Act (SARA). The TRI does not directly regulate plants' emissions. Rather, it simply requires manufacturing firms to report releases or transfers of toxic chemicals to the EPA. The EPA then discloses and disseminates the data to the public. The TRI was expected to drive plants to improve environmental performance to avoid adverse reactions by markets and the public: it was an explicit effort at "regulation-through-information."

The TRI was intended to be used by many sectors and parties, such as private individuals, businesses, public non-profit organizations, or other governmental bodies. In principle, it can be used for evaluating current environmental conditions, for assessing the status of various environmental programs, or for setting environmental agendas at local and state levels. In practice, however, it can be quite difficult for many individuals and organizations to use. The volume of data is massive, including information from nearly 49,000 plants on releases of more than 400 chemicals. Although the EPA publishes a national summary report, and fact sheets for each state as an appendix to the raw data, it is still difficult for most users to find information

relevant to their specific interests at an appropriate level of detail, and it is not easy for them to customize the dataset by re-packaging or restructuring it for further analysis. Moreover, in raw form the TRI reports the number of pounds of each chemical released without adjusting for toxicity, despite the fact that the ultimate purpose of the data is to reduce health risks rather than just the quantity of chemicals released. Thus, use of the TRI necessarily involves significant information processing, including procedures for interpreting and structuring the data.

As a result, the TRI may not be as effective as hoped when it was established. An extensive recent literature on mandatory information disclosure policies in health care shows that simple publication of large volumes of raw data can have little or no effect on the outcomes of most interest. Since the first release of TRI data in 1988, EPA has made an effort to make it more accessible to the public. However, for more than a decade, EPA's activities were largely limited to providing supporting information that facilitates interpretation of TRI data, such as toxicity information on chemicals, or to the provision of risk analyses focused on relatively narrow issues and conducted at the national level.¹

A number of empirical studies have tried to measure the effect of the TRI including: Kennedy, Laplante, & Maxwell (1994); Grant & Downey (1995); Grant (1997); Konar & Cohen (1997); Klenindorfer & Orts (1998); Tietenberg (1998); Grant, Jones, & Bergesen,(2002); Bui & Mayer (2003); Grant & Jones (2004); Shapiro (2005); Bui (2005); Cohen & Santhakumar (2006).

¹ This partial risk analyses have been conducted by the Office of Health Research, the Office of Information Resource management, and Office of Research and Development in the EPA. A more comprehensive and complete risk analysis using the TRI data, which considers toxicity, media, and affective population factors, and is applicable from the national to the local level, was released first in 1999 and was entitled the Risk Screening Environmental Indicators (RSEI), developed by the Office of Pollution Prevention and Toxics (OPPT). (EPA, 2003)

However, the results from these studies have been inconsistent: some have shown the effect to be significant while others have not.

EPCRA also required individual states to set up systems to facilitate public use of the TRI data, although it did not specify particular state-level actions to be carried out. As a result, states have implemented a wide range of TRI programs. State programs include: disseminating hard copy or electronic files of the raw data, providing analyses of the data, creating customized database reports, providing assessments of health effects or carrying out risk analyses, and allowing public access to the state's computer database. State-level data analyses and reports have usually focused on risk-related factors specific to the state (sometimes down to the level of individual plants) and thus provide a more disaggregated level of analysis than available from the EPA.

Prior empirical studies that have tried to identify the overall impact of the TRI have generally not focused on the nature of the disclosed information, and no attempt has been made to analyze the impact of state-level provision of interpreted and processed information. Due to the complexity of the raw data, however, analytical activities by states may play a critical role in determining the effectiveness of the policy. In this study, we extend the empirical literature on the TRI by explicitly examining the effect of state-level policies. We classify various state programs into two broad categories: (1) efforts at straightforward data dissemination, and (2) policies involving more detailed data processing and analysis. We then evaluate the impact of these two types of effort on toxic releases. To explore whether better information leads to better outcomes, we examine the effects of each policy on two outcome measures: total releases measured in pounds ("Toxic release level"), and releases adjusted for the toxicity of each chemical ("Toxic

risk”). We expect that processed and structured information is likely to do more to reduce toxic risk than simple disclosure of raw data.

We proceed by constructing a panel of raw and toxicity-weighted TRI release levels in US counties in 1995, 1996, 1997 and 1999. We then regress those releases on county demographic characteristics, economic status, related state policies and, as a key explanatory variable, state TRI-related policies. We also contribute to the literature by using fixed effects estimation, which has not been used in prior studies of the TRI (Grant, 1997; Grant & Downey, 1995; Grant et al., 2002; Shapiro, 2005; Hamilton, 2005). The fixed effects approach allows us to distinguish between the effects of TRI programs and time-invariant differences in emissions across counties.

PRIOR STUDIES AND THEORY

The disclosure of TRI information involves major actors including firms, local governments, media, shareholders and citizens. Among these, citizens and firms are most important and the others can be regarded as intermediaries (Stephan, 2002). Interactions between plants and their surrounding communities should reveal most clearly the effect of the TRI as a regulatory instrument (Stephan, 2002). It is intended to reduce information costs for communities, which is likely to lead to more frequent and more significant negotiations or other actions, including lawsuits against plants. This increased community activity should drive plants to improve their environmental performance.

However, information disclosure policies do not always work as well as intended. Since the 1980s, a range of disclosure policies have been adopted in attempts to improve the quality of

health care. Empirical studies have shown that the results have been mixed at best, raising various utilization issues beyond the availability of information. First of all, publicly released information is often ignored and is not used. Mennemeyer, Morrissey and Howard (1997) examined the effect of hospital mortality rate data, released to the public by the Health Care Financing Administration (HCFA), on hospital choice by consumers. They found that consumers generally ignored the mortality reports and made little use of the data. On the basis of their findings, the policy was abandoned. This implies that information release itself does not guarantee its utilization and the availability of information is often not enough to influence information users' behavior.

Grant (2005) shows that the attributes and quality of information certainly influence information recipients' behavior. Grant found that data made available on the rates of Cesarean sections by hospitals and physicians was not being used by consumers because it was insufficiently accurate and too aggregated to give correct, useful signals to consumers. He argued that the value of health care quality information might be enhanced by increasing its accuracy, which is determined by the abundance of data, the method of processing data, and the degree of detail conveyed.

These results highlight the importance of providing appropriate information, not just raw data. Abundant information may be useless or irrelevant if it requires too much processing and interpretation on the part of recipients. Too much information can lead to "information overload," a familiar phenomenon that has been formally studied in many fields, including organizational science and the management of information systems.² Information overload arises when the

2 Several other terms have been used in the same context of information overload--data smog (Shenk, 1997), analysis paralysis (Stanley & Clipsham, 1997) and information fatigue syndrome (Oppenheim, 1997).

supply of information exceeds the processing capacity of the recipient (Butcher, 1998; Eppler & Mengis, 2004). When it occurs, it degrades decision quality and decreases decision accuracy (Eppler & Mengis, 2004). Recipients often fail to identify relevant information and relate key details to their overall objectives (Jacoby, 1977).

Although the classic view of information overload focused mainly on the quantity of information, recent literature suggests that the characteristics of the information are also important (Galbraith, 1974; Tushman & Nadler, 1978; Owen, 1992; Iselin, 1993; Sparrow, 1998). Schneider (1987) suggests that ambiguity, uncertainty, or complexity of the information can cause information overload. Providing smaller volumes of higher value-added, more structured information reduces the phenomenon (Simpson & Prusak, 1995; Edmunds & Morris, 2000; Koniger and Janowitz, 1995).³ Increasing the quality of information reduces the likelihood of information overload; in effect, it improves the information processing capacity of the recipients (Simpson & Prusak, 1995).

Even when appropriate information is provided, disclosure policies do not always produce the results intended. Dranove et. al. (2003) found that mandating the disclosure of information on hospitals' and doctors' performance led to improvements in only exactly what the report cards report. Disclosure of information on patient health outcomes caused providers' selections to instantly create a better status for the next published report card, but failed to increase the welfare of patients, particularly of sicker patients. This implies that the outcome of information disclosure often causes only superficial improvement in the way the information

3 Simpson & Prusak (1995) suggested five elements that comprise the value of information which are truth, guidance, scarcity, accessibility and weight. High value-added information represents improved information in terms of these five elements.

appears on the surface, compromising the intended goal of information disclosure. In essence, the form in which information is disclosed determines how related actors respond and finally what we get as a policy outcome.

The lessons from information disclosure policies in health care suggest that the raw data published via the TRI may have little effect on emissions. The volume of information is tremendous: the TRI reports annual data on emissions of almost 400 chemicals by nearly 49,000 plants. Moreover, releases are reported separately by media, including air, ground water, surface water, land, or off-site transfer. In addition to emissions, each plant reveals basic information about its production and also pollution-related information, such as the height of its smoke stacks.

Not only is the volume of information large, it is likely to be of relatively low value to recipients because it focuses on pounds of chemicals released without adjusting for toxicity. Thus, it does not directly address the issue that is likely to be most important to most recipients: health risks. The chronic health risk posed by an emitted chemical depends on its toxicity, on the characteristics of the population exposed, on the release media and on the local climate, among other factors. Interpreting the TRI, therefore, requires enormous expertise. The high volume of data combined with its level of complexity and uncertainty suggests that the TRI could easily result in information overload. Since the resources available to community groups are often limited, recipients may be unable to use the data at all, or may be at risk of using it incorrectly.

A case in point is ActionPA, a Pennsylvania-based non-governmental organization in the grassroots environmental justice movement. It uses the TRI to construct its own analysis of trends in Pennsylvania's toxic emissions.⁴ ActionPA's analysis, which is done on the basis of raw TRI

⁴ <http://www.actionpa.org/tri/>

data, shows that Pennsylvania is the fifth most polluted state in the nation, and that there has been a gradual decreasing trend in emissions since 1999. However, adjusting for risk, which ActionPA does not do, shows a sharply different picture: Pennsylvania's risk related to toxic emissions is the highest in the country.⁵ Moreover, despite a decrease in the quantity of emissions from 1999 to 2002, the toxicity of emissions rose sharply enough that risk during that period actually rose 43 percent. In addition, by focusing on pounds of emissions rather than risk, ActionPA ends up suggesting that action be focused on the wrong industry. It concludes that coal and metal mining are the largest polluters, but the main source of health risks in Pennsylvania is actually the metals industry, which as of 2002 accounted for about 79% of the state's total toxic risk. As with the health care policy discussed by Dranove et. al. (2003), disclosure of high-volume, complex data led the actors involved to focus narrowly on the data itself, rather than on the implications of that data: in this case, on the quantity of emissions rather than the actual risks to human health.

Several prior studies have examined the effect of the TRI program on plants and their neighboring communities (Grant, 1997; Grant & Downey, 1995; Grant et al., 2002; Shapiro, 2005, Bui, 2005; Hamilton, 2005). Grant & Jones (2004) used an organization-theoretic framework to evaluate the impact of state-level TRI programs and the characteristics of neighboring communities on emissions by plants. With cross-sectional plant-level data, they found that state expenditures for TRI programs had no significant net effect on toxic emission level Bui (2005) examined plant level responses of petroleum refineries to the TRI program. She found that states' supplementary actions to the TRI disclosure explain lower level of toxic release.⁶

⁵ These risk indicator measures are based on the RSEI version 2.1.2 by the EPA.

⁶ States' supplementary actions that Bui (2005) included in her model are technical assistance, educational programs, data clearinghouses, tax incentives, government grant to help firms reduce wastes and the establishment of a

Shapiro (2005) and Hamilton (2005) observed that emissions at many plants dropped sharply after the first release of TRI data and tried to identify the factors that influenced the size of the reduction. Using a cross-sectional approach, Shapiro found that state-level TRI programs and community characteristics explain risk reductions over ten years after the TRI's establishment. Hamilton found that the emissions reductions during a three year period after TRI disclosure could be explained by community characteristics indicating the potential for collective action and the toxicity and health risks associated with the emissions.⁷ However, Hamilton is unable to isolate the effect of the TRI itself since toxic release data prior to the TRI is not available (Hamilton 2005, p. 107).

Given the volume and complexity of the data, activities undertaken by individual states to process and interpret TRI data might play a critical role in achieving the original policy goal of the TRI as a regulatory instrument, which was to reduce the risks to human health. States may carry out comprehensive analyses of human health effects and trends in risks. They can also filter the data, providing information on major local polluters and relevant chemicals at the level of individual communities.⁸ Additionally, states can facilitate monitoring and follow-up measures

statewide quantitative goal as regulations for toxic pollutants.

7 Shapiro (2005) and Hamilton (2005) incorporated actual health impact by interpreting emission in quantity into human health risk measure. Shapiro (2005) used human health risk measure as a dependent variable rather than using release in pound and Hamilton (2005) considered toxicity and human health level as one of factors that influence plants' emission behaviors.

8 EPA summary reports and web-based resources give users some ability to find detailed release information on one specific spot at a specific point in time. However, it is still difficult for users to manipulate or tailor the raw dataset to subtract the information relevant to their own specific interests. Moreover, the availability and accessibility of web-based resource was limited before popularization of Internet in mid-90's.

by communities by conducting and publishing analyses on a regular basis.⁹

Our study examines the effectiveness of state-level TRI policies in the 1990's. We classify state programs into the two categories noted above: efforts focused purely on dissemination of data, and deeper analysis with more extensive data processing. We evaluate the effect of each type of activity on the quantity of emissions and the overall toxic risk at the county level. We expect that data dissemination alone may affect total emissions but have little effect on risk. Reductions in risk are likely to be associated with analytical activities instead.

DATA AND METHOD

We examine the impact of state TRI programs on toxic releases and risks using a panel data set covering four years: 1995, 1996, 1997 and 1999; 1998 is excluded because data on key variables are not available for that year. We conduct our analysis at the level of individual counties since those are the jurisdictions most likely to match the level of community monitoring and collective action.¹⁰ The data set consists of a balanced panel of 1700 counties that experienced at least one pound of toxic emissions per year during all four years. We augment the TRI data with a range of demographic variables in order to isolate the impact of state TRI programs by controlling for other factors that might affect toxic release levels in each county.

9 Communities' monitoring and follow up measures could be setting up the target emission reduction goal, negotiating plants' emission scenarios, taking legal suits, pressure on governments' further regulatory action and so on.

10 While we focus on the effect of state policies, we use counties as the level of analysis to account for variation in factors such as community characteristics and regulatory stringency, either through direct measurement or as county fixed effects. We focus on releases in the county, rather than by individual plant, as we expect communities to be influenced by the overall environmental quality in the community, rather than releases from a specific plant.

Dependent Variables

We construct two dependent variables to represent the ostensible and the true policy effect. The first is the “toxic release level,” which is simply the sum of TRI emissions for the county. It can be obtained relatively easily from the raw TRI data and does not include any adjustment for the effects of different chemicals on long-term human health. It is often mistakenly used as an indicator of the health risks of different counties but it differs significantly from the true toxic risk.

Chronic human health risks not only depend on the quantities of chemicals released but also on the characteristics of each chemical, such as its toxicity or the media type where it was emitted. Moreover, the natural environment and weather of the county also play a role. As a result, a county may experience a high release level but have low risk. Focusing on total pounds rather than toxicity might encourage plants to substitute smaller amounts of more toxic chemicals. Lowering toxic release volumes without lowering actual toxic risks would be a failure to achieve the intended policy effect.

Our second dependent variable is “toxic risk,” which more accurately represents the true policy effect. Toxic risk is constructed by multiplying each chemical by a measure of its toxicity and summing the results, an approach based on EPA’s Risk-Screening Environmental Indicators (RSEI) Version 2.1.2, which was published in 2004.¹¹ Figures 1 and 2 show the trends of the

11 EPA’s RSEI model provides two different indicators to measure human health risks. The first is a “hazard score”, which considers only the toxicity of each chemical. It is constructed by multiplying the amount of emissions by a numerical weight reflecting the chemical’s toxicity. The weights range from 0.01 for sulfuric acid to 1,000,000 for thorium dioxide. The second, a more sophisticated indicator, is a “risk score”, which takes into account the

dependent variables during the past fifteen years.¹² Both variables are normalized by their 1988 values.¹³ While the toxic release level has been steadily decreasing since the first TRI information was disclosed in 1988, toxic risk seems to have stagnated and continued to decrease only very slowly after a dramatic decline in the early years. It is worth noting that in 1989, immediately after the first disclosure of TRI information, toxic risk slightly increased, implying that plants changed their emissions to release more high-toxicity chemicals even though they reduced the total quantity of releases in that year. After that spike, plants began to reduce the actual risk.¹⁴

population affected as well as toxicity. Even though the risk score is a more comprehensive measure, we use the hazard score as a risk indicator because county population is already accounted for on the right side of our estimating equations (or is absorbed by fixed effects).

12 The media included in the construction of toxic release measures in this study are fugitive air, stack air, direct water air and water release. The toxic release level and toxic risk measures in this study are constructed using chemicals with unchanged reporting requirements over the study period 1994-1999. The toxic release level variable is constructed with only the number of pounds of chemicals that are modeled and accounted for in toxic risk measure. Thus, the toxic release level and the toxic risk measure contain exactly same set of chemicals.

13 The initial year's toxic release is 1.97 billion pounds. The initial year's toxic risk is a score of 1.70 trillion. Even though the toxicity considers whether the toxin causes cancer or not, the risk score is not a quantitative risk estimate (e.g., excess cases of cancer) (EPA, 2004). It is based on toxicity weights derived from various factors. The expected outcomes of the high level of risk scores and how much more that high risk score is harmful is uncertain. This also reveals the difficulty and uncertainty of interpretation.

14 This could result from a delayed response by the public due to the burden of interpretation of raw TRI data, preventing them from pushing plants to decrease releases of high toxicity chemicals. It is also possible that the trends in the toxic release level and toxic risk could be the result of simple correlation between the two. Even if public attention focused only on reduction of the toxic release level, without any effort to interpret this quantity information into risk, a reduction in the release level without a change in the mix of chemicals being emitted would lower toxic risk.

[Insert Figure 1 and 2]

Explanatory Variables

To isolate the impact of state TRI programs on toxic releases, other factors that might affect county-level emissions are included as controls. Time-invariant factors will be controlled by county-level fixed effects. Categories of time-varying factors appearing as explanatory variables in the regression model include: county demographic characteristics, economic conditions, related state policies, and state TRI programs. All explanatory variables are all lagged in order to link the impacts of the explanatory variables to toxic release levels for subsequent years.

Demographic characteristics are associated with the potential for collective action by communities, which might affect the toxic release levels of neighboring plants. Variables that capture community capacity for collective action include: percent Hispanic (*%Hispanic*), percent African American (*%Black*), and median household income (*Income*). All else being equal, counties with high percentages of minorities tend to have higher toxic release levels, so the coefficients of *Hispanic* and *Black* are expected to be positive. Conversely, median household income might have a negative impact on toxic release levels, implying a negative coefficient on the *Income* variable. Percentages of Hispanics and African Americans are measured at the county level from Census data.¹⁵ Median household incomes are from Small Area Income and Poverty

15 The Census data are collected decennially. The county-level demographic characteristic data are estimated by the Census Bureau, using a mathematical formula to take into account differences between the postcensal time series population estimates for the 1990s and Census 2000. More details on the estimates data can be found at http://www.census.gov/popest/topics/methodology/2006_st_co_meth.html

Estimates (SAIPE) and are measured at the county level.^{16, 17}

Economic status is included as an explanatory variable, as it reveals not only the economic activity of counties, but also economic resources that counties might have. We include the unemployment rate (*Unemploy*) as a measure of economic status, as a higher unemployment rate may reflect a downturn in manufacturing activity, resulting in reduced emissions. Thus, the coefficient of *Unemploy* is expected to be negative. Unemployment rate data come from the Bureau of Labor Statistics and are measured at the county level.

Variables representing related state policies are included because state efforts to deal with pollution might influence the toxic release level in addition to the TRI program.¹⁸ State health expenditure per capita (*Health*) is included as an explanatory variable. Per capita health expenditure is state spending for general health activities and improvement of public health,¹⁹ which includes spending for the regulation of air and water quality, plus expenditures for EPA-

16 The annual county-level median household incomes come from estimates produced by SAIPE. The estimates are based on statistical models that use decennial census data, household survey data, administrative records data, and population estimates. More details on the estimates can be found at <http://www.census.gov/hhes/www/saipe/>

17 Even though demographic characteristic variables are included as explanatory variables, there seems to be little variation over time..

18 Bui (2005) found in her plant-level panel data analysis that states' regulatory stringency of non-toxic pollutants lowered toxic emission levels in petroleum refineries. While Bui used state-level attainment/non-attainment status for the criteria air pollutants as a proxy for states' regulatory stringency of non-toxic air pollution, this study uses the *Health* variable as a proxy for states' general environmental regulatory stringency. We also explored the possibility of using county attainment/non-attainment status as an additional control variable. However, over the years of our sample, this is a fixed effect for all but a few counties, so that attainment status is insignificant when included.

19 States' per capita health expenditure does not include public assistance programs such as the Medicaid/Medicare program spending and nursing home operation.

funded programs, such as the Superfund program for the cleanup of hazardous waste sites.²⁰ It is a state-level variable (rather than county) and is obtained from government censuses. Thus, per capita health expenditure is expected to represent the intensiveness of the state's associated environmental policy. It is expected to have a negative effect on the toxic release level, with a negative sign of *Health* coefficient.

As key explanatory variables, we include state TRI dissemination efforts (*Dissemination*) and state data processing efforts (*Processing*). These variables are generated using the annual States' TRI Program Assessment Survey done by the National Conference of State Legislatures (NCSL).²¹ This survey collects basic information about state TRI programs and includes various questions on state implementation status regarding the TRI data.²² Among a diverse range of questions, items associated with state information provision efforts for the public are selected and categorized into two types, as noted above – the TRI data dissemination efforts and the TRI data processing efforts. Using these, we generate the two key explanatory variables, *Dissemination*

20 The Superfund program, which was enacted by the Comprehensive Environmental Response, Compensation, and Liability Act of 1980, establishes funds and authority to cleanup toxic releases and abandoned hazardous waste, including long-term remedial action to deal with toxic releases. Furthermore, the Superfund designates parties potentially responsible for the contamination of a Superfund site, which affects the efficacy of the TRI program. For instance, Hamilton (1995) also found that the impact of TRI disclosure on stock price was significantly smaller for companies that were already known as polluters through Superfund Liabilities.

21 From 1992 to 1999, The NCSL has annually conducted the State TRI Program Assessment Survey at the request of the Toxic Release Inventory Project of the Forum on State and Tribal Toxics Action (FOSTTA). All 50 states have completed the assessment during 8 years. However, only 1994, 1995, 1996 and 1998 survey data were used for this study since the target questions are commonly found only for those years.

22 The NCSL's State TRI Program Assessment Survey collects basic information and status about states' TRI programs, including states' data use and management, the TRI data dissemination efforts to the public, states' own data processing and health risk analyses, and staffing and funding.

and *Processing*. If a state provides one of the following – EPA’s TRI data document, EPA’s TRI data diskette, or a TRI data reading room – the *Dissemination* variable is coded as 1, indicating that the state is making an effort to facilitate the public’s ability to obtain and access to the EPA’s TRI raw data. If a state provides one of the following -- the state’s own data analysis, annual TRI reports, and other state TRI documents -- the *Processing* variable is coded as 1, indicating that the state is making an effort to provide structured and interpreted information such as health effects and risk analysis or trend and ranking analyses. Table 1 shows the survey questions used to construct these key explanatory variables and the correlations between questions.

[Insert Table 1]

Out of the fifty states, 27 (54%) provided at least one type of dissemination effort during all four years, and only one (2%) did nothing regarding data dissemination during that period. When it comes to data processing efforts, 24 states (48%) provided at least one type of data processing effort during all four years, while seven states (14%) made no data processing efforts during that period. The rest of the states have changed their data dissemination and processing efforts over time, producing time-variant *Dissemination* and *Processing* variables. Table 2 shows each state’s status regarding its data dissemination efforts and data processing efforts during the four target years. Two types of state TRI programs show a slight positive correlation (Pearson’s $R=0.203$, $P\text{-value}=0.004$).

[Insert Table 2]

Table 3 reports descriptive statistics for all variables. Toxic release level and toxic risk are reported for 1995 to 1999, and the explanatory variables are reported for 1994 to 1998. Median household income and state per capita health spending are expressed in 1998 dollars.²³

[Insert Table 3]

Regression Models

The regression models are presented in Equation (1). The dependent variable in the first model is the toxic release level measured in pounds; in the second model it is toxic risk. The dependent variables are converted into logarithmic form to reflect relative scales of toxic release values. All explanatory variables are lagged to incorporate the impact of variables on the toxic releases in subsequent years. Year dummies are included to capture year-specific effects. Time-invariant factors are controlled using county-level fixed effects.

$$\begin{aligned} \ln(Y)_{i,t} = & \beta_{1,0} + \beta_{1,1} \% \text{Hispanic}_{i,t-1} + \beta_{1,2} \% \text{Black}_{i,t-1} + \beta_{1,3} \text{Income}_{i,t-1} + \beta_{1,4} \% \text{College}_{i,t-1} \\ & + \beta_{1,5} \text{Health}_{i,t-1} + \beta_{1,6} \text{Unemploy}_{i,t-1} + \beta_{1,7} \text{Dissemination}_{i,t-1} + \beta_{1,8} \text{Processing}_{i,t-1} \\ & + \beta_{1,9-1,11} \text{Year}_{t-1} + \beta_{1,12-1,1710} \text{County}_i + \text{error}_{i,t-1}, \end{aligned} \quad (1)$$

where $Y = \text{Toxic release level or Toxic Risk}$.

$i = \text{counties}$

²³ We adjust for inflation using the Consumer Price Index (CPI).

t=1995, 1996, 1997 and 1999

ESTIMATION RESULTS

Table 4 presents the ordinary least square estimation results of the toxic release level model and the toxic risk model. Estimation results report standard errors that are robust to heteroskedasticity and serial correlation.²⁴ F-statistics for the 1699 county-level fixed effects confirm that the fixed effects are jointly significant for both models (F=31.90, P-value=0.000; F=25.83, P-value=0.000). Joint significance tests for the year dummies show that they are jointly valid in the toxic release level model (F=18.28, P=0.000) but are not significant in the toxic risk model (F=2.03, P-value=0.107). This is consistent with Figure 1 and 2, in which toxic release level show a dramatic decreasing trend while toxic risk shows a relatively stagnant trend from 1995 to 1999.

[Insert Table 4]

Among the race variables, *%Hispanic* is positive and significant in the toxic release level model, implying that a one percent increase in Hispanic population is associated with 5.6 percent increase in the release level. On the other hand, race is not significant in the toxic risk model regression. However, this result should be interpreted with caution. Since the racial composition

²⁴ The test for serial correlation in the panel data shows there are significant AR(1) serial correlations for the toxic release level model (F=7.425, P-value=0.007) and the toxic risk model (F=9.684, P-value=0.002).

of counties is almost time-invariant over the period of this study, there is little time-series variation in the race variable and most effects associated with race are likely to be absorbed by the county fixed effects.

Median household income is insignificant for both toxic release level and toxic risk. The unemployment rate, however, has a significant impact on both toxic release and toxic risk, indicating that a one percent higher unemployment leads to 3.4 percent fewer pounds of emissions and a 4.2 percent reduction in toxic risk. This result might arise because a high unemployment rate could mean a depressed local economy and limited manufacturing activity, resulting in lower levels of emissions. Additionally, while state per capita health expenditure has a significant impact in the toxic release level model, it is not significant in the risk model. One dollar of additional health expenditure per capita lowered the toxic release level by 0.15 percent.

The coefficients on the year dummies in both models are all negative, consistent with the observation that release levels and risk have decreased significantly year by year. The coefficients of the year dummies in the level model are higher than those of the risk model. This result is consistent with the trends in Figures 1 and 2, which show a relatively steady decreasing trend of toxic release level than toxic risk during the years 1995-1999.

When it comes to the impact of state TRI programs, state dissemination efforts significantly lowered the level of releases but did not have a significant impact on risk. If states made an effort to disseminate the raw TRI data by providing EPA's data document, EPA's data diskette, or a reading room, their efforts reduced the release level by 10.3 percent. However, the same activities are not effective at lowering toxic risk. This implies that state efforts to disseminate raw TRI data do not help to achieve the policy goal; rather, like similar policies in

health care they only lead to superficial improvements.

On the other hand, state data processing efforts had a significant negative impact on risk, but not on release levels. If a state provides processed information to the public through its own data analysis, annual TRI reports, or other state TRI documents, it lowers risk by 14.2 percent, even though those efforts show no significant impact on toxic release level. State data processing efforts thus play a critical role in lowering risk, the underlying goal of the policy.

CONCLUSIONS

This study evaluated two distinct types of state TRI programs: those that disseminate data with little analysis and interpretation, and those that provide deeper analysis based on more extensive data processing. As predicted by information overload theory, programs that produce low-volume, high-quality data are much more effective than those that simply disseminate large volumes of complex data. Although the TRI is intended to lower transaction costs for communities to obtain information and initiate collective action, driving plants to reduce their toxic releases, our results show that the raw data is too large and complex to be useful without further interpretation. State data processing efforts, which provide more structured and interpreted information, contribute significantly to the underlying goal of the TRI by improving the quality and usefulness of the information for end users. Moreover, we also find that simple publication of raw data leads to superficial reductions in emissions that are not necessarily accompanied by real reductions in risk.

Beyond the TRI itself, our findings confirm the predictions of information overload theory. Providing processed or value-added information played a significantly role in reducing

information overload and improving the ability of end users to apply the information.

Finally, this study provides an important general lesson for the design and use of information disclosure strategies as a regulatory tool. Our findings confirm the results seen in health care studies that simply making data available may have little effect. Data will be used only when it clearly and correctly signals underlying information important to end users. Data released without appropriate processing may exceed the analytical capacity of the target user group, fail to be utilized at all, or fail to induce the intended behavioral changes on the part of targeted actors. Thus, the nature of disclosed information and of the information processing capacity of targeted actors must be considered for policies to be designed effectively. In essence, our findings highlight the importance of providing information processed to the degree at which recipients can find the signals they need.

REFERENCES

- Bui, L. T. M. (2005). Public disclosure of private information as a tool for regulating environmental emissions: Firm-level responses by petroleum refineries to the toxic release inventory. *Center for Economic Studies*, Working paper 05-13.
- Bui, L. T. M. & Mayer, J. C. (2003). Regulation and capitalization of environmental amenities: Evidence from the Toxic Release Inventory in Massachusetts. *The Review of Economics and Statistics* 85(3), 693-708.
- Butcher, H. (1998). Information overload in management and business. *IEE Colloquium Digest*, 95(223), 1-2.
- Case, D. W. (2001). The law and economics of environmental information as regulation. *The Environmental Law Reporter News and Analysis*, 31, 10773-10789.
- Cohen, M. A. & Santhakumar, V. (2006). Information disclosure as environmental regulation: A theoretical analysis. *Environmental and Resource Economics*, 37, 599-620.
- DiMaggio, P. & Powell, W. (1983). The iron cage revisited: Institutional isomorphism and collective rationality in organizational fields. *American Sociological Review*, 48, 147-160.
- Dranove, D, Kessler, D., McClellan, M., & Satterthwaite, M. (2003). Is more information better? The effects of "Report cards" on health care providers. *The Journal of Political Economy*, 111(3), 555-588.
- Edmunds, A. & Morris, A. (2000). The problem of information overload in business organizations: A review of the literature. *International Journal of Information*

Management, 20, 17-28.

Environmental Protection Agency, Office of Pollution Prevention and Toxics (2004). Risk-Screening Environmental Indicators (RSEI) (Version 2.1.2) [CD-ROM]

Environmental Protection Agency, Toxic Release Inventory Program Division (2003). How are the toxics release inventory data used?: Government, business, academic and citizen uses.(EPA-260-R-002-004).

Eppler, M. J. & Mengis, J. (2004). The concept of information overload: A review of literature form organization science, accounting, marketing, MIS, and related disciplines. *The Information Society*, 20, 325-344.

Esty, D. C. (2004). Environmental protection in the information age. *NYU Law Review*, 79,1-103.

Galibraith, J. R. (1974). Organization design: An information processing view. *Interfaces*, 3, 28-36.

Grant, D. (1997). Allowing citizen participation in environmental regulation: An empirical analysis of the effects of right-to-sue and right-to-know provisions on industry's toxic emissions. *Social Science Quarterly*, 78(4), 859-875.

Grant, D. (2005). Information and sorting in the market for obstetrical services. *Health Economics*, 14, 703-719.

Grant, D. & Downey, L (1995). Regulation through information: An empirical analysis of the effects of state-sponsored right-to-know programs on industrial toxic pollution. *Policy Studies Review*, 14, 339-352.

Grant, D., Jones, A., & Bergesen, Albert (2002). Organizational size and pollution: The case of the U.S. chemical industry. *American Sociological Review*, 67(3), 389-408

- Grant, D. & Jones, A. W. (2004). Do manufacturers pollute less under the regulation-through-information Regime? *The Sociological Quarterly* ,45(3), 471-486.
- Hamilton, J. T. (1995). Pollution and news: Media and stock market reactions to the toxic release inventory data. *Journal of Environmental Economics*, 28, 98-113.
- Hamilton, J. T. (2005) Regulation through revelation. New York, NY: Cambridge University Press.
- Hannan, M. & Freeman, J. (1989). Organizational ecology. Cambridge, MA: Harvard University Press.
- Iselin, E. R. (1993). The effect of the information and data properties of financial ratios and statements on managerial decision quality. *Journal of Business Finance and Accounting*, 20, 249-267.
- Jacoby, J. (1977). Information load and decision quality: Some contested issues. *Journal of Marketing Research*, 14, 569-573.
- Kennedy, P. W., Laplante, B., & Maxwell, J. (1994). Pollution policy: The role for publicly provided information. *Journal of Environmental Economics and Management*, 26, 31-43.
- Kleindorfer, P. R. & Orts, E. W. (1998). Informational regulations of environmental risks. *Risk Analysis*, 18, 155-156.
- Konar, S. & Cohen, M. A. (1997). Information as regulation: The effect of community right to know laws on toxic emissions. *Journal of Environmental Economics and Management*, 32, 109-124.
- Koniger, P. & Janowitz, K. (1995). Drowning in information, but thirsty for knowledge.

- International Journal of Information Management*, 15(1), 5-16.
- Koyck, L. M. (1954). *Distributed Lags and Investment Analysis*, Amsterdam: North-Holland Publishing Company.
- Mennemeyer, S. T., Morrissey, M. A., & Howard, L. Z. (1997). Death and reputation: How consumers acted upon HCFA mortality information. *Inquiry-Blue Cross and Blue Shield Association*, 34(2), 117-128.
- Oppenheim, C. (1997). Managers' use and handling of information. *International Journal of Information Management*, 17(4), 239-248.
- Owen, R. S. (1992). Clarifying the simple assumption of the information load paradigm. *Advances in Consumer Research*, 19, 770-776.
- Pfeffer, J. & Salanick (1978). *The external control of organizations: A resource dependency perspective*. NY: Harper and Row.
- Schneider, S. C. (1987). Information overload: Causes and consequences. *Human Systems Management*, 7, 143-153.
- Shapiro, M. D. (2005) Equity and information: Information regulation, environmental justice, and risks from toxic chemicals. *Journal of Policy analysis and Management*, 24(2), 373-398.
- Shenk, D. (1997). *In data smog: Surviving the information glut*. London: Abacus.
- Simpson, C. W. & Prusak, L. (1995). Troubles with information overload – Moving from quantity to quality in information provision. *International Journal of Information Management*, 15, 413-425.
- Sparrow, P. R. (1998). Information overload. In the experience of managing. In K. Legge, C.

- Clegg, & S. Walsh (Eds), A skills workbook (pp. 111-118). London: MacMillan.
- Stanely, A. J. & Clipsham, P. S. (1997). Information overload – Myth or reality? *IEE Colloquium Digest*, 97(340), 1-4.
- Stephan, M. (2002). Environmental information disclosure programs: They work, but why? *Social Science Quarterly*, 83(1), 190-205.
- Tietenberg, T. (1998). Disclosure strategies for pollution control. *Environmental and Resource Economics*, 11(3-4), 243-260.
- Tushman, M. L. & Nadler, D. A. (1978). Information processing as an integrating concept in organizational design. *Academy of Management Review*, 3, 613-625.

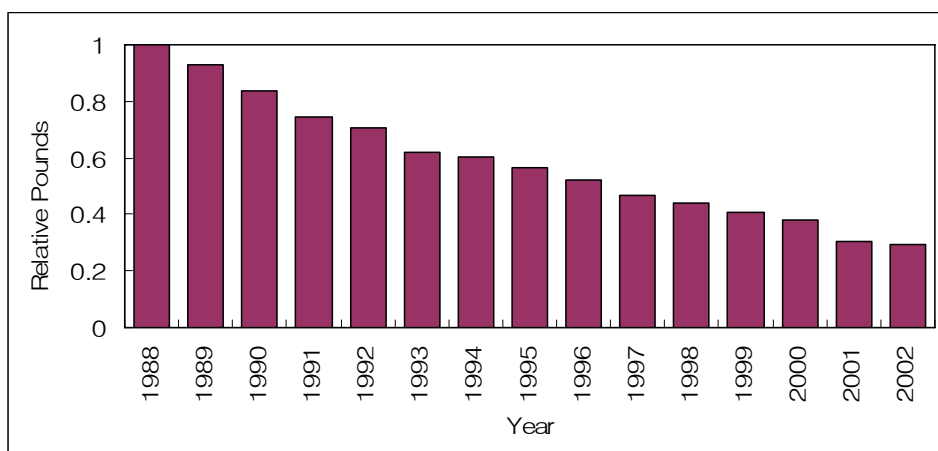


Figure1.Toxic release level in National Total (Relative to the 1988 Release)

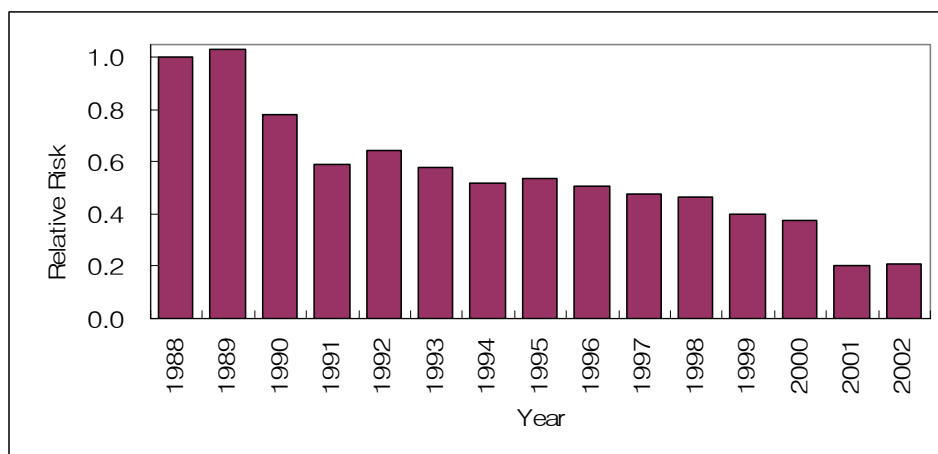


Figure2. Toxic Risk in National Total (Relative to the 1988 Risk Level)

Table 1. Correlation between States' TRI Programs

		Dissemination			Processing		
		EPA's TRI document	EPA's data diskette	Data reading room	State's own data analysis	Annual TRI reports	Other states' documents
1994	EPA's TRI document	1					
1995							
1996							
1998							
1994	EPA's data diskette	0.137	1				
1995		0.248*					
1996		0.176					
1998		0.311**					
1994	Data reading room	0.205	0.128	1			
1995		0.337**	-0.070				
1996		0.157	0.091				
1998		0.009	-0.168				
1994	State's own data analysis	0.301**	0.126	0.179	1		
1995		0.074	0.098	0.098			
1996		0.111	0.020	0.216			
1998		0.047	0.095	0.243			
1994	Annual TRI reports	0.298**	0.017	0.059	0.313**	1	
1995		0.041	0.129	-0.041	0.428***		
1996		0.289**	-0.010	0.227	0.460***		
1998		0.042	0.171	0.306**	0.453***		
1994	Other states' documents	-0.024	-0.168	0.203	0.125	0.141	1
1995		0.099	-0.099	0.183	0.149	-0.027	
1996		0.277*	-0.125	0.058	0.227*	0.206	
1998		-0.032	0.051	0.190	0.342**	0.218*	

*Significant at $p < 0.1$, ** Significant at $p < 0.05$, *** Significant at $p < 0.01$

Columns represent whether states provide each object to the public. "EPA's TRI document" equals one when states provide EPA-published TRI-related documents. "EPA's data diskette" equals one when states send EPA's raw data diskette those who request it or make it downloadable in states' TRI webpage. "Data reading room" equals one when states provide TRI data reading room for the public. "States' own data analysis" equals one

when states have their own database system and run analyses for states' specific interests. "Annual TRI reports" equals one when states publish annual reports with focus of the state-related facts. "Other states' documents" equals one when states provide other states' TRI related documents to the public.

Table 2. States' TRI program Provision during Four Years

State	Dissemination	Processing	State	Dissemination	Processing
AL	Always	Sometimes	MT	Sometimes	Never
AK	Sometimes	Sometimes	NE	Always	Never
AZ	Always	Always	NV	Sometimes	Sometimes
AR	Always	Sometimes	NH	Always	Sometimes
CA	Sometimes	Always	NJ	Always	Always
CO	Always	Sometimes	NM	Always	Never
CT	Sometimes	Sometimes	NY	Sometimes	Never
DE	Always	Always	NC	Sometimes	Always
FL	Sometimes	Always	ND	Always	Always
GA	Sometimes	Always	OH	Always	Never
HI	Always	Always	OK	Sometimes	Always
ID	Always	Sometimes	OR	Sometimes	Sometimes
IL	Sometimes	Always	PA	Sometimes	Always
IN	Always	Always	RI	Never	Sometimes
IA	Sometimes	Sometimes	SC	Always	Always
KS	Always	Sometimes	SD	Always	Always
KY	Sometimes	Always	TN	Sometimes	Never
LA	Always	Always	TX	Always	Always
ME	Always	Sometimes	UT	Sometimes	Always
MD	Always	Sometimes	VT	Always	Sometimes
MA	Sometimes	Always	VA	Sometimes	Sometimes
MI	Always	Sometimes	WA	Always	Always
MN	Always	Always	WV	Sometimes	Sometimes
MS	Always	Always	WI	Always	Always
MO	Sometimes	Sometimes	WY	Sometimes	Sometimes

Table 3. Descriptive Statistics of Variables

Variables	N	Min.	Max.	Mean					Std.
				Total	1995(4)	1996(5)	1997(6)	1999(8)	
Toxic Release Level (Thousand Pound)	6800	0.001	63653	771.37	863.79	800.61	752.47	668.60	2481.60
Toxic Risk (Million Score)	6800	0.01	532356.1	554.18	645.91	569.97	538.95	461.62	12252.33
%Hispanic	6800	0	90	4.11	3.76	3.94	4.14	4.61	8.52
%Black	6800	0	87	10.56	10.39	10.49	10.59	10.77	14.80
Income (Thousand\$)	6800	17.32	75.88	35.20	34.31	34.91	35.07	36.49	8.19
Per Capita Health (\$)	6800	46.79	328.48	113.63	105.23	109.95	111.97	127.37	42.13
Unemployment Rate (%)	6800	1.2	31	5.63	5.82	5.74	5.75	4.89	2.49
Data Dissemination	6800	0	1	0.80	0.79	0.72	0.86	0.84	0.39
Data Processing	6800	0	1	0.74	0.74	0.76	0.72	0.77	0.43

Table 4. Estimation Results

Variables	Toxic release level		Toxic Risk	
	Coefficient	Robust Std. Error	Coefficient	Robust Std. Error
%Hispanic	0.0562***	0.0188	-0.0162	0.0315
%Black	-0.0106	0.0218	-0.0094	0.0315
Median Income	-0.0247	0.0199	-0.0397	0.0268
Per Capita Health	-0.0015*	0.0008	-0.0012	0.0011
Unemployment Rate	-0.0339**	0.0173	-0.0424*	0.0242
Data Dissemination	-0.1032***	0.032	-0.0439	0.0434
Data Processing	0.0425	0.046	-0.1353**	0.0624
Year96	-0.1556***	0.0292	-0.0600	0.0396
Year97	-0.2094***	0.0317	-0.0704	0.0434
Year99	-0.3923***	0.0595	-0.1885**	0.0833
R^2	0.9191		0.9020	
F-test for Fixed Effects	31.90***		25.83 ***	
F-test for Year Dummies	18.28***		2.03	

* Significant at $p < 0.1$, ** Significant at $p < 0.05$, *** Significant at $p < 0.01$