Information Disclosure Policy: Do States' Data Processing Efforts Help More than the Information Disclosure Itself?

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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 invoked by disclosed toxic release information. However, the raw TRI data fails to transmit accurate information fitted to the public's interest. TRI is a massive and complex dataset, published in the pounds of toxics released in its raw form, not a health risk indicator which is the true quantity of interest. Consequently, the raw TRI data needs to be refined and interpreted in terms of health risks by the users/public but those processing data procedures often overwhelms their capability. State governments have attempted to increase of the usefulness of the TRI's information 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 further data analysis. This study assesses the effectiveness of those two types of policies with the hypothesis that the latter might increase the accuracy of the TRI information contributing to the true policy outcome (reducing health risk), more than the former. 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 intended policy goal by providing accurate information with which users can find the right signal of interest.

Key words: Information disclosure policy, Toxics release inventory, Information overload

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 & 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."(Grant & Jones, 2004).

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. More importantly, in raw form, the TRI reports the number of pounds of chemicals released, which is not a human health risk indicator, despite the fact that the ultimate purpose of the data is to reduce health risks rather than just the quantity of chemicals released. The raw TRI data itself is not accurate enough to exhibit the true quantity of interest, failing to give the right signal to the public. Consequently, use of the TRI necessarily involves significant information processing, including procedures for and structuring the data interpreting into health risk measures. The inaccuracy of the raw TRI data and the burden of processing it might prevent the public from utilizing the information and fail to change behavior, as seen in many other information disclosure strategies.[1].

Since the first release of TRI data in 1988, the EPA has made an effort to make it more accessible and useful to the public. However, for more than a decade, the EPA's activities were largely limited to providing supporting information that facilitated the 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.[2]

The 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 is available from the EPA.[3]

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1 Fung et al. (2007) critically analyzed eighteen U.S. and international information disclosure policies encompassing various policy areas including mortgage lending disclosure, restraint hygiene disclosure, food labeling and so on. Fung et al. found that the policies were often ineffective due to barriers such as lack of accuracy, misinterpretation or conflicting preferences.

2 These partial risk analyses have been conducted by the Office of Health Research, the Office of Information Resource management, and the Office of Research and Development at 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 Risk Screening Environmental Indicators (RSEI), developed by the Office of Pollution Prevention and Toxics (OPPT). (EPA, 2003)

3 While the EPA provided only partial and limited data analyses before the development of the first complete risk analysis tool (RSEI) in 1999, as mentioned above, states utilized the TRI data more responsively and produced a wide variety of in-depth data analyses to evaluate states' own environmental problems and initiate environmental programs by the mid 90's. According to a report on uses of the TRI data released in 1996, for example, Colorado, Louisiana, North Carolina and Georgia identify high priority industry sectors and chemicals based on relative risk in the state, using the TRI data. Oregon developed a risk assessment model to evaluate cross-media impacts and to rank the relative risks of pollutant discharges in the state, and New York State developed a risk screening protocol to yield human risk scores and rankings for plants and chemicals within the state. New Jersey used the TRI data combined with a geographical information system (GIS) to prioritize facilities and geographical areas (EPA, 1996).

Most 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 provisions of interpreted and processed data to increase the accuracy of the information. Due to the complexity and inaccuracy 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 examine whether the types of information provided by states determines the types of final policy 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 (the true policy goal), 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.

PRIOR STUDIES AND THEORY

While disclosure policies in the public policy context are designed to change recipients' behavior, they do not always work as well as intended. In particular, while a range of disclosure policies have been adopted in attempts to improve the quality of health care since the 1980s, empirical studies have shown that the results have been mixed at best, raising various utilization issues beyond the availability of information (Mennemeyer, Morrisey & Howard, 1997; Dranove, Kessler, McClellan & Satterthwaite, 2003; Grant, 2005). First of all, simple publication of associated raw data does not guarantee its utilization. Mennemeyer et al. (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 outcome implies that publicly released information is often ignored and fails to be used.

Another study in health care suggests that how accurately the disclosed information reveals users' interest determines the extent to which the information will be utilized. Grant (2007) 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 accuracy, as a key component to making information valuable, can be enhanced by the method of processing data and the degree of detail conveyed.

Providing information as an accurate indicator congruent to the policy goal is critical for effectiveness of the policy because how we measure determines what we get as a policy outcome. 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 of patients in favor of those who are not in serious condition 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 suggests that inaccurate information will skew behavior in the direction of the inaccuracy, compromising the intended goal of information disclosure. Thus, the information should be measured and published accurately matching to what we really intend to achieve.

Making abundant information available does not necessarily mean providing accurate information to users. Abundant information is often less relevant and accurate in that it makes it even harder to find exactly what one is looking for, generating the burden of organizing and structuring the information. Too great a supply of information that exceeds the processing capacity of the recipient 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.[4] Although the classic view of information overload focused mainly on the

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4 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).

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 the ambiguity, uncertainty, or complexity of the information can cause information overload. (Butcher, 1998; Eppler & Mengis, 2004). When information overload occurs, recipients often fail to identify relevant information and relate key details to their overall objectives finally degrading decision quality (Jacoby, 1977; Eppler & Mengis, 2004). Increasing the quality of information with smaller volumes of higher value-added, more structured information reduces the likelihood of information overload; in effect, it improves the information processing capacity of the recipients. (Simpson & Prusak, 1995; Edmunds & Morris, 2000; Koniger & Janowitz, 1995).[5] In other words, with massive and complex information, processing information is to provide more accurate and relevant signals, so users' interest can enhance the value of the information.

The lessons from information disclosure policies in health care and information overload theory suggest that the raw data published via the TRI may not be valuable since it takes a far different form from accurate information that users want, consequently failing to change users' behavior. 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 an inaccurate indicator because it focuses on pounds of chemicals released without adjusting for toxicity. Thus, it does not directly show the quantity that most recipients are truly interested in: 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 to extract the right signal from the raw TRI data. The high volume of data combined with its level of complexity and uncertainty

5 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.

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 they 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.[6] ActionPA's analysis, which is done on the basis of raw 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.[7] 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 oil electric utilities 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), the ActionPA example shows that disclosure of information in inaccurate measure skews the actors' behavior to focus on inaccurate outcomes. Thus, state data processing efforts might be valuable as it provides a more accurate indicator of the true quantity of interest than the user could come up with on their own measure from the raw TRI data.

The disclosure of TRI information involves major actors including firms, local governments, media, shareholders and citizens. To evaluate the effectiveness of the TRI, a number of empirical studies have examined governments' stock/housing markets' or plants/firms' reactions to disclosed TRI information. However, the results from these studies have been inconsistent. Some studies have shown the effect to be significant including: Kennedy, Laplante, & Maxwell (1994); Konar & Cohen (1997); Grant & Downey (1995); Grant, 1997; Khanna et

6 http://www.actionpa.org/tri/

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

al.,1998; Patten, (1998); Graham & Miller, 2001; Patten (2002); Hamilton, 2005; Shapiro (2005); Bui (2005); Oberholzer-Gee, Felix and Mitsunari (2006). Others have found the TRI information was not effective, including: O'Toole et al. (1997); Bui & Mayer (2003); Grant & Jones (2004); Decker, Nielsen & Sindt, 2005.

Among various actors, 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 the key 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.

Among prior studies, several analyses have tried to identify this regulatory effect of the TRI program by focusing on plants' or neighboring communities' environmental performance (Grant & Downey, 1995; Grant, 1997; O'Toole et al., 1997; Grant & Jones, 2004; Shapiro, 2005; Bui, 2005; Hamilton, 2005).

Shapiro (2005) and Hamilton (2005) tried to identify the effect of the EPA's TRI establishment and the factors that influenced the size of the reduction. Using a cross-sectional approach, 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.[8] Shapiro also found that community characteristics explain risk reductions over ten years after the TRI's establishment.

However, evaluating the EPA's TRI establishment, as Hamilton and Shapiro did, one 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). To overcome this problem, several studies tried to identify the effect of TRI by evaluating states' TRI programs. Grant & Jones (2004) used an organization-theoretic framework to evaluate the impact of state-level TRI programs and the characteristics of

8 Shapiro (2005) and Hamilton (2005) incorporated the actual health impact by interpreting emission in quantity into the human health risk measure. Shapiro (2005) used the 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 the factors that influence plants' emission behaviors.

neighboring communities on emissions by plants. With plant-level data, they found that state funding for TRI programs had no significant net effect on toxic emission level. Shapiro (2005) and O'Toole evaluated states TRI programs with the index representing the extensiveness of states TRI program. Shapiro found that states' TRI programs explained risk reductions over ten years after the TRI's establishment in his kilometer-square unit analysis, while O'Toole (1997) found that states' TRI programs were not effective for reducing the state-level toxic release. Bui (2005) examined plant level responses of petroleum refineries to the states TRI program, as well as to traditional command-and-control regulations. She found that states' supplementary actions to the TRI disclosure explain the lower level of toxic release.[9]

None of the studies incorporated the nature of disclosed TRI information in the model. Given the massiveness/complexity and inaccuracy of the raw TRI 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 regulatory instruments, 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.[10] Additionally, states can facilitate monitoring and follow-up measures by communities by conducting and publishing analyses on a regular basis.[11]

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

9 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 statewide quantitative goal as regulations for toxic pollutants.

10 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 resources was limited before the popularization of the Internet in the mid-90's.

11 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.

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. Instead, reductions in risk are likely to be associated with analytical activities instead.

Moreover, most prior studies that evaluated states' TRI programs on plants' or communities' environmental performance used cross-sectional approaches (Grant & Downey, 1995; Grant, 1997; O'Toole et al., 1997; Shapiro, 2005; Hamilton, 2005). We also contribute to the literature by using fixed effects estimation, which allows us to control for time-invariant differences more effectively than do cross-sectional analyses.

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.[12] 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.

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

12 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, who are assumed to be the primary TRI information users in this study, to be influenced by the overall environmental quality in the community, rather than releases from a specific plant. While pollution reductions that communities really aim at can be achieved by driving plants to reduce their emissions, to close permanently, or to enter below reporting thresholds, this study tries to identify the overall county-level pollution dynamics, rather than focusing on specific mechanism with refined plant- level data.

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 fail 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.[13] Figures 1 and 2 show the trends of the dependent variables during the past fifteen years.[14] Both variables are normalized by their 1988 values.[15] 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

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13 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 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).

14 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 the same set of chemicals.

15 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.

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.[16]

[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

16 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. The data shows that the toxic release level and toxic risk are moderately correlated. After controlling for county and year specific effects, the correlation between the residuals are 0.4256 (P-value=0.000).

level from Census data.[17] Median household incomes are from Small Area Income and Poverty Estimates (SAIPE) and are measured at the county level.[18, 19]

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. 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,[20] which includes spending for the regulation of air and water quality, plus expenditures for EPA-funded programs, such as the Superfund program for the cleanup of hazardous waste sites.[21] It is a state-level variable (rather than county) and is obtained from the government censuses. Thus, per capita health expenditure is expected to represent the intensiveness of the state's associated

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17 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

18 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/

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

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

21 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.

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).[22] This survey collects basic information about state TRI programs and includes various questions on state implementation status regarding the TRI data.[23] 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* 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

22 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.

23 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.

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-value=0.004).

[Insert Table 2]

Table 3 reports descriptive statistics for all variables. Toxic release level and toxic risk are and 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.[24]

[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.

, (1)

where = *Toxic release level* or *Toxic Risk.*

i=counties

24 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.[25] F-tests on the county fixed effects confirm their joint significance (F=31.90, P-value=0.000; F=25.83, P-value=0.000), as do those on the year dummies in the toxic release model (F=18.28, P=0.000) but not the toxic risk model (F=2.03, P-value=0.107). This is consistent with Figure 1 and 2, in which toxic release levels 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 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

25 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).

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.

These findings support Dranove et al. (2003)'s conclusion regarding health care: you get exactly what you asked for. We get a reduction in toxic release level when the information is measured in toxic release level, while we get a reduction in toxic risk when the information is measured in toxic risk. Behavior responds congruently to what the information measures, and responds more strongly to more accurate information, which is information that more closely indicates the true quantity of interest, that is, information on toxic risk, not the level of toxic release.

Sensitivity Analyses

The previous baseline results show that EPA's raw TRI data is inaccurate and has little impact on achieving a true policy goal, reducing toxic risk. As mentioned in the prior studies section, a number of studies have tried to evaluate the TRI disclosure and reported inconsistent evidence regarding the effectiveness of the TRI program. Each study takes its own analytic frame to evaluate the TRI program focusing on different time frames, different measures for the TRI programs and outcomes, as well as a unique set of controls. This section tries to examine how differently the state TRI program can be assessed by different analytic frames through additional regression model specification.

Table 5 presents the results from additional model specifications. Column 1 provides the baseline results for comparison and Column 2 reports the model estimating the impact of state dissemination efforts without the variable of state data processing efforts. Previous studies mainly try to identify the impact of the EPA's TRI data establishment itself without considering its limitations or the importance of processing efforts (Grant, 1997; Grant & Downey, 1995; Grant et al., 2002; Hamilton, 2005; Shapiro, 2005). The coefficient of the *Dissemination* variable without the *Processing* variable might provide partial intuition to the impact of the EPA's TRI establishment that were estimated in the previous studies. In column 2, the coefficient of the *Dissemination* variable is still insignificant in the toxic risk model while it is significant in the toxic release level model. This indicates that evaluating the EPA's TRI establishment with toxic risk as an outcome measure might lead to the conclusion of ineffectiveness of the state TRI program. This finding implies that evaluating the TRI information disclosure policy are sensitive to how the policy and outcomes are measured, and also partly explains why there are mixing evidences in previous studies regarding the effectiveness of the TRI.

[Insert Table 5]

Column 3 presents the estimation results of the model incorporating the index form of states TRI programs that were used in O'Toole et al. (1997) and Shapiro (2005). The index that represents the extensiveness of states TRI programs is constructed by scoring six items of state

TRI program types without classifying them into dissemination or processing efforts.[26] The estimation results show the coefficient of the *Index* variable was not significant in the toxic release level model but significant in the toxic risk. This result partly explains why Shapiro found that the states TRI program was effective with toxic risk measure as a policy outcome, while O'Toole found it wasn't with toxic release level.[27] This also implies that measuring states TRI programs without differentiating its types, such as indexation, might lead to confounded results regarding the effectiveness of the TRI program, in which states' dissemination efforts on toxic risk might be overstated by being combined with effect of states' data processing efforts. It might be critical to design evaluation frames with appropriately matching policy measures with outcomes based on careful consideration of the underlying dynamics.

Column 4 and 5 presents the estimation results with different sets of controls. Column 4 reports the pooled cross sectional analysis – the model without the year and county fixed effects. The estimation result shows that states' data processing efforts had a positive impact on toxic release level and toxic risk, as well as state expenditure for health, while states' dissemination efforts did not have a significant impact on toxic releases. This implies that pooled cross-sectional analyses without fixed effects might suffer from omitted variable bias. Most prior studies are based on cross-sectional analyses in which they tried to avoid the problems with a comprehensive set of controls (O'Toole, 19978; Shapiro, 2005; Hamilton 2005, Grant & Jones, 2004).[28] Nevertheless, panel analysis controlling for all time-invariant factors with fixed effects might be more effective in obtaining unbiased estimates than cross-sectional approach in which all necessary controls are hard to set.

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26 O'Toole and Shapiro constructed the index of the states TRI program based on the NCSL survey which is used in this study. While this study utilized six available items of states' TRI program types for longitudinal data, O'Toole used 8 items and Shapiro used 10 items which was available for their cross-sectional study.

27 This does not mean the estimation model in Column 3 replicated exactly the two prior studies with the same regression models. While this study used a county-level panel approach, Shapiro takes a kilometer-square unit cross-sectional analysis and O'Toole is based on a state-level cross-sectional analysis with different time frames. The model in Column3 is a partial and incomplete replication to bridge the previous studies and this study.

28 The model without fixed effects does not mean to replicate the previous cross-sectional studies. Each study has a different analytic frame. The model was estimated only to highlight the importance of the fixed effects to control for time-invariant factors.

Column 5 shows the model with additional states' environmental policy variables that might influence toxic emissions. The primary model includes states' per capita expenditure for health as a general environmental policy control. In addition to the *Health* variable that includes spending for general environmental and pollution control programs, states' expenditure for parks and natural resources are included in the model.[29] The model also includes non-attainment status and the conservation voters' score as a measure of states' environmental regulatory stringency and political environment, which were used in other toxic emission analysis studies (Bui, 2005; Bennear, 2007). Non-attainment status represents states with non-attainment counties that have not satisfied national ambient air quality standards for any of six criteria pollutants under the Clean Air Act. It is assumed that such states will be pressed to adopt more stringent air pollution regulations than attainment states, such as mandatory adoption of specified abatement technology by polluters.[30] Conservation voters' score is the state-level average score from the League of Conservation Voters, National Environmental Scorecard, which is based on the records of senate and house voting on key environmental policies. All additional environmental policy variables turned out to be insignificant, not changing the baseline model. Each of those states' environmental policy variables does not explain counties' toxic releases even when it is included in the model one at a time replacing the *Health* variable. It seems that the variation of those states' environmental policy variables is mostly time-invariant which might be picked up by county fixed effects already in the baseline model.

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. The findings show that states' efforts to produce processed information

29 Since there is no independent "environment" category in classification by function of the Census of State Governments reports, the model in Column 4 included states' spending for parks and natural resources which is often selected as an environmental expenditure in several associated studies, in addition to the *Heath* variable (Patten, 1998; List & Sturm, 2006).

30 Bui (2005) found non-attainment status had a significant impact on plants' toxic releases indicating that traditional command-and-control of non-toxic pollutants also affect toxic releases, while Bennear (2007) found it had not.

indicators are much more effective than those that simply disseminate the raw TRI 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 as a massive/complex form and as an inaccurate indicator was not useful since is requires processing and interpretation. State data processing efforts contributed significantly to the underlying goal of the TRI by providing a more accurate indicator of the true quantity of interest than the user could come up with on their own measure from the raw TRI data. Moreover, we also find that simple publication of raw data which is an inaccurate measure itself leads to compromised policy outcomes, that is, reductions in the level of toxic release that are not necessarily accompanied by real reductions in risk.

Our findings also confirm the predictions of information overload theory. The effect of states' dissemination efforts on toxic release level, but not on toxic risk, might result from degraded decision quality of the public in targeting the high priority polluters/chemicals, due to information overload associated with the massive and complex raw TRI data (Jacoby, 19787; Eppler & Mengis, 2004). States' processing efforts to provide value-added, refined information played a significant role in reducing information overload and improving the ability of end users to apply the information and their decision quality, finally leading to the intended policy outcome, as predicted by information overload theory (Simpson & Prusak, 1995; Edmunds & Morris, 2000; Koniger & Janowitz, 1995).

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 (Mennemeyer et al., 1997; Dranove et al, 2003; Grant, 2005). Information is useful to end users only insofar as it is accurate. Information with noisy signals that fail to tell the user something about the true quantity of interest is not valuable enough to be utilized. Data released without appropriate processing to show an accurate signal may exceed the analytical capacity of the target user group, cause information overload, 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 processing capacity of targeted actors must be considered for policies to be designed effectively. In essence, our findings highlight the importance of providing an accurate form that is fitted to the users' interest, since what disclosed information is measuring determine what we will get as a policy outcome. **REFERENCES**

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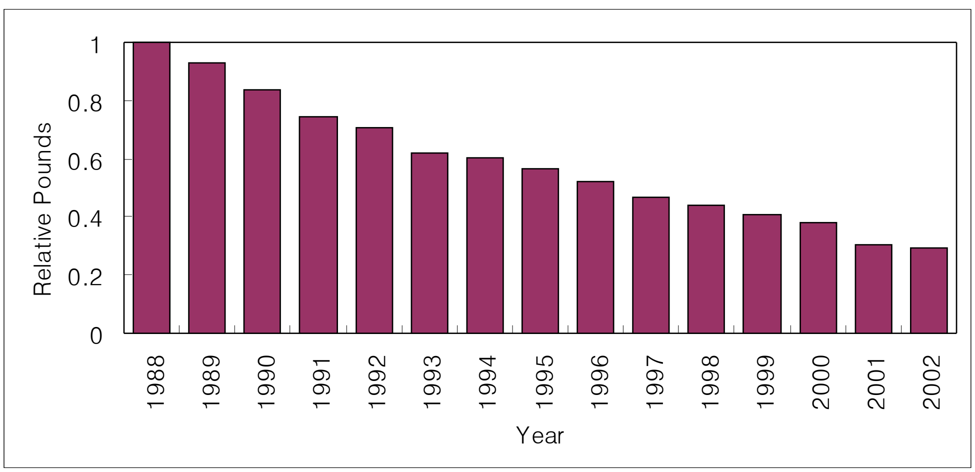

Figure1.Toxic release level in National Total (Relative to the 1988 Release)

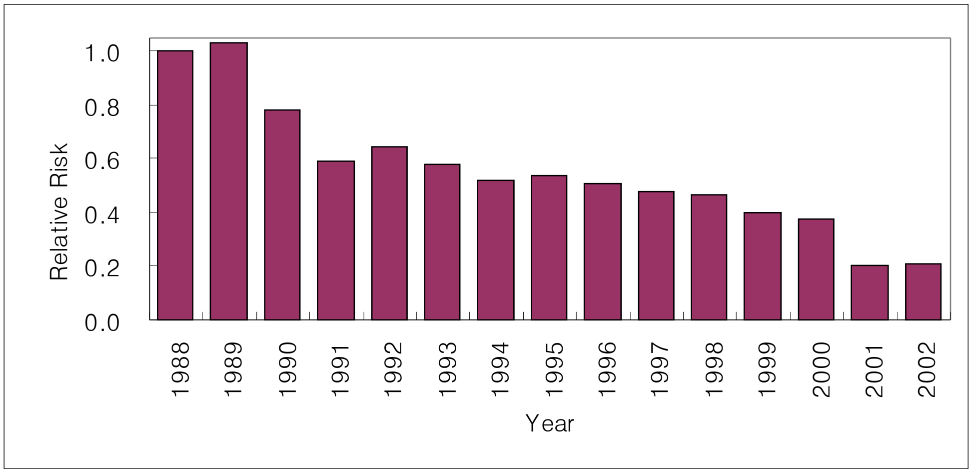

Figure2. Toxic Risk in National Total (Relative to the 1988 Risk Level)

Table 1. Correlation between States' TRI Programs

Year		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	772	864	801	752	669	2482
Toxic Risk (Million Score)	6800	0.01	532356	554	646	569	539	462	12252
%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

	Toxic Release Level		Toxic Risk	
Variables	**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***	0.0320	-0.0439	0.0434
Data Processing	0.0425	0.0460	-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
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

Table 5. Evaluation of States' TRI Program

Model	**Baseline**		**Dissemination Only**		**Index**		**Pooled Cross-Section**		**State Policy Controls**	
Outcome Measure	**Level**	**Risk**	**Level**	**Risk**	**Level**	**Risk**	**Level**	**Risk**	**Level**	**Risk**
Dissemination	-0.103*** (0.032)	-0.044 (0.043)	-0.098*** (0.032)	0.0604 (0.043)			-0.112 (0.081)	0.127 (0.100)	-0.108*** (0.033)	0.046 (0.044)
Processing	0.043 (0.046)	-0.135** (0.062)					0.165** (0.080)	0.282*** (0.096)	0.039 (0.047)	-0.124** (0.063)
Index					-0.017 (0.012)	-0.028* (0.016)				
Health	-0.002* (0.001)	-0.001 (0.001)	-0.002* (0.001)	-0.001 (0.001)	-0.001* (0.001)	-0.001 (0.001)	0.002*** (0.001)	0.003*** (0.001)	-0.002* (0.001)	-0.001 (0.001)
Parks									-0.001 (0.002)	0.004 (0.004)
Natural Resources									0.000 (0.001)	0.001 (0.003)
Conservation Score									-0.001 (0.002)	-0.002 (0.002)
Non-attainment									0.035 (0.057)	0.009 (0.075)
Fixed Effects	Yes		Yes		Yes		No		Yes	

* Significant at p<0.1, ** Significant at p<0.05, *** Significant at p<0.01
Standard errors are in parentheses and robust to heteroskedasticity and serial correlations