Environmental Accidents and Industry Structure

by

Christopher S. Decker

Mark E. Wohar

Department of Economics
College of Business Administration
University of Nebraska at Omaha
Omaha, NE 68182-0048

February 18, 2005

Environmental Accidents and Industry Structure

Abstract

This paper investigates how industry concentration affects the potential for and frequency of environmental accidents. We develop a theoretical model and employ probit and count estimation procedures for annual industry data for the years 1992-1994. While controlling for other relevant information, we find that greater competition reduces both the probability and frequency of environmental accidents. This result obtains irrespective of whether concentration is measured by the Herfindahl-Hershman Index, the eight-firm concentration ratio, or the number of firms in an industry. We also find that as firms become more compliant there is a much lower likelihood that an environmental accident will occur. In addition, we find that the number of inspections conducted in the year prior to an environmental accident has no significant effect on the likelihood that at least one accident occurred during our sample period. Our results suggest that policies that foster competition may perform better than periodic environmental inspections at fostering fewer environmental accidents. Furthermore, there may be unintended consequences to levying environmental taxes on the offending polluting firm. To the extent that such policies may result in exit from an industry leading to higher level of industry concentration could result in a higher likelihood or frequency of accidents.

1. Introduction

According to the United States Environmental Protection Agency's (US EPA) Accidental Release Information Program Database (ARIP), between 1990 and 1999, there were 9,538 accidental chemical releases involving over 3,000 personal injuries, over 700 hospitalizations, and nearly 30 deaths. [1] Accidental toxic releases into the air, water and land amounted to 37 million pounds and, at least according to the data in ARIP, costing releasing facilities a total of roughly $204 million dollars in remediation.[2]

While most of these accidents occurred in certain manufacturing industries that utilize a number of chemicals as production inputs, such as in the chemical manufacturing (Standard Industrial Classification (SIC) 28), petroleum refining (SIC 29), pulp and paper (SIC 26), and food processing industry (SIC 20), a number of accidents occurred in other manufacturing and non-manufacturing industries such as the iron and steel, transportation, and the electric utilities industries.[3] Hence, the data suggests that environmental accidents are a possibility in a variety of different markets, although to varying degrees.

The purpose of this paper is to determine whether or not the potential for, and frequency of environmental accidents are sensitive to industry structure. There is a literature that has looked at environmental accidents from an environmental justice perspective. Derezinski, Lacy, and Stretesky (2003), for instance, investigates the

---

[1] This environmental accident data can be obtained at the US EPA's Accidental Release Information Program (ARIP) web page www.epa.gov/swercepp/. While this database does contain a field indicating the total cost of the accident, there seems to be some discretion on the part of those completing the survey as to whether or not this field is filled in.
[2] While the ARIP database does contain a field indicating the total cost of the accident, there seems to be some discretion on the part of those completing the survey as to whether or not this field is filled in. Therefore, this cost figure might well underestimate the true cost borne by accidental releasers.
[3]Due to data limitations regarding other variables used in the analysis that follows, non-manufacturing industries are excluded from the analysis.

location of ARIP recorded accidents and find that acute health risks associated with these accidents is greater when they occur in lower-income census blocks. There is also a substantial empirical literature that has attempted to measure the impact of environmental variables on company valuation. Perhaps two of the most well known environmental disasters were the 1984 Union Carbide chemical accident in Bhopal India and the 1989 Exxon Valdez oil tanker grounding. The methyl isocyanate leak in Bhopal killed or injured thousands of local residents and ultimately cost Union Carbide $470 million in damages paid to injured parties, at least another $100 million in legal fees, as well as costs associated with dramatic corporate restructuring (Goldsmith, 1996). Similarly, Mansur, Cochran, and Phillips (1991) report substantial losses in Exxon's equity returns as a result of the Exxon Valdez grounding, although interestingly, found little losses in equity in other major oil transporting and processing companies. In an investigation of the relationship between hazardous waste lawsuits and stockholder returns, Muoghalu, Robinson, and Glascock (1990) use event study techniques and find that firm's stockholders suffer on average a 1.2 percent loss in market value (about $33 million) when a suit is filed against a firm for violation of solid waste management laws. Konar and Cohen (2001) show that, ceteris paribus, a company's environmental performance is inversely related to that firm's intangible asset value. They find that a 10 percent decrease in a firm's toxic chemical releases can result in a $34 million increase market value.

The empirical link between environmental performance and industry structure appears less well researched.[4] Farber and Martin (1986) investigate both theoretically and empirically the link between pollution abatement expenditures and market structure.

[4] However, in Carraro, Katsoulacos, and Xepapadeas (1996), a series of theoretical papers investigate the relationship between environmental policy (taxes, standards, incentive structures) and market structure.

Although their theoretical model returns an ambiguous relationship between pollution abatement expenditures and the number of competing firms, they suggest that the effect is most likely to be negative since fewer competitors results in larger per-firm production, larger per-firm profits, and therefore greater ability and incentive to control pollution releases. They also present empirical evidence suggesting that, ceteris paribus, larger per-firm operating and capital pollution abatement expenditures are associated with higher industry concentration (as measured by the four-firm concentration ratio).

Although implied, higher pollution control expenditures do not necessarily imply superior pollution control performance or fewer environmental disasters. Moreover, other measures of environmental performance, such as innovation efforts, suggest a different relationship. One might expect that, in the Schumpeterian tradition, that a less competitive environment might, ceteris paribus, reduce innovation incentives. Indeed, Brunnermeier and Cohen (2003) recently demonstrated that firms competing in more concentrated industries record fewer environmental patents.

The debate surrounding the link between industry structure and firm behavior toward product and process safety issues is far from settled. As a case example, consider the deregulation of the airline industry in 1978. Some argued that the benefits of deregulation (lower fares prompted by entry into the industry) would be offset by reductions in safety as increases in the number of flights could lead to increases in air congestion and airplane accidents. In addition, aggressive competition and tighter profit margins would in turn prompt airlines to cut maintenance and equipment upgrade expenditures to unsafe levels. However, according to data presented in Kaplan (1986) and Walters (1993), fatal airline accidents were actually lower after deregulation.

According to Kaplan (1986), between 1975 and 1978, there were 0.046 fatal airline accidents per 100,000 departures. Between 1979 and 1984, that rate fell to 0.015. While it is difficult to attribute this reduction in airline travel risk to increased competition, many studies have demonstrated airline disasters can have a significant and lasting negative effect on the financial well-being of the company (see, e.g. Chance and Farris, 1987, and Borenstein and Zimmerman, 1988).

When making decisions regarding accident avoidance, whether it be airline crashes or environmental damage avoidance, firms balance the expected costs they incur in the event of an accident with the costs of preventing such accidents from happening. In a competitive environment, as market shares decline and firms face additional pressures to increase profit margins through cost reductions, it may be more cost-effective to take more care to avoid accidents if the expected cost of such an accident is sufficiently high.

In this paper we address from both a theoretical and empirical perspective, what effect industry structure has on the probability and frequency of environmental accidents occurring. As a preview of our results, we find that, when controlling for other relevant information, greater competition reduces both the probability and frequency of environmental accidents. This result obtains irrespective of how industry competition is measured. The paper is organized as follows. In section 2, we present a theoretical model illustrating the essential elements that Cournot-competing firms might consider when making environmental accident avoidance investments. In section 3, we describe the data and the estimating equation based on our theoretical model. In section 4, we address some relevant econometric issues encountered in estimating the empirical model. In section 5, we summarize our primary findings and we conclude with section 6.

2. A Simple Theoretical Model

Consider an industry that consists of N identical Cournot competitors facing a lienear industry demand curve, $P = a - bQ$, where Q is market demand. Since we assume firms are identical, then $Q = Nq_i$ for $i=1\ldots N$, where q_i equals individual firm i's output. For simplicity, assume zero fixed and marginal production costs. However, production does generate dangerous byproducts that prove harmful to the surrounding natural environment if accidentally released. If such a release occurs and is either discovered by or reported to regulatory authorities, the firm is held accountable and is subject to penalty and is required to remediate any damages caused.

It is reasonable to assume that a firm can invest in an effort to lower the probability of an accident occurring. We define the probability that, in a given time period, the firm is able to successfully avoid a potentially costly environmental accident as $p_i \in [0,1]$. Hence, the corresponding probability of an accident of occurring is $1 - p_i$. Clearly, the firm would like to maximize p_i. However, doing so is costly. Allow $x(p_i)$ to represent the cost a firm incurs in an effort to increase the probability of avoiding an environmental accident with the following properties: $x'(p_i) > 0,\ x''(p_i) \geq 0, x(0) = 0, x(1) = \overline{x}$.[5] This cost we refer to as pre-accident avoidance costs.

Consistent with many existing models, we assume that the environmental damages generated as the result of an accident occurring, $C(q_i)$, are increasing in output,

---

[5] This modeling convention is not uncommon in the economics literature (see, e.g. Neilson and Kim, 2001). We assume that the firm can achieve complete accidence avoidance at a cost of $\overline{x}$. Note, however, that this cost could be very high and indeed, could in theory approach infinity. In what follows, however, we assume an interior solution such that $p_i \in (0,1)$.

i.e. $C'(q_i) < 0, C''(q_i) \geq 0$. Again, if regulatory institutions are able to hold the firm accountable for any damages caused, the expected costs to the firm of an environmental accident occurring is $EC(p_i, q_i) = (1 - p_i)C(q_i)$. For simplicity, we assume $C(q_i) = cq_i$, where c is the post-accident remediation cost the firm incurs per unit output. To ensure that nonzero profit maximizing output levels are chosen by firms in this industry, we make the standard assumption that demand is sufficiently large to warrant production, i.e. $a > c$.

The objective, of a representative firm *i*, can be expressed as:

$$\max_{q_i, p_i} \pi_i = \left[a - bq_i - b(N-1)q_{-i} - (1-p_i)c\right]q_i - x(p_i), \tag{1}$$

where q_{-i} represents output decisions from all other firms, not *i*. In standard Cournot fashion, each firm *i* simultaneously chooses a level of output and a level of accident avoidance effort to maximize (1).[6] Assuming interior solutions results in the following 2N first order conditions:

$$\frac{a - (1-p_i)c}{2b} - \frac{N-1}{2} q_{-1} - q_i = 0, \text{ for } i = 1...N, \tag{2}$$

$$cq_i - x'(p_i) = 0, \text{ for } i = 1...N. \tag{3}$$

Equation (2) is the familiar Cournot expression that defines each firm *i*'s best response function in output. Equation (3) represents each firm *i*'s optimal environmental accident avoidance condition. Each firm will invest up to the point where the benefit associated

[6] The reader with recognize that the p_i's are independent, i.e. the probability of an environmental accident occurring at firm *i* is independent of an accident occurring at, say, firm *j*. While a reasonable assumption, it should be pointed out that, to the extent that firms *strategically* manage pollution control, that is, with deference to what their competitors are doing, it is at least possible that the p_i's are inter-related. See, e.g., Decker and Pope (2004). With respect to accidents and accident-control investments specifically, we are unaware of any empirical verification of such a correlation across firms. This, however, would be an interesting avenue for future research.

with avoiding an environmental accident, cq_i, equal the marginal cost of avoiding such an accident, $x'(p_i)$. Since firms are identical, (2) can be expressed as

$$q_i = \frac{a-(1-p_i)c}{b(N+1)}. \qquad (4)$$

Substituting (4) into (3) and re-arranging yields firm *i*'s equilibrium accident avoidance effort condition:

$$c(a-(1-p_i)c) = x'(p_i)b(N+1). \qquad (5)$$

Equation (5) illustrates the effect that industry structure has on the firm's optimal accident avoidance decisions. The left-hand side of (5) embodies, in part, the benefits of investing in p_i, i.e. avoiding c. The right-hand side embodies the marginal cost of accident avoidance, involving both $x'(p_i)$ and *N*. Relative to, say, a monopolist's decision, now the marginal cost of avoidance includes a type of "spill-over" cost. With increased competition, pressures by individual firms to control costs to achieve maximal market share and profitability are increased. However, whether or not increases in p_i result from increases in *N* depends on the relative costs involved. Differentiation of equation (5) with respect to p_i and N yields

$$\frac{dp_i}{dN} = \frac{x'(p_i)b}{c^2 - x''(p_i)b(N+1)}, \qquad (6)$$

which is ambiguous in sign. However, since the source of the ambiguity is in the denominator of (6), it is clear that the relationship between p_i and N depends on the relative magnitudes of the expected post-accident remediation costs (i.e. c) relative to the increase in the marginal pre-accident avoidance cost (i.e. $x''(p_i)$). The key to understanding this relationship, not surprisingly, depends on the impact increased competition places on controlling costs, whether those costs are pre-accident avoidance costs or post-accident remediation costs.

Case 1. If c is sufficiently large relative to $x''(p_i)$, then an increase in the number of competitors will prompt firms to increase their potential for avoiding an accident. Or, stated differently, an increase in competition will result in fewer environmental accidents. With relatively large environmental remediation costs, increased competition places a higher premium on the part of firms to avoid incurring post-accident remediation costs in an effort to avoid excessive loss of market share. Hence $dp_i/dN > 0$.

Case 2. If c is small relative to $x''(p_i)$, then increased competition will result in a higher probability of accidents occurring. Or, an increase in competition will result in more environmental accidents. With relatively large accident avoidance costs, increased competition places a higher premium on firms to limit pre-accident costs in an effort to avoid excessive loss of market share. In a sense, firms are more inclined to take their chances of experiencing and being forced to remediate an environmental accident since the cost of remediation is relatively small. Therefore, $dp_i/dN < 0$

The theoretical ambiguity highlights the need for empirical analysis. Data on $x(p_i)$ is not generally available. Although there is some information on the cost of remediating an environmental accident, c, the data is by no means universally complete. However, there is reliable data for the United States on both environmental accidents (frequency, number and size) and industry structure that can be used to ascertain which costs (remediation or accident avoidance) are likely to dominate. In the section to follow, we attempt to determine the effect that industry structure has on the probability, frequency, and size of environmental accidents.

3. The Empirical Model and Data

The basic empirical model to be estimated is

$$y_t = f(\ln(INDSTR_t), \ln(SHIP_t), \ln(TRI_t / SHIP_t), \ln(INS_{t-1}), \ln(COMP_{t-1}), SIC20, SIC26, SIC28, SIC29, DMY93, DMY94, e_t), \quad (7)$$

where y_t represents one of two different variables we use to measure environmental accidents. As stated above, the primary source of environmental accident data used as the dependent variable in the empirical section of this study is the US EPA's *Accidental Release Information Program (ARIP) Database*. While this database has been used by many other researchers (see, e.g. Deresinski, Lacy, and Stretesky, 2003) some further detail on this database is warranted. Various US environmental statutes have authorized the US EPA to collect and make known to the public information on the frequency and size of chemical release accidents occurring at US manufacturing plants on an ongoing basis. In constructing the ARIP database, the US EPA uses data from their Emergency Response Notification System (ERNS) database to target certain "releasers" to provide additional information via their ARIP questionnaire. ARIP targets accidental releases at fixed facilities that ultimately generate health and safety problems and environmental damages off site.

The primary focus of this database is on "significant" accidental chemical releases into various media (land, air, water, ext) that resulted in death, injury, or severe environmental degradation. [7] Clearly, then, ARIP does not capture the universe of accidental releases. It may reasonable to suppose that the application of ARIP data here

[7] It should be pointed out that what has been considered a "significant" accidental release has changed over time. Prior to 1993, the criteria was the quantity of material released. Since then, focus has been on off-site impact and environmental damages. To be sure, this may raise potential statistical problems. However, as is commonly done in such circumstances, we include yearly dummy variables in part to control for this change.

clouds the link between the theory and the empirics since it is true that our model does not distinguish between "significant" and "less-significant" accidents. However, the model does not preclude significant accidents either. Hence, the basic predictions of the model are still quite reasonably tested even though the focus in the data is on major accidents.[8].

From ARIP then, we aggregated, by year, chemical release information by four-digit Standard Industrial Classification (SIC). In this study we considered the number and amount of total releases irrespective of where the releases occurred (i.e. land, air or water).[9] The dependent variable y_t is measured in two ways. First, we created a binary variable, ACCIDENT_BI, equal to one if at least one chemical accident occurred in a particular industry in a given year, zero otherwise.[10] Equation (7) was then estimated using a probit model. Second, we counted the total number of chemical accidents, called ACCIDENT, which occurred in a particular industry in a given year. Equation (7) was then estimated using regression techniques applicable to count data.

The variable ln(INDSTR) is a measure of the structure of the industry in which the accident(s) is (are) occurring. From the perspective of the model presented in the previous section, the obvious empirical measure for ln(INDSTR) would be the number of

---

[8] That said, it would be a worthy avenue for future research to consider the universe of data in ERNS. Indeed, the empirical links using ARIP might be stronger given the competitive incentives implied in the model to limit environmental accidents. Using the ERNS data may mitigate some of the hypothesized effects. However, using ERNS for this type of exercise is problematic for a couple of reasons. First, the US EPA does not track industry classification in the ERNS database and fields that link plant releases to specific companies are not always complete. Therefore, linking an accident to a specific company in a specific industry may lead to significant data inconsistencies. Second, according to US EPA's ARIP fact sheet (1998) there are many releases reported in ERNS that are not the result of an accident. This would further cloud the link between our model (with its focus on accidents and industry structure) and empirical findings.

[9] To date, nearly all of the US EPA databases still collect and categorize information by SIC, rather than the US Census Bureau's recently implemented North American Industry Classification System (NAICS). As discussed later, this will have some ramifications for the analysis to follow, mostly in terms of the time frame over which we conduct our analysis.

[10] The time subscripts have been dropped for notational convenience.

producers, N. In equation (7), we will first treat ln(INDSTR) equal to ln(N) and would expect by condition (6) a lower propensity for, and frequency of, environmental accidents with *higher* N if the cost of an environmental accident, *c*, were relatively high, and all firms are of equal size. We would expect the opposite to hold if the cost of an accident were relatively low. However, there are other popular measures of industry structure, such as the Herfindahl-Hershman Index (HHI) and the eight-firm concentration ratio (CR8). In addition, then, we estimate equation (7) substituting the ln(HHI) and ln(CR8) for ln(N). We would expect to see a lower propensity for, and frequency of, environmental accidents to be associated with *lower* HHI (CR8) if the cost of such an accident were relatively high since a lower HHI (CR8) indicates a more competitive industry structure. The data on N, HHI, and CR8 come from the US Census of Manufactures, Bureau of the Census.[11]

A number of additional control variables are included in equation (7). The total real ($1996) dollar value of shipments by four-digit SIC (measuring in $millions), obtained from the US Bureau of Economic Analysis at the US Department of Commerce, ln(SHIP) is included to control for industry size.[12] As equation (5) suggests, for a sufficiently high *c*, industries that produce more output, perhaps in response to higher

[11] This data can be obtained at http://landview.census.gov/mcd/historic/mc92cr.txt.
[12] This data can be obtained at http://www.bea.doc.gov/bea/dn2/gpo.htm. The data contains shipments of manufacturing industries by four-digit SIC industry, three-digit SIC industry group, and two-digit SIC major group. Current dollar estimates, chain-weighted quantity indexes, and chain-weighed price indexes are included. We obtained the four-digit nominal shipments data and deflated each series by the corresponding chain-weighted price index for each industry to obtain a real ($1996) value of shipments figure.

demand, are likely to experience a higher propensity for, and frequency of environmental accidents.[13]

Additional control variables are also included as they are likely to impact the probability and frequency of environmental accidents. The variable ln(TRI/SHIP) measures the volume (measured in pounds) of toxic chemical releases (TRI) reported by industry per $million dollars worth of industrial shipments. The TRI data, compiled and made available by the US EPA, is part of the US's 1986 Emergency Response and Community Right to Know law, requiring that facilities meeting certain sector and size criteria report releases of over 650 toxic chemicals into the air, water, land, underground, or shipped off-site. We aggregated total TRI releases by four-digit industry classification and year.[14] We expect that higher polluting industries, as measured by increases in TRI emissions per shipment dollar, are more prone to environmental accidents and therefore expect a positive coefficient to obtain.

Two additional control variables are included to test the impact of monitoring and enforcement of environmental regulations might be having on accident rates. The variable $\ln(INSP_{t-1})$, made available from the US EPA's Office of Enforcement and Compliance Assurance (OECA), measures the total number of inspections conducted in a

[13] From equation (5), we see that $\frac{dp_i}{da} = -\frac{c}{c^2 - x''(p_i)b(N+1)}$, which is likely to be negative for large c. Hence, higher demand (higher a) results in a lower probability of accident avoidance, ceteris paribus.

[14] We obtained this data from the US EPA's online query program at http://www.epa.gov/enviro/html/tris/adhoc.html. For some four-digit industries there were no reported TRI releases. This may be because no firms in those sectors had releases in a given year or it may be because the SIC field in the database was not filled in by the reporting facility (we can safely rule out, however, that these zero observations are because the law requiring TRI reporting does not apply to that sector. TRI reporting is required of all manufacturing sectors and these are the sectors which comprise our database). Unfortunately, there is no way to determine if the latter is true to any appreciable degree so we presume that the data is reasonably accurate. For those industries that presumably had no TRI releases, when taking the natural log of TRI/SHIP one would loose those observations. To avoid this, consistent with Gray and Deily (1996) for instance, we add one to TRI/SHIP across all industries so that in equation (7) ln(TRI/SHIP+1) replaces ln(TRI/SHIP).

particular industry by both state and federal authorities for Clean Air Act, Clean Water Act, and Resource Conservation and Recovery Act (RCRA – solid waste), compliance one year prior to the occurrence of an environmental accident.[15] One might expect that greater scrutiny by regulators might induce greater care by firms and should reduce subsequent accidents.

Additionally, we include $\ln(COMP_{t-1})$ in equation (7), which measures overall industry compliance rates with CAA, CWA and RCRA, one year prior to an accident occurring.[16] We constructed this variable by taking the difference between the total number of inspections conducted and the total number enforcement actions (ENF) levied in an industry in a given year and dividing that difference by total inspections.[17] We

[15] Both the inspection and enforcement data were obtained via OECA's Integrated Data for Enforcement Analysis (IDEA) database. For details regarding this database and access to it, interested readers are directed to http://www.epa.gov/compliance/planning/data/multimedia/idea/index.html. The data we obtained was aggregated to the three-digit SIC level for the years 1991 to 2000 and was provided in December, 2000.

[16] Measuring compliance as an aggregate measure across three different environmental statutes provides a very complete measure of overall environmental compliance behavior within an industry. It is possible, for instance, that some firms in some industries have higher levels of compliance for CAA regulations but very low compliance levels for RCRA regulations. Focusing on just one statute as a measure of compliance may be incomplete from the perspective of capturing the compliance effect on accident rates. However, as a matter of future research, it may be worth including a measure of industrial compliance for all three statutes separately. The data made available to us, unfortunately, did not have this statutory breakdown so further costly data collection would be required.

[17] An enforcement action is a closed administrative or civil judicial government action that has been taken against a facility for violating environmental laws and that has been entered into federal data systems. Strictly speaking, this may not be a completely accurate measure of compliance. For instance, many inspections that reveal noncompliance may not result in a formal recorded enforcement action. They may be handled informally, or a violator may receive a notice of violation (NOV), which are not tracked in IDEA. However, two points are necessary here. First, there are few alternatives to measuring compliance and it is reasonable to assume that significant violations, either in magnitude or in frequency of violation, are met with a formal enforcement action. Second, one might be concerned that it is possible for years to pass between inspections detecting violations and a resulting enforcement action. While possible, this is very rare. In most cases, enforcement actions are recorded within a year of discovered noncompliance (the issue of court hearings, penalty assessments, and final decision can, however, take years or even decades to complete. However, this is less of a concern for the study conducted here).

would expect that those industries with better compliance records to have fewer subsequent environmental accidents.[18]

In addition, we include four broadly defined two-digit SIC dummy variables (SIC20, SIC26, SIC28, and SIC29) equal to one if the industry can be classified under chemical manufacturing (SIC 28), petroleum refining (SIC 29), pulp and paper (SIC 26), and food and kindred products processing (SIC 20), and zero otherwise. These industries both utilize and generate as production byproducts a large volume of toxic chemicals, have recorded frequent environmental accidents during the 1990s, and are considered "high priority" industries for enforcement and compliance by the US EPA. We are likely to see more frequent environmental accidents in these industries. Finally, two time dummies, DMY93, and DMY94 are included to control for any time-related effects that might be influencing accident rates.

The data for this paper covers the period 1992 to 1994. The major reason for this is that we are using industry concentration data from the 1992 Census of Manufacturers (see footnote 4). With the US Census Bureau's change to the NAICS classification system and the US EPA's continued use of the SIC, and given that the correspondence between the two is not exactly direct, we felt that we should be consistent with the SIC code. Also, given the rate of both consolidation and entry that occurred in many industries in the 1990s, and given that the company count and industry concentration data are available only in five-year increments, we felt that it would be far too strong of an

[18] Following common econometric practice, both INSP and COMP are lagged one year in equation (7) to mitigate some concerns over potential endogeneity. For instance, it is quite possible that current year inspections may be higher because an environmental accident occurred earlier that same year. Moreover, contemporaneous compliance may be impacted if an accident occurred that same year. It should be noted, however, that in some cases lagging variables may not solve issues of potential endogeneity. We therefore conducted a Hausman test with these lagged variables and detected no statistical support for endogeneity.

assumption to assume that the 1992 HHI, CR8, and N data would be applicable to environmental data much past that year. Moreover, since our inspection and enforcement data are available only back to 1991 and we needed to include lagged values of these variables, we were forced to start our analysis with accidents that occurred no earlier than 1992.

4. Econometric Methodology and Issues

As evident in Table 1, the low averages and the preponderance of zeros in the accidents variable highlight the discrete nature of the data. This suggests using estimation techniques appropriate for count data. However, there are a number of industries that did not experience an environmental accident. The excessive number of "zero" observations suggests that, in addition to the count data estimation, it is necessary to conduct a probit or logit analysis where the dependent variable is treated as binary equal to one if at least one accident occurred in a particular industry in a given year, zero otherwise. This will help ease concerns that the results obtained in the count data procedures are being driven by a few very accident-prone industries. We employ both a probit estimation procedure and a count modeling procedure to estimate equation (7).

The probit procedures are quite common and relatively easy to implement. Count data estimation procedures are somewhat less prevalent and, while fairly straightforward to implement as well, there is a key feature of such models that we address below.

The most basic count data model utilizes the Poisson density function to perform maximum likelihood estimation of the β coefficients. Typically, when maximum likelihood estimation is performed on count data using the Poisson (or any other) distribution, the independent variables defining the conditional mean of the dependent variable enter the log-likelihood form of the chosen density function in the following way:

$$y = g(y \mid \mathbf{x}, \beta) = \exp(\mathbf{x}'\beta), \tag{8}$$

where *g(.)* is the function defining the conditional density of *y*, **x** is a matrix of independent variables as defined in (7) and β is a vector of estimated coefficients.[19] Therefore, it is readily apparent that the resulting estimated coefficients can be interpreted as semi-elasticities since, for a given independent variable *i*:

$$\frac{\partial y / y}{\partial x_i} = \beta_i . \tag{9}$$

Consistent with much of the existing literature, if we wish to obtain elasticities, the variables defining **x** can be incorporated, as we do in equation (7), into the estimation in their logarithmic representation.[20]

The Poisson density function, however, has the defining characteristic that the conditional mean of the outcome is equal to the conditional variance, a characteristic rarely exhibited in applied analysis. It is most often the case that the data is over-dispersed; that is, the conditional variance exceeds the conditional mean. In fact, inspection of the sample mean and variance on ACCIDENT in Table 1 suggests that over-dispersion is quite likely in our data. Failure of the equi-dispersion assumption inherent in the Poisson distribution has consequences for the estimated standard errors on the β coefficients similar to those that result when heteroskedasticity is present in

---

[19] See Cameron and Trivedi (1990) and Greene (1993) for details regarding such econometric procedures.
[20] The exceptions, of course, are the binary year and industry dummy variables.

standard linear regression models. That is, the estimated variances on the vector of coefficient estimates will be biased estimators of the true variance of these estimated parameters, thus making statistical inference unreliable.[21] Under such a scenario, the Poisson model is usually rejected in favor of the Negative Binomial (NB) regression model whose distributional properties allow for over-dispersion.[22]

There are several ways of testing for over-dispersion. When performing maximum likelihood estimation with the NB distribution, in addition to the vector of β coefficients, an additional "shape" parameter, r, is estimated as well. As Cameron and Travedi (1998, p. 70-79) discuss, the sign of the r coefficient is positive and statistically significant, then we can reject the null hypothesis of equi-dispersion comfortably utilize the NB.[23]

5. Estimation Results

Both the probit and count model results are presented in Tables 2 and 3 respectively. The L-R statistic from Table 2 suggests that when tested against the restricted model where all slope coefficients are assumed to be zero, the probit model as defined by equation (7) is statistically significant. Hence, the empirical model is providing some information as to the probability of an environmental accident occurring.

With respect to the frequency of environmental accidents occurring, we estimated equation (7) using the NB distribution for the count model. As we can see from Table 3, similar to the probit results, the L-R statistic indicates that the various independent variables

[21] In fact, Cameron and Trivedi (1998) illustrate that the magnitude of the standard error bias in a count model that fails to correct for over-dispersion can be much larger than a standard regression model that fails to correct for heteroskedasticity.
[22] It can be shown that the Poisson density function is a special case of the NB density (see Cameron and Trivedi, 1998).
[23] Alternatively, one can test the appropriateness of the NB model by estimating equation (7) using both the Poisson and the NB and perform a likelihood ratio test between the restricted (Poisson) and unrestricted (NB) model. We conduct this test as well.

taken together are statistically significant determinants of the frequency of environmental accidents. Moreover, the shape parameter r is shown to have a positive and significant effect when N and HHI are used to measure market structure. This indicates that the accident data are most likely over-dispersed suggesting that the NB distribution is more appropriate than the Poisson distribution. The coefficient on r, while positive, is insignificant when CR8 is used as a measure of industry structure. However, the resulting p-value is –0.1128 suggesting that it is "near" significant at the 10 percent level. Hence, we are comfortable that the accident data is best modeled using the NB.[24]

We now turn attention to the various independent variables' effect on environmental accidents. Table 2 presents the results of our probit estimation. As stated above, we employ three different measures of concentration; N, HHI, and CR8. Our results are similar for all three measures of concentration. With respect to the number of inspections conducted in the year prior to an environmental accident (INS) we find that this variable has no significant effect on the likelihood that at least one accident occurred during the period 1992-1994. This suggests that inspections have not had their intended effect of reducing the likelihood of an environmental accident. The effect of compliance (COMP) on the likelihood of at least one accident is negative and significant, indicating that, as theory suggests, the more compliant a firm is, the less likely that an environmental accident will occur. This result is robust to the measure of concentration used. Our proxy for market demand (*a* in the theoretical model) is the total (real) value of industrial shipments (SHIP). Regardless of the measure of

[24] We also conducted for each empirical model a L-R test testing whether or not the restricted Poisson regressions (where the *r* coefficient was forced to be zero) resulted in a statistically significantly lower maximized value of the resulting likelihood function when compared to the NB results. The resulting L-R statistics were 136.2 when N is used, 104.7 when HHI is used, and 115.9 when CR8 is used. These statistics, distributed χ^2 with one degree of freedom (one restriction), are all significant at one percent or better suggesting that the maximized value of the Poisson likelihood function is significantly smaller than the NB. Hence, we can reject the null of equi-dispersion.

concentration used, we find that there is a positive and statistically significant correlation between SHIP and the likelihood of at least one accident. The effect of total pounds released of TRI chemicals per million dollars worth of shipments (TRI/SHIP) has a positive and significant coefficient, indicating that the more polluting is an industry, the higher the likelihood of at least one accident occurring in that industry. This is also robust to the measure of concentration employed.

With respect to the measure of concentration, we find that all three measures used have their hypothesized sign and are statistically significant. We find that as the number of firms in an industry (N) increases, the likelihood that at least one accident occurring decreases. With respect to the HHI and CR8, we find that as these measures of concentration increase, the likelihood of at least one accident increases.

The coefficients associated with the dummy variables for the food and kindred products processing (SIC20), and chemical manufacturing (SIC28), and petroleum refining (SIC29) industries, are positive and significant in all three specification, regardless of the measure of concentration, and indicate that in these industries, there is a higher propensity of an environmental accident relative to other industries. The coefficient associated with the dummy variable for pulp and paper (SIC26) is significant and positive in the specifications using HHI and CR8 as measures of concentration but positive and insignificant in the specification employing N as the measure of concentration. (However, the p-value is 0.11) Given that these industries both utilize and generate a large volume of toxic chemicals as byproducts of their production and have recorded a large number of environmental accidents in the 1990s, these industries are considered high-priority industries for enforcement and compliance by the US EPA. Our results indicate that these industries have a higher propensity of accidents relative to other industries in our sample. The coefficients associated with the 1993 and 1994 dummy variables are negative and significant in all three specifications indicating that the likelihood of at least one environmental accident has declined in 1993 and 1994 relative to 1992.[25]

We next turn to our count estimation results that are presented in Table 3. These results are largely consistent with our findings in the probit estimation. However, as discussed above, the coefficients associated with the independent variables in this estimation procedure can be interpreted as elasticities. We begin our discussion with the degree of concentration variable. We find that with respect to the number of firms in an industry that if the number of firms in an industry increases by 10 percent the frequency of occurrence of an environmental accident is reduced by 3.4 percent. Using the HHI as a measure of concentration, we find that when the HHI increases by 10 percent the frequency of an accident increases by 3.3 percent. The specification employing the CR8 indicates that a 10 percent increase in this ratio results in a 7.26 percent increase in the frequency of an accident. Thus, consistent with our probit results, we find that the less concentrated the industry, the higher the frequency of an environmental accident.

Interestingly, unlike the probit model results, the number of inspections conducted in the year prior to an environmental accident has a positive and statistically significant effect

[25] Indeed, the ARIP data show that the number of environmental accidents has dropped over the decade of the 1990s. While this drop can be attributable to a number of things (such as technological innovations, etc.) it might also be attributable to industry structure. Consider two industries, food processing (SIC 20), and chemical manufacturing (SIC 28). As noted above, these are two industries that are quite prone to environmental accidents. As stated earlier, direct comparisons between N, HHI, and CR8 published using the recently adopted NAICS and the traditional SIC are at best difficult to make. However, it is interesting to note that according the US Census Bureau, the number of companies in the food manufacturing industry (SIC 20) was 16,972 in 1992. In 1997 (under NAICS 311) that number increased to 21,958. Moreover, in the chemical manufacturing industry (SIC 28), the number of companies listed by the Census Bureau was 9055 in 1992. In 1997 (under NAICS 325), that number was 9,626 (this data can be obtained at the following web page: http://www.census.gov/epcd/www/concentration.html). Hence, despite the fact that many mergers took place during the 1990s, some industries appear to have witnessed some increase in competition.

on the frequency of environmental accidents. Indeed, we find that given a 10 percent increase in the number of inspections there is between a 2.56 percent and 3.38 percent increase in the frequency of accidents, depending on the measure of concentration employed. This is a rather counter-intuitive result as one would expect that if monitoring is to have a deterring effect of lax environmental performance, then greater regulatory scrutiny should result in fewer environmental accidents. These results seem to run counter to this proposition. Indeed, they might simply be suggesting that regulators give more attention to those sectors more prone to accidents outside of their control in the hope that, rather than resulting in fewer accidents, smaller accidents occur and remediation begins more quickly.

Turning attention to COMP, we find that a 10 percent increase in previous compliance rates results in a subsequent decrease in the frequency of accidents between 72 percent and 79 percent, depending on the measure of concentration employed. Efforts on the part of firms to improve compliance, then, appear to be having a beneficial effect of reducing subsequent accidents. Moreover, the degree of compliance appears to be the most important variable influencing the frequency of environmental accidents. With respect to industry shipments, we find that a 10 percent increase in SHIP results in an increase in the frequency of accidents between 7.68. and 8.87 percent. A 10 percent increase in the total pounds of TRI chemicals released per million dollars worth of product shipments, results in an increase in the frequency of accidents between a 4.5 percent and 4.86 percent, depending on the measure of concentration.

The coefficients associated with the dummy variables for the food and kindred products processing (SIC20), and chemical manufacturing (SIC28), and petroleum refining (SIC29) industries, are positive and significant in all three specification, regardless of the measure of concentration. The coefficient associated with the dummy variable for pulp and paper (SIC26) is significant and positive in the specifications using HHI and CR8 as measures of concentration but positive and insignificant in the specification employing N as the measure of concentration, similar to our probit results. The coefficient associated with SIC20 is the largest, while the coefficient associated with SIC26 is the smallest. The results suggest that the food and kindred product processing industry (SIC20) has about a 2.6 percent higher frequency of accidents relative to other industries. The chemical manufacturing (SIC28), and petroleum refining (SIC29) industries have about a 1.6-to-1.7 percent higher frequency of accidents relative to other industries. The pulp and paper (SIC26) industry has about a 0.7 percent higher frequency of accidents relative to other industries in our sample.

The coefficients associated with our time dummy variables for 1993 and 1994, indicate that 1993 had about a 1.8 percent lower frequency of accidents relative to 1992, while there were about a 3.2 percent lower frequency of accidents in 1994 relative to 1992.

6. Conclusion

While previous research has investigated the link between environmental accidents and location, firm equity and firm asset value, etc., there has been little empirical investigation linking environmental performance and industry structure. The purpose of this paper is to address this by investigating how industry concentration affects the potential for and frequency of environmental accidents.

When making accident avoidance decisions, firms will balance the expected post-accident remediation costs with their marginal pre-accident avoidance costs. In a competitive environment, as market shares fall and firms face additional pressures to increase profit margins through cost reductions, it may be more cost-effective to take more care to avoid accidents if the expected cost of such an accident is sufficiently high.

Our theoretical model links these costs with industry structure with a conditional outcome obtaining. If post expected post-accident remediation costs are large relative to increased marginal pre-accident avoidance costs, then an increase in competition will result in fewer environmental accidents. If expected post-accident remediation costs are small relative to increased marginal pre-accident avoidance costs, then an increase in competition will result in more environmental accidents.

In order to ascertain which effect might dominate we investigate environmental accident incidence empirically by investigating the determinants of both the probability and the frequency of environmental accidents occurring using three different measures of industrial structure (N, HHI, and CR8). Our main finding is that, when controlling for other relevant information, greater competition reduces both the probability and frequency of environmental accidents. As the number of firms in an industry increases, the likelihood that at least one accident occurring decreases. With respect to the HHI and the CR8, we find that as these measures of concentration increase, the likelihood of at least one accident increases.

In addition, we find that the number of inspections conducted in the year prior to an environmental accident has no significant effect on the likelihood that at least one accident occurred during the period 1992-1994. Interestingly, the degree of compliance appears to be the most important variable influencing the frequency of environmental accidents. The effect of compliance on the likelihood of at least one accident is found to be negative and significant, indicating that, as theory suggests, the more compliant a firm is, the less likely that an environmental accident will occur. We find that there is a positive and statistically significant correlation between our proxy for market demand and the likelihood of at least one accident. The effect of total pounds released of chemicals per million dollars worth of shipments has a positive and significant coefficient, indicating that the more polluting is an industry, the higher the likelihood of at least one accident occurring in that industry.

Our results may have some policy implications. Generally speaking, economic regulations designed to increase production and lower product prices are often viewed as at odds with environmental regulations designed to restrict production and increase prices. However, if the environmental externality manifests itself in the form of an environmental accident, then increased market competition may itself be sufficient to limit the propensity for such occurrences if the cost imposed on firms responsible for environmental accidents is sufficiently high. Moreover, if we extend this line if reasoning, there may be unintended consequences to levying Pigovian-type taxes on polluting firms. Taxing in such a way may drive some firms out of an industry leading to higher concentration and in turn resulting in a higher likelihood or frequency of accidents.

References

Borenstein, Severin, and Martine B. Zimmerman. 1988. Market Incentives for Safe Commercial Airline Operation, *American Economic Review* 78(5): 913-935.

Brunnermeier, Smita B., and Mark A. Cohen. 2003. Determinants of Environmental Innovation in the US Manufacturing Industries, *Journal of Environmental Economics and Management* 45(2): 278-293.

Cameron, A. Colin, and Trivedi, Pravin K., 1998. *Regression Analysis of Count Data*. Econometric Society Monographs No. 30.

Carraro, Carlo, Yiannis Katsoulacos, and Anastasios Xepapadeas (editors). 1996. *Environmental Policy and Market Structure,* Fondazione Eni Enrico Mattei Series on Economics, Energy and Environment, vol. 4. Dordrecht; Boston and London: Kluwer Academic Publishers.

Chance, Don M., and Stephen P. Ferris. 1987. The effect of Aviation Disasters on the Air Transport Industry: A Financial Market Perspective, *Journal of Transport Economics and Policy* 21(2): 151-165.

Decker, Christopher S., and Christopher R. Pope. Adherence to Environmental Law: The Strategic Complementarities of Compliance Decisions, *Quarterly Review of Economics and Finance, forthcoming*.

Deresinski, Daniel D., Michael G. Lacy, and Paul B. Stretesky. 2003. Chemical Accidents in the United States, 1990-1996, *Social Science Quarterly* 84(1): 122-143.

Farber, Stephen C., and Robert E. Martin. 1986. Market Structure and Pollution Control Under Imperfect Surveillance, *The Journal of Industrial Economics* 35(2): 147-160.

Goldsmith, Arthur A. 1996. *Business, Government, Society: The Global Political Economy*. Irwin.

Greene, William H. 1993. *Econometric Analysis, 2nd ed*. Prentice Hall.

Kaplan, Daniel P. 1986. The Changing Airline Industry, in Leonard W. Weiss and Michael W. Klass (eds), *Regulatory Reform: What Actually Happened?* Little, Brown, Boston: 40-77.

Konar, Shameek, and Mark A. Cohen. 2001. Does the Market Value Environmental Performance? *The Review of Economics and Statistics* 83(2): 281-289.

Mansur, Iqbal, Steven J. Cochran, and John E. Phillips. 1991. The Relationship Between the Equity Return Levels of Oil Companies and Unanticipated Events: The Case of the Exxon Valdez Accident, *Logistics and Transportation Review* 27(3): 241-255.

Muoghalu, Michael I., David H. Robison, and John L. Glascock. 1990. Hazardous Waste Lawsuits, Stockholder Returns, and Deterrence, *Southern Economic Journal* 57(2): 357-70.

Neilson, William S., and Geum Soo Kim. 2001. A Standard-Setting Agency and Environmental Enforcement, *Southern Economic Journal* 67(3): 757-763.

U.S. Environmental Protection Agency. 2000. *Accidental Release Information Program (ARIP) Database* (computer file). Chemical Emergency Preparedness and Prevention Office, Office of Solid Waste and Emergency Response.

___________. 1998. *Accidental Release Information Program (ARIP) Fact Sheet*. 550-F-98-018. Office of Solid Waste and Emergency Response.

Walters, Stephen J. 1993. *Enterprise, Government, and the Public*. McGraw-Hill, Inc.

Wooldridge. 2002. *Econometric Analysis of Cross Section and Panel Data*

Table 1: Variable definitions and summary statistics

variable name	definition	mean	standard deviation
ACCIDENT	Number of environmental accidents by industry (4 digit SIC) between 1992 and 1994.	1.06	7.81
ACCIDENT_BI	binary indicator equal to one if at least one accident occurred in and industry (4 digit SIC) between 1992 and 1994.	0.14	0.35
HHI	Industry Herfindahl-Hershman Index (4 digit SIC) as of 1992.	727.29	661.25
CR8	Industry eight-firm concentration ratio (4 digit SIC) as of 1992.	52.93	22.69
INS	Number of inspections conducted in an industry (3 digit SIC) in the year prior to an environmental accident.	236.24	303.31
ENF	Number of enforcement actions levied in an industry (3 digit SIC) in the year prior to an environmental accident.	15.04	21.44
N	Total number of companies operating in an industry (4 digit SIC) in 1992.	736.70	2,023.32
SHIP	Total industry value of shipments (4 digit SIC) in real (1996) millions of dollars.	7,095.49	13,931.46
TRI/SHIP	Total pounds released by 4 digit SIC industry classification of TRI chemicals per million dollars worth of industry shipments.	1,730.56	6,047.21

Table 2. Probit Model Results

Dependent variable: ACCIDENT_BI

	with ln(N)	with ln(HHI)	with ln(CR8)
obs.	1,349	1,317	1,334
CONSTANT	-6.938***	-8.307***	-8.492***
	(0.708)	(0.891)	(0.977)
ln(INS)	0.081	0.103	0.117
	(0.081)	(0.084)	(0.084)
ln(COMP)	-3.448**	-3.798***	-3.996***
	(1.343)	(1.376)	(1.367)
ln(SHIP)	0.484***	0.445***	0.435***
	(0.073)	(0.069)	(0.068)
ln(TRI/SHIP)	0.254***	0.271***	0.276***
	(0.046)	(0.047)	(0.047)
ln(N)	-0.113**	------	------
	(0.055)	------	------
ln(HHI)	------	0.128*	------
	------	(0.068)	------
ln(CR8)	------	------	0.242*
	------	------	(0.146)
SIC20	1.451***	1.496***	1.560***
	(0.202)	(0.205)	(0.206)
SIC26	0.471	0.577**	0.568*
	(0.296)	(0.291)	(0.293)
SIC28	0.998***	1.069***	1.055***
	(0.212)	(0.215)	(0.217)
SIC29	0.821*	0.916*	0.878*
	(0.487)	(0.479)	(0.479)
DMY93	-1.017***	-1.001***	-1.049***
	(0.165)	(0.167)	(0.169)
DMY94	-1.665***	-1.729***	-1.675***
	(0.222)	(0.232)	(0.225)
L-R Statistic (11 d.f.)	342.622***	341.750***	348.259***
McFadden - R^2	0.441	0.452	0.456

Standard errors reported in parentheses.

* - Significant at the 10 percent level.

** - Significant at the 5 percent level.

*** - Significant at the 1 percent level.

Note: Differences in sample sizes arise because there were eight industries for which CR8 data was available but, due to disclosure restriction, no HHI was reported and there were two industries where HHI data was available but no CR8 data was reported.

Table 3. Count Model Results

Dependent Variable: ACCIDENT

	with ln(N)	with ln(HHI)	with ln(CR8)
obs.	1,349	1,317	1,334
CONSTANT	-12.187***	-15.812***	-16.681***
	(1.067)	(1.406)	(1.543)
ln(INS)	0.256*	0.327**	0.338**
	(0.135)	(0.138)	(0.138)
ln(COMP)	-7.272***	-7.846***	-7.935***
	(2.013)	(2.004)	(2.003)
ln(SHIP)	0.887***	0.762***	0.768***
	(0.104)	(0.095)	(0.094)
ln(TRI/SHIP)	0.450***	0.485***	0.486***
	(0.074)	(0.074)	(0.074)
ln(N)	-0.340***	------	------
	(0.091)	------	------
ln(HHI)	------	0.334***	------
	------	(0.113)	------
ln(CR8)	------	------	0.726***
	------	------	(0.239)
SIC20	2.584***	2.656***	2.737***
	(0.314)	(0.319)	(0.314)
SIC26	0.476	0.841*	0.775*
	(0.491)	(0.460)	(0.461)
SIC28	1.731***	1.749***	1.738***
	(0.307)	(0.302)	(0.301)
SIC29	1.293**	1.758***	1.676***
	(0.607)	(0.551)	(0.551)
DMY93	-1.889***	-1.814***	-1.890***
	(0.247)	(0.243)	(0.243)
DMY94	-3.330***	-3.325***	-3.265***
	(0.367)	(0.372)	(0.360)
r	0.467**	0.384*	0.359
	(0.214)	(0.230)	(0.227)
L-R Statistic (12 d.f.)	3411.331***	3351.288***	3409.071***
Psuedo - R^2	0.802	0.803	0.805

Standard errors reported in parentheses.

* - Significant at the 10 percent level.

** - Significant at the 5 percent level.

*** - Significant at the 1 percent level.

Note: Differences in sample sizes arise because there were eight industries for which CR8 data was available but, due to disclosure restriction, no HHI was reported and there were two industries where HHI data was available but no CR8 data was reported.