Formation and Political Consequence of Environmental Enforcement Policy

Evidence from the US Industries

by

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Abstract

This thesis investigates the determinants and political consequences of environmental enforcement policy. Three related issues are addressed using the U.S. manufacturing data at the industry level.

In Chapter Two, I estimate the elasticity of the violation rate with respect to the inspection rate for the manufacturing industries. This elasticity reflects the power of monitoring to alter an industry's violation status. I conduct an estimation of the relationship between the violation rate and the inspection rate at the industry level, but the specification is based on an individual firm's dichotomous choice in a logit model. The inspection rate is instrumented with the average of the inspection rates across the other industries that belong to the same sector to deal with the endogeneity problem. I find a substantial variation in the elasticity of the violation rate across industries.

Chapter Three addresses how the inspection rate is determined by the elasticity of the violation rate when the enforcement agency is constrained with a hard monitoring budget. Given the limited monitoring resources, an enforcement agency targets industries where inspections are more likely to be effective in reducing violations to reduce inefficiency, all else equal. Empirical results confirm the positive effect from the absolute elasticity on the inspection rate. But the magnitude of this effect is conditional on the pollutants' damage level to the environment.

In Chapter Four, I focus on the political consequence of the enforcement policy. I employ the campaign contribution presented to the Congress exclusively for environmental issues (EPC) to measure the environmental political activity. The variation of EPC across industries is explained by the enforcement policy stringency. Although the EPC presented to the Congress is targeted directly on environmental regulation rather than the enforcement policy, a stricter enforcement policy increases the marginal benefit from contributing the congress for relaxing the regulation. Empirically, I use the elasticity of the violation rate to isolate the effect of the enforcement policy on EPC. An industry with a larger elasticity of the violation rate is more likely to face a higher inspection rate, it therefore is more likely to engage in the political activity.

Table of Contents

Appendices

List of Tables

List of Figures

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Dedication

To my parents, Qichun and Siyi

Chapter 1

Introduction

The enforcement of environmental legislation is crucial to achieving desirable environmental outcomes. This thesis explores the determinants and consequences of the environmental enforcement policy. Specifically, I address the following three questions using the U.S. manufacturing data: (1) How do industries react to a change in environmental enforcement policy? (Chapter Two) (2) How is the environmental enforcement policy determined at the industry level? (Chapter Three) (3) How does the environmental enforcement policy affect an industry's political activity that is designated for environmental issues? (Chapter Four)

In Chapter Two, I estimate the elasticity of the violation rate with respect to the inspection rate for industries in the manufacturing group. This elasticity reflects the power of monitoring to alter an industry's violation status and is regarded as an industry characteristic. I conduct an estimation of the relationship between the violation rate and the inspection rate at the industry level, but the specification is based on individual firm's dichotomous (violation/compliance) choice in a logit model. The potential endogeneity problem of the inspection rate is dealt with by using an instrument, which is the average of the inspection rates across the other industries that belong to the same sector. I find a substantial variation in the elasticity of the violation rate across industries.

This estimated elasticity is employed to investigate its role in determining the environmental enforcement policy in Chapter Three. The elasticity could be fundamental to the making of environmental enforcement policy when an enforcement agency has limited monitoring resources. In the United States, the Environmental Protection Agency (EPA) explicitly faces a hard budget constraint in monitoring firms to make sure they abide by environmental regulatory policies such as the standard and the emission limit. Each year, the EPA develops a proposed budget defining the funding for the goal of compliance and related priorities. Then, the Congress passes bills to enact amended budgets into law.[1] For example, the FY (fiscal year) 2010 Budget includes approximately $600 million for EPA's Enforcement and Compliance Assurance program, and a $32 million increase over the FY 2009 Enacted level. In particular, for the Agency's Compliance Monitoring program[2], in FY 2010, its proposed budget is $101.1 million. FY 2010 Compliance Monitoring activities will be both environmental media- and sector-based.[3]

Given the limited monitoring resources, an enforcement agency targets industries where inspections are more likely to be effective in reducing violations to reduce inefficiency, all else equal. This implies the important role of the elasticity of the violation rate in determining the inspection stringency. I develop a simple model where the regulator faces a hard budget constraint for its inspection and enforcement activities. If the agency maximizes social welfare subject to this constraint, the model predicts that the inspection rate will be higher in those industries with a higher elasticity of the violation rate with respect to the inspection rate. Empirical results confirm a positive effect from the absolute elasticity on the inspection rate. But the magnitude of the effect of the elasticity of the violation rate is conditional on the pollutants' damage level to the environment.

In Chapter Four, I focus on the political consequence of the environmental enforcement policy. I first construct an index of environmental political contribution (EPC) – the campaign contribution presented to the Congress exclusively for environmental issues, which serves as the direct evidence of political pressure on the environmental regulations – to measure the environmental political activity. Then, I explore the role of the enforcement policy stringency in explaining the variation of the EPC across industries. In a

[1] See details in the U.S. EPA website: http://www.epa.gov/ocfo/budget/.

[2] This Compliance Monitoring program reviews and evaluates the activities of the regulated community to determine compliance with applicable laws, regulations, permit conditions and settlement agreements, and to determine whether conditions presenting imminent and substantial endangerment exist. (FY2010 EPA Budget in Brief, U.S. EPA.)

[3] Source: FY2010 EPA Budget in Brief, U.S. EPA.

multi-agent system, the environmental legislation/regulation is determined by the Congress, but the enforcement policy is set by the EPA[4]. Although the EPC presented to the Congress is targeted directly on environmental legislation/regulation rather than the enforcement policy, the enforcement policy affects the marginal benefit from contributing to the congress for relaxing the legislation/regulation. For example, for an industry with a higher inspection rate (which represents a stringent enforcement policie), its identified pollution amount is larger. This implies that this industry pays more pollution taxes than the industry with a lower inspection rate at the same pollution tax rate. One unit relaxation of the pollution tax rate (which represents an environmental regulation) after the congress receives certain political contribution amount brings more benefits (a larger reduction in pollution tax payment) to this industry. Therefore, industries facing stricter enforcement policies are more likely to engage in the political activity all else equal.

There are two features in the empirical examination. First, I employ EPC to characterize the environmental political activity. This is in contrast to existing works that use total political campaign contributions which may be the result of multiple purposes. Second, I use the elasticity of the violation rate to infer the effect of the enforcement policy on the environmental political contribution. This is because an industry with a larger elasticity of the violation rate is more likely to face a higher inspection rate, as shown in Chapter Three. The reason that I do not use the enforcement policy as a regressor directly is to distinguish the effect of the environmental enforcement policy from that of the environmental regulation. Although the enforcement policy and the environmental policy are determined by separate agencies, the two kinds of policies have many common determinants (e.g., the emission intensity). If the relationship between the enforcement policy and the environmental political contribution arises as a result of these

[4] In the U.S., environmental enforcement takes place in the context of a system (the environmental federalism) consisting of local and state jurisdiction and the Federal enforcement agency. Because this work focuses on the variation across industries instead of that across regions, I partly control for the role of the state and local communities with the geographical concentration variable and focus on the role of EPA.

common determinants, it is hard to isolate the enforcement policy's effect. I find a positive relationship between the absolute elasticity of the violation rate and the EPC. The results are consistent with the predictions.

In sum, this thesis joins the literature on the monitoring and enforcement of environmental policy with that on the political formation of economic policy. The rest of the thesis is organized as follows: Chapter Two empirically investigates environmental policy's deterrence effect on firms' compliance behavior and estimates the elasticities of the violation rate with the inspection rate at the industry level. Chapter Three develops a simple model to explain the variation of environmental enforcement policy when the enforcement agency is constrained with a hard budget. The predictions are empirically examined. Chapter Four provides a descriptive analysis of EPC, focuses on the amounts that industries contribute and uncovers the pattern of environmental political action across industries.

Chapter 2

Estimating the Elasticity of the Violation Rate at the Industry Level

2.1 Introduction

How do industries react to the changes in environmental enforcement policy? Evidence from industry studies suggests that there is variation across industries in the response of the violation rates to inspections. For example, Gray and and Shadbegian (2005) find that pulp mills are less sensitive to inspections than paper mills. This is not surprising because heterogeneities in abatement costs and other industry characteristics are likely to affect violation rates. However, to date there has not been a systematic cross-industry analysis of how violation rates respond to inspections.

This chapter estimates the elasticity of an industry's violation rate with respect to its inspection rate. This elasticity reflects the power of monitoring to alter an industry's violation status. It is fundamental to the design of environmental enforcement policy.[5] When an enforcement agency has limited monitoring resources (economically or politically), it can target industries where inspections are more likely to be effective in reducing violations to reduce inefficiency (all else equal). The next chapter (Chapter three) investigates how the elasticity of the violation rate plays a role in allocating the monitoring resources across industries for an enforcement agency. The

[5]This estimation of the elasticities is also useful for the policy's effectiveness evaluation and environmental consequence forecasting.

estimates from this chapter will play a key role in that analysis.

The estimation of the elasticities for all industries is still absent in the literature. Existing works focuses on certain industries (e.g. pulp/paper[6]/oil spills) and estimate the effectivess of the enforcement policy on firms/plants/facilities within the industries (Magat and Viscusi, 1990; Earnhart 2004a, 2004b; Shimshack and Ward, 2005, 2008; Laplante and Rilstone, 1996; Gray and Deily, 1996; and Telle, 2009). I conduct an estimation at the aggregate level (using the industry-level data) but the specification is based on individual firm's dichotomous (violation/compliance) choice using a logit model. I thus avoid having to collect the data of firm characteristics for all industries, which is difficult.

This chapter applies the BLP demand function estimation technique (Berry, Levinsohn, & Pakes, 1995). Each firm is a rational economic decision-maker who violates its effluent standard when the net benefit of doing so exceeds that of compliance. Each firm's welfare is determined by the regulatory policies imposed on violating/complying firms and individual firm characteristics. Within each industry, firms are subject to the same compliance/violation policies, such as the unit penalty for violation, and the minimum unit abatement investment for compliance. In this work, the enforcement policy I consider is the inspection rate. Individual firm characteristics are idiosyncratic ones across firms, such as the abatement efficiency, the production technology, and the managers' preferences. I assume the individual firm characteristics follow an i.i.d. logit draw. Given the inspection rate imposed on violating firms, the probability of choosing violation is modelled as a realization from the logit distribution with the firm characteristics. I assume further that there are infinitely many firms in each industry. Then, this logit probability can be regarded as the industry violation rate, depending on the policy – the inspection rate. In order to facility the empirical estimation, I incorporate an outside alternative choice (the shutdown choice). It can be deived that the difference between the logarithm of the

[6]Nadeau (1997) focuses on air pollution, and estimates the elasticity of the violation time with respect to the EPA monitoring activity for the pulp and paper industry which is between -0.4 and -0.47.

violation rate and that of the shutdown rate (the log odds ratio) is a linear function of the inspection rate at the industry level.

This approach allows me to apply the linear instrumental variable (IV) approach to combat the endogeneity problem. This endogeneity problem arises when there may exist a reverse causality from the violation rate to the inspection rate. The instrument of the inspection rate I use is the average of the inspection rates across the other industries[7] that belong to the same sector[8]. The instrument is highly correlated with the inspection rate because they pick up common government-regulation shocks (e.g. a budget cut). Meanwhile, the instrument is uncorrelated with the unobserved industry-specific factors. In the literature at the disaggregate level, some ignore the endogeneity problem (e.g. Gawande and Wheeler, 1999[9]). For others, there are two types of instruments[10] used. But the employment of these two different instruments may lead to opposite results about the enforcement policy's deterrent effect: "models using lagged regulatory activity continue to find a negative impact of enforcement on compliance, while models using predicted activity yield positive coefficients, which regulatory activity increasing compliance" (Gray and Shadbegian, 2005).[11]

Empirically, I construct the industry-level inspection rate (proxying the enforcement policy) and the industry-level violation rate (proxying the pollution noncompliance level) using data from "Enforcement & Compliance History Online (ECHO)" provided by the U.S. Environmental Protection

[7] At the 4-digit SIC level.

[8] At the 2-digit SIC level.

[9] Gawande and Wheeler (1999) addresses the need to improve efficiency in governmental organizations. It analyzes the Maritime Safety Program of the U.S. Coast Guard, which is responsible for monitoring the quality of vessels that sail in U.S. waters, and present measures of effectiveness for the Program. The estimation is based on a Poisson regression model.

[10] When policy is regarded to be targeted on individual firm's behavior, the effect of enforcement policy on firm's compliance may encounter reverse causality problem. This can be directly alleviated with instrument variables such as the lagged policy (Magat and Viscusi, 1990; Earnhart 2004a, 2004b; Shimshack and Ward, 2005, 2008) or predicted policy probabilities (e.g., Laplante and Rilstone, 1996; Gray and Deily, 1996; and Telle, 2009) or both (Gray and Shadbegian, 2005).

[11] The other reason that I do not use the lagged value of the inspection rate as the instrument is that the time series is very short (three years).

Agency (EPA). I find that the inspection rates significantly reduce the industry-level violation rates after the endogeneity problem of inspection rate is overcome with the IV approach. The elasticities of the violation rate with respect to the inspection rate at the industry level are calculated, which vary greatly between inspection "elastic" industries (e.g., 1865 and 3313) and inspection "inelastic" industries (e.g., 3845 and 3661). The mean value of the elasticity is about -0.34, implying that a 10% increase in the inspection rate yields a 3% reduction in the violation rate.

The rest of the chapter is organized as follows. In Section 2.2, I derive the industry-level violation rate function for estimation based on the BLP econometric model. In Section 2.3, I discuss how to deal with some econometric issues and present the empirical specification. Section 2.4 describes the data sources and the construction of the variables. Empirical results are presented in Sections 2.5. Section 2.6 concludes. Appendices A contains proofs, data descriptions and the first stage results of the two-stage least square (2SLS) regressions.

2.2 Econometric model of the industry-level violation rate

This section employs the BLP econometric model (Berry, Levinsohn, and Pakes, 1995)[12] to derive the industry-level violation rate function.

2.2.1 Individual firm's welfare

There are infinitely many heterogeneous firms in a polluting industry and each firm makes choices between violation and compliance. Each firm's welfare is determined by choice (compliance vs. violation) characteristics and individual firm characteristics. The equation for each firm's welfare denoted by F_{ljt} can be specified as

$$F_{ljt} = R_{jt} + \xi_{jt} + \gamma_{ljt}$$

[12] See Appendix A.1 for details.

where the subscript l represents firms, $j \in (c$=compliance, υ=violation) is the choice index, and t is the time index in years.

R_{jt} and ξ_{jt} represent the characteristics of choice j that may affect welfare F_{ljt}. That is, they do not vary across firms that make the same choice within an industry. Specifically, R_v is the enforcement policy imposed by the regulator on firms in violation, such as the unit violation penalty or inspection rate[13]; R_c is the regulation that a complying firm has to meet, such as the minimum unit abatement investment. ξ_v represents unobserved sources of welfare resulting from violation (e.g. pollution disutility to violating firms' own employees); ξ_c represents unobserved characteristics for firms in compliance (e.g. a good reputation with their consumers and the community). Besides unobserved choice characteristics, ξ_{jt} may also capture violation/compliance shocks in an industry[14] or measurement errors.

The last term, γ_{ljt}, contains the characteristics of individual firm l that affect welfare F_{ljt}, such as the input amount, the abatement technology and the manager's preference.

2.2.2 Industry-level violation rate function

When γ_{ljt} is assumed to follow an *i.i.d.* logit draw, $W_{jt} = R_{jt} + \xi_{jt}$ can be regarded as the mean welfare from choice j in year t in industry i.

Violation is chosen whenever it leads to a higher welfare than compliance, that is, $F_{lvt} > F_{lct}$. Given any welfare in violation F_{lvt}, the proportion of firms that choose to violate in industry i is the following according to γ_c's density function,

$$Pr_{i,lv} = \Pr(F_{lvt} > F_{lct}) = \Pr(\gamma_{lct} < W_{vt} - W_{ct} + \gamma_{lvt}) = e^{-e^{-(W_{vt} - W_{ct} + \gamma_{lvt})}}$$

Since the welfare in violation F_{lvt} is random, characterized by the *i.i.d.*

[13] This increases violating firms' cost because more violations would be identified as firms are inspected more often.

[14] For example, the price of an industry-specific abatement equipment that prevents firms from violation becomes higher. Because this price may enter the welfare function of choosing compliance only, the welfare of choosing violation is not affected as much as the welfare of choosing compliance. And this is a shock common to all firms in this industry.

logit distribution of γ_v, the violation rate of industry i is the following,

$$\int_{-\infty}^{\infty} \Pr(F_{lvt} > F_{lct}) e^{-\gamma_{lvt}} e^{-e^{-\gamma_{lvt}}} d\gamma_{lvt} = \frac{1}{e^{-(W_{vt}-W_{ct})}+1} = \frac{e^{W_{vt}}}{e^{W_{ct}}+e^{W_{vt}}}$$

Proof. See Appendix A.2. ■

The desirable property of this logit probability (the violation rate, VR) is as follows. The numerator is the exponential function to the power of the welfare of this choice; the denominator is the sum of the exponential functions over all alternative choices. The implication is that the aggregate violation rate at industry level depends on the difference of the welfares, $W_{vt} - W_{ct}$, instead of individual firm characteristics.

Then, I add an outside alternative that is the shutdown of the facility and normalize the welfare of this alternative choice to zero. According to the property shown above, this implies that the violation rate is

$$VR_{it} = \frac{e^{W_{vt}}}{1+e^{W_{ct}}+e^{W_{vt}}}$$

and the closing firm share is $Close_{it} = \frac{e^0}{1+e^{W_{ct}}+e^{W_{vt}}}$. Intuitively, the violation rate is the probability that the choice of violation has a higher welfare than the choices of compliance and the shutdown of the facility.

Taking logarithms of the two equations and canceling out the denominator $\left(1+e^{W_{ct}}+e^{W_{vt}}\right)$ that can not be controlled for, I have

$$\ln VR_{it} - \ln Close_{it} = R_{ivt} + \xi_{ivt} \tag{2.1}$$

This allows us to consider a linear relationship between the logarithm of the violation rate, $lnVR_{it}$, and the enforcement policy on violating firms, R_{ivt}, at the industry level.

2.3 Empirical specification

The following empirical specification based on equation (2.1) is established,

$$\begin{aligned}\ln VR_{it} - \ln Close_{it} &= \beta_0 + \beta_1 IR_{it} + \beta_2 \ln EI_{it} + \beta_3 HHI_{it} + \beta_4 DI_{it} \\ &\quad + \beta_5 \ln EMP_{it} + \beta_6 GC_{it} + G + Y + \xi_{it} \qquad (2.2a)\end{aligned}$$

where i is the industry index, t is the time index, VR_{it} is the industry-level violation rate representing the degree of environmental non-compliance, and IR_{it} is the industry-level inspection rate proxying the enforcement policy for violation (i.e., R_{ivt} in equation (2.1)).

The general industry conditions to be controlled for include the following:

$\ln EI$: the natural log of the level of emission intensity

HHI: the Herfindahl-Hirschman Index measuring the concentration of firms in an industry (industry concentration)

DI: "diverse industry" is a measure describing the number of different segments in which a firm operates

EMP: the number of paid employment as a measure of industry size

GC: "geographic concentration" describes the dispersion of firms according to their locations.

In addition, I also add an election year dummy Y and a group dummy G (Group 2 or 3) to control for the election year effect[15] and the group fixed effect respectively. β_i's are coefficient scalars, and ξ is zero-mean error term.

2.3.1 Endogeneity of enforcement policy

When estimating the effect of the inspection rate on the violation rate using the specification above, I adopt the IV approach to overcome the potential endogeneity problem of the inspection rate. This endogeneity problem arises because the violation rate may have an influence on the choice of the

[15] In List and Sturm (2006), it is argued that the incumbent finds it worthwhile to manipulate the environmental policy to attract additional votes to his platform. Evidence of this effect of electoral incentives on environmental policy is shown in that work.

inspection rate by the enforcement agency as shown below,

$$IR_{it} = \varphi_0 + \varphi_1 VR_{it} + \varphi_2 controls_2 + e_{it} \tag{2.2b}$$

In addition, the endogeneity problem of inspection rate may arise if there are unobserved variables (e.g., local political factors) that influence the industry-level violation rate and are correlated with the inspection rate.

In order to produce unbiased estimated coefficients, I choose valid instruments for IR. The instrument of the inspection rate is the average of the inspection rates across the other 4-digit industries that belong to the same 2-digit sector. For example, there are three industries “2111”, “2131” and “2141” at the 4-digit level in the 2-digit sector of “21” in the dataset. The instrument for the inspection rate of “2111” is the average of the inspection rates of “2131” and “2141”. The instrument is highly correlated with the inspection rate. This is because they pick up common government-regulation shocks. For example, when an enforcement agency’s budget is reduced, the inspection rates across all industries in a sector are expected to be lower. Meanwhile, the instruments are uncorrelated with the unobserved industry-specific factors (e.g., the greater community pressure as a result of an pollution accident or an abatement technology improvement in this 4-digit industry) in the violation rate equation (2.2a) and those in the emission intensity equation (2.2c) below.

2.3.2 Endogeneity of emission intensity

For the emission intensity, I employ a reduced-form specification in equation (2.2c) to show its potential endogeneity problem.

$$\begin{aligned} \ln EI_{it} &= \gamma_0 + \gamma_1 IR_{it} + \gamma_2 \ln w_{it} + \gamma_3 \ln k_{it} + \gamma_4 \ln Material_{it} \\ &\quad + \gamma_5 \ln Energy_{it} + \gamma_6 \left(controls\right) + \varphi_{it} \end{aligned} \tag{2.2c}$$

where EI is the emission intensity, IR is the inspection rate, w is the labor share, k is the capital share, $Material$ is the material share, $Energy$ is the energy share, and $(controls)$ include other industry characteristics.

Equation (2.2c) links EI to the enforcement policy (IR) and input shares of production. This specification is motivated by Hettige et al. (2000) [43]: "The marginal cost of abating pollution from industrial sources is a function of the scale of activity, pollutant concentration in process influent, the degree of abatement, and local input prices".

The endogeneity problem of EI could arise when the error term in equation (2.2a), ξ, is correlated with the error term in equation (2.2c), φ. On the one hand, VR could have an effect on EI through IR based on Equations (2.2b) and (2.2c). On the other hand, some unobserved violation characteristics or shocks may affect the emission intensity. This is because both the violation rate and the emission intensity are aggregated outcomes of firms' problems at the industry level.

As shown above, the full model is supposed to be a simultaneous equation system that consists of equations (2.2a), (2.2b), and (2.2c). However, in this chapter, I only estimate the first equation. Specifically, I adopt the 2SLS estimation: (i) inspection rates and emission intensities are regressed on the instruments of inspection rates, input shares and other exogenous variables to obtain their predicted values respectively; (ii) I estimate Equation (2.2a) with both the predicted emission intensity and the predicted inspection rates.

2.3.3 Elasticity of violation

Last, I discuss the calculations of the marginal effect of the inspection rate on the violation rate and the elasticities of the violation rate with respect to the inspection rate. The marginal effect depends on the estimated coefficient β_1 and the violation rate[16]:

$$\frac{\partial VR_i}{\partial IR_{i,vt}} = \frac{\partial \frac{e^{\beta_1 IR_{i,vt}+\xi_{ivt}}}{1+e^{\lambda IR_{i,ct}+\xi_{ict}}+e^{\beta_1 IR_{i,vt}+\xi_{ivt}}}}{\partial IR_{i,vt}} = VR_i\left(1-VR_i\right)\beta_1 \tag{2.3}$$

Because the violation rate is not larger than 1, the calculated marginal effect is negative as long as the estimate of β_1 is negative. A negative

[16] Please see the appendix A.2 for proof.

marginal effect implies a deterrent effect of the inspection rate.

Further derivation provides the elasticity estimates as follows,

$$e_i = \frac{\partial VR_i}{\partial IR_{i,vt}} \frac{IR_{i,vt}}{VR_i} = IR_{it} \left(1 - VR_i\right) \beta_1 \tag{2.4}$$

2.4 Data sources and variables

Combining information from several sources, the dataset is described in the following and summarized in Table 2.1 and Table 2.2.

2.4.1 Measuring compliance behavior and enforcement policy

The major data source is the ECHO publicly provided by the U.S. EPA. This source provides the definition of formal enforcement action (FEA) with its data by facility within the last five years[17]: in practice, for firms with very high levels of pollution violation, civil or administrative enforcement action that is taken against them in the U.S. is called the formal enforcement action.[18] ECHO also gives us information on the number of inspections by facility within the same time period (See Appendix A.3 for details). The number of formal enforcement actions and the number of inspections at the facility level were aggregated into the SIC 4-digit industry level respectively.[19] Meanwhile, the numbers of total facilities inspected for each 4-digit industry were collected.

[17] ECHO has kept being updated. This paper uses the data last updated on Nov, 2008 at ECHO, so the inspection period starts from 2003.

[18] "In general, a violation at a facility means the facility has been noted as out of compliance with an environmental requirement set forth by the Clean Air Act, Clean Water Act, or Resource Conservation and Recovery Act statutes and their respective regulations...A violation may indicate that the facility released excessive pollutants, that a hazardous waste handling requirement was not met, or that a facility failed to submit a required report...Not all violations receive formal enforcement action. Violations that are minor, short in duration, or quickly corrected by the facility may not warrant formal enforcement action."–cited from the EPA website.

[19] One thing to notice is that I do not use minor facilities which are not required to report because reported facilities may tend to be more environmentally compliant and could lead to bias. The other thing is that industries whose total number of inspected facilities is less than 5 are dropped because the sample is too small.

I constructed the industry-level violation rate (VR) as the ratio of formal enforcement action numbers at the 4-digit industry level to the inspection numbers at the 4-digit level. It represents the probability of serious violation per inspection and is regarded as a measure of the noncompliance level for an industry.

In this paper, I distinguish between serious and minor violations and use serious violations to capture the degree of violation. I use this because it is more likely that serious violations are chosen by facilities on purpose. That is, it is profit-maximizing for facilities to choose to be in non-compliance. On the contrary, minor violations are sometimes caused by accidents or other unexpected shocks. According to EPA, these minor violations are usually short in duration or quickly corrected by the facility, which avoids further formal enforcement actions.[20]

In order to measure the stringency of the enforcement policy, I divided the inspection number at the 4-digit level by the number of total facilities for each industry. The ratio is defined as the industry-level inspection rate (IR) describing the inspection probability that an industry is subject to.

2.4.2 Other variables

Here I describe the other variables used. The data source of the chemical released amounts at the 4-digit level is the U.S. EPA's Risk-Screening Environmental Indicators (RSEI) (Version 2.1.5),[21] which use annually updated Toxic Release Inventory (TRI)[22] data. I constructed emission intensity (EI) by dividing the chemical released amounts at the 4-digit industry level by the value of shipments. The data of the values of shipments are from the 1992 Census of Manufactures report MC92-S-2, "Concentration Ratios in

[20] Nevertheless, in so doing, one would under-estimate the effect of inspection on environmental outcome. This is because minor violations cost little for facilities to correct. Therefore, one can argue that minor violations are more sensitive or responsive to inspections. We leave this for future research.

[21] See Appendix B.2 for details.

[22] "The Toxic Release Inventory (TRI) is a publicly-available EPA database that contains information on toxic chemical releases and other waste management activities reported annually by certain covered industry groups and federal facilities." – User's Manual for RSEI.

Manufacturing". This MC92 is also the data source for HHI (Herfindahl Hirschmann Index) that characterizes industry concentration.[23]

The proportion of firms that choose to shutdown is proxied by the variable 'close'. This is the ratio of the number of Establishments Deaths[24] in 1998 to that of Initial Year Establishments in 1997.[25] The data are recorded in the U.S. government census and are only available at the 3-digit SIC level.[26] The data of inputs were obtained from the 1996 Annual Survey of Manufactures.[27] The values of "production workers wages", "cost of materials", "new capital expenditures", and "cost of purchased fuels and electric energy" are scaled by "value of industry shipments" to proxy the input shares w, k, Material and Energy respectively. The number of paid employees (EMP) is used to measure industry size and is from the 1997 Economic Census.[28]

Measures of Diverse Industry (DI) and Geographic Concentration (GC) were constructed following Grier, Munger and Roberts (1994). The number of segments is reported by each firm, up to a maximum of 10 in COMPUSTAT industrial segment file. The data were averaged by industry (mean=1.7, s.d.=0.65) and a DI is defined as "one with mean number of products more than two s.d. above the sample average, that is, all industries whose firms average more than three products line are coded 1.0 and the others 0.00". Because the data vary little at 4-digit level, I compiled them into 3-digit level data. And the data cover the period of 1998-2006. GC is calculated as $\sum_i \left(\frac{Sales_i}{Sales}\right)^2$ for each industry where i denotes state. The data of sales

[23]The 1997 data are available but are classified by NAICS (North American Industry Classification System) instead of SIC.

[24]Only enterprises whose sizes (the employment of the controlling enterprise in the initial year) are over 20 are included.

[25]Starting with the 2003-2004 tabulations, the industry classification is based on 2002 NAICS. Previous years data are based on 1997 NAICS (1999-2003) and SIC (1990-1998).

[26]Please see http://www.census.gov/csd/susb/susbdyn.htm.

[27]Please check http://www.census.gov/mcd/asm-as1.html.

[28]The Economic Census profiles American business every 5 years and the 2002 data are available. However, the 2002 Economic Census is based on NAICS. Given the violation rate is based on SICs, the conversion of employment based on NAICS into that based on SICs may lead to some bias. The 1997 data are available in both NAICS and SICs. And since the employment number is used to control for industry size that is relatively stable over short periods, I choose the 1997 data.

(DATA12) in each state were collected from COMPUSTAT as well.

Combining non-missing observations from these sources yields an unbalanced panel of 421 observations over the period 2003-2006, which is the sample used in this study.

Table 2.1: Variable Definition and Data Sources I

Variable	**Description**	**Sources**
Violation Rate (VR)	$=\frac{\text{The number of formal enforcement actions}}{\text{The total number of inspections}}$	ECHO, 2003'-2008'
Close Rate ($close$)	$=\frac{\text{The number of Establishments deaths}}{\text{The number of initial year establishments}}$	U.S. gov't census,the initial yr:97',3-digit
Inspection Rate (IR)	$=\frac{\text{The total number of inspections}}{\text{The total number of facilities}}$	ECHO, 2003'-2008'
Emission Intensity (EI)	$=\frac{\text{The chemical released amounts}}{\text{The value of shipments}}$	RSEI, 1992 Economic Census, 1996'-2005'
Industry Concentration (HHI)	Herfindahl Hirschmann Index	1992 Economic Census, 1992'
Industry Diversity (DI)	=1 for a large number of product lines =0 for a small number of product lines	Industrial segment file in COMPUSTAT Grier et al.(1994), 1998'-2006', 3-digit
Industry Size (EMP)	The number of paid employment	1997 Economic Census, 1997'
Geographic Concentration (GC)	$= \sum_i \left(\frac{\text{Sales}_i}{\text{Sales}}\right)^2$ (i: state)	COMPUSTAT, Grier et al.(1994), 95'-06'
Labor Share (w)	$=\frac{\text{Production workers wages}}{\text{The value of industry shipments}}$	1996 ASM, 1996'
Capital Share (k)	$=\frac{\text{New capital expenditures}}{\text{The value of industry shipments}}$	1996 ASM, 1996'
Material Share ($Material$)	$=\frac{\text{Cost of materials}}{\text{The value of industry shipments}}$	1996 ASM, 1996'
Energy Share ($Energy$)	$=\frac{\text{Cost of purchased fuels and electric energy}}{\text{The value of industry shipments}}$	1996 ASM, 1996'

Table 2.2: Summary Statistics I

Variable Indicator	**Number of Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
VR	803	.12	.16	.013	1
$Close$	155	.05	.027	.01	0.16
IR	914	.39	.29	.03	1.69[a]
$\ln EI$	4115	12.68	2.57	-5.29	19.16
HHI	447	0.066	0.06	0.000056	0.297
DI	3950	.04	.20	0	1
$\ln EMP$	419	9.95	1.11	6.20	13.18
GC	5302	.40	.24	.09	1
w	456	.11	.05	.01	.32
k	450	.03	.03	.001	.34
$Material$	455	.50	.13	.17	.90
$Energy$	455	.02	.03	.002	.21

a :IR could be larger than 1 because each facility could be inspected multiple times.

2.5 Empirical results

The second-stage estimation results of equation (2.2a) are reported in Table 2.3.[29] Column (1) of Table 2.3 contains the second-stage empirical results for the 2SLS estimation of the baseline specification with random effects. I use the predicted values of inspection rates (IR) and emission intensities (EI) to estimate specification (2.2a), controlling for the group heterogeneity and the changes in the election year by including $Group2$ and $year2004$. The included random effects account for the unobserved time-invariant industry heterogeneity.

Inspection rate

Our main interest is to find out how the inspection rate (IR) affects the violation rate. The estimated coefficient on the inspection rate is negative and significant at the 1 percent level.[30] It corresponds to a mean marginal effect of -0.087 [31] across 111 industries. The elasticities of the violation rate, evaluated at the mean values of the inspection rate and the mean values of the violation rate over time, vary from -0.089 to -1.03 as shown in Table 2.4. The mean value of the elasticity is about -0.34, implying that a 10 percent increase in the inspection rate yields a 3 percent reduction in the violation rate. The results suggest that a more stringent inspection policy improves the compliance, but the magnitudes vary greatly between inspection "elastic" industries (e.g., 2865 and 3313) and inspection "inelastic" industries (e.g., 3845 and 3661).

Other variables

[29] The first stage results of estimating equation (2.2a) are reported in the appendix A.4.

[30] The subsample during period 2003-2005 is used because data of the emission intensity for 2006 are not available.

[31] The calculation is as follows based on the expression (2.3) in page 13: $VR(1-VR)\beta = 0.107 \times (1-0.107) \times (-0.91) = -0.087$.

Here, the mean value of VR differs a bit from that in Table 2.2. This is because this mean value is across 111 industries whose elasticities can be calculated while the mean value in Table 2.2 is across the whole sample.

Table 2.3: Second-Stage Results of Violation Rates Regressions (2003'-2005')

	Second-Stage Dependent Variable: lnVR-lnClose					
Independent	IV_Random	IV_Pooled	IV_fixed	Random	Pooled	Fixed
Variable	(1)	(2)	(3)	(4)	(5)	(6)
IR	$-.91^{***}$	$-.93^{**}$	-1.04^{***}	$-.44^{**}$	$-.09$	$-.92^{***}$
	(-3.52)	(-2.26)	(-3.95)	(-2.53)	$(-.53)$	(-4.16)
lnEI	$.19^{***}$	$.15^{***}$		.02	.002	.04
	(3.27)	(2.82)		(.72)	(.11)	(.45)
lnEMP	$-.1^{***}$	$-.1^{**}$		$-.14^{***}$	$-.12^{***}$	
	(-1.68)	(-2.20)		(-2.66)	(-3.20)	
HHI	1.9	1.48		1.1	.42	
	(1.58)	(1.48)		(1.03)	(.51)	
DI	.23	.23	.26	.32	.37	.25
	(.80)	(.74)	(.94)	(1.35)	(1.40)	(.95)
GC	$.59^{**}$	$.62^{***}$	.54	$.62^{**}$	$.64^{***}$	.48
	(2.29)	(2.97)	(.63)	(2.59)	(3.47)	(.57)
Group2	0.34^{**}	$.28^{*}$		.05	$-.01$	
	(2.20)	(1.92)		(.45)	$(-.15)$	
Year2004	.02	$-.02$	.02	$-.08$	$-.14$	.006
	(.24)	(-0.21)	(0.25)	(-1.00)	(-1.54)	(.08)
R^2	0.026	–	0.001	0.09	0.10	0.01
Obs.	319	319	319	323	323	323

Note: both IR and EI are endogenous and instrumented.
*** Significant at the 1% level, ** at the 5% level, and * at the 10% level
(t statistics are in parentheses)

Table 2.4: Industries Ranked by the Estimated Elasticities of the Violation Rate (111 Industries)

5 Most Inspection "Elastic" Industries		
SIC	**Description**	**Elasticity**
2865	Cyclic Crudes and Intermediates	-1.03
3313	Electrometallurgical Products	-.88
2621	Paper Mills	-.82
2812	Alkalies and Chlorine	-.81
2631	Paperboard Mills	-.79

5 Most Inspection "Inelastic" Industries		
SIC	**Description**	**Elasticity**
3271	Concrete Block and Brick	-.10
2711	Newspapers	-.10
3825	Instruments for Measuring and Testing of Electricity and Electrical Signals	-.098
3845	Electromedical and Electrotherapeutic Apparatus	-.094
3661	Telephone and Telegraph Apparatus	-.089

In Table 2.3, the estimated coefficient on the emission intensity is positive and significant at the 1% level, after both the endogeneity problems of the inspection rate and the emission intensity are addressed.

Coefficient estimates on the other control variables are also reported in Column (1) of Table 2.3. Their signs and magnitudes fail to provide much information about their marginal effects since the dependent variable is $lnVR - lnclose$. However, their statistical significance does show that whether they are important in explaining the variation of the violation rates across industries. In particular, the estimated coefficient on GC[32] is significantly different from zero at the $p<0.05$ confidence level. The group dummy, Group2, and the election year dummy, Year2004 are also controlled for. The group effect shows that the unobserved fixed differences between industries whose first digit SIC code is 2 and those whose first digit is 3 are captured. The election year effect is found to be insignificant.

Column (2) of Table 2.3 presents the second stage results for the 2SLS estimation using the pooled data.[33] Column (3) contains the second-stage results for the 2SLS estimation of the baseline specification with fixed effects. In columns (4), (5) and (6), they are the results from the random-effect, pooled OLS, and fixed-effect regressions respectively. But IR and EI are not instrumented. As I implement the fixed-effect estimation, some primary

[32] According to the Pollution Haven Hypothesis in existing literature, firms prefer location where environmental regulation/enforcement is weak. Firms, especially polluting firms whose abatement costs are large, agglomerate in places where enforcement is weak. GC can be regarded as a proxy of *local* strictness of environmental enforcement policy and has an influence on the violation rate.

[33] This estimate reports a negative R-squared using STATA. According to “Negative and missing R-squared for 2SLS/IV” by Scribney et. al. (1999), “for two-stage least squares, some of the regressors enter the model as instruments when the parameters are estimated. However, since our goal is to estimate the structural model, the actual values, not the instruments for the endogenous right-hand-side variables, are used to determine the MSS. The model’s residuals are computed over a set of regressors different from those used to fit the model. This means a constant-only model of the dependent variable is not nested within the two-stage least squares model, even though the two-stage model estimates an intercept, and the RSS is no longer constrained to be smaller than the TSS”. Thus, only standard errors matter for the estimates of these parameters produced by the two-stage model regardless of the value of R-squared.

control variables are dropped. This is because the time series for these primary control variables are not available. The results are similar both in terms of magnitudes and significance levels across the first three alternate techniques of estimation in Table 2.3.

2.6 Conclusions

This chapter assesses the impact of the inspection rate on the environmental pollution noncompliance level when the endogeneity problem of the enforcement policy is considered. The elasticity of an industry's violation rate with respect to its inspection rate is estimated. I started with an econometric BLP model to build this work at the industry level while keeping the micro-foundations on firms' optimal decisions. A linear relationship between the logarithm of the industry-level violation rate and the inspection rate is derived, which is convenient for the application of the IV approach.

In the empirical section, I estimated the structural empirical specification with the instruments for the inspection rate. The measures of the key variables at the industry level are firstly introduced and a new dataset is used. It complements the firm-level analysis in the literature. The 2SLS results indicate a significant deterrent effect of the inspection rate on the industry-level violation rate after the endogeneity of the inspection rate is considered. More importantly, I calculate the elasticities of the violation rate with respect to the inspection rate. And a substantial variation of the elasticity across industries is found. These estimates of elasticity would serve as a basis in the next two chapters for identifying the determinants of the environmental enforcement policy and the environmental political activity.

Chapter 3

The Formation of Environmental Enforcement Policy: Evidence from the U.S. Industry-level Data

3.1 Introduction

The enforcement of environmental legislation is crucial for achieving a desirable environmental outcome. How does the environment enforcement agency such as the environmental protection agency (EPA) enforce environmental regulatory policies? This paper intends to address this question in an environment where the environmental protection agency is explicitly constrained with a hard budget in monitoring polluting firms.

Constrained by the hard budget, the enforcement agency has to target industries where inspections are more likely to be effective in achieving its goal, all else equal. This implies the important role of the elasticity of the violation rate with respect to the inspection rate in determining the inspection stringency. For example, when the agency's goal is to maximize the social welfare, if there exists no budget constraint, for the first-best case, inspection rates should be just set to ensure that the expected penalty (inspection rate multiplied by the penalty) equals the marginal damages caused by the pollution violation.[34] But the hard budget leads the inspection rates to deviate from the marginal damages. Then, similar to the Ramsey rule in

[34] At certain maximum penalty.

the optimal tax literature, the distortion is determined by the elasticities of the violation rate with respect to inspection rates to minimize the efficiency loss. Specifically, all else equal, a higher equilibrium inspection rate is set in an industry with a large absolute elasticity of the violation rate. This is because, if one industry is more elastic than the other industry, the deadweight loss at the same inspection rate from inspecting the elastic industry is lower. This paper tries to empirically investigate whether the enforcement agency allocates the limited monitoring resources across industries based on the industry elasticity of the violation rate with respect to the inspection rate.

EPA[35] explicitly faces a hard budget constraint in monitoring firms[36] to make sure they abide by environmental regulatory policies such as standard and limit. Each year, the EPA develops a proposed budget defining the funding for the goal of compliance and related priorities. Then, the Congress[37] passes bills to enact amended budgets into law.[38] For example, the FY (fiscal year) 2010 Budget includes approximately $600 million for EPA's Enforcement and Compliance Assurance program, and a $32 million increase over the FY 2009 Enacted level. In particular, for the Agency's Compliance Monitoring program, in FY 2010, its proposed budget is $101.1 million[39]. As stated in the FY 2010, Compliance Monitoring activities will be both environmental media- and sector-based[40]. And the allocation of the budget involves multiple steps. In designing the allocation rule, the en-

[35]In the U.S., environmental enforcement takes place in the context of a system (the environmental federalism) consisting of local and state jurisdiction and the Federal enforcement agency. Because this work focuses on the variation across industries instead of that across regions, I partly control for the role of the state and local communities with the geographical concentration variable and focus on the role of EPA.

[36]The monitoring process is to discover firms that are in violation of the law and to produce evidence.

[37]In particular, Jones and Scotchmer (1990) states that the enforcement budget is set by the Congressional appropriations committees.

[38]See details in the U.S. EPA website: http://www.epa.gov/ocfo/budget/.

[39]This Compliance Monitoring program reviews and evaluates the activities of the regulated community to determine compliance with applicable laws, regulations, permit conditions and settlement agreements, and to determine whether conditions presenting imminent and substantial endangerment exist. (FY2010 EPA Budget in Brief, U.S. EPA.)

[40]Source: FY2010 EPA Budget in Brief, U.S. EPA.

forcement agency sets some priorities at the industry level first[41]. Then, given the resources allocated to certain industry, more specific amount of resources directed to each firm within this industry would be decided[42]. In this work, I study the allocation rule at the industry level only.

The elasticity of an industry's violation rate with respect to the inspection rate reflects the power of monitoring to alter an industry's violation status. I regard this elasticity as an important characteristic of an industry and estimated the elasticities in Chapter two. As shown by Gray and Shadbegian (2005) that pulp mills are less sensitive to inspections than paper mills, the estimation results of Chapter Two also show the great variation across industries in the elasticity.

The role of the elasticity of the violation rate with respect to the inspection rate in determining the enforcement policy stringency has not been explored in the literature. Existing works empirically paid attention to two groups of factors[43](e.g., Laplante and Rilstone, 1996; Lear, 1998; Helland, 1998; Deily and Gray, 1991, 1996; Dion, Lanoie and Laplante, 1998) in explaining the pattern of inspections. One is the past violation history, which could lead to a higher probability of being inspected in subsequent periods. This is consistent with the dynamic targeting approach described by Harrington (1988) and others[44] which ensures compliance at reduced monitoring costs. For the other group, the role of the factors in determining the

[41]Or, when the priorities are set based on the environmental media, some industries that release these regulated pollutants intensively are subject to more stringent policy than others. That is, priorities on some industries are implicitly defined in this case.

[42]"The priority system adopted by the Michigan Occupational Safety and Health Act (MIOSHA) for conducting scheduled, programmed inspections in private sector workplaces involves two major steps. In the first step, MIOSHA designated target industries. In the second step, MIOSHA generates a priority list of establishments to be inspected based on the targeted industries." Source: "General Industry Inspection Priority System Programmed Scheduled Inspections" by General Industry Safety & Health Division, MOSHA, March 2010

[43]For details, see Cohen (1999).

[44]Cohen (1999) states that this prior history of violation environmental laws can also be explained by the economic theory of regulation (if the public demands it) or compliance maximization (since the agency is most likely to find violations at these firms) besides the social cost minimization (based on the dynamic models) empirically. I emphasize the explanation under social cost minimization in this work.

enforcement policy are explained from the political perspective. The factors include the per-capita level of pollution, the affluence of the community, the affected labor force's percentage of the local population, the compliance cost[45], the firm size[46] and others. Thus, this study provides an additional explanation -the elasticity of the violation rate- for the observed differences in the stringency of enforcement policy.[47][48]

I exploit the variation in the inspection rate and the elasticities of the violation rate (constructed in Chapter Two) from the United States manufacturing industries to test the theoretical predictions. The inspection rate at the industry level is the percentage of inspection number in the number of inspected facility for each industry. That is, it is the inspection number that an inspected facility is subject to. This is used to proxy the enforcement policy stringency.

Moreover, I control for an important industry characteristic – the pollution damage indicator. The damage indicator is defined as a measure of industry-specific pollutants' potential damage to the environment and human health per unit of emission in this work. That is, it describes the toxicity of the chemical and the number of people affected. Pollutants with potential damage have been known to vary across industries for a while (Hettige, Mani and Wheeler, 2000; Olewiler and Dawson, 1998). For instance, Olewiler and Dawson (1998) argue: "they can highlight industries that produce compounds that are more toxic-intensive than others, even though some of these industries may not have very large emissions intensity

[45]In Gray and Deily (1996), plants with a high cost of compliance are more likely to spend money fighting against a stricter enforcement action.

[46]Lear (1998) finds a "deeper pockets" effect with higher fines for larger firms.

[47]Although different theories (along with predictions about factors that affect the enforcement policy) arises based on various assumptions about the enforcement agency's goal (such as the net political support maximization, the bureaucratic benefit maximization or the compliance maximization), the factors are not exclusive to each other in the empirical test.

[48]Theoretical works in this line about the priorities for enforcement are based on how firms differ. For example, firms' prior compliance history or expected compliance behavior (Harrington 1988, Russell 1990 and harford 1991); firms' opportunities to evade and private benefits from polluting (Macho-Stadler and Perez-Castrillo 2006); firms' compliance costs (Jones and Scotchmer 1990).

ratios." It was not rigorously incorporated in a theoretical model and empirically tested until recently (see Michida and Nishikimi, 2007[49]; Antweiler, 2003). Because one unit of violation by an industry with a large damage indicator leads to a high social cost, I predict that a larger inspection rate is set in this industry, all else equal. Data collection of the damage indicator is adopted from the EPA's Risk-Screening Environmental Indicators (RSEI) Version 2.1.5.[50]

I find that both of (the reciprocal of) the elasticity of the violation rate and the damage indicator have significant effects on the inspection rate level in both of the IV and the OLS estimations. In particular, a strong complementary effect between the damage indicator and the elasticity of the violation rate on the inspection rate is found. The net effect of the absolute elasticity is shown to be positive and significant. This supports the prediction that the elasticity of the violation rate determines the inspection rate in a modified Ramsey pricing rule in the presence of a hard budget constraint. The net effect of the damage indicator is conditional on the elasticity of the violation rate. The intuition is as follows: although the violation of an industry with a larger damage indicator may lead to a larger social cost, each inspection of this damaging industry's behavior may be more costly. When the elasticity of the violation rate is small, that is the inspection is not effective, an enforcement agency may choose to inspect this industry less. In contrast, when the elasticity of the violation rate is large enough, an industry with a larger damage indicator is subject to a larger inspection rate.

The rest of the chapter is organized as follows. In Section 3.2, I develop a simple theoretical model to show how the damage indicator and the elasticity of the violation rate determine the environment enforcement policy in equilibrium. Section 3.3 presents the empirical specification and describes the data. In Section 3.4, I present the empirical results. Section 3.5 con-

[49]Industry-specific pollutants are modeled by Michida and Nishikimi (2007)[54]: "in terms of industrial pollution, there exist a large variety of toxic substances, some of which are not common across different industries."

[50]see Appendix B.2 for details.

ducts the robustness checks. Conclusion is provided in Section 3.6. Proofs of propositions and some supplementary data descriptions are contained in Appendix B.

3.2 A simple theoretical model - enforcement with heterogeneous industries

Suppose firms in an industry are identical and polluting. A representative firm could be in compliance or in violation[51]. The firm can control its violation probability by changing the environmental expenditure, e.g., the level of investment in pollution abatement equipment, the number of employees in the pollution management, and the employment of cleaner input in production. It decides its violation probability $v \in (0, 1]$ to maximize its profit. The violation probability decreases as the firm devotes more environmental expenditure, but the environmental expenditure has to be infinitely large to keep the violation probability at zero.

The net benefit from violation $-B(v,k)-$ is increasing in violation probability, v. The functional form of $B(v,k)$ is assumed to be $v^{\theta}k^{1-\theta}$ [52]. The benefit may come from saved abatement cost and related gains from more pollution (e.g. a lower output price as the cost becomes lower). This net benefit also depends on a sector-specific input k. The sector-specific input is limited and inelastically supplied, and the technology shows constant return in both factors but diminishing return in individual factors. This production

[51] The extent of the violation is neglected to focus on the violation rate (as a result of dichotomous compliance/non-compliance determination) in this work. As Oljaca et al. (1998) indicate that the violation size has also been neglected in Viscusi and Zeckhauser (1979), Jones and Scotchmer (1990), Harrington (1988), Harford and Harrington (1991), Jost (1997), Malik (1993). In this line of literature, it is assumed that the agency chooses the maximum fine level within certain externally-imposed limit (e.g. the wealth of the offender, the social norms of fairness) to achieve the greatest deterrence.

In practice, the U.S. EPA calculates its civil penalty with a 'gravity' component which is based on the harm from the offense. This component of the EPA penalty is based on qualitative descriptions of harm and is not directly related to any quantitative measure of harm (Cohen, 1999).

[52] This power function form is necessary to derive a constant elasticity of the violation rate with respect to the inspection rate in the following.

structure leads to a quasi-rent π for the fixed factor. At the industry level, v is regarded as the industry-level violation rate because firms are identical in an industry.

An agency that enforces a pollution standard monitors and imposes a sanction once a violation is detected. A sanction could be a fine or some other costly penalty and its level is assumed to be exogenous [53]. The enforcement agency decides the inspection rate $p \in [0, 1]$ to maximize the social welfare. This is a Stackleberg game: the enforcement agency announces the inspection rate and the firms decide their violation probabilities afterwards. Therefore, a firm's choice of violation probability is influenced by the inspection rate announced by the enforcement agency.

The optimization problem of a representative firm can be written as

$$\underset{v}{Max}\ \pi = B\left(v, k\right) - ptv \tag{3.1}$$

where v is the violation probability, and $B\left(v, k\right)$ is the benefit from violating the pollution standard. The detected violation rate is pv. The total fine is ptv which depends on both the detected violation rate and the penalty t[54].

The first order condition is:

$$B_v\left(v, k\right) - pt = 0 \tag{3.2}$$

This shows that the marginal benefit of increasing the violation probability is equal to its marginal penalty. A firm's violation probability is decreasing in the inspection rate.

The enforcement agency has to incur costs in monitoring firms so as to discover and verify a violation. And the agency's inspection expenditure is increasing with a larger violation probability for each firm. I assume that the inspection expenditure on a representative firm in industry i is ep_iv_i,

[53] In Garvie and Keeler (1994), it is pointed out that the size of financial penalties is dependent on institutional factors (e.g. judicial attitudes, higher level support from the executive branch, and public opinion) largely outside the control of both firms and regulators.

[54] A relatively more general functional form, a power function of v, is also easy to be used to derive the same propositions and predictions.

where e is the monitoring expenditure coefficient and it is the same across industries. [55] The total inspection budget is assigned by the Congress and is limited. The enforcement agency chooses an industry-specific inspection strategy to maximize the social welfare subject to the budget constraint and firms' reaction functions in equation (3.2),

$$\begin{aligned} \underset{p_i}{Max}\ \Omega = \sum_i p_i t v_i - \sum_i \rho_i v_i + \sum_i \pi_i \\ s.t. \quad \sum_i e p_i v_i \ \leq \ E \\ B_v(v,k) - pt = 0 \end{aligned} \tag{3.3}$$

where ρ_j is the pollution damage indicator in industry i so that $\rho_i v_i$ represents the pollution disutility from this industrial pollution violation. Here, the pollution damage indicator is an important characteristic of industry-specific pollutant. It represents different levels of risks to the environment and human health, including information such as the toxicity or the proximity to consumers. This corresponds to the sector-specific input. $p_i t v_i$ is the penalty collected from industry i and is redistributed lump-sum to all individuals. Thus, the social welfare is defined as the sum of the pollution disutility, the expected collected penalty and the total profits across all industries. In the budget constraint, $e p_i v_i$ is the inspection cost function. E is the total budget assigned by the congress.

I define $\varepsilon_i = \frac{\partial v_i}{\partial p_i}\frac{p_i}{v_i} = \frac{1}{\theta - 1}$ [56] as the elasticity of the violation rate with respect to the inspection rate. In equilibrium, the industry i's inspection

[55] The inspection expenditure depends on both the inspection probability and the violation probability in this thesis. It can be expected that the inspection cost is higher for a serious and large amount violation because the workload is high. But the extent of the violation has been neglected to focus on the violation rate as a result of dichotomous compliance/noncompliance decision (The explanation is in footnote 47 in page 29.). I use the violation probability to proxy the expected violation size assuming that the mean violation amount is the same across industries. That is, if an industry has a larger violation probability, its expected violation size is larger. Each inspection may incur a higher cost and the total inspection expenditure is larger.

In addition, there may exist additional enforcement actions required for firms that are found violating, such as control orders, phone calls, meetings etc., so the total inspection costs are higher when more firms are found in violation.

[56] This is derived from Equation (3.2) when $B(v,k) = v^{\theta} k^{1-\theta}$

frequency the agency chooses satisfies:

$$p_i = \frac{1}{t - \lambda e \left(1 + \frac{1}{\varepsilon_i}\right)} \rho_i \tag{3.4}$$

Proof. See Appendix B.1 ■
where the Lagrangian multiplier λ is positive because an increase in the budge E implies a gain in social welfare. It reflects the opportunity cost of a dollar in terms of gaining the social welfare. This gives the following relationships for the inspection rate:

Proposition 1 *In equilibrium, all else equal, the enforcement agency inspects the following industries more frequently:*

(i) the industries with larger absolute values of the elasticity of the violation rate with respect to the inspection rate $|\varepsilon|$*;*

(ii) the industries whose damage indictor ρ *is larger.*

If one industry is more elastic than the other industry, the deadweight loss at the same inspection rate from inspecting the elastic industry is lower. Then the enforcement agency may devote more resources to inspecting the industry whose absolute elasticity of violation rate is large. And a high equilibrium inspection rate is set in this industry.

Equation (3.4) provides a suitable platform for empirical analysis and identification with data from the USA.

3.3 Empirical specification and data

3.3.1 The inspection rate equation

Equation (3.4) suggests the central roles of two variables (the damage indictor ρ and the reciprocal of the elasticity of the violation rate $\frac{1}{\varepsilon}$) in determining the inspection rate that represents the enforcement policy level. I estimate three specifications below from a simplified linear approximation to a general nonlinear functional form.[57]

Specification one

I incorporate $\frac{1}{\varepsilon}$ and $\ln \rho$ as regressors in Specification One in a linear way as follows,

$$\begin{aligned} \ln IR_i &= \beta_0 + \beta_1 \left(\frac{1}{\varepsilon}\right)_i + \beta_2 \ln \rho_i + \beta_3 \ln EI_i + \beta_4 \ln EMP_i + \beta_5 HHI_i + \\ & \quad \beta_6 DI_i + \beta_7 GC_i + \beta_8 Group_i + \epsilon_i \end{aligned} \tag{3.5a}$$

where IR is the industry-level inspection rate, ρ is the pollution damage indicator, $\frac{1}{\varepsilon}$ is the reciprocal of the elasticity of the violation rate, $Group$ is a group dummy (the first digit of SIC code is 2 or 3), ϵ is a zero-mean error term, i is the industry index.

The general industry conditions to be controlled for include the following:

EI: the level of emission intensity.

HHI: the Herfindahl-Hirschman Index measuring the concentration of firms in an industry (the industry concentration).

DI: "diverse industry" is a measure describing the number of different segments in which a firm operates.

EMP: the number of paid employment as a measure of industry size.

[57]The elasticity of the violation rate is regarded to be exogenous in the estimations. On the one hand, it is regarded as an industry characteristics. As shown by the theoretical work, $\varepsilon_i = \frac{\partial v_i}{\partial p_i}\frac{p_i}{v_i} = \frac{1}{\theta - 1}$ in a simplified framework. At the micro-level(the facility level), the elasticity of violation may be endogenous, while we aggregate the data to the industry level, which lessens the degree of endogeneity of the violation elasticity. Moreover, in the empirical papers that test the predictions of Grossman and Helpman (1994), elasticity (although different from that in my paper) is treated as exogenous (as an industry characteristic) to explain the differences in tariff across industries (see Gawande and Bandyopadhyay, 2000). Nevertheless, the estimated coefficients on the elasticity of violation may be biased to some extent. However, since the estimated coefficients are generally significant at the 1% level, the potential bias might not affect the main predictions much.

GC: "geographic concentration" describes the dispersion of firms according to their locations.

Specification two

I amend Specification One by adding an interaction term between $\ln \rho$ and $\frac{1}{e}$ as Specification Two. This is to catch the possibility that the effect of the elasticity of violation may be conditional on an industry's damaging level (represented by the value of the damage indicator ρ). I therefore use the following as Specification Two,

$$\begin{aligned}\ln IR_i \quad = \quad & \beta'_0 + \beta'_1 \left(\frac{1}{\varepsilon}\right)_i + \beta'_2 \ln \rho_i + \beta'_{1,2} \left(\ln \rho_i \times \frac{1}{\varepsilon}_i\right) + \beta'_3 \ln EI_i + \beta'_4 \ln EMP_i \\ & + \beta'_5 HHI_i + \beta'_6 DI_i + \beta'_7 GC_i + \beta'_8 Group_i + \epsilon_i \qquad (3.5\text{b})\end{aligned}$$

Specification three

I consider a general nonlinear functional form by adding higher order terms for $\ln \rho$, $\frac{1}{e}$ and their interaction term as follows,

$$\begin{aligned}\ln IR_i \quad = \quad & \beta''_0 + \beta''_1 \ln \rho_i + \beta''_{11} \left(\ln \rho_i\right)^2 + \beta''_2 \left(\frac{1}{\varepsilon}\right)_i + \beta''_{22} \left(\frac{1}{\varepsilon}_i\right)^2 + \\ & \beta''_{1,2} \left(\ln \rho_i \times \frac{1}{\varepsilon}_i\right) + \beta''_{11,22} \left(\ln \rho_i \times \frac{1}{\varepsilon}_i\right)^2 + \beta''_3 \ln EI_i + \\ & \beta''_4 \ln EMP_i + \beta''_5 HHI_i + \beta''_6 DI_i + \beta''_7 GC_i \\ & + \beta''_8 Group_i + \epsilon_i \qquad (3.5\text{c})\end{aligned}$$

3.3.2 Endogeneity of the emission intensity

When estimating the three specifications above, I adopt the IV approach to overcome the potential endogeneity problem of the emission intensity. This endogeneity problem arises because the inspection rate has an influence on the emission intensity as shown below in a reduced-form specification[58].

$$\begin{aligned} \ln EI_i &= \gamma_0 + \gamma_1 IR_i + \gamma_2 \ln w_i + \gamma_3 \ln k_i + \gamma_4 \ln Material_i \\ &\quad + \gamma_5 \ln Energy_i + \gamma_6 \left(controls\right) + \varphi_{it} \end{aligned} \tag{3.6}$$

where EI is the emission intensity, w is the labor share, k is the capital share, $Material$ is the material share, $Energy$ is the energy share, $(controls)$ include industry characteristics, and $Group_i$ is the group dummy.

In estimating equations (3.5a), (3.5b) and (3.5c), $\ln EI$ is instrumented with the input shares $(\ln w, \ln k, \ln material, \ln energy)$.

3.3.3 Data description

This section describes the data sources and how they are utilized to construct measures of the interested variables. Table 3.1 provides definitions and sources of the variables, and Table 3.2 summarizes the descriptive statistics of the variables used in the empirical analysis.[59]

Regulatory variable

The dependent variable that measures the environmental enforcement policy is the inspection rate (IR). The data source of IR is the "Enforcement & Compliance History Online (ECHO)" publicly provided by the U.S. EPA. This source provides information on the number and dates of inspections by facility within last five years[60] (See Appendix A.3 for details). The number of inspections at the facility level was aggregated into the SIC 4-digit industry

[58]This is similar to the Equation (2.2c) in Chapter Two. But in estimation of Equation (2.2c), I use a panel data and time varies from 2003' to 2005'. In estimating Equation (3.6), I conduct a cross-industry analysis only.

[59]Some variables are used for estimation both in this chapter and Chapter Two. Thus, the description of the measurement and data sources for these variables are the same as those in Chapter Two.

[60]ECHO has been keeping updated. This paper uses the data last updated on Nov, 2008 at ECHO. So the inspection period starts from 2003.

level respectively.[61] Meanwhile, the total number of facilities for each 4-digit industry was collected. I divided the inspection number at the 4-digit level by the number of facilities for each industry. The ratio is defined as the industry-level inspection rate IR describing the inspection number that an industry is subject to.

I also use the abatement cost per unit emission ($AC\_emission$) as a proxy of the enforcement policy in the robustness checks in Section 3.5. The data source of AC is the file of "Pollution abatement costs and expenditures: 1994" from U.S. Bureau of the Census. $AC\_emission$ is defined as the ratio of the sum of operating costs for all media (PAOC) and capital expenditure for pollution abatement (PACE) to the "TRI pounds".[62] "TRI pounds" refer to the pounds released or transferred by industries, and are reported in the U.S. EPA's Risk-Screening Environmental Indicators (RSEI Version 2.1.5).

Damage indicator and elasticity of the violation rate

The damage indicator ρ and the elasticity of the violation rate ε are two important independent variables. Data source of the damage indicator is also the U.S. EPA's Risk-Screening Environmental Indicators (RSEI Version 2.1.5)[63]. RSEI contains "risk-related results", which imposes a risk score on industries at different SIC levels. The toxicity, surrogate dose, and population components are multiplied to calculate this risk score. It is used to assess the potential impact of industrial releases. The data are available for 1996'-2005'. The risk score ("risk-related results") is defined as the damage indicator in this chapter. This dataset has been seldom explored to my knowledge. The damage indicator is similar to the measure of environmental

[61] I do not use minor facilities which are not required to report because reported facilities may tend to be more environmentally compliant and could lead to bias. And industries whose total number of inspected facilities is less than 5 are dropped because the sample is too small.

[62] The data in some industries are withheld to avoid disclosure, and no industries are shown where PAOC or PACE is less than $1.0 million.

[63] See Appendix B.2 for details. Data of the damage multiplier is available with the SIC code instead of NAICs.

exposure in Antweiler (2003) to some extent[64].

Elasticity of the violation rate with respect to the inspection rate is the measure of responsiveness in the industry-level pollution violation rate as a result of change in the enforcement policy. It was calculated in Chapter Two.

Other variables

I describe the other variables used in the analysis as follows. The number of paid employees (EMP) is used to measure industry size and is from the 1997 Economic Census.[65] The 1992 Census of Manufactures report MC92-S-2, "Concentration Ratios in Manufacturing", is the data source for HHI (Herfindahl Hirschmann Index) that characterizes the industry concentration[66]. I constructed the emission intensity (EI) by dividing the chemical released amounts at the 4-digit industry level in 1996'[67] by the value of shipments. The data source of the chemical released amounts at the 4-digit level is the U.S. EPA's Risk-Screening Environmental Indicators (RSEI) (Version 2.1.5)[68] that uses annually updated Toxic Release Inventory[69] data. The

[64] It combines a firm's composition and toxicity of emissions and its location that determines the size of the population at risk with the firm's size and intensity of pollution. This measure of environmental exposure is utilized as one of firm characteristics to investigate its effect on firm's abatement effort. This effect is used to back out the effect of green regulatory threat which is not directly measurable. Because environmental exposure triggers regulation, it has been shown that the effectiveness of threat depends on environmental exposure of a firm. It also depends on abatement ladder rung of a firm and government's incentive scheme as argued in this paper.

[65] The Economic Census profiles American business every 5 years and the 2002 data are available. However, the 2002 Economic Census is based on North American Industry Classification System (NAICS). Given the violation rate is based on SICs, the conversion of employment based on NAICS into that based on SICs may lead to some bias. The 1997 data are available in both NAICS and SICs. And since the employment number is used to control for industry size which is relatively stable over short periods, I choose the 1997 data.

[66] The 1997 data are available but are classified by NAICS instead of SIC.

[67] I use the data in 1996' because the data of inputs are in 1996'.

[68] See Appendix B.2 for details.

[69] "The toxic Release Inventory (TRI) is a publicly-available EPA database That contains information on toxic chemical releases and other waste management activities reported annually by certain covered industry groups and federal facilities." – User's Manual for RSEI

data of the values of shipments are from the 1992 Census of Manufactures report MC92-S-2, "Concentration Ratios in Manufacturing". The data of inputs were obtained from the 1996 Annual Survey of Manufactures.[70] The values of "production workers wages", "cost of materials", "new capital expenditures", and "cost of purchased fuels and electric energy" are scaled by "value of industry shipments" to proxy the input shares w, k, Material and Energy respectively. The value of industry shipments is from the 1996' ASM.

Measures of Diverse industry (DI) and Geographic Concentration (GC) were constructed following Grier, Munger and Roberts (1994). The number of segments is reported by each firm, up to a maximum of 10 in COMPUSTAT industrial segment file. The data were averaged by industry (mean=1.7, s.d.=0.65) and a diverse industry is defined as "one with mean number of products more than two s.d. above the sample average, that is, all industries whose firms average more than three products line are coded 1.0 and the others 0.00". Because the data vary little at 4-digit level, I compiled them into 3-digit level data. And the data cover the period of 1998-2006. Geographic concentration is calculated as $\sum_i \left(\frac{Sales_i}{Sales}\right)^2$ for each industry where i denotes state. The data of sales (DATA12) for each state were collected from COMPUSTAT as well.

Combining non-missing observations from these sources yields an unbalanced panel of 331 observations over the period 2003'-2005'. I take the mean values over the three years as the sample used in this chapter in estimation.

[70] http://www.census.gov/mcd/asm-as1.html.

Table 3.1: Variable Definition and Data Sources II

Variable	**Description**	**Sources**
Inspection Rate (IR)	$=\frac{\text{The total number of inspections}}{\text{The total number of facilities}}$	ECHO, 2003'-2008'
Industry Concentration (HHI)	Herfindahl Hirschmann Index	1992 Economic Census, 1992'
Industry Diversity (DI)	=1 for a large number of product lines =0 for a small number of product lines	Industrial segment file in COMPUSTAT, 3-digit Grier et al.(1994), 98'-06'
Industry Size (EMP)	The number of paid employment	1997 Economic Census, 97'
Geographic Concentration (GC)	$= \sum_i \left(\frac{\text{Sales}_i}{\text{Sales}}\right)^2$ (i: state)	COMPUSTAT,95'-06' Grier et al.(1994)
Damage Indicator (ρ)	Risk-related results	RSEI, 1996'-2005'
Elasticity of Violation Rate (ε)	A measure of responsiveness in the violation rate as a result of change in inspection rate	Chapter Two, no time series
Variables that appear in the robustness checks only		
Abatement Cost ($\ln \frac{AC}{Emission}$)	$=\frac{\text{Abatement operating costs+Capital expenditure}}{\text{TRI pounds}}$	"PACE1994" and 1996 ASM, 1994'

Table 3.2: Summary Statistics II

Variable Indicator	Number of Observations	Mean	Standard Deviation	Minimum	Maximum
IR	914	.39	.29	.03	1.69[a]
$\ln EI$	4115	12.68	2.57	-5.29	19.16
HHI	447	0.066	0.06	0.000056	0.297
DI	3950	.04	.20	0	1
$\ln EMP$	419	9.95	1.11	6.20	13.18
GC	5302	.40	.24	.09	1
$\ln \rho$	4134	7.91	3.50	-10	16
$1/\varepsilon$	111	-.4.0	2.19	-11.3	-0.9
Variable that appears in the robustness checks only					
$\ln \frac{AC}{Emission}$	109	-11.76	2.11	-16.18	-2.64
a: IR could be larger than 1 because each facility could be inspected multiple times.					

3.4 Empirical results

The results are reported in Table 3.3. Columns (1)-(3) correspond to the three specifications 3.5a-3.5c with the OLS estimation. In Column (4), $\ln EI$ is instrumented with the input shares ($\ln w, \ln k, \ln material, \ln energy$). This is a cross-industry analysis. In all regressions, the observed industry heterogeneity ($\ln EMP$, HHI, GC, DI), and the group effect are controlled for.

In column (1), the result shows that the estimated coefficient on the inverse elasticity $1/\varepsilon$ is positive and significant at the 1% level. This positive sign is consistent with the prediction implied by equation (3.4). That is, the enforcement policy is more stringent (a higher level of inspection rate) for industries with large absolute elasticities. The natural log of the pollution damage indicator $\ln \rho$ has a positive effect on the inspection rate, but the coefficient is not statistically significant. $\ln EI$ has a positive and significant estimated coefficient.

Column (2) reports the results when the interaction between $\ln \rho$ and $1/\varepsilon$ is included. It shows that the estimated coefficients on $\ln \rho$ is still positive and becomes significant. The interaction term $\ln \rho \times 1/\varepsilon$ has a positive and statistically significant estimated coefficient at the 1% level. The strong significance level of the estimated coefficient on the interaction term suggests the existence of a complementary effect between $\ln \rho$ and $1/\varepsilon$. I conducted two other tests for additional evidences about the existence of this interaction term. First, because Specification one is nested in Specification two, I test the restrictions imposed in Specification one via a likelihood ratio (LR) test. The LR test statistic is presented at the bottom of Column (1) and is very significant. The restrictions are rejected and the result is in favor of Specification two. Second, in Column (2), I report the result of the joint significance test of $\ln \rho$ and the interaction term and the result of the joint significance test of $1/\varepsilon$ and the interaction term. The null hypothesis that the coefficients of both $\ln \rho$ and the interaction term are zero is strongly rejected. The result of the joint significance test for $1/\varepsilon$ and the interaction term is similar.

I explore their effects in determining the inspection level further by calculating the net effect. The net effect of the reciprocal of the elasticity of violation $1/\varepsilon$ on the inspection rate, $\ln IR$, is positive for around 98.8 percent of industries. In particular, at the sample mean of $\ln \rho$[71], one standard deviation increase in $1/\varepsilon$ would approximately increase the inspection rate level $\ln IR$ by 0.49.[72] The net effect of the damage indicator is conditional on the elasticity. At a larger absolute elasticity of violation rate, the net effect of the damage indicator is positive. But when the absolute elasticity is small enough, the net effect becomes negative. This is because each inspection of an industry with a larger damage indicator has to incur more inspection cost. When the inspection is not effective at deterring violation for this industry, the enforcement agency chooses to inspect less.[73]

In Column (3), I estimate Specification three which is a more general nonlinear function by adding $(\ln \rho)^2$, $\left(\frac{1}{\varepsilon}\right)^2$, and $\left(\ln \rho \times \frac{1}{\varepsilon}\right)^2$ to Specification Two. The estimated coefficients on $\ln \rho$, $1/\varepsilon$ and the interaction term $\ln \rho \times 1/\varepsilon$ are positive. The estimated coefficient on $1/\varepsilon$ is still significant. This is similar to the results of Specification two in Column (2). The estimation finds significantly effects of the quadratic term of $1/\varepsilon$ and that of the interaction term $\left(\ln \rho \times \frac{1}{\varepsilon}\right)$. This serves as further evidence that the interaction terms are necessary to be considered. As shown at the bottom of Column (2), the result of the LR test that tests the restrictions on Specification Two is very significant. Moreover, R^2 increases from 0.88 to 0.95. Thus, considering the role of higher orders for the interaction term may improve the performance of the regression. However, there exists concern that the specification with

[71] The summary statistics of $\ln \rho$ in this sample: mean=7.91, s.d.=3.50, min=-10, max=16.

[72] The calculation is as follows: $[0.04 + (0.023) \times 7.91] \times 2.2 = 0.49$, where the standard deviation of $1/\varepsilon$ is 2.2.

[73] This result can be obtained by slightly modifying the theoretical model. In the enforcement agency's maximization problem (6), I assume the monitoring expenditure coefficient e is an increasing function of the damage indicator ρ. Then Equation (7) can be rewritten as $p_i = \dfrac{1}{t - \lambda e(\rho_i)\left(1 + \frac{1}{\varepsilon_i}\right)}\rho_i = \dfrac{1}{t + \lambda e(\rho_i)\left(\frac{1}{|\varepsilon_i|} - 1\right)}\rho_i$. It shows clearly that the effect of the damage indicator is conditional on the absolute elasticity. When the absolute elasticity is small enough, an increase in the damage indicator may lower the inspection rate due to a higher inspection expenditure.

higher orders for the interaction term may be subject to the multicollinearity problem to some extent. And the estimated coefficients in Specification (3) are not directly interpretable. Thus, of the three specifications in the first three columns, I put more emphasis on Specification (2).

Based on Specification Two (Equation 3.5b), I control for the endogeneity of $\ln EI$ using the IV method and report the results in Column (4). The estimated coefficients in Column (4) are similar to those in Column (2) both in terms of the magnitude and the significance level. The only big difference is that the estimated coefficient on $\ln EI$ becomes bigger after its endogeneity is controlled for. In sum, it confirms the hypothesis that the inspection rate structure across industries depends on the inverse elasticity of the violation rate. Moreover, there exists a strong complementary effect between $\ln \rho$ and $1/\varepsilon$ in determining the inspection rate.

3.5 Robustness and sensitivity analysis

To investigate the robustness of the findings, I run another group of regressions, with the results reported in Table 3.4. Table 3.4 contains estimates based on the second measure of the enforcement policy, the abatement cost per unit emission. The abatement cost per unit emission replaces the inspection rate and the logarithm of the abatement cost ($\ln \frac{AC}{Emission}$) is employed as the dependent variable. Columns (1)-(4) correspond to the four columns in Table 9 respectively. The abatement cost data are one year (1994') cross-industry data. The mean values over time are used for time varying independent variables ($\ln \rho$, DI, GC) and the number of observations reduces to 108.

Results in Columns (2)-(3) show the existence of the interaction term's effect on the enforcement policy level. The estimated coefficient on the inverse elasticity $1/\varepsilon$ is negative. This is perhaps because $\ln \frac{AC}{Emission}$ captures not only the stringency of the enforcement policy, but also that of the environmental regulation (e.g. the emission limit). $\ln EI$ has a negative and significant estimated coefficient in contrast to the positive estimated coefficient in Table 3.3.

Table 3.3: Inspection Rates Regressions

Independent Variable	Dependent variable: $\ln IR$ OLS (1)	OLS (2)	OLS (3)	IV (4)
$\ln\rho$	.013 (1.07)	.10*** (6.8)	.12** (2.09)	.10*** (5.38)
$1/\varepsilon$	.19*** (11.50)	.04* (1.86)	.35*** (3.45)	.04* (1.84)
$\ln\rho\times(1/\varepsilon)$		.023*** (7.73)	.04*** (2.78)	.023*** (7.56)
$(\ln\rho)^2$			$-.004$ (-1.65)	
$(1/\varepsilon)^2$			.02*** (3.94)	
$(\ln\rho\times 1/\varepsilon)^2$			.0003*** (3.31)	
$\ln EI$	.02 (1.08)	.01 (0.62)	-0.002 (-0.28)	0.007 (0.25)
$\ln EMP$	$-.04$ (-1.56)	$-.02$ (-1.22)	.008 (0.63)	$-.02$ (-1.16)
HHI	.54 (1.10)	.15 (0.38)	.08 (0.32)	.15 (0.37)
DI	.22 (0.90)	-0.06 (-0.31)	$-.09$ (-0.75)	$-.06$ (-0.30)
GC	$-.03$ (-0.29)	0.05 (0.54)	.06 (1.04)	.05 (0.51)
$Group2$	.11* (1.93)	.10** (2.06)	.07** (2.35)	.09* (1.76)
R^2	0.81	0.88	0.95	0.88
Obs.	110	110	110	110
F-statistic for the joint significance test (Prob>F)				
$\ln\rho, \ln\rho\times(1/\varepsilon)$		30.74***		
$1/\varepsilon, \ln\rho\times(1/\varepsilon)$		134.37***		
$\ln\rho, \ln\rho\times(1/\varepsilon), (\ln\rho)^2, (\ln\rho\times 1/\varepsilon)^2$			4.41***	
$1/\varepsilon, \ln\rho\times(1/\varepsilon), (1/\varepsilon)^2, (\ln\rho\times 1/\varepsilon)^2$			199.82***	
LR test $/\chi^2$	51.48***	102.39***		

*** Significant at the 1% level, ** at the 5% level, and * at the 10% level
(t statistics in parentheses)

In addition, for the four columns in Table 3.3, I run regressions for each year from 2003'-2005' instead of using the mean value over the three years. The results are similar and not reported here.

3.6 Conclusions

This chapter investigates the determinants of the environmental enforcement policy when the enforcement agency is constrained by a hard monitoring budget. I started with a simple theoretical model to emphasize two industry characteristics: the damage indicator and the elasticity of the violation rate with respect to the inspection rate. The damage indicator measures the industry-specific pollutants' potential damage to the environment and human health. Industries with large damage indicators may be subject to more inspections because of the high social costs resulting from their violation, all else being equal. The elasticity of violation reflects the responsiveness in the industry-level pollution violation rate as a result of change in the enforcement policy. Deadweight loss from inspection is smaller in industries with large absolute elasticities of the violation rate so that the enforcement agency tends to direct more resources to these industries and inspect them more frequently, all else being equal.

In the empirical section, I estimated the linearized specification and its more general forms. The results identified the effects of the damage indicator and (the reciprocal of) the elasticity of the violation rate on the inspection rate level. In particular, a strong complementary effect between the damage indicator and the elasticity of the violation rate on the inspection rate is found.

Existing works have not empirically linked these two industry characteristics to the enforcement level. The dataset about the damage indicator has been seldom explored, and the data of the elasticities that are calculated in Chapter Two are unique. This chapter calls for more attention on the indicators that measure the overall damage to the environment and human health in addition to the traditional pollution measurement – the emission intensity.

Table 3.4: Robustness of Inspection Rates Regressions

Independent Variable	Dependent variable: $\ln \frac{AC}{Emission}$ [a] OLS (1)	OLS (2)	OLS (3)	IV (4)
$\ln\rho$	.001 (.02)	.17* (1.78)	.73 (1.35)	.15 (1.16)
$1/\varepsilon$	.23*** (2.87)	−.03 (−.24)	−.75 (−.80)	−.04 (−.26)
$\ln\rho\times(1/\varepsilon)$		.04** (2.32)	.20* (1.71)	.04** (2.20)
$(\ln\rho)^2$			−.02 (−1.06)	
$(1/\varepsilon)^2$			−.03 (−.64)	
$(\ln\rho\times 1/\varepsilon)^2$			.001* (1.67)	
$\ln EI$	−.85*** (−11.11)	−.87*** (−11.53)	−.88*** (−11.73)	−.83*** (−4.36)
$\ln EMP$	−.06 (−.47)	−.03 (−.27)	.01 (.08)	−.02 (−.13)
HHI	1.33 (.56)	.65 (.28)	1.38 (.57)	.76 (.31)
DI	.078 (.07)	−.40 (−.35)	−.51 (−.45)	−.48 (−.40)
GC	.14 (.26)	.28 (.54)	.41 (.76)	.31 (.57)
$Group2$	.33 (1.17)	.29 (1.06)	.25 (.92)	.33 (.95)
R^2	0.71	0.72	0.73	0.72
Obs.	108	108	108	108
F-statistic for the joint significance test (Prob>F)				
$\ln\rho, \ln\rho\times(1/\varepsilon)$		2.68*		
$1/\varepsilon, \ln\rho\times(1/\varepsilon)$		6.98***		
$\ln\rho, \ln\rho\times(1/\varepsilon), (\ln\rho)^2, (\ln\rho\times 1/\varepsilon)^2$			.79	
$1/\varepsilon, \ln\rho\times(1/\varepsilon), (1/\varepsilon)^2, (\ln\rho\times 1/\varepsilon)^2$			4.42***	
LR test $/\chi^2$	5.76**	4.95		

*** Significant at the 1% level, ** at the 5% level, and * at the 10% level
(t statistics in parentheses)
a: The dependent variable is used to proxy the enforcement policy.

Chapter 4

Determinants of Environmental Political Contribution

4.1 Introduction

Is environmental protection for sale? There have been overwhelming concern and evidence that pro-environment policies are obstructed by politics (e.g., Pittman, 1977; Kraft and Vig, 2009[74]; Mixon, 1995; Cropper et al., 1992; Pashigian, 1985[75]; Damania et al., 2003[76]). In this paper, I first construct an index of environmental political contribution (EPC) – the campaign contribution presented to the congress exclusively for environmental issues, which serves as the direct evidence of environmental protection for sale (EPFS) – to measure the environmental political activity. The data show that there

[74]Kraft and Vig (2009) argue that "intense opposition to environmental and natural resource policies arose in the 104th Congress (1995-1997), when the Republican Party took control of both the House and Senate for the first time in forty years...pitched battles over environmental and energy policy continued in every Congress through the 110th (2007-2009), and they were equally evident in the executive branch as the Bush White House sought to rewrite environmental rules and regulations to favor industry..."

[75]Mixon (1995) provides evidence that the ratio of the number of registered lobbyists in the state population has an effect on the degree of an environmental protection agency (EPA) citation for carbon emissions standards; Cropper *et al.* (1992) indicate that comments in the regulatory political process by grower organizations significantly reduced the probability of cancellation of certain pesticide; Pashigian (1985) points out that votes from the South and the West with higher growth rates and superior air quality oppose the environmental policy of prevention of significant deterioration in the locational competition.

[76]Damania et al. find that corruption reduces environmental policy stringency in a cross-country analysis.

is a substantive variation across industry and time in the intensity of EPC (EPC/employment) as shown in Figure 4.1.[77] I intend to identify what explains the variation across industries in the intensity of EPC.

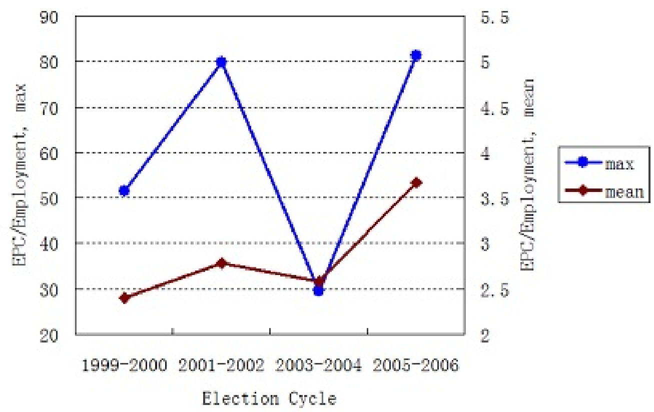

Figure 4.1: The Variation of the EPC Intensity

I explore the role of the enforcement policy stringency in explaining the variation. The intuition is as follows. Although the EPC presented to the Congress is targeted directly on environmental legislation/regulation rather than the enforcement policy set by the environmental protection agency (EPA), the enforcement policy affects the marginal benefit from contributing the congress for relaxing the legislation/regulation.[78] For example, an industry that has higher expected sanctions/penalties from violating an emission standard has more to gain from spending a dollar to get the standard lowered than an industry with lower expected penalties. In this way, I predict that industries facing stricter enforcement policies are more likely to engage in the political activity all else equal. And the enforcement policy has a po-

[77]Because industries vary a lot in size, the environmental political contribution (EPC) is divided by the number of paid employment. EPC/employment is defined as the EPC intensity in this chapter implying the amount of EPC in dollars made by each employee. The unit is the the U.S. Dollar. The details will be discussed in Section 4.3.

[78]One reason to test EPFS indirectly this way is that I do not have data on regulation (i.e., the elasticity of violation with respect to regulation). Instead, I have data on the elasticities of violation with respect to enforcement estimated in Chapter 2.

litical consequence. We then test the prediction on the industry-level panel data of the U.S.A.

This chapter builds on prevous empirical work that studies the determinants of the industrial political activity. They are based on the theory of regulation (Stigler, 1971; Olson 1965): well-organized groups can exert political influence on a government which maximizes its political support to relax the environmental policy stringency that imposes a deadweight loss on the general voter.[79] The industrial political activity is related to the environmental regulations as well as other government regulations empirically. For example, Gawande and Bandyopadhyay (2000) shows that the tariff barrier is a factor that determines the trade-related political contribution. In Pittman (1977), environmental regulations are found to be positively related with total political contributions. In sum, the campaign contributions are used to measure the industrial political activity and the attention is paid to the government regulations themselves as determinants.

This work makes two key contributions to the literature. One is the characterization of the environmental political activity using EPC. In the literature, the total campaign contribution has been employed to proxy the industrial political activity (e.g., Pittman, 1977; Grier and Munger, 1991, 1993; Gopoian, 1984)[80]. However, there are concerns about using the total contributions to evaluate the impact on a certain policy (such as trade policy[81] or environmental policy) since total amounts of contributions may be the result of multiple purposes. As argued by Gawande and Krishna (2001),

> "Taking trade policy as an example, lobbying data come as a bundle so it is not easy to disentangle the purely trade-related component of lobbying data. Although this problem may be alle-

[79] For the theoretical works that characterize the formation of environmental policy as a result of the interaction between the government and organized lobbying groups, see Fredriksson (1997) and Damania (2001).

[80] This is because, although payments for political favors can take many forms, campaign contributions from the political interest groups are the most visible and contentious, as argued by Doren et al. (1999).

[81] In Gawande and Bandyopadhyay (2000) and Gawande (1998), the trade-related political contribution is calculated and employed. But the approach is different from the one that this chapter employs.

> viated by considering a set of industries whose primary lobbying concern is trade protection (e.g., Lopez & Pagoulatos, 1996), it requires more care to do a full cross-sectional study for all of manufacturing, both in the measurement of lobbying as well as its econometric treatment."

I calculate EPC as follows: key members of House/Senate environmental committee/subcommittee were identified. Then, campaign contributions from each corporate PAC (political action committee) to those members were collected and summarized. Finally, individual corporate PAC contributions with their SICs were aggregated up to the SIC four-digit industry level. This calculation is based on the insight that PACs target incumbents who have seats on committees with jurisdiction over the PACs' areas of interest or committee membership, as pointed out by many existing works (Grier and Munger, 1991, 1993; Riddel, 2003; Gardner, 1995). A firm's EPC is supposed to be a better measure of its environmental political activity than its total political contribution.

The other contribution is to isolate the effect of the environmental enforcement policy from that of the environmental regulation on the environmental political contribution using the elasticity of the violation rate. Although the enforcement policy and the environmental policy are determined by separate agencies, the two kinds of policies have many common determinants (e.g. the emission intensity). If the relationship between the enforcement policy and the environmental political contribution arises as a result of these common determinants, it is hard to distinguish the enforcement policy's effect from the environmental policy's effect.

In this work, I use the elasticity of the violation rate with respect to the inspection rate to infer the enforcement policy's effect on the environmental political contribution. The elasticity of the violation rate is a measure of responsiveness in the industrial pollution violation rate as a result of change in the inspection rate. It is regarded as an exogenous industry characteristic and has been estimated in Chapter Two. When an enforcement agency is constrained by a hard enforcement budget, it tends to target industries with larger absolute elasticities of the violation rate. This is because inspections in these industries are more likely to be effective in achieving the enforcement's goal all else equal. I regard the elasticity of the violation rate as a major determinant of the inspection rate and found empirical evidence in Chapter Three. Based on these, I predict that industries with larger absolute elasticities of the violation rate are subject to stricter enforcement policies and therefore present more political contributions.

Empirically, I also highlight the risk-weighted emission intensity and its interaction term with the inverse elasticity of the violation rate, as well as the industry concentration as determinants of the environmental contribution expenditures.

First, the risk-weighted emission intensity is defined as a measure of pollutants' potential damage to the environment and human health per unit of production. It can be regarded as the emission intensity weighted by the damage indicator[82]. The risk-weighted emission intensity has an effect on the environmental political contribution through two channels: the environmental regulation (the direct effect) and the enforcement policy (the indirect effect).

For the direct effect, a damaging industry (an industry with a larger risk-weighted emission intensity) is subject to more stringent environmental regulations (e.g. the pollution tax). Then, this industry has incentives to contribute to the congress to relax the environmental policies.

For the indirect effect, whether a damaging industry is subject to a strict enforcement policy may be conditional on the elasticity of the violation rate. This is because the damage indicator is a key component of the risk-weighted emission intensity. And I find a complementary effect between the damage indicator and the inverse elasticity in determining the inspection rate in Chapter Three. Therefore, I include an interaction term of the risk-weighted emission intensity and the inverse elasticity in the estimation. The underlying mechanism is as follows: when the absolute elasticity

[82]The damage indicator can be regarded as the damage level per unit of emission, while the risk-weighted emission intensity represents the damage level per unit of output. See Chapter Three for details about the damage indicator.

of violation rate is large, the inspection of a damaging industry is effective. Although its inspection has to incur a higher inspection cost compared with the inspection of a less damaging industry, the inspection rate is higher for a damaging industry. In other word, the risk-weighted emission intensity is positively associated with the inspection rate. That is, a damaging industry is subject to a higher inspection rate. Furthermore, for this industry, a one-unit decrease in the pollution limit as a result of the political contribution can lead to a larger reduced sanction amount and this industry tends to present more environmental political contribution. Otherwise, when the absolute elasticity of violation rate is small, the inspection of an industry with a large damage indicator is not effective and has to incur a higher cost. The enforcement agency may be reluctant to impose a strict enforcement policy. As a result, a damaging industry is not inspected more frequently than other industries and does not contribute more. That is, the indirect effect of the risk-weighted emission intensity on the EPC through the enforcement policy is negative.

Thus, the overall effect of the risk-weighted emission intensity is ambiguous depending on the magnitudes of the indirect effect and the direct effect. But it is predicted to be positive when the elasticity of the violation rate is large.

Second, the industry concentration measuring obstacles to collective action is an important factor of the environmental political contribution. Polluting firms that have common interest in changing certain environmental policy usually organize and form a lobby group to present the contributions. Based on the lobbying function in Gawande (1998), I predict that industries that are less concentrated are hard to overcome the difficulty in collective action and thus present less environmental political contributions.

The empirical findings using the environmental political contribution as the dependent variable are summarized as follows. (1) The net effects of the absolute elasticity of violation rate on the environmental political contribution, evaluated at most industries' risk-weighted emission intensity levels, are positive. This implies that a damaging industry is subject to a higher inspection rate and tend to make more contributions. In particular, at the sample mean level of the risk-weighted emission intensity, one standard deviation increase in the inverse elasticity would approximately increase the natural log of the environmental political contribution intensity by 0.35. (2) The net effect of the risk-weighted emission intensity is positive as long as the absolute elasticity of the violation rate is large enough. One example is that one standard deviation increase in the natural log of the risk-weighted emission intensity would lead to a 0.024 increase in the natural log of the environmental political contribution intensity, evaluated at the median value of the inverse elasticity. (3) The industry concentration affects EPC (intensity) significantly and positively which is consistent with existing literature.

In addition, I repeat the estimations, but replace the environmental political contribution by the House environmental political contribution and the total political contribution as the dependent variables respectively. The results using the House environmental political contribution are similar with those using the environmental political contribution, both in terms of the estimated magnitude and the significance level. But when I use the total political contribution as a measure of the environmental political activity, the significance levels of the estimated coefficients on some key independent variables are reduced. This suggests that the environmental political contribution constructed in this work serves as a better measure than the total political contribution in finding evidence for the roles of the elasticity of the violation rate and the risk-weighted emission intensity.

The rest of the chapter is organized as follows. In Section 4.2, I derive the lobbying function to identify the determinants of EPC. In Section 4.3, I describe how to construct the environmental political contribution and summarize its statistics. Section 4.4 introduces the empirical specification and describes data sources. Section 4.5 presents the empirical results. In Section 4.6, I conduct the robustness checks. Conclusion is provided in Section 4.7. Some supplementary data descriptions are contained in Appendix C.

4.2 Theoretical perspective

The following simple theoretical model is to shed light on the factors that affect each lobby group member's private contribution amount in a multi-agent system. I emphasize the roles of the enforcement policy stringency and the lobbying organization.

A political economy is composed of a congress, an enforcement agency and polluting firms. The congress formulates the environmental regulation which is the emission limit $\overline{z}$. I assume, for simplicity, that the emission limit is the same for all firms in each industry. The emission limit $\overline{z}$ depends on the total campaign contribution amounts presented to the congress. This is because the congress cares about both the social welfare and contributions[83], and so it is willing to adjust the emission limit away from the value that maximizes social welfare in exchange for more political contributions. The enforcement agency sets the enforcement policy – the sanction level s for each unit of violation (the emission amount z that exceeds the emission limit $\overline{z}$). Because the campaign contributions are presented to the congress, their amounts do not affect the enforcement agency's decision. Both of the emission limit and the sanction rate are the same for all firms in each industry.

Polluting firms that have common interests in changing the emission limit $\overline{z}$ could organize and form a lobby group. The total contribution amount presented by each lobby group to the congress is the sum of its members' private provisions of campaign contribution. I assume $\overline{z} = \log\left(\sum \Lambda_{-i} + \Lambda_i\right)$, where Λ_i is the campaign contributions presented by firm i and $\sum \Lambda_{-i}$ is the total campaign contributions by contributing firms except firm i. This function shows that the emission limit level depends on the total contribution amount $(\sum \Lambda_{-i} + \Lambda_i)$. Given the contribution amount $\sum \Lambda_{-i}$ by other firms in this lobby group, firm i independently decides its individual contribution amount Λ_i. An increase in Λ_i can lead to a larger $\overline{z}$.

The net cost to contributing firm i, G_i, is composed of the total sanction

[83] This welfare function is common in the political economy literature (e.g. Grossman and Helpman, 1994).

and its own contribution amount. It takes the following form based on Gawande (1998),

$$\underset{\Lambda_i}{Min}\ G_i = s\left[z - \log\left(\sum \Lambda_{-i} + \Lambda_i\right)\right] + \Lambda_i$$

where z is the total pollution level. I assume that the contribution decision is independent of the production decision so that z is regarded as a constant in this political contribution minimization problem. And it is the same for all firms in an industry.[84] The emission limit $\overline{z}$ is also the same for all firms in each industry. Therefore, an individual firms' net cost of making a contribution depends on its excess pollution $(z - \overline{z})$ which is symmetric for all firms in an industry.

Given the sanction rate s, each member of a lobby group decides its contribution amount. Taking first order condition and assuming each protectionist firm is of the same size (the number of equal-size-equivalent firms in an industry n can be approximately measured as the inverse of the Herfindahl index of that industry $1/H$), individual firm's contribution is shown as the following[85],

$$1 = s/n\Lambda_i$$

In the equation above, the LHS is the marginal cost of contribution, while the RHS is the marginal benefit of contribution. The marginal benefit is a linear increasing function of s. That is, for an industry with a larger s, the marginal benefit of contribution is larger at the same amount of EPC, $Lambda_i$. Given the constant marginal cost of contribution, the firm tends to contribution more. The variant of this lobbying function by log-

[84] I am assuming firms in each industry producing the same amount of output and emissions so that z is not indexed by i. In this setup, I assume that firms make emission decisions before they make the contribution decisions. When they make the emission decision, they are symmetric and I do not consider this step here. When they make the contribution decision, their behaviors are strategic, as shown by the minimization problem above.

[85] The first order condition with respect to Λ_i is the following, $-\dfrac{s}{\sum \Lambda_{-i} + \Lambda_i} + 1 = 0$. Because firms are assumed to be symmetric in making the contribution decision and there are n firms, $\sum \Lambda_{-i} + \Lambda_i$ is equal to $n\Lambda_i$. Therefore, this first order condition is rearranged to be $1 = s/n\Lambda_i$.

transformation and linear approximation is as follows[86],

$$\ln \Lambda_i = \ln S + H \tag{4.6}$$

Proposition 2 summarizes the prediction.

Proposition 2 *All else equal, firms in an industry that is subject to a more stringent enforcement policy tend to contribute more to relax the emission limit.*

Then, I have the following Lemma based on Prosposition 1 in Chapter Three and Proposition 2.

Lemma 1 *Industries with larger absolute elasticities of the violation rate with respect to the inspection rate tend to contribute more.*

Here, the elasticity of the violation rate is a measure of responsiveness in the industrial pollution violation rate as a result of change in the inspection rate. As stated in the Proposition 1 in Chapter Three, if the enforcement agency maximizes social welfare subject to a hard budget constraint for its enforcement activities, the inspection rate will be higher in those industries with a higher elasticity of the violation rate. And as the industries are subject to more frequent inspections, they tend to contribute more. Consequently, the absolute elasticity of the violation rate is predicted to be positively associated with EPCI all else equal.

Equation 4.6 also shows clearly that the industry concentration measuring obstacles to collective action as indicated by H is an important factor of contribution, which is summarized in the following proposition.

Proposition 3 *The industry concentration affects the average contribution positively.*

[86] I estimate the log-log version of the first order condition as shown below, $\ln \Lambda_i = \ln s + \ln \frac{1}{n}$. Because firms are assumed to be symmetric, $H = \frac{1}{n}$. Then, the equation above becomes $\ln \Lambda_i = \ln s + \ln H$. In this work, I allow the industry concentration to enter the specification linearly as most empirical works do, and the specification becomes $\ln \Lambda_i = \ln s + H$.

4.3 Descriptive analysis of environmental political contribution

This section provides the methodology for constructing the environmental political contribution and summarizes its variation across industries. As argued, this serves as the evidence that the political pressure to distort the environmental policy exists, and will be used for estimating Equation 4.6 as the dependent variable.

4.3.1 Measuring environmental political activity

Many existing works have given insights into the candidate characteristics that political action committees prefer when they make funding decisions. As stated by Riddel (2003), many reduced-form models of PAC funding choice include legislator characteristics such as party affiliation, voting records, *committee membership*, seniority, and state-specific data pertaining to each legislator to explain contributions to candidates from various special interest groups such as agriculture, labor, and oil. In particular, Gardner (1995) argues that agriculture PACs target funds to where they have the highest payoffs. His results demonstrate the importance of the senate key committees. Agricultural PACs will contribute more to senators on key committees.[87] Similarly, according to Grier and Munger (1991, 1993), corporate, union, and trade association PACs target incumbents who win by moderate margins, have voted sympathetically, and *have seats on committees with jurisdiction over the PACs area of interest.*

Based on these insights, I first obtain the key House/Senate environmental committee/subcommittees whose jurisdictions are related with Environmental issues from the League of Conservation Voters. They include Subcommittee on Labor, Health and Human Services, Education, and Related Agencies in Committee on Appropriations; Subcommittee on Environment and Hazardous Materials in Committee on Energy and Commerce;

[87] Cotton interest groups contribute more to agricultural appropriations subcommittee members than they contribute to nonmembers.

Subcommittee on Energy and Resources in Committee on Government Reform; Committee on Resources; Subcommittee on Environment, Technology, and Standards in Committee on Science and Subcommittee on Water Resources and Environment in Committee on Transportation and Infrastructure. Then, from the U.S. Government Printing Office, I find the name lists of the members of each key House/Senate environmental Committee/subcommittee.

Second, each PAC is then matched against the COMPUSTAT database and various data sources to obtain its SIC code. This will be used for aggregation to the industry level.

Third, I collect the campaign contributions presented by each corporate PAC[88] to each member in the key committees/subcommittees. The amount of aggregated contribution by each corporate PAC to all the members in the key committees/subcommittees indicates the level of each corporate's political activity targeting on environmental issues. These data of campaign contributions are available in the Federal Election Commission.

Finally, I merged individual corporate PAC contributions with their SICs and then aggregated up to the four-digit industry level. Thus, the total environmental political contribution for each industry (the sum of the contributions received by all the candidates in the key environmental committees/subcommittees presented by the corporate PACs in this industry) is obtained. The total environmental political contribution is then divided by the number of PAC to calculate the environmental political contribution per PAC.

Because industries vary a lot in size, the environmental contribution is scaled by the number of paid employment. The data source of the number of

[88] Grier et al. (1994)[36] state: "It is useful to distinguish PACs sponsored by corporations and the trade association PACs that represent the same industry. corporate PAC contributions at the industry level are important in their own right for at least three reasons: first, trade associations are subject to the statutory limit of $10,000 per election cycle per candidate. Second, we address collective action directly, by explaining differences in industries' ability to overcome free-rider problems and induce corporations to act.; Since the pattern of contributions observed just one firm at a time could be consistent with either pure cooperation or purely atomistic behavior, we use the industry as the unit of analysis."

paid employment proxying the industry size is the 1997 Economic Census. This scaled environmental contribution is defined as Environmental Political Contribution Intensity ($EPCI$) in this paper and will be used as the main dependent variable.

The details of the data sources and methodology are presented in Appendix C.2.

Meanwhile, I calculate the total political contribution intensity (PCI) similarly. Although $EPCI$ is a better proxy of environmental political activity, PCI contains the information of $EPCI$ and will be used for comparison. $EPCI\_H$ is the intensity of the environmental political contribution to the candidates in the key House environmental committees/subcommittees.

The statistic analysis in this section is based on data covering four election cycles 1999'-2006'. It is noteworthy that I focus on the manufacturing sector (2000 to 3999 SIC code) only. This is not only because of the data richness, but also because a large share of the contributions are presented by the PACs in this sector. Specifically, the corporate PACs in manufacturing sector captures around 35 percent of the corporate PACs listed in the Federal Election Commission data and recorded with a SIC code in one election cycle.

4.3.2 Trend analysis

Table 11 shows the growth of campaign contribution per PAC.[89] The sample comprises 124 industries in the manufacturing group. Average contributions per PAC across industries have increased from around $50 thousand in 1999 to more than $80 thousand in 2006. Both the average environmental contributions per PAC, and those to the House candidates only, grow significantly. The largest environmental contribution per PAC by a single industry rises from $133500 to $229740[90].

[89] The environmental campaign contribution per PAC is not the dependent variable that will be used later. The dependent variable is the environmental campaign contribution intensity, which is the ratio of the EPC over the paid employment.

[90] The expenditures are not adjusted for inflation. This chapter focuses on the variations across industries, not those over time.

Table 4.1: Environmental Political Contribution to Congressional Candidates (124 Industries in Manufacturing Group)

Election Cycle (year)	Average Nonzero Contributions per PAC($)	Average Nonzero Environmental Contributions per PAC($)	Largest Single-Industry Environmental Contributions per PAC($)	EPC per PAC to Members in House Committees($)
1999-2000	53768.99	20225.72	133500	14447.62
2001-2002	52605.98	23266.94	170730.6	15736.58
2003-2004	64551.49	27344.44	202603.2	18741.86
2005-2006	82203.08	33345.63	229740	21640.89

There are 160 industries with EPC data available in the election cycle 2005-2006.[91] Table 4.2 lists the ranks of industries according to the total environmental contribution (EPC). These show the large variation across industries. Meanwhile, The mean value of EPC per PAC is 33345.63, and that of PC per PAC is 82203.08. This implies that about 40% of the total political contribution presented by a PAC is accounted as the contributions for environmental purposes. This is considered as the upper limit of the proportion of environmental political contribution in total political contribution. The reason is that the key environmental committee members may have positions in other committees so that the contributions could be presented for other purposes as well.

In sum, this section constructs the data on EPC to provide evidence that government cares about both the social welfare and EPC and trades political protection for EPC. Given this, the following studies what drives the variation of the environmental political contribution across industries.

4.4 Empirical specification and data sources

The reduced-form specification is established based on Equation 4.6, which suggests the central roles of the inverse elasticity of violation rate with respect to inspection rate $\frac{1}{\varepsilon}$ (via its effect on the inspection rate) and the industry concentration H in determining the environmental political contribution.

The estimation is based on the following specification:

$$\begin{aligned}\ln EPCI_{j,t} \quad = \quad & \alpha_1 \ln score_{j,t} + \alpha_2 \frac{1}{\varepsilon_j} + \alpha_{12}\left(\ln score_{j,t} \times \frac{1}{\varepsilon_j}\right) + \alpha_3 HHI_j \\ & + \alpha_4 PT\_rate_j + \alpha_5 ISO_j + \alpha_6 \ln EMP_j + \alpha_7 GC_{j,t} \\ & + \alpha_8 DI_{j,t} + \alpha_9 Group_j + \alpha_{10} Year_j + \varepsilon_j \end{aligned} \tag{4.7}$$

where $\ln score$ represents the natural log of the risk-weighted emission intensity, $\frac{1}{\varepsilon}$ is the reciprocal of the elasticity of the violation rate, HHI is the

[91] The ranks in other election cycles do not differ from those much.

Table 4.2: Industries in Manufacturing Group Ranked by Environmental Political Contribution Amounts, 2005-2006

5 Industries with the Most EPC (160 industries)	
Industry Name	EPC
2834 Pharmaceutical Preparations	2529469
2911 Petroleum Refining	1621337
3721 Aircraft	1148700
3812 SDNGAN Systems and Instruments	1118461
3711 Motor Vehicles and Passenger Car Bodies	1024220
5 Industries with the Least EPC	
Industry Name	EPC
3949 Toys and Sporting Goods	49
2741 Miscellaneous Publishing	700
3699 Misc. Electrical Equipment&Supplies	1000
3421 Cutlery, Handtools, and Hardware	1000
3569 General Industrial Machinery	1000

*1987 US SIC division classification

5 Industries with the Most EPCI (142 industries)	
Industry Name	EPCI
2021 Creamery Butter	81.28
2076 Vegetable Oil Mills, Except Corn, Cottonseed, and Soybean	43.55
2111 Cigarettes	28.3
2911 Petroleum Refining	24.76
2834 Pharmaceutical Preparations	22.50
5 Industries with the Least EPCI	
Industry Name	EPCI
3949 Toys and Sporting Goods	0.0007
2741 Miscellaneous Publishing	0.0089
3089 Plastics Products, NEC	0.01
3569 General Industrial Machinery	0.02
2657 Folding Paperboard Boxes, Including Sanitary	0.04

*1987 US SIC division classification

industry concentration, PT_rate is the ratio of the facilities that participate the voluntary program (performance track), ISO is the number of firms that voluntarily adopt the international standard ISO14001, EMP is the paid employment, GC is the geographical concentration, DI is the diverse industry, and $Group$ is the group fixed effect and $Year$ is the year dummies to capture the fixed year effects.

According to Lemma 1, I predict the coefficient of the inverse elasticity of violation rate $\frac{1}{\varepsilon}$ is positive. It is noteworthy that I am using the elasticity of the violation rate to infer the relationship between the enforcement policy and the political contribution level. That is, the enforcement policy does not appear in the regression directly. If I include the enforcement policy in the regression, it is hard to isolate the enforcement policy's effect from the environmental regulation's effect. Although the enforcement policy and the environmental regulation are determined by separate agencies, the two kinds of policies have many common determinants (e.g. the emission intensity). The correlation between the enforcement policy and the environmental political contribution may arise as a result of these common determinants.

As shown by the specification 4.7 above, I also control for the natural log of the risk-weighted emission intensity $\ln score$ and include its interaction term with the elasticity of the violation rate $\ln score \times \frac{1}{\varepsilon}$. The reasons are as follows.

The risk-weighted emission intensity *score* is defined as a measure of pollutants' potential damage to the environment and human health per unit of production. In the US EPA's Risk-Screening Environmental Indicators (RSEI Version 2.1.5),[92] RSEI contains "risk-related results", which imposes a risk score on industries at different SIC levels. The toxicity, surrogate dose, and population components are multiplied to calculate this risk score. It is used to assess the potential impact of industrial releases. The "risk-related results" are scaled by paid employment[93] and is denoted by "score"

[92] See Appendix B.2 for details. Data of the risk-weighted emission intensity is available with the SIC code.

[93] It can also be scaled by value added. The regression results are similar if EPC is also scaled by value added to calculate EPCI.

in this chapter[94]. The risk-weighted emission intensity can be regarded as the emission intensity weighted by the damage indicator (which is the potential damage per unit of emission).

The risk-weighted emission intensity has an effect on the environmental political contribution through two channels: the environmental regulation (the direct effect) and the enforcement policy (the indirect effect). For the direct effect, a damaging industry (an industry with a larger risk-related emission intensity) is more likely to be subject to a stringent environmental regulation (e.g. the pollution tax) directly. Then, this industry has incentives to contribute to the congress to relax the environmental regulation. For the indirect effect, if a damaging industry is subject to strict enforcement policies, a one-unit decrease in the pollution limit as a result of the political contribution can lead to a larger reduced sanction amount for this industry, so that this industry tend to contribute more. In this case, the overall effect of the risk-weighted emission intensity on the environmental political contribution is positive. However, if a damaging industry is subject to lax enforcement policies, this industry tend to make less contribution. And the overall effect of the risk-weighted emission intensity is ambiguous.

In order to investigate further when the effect of the risk-weighted emission intensity on the inspection rate is positive so that the effect of the risk-weighted emission intensity on the environmental political contribution can be identified, I add an interaction term of the risk-weighted emission intensity and the inverse elasticity in the estimation. In Chapter Three, it has been found that there exists a complementary effect between the damage indicator and the inverse elasticity in determining the inspection rate. Because the damage indicator is a key component of the risk-weighted emis-

[94] This is similar to the measure of environmental exposure in Antweiler (2003). It combines a firm's composition and toxicity of emissions and its location that determines the size of the population at risk with the firm's size and intensity of pollution. This measure of environmental exposure is utilized as one of firm characteristics to investigate its effect on firm's abatement effort. This effect is used to back out the effect of green regulatory threat which is not directly measurable. Because environmental exposure triggers regulation, it has been shown that the effectiveness of threat depends on environmental exposure of a firm. It also depends on abatement ladder rung of a firm and government's incentive scheme as argued in this paper.

sion intensity, it is hypothesized that the effect of the risk-weighted emission intensity on the inspection rate is conditional on the elasticity of the violation rate. The underlying mechanism is as follows: when the absolute elasticity of violation rate is large, the inspection of a damaging industry is effective. Although its inspection has to incur a higher inspection cost compared with the inspection of a less damaging industry, the inspection rate is higher for a damaging industry. In other word, the risk-weighted emission intensity is positively associated with the inspection rate, hence the environmental political contribution, when the absolute elasticity of violation rate is large. Otherwise, when the absolute elasticity of violation rate is small, the inspection is not effective and has to incur a higher cost. The enforcement agency may be reluctant to impose a strict enforcement policy. As a result, a damaging industry is not inspected more frequently than the less damaging industry. That is, the indirect effect is negative. As the indirect effect dominate the direct effect, a damaging industry may not make a larger contribution.

I describe the other variables used in the analysis as follows. The number of paid employees (EMP) is used to measure industry size and is from the 1997 Economic Census.[95] The 1992 Census of Manufactures report MC92-S-2, "Concentration Ratios in Manufacturing", is the data source for HHI (Herfindahl Hirschmann Index) that characterizes the industry concentration[96].

DI and GC may also impact the collective action to seek political influence because they are measures of the extent to which the industry has common interest. Measures of Diverse industry (DI) and Geographic Concentration (GC) were constructed as described by Grier, Munger and Roberts (1994). The number of segments is reported by each firm, up to a maximum

[95] The Economic Census profiles American business every 5 years and the 2002 data are available. However, the 2002 Economic Census is based on North American Industry Classification System (NAICS). Given the violation rate is based on SICs, the conversion of employment based on NAICS into that based on SICs may lead to some bias. The 1997 data are available in both NAICS and SICs. And since the employment number is used to control for industry size which is relatively stable over short periods, I choose the 1997 data.

[96] The 1997 data are available but are classified by NAICS instead of SIC.

of 10 in COMPUSTAT industrial segment file. The data were averaged by industry (mean=1.7, s.d.=0.65) and a diverse industry is defined as "one with mean number of products more than two s.d. above the sample average, that is, all industries whose firms average more than three products line are coded 1.0 and the others 0.00". Because the data vary little at 4-digit level, I compiled them into 3-digit level data. And the data cover the period of 1998-2006. Industries with greater product diversity have weaker common interests among firms within the industry, so we expect contributions to be lower. Geographic concentration is calculated as $\sum_i \left(\frac{Sales_i}{Sales}\right)^2$ for each industry where i denotes state. The data of sales (DATA12) in each state were collected from COMPUSTAT as well. GC is a measure of whether an industry has good alternatives to contributions as means of gaining political influence (e.g., lobbying, direct appeals to voters). If an industry is located entirely in a single state, its employees are an important voting block for legislators in that state. The expected sign for the coefficient on GC is negative, since votes can substitute for contributions.

I include PT_rate and ISO to take into account of the competition between opposing lobbies and pressures from other groups. Performance-track is a program that firms can voluntarily participate. The "Enforcement & Compliance History Online (ECHO)" publicly provided by the U.S. EPA records the facilities that are performance track members. The PT_rate is calculated as the ratio of the number of facilities the are performance track members in total facilities inspected within the last 5 years. Because the variation at the 4 digit is too small, I aggregate the data according to the SIC code to the 3-digit level. ISO is the number of firms that certify their environmental management system (EMS) to the international standard of ISO14001, scaled by the number of paid employees, and the data source is Darnall (2003).[97] The participation of the voluntary program and the adoption of voluntary standard are both indicators of firms'

[97]It is described in this paper that "lists of all ISO 14001-certified facilities (1996-1999) were obtained from Global International Quality Group and McGraw-Hill. In addition, the websites of state environmental agencies were searched for additional ISO 14001 certified facilities." However, I do not have the time series, and the data used in my work are the average values across industries only found in the descriptive statistics table of Darnall's.

voluntary abatement behavior. It has been argued that conflicts between industry and environmental group's pressure (such as green consumers and ecologist groups) are incentives, at least partly, for voluntary abatement behavior in the literature (e.g., Arora and Gangopadhayay, 1995; Vidovic and Khanna, 2007; and Blackman and Bannister, 1998). Thus, higher PT_rate and ISO are employed to measure higher level of political strategic competitions among lobby groups and greater pressure from environmental groups and the community. It implies that industries with more intense competitions and greater pressure have to contribute more.

The dataset combining information from several sources is summarized below in Table 4.3 and Table 4.4.

Table 4.3: Variable Definition and Data Sources III

Variable	**Description**	**Sources**
$EPCI$	$=\frac{\text{Environmental campaign contribution}}{\text{The number of paid employment}}$	FEC and various sources 4 election cycles over 99'-06'
PCI	$=\frac{\text{Total campaign contribution}}{\text{The number of paid employment}}$	FEC and various sources 4 election cycles over 99'-06'
$EPCI\_H$	$=\frac{\text{PC to candidates in the key House environmental committee}}{\text{The number of paid employment}}$	FEC and various sources 4 election cycles over 99'-06'
$score$	$=\frac{\text{Risk-related results}}{\text{The number of paid employment}}$	RSEI, 1996'-2005'
ε	A measure of responsiveness in the pollution violation rate as a result of change in enforcement policy	Chapter Two, no time series
w	$=\frac{\text{Production workers wages}}{\text{The value of industry shipments}}$	1996 ASM, 1996'
k	$=\frac{\text{New capital expenditures}}{\text{The value of industry shipments}}$	1996 ASM, 1996'
$Material$	$=\frac{\text{Cost of materials}}{\text{The value of industry shipments}}$	1996 ASM, 1996'
$Energy$	$=\frac{\text{Cost of purchased fuels and electric energy}}{\text{The value of industry shipments}}$	1996 ASM, 1996'
EMP	The number of paid employment	1997 Economic Census, 1997'
HHI	Industrial concentration normalized between 0 and 1	1992 Economic Census, 1992'
DI	=1 for a large number of product lines =0 for a small number of product lines	Industrial segment file in COMPUSTAT Grier et al.(1994), 1998'-2006', 3-digit
GC	$= \sum_i \left(\frac{\text{Sales}_i}{\text{Sales}}\right)^2$ (i: state)	COMPUSTAT, Grier et al.(1994), 1995'-2006'
PT_rate	$=\frac{\text{The number of facilities that are Performance Track members}}{\text{The number of facilities}}$	ECHO, 3-digit, no time series
ISO	$=\frac{\text{The number of firms that certify their EMSs to ISO14001}}{\text{The number of paid employment}}$	Darnall (2003), 2-digit, no time series

Table 4.4: Summary Statistics III

Variable	**Number of Observations**	**Mean**	**Standard Deviation**	**Minimum**	**Maximum**
Industry Concentration (HHI)	447	0.066	0.06	0.000056	0.297
Industry Diversity (DI)	3950	.04	.20	0	1
Industry Size ($\ln EMP$)	419	9.95	1.11	6.20	13.18
Geographic Concentration (GC)	5302	.40	.24	.09	1
Damage Score ($\ln score$)	3709	18.78	3.28	1.02	27.57
Inverse Elasticity of the Violation Rate($1/\varepsilon$)	111	-4.0	2.19	-11.3	-0.9
Environmental Political Contribution Intensity ($EPCI$)	563	2.86	7.00	.0007	81.28
Contribution Intensity (PCI)	607	7.26	18.65	.0007	213.74
House EPCI ($EPCI\_H$)	540	1.77	4.12	.0009	50.08
Performance-Track Member (PT_rate)	94	1.0	1.26	.019	7.17
ISO14001 (ISO)	20	.08	.05	.01	.18
Labor Share (w)	456	.11	.05	.01	.32
Capital Share (k)	450	.03	.03	.001	.34
Material Share ($Material$)	455	.50	.13	.17	.90
Energy Share ($Energy$)	455	.02	.03	.002	.21

4.5 Empirical results

The results are presented in Table 4.5. The three columns of Table 4.5 use different political activity measures as the dependent variables. They are $EPCI$ (Environmental Political Contribution Intensity: the sum of the campaign contribution amounts made to candidates in the key environmental committees weighted by the number of paid employment), $EPCI\_H$ (Environmental Political Contribution Intensity: the sum of the campaign contribution amounts made to candidates in the key HOUSE environmental committees weighted by the number of paid employment), and PCI (Political Contribution Intensity: the sum of the campaign contribution amounts weighted by the number of paid employment) respectively[98]. Although the dataset covers four election cycles for the dependent variable, 1999-2000, 2001-2002, 2003-2004 and 2005-2006, many of the independent variables are not time-varying. I use the pooled OLS and control for the year dummies. In all regressions, the political pressure (PT_rate and ISO), some industry heterogeneities ($\ln EMP$, GC, DI), and the group effect ($Group$) are controlled for.

In Column (1), I use the environmental political contribution intensity to measure the political activity and its natural log is the dependent variable ($\ln EPCI$). The result shows that the risk-weighted emission intensity $\ln score$ has a positive estimated coefficient on the environmental political contribution intensity and is strongly significant at the 1% level. The estimated coefficient on the reciprocal of the elasticity of violation $\frac{1}{\varepsilon}$ is negative and significant at the 1% level. Their interaction term $\ln score \times \frac{1}{\varepsilon}$ has a positive and significant estimated coefficient.

I calculate the net effect of the reciprocal of the elasticity of violation on EPCI first. The net effects are positive evaluated for most of the industries (around 87 percent). This is consistent with Lemma 1. In particular, at

[98] $EPCI\_H$ is a subset of $EPCI$ because the campaign contribution amounts made to candidates in the key Senate environmental committees are excluded. $EPCI$ is a subset of PCI because the campaign contribution amounts made to candidates that are not in the key environmental committees are excluded.

the sample mean level of $\ln score$[99], one standard deviation increase in the $\frac{1}{\varepsilon}$ would approximately increase the environmental political contribution intensity by 0.35.[100]

The effect of $\ln score$ on $\ln EPCI$ depends on the magnitude of the elasticity of the violation rate. That is, the net effect of $\ln score$ is conditional. It is calculated by using the estimated coefficients on $\ln score$ and $\ln score \times \frac{1}{\varepsilon}$. When the absolute elasticity of violation rate is large, the effect of $\ln score$ is positive. For example, one standard deviation increase in $\ln score$ at the median value of $\frac{1}{\varepsilon}$ would approximately increase $\ln EPCI$ by 0.024.[101] This shows that the net effect of the risk-weighted emission intensity at the median value of the inverse elasticity is positive. It implies that, for industries whose inverse elasticities are at the median value, the damaging industries are subject to more stringent environmental policy and inspections. They have incentive to make more contribution. When the absolute elasticity is small, the effect of $\ln score$ may become negative. For example, The estimated coefficient of $\ln score$ at the mean value of $\frac{1}{\varepsilon}$ ($= -4.0$, lower than its median value) is negative.

HHI's estimated coefficient is significantly positive at the 1% level, which is as predicted. When HHI is low, it implies this industry is less concentrated, so that the behavior of each firm is less noticeable. Hence, the free-rider problem is more serious and each firm contributes less. Furthermore, the large number of similar-sized firms complicates formation and enforcement of agreements over contribution strategies. That is, the cost of collective action is high. In addition, less concentrated industries do not have as much market power to earn maximal profits as highly concentrated industries. Less concentrated industries are not easy to overcome the difficulty in collective action and thus present little environmental political contribution. This result is consistent with the existing literature.

[99] The risk-weighted emission intensity has been scaled to keep its natural log positive.

[100] The calculation is as follows: $[-0.6 + 0.04 \times 19] \times 2.2 = 0.352$, where the sample mean of $\ln \rho$ is 19, the standard deviation of $\frac{1}{e}$ is 2.2

[101] The net effects were calculated as follows: $[0.15 + 0.04 \times (-3.57)] \times 3.28 = 0.024$, where $median(\frac{1}{e}) = -3.57$ and the standard deviation of $\ln score$ is 3.28.

In Column (2), I use the environmental political contribution presented to the key House environmental committees/subcommittees per PAC (scaled by the number of paid employment) to measure the political activity and its natural log is the dependent variable ($\ln EPCI\_H$). The House environmental committee members are 40% of the total committee members that accepted contributions from the listed PACs in the manufacturing group. The Senate has a higher ratio that is about 50% because many candidates are performing duties in multiple committees. That is, the contributions to the key Senate committee members are more likely to target on non-environmental issues than the contributions to the key House committee members. Nevertheless, the results are similar to that in Column (1) of Table 4.5 both in terms of the estimated magnitude and the significance level.

Column (3) reports the results when the total political contribution intensity is used as a measure of the environmental political activity. The dependent variable is $\ln PCI$. The estimated coefficients on $\frac{1}{\varepsilon}$ and $\ln score$ are not as significant as those in Columns (1) and (2). This suggests that EPCI is a better measure than PCI for finding evidence for Propositions 2 in this framework.

4.6 Robustness checks

I conduct five robustness checks based on the regression in Column (1) of Table 4.5 and report the results in Table 4.6. In column (1) of Table 4.6, the main determinant of the inspection rate $\frac{1}{\varepsilon}$ is omitted in the regression to focus on the effects of the industry concentration (HHI) and the risk-weighted emission intensity ($\ln score$) on the environmental contribution intensity ($\ln EPCI$). And the risk-weighted emission intensity ($\ln score$) is instrumented with the damage indicator ($\ln \rho$) and the input shares ($\ln wage$, $\ln material$, $\ln k$ and $\ln energy$) to alleviate its potential endogeneity problem. The estimated coefficients on $\ln score$ and HHI are both significant and positive. The magnitude of HHI's estimated coefficient is stable compared with those in Table 4.5. The R^2 is about 0.3, which is 0.1 less than

Table 4.5: Results of Environmental Political Contribution Intensities Regressions: Election Cycles of 2000, 2002, 2004 and 2006

	Dependent Variable is		
	$\ln EPCI$	$\ln EPCI\_H$	$\ln PCI$
Independent	Pooled OLS		
Variable	(1)	(2)	(3)
$\ln score$	.15***	.15***	.08
	(3.04)	(2.99)	(1.61)
$1/\varepsilon$	−.60***	−.54***	−.45**
	(−3.23)	(−2.93)	(−2.26)
$\ln score \times \frac{1}{\varepsilon}$	.04***	.04***	.03***
	(4.03)	(3.67)	(2.86)
$\ln EMP$	−.61***	−.61***	−.56***
	(−8.43)	(−8.26)	(−7.28)
HHI	4.37***	4.80***	6.31***
	(2.92)	(3.17)	(3.94)
DI	.18	.12	.54
	(0.56)	(0.37)	(1.56)
GC	−.15	−.28	.09
	(−0.42)	(−0.80)	(0.25)
PT_rate	.35***	.34***	.35***
	(5.52)	(5.34)	(5.12)
ISO	4.00***	4.72***	4.30***
	(2.65)	(3.08)	(2.68)
$Group$	.16	.26	.33
	(.83)	(1.34)	(1.59)
Year	Y	Y	Y
R^2	0.402	0.398	0.4583
Obs.	372	360	180

*** Significant at the 1% level, ** at the 5% level, and * at the 10% level (t statistics in parentheses) that in Column (1) of Table 4.5. This implies the important explanatory power of the inverse elasticity.

Column (2) presents the results using the random-effect estimation. I keep the key control variables only in the regression. The signs and magnitudes of the estimated coefficients on $\ln score$, $\frac{1}{\varepsilon}$, and $\ln score \times \frac{1}{\varepsilon}$ are similar compared with those in Column (1) of Table 4.5. This is not used as the baseline regression because many of the control variables do not have time series.

The estimation in Column (3) is the same as that in Column (1) of Table 4.5 except that PT_rate and ISO are omitted. The damaging industries may be more likely to participate the voluntary programs. This is to avoid their collinearity with $\ln score$. In Column (4), the sample is reduced to contain two election cycles (2003'-2004' and 2005'-2006'). In Column (5), I employ the weighted least squares. The weights are the value of shipments. The overall results are stable.

4.7 Conclusions

This chapter investigates the determinants of the firms' environmental political activity. I started with the data construction of the environmental political contribution (EPC), which is defined as the political campaign donations by firms exclusively for the purposes of environmental issues and is employed to measure firms' environmental political activity. The constructed dataset shows that the EPC changes over time and varies significantly across industries. I highlight three factors' roles in explaining the variation of the environmental political contribution across industries using the U.S. data: the industry concentration, the elasticity of the violation rate, and the risk-weighted emission intensity.

The empirical findings are summarized as follows. (1) The net effects of the absolute elasticity of violation rate on the environmental political contribution, evaluated at most industries' risk-weighted emission intensity levels, are positive. This implies that an elastic industry is subject to a higher inspection rate and tends to make more contributions. In particu-

Table 4.6: Robustness of Environmental Political Contribution Intensities Regressions

	Dependent Variable is $\ln EPCI$				
Independent	IV_OLS	Random	OLS	OLS(03'-06')	WLS
Variable	(1)	(2)	(3)	(4)	(5)
$\ln score$	.07**	.15**	.18***	.11	.11**
	(2.39)	(2.21)	(3.53)	(1.53)	(2.28)
$1/\varepsilon$		−.38*	−.80***	−.51**	−.48***
		(−1.65)	(−4.22)	(−2.05)	(−2.58)
$\ln score \times \frac{1}{\varepsilon}$		.03**	.06***	.04***	.04***
		(2.11)	(5.10)	(2.59)	(3.25)
$\ln EMP$	−.51***	−.41***	−.45***	−.69***	−.67***
	(−7.39)	(−3.38)	(−6.47)	(−6.58)	(−9.15)
HHI	5.71***	9.77***	6.63***	1.93	4.69***
	(4.44)	(3.65)	(4.37)	(.86)	(3.06)
DI	.13		.52	.50	.24
	(0.43)		(1.57)	(.78)	(.76)
GC	.26		−.08	−.27	−.20
	(.84)		(−0.23)	(−0.55)	(−.59)
PT_rate	.32***			.41***	.35***
	(5.31)			(4.58)	(5.35)
ISO	2.04			3.73*	2.91*
	(1.42)			(1.66)	(2.09)
$Group$	.43***	−.01	−.24	−.02	.03
	(2.6)	(−0.03)	(−1.34)	(−.05)	(.13)
$Year$	Y	Y	Y	Y	Y
R^2	0.291	0.307	0.341	0.406	0.407
Obs.	469	372	372	172	372

*** Significant at the 1% level, ** at the 5% level,
and * at the 10% level (t statistics in parentheses)

lar, at the sample mean level of the risk-weighted emission intensity, one standard deviation increase in the inverse elasticity would approximately increase the natural log of the environmental political contribution intensity by 0.35. (2) The net effect of the risk-weighted emission intensity is positive as long as the absolute elasticity of violation rate is large enough. One example is that one standard deviation increase in the natural log of the risk-weighted emission intensity would lead to a 0.024 increase in the natural log of the environmental political contribution intensity, evaluated at the median value of the inverse elasticity. (3) The industry concentration affects EPC (intensity) significantly and positively which is consistent with existing literature.

In addition, when I use the total political contribution as a measure of the environmental political activity, the significance levels of the estimated coefficients on some key independent variables are reduced. This suggests that the environmental political contribution constructed in this work serves as a better measure than the total political contribution in finding evidence for the roles of the elasticity of the violation rate and the risk-weighted emission intensity.

This chapter could be extended in the following ways. (1) Although the contribution takes effect at the industry level, an empirical examination of individual-firm contribution about the lobbying organization would be interesting. (2) This chapter considers politically organized and contributing industries only. If the complete data were collected, a probit equation could be used to identify which industry tends to be more politically active/inactive. This is because, as argued by previous works, it is possible that variables influencing whether firms in an industry establish a PAC correlate with those determining how much money that a PAC spends.

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Appendix A

Appendix to Chapter 2

A.1 The BLP model

In the demand function estimation in the empirical industrial organization, the goods characteristics and price determine each goods' mean value δ to consumers. The total value to individual consumer choosing one goods depends on this goods' mean value and consumer's individual taste which is assumed to follow an i.i.d. logit draw given infinite consumers.

Here, the mean values for choice between compliance and violation are different. That is, when a firm is in violation, the unit penalty is R_v, otherwise, it has to meet the effluent standard by investing the minimum R_c. The total value to an individual firm choosing to violate depends on R_v with the other violation utility ξ_v and its individual characteristics which is assumed to follow an i.i.d. logit distribution given infinite firms in one industry.

In the original BLP model, the market share for each goods is found. Then, each market share can be sorted over time or according to location as observations.

Similarly, in this modified model, I find the violation rate for each industry, then I control for industry characteristics to focus on the observations sorted by industries and over time.

The difference is that, one of the variation sources in the original model is the goods differentiation. Here, I just focus on one choice, the violation rate. That is, I do not study the compliance rate.

Table A.1: Comparision with the BLP Model

Consumer/Goods	a	b	$\cdots$	J
1	$\delta_a + v_{1a}$	$\delta_b + v_{1b}$	$\cdots$	$\delta_J + v_{1J}$
2	$\delta_a + v_{2a}$	$\delta_b + v_{2b}$	$\cdots$	$\delta_J + v_{2J}$
$\vdots$	$\vdots$	$\vdots$	$\vdots$	$\vdots$
n	$\delta_a + v_{nb}$	$\delta_a + v_{nb}$	$\cdots$	$\delta_J + v_{nJ}$

Industry	Firm	Compliance	Violation
i	1	$W_c^i + \gamma_{1c}^i$	$W_v^i + \gamma_{1v}^i$
i	2	$W_c^i + \gamma_{2c}^i$	$W_v^i + \gamma_{2v}^i$
$\vdots$	$\vdots$	$\vdots$	$\vdots$
i	n_i	$W_c^i + \gamma_{nc}^i$	$W_v^i + \gamma_{nv}^i$

A.2 Econometric model of the industry-level violation rate

Following Train (2003)[71], I show how to derive the equation of aggregate violation rates at industry level in the difference of the welfares and to calculate the elasticities of violation below.

Probability of choosing to violate for firm l in industry I is the following according to γ's density function,

$$\Pr_{i,lv} = \Pr(F_{lvt} > F_{lct})$$
$$= \Pr(W_{vt} + \gamma_{lvt} > W_{ct} + \gamma_{lct})$$
$$= \Pr(\gamma_{lct} < W_{vt} - W_{ct} + \gamma_{lvt})$$
$$= e^{-e^{-(W_{vt}-W_{ct}+\gamma_{lvt})}}$$

As a result, the violation rate in industry i is the following,

$$VR_{it} = \int_{-\infty}^{\infty} \Pr(F_{lvt} > F_{lct}) e^{-\gamma_{lvt}} e^{-e^{-\gamma_{lvt}}} d\gamma_{lvt}$$
$$= \int_{-\infty}^{\infty} e^{-e^{-(W_{vt}-W_{ct}+\gamma_{lvt})} - e^{-\gamma_{lvt}}} e^{-\gamma_{lvt}} d\gamma_{lvt}$$
$$= \int_{-\infty}^{\infty} e^{-e^{-\gamma_{lvt}}\left(e^{-(W_{vt}-W_{ct})}+1\right)} e^{-\gamma_{lvt}} d\gamma_{lvt}$$
$$= \int_{0}^{\infty} e^{-\mu\left(e^{-(W_{vt}-W_{ct})}+1\right)} d\mu$$

where $\mu \equiv e^{-\gamma_{lvt}}$, as $\gamma_{lvt} \to \infty$, $\mu \to 0$, and as $\gamma_{lvt} \to -\infty$, $\mu \to \infty$.

$$= -\frac{e^{-\mu\left(e^{-(W_{vt}-W_{ct})}+1\right)}}{e^{W_{vt}-W_{ct}+1}} \Big|_0^{\infty}$$
$$= \frac{1}{e^{-(W_{vt}-W_{ct})}+1}$$

$$
\begin{aligned}
&= \frac{e^{W_{vt}}}{e^{W_{ct}}+e^{W_{vt}}} \\
e &= \frac{\partial VR}{\partial IR_{vt}} \frac{IR_{vt}}{VR} \\
&= \frac{\partial \frac{e^{\beta_1 IR_{i,vt}+\xi_{ivt}}}{e^{\lambda IR_{i,ct}+\xi_{ict}}+e^{\beta_1 IR_{i,vt}+\xi_{ivt}}}}{\partial IR_{vt}} \frac{IR_{vt}}{VR} \\
&= IR_{vt} \frac{\partial W_{vt}}{\partial IR_{vt}} (1 - VR) \\
&= IR_{vt} (1 - VR) \beta_1
\end{aligned}
$$

A.3 Data of the inspection rate and the violation rate

Inspection number In ECHO (All Data), I search by the following criteria: a four-digit SIC code in Facility Characteristics; "within 5 years since last inspection" in Inspection/Enforcement History. The result is a list of facilities that were inspected within last five years. In each facility's detailed report, "Compliance Monitoring History" lists the dates for each inspection. A facility could be inspected from zero to multiple times in a year. I count them by years. For example, if there is a "State Conducted FCE/On-Site" on 08/22/2006, the inspection number in 2006 is increased by 1. Then, for each year, the inspection numbers of all facilities listed in the search result are summed up as the inspection number in that year for this industry.

Inspection type The Detailed Facility Report includes inspections which were conducted within the last five years. Some inspection types are included in official counts, but italicized inspection types are not part of EPA official counts. In this thesis, I only consider the official counts such as FE - EPA Conducted FCE/On-Site and FZ - EPA Conducted FCE/Off-Site. For a detailed list, please refer to the section "Compliance Monitoring History" in http://www.epa-echo.gov/echo/dfr_data_dictionary.html#ih.

Violation number In ECHO (All Data), search by the following criteria: a four-digit SIC code in Facility Characteristics; "within 5 years since last inspection" in Inspection/Enforcement History; "formal enforcement actions within 5 years" in Inspection/Enforcement History. The result is a list of facilities that were inspected and were subject to formal enforcement actions within last five years. In each facility's detailed report, "Formal Enforcement Actions" lists the dates for each formal enforcement action. I count them by years. For example, if there is a "State Administrative Order Issued" on 08/10/2007, the violation number in 2007 is increased by 1. Then, for each year, the violation numbers of all facilities listed in the search result are summed up as the violation number in that year for this industry.

Formal enforcement actions Enforcement actions under the Clean Air Act, Clean Water Act, Resources Conservation and Recovery Act, Emergency Planning and Community Right-to-know Act Section 313, Federal Insecticide, Fungicide, and Rodenticide Act, and Toxic Substances Control Act are all included, such as CWA 404 Penalty AO Class I Init, Administrative Order, and Judicial. For the detailed list of the action types, please refer to http://www.epa-echo.gov/echo/dfr_data_dictionary.html#cea.

I do not include the Notices of Violation or Informal Enforcement Actions. As indicated by the EPA, "in many cases, a notice of violation causes a facility to correct problems and return to compliance. Many notices of violation are not escalated to formal enforcement action because the facility quickly corrects the problem(s) indicated in the notice.".

A.4 First stage results of 2SLS in Table 2.3

Independent Variable	Column (1) IR	Column (1) lnEI	Column (2) IR	Column (2) lnEI	Column(3) IR	Column(3) lnEI
IR_IV	$.79^{***}$	1.18^{***}	$.69^{***}$	2.16^{***}	$.91^{***}$	$-.09$
	(17.55)	(2.70)	(13.02)	(3.86)	(24.16)	(-0.44)
lnEMP	$-.01$	$-.32^{**}$	$-.01$	$-.31^{**}$		
	(-1.03)	(-2.50)	(-1.27)	(-2.50)		
lnwage	$-.05^{*}$	$-.18$	$-.05^{**}$	$-.15$		
	(-1.81)	(-0.73)	(-2.34)	$(sl{-0.61})$		
lnmaterial	$.13^{***}$	3.48^{***}	$.13^{***}$	3.56^{***}		
	(2.77)	(7.50)	(3.02)	(8.06)		
lnk	$.07^{**}$	1.69^{***}	$.07^{**}$	1.69^{***}		
	(2.22)	(5.54)	(2.51)	(5.79)		
lnenergy	$.05^{**}$	.28	$.06^{***}$	.17		
	(2.43)	(1.30)	(3.21)	(0.82)		
HHI	$.63^{***}$	-2.81^{**}	$.64^{***}$	-2.71		
	(2.73)	(-2.50)	(3.10)	(-1.24)		
DI	$-.05$	.66	$-.06$	1.20	$-.03$	$-.01$
	(-0.88)	(1.22)	(-0.84)	(1.65)	$(-0.63$	(-0.04)
GC	$.11^{**}$	.032	$.11^{**}$	.08	$-.12$	.50
	(2.20)	(0.06)	(2.34)	(0.16)	(-0.89)	(0.66)
Group2	$-.05$	-1.96^{***}	$-.03$	-2.07^{***}		
	(-1.55)	(-6.89)	(-1.35)	(-7.58)		
Year2004	.03	$-.22$	$.04^{*}$	$-.36$	.01	$-.03$
	(1.59)	(-1.31)	(1.75)	(-1.46)	(0.60)	(-0.48)

*** Significant at the 1% level, ** at the 5% level, and * at the 10% level
(t statistics are in parentheses)

Appendix B

Appendix to Chapter 3

B.1 Proof of equation 3.4

By maximizing Ω subject to the constraint, I have

$$\frac{\partial \Omega^A}{\partial p_i} = t_i v_i + p_i t_i \frac{\partial v_i}{\partial p_i} - \rho_i \frac{\partial v_i}{\partial p_i} - t_i v_i - \lambda e \left(v_i + p_i \frac{\partial v_i}{\partial p_i} \right) = 0 \tag{B.1}$$

Because $\xi_i = \dfrac{\partial v_i}{\partial p_i} \dfrac{p_i}{v_i}$ is the elasticity of the violation rate with respect to the inspection rate, it is plugged into the equation above and Equation (B.1) can be simplified to the following,

$$\xi_i t_i v_i - \rho_i \frac{\xi_i v_i}{p_i} = \lambda e \left(v_i + \xi_i v_i \right) \tag{B.2}$$

That is,

$$\frac{t_i p_i - \rho_i}{p_i} = \lambda e \left(1 + \frac{1}{\xi_i} \right) \tag{B.3}$$

B.2 Risk-screening environmental indicators

The data used to calculate ρ are from U.S. EPA's Risk-Screening Environmental Indicators (RSEI Version 2.1.5). This model is a screening-level tool that assesses the potential impact of industrial releases from pounds-based, hazard-based, and risk-related perspectives. It uses risk concepts to screen large amounts of Toxics Release Inventory (TRI) data (1996-2005 TRI data). RSEI considers the following information: the amount of chemical released, the toxicity of the chemical, its fate and transport though the environment, the route and extent of human exposure, and the number of people affected.

Table B.1: Industries at the Four-Digit SIC Level Ranked by Average Values of the Damage Indicator over 2003'-2005' (410 Industries)

Five most damaging industries		
SIC	**Industry**	ρ
3312	Steel Works, Blast Furnaces (Including Coke Ovens), and Rolling Mills	3493272
2869	Industrial Organic Chemicals, NEC	2445291
3585	Air-Conditioning and Warm Air Heating Equipment and Commercial and Industrial Refrigeration Equipment	1606799
2911	Petroleum Refining	1253189
3443	Fabricated Plate Work (Boiler Shops)	955570.6

Five least damaging industries		
SIC	**Industry**	ρ
2448	Wood Pallets and Skids	0.108
3451	Screw Machine Products	0.107
2259	Knitting Mills, NEC	0.086
3952	Lead Pencils, Crayons, Artists' Materials	0.044
2385	Waterproof Outerwear	0.017

Risk-related results: the toxicity, surrogate dose, and population components are multiplied to obtain a risk score for the Indicator Element.

Pounds-based results: these results include only the pounds of releases reported to TRI.

What should be noted is that the values are for comparative purposes and only meaningful when compared to other values produced by RSEI.

Detailed information and related analyses can be found on the website: http://www.epa.gov/oppt/rsei.

Appendix C

Appendix to Chapter 4

C.1 Background

The process of environmental policy creation is the same as those of other policies. A proposal may be introduced in Congress as a bill (or joint resolutions), which addresses the environmental issue and provides potential solutions for the problem. Each bill can be introduced by any member of Congress and has to go through several stages to come into laws. First, the bill is considered by standing committees whose jurisdictions are over this environmental issue. They investigate the details of these proposals, collect evidence and vote to decide whether the bill should be reported to the full house. Second, the full house debate and amend the bill once it is reported by the standing committees. The bill can not become law unless it is approved by both houses. Lastly, a bill that passes both houses becomes a law if the president agrees to sign it.[102] Given this process of policy creation, it is regarded that special interest groups could exert political pressure on congress members to influence the policy outcome. Table 1 lists some of the environmental bills and whether they failed or passed.

[102]If the President choses to take no action, the bill can also automatically becomes law after ten days. See details from http://en.wikipedia.org/wiki/United_States_Congress.

Table C.1: Selected Vote Description

Year	**Senate/House**	**Bill**	Note
2008	S	S.2191 The Climate Security Act	Failed
2008	H	H.R.5351 The Renewable Energy and Energy Conservation Tax Act	Passed
2007	S	H.R.6 A Comprehensive Energy Legislation	Failed
2007	H	H.R. 2643 The Interior-Environment appropriations bill	Passed
2005	S	H.R. 2361 The Interior Appropriations Bill	Passed
2005	S	S.J. Res. 20 A resolution	Failed
Sources: "National Environmental Scorecard", League of Conservation Voters			

Description:

Bill S.2191: To cut global warming pollution and drive rapid investment in the clean energy economy. The bill allowed major polluters to choose the most cost-efficient way to reduce pollution and buy pollution allowances to cover each ton of pollution that they continue to emit.

Bill H.R.5351: To extend the tax credit for wind and other renewables by three years and reinstated expired credits for commercial and resident building.

Bill H.R.6: To raise automobile fuel efficiency standards to 35 miles per gallon by 2020. To establish new energy efficiency standards for appliances and federal buildings etc.

Bill H.R.2643: The Clean Air Act requires many of the largest emitters of toxic air pollutants to reduce their emissions by the maximum degree possible. The EPA proposed a rule change that would allow polluters to sidestep the requirement if they release less than 10 tons per year of a single pollutant or less than 25 tons per year of combined pollutants. This bill is to deny funds for implementing the proposed rule change.

Bill H.R.2361: Chemical companies seeking pesticide approvals from EPA have submitted data from dozens of experiments in which human were intentionally dosed with these toxic chemicals. EPA have imposed a moratorium on considering such test. This bill is to create a one-year moratorium prohibiting EPA from using any of its funds to consider or conduct research that intentionally expose humans to pesticide.

Bill S.J.Res.20: Coal-burning power plants are the largest U.S. source of mercury pollution. Rather than enforce the Clean Air Act, which requires all power plants to reduce their mercury emissions by 2008, the Bush Administration in March 2005 issued a rule that delays meaningful reductions for another two decades and encourages power plants to buy and sell mercury pollution credits. A bipartisan groups of Senators introduced a resolution to reject the EPA rule.

C.2 Data of environmental political contribution

This appendix provides the data sources and methodology I employ in calculation of environmental political contribution. Part of descriptions are cited from the sources directly for accuracy.

C.2.1 Members of key House/Senate environmental committee/subcommittee

(1) The list of key House/Senate environmental committee/subcommittee is from League of Conservation Voters (http://www.lcv.org/president-and-congress/house and http:// www.lcv.org/president-and-congress/senate). The League of Conservation Voters is a national organization working full time to hold members of Congress accountable for their environmental votes. It provides description of the jurisdiction of the key committees/subcommittees with respect to environmental issues.
(2) The U.S. Government Printing Office (http://www.gpoaccess.gov /cdirectory/browse.html) contains the congressional directory, which is the official directory of the U.S. Congress prepared by the Joint Committee on Printing. It presents short biographies of each member of the Senate and House, listed by state or district, and additional data, such as committee memberships. Two files are used to collect the names of the members of the key environmental committees/subcommittees: "Standing Committees of the House" and "Standing Committees of the Senate".

With these two data sources, I compile a dataset containing the names of the members of the key House/Senate environmental committees/subcommittees. ("Name file")

Take data in election cycle 2003-2004 for example (data over other election cycles are similar). There are 234 candidates in the key environmental committees/subcommittees out of 3553 candidates.

C.2.2 Campaign contribution

In the website of the Federal Election Commission (http://www.fec.gov/finance/disclosure/ftpdet.shtml), there are three files that are used in this work for each election cycle. I list them below and some descriptions are cited from the website directly for accuracy:

(1) The committee master file contains one record for each committee registered with the Federal Election Commission. The file contains basic information about the committees, including the ID number the Commission assigned to the committee and the name of the committee.

(2) The candidate master file contains one record for each candidate who has either registered with the Federal Election Commission or appeared on a ballot list prepared by a state elections office. The file contains basic information about the candidate, including name and the ID number assigned to the candidate by the FEC which is used in tracking campaign finance information about the campaign.

(3) The itemized committee contributions file contains each contribution or independent expenditure made by a PAC, party committee, candidate committee, or other federal committee to a candidate during the two-year election cycle. It includes the ID number of the contributing committee and the ID number of the recipient.

The committee master and candidate master files are used in conjunction with the itemized committee file to set up a relational database. They are merged according to the committee ID number and the candidate ID number respectively.

C.2.3 SIC code

There are various data sources used to search for the SIC code for each committee listed in the committee master file according to the name of the committee (usually a company name), e.g. COMPUSTAT, siccode.com, and websteronline.com. This data collection is difficult for the following reasons: multiple sources were used; and each committee may be assigned two or more SIC codes because of multiple production lines. However, it still contains information that can be explored across industries. ("SIC file")

Take data in election cycle 2003-2004 for example (data over other election cycles are similar). Of the totally 1759 corporate PACS, the SIC codes are found for 1280 PACs, in which 470 PACs belong to the manufacturing group.

C.2.4 Data summary

In order to obtain the complete dataset, (a) I compile the "SIC file" with the committee master file and only keep the corporate committees. (b) I use the "name file" to label the candidates in the key committees/subcommittees in the candidate master file. These labelled candidates are kept for study. (c) The arranged files in (a) and (b) are merged with the itemized committee contributions file. Then, this dataset contains the following information for each corporate committee: the corporate committee' ID, its SIC code, the contribution amounts of the candidates that are in the key committees/subcommittees and receive contributions from this corporate committee. This is the raw dataset that can be summarized at the four-digit industry level and scaled by the industry size to calculate the environmental political contribution intensity.