ABSTRACT

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Directed By: Professor Erik Lichtenberg
Department of Agricultural and Resource Economics

Understanding the potential link between environmental regulations and economic activities is crucial to both the regulated industries and policy makers. This dissertation explores three key questions in order to understand environmental regulations and their impacts. 1) How to measure environmental regulatory burden? 2) What are the impacts of environmental regulations on competitiveness? 3) What are the determinants of regulatory stringency?

The theory of the Pollution Haven Effect (PHE) predicts that tightening up environmental regulations will affect regulated industries' competitiveness and trade flows. In the first part of this dissertation, I construct a measure from pollution abatement costs (PAC) to quantify the changes in regulatory stringency and empirically test PHE while controlling for firm dynamics and industry composition. Previous studies have used PAC as a measure for environmental regulations. I build a theory model to show that regulation-induced changes in abatement costs contain an extensive margin (i.e. cost change due to changes in industry composition) in addition

to the intensive margin (i.e. cost change for a fixed set of firms). Results from decomposition analysis confirm that, compared to the intensive margin, overall changes in PAC underestimate changes in regulatory stringency and may further lead to overestimated PHE. I then use the two margins as separate explanatory variables to explain the US's net imports from Canada, Mexico and the rest of the world. Estimation results indicate that PHE driven by the intensive margin is smaller than that estimated previously, which corrects the overestimation of using overall abatement costs.

The second part of this dissertation empirically explores the determinants of regulatory stringency in the context of the US water pollution regulations. I argue that state regulators use facilities' compliance performance to infer their abatement efforts and technology in order to implement the technology-based and water quality-based control of the National Pollutant Discharge Elimination System (NPDES) permits. Results from econometric analyses confirm that regulators make permitting decisions based on information inferred from compliance history as well as that discovered during inspection activities. Self-disclosed violations are regarded as a signal for cooperation (i.e. adequate abatement effort under technology constraint) and will be rewarded with relaxed future permits. Non-cooperating behaviors, such as absent monitoring reports, improper operation and maintenance as detected during inspections and violations that lead to high penalties will likely result in more stringent future limit. In addition, regulators will also modify the limit levels in response to local water quality. Taken together, these results indicate that the regulators aim to ensure a certain water quality standard by inducing higher abatement efforts within the constraint of best available technology.

ESSAYS ON THE ECONOMICS OF ENVIRONMENTAL REGULATIONS

By

Fanqing Ye

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Advisory Committee:

Professor Erik Lichtenberg, Chair
Professor Roberton C. Williams III
Professor Kenneth E. McConnell
Professor Charles Towe
Professor Gerrit J. Knaap

To my parents and my husband

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Table of Contents

List of Tables

List of Figures

Chapter 1: Introduction

Environmental regulations aim to protect environmental quality and solve problems rising in the relationship between the environment and the economy. Environmental consequences of industrial and residential activities (e.g. pollution) are classic examples of negative externality where the costs are borne by the entire society. The fundamental theoretical foundation of environmental regulations lies in providing incentives for the economic agents to internalize the externality. In the US, environmental regulations cover almost all aspects of unintended environmental consequences, including reducing air and water pollution, controlling toxic releases, and conservation of natural resources, to name a few (US EPA, 2012a).

One major concern of environmental regulations is that they may impose significant costs on the regulated firms and industries and harm their competitiveness in the domestic and global markets (Becker, 2005; Jaffe et al., 1995). For example, economic analyses on the impacts of environmental regulations suggest that regulations may slow employment, investment and productivity (Greenstone, 2002). These negative effects may further create an incentive for plants to strategically choose their locations across states and even relocate to developing countries with lax environmental regulations (Becker & Henderson, 2000; Ederington et al., 2005; Gray & Shadbegian, 2002) . It is crucial to understand whether or to what extent environmental regulations have undermined the competitiveness of the regulated industries in order to inform the scope and stringency of the regulations. Despite a sizable literature in the past decade, the direction and magnitude of environmental regulations' impacts on competitiveness have remained a debatable empirical question. The first objective of this dissertation is to provide empirical evidence for the hypothesis of the "Pollution Haven Effect" (PHE) (Copeland & Taylor, 2004), or the impacts of environmental regulations on international competitiveness.

In order to correctly quantify the economic impacts, a crucial first step is to find an appropriate measure for changes in environmental regulatory stringency. Economists have been using the pollution abatement cost (PAC) as a proxy for regulatory stringency (e.g. Morgenstern, Pizer, & Shih, 1998). PAC involves the cost of purchasing, installing and operating equipment in order to prevent and reduce the level of pollution (U.S. Bureau of the Census, 1977). This measure is desirable for a number of reasons. First of all, PAC provides a comparable and consistent measure of regulatory stringency so that we can compare regulations across different industries and countries and over time. Secondly, PAC provides a quantitative and continuous measure which is able to capture the phase-in of many regulation programs. Finally, PAC captures the effect of enforcement and compliance of regulations. Stringency of a regulation depends on how much it is enforced, which is the actual burden on the regulated parties. The PAC measure is widely used by economists trying to quantify the economic impacts of environmental regulations (e.g. Ederington et al., 2005; Levinson & Taylor, 2008). In this dissertation, I examine whether PAC is an appropriate measure to evaluate the competitiveness implications of environmental regulations. Under the circumstances of firm-heterogeneity and industry composition change, aggregate PAC may fail to fully capture the change in environmental regulatory stringency.

Observing increasing abatement costs and potential loss of competitiveness, a natural question to ask is what should be the optimal level of regulation and what factors drive the change of regulatory stringency. For a command and control system, theoretical models show that the optimal regulatory strategy should be one that minimizes social costs given the regulated firms minimize private costs (Cohen, 1999). Despite a great deal of theoretical endeavor, little empirical evidence exists on the determinants of regulatory stringency. A final objective of this dissertation is to explore the question of environmental standard setting and to provide empirical evidence in the context of the water pollution regulations in the US.

To address the abovementioned issues, the remainder of this dissertation is organized as follows. In Chapter 2, I explore: 1) how to measure environmental regulations? and 2) what are the impacts of environmental regulations on international trade flows, or PHE? To answer the first question, I build a simple theory model to show that regulation-induced changes in abatement costs contain an extensive margin (cost change due to changes in industry composition) in addition to the intensive margin (cost increase for a fixed set of firms). Using abatement cost data from the US manufacturing industry, I perform a decomposition analysis to empirically identify these intensive margins, which more accurately represent the effects of regulation changes on abatement costs. The overall change in the aggregate abatement cost is shown to under-measure the change in regulatory stringency. To explore the second question of the empirical validity of PHE, I use the intensive and extensive margins as separate explanatory variables to explain the US's net imports from Canada, Mexico and the rest of the world. Estimation results indicate that PHE driven by the intensive margin is smaller than previously estimated. This demonstrates that using the intensive margin corrects the overestimation of PHE as in previous studies.

In Chapter 3, I explore the determinants of regulatory stringency in the context of the National Pollutant Discharge Elimination System (NPDES) permit program under the Clean Water Act (CWA). I propose that the regulatory standards are determined by regulators' perception of plants' abatement effort and technology inferred from the past performance. Using data from the US chemical manufacturing industry, I find that the regulators (permitting authorities) are trying to decide an optimal limit to induce the highest effort under the capacity of best available technology. They further use past environmental performance, including different types of violations and enforcement actions, together with findings from inspection activities to infer the level of effort and technology capacity. Nevertheless, the ultimate goal of the NPDES program is to protect local water quality. The permitting decisions will therefore depend on the water-quality based control when the technology-based control is not sufficient to protect a water body for its designated use.

Finally I summarize the findings of this dissertation and discuss contributions and policy implications in Chapter 4.

Chapter 2: Firm heterogeneity, industry composition change and the Pollution Haven Effect

2.1 Introduction

Understanding the potential link between environmental regulations and economic activities is crucial to both the regulated industries and policy makers. There are concerns that stringent environmental regulations may impose significant costs and harm the regulated industries' competitiveness in the global market (e.g. Jaffe et al., 1995). The theory of "Pollution Haven Effect" (PHE) predicts that *"tightening up of pollution regulation will, at the margin, have an effect on plant location decisions and trade flows"*(Copeland & Taylor, 2004). The direction and magnitude of PHE remains an important empirical question. Previous studies that aim to empirically assess PHE have generated mixed results (Ederington et al., 2005; Jaffe et al., 1995; Levinson & Taylor, 2008). Notably, most of these studies have been using the pollution abatement cost (PAC) as a measure for regulatory stringency of environmental policies. However, industry-level PAC may fail to capture the full effect of regulation changes due to firm-heterogeneity and changes in the industry structure. In fact, various empirical papers as well as theoretical models have documented that firms are differentiated and may respond differently to changes in regulations (Heyes, 2009; Millimet et al., 2009). Environmental regulations may, among others, favor firms of different sizes, change entry conditions, and affect market competition. Industry level compliance costs may thus fail to fully capture the change in regulatory stringency because the composition of the manufacturing industry has changed.

My research aims to explore theoretically and empirically the effect of environmental regulations represented by PAC on international trade flows, controlling for the presence of firm-heterogeneity in abatement abilities and changes in the industry structure. To understand changes in environmental regulations, I setup a heterogeneous firm model which shows that regulation-induced changes in industry-level abatement costs contain two components: an intensive margin (cost change for a fixed set of firms) and an extensive margin (cost change due to changes in industry composition led by firm entry and exit as well as expansion and shrinkage of existing firms). I further use decomposition analysis to empirically identify these intensive margin effects, which more accurately represent the effects of regulation changes on abatement costs, from the extensive margins.

Using the abatement cost and output data from the US manufacturing sector at 4-digit Standard Industrial Classification (SIC) level for the period from 1977 to 1986, I show that the intensive margin effects differ substantially from the aggregated changes in PAC. These results indicate that aggregating industry-level PAC likely underestimates the full effects of changes in regulatory stringency of environmental policies. The impacts of environment regulations on trade flows are therefore overestimated when the undervalued regulation change is used as the explanatory variable in testing PHE.

To re-examine PHE, I use the intensive and extensive margins of abatement costs as separate explanatory variables to explain changes in the US's net imports from Canada, Mexico and the rest of the world. Results from fixed effects estimations suggest that abatement cost change at the intensive margin and the extensive margin may lead to different or even opposite PHE. Specifically, the intensive margin has a positive and statistically significant impact on net imports, which supports the PHE hypothesis. As the composition change is controlled for by including the extensive margin, the magnitude of PHE driven by the intensive margin is smaller than previously estimated, which corrects the overestimation as in previous studies. To the best of my knowledge, this study is the first to systematically study the effects of environmental regulations on trade flows while controlling for changes in industry structure.

The remainder of this chapter is organized as follows. Section 2.2 reviews previous work on the economic impacts of environmental regulations, and explains why changes in industry structure may cause PAC to be an inaccurate measure of regulatory stringency. Section 2.3 describes a theoretical framework to show the existence and magnitude of the intensive and extensive margins of PAC. Section 2.4 presents empirical evidence from decomposition analysis using the industry level data. I separate the intensive and extensive margins to empirically estimate PHE in Section 2.5 and conclude in Section 2.6.

2.2. Literature review

2.2.1. The Pollution Haven Effect

In addition to rising compliance cost, tightening up regulations may also lead to, among others, loss of employment, capital stock and final output (Greenstone, 2002). Firms may relocate to countries or regions with lax regulations to avoid extra costs associated with such regulations. Those unable to move may suffer from a competitive disadvantage compared with their global competitors. In either case we may expect to observe an increase in trade flows from the less regulated places to the more regulated regions (Copeland & Taylor, 2004).

Pollution abatement expenditure per unit of output has been widely used as a measure of regulatory stringency in PHE literature (see for example Ederington & Minier, 2003; Levinson & Taylor, 2008). The main reason for this popularity is due to the difficulty to compare regulatory stringency using specific constraints given various environmental standards that different firms and industries have to meet. The abatement cost provides a comprehensive and comparable measure of regulatory stringency across firms and industries. In addition, the abatement cost captures not only changes in regulations per se but also the severity of enforcement of the regulations, as well as legal and political battles (Joshi et al., 2001). After all, the stringency of regulations is determined by the extent to which they are actually enforced. In addition, the abatement cost as a quantitative and continuous measure also captures the phase-in of many regulations over time and provides ease in conducting statistical analyses.

To date, there is a sizable literature that empirically examines the existence and magnitude of PHE by testing the impact of regulations on international trade flows. Copeland and Taylor (2004) provide an extensive survey of the trade and environment literature. Earlier research has examined the relationship between variations in trade flows and regulatory costs using cross sectional data, but most studies of this type find no supporting evidence of PHE (e.g. Grossman & Krueger, 1993). Common with studies using cross-sectional data, these studies suffer from the endogeneity problem that arises as unobserved industry characteristics or government policy making affect trade flows and environmental costs at the same time. Under these circumstances, net imports and PAC are determined simultaneously, which may lead to insignificant or even counterintuitive results when testing PHE.

Recent papers attempt to control for endogeneity by using either the instrumental variable or structural equation approach. Ederington and Minier (2003) model US net imports and environmental regulations as determined by a simultaneous equation system, where the level of environmental regulations in an industry as a function of trade flows, tariffs, and a vector of political-economy variables. In both equations, regulatory stringency is measured using PAC of 4-digit SIC industries from 1978 to 1992. Controlling for both simultaneity and cross-equation correlations of disturbances in the model, their 3-stage least squares (3SLS) implementation yields a statistically significant and fairly large impact of environmental costs on trade flows.

Using environmental costs as a measure for the stringency of environmental regulations, Ederington et al (2005) discuss and empirically test a couple of potential reasons that have led to mixed results in the PHE literature. After controlling for the issues like regulation similarity, mobility, and relative importance of PAC, they find a significant effect of PAC on net imports for the following cases, 1) trade transactions between developed and developing countries, 2) industries with high pollution intensity, and 3) footloose industries, defined as industries with higher mobility and lower fixed costs. More recently, Levinson and Taylor (2008) develop a theoretical model of environmental costs and international trade, and demonstrate how unobserved heterogeneity, endogeneity, and aggregation issues prevent previous studies from detecting PHE. In their empirical analyses, the authors use weighted average of states' characteristics as instruments for PAC in order to control for the issues identified in the theoretical model. Using data on PAC and US trade with Canada and Mexico for 130 manufacturing industries from 1977 to 1986, Levinson and Taylor (2008) find that industries facing increasing abatement costs experienced significant increases in net imports. Although briefly mentioning that using aggregate abatement cost may lead to a biased measure of regulation change, the authors make no effort to examine this issue in more detail.

2.2.2. Impacts of environmental regulations on the industry structure

By using the industry average PAC as a proxy for regulatory stringency to test the impacts of environmental regulations on international trade flows, the PHE literature makes two implicit assumptions so that changes in PAC can fully reflect changes in regulatory stringency. Firstly, firms within an industry respond to changes in regulations in an identical way - they will use the same pollution control method and exert the same level of abatement efforts to meet the new regulation requirement in order to have the same level change of PAC. Secondly, it is implicitly assumed that there is no intra-industry reallocation in terms of production and market share, and thus each firm fully absorbs the impacts of regulation changes. However, these two assumptions may not be the case under many circumstances.

With the availability of micro-level data since the 1990s, various empirical studies using plant or firm level data have demonstrated the existence of large and persistent productivity differences among firms in the same narrowly defined industry (Bartelsman & Doms, 2000; Melitz, 2003; Tybout, 2000). Not only firms are heterogeneous, they respond differently to changes in regulations which will result in a new equilibrium of the market structure. Millimet et al. (2009) provide an extensive discussion of theoretical studies analyzing the potential effect of environmental regulations on the market structure through changes in production costs. These models allow endogenous entry and exit, but assume identical/symmetric firms, and abstract from economies of scale and technological innovation. The universal conclusion is that under certain conditions, tighter regulation discourages entry, induces exit, and has a negative impact on the equilibrium number of active firms (e.g. Farzin, 2003; Lahiri & Ono, 2007; Requate, 2005). Focusing on market competition, Heyes (2000) finds that environmental regulations may favor large firms, increase entry barriers and may encourage predatory behavior by incumbents.

On the empirical side, a handful of papers have examined firm dynamics and changes in the industry structure following changes in environmental regulations. Dean et al. (2000) demonstrate that the greater stringency of environmental regulations discourages small business formations, but has no effect on the formation of large plants. Focusing on the attainment/non-attainment designation of the air quality regulation, Becker and Henderson (2000) find that the tougher regulation in the non-attainment area favors the less regulated single-plant firms while creating an incentive for the larger plants to relocate to the attainment areas with less stringent regulations. Ollinger and Fernandez-Cornejo (1998) find greater sunk costs encourage firms to expand in order to bear the regulatory burden. Those unable to do so suffer a loss in profitability and are ultimately forced to exit the industry. In the same spirit, Snyder et al. (2003) examine the impacts of tighter regulations on chlorine-manufacturing plants and find that tightening up regulations accelerates plant closures, which further lead to a market share increase by cleaner firms. Using panels of plants from the Census of Manufactures, Gray and Shadbegian (2003; 2002) specifically examine differences in the impacts of regulations across different plants in the pulp and paper industry. Both papers provide direct evidence of significant heterogeneity across firms in productivity levels and their sensitivity to regulatory stringency.

Findings from the above literature suggest that 1) firms are heterogeneous within even a very narrowly defined industry, and will respond to changes in regulations differently, and 2) changes in environmental regulations together with firm-heterogeneity may lead to intra-industry reallocation. In the following sections of this chapter, I develop a firm-heterogeneity model and show that tightening up environmental regulations will induce the heavily polluting, high abatement cost firms to contract or even exit the market, while the relatively low cost firms to stay in the market and expand. The asymmetric composition change within the industry prevents the industry level PAC from fully capturing effects of changes in the environmental regulatory stringency.

2.3. A model of firm heterogeneity in abatement efficiency

Consider a narrowly defined industry that consists of a continuum of heterogeneous firms. Each firm uses capital and labor to produce an intermediate output F and generates pollution Z as a joint output. Under the pressure of environmental regulations, each firm chooses a fraction of F for abatement activities in order to reduce the level of pollution. The setup of firms choosing a fraction of F for abatement closely follows Copeland and Taylor (2003). I expand the standard Copeland and Taylor model by adding firm-heterogeneity in abatement efficiency. Within each narrowly-defined industry, firms are differentiated only in their productivity in the abatement process, denoted by η. And the final output y is the level of output left after the abatement activity (Equation 2-1).

$$y = (1 - \theta)F(K, L)$$

$$Z = g(F, \theta;\ \eta) \qquad (2-1)$$

In practice, there are various sources that can lead to firm-heterogeneity in the abatement process and abatement costs. For example, large firms may have higher level of η and lower per unit abatement cost compared with small firms due to economies of scale, or because they can afford the cost of research and development for better abatement technologies. In addition, firms may be at different stages of a learning curve complying complex environmental regulations. The more experience a firm has in pollution control activities and dealing with regulations, the better they perform at choosing abatement technologies and using them more effectively. Firms may also be able to lower the transaction cost in the administrative process complying with a certain regulation as they become more experienced, e.g. the cost associated with applying for a water discharge permit is much higher for the first time than renewing one afterwards.

Consider the properties of the pollution level $Z = g(F, \theta;\ \eta)$. Pollution is increasing and convex in potential output F, meaning the more a firm produces the higher level of pollution it will generate, and at a higher speed ($g_F > 0, g_{FF} > 0$). On the other hand, the more a firm devotes the intermediate product to abatement activities, the lower level the pollution is left ($g_\theta < 0$). An important feature of this model is $g_\eta < 0$, which implies that a firm with higher abatement efficiency will have lower level of pollution, all else equal. Now assume pollution regulation is in the form of a pollution tax[1]. Each firm chooses its output level and the input share for abatement in order to maximize its profit, which is equal to the revenue left after paying pollution tax, variable production cost and fixed cost.

$$\max_{y,\theta} \quad py - t * g\left(\frac{y}{1-\theta}, \theta;\ \eta\right) - c^F \frac{y}{1-\theta} - f \qquad (2-2)$$

Optimal level of choice variables:

$$y^* = -\frac{tg_\theta(tg_F + c^F)}{p^2}$$

$$\theta^* = 1 - \frac{(tg_F + c^F)}{p} \qquad (2-3)$$

Firms' profits are increasing in abatement ability within a certain industry, as suggested by Equation 2-4[2]. This is straightforward from the setup of the model---because firms of the same industry are only differentiated in their ability to abate, different levels of pollution and thus compliance cost is the only factor that differentiates firms in the profitability.

$$\frac{d\pi^*}{d\eta} = \left.\frac{d\pi^*}{d\eta}\right|_{y=y^*,\theta=\theta^*} = -tg_\theta|_{y=y^*,\theta=\theta^*} > 0 \qquad (2-4)$$

Assume that in a given industry, the spectrum of differentiated firms has abatement productivity within the range $\eta \in [\eta_L, \eta_H]$. For the industry to be non-trivial, assume

[1] Change of the tax to either a pollution cap or a standard will not change the results qualitatively.
[2] Equation 2-4 is obtained by the Envelope Theorem.

that the most abatement productive firm in the industry has a positive profit, i.e. there will exist at least one firm with $\eta_H$such that $\pi(\eta_H) > 0$[3]. When an industry is in equilibrium, the least productive firm active in the industry has abatement productivity level η_L such that $\pi(\eta_L) = 0$. Thus η_L is the zero-profit cutoff value of productivity, such that any firm that has productivity below this value will immediately exit.

In the dynamic version of the model, a fraction of firms enter and exit the market randomly in each and every period. At the beginning of each period, there is a large pool of potential entrants with productivity level ranging $\eta \in [\widetilde{\eta_L}, \eta_H]$ and each has a probability p_1 of entering the market. Note that only the firms with productivity level above the cutoff value will actually enter the market and start production. For every existing firm, there is a probability of death p_2 in every period, irrespective of its productivity, due to idiosyncratic shocks.

In the steady state, a fraction p_2 of the existing firms randomly exit the market every period. At the same time, there is a constant inflow of potential entrants with $\eta > \eta_L$ to replace those exit. In the steady state equilibrium, the inflow equals the outflow ($p_1 = p_2$), so that the average productivity levels of entering and exiting firms are equal (Equation 2-5). This leads the average industry-level productivity to remain the same in each period.

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[3] Positive profit is possible in equilibrium here because firms are differentiated within the industry.

$$\int_{i \in Entry} \eta_i p(\eta) d\eta = \int_{i \in Exit} \eta_i p(\eta) d\eta \qquad (2-5)$$

To examine the impacts of regulations on the industry dynamics, consider the case of tightening up environmental regulations, which raises compliance costs and reduces profits for all firms[4]. The reduction in profitability will thus raise the requirement on the abatement productivity to maintain a zero profit, as suggested by Equation 2-6[5].

$$\frac{d\eta_L}{dt} = -\frac{g(\eta_L)}{tg_{\eta_L}} > 0 \qquad (2-6)$$

Therefore, the increase in regulatory stringency results in a new zero-profit cutoff η_L' with $\eta_L' > \eta_L$. Any existing firms with the productivity level below the new cutoff, $\eta_L \leq \eta < \eta_L'$, will be forced to shut down. It also raises the entry requirement in terms of abatement productivity, i.e. potential entrants with productivity level $\eta_L \leq \eta < \eta_L'$will no longer be able to enter and stay in the market. More stringent environmental regulation will therefore reallocate resources and the market share toward more abatement efficient producers by inducing only the more productive (in the abatement process) firms to survive and expand, the less productive firms to shrink and exit the market, and at the same time by allowing only the more abatement productive potential entrants to actually enter the market. The entry of more abatement-efficient firms and exit of less efficient firms thus cause an intra-industry

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[4] Profit is decreasing in environmental tax: $\frac{d\pi^*}{dt} = \frac{\partial \pi^*}{\partial t}\Big|_{y=y^*,\theta=\theta^*} = -g\left(\frac{y^*}{1-\theta^*}, \theta^*; \eta\right) < 0$

[5] Equation 2-6 is obtained by total differentiating the zero-profit condition.

composition change, where resources are reallocated towards more abatement-productive, low abatement cost firms.

Now consider the following measure, the industry level PAC per unit of value added (Equation 2-7). As reviewed in Section 2.2, this ratio is widely used as a proxy of regulatory stringency in the empirical literature examining the impact of environmental regulations on international trade flows. Here PAC is measured as θ times total production cost as each firm devotes a share θ of their total inputs for abatement. Value added is by definition the value of output less the value of input.

$$\varphi = \frac{\int_{\eta_L}^{\eta_H} PAC\, d\eta}{\int_{\eta_L}^{\eta_H} VADD\, d\eta} = \frac{\int_{\eta_L}^{\eta_H} \left(\theta c^F \frac{y}{1-\theta}\right) d\eta}{\int_{\eta_L}^{\eta_H} (py - c^F F)\, d\eta} \qquad (2-7)$$

To see whether φ can actually reflect the changes of regulatory stringency, I will examine in further detail of the expression $\frac{d\varphi}{dt}$, which is the change in PAC caused by a marginal change in environmental tax. The results in Equation 2-8 show that changes in the aggregate level PAC led by a change in the emission tax includes two components: 1) an intensive margin λ_0, i.e. the abatement cost change if all firms would survive and there were no composition change; and 2) the extensive margin $\lambda_1 * \frac{d\eta_L}{dt}$, which depends on how the cutoff productivity will change in response to the regulation change, and indicates the cost change due to firm entry and exit, and the resultant industry expansion and shrinkage (see Appendix A. for derivations).

$$\frac{d\varphi}{dt} = \lambda_0(p,t,c^F;\eta_H,\eta_L) - \lambda_1(p,t,c^F;\eta_H,\eta_L)\frac{d\eta_L}{dt} \qquad (2-8)$$

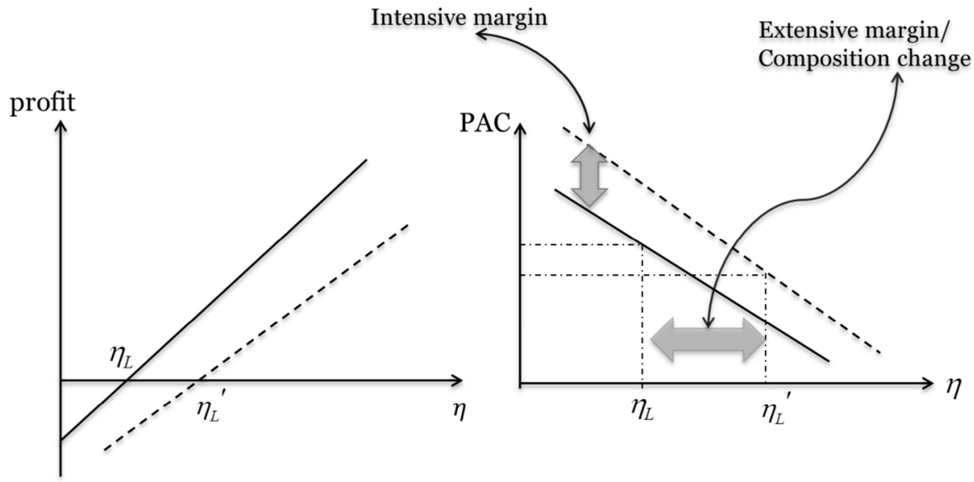

Figure 2-1. Intensive and extensive margins of abatement cost change

The aggregate level abatement cost, which is a mix of the two margins, may understate the change in regulatory stringency if the extensive margin offsets some of the intensive margin effect. To see whether this is the case, take an increase in pollution tax for example. The PAC of each firm, and thus the industry-wide PAC, will rise due to increase in regulatory stringency (the intensive margin). At the same time, existing firms with low efficiency and high abatement cost will be forced to shut down. Similarly, potential entering firms with relatively low efficiency and high cost will no longer be able to enter the market (while as they were able to enter before the regulation change). At the same time, only the high efficiency, low abatement cost firms will survive and expand. The extensive margin will therefore lead to a decrease in the average PAC in an industry as the market share is allocated to the more abatement efficient and low abatement cost firms (Figure 2-1). Therefore, the industry level PAC does not rise as much as it should in order to reflect the actual change in regulations. The above analysis also implies that the existence of the extensive margin may cast doubts on the empirical results in the previous literature that uses the aggregate level PAC in testing PHE.

2.4. Empirical evidence from decomposition analysis

In this section, I use decomposition analysis to empirically identify these intensive margin effects, which more accurately represent the effects of changes in regulations on cost, from the extensive margin effects. The basic methodology of decomposition analysis is to separate the total change of an economic variable into the impacts of a couple of factors that affect the variable of interest, by allowing only one factor to change at a time while holding all others constant. To examine the change in the abatement cost, I decompose the aggregate cost change into the change for a fixed set of industries and that due to changes in the industry structure. In recent years, decomposition analysis has gained its popularity among energy and environment economists to analyze the change of the industrial energy intensity and pollution emissions (e.g. Ang & Zhang, 2000). The goal of decomposition in these studies is to separate the changes of the energy intensity or pollution reduction in each sector, those associated with the industry structure shift, and any technological progress (Ang & Zhang, 2000; Levinson, 2009; Selden et al., 1999).

2.4.1. Methodology

For any aggregate *n*-digit SIC sector, the change in the abatement cost per unit of output can be decomposed into two changing factors: 1) cost intensity change at *m*-digit SIC sub-industry level (with *m>n*, i.e. *m*-digit SIC is at a more disaggregated industry level), which corresponds to the intensive margin; and 2) change in the composition of industries, or the structure of the sector, which corresponds to the extensive margin[6]. Firms' entry and exit will alter the relative importance of industries and lead to industry expansion and contraction. I use the share of value added[7] to denote the relative importance of each industry.

The goal of this analysis is to explain the change in PAC/value added (PAC/VA) in an *n*-digit SIC sector, *k*, which contains several *m (m>n)* digit SIC industries. The aggregate cost intensity is denoted as the weighted average of the cost intensity at the disaggregated industry level, using the share of value added as weights. Further let $\sigma_{jk}^{t} = \frac{VA_j}{VA_k}$ denote the share of value added of a certain *m*-digit industry *j* in *n*-digit SIC industry at time *t*, where $VA_k = \sum_j VA_j$. And let $\varphi_j^t = \frac{PAC_j}{VA_j}$ denote the PAC per unit in industry *j* at time *t*. The change in PAC/VA in aggregate industry *k* is $\sum_j \sigma_{jk}^{t}\varphi_j^t - \sum_j \sigma_{jk}^{t-1}\varphi_j^{t-1}$.

[6] With firm-level data, the decomposition analysis can be applied at firm-to-industry level. I perform the decomposition at a more aggregated level (4-digit to 3-digit and 2-digit SIC level) due to data constraint. These results should be indicative of what is happening at a higher level of disaggregation.
[7] The two terms "share of value added" and "output share" are used interchangeably in the rest of the chapter to refer to the same concept.

The annual abatement cost change at the aggregated sector is represented by the difference between the weighted average of the sector's cost intensities across two years. The relative importance of industries, which may be altered by firm entry/exit and industry expansion/shrinkage, is denoted by the share of value added. As shown in Equation 2-9, the total cost change *D* can then be decomposed additively to the intensive margin at before change output share, the extensive margin at before change abatement cost intensity, and an interaction term[8].

Total cost change:

$$D = \sum_j \sigma_j^t * \varphi_j^t - \sum_j \sigma_j^{t-1} * \varphi_j^{t-1} = D_{int} + D_{ext} + D_{interaction} \qquad (2-9)$$

Intensive margin: $D_{int} = \sum_j \sigma_j^{t-1} * \left(\varphi_j^t - \varphi_j^{t-1}\right)$ $\qquad (2-10)$

Extensive margin: $D_{ext} = \sum_j (\sigma_j^t - \sigma_j^{t-1}) * \varphi_j^{t-1}$ $\qquad (2-11)$

Interaction term: $D_{interaction} = \sum_j (\sigma_j^t - \sigma_j^{t-1}) * (\varphi_j^t - \varphi_j^{t-1})$ $\qquad (2-12)$

The measure of D_{int} calculates the intensive margin effect at before-change output shares by holding each industry's share of value added constant at time *t-1*. As shown in Equation 2-10, it calculates what the PAC change would be if all 4-digit industries had produced last year's output and generated the concurrent abatement costs. By holding the relative contribution of each industry unchanged, D_{int} shows only the

[8] This decomposition is analogous to the product rule in calculus where $d(\sigma * \varphi) = \sigma * d\varphi + \varphi * d\sigma + d\sigma * d\varphi$.

intensive margin of changes in PAC, and is thus indicative of the direction and magnitude of the change in the environmental regulatory stringency.

On the other hand, the extensive margin D_{ext} shows the change in PAC/VA due to changes solely in output shares, and is calculated as the level of PAC that would have been if each industry had generated last year's cost intensity, allowing only the industry composition (measured as share of value added) to change. It provides an answer to the question that if the abatement cost intensity of each industry remains the same as last period, what would be the aggregate cost intensity change due solely to the change industry mix.

Finally, the last term is the interaction of the intensive and extensive margins. More specifically, the interaction is the difference between two "intensive" changes, evaluated at the before-change composition $\sum_j \sigma_j^{t-1}(\varphi_j^t - \varphi_j^{t-1})$ and the after-change composition $\sum_j \sigma_j^t(\varphi_j^t - \varphi_j^{t-1})$, respectively. This interaction term captures the dynamic effect of the cost intensity and the industry composition changing simultaneously. This dynamic effect is missing from the two static effects, D_{ext} and D_{int}, as they are both calculated using the before-change year as the base year.

2.4.2. Data and descriptive statistics

I perform the above decomposition analysis using the data from the survey of Pollution Abatement Costs and Expenditures (PACE) combined with the data on other industry characteristics from 1977 to 1986. The PACE survey is conducted by the Bureau of Census, and draws from a probability sample of manufacturing firms/plants based on frames created from the previous years' Census of Manufactures and Annual Survey of Manufactures (U.S. Bureau of the Census, 1977). The PACE survey collects data on capital expenditures and operating costs related to pollution abatement. Pollution abatement operating costs (PAOC) contain depreciation, labor, materials and supplies, services and equipment leasing, and other costs related to operating and maintaining equipment for pollution treatment and prevention. Capital expenditures are used for purchasing and installing devices to abate pollutants through either end of line (EOL) technique or through changes in production process (CIPP). The survey results are published on the Current Industrial Reports, which report abatement capital expenditures and operating costs, and separately for different media (air, water, solid waste) as well as for hazardous/non-hazardous pollutants (U.S. Bureau of the Census, 1977). For various reasons listed in Appendix B, I use only the operating costs in decomposition analysis as they are more reliable. In addition, the decomposition process requires the data to be a balanced panel. Missing values in PAC thus pose a major challenge. Assuming these data are missing at random, I interpolate the missing data using the average cost intensity at higher levels of aggregation. The process of data interpolation is described in Appendix C.

Two issues may affect over time comparison of the abatement costs and expenditures. The PACE survey was conducted annually from 1977 to 1994 (except year 1987). After a redesign, the survey was continued to collect cost information in 1999, and was redesigned and conducted again in 2005. Due to substantial changes made during the last two surveys, a historic comparison to earlier surveys was difficult[9]. Another issue relates to the definition of an industry. The Office of Management and Budget (OMB) updated SIC classification in 1987 and the SIC codes changed substantially. For all these reasons mentioned above, I use only the survey data up to year 1986 in this study to keep consistency. (More issues related to the PACE survey are discussed in Appendix B.)

Besides the abatement cost information, data on other industry characteristics come from the NBER-CES Manufacturing Industry Database, which is a joint effort between the National Bureau of Economic Research (NBER) and the Center for Economic Studies (CES) at the U.S. Census Bureau. This database contains information on inputs, outputs, investment and productivity measures for all 4-digit manufacturing industries from 1958-1996, and are available in both SIC72 and SIC87 versions (Bartelsman et al., 2000). This database was constructed using data from multiple official sources including mainly the Census of Manufactures (CM) and Annual Survey of Manufactures (ASM).

Table 2-1 presents summary statistics for data used in the decomposition analyses. Variables of interest include PAOC, value added, PAOC per dollar of value added, and output share, of 4-digit SIC industries in 2-digit and 3-digit sectors, for the 345 4-

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[9] "…*these changes prevent direct comparisons to earlier surveys.*" PACE 1999 report, introduction, page v.

digit SIC industries from 1977 to 1986[10]. The absolute value of pollution abatement expenditures exhibit substantial variations across industries, which is mainly due to the sizes of the industries. After normalizing by the output level, the abatement cost intensity still varies substantially across industries. Tables 2-1 and 2-2 suggest per unit abatement cost over value added is 1.4% on average for the manufacturing industry, but range from 0.2% for the printing and publishing industries (SIC code 27) to 6.6% of the primary metal industries (SIC code 33).

Table 2-1. Summary statistics for 4-digit SIC industries, 1977-1986

Variable	Definition	Mean	Std. Dev.	Obs.
paoc_va4	pollution abatement cost/value added	0.014	0.071	3428
paoc4	pollution abatement costs, 4-digit SIC, $1m	26.227	112.202	3428
paoc3	pollution abatement costs, 3-digit SIC, $1m	84.731	176.106	3428
paoc2	pollution abatement costs, 2-digit SIC, $1m	579.541	629.393	3428
vadd4	value added, 4-digit SIC, $1m	2259.031	3417.656	3428
vadd3	value added, 3-digit SIC, $1m	8240.804	7131.201	3428
vadd2	value added, 2-digit SIC, $1m	58223.400	31331.070	3428
weight3	share of value added of a 4-digit in 3-digit industry	0.344	0.313	3428
weight2	share of value added of a 4-digit in 2-digit industry	0.050	0.090	3428

Table 2-2. Average PAOC/VA for 2-digit SIC sectors, 1977-1986

SIC code	Industry	PAOC/value added (sort from high to low)
33	Primary metal industries	0.066
29	Petroleum and coal products	0.036
28	Chemical and allied products	0.030
26	Paper and allied producs	0.020
32	Stone, clay, glass products	0.013
20	Food and kindred products	0.010
24	Lumber and wood products	0.008
21	Tobacco products	0.008

[10] Excluding miscellaneous manufacturing industries (SIC 39).

22	Textile mill products	0.007
34	Fabricated metal products	0.005
30	Rubber, miscellaneous plastics products	0.005
36	Electric, electronic equipment	0.005
37	Transportation equipment	0.004
25	Furniture and fixtures	0.003
38	Instruments, related products	0.003
35	Machinery, except electrical	0.003
27	Printing and publishing	0.002

Figure 2-2 shows PAC as a share of value added for the whole manufacturing sector from 1977 to 1986, and provides some evidence of the existence of the extensive margin effect. This graph follows Figure 2 in Levinson and Taylor (2008). I expand their graph by showing the trend at a more disaggregated industry (4-digit SIC) level. The top line plots PAC as a share of value added over time, holding the composition of 4-digit SIC industries fixed as in year 1977[11]. The top line is best interpreted as the intensive margin as it shows the impact of changes in regulations on a fixed set of 4-digit industries. The second line from the top plots PAC/VA over time while holding the composition of 3-digit industries fixed at the base year 1977, and it suggests what PAC would have been if these industries and the share of each industry had remained unchanged. This second line thus represents the intensive margin at the 4-digit level plus the extensive margin among 4-digit industries (or the extensive margin within 3-digit industries). Similarly, the third line from the top represents the intensive margin, plus the extensive margin within 3-digit industries and 2-digit industries. And finally,

[11] More specifically, each point corresponds to weighted average PAC per unit of value added at different levels of aggregation, i.e. $\sum_{j \in industry_{1977}} \sigma_j^{1977} \varphi_j^t$, where *t* is the current year.

the line at the bottom plots PAC/VA for the whole manufacturing sector, and it is the sum of the intensive margin plus the extensive margin at all levels of aggregation.

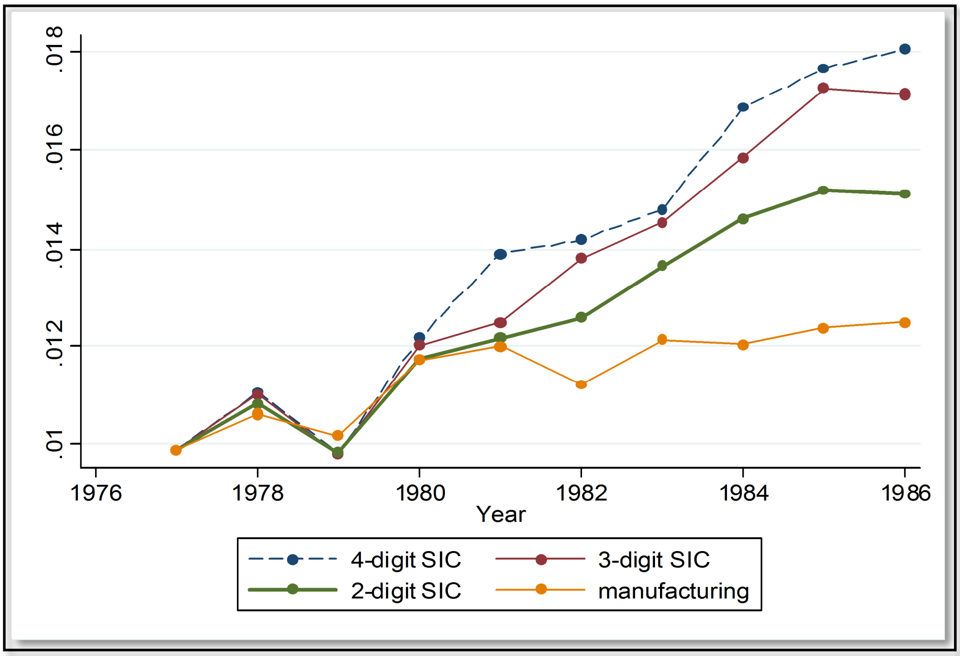

Figure 2-2. Pollution abatement cost as a share of value added, 1977-1986

The pattern in Figure 2-2 is indicative for the hypothesis that the aggregate level PACE data may understate the change in regulatory stringency due to the existence of the extensive margin. As regulatory stringency is gradually tightening up, the more polluting, high abatement cost firms and industries shrink while the lower cost firms and industries expand. Aggregate pollution abatement costs end up rising much less than what it should have been because the composition of industries has changed.

2.4.3. Decomposition of the abatement cost intensity

Using the methodology outlined in Section 2.4.1, I decompose the PAC change at the

2-digit SIC sectors using the production and abatement cost data from the 4-digit SIC industries. Table 2-3 presents the decomposition results at the 2-digit to 4-digit SIC level. I calculate the annual change of the weighted average PAC/VA compared to the previous year, using as weights of the share of value added of each 4-digit SIC industry in the 2-digit SIC sector. All changes are expressed as a percentage of the mean PAC/VA value in the previous year, which is presented in Column 1 of Table 2-3. Columns 2 to 5 present the average of the overall change, intensive margins, extensive margins and the interaction term respectively.

The interpretation of these results is straightforward from the methodology. Take the year 1981 for example. The pollution abatement cost as a share of value added increased about 4% for an average 2-digit SIC sector compared to 1977. It is premature to conclude that this change in PAC correctly proxies the magnitude of regulation changes. Actually the increase of PAC/VA should have been 10% if the mix of the industries is held the same as in the previous year. However, with the high PAC firms dropping out and industries shrinking, and the surviving firms and industries (together with the firms that just entered) have a cost advantage compared to those that exit. This change in the composition of industries leads to a 6% decrease (the extensive margin and interaction term together) in the observed sector-wise PAC. Thus the composition change offsets some of the intensive margin of the total abatement cost change, leading the total change to be underestimated.

Table 2-3. Decomposition results for 2-digit SIC sectors (annual change), 1977-1986

Year	Mean paoc_va2	Total change	Intensive margin	Extensive margin	Interaction term

1977	0.0108				
1978	0.0118	8.75%	11.19%	-1.64%	-0.80%
1979	0.0102	-13.58%	-15.11%	3.45%	-1.92%
1980	0.0125	23.05%	26.62%	-1.49%	-2.08%
1981	0.0130	4.04%	10.29%	0.06%	-6.31%
1982	0.0138	5.64%	12.65%	0.08%	-7.09%
1983	0.0152	10.15%	9.72%	1.30%	-0.87%
1984	0.0172	13.20%	20.08%	-2.30%	-4.58%
1985	0.0175	1.96%	4.15%	-0.45%	-1.75%
1986	0.0173	-1.44%	0.63%	-1.00%	-1.07%

To further examine the variation of cost change across the 20 2-digit SIC industries, I present the decomposition results for each of those industries over years 1977 to 1986. Table 2-4 presents the mean of changes of abatement cost intensity (weighted average PAC/VA) over the years 1977 to 1986 for each of the 2-digit SIC industries. Again, these numbers are all expressed as a share of the average PAOC/VA value of 1.4% to facilitate understanding of the magnitude. Almost all industries experienced abatement cost increase over the study period and there exisit considrable variations among different industries, from 0.6% for the tobacco products industry (SIC 21) to more than 400% for the petroleum and coal industry (SIC 29). Again, I further decompose this cost change to the intensive, extensive margin and the interaction term using the 4-digit SIC data. If the industry composition had remained the same as in the year 1977, the weighted average of PAC would have increased even more (Column 2).The extensive margin effect offsets some of the cost increase by altering the mix of industries. More likely than not, firms in the relatively highly polluting industries shut down or lose market share to their competitors as the environmental regulations are tightening up over the years.Therefore the overall industry structure has shifted toward a cleaner mix of firms and industries.

Table 2-4. Decomposition results by 2-digit SIC sectors, 1977-1986

2 digit SIC code	Total change	Intensive margin	Extensive margin	Interaction term
20	14.30%	17.30%	0.10%	-3.10%
21	0.60%	6.80%	-2.00%	-4.10%
22	20.90%	25.40%	-1.40%	-3.10%
24	23.00%	19.70%	0.30%	3.10%
25	17.60%	16.90%	-1.10%	1.80%
26	18.30%	27.50%	-4.00%	-5.20%
27	3.10%	2.70%	0.10%	0.30%
28	34.10%	88.80%	-27.10%	-27.70%
29	405.20%	491.70%	-35.20%	-51.30%
30	16.60%	18.90%	-0.20%	-2.10%
32	19.00%	26.00%	-4.30%	-2.70%
33	117.00%	267.40%	-43.70%	-106.60%
34	29.30%	27.80%	1.40%	0.10%
35	9.50%	12.80%	-1.30%	-2.00%
36	15.70%	17.80%	-1.60%	-0.50%
37	21.60%	29.30%	-2.30%	-5.40%
38	11.30%	12.70%	-1.10%	-0.30%

Finally, I decompose the PAC change at each 3-digit SIC industry using the production and abatement cost data from the 4-digit SIC industries. Table 2-5 presents the mean of decomposition results at this level, expressed as a percentage of average PAC/VA last year. The abatement cost change at the 3 to 4-digit level is smaller in magnitude for both the overall change and the decomposed intensive and extensive margins. These results are later used in the econometric analyses of PHE in Section 2.5.

Table 2-5. Decomposition results at 3 to 4-digit SIC level, 1977-1986

Year	Mean pac_va2	Overall change	Intensive margin	Extensive margin	Interaction term	Composition change = extensive + interaction

1977	0.0108					
1978	0.0118	11.81%	12.14%	-0.17%	-0.16%	-0.33%
1979	0.0102	-9.51%	-9.40%	0.62%	-0.72%	-0.10%
1980	0.0125	15.62%	17.30%	0.23%	-1.92%	-1.69%
1981	0.0130	5.07%	14.07%	0.09%	-9.09%	-9.00%
1982	0.0138	3.16%	5.04%	9.20%	-11.09%	-1.89%
1983	0.0152	6.04%	5.94%	0.65%	-0.55%	0.10%
1984	0.0172	4.86%	10.09%	-0.43%	-4.80%	-5.23%
1985	0.0175	8.95%	7.61%	4.23%	-2.88%	1.35%
1986	0.0173	1.34%	4.08%	-1.05%	-1.68%	-2.74%

2.5. A re-examination of the PHE

2.5.1. Potential issues with previous studies on PHE

The empirical studies on PHE seek to detect the effect of environmental regulations on the international trade and investment flows, using PAC as a measure of regulatory stringency. Results from the theoretical model and decomposition analyses earlier in this chapter suggest that changes in PAC contain an extensive margin caused by the firm dynamics and the industry composition change in addition to the commonly perceived intensive margin. Therefore the aggregate level PAC will likely underestimate the changes in regulatory stringency and lead to three econometric issues in estimating PHE.

First of all, PHE in previous studies is estimated using PAC based on a truncated distribution that is conditional on firm survival and the realized industry composition. Aggregate PAC may fail to capture the full effect of changes in regulatory stringency if the composition has moved towards more abatement efficient and low abatement cost firms and industries. This selection issue implies previous studies may under-measure regulation change and may thus overestimate the true PHE. Secondly, the existence of the extensive margins becomes a source of nonrandom measurement error in the PAC variable as the aggregate PAC deviates from the intensive margin, which accurately reflect the changes in regulatory stringency. The measurement error issue may lead to biased and inconsistent estimates of PHE. Finally, international trade flows and the composition of firms and industries may be jointly determined, which leads to the potential problem of reverse causality in the PAC measure. Firms' entry and exit as well as industries' expansion and contraction can be partly the results of global (as well as domestic) competition. In fact, theories of international trade have suggested that industrial structures at different levels of aggregation will change during trade liberalization (e.g. Helpman, 1999; Melitz, 2003). By using the overall PAC as the explanatory variable, previous studies on PHE lump together the intensive changes in PAC and the composition change, which is subject to the reverse causality issue.

2.5.2. Empirical strategy: separating intensive and extensive margins when estimating PHE

To solve the above mentioned econometric problems, I separate the intensive margins and extensive margins in estimating PHE, where the intensive margins are used to capture the variation in regulatory stringency, and the extensive margin will control for any composition change caused by both environmental regulations and other types of changes. More specifically, previous studies in the PHE literature generally examine the relationship between environmental regulation stringency and net imports, as shown in Equation 2-14, where *NI* denotes net trade flows, $\varphi_{it} = paoc/va$ denotes PAC intensity, the *X*s are measures of trade barriers, D_ts are time dummies, and c_is are time-invariant industry fixed effects. The key assumption to obtain consistent estimate of γ is $E(\Delta\varphi'_{it}\Delta\varepsilon_{is}) = 0, \forall s, t.$ However, endogeneity problems discussed in Section 2.5.1 may prevent consistent estimations.

$$NI_{it} = X_{it}\beta + \varphi_{it}\gamma + D_t + c_i + \varepsilon_{it} \qquad (2-14)$$

I will separate the intensive and extensive margins, and estimate the relationship in Equation 2-15, where all variables are defined the same except the three abatement cost measures[12].

$$NI_{it} = X_{it}\beta + \varphi_{(int)it}\gamma_1 + \varphi_{(ext)it}\gamma_2 + \varphi_{(interaction)it}\gamma_3 + D_t + c_i + \varepsilon_{it} \quad (2-15)$$

$$\varphi_{(int)it} = \varphi_{i77} + \sum_{y=77}^{t} \Delta\varphi_{(int)iy}$$

$$\varphi_{(ext)it} = \varphi_{i77} + \sum_{y=77}^{t} \Delta\varphi_{(ext)iy}$$

[12] An alternative way of estimating PHE while separating the intensive margins and extensive margins would be to first difference Equation 2-14, and use the first-differenced $\Delta\varphi_{(int)}$, $\Delta\varphi_{(ext)}$, and $\Delta\varphi_{(interaction)}$ as separate explanatory variables to substitute the overall PAC change. Theoretically first-difference (FD) and fixed effects (FE) estimations would generate similar results (with different standard errors when t>2). However, chapter 10.7.1 in Wooldridge (2010) suggests when strict exogeneity fails and only contemporaneous exogeneity holds, both FE and FD estimator have an "asymptotic bias". In this case, FE estimators has an advantage over FD estimators with large T, as the bias in FE shrinks to zero at the rate 1/T while that in the FD estimator is independent of T.

$$\varphi_{(interaction)it} = \varphi_{i77} + \sum_{y=77}^{t} \Delta\varphi_{(interaction)iy}$$

The intensive margin of PAC in Equation 2-15, $\varphi_{(int)it}$, is derived as the abatement cost measure in the year 1977 at the 3-digit SIC level plus the sum of all intensive changes ($\Delta\varphi_{(int)}$) within 3-digit SIC industries up to the year *t*. Each of the intensive changes ($\Delta\varphi_{(int)}$) is calculated at 4 to 3 digit SIC levels using the decomposition methodology described in Section 2.4. This variable thus measures the environmental regulation induced the abatement cost change for a fixed set of industries (fixed at the 4-digit level in previous year), which is free of changes in the industry composition. The coefficient on the intensive margin, γ_1, measures the marginal impact of the abatement cost change at the intensive margin on trade flows. Estimates of $\gamma_1$will be unbiased and consistent since the selection issue, the measurement error and the reverse causality issue are now controlled by including the extensive margins. This model is identified as environmental regulations and abatement costs are changing sharply during the sample period while other factors affecting trade flows are only moving slowly.

The extensive margins and interaction terms are obtained by adding the decomposed extensive changes and interaction terms to the base year PAC value. The two variables together indicate the changes in the abatement cost caused solely by changes in the industry composition at different levels, that is, the entry, exit, expansion and shrinkage of firms, as well as the resulted expansion and shrinkage of industries. As the environmental regulation tightens, for example, resources and market shares are allocated towards the relatively high abatement-efficiency firms compared to the low efficiency ones. The coefficients γ_2 and γ_3 thus measure the marginal impact on trade flows of potential changes in the industry composition.

Note that the extensive margin in Equation 2-15 may still contain the reverse causality issue as discussed in Section 2.5.1. Nonetheless, by using the decomposed PAC, my empirical strategy improves in the following ways. First of all, the variable of interest when estimating PHE is the intensive margin, which captures the effect of the regulation change on PAC for a fixed set of firms/industries and serves as an accurate proxy for the regulation change. While previous studies suffer from the selection issue and the measure error, I ensure that the estimated coefficient on the intensive margin is an unbiased and consistent estimate of PHE by separating the intensive and extensive margins. Further, the reverse causality issue mentioned above provides an additional source of bias in previous studies that lump together the intensive and extensive margin effect. By separating these two effects, I ensure the estimate of γ_1, the one we are more interested in, is consistent. In other words, the extensive margin serves as “quarantine” for the intensive margin effects.

Other control variables in Equation 2-15 include trade barriers between the two trading partners: import tariffs and transportation costs. The international trade literature has suggested that these measures of trade barriers are major explanatory variables of the trade structure and volume. Previous studies in PHE have used trade barriers in their estimates as well. Here import tariffs are calculated as import duties divided by custom values of imports. Transportation costs are derived as the freight and insurance as a fraction of the net import value, or mathematically equal to $(CIF\ value - FAS\ value)/FAS\ value$. CIF and FAS are terms used in international trade contracts, standing for cost, insurance and freight, and free alongside respectively.

2.5.3. Data and summary statistics

Equations 2-14 and 2-15 will be estimated at the 3-digit SIC level using the US trade flows with Canada, Mexico and the rest of the world from 1977 to 1986. As before, the data on PAC are from the PACE survey and the data on industry characteristics are from the NBER-CES database. Measures of the intensive and extensive margins are calculated by decomposing PAC of the US manufacturing sector at the 3-digit to 4-digit SIC levels. The US trade data including imports, exports, tariffs and transportation costs by the 4-digit SIC category are obtained from the Center for International Data at the University of California, Davis (Feenstra, 2002), and are further converted to the 1972 SIC classifications and aggregated to the 3-digit SIC levels. Table 2-5 provides definitions and summary statistics of these variables.

Table 2-6. Summary statistics for 3-digit SIC industries, 1977-1986

Variable	Definition	Mean	Std. Dev.	Obs.
niw	net imports/value of shipment, world	0.0368	0.1759	1133
dep1can	net imports/value of shipment, Canada	0.0041	0.0514	1133
dep1mex	net imports/value of shipment, Mexico	-0.0012	0.0070	1133
paoc_va3	PAC/value added	0.0116	0.0207	1133
pac_int	intensive margin	0.0129	0.0312	1133

pac_ext	extensive margin	0.0095	0.0204	1133
pac_rsd	interaction term	0.0066	0.0271	1133
tariff	tariff/value of imports	0.0518	0.0395	1133
transp	transportation cost/value of imports	0.0637	0.0398	1133

2.5.4. Estimation results and discussions

Estimation results from Equation 2-14 and 2-15 are presented in Table 2-7, where I test PHE using the US net imports from Canada (Columns 1 to 3), Mexico (Columns 4 to 6) and the rest of the world (Columns 7 to 9). For each of these regions, I estimate three specifications. The first one is the standard PHE specification as in Equation 2-14 using fixed effects, and is a replicate of Equation 2-9 in Levinson and Taylor (2008) (L&T hereafter) using the interpolated data. The second specification is based on Equation 2-15 where intensive and extensive margins are included as separate explanatory variables. The coefficients of these two variables measures the marginal impact on trade flows of abatement cost change within the 3-digit SIC industries (the intensive margin) versus the impact of changes in the market structure (extensive margin and interaction term). In the third specification, I include both tariffs and transportation costs as measures for trade costs.

For the first specification, the standard specification as in previous studies, the coefficients on PAC are positive and statistically significant as expected. Moving to the second specification, the estimated coefficients on the intensive margin are positive and statistically significant for all three regions. This result suggests that tightened environmental regulations reflected by higher abatement costs at the intensive margins will significantly increase net imports, which supports the PHE hypotheses. Specifically, coefficients in Columns 2 and 4 implies that net imports from Canada and from Mexico scaled by value of shipment are expected to increase by 0.362 and 0.047 percentage-point respectively when PAC as a share of value added increases by 1 percentage-point. This effect is greater in magnitude though less significant when looking at the results from the rest of the world (Column 8). However, I do not find evidence that the composition change (represented by the sum of the extensive margin and the interaction term) will lead to an opposite PHE. The estimated coefficient on the variable of the composition change is not statistically different from zero.

Control variables representing the cost of trade have the expected negative impact on the trade volume. Higher import tariffs will lead to statistically significant lower levels of net import volumes, which is consistent for all geographic regions and for all specifications. The effect of the transportation cost is unclear. I only find a statistically significant negative effect for the international trade between the US and the rest of the world as a whole. This may suggest the transportation cost is only one of the factors affecting the trade volume in general, but not for each and every country. There may be cases where other factors are the driving force of the trade structure and volume between the US and the foreign countries.

Table 2-7. Impact of environmental regulation on trade flows, 1977-1986

Variables	Canada			Mexico			The world		
	Original (1)	**Decom. (2)**	**Decom. (3)**	**Original (4)**	**Decom. (5)**	**Decom. (6)**	**Original (7)**	**Decom. (8)**	**Decom. (9)**
PAOC/VA, imputed	0.537**			0.076**			1.003**		
	(0.040)			(0.015)			(0.233)		
intensive margins		0.362**	0.362**		0.047**	0.047**		0.526*	0.519*
		(0.047)	(0.047)		(0.018)	(0.018)		(0.277)	(0.265)
composition change		0.117	0.118		0.008	0.006		-0.140	-0.100
		(0.073)	(0.073)		(0.028)	(0.027)		(0.430)	(0.411)
Tariffs	-0.090*	-0.084*	-0.086*	-0.070**	-0.070**	-0.067**	-0.964**	-0.949**	-0.900**
	(0.047)	(0.046)	(0.046)	(0.017)	(0.017)	(0.017)	(0.271)	(0.270)	(0.261)
transportation cost			-0.013			0.026**			-0.826**
			(0.017)			(0.006)			(0.094)
Observations	1,133	1,133	1,133	1,133	1,133	1,133	1,133	1,133	1,133
Number of SIC3	114	114	114	114	114	114	114	114	114
R^2	0.967	0.969	0.967	0.745	0.747	0.753	0.902	0.903	0.912

Standard errors in parentheses

** p<0.05, * p<0.10

Notes: Dependent variable is net imports scaled by value of shipments. All specifications include year and 3-digit SIC level industry fixed effects. Coefficients for regression constants and dummy variables are suppressed.

These results provide supporting evidence for my hypothesis that the intensive margin corrects the downward bias in using the overall PAC to measure regulatory stringency and thus leads to a more accurate estimate of PHE. The coefficients on the intensive margin variable are positive and statistically significant, which supports the PHE hypothesis that tightening up environmental regulations will lead to increased net imports. The magnitude of PHE is smaller for all three regions when using decomposed cost measures than using overall cost changes, which suggests that the overall abatement cost changes may underestimate the regulation changes and thus lead to overestimated PHE. On the other hand, the extensive component of PAC changes has a very different, or even opposite impact on international trade flows as opposed to that of the intensive margin. The change in industry mix is likely to lead to decreased net imports through the expansion of more abatement efficient, low abatement cost firms and industries, and shrinkage of the less efficient and high cost firms and industries. At the same time, other factors including other types of regulations, changes in trade conditions and demand side shocks may also affect the composition of industries. The results thus call into question earlier estimates of PHE that fail to account for the composition change.

The lack of significance of the extensive margins and interaction terms here may suggest the composition change across the 4-digit SIC and within 3-digit SIC industries alone may not be significant enough to drive an opposite of PHE. It is interesting to explore whether the composition change at a finer level (e.g., within 4-digit SIC industries and across firms) together with those at a more aggregate level will have a significant impact on trade flows. In addition, the composition of industries may be affected by other factors than environmental regulations, such as other government policies or demand side shocks.

Understanding the magnitude of the estimation results

It may seem counterintuitive that the PHE is larger for Canada than that for Mexico---that the coefficients on the abatement cost measures are larger. However, the trade volume between the US and Canada is much higher than that with Mexico. The volume of imports from and exports to Mexcio are on average \$42.8 and \$67.1 million per year while imports and exports with Canada amount to \$278.5 and \$225.3 million per year over the sample period[13], which means we cannot simply compare the coefficients and conclude the magnitude of PHE. To get a sense of the magnitude of PHE, or how much trade volumes is changing in response to abatement cost change, I use the following elasticities as derived by L&T. Let $\xi_1 = \gamma \frac{\bar{\varphi}}{\bar{M}}$ denote the trade elasticity with respect to abatement costs if the change in trade volume comes entirely from imports. Similarly, $\xi_2 = \gamma \frac{\bar{\varphi}}{\bar{X}}$ denotes the elasticity if the change in trade comes entirely from exports. Let φ denote PAC/VA, *M* denote imports, and *X* denote exports.

$$\xi_1 = \gamma \frac{\bar{\varphi}}{\bar{M}} = \frac{\partial M}{\partial \varphi}\frac{\bar{\varphi}}{\bar{M}} - \frac{\partial X}{\partial \varphi}\frac{\bar{\varphi}}{\bar{M}} = \xi_{M\varphi} - \xi_{X\varphi}\frac{\bar{X}}{\bar{M}} \qquad (2-16)$$

[13] Author’s calculation based on US trade data (Feenstra, 2002).

$$\xi_2 = \gamma \frac{\bar{\varphi}}{\bar{X}} = \xi_{M\varphi} \frac{\bar{M}}{\bar{X}} - \xi_{X\varphi} \qquad (2-17)$$

These two measures provide the upper and lower bound of how much the trade volume may change induced by the abatement cost change. I present the magnitude of the two elasticity measures in Table 2-8 and compare them with those in L&T. First of all, comparing results between Canada and Mexico suggest that the estimated PHE is of similar magnitude although the estimated coefficients differ by a large margin. Secondly, the elasticity measures further confirm that using the overall abatement cost change could overestimate PHE. Based on the elasticity measures, previous studies have overestimated PHE by a third on average.

Table 2-8. Trade elasticities with respect to PAC

		Canada		**Mexico**	
		In L&T	**My result**	**In L&T**	**My result**
Trade elasticity with respect to abatement costs	If the change in trade comes entirely from imports	0.32	0.24	0.22	0.18
	If the change in trade comes entirely from exports	0.45	0.32	0.17	0.11

Robustness check

One primary concern of interpreting the results involves using the interpolated abatement cost data (see Appendix C for more detail). To perform the data interpolation, I assume that the missing abatement cost data are missing at random. This assumption is not inconsistent with the fact that a major fraction of these missing values are withheld to avoid disclosing operations of individual companies. T-tests of the original and the interpolated sample suggest that neither the mean nor the standard deviations of the variables are statistically different. To further explore whether the data interpolation affect estimation results, I compare estimation results obtained by using the original 3-digit SIC PAOC data with those obtained from the same specification but using 3-digit PAOC derived from aggregating 4-digit level interpolated data. Results are presented in Table 2-9. Columns 1, 3 and 5 of Table 2-9 present results of Equation 2-14 using the original 3-digit PAOC data, while Columns 2, 4 and 6 re-estimate the same specification using 3-digit SIC PAOC derived from aggregating 4-digit level interpolated data. The estimated coefficients using the interpolated data are not qualitatively different from the results obtained from the original data. Comparing these two sets of results suggest that the estimated coefficients of the PHE are robust to the replacement of the missing values with the interpolated data.

Table 2-9. Robustness check for using imputed data

Variables	**Canada**		**Mexico**		**World**	
	(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**
PAOC/VA	0.544***		0.070***		0.928***	
	(0.048)		(0.018)		(0.226)	
PAOC/VA, imputed		0.537***		0.076***		1.003***
		(0.040)		(0.015)		(0.233)
Obs.	920	1,133	920	1,133	920	1,133
Number of SIC3	114	114	114	114	114	114
R^2	0.970	0.967	0.765	0.745	0.906	0.902

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Notes: Dependent variable is net imports scaled by shipments. All specifications include year and 3-digit SIC level industry fixed effects. Coefficients for other control variables, regression constants and dummy variables are suppressed.

2.6. Conclusion

This chapter investigates the impacts of environmental regulations on PAC and international trade flows, controlling for firm dynamics and changes in the industrial structure. PAC is widely used as a measure for the regulatory intensity in empirical papers examining the impact of environmental regulations on trade flows. However, environmental regulations affect not only the cost of each firm/industry but also the composition of the industries. Using a heterogeneous-firm model, this chapter shows that the industry composition change may lead to an extensive margin effect of the regulation in addition to changes at the intensive margins. This may cast doubts on the previous empirical research on PHE as aggregate abatement costs will likely understate the changes in regulatory stringency. I conduct decomposition analysis to demonstrate the existence and the magnitude of the extensive margin at the 4-digit SIC industry level.

Using the decomposition results at the 3-digit SIC industry level, I estimate a modified version of PHE that allows separate impacts of PAC at the intensive and extensive margins to re-examine the relationship between abatement costs and trade flows. By separating the composition change, the intensive margin corrects the downward bias by using the overall PAC as a measure of regulation change. Results from the fixed effects estimations suggest that the estimated PHE, represented by the coefficients on the intensive margin variable, is smaller than the values in previous studies. This confirms my hypothesis that the previous studies have overestimated

PHE by using the overall PAC measure.

Analyses in the chapter suggest the needs for further research in understanding the economic impacts of environmental regulations. A natural extension would be to examine in further detail the extensive margin effects. Trade conditions can be used as instruments for the extensive margins in estimating PHE as trade theories have suggested that the trade liberalization will have an impact on trading partners' industrial structure. It would also be interesting in the future work to take into account the role of innovation, which could simultaneously reduce abatement costs at the intensive margin and enhance the competitiveness of domestic firms and industries.

Chapter 3: Determinants of the environmental standard setting: evidence from the NPDES program

3.1. Introduction

Environmental regulations and standards, together with effective enforcement actions to ensure compliance, are crucial to enhance environmental quality. The National Pollutant Discharge Elimination System (NPDES) permit program is the main device to implement the Clean Water Act (CWA), and has resulted in significant improvement of water quality over the past few decades (US EPA, Office of Wastewater Management, 2012). Under the NPDES program, all point sources that discharge pollutants into the waters of the US are required to obtain permits from the regulatory agencies. One major component of the NPDES permit is an effluent limitation that specifies the maximum allowable quantity or concentration of a certain pollutant at the discharge points. Currently there are two types of effluent limitations, including the technology-based effluent limitations (TBELs) developed from the federal effluent limit guidelines for specific industrial sectors and the water quality based effluent limitations (WQBELs) if TBELs are not sufficient to ensure the level of water quality for its designated use (US EPA, Office of Wastewater Management, 2012). The TBELs require industrial plants to meet two technology-based standards, namely Best Conventional Pollutant Control Technology (BCT) for conventional pollutants and Best Available Technology Economically Achievable (BAT) for toxic and non-conventional pollutants (US EPA, 2010).

Little is understood, however, about how regulators obtain knowledge about the regulated plants' technology and then make permit setting decisions. EPA's effluent guidelines specify a technology-based standard for each industrial sector while the regulated plants are free to choose the type of technology as long as the final results meet the required standard. In fact there is substantial heterogeneity across plants in the same industrial sector in terms of the technology choice (e.g. Section 4 in Millimet et al., 2009) and productivity (e.g. see Bartelsman & Doms 2000 for an extensive discussion). The permitting authority has limited information about the exact capacity of the best available technology implemented at the regulated plants. It is unclear to the regulator, for example, whether a violation is due to inadequate abatement effort or technology constraint. The absence of complete information may lead to a non-optimal standard level. On one hand, a standard level lower than the technology capacity fails to fully capture the benefit of the best available abatement technology. On the other hand, a standard level beyond the technology constraint will discourage compliance as it may be too costly to comply – the plant may find it optimal to just violate the standard and pay the penalty. This may be especially true when the penalty amount is constrained, which is the case for the water regulation in the US (e.g. Harrington, 1988; Heyes, 2000).

In fact, there is a rich theoretical literature on what should be the optimal standards and how the standards should be determined (Cohen, 1999). There is little empirical evidence, however, on how the regulatory standards are determined and what factors affect regulators' decision making. In this chapter, I propose that the regulators use plants' environmental performance in the past to infer the information about the technology and abatement effort and to inform permit setting decisions. Previous empirical studies on environmental regulations have suggested that regulators make inspection and enforcement decisions based on plants' performance and compliance history (Helland 1998; Stafford 2002; Kleit et al. 1998). These studies find that regulators tend to target inspections and enforcement on the plants with poor past performance. But none of them have examined the standard setting. To examine how past performance may reveal abatement effort, theoretical models have indicated that self-reporting behavior can be used as a signal of cooperation and that the self-reporting plants will perform better than the non-reporting plants (Innes 1999a; Innes 2001). Empirical papers generally provide supporting evidence that the self-reporting plants have lower future violations (Toffel & Short, 2011). Regulators therefore reward self-reporting behaviors with less regulatory scrutiny (Stafford 2007; Innes and Sam 2008). For the NPDES program, regulated plants are required to report their discharge levels. In this chapter, I would like to examine whether these required self-reports still provide useful information for the permit setting decisions.

The question of the permit setting also has great implications for the examination of enforcement and compliance as compliance is defined as the actual discharge to the permitted level. There is a sizable empirical literature examining whether enforcement activities are effective at inducing better environmental performance

(Heyes, 2000). A common feature of these studies is to treat regulatory standards as fixed when examining how inspections and enforcement actions could bring compliance (see Stafford 2002, Shimshack and Ward 2005, 2008 for example). Regulatory standards used to define compliance status, however, is a choice variable of the regulator's decision making process. The change of standards alone can change compliance status without any change in the actual discharge level.

The NPDES program provides a good opportunity to explore the question of the permit setting. First of all, The NPDES permits are determined on a plant-by-plant basis and are required to be renewed at least every five years. At the time of the permit renewal, the permitting authority will review and adjust permitted limits (if necessary) to reflect changes in the production process and regulatory requirements (US EPA, 2010). These renewal events provide a great opportunity to examine the regulators' permit setting decisions. Secondly, important technical and compliance information, such as production process, discharge level, compliance history and regulatory activities, is available to the permit writer as well as outside researchers through the EPA's Permit Compliance System (PCS). We can therefore use these pieces of information to explore the determinants of the permit changes.

Built on the theoretical framework of optimal standards (Cohen 1999; Malik 2007; Arguedas 2008), I propose that the regulatory standards are determined by regulators' perception of plants' abatement effort and technology inferred from the past performance. More specifically, cooperative behaviors like self-reported violations are a signal of pollution control efforts under the temporary technology constraint while certain non-cooperative behaviors indicate inadequate abatement efforts. The regulators (permitting authorities) are trying to decide an optimal limit to induce the highest efforts under the technology capacity. Using the permit and compliance data of the chemical manufacturing industry from 1990 to 2010, I investigate the determinants of the permit setting by estimating a multinomial logit and an ordered logit model that explain the relationship between plants' environmental performance and the level of effluent limits in their NPDES permits. EPA's PCS dataset provides the primary source for data on the NPDES regulation, enforcement, and plants discharge and compliance history. Estimation results suggest that the plants with cooperative behaviors are more likely to receive lenient limits while violations due to inadequate efforts will get punished. These results lend support to the hypothesis that regulators decide the standard level based on the information received from past compliance history and on their perception of plants' abatement effort. To the best of my knowledge, this study is among the first empirically examining the permit setting decision in the context of the water pollution regulation.

This chapter is organized as follows. Section 3.2 reviews the literature and introduces the background of the NPDES program in regulating the US water pollution. Section 3.3 describes hypotheses, econometric models and data used. Section 3.4 presents estimation results. Section 3.5 concludes and discusses venues for the future research.

3.2. Literature review and background

This section reviews the literature this study builds on and introduces the background of the NPDES program. After reviewing the theoretical models on the regulatory standard setting and noting the lack of empirical evidence (Section 3.2.1.A), I examine two branches of the literature related to the regulatory decision making, namely the determinants of inspections and enforcement actions based on the past performance (Section 3.2.1.B) and self-disclosure behavior as a signal of cooperation (Section 3.2.1.C). A final literature this study contributes to is the one on the effectiveness of enforcement at ensuring compliance (Section 3.2.1.D). The second part of this section describes the permit setting process and other requirements of the NPDES program.

3.2.1. Literature review

A. Regulatory standard setting

This chapter is closely related to the study on the standard setting in environmental regulations. There has been a rich literature that theoretically examines optimal regulatory strategies (see Cohen 1999 for an extensive review). The typical setup of these models is a principle-agent model where that the regulators choose the regulatory standard, probability of inspection, and penalty levels in order to induce the compliance behavior. The standard result for an optimal policy is determined by the firm minimizing private cost (compliance cost) as well as regulator optimizing its objective, for example, minimizing social costs as a sum of regulatory cost, expected damage from pollution and firms' compliance cost. The basic models have been further expanded in several ways, such as imposing costs of enforcement (Polinsky and Shavell 1992; Arguedas 2008), allowing self-disclosing behavior (Malik 1993; Innes 1999), and moving to a dynamic setting with state-dependent enforcement strategies (Harford & Harrington, 1991; Harrington, 1988).

A common feature of these models is that the final emission level is the only variable that the regulators care and used to determine compliance status. This is not the case, however, in the NPDES program, where complying with monitoring and reporting requirements is a major component of the regulation. In accordance with these requirements, Malik (2007) extends previous models by including an additional signal on the abatement effort that regulators would like to observe and make decision on. The additional signal can be obtained by the compliance inspection, which consists of examining the production and abatement process, reviewing records, verifying self-reports, and checking whether plants adopt the required procedures. By collecting information on efforts, the regulator can better assess whether a violation is due to inadequate abatement effort, or due to factors the firm are not able to control, like technology constraints. Malik (2007) concludes that in this case the optimal policy is more complex as it depends on both the final discharge level as well as the abatement effort revealed by the second signal. The results suggest that regulators are more likely to conduct investigations when the discharge level is in the middle range, or "gray area" as the author puts it, where the regulator has limited information about the plants’ choice of effort.

Noticing the distinction between effort and technology, Arguedas and Hamoudi (2004) analyze a model of optimal environmental policies where penalties will be contingent on the technology and the degree of violation. Firms will receive a more lenient regulation if it invests in better environmental technology. This arrangement could further save regulators’ inspection costs. Results from the theoretical model suggest that the regulator takes into account of technology constraint in the production and abatement process. Installing proper treatment equipment is taken by the regulator as a signal for cooperation as investing in better technology can save monitoring costs and reduce environmental damages.

Despite the rich theoretical literature, empirical examination of standard setting in water pollution regulation is almost non-existence. One exception is Chakraborti and McConnell (2012), who empirically study the determination of NPDES permits for both industrial plants and public-owned treatment works (POTWs). Using a panel of permits for 100 plants in Maryland, Virginia and Pennsylvania, the authors find that permit level gets relaxed when downstream water quality improves. Although studying NPDES permit setting, Chakraborti and McConnell (2012) focus on ambient water quality as a determinant of the limit level and have not examined limit levels based on the interaction between the regulator and regulated plants.

Instead of directly studying optimal limit, there are a handful of papers trying to draw implications by looking at how permit conditions will affect plants’ behavior.

Theories predict that the effect of stringency on compliance levels will depend on the slope of the marginal compliance cost function. Brännlund and Löfgren (1996), for example, find that different groups of plants will respond to limit changes differently as shadow prices differ. Empirical studies generally support the theoretical prediction that plants' responses depend on abatement costs. Using three measures to measure the limit stringency, Earnhart (2007) finds that compliance cost increases with limit stringency as limit level more stringent than federal standard will increasingly undermine environmental performance measured by actual-to-limit discharge. Plants will perform better, on the other hand, if the limit level is more stringent than the sample period mean. This suggests that the plants are able to adjust to temporary fluctuations in the limit, although the adjustment is non-smooth. In addition, better abatement technology and treatment process is time-consuming to implement. Earnhart (2009) explores whether permit conditions will affect plants' response to enforcement. The author finds no evidence that more stringent limit level will undermine the effectiveness of inspection and enforcement, in terms of relative discharge. There is some supporting evidence that permit modification, an indicator of a more cooperative relationship between the facility and the regulator, will improve the effectiveness of regulator intervention.

B. Decision making of inspections and enforcement based on past performance

This chapter aims to provide empirical evidence on optimal permit setting and explore factors that will affect the regulator's decision making. I propose that the regulators decide the permit level mainly based on their perception of technology and abatement effort inferred from plants' past performance. For this reason, this chapter is related to a sizable literature on how regulatory activities are decided on plants' performance history. Focusing on inspection and enforcement actions, these papers have not studied the decision on standard setting.

A paper by Gray and Deily (1996) is among the first empirical studies that use plant level data to examine the how regulators respond to compliance history in the US steel industry. Results from structural equation estimation show that regulators use plants' compliance history in their decision making process, and that greater compliance leads to significantly less enforcement in the future. Helland (1998) obtains similar results by examining inspection, violation and self-reporting of pulp and paper plants in the US. The author finds that plants with a recent violation recently or with higher pollution levels are more likely to be inspected. Rather than studying the number of inspections, Rousseau (2007) examines the frequency of inspections on the textile industry in Belgium. Using firm-level inspection data from 1991 to 2003, Rousseau (2007) estimates the time elapsed between inspections using a hazard model, where the hazard rate (length of time until inspection) is a function of variables denoting past inspection and past compliance status. Estimation results suggest that the likelihood of all types of inspections depend on previous inspection history and firms' past performance, including past violations and complaints received. In addition to compliance and inspection history, the strategy for routine inspection is also affected by firms' production capacity.

Previous studies have also examined the probability of inspections as determined by plants past environmental performance. Estimating the inspection and compliance simultaneously with a bivariate probit model, Stafford (2002) finds the probability of being inspected is higher if a plant was inspected or found in violation in the past year, or has higher probability of violation in the context of hazardous waste regulation in the US. The results suggest that the regulators target inspection resources towards plants that have had a poor environmental performance in the past and are suspects of being out of compliance. Hanna and Oliva (2010) have also concluded that lagged inspections, penalties, as well as emissions levels have a significant positive impact on the probability of inspection on air emissions. Eckert and Eckert (2010) explore response of inspection to past compliance even further by studying whether inspections are spatially correlated. The probability of inspection is modeled as a function of compliance history at own and neighboring sites. Results from probit estimations imply that regulatory and compliance history at neighboring sites also matters for regulator's decision on inspection in addition to a plant's own history.

The above mentioned papers have all focused on inspection decision. Kleit et al. (1998), on the other hand, explore decision making on penalty issuance in the context of water pollution regulation in Louisiana. Using inspection data during a 13-month period from 1993 to 1994, the authors estimate a probit and a tobit model to study the likelihood and severity of penalties respectively. Estimation results suggest that the occurrence of past violations tend to increase both the likelihood and the severity of penalties. In addition, both initial penalties and final penalties after appeals are higher for more serious violations, like discharge without a permit or illegal discharge.

C. Information gathering through self-reports

As reviewed below, the idea of regulator decision making based on perceived information about abatement technology and effort is illustrated in the literature on environmental self-reporting. These studies generally show that 1) self-reported violations contain rich information on effort, 2) self-reporting plants are performing better than the non-reporting plants, and 3) regulators will make decisions based on information contained in the self-reports.

Regarding the first aspect, Helland (1998) is among the first to empirically examine self-reporting behavior as a signal of cooperation. The results that plants with recently detected violations are more likely to self-report suggest that violations are costly and time-consuming to correct. Instead, violating plants use self-reporting as a way to signal their abatement effort and to demonstrate their willingness to cooperate. In fact, Earnhart (2007) finds supporting evidence that adjustment in the abatement process is non-smooth and time-consuming by examining the response of relative discharge levels to changes in effluent limits. For the same reason of signaling effort to regulators, other empirical studies have found that plants are more likely to self-disclose a violation if they are inspected frequently (Stafford 2007), are recently subjected to regulatory activities (inspections, detected violations and enforcement actions), and if the plants are provided with relief from punishment for self-disclosed violations (Short & Toffel, 2008). In the framework of Malik (2007), these results suggest that plants are trying to send the second signal on their own monitoring and abatement effort in order to decrease the gravity and frequency of future enforcement actions.

Not only are these plants sending signals, the self-reporting plants have better environmental performance than the non-reporters. Theoretical models in Innes (1999) show that self-reporting plants will always engage in remediation effort whereas non-reporting firms only clean up when a violation is detected by the regulator. Furthermore, self-reporters do not engage in avoidance activities, defined as activities aimed to lower the risk of being detected and punished (Innes 2001). Toffel and Short (2011) provide empirical evidence that self-reporting is a reliable indicator of higher effort and better performance. By examining self-reporting and compliance behavior of air polluting plants, the authors find that self-disclosing plants have lower probability of violations later and are less likely to have accidental toxic releases.

The regulators indeed receive the signals and make regulation decisions based on the information about abatement effort and cooperation sent through self-disclosure. Stafford (2007) finds that self-reporting is rewarded with a significantly lower probability of future inspections in the context of US hazardous waste regulation.

Studying enforcement and compliance of the Clean Air Act, Toffel and Short (2011) find significant reduction in both the probability and the number of inspections for plants that voluntarily disclosed a violation. The result that regulators shift enforcement resources away from these self-reporters indicates that signals are received and the regulators rely on this information to design their enforcement strategy. In addition to self-reports, participation in voluntary pollution reduction program (VPR) also reveals the abatement effort as it involves investment in self-auditing and more efficient abatement technology. Innes and Sam (2008) empirically examine plants' participation in EPA's 33/50 VPR, and concluded that VPR participation gets rewarded by the regulator in terms of less frequent inspections and enforcement actions.

D. Environmental enforcement and compliance

This chapter also contributes to the literature examining effectiveness of enforcement at inducing compliance and better environmental performances (Cohen, 1999; Heyes, 2000). Despite the theoretical frameworks on optimal standard, regulatory standard is assumed to be fixed and exogenous in almost all of the empirical papers. Few studies have paid attention to the role regulatory standards play in the interaction between regulators and regulated plants.

A number of papers have concluded that the threat of inspection is effective at inducing compliance. Laplante and Rilstone (1996), for example, examine the impact of inspection threat on water pollution discharge of the pulp and paper industry in

Quebec. The predicted probability (or the threat) of inspection, estimated as a function of plant characteristics and previous inspections, is found to have a strong negative impact on pollution levels. Telle (2009) adopts a similar approach to study the effect of inspection threats on both compliance decision and the levels of emission using a sample of Norwegian manufacturing plants. After controlling for unobserved plant heterogeneity, estimations results suggest that inspection threats have a substantial negative effect on violations, but the effects on emission levels are not clear. Eckert (2004) examines threat of inspection through warnings in the context of petroleum storage regulation in Canada. The author estimates a two-stage probit model of an inspection equation and a compliance equation, and finds that past warnings increase the probability of an inspection, which further decreases the probability of a violation. The results thus imply that warnings can deter future violations through the threat of stronger enforcement.

Besides the threat of inspection, Shimshack and Ward (2005, 2008) find that the threat of penalties could significantly reduce violation as well as pollution levels, even for the complying plants. Using data from the pulp and paper industry for 1988-1996, Shimshack and Ward (2005) find a two-third drop in state-level violation rate the year after a penalty. Notably, the deterrence impact on the non-sanctioned plants in the same state is almost as strong as the actual impact on the sanctioned plant. The authors further indicate that the substantial effect is obtained by the regulator's increased credibility to impose a penalty. Using a similar dataset, Shimshack and Ward (2008) find the complying plants (at every quantile of discharge level) will reduce discharge level even further after observing a penalty on another plant in the same state in the past year.

In all of the papers mentioned above, regulation standards are assumed to be fixed when assessing compliance. There are two problems with this assumption. First of all, environmental compliance is defined as actual discharge or emission level relative to the standard level. Compliance status will change as the standard level changes even if the actual performance is staying the same. For example, a previously violating plant may be categorized as in compliance if its NPDES permit gets relaxed while actual discharge level remains the same. Secondly, theoretical models on environmental enforcement and compliance indicate that the standard level can be determined jointly with probability of inspection and level of penalty in the regulator’s optimization problem (see for example Amacher and Malik 1996; Arguedas 2005). This chapter therefore contributes to the understanding of enforcement and compliance by incorporating permit setting into the regulator’s decision making process.

3.2.2. Background of the NPDES program

The NPDES permit program is the main tool under the Clean Water Act to control water pollution in the US. Under the NPDES program, all point sources, including industrial plants and POTWs, that discharge pollutant into the waters of the US have to obtain a permit. An NPDES permit is a license for discharge, which typically consists of wastewater effluent limitations as well as monitoring, record keeping, and reporting requirements (US EPA, 2010). The current NPDES program requires two levels of control – the technology-based effluent limitations (TBELs) and water quality-based effluent limitations (WQBELs) if technology-based limits are not sufficient to provide protection of the water body (US EPA, Office of Wastewater Management, 2012). Following is a brief summary of the permitting and renewal process, as well as other NPDES requirements. For more details, please refer to EPA's documents and a web-based NPDES permit writer training program (US EPA, 2010; US EPA, Office of Wastewater Management, 2012).

Chemical manufacturing plants, as well as other industrial facilities, are required to renew their NPDES permits at least once every five years. At the time of permit renewal, the permitting authorities (typically the states) will review and adjust the effluent limits, if necessary, for changes in production and abatement process, water quality standards, and other regulatory requirements.

The NPDES permitting process starts from the facilities submitting a permit application. After verifying the completeness and accuracy of the application, the permit writers of the issuing authority start developing a permit on both technical and regulatory basis. The first major step in the development process is to establish TBELs based on federal effluent limitation guidelines (ELGs) for a specific industrial sector. The TBELs require industrial plants to meet two technology-based standards, namely BCT for conventional pollutants and BAT for toxic and non-conventional pollutants. CWA designated the following 5 pollutants as conventional pollutants:

biochemical oxygen demand (BOD), total suspended solids (TSS), pH, fecal coliform, and oil and grease (US EPA, Office of Wastewater Management, 2012). This dissertation studies the discharge of BOD from chemical plants. As BOD is defined as a conventional pollutant, only BCT is relevant for the discussion in the rest of this chapter. TBELs are performance-based pollutant controls with no specific technology required. Instead, the facility can choose any technology as long as final results meet the specific levels of performance (e.g. BCT) established in the CWA.

The next step in the permitting process is to develop water quality based effluent limits. To develop WQBELs, the permit writer first identifies pollutants of concern and the applicable water quality standards (WQS), which are criteria for designated uses of specific water bodies as specified by the states. The permit writer then determines the need of WQBEL by characterizing the interaction between the effluents and receiving water using engineering models. WQBELs must be established if the discharged pollutants have "*reasonable potential*" to cause the state WQS to be violated. Chemical-specific limits (maximum daily and average monthly limits) for a facility are then calculated based on waste load allocation (WLA) developed by engineering models. Comparing the TBELs and WQBELs, the more stringent of the two will be decided as the final limit.

The permitted plants are further required under the NPDES program to conduct their own monitoring and report the results to the permitting authority using the Discharge Monitoring Report (DMR), which is a standard form that facilitates data entry and compliance review. The permitting authorities conduct compliance inspections occasionally to examine the monitoring process, verify the accuracy of the reports and make their own assessment about the compliance status. To ensure that the self-reported monitoring results are accurate and reliable, appropriate self-monitoring and reporting requirements are also specified in the NPDES permit. Nonetheless, the plants have the flexibility to choose from a range of EPA-approved methods for analyzing the samples (US EPA, 2010). This creates the possibility for the plants to strategically use an analytical method for their benefit.

3.3. Empirical methodology and data

In this section, I propose three testable hypotheses on how the plants' behavior will affect permit setting decisions based on previous literature on regulation and enforcement. I further present econometric models and data to perform the empirical analyses to test these hypotheses.

3.3.1. Hypotheses

The ultimate goal of the NPDES permits is to protect water quality for a water body's designated use by controlling the end-of-pipe pollutant discharge. The regulated plants aims to minimize private costs consisted of abatement cost (positively correlated with abatement effort) and expected penalty once found in violation. The effort level is not observable to the regulator, while the discharge level is observable and verifiable during inspections. The objective of the permitting authority is to minimize social costs consist of water pollution damage, enforcement costs and plants' compliance costs by choosing a standard level and enforcement strategy. The derived optimal standard is a function of plants' abatement effort given technology capacity as well as enforcement costs. Since neither the effort level nor the specific technology is observable to the regulator, the regulator will use information received from plants' past performance to infer actual level of effort and technology.

The first source of information about technology and effort is revealed from self-reported numeric violation in the monthly DMRs, which is a requirement by the NPDES program. On one hand, the outcome that actual discharge exceeds the permitted level could be results of either technology constraint or lack of abatement effort. The regulators do not have enough information about which is the case by simply judging from the monitoring reports. Permitting decisions will likely depend on numeric violations together with other sources of information. On the other hand, the fact that a numeric violation is truthfully recorded and reported in the DMR reveals additional information about effort level.

Although the program specifies certain monitoring and reporting requirements, a careful examination of the regulation suggests that plants have the flexibility to choose different methods analyzing the samples for reporting. Therefore, truthfully reporting numeric violation can be viewed as self-disclosing behavior to some extent. It may imply, for example, that the plant has already spent a reasonable amount of abatement effort but still fail to achieve the limit level specified in the permit due to temporary technology constraint. As suggested by previous studies, adjustment in the abatement process is time-consuming, which causes the plants to choose self-disclosure as a way to signal their abatement effort before a better result (e.g. lower level of discharge) can be observed. Self-reporting plants will later keep their promise and indeed perform better than the non-reporting plants (Earnhart, 2007; Helland, 1998; Malik, 2007). Theoretical models suggest that self-reporting plants will always engage in efficient remediation and will not engage in avoidance behaviors (Innes 1999; Innes 2001). Empirical studies provided supporting evidence that self-reporting plants are more likely to stay in compliance and less likely to have accidental toxic releases (Toffel & Short, 2011). Because federal regulations require the NPDES permits be developed based on best available technology, violations due to technology constraints suggest that the previous limit level might be too tight given the current technology and should be relaxed. The first hypothesis concerns whether self-reported violations reveal additional information and whether they are used by the regulators during the permitting process.

Hypothesis 1: To the extent that the plants have the flexibility in analyzing samples for reporting purposes, truthfully reporting a violation can be viewed as a cooperating behavior and will lead to more lenient limit levels.

The second source of information involves explicit non-cooperative behaviors, which can be detected electronically in EPA's Permit Compliance System or during compliance inspections. First of all, there are certain monitoring and reporting requirements specified in NPDES permits, for example, reporting using DMRs. Failure to submit DMRs or submitting DMRs with substantial missing data indicate at least inadequate abatement effort. These behaviors are not inconsistent with avoidance activities where the plants are trying to prevent serious violations from being discovered (Innes 2001). Secondly, one of the major objectives of inspections is to examine pollution control operation and maintenance (US EPA, Office of Enforcement and Compliance Assurance, 2007). Improper operation and maintenance detected during inspections will be regarded by the regulator as lack of abatement effort. Although the exact level of technology capacity is not identified, these explicit non-cooperative behaviors imply that it is technically feasible to perform better given appropriate incentives. Therefore, violations resulted from inadequate abatement effort are expected to encourage tightening up regulatory stringency in addition to imposing enforcement actions. In fact, previous studies have shown that more stringent limit will induce higher effort within the technology constraint (Alberini et al., 2008; Earnhart, 2007). Furthermore, tighter permit is in effect an additional penalty - extra cost in order to achieve compliance status - which is expected to have a deterrence effect. These observations lead to the following hypothesis.

Hypothesis 2: Violations due to inadequate abatement effort or avoidance activities (defined as activities to avoid being discovered) will lead to more stringent limit levels.

Finally, as the NPDES permit contains water quality-based control, I expect ambient water quality to have an impact on the permitted effluent levels. In fact, Chakraborti and McConnell (2012) have found that regulators in Maryland, Virginia and Pennsylvania respond to downstream water quality when writing permits for both POTWs and industrial facilities. Focusing on chemical manufacturing plants, I would like to test whether this is a common practice of permitting authorities in other states. In addition, the impact of other variables will also depend on water quality, which defines the bottom line of NPDES permits. The final level of effluent limits is determined by WQBELs if TBELs are not sufficient to protect the water body for its designated use. This implies that if a violation is serious enough to affect local water quality, it is expected that the limit level will be tightened no matter what are the reasons for the violation (either effort or technology related).

Hypothesis 3: The regulator will relax (tighten) the limit level if downstream water quality is good (poor).

3.3.2. Econometric models

There are three outcomes of a permit renewal event: a higher (relaxed), unchanged or lower (more stringent) limit, denoted by 0, 1, and 2 respectively. Define the probability that outcome j is chosen as

$$p_j = prob[y = j], \qquad j = 0,1,2$$

These probabilities are modeled as a function of variables representing plants' environmental performance and regulatory activities in the past. I first estimate a multinomial logit (MNL) model, where the explanatory variables are outcome-invariant while the coefficients vary across outcomes[14](Cameron & Trivedi, 2005). More specifically, the probability of observing outcome *j* is

$$p_j = prob[y = j] = \frac{exp\left(\alpha_j + \beta_j x\right)}{\sum_{k\in\{0,1,2\}} exp(\alpha_k + \beta_k x)}, \quad j = 0,1,2$$

I will also use an ordered logit (OL) model (Cameron & Trivedi, 2005). In the ordered logit model, outcome *j* will occur if the later variable y^*lies in between two thresholds, $\alpha_{j-1} < y_i^* \leq \alpha_j$. And the probability of observing outcome *j* is

$$p_j = prob[y = j] = prob\left[\alpha_{j-1} < y_i^* \leq \alpha_j\right]$$

$$= \frac{exp\left(\alpha_j + \beta_j x\right)}{1 + exp\left(\alpha_j + \beta_j x\right)} - \frac{exp\left(\alpha_{j-1} + \beta_j x\right)}{1 + exp\left(\alpha_{j-1} + \beta_j x\right)},$$

$$j = 0,1,2$$

The assumption for the OL model is that the odds across each two outcomes are proportional. If the data satisfy the proportional odds assumption, the ordered logit estimation is more efficient than the multinomial logit. Later when I present the results, I will test for the proportional odds assumption. The sign of the coefficients of

[14] A conditional logit model, on the other hand, is one with alternative-specific regressors that vary across alternatives/outcomes.

the ordered logit model can be interpreted as determining whether or not the latent variable y^* increases with the regressors. Both the MNL and OL models are estimated by maximizing the log likelihood function.

$$L = lnL_N = \sum_{i=1}^{N} \sum_{j \in \{0,1,2\}} y_{ij} lnp_{ij}.$$

In addition to estimating the coefficients, it is also interesting to interpret the estimation results in terms of marginal effects on the predicted probabilities of a change in the explanatory variables, calculated as $\frac{\partial p_{ij}}{\partial x_i} = p_{ij}(\beta_j - \bar{\beta}_i)$ with $\bar{\beta}_i = \sum_l p_{il}\beta_l$ for continuous variables, and $\frac{\Delta p_{ij}}{\Delta x_i} = prob[y = j|x, x_i = 1] - prob[y = j|\ x, x_i = 0]$ for dummy variables.

3.3.3. Data and variables

My sample consists of 303 major chemical manufacturing plants (SIC code 28) for the time period from 1990 to 2010[15] (see Figure 3-1 for a map of these plants). The chemical manufacturing industry is one of the most water polluting industries in terms of conventional pollutants like BOD and TSS. "Major" industrial facilities are determined based on specific criteria developed by EPA or the states, and generally depends on the significance of the discharger's impact on the environment (US EPA, 2012b). I focus on major facilities because they discharge the majority of wastewater from this industry. Plant-level data on effluent limits, pollutant discharge level,

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[15] There are 416 major chemical manufacturing plants, with only 303 plants with numeric limitations on BOD in their NPDES permits over the sample period.

compliance history, inspections and enforcement actions come from EPA's Permit Compliance System (PCS). The PCS also contains information on permit issuance and expiration date, which is used to identify permit renewal events. This study examines effluent limits on BOD, which are the most common pollutant in this industry and one of the five conventional pollutants EPA is focusing on. The corresponding ambient water quality is measured by dissolved oxygen (DO). Data on water quality come from EPA's Storage and Retrieval (STORET) data warehouse, US Geological Survey (USGS) National Water Information System (NWIS) and state regulatory agencies in the case where data are not available from the other two sources.

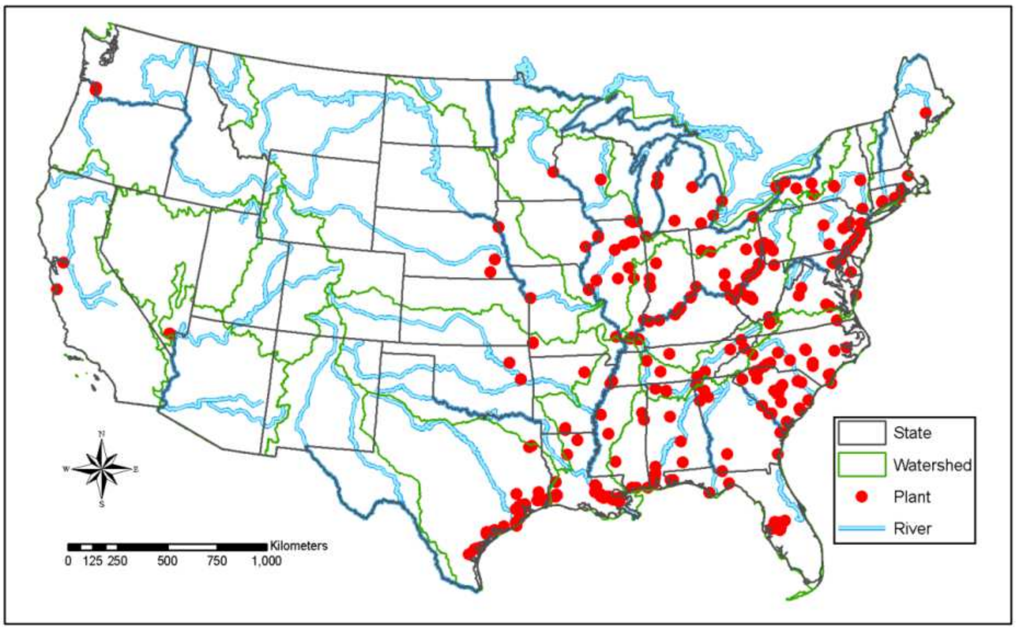

Figure 3-1. Map of major chemical manufacturing plants in the U.S.

The dependent variable: permit renewal outcome

The dependent variable is the outcome of a permit renewal event, whether and to what direction the effluent limits specified in the NPDES permit will change.

$$y = \begin{cases} 0, & if\ P_c - P_{c-1} < 0 \\ 1, & if\ P_c - P_{c-1} = 0 \\ 2, & if\ P_c - P_{c-1} > 0 \end{cases}$$

P_c is the limit level for a specific discharge point of a plant in cycle *c*, and is measured as pounds per day (lb/day) for either daily or a 30-day average. According to the NPDES program, these numeric limitations are expressed as mass limitations unless the guideline allows or requires concentration limitations. For most of the effluent guidelines, the numeric standards are expressed in terms of mass and are based on some measure of the level of production at the facility. For example, if the effluent guideline is expressed as 5 pounds of pollutants per 1000lb of raw materials, the calculated limits will be 50 pounds per day for a plant that uses 10,000 pounds of raw material a day.

One data issue involves multiple limit levels for a specific discharge point at a plant within a cycle, which is most likely due to tiered limits. Tiered permit limits are defined as limits that only apply to the discharge when a certain threshold (e.g., production level), specific circumstance (e.g., batch discharge), or timeframe (e.g., after 6 months) triggers their use (US EPA 2012). About 15% of all permits in the Chemical Manufacturing industry (SIC28) are tiered limits. In this study, I keep only the lowest limit level for the case of tiered limits to avoid double counting of permit change. The calculated dependent variable would be the change of the lowest tier across cycles.

Explanatory variables

The dependent variable, permit renewal outcome, is modeled as a function of variables describing past performance and regulatory activities. Summary statistics are presented in Table 3-1.

A. Numeric violations

I include the number of self-reported numeric violations in the past three years as explanatory variables to examine the impact of numeric violations and any information revealed on the permitting decision. A numeric violation is identified if the actual discharge reported in DMR exceeds the permitted effluent limits. Plants are required to monitor, record, and report their pollutant discharge in the monthly DMRs. The submitted DMRs containing monitoring results are electronically compared with the effluent limits and other requirement specified in the NPDES permit in EPA's system to decide compliance status. Although the monthly DMR is a requirement by the NPDES program, the plants have the flexibility to choose from a range of EPA-approved methods for analyzing the samples (US EPA, 2010). Plants may therefore have the incentive and possibility to strategically choose an analytical method for their benefit. To this extent, truthfully reporting numeric violations may still be regarded as a cooperating behavior by the regulators and may lead to more lenient future permits. Nevertheless, numeric violations in DMRs provide regulators just one source of information as these violations could be results of either inadequate abatement effort or technology constraints. Final permitting decisions will depend on self-reported numeric violations together with other sources of information such as those from inspection activities.

B. Absent DMRs

Failure to submit DMRs or missing important data entries in the DMR can be a violation that reaches the level of significant non-compliance (SNC) classification (US EPA 2012, CWA/NPDES Compliance Status). Absent DMRs classified as SNC will typically trigger a review by the regulator to further collect information, to determine compliance status, and to determine the need for a permit modification. Absent DMRs could therefore affect permit setting decisions to both directions. On one hand, absent monitoring reports may imply that the plant is trying to hide performance and other important information from being discovered by the regulator, which is a non-cooperating behavior. If this is the case, the permit level will be tightened as stated in Hypothesis 2. On the other hand, absent DMR consists of very limited information while final permitting decisions will depend on more comprehensive information. There will be reviews conducted by the regulators after absent DMR violation to find out more information about the plant's performance and monitoring and reporting process.

C. Past Inspection and inspection results

The third factor that may affect permit level is inspection. NPDES permits are expected to be tightened up if non-cooperative behaviors or lack of abatement effort are detected during inspections (Hypothesis 2). Besides determining compliance status with permit conditions, one of the main objectives of inspection is to obtain information about abatement effort, for example, to examine operation and monitoring process and to verify the accuracy of the self-submitted DMRs (UA EPA, 2004). Although the exact level of maximum feasible effort is highly costly to identify, the lack of appropriate maintenance and abatement effort is relatively easy for the inspector to discover. Inspections could be either sampling or non-sampling inspections. During sampling inspections, the inspector will take representative samples in order to decide compliance status with discharge limits and verify the self-submitted reports as well. During non-sampling inspections, such as compliance evaluation inspections, the inspection will review documents and visually examine facilities, effluents and receiving waters to verify whether the permitted facility is in compliance with operational requirements and effluent limits.

Violations detected during inspections, or “single event violations” are also included in the model. The most frequent single event violations are 1) violation detected during inspection 2) improper operation, maintenance, monitoring or sampling, 3) unauthorized discharge or by-pass, 4) late or inaccurate DMRs. These are indicators of insufficient effort in the abatement process (improper operation and unauthorized discharge), not cooperating with regulators (unauthorized discharge and late DMRs), and even trying to avoid being discovered of a violation (not submitting DMRs).

These violations are related with the lack abatement effort rather than technology constraint of a plant. In this case, it is expected that the regulator will use a tighter permit to prompt higher abatement effort from these plants (Hypothesis 2). In addition, when a violation is found during inspection, the inspector is able to collect related information about the violation in order to decide the cause, e.g. whether it is technology or effort related.

D. Past enforcement actions

A fourth factor that regulators use to obtain information when deciding the permit renewal is the enforcement history. Enforcement actions are expected to be followed with tighter NPDES permits if they indicate serious violations that harm the local water quality (Hypothesis 3). Enforcement actions occur when violations (of any type, e.g. violations of discharge limits, violations related to operation and maintenance, unauthorized discharge, other reporting violations) are found, either through self-reporting or inspection. The types of actions include monetary penalties and non-monetary enforcement actions, for example, notice of violations and administrative orders that require the plants to correct the violations. In the estimation, I separate monetary penalties from non-monetary enforcement actions[16]. For penalty I include in the estimation both a dummy indicator and the natural logarithm of the dollar amount of penalty in the past three years. I expect the dollar amount of penalty to have an impact on permit levels as it reveals both the severity of

[16] A complete list of formal and informal enforcement actions can be found in EPA's data dictionary (US EPA, 2012b).

violations (the extent of deviation from compliance) and regulator's ability to use monetary sanctions as an enforcement tool. When a regulator is capable to levy penalty without constraint, the regulator is less likely to change the permit level as an additional enforcement tool.

E. Water Quality

The final set of variables that may affect permit level is ambient water quality. The corresponding ambient water quality measure for BOD discharge is dissolved oxygen (DO). Higher level of DO generally indicates better water quality, as insufficient oxygen dissolved in the water will harm aquatic lives like fish. Low levels of DO are expected to be associated with tightened permits if the regulators do respond to local water quality. In addition, the impact of other variables will also depend on water quality as the final level of effluent limits is determined by WQBELs if TBELs are not sufficient to protect the water body for its designated use. This implies that if a serious violation will lead to tighter permit no matter what are the reasons for the violation (either effort or technology related).

Data on ambient water quality is obtained from three sources 1) EPA's Storage and Retrieval (STORET) data warehouse, 2) USGS National Water Information System (NWIS), and 3) state's department of environmental quality in states where water quality data is not available in the previous two sources (e.g., Texas, Louisiana and Illinois). Water quality data is then matched with manufacturing plants using ArcMap®. I find the nearest one or two monitoring stations with DO data to a plant on

ArcMap®, and retrieve the water quality data from the station(s). A majority of the missing data results from 1) failure to identify a nearby monitoring station; or 2) the sample periods of the NPDES permits and the observations from monitoring stations do not overlap or have limited overlap.

F. Other control variables

To control for unobserved heterogeneity in plant characteristics, I include in the estimation a dummy variable indicating whether a plant belongs to a multi-plant or single-plant firm. The status of a multi-plant firm may affect permitting decisions in two aspects. Compared with single-plant firms, multi-plant firms may be heavy emitters as they are generally larger in size and have higher production capacity. Plants belong to the multi-plant firms may become the target of state regulators and draw more regulatory scrutiny. On the other hand, the multi-plant firms may be have more experience complying with regulations, more likely to afford to hire experts or consultants dealing with regulatory issues, and may have larger bargaining power compared with those smaller, single-plant firms.

Because of missing values in the water quality data, I include watershed fixed effects together with time fixed effects to control for water quality as an alternative. The watershed fixed effects would capture any time invariant watershed-specific heterogeneity. Watersheds are identified using the USGS Hydrologic Unit Code (HUCs) at the region level, which is the highest level of HUCs.

In addition, to control for unobserved heterogeneity of regulators (e.g. tougher regulators may be more likely to levy a penalty and lower the limit level at the same time), I use state fixed effects as a measure for general regulatory stringency and other state characteristics. In most cases, the states are the permitting authorities - they issue permits, conduct compliance and monitoring activities, and take enforcement actions - while EPA only plays an oversight role[17]. State fixed effects would capture unobserved heterogeneity in terms of toughness across different state regulators. I have also included presidential administration fixed effects to control for any political and economy-wide factors that could affect state regulators decision making.

Table 3-1. Summary statistics of explanatory variables

Variable	**Description**	**Obs.**	**Mean**	**Std. dev.**
numviol:1	Dummy variable equal to 1 if plant had 1 self-reported numeric violation in the past 3 years	840	0.074	0.262
numviol:2	Dummy variable equal to 1 if plant had 2 self-reported numeric violation in the past 3 years	840	0.031	0.173
numviol:>=3	Dummy variable equal to 1 if plant had 3 or more self-reported numeric violation in the past 3 years	840	0.037	0.189
d_absent	Dummy variable equal to 1 if plant had absent DMRs in the past 3 years	840	0.121	0.327
d_singviol	Dummy variable equal to 1 if plant had a violation detected during inspection in the past 3 years	840	0.052	0.223
insp: 2-3	Dummy variable equal to 1 if plant was inspected 2 or 3 times in the past 3 years	840	0.429	0.495
insp: 4-9	Dummy variable equal to 1 if plant was inspected 4 to 9 times in the past 3 years	840	0.367	0.482
insp:>=10	Dummy variable equal to 1 if plant was	840	0.067	0.250

[17] There are 46 states that have the permitting authority. Idaho, Massachusetts, New Hampshire, New Mexico, and DC and all territories (excluding US Virgin Island) do not have NPDES program authorizations (US EPA, 2010).

	inspected10 times or more in the past 3 years			
EA:1	Dummy variable equal to 1 if plant received 1 enforcement action in the past 3 years	840	0.121	0.327
EA:>=2	Dummy variable equal to 1 if plant received 2 or more enforcement action in the past 3 years	840	0.082	0.275
d_pen	Dummy variable equal to 1 if plant received penalty in the past 3 years	840	0.083	0.277
ln(penalty)	Natural log of the dollar amount of penalty	840	0.786	2.648
DO <= 5mg/L	Spline for level of dissolved oxygen <= 5mg/L	179	4.966	0.258
DO > 5mg/L	Spline for level of dissolved oxygen > 5mg/L	179	3.170	1.695
d_multi	Dummy variable equal to 1 if a plant belongs to a multi-plant firm	840	0.660	0.474

3.4. Empirical results

Tables 3-2 and 3-3 present results from MNL and OL regressions of NPDES permit renewal outcomes respectively. In both tables, Model 1 contains all explanatory variables except the water quality variable and is estimated using the full sample, Model 2 includes additionally state and administration fixed effects, and Model 3 includes watershed and administration fixed effects. Model 4 and Model 5 contain water quality as an additional explanatory variable and are estimated using the subsample that has water quality data. Model 5 contains additionally state and administration fixed effects. For each of these specifications, I presented both the estimated coefficients and marginal effects. The marginal effects reported here are average marginal effects, or sample means of the marginal effects at different points of observation (Bartus, 2005). Average marginal effect (AME) is more suitable than the marginal effect at the mean (MEM) for my case as the several of the explanatory variables are dummy variables that indicate different levels of a single categorical variable. For the dummy variables, the reported AMEs imply that the average change in predicted probability of a permit renewal outcome if the dummy variable changes from 0 to 1. I further tested for proportional odds in order to implement the ordered logit model. The null hypothesis of proportional odds is rejected using the full sample but I fail to reject the null for the subsample with water quality data at 10% significance level.

3.4.1. Numeric violations

As the plants have the flexibility to choose different methods in analyzing discharge samples, they are able to choose one that result in no or fewer numeric violations. To this extent, self-reported numeric violations may be viewed as an indicator of pollution control effort under technology constraint. Further, such cooperating behavior is hypothesized to lead to more lenient NPDES permits. To quantify the impact of past numeric violations, I include in the regression dummies for different levels of accumulated number of violations in the three years preceding the permit renewal event. The dummies for zero violations are omitted as the base group, and the results on other dummies indicate effects relative to the no violation case. An alternative way is to include a continuous variable denoting number of violations. Nevertheless, including dummies for different ranges allows for possible non-linearity in the effect of violations on permit setting decisions.

In the first three models (Column 1 to 6), the effect of numeric violations do not have a significant impact on permit change. Once water quality is controlled for (Column 7 to 10), reporting two or more numeric violations makes it significantly more likely for a plant to receive a more relaxed permit, and less likely to receive a tighter permit. The results indicate that although DMRs are required, truthfully reporting numeric violations is still regarded by the regulator as a compliance effort. It is an indicator that the plants have already adopted best pollution control technology and have spent adequate abatement effort but still fail to reach the limit level due to technology constraint. This implies that the current NPDES limit is more stringent than required by the best available technology and is thus more likely to be relaxed in the future. In addition, plants may choose to use self-disclosure to send a signal of cooperation as adjustment in treatment technology and process is time-consuming (Earnhart, 2007; Helland, 1998). In this case, the regulator is more likely to relax the permit as a reward for the cooperation with the belief that the plants will adjust the abatement process as promised given enough time. This result lends support for Hypothesis 1, and is in accordance with the conclusions in previous studies that self-disclosure behavior is rewarded with less inspection and enforcement (Stafford 2007; Toffel and Short 2011). This finding suggests that self-reporting plants are rewarded with less stringent performance standard in addition to relaxed regulatory scrutiny. Nevertheless, the fact that actual discharge exceeds the permitted level could be results of either inadequate effort or technology constraints. Permitting decisions will depend on reported numeric violations together with other sources of information.

3.4.2. Absent DMRs

Absent DMRs is a type of significant non-compliance that will trigger a compliance review by the regulator. To examine the effect of absent DMR on permitting decisions, I use a dummy variable indicating whether there has been such a violation in the three years preceding a permit renewal event. I find little supporting evidence for the hypothesis that absent monitoring reports will lead to tighter limit as they imply plants are hiding information from the regulator. Regression results from the MNL model show that absent DMR makes it more possible to both a more relaxed and a more tightened limit in the next cycle when water quality and state fixed effects are taken into account (Model 1-5). This result is best explained by the case where the regulators do not acquire enough information from missing monitoring reports per se. As mentioned in Section 3.3.3., absent DMRs will trigger reviews by the regulator to further investigate the facility and the cause of missing reports. The permit setting decision will depend on additional information obtained from the review process following absent DMRs or a more extensive inspection process.

3.4.3. Inspections and inspection results

A. Inspections

Inspection is an information gathering process for the regulators, with a focus on abatement operation and maintenance in addition to verifying final discharge level. Compared to receiving zero or one inspection, plants that received two or more inspections in the past three years are significantly less likely to receive a relaxed limit and more likely to receive a tighter permit, with different bins of the inspection variable having similar effects in terms of magnitude. This effect is consistent across almost all specifications in the lower equation, and for both the MNL and OL models. This result can be explained together with the objective of inspections and what previous studies have found about inspection. First of all, previous studies suggested that regulators target suspicious plants for inspection, especially those with a poor environmental performance (see for example Gray and Deily 1996; Stafford 2002). Next, the regulators are paying more attention finding out effort level rather than measuring end result during the inspections. One of the major objectives of inspection is to examine abatement operation, monitoring and reporting processes besides verifying the discharge level. With these two points in mind, the estimation results are best explained by the scenario where the regulator’s suspicion of violating plants is confirmed during inspections. The suspects of violations - plants with frequent (two or more) inspections - are found not spending enough abatement effort. Consistent with Hypothesis 2, observing inadequate effort during inspections encourages the regulators to tighten up the permitted level in order to prompt a higher abatement effort from the plants. Having just one inspection, on the other hand, is probably the result of the EPA requirement that major plants should be inspected at least every two years, and may have less to do with the plants’ performance. The results further justify regulators’ strategic use of limited inspection resource by targeting plants with poor performance.

B. Violations detected during inspection

Non-cooperative behaviors discovered during inspections are indicators of inadequate effort and are hypothesized to result in more stringent future permit. Once water quality is controlled for, violations detected during inspection (i.e. single event violation) will significantly increase the probability of tightening up the permit level in both the MNL and OL models (Columns 7 to 10 in Table 3-3 and Columns 4 to 5 in Table 3-4 for the lower equation). This result provides supporting evidence for Hypothesis 2. As regulators observe improper operation and inadequate pollution control effort, they tend to use tighter permit to induce higher level of effort. The lack of adequate effort indicates that it is technically feasible for the plant to achieve a better performance level given appropriate incentive.

For predicting a higher permit in the MNL model, however, having a single event violation makes it more likely to relax the permit (Column 7 to 10 in Table 3-3 for the higher equation). This seemingly counterintuitive result nevertheless confirms that inspection is an information-gathering process. The permitting decision will depend on information revealed during the inspection process in addition to the compliance status. In addition, these results should be considered together with the effect of enforcement actions. Regulator’s first response to a violation should be various forms of enforcement actions, e.g. notice of violations, administrative orders, and penalties. When the lack of effort observed during inspection does not reach the level of a violation, it is an indicator that the limit level might be too relaxed. As the regulators are not able to take enforcement actions in this case (no violation is identified), they have lower incentive to further relax the permit level. This explains why detected violations, compared to no violations, seem to encourage relaxing the permit level.

These results together provide supporting evidence for Hypothesis 2. Both the procedure and findings of an inspection serve as an information-gathering process which will update the regulator's previous assumptions. Common types of detected violations include improper operation and monitoring, late or inaccurate DMRs, as well as unauthorized discharge. As these detected violations are more effort-related (rather than technology related), the regulators tend to use tighter permit to induce higher level of effort if they decide that it is technically feasible for the plant to achieve a better performance level given appropriate incentive. On the other hand, a tighter permit also serves as an additional source of punishment as it implies higher cost to achieve compliance status. When inadequate effort is identified during inspections, regulators may change permit level as an alternative method to encourage abatement effort.

3.4.4. Monetary and non-monetary enforcement actions

Enforcement actions are correlated with violations, and are expected to affect permit setting decisions only if they reveal additional information about the violation, for example, the severity or the degree of water quality damage. In general, I find little evidence that past non-monetary enforcement actions will affect permit setting decisions. In both MNL and OL models, when not including water quality variable, past enforcement actions (excluding penalties) generally have no significant impact on permit change. When water quality is controlled for, one enforcement action makes it more (less) possible for a tighter (relaxed) permit, but two or more enforcement actions have no additional effect if state FE is also controlled for (Model 5). Non-monetary enforcement is typically in the form of notice of violations or administrative orders, which require facilities to correct non-compliance behaviors and results. The lack of significance on these variables seems to suggest that the plants are able to meet the correction requirements within a short period of time. The regulators therefore have no further incentive to revise the permit.

I find supporting evidence that previous penalties have an impact on limit levels of NPDES permits as it reveals the severity of violations and regulator's ability to use penalty as an enforcement tool. Results from the MNL model indicate that large amount of penalty discourage permit change to either direction. The dummy variable for past penalty alone indicates that a plant is more likely to have a relaxed permit if it had penalties before (Model 1-1 to Model 1-4), while there is no significant effect once state FE is controlled for (Model 1-5). In addition, this positive effect of penalty diminishes and eventually leads to the opposite if the amount of penalty is large enough, as suggested by the negative coefficients and marginal effects on the natural logarithm of the penalty amount. The turning point for Model 1-4 is around $1100, which indicates that an increase in penalty will less likely lead to a relaxed limit if the penalty amount is greater than $1100. The effects of past penalties are consistent across different specifications in the MNL model, though it is only marginally significant in the OL model. This result lends support to the hypothesis that the regulators are targeting the highly severe violations that may harm local water quality, as monetary penalty per se is an indicator of severe violation and the amount of penalty is positively correlated with the severity of the violation.

The results in the MNL model in predicting a tighter permit may seem counter-intuitive – past penalties would discourage a tighter permit, and the larger the penalty amount, the stronger the effect. In the OL model, the amount of penalty encourage tightening up the permit (Model 2-4), but this effect becomes insignificant once the state FE is also controlled for (Model 2-5). These results suggest that simply having a penalty makes it no more likely to receive a more stringent permit. A large amount of penalty, however, would discourage permit change to either direction and will more likely keep the permit level unchanged. This is consistent with the hypothesis that regulators have less incentive to tighten permit level if they are able to use penalty as an enforcement tool. On the other hand, the regulators have higher incentive to revise the permit level as an additional enforcement if the ability of levying penalty is restricted. In addition, these findings are not inconsistent with Hypotheses 1 and 2. Highly severe violations (and thus high penalty) are more likely the combined results of both insufficient technology and inadequate abatement effort. When making permitting decisions, the regulators have no incentive to relax the limit level as the plant should be spending more abatement effort. On the other hand, the regulators are reluctant to tighten up the limit either because of the temporary technology constraint. As suggested by Earnhart (2007), regulations more stringent than a certain level can undermine environmental performance. In this case, the best strategy is to keep the current permit level, while hoping the penalty alone will have the desired deterrence effect and encourage the plant to spend more abatement effort.

3.4.5. Water quality

I expect that the permitting authority will respond to local water quality when making permit setting decisions (Hypothesis 3). I use a spline for water quality with a knot at DO equal to 5mg/L as the effect may be different across different level of DO. DO level below 5mg/L is considered a distressed condition for aqua life. In the MNL model, neither of the spline terms for the level of DO have a significant impact on predicting relaxing the limit. In predicting a lower/tighter limit, a marginal improvement in water quality when DO smaller than 5mg/L will make it more likely to tighten the limit in the MNL model, while a marginal improvement beyond 5mg/L will discourage tighter permit in both the MNL and OL models (when state dummies are included). These results are consistent with the hypothesis that the regulator aims to protect local water quality: the permits are more likely tightened up when DO level is low (e.g. water quality is poor below 5mg/L) even though the quality may be improving. Once the water quality improve beyond the critical condition of 5mg/L, a plant is more likely to receive a relaxed permit as expected in Hypothesis 3. These results suggest that state regulators in general do respond to local water quality when determining NPDES permit levels, consistent with findings in Chakraborti and McConnell (2012).

The results with water quality should be explained with caution for the following issues. First of all, data on monitored dissolved oxygen are limited. One of the reasons is failure to identify a nearby monitoring station from all possible sources including STORET, USGS and the state regulatory agencies. Table 3-4 presents number of plants matched and unmatched with a nearby water quality stations by state. In addition, the matched monitoring stations may have limited years of observation. For example, the matched monitoring station of a plant with NPDES permit from 1990 to 2010 may have water quality data only from 2003 to 2007. Figure 3-2 presents the frequency of plant-by-year observations matched and unmatched with water quality data. Finally, there are cases where one plant is matched with multiple monitoring stations to obtain more years of observation. There may be inconsistency across these data since stations from different sources may use different methods to monitor the level of dissolved oxygen.

Summary statistics for the two sub-samples with and without water quality data is presented in Table 3-6, together with results from t-test for equality of sample means. To examine the impact of missing water quality data, I performed a chow-test and failed to reject the null that there is no structural change across the two sub-samples at predicting permit levels (the p-value for the test statistic $\chi^2(30)$ is 0.708).

3.4.6. Multi-plant status

Multi-plant firms, compared to single plant firms, are significantly more likely to receive a tightened limit and less likely to receive a relaxed limit in both the MNL and OL models. This is consistent with the hypothesis that regulators may target multi-plant firms as they are typically heavy dischargers of the water pollutants. In addition, this result could imply that multi-plant firms are more experienced at complying with the NPDES regulation and have more bargaining power when applying for NPDES permits. Therefore they have already obtained the most favorable condition at earlier rounds of permitting less likely to receive permit relaxed even further.

Table 3-2. Multinomial logit results: permit level change

		Model 1-1		Model 1-2		Model 1-3		Model 1-4		Model 1-5	
Equation	**Variables**	**coef.**	**marginal effect**	**coef.**	**marginal effect**	**coef.**	**marginal effect**	**coef.**	**marginal effect**	**coef.**	**marginal effect**
		(1)	**(2)**	**(3)**	**(4)**	**(5)**	**(6)**	**(7)**	**(8)**	**(9)**	**(10)**
Higher	d_absent	-0.049	0.023	0.297	0.068	0.211	0.054	0.482	0.058**	1.876*	0.159***
		(0.290)	(0.045)	(0.332)	(0.048)	(0.322)	(0.049)	(0.714)	(0.024)	(1.102)	(0.030)
	numviol:1	0.506	0.103*	0.638*	0.113*	0.605*	0.110*	-1.795	-0.161***	-1.883	-0.151***
		(0.334)	(0.060)	(0.383)	(0.058)	(0.363)	(0.060)	(1.138)	(0.012)	(1.216)	(0.013)
	numviol:2	0.208	0.071	0.386	0.099	0.484	0.110	0.378	0.150***	0.549	0.164***
		(0.506)	(0.087)	(0.558)	(0.086)	(0.542)	(0.092)	(0.749)	(0.029)	(0.946)	(0.027)
	numviol:>=3	-0.642	-0.034	-0.393	0.009	-0.522	-0.008	-0.444	0.033	1.079	0.254***
		(0.528)	(0.067)	(0.611)	(0.078)	(0.566)	(0.074)	(0.837)	(0.026)	(1.162)	(0.035)
	d_singviol	1.810***	0.301***	1.307**	0.175**	1.236**	0.184**	2.288*	0.131***	2.276	0.123***
		(0.466)	(0.090)	(0.513)	(0.078)	(0.499)	(0.083)	(1.357)	(0.038)	(1.555)	(0.037)
	insp: 2-3	0.316	-0.016	-0.145	-0.056	-0.039	-0.045	0.040	-0.104***	-0.067	-0.097***
		(0.299)	(0.042)	(0.363)	(0.042)	(0.347)	(0.043)	(0.779)	(0.022)	(0.985)	(0.024)
	insp: 4-9	0.559*	-0.008	0.186	-0.041	0.353	-0.012	0.209	-0.085***	0.054	-0.087***
		(0.311)	(0.045)	(0.424)	(0.049)	(0.393)	(0.052)	(0.808)	(0.021)	(1.092)	(0.023)
	insp:>=10	0.549	0.060	1.267*	0.092	0.852	0.072	-0.149	-0.092***	-0.696	-0.098**
		(0.423)	(0.074)	(0.668)	(0.104)	(0.540)	(0.091)	(1.486)	(0.032)	(2.670)	(0.038)
	EA:1	0.005	-0.020	-0.166	-0.042	-0.128	-0.035	0.510	-0.008	-0.511	-0.097***
		(0.319)	(0.041)	(0.361)	(0.037)	(0.349)	(0.039)	(0.914)	(0.024)	(1.038)	(0.017)
	EA:>=2	-0.031	0.012	-0.241	-0.023	-0.171	-0.008	0.495	0.109***	-0.102	-0.011
		(0.360)	(0.052)	(0.418)	(0.045)	(0.390)	(0.048)	(0.920)	(0.033)	(1.176)	(0.026)
	d_pen	4.352**	0.666***	5.044**	0.652***	4.985**	0.685***	8.056	0.546***	9.088	0.260
		(2.004)	(0.175)	(2.265)	(0.125)	(2.102)	(0.112)	(5.690)	(0.155)	(6.291)	(0.172)
	penalty amount, log	-0.436**	-0.058**	-0.499**	-0.061**	-0.486**	-0.064**	-0.840	-0.085***	-0.890	-0.057***
		(0.214)	(0.028)	(0.242)	(0.028)	(0.224)	(0.028)	(0.630)	(0.016)	(0.694)	(0.014)
	DO level <=5							0.784	0.046	1.601	0.118**

								(1.602)	(0.052)	(2.086)	(0.053)
	DO level >5							-0.005	-0.007*	0.027	0.008
								(0.140)	(0.004)	(0.228)	(0.005)
	dummy for multi-plant firms							-1.085**	-0.146***	-0.808	-0.096***
								(0.459)	(0.010)	(0.584)	(0.012)
Lower	d_absent	-0.442*	-0.092*	-0.356	-0.092*	-0.296	-0.077	0.237	0.012	1.214	0.069**
		(0.264)	(0.050)	(0.291)	(0.051)	(0.284)	(0.053)	(0.663)	(0.028)	(0.949)	(0.032)
	numviol:1	-0.184	-0.080	-0.217	-0.092	-0.150	-0.079	-0.507	-0.024	-0.439	0.006
		(0.328)	(0.061)	(0.354)	(0.059)	(0.345)	(0.061)	(0.641)	(0.026)	(0.707)	(0.026)
	numviol:2	-0.506	-0.120	-0.591	-0.139*	-0.412	-0.118	-1.373	-0.248***	-1.588	-0.262***
		(0.493)	(0.086)	(0.524)	(0.081)	(0.507)	(0.084)	(0.980)	(0.020)	(1.008)	(0.018)
	numviol:>=3	-1.106**	-0.183**	-1.060*	-0.172**	-1.174**	-0.188**	-2.176*	-0.295***	-2.018	-0.312***
		(0.486)	(0.074)	(0.556)	(0.082)	(0.524)	(0.074)	(1.157)	(0.017)	(1.258)	(0.014)
	d_singviol	0.638	-0.062	0.420	-0.031	0.370	-0.037	2.324*	0.235***	2.059	0.190***
		(0.469)	(0.078)	(0.500)	(0.080)	(0.492)	(0.081)	(1.317)	(0.040)	(1.356)	(0.042)
	insp: 2-3	0.880***	0.170***	0.541*	0.121*	0.561*	0.121*	1.872*	0.326***	1.491	0.263***
		(0.265)	(0.059)	(0.308)	(0.063)	(0.297)	(0.062)	(1.132)	(0.047)	(1.243)	(0.049)
	insp: 4-9	1.196***	0.227***	0.913**	0.179**	0.832**	0.155**	1.809	0.319***	1.559	0.268***
		(0.273)	(0.062)	(0.355)	(0.073)	(0.336)	(0.072)	(1.159)	(0.042)	(1.305)	(0.047)
	insp:>=10	0.365	0.036	1.071*	0.108	0.697	0.077	1.121	0.245***	0.499	0.136*
		(0.402)	(0.089)	(0.566)	(0.113)	(0.484)	(0.104)	(1.634)	(0.068)	(2.213)	(0.081)
	EA:1	0.279	0.064	0.302	0.076	0.254	0.064	1.034	0.183***	0.711	0.170***
		(0.254)	(0.054)	(0.283)	(0.055)	(0.276)	(0.055)	(0.780)	(0.031)	(0.871)	(0.033)
	EA:>=2	-0.244	-0.051	-0.112	-0.007	-0.228	-0.036	-0.354	-0.104***	-0.015	0.004
		(0.317)	(0.061)	(0.372)	(0.068)	(0.351)	(0.065)	(0.949)	(0.032)	(1.117)	(0.040)
	d_pen	1.132	-0.268*	0.831	-0.281***	0.801	-0.299***	5.995	-0.078	8.190	0.198
		(1.835)	(0.146)	(1.970)	(0.107)	(1.905)	(0.097)	(5.210)	(0.154)	(6.080)	(0.173)
	penalty amount, log	-0.114	0.006	-0.069	0.021	-0.067	0.020	-0.565	-0.059***	-0.798	-0.092***
		(0.190)	(0.037)	(0.205)	(0.037)	(0.197)	(0.037)	(0.561)	(0.020)	(0.667)	(0.022)
	DO level <=5							1.015	0.155**	1.200	0.122*
								(1.639)	(0.071)	(1.714)	(0.067)

DO level >5							0.096	0.020***	-0.074	-0.016**
							(0.116)	(0.005)	(0.176)	(0.006)
dummy for multi-plant firms							-0.323	0.013	-0.083	0.037**
							(0.398)	(0.016)	(0.510)	(0.018)
Observations	840	840	840	840	840	840	179	179	179	179
log likelihood	-847.0		-749.5		-790.5		-168.3		-143.5	
χ^2	71.95		267.10		185.10		41.36		90.93	
p> χ^2	0.000		0.000		0.000		0.081		0.047	
Pseudo R^2	0.041		0.151		0.105		0.109		0.241	
president FE			yes		yes				yes	
state FE			yes						yes	
watershed FE					yes					

Standard errors in parentheses
*** p<0.01, ** p<0.05, * p<0.1
Notes: Dependent variable is permit level change.

Table 3-3. Ordered logit results: marginal effects of permit level change

Equation	Variables	Model 2-1 marginal effect (1)	Model 2-2 marginal effect (2)	Model 2-3 marginal effect (3)	Model 2-4 marginal effect (4)	Model 2-5 marginal effect (5)
Higher	d_absent	0.044	0.056	0.039	-0.001	-0.029*
		(0.035)	(0.037)	(0.036)	(0.016)	(0.017)
	numviol:1	0.078	0.089*	0.076	-0.044***	-0.056***
		(0.048)	(0.050)	(0.048)	(0.014)	(0.014)
	numviol:2	0.095	0.107	0.097	0.237***	0.250***
		(0.074)	(0.075)	(0.073)	(0.030)	(0.029)
	numviol:>=3	0.065	0.062	0.072	0.222***	0.319***
		(0.061)	(0.061)	(0.062)	(0.031)	(0.034)
	d_singviol	0.182**	0.124*	0.126*	-0.057***	-0.049**
		(0.077)	(0.072)	(0.073)	(0.020)	(0.022)
	insp: 2-3	-0.064**	-0.055*	-0.052*	-0.150***	-0.093***
		(0.026)	(0.030)	(0.030)	(0.014)	(0.018)
	insp: 4-9	-0.084***	-0.073**	-0.056*	-0.120***	-0.090***
		(0.025)	(0.033)	(0.033)	(0.014)	(0.018)
	insp:>=10	0.017	0.017	0.003	-0.084***	-0.059*
		(0.048)	(0.065)	(0.055)	(0.022)	(0.033)
	EA:1	-0.037	-0.049*	-0.036	-0.069***	-0.099***
		(0.028)	(0.028)	(0.029)	(0.014)	(0.013)
	EA:>=2	0.032	-0.004	0.023	0.115***	0.021
		(0.043)	(0.041)	(0.043)	(0.027)	(0.024)
	d_pen	0.395	0.454	0.494*	0.301**	0.178
		(0.323)	(0.302)	(0.281)	(0.153)	(0.155)
	penalty amount, log	-0.029	-0.034	-0.037	-0.033***	-0.020*
		(0.023)	(0.024)	(0.023)	(0.011)	(0.012)
	DO level <=5				-0.015	-0.005
					(0.018)	(0.019)
	DO level >5				-0.011***	0.011***

					(0.003)	(0.004)
	dummy for multi-plant firms				-0.053***	-0.055***
					(0.009)	(0.011)
Lower	d_absent	-0.061	-0.073*	-0.053	0.001	0.043
		(0.043)	(0.042)	(0.044)	(0.024)	(0.027)
	numviol:1	-0.099*	-0.108**	-0.095*	0.070***	0.088***
		(0.051)	(0.049)	(0.051)	(0.025)	(0.026)
	numviol:2	-0.115	-0.123*	-0.116*	-0.220***	-0.225***
		(0.071)	(0.068)	(0.070)	(0.017)	(0.016)
	numviol:>=3	-0.084	-0.078	-0.090	-0.211***	-0.262***
		(0.067)	(0.067)	(0.066)	(0.018)	(0.015)
	d_singviol	-0.190***	-0.139**	-0.144**	0.095**	0.077*
		(0.054)	(0.061)	(0.062)	(0.039)	(0.039)
	insp: 2-3	0.096**	0.079	0.076	0.197***	0.124***
		(0.046)	(0.050)	(0.050)	(0.027)	(0.030)
	insp: 4-9	0.133***	0.111*	0.086	0.184***	0.132***
		(0.049)	(0.060)	(0.059)	(0.028)	(0.033)
	insp:>=10	-0.024	-0.024	-0.005	0.151***	0.096
		(0.067)	(0.086)	(0.079)	(0.050)	(0.063)
	EA:1	0.060	0.077	0.058	0.116***	0.171***
		(0.050)	(0.051)	(0.051)	(0.029)	(0.030)
	EA:>=2	-0.045	0.006	-0.033	-0.132***	-0.028
		(0.055)	(0.061)	(0.057)	(0.024)	(0.031)
	d_pen	-0.308**	-0.325***	-0.342***	-0.257***	-0.181*
		(0.128)	(0.107)	(0.095)	(0.073)	(0.109)
	penalty amount, log	0.043	0.049	0.054	0.047***	0.028*
		(0.034)	(0.034)	(0.034)	(0.016)	(0.017)
	DO level <=5				0.021	0.007
					(0.026)	(0.027)
	DO level >5				0.015***	-0.016***
					(0.004)	(0.006)
	dummy for multi-plant firms				0.074***	0.075***

				(0.015)	(0.017)
Observations	840	840	840	179	179
log likelihood	-865.7	-833.3	-846.8	-180.5	-172.7
χ^2	34.54	99.35	72.50	16.84	32.50
p> χ^2	0.001	0.000	0.000	0.328	0.589
Pseudo R^2	0.020	0.056	0.041	0.045	0.086
president FE		yes	yes		yes
state FE		yes			yes
watershed FE			yes		

Standard errors in parentheses

*** p<0.01, ** p<0.05, * p<0.1

Notes: Dependent variable is permit level change.

Table 3-4. Number of chemical plants with and without a nearby monitoring station, categorized by states

State	Number of matched plants	Number of unmatched plants
AL	12	4
AR	1	1
CA	1	0
CT	0	4
DE	4	1
FL	3	0
GA	4	1
IA	1	2
IL	2	11
IN	1	5
KY	6	5
LA	54	1
MD	2	0
MI	1	1
MO	1	3
MS	0	4
NC	14	0
NE	1	0
NJ	11	0
NY	9	3
OH	10	0
OK	0	1
PA	6	1
PR	0	4
RI	0	2
SC	19	0
TN	2	5
TX	42	20
VA	1	7
WA	1	0
WV	16	0
Total	**225**	**86**

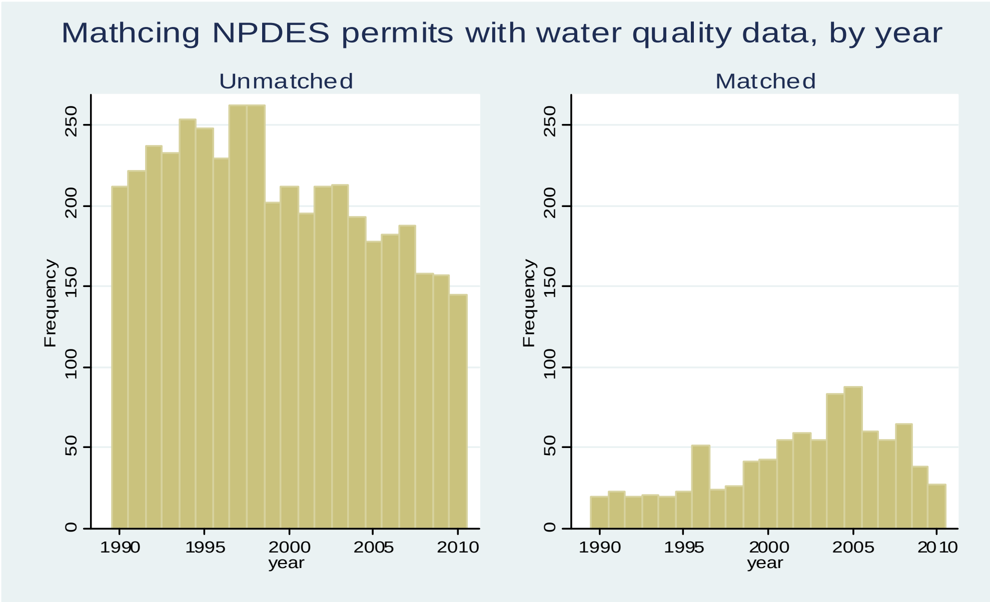

Figure 3-2. Number of NPDES permits matched vs. unmatched with water quality data

Table 3-5. Summary statistics for the sub-samples with and without water quality data

Variable	**Mean of subsample 1 (n=664)**	**Mean of subsample 2 (n=176)**	**p-value for H_0: diff = 0**
numviol:1	0.068	0.095	0.265
numviol:2	0.021	0.067	0.020
numviol:>=3	0.029	0.067	0.055
d_absent	0.124	0.112	0.647
d_singviol	0.050	0.061	0.563
insp: 2-3	0.392	0.564	0.000
insp: 4-9	0.375	0.335	0.319
insp:>=10	0.077	0.028	0.002
EA:1	0.130	0.089	0.105
EA:>=2	0.086	0.067	0.377
d_pen	0.079	0.101	0.379
ln_penalty	0.756	0.897	0.538
d_multi	0.678	0.592	0.038

3.5. Conclusion

3.5.1. Summary and main contributions

This chapter explores determinants of NPDES permit setting in the context of US chemical manufacturing industry. I argue that the regulatory standards are determined by regulators' perception of plants' abatement effort and technology inferred from past performance. Using data on permitting, enforcement and compliance of the chemical industry from 1990 to 2010, I model and estimate the change in limit level as a function of plants past performance and regulatory activities received. Estimation results support the hypothesis that the regulators use plants' past performance to obtain information on abatement effort and technology when making regulatory decisions. More specifically, I find that self-disclosed violations are regarded as a signal for cooperation (adequate abatement effort under technology constraint) and will be rewarded with relaxed future permit. Inspection is an information-gathering process and provides information not otherwise available for the permitting decision. Inadequate abatement effort detected during inspections (e.g. improper operation and maintenance) will lead to more stringent future limit as it is technically feasible. The regulators are hesitant about their decisions in the case of violations due to the combination of inadequate effort and insufficient technology (e.g. violations that lead to high penalties). In addition, the permitting decision will also depend on regulator's ability to use enforcement tools. As tighter permits can be used as an additional tool to encourage higher abatement effort, the regulators are less likely to change the limit if they are capable of using the usual enforcement tools like penalties without constraint. I have also found supporting evidence that the permitting authorities do respond to local water quality. These results, however, should be explained with caution as data on water quality are limited.

This chapter contributes to the literature on environmental regulatory standard setting by providing the first empirical evidence on factors that affect standard setting decisions – the tradeoff between technology constraint and pollution control effort – in the context of water pollution regulation. Setting and enforcing performance standards are an integral strategy from the regulator’s point of view. Findings from this chapter confirm that regulators adjust not only enforcement strategy but also performance standards in response to facilities’ compliance history. This implies for the plants that maintaining a good environmental performance may have the additional benefit of relaxed permit in addition to reduced scrutiny as found in previous studies. Finally, as compliance status is defined as actual performance relative to the standard, this chapter also contributes to the understanding of enforcement and compliance by internalizing the decision making on standard setting.

3.5.2. Future research

This study can be extended in a number of ways. First of all, this chapter examines the relationship between permit setting and compliance history only for the chemical manufacturing industry and only for one pollutant. It is interesting to explore whether similar relationship holds for a broader set of industries and other pollutants. In addition, a natural follow-up question to ask is whether the regulators make permitting and inspection decisions simultaneously or sequentially. A structural equation estimation of permit setting, inspection and enforcement actions can be used to examine the joint decision of standard setting and enforcement strategies. The results of this study suggest regulators will tighten the NPDES permit to prompt a higher level of abatement effort if inadequate effort is observed. Following the result, it will be interesting to test whether a tightening up of the permit will indeed have the desired effect and lead to greater abatement effort by the regulated plants. Finally, it is also worth exploring how to strategically use a combination of permitting and enforcement to provide an incentive for adoption of cleaner technology in addition to higher abatement effort. Better technology would relax the current technology constraint and lead to more efficient pollution reduction.

Chapter 4: Concluding remarks

The implementation of environmental regulations has led to substantial improvement of environmental quality in the nation for the past few decades. Affected businesses and political groups, on the other hand, argue that these regulations impose significant costs and lead to loss of productivity and competitiveness. The heated debate on environmental regulations has focused on tradeoff between protecting the environment and reducing the regulatory burdens for the regulated firms and industries. However, it is not possible to reach a consensus or even a common ground for discussion without defining a proper measure for such regulatory burden and quantifying the economic impact of regulations. Regulators face the tradeoff between environmental quality and cost/technology feasibility when determining an exact level of regulatory stringency. It is crucial to understand the factors regulators take into account when facing these tradeoffs and making regulation decisions. This dissertation aims to contribute to this debate by defining a more accurate measure of regulatory stringency, quantifying the competitiveness impact of environmental regulations, and exploring factors affecting regulatory decision making.

In the first part of Chapter 2, I examine whether PAC provides a good measure of regulatory burdens on affected industries. I construct a heterogeneous firm model to show that regulation-induced changes in industry-level abatement costs contain both an intensive margin and an extensive margin. I apply decomposition analysis to identify the magnitude of the intensive margin and extensive margin effects. Results from the analysis confirm that the intensive margin more accurately represents the direction and magnitude of regulation changes, while overall abatement cost change tends to underestimate changes in regulatory stringency.

Beyond the issue of measurement, I quantify the competitiveness impacts of environmental regulations in the second part of Chapter 2. The impact of regulation on trade flows is likely to be overestimated if the undervalued regulation change is used as the explanatory variable in testing PHE. To address this issue, I use the intensive and extensive margins as separate explanatory variables to explain changes in the US net imports from Canada, Mexico and the rest of the world. Results from fixed effects estimations suggest that abatement cost changes on the intensive margin and the extensive margin may lead to different or even opposite of PHE. The PHE led by intensive margins is much smaller than previously estimated, which suggests that the overestimation is corrected by using the intensive margin as a measure of regulation.

Do regulators take into account cost and technology feasibility at all when trying to protect the local environment? In Chapter 3 of the dissertation, I explore regulatory decision making in the context of the NPDES permit program of the water pollution regulation. The NPDES program requires both a technology-based and a water quality-based effluent limitation in order to protect local water quality. Results from empirical analyses confirm that regulators use facility's compliance history to infer their technology capacity and abatement effort. More specifically, I find that abatement effort under technology constraint as reflected by self-disclosure behavior is regarded as a cooperating behavior and will be rewarded by relaxed limit levels in the future. On the other hand, inadequate pollution control effort such as improper operation and maintenance will result in more stringent future NPDES permit. Estimation results in this dissertation also support the hypothesis that permitting authorities in the US do respond to water quality when making permitting decisions.

This dissertation contributes to the understanding of the economic impacts of environmental regulations in the following ways. First of all, I identify a more accurate measure for changes in regulatory stringency that is derived from facilities' PAC. This measure controls for industry composition change caused by firm-heterogeneity in technology and differentiated response to regulation. A proper measure of regulatory stringency forms the basis for evaluating any economic impact of regulations on the affected industries. Secondly, I correct the overestimation of PHE in previous studies by using the more accurate measure of regulation change. Environmental regulations do harm manufacturing industries' competitiveness to the extent that tighter regulations will lead to increased net imports, but the negative impact is not as bad as previously thought if we take into account the changes in market structure. Finally, this dissertation is the first to systematically study the effects of regulation on trade flows while controlling for changes in industry structure. By using the intensive margin and composition change as separate explanatory variables to explain trade flows, I differentiate the impacts of regulation caused by increasing regulatory burden on a fixed set of firms/industries from those caused by change in composition.

By studying the NPDES permit program, this dissertation contributes to the literature on environmental regulatory decision making. Previous studies on environmental regulations have focused on the determinants of inspections and enforcement activities. To the best of my knowledge, this study provides the first empirical evidence of factors affecting regulatory standard setting in the context of water pollution regulations. Results from econometric analyses suggest that regulators aim to protect water quality by inducing higher abatement effort within technology constraint, on which the information is inferred from facilities' compliance behavior. Chapter 3 of the dissertation implies that the tradeoff between the level of environmental protection effort and technology feasibility is the main consideration for determining the stringency of water regulation. Finally, setting and enforcing performance standards are an integral strategy from the regulator's point of view. Findings from Chapter 3 confirm that regulators adjust not only enforcement strategy but also performance standards in response to facilities' compliance history.

Appendices

Appendix A. Derivation of the intensive and extensive margins

The industry level PAC intensity can be written as

$$\varphi = \frac{\int_{\eta_L}^{\eta_H} PAC\, d\eta}{\int_{\eta_L}^{\eta_H} VADD\, d\eta} = \frac{\int_{\eta_L}^{\eta_H} \left(\theta c^F \frac{y}{1-\theta}\right) d\eta}{\int_{\eta_L}^{\eta_H} (py - c^F F)\, d\eta} = \frac{N}{D} \qquad (A-1)$$

The impact of an environmental tax change is

$$\frac{d\varphi}{dt} = \frac{dN}{dt}\frac{1}{D} - \frac{N}{D^2}\frac{dD}{dt} \qquad (A-2)$$

where

$$\frac{dN}{dt} = \int_{\eta_L}^{\eta_H} \frac{dPACE}{dt} d\eta - PACE|_{\eta=\eta_L} \frac{d\eta_L}{dt} = B_1 - C_1 \frac{d\eta_L}{dt} \qquad (A-3)$$

$$\frac{dD}{dt} = \int_{\eta_L}^{\eta_H} \frac{d(p - c^F \frac{1}{1-\theta})}{dt} d\eta - \left(py - c^F \frac{y}{1-\theta}\right)\Big|_{\eta=\eta_L} \frac{d\eta_L}{dt}$$

$$= B_2 - C_2 \frac{d\eta_L}{dt} \qquad (A-4)$$

Equations (A-3) and (A-4) are obtained using the Leibniz integral rule and assuming that η_H does not change with respect to regulation. Note that the terms B_1, B_2, C_1, C_2, D are functions of model parameters$(p, t, c^F; \eta_H, \eta_L)$, where $\eta_L$is the before change cutoff value. However, the second terms of (A-3) and (A-4) depend on how the cutoff value will change in response to the changes in regulation. Now plug dN/dt and dD/dt back into $d\varphi/dt$, and we have

$$\frac{d\varphi}{dt} = \frac{dN}{dt}\frac{1}{D} - \frac{N}{D^2}\frac{dD}{dt} = \left(\frac{B_1}{D} - \frac{NB_2}{D^2}\right) - \left(\frac{C_1}{D} + \frac{NC_2}{D^2}\right)\frac{d\eta_L}{dt}$$

$$= \lambda_0(p, t, c^F; \eta_H, \eta_L) - \lambda_1(p, t, c^F; \eta_H, \eta_L)\frac{d\eta_L}{dt} \qquad (A-5)$$

where the first part is the aggregate cost change for a fixed set firms as if the cutoff values remained the same, and the second part denotes abatement cost change that depends on firm dynamics and the change of the cutoff abatement productivity.

Appendix B. Discussion of the PACE survey

As described in Section 2.4.1, the PACE survey collects data on costs related to pollution treatment, prevention and other activities from manufacturing facilities. It thus provides the single most comprehensive source of abatement costs and expenditures (U.S. Bureau of the Census, 1977). This information on compliance cost is crucial for the purpose of examining the economic impact of environmental regulations. Therefore data from the PACE survey have been widely used by economists in analyzing firms' response to regulations (decisions on location and size) as well as the impact of regulations on investment, employment and productivity at industry level.

Overtime, however, the researchers using the PACE data have identified several issues of the PACE survey related to whether it accurately collects and measures pollution-related expenditures. Main issues include, firstly, that not all pollution related costs are captured by the PACE survey and the data may under-estimate true compliance cost (Morgenstern et al., 1998). Expenditures spent on changes in production process or input substitution may serve the dual purposes of abatement and profit-generating, and it is difficult for the facility accountant/manager to record this cost as abatement cost. In addition, additional constraint imposed by environmental regulation may reduce productivity of other (non-abatement) inputs or overall productivity (Gray & Shadbegian, 2002; Jorgenson & Wilcoxen, 1990; Levinson, 1996) . However, when firm heterogeneity is accounted for using fixed effects estimations, the magnitude of underestimation becomes negligible or even to the opposite. This is because the unobserved firm heterogeneity in productivity will generate different estimates of costs (Morgenstern et al., 1998). Secondly, facilities lack appropriate baseline against which to compare cost (Berman & Bui, 2001; Jaffe et al., 1995; A. Levinson, 1996). The accurate cost data should compare the actual scenario with the counterfactual by measuring the costs above and beyond the amount a plant would have spent in the absence of pollution control effort. The PACE reports mentioned in their introduction section that telephone conversations and interviews with survey respondents indicate that in many instances estimating the baseline and the incremental costs related to pollution control is very difficult.

I use only operating costs in this study because the above mentioned concerns are more severe for capital expenditures. The PACE survey reports the baseline issue as a major limitation of the data and therefore warns users to explain the CIPP data with caution (U.S. Bureau of the Census, 1977). In addition, capital expenditures are for new investment during the survey year instead of annualized costs (Levinson & Taylor, 2008). Focusing on a single year's capital expenditure can be problematic as it only reflects one-time purchasing expenditures and installation costs. However, the effects of environmental regulations usually last several years after they are first enacted. Therefore the capital expenditures occurred for the purpose of complying with regulations should be allocated over the years instead of counting them as a one-time cost. Lastly, there are considerable missing values for capital expenditures in the published survey results at the 4-digit SIC industry level. A major part of these missing values are withheld to avoid disclosing operations of individual companies. Considerable information is lost due to the missing values, which makes comparisons over time less robust. Therefore, I use only operating costs for which the missing data issue is much less severe.

Appendix C. Dealing with missing values in PAOC data

Missing values in the pollution abatement cost measures pose a major challenge for the decomposition analyses. We need a balanced panel in order to obtain consistent output shares and abatement cost intensities to calculate the differences. To deal with the missing values, I proceed in the following 2 steps.

I have a total of 17 years of data (1977 to 1994, except 1987) for the pollution abatement costs. I first dropped any 4-digit industry that has missing PAOC data for 9 or more years. By doing so, I dropped about 20% of the total data (1496 out of 7616).

Any industry with missing PAOC less than 8 year will remain in the data (80.36%), where the missing data will be interpolated. Next I dropped two 2-digit SIC sectors, Leather and leather products (31) and Miscellaneous manufacturing industries (SIC39), because the majority of them are missing values. In other words, the 4-digit industries within these 2 sectors have very limited data in the PACE survey. The second step is to interpolate the missing values of PAOC. The basic idea is to assign those 4-digit industries the average abatement cost intensity of an average industry within the same 3-digit or 2-digit sector. Now there are a total of 5831 observations in the dataset, but only 4873 of them have the abatement cost measure, with 958 missing values. I calculate the average abatement cost intensity (PAC/value added) at 3-digit and 2-digit SIC levels, where the PAOC data are not missing at these higher levels of aggregation. Any missing 4-digit SIC abatement cost data is first replaced by the 4-digit value added multiplied by the 3-digit average cost intensity. Any remaining missing values are further replaced by multiplying the 2-digit average cost intensity. At the end, 956 of the 958 missing 4-digit PAOC observations are interpolated. The remaining 2 missing values are because the PAOC data is missing at even 2-digit level (SIC21, tobacco products in 1981). These interpolated PAOC data are used in the decomposition analyses in Section 2.4 and PHE estimation in Section 2.5. The original and the interpolated PAC data are not statistically different according to classical t test. Finally, I restrict the sample period from 1977 to 1986 for the reasons mentioned in Section 2.4.2 and Appendix B.

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