Jobs versus the Environment: An Industry-level Perspective

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Abstract

The possibility that workers could be adversely affected by environmental policies imposed on heavily regulated industries has led to claims of a “jobs versus the environment” trade-off by both business and labor leaders. The present research examines this claim at the industry level for four heavily polluting industries: pulp and paper mills, plastic manufacturers, petroleum refiners, and iron and steel mills. By focusing on labor effects across an entire industry, we construct a measure relevant to the concerns of key stakeholders, such as labor unions and trade groups.

We decompose the link between environmental regulation and employment into three distinct components: factor shifts to more or less labor intensity, changes in total expenditures, and changes in the quantity of output demanded. We use detailed plant-level data to estimate the key parameters describing factor shifts and changes in total expenditures. We then use aggregate time-series data on industry supply shocks and output responses to estimate the demand effect.

We find that increased environmental spending generally does *not* cause a significant change in industry-level employment. Our average across all four industries is a net gain of 1.5 jobs per $1 million in additional environmental spending, with a standard error of 2.2 jobs—an insignificant effect. In the plastics and petroleum sectors, however, there are small but significantly positive effects: 6.9 and 2.2 jobs, respectively, per $1 million in additional expenditures. These effects can be linked to favorable factor shifts—environmental spending is more labor intensive than ordinary production—and relatively inelastic estimated demand.

Key Words: Jobs-environment trade-off, distribution of environmental costs, translog cost function

JEL Classification Numbers: C33, D24, J40, Q28

Contents

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1. Introduction

Environmental polices involve economic costs that are unevenly borne by individuals and industries across the economy. The possibility that workers could be adversely affected in heavily regulated industries has led to claims of a "jobs versus the environment" trade-off, a mantra echoed by both business and labor leaders. At a minimum, the visibility and emotion associated with potential job loss make it a crucial issue in ongoing policy debates. Interest groups now routinely develop Congressional district-level estimates of job losses associated with proposed legislation (Hahn and Steger 1990). Not surprisingly, a third of the respondents to a 1990 poll thought it somewhat or very likely that their own job was threatened by environmental regulation (Rosewicz 1990).

Accepting the notion that potential job loss due to regulation is an important phenomena to understand, one of the challenges for researchers in this field is how best to measure job loss. An individual separated from an existing job because of an environmental regulation has clearly suffered a loss. Yet, pollution abatement activities themselves require labor input. Thus, environmental regulations may also create jobs—sometimes in the same industry, or even in the same firm. In addition, environmental regulation may cause firms in a particular industry to shift production and jobs from areas not attaining federal air quality standards to those in attainment. Job loss in one area is then accompanied by job creation in another.

Key stakeholders, such as labor unions and trade groups, typically focus on *gross* job changes and the cost of rearranging workers within an industry. However, *net* job loss within an industry—which recognizes all intra-industry employment changes associated with

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environmental regulation—also is a relevant measure for ongoing policy debates. Such a measure recognizes that many firms endeavor to relocate employees in other units of the same company, and that remaining plants in the industry often expand output to make up for the shut-down production, thereby offsetting at least some of the initial job losses. Not surprisingly, consideration of *net* employment impacts at the industry level has figured prominently in a number of major environmental decisions. These include:

- the Clean Air Act Amendments (1990), Title IV (acid rain), vis-a-vis potential impacts on coal miner jobs;
- the Iron and Steel Effluent Guideline issued by the U.S. Environmental Protection Agency (1982);
- the Spotted Owl decision under the Endangered Species Act (1995) vis-à-vis potential impacts on loggers; and
- major regulatory decisions carried out under the Clean Water Act.

Using reported environmental spending as a measure of regulation we decompose the labor consequences of increased spending into three distinct components. These include: increases in all factor inputs, holding output factor shares constant (cost effect); changes in factor intensities (factor shift); and changes in the quantity of output demanded (demand effect). This decomposition gives a structural interpretation to the link between environmental spending and employment. We then use plant-level data to estimate a cost function that allows us to assess the first two components. These estimates are combined with estimates of industrywide demand elasticities to calculate the third component as well as the overall change in employment associated with increases in reported environmental spending. Estimates are developed for four heavily polluting industries (pulp and paper, plastics, petroleum, and steel).

2. Literature Review

A wide range of research efforts have been used to address the connection between environmental regulation and employment, including aggregate policy modeling (macroeconomic and general equilibrium), economywide microeconomic studies, industry-specific studies, and analyses of plant location and growth. Estimates of the economywide job impacts of environmental regulations traditionally are based on simulations of large macroeconomic and general equilibrium models. In a review of macroeconomic modeling efforts published in journals, OECD publications, and by the U.S. EPA, Goodstein (1994) found that seven of the nine studies showed increases in employment, one showed a decrease and one was mixed. He concludes, "on balance, the available studies indicate that environmental spending… has probably led to a net increase in the number of jobs in the U.S. economy… (although) if it exists, this effect is not large."

General equilibrium assessments of environmental regulation, such as Hazilla and Kopp (1990) and Jorgenson and Wilcoxen (1990), typically assume full employment; specifically, the real wage adjusts so that labor demand equals labor supply. Any changes in the number of jobs in the economy therefore hinge on workers choosing to work more or less based on changes in the real wage. Since the real wage falls with increased environmental regulation due to reductions in productivity, employment will likely decline.[1] In these models, environmental regulation leads to job loss because individuals decide to work less in response to a lower relative price of leisure. However, such labor-leisure choices are unlikely to be the object of concern voiced by labor leaders or respondents to public opinion polls.

At the individual firm or plant level, business and labor experts typically argue that environmental regulation increases a company's production costs and puts upward pressure on prices. Price increases, in turn, result in a loss of sales and at least some reduction in plant-level employment. Employer responses to surveys by the U.S. Department of Labor (various years) indicate that environmental spending accounts for only about 650 job losses per year, or less than one-tenth of one percent of all mass layoffs in the United States. Of course, these surveys may understate potential job losses because they ignore the effects on smaller firms as well as the possibility that environmental regulation may be an important secondary factor in plant closure decisions. Conversely, such estimates may overstate the net job impacts by failing to account for employment increases associated with environmental regulation (control activities and/or shifts in employment to other plants).

[1] Of course, employment could rise as the real wage falls, depending on whether the uncompensated labor supply curve is upward sloping or backward bending. See Hausman (1985).

Studies of specific industries are less common than economywide analyses. Early research on the electric power industry by Gollup and Roberts (1983) found significant job loss associated with increased environmental regulations. More recent work by Berman and Bui (1997) compares petroleum refineries in the Los Angeles area to all other U.S refineries. The authors find no evidence that environmental regulation decreased labor demand, even when allowing for induced plant exit and dissuaded plant entry. "If anything," they note, "air quality regulation probably increased employment slightly."

An area of related work has focused on the possible influence of environmental regulation on plant location, capturing the notion that heavily regulated and generally more polluted areas may suffer a *relative* penalization. Although new environmental regulations may not cause firms to relocate existing plants, firms have considerable flexibility in making decisions about the siting of new plants. Studies by Bartik (1988), Low and Yeats (1992), and Crandall (1993) suggest that firms are sensitive, in general terms, to cost variations among states when deciding where to locate new facilities. However, there is little direct evidence of a relationship between stringency of environmental regulation and plant location choices. In an analysis that includes measures of environmental stringency, Bartik found that neither measures of expenditures nor emission standards had significant effects on plant location decisions. These results are similar to those of Levinson (1996) and McConnell and Schwab (1990), although Levinson did find that the locations of new branch plants of large multiplant companies in pollution-intensive industries were somewhat sensitive to differences in regulations. In contrast, a recent study by Gray (1996) finds that states with more stringent regulation (measured by a variety of state-specific measures) have fewer plant openings.

Finally, several studies have compared rates of manufacturing employment growth—not just new plants—in attainment areas versus non-attainment areas.[2] Papers by Henderson (1996) and Kahn (1997) found relatively lower growth rates in manufacturing employment in non-attainment counties compared to those that attained the air quality standard. Becker and Henderson (1997) found that environmental regulation reduced births and increased deaths in

[2] Attainment status refers to whether a county meets federal air quality standards.

non-attainment areas, shifting polluting activity to cleaner areas. With a similar approach, Greenstone (1997) estimates an annual loss of about 8000 jobs over the period 1972-1987. Importantly, his estimates assume that employment growth at polluting plants in less regulated areas is an appropriate control group from which to infer the likely change in employment in the absence of regulation.[3]

Overall, existing work on the possible jobs versus the environment trade-off presents a bit of a puzzle. Environmental factors typically are secondary considerations behind labor and geographic issues in the siting of new plants. However, there is evidence that employment growth rates do vary according to attainment status. Whether such results indicate either a net decline in employment, a spatial reallocation of production, or even an employment increase in cleaner areas, is unclear.

Most of the research in this field has been limited to the use of reduced form models. Such models do not generally yield insights into the causes of observed employment effects, making it difficult to understand the mechanism by which job loss occurs or to have confidence in the robustness of the results. By looking across several industries and decomposing employment effects into distinct supply- and demand-side components, we are able to look for patterns of employment changes. This perspective gives us more confidence in our results and a greater ability to understand the likely consequences under different conditions. In the following sections we derive expressions for the different components of labor effects at the plant level, develop an estimation strategy for computing their magnitudes, and present our results.

3. Decomposing the Effect of Environmental Regulation on Employment

When environmental regulations are tightened, employment will adjust to both a rearrangement of production activities as well as a potential output contraction. Rhetoric surrounding the jobs versus the environment debate focuses on the output contraction: increased regulation raises production costs, reduces demand and eventually costs jobs. This reasoning

[3] Alternatively, one could postulate that polluting plants in more regulated areas are the appropriate control and that environmental regulation has actually created 8000 jobs per year in the less regulated areas.

ignores the fact that employment could rise if demand is less than unit elastic or if production becomes more labor intensive. For that reason, it is useful to closely examine how increased regulation translates into changes in employment.

On the production side, there are two arguments for increased employment. First, environmental regulation usually raises production costs. Although Porter and van der Linde (1995) have argued the reverse—that increased regulation lowers production costs—the bulk of the economics literature, as recently summarized by Jaffe, Peterson et al. (1995), is unsupportive of that view. If production costs rise, more inputs, including labor, are used to produce the same amount of output. We refer to this as the cost effect.

Second, environmental activities may be more labor intensive than conventional production. For example, cleaner operations may involve more inspection and maintenance activities, or reduced use of fuel and materials. In both instances, the amount of labor per dollar of output will rise. This argument obviously can go the other way: cleaner operations could involve automation and less employment, for example. We refer to this effect as a factor shift.

The more traditional concern is that as production costs rise in response to increased environmental regulation, output prices will rise, quantity demanded will fall, and plants will reduce employment levels. The extent of this effect depends on the cost increase passed on to consumers as well as the demand elasticity of industry output. These two features may not be independent: industries facing elastic output demand due to stiff competition may prove more adept at lowering the cost of environmental compliance. Less competitive industries with inelastic demand may be less concerned about cost increases associated with regulation. We refer to this as the demand effect.

3.1 Production effects

We consider the effect of increased regulation in three distinct steps. First, we examine how changes in regulation affect employment at the plant level, holding output constant. Second, we consider how these effects will affect market prices in a particular industry. An important element of this analysis will be our assumptions about the competitive structure of the industry as well as how new regulation is likely to affect each plant differently. Finally, we consider the aggregate demand response to industry-level price changes and how they relate back to individual plant-level employment.

To compute the effects of regulation at the plant level, we rearrange the definition of plant-level employment in a particularly convenient form. Specifically,

$$(1) \qquad L = \frac{1}{P_l} v_l \cdot TC$$

where L is employment, P_l is the wage, v_l is the share of labor in total costs, and TC are total costs (including both conventional production and regulatory costs). With this rearrangement, the derivative of plant-level employment with respect to regulation can be written:

$$(2) \qquad \left.\frac{\partial L}{\partial RC}\right|_{Y=\bar{Y}} = \underbrace{\frac{TC}{P_l}\frac{\partial v_l}{\partial RC}}_{\text{factor shift}} + \underbrace{\frac{v_l}{P_l}\frac{\partial TC}{\partial RC}}_{\text{cost effect}}$$

where RC is a dollar measure of regulatory burden and $Y = \bar{Y}$ indicates explicitly the constant output assumption. Expressing the derivative in this way allows us to identify the cost effect and factor shift. The first term on the right-hand side (2) represents factor shift. Changes in the share of labor translate directly into changes in employment as production becomes more or less labor intensive. The second term represents the cost effect as total costs rise with higher regulation. Higher costs, holding input shares constant, yield larger expenditures on labor. Note that higher regulatory costs, as measured by direct expenditures on environmental activities, does not necessarily affect total costs one-for-one. There may be uncounted burdens and benefits associated with these environmental expenditures.[4]

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[4] Our allowance for uncounted costs and benefits does not completely solve the problem of using regulatory expenditures as a proxy for regulation—since there may be other costs associated with regulation that are completely uncorrelated with the reported expenditures *RC*. This is, however, a common approach (Hazilla and Kopp 1990; Gray 1987; Jorgenson and Wilcoxen 1990).

3.2 Aggregating plant level effects

Expression (2) reveals the change in employment associated with increases in a regulation for a single plant. In order to compute an industrywide effect—still holding output constant—we need to make assumptions about how different plants are affected by the same regulation and then add these effects across plants. That is

$$(3) \qquad \left.\frac{\partial L_{\text{agg}}}{\partial RC}\right|_{Y=\bar{Y}} = \sum_{i=1}^{I} \frac{\partial L_i}{\partial RC_i} = \sum_{i=1}^{I} \frac{TC_i}{w_i} \frac{\partial v_{L,i}}{\partial RC_i} + \sum_{i=1}^{I} \frac{v_{L,i}}{w_i} \frac{\partial TC_i}{\partial RC_i},$$

where there are I plants, L_{agg} is the aggregate employment level, and i subscripts indicate plant-level values for each variable, in particular, the specific regulatory burden RC_i of plant i.

At this point, we are forced to make an assumption about how regulations differentially affect plants. As noted in Section 1, environmental regulations typically focus on polluting industries, not individual plants, so the problem is specifying the likely distribution of burden. For simplicity, we assume that regulations affect plants in proportion to their total costs.[5] That is, we assume that an extra dollar of regulatory burden affects plant i by an amount equal to plant i 's total costs as a share of the industrywide total costs, $TC_i / \Sigma_{j \le I} TC_j$. Assuming that the relation between costs and regulatory burden, $\partial TC / \partial RC$, is the same for all plants (which is true in our production model below), regulation then raises the costs of production at all plants by the same proportion. In particular, new industrywide regulation raises costs by a fraction:

$$(4) \qquad \frac{1}{TC_i}\frac{\partial TC_i}{\partial RC_{\text{agg}}} = \frac{1}{TC_i}\left(\frac{\partial TC_i}{\partial RC_i}\right)\left(\frac{\partial RC_i}{\partial RC_{\text{agg}}}\right) = \frac{1}{TC_i}\left(\frac{\partial TC}{\partial RC}\right)\frac{TC_i}{TC_{\text{agg}}} = \left(\frac{\partial TC}{\partial RC}\right)\frac{1}{TC_{\text{agg}}}$$

at each plant i. Expression (3) becomes

[5] Generally, larger plants face larger costs in response to new regulations. This specification also simplifies the question of aggregation discussed below. In earlier work, we assumed the burden of additional regulation was proportional to the level of existing regulation $RC_i/\Sigma_j RC_j$. The choice has little impact on our results.

(5)
$$\left.\frac{\partial L_{\text{agg}}}{\partial RC_{\text{agg}}}\right|_{Y=\bar{Y}} = \frac{1}{TC_{\text{agg}}}\sum_{i=1}^{I}\frac{TC_i^2}{P_{l,i}}\frac{\partial v_{l,i}}{\partial RC_i} + \left(\frac{\partial TC}{\partial RC}\right)\frac{1}{TC_{\text{agg}}}\sum_{i=1}^{I}\frac{v_{l,i}TC_i}{P_{l,i}}$$
$$= \frac{1}{TC_{\text{agg}}}\sum_{i=1}^{I}\frac{TC_i^2}{P_{l,i}}\frac{\partial v_{l,i}}{\partial RC_i} + \left(\frac{\partial TC}{\partial RC}\right)\frac{L_{\text{agg}}}{TC_{\text{agg}}}.$$

We must also consider how plant-level cost effects translate into industry-level price effects in order to address demand consequences at the industry level. To do this, we assume that there is monopolistic competition within the industry. Specifically, suppose that output from different plants can be aggregated into a composite good that is demanded by other agents in the economy. This composite good is defined by:

(6)
$$q_{\text{agg}} = \left(\sum \omega_i q_i^{\frac{\rho-1}{\rho}}\right)^{\frac{\rho}{\rho-1}}$$

(e.g., Dixit and Stiglitz 1977), where q_i is the output of plant i, q_{agg} is the aggregated output and ω_i and ρ are aggregation parameters. This aggregation formula recognizes that even at the 4-digit Standard Industrial Classification code level, there can still be heterogeneity in output. The elasticity of substitution ρ among the output of different plants captures this heterogeneity and leads to a fixed mark-up of equilibrium price over cost.[6] This assumption further supports both the observation that costs do differ among plants and that market concentration may lead to noncompetitive pricing behavior.

Our assumptions about market structure allow us to explicitly determine both how changes in production costs at individual plants will affect market prices and demand, as well as how changes in demand will, in turn, affect individual plants. In particular, if costs at each plant rise by the same proportion, the market price for each plant's output will rise by that proportion. Further, if aggregate demand falls by some fraction, output demand at each plant will fall by that same fraction. We use this result when we compute our demand effect below.

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[6] The important practical assumption for our results is that prices rise in proportion to costs. This remains true in the limit of perfect competition as ρ tends to infinity as well as for more general specfications.

3.3 Demand effect

Our measurement of the demand effect is based on the assumption that demand for the composite industry output good q_{agg} exhibits a constant elasticity σ_d. When environmental regulations are tightened and total costs rise based on (4), each plant faces a proportional rise in costs, say θ. Based on the industry model (6), this leads to a proportional rise θ in the price of each plant's output as well as the price of the composite good q_{agg}. Demand for the composite good then falls by $\sigma_d \theta \cdot q_{agg}$.

From (4) and (6) we can therefore write:

$$(7) \qquad \frac{\partial q_{\text{agg}}}{\partial RC_{\text{agg}}} = -\sigma_d \frac{(\partial TC / \partial RC)}{TC_{\text{agg}}} \times q_{\text{agg}} \quad ,$$

where σ_d is the industry-level elasticity of demand, q_{agg} is output of the composite good, and $(\partial TC/\partial RC)(1/TC_{\text{agg}})$ is the fractional rise in cost at each plant. This contraction in aggregate demand leads to a proportional output contraction $\sigma_d\,(\partial TC/\partial RC)(1/TC_{\text{agg}})$ at each plant and, in turn, a proportional reduction in employment. Adding the affects across plants, we have:

$$(8) \qquad \left.\frac{\partial L_{\text{agg}}}{\partial RC_{\text{agg}}}\right|_{\substack{\text{demand}\\ \text{effect}}} = -\sigma_d \frac{(\partial TC / \partial RC)}{TC_{\text{agg}}} \times L_{\text{agg}} \, .$$

That is, the demand effect per dollar of additional regulatory burden equals the fractional change in total costs, adjusted for any incidental savings or costs $(\partial TC/\partial RC)$, scaled by the elasticity of demand σ_d and the aggregate employment level L_{agg}.

3.4 Total employment effect

Combining the demand effect (8) with the previous production effects (5) yields an expression for the entire employment effect,

$$(9) \qquad \frac{\partial L_{\text{agg}}}{\partial RC_{\text{agg}}} = \frac{1}{TC_{\text{agg}}} \sum_{i=1}^{I} \frac{TC_i^2}{P_{l,i}} \frac{\partial v_{L,i}}{\partial RC_i} + (1-\sigma_d)\left(\frac{\partial TC}{\partial RC}\right)\frac{L_{\text{agg}}}{TC_{\text{agg}}} \, .$$

Unlike studies that focus solely on negative demand effects, (9) explicitly allows for supply-side labor effects that may offset any industrywide contraction. Equation (9) also allows us to look at each piece of the employment effect separately, assess its economic and statistical significance, and potentially design policy to properly address labor and industry concerns. Evaluation of this expression requires estimates of a structural model of production costs along with an industry-level demand elasticity. We now address these issues.

4. Estimation of Production Technology and Demand Elasticity

With the exception of the elasticity of demand, the parameters that describe the relation between employment and environmental regulation are determined by production technology. In recent work (Morgenstern, Pizer, and Shih 1999), we have developed a flexible approach to estimating production and pollution abatement technology, which we use to estimate these parameters and their standard errors. We describe that model along with our approach to estimating aggregate demand elasticities, and how all of these results can be combined to compute each term in Equation (9).

4.1 Cost model

We begin with the assumption that the production of non-environmental outputs and environmental activities are distinct and described by separate cost functions. Specifically, $PC = G(Y, \mathbf{P}, i, t)$ describes the cost (*PC*) of producing non-environmental output *Y* based on input price vector **P** at plant *i* at time *t*. Similarly, let $RC = H(Y, \mathbf{P}, i, t)$ describe the cost (*RC*) of producing environmental "output" *R* similarly based on input price vector **P** at plant *i* at time *t*. Inputs include capital, labor, energy and materials.

We then allow for the possibility that these two activities are not, in fact, distinct by rewriting $PC = G(Y, \mathbf{P}, i, t)\left(f(RC)\right)^{\alpha_r}$ where $f(RC)$ is an increasing function of regulatory expenditure. The parameter α_r describes the degree of interaction. If zero, it indicates no signficant interaction; negative values indicate cost savings and positive values indicate additional burden.

We choose the following translog parameterization for $G(\cdot)$ and $H(\cdot)$

$$\text{(10)} \qquad \ln PC = \alpha_i + \alpha_t + \alpha_{i,p}' \ln \mathbf{P} + \alpha_y \ln Y + \tfrac{1}{2} \ln \mathbf{P}' \beta_{pp} \ln \mathbf{P} + \tfrac{1}{2} \beta_y \left(\ln Y\right)^2$$
$$\beta_{t,p} \ln \mathbf{P} + \beta_{yp} \ln Y \ln \mathbf{P} + \beta_{yt} t \cdot Y + \alpha_r \frac{RC}{PC}$$

$$\text{(11)} \qquad \ln RC = \ln R + \boldsymbol{\gamma}_p' \ln \mathbf{P} + \tfrac{1}{2} \ln \mathbf{P}' \boldsymbol{\delta}_{pp} \ln \mathbf{P} + \gamma_t t + \boldsymbol{\delta}_{pt}' \ln \mathbf{P} \cdot t \, ,$$

where **P** is a vector of input prices (capital, labor, energy and materials), *PC* are costs related to non-environmental output *Y*, *RC* are costs related to environmental output *R*, and *t* is time. The parameters have the following interpretations: α_i are plant-specific, Hicks-neutral productivity effects; α_t are time dummies, capturing aggregate Hicks-neutral productivity trends; $\boldsymbol{\alpha}_{i,p}$ are vectors of plant-specific, cost-share parameters; $\boldsymbol{\beta}_{pp}$ is a matrix of share elasticities; α_y and β_y capture scale economies; $\boldsymbol{\beta}_{t,p}$ are year-specific productivity biases; $\boldsymbol{\beta}_{yp}$ reflects biases of scale; and β_{yt} captures any aggregate time trend in scale economies. All of these parameters refer to non-environmental production. The environmental production parameters have the following interpretations: $\boldsymbol{\gamma}_p$ is a vector of aggregate cost share parameters; $\boldsymbol{\delta}_{pp}$ is a matrix of share elasticities; γ_t describes the Hicks-neutral productivity trend; and $\boldsymbol{\delta}_{pt}$ captures factor trends. Finally, α_r describes any interaction between environmental and non-environmental activities.

4.2 Cost function estimation

The standard approach to estimate models such as (10) and (11) is to specify a system of cost shares based on the first derivatives with respect to log prices. Stochastic disturbances are appended to each equation and the system is estimated simultaneously (with cross-equation restrictions) in order to improve efficiency. The problem with this approach in the current context is that factor inputs used for environmental activities cannot be distinguished from those used for conventional production; and we have no direct measure of *R*, environmental output. Since factor inputs cannot be disaggregated in the data, the cost shares associated with (10) and (11) are not observed. Further, since we have no direct measure of *R*, (11) cannot be estimated.

We work around these problems by noting that our assumption of homothetic environmental costs $H(\cdot)$ allows us to write the environmental cost shares solely as a function of input prices and time (and not *R*):

$$
(12)\qquad
\begin{aligned}
v_{k,r} &= \gamma_k + \boldsymbol{\delta}_k' \ln \mathbf{P} + \delta_{kt} t \\
v_{l,r} &= \gamma_l + \boldsymbol{\delta}_l' \ln \mathbf{P} + \delta_{lt} t \\
v_{e,r} &= \gamma_e + \boldsymbol{\delta}_e' \ln \mathbf{P} + \delta_{et} t \\
v_{m,r} &= \gamma_m + \boldsymbol{\delta}_m' \ln \mathbf{P} + \delta_{mt} t
\end{aligned}
\;.
$$

Coupled with non-environmental cost shares derived from (10),

$$
(13)\qquad
\begin{aligned}
v_{k,y} &= \alpha_{i,k} + \beta_k' \ln \mathbf{P} + \beta_{yk} \ln Y + \beta_{t,k} \\
v_{l,y} &= \alpha_{i,l} + \beta_l' \ln \mathbf{P} + \beta_{yl} \ln Y + \beta_{t,l} \\
v_{e,y} &= \alpha_{i,e} + \beta_e' \ln \mathbf{P} + \beta_{ye} \ln Y + \beta_{t,e} \\
v_{m,y} &= \alpha_{i,m} + \beta_m' \ln \mathbf{P} + \beta_{ym} \ln Y + \beta_{t,m}
\end{aligned}
$$

we can write the observed total cost shares as

$$
(14)\qquad
\begin{aligned}
v_k &= \frac{RC}{RC+PC} v_{k,r} + \left(1 - \frac{RC}{RC+PC}\right) v_{k,y} \\
v_l &= \frac{RC}{RC+PC} v_{l,r} + \left(1 - \frac{RC}{RC+PC}\right) v_{l,y} \\
v_e &= \frac{RC}{RC+PC} v_{e,r} + \left(1 - \frac{RC}{RC+PC}\right) v_{e,y} \\
v_m &= \frac{RC}{RC+PC} v_{m,r} + \left(1 - \frac{RC}{RC+PC}\right) v_{m,y}
\end{aligned}
\;.
$$

These aggregate cost shares (over both non-environmental and environmental expenditures) are both observable themselves and defined in terms of other observable variables (prices, output, time and regulation as a share of total costs). The equations in (14) can therefore be estimated alongside the production cost function (10) by treating each as a stochastic relation and adding random disturbances.

Because the endogenous variable *PC* appears on the right-hand side of the production cost function and aggregate share equations, we use a two-step approach. We first estimate the system of equations setting *RC* = 0 (which elimates *PC* on the right-hand side as well as the regulatory cost share parameters $\boldsymbol{\gamma}$ and $\boldsymbol{\delta}$). We use these parameter estimates to construct exogenous predicted values $\widehat{PC}$ to replace the actual values *PC* on the right-hand side of (10) and (14). These predicted values are then used to re-estimate the system without the endogeneity problem. At both estimation stages, we impose symmetry ($\beta_{ij} = \beta_{ij}$ and $\delta_{ij} = \delta_{ji}$) and homogeniety of degree one in prices (which allows us to arbitrarily drop a share equation). We use a maximum likelihood estimator that iterates on the covariance matrix estimate until it converges.[7]

4.3 Distinguishing Features

Two key features of this approach are its distinction between environmental and non-environmental production activities and the extensive use of fixed effects (in both the cost function and share equation). The distinction between environmental and non-environmental activities allows us to consider the possibility that these are, in fact, distinct. This hypothesis—that α_r = 0—is easy to test and, further, non-zero values of α_r can be interpreted as the dollar-for-dollar offset in production costs associated with an increase in environmental expenditures (Morgenstern, Pizer, and Shih 1999). That is, $\partial PC \big/ \partial RC = \alpha_r \big/ \left(1 + \alpha_r \, RC/PC\right)$ which is roughly equal to α_r for small values of α_r and when $RC \ll PC$ (empirically below 5%).

This distinction also allows us to estimate differences between pollution control technology and normal production technology. The identification of this effect hinges on variation in $RC \big/ \left(RC + PC\right)$ in the data. Plants with higher values of this ratio are more tilted towards pollution control; plants with lower values towards normal production. When we look at the estimation results, we will see that pollution control is often labor-intensive, leading to higher employment as environmental regulation increases.

The extensive use of fixed effects is important in the context of correctly identifying any difference between pollution control technology and conventional production. Productivity and differences in factor usage may vary among plants due to unobserved or unquantifiable plant differences, or differences in the output mix. Since these differences are potentially correlated with environmental activities—but are not caused by them—failing to control for plant differences may bias the results. For example, plants with older capital vintages or poor management might use different and/or less efficient combinations of inputs. If these same

[7] With the exception of our use of fixed effects, the modification of the share equations (14), and instrumenting for *PC*, Chapter 9.4 of Berndt (1990) describes our methodology in detail. Caves, Christensen et al. (1984) discusses the use of fixed effects in the cost function.

plants also have higher environmental costs, these differences would falsely be attributed to environmental activities. Our earlier work focusing on the parameter α_r demonstrated this is indeed the case: inclusion of fixed effects suggests that α_r is, if anything, negative. However, ignoring plant-level differences indicates that α_r is significantly positive.[8] In addition to supporting the use of fixed effects, this is evidence against the hypothesis that the fixed-effect model reduces to a random-effects model since the pooled estimate has the same probability limit as a random-effects estimate.[9]

The benefits of the fixed-effects model come at a price. In similar work, Gray and Shadbegian (1994) emphasize the potential problems with measurement error in fixed-effects models and advocate pooled estimates to estimate the added burden of environmental regulation. More generally, Griliches (1979), Chamberlain (1984) and Hsiao (1986) all point out that fixed-effect estimation exacerbates the bias toward zero when measurement error is primarily within units rather than among units. However, we have no alternative to control for the plant-level differences that we know introduce significant bias. Further, we have no direct evidence that measurement error is primarily within units rather than between units: long-difference estimates, where possible, reveal similar estimates with larger standard errors.[10]

4.4 General Results

Parameter estimates for the model are provided in Table 5 in the appendix along with additional detail concerning the data. Here, we briefly discuss those results. Roughly half the estimated parameters are significant at the 5% level. However, it is difficult to systematically simplify the model. Restrictions on the fixed effects (both share equations and cost function) are

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[8] Estimates of α_r based on a pooled model ignoring fixed effects are –0.08 (0.25), –0.13 (0.57), 1.56 (0.55), and 1.98 (0.39).

[9] A Hausman (1978) test is based on exactly this discrepancy.

[10] Griliches and Hausman (1986) suggest long-difference estimators as a way to reduce measurement error bias.

rejected in all industries.[11] Tests of Cobb-Douglas restrictions on the quadratic terms δ_{pp} and β_{pp} are similarly rejected.[12]

Theory tells us that the cost function should be monotone and concave.[13] Evaluating these conditions at each data point, we find our estimates to be locally monotone more than 99% of the time. However, concavity (as captured by the sign of the own-price elasticities) is frequently violated with capital demand sloping upward more than half the time in two of the four industries. Unfortunately, this is a well-known consequence of using translog cost functions when elasticities deviate significantly away from unity (Caves and Christensen 1980; Perroni and Rutherford 1998). The specific problem with capital demand may also be a consequence of imprecise measures of the price of capital based on the Hall and Jorgenson (1967) approach. A Cobb-Douglas version of the model—which forces concavity by restricting the δ_{pp} and β_{pp} terms to be zero—leads to only minor differences in α_r and γ_l, the key parameters in our calculation of the labor effects below.[14] While we check the sensitivity of our main results to this assumption, we continue to focus on the general translog results since our interest is estimation and the Cobb-Douglas model is rejected by the data.

A key parameter in our analysis of the labor effects is the estimated labor cost share associated with environmental activities. From Table 5, we find estimates for γ_l of 0.15, 0.36, 0.07 and 0.16 for pulp and paper, plastics, petroleum and steel, respectively. Only steel is not significant at the 5% level. Comparing those estimates to the observed total cost shares in Table 1, 0.20, 0.08, 0.02, and 0.23, respectively, we see higher environmental labor shares in plastics

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[11] Since the pooled model (when fixed effects are restricted) provides an unbiased, though less efficient, estimate of the random effects model, this is evidence against the random effects model. As noted above, the pooled estimates of α_r are both statistically and economically different than the fixed effect estimates.

[12] The LR statistics are 143, 50, 127, and 29 for pulp and paper, plastics, petroleum and steel testing the Cobb-Douglas restrictions on the production cost function, and 16, 18, 29, and 26 for the same industries, respectively, testing the environmental cost functions. With six degrees of freedom, the 1% critical value is 17.

[13] See Jorgenson (1986)

[14] Based on the Cobb-Douglas model, the estimates of α_r are –0.56, 0.37, 0.60, and –0.05 for pulp and paper, plastics, petroleum and steel, respectively. The corresponding Cobb-Douglas estimates of γ_l are 0.23, 0.25, 0.04, and 0.16. These can be compared to the translog parameter estimates in Table 5.

Table 1: Industry Statistics

Industry	*PACE as a share of total costs* (*RC/TC*)	*Labor as a share of total costs* ($v_l = P_l L/TC$)	*Price of labor ($000/year)* ($P_l$)
Pulp and Paper	0.028	0.201	34.8
Plastic Material	0.020	0.085	35.0
Petroleum	0.011	0.019	36.7
Steel	0.022	0.230	38.2

PACE refers to expenditures on environmental regulation as measured by the Pollution Abatement Costs and Expenditures survey.

and petroleum and lower environmental labor shares in pulp and paper and steel. Note that the while higher environmental labor shares in plastics and petroleum are significantly higher in a statistical sense, the lower environmental labor shares in pulp and paper and steel are insignificantly lower.

A few simple calculations are also possible using the aggregate summary statistics in Table 1 and the estimates of γ_l. For example, switching a million dollars from production to regulatory expenditures would lower employment expenditures by roughly $50,000—(0.15 – 0.20) x $1 million—in the pulp and paper industry. Based on an average salary of $35,000, this would mean 1.4 fewer jobs. The number would be +8.0, –1.4, and –1.6 jobs in plastics, petroleum, and steel, respectively. We return to these kinds of calculations in more detail after discussing demand elasticities.

4.5 Estimating aggregate demand elasticities

In addition to our estimate of supply-side cost functions, we also require aggregate demand elasticities to compute (9). We estimate these elasticities using historical data on aggregate output and industry productivity. Changes in industry productivity represent an exogenous shift in the cost of supply and therefore allow us to identify the demand elasticity. As long as the industry in question is small relative to the entire economy, it is reasonable to assume that this change in industry productivity will not shift the demand schedule.

We use publicly available data developed by Dale Jorgenson and his associates (Jorgenson 1990; Jorgenson, Gollop, and Fraumeni 1987) for both our industry-level output and productivity measures.[15] Annual productivity growth is computed as the logarithmic difference between the annual change in input price and the annual change in output price, where input price is computed as a divisia index of capital, labor, energy and material prices (see Diewert 1978). That is, it is the portion of any price change that is not captured by changes in input prices.[16] We then perform a simple regression of the annual change in log output on annual productivity growth:

$$\text{(15)} \qquad \Delta \ln output_t = \sigma_d \, \Delta \ln prod_t + \varepsilon_t$$

where $output_t$ is the industry level output in period t, $prod_t$ is the change in productivity level measured by

$$\text{(16)} \qquad \Delta \ln prod_t = \sum_{sh=k,l,e,m} \frac{v_{sh,t} + v_{sh,t-1}}{2} \left(\ln P_{sh,t} - \ln P_{sh,t-1} \right) - \left(\ln PO_t - \ln PO_{t-1} \right),$$

ε_t is a random disturbance and σ_d is the demand elasticity being estimated. The variables $P_{sh,t}$ are input prices, PO_t are output prices, and $v_{sh,t}$ are input shares. The results of these regressions are shown in Table 2.[17]

The elasticity estimates are significant and negative in three of the four industries, ranging from slightly inelastic (0.40) to slightly elastic (1.86). For comparison, we also simulate the effect of an exogenous productivity change in a dynamic general equilibrium model (Jorgenson and Wilcoxen 1990; Wilcoxen 1988) and compute an elasticity in the last column of Table 2.

[15] This data is available at http://www.economics.harvard.edu/faculty/jorgenson/data/35klem.html.

[16] While the typical assumption in a productivity calculation is competitive output markets, a constant markup of price over costs would not interfere.

[17] We also considered models with lagged productivity changes on the right-hand side as well as controls for aggregate productivity changes. With the exception of pulp and paper, these variations led to uniformly less elastic demand so that our results, if anything, *overstate* the adverse consequences of environmental regulation. In the pulp and paper industry, the elasticity estimate rose to 1.99.

Table 2: Demand Elasticity Estimates

Industry	*Sector (IGEM:BLS)*	*Demand Elasticity* σ *(standard error)*	*Values from Simulation*
Pulp and Paper	Paper and Allied (13:123–125)	1.34 (0.17)	1.86
Plastic Material	Rubber and Plastic (17:135,143–145)	0.49 (0.29)	2.55
Petroleum	Petroleum Refining (16:141,142)	0.40 (0.19)	1.10
Steel	Primary Metals (20:42–52,58)	1.86 (0.35)	2.38

Note that positive values of σ reflect an increase in demand as prices fall. See (15).

These estimates are uniformly larger which is not surprising given the more elastic properties of the translog cost function noted earlier, especially when concavity is imposed for their simulation purposes.

5. The Effect of Regulation on Industry Employment

We now combine the estimation results of the preceding section with the formula (9) in order to compute the effect of environmental regulation on industry employment. There are two terms in (9) that cannot be computed directly from the data: $\frac{\partial v_{L,i}}{\partial RC_i}$ and $\frac{\partial TC}{\partial RC}$. We first discuss the relationship between these expressions and the parameters estimated in (10) and (14), then present our results.

5.1 Relation to structural cost model

As noted earlier, the parameter α_r captures the potential non-zero effect of expenditures on environmental protection on conventional production costs, with $\partial PC/\partial RC = \alpha_r/(1+\alpha_r\, RC/PC)$. The expression *PC* is conventional production cost and *RC* is environmental expenditures. From Table 1 we know that *RC/PC* is on the order of 1–3% in the aggregate, and therefore $\partial PC/\partial TC \approx \alpha_r$. Further, since *TC* = *PC* + *RC*, we have $\partial TC/\partial RC = 1+\alpha_r$ for all plants.

The expression for $\frac{\partial v_{l,i}}{\partial RC_i}$ is only slightly more complex. From (14) we have

$$v_l = v_{l,r} + \left(\frac{PC}{RC + PC}\right)\left(v_{l,y} - v_{l,r}\right)$$

where $v_{l,y}$ and $v_{l,r}$, from (12) and (13) do not depend on RC. Therefore,

$$\begin{aligned}\frac{\partial v_{l,i}}{\partial RC_i} &= -\frac{PC_i}{\left(RC_i + PC_i\right)^2}\left(v_{l,y} - v_{l,r}\right) \\ &= -\frac{PC_i}{\left(RC_i + PC_i\right)^2}\left(\alpha_{i,l} + \beta_l' \ln \mathbf{P} + \beta_{yl} \ln Y + \beta_{t,l} - \gamma_l - \delta_l' \ln \mathbf{P} - \delta_{lt} t\right)\end{aligned} \tag{17}$$

We use (17) to compute $\frac{\partial v_{l,i}}{\partial RC_i}$ for each observation and then use (9) to aggregate the effects.

We can now write (9) in terms of estimated parameters and sample statistics in the following way:

$$\frac{\partial L_{\text{agg}}}{\partial RC_{\text{agg}}} = \mathbf{F}\left(\overline{PC/P_l}, \overline{TC}, \ldots\right) \cdot \mathbf{G}\left(\sigma_d, \alpha_r, \gamma_l, \ldots\right)$$

where

$$\mathbf{F} = \begin{bmatrix} \frac{\overline{(PC/P_l)}}{\overline{TC}}, \frac{\overline{(t \cdot PC/P_l)}}{\overline{TC}}, \frac{\overline{(\ln P_k \cdot PC/P_l)}}{\overline{TC}}, \frac{\overline{(\ln P_l \cdot PC/P_l)}}{\overline{TC}}, \frac{\overline{(\ln P_e \cdot PC/P_l)}}{\overline{TC}}, \\ \frac{\overline{(\ln Y\, PC/P_l)}}{\overline{TC}}, \frac{\overline{(t_{80}\, PC/P_l)}}{\overline{TC}}, \frac{\overline{(t_{81}\, PC/P_l)}}{\overline{TC}}, \frac{\overline{(t_{85}\, PC/P_l)}}{\overline{TC}}, \frac{\overline{(t_{88}\, PC/P_l)}}{\overline{TC}}, \\ \frac{\overline{(t_{91}\, PC/P_l)}}{\overline{TC}}, \frac{\overline{(d_1\, PC/P_l)}}{\overline{TC}}, \frac{\overline{(d_2\, PC/P_l)}}{\overline{TC}}, \ldots, \frac{\overline{(d_I\, PC/P_l)}}{\overline{TC}}, \frac{\overline{L}}{\overline{TC}} \end{bmatrix}$$

$$\mathbf{G} = \begin{bmatrix} \gamma_l, \delta_{lt}, \delta_{lk} - \beta_{lk}, \delta_{ll} - \beta_{ll}, \delta_{le} - \beta_{le}, -\beta_{yl}, -\beta_{80,l}, -\beta_{81,l}, \\ -\beta_{85,l}, -\beta_{88,l}, -\beta_{91,l}, -\alpha_{1,l}, -\alpha_{2,l}, \ldots, -\alpha_{I,l}, (1+\alpha_r)(1-\sigma_d) \end{bmatrix}$$

F is a vector of sample means based directly on the data and **G** is a vector of estimated parameters from (10) and (14) and reported in Table 5 and Table 2. Overbars ($\overline{x}$) in **F** indicate means computed over the entire sample of plant-year observations, with t_{80}, etc. indicating time dummies in the noted year and d_1 etc. indicating plant dummies for the particular plant. As before, TC is total cost, PC is production cost, P_l is the price of labor, P_k is the price of capital, P_e is the price of energy, Y is the output level, and L is the employment level. To compute standard errors, we ignore sampling variation in **F**, which is relatively small, and focus on the covariance matrix of **G**.[18] Note that all but the last element of $\mathbf{F} \cdot \mathbf{G}$ explains any factor shift, while the last term includes both the cost and demand effects.

5.2 Estimated effects

Table 5 displays our principal results, expressed as a change in employment associated with an additional $1 million ($1987) in environmental spending, for each of the four heavily regulated manufacturing industries under review (pulp and paper, plastics, petroleum, and steel). Results are presented separately for the cost, factor shift, and demand effects, as well as the net effect, which is the sum of the components in Equation (9). The grand total combines the four industrywide estimates, weighting by each industry's share of environmental expenditures.[19] To test the sensitivity of these results to the noted violations of cost function behavior, we estimated a Cobb-Douglas version of the model and found similar results.[20]

Line 1 displays the employment changes per million-dollar increase in environmental spending caused by the overall increase in costs, holding output constant. As expected, these values are positive in all industries, increasing employment by somewhere between one-half and five and one-half jobs per million dollars of spending. The variation among industries is explained primarily by the differences in labor cost shares, v_l, and to a lesser extent by estimated differences in indirect costs captured by the parameter α_r in the model. For example, labor accounts for less than 2% of total costs in the petroleum industry, so $1 million in increased total

[18] We assume the estimated demand elasticity is uncorrelated with the other parameters. This is sensible since the demand elasticity is based on aggregate time series data and the remaining parameters are estimated from a relatively short panel of cross-sectional data.

[19] Average industry level expenditures measured by the PACE survey as a share of total, computed over all years in the sample.

[20] Estimates of the total employment effect are 0.91 (2.8), 6.05 (2.9), 1.21 (0.7), and –4.41(6.2), respectively, for pulp and paper, plastics, petroleum, and steel, based on the Cobb-Douglas model (standard errors are in parentheses).

costs translates into roughly $15,000 in labor costs—or about one-half of one job. When α_r is significantly negative, as it is in the pulp and paper industry, this indicates uncounted savings associated with environmental expenditures. That is, a $1 million increase in environmental expenditures reflects less than $1 million in increased total costs. These uncounted savings reduce the cost effect and leads to a lower estimated employment consequence. The average across all four industries is 2-3 jobs per million dollars of increase in environmental expenditures.

Line 2 displays the employment changes attributable to the factor shift associated with relatively more environmental and less production cost. Overall, it appears that environmental spending increases labor demand through factor shifting, reflecting the fact that environmental activities are estimated, on average, to be more labor intensive than conventional production. This pattern of signs and significance corresponds to the rough estimates in Section 3 (except steel), with the weighted average across all four industries indicating 2-3 jobs gained per million dollars of spending.

In some industries, such as petroleum, the explanation for the factor shift is fairly obvious. Materials are such a large (>90%) share of production costs that it would be virtually impossible for environmental activities to be any less labor intensive. A similar, though not so extreme story holds for plastics, where labor is still less than 10% of production costs. This contrasts with steel and pulp and paper where labor accounts for about 20% of total expenditures. In those industries, we see ambiguous labor effects as both the environmental and production-cost shares are large.

Line 3 displays the employment changes per million-dollar increase in environmental spending associated with a drop in demand for final products as prices rise. As expected, these values are negative in all industries, reflecting the combined effects of increased costs, a constant markup of price over cost, and downward-sloping demand curves. Averaged across industries, reductions in demand cause a loss of around 3-4 jobs per million dollars of spending. This loss conceals wide variation within industries: in steel, the estimated loss is nearly ten jobs per million dollars of spending, while in petroleum the job losses are negligible. These differences

Table 3: Employment Change per $1 Million Additional Environmental Expenditure

(standard errors in parentheses; asterisks indicate significance at the 5% level)

	Pulp and Paper	*Plastics*	*Petroleum*	*Steel*	*Total*
Cost	2.18	3.23*	0.65*	5.52*	2.42*
	(1.58)	(1.63)	(0.24)	(2.78)	(0.83)
Factor Shift	–0.37	5.25*	1.77*	5.28	2.68*
	(2.05)	(2.46)	(0.81)	(4.41)	(1.35)
Demand	–2.94	–1.58	–0.26	–10.27	–3.56
	(2.51)	(1.74)	(0.22)	(7.10)	(2.03)
Total	–1.13	6.90*	2.17*	0.53	1.55
	(2.72)	(3.21)	(0.88)	(7.68)	(2.24)
Weight	0.15	0.07	0.50	0.28	

As noted in Section 3.2, additional environmental expenditures are allocated to individual observations in the sample in proportion to their share of aggregate total costs (*TC*). Weights reflect the magnitude of industrywide environmental expenditures.

are consistent with the results in Table 2, indicating much higher demand elasticities for steel. Our results are also consistent with Berman and Bui's (1997) findings that labor demand at petroleum refineries may increase with regulation. None of the estimated demand effects are significant, reflecting the combined uncertainty about the increase in total costs and the demand elasticity.

Combining these three effects in line 4, we find significant job gains in plastics and petroleum with insignificant effects in pulp and paper and steel. These results follow from the fact that both plastics and petroleum had significantly positive factor shifts coupled with relatively small demand elasticities. The average across industries works out to be an insignificant gain of one and one-half jobs per million dollars of additional environmental expenditures. This reflects both weak evidence of job loss due to declining demand coupled with potentially large factor shifts favoring employment. Our analysis shows that the net effect on regulated industries appears to be, if anything, positive.

6. Conclusions

Economists traditionally focus on welfare and other well-grounded measures of social cost when evaluating public policy. Job loss is not a real social cost to the extent that a job lost in one area or industry is quickly replaced in another. Yet, as the recent debate on trade with China suggests, discussions of job loss, especially at the industry level, are often central to the policy process (Greenhouse 2000).

Our study of environmental regulation in the pulp and paper, plastics, petroleum and steel sectors suggests that a million dollars of additional environmental expenditure is associated with an insignificant change in employment, with a 95% confidence interval ranging from –2.8 to +5.9 jobs. To put these numbers in context, it is useful to think about them in light of actual changes in employment and environmental spending observed in recent years. Between 1984 and 1994, total environmental expenditures measured by the Pollution Abatement Cost and Expenditure (PACE) survey in all manufacturing industries rose by $4.9 billion ($1987). During that same period, total production employment in the same industries declined by almost 632,000 jobs. Applying the most adverse estimate in our 95% confidence interval—a loss of 2.8 jobs per million dollars of environmental expenditures—we see that environmental spending may have accounted for the loss of at most 14,000 jobs, or about two percent of the jobs lost over the period.

Our structural model allows us to peer inside these results and understand why the conventional wisdom might be wrong. Most importantly, there are strong positive employment effects in industries where environmental activities are relatively labor intensive and where demand is relatively inelastic, such as plastics and petroleum. In others, where labor already represents a large share of production costs and where demand is more elastic, such as steel and pulp and paper, there is little evidence of a significant employment consequence either way.

If our model results do not support the notion of a jobs versus the environment tradeoff, why does this theme remain so steadfast in the business and labor communities? Obviously, it is a politically and emotionally-charged topic that attracts attention. Beyond posturing in a public debate, however, it is possible that both employers and employees honestly overestimate the potential for job loss associated with environmental regulation by confusing the product demand schedule faced by the plant with the schedule faced by the entire industry. The former is certainly more price elastic due to competition, monopolistic or otherwise, from other firms. However, if all firms and plants in an industry are faced with the same or very similar cost-increasing regulatory changes—which we believe is typically the case—plants should not be so worried about loosing business to other plants facing the same regulation.

A similar story might apply regarding the job-creating aspects of environmental spending. Neither employers nor employees may be completely familiar with the nature or type of changes in production technologies associated with environmental protection. In that case, there might be a tendency to underestimate the employment increases associated with the new environmental spending itself or with changes in the mix of factor inputs. Our analysis suggests that these increases can more than offset the loss in sales associated with rising prices and depressed demand. Ignoring these aspects of environmental regulation, it is possible that both employers and employees may overstate the job destructive aspects of environmental regulation and understate its job creation potential.

Focusing instead on our results, there are reasons why these estimates might be both over- and understated. We might overestimate job loss by using industry-level elasticities when, in fact, regulation affects the entire economy. Alternatively, we might underestimate job loss for exactly the opposite reason: if regulatory consequences are relatively concentrated in certain areas and at certain plants, the industry-level elasicities are likely too small. Further, our focus on industry-level employment misses any costs that might be associated with shifting jobs among or within plants while industry level employment remains unchanged.

Notwithstanding these caveats, our results do cast doubt on the idea of a jobs versus the environment trade-off at the industry level. While environmental spending clearly has consequences for business and labor, the hypothesis that such spending significantly reduces employment in heavily polluting industries is not supported by the data.

Data Appendix

The central data source for this research is the Longitudinal Research Database collected by the U.S. Census Bureau. Environmental spending is measured by the Pollution Abatement Cost and Expenditure Survey. Energy expenditures are derived from the Manufacturing Energy Consumption Survey and the Annual Survey of Manufactures. We normalize all variables by dividing each by the sample mean.

- *The Longitudinal Research Database* (LRD) is a pooled, cross-section, time series comprised of the establishment responses to the Annual Survey of Manufacture (ASM) and the quinquennial Census of Manufactures (CM) for over 50,000 establishments in each year. The LRD contains information on cost, outputs, and inputs at the plant level. Detailed quantity and expenditure information for energy consumption are only available up to 1981.
- *The Manufacturing Energy Consumption Survey* (MECS) is a triennial survey conducted by the U.S. Department of Energy. The survey contains detailed fuel consumption and expenditure data by establishment.
- *The Pollution Abatement Cost and Expenditure* (PACE) survey contains pollution abatement investment spending and operating expenditures at the establishment level. The Census Bureau conducted this survey annually between 1979 and 1991, except 1983 and 1987.

Based on the availability of detailed energy and environmental expenditure data, our analysis includes the years 1979, 1980, 1981, 1985, 1988, and 1991. Sample sizes are shown in Table 3.

Data on input and output quantities and prices are constructed as follows:

- *Output*. Data on the total value of shipments, by individual product codes, are contained in the LRD. We construct a divisia index (Caves, Christensen, and Diewert 1982, 1982) of output price based on the corresponding producer prices of different product obtained from the U.S. Department of Labor's Bureau of Labor Statistics. The quantity index is obtained by dividing total value of shipments, adjusted for inventory, by this aggregate output price index.

Table 4: Sample Size by Industry

Industry	*Plants*	*Observations*
Pulp and Paper	142	615
Plastic Material	107	404
Petroleum	165	717
Steel	128	536

- *Regulation*. Data on (nominal) annual pollution abatement operating costs at the plant level are from the annual Pollution Abatement Costs and Expenditure (PACE) Survey. Operating expenses for pollution abatement include depreciation on the pollution-abatement capital. Real regulatory expenditures are computed by deflating nominal pollution-abatement operating costs by the GDP deflator.

- *Capital Stock*. The gross book value of the capital stock at the beginning of the year and new capital expenditures each year are reported in the LRD. Gross book value is used to compute the capital stock in 1979. A perpetual inventory method (Christensen and Jorgenson 1969) is then used to generate a real capital stock series covering the period 1980-1991 based on the following formula:

  $$k_t = (1-\delta)k_{t-1} + \frac{q_0}{q_t} I_t$$

  where k_t is the period t capital stock, and I_t is new capital expenditure measured in current dollars. The industry-specific economic depreciation rate (δ) is from Hulten and Wykoff (1981). The capital stock price indices (q_t) for various industries are drawn from a dataset developed by Bartelsman and Gray (1994).

- *Service Price of Capital*. The service price of capital is calculated using the Hall and Jorgenson (1967) procedure. The service price of capital is given by

  $$p_{k(t)} = \left(q_{t-1}r_t + \delta q_t - (q_t - q_{t-1}) + q_t C_t\right)\frac{1-u_t z_t - k_t}{1-u_t}$$

  where:

  $p_{k(t)} =$ service price of capital,

  $q_t =$ price index of new capital equipment,

  $r_t =$ after tax rate of return on capital (opportunity cost),

  $\delta =$ rate of economic depreciation,

  $C_t =$ effective property tax rate,

$u_t =$ effective corporate income tax rate,

$z_t =$ present value of allowed depreciation tax deductions on a dollar's investment over the life time of an asset,

$k_t =$ investment tax credit, and

$t =$ year.

We use the average yield on Moody's "Baa" bonds for the after-tax rate of return on capital. The data on the tax-policy variables are from Jorgenson and Yun (1991) and Jorgenson and Landau (1993).

- *Capital Costs*. The capital costs were constructed as the product of the service price of capital and the stock of capital.
- *Labor*. The quantity of labor is defined as the number of production workers. The cost of labor includes production worker wages plus supplemental labor cost (which accured to both production workers and nonproduction workers) adjusted to reflect the production-worker share. The price of labor is defined as the cost of production workers divided by the number of production workers.
- *Price of Materials*. Expenditure data on individual materials are collected on a five-year cycle by the Census of Manufacturers (CM). We derive a divisia index of the price of materials for each plant for the years 1977, 1982, 1987, and 1992. We linearly interpolate estimates for intervening years
- *Cost of Materials*. We use reported total expenditures on materials and parts in the LRD to calculate material costs.
- *Price of Energy*. Detailed data on total quantities consumed and total expenditures on various fuels were collected in LRD (through 1981) and MECS (1985, 1988, 1991). These data are used to calculate the prices of individual fuels ($/million Btu) paid by each plant. The individual fuels include coal, natural gas, distillate fuel oil, residual fuel oil, liquefied petroleum gases, and electricity. These fuels typically account for about 90% of total energy cost. The price of energy is computed as a divisia index of these fuels.
- *Cost of Energy*. The cost of energy is the summation of expenditures for the six individual fuels.

Table 5: Parameter Estimates

	Pulp and Paper	Plastics	Petroleum	Steel		Pulp and Paper	Plastics	Petroleum	Steel
α_y	0.7161*	0.8314*	0.7433*	0.7136*	γ_k	0.1276	-0.0510	0.0532	0.1460*
	(0.0273)	(0.0362)	(0.0281)	(0.0304)		(0.1085)	(0.1053)	(0.0545)	(0.0715)
α_r	-0.6221*	0.3774	0.5900	-0.0726	γ_l	0.1531*	0.3621*	0.0748*	0.1565
	(0.2746)	(0.6958)	(0.5905)	(0.4671)		(0.0770)	(0.0914)	(0.0292)	(0.1610)
β_{kk}	0.1095*	0.0029	0.0070*	0.0664*	γ_e	0.1967*	0.2930	-0.0225	-0.7126*
	(0.0379)	(0.0190)	(0.0019)	(0.0172)		(0.0846)	(0.2028)	(0.0387)	(0.1952)
β_{ll}	0.1120*	0.0668*	0.0133*	0.0491*	δ_{kt}	0.0013	0.0627*	-0.0043	-0.0122
	(0.0114)	(0.0094)	(0.0016)	(0.0201)		(0.0171)	(0.0186)	(0.0110)	(0.0160)
β_{ee}	0.0579*	-0.0027	0.0128*	0.0211	δ_{kk}	0.9811*	0.4311	0.3400*	0.5153*
	(0.0090)	(0.0163)	(0.0018)	(0.0209)		(0.4718)	(0.4545)	(0.0964)	(0.2243)
β_{yy}	-0.0336	-0.0408	0.0039	0.0389*	δ_{kl}	-0.0764	0.0251	0.0078	-0.1398
	(0.0316)	(0.0328)	(0.0184)	(0.0191)		(0.2554)	(0.2843)	(0.0394)	(0.2375)
β_{kl}	-0.0347*	-0.0030	-0.0017*	-0.0035	δ_{ke}	-0.1040	0.1902	0.1260*	0.4567*
	(0.0128)	(0.0092)	(0.0008)	(0.0088)		(0.1996)	(0.2624)	(0.0554)	(0.1942)
β_{ke}	-0.0116	0.0103	0.0005	-0.0264*	δ_{lt}	-0.0154	0.0516*	0.0097	-0.0935*
	(0.0112)	(0.0086)	(0.0012)	(0.0073)		(0.0126)	(0.0181)	(0.0067)	(0.0355)
β_{ky}	0.0100	-0.0365*	-0.0132*	-0.0383*	δ_{ll}	-0.3011	-1.1840*	-0.2801*	1.4959*
	(0.0071)	(0.0049)	(0.0021)	(0.0031)		(0.3037)	(0.3458)	(0.0986)	(0.5676)
β_{le}	-0.0114	-0.0016	0.0003	0.0156	δ_{le}	-0.2485	0.1503	0.0026	-0.8998*
	(0.0065)	(0.0068)	(0.0010)	(0.0138)		(0.1375)	(0.2211)	(0.0398)	(0.3833)
β_{ly}	-0.0446*	-0.0302*	-0.0078*	0.0066	δ_{et}	-0.0232*	-0.0426	-0.0115	0.0501
	(0.0052)	(0.0041)	(0.0010)	(0.0072)		(0.0107)	(0.0290)	(0.0076)	(0.0346)
β_{ey}	-0.0041*	0.0085	-0.0104*	-0.0177*	δ_{ee}	0.4141*	-0.3730	-0.1483*	-0.1428
	(0.0053)	(0.0092)	(0.0015)	(0.0087)		(0.1679)	(0.5119)	(0.0690)	(0.5534)
β_{yt}	0.0041	0.0110*	-0.0028*	-0.0004					
	(0.0014)	(0.0020)	(0.0013)	(0.0014)					

	Pulp and Paper	Plastics	Petroleum	Steel
Number of Observations	615	404	717	536
Number of Plants	142	107	165	128
Fraction of observations with negative estimated share values (zeros are omitted)				
Capital	0.003		0.054	0.017
Labor		0.002	0.006	
Energy	0.002	0.012	0.010	
Materials				
Fraction of observations with positive own-price elasticities (zeros are omitted)				
Capital	0.763		0.216	0.666
Labor	0.055	0.522	0.353	0.002
Energy	0.104	0.010	0.285	0.011
Materials	0.006	0.084	0.187	0.011

Note: Plant and time dummies are not reported due to confidentially requirements.

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