The Cost of Environmental Protection

Richard D. Morgenstern
William A. Pizer
Jhih-Shyang Shih

August 1999

The Cost of Environmental Protection

Richard D. Morgenstern, William A. Pizer, and Jhih-Shyang Shih

<u>Abstract</u>

Expenditures for environmental protection, estimated to exceed 2% of U.S. GDP, are often cited as an assessment of the burden of current regulatory efforts and a standard against which the associated benefits are measured. Little is known, however, about how well these largely self-reported expenditure estimates relate to true costs. The potential for both incidental savings and uncounted burdens means that actual costs could be either higher or lower than reported expenditures.

This paper explores the relationship between reported expenditures and actual factor costs in the manufacturing sector based on a large panel of plant-level data. Our approach is based on a model that explicitly distinguishes between environmental and non-environmental expenditures. We then directly estimate the dollar-for-dollar offset in non-environmental productions costs arising from a dollar in increased environmental expenditures.

While a recent literature supports the notion that increases in reported environmental expenditures probably understate actual economic costs, we find no such evidence. In one industry we find statistically significant overstatement. In three others, we find no significant deviation in either direction.

Our results hinge on the use of a fixed effect estimator that allows for unspecified differences in productivity and factor intensities among plants. An alternative pooled model generates uniformly higher estimates indicating statistically significant understatement. Although consistent with previous results, we believe these higher estimates are biased by plant-level omitted variables.

We conclude that while aggregate cost estimates do not appear under- or overstated on average, considerable variation and uncertainty exists at the industry level.

Contents

List of Tables

The Cost of Environmental Protection

Richard D. Morgenstern, William A. Pizer, and Jhih-Shyang Shih[1]

1 Introduction

Expenditures for environmental protection in the U.S., estimated to exceed $150 billion annually or about 2% of GDP, are often cited as an assessment of the burden of current regulatory efforts and a standard against which the associated benefits are measured.[2] However, these estimates are based largely on self-reported assessments of compliance costs. Little is known about how well these reported expenditures reflect true costs. Systematic bias, if it exists, could have important consequences for ongoing debates about future regulatory stringency.

Whether a dollar of reported environmental expenditures translates into a more or less than a dollar of total costs involves netting out a number of complex, often competing effects. Frequently posed in terms of competitiveness or productivity, the prevailing view in the economics literature is that an incremental dollar of reported environmental expenditures entails somewhat higher total costs to the firm. This suggests that, at the margin, the cost of environmental protection is higher than indicated by direct measures.

To better understand this relationship between increases in reported environmental expenditures and increases in total costs, we develop a model that explicitly distinguishes between environment and non-environment production activities. A useful feature of our specification is that

[2]U.S. Environmental Protection Agency (1990). The EPA estimates are somewhat higher than those developed by Census Bureau largely because: 1) EPA annualizes investment outlays (at a 7 percent discount rate) rather than directly reporting annual expenditures; and 2) the EPA data includes some programs not covered by Census, e.g., drinking water and Superfund.

a single estimated parameter captures the dollar-for-dollar effect of environmental expenditure on non-environmental production costs. Plant-level panel data is then used to test the null hypothesis that these activities are, in fact, distinct using a fixed effects specification. Among those industries with the largest share of pollution expenditures—plastics, pulp and paper, petroleum refining and steel—three of the four accept this null hypothesis. We find evidence of overstatement of costs in the pulp and paper industry. Using an alternative pooled model we find uniformly higher estimates that instead suggest understatement. Although consistent with previous results, we believe these higher estimates are biased by omitted variables characterizing differences among plants.

Following the literature review in Section 2, Section 3 develops our cost model distinguishing environmental and non-environmental production activities. Our estimation and results are presented in Section 4. Section 5 offers a set of concluding observations. Additional details concerning construction of the dataset and estimation of the model parameters are contained in the Appendix.

2 Distinguishing Reported Expenditures and Economic Costs

This paper explores the possible gap between the true cost of environmental regulation and readily available, self-reported expenditure estimates. To create an accurate measure of true economic cost, one can imagine seeking accurate responses to the following (hypothetical) survey question:

> "Identify the increase in costs associated with your efforts to reduce environmental emissions or discharges from your facility. In preparing your estimates, be sure to consider the extent to which environmental activities : (a) involve direct outlays of capital and operating costs; (b) reduce other (i.e., non-environmental) capital and operating costs; (c) lead to cost-saving innovations; (d) affect operating flexibility; (e) crowd out non-environmental investments; or (f) discourage the purchase of new equipment because of differential performance requirements for new versus existing equipment. Include estimates of the plant managers' time and other overhead items associated with these activities. Exclude expenditures related to occupational health and safety. When process changes (as opposed to end-of-the pipe additions) are involved, allocate only that portion of the costs attributable to environmental protection."

Even if asked, few firms possess the information to reliably answer such a complex and comprehensive question. Instead, we have access to the Pollution Abatement Costs and Expenditures

2

(PACE) Survey, conducted by the U.S. Census Bureau from 1973 until 1994. The PACE questionnaire asks a sample of manufacturing plants to provide information on capital and operating expenditures related to environmental regulation, including depreciation, labor, materials, energy and other inputs. That is, essentially item (a) of our hypothetical question.[3] The results of this survey represent the most comprehensive source of information on environmental expenditures and form the basis of aggregate cost estimates in the United States.

Despite its widespread use, little is known about the accuracy of the survey responses. Plant managers may systematically over- or underestimate direct control costs. Alternatively, the indirect effects suggested by our hypothetical question could significantly alter the true cost to the firm.

2.1 The Case for Understatement

Many studies suggest that responses to items (d-f) in the hypothetical question would likely raise cost estimates above those implied by the PACE expenditure data alone (for recent surveys, see Jaffee, Peterson, Portney, and Stavins 1995; Schmalensee 1993). In particular, economic theory suggests at least three reasons why reported expenditures might understate costs. First, it is possible that environmental investments may crowd out other productive investments by firms (Rose 1983). Second, many environmental regulations contain a new source bias that may discourage investment in new, more efficient facilities and thereby raise production costs (Gruenspecht 1982; Nelson, Tietenberg, and Donihue 1993). Finally, pollution control requirements may also reduce operating flexibility which, in turn, could lead to higher costs (Joshi et al. 1997).

Other evidence suggesting understatement comes from analyses of productivity growth in the 1970's and 1980's. In a survey of empirical studies, the U.S. Office of Technology Assessment found that between 8 and 44 percent of industry-level declines in productivity growth were attributable to environmental regulations. This is consistent with an aggregate study by Barbera

---

[3]The Census Bureau ceased collecting PACE in 1994 for budgetary reasons. The PACE questionnaire asks plant managers how expenditures compare to what they would have been in the absence of environmental regulation. This raises the issue of the appropriate baseline. Absent regulation, firms might still engage in some pollution control to limit tort liability, maintain good relations with communities in which they are located, maintain a good environmental image, and other reasons. However, it is unclear whether survey respondents are able to determine what environmental expenditures would have been made in the absence of regulation.

and McConnell (1990). Dynamic general equilibrium analyses by Hazilla and Kopp (1990) and Jorgenson and Wilcoxen (1990) similarly find that environmental expenditures slow capital accumulation, reducing output by 30-50 percent above direct costs.

Perhaps the strongest evidence for understatement comes from recent studies of plant-level data by Gray and Shadbegian (1994), hereafter refered to as GS, and Joshi, Lave, Shih, and McMichael (1997), hereafter JLSM. If reported environmental expenditures reflect actual firm costs, Gray (1987) shows that a 1% rise in the ratio of environmental expenditures to total costs should lead to a 1% fall in measured total factor productivity. Exploiting this accounting identity, GS find that productivity falls more than one-for-one with the ratio of environmental expenditures—though not at a statistically significantly level—suggesting some understatement of cost. Converted to dollar measures, their best estimate is that a dollar of additional reported expenditures raises total costs by $1.74, $1.34 and $3.28 for paper mills, oil refineries and steel mills, respectively.

A more detailed study of steel mills by JLSM finds even larger effects. Unlike GS, who use a growth accounting framework to compute total factor productivity measures, JLSM estimate translog cost functions. To investigate the potential over- or understatement of reported environmental expenditures, they include reported environmental expenditures as an additional predictor of total costs (in logarithms). Based on this specification they find a statistically significant effect, with a 1% increase in regulatory costs generating a 0.3% increase in total costs. Based on the range of total cost/regulatory cost ratios observed at minimills and integrated steel plants, they estimate that a marginal dollar of reported expenditures raises total costs by between $7 and $12.

An important aspect of both the JLSM and GS study is their treatment of unexplained productivity differences between plants. Despite their use of panel data, both papers focus on pooled estimates. This means that the estimated coefficients on reported environmental expenditures may be biased by omitted plant characteristics such as management, age and location. Both papers also specify models involving an elasticity of total costs to reported environmental expenditures despite their keen interest in the dollar-for-dollar effects. We discuss these issues in Section 3.

4

2.2 The Case for Overstatement

In contrast to items (d-f), items (b) and (c) in the hypothetical survey question suggest that true costs may be overstated by the PACE survey. Item (b) posits that complementarities between conventional production and environmental expenditures may partially offset reported environmental expenditures. Especially when process changes are involved (as opposed to end-of-the-pipe treatment), the cost of jointly producing both conventional output and a cleaner environment may be lower than the cost of producing them separately (Bailey and Friedlaender 1982). Or, when plants are required to recover or recycle effluents, those effluents may have value that is not counted against the cost of recovery. While the PACE survey has attempted to estimate such savings, they are among the items thought to be most subject to measurement error (Streitweiser 1996).

Another source of complementarity arises when the costs of shutting down a production line are substantial. If it becomes necessary to stop production in order to make environmentally motivated modifications, then other, non-environmentally motivated projects can be implemented at the same time. This "harvesting" of non-environmental projects alongside necessary environmental ones reduces the expense associated with the non-environmental projects and partially offsets the installation costs associated with the environmental regulation.[4]

In contrast to these complementarity arguments which suggest *partial* offsets, item (c) raises the more controversial possibility of a *complete* offset or even net savings as a consequence of environmental regulation. The underlying notion is that environmental requirements may stimulate plant managers to innovate and thus offset the costs associated with environmental protection. This argument has its roots in the work of Leibenstein (1966) and others who have written about suboptimal firm behavior. The most recent discussion is associated with Porter (1991) who claims that "environmental standards can trigger innovation that may partially or more than fully offset the costs of complying with them" (Porter and Van der Linde 1995).

The empirical basis for assessing this claim is quite limited. A study by Meyer (1993) examines whether states with strict environmental laws demonstrate poor economic performance

---

[4]We thank Dallas Burtraw for this observation.

5

relative to states with more lax standards, and is frequently cited in support of the Porter hypothesis. Althought the study found that states with stricter laws actually performed better, the paper sheds little light on a possible causal relationship between regulation and economic performance because it does not control for many of the factors relevant to a state's economic performance. Various case studies of particular plants have been conducted but problems of selection bias make it impossible to generalize from the results (Palmer, Oates, and Portney 1995). As a consequence, most economists have been unsympathetic to Porter's claims.

3 Model

Based on the preceding arguments for both over- and understatement, the true cost of environmental protection remains an open question. This paper contributes to the debate by offering plant-level, empirical evidence based on an improved model of environmental expenditures. In particular, our model provides a clean test of the null hypothesis that reported expenditures are accurate as well as a direct estimate of any inaccuracies in dollar-for-dollar terms. We also provide a careful consideration of the potential differences among plants based on panel data.

To test this hypothesis, we would ideally like to subject a random group of plants to more stringent regulation. By comparing this group to a control group, we could isolate how the stricter regulation raises both reported expenditures and total costs—and see if the increases are one-for-one. Randomization would insure that regulation was the only source of variation and that omitted variables were not confounding the measured effect.

Without this idealized experiment, we are forced to explicitly model the determinants of production costs and the potential relation to regulatory costs. We begin with a standard translog model of non-environmental production costs, and then include a term allowing for the possible influence of environmental expenditures. By carefully constructing this term, not only does a coefficient of zero represent the null hypothesis that true costs equal reported costs, but the estimated value can be interpreted as the dollar-for-dollar uncounted burden or savings at the margin.

3.1 Distinguishing Environmental and Non-Environmental Costs

We begin with separate models of environmental and non-environmental production costs. Suppose $PC = G(Y, \mathbf{P}, i, t)$ describes the cost (PC) of producing non-environmental output Y based on input price vector $\mathbf{P}$ at plant i and time t. Let $RC = H(R, \mathbf{P}, i, t)$ describe the cost (RC) of producing environmental "output" R, similarly based on input prices $\mathbf{P}$ at plant i and time t.

Our null hypothesis is that regulatory costs RC and production costs PC are distinct and unrelated. To test this hypothesis, we (conceptually) specify and estimate a model of the form $PC = G(Y, \mathbf{P}, i, t) + \alpha_r RC$. If α_r is not statistically significant, we accept this hypothesis. If it *is* statistically significant, the estimate quantifies the added burden or saving—the *offset*—associated with a dollar of additional environmental expenditure.

The standard apporach would be to estimate the cost function $PC = G(Y, \mathbf{P}, i, t) + \alpha_r RC$ along with factor demand or share equation for non-environmental production of Y. Under cost minimization assumptions, the factor equations involve the same parameters as $G(\cdot)$ and simultaneous estimation of these relations greatly improves efficiency.

Unfortunately, we have no way of distinguishing among factors used for environmental (R) and non-environmental (Y) purposes—reported environmental expenditures are not broken down by factor inputs. This prevents us from estimating factor equations for non-environmental production alone. Furthermore, we have no direct measure of environmental output, only environmental *expenditure*. This prevents us from estimating $RC = H(R, \mathbf{P}, i, t)$ as well as factor demands related to environmental activities since they necessarily depend on the scale of environmental output.

3.2 Modeling Production Costs and Factor Shares

The absence of some measure of environmental output precludes specification and estimation of an environmental cost function and environmental factor demand levels. However, we can specify and estimate a model of environmental factor demand *shares*, provided we assume homothetic production economies for the environmental output R. In particular, we can specify environmental

7

factor shares

$$v_{k,r} = \gamma_k + \boldsymbol{\delta}'_k \log \mathbf{P} + \delta_{kt} t$$

$$v_{l,r} = \gamma_l + \boldsymbol{\delta}'_l \log \mathbf{P} + \delta_{lt} t$$

$$v_{e,r} = \gamma_e + \boldsymbol{\delta}'_e \log \mathbf{P} + \delta_{et} t$$

$$v_{m,r} = \gamma_m + \boldsymbol{\delta}'_m \log \mathbf{P} + \delta_{mt} t$$

where $v_{k,r}$, $v_{l,r}$, $v_{e,r}$ and $v_{m,r}$ are the shares of capital, labor, energy and materials, respectively, associated with regulatory expenditure RC, $\mathbf{P}$ is a vector of input prices for those same inputs, $\{\gamma_k, \gamma_l, \gamma_e, \gamma_m\}$ are constants, $\{\delta_{kt}, \delta_{lt}, \delta_{et}, \delta_{mt}\}$ are factor biases, and $\boldsymbol{\delta}_k = \{\delta_{kk}, \delta_{kl}, \delta_{ke}, \delta_{km}\}'$, etc. are the own- and cross-price share elasticities.

We then specify production costs PC and production factor shares based on a modified translog cost function.[5] In particular,

$$\log(PC) = \alpha_i + \alpha_t + \boldsymbol{\alpha}'_{i,p} \log \mathbf{P} + \alpha_y \log Y + \frac{1}{2} \log \mathbf{P}' \boldsymbol{\beta}_{pp} \log \mathbf{P} + \frac{1}{2} \beta_{yy} (\log Y)^2 \qquad (1)$$
$$\boldsymbol{\beta}'_{t,p} \log \mathbf{P} + \boldsymbol{\beta}'_{py} \log Y \log \mathbf{P} + \beta_{yt} t Y + \alpha_r \frac{RC}{PC}$$
$$v_{k,y} = \alpha_{i,k} + \boldsymbol{\beta}'_k \log \mathbf{P} + \beta_{ky} \log Y + \beta_{t,k}$$
$$v_{l,y} = \alpha_{i,l} + \boldsymbol{\beta}'_l \log \mathbf{P} + \beta_{ly} \log Y + \beta_{t,l}$$
$$v_{e,y} = \alpha_{i,e} + \boldsymbol{\beta}'_e \log \mathbf{P} + \beta_{ey} \log Y + \beta_{t,e}$$
$$v_{m,y} = \alpha_{i,m} + \boldsymbol{\beta}'_m \log \mathbf{P} + \beta_{my} \log Y + \beta_{t,m}$$

where PC are production costs, $v_{k,y}$, $v_{l,y}$, $v_{e,y}$ and $v_{m,y}$ are the *production* factor shares associated with capital, labor, energy, and materials, respectively, $\mathbf{P}$ are the corresponding input prices, Y is output, t is time and RC are reported environmental expenditures. $\boldsymbol{\beta}_{pp} = \{\boldsymbol{\beta}_k, \boldsymbol{\beta}_l, \boldsymbol{\beta}_e, \boldsymbol{\beta}_m\}$, $\boldsymbol{\alpha}_{i,p} = \{\alpha_{i,k}, \alpha_{i,l}, \alpha_{i,e}, \alpha_{i,m}\}'$ and, more generally, the α and β are parameters to be estimated. Those parameters with a subscript i (α_i and $\boldsymbol{\alpha}_{i,p}$) are allowed to vary across plants while those with a subscript t (α_t and $\boldsymbol{\beta}_{t,p}$) are allowed to vary across time.

---

[5] See Diewert and Wales (1987) for a discussion of the translog and other flexible functional forms.

Together, these two descriptions of factor shares can be combined to specify aggregate factor shares which are observable:

$$
\begin{aligned}
v_k =& \frac{RC}{PC + RC} v_{k,r} + \left(1 - \frac{RC}{PC + RC} \right) v_{k,y} \\
v_l =& \frac{RC}{PC + RC} v_{l,r} + \left(1 - \frac{RC}{PC + RC} \right) v_{l,y} \\
v_e =& \frac{RC}{PC + RC} v_{e,r} + \left(1 - \frac{RC}{PC + RC} \right) v_{e,y} \\
v_m =& \frac{RC}{PC + RC} v_{m,r} + \left(1 - \frac{RC}{PC + RC} \right) v_{m,y}
\end{aligned}
\tag{2}
$$

where v_k, v_l, v_e and v_m are total cost factor shares, and $RC/(PC + RC)$ is the share of total costs associated with regulatory expenditures. These aggregate factor share equations can then be estimated alongside the translog cost function for productions costs PC in (1).

3.3 Offset Measurement

This specification offers a notable improvement over previous work by providing a direct parameter estimate of the dollar-for-dollar offset from ordinary production costs associated with reported environmental expenditures. Based on (1), we have

$$
\frac{\partial PC}{\partial RC} = \alpha_r \frac{1}{1 + \alpha_r (RC/PC)}
$$

This indicates that the derivative we care about, $\partial PC/\partial RC$, varies from plant to plant. However, for small values of α_r and small ratios of RC/PC, this variation is negligible. For example, if α_r is around one in magnitude and RC/PC is between 1-3%, the true dollar-for-dollar offset would differ from α_r by no more than 3%. These are in fact the magnitudes we observe, leading us to ignore the distinction between α_r and $\partial PC/\partial RC$ (values of RC/PC are shown in Table A.1).

Our approach contrasts sharply with previous work where the *elasticity* is often specified as constant, with $\partial PC/\partial RC = \alpha(PC/RC)$. This means that the derivative is largest for firms with the smallest levels of regulation. Since the ratio PC/RC can vary by a factor of 10^4 within an industry, the corresponding variation in $\partial PC/\partial RC$ is enormous. Not only do we find this implausible, such a specification then requires careful attention to how the derivatives are aggregated

9

across plants.[6]

3.4 Plant-specific Effects

Another key feature of the model is our treatment of plant level productivity differences. As we will see in the next section, our quantitative and qualitative results hinge on the inclusion of plant-specific or *fixed* effects in our model of production costs (α_i and $\boldsymbol{\alpha}_{i,p}$ in (1)). While fixed effects are not new to cost modeling, their inclusion inevitably leads to two concerns relative to a simpler pooled model where $\alpha_i = \alpha$ and $\boldsymbol{\alpha}_{i,p} = \boldsymbol{\alpha}_p$:[7] Does the fixed-effects model waste valuable cross-sectional information and does it exacerbate measurement error?

Certainly, there is more cross-sectional variation in production costs and factor shares than there is within individual plants over time.[8] Ideally, we would like to use that cross-sectional variation to better estimate the parameters, especially α_r. However, such variation is useful only to the extent that it reflects variation in the dependent variables that is causally linked to the specified right-hand side variables. With our data, we are concerned that the cross-sectional variation instead reflects considerable variation in unobserved plant characteristics, such as management style, location and age. Therefore, we suspect that omitted variable bias taints our pooled model as well as previous work using cross-sectional identification. Since these omitted variables are arguably related to both higher environmental expenditures and higher production costs, this bias will tend to make environmental expenditures appear *understated*.[9]

A more subtle question is whether a fixed effects model worsens the bias due to measurement error, especially in reported environmental expenditures. If the variation observed within individual plants is mostly measurement error, the fixed effects model will eliminate the "real" variation and leave only noise. Such noise will bias the associated parameter estimates towards zero (Griliches

---

[6]We are particularly grateful to an anonymous referee who drew our attention to this fact in an earlier version of our work and motivated the improved specification.

[7]Gray and Shadbegian (1994) difference out plant effects in their sensitivity analyses and obtain results similar to our own. Caves, Christensen, Tretheway, and Windle (1985) use a fixed-effects model to differentiate returns to scale from returns to density in the U.S. railroad industry.

[8]The variation between plants is up to twenty times the variation within plants for these variables.

[9]That is, higher environmental expenditures will appear to cause higher production costs when, in fact, they are both caused by worse management, adverse location, older equipment, etc.

1979; Chamberlain 1984; Hsiao 1986). Confronting this same dilemma, GS argue in favor of a pooled estimate.

Two facts are worth noting in this regard. It is not clear why measurement error is more likely within plant observation rather than between them. Measurement error between plants would be eliminated by a fixed effect estimator. More importantly, we find *negative* parameter estimates in the fixed-effect model. Measurement error would bias these estimates towards zero, suggesting that any overstatement that we report is even *larger* once we adjust for measurement error.[10]

Generally speaking, the choice between pooled and fixed-effect models offers a trade-off between omitted variable bias in the pooled model and increased measurement error in the fixed-effect model. Since we believe the omitted variable bias is a more serious problem, and deduce that the possibility of measurement error only re-enforces our qualitative conclusions, we have chosen the fixed-effect estimator as our preferred model.

4   Estimation and Results

We estimate our model using plant-level data collected by the Census Bureau in the Longitudinal Research Database, the Manufacturing Energy Consumption Survey and the Pollution Abatement Control Expenditure Survey. Details concerning the data construction can be found in the Appendix.

We build an estimable model from the translog production cost function (1) and aggregate share equations (2) by appending error terms to each of the five equations. Assuming the cost shares add up to unity, one of the share equations is redundant. Further, assuming homogeniety of degree one in prices, we can divide the nominal variables (PC, RC, and $\mathbf{P}$) by a reference price, further simplifying the model. As usual, symmetry is imposed by assuming $\beta_{kl} = \beta_{lk}$, etc. Finally, we demean all the variables, thus allowing us to interpret the estimated $\alpha_{i,p}$ and δ as the cost shares

---

[10]Following Griliches and Hausman (1986), we also consider estimators based on long differences which should reduce the bias due to measurement error. However, the unbalanced nature of our panel leads to considerable attrition when we require observation in both the first and last periods. In industries where long-difference estimates are feasible, we obtain results similar to the fixed-effect estimates but with much larger standard errors. This further supports our claim that measurement error is not a significant concern.

for production and environmental activities, respectively, at the mean price level. This leaves us with the following model:

$$
\begin{aligned}
\log(PC/P_m) &= \alpha_i + \alpha_t + \boldsymbol{\alpha}'_{i,p} \log(\mathbf{P}/P_m) + \alpha_y \log Y + \frac{1}{2} \log(\mathbf{P}/P_m)' \boldsymbol{\beta}_{pp} \log(\mathbf{P}/P_m) \\
&\quad + \frac{1}{2} \beta_{yy} (\log Y)^2 + \boldsymbol{\beta}'_{t,p} \log(\mathbf{P}/P_m) + \boldsymbol{\beta}'_{py} \log Y \log(\mathbf{P}/P_m) + \beta_{yt} t Y + \alpha_r \frac{RC}{PC} + \epsilon_1 \\
v_k &= \frac{RC}{RC + PC} \left(\gamma_k + \boldsymbol{\delta}'_k \log(\mathbf{P}/P_m) + \delta_{kt} t \right) \\
&\quad + \left(1 - \frac{RC}{RC + PC} \right) \left(\alpha_{i,k} + \boldsymbol{\beta}'_{pk} \log(\mathbf{P}/P_m) + \beta_{ky} \log Y + \beta_{t,k} \right) + \epsilon_2 \\
v_l &= \frac{RC}{RC + PC} \left(\gamma_l + \boldsymbol{\delta}'_l \log(\mathbf{P}/P_m) + \delta_{lt} t \right) \\
&\quad + \left(1 - \frac{RC}{RC + PC} \right) \left(\alpha_{i,l} + \boldsymbol{\beta}'_{pl} \log(\mathbf{P}/P_m) + \beta_{ly} \log Y + \beta_{t,l} \right) + \epsilon_3 \\
v_e &= \frac{RC}{RC + PC} \left(\gamma_e + \boldsymbol{\delta}'_e \log(\mathbf{P}/P_m) + \delta_{et} t \right) \\
&\quad + \left(1 - \frac{RC}{RC + PC} \right) \left(\alpha_{i,e} + \boldsymbol{\beta}'_{pe} \log(\mathbf{P}/P_m) + \beta_{ey} \log Y + \beta_{t,e} \right) + \epsilon_4
\end{aligned}
\tag{3}
$$

As before, PC are production costs, RC are reported environmental costs, v_k, v_l, v_e and v_m are the overall factor shares associated with capital, labor, energy, and materials, respectively, $\mathbf{P} = \{P_k, P_l, P_e, P_m\}'$ are the corresponding input prices, Y is output, and t is time. $\boldsymbol{\beta}_{pp} = \{\boldsymbol{\beta}_k, \boldsymbol{\beta}_l, \boldsymbol{\beta}_e, \boldsymbol{\beta}_m\}$, $\boldsymbol{\beta}_k = \{\beta_{kk}, \beta_{kl}, \beta_{ke}, \beta_{km}\}'$, etc., $\boldsymbol{\alpha}_{i,p} = \{\alpha_{i,k}, \alpha_{i,l}, \alpha_{i,e}, \alpha_{i,m}\}'$, and α, β, γ, and δ are parameters to be estimated. The vector of disturbances ϵ are assumed to be normally, identically and independently distributed across time, with contemporaneous correlation matrix Σ.

We estimate (3) in two steps. Noting that the endogenous variable PC appears on the right-hand side, we first estimate the entire model setting $RC = 0$. This leads to a predicted value, $\widehat{PC}$, that is exogenous. We then use this predicted value to create the variables $RC/\widehat{PC}$ and $RC/(RC + \widehat{PC})$ which are substituted for their endogenous counterparts in (3). Note that since $\widehat{PC}$ is only used to scale otherwise exogenous right-hand side variables, additional instruments are not necessary. The model is then re-estimated. In both steps, we estimate the model in a seemingly unrelated regression framework, applying cross-equation restrictions wherever parameters appear in more than one equation, and iterating on the covariance matrix Σ until it converges.[11]

In addition to estimating the model given by (3), we also estimate a pooled model assuming

---

[11]For a complete discussion of translog cost function estimation, see discussion in Berndt (1990), Chapter 9.4.

Table 1: Dollar-for-Dollar Effect of Environmental Expenditures on
Non-Environmental Costs in Large Expenditure Industries
(standard errors are in parentheses)

Industry:	pulp and paper	plastics	petroleum	steel	cross-industry average[†*]
Full sample # of obs.	615	404	717	536	
fixed effect	–0.62* (0.27)	0.38 (0.70)	0.59 (0.59)	–0.07 (0.47)	–0.27 (0.21)
pooled	–0.08 (0.25)	–0.13 (0.57)	1.56* (0.55)	1.98* (0.39)	0.57* (0.19)
PACE share [†]	0.130	0.089	0.430	0.166	0.816

*Significant at the 5% level.
[†]Reported PACE expenditures (in 1994) as a share of eleven-industry total.
[†*]Cross-industry average is a precision-weighted average across all four industries.

$\alpha_i = \alpha$ and $\boldsymbol{\alpha}_{i,p} = \boldsymbol{\alpha}_p$ (again in two steps). A complete table of parameters estimates for the fixed effect model along with consistency checks can be found in the Appendix. Tables 1 and 2 summarize the results of both models for the parameter of interest α_r, the dollar-for-dollar effect of environmental expenditures on non-environmental production costs.

4.1 Large Expenditure Industries

We focus our discussion on Table 1 which summarizes the effect of environmental expenditures on non-environmental activities for four industries: pulp and paper, plastics, petroleum and steel.[12] These industries have the largest aggregate expenditures on pollution abatement, the largest sample sizes, and, not coincidently, the most accurate estimates (based on their standard errors). The

---

[12]SIC codes 2621, 2821, 2911 and 3312, respectively.

reported values correspond to the parameter α_r in (3) for both the fixed effect (first row) and pooled (second row) models. The estimates reflect the dollar-for-dollar uncounted burden (if positive) or savings (if negative) associated with reported environmental expenditures.

The main conclusion of this paper is that there is no evidence of understatement and some evidence of overstatement based on our preferred fixed-effects model. In the first row, three of the four industries reveal offsets insignificantly different from zero while pulp and paper shows a significantly negative offset. An extra dollar of reported environmental expenditures in the pulp and paper industry is associated with only thirty-eight cents of increased total costs (one dollar minus sixty-two cents). The precision-weighted average across the four industries indicates a statistically insignificant twenty-seven cent overstatement per dollar of reported environmental expenditure.

These results are quantitatively and qualitatively opposed to previous plant-level analyses such as GS and JLSM that suggest large uncounted burdens.[13] This contrast is at least partially explained by the pooled results shown in the second line of Table 1. The pooled estimates reveal insignificant offsets in two industries but large and significantly *positive* offsets in petroleum and steel. In steel, each dollar of reported environmental expenditures is associated with nearly three dollars in increased total costs (one dollar plus $1.98). The expenditure-weighted average across all four industries is statistically significant $0.57 of uncounted costs.

The deeper explanation of this contrast is the cross-sectional cost and environmental expenditure variation among plants discussed in the previous section. This variation points to large uncounted burdens and underlies the pooled estimates (but not the fixed effect estimates). Our view is that the cross-sectional variation is tainted by omitted variables describing important differences among plants. Characteristics such as age, management style and location could easily generate a confounding and positive correlation between environmental expenditures and total costs. For this reason, we prefer the fixed-effects estimates.

None of these results suggest that increased environmental regulation is free (e.g., $\alpha_r < -1$). All four estimated values are higher than minus one, indicating that reported expenditures are at

___

[13]Gray and Shadbegian (1994) do observe a similar, though statistically insignificant, pattern among their pooled and growth (fixed-effect) models.

14

Table 2: Dollar-for-Dollar Effect of Environmental Expenditures on
Non-Environmental Costs in Small Expenditure Industries
(standard errors are in parentheses)

Industry:	malt beverages	printing	pharmaceuticals	refrigeration	semiconductors	motor vehicles	aircraft engines	cross-industry average[†*]	small and large average[†*]
Full sample # of obs.	185	114	260	224	80	257	102		
fixed effect	–0.10 (1.55)	6.13 (3.90)	2.05 (1.47)	–1.38 (3.40)	16.15* (5.54)	19.66* (5.05)	7.10 (5.69)	2.39* (0.94)	–0.14 (0.20)
pooled	–2.83* (1.49)	11.93* (3.92)	5.05* (1.18)	15.34* (4.70)	28.67* (7.87)	34.14* (4.69)	13.74* (3.87)	4.81* (0.85)	0.77* (0.18)
PACE share[†]	0.026	0.019	0.033	0.010	0.026	0.060	0.009	0.184	1.000

*Significant at the 5% level.
[†]Reported PACE expenditures (in 1994) as a share of eleven-industry total.
[†*]Cross-industry average is a precision-weighted average across all seven/eleven industries.

most partially offset. The cross-industry average of -0.27 formally rejects the hypothesis that $\alpha_r = -1$ at any level of significance.

However, the standard errors and range of estimates for the individual industry estimates are large: A ninety-five percent confidence interval for petroleum ranges from -0.57 to $+1.75$ and for pulp and paper from -1.15 to -0.09. This means we are unable to reject hypotheses of either understatment, overstatement or even net savings in some industries. This is a real limitation of the available data. Using similar plant-level census data, GS and JLSB report standard errors equal to or larger than our own.

4.2 Small Expenditure Industries

We separate out the small expenditure industries in Table 2 for several reasons.[14] First, none of these industries account for more than 3% of total environmental expenditures among the entire eleven-industry group. Second, the estimated parameters have much larger standard errors, in part due to smaller sample sizes. Finally, the somewhat "wild" estimates themselves suggest that our modeling strategy might simply fail to capture the production technologies of these industries. That is, there may be more heterogeniety than we recognize, the output and input mixes may be not be satisfactorily represented in the single output, KLEM framework that we have adopted, or the notion of a single, industry-wide production function may be inappropriate.

Despite these shortcomings, the qualitative patterns observed with the large expenditure industries remain. With the exception of semiconductors and motor vehicles, none of the fixed-effect estimates are statistically significant, providing no evidence of over- or understatement of reported environmental costs.[15] More importantly, six of the seven industries reveal significantly higher and positive estimates based on the pooled model. This continues to support the two qualitative results from the analysis of large expenditure industries: no evidence of understatement in the fixed-effect model coupled with large, significant understatment in the pooled model.

5 Conclusion

Most previous analyses argue that reported environmental expenditures are likely to understate the true economic cost of environmental protection. In contrast, our results rule out any significant understatement and indicate, if anything, some degree of overstatement. We reject the hypothesis that additional regulation is "free" based on a cross-industry average.

---

[14]The industries (with SIC codes in parentheses) are malt beverages (2082), printing (2752), pharmaceuticals (2834), refrigeration (3585), semiconductors (3674), motor vehicles (3711) and aircraft engines (3724). Note that the entire set of large and small expenditure industries were chosen to include a mix of both traditional and non-traditional polluting industries. This choice was made long before we had any sense of the results.

[15]The estimate for motor vehicles is possibly biased by positive correlation between environmental regulations on automotive manufacturing plants and environmental regulations on motor vehicles themselves. Meanwhile, our consistency checks in the Appendix indicate that the estimated labor demand for semiconductors is always upward sloping—suggesting a failure of our modeling approach.

These qualitative results are sensitive to alternative assumptions about productivity differences among plants. While the preferred fixed-effect model suggests overstatement in one industry, a pooled model indicates significant understatement in two others. Although consistent with previous work, we argue that the pooled model is biased by omitted variables describing important differences among plants. These differences would tend to bias the results towards understatement.

This literature suggesting understatement has leaned on several explanations. Reduced flexibility, the crowding out of new investments, and new source bias are all plausible reasons why reported costs would understate actual costs. In contrast, our findings of possible overstatement lean on an alternative explanation. In particular, plant managers may fail to consider important complementarities that exist between environmental activities and conventional, non-environmental production. These complementarities might reflect economies of scope, valuable recycled effluents, or the harvesting of non-environmental process improvements when production is halted for an environmental modification. As always, we cannot distinguish this explanation from the alternative that plant managers systematically misstate their direct costs.

Our quantitative results offer an improved approach based on direct estimates of the dollar-for-dollar offset associated with environmental expenditures. This avoids the arguably implausible assumption that the *elasticity* of total costs with respect to environmental expenditures is constant. However, our estimates are still imprecise: The estimated standard errors range from thirty to seventy cents among the four large expenditure industries.

While average (cross-industry) environmental costs appear neither significantly under- nor overstated, the variation and imprecision of our industry-level estimates leaves considerable room for interpretation. With 95% confidence intervals for individual industries including values from -1.15 to $+1.75$, it is impossible to convincingly rule out understatement, overstatement, or even net savings. In the context of ongoing debates about the costs and benefits of environmental regulation this conclusion is particularly troubling. While current discussions emphasize the need for improved measurement of the benefits associated with environmental protection, our results highlight the importance of further research on the costs.

17

References

Bailey, E. E. and A. F. Friedlaender (1982). Market structure and multiproduct industries. *Journal of Economic Literature 20*, 1024–1048.

Barbera, A. J. and V. D. McConnell (1990). The impact of environmental regulation on industry productivity: Direct and indirect effects. *Journal of Environmental Economics and Management 18*, 50–65.

Bartelsman, E. J. and W. B. Gray (1994). *NBER Productivity Database* [online]. URL:ftp://nber.nber.org/pub/productivity.

Berndt, E. R. (1990). *The Practice of Econometrics: Classic and Contemporary*. New York: Addison-Wesley.

Caves, D. W., L. R. Christensen, and W. E. Diewert (1982a). The economic theory of index numbers and the measurement of input, output, and productivity. *Econometrica 50*(6), 1393–1414.

Caves, D. W., L. R. Christensen, and W. E. Diewert (1982b). Multilateral comparisons of output, input and productivity using superlative index numbers. *Economic Journal 92*, 73–86.

Caves, D. W., L. R. Christensen, M. W. Tretheway, and R. J. Windle (1985). Network effects and the measurement of returns to scale and density for U.S. railroads. In A. F. Daughety (Ed.), *Analytical Studies in Transport Economics*, pp. 97–120. Cambridge University Press.

Chamberlain, G. (1984). Panel data. In Griliches and Intriligator (Eds.), *Handbook of Econometrics, Volume 2*, pp. 1247–1318. Amsterdam: North-Holland.

Christensen, L. and D. Jorgenson (1969). The measurement of U.S. real capital input, 1929-1967. *Review of Income and Wealth*, 293–320.

Deily, M. E. and W. B. Gray (1991). Enforcement of pollution regulation in a declining industry. *Journal of Environmental Economics and Management 21*, 260–274.

Diewert, W. and T. Wales (1987). Flexible functional forms and global curvature conditions. *Econometrica 55*(1), 43–68.

Engle, R. F., D. F. Hendry, and J.-F. Richard (1983). Exogeneity. *Econometrica 51*(2), 277–304.

Gray, W. B. (1987). The cost of regulation: OSHA, EPA and the productivity slowdown. *American Economic Review 77*(5), 998–1006.

Gray, W. B. and R. J. Shadbegian (1994). Pollution abatement costs, regulation and plant-level productivity. Discussion Paper, U.S. Department of Commerce, Center for Economic Studies.

Greene, W. H. (1990). *Econometric Analysis*. New York: MacMillan.

Griliches, Z. (1979). Sibling models and data in economics: Beginnings of a survey. *Journal of Political Economy 87*(5, part 2), S37–S64.

Griliches, Z. and J. A. Hausman (1986). Errors in variables in panel data. *Journal of Econometrics 31*, 93–118.

Gruenspecht, H. K. (1982). Differentiated regulation: the case of auto emission standards. *American Economic Review 72*, 328–331.

Hall, R. and D. Jorgenson (1967). Tax policy and investment behavior. *American Economic Review 57*, 391–414.

Hazilla, M. and R. J. Kopp (1986). The social cost of alternative ambient air quality standards for total suspended particulates: A general equilibrium analysis (final report). Technical report, Office of Air Quality, Planning and Standards, U.S. Environmental Protection Agency, Research Triangle Park, NC.

Hazilla, M. and R. J. Kopp (1990). Social cost of environmental quality regulation: A general equilibrium analysis. *Journal of Political Economy 98*(4), 853–873.

Hsiao, C. (1986). *Analysis of Panel Data*. Cambridge: Cambridge University Press.

Hulten, C. R. and F. C. Wykoff (1981). The measurement of economic depreciation. In C. R. Hulten (Ed.), *Depreciation, Inflation, and the Taxation of Income from Capital*. Washington: Urban Institute Press.

Jaffee, A. B., S. R. Peterson, P. R. Portney, and R. N. Stavins (1995). Environmental regulation and the competitiveness of U.S. manufacturing: What does the evidence tell us? *Journal of Economic Literature 33*, 132–163.

Jorgenson, D. and R. Landau (1993). *Tax Reform and the Cost of Capital: An International Comparison*. Washington: Brookings.

Jorgenson, D. and K.-Y. Yun (1991). *Tax Reform and the Cost of Capital*. Oxford: Claredon Press.

Jorgenson, D. W. and P. J. Wilcoxen (1990). Environmental regulation and U.S. economic growth. *Rand Journal of Economics 21*(2), 314–340.

Joshi, S., L. Lave, J.-S. Shih, and F. McMichael (1997). Impact of environmental regulations on the U.S. steel industry. Mimeo, Carnegie Mellon University.

Leibenstein, H. (1966). Allocative efficiency vs. 'X-efficiency'. *American Economic Review 56*, 392–415.

Meyer, S. M. (1993). Environmentalism and economic prosperity: Testing the environmental impact hypothesis. M.I.T. Mimeo, Cambridge, MA.

Nelson, R. A., T. Tietenberg, and M. R. Donihue (1993). Differential environmental regulation: Effects on electric utility capital turnover and emissions. *Review of Economics and Statistics 77*(2), 368–373.

Palmer, K. L., W. E. Oates, and P. R. Portney (1995). Tightening environmental standards: The benefit-cost or the no-cost paradigm? *Journal of Economic Perspectives 9*(4), 119–132.

Perroni, C. and T. F. Rutherford (1996). A comparison of the performance of flexible functional forms for use in applied general equilibrium modelling. Mimeo, University of Colorado.

Porter, M. E. (1991, April). America's green strategy. *Scientific American*.

Porter, M. E. and C. Van der Linde (1995). Toward a new conception of the environment-competitiveness relationship. *Journal of Economic Perspectives 9*(4).

Rose, A. (1983). Modeling the macroeconomic impact of air pollution abatement. *Journal of Regulatory Science 23*(4), 441–459.

Schmalensee, R. (1993). The costs of environmental protection. In *Balancing Economic Growth and Environmental Goods*, pp. 53–80. Washington, DC: American Council for Capital Formation.

Streitweiser, M. L. (1996). Evaluation and use of the pollution abatement costs and expenditure survey. Mimeo, Center for Economic Studies, Bureau of Census.

U.S. Department of Commerce (various issues). *Survey of Current Business*.

U.S. Environmental Protection Agency (1990). Environmental investments: The cost of a clean environment.

U.S. Office of Technology Assessment (1994). Industry, technology and the environment: Competitiveness, challenges, and business opportunities. OTA-ITE-586, Washington, DC.

A Appendix

A.1 Data Sources

The data used in this paper are drawn from several plant-level datasets developed by the U.S. Census Bureau:

- *The Longitudinal Research Database (LRD)*. This 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)*. Collected by the Department of Energy every three years beginning 1985, MECS contains detailed fuel consumption and expenditure data by establishment.

- *The Pollution Abatement Control Expenditure (PACE)*. This dataset includes pollution abatement investment spending and operating expenditures at the establishment level and has been collected by the Census Bureau for most years between 1979 and 1991, except 1983 and 1987.

For 11 four-digit SIC industries, our analysis includes the years 1979, 1980, 1981, 1985, 1988, and 1991. This allows us to use the detailed energy data available prior to 1981 in the LRD and subsequently in the MECS. Sample sizes are shown in Table A.1.

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

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

- *Reported Environmental Expenditures (RC)*. 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 as well as annual expenses on labor, energy and materials. Data are available for the years 1979-1991, except 1983 and 1987.

- *Capital Stock (K)*. 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.[16] A perpetual inventory method (Christensen and

---

[16]Specifically, capital stock is initialized to 0.45 times the gross book value in 1979. This ratio is based on the aggregate net asset to gross book value ratio computed in the steel industry where firm 10-Ks were available.

Table A.1: Sample Size by Industry

Industry	Plants	Sample Size	RC/PC
Malt Beverage	45	185	0.007
Pulp and Paper	142	615	0.029
Printing	45	114	0.004
Plastic Material	107	404	0.020
Pharmaceutical	73	260	0.011
Petroleum	165	717	0.011
Steel	128	536	0.023
Refrigeration	76	224	0.003
Semiconductors	28	80	0.009
Motor Vehicles and Car Body	59	257	0.003
Aircraft Engine	29	102	0.004

Jorgenson 1969) is then used to generate a real capital stock series covering the period 1980-1991 based on the following formula:

$$K_t = (1 - \delta)K_{t-1} + \frac{q_0}{q_t}I_t \qquad (A.1)$$

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).

- *Price of Capital (P_k).* The service price of capital is calculated using the Hall-Jorgenson (1969) procedure. The service price of capital is given by:

$$P_{k(t)} = [q_{t-1}r_t + \delta q_t - (q_t - q_{t-1}) + q_t C_t]\frac{1 - u_t z_t - k_t}{1 - u_t} \qquad (A.2)$$

where,

$$
\begin{aligned}
P_{k(t)} &= \text{ service price of capital,} \\
q_t &= \text{ price index of new capital equipment,} \\
r_t &= \text{ after tax rate of return on capital (opportunity cost),} \\
\delta &= \text{ rate of economic depreciation,} \\
C_t &= \text{ effective property tax rate,} \\
u_t &= \text{ effective corporate income tax rate,} \\
z_t &= \text{ present value of allowed depreciation tax deductions on a dollar's} \\
&\quad \text{ investment over the life time of an asset,} \\
k_t &= \text{ investment tax credit,} \\
t &= \text{ year.}
\end{aligned}
$$

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).

- *Labor (P_l, L).* 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 non-production 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.

- *Materials (P_m, M).* 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, 1992. Estimates for intervening years are linearly interpolated. We use reported total expenditures on materials and parts in the LRD to calculate material costs; dividing by price yields our quantity estimate.

- *Energy (P_e, E).* Detailed data on total quantities consumed and total expenditures on various fuels were collected in LRD (through 1981) and MECS (1985, 88, 91). These data are used to calculate the prices of individual fuels ($/Mbtu) paid by each plant. The individual fuels include coal, natural gas, dfo, rfo, lpg and electricity. These fuels typically account for about 90 percent of total energy cost. The price of energy is computed as a divisia index of these fuels.

- *Production Costs (PC).* Total cost is the sum of factor costs, $TC = P_k K + P_l L + P_e E + P_m M$. Production costs are total costs minus reported environmental expenditures, $PC = TC - RC$.

- *Factor Shares (v_k, v_l, v_e, v_m).* Factor shares are calculated as the expenditure on individual factors divided by total costs, e.g., $v_k = (P_k K)/TC$, etc.

A.2 Estimation

Table A.2 presents detailed estimation results for the eleven industries considered in this study using the fixed-effects model discussed in Section 3. Parameter estimates for the 25 free slope parameters in Equation (3), standard errors, goodness of fit and likelihood statistics are reported. Estimates of year and plant dummies are not included.

Over half of the estimated parameters are significant at the 5% level. Many of the second order price coefficients are among the significant parameter estimates, both for conventional production (β_{pp}) and environmental activities (δ_{pp}). It is therefore not surprising that tests of Cobb-Douglas restrictions on these parameters reject eighteen out of twenty-two times (only the restrictions on

Table A.2: Estimation results
(standard errors are in parentheses)

Sector:	malt beverages	pulp and paper	printing	plastics	pharmaceuticals	petroleum	steel	refrigeration	semiconductors	motor vehicles	aircraft engines
α_y	0.7882*	0.7161*	0.8723*	0.8314*	0.4863*	0.7433*	0.7136*	0.7295*	0.5485*	0.7915*	0.7845*
	(0.0289)	(0.0273)	(0.0613)	(0.0362)	(0.0461)	(0.0281)	(0.0304)	(0.0273)	(0.0817)	(0.0246)	(0.0443)
α_r	–0.0974	–0.6221*	6.1281	0.3774	2.0495	0.5900	–0.0726	–1.3842	16.1466*	19.6551*	7.0990
	(1.5514)	(0.2746)	(3.9019)	(0.6958)	(1.4705)	(0.5905)	(0.4671)	(3.4009)	(5.5400)	(5.0468)	(5.6911)
β_{kk}	0.1563*	0.1095*	0.0167	0.0029	0.0673*	0.0070*	0.0664*	0.0007	–0.0985	–0.0005	0.0548
	(0.0301)	(0.0379)	(0.0212)	(0.0190)	(0.0218)	(0.0019)	(0.0172)	(0.0080)	(0.1173)	(0.0067)	(0.0337)
β_{ll}	0.0195	0.1120*	0.0781*	0.0668*	0.1550*	0.0133*	0.0491*	0.0758*	0.2936*	0.0454*	0.1818*
	(0.0166)	(0.0114)	(0.0344)	(0.0094)	(0.0203)	(0.0016)	(0.0201)	(0.0149)	(0.0506)	(0.0140)	(0.0455)
β_{ee}	0.0155*	0.0597*	0.0048	–0.0027	0.0069	0.0128*	0.0211	0.0058*	0.0255*	0.0011	0.0032
	(0.0043)	(0.0090)	(0.0043)	(0.0163)	(0.0098)	(0.0018)	(0.0209)	(0.0018)	(0.0076)	(0.0008)	(0.0029)
β_{yy}	–0.0785*	–0.0336	0.2285*	–0.0408	0.0493	0.0039	0.0389*	–0.0181	0.1645*	0.1493*	0.1023*
	(0.0370)	(0.0316)	(0.0943)	(0.0328)	(0.0457)	(0.0184)	(0.0191)	(0.0218)	(0.0422)	(0.0245)	(0.0181)
β_{kl}	–0.0234	–0.0347*	0.0149	–0.0030	–0.0115	–0.0017*	–0.0035	0.0214*	–0.0264	–0.0068	–0.0284
	(0.0149)	(0.0128)	(0.0095)	(0.0092)	(0.0111)	(0.0008)	(0.0088)	(0.0057)	(0.0440)	(0.0053)	(0.0225)
β_{ke}	0.0023	–0.0116	0.0027	0.0103	–0.0199*	0.0005	–0.0264*	–0.0050*	–0.0097	0.0008	0.0093
	(0.0058)	(0.0112)	(0.0065)	(0.0086)	(0.0100)	(0.0012)	(0.0073)	(0.0022)	(0.0150)	(0.0008)	(0.0064)
β_{ky}	0.0067	0.0100	0.0087	–0.0365*	–0.0258*	–0.0132*	–0.0383*	–0.0151*	–0.0465*	–0.0088*	–0.0070
	(0.0071)	(0.0071)	(0.0062)	(0.0049)	(0.0071)	(0.0021)	(0.0031)	(0.0023)	(0.0185)	(0.0015)	(0.0064)
β_{le}	0.0108*	–0.0114	0.0003	–0.0016	–0.0105	0.0003	0.0156	–0.0051*	–0.0215*	–0.0001	–0.0092
	(0.0044)	(0.0065)	(0.0052)	(0.0068)	(0.0084)	(0.0010)	(0.0138)	(0.0017)	(0.0059)	(0.0007)	(0.0050)
β_{ly}	–0.0028	–0.0446*	0.0036	–0.0302*	–0.0724*	–0.0078*	0.0066	–0.0162*	–0.0568*	–0.0381*	–0.0544*
	(0.0054)	(0.0052)	(0.0225)	(0.0041)	(0.0126)	(0.0010)	(0.0072)	(0.0057)	(0.0226)	(0.0036)	(0.0133)
β_{ey}	–0.0055*	–0.0041	–0.0041	0.0085	–0.0043	–0.0104*	–0.0177*	–0.0063*	–0.0093*	–0.0025*	–0.0088*
	(0.0014)	(0.0053)	(0.0034)	(0.0092)	(0.0052)	(0.0015)	(0.0087)	(0.0007)	(0.0033)	(0.0002)	(0.0015)
β_{yt}	–0.0053*	0.0041*	0.0057	0.0110*	0.0131*	–0.0028*	–0.0004	–0.0013	–0.0094	–0.0149*	0.0114*
	(0.0023)	(0.0014)	(0.0041)	(0.0020)	(0.0029)	(0.0013)	(0.0014)	(0.0022)	(0.0074)	(0.0026)	(0.0020)
γ_k	1.0546*	0.1276	1.1609*	–0.0510	–0.0389	0.0532	0.1460*	1.1264*	–3.1629	1.2738*	5.7989*
	(0.4407)	(0.1085)	(0.4767)	(0.1053)	(0.2871)	(0.0545)	(0.0715)	(0.4090)	(2.1018)	(0.3541)	(0.9130)
γ_l	0.6379	0.1531*	6.0330*	0.3621*	1.2923*	0.0748*	0.1565	2.5888*	6.6070*	–0.1102	–0.0699
	(0.3582)	(0.0770)	(1.6672)	(0.0914)	(0.5079)	(0.0292)	(0.1610)	(0.9142)	(2.3756)	(0.8902)	(1.9241)
γ_e	0.1135	0.1967*	0.3780	0.2930	0.4354*	–0.0225	–0.7126*	–0.1277	–0.2162	0.2498*	0.2290
	(0.1011)	(0.0846)	(0.2530)	(0.2028)	(0.2146)	(0.0387)	(0.1952)	(0.1230)	(0.3312)	(0.0513)	(0.2171)

Sector:	malt beverages	pulp and paper	printing	plastics	pharmaceuticals	petroleum	steel	refrigeration	semiconductors	motor vehicles	aircraft engines
δ_{kt}	−0.0940	0.0013	0.0403	0.0627*	0.0917*	−0.0043	−0.0122	−0.0652	−0.3513	−0.0735	1.0761*
	(0.0814)	(0.0171)	(0.1293)	(0.0186)	(0.0374)	(0.0110)	(0.0160)	(0.0615)	(0.4732)	(0.0926)	(0.2196)
δ_{kk}	0.1902	0.9811*	3.8019	0.4311	0.9956	0.3400*	0.5153*	4.5394*	3.9218	1.9357	−6.6620*
	(1.5071)	(0.4718)	(2.4452)	(0.4545)	(0.7467)	(0.0964)	(0.2243)	(1.4318)	(9.6598)	(1.0961)	(3.0742)
δ_{kl}	2.1486*	−0.0764	−3.4448*	0.0251	0.3531	0.0078	−0.1398	−3.6810*	−6.6716	0.6079	−2.0317
	(1.0661)	(0.2554)	(1.4191)	(0.2843)	(0.7403)	(0.0394)	(0.2375)	(0.7148)	(4.5770)	(1.2747)	(3.9311)
δ_{ke}	−0.0264	−0.1040	0.7696	0.1902	−0.0934	0.1260*	0.4567*	1.0097*	−1.3563	−0.2860*	−0.8783
	(0.3323)	(0.1996)	(0.8803)	(0.2624)	(0.4097)	(0.0554)	(0.1942)	(0.3899)	(1.2571)	(0.1396)	(0.6875)
δ_{lt}	0.1992*	−0.0154	0.6728	0.0516*	0.0589	0.0097	−0.0935*	0.2611*	1.4596*	0.1625	1.1430*
	(0.0626)	(0.0126)	(0.3676)	(0.0181)	(0.0651)	(0.0067)	(0.0355)	(0.1316)	(0.4769)	(0.2179)	(0.4438)
δ_{ll}	−0.8532	−0.3011	−14.3137*	−1.1840*	−4.8394*	−0.2801*	1.4959*	2.4797	−18.8924*	−6.1395	−26.6317*
	(2.0325)	(0.3037)	(4.8606)	(0.3458)	(1.4341)	(0.0986)	(0.5676)	(1.8203)	(5.2619)	(3.5371)	(9.8329)
δ_{le}	−0.1111	−0.2485	−0.3801	0.1503	−0.2808	0.0026	−0.8998*	−0.0453	−0.0010	−0.2111	4.8883*
	(0.4936)	(0.1375)	(0.7514)	(0.2211)	(0.5472)	(0.0398)	(0.3833)	(0.2326)	(0.6862)	(0.1864)	(1.1383)
δ_{et}	−0.0270	−0.0232*	−0.0586	−0.0426	−0.0186	−0.0115	0.0501	−0.0311	−0.0423	−0.0143	−0.1668*
	(0.0173)	(0.0107)	(0.0634)	(0.0290)	(0.0293)	(0.0076)	(0.0346)	(0.0204)	(0.0640)	(0.0124)	(0.0543)
δ_{ee}	0.2782	0.4141*	−0.4121	−0.3730	0.7877	−0.1483*	−0.1428	−0.1080	1.3754*	1.2016*	0.8885
	(0.3017)	(0.1679)	(0.6424)	(0.5119)	(0.4238)	(0.0690)	(0.5534)	(0.3072)	(0.5018)	(0.2047)	(0.7247)
observations	185	615	114	404	260	717	536	224	80	257	102
firms	45	142	45	107	73	165	128	76	28	59	29
R^2 total costs	0.99	0.98	1.00	0.98	0.98	0.99	0.99	1.00	0.98	0.99	1.00
R^2 capital share	0.72	0.80	0.98	0.83	0.85	0.77	0.82	0.91	0.90	0.74	0.90
R^2 labor share	0.87	0.86	0.94	0.91	0.85	0.89	0.81	0.96	0.85	0.86	0.95
R^2 energy share	0.82	0.87	0.93	0.70	0.77	0.88	0.49	0.94	0.92	0.91	0.94
log-likelihood	1970	5167	1314	3351	1974	8236	3753	2840	662	3297	1130

*Significant at the 5% level.

β for printing, motor vehicles and aircraft engines are accepted). Similarly, tests that the model reduces to a pooled form strongly rejects in all eleven industries. These tests suggest that the flexible functional form being estimated cannot be reduced in a substantial way without significantly reducing the model's fit.

Table A.3 provides additional information about the consistency of the estimated share values, fitted share values and own-price demand elasticities in light of economic theory. We first compare the observed cost shares to values found in both aggregate data (U.S. Department of Commerce) and another microeconomic study (Hazilla and Kopp 1990). Our estimates generally fall between the two estimates reflecting the fact that the historical scope of our data lies between the the more recent aggregate data and the older Hazilla and Kopp study.

Next we examine whether the fitted cost shares for production are positive and whether the own-price elasticities are negative.[17] Only a few of the fitted cost shares turn out to be negative. This typically occurs in those industries where one or more shares is near zero (petroleum, for example, where materials account for over 90% of costs). However, a large number of the own-price elasticities are positive, especially capital. This means that the factor demand schedules are locally upward sloping and contradicts economic theory.

This is unfortunately a common occurance with translog cost functions when factor demands are relatively inelastic (Perroni and Rutherford 1996). Because the elasticity varies with the factor shares, an average own-price elasticity near zero will imply that many of the locally evaluated elasticities will be positive. This is in fact what we observe.

We estimate an alternative Cobb-Douglas model in order to verify that our primary results concerning α_r are not influenced by these contradictions with economic theory. In this estimation, we restrict the second order price terms for both production and environmental activities to be zero ($\beta_{kk} = \beta_{ll} = \beta_{ee} = \beta_{kl} = \beta_{ke} = \beta_{le} = 0$ and $\delta_{kk} = \delta_{ll} = \delta_{ee} = \delta_{kl} = \delta_{ke} = \delta_{le} = 0$) implying own-price elasticities of -1. The resulting industrly-level estimates of α_r change only slightly, with the average over pulp and paper, plastics, petroleum and steel becoming -0.23 versus the

---

[17]This is less restrictive than the concavity required by economic theory but is simpler to verify.

original value of -0.27. Since the Cobb-Douglas restriction is rejected based on log-likelihood tests (noted above), we continue to focus our attention on the unrestricted translog model.

Table A.3: Assessment of Model Consistency

Industry:	malt beverages	pulp and paper	printing	plastics	pharmaceuticals	petroleum	steel	refrigeration	semiconductors	motor vehicles	aircraft engines
Comparison of average value shares											
Table A.2 estimates[a] capital	0.056	0.092	0.059	0.063	0.074	0.020	0.060	0.026	0.136	0.015	0.047
labor	0.141	0.201	0.359	0.085	0.238	0.019	0.230	0.236	0.370	0.118	0.333
energy	0.028	0.120	0.024	0.057	0.032	0.022	0.104	0.016	0.046	0.006	0.022
material	0.774	0.587	0.558	0.794	0.657	0.939	0.606	0.723	0.448	0.861	0.598
1987 I-O tables[b] capital	0.131	0.153	0.166	0.173	0.302	0.105	0.074	0.099	0.166	0.063	0.067
labor	0.177	0.265	0.350	0.180	0.314	0.071	0.299	0.366	0.387	0.123	0.414
energy	0.014	0.052	0.012	0.049	0.014	0.021	0.095	0.012	0.019	0.008	0.011
material	0.678	0.530	0.471	0.598	0.370	0.803	0.532	0.523	0.428	0.805	0.508
Hazilla and Kopp[c] capital	0.020	0.066	0.054	0.059	0.071	0.055	0.061	0.032	0.166	0.032	0.021
labor	0.116	0.202	0.362	0.212	0.146	0.039	0.258	0.292	0.387	0.231	0.298
energy	0.013	0.046	0.009	0.040	0.112	0.037	0.034	0.016	0.019	0.010	0.013
material	0.852	0.685	0.574	0.689	0.672	0.870	0.647	0.660	0.428	0.727	0.668
Fraction of observations with negative estimated share values (zeros are omitted)											
capital	0.016	0.003	0.009		0.012	0.054	0.017	0.036	0.025	0.109	0.049
labor				0.002	0.004	0.006			0.013		
energy		0.002		0.012	0.058	0.010					0.020
material											
Fraction of observations with positive own-price elasticities (zeros are omitted)											
capital	1.000	0.763	0.053		0.512	0.216	0.666	0.036		0.093	0.814
labor		0.055		0.522	0.342	0.353	0.002		1.000		0.235
energy	0.027	0.104	0.026	0.010	0.165	0.285	0.011	0.036	0.113	0.008	0.029
material	0.541	0.006	0.009	0.084	0.096	0.187	0.011	0.009	0.038		0.118

[a]Average of the observed share values in each industry.

[b]Energy, materials and value added expenditures are from the 1987 Benchmark Input-Output Tables, U.S. Department of Commerce (April, 1994). Further breakdown of value added is based on a more detailed version of Gross Product Originating data, U.S. Department of Commerce (August, 1996).

[c]From Hazilla and Kopp (1986).