



Pollution Abatement Expenditures and Plant-Level
Productivity: A Production Function Approach

Ronald J. Shadbegian and Wayne B. Gray

Working Paper Series

Working Paper # 03-05
August, 2003



U.S. Environmental Protection Agency
National Center for Environmental Economics
1200 Pennsylvania Avenue, NW (MC 1809)
Washington, DC 20460
<http://www.epa.gov/economics>

Pollution Abatement Expenditures and Plant-Level Productivity: A Production Function Approach

Ronald J. Shadbegian and Wayne B. Gray

Correspondence:

Ronald J. Shadbegian
UMass Dartmouth
Department of Economics
North Dartmouth, MA 02747
email: rshadbegian@umassd.edu
508-999-8337

and

U.S. Environmental Protection Agency
National Center for Environmental Economics
email: shadbegian.ron@epa.gov

NCEE Working Paper Series

Working Paper # 03-05
August, 2003

DISCLAIMER

The views expressed in this paper are those of the author(s) and do not necessarily represent those of the U.S. Environmental Protection Agency. In addition, although the research described in this paper may have been funded entirely or in part by the U.S. Environmental Protection Agency, it has not been subjected to the Agency's required peer and policy review. No official Agency endorsement should be inferred.

Pollution Abatement Expenditures and Plant-Level Productivity: A Production Function Approach

Ronald J. Shadbegian and Wayne B. Gray

Abstract: In this paper we investigate the impact of environmental regulation on productivity using a Cobb-Douglas production function framework. Estimating the effects of regulation on productivity can be done with a top-down approach using data for broad sectors of the economy, or a more disaggregated bottom-up approach. Our study follows a bottom-up approach using data from the U.S. paper, steel, and oil industries. We measure environmental regulation using plant-level information on pollution abatement expenditures, which allows us to distinguish between productive and abatement expenditures on each input. We use annual Census Bureau information (1979-1990) on output, labor, capital, and material inputs, and pollution abatement operating costs and capital expenditures for 68 pulp and paper mills, 55 oil refineries, and 27 steel mills.

We find that pollution abatement inputs generally contribute little or nothing to output, especially when compared to their ‘productive’ equivalents. Adding an aggregate pollution abatement cost measure to a Cobb-Douglas production function, we find that a \$1 increase in pollution abatement costs leads to an estimated productivity decline of \$3.11, \$1.80, and \$5.98 in the paper, oil, and steel industries respectively. These findings imply substantial differences across industries in their sensitivity to pollution abatement costs, arguing for a bottom-up approach that can capture these differences. Further differentiating plants by their production technology, we find substantial differences in the impact of pollution abatement costs even within industries, with higher marginal costs at plants with more polluting technologies. Finally, in all three industries, plants concentrating on change-in-production-process abatement techniques have higher productivity than plants doing predominantly end-of-line abatement, but also seem to be more affected by pollution abatement operating costs. Overall, our results point to the importance using detailed, disaggregated analyses, even below the industry level, when trying to model the costs of forcing plants to reduce their emissions.

Subject Area: Costs of Pollution Control and Environmental Policy

Key Words: 1) Environmental Regulation; 2) Productivity; 3) Pollution Abatement Costs; 4) Technology

Financial support for the research from the National Science Foundation (grant # SBR-9410059) and the Environmental Protection Agency (grant #R-826155-01-0) is gratefully acknowledged, as is access to Census data at the Boston Research Data Center. We are also grateful to the many people in the paper industry who were willing to share their knowledge of the industry with us. We would also like to thank the participants at the “Environmental Policy, Energy Use and Technological Change” (Amsterdam, 2002) and the 2003 Western Economic Association Meetings for their insightful comments. The opinions and conclusions expressed are those of the author and not the Census Bureau, EPA, or NSF. All papers are screened to ensure that they do not disclose confidential information. Any remaining errors or omissions are the authors’.

1. Introduction

Environmental regulation has become increasingly stringent over time, driven by a concern that the unregulated process of economic growth was becoming unsustainable, causing too much damage to the environment and imposing too many costs on society in terms of air and water pollution. Restrictions on business activity grew from primarily local regulations on smoke and fumes to state-level regulations, and finally expanded to national regulation in the 1970s in the U.S. and other developed countries. In those cases where air or water pollution spilled across national borders there have also been international agreements to control pollution (e.g. dealing with acid rain concerns in Europe and between the U.S. and Canada). These regulations have been remarkably effective in improving the overall sustainability of the economy, achieving both continued economic growth and reductions in most forms of air and water pollution.

In recent years, sustainability issues have shifted to an even larger playing field, with concerns about global warming and climate change, where emissions of greenhouse gases from one country could affect all other countries. There has been a continuing debate about the appropriate policy response (if any): the Kyoto Protocol, designed as an initial response to global warming, has not been universally accepted. Uncertainty about the likelihood and costs of global warming has dominated the discussions, but there has also been considerable uncertainty about the costs of policies designed to reduce emissions. The detailed examination of the costs of reducing emissions of traditional pollutants we present here may help identify important factors to consider in the broader global context.

A variety of methods have been used to measure pollution abatement costs. The

Pollution Abatement Cost and Expenditure Survey indicates that pollution abatement operating costs at U.S. manufacturing plants grew from \$7 billion to over \$18 billion (inflation-adjusted) between 1973 and 1993, though even the latter number represents less than one percent of total operating costs in manufacturing. Not all consequences of environmental regulation need be negative for the affected firms, as pointed out by Porter (1991, 1995), since firms could discover more efficient methods of production in the search for cleaner ones. Given the difficulties of appropriately measuring (or even defining) abatement costs when inputs can contribute to both abatement and production, other approaches have been tried, including econometric models focused on the productivity effects of regulation. Estimating these productivity models can be done with a top-down approach, using data for broad sectors of the economy, or a more disaggregated bottom-up approach.

Over the past 25 years there have been a number of studies on the impact of environmental regulation on productivity, ranging from growth accounting studies like Denison (1979) that use abatement cost survey data to infer productivity effects to econometric studies with industry-level data like Gray (1986,1987), Barbera and McConnell (1986), and Shadbegian (1996). Studies using plant-level data tend to find larger (more negative) effects of regulation on productivity: Gollop and Roberts (1983) for electric utilities, Joshi et. al. (2001) for steel mills, and Gray and Shadbegian (2003), Boyd and McClelland (1999), and Fare, Grosskopf, Lovell, and Pasurka (1989) for the pulp and paper industry, though Berman and Bui (2001) find smaller effects for oil refineries. The earlier work most similar to the current paper, Gray and Shadbegian (2002), finds that pollution abatement costs are associated with lower productivity levels

at plants in the steel, oil, and paper industries.

In this paper we follow a bottom-up approach to investigate the impact of environmental regulation on productivity, using confidential plant-level U.S. Census Bureau data on 68 paper mills, 55 oil refineries, and 27 steel mills from 1979-1990. Adding pollution abatement costs to a standard Cobb-Douglas production function, we find that a \$1 increase in pollution abatement costs leads to an estimated productivity decline of \$3.11, \$1.80, and \$5.98 in the paper, oil, and steel industries respectively. These findings imply substantial differences across industries in their sensitivity to pollution abatement costs, arguing for a bottom-up approach that can capture these differences. The findings also suggest that reported abatement costs understate the true economic impact of environmental regulation.

We then examine the connection between abatement costs and productivity in more disaggregated ways. Detailed data on pollution abatement expenditures allow us to separate inputs (capital, labor, and materials) into abatement and production components, and we find little evidence that abatement inputs contribute to production (with the exception of abatement capital in the paper industry). Even within an industry, plants differ in the impact of abatement costs on their productivity. In each industry, plants using a more polluting production technology show a greater productivity impact per dollar of abatement cost – possibly suggesting non-linearities in marginal abatement costs. Plants whose abatement investments focus on change-in-production-process techniques (e.g. closed loop processes) rather than end-of-line techniques (e.g. scrubbers and treatment plants) are more productive. However, they also seem to face higher productivity impacts of abatement operating costs (perhaps because the PACE survey

tends to understate operating costs for those plants). Overall, our results point to the importance using detailed, disaggregated analyses, even below the industry level, when trying to model the costs of shifting production processes to reduce emissions.

Section 2 describes how regulation might impact productivity, along with a model of the impact of regulation on productivity. Section 3 describes the data used in the analyses. In Section 4 we present the results, with concluding remarks in Section 5.

2. Environmental Regulation and Productivity

Standard Neoclassical microeconomic analysis concludes that government regulation will reduce productivity. Neoclassical analysis begins with the assumption that firms are profit-maximizers. Therefore, any government regulation that constrains the profit-maximizing behavior of firms will force firms away from their optimal production choices. Higher levels of regulation should, therefore, push firms further away from their optimal production choices. Also increases in regulation may lead firms to become less certain about future regulatory policies. This in turn could lead firms them to delay investment (Viscusi [1983]), the development of new products (Hoerger, Beamer, and Hanson [1983]), or research on new production technologies. We would expect similar effects to result if firms have limited budgets for research and development, and regulation requires them to invest in the development of new pollution abatement or cleaner technologies rather than more efficient ones.

Besides forcing firms away from their profit maximizing choices, most regulations require firms to use inputs directly for regulatory compliance: a scrubber on a smokestack to reduce SO₂ emissions, a water treatment plant to reduce TSS or BOD, or

extra employees to monitor pollution abatement equipment or simply to fill out government forms. Current methods of measuring productivity do not distinguish between inputs used to produce ‘traditional’ output and inputs used to produce a cleaner environment, so inputs are overstated and productivity is understated. This productivity ‘mismeasurement’ effect combined with the constraints described above, motivate the prevailing belief that firms facing more stringent regulation will have lower productivity.

In recent years there have been some suggestions that regulation can have favorable impacts on the economy. Most, if not all, of these suggestions are based on anecdotal evidence that some firms, required to modify their production processes for environmental reasons, later discovered that the new process was also preferred in strictly economic terms.¹ In most cases, the savings come from process redesigns that eliminate waste and recycle production by-products (so-called 'closed loop' production technologies). Of course, even in such cases there may be hidden costs of making these particular innovations: without any constraints on innovation the firm might have achieved even better growth in productivity. The only way regulation will consistently improve a firm’s innovation is if the firm is currently making systematic errors. One possible way for this to occur could be due to ‘X-inefficiency’ in technology choice, as described in Leibenstein (1966). If firms are content to accept current production technologies rather than aggressively pursuing new ones, innovation will only occur under regulatory pressure. A variation of this argument is put forth by Porter (1991, 1995) who argues that the demand for ‘clean’ production technologies will greatly

¹ Palmer, Oates, and Portney (1995) provide some counter-arguments for why these occasional economic benefits from pollution abatement efforts for a few firms are unlikely to outweigh the costs of those abatement efforts when averaged across all firms.

expand in the future, and that firms (or countries) which develop the technology first will have competitive advantages in later years.²

Productivity Analysis

To describe our analysis more formally we assume there is a production function relating output to factor inputs as follows:

$$(1) \quad Q = F(X, O)$$

where Q is output, X is a vector of inputs (capital, labor, and materials), and O is a vector of other factors which may affect output, like pollution abatement operating costs or macroeconomic effects. The production function above assumes that all measured inputs are used to produce output. However, when some inputs are used to comply with regulation (such as workers used to monitor pollution abatement equipment), the measured inputs will overstate the amounts of inputs actually used in production, thereby understating ‘true’ productivity. Since productivity is calculated as the ratio of measured output to measured inputs, if a plant uses 2 percent of its inputs for pollution abatement (not producing any measured output, as the social benefits of less pollution emissions do not produce any revenue for the plant) it will have 2 percent lower measured productivity.

The productivity ‘mismeasurement’ effect is the basis for the analysis in Gray and Shadbegian (2002): a plant's total factor productivity is regressed on the share of its

² Such advantages attributed to regulation would not show up for many years, and are unlikely to be captured in our data.

pollution abatement expenditures in its total inputs, and the ‘expected’ coefficient on pollution abatement is -1.0 (spending 2 percent of its inputs on pollution abatement should lower productivity by exactly 2 percent). Thus, an estimated coefficient more negative than -1 would imply productivity affects over and above this ‘mismeasurement’ effect. In this study, we include an aggregate measure of pollution abatement operating costs to test for productivity effects beyond the ‘mismeasurement’ effect. In particular, we estimate the following log-linear Cobb-Douglas production function:

$$(2) \ln Q = \alpha + \beta_K \ln K + \beta_L \ln L + \beta_M \ln M + \beta_{PAOC} PAOC + YEARS + e,$$

where:

- K = real capital stock (productive + pollution abatement)
- L = number of production worker hours (productive + pollution abatement)
- M = real materials (productive + pollution abatement)
- PAOC = pollution abatement operating costs/capacity
- YEARS = year dummies (in some models we also include a set of plant dummies)

It is likely that there will be some degree of underreporting of pollution abatement expenditures as some costs associated with pollution abatement are not included on the Census Bureau’s Pollution Abatement Costs and Expenditures (PACE) Survey (e.g. foregone output from plant shutdown during installation of pollution control equipment). Also it appears that respondents to the PACE survey tend to leave out costs that are hard to quantify (e.g. time spent by production workers performing pollution abatement related tasks).³ Potential under-reporting of pollution abatement expenditures complicates the interpretation of the β_{PAOC} coefficient from this regression. As mentioned earlier, the ‘productivity mismeasurement’ effect of pollution abatement expenditures leads to an expected coefficient of -1.0 on β_{PAOC} . Proportional

underreporting of pollution abatement costs would increase the magnitude of the estimated productivity impacts (i.e. result in $\beta_{PAOC} < -1$), without affecting the predicted total impact of abatement on productivity.⁴ If there is variation in the degree of the underreporting across plants, then this would introduce an ‘errors in variables’ problem, biasing the estimated effects of abatement on productivity towards zero.

An alternative explanation for large β_{PAOC} effects is that the productivity of other inputs (used for production) might be ‘sensitive’ to pollution abatement activities. For example, if a plant is close to exceeding its monthly water pollution discharge limit it may have to limit its output for a few days. Assuming fixed capital and quasi-fixed labor inputs this would tend to reduce the productivity of other inputs. It is possible to argue that these types of output reductions should be counted as a pollution abatement cost (though it is not included in the PACE survey) – in which such ‘sensitivity’ effects could be classified as ‘underreporting’ (and the true β_{PAOC} would always be -1.0, by definition). Thus, the difference between productivity ‘sensitivity’ and abatement underreporting is an issue of semantics, irresolvable without some agreed-upon measure of true pollution abatement costs. In any event, the reported pollution abatement costs from the PACE survey are the principal source of information for benefit-cost calculations, and our estimates of the predicted total impact of abatement expenditures on

³ Based on conversations with environmental managers at paper mills.

⁴ For example, suppose true pollution abatement expenditures are 1% of total inputs for half the plants and 3% of inputs for the other half, and that the true value of β_{PAOC} is -1.0. Then TFP levels would be 99% of the zero-abatement level in the low-abatement group and 97% in the high-abatement group. If plants reported only one-half of their abatement expenditures, we would have 0.5% and 1.5% for the reported abatement values and a regression would give a β_{PAOC} value of -2.0. However, the predicted total impact of abatement on productivity would be correct: the average reported abatement expenditures of 1.0% times the estimated β_{PAOC} value of -2.0 would predict 2% lower productivity (the same as the actual average abatement expenditures of 2% times the true β_{PAOC} coefficient of -1.0).

productivity provides evidence of the accuracy of this reporting.

In a separate analysis we divide our original inputs (X) into productive (X_P) and pollution abatement (X_A) inputs, yielding the following production function:

$$(3) Q = F(X_P, X_A, O)$$

Since pollution abatement inputs are not used to produce measured output we expect the pollution abatement inputs to either have a zero effect on output or a negative effect, if pollution abatement efforts reduce the productivity of other inputs. The particular form of equation (3) we estimate is as follows:

$$(4) \ln Q = \alpha + \beta_{K_P} \ln K_P + \beta_{K_A} \ln K_A + \beta_{L_P} \ln L_P + \beta_{L_A} \ln L_A + \beta_{M_P} \ln M_P + \beta_{M_A} \ln M_A + \text{YEARS} + U,$$

where:

K_P = real productive capital stock

K_A = real pollution abatement capital stock

L_P = number of production worker hours for production

L_A = number of production worker hours for pollution abatement

M_P = real materials used for production

M_A = real materials used for pollution abatement

In addition to estimating equations (2) and (4) for each of our three industries, we also estimate variations that allow for differences across plants within each industry. One set of analyses identifies the plants in each industry that will face the most stringent regulatory pressure, based on the polluting nature of their production technology. We interact TECH (a dummy variable for the more-polluting plants) with PAOC in equation (2), and also interact TECH with each of the inputs in equation (2).

Our last set of analyses allows for differences between plants whose abatement capital investments are predominantly in “change-in- production-process” abatement techniques, rather than relying on “end-of-line” abatement techniques. We create CIPP

(a dummy variable for a plant with a large share of CIPP investment, relative to other plants in the industry), and interact it with the pollution abatement capital stock in equation (2). Plants that are ‘progressive’ with respect to pollution abatement by investing in new less polluting production processes may be progressive in other ways (such as being more productive), and may also be less impacted by environmental regulation. We do a similar analysis interacting the CIPP dummy variable with PAOC, expecting plants which invest greater amounts in CIPP capital to be less affected by pollution abatement operating costs.

3. Data and Econometric Issues

The two sources of plant-level data for this study are the Longitudinal Research Database (LRD) and the Pollution Abatement Cost and Expenditure (PACE) survey both maintained by the Center for Economic Studies at the U.S. Census Bureau.⁵ The LRD contains annual data for U.S. manufacturing plants from the Annual Surveys of Manufacturers and the Censuses of Manufactures linked over time – we use LRD data from 1979 - 1990. From the LRD we use the value of shipments adjusted for inventory changes and deflated by the industry price of shipments (using the appropriate industry deflator from Bartelsman and Gray [1996]) to measure a plant’s output. We use three inputs: labor, capital, and materials (which includes energy). Labor is the number of worker hours, summing production worker hours and non-production worker hours.⁶ The dollar expenditures on materials are divided by an industry specific price index to put

⁵ For a detailed description of the LRD data, see McGuckin and Pascoe (1988). Several published studies have examined productivity issues using the LRD, including Lichtenberg and Siegel (1990,1991) and Nguyen and Kokkelenberg (1992). For a detailed description of the PACE survey see Streitwieser (1996).

⁶ The LRD does not contain information on non-production worker hours so we assume each non-

them in real terms. We measure each plant's real capital stock based on a standard perpetual-inventory method, applied to the Census data on new investment in the plant.

We combine this productivity data with data from the PACE survey conducted by the Census Bureau, which provides annual data on pollution abatement operating costs for 1973-1994.⁷ We work with the PACE surveys beginning from 1979 (the first available year of micro-data) through 1990. The PACE survey samples about 20,000 plants each year, concentrating on large plants in heavily polluting manufacturing industries. The plants are asked about both new capital expenditures and total annual operating costs for pollution abatement, which are disaggregated into labor, material, and depreciation. From the PACE survey we use a plant's aggregate pollution abatement operating costs divided by its peak shipments to summarize the plant's pollution abatement expenditures (PAOC).⁸ We also use pollution abatement expenditures on labor and materials, deflated by industry specific price indices to put them in real terms, to divide measured labor and materials into production and pollution abatement labor and materials. Finally, we also use information on pollution abatement depreciation and new capital expenditures (appropriately deflated) to calculate a real pollution abatement capital stock using a perpetual inventory method.⁹

Using these data, we estimate production functions for our three industries (paper,

production worker works 2000 hours per year.

⁷ No survey was done in 1987 for budget reasons, and we interpolate that year's data.

⁸ We use the plant's peak two years of shipments for the denominator of PAOC, rather than dividing by the same year's shipments, to avoid building in endogeneity (since shipments are in the numerator of TFP and the denominator of PAOC).

⁹ Much of these industries' investment in pollution abatement capital occurred before 1979 when our data begin. To account for this we impute a pollution abatement capital stock back to 1973 (assuming it was zero in 1972). We estimate each plant's annual pollution abatement investment from 1973-1978 by multiplying its total new investment by the ratio of its industry's pollution abatement investment to total investment, taken from published sources. This becomes the 1979 base value for our perpetual inventory calculations with the annual PACE data.

oil, and steel). We selected plants with continuous LRD and PACE data through the period, and with adequate data to construct a capital stock measure, dropping a few plants with implausible values for key variables. Our final sample contains 68 paper mills (816 plant-year observations), 55 oil refineries (660 plant year observations), and 27 steel mills (324 plant-year observations).

We estimate both OLS and FE versions of equations (2) and (4). However, we focus mainly on the OLS models, since most of the variation of our key “PACE” variables is cross-sectional, so moving to an FE model would greatly reduce the explanatory power of these variables. Furthermore, if there is substantial measurement error over time, using fixed-effects estimators may also result in a considerable level of bias in the estimated coefficients, based Griliches and Hausman (1986). Therefore, except for a short exploration of the effect of introducing fixed-effects into our OLS version of our Cobb-Douglas production function model, we do not pursue fixed-effects models in our analysis.

4. Estimation Results

Table 1 presents summary statistics for all the variables used in the analysis, along with their definitions. Plants in the paper industry spend the most on pollution abatement operating costs, 1.55% of their shipments (PAOC), while plants in the steel and oil industries spend 1.00% and 0.84% respectively. Plants in the paper and steel industries are similar in their cost shares for both regular and pollution abatement inputs, with about 70% materials, 20% labor, and 10% capital cost shares. The oil industry is more materials-intensive, with materials costs making up 95% of total costs. This is

reflected in their pollution abatement spending, which has a relatively high share of materials costs, compared to paper and steel, where capital makes up over 60% of pollution abatement inputs. Another difference across industries is seen in the share of pollution abatement capital devoted to “change-in-production-process” (CIPP) investments: paper and oil plants devote about 35% of their pollution abatement capital to CIPP while steel mills devote only 5%.

Table 2 presents OLS and fixed-effect estimates of a simple log-linear Cobb-Douglas production function for each industry – without differentiating between pollution abatement inputs and productive inputs. All the OLS production functions exhibit approximately constant returns to scale: estimated returns to scale are 0.96, 0.95 and 0.99 in the paper, oil, and steel industries respectively. As expected, capital, labor, and materials always have a significant positive impact on output, except for labor in the oil industry, which has an insignificant positive effect on output (consistent with its tiny cost share). The input coefficients are similar in magnitude to their cost shares from Table 1, although the estimated capital coefficients are somewhat larger, and the estimated materials coefficients are somewhat smaller than their cost shares. These simple models explain nearly all of the variation in output across plants and over time, with R-squared values ranging from .92 to .98.

The results change when we move to a fixed effect estimator. The most noticeable impact is on the capital coefficients, which move from being significantly positive to being negative (though insignificant) in the oil and steel industries. This is not unexpected, giving the largely cross-sectional nature of the variation in output (large plants tend to remain large and small plants to remain small). What variation does occur

on a year-to-year basis in capital indicates that new investment is being added to plants, which may take some time and effort before it is fully integrated in the production process. Griliches and Mairesse (1995) note similar concerns with estimating capital's contribution to output in earlier plant-level research. The coefficients on materials also tend to drop in the fixed-effects runs, while the labor coefficients increase.

Table 3 shows what happens when we distinguish between productive and pollution abatement inputs in the production process. In Model 1 for each industry we estimate a simple Cobb-Douglas model with 6 inputs, dividing each of capital, labor, and materials inputs into pollution abatement and productive inputs. In general we find that pollution abatement inputs contribute much less to output than do their productive equivalents. The only exception to this is the positive contribution that pollution abatement capital makes to output in the paper industry, which is similar in magnitude to that of productive capital.

In Model 2 for each industry we consider an alternative estimation method, where the pollution abatement inputs are aggregated into a single PAOC term added to the simple Cobb-Douglas production function above. The coefficients on the productive inputs are very similar to those in Table 2, so the returns to scale still seem to be nearly constant. As discussed earlier, we would expect the coefficient on PAOC to be -1 if the only effect of pollution abatement costs was the productivity 'mismeasurement' effect arising from overstating the amounts of inputs that directly contribute to production. For all three industries the impact of PAOC exceeds unity – the difference is significant for plants in the paper industry (and nearly significant for plants in the steel industry). A \$1 increase pollution abatement costs leads to an estimated \$3.11, \$1.80, and \$5.09 decline

in productivity in the paper, oil, and steel industries respectively.

Table 4 shows the fixed effects estimates of distinguishing between productive and abatement inputs. Similar to what we saw in Table 2, the contribution of productive capital turns insignificant (and negative in the case of the paper industry), though surprisingly the coefficient on pollution abatement capital is positive for paper and steel (and significantly so for paper). The coefficients for pollution abatement spending on labor and capital inputs are similar to those found in Table 3 (near zero and insignificant, except for paper industry labor). The results when we aggregate the pollution abatement inputs into PAOC are noticeably different from those obtained in Table 3, with an insignificant positive coefficient for steel, an insignificant negative coefficient for paper, and a large and significant negative coefficient for oil (which had shown the smallest impact in the earlier regressions). This may be related to the positive coefficients on the capital input. We do not have a clear explanation of the fixed-effect results - perhaps plants with growing productivity are willing or able to invest more in pollution abatement capital or perhaps this just reflects the difficulties associated with estimating fixed effect models of production functions seen earlier in Table 2.

In Table 5 we further disaggregate the plants in each industry into high- and low-pollution plants, based on the production technology in use at that plant. The TECH variable always refers to plants using the high-pollution technology. Here paper mills that use a pulping process, oil refineries that use catalytic cracking, and steel mills that use blast furnaces, have the TECH dummy turned on. Model (1) shows the effect of interacting TECH with PAOC, while keeping the simpler Cobb-Douglas production function for the inputs. The negative coefficients on the interaction terms indicate that

the dirtier (TECH) plants show a greater (more negative) impact of abatement costs on production (the coefficients are large in all cases, though only statistically significant for paper mills). Note that this is a greater impact per dollar of abatement costs: since the TECH plants, being dirtier, are expected to spend more dollars on pollution abatement, they are likely to be much more impacted overall by regulatory pressures. The result suggests an increasing marginal cost of abatement (at least as measured across plants using different production technologies within the same industry). Model (2) adds interactions between the TECH dummy and each of the inputs in the production function. Although these show some differences in the input contributions for TECH plants, these do not greatly affect the interactions with PAOC, and now the results are at least marginally significant for both paper and oil.

Our final analyses, in Table 6, look at how the impact of pollution abatement capital and operating costs differs between plants that make large amounts of capital expenditures on “change-in- production-process” (CIPP) abatement techniques, as compared to those plants that rely primarily on “end-of-line” abatement techniques. The results of these analyses are in Table 6. We define a CIPP-intensive plant as one whose 1979-90 CIPP investments are a larger share of their total pollution abatement investments than the median value for their industry.¹⁰ We find that CIPP-intensive plants in all three industries have higher productivity, perhaps reflecting a more innovative approach to the design of their production processes. In particular, we find in Model 1 that productivity is 4.4%, 0.6%, and 5.4% higher for CIPP-intensive plants in the paper, oil, and steel industries respectively – though this effect is not significant for

¹⁰ Due to Census disclosure rules we cannot report the median CIPP shares used, but they range from 10-

plants in the oil industry. In Model 2, we interact the CIPP dummy with the pollution abatement capital input and find (for the paper and oil industries) that the positive CIPP effect is concentrated in those plants which are doing substantial amounts of pollution abatement capital investment (seen in the now negative coefficient on the CIPP dummy, which here reflects the CIPP impact for a plant doing zero abatement investment).

Finally we examine whether accounting for CIPP-intensity influences the estimated impact of PAOC on productivity. When we simply include the CIPP dummy in a PAOC regression (Model 3) we find a larger negative impact of PAOC, for the paper and oil industries, than those we found in Table 3. The positive CIPP impacts are quite similar to those we found in Model 1. In Model 4 we interact the CIPP dummy with PAOC, finding consistent results (though only significant for paper): CIPP-intensive plants show a larger impact of PAOC on their productivity. This runs counter to our expectations, but may reflect a tendency for CIPP-intensive plants to understate their operating costs, since many of their abatement expenditures would be related to shifting their production processes. Greater understatement of abatement costs would result in larger estimated PAOC coefficients. In any event, this points out the difficulty of properly measuring the costs of changing production processes to reduce emissions, showing substantial heterogeneity in costs across plants, even within the same industry.

5. Conclusions

In this paper we follow a bottom-up approach to measuring the cost of forcing plants to adjust their production processes in order to reduce emissions. We examine the

30%.

impact of traditional environmental regulation on productivity in U.S. paper mills, oil refineries, and steel mills. Adding pollution abatement costs to a standard Cobb-Douglas production function, we find that a \$1 increase in pollution abatement costs leads to an estimated productivity decline of \$3.11, \$1.80, and \$5.98 in the paper, oil, and steel industries respectively. These findings imply substantial differences across industries in their sensitivity to pollution abatement costs, arguing for a bottom-up modeling approach that is capable of identifying these differences. The magnitudes of the coefficients (greater than \$1.00) indicate either that pollution abatement costs are under-reported or that the productivity of other inputs (used for production) at a plant might be reduced by the plant's pollution abatement activities. In our study we cannot distinguish between the underreporting and sensitivity explanations, but in either case the findings suggest that reported abatement costs understate the true economic impact of environmental regulation.

We also examine the connection between abatement costs and productivity in more disaggregated ways. Detailed data on pollution abatement expenditures allow us to separate inputs (capital, labor, and materials) into abatement and production components, and we find little evidence that abatement inputs contribute to production (with the exception of abatement capital in the paper industry). Even within an industry, plants differ in the impact of abatement costs on their productivity. In each industry, plants using a more polluting production technology show a greater productivity impact per dollar of abatement cost – possibly suggesting non-linearities in marginal abatement costs across plants in these industries. Plants whose abatement investments focus on change-in-production-process techniques (e.g. closed loop processes) rather than end-of-

line techniques (e.g. scrubbers and treatment plants) are more productive. However, they also seem to face higher productivity impacts of abatement operating costs (perhaps explained by these plants being more likely to understate their operating costs). Overall, our results point to the importance using detailed, disaggregated analyses, even below the industry level, when trying to model the costs of forcing plants to reduce their emissions. These results, based on the regulation of traditional pollutants, may also be applicable to future regulations related to concerns with climate change and global warming, where regulatory pressures may also have very different impacts on different plants, even those within the same industry.

REFERENCES

- Barbera, A.J. and V.D. McConnell, "Effects of Pollution Control on Industry Productivity: A Factor Demand Approach," *Journal of Industrial Economics*, 1986:161-72.
- Bartelsman, E.J. and W.B. Gray, "The NBER Manufacturing Productivity Database," *NBER Technical Working Paper 205*, 1996.
- Berman, E., and L.T. Bui, "Environmental Regulation and Productivity: Evidence from Oil Refineries," *Review of Economics and Statistics*, 2001:498-510.
- Boyd, G. A. and J. D. McClelland, "The Impact of Environmental Constraints on Productivity Improvement in Integrated Paper Plants," *Journal of Environmental Economics and Management*, 1999:121-142.
- Denison, E.P., Accounting for Slower Economic Growth: The U.S. in the 1970s. Washington: The Brookings Institution, 1979.
- Fare, R., S. Grosskopf, C. Lovell, and C. Pasurka, "Multilateral Productivity Comparisons When Some Outputs are Undesirable: A Nonparametric Approach," *Review of Economics and Statistics*, 1989:90-98.
- Gollop, F.M. and M.J. Roberts, "Environmental regulations and productivity growth: the case of fossil-fueled electric power generation," *Journal of Political Economy*, 1983:654-74.
- Gray, W.B., "The cost of regulation: OSHA, EPA and the productivity slowdown," *American Economic Review*, 1987:998-1006.
- _____, Productivity versus OSHA and EPA Regulations. UMI Research Press, Ann Arbor, MI, 1986.
- Gray, W.B. and R.J. Shadbegian, "Pollution Abatement Costs, Regulation, and Plant-Level Productivity," in The Economic Costs and Consequences of Environmental Regulation, W. Gray, ed., Ashgate Publications, 2002
- _____, "Plant Vintage, Technology, and Environmental Regulation," *Journal of Environmental Economics and Management* (forthcoming 2003).
- Griliches, Z. and J. A. Hausman, "Errors in Variables in Panel Data," *Journal of Econometrics*, 1986:93-118.

REFERENCES (cont.)

- Griliches, Z. and J. Mairesse, "Production Functions: The Search for Identification," *NBER Working Paper 5067*, 1995.
- Hoerger, F., W.H. Beamer, and J.S. Hanson, "The cumulative impact of health, environmental, and safety concerns on the chemical industry during the seventies," *Law and Contemporary Problems*, Summer 1983: 59-107.
- Joshi, S., R. Krishnan, and L. Lave, "Estimating the Hidden Costs of Environmental Regulation," *Accounting Review*, 2001:171-198.
- Leibenstein, H., "Allocative efficiency versus x-efficiency," *American Economic Review*, June 1966:392-415.
- Lichtenberg, F.R. and D. Siegel, "The impact of R&D investment on productivity - new evidence using linked R&D-LRD data," *Economic Inquiry*, 1991:2-13.
- Lichtenberg, F.R. and D. Siegel, "The effects of leveraged buyouts on productivity and related aspects of firm behavior," *Journal of Financial Economics*, 1990:165-94.
- McGuckin, R.H. and G.A. Pascoe, "The Longitudinal Research Database: status and research possibilities," *Survey of Current Business*, November 1988.
- Nguyen, S.V. and E.C. Kokkelenberg, "Measuring total factor productivity, technical change, and the rate of returns to research and development," *Journal of Productivity Analysis*, 1992:269-82.
- Palmer, K., Oates, W.E., and P.R. Portney, "Tightening Environmental Standards: The Benefit-cost or the No-cost Paradigm?" *Journal of Economic Perspectives*, 1995:119-132.
- Porter, M.E., "America's green strategy," *Scientific American*, 1991, 168.
- Porter, M.E. and C. van der Linde, "Towards a New Conception of the Environment-Competitiveness Relationship," *Journal of Economic Perspectives*, 1995:97-118.
- Shadbegian, R.J., "How Costly is Environmental Regulation? Evidence from U.S. Manufacturing" Our Natural Environment: Concepts & Solutions, Proceedings of the 2nd International Interdisciplinary Conference on the Environment (Kevin Hickey and Demetrius Kantarelis, Eds.), 1996:279-286.
- Streitwieser, M., "Evaluation and Use of the Pollution Abatement Cost and Expenditure Survey Micro Data," *Center For Economic Studies Working Paper no. 96-1*.

U.S. Bureau of the Census, "Pollution Abatement Costs and Expenditures", U.S. Govt. Printing Office, Washington, DC, various issues.

Viscusi, W.K., "Frameworks for analyzing the effects of risk and environmental regulation on productivity," *American Economic Review*, 1983:793-801.

TABLE 1
Descriptive Statistics

VARIABLE	PAPER	OIL	STEEL	DESCRIPTION
	MEAN (STD DEV) N=816	MEAN (STD DEV) N=660	MEAN (STD DEV) N=324	
PAOC*100	1.547 (1.139)	0.835 (0.824)	1.005 (0.636)	Pollution abatement operating costs/ capacity
SHIPMENTS	10.295 (0.807)	12.069 (0.930)	11.910 (0.804)	Log(real shipments adjusted for inventories)
CAPITAL	10.745 (0.926)	11.286 (1.169)	12.040 (0.983)	Log(real capital stock)
PRODUCTIVE CAPITAL	10.533 (0.910)	11.026 (1.178)	11.864 (0.968)	Log(real 'productive' capital stock)
ABATEMENT CAPITAL	8.968 (1.144)	9.643 (1.301)	10.115 (1.165)	Log(real pollution abatement capital stock)
LABOR hours)	7.024 (0.640)	6.513 (0.944)	8.323 (0.815)	Log(production+non-production worker hours)
PRODUCTIVE LABOR	6.992 (0.644)	6.379 (0.923)	8.306 (0.820)	Log('productive' worker hours)
ABATEMENT LABOR	2.938 (2.087)	3.800 (2.559)	3.859 (2.475)	Log(pollution abatement worker hours)
MATERIALS	10.249 (0.572)	11.762 (0.952)	11.444 (0.774)	Log(real materials+energy)
PRODUCTIVE MATERIALS	10.235 (0.570)	11.756 (0.950)	11.431 (0.774)	Log('productive' materials)
ABATEMENT MATERIALS	4.914 (3.075)	5.558 (2.488)	6.425 (1.826)	Log(pollution abatement materials)
PAOC DEPRECIATION	24.43% (16.3)	14.63% (12.2)	21.53% (15.1)	Cost Share of PAOC Depreciation
PAOC MATERIALS	33.50% (18.4)	37.27% (22.9)	33.26% (18.8)	Cost Share of PAOC Materials
PAOC LABOR	18.69% (11.5)	21.65% (15.3)	16.77% (10.1)	Cost Share of PAOC Labor
PAOC OTHER	23.44% (21.0)	26.46% (23.7)	28.44% (21.1)	Cost Share of 'Other' PAOC Costs
SH_PROD_LABOR	16.50%	1.44%	19.71%	Share of 'Productive' Labor in Total Cost
SH_PROD_MATERIALS	70.25%	95.10%	66.62%	Share of 'Productive' Mat. in Total Cost
SH_PROD_CAPITAL	9.50%	2.06%	10.25%	Share of 'Productive' Capital in Total Cost
SH_PAOC_LABOR	0.48%	0.21%	0.41%	Share of Abatement Labor in Total Cost
SH_PAOC_MATERIALS	1.04%	0.58%	0.88%	Share of Abatement Mat. in Total Cost
SH_PAOC_CAPITAL	2.28%	0.61%	2.14%	Share of Abatement Capital in Total Cost

TABLE 2
Traditional Cobb-Douglas Model
(All Original Inputs)

INDUSTRY	CAPITAL	LABOR	MATERIALS	R2	OBSERVATIONS	ESTIMATOR
PAPER						
(1)	0.153 (13.18)	0.208 (14.27)	0.600 (26.60)	0.93	816	OLS
(2)	0.007 (0.24)	0.272 (7.36)	0.517 (17.45)	0.97	816	FE
OIL						
(1)	0.124 (8.04)	0.010 (0.60)	0.819 (50.40)	0.98	660	OLS
(2)	-0.021 (0.83)	0.124 (4.27)	0.547 (22.22)	0.99	660	FE
STEEL						
(1)	0.055 (2.33)	0.251 (7.09)	0.680 (17.61)	0.92	324	OLS
(2)	-0.038 (0.36)	0.283 (5.94)	0.627 (12.54)	0.95	324	FE

All regressions include an intercept and year dummies
(t-statistics)

TABLE 3
Extended Cobb-Douglas Model
(Including PAOC; OLS)

INDUSTRY	CAPITAL		LABOR		MATERIALS		PAOC	R2
	PROD	ABATE	PROD	ABATE	PROD	ABATE		
PAPER								
(1)	0.083 (5.40)	0.062 (5.75)	0.206 (14.60)	0.012 (3.17)	0.595 (26.65)	-0.004 (1.82)		0.93
(2)	0.169 (14.42)		0.203 (14.18)		0.600 (27.10)		-3.105 (5.75)	0.93
OIL								
(1)	0.119 (8.16)	-0.007 (0.66)	0.013 (0.87)	-0.002 (0.60)	0.820 (51.43)	0.009 (2.18)		0.98
(2)	0.131 (8.34)		0.011 (0.67)		0.815 (50.03)		-1.797 (2.17)	0.98
STEEL								
(1)	0.106 (2.35)	-0.028 (0.91)	0.232 (6.52)	0.004 (0.68)	0.679 (17.93)	-0.008 (0.92)		0.92
(2)	0.052 (2.18)		0.265 (7.37)		0.694 (17.75)		-5.085 (1.97)	0.92

All regressions include an intercept and year dummies
(t-statistics)

TABLE 4
Extended Cobb-Douglas Model
(Including PAOC; Fixed Effects)

INDUSTRY	CAPITAL		LABOR		MATERIALS		PAOC	R2
	PROD	ABATE	PROD	ABATE	PROD	ABATE		
PAPER								
(1)	-0.017 (0.80)	0.076 (2.51)	0.258 (7.36)	0.004 (1.23)	0.514 (17.58)	-0.001 (0.30)		0.97
(2)	0.007 (0.26)		0.271 (7.34)		0.518 (17.30)		-0.315 (0.39)	0.97
OIL								
(1)	0.006 (0.25)	-0.021 (1.21)	0.051 (1.91)	-0.000 (0.12)	0.571 (23.95)	0.006 (2.14)		0.99
(2)	-0.012 (0.47)		0.136 (4.65)		0.545 (22.28)		-3.446 (2.89)	0.99
STEEL								
(1)	0.021 (0.23)	0.066 (0.71)	0.225 (4.93)	0.001 (0.21)	0.644 (12.79)	0.008 (1.01)		0.95
(2)	-0.037 (0.35)		0.274 (5.57)		0.627 (12.53)		1.970 (0.65)	0.95

All regressions include an intercept and year dummies
(t-statistics)

TABLE 5
Cobb-Douglas Models
Disaggregated by Production Technology
(OLS)

INDUSTRY	CAPITAL	CAPITAL	LABOR	LABOR	MATERIALS	MAT	TECH	PAOC	PAOC	R2
		*TECH		*TECH		*TECH	dummy		*TECH	
PAPER										
(1)	0.159 (11.194)		0.201 (13.764)		0.610 (25.357)		++	-0.945 (-0.827)	-2.991 (-2.294)	0.932
(2)	0.105 (5.316)	0.079 (2.837)	0.101 (4.784)	0.166 (5.836)	0.709 (21.811)	-0.161 (-3.494)	-	-0.288 (-0.254)	-3.449 (-2.663)	0.936
OIL										
(1)	0.128 (7.922)		0.012 (0.713)		0.821 (49.959)		-	0.765 (0.423)	-3.550 (-1.878)	0.976
(2)	0.129 (3.227)	0.003 (0.058)	0.095 (2.185)	-0.096 (-2.022)	0.731 (13.977)	0.099 (1.811)	--	-0.277 (-0.128)	-2.545 (-1.106)	0.976
STEEL										
(1)	0.055 (1.885)		0.266 (7.287)		0.693 (17.606)		++	-3.204 (-0.443)	-2.079 (-0.279)	0.922
(2)	-0.010 (-0.101)	0.078 (0.755)	0.324 (4.325)	-0.074 (-0.880)	0.614 (6.371)	0.109 (1.061)	--	1.930 (0.257)	-8.359 (-1.056)	0.923

All regressions include an intercept and year dummies
(t-statistics)

TECH plant technology dummies

Paper industry = pulping mills
Oil industry = catalytic cracking
Steel industry = blast furnaces

Exact coefficients on TECH dummy suppressed due to Census disclosure rules:

+ = insignificant positive coefficient
++ = significant positive coefficient
- = insignificant negative coefficient
-- = significant negative coefficient

TABLE 6
Cobb-Douglas Models
Disaggregated by Change-in-Production-Process Investment
(OLS)

INDUSTRY	CAPITAL		LABOR		MATERIALS		CIPP	PAOC	CIPP	R2
	PROD	ABATE	PROD	ABATE	PROD	ABATE	Dummy		Interact	
PAPER										
(1)	0.079 (5.15)	0.068 (6.29)	0.198 (14.01)	0.009 (2.58)	0.598 (26.97)	-0.005 (1.94)	0.044 (3.70)			0.93
(2)	0.086 (5.57)	0.046 (3.70)	0.190 (13.36)	0.012 (3.17)	0.599 (27.24)	-0.005 (2.01)	-0.306 (3.32)		0.039 (3.83)	0.93
(3)	0.171 (14.71)		0.195 (13.56)		0.601 (27.37)		0.043 (3.78)	-3.255 (0.521)		0.93
(4)	0.170 (14.66)		0.196 (13.64)		0.600 (27.38)		0.066 (3.49)	-2.504 (3.44)	-1.512 (1.53)	0.93
OIL										
(1)	0.119 (8.16)	-0.006 (0.61)	0.011 (0.68)	-0.002 (0.67)	0.822 (49.92)	0.009 (2.67)	0.006 (0.48)			0.98
(2)	0.119 (8.17)	-0.010 (0.89)	0.012 (0.72)	-0.002 (0.73)	0.821 (49.54)	0.009 (2.64)	-0.066 (0.76)		0.007 (0.83)	0.98
(3)	0.133 (8.41)		0.004 (0.25)		0.819 (48.88)		0.014 (1.10)	-1.934 (2.31)		0.98
(4)	0.073 (0.014)		-0.003 (0.017)		0.896 (0.017)		0.024 (1.37)	-1.196 (0.98)	-1.205 (0.83)	0.98
STEEL										
(1)	0.095 (2.09)	-0.009 (0.28)	0.236 (6.65)	0.001 (0.13)	0.668 (17.52)	-0.006 (0.66)	0.054 (1.89)			0.92
(2)	0.094 (2.07)	-0.008 (0.24)	0.236 (6.63)	0.001 (0.12)	0.668 (17.49)	-0.006 (0.65)	0.070 (0.29)		-0.002 (0.07)	0.92
(3)	0.064 (2.64)		0.263 (7.34)		0.680 (17.27)		0.056 (2.12)	-4.636 (1.80)		0.92
(4)	0.063 (0.030)		0.292 (0.039)		0.637 (0.039)		0.086 (1.74)	-2.874 (0.81)	-3.037 (0.72)	0.92

All regressions include an intercept and year dummies (t-statistics)

CIPP = dummy indicating the plant's share of Change-In-Production-Process (CIPP) investment in its total pollution abatement investment (1979-90) exceeds the median share for the other plants in that industry

CIPP interactions in Model (2) refer to CIPP*(Abatement Capital)

CIPP interactions in Model (4) refer to CIPP*PAOC