THE IMPACT OF EPA REGULATIONS ON THE U.S. MANUFACTURING INDUSTRIES

Soumendra Nath Banerjee, Misericordia University

ABSTRACT

This research reassesses the impact of environmental regulations on economic performances in the U.S. manufacturing sector from 1973 to 2005. This paper uses information on NAICS-based 440 manufacturing industries from the NBER Manufacturing Productivity database and EPA's PACE survey. Performing several econometric techniques and focusing on output and productivity, negative impacts of EPA regulations on both of them have been noticed. However, regulations cannot be blamed alone for output and productivity slow down. Dirty industries could avoid some output and productivity losses by spending more on pollution abatement. Evidence proves the presence of a "measurement effect" and a "real effect." **JEL Classification**: D24, L60, Q58

INTRODUCTION

The goal of this research is to reassess the impact of environmental regulations on economic performances in the U.S. manufacturing sector. Outcomes of this analysis will help in understanding the dynamics of the regulation-productivity relationship in the long run. The analysis is done from 1973 to 2005 using information on North American Industry Classification System (NAICS)-based 440 manufacturing industries from the NBER Manufacturing Productivity (MP) database, and from the Environmental Protection Agency's (EPA's) Pollution Abatement Costs and Expenditures (PACE) survey. The EPA discontinued the PACE survey after 2005 due to their resource constraint. Nevertheless, the analysis over several years might help identify whether the main cost is one of adjusting to regulations in the first place, or if there are continuing costs—assuming that someone is willing to accept industry-level regressions as evidence. This essay involves performing the ordinary least squares (OLS) at levels, fixed-effects (FE), OLS-first differences (FD), instrumental variables (IV) in FD, quantiles, OLS-first and second lagged, difference and system GMM, and Chow procedures focusing on output and "measured" productivity. The research results indicate strong adverse effect of EPA regulations and industry status (whether an industry is considered as a "dirty" one) on industries' outputs and productivities. This adversity becomes somewhat less intense if an average dirty industry incurs more pollution abatement costs. Industries actually incur additional costs to comply. In fact, regulations alone cannot be blamed for productivity or output slow down.

These results in no way imply that regulation is a bad idea, but there are people (even if they are not economists) who hold the 'null hypothesis' that regulation is costless, which the paper is testing. In fact, the actual benefits from regulations might be bigger than the costs (Porter, 1995). For example, benefits from air pollution reduction could be many billions of dollars due to lives saved. However, this issue is out of the scope of this study. This is the first industry-level study covering information from 1973 to 2005 considering data from all PACE surveys to date.

The research unfolds as follows—next the literature and motivations have been reviewed briefly. The former section is followed by a description of empirical models, databases used, and econometric specifications. Then the estimation results are explored. Last, the research is summarized and concluded.

LITERATURE REVIEW

The whole debate in the literature about the relationship between industrial productivity and environmental regulations has started since the1970's, the first years to experience the co-existence of a slowdown in productivity growth in the U.S. economy and the introduction of public environmental regulations in an unprecedented massive scale. Both the estimation technique and the type of data used to examine the relationship have evolved over time. As a result, different researchers have come up with different findings that vary from a negative impact to a positive one. For example, early researches like Norsworthy et al. (1979) and Portney (1981) used the "growth accounting" method and found an insubstantial regulation-productivity relationship. Gradually econometric analysis gets preference over the growth accounting procedure in later investigations. The logical appeal of using a combination of multiple databases containing more detailed information on a set of public policies and other factors like production inputs, through which regulation might affect productivity indirectly, replaces the use of single database like abatement cost survey containing only pollution-regulation related information. Christainsen and Haveman (1981), Gollop and Roberts (1983), Barbera and McConnell (1986), and Gray (1987) are examples of such studies, which revealed an unwanted adverse impact of regulations on productivity. The use of industry-level data becomes less attractive with the increasing accessibility to firm- and plant-level databases. For example, Gray and Shadbegian (1993) is the first study to find the negative impact of regulation on productivity at establishment-level. Several other studies (Gray & Shadbegian, 1995, 2003; Berman & Bui, 2001; Greenstone, 2002) use plant-level data for same purpose.

Unfortunately, less is known about the impact on output and productivity of regulation in the 1980s, 1990s, and 2000s at the industry level. The lack of consensus, along with the availability of a large set of data, motivates this long-run industry-level study to look into the dynamics of the regulation-performance relationship.

MODEL, DATA DESCRIPTION, AND ECONOMETRIC SPECIFICATION

A four-input (labor, capital, investment, and materials) Cobb-Douglas production function is assumed in equation:

$$Y = T * L^{\alpha} * K^{\beta} * I^{\gamma} * M^{\delta} \quad (1)$$
$$\text{or } \log(T) = \log(Y) - \alpha * \log(L) - \beta * \log(K) - \gamma * \log(I) - \delta * \log(M)$$
$$\text{or } TFP = OUTPUT - \alpha * LABOR - \beta * CAPITAL - \gamma * INVESTMENT - \delta * MATERIAL$$

where *Y*, *T*, *L*, *K*, *I*, and *M* stand for output, technology, labor, capital, investment, and materials, respectively. α, β, γ, and δ are the factor weights. *OUTPUT*, log of value of industry shipments after deflating by the industry price of shipments; *LABOR*, log of number of production workers hours; *CAPITAL*, log of real capital stock; *INVESTMENT*, log of new capital spending after deflating by an industry-specific price index; *MATERIAL*, log of cost of materials after deflating by an industry-specific price index are taken from the NBER Manufacturing Productivity (MP) database, which covers 473 separate NAICS-based industries from 1958 to 2009. *DIRTY*, a dummy variable indicating whether an industry belongs to SIC 26, 28, 29, 30, 32, 33, or 34 is created. Besides these four inputs, *OUTPUT* is regressed on *DIRTY* and year dummies in order to obtain the factor weights to calculate *TFP*, the difference between *OUTPUT* and weighted factors (Gray & Shadbegian, 1995, p. 9).

However, to incorporate the fact that some inputs are used to be in compliance with the environmental regulation, equation can be rewritten as equation:

$$TFP' = \log(Y) - \alpha * \log(L - L_{ER}) - \beta * \log(K - K_{ER}) - \gamma * \log(I - I_{ER}) - \delta * \log(M - M_{ER}) \quad (1')$$
$$\text{or } TFP' = TFP + \varepsilon$$

where the subscript 'ER' stands for inputs used to comply with environmental regulation, and ε is the share of compliance costs. Industry's annual pollution-abatement operating cost (*PAOC*) is chosen to control for environmental regulation (Gray & Shadbegian, 1995, p. 7). The data comes from the Environmental Protection Agency's (EPA's) Pollution Abatement Costs and Expenditures (PACE) survey. The compliance costs are divided by the value of shipments for the respective industry. Starting in 1973, the annual survey was discontinued after 1994. Since then the Bureau of Census collected this data only twice, once in 1999 and then again in 2005. So after the necessary adjustments to 1999 and 2005 *PAOC*, values for the remaining years with missing information on *PAOC* are interpolated. The final dataset contains 440 NAICS-based industries with continuous data from 1973 to 2005.

A couple of econometric issues arise in estimating the impact on *OUTPUT* and *TFP* of the regulation—serial correlation and endogeneity issues.

The former issue could arise if industry-specific unobserved factors bias the relation between explained and explanatories. To tackle this issue, fixed-effects (FE) and OLS-first differenced (FD) estimation procedures are used. The instrumental variable (IV) approach in the FD models is also applied, should sequential exogeneity be failing.

A more salient issue, which a researcher has to face while estimating the regulation-performance relationship, is the latter issue: higher abatement costs might lead to lower output and productivity and again, lower output and productivity might lead to higher abatement cost. Two methods have been tried to overcome the endogeneity issue: lagging the explanatory variables and considering the GMM models proposed by Arellano and Bond (1991). Both of these methods arguably provide somewhat of a solution for the endogeneity concern.

Besides first-lagged instruments, second-lagged instruments are used (Mileva, 2007, p. 6). Endogeneity may persist even after lagging the explanatory variables if there is a serial correlation in *PAOC*. Again, a deep lag might result in little correlation between actual value of a variable and its instrument.

All GMM models in this paper instrument the current values of the explanatory variables with their all-possible lagged values in order to enhance the efficiency of the specifications (Doornik et al., 2002, p. 6). Both difference and system GMM are performed because, should the lagged explanatory variables be poor instruments for the first-differenced explanatory variables, system GMM is a better fit (Mileva, 2007, p. 7). The GMM model remains susceptible to endogeneity in cases where the instruments are not completely exogenous and/or they perform weakly. It is needless to mention that the complexity of the GMM model can easily generate invalid estimates, should researcher be unaware of its purpose, design, and limitations (Roodman, 2009, p. 2).

In addition to the above-mentioned econometric tools, the Chow test is carried out every time an interaction variable is used.

RESULTS

Table 1 presents the descriptive statistics of the key variables used in this analysis. An average industry's pollution abatement spending is a very small percentage of its output. Almost 40 percent of the industries in this sample belong to "dirty" industries. Although an average dirty industry bears more abatement costs than an average other industry, the costs tend not to be substantially different.

The basic regression results are presented in Table 2. Factor weights are obtained by regressing *OUTPUT* on *LABOR*, *CAPITAL*, *INVESTMENT*, *MATERIAL*, *DIRTY*, and year dummies in Model 2A to calculate *TFP*. Industry characteristics yield expected and strong results. High R^2 (.945) signifies well-explained variations in *OUTPUT* across industries and over time. The results are similar across the OLS-level models 2A-2D: high pollution abatement costs tend to reduce both *OUTPUT* and *TFP* significantly. A percentage point increase in *PAOC* reduces both the estimators by almost 5 percentage points. Although the interactive explanatory shows a 3.5 percentage point significant increase in both output and total factor productivity, the net effect of abatement cost is still greater than a 1 percentage point reduction. This suggests the presence of the "real effect" (Gray, 1987, p. 999). Model 2B and 2D produce little or no change at all to R^2s even after including *PAOC* and *DIRTY*PAOC* variables. This indicates other factors' responsibility in explaining the rest of the variations in output and productivity.

Now the regulation-*OUTPUT* and regulation-*TFP* relationships are presented quantile wise in Table 3. The former relationship is always negative and statistically significant, the second quantile being the strongest one. The latter relationship is always negative like the former relationship, but only the third quantile includes a statistically significant coefficient.

FE and FD models are used in Table 4 to control for industry-specific unobserved differences. *PAOC* produces smaller and statistically weak impacts than those shown in Table 2. In Model 4B, *PAOC* yields a less than 1 coefficient that indicates an absence of "real effect." In addition, FE and FD results look very different. This suggests the failure of sequential exogeneity. So *PAOC* and *DIRTY*PAOC* are instrumented by their second lags, and the results are presented in Model 4C and 4F. According to both specifications, the estimators get weak positive boosts from abatement spending like FE models do. This might suggest the presence of either "measurement error" or the benefits of regulations (Gray & Shadbegian, 1995, p. 16).

The endogeneity of *PAOC* might plague the results both at levels and at first differences. Thus, the OLS-lagged approach is resorted in Table 5. In Model 5A (5C) and 5B (5D), present level of *OUTPUT* (*TFP*) is regressed on first- and second-lagged explanatory variables, respectively. In all models, results look very similar to those of Table 2. *PAOC* yields substantially bigger adverse impacts on the estimators: 7.2 and 5.3 percentage points in Model 5B and 5C being the highest and lowest ones, respectively.

In addition, the impacts of regulation on *OUTPUT* and *TFP* are estimated using GMM. The difference and system GMM results are reported in 6A, 6C and 6B, 6D, respectively. Interesting enough, these two methods produce very different results. As expected from Model 4C and 4F, Model 6A and 6C are also unable to produce any noticeable result. In contrast, both Model 6B and 6D produce expected and statistically significant results: a percentage point increase in *PAOC* reduces *OUTPUT* and *TFP* by almost 4.4 and 2.8 percentage points, respectively. System GMM has also increased the overall efficiency with higher p-values for both *AR (1)* and *AR (2)*, and *Hansen J* statistics.

In this analysis, *PAOC*, *DIRTY*, and *DIRTY*PAOC* are main of focus. Throughout the estimation process, *PAOC* yields the most consistent, expected, and statistically significant coefficients. *DIRTY* and *DIRTY*PAOC* yield strong expected results across OLS models, but both of them become inconsistent in GMM models.

SUMMARY AND CONCLUSION

Five main conclusions of this study are—an industry with higher pollution abatement spending experiences significantly lower output and productivity levels; an average dirty industry experiences significant reduction in both output and productivity compared to an average other industry; an average dirty industry with higher abatement costs, experiences less severe negative impact from environmental regulations; both measurement and real effects are present (unlike Gray, 1987, p. 1003); and environmental regulations studied cannot alone be blamed for the slowdown in output and productivity (like Gray, 1987, p. 1003).

In general, OLS models at levels suggest a 5-percentage point reduction in output and productivity for each percentage point increase in abatement spending. OLS-first differenced models perform better than fixed-effects and IV specifications. However, the abatement costs coefficient is statistically significant only once, showing a significant reduction by almost 0.9 percentage points in output. According to the OLS-lagged models, every percentage point increase in abatement costs reduces the output by 6-7 percentage points and productivity by 5-6 percentage points. System GMM models conform to OLS and OLS-lagged models and confirm a 3-4 percentage point negative economic consequence for each percentage point in extra pollution abatement costs.

Generally speaking, switching from clean to dirty status costs an average industry a 4-7 percentage point reduction in output and productivity. Industry status and the abatement costs variable are interacted. The interactive variable indicates that in the end an average dirty industry could be benefited economically by incurring higher abatement costs. However, these two different groups of industries do not seem to incur substantially different abatement costs (Table 1).

Abatement costs coefficients always remain strongly greater than 1 in magnitude. This confirms that the industries incur additional costs to comply with the environmental regulation.

It is evident from the R^2s that variations in firm characteristics explain most of the variations in output. Even after including regulatory and the interactive variables, a 5-6 percent of output variation is left to be explained by other factors.

REFERENCES

Arellano, Manuel, & Bond, Stephen (April 1991). Some tests of specification for panel data: Monte Carlo evidence and an application to employment equations. *The review of economic studies*, 58(2), 277-297.

Barbera, Anthony J., & McConnell, Virginia D. (December 1986). Effects of pollution control on industry productivity: a factor demand approach. *The Journal of Industrial Economics*, 35(2), 161-172.

Berman, Eli, & Bui, Linda TM. (August 2001). Environmental regulation and productivity: evidence from oil refineries. *Review of Economics and Statistics*, 83(3), 498-510.

Christainsen, Gregoty B., & Haveman, Robert H. (May 1981). Public Regulations and the Slowdown in Productivity Growth. *American Economic Review*, 71(2), 320-325.

Doornik, Jurgen. A., Arellano, Manuel, & Bond, Stephen (June 2001). Panel data estimation using DPD for Ox. Nuffield College, Oxford, U.K.

Gollop, Frank M., & Roberts, Mark J. (August 1983). Environmental regulations and productivity growth: the case of fossil-fueled electric power generation. *The Journal of Political Economy*, 91(4), 654-674.

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

Gray, Wayne B., & Shadbegian, Ronald J. (April 1993). Environmental regulation and manufacturing productivity at the plant level (No. w4321). National Bureau of Economic Research, U.S.A.

Gray, Wayne B., & Shadbegian, Ronald J. (January 1995). Pollution abatement costs, regulation, and plant-level productivity (No. w4994). National Bureau of Economic Research, U.S.A.

Gray, Wayne B., & Shadbegian, Ronald J. (May 2003). Plant vintage, technology, and environmental regulation. *Journal of Environmental Economics and Management*, 46(3), 384-402.

Greenstone, Michael (December 2002). The impacts of environmental regulations on industrial activity: evidence from the 1970 and 1977 Clean Air Act Amendments and the Census of Manufacturers. *Journal of Political Economy*, 110(6), 1175-1219.

Mileva, Elitza (July 2007). Using Arellano-Bond dynamic panel GMM estimators in Stata. Economic Department, Fordhan University, U.S.A.

Norsworthy, J. Randolph, Harper, Michael J., & Kunze, Kent (1979). The slowdown in productivity growth Analysis of some contributing factors. *Brookings Papers on Economic Activity*, 1979(2), 387-421.

Porter, Michael E., & Van der Linde, Claas (Autumn 1995). Toward a new conception of the environment competitiveness relationship. *Journal of economic perspectives*, 9(4), 97-118.

Portney, Paul R. (July 1981). Macroeconomic impacts of federal environmental regulation. *Natural Resources Journal*, 21, 459-488.

Roodman, David (December 2006). How to do xtabond2: An introduction to difference and system GMM in Stata (No.w103). Washington: Center for Global Development, U.S.A.

TABLE 1. SUMMARY STATISTICS (FULL SAMPLE, 440 INDUSTRIES FROM 1973 TO 2005)

Variable	Mean (s.d.)	Description
Dependent variables		
OUTPUT	8.1769 (1.093)	Log of real output
TFP	1.7158 (.261)	Total factor productivity
Regulatory variable		
PAOC	.0042 (.008)	Pollution abatement operating costs, divided by value of industry shipments
Industry characteristics		
LABOR	3.4188 (.993)	Log of production hours
CAPITAL	7.3595 (1.142)	Log of real capital stock
INVESTMENT	4.6282 (1.272)	Log of real new capital spending
MATERIAL	7.4471 (1.148)	Log of real material
DIRTY	.3796 (.485)	Dummy variable = 1 if an industry is in SIC 26, 28, 29, 30, 32, 33 or 34
PAOC	*DIRTY* = 0	*DIRTY* = 1
	.0022 (.005)	.0076 (.011)

TABLE 2. INITIAL OLS REGRESSION RESULTS (DEPENDENT VARIABLE = OUTPUT OR TFP)

Model	A	B	C	D
	Level			
	OUTPUT		*TFP*	
PAOC		-4.9946*** (.8106)		-4.7569*** (.7520)
*DIRTY**PAOC*		3.4990*** (.8268)		3.6254*** (.7924)
DIRTY	-.0545*** (.0050)	-.0583*** (.0054)	-.0545*** (.0040)	-.0561*** (.0048)
LABOR	.1577*** (.0035)	.1507*** (.0038)		
CAPITAL	.0960*** (.0060)	.1057*** (.0064)		
INVESTMENT	.0827*** (.0059)	.0834*** (.0059)		
MATERIAL	.6490*** (.0069)	.6464*** (.0069)		
R^2	.945	.945	.031	.036
No. of obs.	14520	14520	14520	14520

* p<0.05, ** p<0.01, *** p<0.001

Note: Robust standard errors are in the parentheses.
All models include a constant term and year dummies.
Chow tests, on *DIRTY*PAOC*, reject the null strongly in all cases.

TABLE 3. PERFORMANCE BY QUANTILES (DEPENDENT VARIABLE = OUTPUT OR TFP)

Model	Q25		Q50		Q75	
	OUTPUT	*TFP*	*OUTPUT*	*TFP*	*OUTPUT*	*TFP*
PAOC	-5.1550*** (1.337)	-6.7426 (72.006)	-8.0025*** (1.122)	-7.1497 (20.816)	-6.6410*** (1.011)	-5.5552*** (1.400)
*DIRTY*PAOC*	4.8430*** (1.318)	5.0941 (71.975)	7.3923*** (.964)	6.7662 (21.020)	5.1078*** (.963)	5.5724*** (1.491)
DIRTY	-.0362*** (.006)	-.0439 (.164)	-.0975*** (.004)	-.0912 (.048)	-.1085*** (.005)	-.1033*** (.007)
LABOR	.1813*** (.003)		.1616*** (.003)		.1413*** (.002)	
CAPITAL	.0756*** (.006)		.1037*** (.004)		.1138*** (.007)	
INVESTMENT	.0763*** (.006)		.1085*** (.004)		.1461*** (.006)	
MATERIAL	.6532*** (.004)		.6082*** (.004)		.5776*** (.004)	
Pseudo R^2	.804	.045	.806	.033	.805	.030
No. of obs.	14520	14520	14520	14520	14520	14520

* p<0.05, ** p<0.01, *** p<0.001

Note: Standard errors are in the parentheses.

All models include a constant term and year dummies in each quantile.

Chow tests, on *DIRTY*PAOC*, always reject the null strongly.

TABLE 4. FIXED EFFECTS, FIRST DIFFERENCES, IV REGRESSION RESULTS (DEPENDENT VARIABLE = OUTPUT OR TFP)

Model	A	B	C	D	E	F
	FE	1st diff.	IV	FE	1st diff.	IV
	OUTPUT			TFP		
PAOC	1.4205 (1.158)	-.8816* (.4722)	.2707 (.166)	1.8030 (1.136)	-.3877 (.5035)	.2916 (.178)
*DIRTY*PAOC*	-1.4199 (2.145)	.4641 (.5830)	-.2578 (.177)	-2.0671 (1.690)	.3058 (.6269)	-.2287 (.196)
LABOR	.0932 (.097)	.2701*** (.0148)	.2631*** (.015)			
CAPITAL	.1497* (.064)	.1177*** (.0212)	.1212*** (.022)			
INVESTMENT	.0172 (.011)	.0136*** (.0026)	.0141*** (.003)			
MATERIAL	.7895*** (.105)	.5813*** (.0116)	.5903*** (.012)			
R^2	.940	.735	.744	.019	.044	.045
No. of obs.	14520	14080	13640	14520	14080	13640

* p<0.05, ** p<0.01, *** p<0.001

Note: Robust standard errors are in the parentheses.
All models include a constant term and year dummies.
Chow tests, on *DIRTY*PAOC*, do not reject the null at all.

TABLE 5. OLS REGRESSION RESULTS WITH LAGGED EXPLANATORY VARIABLE (DEPENDENT VARIABLE = OUTPUT OR TFP)

Model	A	B	C	D
	1st lag	2nd lag	1st lag	2nd lag
	OUTPUT		*TFP*	
PAOC	-5.9627*** (1.031)	-7.2093*** (1.310)	-5.3153*** (.831)	-5.9341*** (.906)
*DIRTY*PAOC*	3.7711*** (1.041)	4.3133*** (1.309)	4.2511*** (.866)	4.8892*** (.935)
DIRTY	-.0627*** (.006)	-.0686*** (.007)	-.0590*** (.005)	-.0607*** (.005)
LABOR	.1484*** (.004)	.1462*** (.004)		
CAPITAL	.0969*** (.007)	.0897*** (.008)		
INVESTMENT	.1047*** (.006)	.1261*** (.007)		
MATERIAL	.6357*** (.007)	.6232*** (.007)		
R^2	.940	.934	.038	.038
No. of obs.	14080	13640	14080	13640

* p<0.05, ** p<0.01, *** p<0.001

Note: Robust standard errors are in the parentheses.

All models include a constant term and year dummies.

Chow tests, on *DIRTY*PAOC*, reject the null strongly in all specifications.

TABLE 6. GMM REGRESSION RESULTS (DEPENDENT VARIABLE = OUTPUT OR TFP)

Model	A	B	C	D
	Difference	System	Difference	System
	OUTPUT		*TFP*	
PAOC	3.1010 (2.206)	-4.3656* (1.832)	3.4269 (2.064)	-2.8245** (1.052)
*DIRTY*PAOC*	-2.7810 (2.776)	2.6875 (1.957)	-2.8679 (2.505)	-.2092 (1.312)
DIRTY		-.0494 (.026)		.0046 (.022)
LABOR	.1153 (.113)	.1583*** (.018)		
CAPITAL	.1050*** (.031)	.1105*** (.022)		
INVESTMENT	.0050 (.014)	.0840*** (.021)		
MATERIAL	.8083*** (.114)	.6350*** (.033)		
No. of obs.	14080	14520	14080	14520
AR(1)	-1.66	-1.33	-1.75	-1.65
Pr>z	0.097	0.185	0.081	0.099
AR(2)	-1.60	-1.23	-1.33	-1.42
Pr>z	0.110	0.218	0.184	0.156
Hansen test	412.02	427.03	407.28	415.68
Prob>chi2	1.000	1.000	1.000	1.000

* p<0.05, ** p<0.01, *** p<0.001

Note: Robust standard errors are in the parentheses.

All models include a constant term and year dummies.

Chow tests, on *DIRTY*PAOC*, do not reject the null in all specifications.