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Do Painless Environmental Policies Exist?*

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Abstract

This paper reports an experimental test of the Porter Hypothesis that environmental regulations create innovation offsets that would not otherwise be undertaken. Using a process analysis framework to consistently account for non-separabilities in production and pollution abatement practices, the findings suggest productivity gains can appear to be greater with environmental regulations than without even though they are not. This result which would seem to support the Porter argument, is the result of inadequacies in the methods used to decompose the influences to productivity change. Thus, the experiments offer one explanation for why it has been difficult in practice to reject the hypothesis.

Key words: environmental regulation, productivity, innovation

JEL Classification: O31, D24, O38

I. Introduction

Everyone likes a free lunch. This insight no doubt explains the appeal of Porter's (1991) suggestion that *innovation offsets* can make environmental regulations painless. Careful reviews and detailed micro econometric analyses of the joint effects of these regulations and technological innovation have not supported Porter's arguments for PEP (i.e. painless environmental policy).[1] Of course, it should also be acknowledged that they have not offered decisive evidence rejecting it either! To most neoclassical economists, the conceptual arguments are clear. Environmental regulations do have opportunity costs and require that real resources be diverted for controlling pollution. While these allocations may be warranted by the benefits people realize from pollution reductions, a constrained production setting, including the activities required to uncover innovations and develop new technologies from them, can never have lower costs than an uncon-

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strained one. Why then is the available empirical evidence inconclusive? This paper provides one answer.

Separating the effects of changes in input prices on static substitution, new (or more stringent) regulatory constraints affecting the prospects for substitution, and induced innovation in response to both types of incentives, requires partitioning activities that are often non-separable into distinct effects. Our ability to control each influence on observed production patterns in the real world is imperfect and can, as we demonstrate, lead to misconceptions about how environmental regulations increase productivity. Our bottom line is that there are no painless environmental policies! When they are claimed the result is more often than not the result of an incorrectly specified model.

This paper was prepared as part of a special issue to honor Wes Magat's contributions to environmental economics. Wes' writings in environmental economics began with his PhD thesis twenty-five years ago (in 1975) on the role of different environmental policy instruments for induced innovation. His 1978 paper is the conceptual antecedent for all that environmental economists believe they know about how policy instruments affect technological innovation. It provides the basis for the developing neoclassical alternative to Porter's arguments. In the next section we discuss how his analyses compares with recent theoretical research on environmental regulation and innovation. Section III describes our experiment and the models we use to evaluate why it is difficult to reject PEP. Section IV summarizes our findings and confirms that environmental regulations can be misconstrued as productivity enhancing measures. We demonstrate that the error stems from a failure to define the correct baseline. The last section discusses the importance of maintaining realistic expectations for technological innovation in costing large scale environmental policies.

II. Environmental policies and innovation

Static analyses of the effects of alternative policy instruments on the incentives for innovation use a comparison of the abatement cost savings associated with each form of regulation. Consider an example in Fig. 1 with C_1 designating the marginal cost of abatement before an innovation and C_2 the marginal cost after.[2] In this context, the comparisons used to evaluate alternative policies focus on how different instruments affect innovating and non-innovating firms. Assuming a fixed level of emissions, an innovating firm faced with an effluent charge of ot or a standard permitting A_1e emissions realizes the same savings in abatement costs from adopting the innovation associated with reducing abatement costs—0RG—the area between C_1 and C_2. However, with the effluent charge, the firm confronts continuing costs of A_1GTe for the emissions after adopting the new technology. The firm could realize additional savings of GTMR if it reduced emissions to zero (i.e. selected oe abatement). No such payments are required with a standard. Our figure is constructed so that e designates the point of no emissions and the origin a

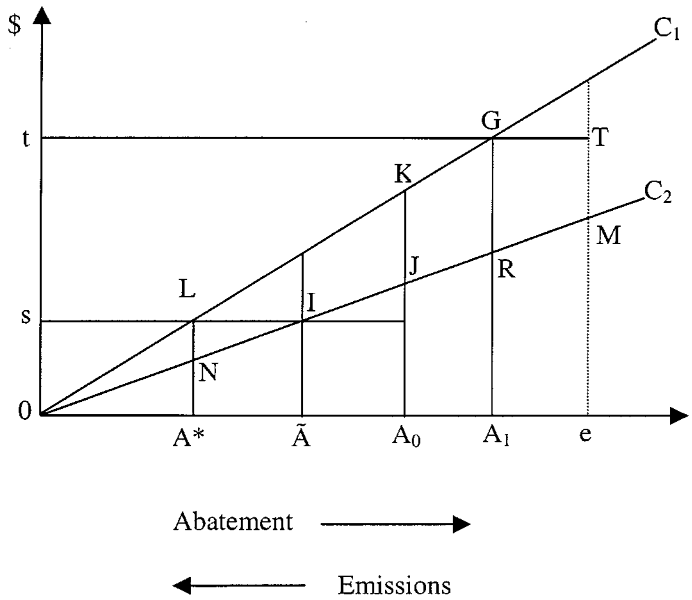

Figure 1. Static description of incentives effects of environmental policy for innovation.

zero level of abatement. At zero abatement, the amount of pollution corresponds to the horizontal distance $0e$. Marketable permits will be comparable to charges if ot is the price for a permit and all permits must be purchased. If they are grandfathered (i.e. distributed free), then the comparison can depend on the assignments to each firm.

The incentives to non-innovating firms depend upon the royalty rate paid for having access to the innovation in abatement activities as well as what is assumed about the format for each policy alternative.[3] Most authors using this framework rank effluent charges, marketable permits (that are auctioned), and subsidies as comparable in their incentives to promote innovation. The relative performance of standards and free pollution permits in comparison to the other instruments depends on what is assumed. Malueg (1989), for example, suggests that if a firm is a buyer of emission credits both before and after investing in an innovation to the abatement technology, then a fixed emission standard provides a greater abatement cost saving. This situation would arise with a standard of A_o and a permit price of $0s$. Under the old abatement cost (C_1), the firm would control up to A^* and purchase A^*A_o permits. Under the new cost (C_2), control would increase to $\tilde{A}$. Less permits would be required, but the firm facing a permit system can, nonetheless, have an obligation to purchase permits for all its emissions in excess of the standard A_o at a price of $0s$. Maleug ignored the role of $0s * \tilde{A}A_o$ as an added cost attributed to permits. His analysis compared the cost savings from a new technology with access to a permit trading market and grandfathered levels of pollution permitted by setting the standard at A_o. This formulation assumes $A_o e$ limits of emissions are allowed. The cost savings are OKJ for a firm facing a fixed standard that allows $A_o e$ emissions. When the firm must purchase marketable permits for emissions in excess of $A_o e$, the cost saving is OLI. The remaining permits to be purchased is reduced to $\tilde{A}A_o$ but not completely eliminated. This result hinges on the critical assumption, implicit in Maleug (1989) that there has been some grandfathering of permits.

While all of these recent analyses cite the Magat (1978) paper on the incentives provided by environmental policy instruments for innovations, none explicitly discusses the contrasts in their conclusions compared to those from his analysis.[4] The Magat analysis concluded that there were not marked differences in the growth in a firm's budget for innovation under a constant effluent charge versus a constant standard. This conclusion seems at odds with nearly all of the rankings of these policy instruments based on the static models which identify clear favorites in promoting greater innovation (and presumably larger R and D budgets).

The reason for this disparity is not solely the result of Magat's use of a dynamic framework to study incentives. Rather it is the assumed link between emissions and output. All of the static models treat the firm's choice process as if the control of emission rates through abatement activities was separable from the production processes associated with marketed output. In Magat's analysis they are not. Indeed, for given returns to scale, it is the size of the transformation elasticity measuring ease of moving inputs between producing marketable output and undertaking pollution abatement in comparison to the expenditure share attributed to abatement that determines whether innovation budgets rise over time.[5] Only serious limits to this substitution elasticity would create declining innovation expenditures and the potential for differences between charges and standards. In the Magat model, a firm's output grows over time. The specification of the production process implies the tasks of managing residuals will increase with that output growth. Thus, effluent charges must increase to provide the equivalent incentive created by the rising virtual price due to a standard's requirement that a fixed quantity of pollution be emitted.

This distinction in how abatement activities are described in relation to the production processes for marketed output is also important to interpreting Porter's argument that environmental regulations "trigger" innovations. Porter and van der Lind (1995) describe *process offsets* that are stimulated by these regulations, noting that:

> Process offsets occur when environmental regulation not only leads to reduced pollution, but also results in higher resource productivity such as higher process yields, less down time through more careful monitoring and maintenance, materials savings (due to substitution reuse or recycling of production inputs), better utilization of byproducts... (p. 101)

Their descriptions imply that neoclassical models that treat abatement and production activities as separable could overlook how PEP can work. As a result, we designed our evaluation of the response of innovations to environmental regulations using a framework that treats abatement and output production activities as non-separable. Innovations in abatement practices can require different mixes of inputs and equipment that also affects the yields of marketed outputs. They can also involve the inputs used to remove residuals from the waste stream emitted by a plant as a separable set of activities.[6]

The task of distinguishing innovations in response to regulations from static substitution or the innovations that would arise in response to changes in relative prices is confounded by input aggregation. As a rule, process innovations can require the use of both new capital equipment and new materials inputs. Most detailed econometric analyses of production adopt a KLEM input specification (e.g. capital, labor, energy, and materials are the categories used to define inputs).[7] This specification means that capital equipment for pollution abatement is often included with the overall capital associated with producing marketable outputs. Energy to run the equipment or materials used with it are aggregated with the amounts of these inputs used for production. Thus, measuring the differences in the mix of capital or material inputs attributed to static substitution in response to price changes versus innovation in response to environmental constraints relies on separating these subtle effects.

Compromises in findings or modeling assumptions due to this type of input aggregation can be found in several of the recent efforts to evaluate the costs of environmental regulations. This influence, arguably a result of an implicit separability assumption that conditions most data collection practices, is most directly seen in Morgenstern et al.'s (1998) plant level analysis. They estimate neoclassical cost functions at the plant level and include the PACE (Pollution Abatement Cost and Expenditure Survey) reports of annual pollution abatement operating costs (including depreciation on abatement capital) as an independent determinant of the plant level costs. All the expenditures on inputs required for abatement, that are included in the PACE operating costs, would also be a part of the capital, labor, energy, and materials inputs these authors used in defining their plant level total production costs. Thus, there is double counting in the cost measures from their two data sources. The data collection practices providing their basic information about plant level activities prevent them from being distinguished. Equally important, the inputs composing of their regulatory cost measure must be assumed to be jointly determined with their production inputs. Thus, the PACE measure is not an exogenous influence on plant level costs as assumed in the neoclassical formulation. It is the result of choices in response to both relative factor prices and regulatory constraints.

Few empirical studies have had access to the micro detail of the data assembled by Morgenstern et al. (1998). Barbera and McConnell (1990), for example, relied on aggregate time series. They assumed that the primary effect of regulation was to mandate abatement capital. As a result, they treated abatement capital as an exogenous, quasi fixed input. It was deducted from their estimates of overall industry capital stock in measuring the costs of capital services used in their cost function analysis. Increases in this quasi-fixed input over time are assumed to take place in response to exogenously imposed changes in environmental regulations. This approach consistently accounts for production and abatement control activities and their respective effects on observed patterns of input usage. However, it relies on maintaining that regulations' sole effect is associated with mandating abatement capital. To the extent firms can respond to regulations by altering the mix of abatement capital relative to other inputs, in response to the joint effect of regulatory controls and factor prices, then this specification will bias the estimates of the impacts of regulation.

Addressing these issues requires control of the incentives (e.g. price and regulatory constraints) facing firms and the ability to record the full details of the responses they make to these incentives. To meet these needs, we adopt an approach originally proposed by Kopp and Smith (1985) for evaluating Binswanger's (1974) method to estimate the factor biases from induced technical change. The approach relies on a cost minimizing programming model that uses a detailed engineering description to characterize the "true" production technology and innovations to it. We use the same model as Kopp and Smith—Vaughan, Russell, and Cochrane's (1976) description of the *ex ante* decisions in designing a steel making plant. Their model (designated VRC) was developed as part of Resources for the Future's Industry Studies program. It incorporates a full set of heat and materials balance conditions for all the production activities. The model also provides a detailed description of the input choices for steel production, including three types of steel making furnaces—basic, oxygen, open hearth, and electric arc as well as all the necessary pre and post process activities.[8]

The model was developed in two versions—with and without six process innovations that increase the size of the technology matrix describing a steel plant's production activities by nineteen percent (from 694 to 826 columns). The innovations were based on actual technologies considered for plants in the industry at the time the model was developed (in the mid-seventies). The actual details of the innovations are not especially important here. (See Appendix A.) At base prices the innovations reduce the costs of producing a constant mix of steel products by 10.35%.

The framework is well suited to our objective because it incorporates residual control activities as non-separable components of production and is consistent with a simple, but admittedly static, neoclassical model of innovation. There are no surprises or internal sources of inertia requiring regulators to prompt the firm to undertake innovations. Finally, the model identifies factor inputs at a highly disaggregated level, allowing us to keep track of intermediate responses to factor price and environmental constraints, yet aggregate these detailed changes in a way that corresponds to the conventional practice used in neoclassical production analysis.

The selection of steel production is fortunate for other reasons as well. Barbera and McConnell's (1990) aggregate analysis for the seventies suggests that environmental regulations caused the largest decline in total factor productivity for steel—0.43%. More recently, Morgenstern et al. (1998) also highlight differences in their results for steel plants. They observed that of the four industries in their sample with the largest abatement expenditures, steel was the only one where their fixed-effects model indicated that a dollar increase in PACE expenditures lead to an *increase* in total production costs. All the others sectors' models indicated smaller production costs. Overall, they reported an average (across industries) increase of \$0.82 in total production costs for each \$1.00 of pollution abatement expenditures. Thus, steel production seems to require more costly responses to abatement controls. As a result we would expect that this sector would be among the least likely to display a "painless" response to environmental policies.

III. Experimental design and models

Three sets of cost minimizing solutions create the data used in our evaluation of the effects of environmental constraints on total factor productivity. The first of these uses the VRC model without the activities corresponding to the six process innovations. Thirty-one separate factor inputs were defined from the activities represented in the model. (See Appendix A.) Four different variations in each factor input's price were considered. These were defined as independent multiples (k) of the base price with $k = 0.10$, 0.75, 1.45, and 3.0.

The remaining sets of solutions use the VRC model's technology matrix augmented with the six innovations. One of these samples is composed from the same price variations (as the no innovations case) using the technology matrix that includes the innovations. The last sample considers combinations of constraints on air and waterborne emissions along with variations in factor prices. One hundred thirty-two solutions were composed by considering three pairs of changes. Twenty-one factor inputs each varied to a low price multiple (0.10) and an intermediate multiple (1.45) of the base price together with the low and high constraints on airborne residuals. Eleven inputs had their prices varied to low and intermediate multiplies (i.e. 0.10 and 1.45) of the base levels along with two levels of constraints to waterborne residuals. Because all these solutions treat each source separately, we also included four solutions at base prices for all inputs with variation in the restrictions on air and waterborne residuals. Appendix A identifies the inputs whose prices varied jointly with each type of restriction on residuals. The restrictions on atmospheric and waterborne emissions were imposed as twenty-five and fifty percent reductions from the uncontrolled baseline levels of emissions. These were imposed as a group on the residuals entering each disposal medium.

Using these data, we construct our measures of total factor productivity (TFP) change (estimated as the proportionate change in the costs of producing a fixed output vector) in three ways. The first uses a translog cost function, estimated based on solutions to the *ex ante* model without innovations, the "static sample." This function provides the basis for computing how factor inputs' cost shares change with factor price changes and uses the neoclassical description of static substitution to estimate TFP. The productivity change, T, is then computed using the proportionate change in aggregate input usage (over the levels selected at the base prices, designated by b) weighted by the predicted cost shares, $\hat{s}_{ij}$, from the translog function as defined in Eq. (1).

$$T_j = -\hat{s}_{Kj}\left(\frac{K_j - K_b}{K_b}\right) - \hat{s}_{Lj}\left(\frac{L_j - L_b}{L_b}\right) - \hat{s}_{Ej}\left(\frac{E_j - E_b}{E_b}\right) - \hat{s}_{Mj}\left(\frac{M_j - M_b}{M_b}\right) \tag{1}$$

where: K_j = estimated capital used in solution j
L_j = estimated labor used in solution j
E_j = estimated energy used in solution j
M_j = estimated materials used in solution j

The levels of each aggregate input are computed from the values for expenditures on factor inputs in the solutions subject to environmental constraints with access to the six innovations. Aggregates of the expenditures were divided by the relevant aggregate factor price index. Because the output mix does not change the total factor productivity can be derived exclusively from the change in the input mix with and without innovations. This approach parallels the logic used in Barbera and McConnell (1990).

Our second measure of productivity is more direct. It compares the total costs, C_j, for the constrained solutions with the base case costs as in Eq. (2):

$$P_j = \frac{C_j - C_B}{C_B} \tag{2}$$

With both of these strategies, the total factor productivity measure reflects the mix of innovations (and existing *ex ante* input selections) made in response to new relative factor prices *and* the different levels of environmental restrictions. T relies on the static neoclassical cost model to distinguish the effects of factor prices, through static substitution, from environmental regulations as a separate influence. P implicitly assumes a further set of analysis will separate the role for environmental constraints. The proportionate cost change incorporates static substitution as well as innovations adopted in response to changes in factor prices and environmental regulations. T is directly affected by the input aggregation and the specification of a neoclassical cost function. P is not. These two measures parallel the early efforts with actual data to decompose measures of total factor productivity.

Morgenstern et al. (1998) is one of the first studies to use detailed, plant level, panel data to attempt to control the potential influences on measures of the productivity effects of environmental regulations.[9] By allowing a fixed effects models to be estimated, the panel data permit a more discriminating approach for isolating the effects of environmental regulations from plant specific impacts on costs. An analogy to this type of control in our experimental context would be to match cost minimizing solutions that correspond to the same factor prices. For example, one possibility would combine the static *ex ante* choices and the choices made for the same factor inputs with access to the innovations and constraints on residuals emissions. Computing the cost savings for these cases would eliminate the effects of static substitution in response to differences in relative factor prices in evaluating the effects of environmental regulations on productivity. Designated, *PP*, this estimate is comparable to the definition in Eq. (2) but replaces C_B with the total costs for the unconstrained, *ex ante* static solutions with matching factor prices.

We know by design that the VRC decision process implies environmental constraints *reduce* the gains that could be realized from these innovations by 0.4 to 9.7 percent, depending on the type of residuals being controlled (air versus water) and the stringency of the environmental constraint. Table 1 reports specific comparisons using the constrained solutions with innovations versus the static (no innovation) case. The model's solutions are consistent with the "neoclassical story."

Table 1. Effects of environmental constraints on the potential Gains from innovation[a]

	Level of environmental constraints[b]					
	Low			High		
Solution	Cost[c]	Sav-Static	Sav-UC	Cost	Sav-Static	Sav-UC
Constrain Water Only	310,972	.1019	−.0017 (−2.7)	312,400	.0978	−.0063 (−6.4)
Constrain Air Only	310,576	.1030	−.0004 (−0.4)	311,342	.1008	−.0029 (−2.9)
Constrain Both	311,122	.1015	−.0022 (−2.2)	313,288	.0952	−.0092 (−9.7)

[a] The total cost for the static *ex ante* solution at base prices is 346,252. With innovations present and no environmental constraints, the total cost is reduced to 310,430, a 10.3% cost savings from the base case.

[b] Sav-Static compares the computed costs with innovations and the identified environmental constraint to the costs from producing the same outputs at base prices without innovations or environmental constraints (e.g. the proportionate cost savings). The column reports the proportionate cost reduction. With a constant output vector, this corresponds to a total factor productivity measure. The SAV-UC compares the costs with innovations and constraints to the base with innovations and no constraints. The numbers in parentheses are the percentage reduction in productivity gains due to the environmental constraints.

[c] These costs are for 1973 in dollars per day of operation.

Innovations can reduce the costs of meeting environmental restrictions. However, there remains an opportunity cost to the environmental constraints. If these solutions are compared with the case having the same factor prices, the same innovations available, and no environmental constraints, then costs would be reduced to a greater extent. Thus, we know these solutions and their input selections are consistent with the neoclassical argument. In what follows, we follow conventional practices for measuring the effects of environmental constraints which attempt to distinguish separate effects for environmental regulations on the three TFP measures productivity change.

IV. Results

Table 2 provides summary statistics for our three productivity measures. These comparisons highlight the difficulties associated with controlling for price effects using aggregate price indexes. The three ways to control the effects of prices and restrictions are distinguished based on whether they rely on a model or a sub-sample to attempt to control each influence. Price related influences to static substitution and induced innovations are logically separate from the effects of increased environmental restrictions on the incentives to adopt innovations. At an aggregate level, the price measures will depend upon the weights used to compose the aggregates. The first two sets of results compute productivity statistics holding aggregate prices constant but define these aggregate price indexes differently. In the first row we use the solutions to the model with innovations and environmental restrictions and the second defines base prices (to be held constant by sample selection) using weights from the solutions to the model without innovations.

Table 1 reported the correct values for the productivity increases with the base prices defined at the most disaggregate level. Without environmental restrictions this was 10.35%. With restrictions, it ranges from 9.52% (for the most stringent level of constraints on both air and water emissions) to 10.30% with the low level of restrictions on airborne residuals alone. The direction of the differences between the unconstrained and constrained situations is consistent using the sample averages of *T, P* and *PP* in the first panel of Table 2. That is, adding environmental restrictions tends to reduce the size of the productivity increase from new innovations as the neoclassical perspective underlying the VRC model implies. These estimates are not the same as the "true" in Table 1. They reflect the confounding influences of aggregation and price changes in a non-separable framework. These estimates define "constant" factor prices using aggregate indexes constructed from solutions with innovations to define the expenditure weights. All are below the 10.35% gain expected at base prices without environmental constraints. When we consider the estimates for each solution, there appear to be cases where TFP estimates would contradict the neoclassical expectation.

The second panel in Table 2 repeats the comparison holding the aggregate factor prices constant, but using weights based on the expenditures from unconstrained

Table 2. Alternative measures of productivity change

Sample	Summary statistic[b]	Productivity (TFP) change[a]		
		T	*P*	*PP*
Constant Aggregate Base Prices Using Prices based on Weights from Environmentally Constrained Innovations with Solutions $n = 32$	Mean	.1018	.1012	.1016
	Min	.0984	.0978	.0978
	Max	.1036	.1030	.1055
Constant Aggregate Base Prices Using Prices based on Weights from Unconstrained Static Solutions $n = 38$	Mean	.1041	.1036	.1037
	Min	.0984	.0765	.0765
	Max	.1325	.1444	.1444
Sample with Price and Environmentally Constrained Solutions $n = 128$	Mean	.1093	.1118	.1027
	Min	.0834	.0548	.0397
	Max	.2833	.3847	.1747

[a] These cost reductions are measured as the proportionate change. A positive value implies a cost reduction (or productivity increase).
[b] Mean designates the mean value; Min is the minimum value; and Max is the maximum value; n is the number of solutions in the sample.

static solutions. In this case, notice that there can appear to be contradictions to the neoclassical model using the sample averages. The TFP averages seem consistent with larger productivity gains in some solutions with environmental constraints compared to the unconstrained cases. Of course, Table 1 documents that this interpretation is *incorrect*. When the sample and definitions for TFP hold price constant correctly, we see that measured gains with environmental restrictions cannot exceed what is possible without constraints.

Thus, the simple findings for point estimates of TFP indicate that existing practices can yield TFP estimates with constraints that exceed TFP measure for the unconstrained case (e.g. 10.35%). This result *cannot* be due to the Porter effects—the model does *not* allow them. They are due to the inability of our techniques to draw the distinctions we made conceptually. To further support this conclusion, Table 3 reports ordinary least squares (OLS) estimates for models

Table 3. Productivity models with environmental restrictions

Model:	1	2	3	4	5	6
# obs:	128	128	128	128	128	128
Depvar:	P	P	PP	PP	T	T
$\ln p_k$	−0.354		0.090		−0.124	
	(−21.82)		(3.56)		(−7.37)	
$\ln p_m$	−1.025		−0.203		−0.636	
	(−63.92)		(−8.16)		(−38.21)	
$\ln p_e$	0.040		0.012		−0.015	
	(−5.47)		(1.05)		(−2.02)	
air2	0.104	0.116	0.104	0.106	0.105	0.112
	(95.03)	(17.56)	(61.22)	(49.38)	(91.97)	(27.50)
air4	−0.002	−0.003	−0.003	−0.003	−0.002	−0.002
	(−1.28)	(−0.29)	(−1.21)	(−0.90)	(−1.20)	(−0.38)
water2	0.108	0.108	0.101	0.102	0.109	0.109
	(74.87)	(12.28)	(45.19)	(35.60)	(72.67)	(20.19)
water4	−0.004	−0.004	−0.004	−0.004	−0.004	−0.004
	(−2.00)	(−0.33)	(−1.31)	(−1.03)	(−1.92)	(−0.53)
R-sq	0.997	0.878	0.99	0.983	0.996	0.948
Ho_1: Pr > F	0.000		0.000		0.000	
Ho_2: Pr > F	0.000		0.000		0.000	

Ho_1, F: air2, air4 = 0
Ho_2, F: water2, water4 = 0
(t-statistics in parentheses)

describing the factors that are usually cited as influences to productivity change. We use the solutions from the model with innovations, facing different relative factor prices and environmental constraints. These models follow conventional practice and relate each of our measures of TPF to the characteristics of the solutions used to construct them. We use the change in aggregate factor prices from the base levels as well as four qualitative variables to gauge the effects of the environmental constraints. Because our sample is composed of variations in prices with different levels of environmental restrictions, we estimate the models with the intercepts constrained to be zero. This format allows us to recover the direct effect of the different levels for the environmental restrictions. Two models for each of the three productivity measures-with and without terms to reflect the percent change in the aggregate factor prices that also vary in these solutions are reported in the table. These models seem to provide clear-cut conclusions. They appear to support Porter's PEP! That is, at low levels of environmental restrictions for both air and water, all TFP measures indicate that restrictions *increase* productivity. This finding would be judged to be highly significant and consistent.[10] The effects of environmental restrictions turns negative only at the higher level of the restrictions and would, for some TFP measures and model specifications, be judged significant.

This result is the opposite of what we know to be the case. Environmental regulations *reduce* the magnitude of the productivity gains in this model. Table 1 documented this pattern. The results in Table 3 are an artifact. They arise because what we can observe is a composite of responses that are distinguished to facilitate how they might take place.

Regulations do create incentives in this optimizing model to use some of the new activities VRC labeled as associated with process innovations. Of course, some of these same activities along with others may have been adopted at base prices without the restrictions and Table 1 confirms as much. Change factor prices and environmental restrictions simultaneously and the "brew" a model must separate becomes even more complex. The most important insight illustrated by our simple experiments concerns the extent of "control" required to correctly mimic the behavior described in the neoclassical argument. It requires matching the regulated case with *the* appropriate standard for comparison—unregulated solutions with access to the same innovation possibilities facing the *same* factor prices.

In practice this counterfactual is not available. As a result, analysts have come to rely on statistical analyses or judgment based sub sampling to attempt to construct the results for a "controlled" comparison. Without this control, we have found that these approaches can assign "credit" for innovations that would have been adopted without the environmental restrictions. If we develop a simple model for the residual TFP by matching solutions based on the technology matrix with innovations and environmental restrictions to those solutions derived from the same technology matrix without restrictions, we see what Table 1 implies. Environmental regulations *reduce* the size of productivity gains between .002 and 1.5 percentage points depending on their stringency and other factor prices. This conclusion is clear once TFP is measured using the correct controls. Equation (3) provides the OLS response function for this case with C_{jE} the total costs for solutions to the jth factor price vector with environmental constraints and C_j, the total cost for the same factor prices with no environmental constraints.

$$\begin{aligned}\frac{C_j - C_{jE}}{C_j} = {} & \underset{(1.15)}{.003\,\Delta p_{jk}} + \underset{(6.61)}{.008\,\Delta p_{je}} + \underset{(1.14)}{.003\,\Delta p_{jm}} - \underset{(-3.78)}{.001 air2_j} \\ & - \underset{(-10.18)}{.003 air4_j} - \underset{(-6.55)}{.002 water2_j} - \underset{(-11.63)}{.005 water4_j} \end{aligned} \tag{3}$$

The numbers in parentheses are t-ratios. Δp_{jt} $(i = k, e, m)$ corresponds to the proportionate difference in factor prices measured as $\Delta p_{jt} = \ln p_{ij} - \ln p_{ib} = \ln p_{if}$ (because p_{ib} has been normalized to unity). The neoclassical framework implies $((C_j - C_{jE})/C_j)$ should be negative and it is. The results in Eq. (3) confirm that more stringent air and water restrictions do reduce productivity gains (i.e. in this case, make the cost difference a larger, in absolute magnitude, negative differential). However, the equation also provides some insights into why the separate effects are difficult to isolate. Increases in energy prices reduce the discrepancy caused by environmental restrictions. Energy inputs are associated with residuals. A positive coefficient for the energy price term suggests that an increase in energy prices increases C_j more than C_{jE}, implying that energy conservation is complementary to pollution abatement. Equally important, this link highlights the importance of nonseparabilities in describing the responses a plant can make to environmental regulations on emissions. Our inability to observe C_j in practice precludes isolating these effects with actual plants.

Our analysis suggests that efforts to approximate this differential in TFP with statistical decompositions, neoclassical models, or incomplete sample controls cannot be assured to provide an informative test of the Porter hypothesis. We escape this outcome only if our model "builds in" a reason for complacency—and then the "architect" (or economic analyst) must explain why environmental stimuli are superior to others. Many economists have already made this point, but they were unable to explain why if the phenomenon is so clear-cut—the supporting empirical evidence is not present. We have shown how seemingly contradictory (to a neoclassical model) results can arise due to inadequate control over the comparisons defining the TFP measures. Equally important, the lessons from using a more direct link between the engineering models describing how innovations transform production activities and the neoclassical models that summarize their results are not simple methodological points. They have direct implications for policy analyses that count on technological "bailouts" to pay for costly environmental policies as we discuss below.

V. Implications

Recent analyses of large-scale environmental policies have been significantly influenced by the dramatic differences between the actual costs of controlling sulfur emissions from electric power plants and the projected costs in the policy analyses conducted prior to implementing the SO_2 emission permit trading system. As a result, incentive based (IB) policies are now fashionable and there is a tendency to expect equivalent cost savings whenever an IB approach is used. A part of the explanation cited for these expectations is always the induced technical changes promoted by the requirement to pay to pollute. The conceptual logic underlying this suggestion is what we described at the outset. More generally it reflects the growth optimism of most economists, and follows from a belief:

> ... that human ingenuity will always rescue the day because, in the words of J. M. Clark, 'knowledge is the only instrument of production not subject to diminishing returns.' ... Like a magic cook in a fairy tale, we seem always to be

> able to conjure up fantastic new recipes for combining inputs to make bigger portions of food out of the same base of raw ingredients. (Weitzman, 1999, p. 25).

The Clinton Administration's initial evaluation of the cost implications of the Kyoto Protocol is a good example of these tendencies. It assumed two sources of policy induced technological change would lead to progressive reductions in the U.S. economy's energy-intensity (e.g. energy per unit of output) without added costs. The first was an increase from 1.0 percent to 1.25 percent in autonomous improvements in energy intensity. The increase was attributed to accelerating the learning effects as a result of assumed "announcement effect" due to the stating of a policy goal. The second involves a reduction due to innovations that allow further decreases in energy requirements. These "policy induced" innovations were estimated in the most optimistic scenarios to increase the annual rate of decline in the energy intensity to 1.75 percent. Our experiments suggest that we cannot reliably measure the separate effects of environmental restrictions on innovations with existing data and methods. The control required to mimic the results in Eq. (3) from actual records does not exist. Re-directions in effort in response to regulations have an opportunity cost and *reduce* the overall level of productivity. The same reasoning underlying our arguments concerning the ability of existing models to distinguish separate effects of environmental restrictions for productivity would seem relevant to efforts to isolate exactly what can be expected from policies that seek to redirect how innovations affect relative input usage.

Overall, our findings imply that any difficulties experienced in rejecting Porter's PEPs should not be interpreted as supporting their plausibility. They are a reflection of the limitations in economic methods of decomposing productivity changes. Of course, this inability does not imply that policies seeking to reduce emissions should not be undertaken. It implies that we cannot avoid considering what the environmental quality improvements (or reduced risk of climate change) will be worth to people.

Appendix A

The Vaughan, Russell, and Cochrane (1976) model was developed to investigate how induced technological change would affect the costs of controlling the primary emissions from steel production. The RFF Industry Studies program used a materials and energy balance system to construct an accounting scheme that measured and tracked residuals at each stage in the production process. This framework required a detailed identification of inputs and understanding of the specific engineering features of the production activities. Russell and Vaughan developed several of the most detailed models in this research program (i.e. for petroleum refining and steel production). This analysis could not have been undertaken without their carefully documented model. Table 1A reproduces (from Kopp and Smith, 1985) the input definitions at the disaggregate levels we used to construct our input aggregates. In some cases the model actually has a more detailed specification keeping track of, for example, the sulfur and other components of materials inputs and process specific components of capital. As indicated at the bottom of the table, the inputs with asterisks are exclusively associated with innovations.

Table 1A. Definition of factor inputs for experimental design

Input number	Input description
1	Maintenance
2	Metallurgical and Eastern Coal
3	Western Coal
4	Natural Gas
5	Fuel Oil
6	Iron Ore
7	Purchased Scrap
8	Labor
9	All Other Operating Inputs
10	Silicon Carbide
11	Lime
12	Liquid Nitrogen
13	Coking Capital
14	Boiler-Turbine Generator Capital
15	Sinter Capital
16	Blast Furnace Capital
17*	Extended Fuel Injection Capital (Innovations)
18	BOF Steelmaking Furnace Capital
19*	Scrap Preheating Capital (Innovation)
20	OH Steelmaking Furnace Capital
21	ARC Steelmaking Furnace Capital
22	Finishing Capital
23*	Continuous Casting Capital (Innovation)
24*	Direct Reduction Capital (Innovation)
25*	Coal Gasification Capital (innovation)
26	Scrap Processing Capital (Innovation)
27*	Cryogenic Shredding Capital (Innovation)
28	Air Pollution Control Equipment Capital
29	Air Pollution by-product Recovery Equipment Capital
30	Water Pollution Control Equipment Capital
31	Water Pollution By-product Recovery Equipment Capital

* Indicates a process innovation measure.

These thirty-one inputs are aggregated using Stone price indexes. Given our normalization (i.e. for the ln $p_{sb} = 0$, because $p_{sb} = 1$), the aggregate Stone Price for input s will be equivalent to the Tornqvist approximation to a Divisia with each price multiple treated as a variation from the baseline. Labor is not distinguished in the VRC framework and does not need to be aggregated. Capital includes 19 of the disaggregated inputs. These components of capital include the inputs identified by row numbers: 13, 14, 15, 16, 17, 18, 19, 20, 21, 22, 23, 24, 25, 26, 27, 28, 29, 30, and 31. Materials includes nine primary inputs, again using the row indexes from Table 1A they are: 1, 2, 3, 6, 7, 9, 10, 11, and 12. Energy includes two inputs rows 4 and 5. Notice that capital must include pollution abatement capital to be consistent with the four input framework. Materials also include some inputs not used in any other process except one or more of the innovations (e.g. liquid nitrogen for cryogenic shredding of automobile hulks).

Table 2A identifies the types of emissions and the levels associated with the uncontrolled baseline and the levels of twenty-five and fifty percent reductions from that baseline. Table 3A summarizes the experimental design used to investigate the joint effects of factor price changes and environmental restrictions. Table 4A summarizes the six innovations and the factor inputs used and saved with each.

To estimate the index of productivity using the static substitution weights, we estimate the second order translog parameters (i.e. the γ_{ik}'s and the β_i's) using

Table 2A. Discharge levels for the VRC model with innovations

Discharges	Baseline uncontrolled	25% reduction	50% reduction
Waterborne Emissions			
Biochemical Oxygen Demand	6950.44200	5276.0993	1927.4139
OIL	6291.65592	4795.9998	1804.6887
Phenols	183.68905	137.77778	45.95524
NH3	418.32784	313.80171	104.74945
Suspended Solids	9990.63142	7650.3735	2969.8577
Sulfur	64.27970	48.212113	16.076938
Heat (measured in BTUs)	12855.86483	9641.8988	3213.9663
Atmospheric Emissions			
SO_2	29411.91421	22064.962	7371.0571
Particulates	4343.49561	3405.4416	1529.3337

Table 3A. Experimental design for solutions varying factor prices and restrictions on waterborne and atmospheric emissions

Type of solution	Factors[a]	Number of solutions
Factor price and restriction on atmospheric emissions	2, 3, 5, 6, 7, 12, 13, 14, 15, 16, 17, 18, 19, 20, 21, 24, 25, 28, 29, 30, 31	84
Factor price and restriction on waterborne emissions	2, 3, 13, 14, 18, 22, 23, 28, 29, 30, 31	44
Restrictions[b] on environmental emissions	None	4

[a] Numbers refer to the rows of Table 1A identifying factor inputs
[b] The four solutions for the environmental constraints included atmospheric emissions at low and high with waterborne unconstrained and the waterborne restricted to low and high with atmospheric unconstraints. All four held factor prices at the base levels.

Table 4A. Summary of input biases associated with six process innovations

Innovation	Inputs saved	Inputs used
Scrap Preheating	Iron Ore*	Scrap*, BOF Capital, Fuel Oil, Natural Gas, Recovered Energy
Direct Reduction	BOF and OH Capital	ARC Capital Natural Gas
Coal Gasification	Natural Gas	Non-Metallurgical Coal Capital
Cryogenic Shredding	BOF and OH Capital Iron Ore Energy (Electricity)	ARC Capital
Continuous Casting	Finishing Capital Energy	Scrap
Extended Fuel Injection	Metallurgical Coal	Fuel Oil Capital

* This prediction is not clearcut in an *ex ante* framework where steelmaking capacity using an electric arc furnace can be chosen along with BOF capacity.

three cost share equations. The translog cost function holding outputs constant is given in Eq. (A1) and the cost share for the jth input in (A2).

$$\ln C = \alpha_0 + \sum_i \beta_i \ln p_i + \frac{1}{2} \sum_i \sum_k \gamma_{ik} \ln p_i \ln p_k \tag{A1}$$

$$\frac{X_j P_j}{C} = \beta_j + \sum_k \gamma_{jk} \ln p_k \tag{A2}$$

A neoclassical cost function is homogeneous of degree one in factor prices so,

$$\sum \beta_k = 1, \qquad \sum_i \gamma_{ik} = \sum_k \gamma_{ik} = \sum_i \sum_k \gamma_{ik} = 0 \tag{A3}$$

and $\gamma_{ik} = \gamma_{ki}$ by symmetry. Table 5A reports the estimated cost shares using the static *ex ante* solutions with no innovations. These results were derived with iterated seemingly unrelated regressions subject to the symmetry restrictions. Dropping one share equation (given the shares sum to unity) and imposing one of the restrictions on the γ_{ik}'s assures the other are satisfied.

To investigate whether innovations imply large changes in factor substitutions in response to factor price changes, we estimated the same specification and tested using a Wald test (see Gallant and Jorgenson, 1979) that the two models were equivalent. As noted earlier, the nature of our data precludes the conventional statistical interpretation of the test. We used it to provide an approximate gauge of the extent to which the two models imply different patterns of input usage. The test

Table 5A. Translog cost share models: Solutions without innovations

Independent variable	Factor share equations[a]		
	Capital	Labor	Materials
Intercept (β_i)	.254	.127	.581
	(189.22)	(118.81)	(381.74)
$\ln p_k$	.202	−.024	−.171
	(19.82)	(−5.29)	(−18.34)
$\ln p_l$	−.024	.07	−.047
	(−5.29)	(16.86)	(−8.59)
$\ln p_e$	−.007	−.001	−.010
	(−1.711)	(−0.47)	(−2.73)
$\ln p_m$	−.171	−.047	.229
	(−18.34)	(−8.59)	(20.65)

[a]Numbers in parentheses are the estimated t-ratios for the null hypothesis of no association.

Table 6A. Selected Allen elasticities of substitution: Static *ex ante* solutions[c]

Capital	Labor	Energy	Materials	
Capital	—	—	—	—
Labor	.202	—	—	—
Energy	.184	.726	—	—
Materials	−.170	.318	.432	—

statistic is large enough to imply a decisive rejection of the null hypothesis that they are equivalent.

Finally, Table 6A reports estimates of the average values for selected Allen statistics of substitution from the translog model estimated with the no innovations solutions using the predicted cost shares.

Notes

1. A careful review of the evidence of the early nineties is provided in Jaffe et al. (1995). More recently, two sets of econometric analyses have used plant level data to investigate the influence of environmental regulations on costs. Morgenstern et al. (1998) found their conclusions about the extent to which total costs increase by more or less than reported pollution abatement costs depends on the treatment of plant specific effects in the costs analyses. Treating these factors as fixed effects implies lower costs (about eighteen percent less). Treating these factors as nonsystematic influences implies that costs are understated by over one hundred percent.

   The second analysis by Harrington et al. (1999) evaluates the effect of policy on the pace of diffusion of existing innovations and finds a significant but small overall impact when measured in terms of the present value of the accumulated energy savings in the accelerated diffusion path in comparison to the baseline path. The total effect is small and the analysis could not address the effects of pricing policy on enhancing the pace of development for new technologies.
2. This approach was introduced by Milliman and Price (1989) and has been used by most other authors to either develop their arguments or to illustrate the logic of a more complex structure. See Jung
   et al. (1996), Malueg (1989) and Fischer et al. (1998) as examples.
3. See Jung et al. (1986) for more specific discussion.
4. Jung et al. (1996) do acknowledge in a footnote that Malueg's analyses of standards and charges suggested they had the same effect on the level of R & D.
5. The Magat model describes production activities as a joint production process with output (Q) and effluent discharge rates (E) as the "products." Output augmentation rates are selected in response to incentives. The models compares the elasticity of transformation between Q and E as the reciprocal of the proportionate change in the marginal products of the one input in each production activity relative to a proportional change in the Q/E ratio.

   The effluent discharge rate's increase depends on the size of this elasticity compared to the share of expenditures required by effluent emissions in comparison to revenue form marketed output and the degree of returns to scale. See his Theorems 2 and 9 and pp. 20–21.
6. See Kopp and Smith (1985) for a summary of the VRC descriptions for each innovation. Their figure 1 identifies the relationship between the new processes and the activities represented in the static steel production process.

7. As an example, see Berndt and Khaled (1979) or Baltagi and Griffin (1988) for a specific discussion in the context of measuring technological change.
8. These could be considered a measure of the separability in these decisions. See Appendix A for a description of the specific inputs and aggregation practices.
9. Gray and Shadbegian (1995) have also conducted micro analyses of TFP for the paper industry using plant level data.
10. Our tests of statistical significance are best interpreted as gauges of importance of the effects. There are not stochastic influences on choices in the model. Any errors in the statistical models arise as approximation errors. For further discussion of these issues, see Kopp and Smith (1980, 1985).

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