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Abstract

We examine the relationship between environmental regulations and innovation, using data from UK manufacturing industry during 2000-2006. We estimate a dynamic model of innovation behaviour, and explicitly account for the likely endogeneity of our measure of the burden of environmental regulations (pollution abatement costs). Our results indicate that environmental R&D and investment in environmental capital are stimulated by greater pollution abatement pressures. However, we do not find a positive impact of environmental compliance costs on total R&D or total capital accumulation. New environmental innovations may therefore have a crowding out effect on other potentially more productive investments or avenues for innovation.

Keywords: Innovation, Pollution abatement expenditures, Panel data.

JEL classification: Q52, Q55, Q58.

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1 Introduction

"...we have used a variety of market-based policies...to reduce carbon emissions in the most cost-effective way, stimulating technological innovation, and harnessing entrepreneurialism."

Chancellor of the Exchequer Gordon Brown, 2005.

Policymakers often put forward the argument that environmental regulation can foster innovation. As the environmental impact of economic activity is largely determined by technology, this possible link could be crucial to the progression of society towards environmental sustainability. In fact, the seminal work of Porter (1991) and Porter and van der Linde (1995) argues that environmental regulations can spur on innovation that may even fully offset the costs of regulatory compliance, thereby improving competitiveness. Known as the Porter hypothesis, this implies that the regulation would be socially desirable, even overlooking the environmental concerns it is designed to address. Partly in response to Porter (1991) and Porter and van der Linde (1995), a large literature has developed that investigates the impact of environmental regulation on costs, profits, factor productivity and productive efficiency. However, the causal mechanism underlying such relationships, and in particular the role of innovation, remains the subject of only limited empirical scrutiny. As a result, statistical evidence demonstrating a link between environmental regulation and innovation is sparse.

In this paper, we provide evidence on the determinants of innovation activity using a panel data set that covers 25 UK manufacturing industries from 2000 to 2006. We consider both environmental innovation and total innovation expenditures, in the form of either R&D or capital investment. We capture the burden imposed upon industries by environmental regulation in the form of environmental protection expenditure. Our sample period is of particular interest because it covers a time in which the UK had a variety of market-based environmental policies in place, with environmental regulations focused on outcomes and not processes. Porter (1991) and Porter and van der Linde (1995) argue that such flexible environmental policy is necessary to encourage innovation.[3] Our data are therefore

[3] The theoretical literature has traditionally favoured the proposition that flexible regulations foster innovation to a greater extent than prescriptive regulations, which are more restrictive. For example, both Milliman and Prince (1989) and Jung et al. (1996) find that auctioned emission permits, emission taxes and grandfathered emission permits all provide greater incentives for innovation than direct controls or performance standards. However, more recently some studies challenge this consensus. Ulph (1998) and Fischer et al. (2003) find that an unambiguous ranking of policy instruments according

ideal for directly testing the relationships underpinning the Porter hypothesis. This is in contrast to previous studies of environmental compliance costs and innovation, which use environmental protection expenditure data from the US PACE survey, conducted annually between 1973 and 1994 (Jaffe and Palmer (1997); Brunnermeier and Cohen (2003)). During that period of time, Porter and van der Linde (1995) explain that US environmental regulations were often crafted in a way that deterred innovative solutions, or even rendered them impossible.

We also make an important methodological contribution to the literature by using a generalised method of moments (GMM) estimation procedure. This allows for the possibility that innovation is dynamic in nature, such that it depends upon its own past realisations. Hence our analysis is consistent with the paradigm of dynamic competitiveness emphasised by Porter and van der Linde (1995). In addition, the estimation framework explicitly accounts for the likely endogeneity of environmental costs. As we are investigating the possibility that environmental compliance costs stimulate innovation designed to lower such costs, a direct corollary is that we are estimating a simultaneously determined relationship. This is not explicitly taken into account by Jaffe and Palmer (1997) and Brunnermeier and Cohen (2003).

From the analysis we find that environmental R&D and investment in environmental capital are stimulated by greater pollution abatement pressures. We therefore find evidence of a specific component of the Porter hypothesis; industry does indeed engage in innovation-based solutions to meet the requirements of environmental regulations. However, we do not find a positive impact of environmental compliance costs on total R&D or total capital accumulation. This supports the counter-argument to the Porter hypothesis that the new environmental innovations have a crowding out effect on other (potentially more productive) investments or avenues for innovation.

The rest of this paper is organised as follows. The next section provides a brief review of the prior literature on the relationship between environmental regulation and innovation. Section 3 then describes the econometric model and our estimation procedure. Section 4 explains our approach to measuring innovation and environmental regulation. This section also provides descriptive statistics. In section 5

to their innovation-stimulating effects is not possible. Furthermore, Bauman et al. (2008) criticise previous papers (in particular Milliman and Prince (1989) and Jung et al. (1996)) that make the assumption that innovation reduces marginal abatement costs at all margins. Bauman et al. (2008) argue that this connection is non-existent in the case of production process innovations, in which case marginal abatement costs are likely to increase at some margins (and in important cases, at all margins). Bauman et al. (2008) then demonstrate that direct controls are not universally inferior to market-based instruments in providing strong incentives for production process innovations that increase marginal abatement costs.

we present, explain and discuss our results. Finally, section 6 concludes.

2 Prior literature on environmental regulations and innovation

The paradigm of dynamic competitiveness postulates that successful firms are those which have a capacity to adjust in order to favourably shift constraints. Regulatory pressures to abate pollution that raise costs might therefore encourage firms to find innovative ways to reduce their pollution emissions, in an effort to establish a long-run competitive advantage. This is classified as the 'weak' Porter hypothesis by Jaffe and Palmer (1997), following Porter and van der Linde's (1995) discussion of the environment-competitiveness relationship.[4]

A small number of empirical studies have now shed light on the 'weak' formulation of the Porter hypothesis by examining in a systematic way the relationship between the stringency of environmental regulation and innovative activity or technological diffusion. Lanjouw and Mody (1996) provide one of the first attempts. They show that across the US, Japan and Germany, in the 1970s and 1980s, environmental patents respond to abatement expenditure. Innovation in a country is also found to respond to regulation in other countries. However, Lanjouw and Mody (1996) simply focus on the correlation between environmental innovation and regulation, and do not control for other variables.

Jaffe and Palmer (1997) analyse the relationship between the stringency of environmental regulation and innovative activity by manufacturing firms using US industry-level data, from the late 1970s to early 1990s. As with Lanjouw and Mody (1996), Jaffe and Palmer (1997) use information on environmental regulatory compliance expenditures to measure stringency. However, they take a broader view of innovation in the sense that they look at aggregate R&D activity, and the total number of successful patent applications, rather than environmental innovation in particular. They consider data at the two- or three-digit SIC level, and estimate parsimonious model specifications. The results are mixed in the sense that the relationship between regulatory stringency and innovative activity depends on the measure of innovation. Environmental compliance expenditures are found to have a positive and significant effect

[4] Jaffe and Palmer (1997) also propose a 'narrow' Porter hypothesis that certain types of environmental regulation stimulate innovation. In particular, environmental regulation that focuses on outcomes i.e. the goals of the regulation, and not the processes by which to achieve these goals, will foster innovation. In addition, Jaffe and Palmer (1997) formulate a 'strong' Porter hypothesis that environmental regulation induces firms to find new products or processes that both comply with the regulation and improve performance. There is a relatively extensive empirical literature that addresses the 'stong' Porter hypothesis (e.g. Boyd and McClelland (1999), Smith and Walsh (2000), Gray and Shadbegian (2003), Murty and Kumar (2003), Piot-Lepetit and Le Moing (2007)).

on R&D expenditures when industry-specific effects are controlled for, although the magnitude of the effect is small. This result is robust to changes in the model specification. On the other hand, the effect on successful patent applications is insignificant. As Jaffe and Palmer (1997) note, however, their data on patents are only a crude measure of inventive output by that industry, in part due to the problems associated with classifying patents by industry of origin. Overall, Jaffe and Palmer (1997) conclude that to some extent their results are consistent with the 'weak' version of the Porter hypothesis.

Brunnermeier and Cohen (2003) provide panel data evidence on the determinants of environmental innovation in 146 three-digit SIC level US manufacturing industries. Over the period 1983 to 1992, it is found that increases in pollution abatement expenditure were associated with a small but statistically significant increase in the number of successful environmental patent applications granted to an industry. A 0.04% increase in patents arises per $1million of abatement expenditure. However, measures of regulatory monitoring and enforcement were found to be an insignificant determinant of environmental innovation.

Popp (2006) examines innovation and the diffusion of air pollution control equipment. Using patent data from the US, Japan and Germany, it is found overall that innovation does indeed respond to environmental regulatory pressure in the home country. The US was an early adopter of stringent SO_2 standards, and shortly afterwards this was followed by a very significant increase in the number of patents. Similar trends are observed in Japan and Germany following the implementation of stringent nitrogen oxide (NO_x) regulations. However, in contrast to Lanjouw and Mody (1996), inventors are not found to respond to foreign environmental regulations.

Arimura et al. (2007) use a unique database collected by the OECD in 2003 on environmental policy, environmental R&D expenditure, environmental performance and commercial performance in seven OECD countries. They find a positive and significant relationship between the probability of a facility investing in environmental R&D and the stringency of environmental regulations. Horbach (2008) also estimates discrete choice models of the determinants of environmental innovation using two firm-level German panel datasets. In support of the arguments made by Porter and van der Linde (1995), Horbach (2008) finds that environmental regulation, environmental management tools and general organisational changes and improvements are all significant motivations for conducting environmental innovation.

3 Econometric model

We analyse the relationship between the costs of environmental regulations and innovative activity by manufacturing firms using industry level data over time. We follow the existing literature (Jaffe and Palmer (1997); Brunnermeier and Cohen (2003)) in estimating a reduced-form regression, which takes the form:

$$Innovation_{it} = \alpha_i + \mu_t + \beta_1 Innovation_{it-1} + \beta_2 EnvironmentalCosts_{it} + \beta_n X^n_{it} + \varepsilon_{it} \tag{1}$$

where i denotes industries and t years. *Innovation* is a measure of investment in innovation and *EnvironmentalCosts* is a measure of the costs of achieving compliance with environmental regulations. We use a variety of different measures of both innovation and environmental costs. The following section discusses in detail the various alternative proxy variables used. X^n_{it} is a set of control variables, α_i is an individual (industry) effect and μ_t is a year effect. Time effects (μ_t) are included in order to control for time-dependent determinants of innovation that are common to all industries, such as changes in policy affecting overall innovation incentives. Finally, ε_{it} is a residual error term capturing all other effects.

The inclusion of industry effects implies that the identification of the parameters in equation (1) will come from across time variation within industries. This captures the response of industries to regulatory shocks, rather than unobserved time-independent industry characteristics which generate inherent differences in between-industry innovation activity. As model (1) sheds light on the overall industry response to the burden of environmental regulations, the results are particularly relevant to efforts to advance towards a clean national economy. Potential problems which may arise in modelling spillovers of investment in innovation between firms within an industry are avoided. In addition, the fact that we do not merely focus on a given industry allows us to account for inter-industry spillovers which may arise due to the close linkages associated with many different sectors in the manufacturing process. Furthermore, by considering a range of channels through which industries may attempt to evolve and develop their products and/or related processes to meet environmental objectives, some of which are novel to the literature, we aim to overcome the inherently imprecise nature of innovative activity.

Equation (1) is a dynamic model in which innovation is determined by past realisations of itself. The argument that firms/industries which exhibit greater investment in technological development are also more likely to engage in innovative practices in the future is emphasised by Baumol (2002). There are many reasons why; one idea may simply lead to another, or a new product may invite investment aimed at its improvement or the creation of superior substitutes. Baumol (2002) also discusses how firms may develop a greater understanding of the innovation process itself with the more innovation they undertake. As a result, innovation activity is likely to be persistent. In addition to overall innovation expenditure, this hypothesis might also be relevant to innovation specifically designed to reduce environmental impacts (Horbach, 2008).

We also consider extensions to the baseline regression (1). These include introducing quadratic or interaction terms where they might be motivated by previous empirical work or justified by economic theory. In particular, we allow for possible non-linearities in the response of industries to environmental costs.

3.1 Estimation methodology

We are testing the hypothesis that industries will respond to stringent environmental regulations by investing in technological improvement. In this way, industries aim to reduce their environmental costs. However, we take the approach of measuring the regulatory burden in terms of environmental costs. A corollary is that $EnvironmentalCosts$ is simultaneously determined with $Innovation$. Failure to take account of this two-way relationship will in general lead to a simultaneity bias. One solution is to use exogenous instruments for environmental costs. Unfortunately, possible exogenous instruments for $EnvironmentalCosts$ are likely to be determined by innovation expenditure, and consequently will also be correlated with the error term. We must therefore focus on estimation methods that can be used in the absence of strictly exogenous explanatory variables or instruments.

We use generalised method of moments (GMM) estimators developed for dynamic models of panel data. These models include lags of the dependent variable as covariates, and contain unobserved individual-level effects (fixed or random). A consistent GMM estimator of dynamic panel models was derived by

Arellano and Bond (1991). It involves eliminating the individual effect by first-differencing equation (1):

$$\Delta Innovation_{it} = \mu_t + \beta_1 \Delta Innovation_{it-1} + \beta_2 \Delta EnvironmentalCosts_{it} + \beta_n \Delta X_{it}^n + \Delta\varepsilon_{it} \tag{2}$$

This difference GMM estimator uses previous observations of the endogenous explanatory variable $EnvironmentalCosts$ and lagged-dependent variable as instruments.[5] It makes the assumption that the error term ε_{it} is not serially correlated and that the explanatory variables are uncorrelated with future realisations of the error term. We then use the following moment conditions in our application of the Arellano-Bond (1991) estimator:

$$E[Innovation_{it-2}(\varepsilon_{it} - \varepsilon_{it-1})] = 0 \tag{3}$$

$$E[EnvironmentalCosts_{it-2}(\varepsilon_{it} - \varepsilon_{it-1})] = 0 \tag{4}$$

for $t = 3, ..., T$.[6] In our estimations below, we have a reasonably large set of instruments available because T is 7. However, as there are only few cross-sectional units (20-25 industries), we should restrict the set of moment conditions to avoid an overfitting bias (see Roodman, 2009). Hence we use as instruments only the first appropriate previous observation of the lagged dependent variable and $EnvironmentalCosts$ variable. All other explanatory variables are treated as exogenous.

The difference estimator based on the moment conditions (3) and (4) does however have important limitations. In particular, it has been shown to have a large finite sample bias and poor precision (Alonso-Borrego and Arellano, 1999). This has been attributed to the lagged levels providing weak instruments for the first-differences when the explanatory variables are persistent over time. Arellano and Bover (1995) and Blundell and Bond (1998) show that the bias and imprecision can be overcome by building a system of two equations. This system combines the difference equation (2) using lagged levels as instruments, with the equation in levels (1) for which lagged differences of the explanatory variables are used as instruments. The additional moment conditions for the second part of the system (i.e. the regression in levels) include:

$$E[(Innovation_{it-1} - Innovation_{it-2})(\alpha_i + \varepsilon_{it})] = 0 \tag{5}$$

$$E[(EnvironmentalCosts_{it-1} - EnvironmentalCosts_{it-2})(\alpha_i + \varepsilon_{it})] = 0 \tag{6}$$

[5] The control variables in the vector X_{it}^n are exogenous and so are used to instrument themselves.

[6] We also have an additional, trivial moment condition in which the vector of control variables instruments for itself.

where recall that α_i is the individual-effect. Hence these additional moment conditions are only valid if the individual-level effects are uncorrelated with the first difference of the first observation of the dependent and endogenous variables.

We therefore aim to generate consistent and efficient parameter estimates by employing the system GMM estimator that uses the moment conditions (3), (4), (5) and (6). We perform a misspecification test for second-order serial correlation in the first-differenced error term i.e. a test of whether $\Delta\varepsilon_{it}$ is correlated with $\Delta\varepsilon_{it-2}$. Failure to reject the null hypothesis indicates that the original error term ε_{it} (in levels) is not serially correlated at order 1, thereby supporting the estimated model.[7] Evidence of second-order serial correlation in the differenced residual suggests that ε_{it} is serially correlated at order 1 (and perhaps higher orders). In this case we might consider re-specifying the model using higher order lags as instruments. We also test for the validity of the instruments using a Sargan test of overidentifying restrictions. This involves testing the null hypothesis that the overidentifying restrictions are valid by analysing the sample analogue of the moment conditions used in the estimation process. The alternative hypothesis is that at least one of the instruments is correlated with the error term ε_{it} and therefore not valid.[8]

4 Data

In order to assess the robustness of any relationship between the burden of environmental regulations and innovation, we use a variety of measures for both. In each case, we deflate the data using industry-specific price deflators to obtain real series. We now discuss these variables in more detail.

4.1 Innovation

Porter and van der Linde (1995) can be interpreted in different ways regarding the nature of the innovation they describe at the centre of the Porter hypothesis. They mention that they use the term 'innovation' broadly, to include "a product's or service's design, the segments it serves, how it is produced, how it is marketed and how it is supported" (pp. 98). We consider both innovation that is conducted in-house or by a third party. We also consider the adoption of successful innovation by others (technology

[7] We do not test for first-order serial correlation (i.e. correlation between $\Delta\varepsilon_{it}$ and $\Delta\varepsilon_{it-1}$) as it expected even if ε_{it} is serially uncorrelated.

[8] The Sargan test requires homoscedastic errors for consistency.

diffusion). We focus on input measures of innovation that have uncertain outcomes, rather than output measures. This is because the hypothesis we are investigating is that environmental regulations provide a greater incentive to invest in innovation. The innovation may or may not be successful in actually raising productivity or lowering costs.

Bearing all this in mind, we therefore use four alternative measures of innovation. The first two aim to directly measure environmental innovation. They are obtained from the Environmental Protection Expenditure survey. One is expenditure on environmental R&D ($EnvironR\&D$). This is defined as the R&D conducted by a firm specifically to reduce the environmental impact of its activities. It includes both in-house R&D and amounts paid to others, such as trade associations and consultants for R&D. The other direct measure of environmental innovation considered is integrated environmental protection capital expenditures ($EnvironCapital$). This is defined as capital expenditure on new or modified production facilities which are designed to integrate environmental protection into the production process. This might involve adapting an existing process, in which case the expenditure counted is the total cost of the adaptation. Alternatively, it might include installing an entirely new process, in which case the expenditure counted is the extra cost compared to the installation of a less environmentally friendly alternative (DEFRA, 2009, pp. 4). Considering integrated environmental protection capital expenditures recognises that purchased capital may embody R&D investments made by others. Environmental capital therefore captures a different side to environmental innovation than environmental R&D, and also fits well with some of the kinds of innovation that Porter hypothesises would take place.

The other two measures of innovation considered take a broader view of innovation, and are taken from the OECD database. These include, following Jaffe and Palmer (1997), total R&D activity ($TotalR\&D$). In addition, we investigate whether total investment in physical capital ($TotalCapital$) is determined by environmental regulations. Capital formation captures the extent to which companies integrate newer technologies into their operations, in which innovation is embodied. Again, the possibility that firms 'buy in' innovation in this way is overlooked by measures such as R&D. There are existing studies of the relationship between capital investment and environmental regulations (e.g. Nelson et al. (1993) and Gray and Shadbegian (1998)). However, these studies do not couch capital formation as a means of generating innovation offsets.

We consider broader forms of innovation, rather than only focusing on environmental innovation, for a number of reasons. In particular, even if innovation is motivated primarily by a desire to address environmental impacts, in practice this is often synonymous with creating better performing, higher quality products and/or production processes in general. Indeed, this point is emphasised by Porter and van der Linde (1995). It may therefore be that environmental regulation encourages broader forms of innovation that are not fully captured by, for instance, measuring environmental R&D expenditure. Alternatively, environmental regulation could stimulate environmental innovation at the expense of other innovative activities. This would be the case if the supply of inputs to innovation is inelastic. Consequently, the induced-innovation may create an opportunity cost that negates the effects observed in the regulated part of the economy (Jaffe et al., 2002). This opportunity cost could be large if there is an impact on successful innovation elsewhere. We cannot estimate the opportunity cost of any increase in environmental R&D expenditure, or integrated environmental protection expenditure. However, by measuring the impact of regulation on total R&D investment/capital formation we at least ensure that the dependent variable is unaffected by an increase in environmental innovation that simply crowds out R&D/capital expenditure by the industry elsewhere. In other words, greater consideration can be given to the general equilibrium effects of induced-innovation.

4.2 Environmental regulations

In the UK, formal environmental regulations are the responsibility of both the Environment Agency and local authorities. The local authorities regulate small plants whilst larger plants whose polluting output is of national significance are regulated by the Environment Agency. The traditional approach to environmental regulation in the UK is direct regulation, which operates through various environmental 'permits', including licences, consents, registrations, notices and direct application of the legislation. UK plants have to apply to either the local authority or the Environment Agency for a permit if they are to operate certain industrial processes. The regulator can either reject the application, or accept with certain conditions attached. The permits typically limit the level of air, water or land pollution that can be generated by a particular site. For instance, in the case of air pollutants, safe concentration levels should not be exceeded. This implies that regulations are often more stringent in urban areas, where background concentration levels will already be quite high. The permits are reviewed periodically to make sure they keep pace with changing circumstances. In addition to direct regulation, increasing emphasis is now placed on alternative methods of regulation. These include environmental taxes, such as the 2001 landfill tax or 2001 climate change levy and associated climate change agreements. Enhanced capital allowances have been recently introduced to encourage the take-up of innovative energy-efficient technologies. Also more common are negotiated/voluntary agreements, which achieve higher than required environmental outcomes, usually to avoid the threat of legislation or regulation. Examples include the motor industry's emission reduction targets agreed with the European Union, and the chemical industry's voluntary commitment to achieve a certain environmental target. There is also a voluntary agreement on the use of pesticides. Finally, trading schemes are growing in popularity as a means of achieving environmental objectives is trading schemes, with examples including the (voluntary) UK Emissions Trading Scheme, which ran from 2002-2006, prior to the EU Emission Trading Scheme, and the 2008 UK National Emissions Reduction Plan.[9]

Ideally, we would like to look at the relationship between innovation and the shadow price of pollution or environmental inputs (Jaffe et al. 2002). However, we do not easily observe such shadow prices. We therefore use pollution abatement expenditure data as a proxy for the shadow price of pollution, or more loosely, the burden (costs) of environmental regulation upon firms. The source of these data for the UK is the Environmental Protection Expenditure survey, which provides the best available pollution abatement cost data outside the US, in terms of industry and year coverage (Cole and Elliott, 2007).

Environmental protection expenditure is defined by the Statistical Office of the European Community as the sum of capital and current expenditure on environmental protection activities. An environmental protection activity is one whose primary objective is "to collect, treat, reduce, prevent or eliminate pollutants and pollution or any other degradation of the environment resulting from the activity of the company" (DEFRA, 2009, pp. 3). Environmental protection activities may involve "the use of equipment, labour, manufacturing techniques and practices, information networks or products" (DEFRA, 2009, pp.

[9] It is also worth noting that the UK environment agency makes use of educational programmes which help facilitate the identification of potential cost-saving improvements.

3). Environmental protection expenditure is reported gross of any cost offsets, which is important to this analysis, given that it is being used as a proxy for the stringency of environmental regulations. Such cost offsets may for instance take the form of marketable by-products, savings or subsidies/capital allowances generated by environmental protection expenditure (DEFRA, 2009, pp. 3).

Environmental protection expenditure has two components. The first component is environmental operating expenditure (*Operating*). This is defined as the in-house operating costs of a company's own environmental protection activities. It includes labour costs, leasing payments and maintenance costs for equipment. It also includes payments to others for environmental protection services including treatment and disposal of waste (DEFRA, 2009, pp. 4). The second component is 'end of pipe' pollution control expenditure ($EndOfPipe$). This expenditure is defined as expenditure on equipment used to treat, handle, measure or dispose of emissions and wastes from production (DEFRA, 2009, pp. 4). In other words, it is expenditure on equipment designed to clean up at the end of the production process. For example, this might include effluent treatment plants, exhaust air scrubbing systems and solid waste compactors.

Excluded from either environmental operating or 'end of pipe' expenditure is expenditure on environmental R&D. Also excluded are energy costs (except where it is specifically used to run the environmental protection equipment/services), and expenditure on health and safety equipment/services.

Measuring regulatory costs in terms of pollution abatement expenditure is the standard approach of a wide range of empirical environmental economics literature, which includes studies of the impact of environmental regulations on trade, foreign direct investment or competitiveness (e.g. Levinson and Taylor (2008), Keller and Levinson (2002), Cole and Elliott (2005), Morgenstern et al. (2002)). Most of these studies focus on the US. In common with this literature, we assume that the direct costs of environmental regulations are a major component of total environmental protection expenditure.[10,11]

[10] Pollution abatement expenditure, as noted by Jaffe and Palmer (1997), is not a truly exogenous measure of regulatory burden since the level of abatement expenditure also depends on the nature of an industry's response to the regulation. In addition, informal regulation from interest groups or customers, or perhaps simply a social awareness of the firm for environmental issues, may lead to overcompliance with the formal regulation in place. We do not distinguish between regulatory and overcompliance pressures in this analysis. In principle this could lead to a selection bias: voluntary abatement expenditure may be more likely to occur within firms that currently have low pollution abatement costs, and these firms may also typically have the lowest incentive to innovate in response to the environmental regulation. In this paper, however, we believe we overcome this potential problem to a large extent by exploiting the panel data to control for fixed industry effects. Hence our estimates will only be biased if industry heterogeneity in voluntary abatement expenditure is time-varying.

[11] There may be concern that pollution abatement expenditure data is measured with error. Expenditure may be systematically over-reported if firms overstate compliance costs with the aim of deterring a further tightening of existing standards.

4.3 Control variables

We include a variety of control variables which have been shown elsewhere to be important determinants of innovation. Firstly, we include industry value added ($ValueAdded$) as this is expected to be correlated with both innovation and pollution abatement expenditure. Larger industries are likely to have greater absolute levels of abatement expenditure, and are also more likely to have the resources necessary to meet the fixed costs, and bear the risks, involved with undertaking investments in innovation.

Secondly, we include (domestic) market power as a determinant of innovation ($Concentration$). We measure this as the number of enterprises in the industry with 250 or more employees, as a percentage of the total number of enterprises. Recently, Aghion et al. (2005) find strong evidence of an inverted-U relationship between product market competition and innovation. To examine whether this is appropriate in our dataset we also experiment with a concentration-squared term. Thirdly, we include the intensity of human capital ($HumanCapital$), measured as the share of value added paid to skilled workers. Firms with a greater intensity of human capital may have greater opportunities for technological advancement and therefore be more innovative.

Fourthly, industry exposure to foreign competition could affect innovation. One argument is that strong competition from abroad will give firms a greater incentive to reduce costs, thereby encouraging innovation, especially if they are competing with firms in countries with less stringent environmental regulations and lower wages. For example, Scott (1997) uses survey data from 1993 to find that foreign competition in the US manufacturing sector increases R&D investments that aim to reduce emissions of hazardous air pollutants. On the other hand we have the Schumpeterian argument (Schumpeter, 1942). Hence we include the openness of the sector to trade ($Openness$), measured as total exports and imports as a share of value added.

On the other hand, abatement expenditure could systematically under-represent true regulatory costs if, for instance, it does not capture costs such as managerial time spent dealing with environmental regulators. Empirical evidence is not conclusive on this issue (contrast for example Gray and Shadbegian (2003) with Morgenstern et al. (2001)). In any case, we do not believe that this will impact the conclusions of our analysis, as systematic over- or under- reporting of abatement costs should be captured by industry fixed effects.

4.4 Descriptive statistics

As discussed above, we use data from the Environmental Protection Expenditure survey to measure environmental costs in the form of operating and 'end of pipe' pollution abatement expenditure (*Operating* and *EndOfPipe* respectively). We also use the survey to measure environmental innovation in the form of environmental R&D (*EnvironR&D*) and integrated environmental protection (*EnvironCapital*). The survey is carried out annually by DEFRA and is publically available. It covers the period 2000-2006.[12]

As a first step to describing our data, we graph our measures of environmental costs and environmental innovation expenditure in Figure 1, and total innovation expenditure in Figure 2, at the aggregate level. Figure 1 shows that expenditure on operating costs by UK manufacturing industry fluctuated between £2-3billion over the sample period. In comparison, aggregate 'end of pipe' pollution abatement expenditure is far smaller, declining from £630million in 2000 to £270million in 2002, and then remaining around £300-400million for the rest of the sample period. *EnvironR&D* seems to follow *EndOfPipe* closely, exhibiting an initial decline in investment from 2000 to 2002 before remaining approximately constant at around £80 million, with a slight peak in 2004 of £110million. Investment in environmental capital is less closely linked to either *Operating* or *EndOfPipe*; *EnvironCapital* declines from £800million in 2000 to below £200million in 2003 and 2004, and then increases to £780million by 2006. Turning to Figure 2, we see the pattern of total R&D expenditures over time is similar to environmental R&D expenditures, remaining approximately constant between £0.9-1billion with a slight peak in 2004. Total capital expenditures are far higher, but decline from £25billion in 2000 to around £18billion from 2004 onwards.

We now consider our variables as measured at the industry level. Table 1 gives summary statistics. The variables are observed for up to 25 two-digit UK SIC (2003) industries covering the manufacturing sector, and also electricity & gas and the water supply (SIC 40 and 41). All variables are measured in real £'s apart from *Concentration*, *HumanCapital* and *Openness*, which are scaled as described above. The appendix provides more detailed information on definitions, data sources and units of measurement. Table 1 shows that with the exception of *EndOfPipe*, the within variation is smaller than the between

[12] The Environmental Protection Expenditure survey was also carried out in 2007, although with coverage limited to large companies in high environmental protection expenditure industries. As this could introduce a variety of estimation problems, we do not include the 2007 data in our sample.

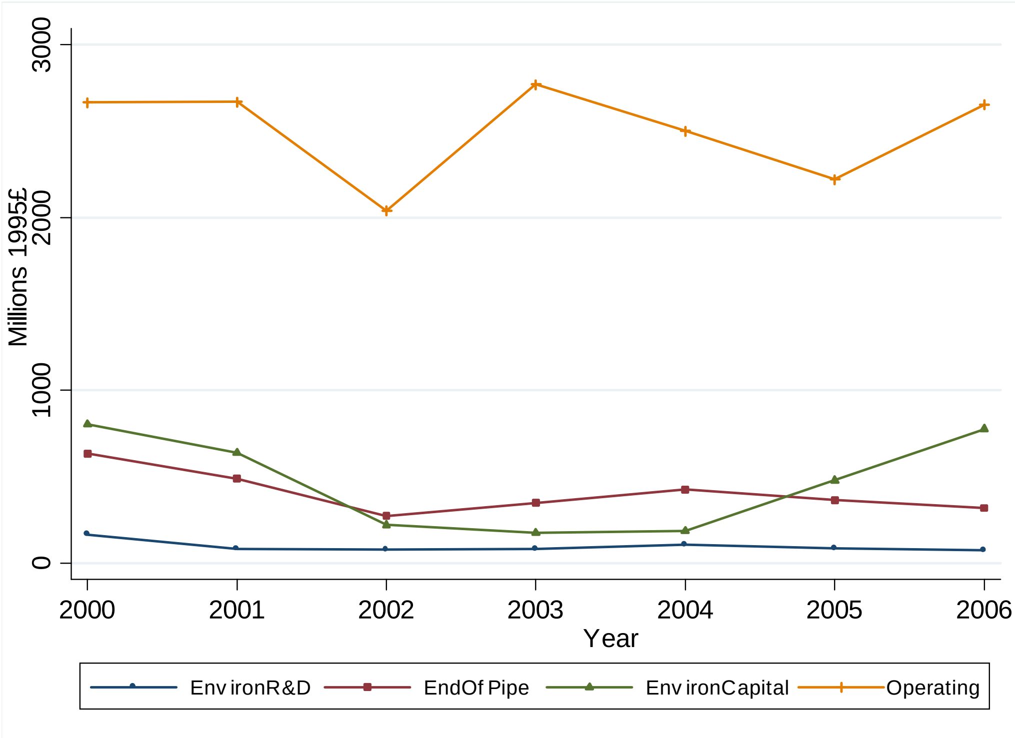

Figure 1: Aggregate pollution abatement expenditures and environmental innovation

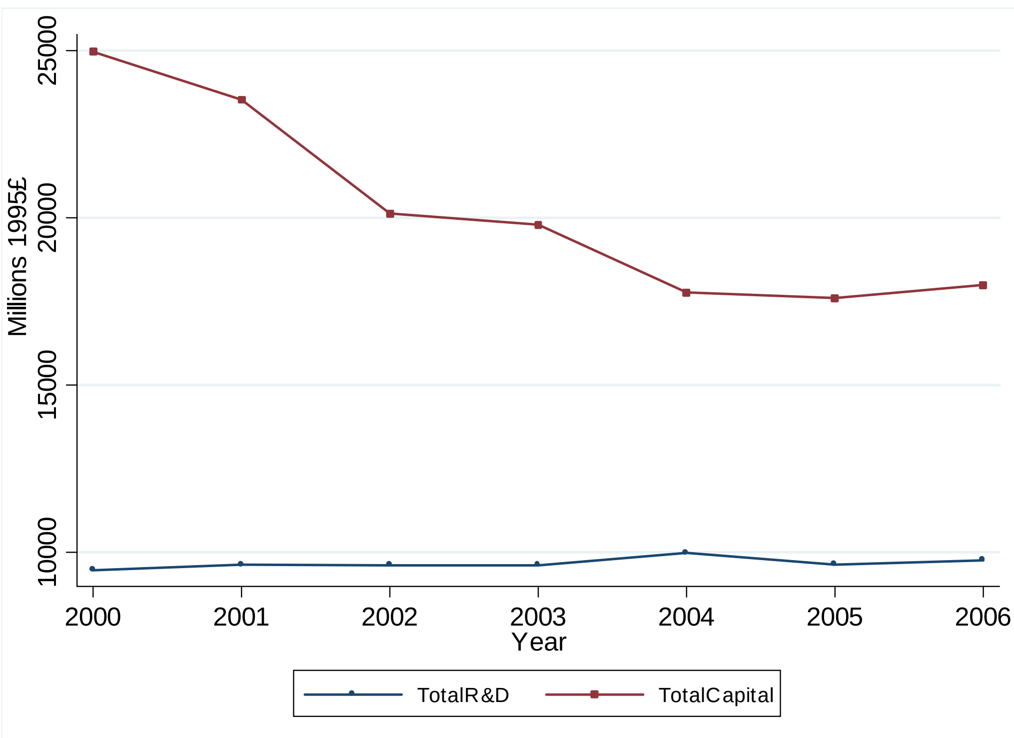

Figure 2: Aggregate pollution abatement expenditures and total innovation

variation for all variables. Sometimes this difference is substantial - for example the between variation for $TotalR\&D$ is more than ten times greater than the within variation. Fixed effects estimation may therefore lead to considerable efficiency loss, and in turn be less likely to produce statistically significant results, given that it relies on within-group variation to identify the parameters. We may also expect strongly significant individual effects.[13]

Table 2 reports environmental operating expenditure ($Operating$) and 'end of pipe' pollution control expenditure ($EndOfPipe$) as a percentage of value added, averaged over the sample period (2000-2006) for each industry.[14] For the industries with data available for 2007, we average over 2000-2007. Scaling by value added is necessary to account for the size of the industry.

It is clear that there is substantial heterogeneity in pollution abatement expenditures across industries. In terms of environmental operating expenditure, leather products faces the greatest burden, with 4.18% of value added spent on environmental operating expenditure. Coke, petroleum & nuclear fuel (3.40%), chemicals excluding pharmaceuticals (3.35%), and basic metals (3.32%) also have high operating expenditure. New technology industries such as medical & optical products and office machinery & equipment tend to have the lowest operating expenditure, at less than 0.5% of value added. For each industry, environmental 'end of pipe' capital expenditure typically represents a smaller proportion of value added than operating expenditure, with relatively little between-industry variation. Coke, petroleum & nuclear fuel has the highest environmental capital expenditure at 1.85% of value added, followed by chemicals excluding pharmaceuticals at 0.7%. Clothing, office machinery & equipment, and medical & optical products have the lowest environmental capital expenditure. To give these figures some context, they are similar to those observed for other Western economies. For example, the 2005 US PACE survey suggests that pollution abatement operating expenditure across manufacturing industries in the US is very highly correlated with the 2005 data for the UK.[15]

Table 2 also reports average innovation expenditure for our four measures of innovation ($EnvironR\&D$,

[13] Table 1 also reveals that $TotalCapital$ has a negative minimum value. This implies that additions to fixed assets were outweighed by disposals of fixed assets (i.e. assets being sold off or scrapped). Negative $TotalCapital$ was only observed once (for electrical apparatus in 2002).

[14] Note that some two-digit industries are included as rollup categories. In addition, Chemicals (SIC 24) is disaggregated into Pharmaceuticals (SIC 244) and other Chemicals industries (SIC 24X).

[15] This is demonstrated by Table 7 in the appendix. We cannot compare the UK and US data in any other year because during our sample period the US PACE Survey was only conducted once (in 2005).

Table 1: Summary statistics of variables

Variable	Observations	Mean	SD, overall	SD, between/within	Minimum	Maximum
EnvironR&D	170	4042433	9067036	1.7584	23992	7.97e+07
EnvironCapital	172	1.78e+07	4.65e+07	1.6810	13535	4.36e+08
TotalR&D	147	5.02e+08	7.77e+08	12.6675	1.11e+07	3.89e+09
TotalCapital	163	9.73e+08	1.00e+09	4.5607	-4.29e+07	4.67e+09
Operating	207	1.24e+08	1.42e+08	1.7504	2383863	8.48e+08
EndOfPipe	198	1.86e+07	3.03e+07	0.9633	21186	1.78e+08
ValueAdded	216	8.24e+09	5.69e+09	4.5492	4.13e+08	1.99e+10
Concentration	203	0.036	0.047	2.15	0.002	0.375
HumanCapital	196	0.640	0.190	5.4286	0.097	0.891
Openness	196	3.157	3.047	2.7667	0	18.994

All variables are real expenditures in £s, apart from Concentration, HumanCapital and Openness, which are scaled variables. All variables are measured at the two-digit SIC level.

Table 2: Environmental protection expenditure as a percentage of value added, averaged over 2000-2006

SIC code	Industry	Operating	EndOfPipe	EnvironR&D	EnvironCapital	TotalR&D	TotalCapital
10-14	Mining & quarrying	0.53	0.20	0.03	0.17	0.19	18.66
15-16	Food products, beverages & tobacco	1.84	0.24	0.03	0.20	1.32	10.05
17-19	Textiles& textile products					0.41	
17	Textiles	1.71	0.16	0.03	0.10		5.83
18	Clothing	0.42	0.01	0.00	0.00		3.52
19	Leather products	4.18	0.25	0.12	0.23		2.95
20-22	Wood, paper, printing, publishing					0.39	
20	Timber & wood products	1.68	0.14	0.05	0.23		7.59
21	Pulp & paper	2.87	0.21	0.04	0.14		11.95
22	Publishing & printing	0.39	0.06	0.01	0.05		9.38
23	Coke, petroleum & nuclear fuel	3.40	1.85	0.11	0.21	10.47	22.13
244	Pharmaceuticals	0.79	0.14	0.01	0.17	46.10	14.52
24X	Chemicals excluding pharmaceuticals	3.35	0.70	0.26	0.24	6.64	18.98
25	Rubber & plastics	1.52	0.20	0.04	0.32	0.82	8.58
26	Non-metallic mineral products	1.47	0.47	0.05	0.14	0.95	11.15
27	Basic metals	3.32	0.28	0.14	0.34	1.16	11.07
28	Fabricated metal products	1.09	0.10	0.02	0.08	0.62	6.60
29	Machinery	1.11	0.07	0.08	0.08	5.94	6.43
30	Office machinery & equipment	0.45	0.01	0.03	0.03	2.78	6.04
31	Electrical apparatus	0.72	0.03	0.07	0.02	8.14	6.04
32	Radio, TV & communications	0.63	0.07	0.05	0.04	22.45	10.28
33	Medical & optical products	0.38	0.01	0.01	0.03	9.35	7.62
34	Motor vehicles	1.30	0.09	0.08	0.19	9.98	20.41
35	Other transport equipment	0.62	0.03	0.01	0.04	23.41	12.24
36	Furniture	0.98	0.11	0.05	0.10	0.57	7.42
40-41	Energy, gas & water			0.29			
40	Electricity, gas, steam & hot water	2.47	0.44	0.04	1.24		29.53
41	Water supply	1.49	0.07	0.01	0.92		59.00

For SIC 10-14, 15-16, 23, 24, 40 and 41, data are available until 2007 and so averages are calculated over the period 2000-2007 Operating is environmental operating expenditure, and EndOfPipe is end of pipe capital expenditure. EnvironR&D is environmental R&D, EnvironCapital is intregrated environmental protection, TotalR&D is total R&D and TotalCapital is gross fixed capital formation. All variables are given as a percentage of gross value added.

EnvironCapital, *TotalR&D* and *TotalCapital*), each as a percentage of industry value added. *EnvironR&D* and *EnvironCapital* are only a small percentage of value added. For example, the industry most intensive in environmental R&D investment is chemicals excluding pharmaceuticals, although even this industry invests just 0.26% of its value added in environmental R&D. The vast majority of industries spend less than one-tenth of a percent of their value added on environmental R&D on average over the sample period. Spending is generally slightly higher for *EnvironCapital*, but is still only greater than 1% of value added for one industry (electricity, gas, steam & hot water).

The two broader forms of innovation, *TotalR&D* and *TotalCapital*, are as expected of much greater economic significance. In the case of pharmaceuticals, *TotalR&D* is extremely high at 46% of value added on average over the sample period. (Incidentally, this average actually disguises a marked decline in pharmaceuticals' R&D expenditure over 2000 to 2006, from 51% to 42% of value added.) In addition, *TotalR&D* is almost one quarter of value added for radio, TV & communications, and other transport equipment. It should be noted that slightly less aggregated data are available for *TotalR&D* and hence some previously two-digit industries are now included as rollup categories (i.e. SIC 17-19, 20-22 and 40-41). Thus the total number of industry categories falls to 20 for *TotalR&D*.[16] Meanwhile, Table 2 shows that water supply; electricity, gas, steam & hot water; motor vehicles; and coke, petroleum & nuclear fuel all invest more than 20% of their value added in capital.[17]

Table 3 reports the correlations between the average values of the environmental costs and innovation variables, as observed over the sample period 2000-2006. We note that environmental R&D expenditure is strongly positively correlated with environmental operating expenditure across industries (0.706), and is also quite strongly positively correlated with 'end of pipe' capital expenditure (0.489). *EnvironCapital* also has a positive and significant correlation with both measures of environmental protection expenditure across industries, although the correlation is weaker than for *EnvironR&D*. In contrast, industries with higher total R&D expenditure actually tend to have lower environmental operating and 'end of pipe' expenditure (although in the case of that latter the correlation is insignificant). The correlations

[16] If we compare these figures to average total R&D expenditure by industry in the US, we find expenditure is generally higher in the US than for the corresponding UK industry. Exceptions are coke, petroleum & nuclear fuel (3% of value added) and pharmaceuticals (30% of value added) which display substantially lower average R&D expenditure in the US.

[17] Average capital formation in US industries is, with some exceptions, quite similar to that in the UK.

Table 3: Correlations between variables averaged over 2000-2006

Innovation	Operating	EndOfPipe	EnvironR&D	EnvironCapital	TotalR&D	TotalCapital
Operating	N/A					
EndOfPipe	0.565***	N/A				
EnvironR&D	0.706***	0.489***	N/A			
EnvironCapital	0.386***	0.200***	0.161**	N/A		
TotalR&D	-0.247***	-0.028	-0.182**	-0.170*	N/A	
TotalCapital	0.163**	0.224***	-0.000	0.757***	0.077	N/A

Correlations are calculated between the average values of the variables as observed over the sample period 2000-2006, with each variable scaled by value added. Operating is environmental operating expenditure and EndOfPipe is end of pipe environmental capital expenditure. *** indicates significance at the 1% level, ** significance at the 5% level and * significance at the 10% level.

between the alternative measures of innovation tend to be quite low. In fact, the correlation is negative between $EnvironR\&D$ and $TotalR\&D$, and almost zero between $EnvironR\&D$ and $TotalCapital$, and $TotalR\&D$ and $TotalCapital$. Hence it appears as though these measures do indeed capture very different aspects of the innovation process. We may therefore expect to obtain different results in each case.

5 Empirical results

5.1 Baseline regression results

Table 4 reports the system GMM estimation results for the two measures of environmental innovation (environmental R&D and integrated environmental protection).[18] As mentioned, we use only one lag of the endogenous explanatory variables as instruments. The model is overidentified and so it is possible to use the optimal/two-step GMM estimator, which allows for more efficient estimation than the one-step. However, in finite samples the two-step estimator generates standard errors that are biased downwards, and so we correct for this using the standard errors proposed by Windmeijer (2005). These standard

[18] We focus on levels specifications as they tend to fit the data better than logarithmic specifications. We determine the specification with the higher goodness-of-fit by comparing a transformed R-squared from the logarithmic regressions with the standard R-squared from the levels regressions. If y is the dependent variable then the transformed R-squared is calculated as the squared correlation between y_i and $\widehat{y}_i = \exp(\widehat{\log y_i})$ (see Wooldridge, 2009).

errors permit heteroscedasticity in the underlying error ε_{it}.[19]

Four different specifications are estimated for environmental R&D. Specification (a) measures environmental costs in terms of pollution abatement operating expenditure (*Operating*), while specification (b) uses 'end of pipe' expenditure (*EndOfPipe*). Both (a) and (b) include only industry value added (*ValueAdded*) as a single control variable. Specifications (c) and (d) then repeat these two regressions, but with three additional control variables included (*Concentration*, *HumanCapital* and *Openness*). We also estimate the same four specifications for integrated environmental protection (specifications (e)-(h)).

The models seem to perform very strongly, with very large Wald statistics convincingly indicating that the models have overall statistical significance. The specification tests also show no signs of invalid overidentifiying restrictions, or second-order serial correlation at the 5% level. Moreover, both operating and 'end of pipe' protection expenditure are consistently found to have a positive and strongly significant effect on environmental R&D. In terms of the magnitude of the effect, environmental R&D is around twice as responsive to 'end of pipe' than operating expenditure. In particular, the models predict that a £100 increase in *Operating* would raise *EnvironR&D* by between £5-6, while a £100 increase in *EndOfPipe* would raise *EnvironR&D* by between £10-12.[20] There is also evidence to suggest that modifications to the production process, which specifically aim to reduce environmental impacts, could be stimulated by more stringent environmental regulation. In particular, *EndOfPipe* has a positive and strongly significant impact on *EnvironCapital*, shown by regressions (f) and (h). The magnitude of the effect is relatively substantial, with a £100 increase in *EndOfPipe* predicted to raise *EnvironCapital* by £31-£34.[21] However, this result is not robust to measuring regulatory compliance costs in terms of operating expenditure; *Operating* is found to be an insignificant determinant of integrated environmental protection in specifications (e) and (g). Hence this evidence suggests that expenditure on environmental capital aims to reduce the cost of cleaning up emissions and discharges, but does not aim to reduce expenditure on operating pollution abatement equipment and services.

[19] Note however that the Windmeijer (2005) standard errors do not permit any serial correlation in ε_{it} because then the estimator is inconsistent.

[20] We can alternatively express these marginal effects as beta coefficients. If *Operating* increases by 1 within-group standard deviation, then *EnvironR&D* would increase by between 0.7-0.8 within-group standard deviation units. Similarly, if *EndOfPipe* increases by 1 within-group standard deviation, then *EnvironR&D* would increase by 0.4-0.5 within-group standard deviation units.

[21] The corresponding beta coefficients tell us that if *EndOfPipe* increases by 1 within-group standard deviation, then *EnvironCapital* would increase by 0.3-0.4 within-group standard deviation units.

Table 4 also provides evidence to suggest that environmental innovation is persistent. Spending £100 more on environmental R&D in the last period is estimated to raise current expenditure by between £15-20, while spending £100 more on integrated environmental protection in the last period raises current expenditure by between £8-23. Turning to the control variables, (g) and (h) show highly concentrated industries are statistically less likely to invest in integrated environmental protection.[22] This indicates that competitive pressures may enhance the capabilities and/or incentives that firms have to reconfigure processes in order to avoid costly 'end of pipe' treatment to emissions and discharges. This possibility was anticipated by Porter and van der Linde (1995). Finally, there is surprisingly some evidence to suggest that *HumanCapital* reduces environmental innovation (specifications (c) and (h)), although this result is not statistically significant across all regressions.

We now consider the system GMM results for the impact of environmental costs on total innovation expenditure, measured in terms of total R&D expenditure or total capital formation. In both cases, we consider the same four specifications estimated previously. Table 5 reports these regression results. Again, the Wald statistics indicate that the explanatory variables are jointly very statistically significant, and there is no evidence of model misspecification. In contrast to the results in Table 4, *Operating* is estimated to have a negative impact on total R&D regressions in regressions (a) and (c). The coefficient on *EndOfPipe* is also estimated to be negative in regressions (b) and (d), although it is only significant at the 10% level at most. The increase in environmental R&D expenditure due to higher environmental costs therefore seems to be offset by decreased R&D expenditure elsewhere (and the offsetting reduction could possibly even be large enough for total R&D to fall). This result contrasts with Jaffe and Palmer's (1997) finding in the US that total R&D is stimulated by environmental costs, but supports the findings of Lanoie et al. (2007), who use a 2003 database for seven OECD countries.

Turning to the impact of environmental costs on total capital formation, the results are now somewhat mixed. Model (e) suggests that *Operating* has a strongly significant and positive impact on capital formation, but this becomes a negative impact which is insignificant when additional controls are added in model (g). Meanwhile, *EndOfPipe* has a negative impact on capital formation, although regression (h) shows that this is only weakly significant with additional controls. We therefore have a similar story

[22] The concentration-squared term is omitted as it is highly insignificant and leads to estimation difficulties.

Table 4: Two-step system GMM estimates of industry-level environmental innovation

	Environmental R&D				Integrated Environmental Protection			
Variable	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Lagged EnvironR&D	0.202	0.158	0.199	0.153				
	(9.18)***	(13.44)***	(6.44)***	(4.84)***				
Lagged EnvironCapital					0.126	0.083	0.226	0.206
					(6.39)***	(14.06)***	(8.31)***	(3.95)***
Operating	0.049		0.057		-0.015		-0.016	
	(34.18)***		(13.02)***		(-1.45)		(-0.46)	
EndOfPipe		0.096		0.117		0.335		0.305
		(15.77)***		(4.78)***		(15.12)***		(4.80)***
ValueAdded	-0.001	0.000	-0.001	0.000	0.002	0.002	0.002	0.002
	(-8.91)***	(4.80)***	(-4.16)***	(0.19)	(4.51)***	(18.55)***	(2.25)**	(4.92)***
Concentration			-6658791	-5.43e+07			-3.24e+08	-3.47e+08
			(-0.14)	(-1.35)			(-2.01)**	(-5.59)***
HumanCapital			-2.68e+07	-8042967			-2.25e+07	-2.01e+07
			(-2.60)***	(-0.62)			(-0.93)	(-2.17)**
Openness			734647	470225			1328933	1691409
			(1.14)	(0.65)			(0.97)	(1.50)
Wald test of significance	17774.54***	4013.48***	4450.49***	8538.81***	997.50***	7366.28***	1997.76***	367.75***
Instrument count	27	27	30	30	27	27	30	30
Specification tests (p-values)								
2nd order serial correlation	0.1707	0.2525	0.2268	0.2274	0.1184	0.0801	0.2108	0.0808
Sargan	0.2849	0.2414	0.4023	0.6757	0.2576	0.2237	0.5816	0.8335
Observations	138	138	132	132	137	137	131	131
R-squared	0.2259	0.1976	0.1011	0.1170	0.2949	0.3446	0.1051	0.1752

Note: Industry and year effects are included in all regressions. Z statistics are in parenthesis. R-squared defined as the squared correlation between the actual and predicted value of the dependent variable. *** indicates statistical significance at the 1% significance level, ** at the 5% level, and * at the 10% level. Sargan is a test of overidentifying restrictions. Standard errors are Windmeijer WC-robust. All variables are in levels.

Table 5: Two-step system GMM estimates of industry-level total innovation

	TotalR&D				TotalCapital			
Variable	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Lagged TotalR&D	0.959	0.956	0.881	0.948				
	(95.63)***	(78.23)***	(22.22)***	(28.79)***				
Lagged TotalCapital					1.060	0.848	0.723	0.468
					(39.46)***	(16.69)***	(6.52)***	(3.15)***
Operating	-0.186		-1.175		0.533		-0.196	
	(-2.63)***		(-2.03)**		(5.70)***		(-0.60)	
EndOfPipe		-0.850		-0.771		-1.895		-2.501
		(-1.67)*		(-0.75)		(-3.03)***		(-1.89)*
ValueAdded	0.001	0.004	-0.010	-0.005	-0.001	0.051	0.032	0.076
	(0.35)	(1.97)**	(-0.74)	(-0.42)	(-0.12)	(4.93)***	(0.98)	(3.68)***
Concentration			1.354e+09	5.140e+08			5.211e+09	4.944e+09
			(0.90)	(0.38)			(2.12)**	(1.72)*
HumanCapital			-2.262e+08	57389826.292			-8.609e+08	-1.245e+09
			(-0.76)	(0.15)			(-2.62)***	(-2.42)**
Openness			-2.042e+07	-2.191e+07			-2103117.662	31226815.052
			(-1.27)	(-1.28)			(-0.14)	(0.85)
Wald test of significance	56613.36***	25983.08***	14990.53***	46.42***	144467.58***	14970.91***	5128.90***	266.17***
Instrument count	32	32	30	30	32	32	30	30
Specification tests (p-values)								
2nd order serial correlation	0.3480	0.3133	0.4203	0.3470	0.1229	0.2145	0.1253	0.1838
Sargan	0.9905	0.9948	0.9813	0.9906	0.8584	0.7473	0.8513	0.8248
Observations	124	124	114	114	136	136	128	128
R-squared	0.9857	0.9857	0.9532	0.9832	0.9387	0.9226	0.9342	0.9135

Note: Industry and year effects are included in all regressions. Z statistics are in parenthesis. R-squared defined as the squared correlation between the actual and predicted value of the dependent variable. *** indicates statistical significance at the 1% significance level, ** at the 5% level, and * at the 10% level. Sargan is a test of overidentifying restrictions. Standard errors are Windmeijer WC-robust. All variables are in levels.

to that observed for total R&D: the increased investment in environmental capital due to higher 'end of pipe' expenditure does not remain when considering total capital expenditure. It therefore appears that there are offsetting effects due to decreased expenditure on other forms of capital, and moreover total capital expenditure may in fact fall.

A possible negative relationship between abatement requirements and total capital investment could arise if more stringent environmental regulations are applied to new sources pollution. Nelson et al. (1993) argue this is the case in the US, and find evidence that it increases the attractiveness of old capital relative to new capital, thus reducing the rate of capital turnover. The UK may be similar to the US. Indeed, the environmental regulation in the UK is such that all new firms have to reach a new plant standard, while existing plants have some time over which to reach this standard. In addition, if emissions are already particularly high in a region, economic activity from new capital investments may have to meet particularly stringent regulatory requirements in order for this to be approved. The differential nature of environmental regulations in this respect could be the reason why the positive effect of environmental compliance costs on environmental capital is offset.

Of the remaining control variables within Table 4, the results suggest a high degree of persistence, in particular in the case of total R&D. This perhaps explains the insignificance of the remaining control variables in this regression. For total capital formation the regressions show that higher industry concentration may lead to higher rates of capital accumulation, while higher human capital leads to a lower rate of physical capital accumulation. The latter finding may arise because a weaker capability for an industry to conduct its own innovation research may increase the industry's tendency to 'buy in' innovative investments made by others in the form of capital formation.

5.2 Extensions to baseline regressions

All the models considered thus far assume that the slope coefficients β in equation (1) are constant across industries. This assumption may be inappropriate. In particular, industries may be heterogeneous in their response to changes in environmental costs. We might expect that the higher the environmental costs of the industry, the greater the extent to which further increases in compliance costs generate opportunities for profitable investment in innovation. Porter and van der Linde (1995) could be interpreted as discussing this possibility: they mention how lax regulation can be dealt with using secondary treatment solutions and without innovation, but as the cost of compliance rises with the stringency of regulations, "the potential for innovation offsets may rise even faster" (pp. 100).

We examine whether or not there are non-linearities in environmental costs by introducing interaction terms between dummy variables for medium and high environmental cost sectors ($MediumCosts$ and $HighCosts$ respectively), and *Operating* or $EndOfPipe$.[23] Low environmental cost industries are therefore the reference category. We consider high environmental cost sectors as the five sectors with the highest total environmental protection expenditure (i.e. operating plus 'end of pipe' expenditure) as a percentage of value added, on average over the sample period. From Table 2, these include leather products; pulp & paper; coke, petroleum & nuclear fuel; chemicals excluding pharmaceuticals; and basic metals. Each of these sectors spent more than 3% of their value added on pollution abatement. We consider low environmental cost sectors as the five sectors with the lowest pollution abatement expenditure. These industries are clothing; publishing and printing; office machinery & equipment; medial and optical products; and other transport equipment. Each of these sectors spent less than 0.7% of their value added on environmental protection expenditure. The remaining industries are classified as having medium environmental costs.

Table 6 reports the estimation results with the interaction terms. We do not include the additional control variables as they are almost always insignificant.[24] From regressions (a) and (b), we find there is evidence to suggest that the impact of environmental compliance costs on environmental R&D differs between high, medium and low cost industries. In low compliance cost industries, both *Operating* and $EndOfPipe$ have a negative and statistically significant impact on $EnvironR\&D$. Hence firms in low cost industries actually seem to direct resources away from environmental innovation as compliance costs rise. This could be because these firms focus instead on direct abatement measures, as Porter and van der Linde (1995) suggest. Meanwhile, the coefficient on the interaction term with medium cost industries is positive, for both *Operating* and $EndOfPipe$. However, it is not quite of a sufficient magnitude for

[23] As with *Operating* and $EndOfPipe$, the interaction terms are treated as endogenous, instrumented with only the first appropriate lag.

[24] In addition, including additional control variables tends to generate estimation difficulties due to a nonsymmetric or highly singular variance matrix.

Table 6: Two-step system GMM estimates of industry-level innovation: Heterogeneity in response to environmental costs

	EnvironR&D		EnvironCapital		TotalR&D		TotalCapital	
Variable	(a)	(b)	(c)	(d)	(e)	(f)	(g)	(h)
Lagged EnvironR&D	-0.108	0.174						
	(-5.93)***	(3.50)***						
Lagged EnvironCapital			0.119	-0.013				
			(4.64)***	(-0.63)				
Lagged TotalR&D					0.953	0.969		
					(54.61)***	(34.32)***		
Lagged TotalCapital							1.008	0.866
							(16.03)***	(34.42)***
Operating	-0.057		-0.104		2.459		-5.390	
	(-2.05)**		(-0.30)		(0.88)		(-0.75)	
Operating*MediumCosts	0.053		0.075		-2.553		6.449	
	(1.90)*		(0.22)		(-1.02)		(0.84)	
Operating*HighCosts	0.136		0.103		-2.603		6.433	
	(4.76)***		(0.28)		(-0.88)		(0.93)	
EndOfPipe		-0.616		-2.314		100.593		-46.525
		(-1.74)*		(-0.58)		(5.01)***		(-1.49)
EndOfPipe*MediumCosts		0.564		2.813		-101.233		43.591
		(1.62)		(0.71)		(-5.19)***		(1.36)
EndOfPipe*HighCosts		0.694		2.311		-100.217		47.115
		(2.01)**		(0.58)		(-5.01)***		(1.51)
ValueAdded	0.000	0.001	0.001	0.001	0.003	0.008	0.009	0.050
	(6.38)***	(3.72)***	(3.20)***	(5.61)***	(0.93)	(0.91)	(1.02)	(4.94)***
Wald test of significance	45238.67***	3698.69***	3000.70***	69539.25***	41175.18***	10934.53***	1597.65***	54852.03***
Instrument count	46	47	47	47	55	54	55	55
Specification tests (p-values)								
2nd order serial correlation	0.2117	0.4488	0.1047	0.1845	0.3084	0.1993	0.1355	0.3763
Sargan	0.9999	0.9999	0.9999	1.0000	1.0000	1.0000	1.0000	0.9999
Observations	138	138	137	137	124	124	136	136
R-squared	0.3839	0.2735	0.2356	0.4018	0.9840	0.9770	0.9301	0.9247

Note: Industry and year effects are included in all regressions. Z statistics are in parenthesis. R-squared defined as the squared correlation between the actual and predicted value of the dependent variable. *** indicates statistical significance at the 1% significance level, ** at the 5% level, and * at the 10% level. Sargan is a test of overidentifying restrictions. Standard errors are Windmeijer WC-robust. All variables are in levels.

there to overall be a positive relationship between environmental R&D and compliance costs in medium cost industries. In contrast, and as expected, environmental R&D does have a positive relationship with environmental compliance costs in high cost industries. The positive coefficient on the interaction term is also found to be statistically different to the negative coefficient for low cost industries (i.e. both $Operating * HighCosts$ and $EndOfPipe * HighCosts$ are significant). The strength of the positive relationship for high cost industries must therefore drive the overall positive relationship observed in Table 4. It is also interesting to note that the models of environmental R&D with interaction terms appear to fit the data better than any of the previous baseline regressions.

However, the results observed for environmental R&D are not observed for any other measure of innovation. The interaction terms for integrated environmental protection and total capital expenditure are found to be insignificant. In the case of total R&D, the pattern of coefficient signs is the opposite to that for environmental R&D. In particular, model (f) shows the coefficient on $EndOfPipe$ is strongly positive and significant for low cost industries. Meanwhile, $EndOfPipe$ is statistically insignificant for medium and high cost industries (the interaction terms are strongly negative and significant relative to the low cost industry base category). Regression (e) shows a similar pattern in terms of the signs of the coefficients for $Operating$, although the difference between industries is no longer significant. The finding that increased environmental R&D is offset by reductions in R&D elsewhere following a rise in compliance costs, as discussed previously, therefore appears to be largely taking place in the medium and high environmental cost industries.

6 Conclusion

This paper has provided an empirical investigation of the hypothesis that environmental regulations stimulate investment in innovation. We find that dynamic panel estimators - which allow current innovation expenditure to depend on its previous values, and explicitly address possible endogeneity - are able to identify statistically significant relationships. In particular, they provide generally robust evidence that environmental compliance costs stimulate environmental R&D, and also encourage industries to adapt their production facilities in order to integrate environmental protection into the production process. However, we do not find a positive impact of environmental compliance costs on total R&D or total capital investment. Hence any increased environmental innovation is possibly being offset by lower innovation expenditure elsewhere. We also identify that the relationship between environmental R&D and environmental compliance costs is heterogeneous across industries; in fact it is only positive for high environmental cost ('dirty') industries.

The analysis suggests that although environmental regulations may stimulate environmental innovation, this is only achieved by diverting resources away from alternative investments in innovation. Hence the assertion by Porter (1991) and Porter and van der Linde (1995) that firms themselves benefit from properly crafted environmental regulation can only be justified if the new environmental innovations are more productive than the innovations the firm would have made otherwise. Porter and van der Linde (1995) argue this may be the case, given that their case study evidence demonstrates that environmental innovations can exhibit high returns. The obvious next step to the analysis would be to explore this issue further, and attempt to determine whether the increased environmental innovation comes at the expense of industry profitability.

In this analysis we have used the Environmental Protection Expenditure survey dataset, which is the best available dataset outside the US in terms of industry and year coverage. Nonetheless, it has limitations that should be taken into account. For instance, DEFRA cautions that the survey data are subject to large confidence intervals due to relatively low response rates. Furthermore, in this analysis, the manufacturing sector is divided into just 25 industry categories, which is a very high level of aggregation. We also only have 7 years of data. Unfortunately the Environmental Protection Expenditure survey has from 2007 onwards reduced somewhat in size and scope and so economists will have to turn to other datasets to solve these issues. In particular, it would be interesting to conduct a similar study for the UK using a firm level dataset.

Appendix

Dependent variables

EnvironR&D: Real expenditure on R&D to reduce the environmental impacts of economic activity. This includes in-house R&D and amounts paid to others, such as trade associations and consultants for R&D. Source: Environmental Protection Expenditure survey.

EnvironCapital: Real capital expenditure on integrated processes designed to integrate environmental protection into the production process. This might include adaptation of an existing installation/process whereby the integrated expenditure is then the total purchase cost of the adaptation. It also includes installing a new process in which the design takes environmental protection into account. In this case the expenditure counted is only the extra cost compared with installing a less environmental friendly alternative. Examples include installations for the reuse of water and waste gas. Source: Environmental Protection Expenditure survey.

TotalR&D: Real total R&D expenditure. Source: OECD.

TotalCapital: Real gross fixed capital formation. These capital expenditures exclude the *EndOfPipe* capital expenditures. Source: OECD.

Explanatory variables

Operating: Real pollution abatement operating expenditure. Includes in-house expenditure associated with the operation of pollution control abatement equipment and services, and also payments to external organisations for environmental protection services (including waste disposal and sewage treatment). Source: Environmental Protection Expenditure survey.

EndOfPipe: Real expenditure on 'end of pipe' pollution control equipment. This is equipment used to treat, handle, measure or dispose of emissions and wastes from production. Examples include effluent treatment plants, exhaust air scrubbing systems and solid waste compactors. Source: Environmental Protection Expenditure survey.

ValueAdded: Real value added. Source: OECD.

Concentration: The total number of enterprises in the industry with 250 or more employees, divided by the total number of enterprises in the industry. Source: OECD.

HumanCapital: The share of value added paid to skilled workers: (Employee Compensation/valueadded)-((Minimum wage*NumberEmployees)/valueadded). Source: OECD.

Openness: Total exports and imports as a share of value added: (Exports + Imports)/valueadded. Source: OECD.

Table 7: UK and US pollution abatement operating costs (PAOCs) as % of value added by industry, 2005

Industry	SIC code	UK PAOCs	NAICS code	US PAOCs
Food products, beverages & tobacco	15 & 16	1.5701	311 & 312	1.1623
Textiles	17	1.8160	314	0.9245
Clothing	18	1.0665	315	N/A
Leather products	19	3.7736	316	2.8905
Timber & wood products	20	1.5793	321	1.4741
Pulp & paper	21	3.3926	322	3.5749
Publishing & printing	22	0.3628	323	0.1259
Coke, petroleum & nuclear fuel	23	3.0684	324	5.2834
Pharmaceuticals	244	1.0835	3254	0.5635
Chemicals excluding pharmaceuticals	24X	3.2015	325X	3.8271
Rubber & plastics	25	1.8881	326	0.7504
Non-metallic mineral products	26	1.2613	327	1.3128
Basic metals	27	1.8956	331	4.0657
Fabricated metal products	28	0.8640	332	0.6169
Machinery	29	0.7305	333	0.2829
Office machinery &equipment	30	0.6569		
Electrical apparatus	31	0.5518		
			334 & 335	0.4525
Radio, TV & communications	32	0.5152		
Medical & optical products	33	0.1657		
Motor vehicles	34	0.9073		
			336	0.7378
Other transport equipment	35	0.7318		
Furniture	36	1.0760	337	0.1338
Correlation coefficient between UK and US PAOCs				0.825
Spearman's rank correlation coefficient between UK and US PAOCs				0.870

Note: US PAOCs for clothing (NAICS 315) is omitted due to missing data. NAICS 334 and 335 cover SIC 30, 31, 32 and 33, and NAICS 336 covers SIC 34 and 35. In calculating the correlation coefficient we use total PAOCs as a percentage of total value added for these combined SIC categories.

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