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Environmental Policy Design, Innovation And Efficiency Gains In Electricity Generation

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ENVIRONMENTAL POLICY DESIGN, INNOVATION AND EFFICIENCY GAINS IN ELECTRICITY GENERATION - ENVIRONMENT WORKING PAPER No. 104

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TABLE OF CONTENTS

Tables

Figures

ABSTRACT

This paper explores the relationship between environmental regulation, innovation, and competitiveness, drawing upon a unique dataset on environmental regulations directed at combustion plants, a global dataset of power plants, and a global dataset of 'environmental' patents. The analysis is conducted in two stages. First, a nonparametric frontier analysis is implemented to estimate efficiency scores, including a measure of technological innovation based on patent stocks. Second, econometric methods are applied to analyse the role of policy stringency and policy design on efficiency. Our estimation sample covers thermal power plant sectors in 20 countries from 1990 to 2009. The results show that the stringency of environmental regulations is a significant determinant of productive efficiency with respect to pollutant emissions as well as fuel use. However, these effects turn negative once the level of stringency leaps over a certain threshold. In addition, the paper concludes that the positive effect of regulatory stringency can be diminished by a negative effect of regulatory differentiation with measures which are differentiated across plant size and age having negative consequences, and these effects are increasing over time. This finding is important given the prevalence of size- and vintage-differentiated policies in many countries. Finally, it is found that integrated approaches to environmental innovation are more likely to bring about efficiency improvements than end-of-pipe technologies.

JEL Classification: O33, Q48, Q55

Keywords: policy design, regulatory differentiation, productive efficiency, directional distance function, environmental innovation

RÉSUMÉ

Cet article étudie les relations entre réglementation environnementale, innovation et efficacité, en s'appuyant sur un ensemble de données mondiales sur les inventions « environnementales » brevetées et sur les centrales électriques, ainsi que sur un jeu unique de données sur la réglementation environnementale applicable aux installations de combustion. Cette étude comporte deux étapes. Dans un premier temps, des scores d'efficience sont estimés à l'aide d'une analyse non-paramétrique de la frontière efficiente de production, en utilisant notamment des indicateurs d'innovation comme les stocks de brevets. Ensuite, l'impact des politiques environnementales sur ces scores d'efficience est analysé économétriquement. Notre analyse couvre le secteur des centrales thermiques dans 20 pays entre 1990 et 2009. Les résultats montrent que des politiques environnementales contraignantes ont un effet positif sur l'efficacité de la production tant concernant l'émission de polluants que la consommation de carburant. Néanmoins, cet effet devient négatif lorsque la contrainte réglementaire dépasse un certain seuil. Par ailleurs, l'effet positif d'une réglementation contraignante peut être atténué lorsque celle-ci est différentiée en fonction de l'âge ou de la taille de la centrale. Les conséquences négatives d'une telle différentiation se font alors souvent sentir à long terme. Compte tenu de la prédominance d'une telle approche dans de nombreux pays, ce constat invite à une refonte des politiques environnementales en matière de limitation des émissions polluantes. Enfin, il est également constaté que des innovations environnementales intégrées (modifiant l'ensemble de la chaine de production) ont un impact plus important sur l'efficacité de la production que les innovations de fin de processus.

Classification JEL : O33, Q48, Q55

Mots clés : élaboration des politiques, différentiation de la réglementation, efficience productive, fonction de distance directionnelle, innovation environnementale

FOREWORD

This paper has been authored by Nick Johnstone (OECD Directorate for Science, Technology and Innovation), Shunsuke Managi (Kyushu University, Japan), Miguel Cárdenas Rodríguez (OECD Environment Directorate), Ivan Haščič (OECD Environment Directorate), Hidemichi Fujii (Nagasaki University, Japan), and Martin Souchier (OECD Environment Directorate; Ecole Polytechnique, France; SciencesPo, Paris, France).

The paper was reviewed by the Environmental Policy Committee and its Working Party on Integration of Environmental and Economic Policies, and benefited from the comments received.

EXECUTIVE SUMMARY

Discovering new ways to decouple economic growth from environmental impacts is a major challenge. However, it is a widely held belief, among economists and regulators, that environmental regulation impairs economic growth. There is no need to look further than the difficulties international negotiations to limit greenhouse gas emissions have encountered to see the implications of this belief in practical policy terms. However, there is little question that in the long-run unconstrained emissions of greenhouse gases will have important implications for economic growth prospects.

As such, it is important to recast the debate in terms of the efficient realisation of the joint objectives of production of economic outputs and mitigation of adverse environmental outcomes. This is largely a function of policy design, rather than the stringency of the policy regime. As they say, the "devil is in the details". Indeed, depending on their design, environmental regulations can potentially result in increased long term efficiency in the joint production of market and non-market products.

That is, if there is a decrease in productive efficiency of market outputs, it may be compensated for by increased productivity in the mitigation of non-market, environmental outputs. This implies that when firms are faced with environmental regulations, they might develop innovative means of dealing with them, thereby shifting out the multi-product production frontier. The specific objective of this research is to clarify the determinant factors to improve productive efficiency as well as mitigation efficiency with respect to air pollutants (SO_X and NO_X).

This paper explores the relationship between environmental regulation, innovation, and competitiveness, drawing upon a global dataset of power plants and a unique dataset developed specifically for this project on environmental regulations directed at combustion. In order to better understand the relationship between policy design and economic outcomes the analysis applies a wider set of policy variables, which reflect not just stringency, but also fuel composition, plant size and plant vintage.

The paper also draws upon a dataset of patented ‘environmental’ inventions which distinguishes between different abatement strategies. This allows for an analysis of the effects of different types of innovation on productive and mitigation efficiency. In particular, the study distinguishes between the effect of end-of-pipe abatement and more integrated strategies on productive efficiency.

More specifically, using data on emissions, plant characteristics, patent stocks and policy characteristics we have explored how innovation and policy design characteristics affect the efficiency of the production of goods (i.e. electricity) and bads (i.e. pollutants). We proceed in two stages: a) first, a nonparametric frontier analysis is implemented using data envelopment analysis (DEA) to generate measures of efficiency ("scores"); and, b) second, use the results of an econometric model to analyse the role of policy design on efficiency scores.

The results indicate that while more stringent emission standards encourage firms to search for efficiency improvements, these effects differ over time. Whereas policy stringency in emission standards has a small impact in the short term, the effect is strongly significant 5 and even 10 years after the regulation has been adopted. However, the impact will be diminished if the levels of regulatory stringency leap over a certain threshold. Beyond a certain level of environmental policy stringency, efficiency gains in terms of the joint production of abatement and the marketed output turn negative.

In a related vein, we find evidence that the nature of technological innovation plays a role, with integrated approaches more likely to bring about efficiency improvements than end-of-pipe innovations. This is important insofar as such innovations have the potential to decrease the cost of emissions abatement over the longer run by encouraging firms to "mainstream" their efforts to achieve environmental objectives, seeing production of their primary outputs and abatement as joint decisions.

Moreover, the results show that if the standards are implemented in a differentiated manner there can be significant adverse implications in terms of productive efficiency. When regulators discriminate across plant types in setting polluting standards, this tends to lead to greater inefficiencies in the longer run. For example, vintage-bases regulations, which might be appealing politically insofar as incumbents are likely to apply pressure for less stringent regulation, show increasingly strong adverse implications over time in terms of productive efficiency.

Similarly, discrimination based on plant size, which may arise because operators of large plants are likely to exercise greater political influence, also shows greater negative impact on efficiency over the longer run. Regulatory differentiation can thus generate inefficiencies by inducing a sub-optimal investment over time in cleaner generation capacities.

And finally, there is some differentiation across pollutants. While reductions in SO_X emissions can be achieved more efficiently through increases in coal prices (which are likely to encourage substitution for cleaner, low-sulphur fuels) reductions in NO_X emission have been achieved more efficiently if they focused on improving the technology rather the type of fuel used.

SYNTHÈSE

Découpler la croissance économique des impacts environnementaux constitue un défi majeur. Or l'idée que la réglementation environnementale freine la croissance économique est largement répandue chez les économistes et au sein des autorités de réglementation : il suffit de constater les difficultés rencontrées par les négociations internationales visant à limiter les émissions de gaz à effet de serre pour en mesurer les conséquences. Pour autant, il ne fait guère de doute que, sur long terme, la non-limitation des émissions de gaz à effet de serre aurait d'importantes répercussions sur les perspectives de croissance économique.

Par conséquent, il est important de repenser le débat sous l'angle de la réalisation efficiente des objectifs conjugués de production et d'atténuation des effets préjudiciables à l'environnement. Cet article y contribue en développant une mesure de l'efficience de la production lorsque les émissions de polluants sont prises en compte et en analysant l'impact de différents facteurs sur cette efficience de production. Nous analysons notamment l'impact de différentes catégories d'innovations technologiques et l'impact de la régulation environnementale en soulignant les différentes approches prises par les États.

Selon leur conception, les réglementations environnementales pourraient accroître l'efficience à long terme de la production de produits marchands et de déchets environnementaux. Cela signifie qu'une diminution de la production de produits marchands pourrait être compensée par une efficacité accrue concernant les émissions de polluants. En effet, lorsque les entreprises sont soumises à une réglementation environnementale plus contraignante, elles peuvent développer des moyens innovants pour y faire face et ainsi compenser la baisse de la production par une baisse des émissions.

Pour analyser ces relations entre réglementation environnementale, innovation et efficacité, nous utilisons un ensemble de données mondiales sur les inventions « environnementales » brevetées et sur les centrales électriques, ainsi qu'un jeu unique de données sur la réglementation environnementale applicable aux installations de combustion. Plus précisément, l'objectif de cet article est de mieux comprendre l'impact de différents facteurs sur l'efficience de la production lorsque les émissions de polluants atmosphériques (SO_X et NO_X) sont prises en compte.

L'analyse met en application un vaste ensemble de variables de politiques publiques qui reflètent non seulement la contrainte réglementaire, mais aussi la répartition par combustible, les caractéristiques des polluants, la puissance et l'âge des centrales. En outre, la présente étude utilise des données sur les brevets de technologies de réduction de la pollution atmosphérique pour comprendre l'effet des différents types d'innovations sur l'efficience de la production. En particulier, l'étude compare l'effet des technologies post-combustion de dénitrification/désulfuration des fumées, à celle des technologies intégrées visant l'amélioration de l'efficience de la production dans son ensemble.

Pour analyser l'impact de différents facteurs sur l'efficience de la production d'extrants désirables et indésirables, nous procédons en deux étapes : a) dans un premier temps, des scores d'efficience sont estimés à l'aide d'une analyse non-paramétrique de la frontière efficiente de production, en utilisant notamment des indicateurs d'innovation comme les stocks de brevets; et b) ensuite, l'impact des politiques environnementales sur ces scores d'efficience est analysé économétriquement.

Nos résultats suggèrent qu'un plafonnement des émissions plus contraignant incite les entreprises à rechercher des gains d'efficacité dans la production et que cet effet augmente avec le temps. En effet, l'effet de telles politiques environnementales est faible à court terme, mais augmente après 5 ans et encore davantage après 10 ans. En revanche, l'impact positif de ces politiques diminue lorsque les limites d'émissions dépassent un certain seuil. En effet, à partir d'une certaine limite, une augmentation de la contrainte règlementaire semble susciter une diminution de l'efficience productive et environnementale de la firme.

La nature des innovations technologiques joue également un rôle important dans l'efficacité productive : les innovations intégrées semblent plus susceptibles de générer des gains d'efficacité que les innovations de fin de processus (post-combustion). Dans la mesure où les innovations intégrées peuvent aussi générer des gains de productivité concernant les produits marchands, ces résultats suggèrent qu'il est possible pour la firme d'améliorer conjointement l'efficacité de production de biens marchands et le rejet d'émissions polluantes en investissant dans ce type de technologies.

Par ailleurs, les résultats montrent que la différentiation des politiques environnementales selon les caractéristiques de la firme est susceptible de nuire à l'efficience de la production et des émissions. De plus, les effets négatifs d'une telle différentiation se font davantage sentir à long terme. Par exemple, les résultats montrent que la différenciation selon l'âge de la centrale thermique induit une baisse de l'efficience de production qui est croissante avec le temps. De façon similaire, différencier selon la taille de la centrale peut conduire à un sous-investissement à moyen terme dans des moyens de production plus efficaces.

Enfin, les résultats présentent des différences notables selon les polluants considérés. Ainsi, une augmentation du prix du charbon semble entrainer une réduction des émissions de SOx (en incitant les firmes à utiliser un charbon de meilleure qualité par exemple) alors que les émissions de NOx semblent davantage liées à l'amélioration de la technologie qu'aux variations du prix du charbon.

1. INTRODUCTION

Discovering new ways to decouple economic growth from environmental impacts is a major challenge. However, there is a widely-held belief among economists and policy makers, that environmental regulation impairs economic growth. While Porter and others have argued that environmental policy can have positive implications for productivity (e.g., Porter and van der Linde 1995) there is no need to look further than the difficulties international negotiations to limit greenhouse gas emissions have encountered to witness the implications of the perception of this impediment in practical policy terms.

While there has been considerable controversy about the conceptual validity and empirical evidence of the Porter Hypothesis (see Ambec et al., 2013), there is no question that it is important to recast the debate in terms of the effect of policy on the efficient realisation of the joint objectives of production of economic outputs and mitigation of adverse environmental outcomes. The two outcomes (economic and environmental) need to be analysed within the same framework.

Considering the importance of the role of power plants in economic, technological and environmental terms, this paper explores the relationship between environmental regulation, innovation, and competitiveness for power plants drawing upon data on power plant characteristics, and a unique dataset developed specifically for this project on the design of environmental regulations directed at combustion plants, as well as supplementary data sources (i.e. data on patent applications which allows for the distinction between innovation in end-of-pipe abatement and integrated strategies).

The literature that has analysed the relationship between environmental regulation, innovation and competiveness has produced widely divergent findings on many key points (for a recent overview see Ambec et al., 2013 and OECD, 2010). For example, while most studies find that environmental regulation generally spurs innovation, there is significant disagreement over the strength of this signal as reflected in terms of policy design characteristics and the nature of the resulting innovation (Hascic et al., 2010; Haščič and Johnstone, 2011).

The greatest conflict surrounds how environmental regulation affects competitiveness, normally measured through productivity (Managi et al., 2005). To summarise, most of the early studies concluded that it negatively affected productivity – often significantly (Palmer et al., 1995). More recent research has produced more mixed results. A growing number of studies find that environmental rules can have a positive effect on productivity if they are designed efficiently (Berman and Bui, 2001; Lanoie et al., 2008).

It is important to understand why these various studies have reached divergent conclusions. To what extent is this due to methodological differences (e.g. how productivity or regulatory stringency are measured)? To what extent do these differences arise from the characteristics of the firm (e.g. the sector, or degree of competitiveness). The main focus of this paper is to better understand how differences in policy design can affect the relationship between policy incentives and productivity, and the role that different abatement strategies can play. While this study focuses on energy generation, specifically coal power plants, the lessons are of wider relevance.

Depending on their design, environmental regulations can potentially result in increased long term efficiency in the joint production of market goods (e.g. electricity and heat) and non-market products (e.g. SOx and NOx). That is, if there is a decrease in productive efficiency of market outputs, it may be compensated for by increased productivity in the mitigation of non-market environmental outputs. This implies that when firms are faced with environmental regulations, they might develop innovative means of dealing with them, thereby shifting out the multi-product production frontier.[1]

This paper seeks to investigate the relationship between regulation, innovation and productivity when both desirable and undesirable inputs and outputs are considered. The analysis is undertaken by combining nonparametric production frontier analysis with a subsequent econometric analysis.

The contributions of this paper are manifold. First, we measure efficiency and productivity by accounting not only for inputs and (desirable) outputs from production, but also the undesirable outputs (pollution). Several studies have applied nonparametric production frontier methods to evaluate cross-country performance and time-series productivity growth while accounting for carbon dioxide (CO_2) and other emissions (e.g., Färe et al. (2004); Managi et al. (2004), Kumar and Managi (2010), Managi (2011)). However, few studies gauge performance in terms of increased good outputs and decreased bad outputs and inputs simultaneously. We do so in this paper and in addition, we account for the role of innovation as an input in production, this is done with a measure of innovation that represents a significant improvement upon previous approaches, and is based on a state-of-the-art measure of patent stocks.

The second contribution of the paper is to seek to explain the efficiency scores using econometric techniques, with a specific focus on the effect of environmental policy choice and design. We investigate the effect of different policies in the measures of efficiency. Moreover, we investigate the role of policy stringency, and the effect that policy measures which are differentiated according to factors such as plant vintage and size have on productive efficiency.

The third contribution of the paper is to take into account the technological characteristics of production and abatement, treating capital stocks in an differentiated manner, and in particular the extent to which they reflect end-of-pipe abatement or more integrated strategies to mitigate emissions.

The methodological approach of this paper proceeds in two steps. First, we estimate productive efficiency in terms of both goods (electricity) and bads (pollutants) taking into account measures of environmental innovation. Second, we then try to explain these differences in efficiency scores with i) a set of policy variables, ii) a novel approach to measuring the role of policy stringency and policy differentiation, as well as iii) the characteristics of technological means of abatement undertaken.

The results indicate that while more stringent emission standards encourage firms to search for efficiency improvements, these effects differ over time. Whereas policy stringency in emission standards has a negligible effect in the short term, the effect is strongly significant 5 and even 10 years after the regulation has been adopted. However, as the level of regulatory stringency increases the impact will be diminished, and, beyond a certain 'threshold' level of environmental policy stringency, efficiency gains in terms of the joint production of abatement and the marketed output turn negative.

Additionally, we find evidence that the nature of technological innovation plays a role, with integrated approaches more likely to bring about efficiency improvements than end-of-pipe innovations. This is important insofar as these innovations have the potential to decrease the cost of emissions abatement over the longer run by encouraging firms to "mainstream" their efforts to achieve environmental objectives, seeing production of their primary outputs and abatement as joint decisions.

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[1] See Managi et al. (2005) for application of production framework on testing the Porter Hypothesis.

The results show that if the standards are implemented in a differentiated manner there can be significant adverse implications in terms of productive efficiency. When regulators discriminate across plant types in setting polluting standards, this tends to lead to greater inefficiencies in the longer run. For example, vintage-bases regulations, which might be appealing politically insofar as incumbents are likely to apply pressure for less stringent regulation, show increasingly strong adverse implications over time in terms of productive efficiency. Similarly, discrimination based on plant size, which may arise because operators of large plants are likely to exercise greater political influence, also shows greater negative impact on efficiency over the longer run. Regulatory differentiation can thus generate inefficiencies by inducing a sub-optimal investment over time in cleaner generation capacities.

And finally, we find that there are some differences across pollutants. For example, while reductions in SO_X emissions can be achieved more efficiently through increases in coal prices (changes in relative prices are likely to encourage substitution for cleaner, low-sulphur fuels) reductions in NO_X emission have been achieved more efficiently if they focused on improving the technology rather the type of fuel used.

The remainder of the paper is organised as follows: Section 2 discusses the role of policy stringency and design and possible implications for the efficiency in the joint production of goods and bads. Section 3 discusses the methodology, data, and results of the implementation of nonparametric production frontier analysis. This is followed by a discussion of the econometric analysis of the policy (and other) determinants of the efficiency scores generated in the nonparametric production frontier analysis. Our conclusions are presented in Section 4.

2. POWER PLANT EMISSIONS AND ENVIRONMENTAL REGULATIONS

The effects of air pollution on ecosystems and human health have been documented for more than a century. Environmental regulations such as emission standards seek to reduce these adverse effects. If designed efficiently, the costs of meeting such regulations and standards will be in line with the associated benefits. While there is variation across plant types, coal-fired generation emits approximately two times the level of emissions of carbon dioxide per megawatt-hour generated compared to electricity generation using natural gas. This is of great importance as coal is responsible for 40% of electricity generation worldwide.[2] In this section, the determinant factors of air pollution mitigation and emissions are discussed, taking into account the policy design, and distinguishing between types of pollutants, coal types, plant sizes and plant vintages. This analysis draws upon a unique dataset of emission regulations.

2.1 Policy instrument choice and design

A general principle of environmental economics is that cost-efficient abatement is realised through the use of measures in which marginal abatement costs are equalised across different sources. For uniformly-mixed global pollutants (such as greenhouse gas emissions) this will also result in economic efficiency if the level of stringency is optimal since marginal abatement costs from all sources will equal marginal benefits. In addition, such measures often provide stronger incentives for innovation, both because the emitter is given greater flexibility in the choice of abatement option and because there are incentives to identify abatement options across the whole range of possible outcomes. It is for this reason that carbon taxes or tradable permits are frequently advocated.

However, in the case of local and regional air pollutants (e.g. SO_X and NO_X) the marginal benefits of abatement will differ by location. In addition, there may be administrative barriers to implementing and enforcing those measures which treat sources in an undifferentiated manner. For these two reasons, policymakers may choose to introduce policies which differ according to the source of emission.

Therefore, apart for variations by year and country, emission standards are often also differentiated across other dimensions, and notably: pollutant, fuel type, plant size and plant vintage. The effect of this differentiation on innovation and thus on the efficiency of the production of goods and bads can be significant. If well-designed, such a strategy may be cost-effective in the short-run when the plant stock is fixed since they can reflect abatement costs across different plant characteristics. However, to the extent that they can influence the composition of the portfolio of plants over the medium- and long-term, such differentiation is unlikely to be efficient. Moreover, inefficiencies will also arise over time since the rate of change of technological opportunities for abatement of plants with different characteristics is likely to vary. Some of these aspects are examined in this paper. Next, we present the state and characteristics of current environmental regulations directed to coal power plants

2.2 Measuring the stringency of emission regulations

In order to investigate the role of policy stringency and design on efficiency in the electricity supply, we construct a dataset with information on emission standards to. Emission standards are formulated as

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[2] *www.iea.org/publications/freepublications/publication/KeyWorld2013.pdf*.

concentration limits (mg/m3) for air pollutants released into the environment from fuel combustion. Emission standards were collected from national databases of environmental regulations and the Emission Standards Database of the International Energy Agency's Clean Coal Centre.[3] The dataset constructed contains standards from the first regulation of air pollution setting limits for stationary sources.[4] Variables reflecting emission standards are developed across six dimensions: country, year, pollutant, fuel (coal type), plant size, and plant vintage. A variable of regulatory stringency is constructed as the inverse of the emission limit (i.e. stringency=0 in the absence of regulation).

The dataset covers 34 countries including most OECD member countries and 5 non-OECD countries.[5] First regulations setting emission standards were introduced in the early 1960s. Japan was the first country to set a national emission standard for stationary sources, with the introduction of the Smoke and Soot Regulation Law in 1962, limiting the emission of particulate matter. In the United States the 1963 Clean Air Act was the first environmental regulation of air pollution. The 1972 Environmental Action Programme was the first environmental policy adopted across the European Union. The programme set the general framework of objectives and principles for a Community-wide environmental policy. This was followed by national regulations, first introduced in Germany and France in 1974 and 1976, respectively. Since the mid-1980s national emission standards in Europe have been implemented following European Commission's Directives. Non-OECD countries covered in our database such as Brazil, India and the People's Republic of China introduced their emission standards for combustion plants in the early 1990s.

2.3 Type of pollutants

Several pollutants generated in the electricity sector are covered by regulations in different jurisdictions around the world. Across countries, the majority of regulations are aimed at limiting the emission of sulphur oxides (SO_2 and SO_3), nitrogen dioxide (NO_2), particulate matter (PM_{10} and $PM_{2.5}$) and, to a lesser extent, mercury (Hg) and carbon monoxide (CO). Emission standards of these pollutants are generally expressed in mg/m^3, although some countries set their emission limits in different units. In order to standardise these limits it was necessary to make some assumptions of the heat content of the fuel and the flue gas volume generated on its combustion. Conversion into mg/m^3 was made following the conversion factors and methodology used by IEA's Clean Coal Centre:[6] concentrations are measured at 6% of oxygen content, on a dry gas volume, at 0°C (273 K) and 101.3 kPa (1 atm). In some cases, regulations are defined using a different percentage of oxygen content (e.g. United States) and in such cases conversions were made using the law of volumes.[7] When the flue gas conditions are not known, the above conditions are assumed.

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[3] See, McConville, Alessandra, Emission Standards Handbook (Appendix: calculating and converting emission standards), International Association for Cryptologic Research (IEACR)/96, August 1997, IEA Coal Research – The Clean Coal Centre, London; Sloss (2003) Trends in Emission Standards, CCC/77, November 2003, IEA Clean Coal Centre, London.; Country specific documents (*www.iea-coal.org.uk/site/2010/database-section/emission-standards*) Extraction on 11 March 2013.

[4] Ambient quality standards are not included in this dataset.

[5] Countries covered are: Australia, Austria, Belgium, Brazil, Bulgaria, Canada, Chile, P. R. of China, Croatia, Czech Republic, Denmark, Estonia, Finland, France, Germany, Greece, Hungary, Iceland, India, Ireland, Israel, Italy, Japan, Luxembourg, Mexico, Netherlands, New Zealand, Norway, Poland, Portugal, Slovak Republic, Sweden, the United Kingdom and the United States.

[6] See Appendix: calculating and converting emission standards. Emission Standards Handbook, IEACR/96, August 1997, IEA Coal Research – The Clean Coal Centre, London.

[7] The volume of a given mass of an ideal gas is directly proportional to its temperature on the absolute temperature scale (in Kelvins) if pressure and the amount of gas remain constant; that is, the volume of the gas increases or decreases by the same factor as its temperature. (Fullick, Patrick. Physics. Oxford: Heinemann Educational, 1994. Print)

2.4 Coal types

Coal is created as geological processes apply pressure to dead biotic material. Under some conditions it can be transformed into peat, lignite, sub-bituminous coal, bituminous coal, anthracite, and graphite. For our study, we followed the U.S. Classification[8] of coal types and grouped lignite and sub-bituminous coal into “soft coal”, and bituminous coal and anthracite into “hard coal”. Emission standards were averaged in cases of regulations setting different limits for more specific types of coal.

The use of different coal types in the combustion process will have very different implications for emissions. If emission regulations could be targeted on different pollutants directly then it would be possible to apply policies which equated marginal benefits and costs of abatement. However, this is not possible for reasons of administrative cost. It is for this reason that in many cases such standards are differentiated according to the coal types used in combustion. Our data shows that, overall, fuel differentiation remains rather infrequent, and when it occurs NO_X standards tend to be somewhat tighter for soft coal, while SO_X standards are sometimes slightly tighter for hard coal.

2.5 Plant size

In addition, regulations often set different concentration limits according to the size of the plant, which is expressed in megawatts of thermal input (MWth). To capture such differences and make them comparable across countries we have taken four different representative plant sizes (vignettes): 15MWth, 60MWth, 240MWth and 600MWth. Where plant size was originally expressed in other units, they have been converted[9] to MWth.

To give a clearer picture of the vignettes chosen, note that the five representative power plants chosen correspond respectively to the 10th, 28th, 58th and 75th percentile of coal power plants in UDI’s World Electric Power Plant Database (WEPP). To better visualise the differences in stringency we compute ratios of regulatory stringency for large plants (600MWth) to small plants (60MWth). As can be seen in Figure 1 these variations are considerable. A ratio greater than 1 indicates that large plants face a more stringent regulation than small plants (or said differently: large plants are permitted to emit less per m^3 than small plants). This differentiation could also be understood as a “large source bias” where regulators favour smaller plants (perhaps due to concerns over competitiveness of domestic industry where the smaller plants are typically located).

This is important since, as noted above, size biases might translate into a loss of overall efficiency because they misallocate abatement efforts across sources, unless they are precisely calibrated with marginal abatement costs at different plant sizes. Moreover, even if this calibration is optimal at a point in time it may introduce dynamic inefficiency as conditions change (i.e. changes in the technological opportunities for abatement across different plant size). In effect, a sub-optimal distribution of plant sizes will be induced.

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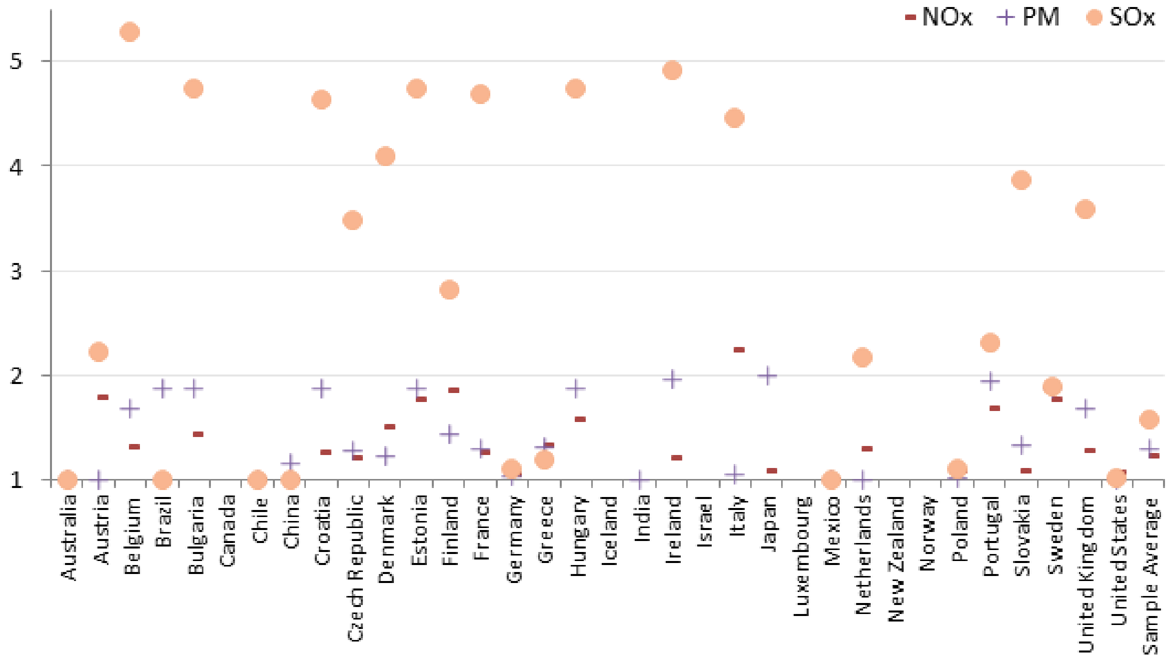
[8] ASTM D388 – 12 Standard Classification of Coals by Rank (*www.astm.org/Standards/D388.htm*, also available at *www.new.dli.ernet.in/rawdataupload/upload/insa/INSA_1/20005b80_549.pdf* page 556).

[9] Conversions from MWe to MWth are calculated on the assumption of a plant efficiency of 30%, however, note that vignettes where chosen such that a reasonable difference in plant efficiency (25%, 30% or 35%) would still fall under the “vignettes” used in the European Commission’s LCP Directive.

Figure 1. Large source bias in emission standards, by pollutant



Note: The Figure shows the ratio of stringency for large plants relative to small plants.

2.6 Plant vintage (new versus old)

It has been recognized that exempting or applying less stringent regulations for existing facilities relative to new facilities generates a bias against investment in new sources (so-called "new source bias"). In static terms this may be efficient since in capital-intensive sectors with significant sunk costs new plants can abate at relatively lower (opportunity) cost. However, over time this can reduce plant entry and exit, with implications for efficiency of the plant stock as a whole. Grandfathering regulations are well-documented in the case of power plants (see e.g., Ellerman 1998; Levinson 1999; Bushnell et al. 2007). To capture these regulatory differentials information was collected for every regulated vintage.

The specific information related to the vintage of the power plant regulated allows for a number of different ways of constructing a vintage-differentiated policy variable. Given that this paper conducts a macro-level analysis, we construct two vectors corresponding to "old" and "new" power plants. These vectors are computed as the mean emission standards that apply to power plants constructed prior (old) or posterior (new) to the effective date of the regulation. Figure 2 plots the ratio of regulatory stringency for new plants over regulatory stringency for old plants, by selected pollutants. A ratio of 1 implies no bias, while a ratio higher than 1 characterises regulations setting higher standards for new plants.[10] The Figure shows different plant sizes for different pollutants simply to illustrate that the 'new source bias' occurs with any pollutant and any plant size.

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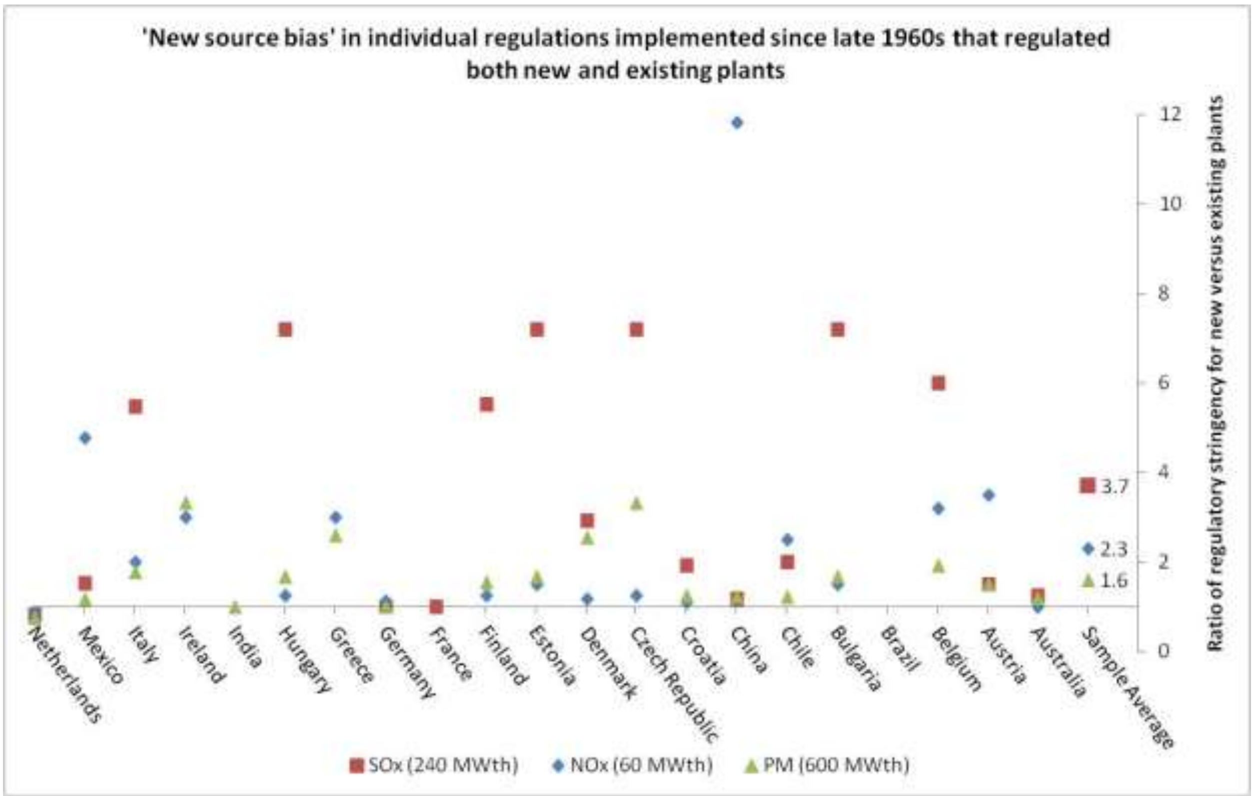
[10] The sample average (and the y-axis) can be interpreted as follows: For a representative plant of 60 MW of thermal input, new plants have, on average, 1.6 times more stringent regulations of particulate matter emissions than old plants (for the countries in the sample). For each country, the figures are the average across all the policies implemented through time. Each of the selected pollutants is plotted for a different representative plant size. The graphic shows only cases when it is possible to compare standards for old vs new plants. Excluded are cases when countries regulate only new plants (in some cases only old plants).

Figure 2. New source bias in emission standards, by pollutant



Note: The Figure shows the ratio of stringency for new plants relative to existing plants.

3. EMPIRICAL ANALYSIS

The analysis is conducted in two stages. First, a nonparametric frontier analysis is implemented to estimate efficiency scores, including a measure of technological innovation based on patent stocks. Second, econometric methods are applied to analyse the role of the stringency and design of emission regulations on efficiency.

3.1 Assessment of productive efficiency

We apply a nonparametric production function framework to estimate the efficiency of the electricity supply sector. A nonparametric production frontier approach is particularly useful for the computation of multiple input and output production correspondences. Yet, previous literature has ignored the undesirable outputs or “environmental bads”. In practice, there are cases in which both desirable (goods) and undesirable (bads) outputs are produced jointly (Fujii et al., 2010). Thus, proper analysis should consider all possible sources of inefficiency – including marketed inputs, desirable outputs, as well as the inefficiency related to undesirable outputs. To our knowledge, only Zhou et al. (2006) and Zhou et al. (2007) have extended the slacks-based model (SBM) and Russell measure to incorporate undesirable outputs. Yet, these models do not account for all inefficiency sources (e.g. they are not comprehensive with respect to undesirable outputs) or only measure the performance of undesirable outputs (Zhou et al., 2007), thus ignoring the inefficiency sources of marketed inputs and desirable outputs.

In this paper, we apply a model that comprehensively examines efficiency in light of both environmental and economic factors. Specifically, we apply a weighted Russell directional distance model (WRDDM) drawing on Chen et al. (2011) and Barros et al. (2012). In this model, countries are compared to the most efficient ones in terms of inputs used and good and bad outputs produced. The WRDDM is given as follows:

$$\vec{D}(x_k, y_k, b_k \mid g) = \beta_{overall} = Maximize \ \left\{\tfrac{1}{2}\left(\tfrac{1}{2}\beta^{k}_{NOx} + \tfrac{1}{2}\beta^{k}_{SOx}\right) + \tfrac{1}{2}\left(\beta^{k}_{coal}\right)\right\} \qquad [1]$$

subject to

$$\sum_{j=1}^{J} z_j Labour_j \leq Labour_k \qquad [2]$$

$$\sum_{j=1}^{J} z_j Capacity_j \leq Capacity_k \qquad [3]$$

$$\sum_{j=1}^{J} z_j Coal_j \leq Coal_k (1 - \beta^{k}_{Coal}) \qquad [4]$$

$$\sum_{j=1}^{J} z_j Patents_j \leq Patents_k \quad [5]$$

$$\sum_{j=1}^{J} z_j Electricity_j \geq Electricity_k \quad [6]$$

$$\sum_{j=1}^{J} z_j Heat_j \geq Heat_k \quad [7]$$

$$\sum_{j=1}^{J} z_j SOx_j = SOx_k (1-\beta_{SOx}^{k}) \quad [8]$$

$$\sum_{j=1}^{J} z_j NOx_j = NOx_k (1-\beta_{NOx}^{k}) \quad [9]$$

$$z_j \geq 0, \qquad j = 1,2,\ldots,J \quad [10]$$

where Z_j is an intensity variable to shrink or expand the individual observed activities of decision-making units for the purpose of constructing convex combinations of the observed inputs and outputs.

$\beta_{overall}$ is the overall inefficiency score. In line with the literature we include labour, produced capital (installed coal-fired capacity) and fuel (hard and soft coal) as inputs. Moreover we expand this framework by including a measure of environmental technology stock (the quality of produced capital, measured by patent stocks) as input in order to fully capture the potential environmental improvements due to technological change. On the output side, electricity and heat are included as desirable outputs, and SO_X and NO_X emissions as undesirable outputs. We follow the research framework of Jaraitė and Di Maria (2012) and calculate efficiency by setting the directional vector as follows: electricity, heat, labour, technology stock and capacity are fixed; (in)efficiency is then reflected by the reduction potential of coal input and bad outputs (SO_X, NO_X).

Concerning inputs, we use the IEA Electricity Information Statistics Database (IEA 2011) and extract data on the consumption of coal (in metric tonnes) by power plants for generation of electricity, heat, or both (i.e. combined heat and power). To construct the labour variable, we take data on labour cost from the World Input Output Database, WIOD (Marcel 2012); for countries with missing data we estimate the cost using the number of employees from OECD Labour Statistics and applying the average cost per employee from WIOD. To construct the capacity stock variable we use micro-data on the installed capacity of electric power plants (in giga-watts, GWe) taken from the World Electric Power Plant Database (see Annex A for details). To construct technology stocks we use micro-data on patent applications in the relevant abatement technologies extracted from the PATSTAT database to construct discounted stocks of patent applications by country (jurisdiction) (see Annex B for details).

Concerning desirable outputs, we use the IEA Electricity Information database (IEA 2011) to construct variables representing production of electricity and heat (e.g. used for district heating). Including both the electricity and heat output is important if efficiency is to be estimated correctly (some previous studies only included electricity output of power plants). We extract data on the generation of electricity (in gigawatt-hours, GWh) and heat (in terajoules, TJ) from coal combustion; that is, we do not include energy generation from combustion of other fuels, such as oil and gas.

Finally, concerning undesirable outputs, we use the OECD Environment Statistics (OECD 2011) to construct the variables representing emissions of sulphur oxides (SO_X) and nitrogen oxides (NO_X) from power plants (in thousand tonnes); that is, we do not include emissions from other stationary sources nor from mobile sources. We obtain a balanced panel for 25 countries over 1990-2009 (the remaining 9 OECD countries are excluded due to missing data). Table 1 describes the estimation sample.

Table 1. Summary statistics for the DEA analysis

Variable	Obs	Mean	Std. Dev.	Min	Max
Labour	500	13337	27899	38	239637
Capacity	500	24558	65217	299	339426
Coal	500	68457	166646	108	948137
Patent stock	500	566	829	2	4167
Electricity	500	129576	374931	243	2127406
Heat	500	31510	68809	0	371761
SOx	500	764	2143	1	14433
NOx	500	326	933	6	6045

We conduct a nonparametric production frontier analysis and obtain inefficiency scores with respect to SO_X, NO_X and coal. For ease of interpretation, in the remainder of this paper the scores are reported as "efficiency" scores, constructed as the complement of the inefficiency score.[11] Each score represents the performance of a country with respect to the frontier, as reflected in the data for the most efficient countries, including Denmark, Finland, Ireland, Netherlands, Portugal and Sweden (Table 3). Countries such as Australia, Austria, Germany, Japan and the United States are also assessed as relatively efficient (their efficiency scores are high, overall). Conversely, New Zealand, Hungary, Slovakia and Turkey are assessed as relatively inefficient countries (their efficiency scores are low, overall). Moreover, countries such as France, the United Kingdom, Belgium and Italy are highly efficient in their coal use but inefficient in their SO_X mitigation (Figure 3);[12] countries such as the Slovak Republic and Italy have both succeeded in dramatically improving their NO_X emissions efficiency albeit from very different levels of coal efficiency (Figure 4).

Table 2. Estimated efficiency scores, country averages

Country	SOx	NOx	Coal
Denmark	1.000	1.000	1.000
Finland	1.000	1.000	1.000
Ireland	1.000	1.000	1.000
Netherlands	1.000	1.000	1.000
Portugal	1.000	1.000	1.000
Sweden	1.000	1.000	1.000
Australia	0.999	0.997	0.979

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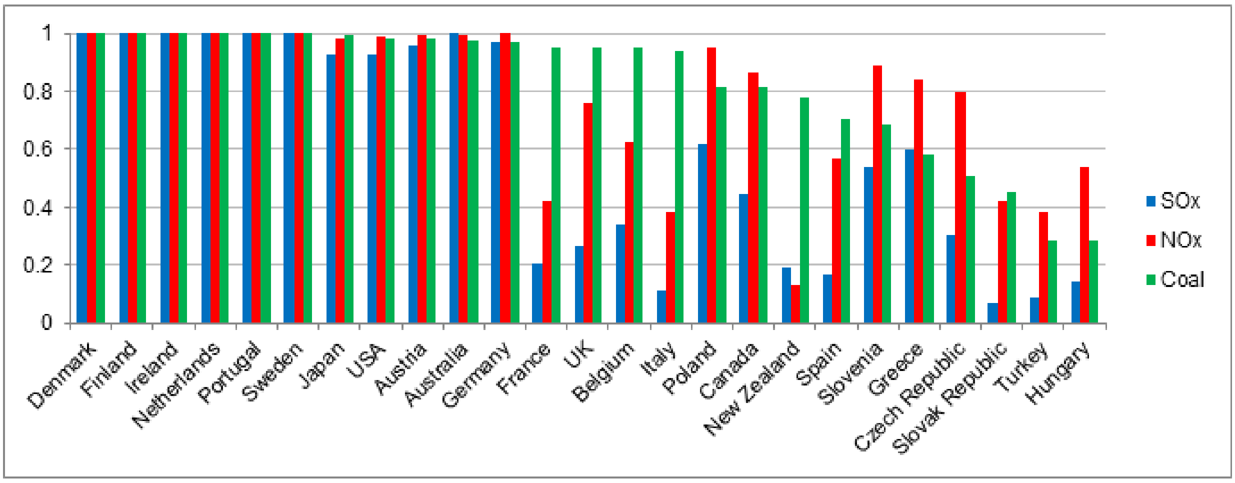
[11] $E = 1 - \beta_{inefficiency}$

[12] In addition to obsolete technology, inefficiencies might arise also due to suboptimal operation conditions. For example, in France coal power plants are used exclusively as back-up sources of intermittent supply, mostly to meet peak electricity demand. The low rate of capacity utilisation explains, in part, the low SO_X emission efficiency.

Austria	0.959	0.995	0.984
Germany	0.972	0.998	0.973
Japan	0.925	0.983	0.995
USA	0.928	0.989	0.984
Poland	0.621	0.95	0.818
Canada	0.445	0.865	0.817
UK	0.264	0.761	0.950
Belgium	0.343	0.625	0.949
Slovenia	0.539	0.889	0.684
Greece	0.603	0.839	0.582
France	0.208	0.419	0.950
Italy	0.111	0.385	0.942
Spain	0.170	0.567	0.704
Czech Republic	0.304	0.800	0.509
New Zealand	0.191	0.129	0.777
Slovak Republic	0.072	0.420	0.454
Hungary	0.144	0.540	0.283
Turkey	0.085	0.383	0.286

Note: Efficiency scores range from 0 to 1, where score =1 represents most efficient observation by country-year. Low efficiency score indicates low efficiency of energy production. The model is estimated under constant returns to scale.[13]

Figure 3. Estimated efficiency scores, country averages



Note: Countries sorted in descending order by coal efficiency.

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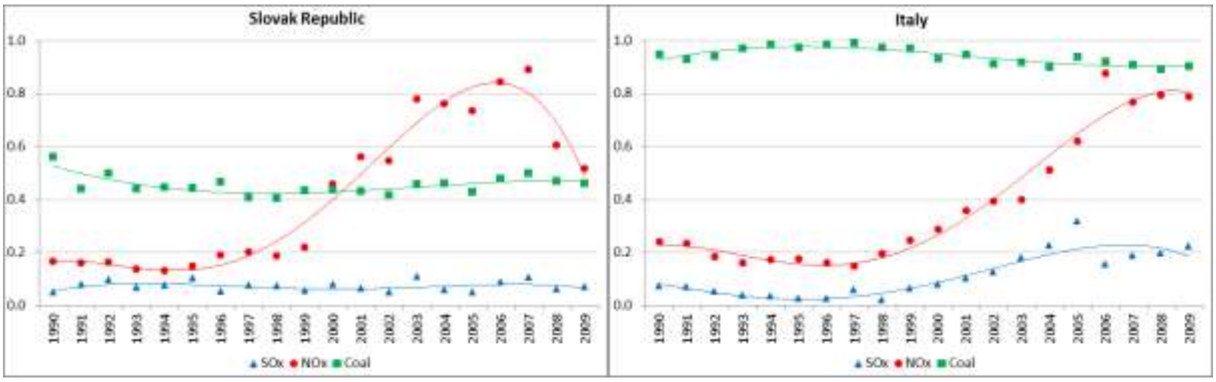
[13] The nonparametric production frontier model commonly assumes either constant return to scale (CRS) or variable return to scale (VRS). If we set the VRS model, equation ($\Sigma_j Z_j=1$) is added to the model. In this study, we apply CRS to reduce the number of countries which would be considered efficient (inefficiency score = 0). This is because the range of intensity weight variable Z_j is limited by the number of input and output variables in small sample sizes. Furthermore, VRS assumption imposes the additional restriction noted above, this decreases the flexibility of intensity variable Z. Nonetheless, an additional set of efficiency scores is calculated under VRS and the results do not differ substantially. Thus, we opt to use the results from the CRS for the econometric analysis.

Figure 4. Efficiency scores in selected countries



3.2 Analysis of the policy determinants of efficiency

Next, econometric techniques are used to explain the differences in efficiency scores over time and across countries. The efficiency scores range between zero and one and are used as a dependent variable. The explanatory variables of primary interest are those which relate to the characteristics of policy design, as discussed in Section 2 above. We apply a generalised linear model using a logit linking function. This refers to the fractional logit estimation method first developed by Mundlak (1978) and adapted by Papke and Wooldridge (1996; 2008). Due to the small sample size and the percentage of observations on the frontier, we are constrained to perform a pooled estimation to achieve convergence.[14] The following model is estimated:

$$E^*_{it,m} = \alpha_0 + \boldsymbol{\gamma}\mathbf{X}_{it} + \boldsymbol{\delta}\mathbf{Z}_{it} + \mu_t + \epsilon_{it} \qquad [10]$$

$$E_m = E^*_m \quad if \;\; 1 \geq E^*_m \geq 0 \qquad [11]$$

$$E_m = 0, \;\; if \;\; 0 \geq E^*_m \qquad [12]$$

$$E_m = 1, \;\; if \;\; 1 \leq E^*_m \qquad [13]$$

where m = SO_X, NO_X, coal. Vector $\mathbf{X}$ includes policy variables that might influence the efficiency of coal-based electricity generation, including three types of policy instruments – pricing, public RD&D and regulatory instruments. First, we include the **price** of coal. This is included in the vector of policy variables because governments either regulate coal prices directly, for example through the introduction of pricing rules or price caps, or by levying excise taxes on coal. We use data from the IEA Energy prices and taxes database (IEA 2012a) on the end-use prices (final, including taxes) of steam coal[15] for electricity generation, expressed in USD per tonne using PPP. We take the natural logarithm of the coal price to limit the influence of extreme values.

Second, we also include covariates for public **RD&D** expenditures directed at improving the fuel efficiency of coal combustion. We use data from the IEA Energy technology RD&D budgets database

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[14] The panel data version of this estimator is a "correlated random effects" fractional logit. It requires the inclusion of year fixed effects and mean independent variable fixed effects, however, this loss of degrees of freedom does not allow achieving convergence in our case. Therefore, we only include year dummies and controls in the regressions.

[15] Steam coal is the only option; unfortunately, price data are not distinguished by coal type (e.g. soft and hard coal).

(IEA 2012b) for the subcategory "2.2.2 Coal combustion (incl. IGCC)", expressed in million USD using 2011 prices and PPP. The values are divided by the corresponding coal capacity to obtain the RD&D intensity of the coal-fired energy production. This is because public RD&D is closely linked to the size of the economy while the estimated efficiency scores are independent of country size. It should be noted that we cannot include lagged values because RD&D data prior to 1990 are not available.

Third, we include covariates representing the **stringency** of emissions standards directed at power plant emissions. The stringency variables are constructed along 4 dimensions – plant size, plant vintage, pollutant type and fuel type – i.e. 32 different regulatory stringency measures.[16] The variable is computed as the inverse of the emission standard in place, thus an absence of regulation would translate into a stringency of zero. We also include coefficients of variation of the stringency variables for selected dimensions (size, fuel or vintage[17]). These variables are intended to capture the degree of **differentiation** in a country's environmental regulations. For example, a high CV with respect to size means that a country applies different polluting targets depending of the size of the plant. Note that the regulations in our sample are always more stringent for new plants (except for Greece); the CV with respect to plant age can thus be interpreted as the magnitude of the new-source bias. All coefficients of variation have a lower bound of zero denoting regulations setting the same emission standard across a chosen dimension. Including these variables as regressors helps us understand how regulatory differentiation affects productive efficiency.

Note that we have 32 stringency variables for each country-year combination and several coefficients of variation per dimension. In order to summarize the information for a country-year into a single set of policy stringency and coefficients of variation variables we take the unweighted average across all 32 dimensions.[18] This exercise will also tackle any potential multicollinearity issues that could arise since the 32 stringency variables (and the corresponding CV variables) are highly correlated among each other. Furthermore, we expect regulation to have a delayed impact on plant's performance, thus, the stringency and differentiation variables are lagged 5 years. Other lags are also tested and discussed with the empirical results.

In terms of expected signs, we expect coal prices to have a positive impact on efficiency, and similarly we expect that increases in RD&D intensity to translate into higher efficiency. The expected sign on the level of regulatory stringency of emission standards is positive with respect to SO_X and NO_X emissions. The expected sign on the CV variables for size, fuel and vintage (greater differentiation) is ambiguous. It may be positive in the short run when the distribution of plant and input characteristics is given, but negative in the long run since such differentiation may discourage adjustments across the different plant characteristics. For example lower stringency on small plants may result in lower overall abatement costs for a given distribution of plant sizes, but by discouraging adjustment in the plant size portfolio it may have negative effects in the long term.

Vector **Z** includes control variables such as the *average size of coal power plants* in country i and year t and the *ratio of soft coal over total coal* (i.e. the share of low-quality coal such as peat, lignite or sub-bituminous coal over total coal including also high-quality coal fuels such as anthracite, bituminous coal or patent fuel).

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[16] 32 = 4 plant sizes (15, 60, 240 and 600) x 2 fuel types (hard, soft coal) x 2 plant vintages (new, old) x 2 pollutants(NO_X, SO_X)

[17] We do not include a coefficient of variation for pollutant type because inherent differences in the environmental damages, and the resulting economic costs of the pollutants, justify different emission limit values.

[18] Moreover, the estimated eigenvalues corresponding to the first principal component (using the PCA) are fairly evenly distributed across the 32 variables, suggesting that an unweighted mean is a good approximation of the overall variation.

We also test a hypothesis concerning the nature of technological innovation: integrated approaches are more likely to bring about efficiency improvements than end-of-pipe innovation, as suggested by the theoretical literature. The reason for this is that integrated approaches allow for the exploitation of the complementarity of input use in production of the plant's primary output (i.e. electricity) as well as abatement, while end-of-pipe abatement is analogous to having two separate plants in a single facility.[19]

To test this hypothesis, an additional regressor is included – the share of post-combustion abatement technologies over all relevant abatement technologies, as measured by registered patent applications by country and year, lagged 10 years.[20] The expected sign is negative. (See Annex B for details on the construction of the patent stock variables and a discussion of patent classification symbols corresponding to selected innovation types.)

Finally, we introduce unobserved time-specific effects μ in order to capture temporal shocks common to all countries in the sample (year fixed effects). γ and δ are vectors of estimated coefficients and ε is an idiosyncratic error term. Our maximum estimation sample includes 325 observations – an unbalanced panel of 20 years (1990-2009) and 20 countries (including Australia, Canada, Japan, the United States and European OECD countries). The descriptive statistics of the variables used in the econometric analysis are summarised in Table 3.

Table 3. Descriptive statistics for the econometric analysis

Variable	Obs	Mean	Std. Dev.	Min	Max
Efficiency score (SO_X)	325	0.84	0.31	0.05	1.00
Efficiency score (NO_X)	325	0.90	0.21	0.24	1.00
Efficiency score (coal)	325	0.93	0.18	0.22	1.00
Price of steam coal (USD per tonne using PPP)	325	57.88	24.26	20.41	171.77
Price of steam coal (ln)	325	3.98	0.41	3.02	5.15
Public RD&D spending on coal combustion (million 2011 USD PPP)	325	23.85	170.09	0.00	2937.51
Public RD&D intensity (spending divided by coal capacity)	325	3.98	0.41	3.02	5.15
Regulatory stringency	325	0.00	0.00	0.00	0.01
Regulatory differentiation by size	325	0.52	0.34	0.00	1.12
Regulatory differentiation by fuel	325	0.02	0.05	0.00	0.19
Regulatory differentiation by vintage	325	0.33	0.34	0.00	1.24
Share of soft coal	325	0.39	0.37	0.00	1.00
Average plant size (GWe installed)	325	199.05	102.21	47.45	527.00
Share of end-of-pipe patents (A over AB)	325	0.55	0.11	0.18	0.74

Now we turn to the equation of interest (equation 10) to examine the role of environmental policy in generating efficiency gains. Three sets of models are estimated using the three different endogenous variables: efficiency of SO_X and NO_X abatement, and efficiency in the use of coal as an input (Tables 4-6).

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[19] See Johnstone et al. (2008). Ex-post strategy (or "end-of-pipe" abatement) is considered to reflect evidence of the existence of a separable production function (i.e., with production of the conventional output and abatement of pollution as essentially separate plants within a single facility). Different resources are used for each "plant". An integrated abatement strategy (or "change in production process" abatement) is considered to reflect a production process in which abatement and production of the conventional output are integrated, allowing for the complementary use of inputs in both abatement and production; that is, the realization of economies of scope.

[20] Technology stock is included in the DEA step of the analysis; to avoid potential endogeneity of this variable and account for the often slow process of technology adoption, this variable is lagged 10 years.

In each case, we first regress the efficiency scores on the three policy variables (coal price, RD&D, regulatory stringency), on control variables (share of soft coal, average plant size) and on year fixed effects[21] (column 1). Next, we add a measure of regulatory differentiation (by size, fuel or age) – one at a time (columns 2-4), and then all three together (column 5). Finally, we run models that include an additional control variable measuring the type of innovation in clean technologies (column 6). Comparing these models allows us to examine whether the findings are robust to the potential presence of multicollinearity (the CV variables are correlated only to a limited extent, ranging between 0.10 and 0.21, and in one case 0.41). The results using the fractional logit model on a pooled dataset are discussed next and more general conclusions are provided at the end of this section. Reported statistical significance is based on robust standard errors.

The results show that coal price has a positive effect on SO_X efficiency (albeit significant only at the 10% level in most specifications) suggesting that more expensive higher-quality coal allows SO_X emissions to be reduced more efficiently. No evidence to this end is found for NO_X efficiency, suggesting that mechanisms other than fuel substitution might be more efficient at reducing emissions. Indeed, the results for RD&D show that higher RD&D has a positive effect on the efficiency of NO_X abatement (significant at the 1% level). In turn, no such evidence is found for SO_X efficiency. These results suggest that **while reductions in SO_X emissions can be achieved more efficiently through increases in coal prices (changes in relative prices are likely to encourage substitution for cleaner, low-sulphur fuels) reductions in NO_X emission have been more efficient if they focused on improving the technology (because of RD&D expenditures) rather than the type of fuel used (because of coal price variations).** However, it's important to note that the generally weak evidence for the role of coal prices is surprising and may reflect the difficulty in capturing such effects through a slow-moving dependent variable.

The results also show that regulatory stringency has a positive effect on efficiency – this finding is very robust across all models estimated (and statistically significant at the 1% level), suggesting that more stringent emission standards lead firms to search for more efficient ways of fuel use and emissions abatement. Yet, the results also show that the way such regulations are implemented also plays a role. In particular, regulations that are differentiated by plant size, fuel used or plant age have a negative effect on efficiency. All three types of regulatory differentiation are found to negatively impact efficiency of the mitigation of both SO_X and NO_X (significant at the 5% level). This indicates that giving preferential treatment to existing plants over new entrants, or to large plants over small facilities, has negative consequences for the efficiency of abatement for the plant stock as a whole. Differentiation by fuel type is found to play a key role in the case of efficiency of coal use (significant at the 1% level).

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[21] We are not able to include country fixed effects because of the relatively small sample size, and since the regression already includes several regressors that vary importantly across countries, but relatively little over time, capturing the essence of the cross-sectional variation.

Table 4. Regression estimates of SO_X efficiency

Dependent variable: SO_X efficiency score	(1)	(2)	(3)	(4)	(5)	(6)
Price of coal	0.47	0.68*	0.71*	0.24	0.80*	1.18***
Public RD&D intensity	539.09*	416.46	428.64	455.74*	199.14	386.22
Regulatory stringency	1332.64***	2374.96***	1695.78***	1404.50***	2697.63***	2893.04***
Size differentiation		-2.60***			-2.92***	-2.69***
Fuel differentiation			-12.44***		-17.40***	-21.04***
Age differentiation				-1.15***	-0.34	-0.35
Share of end-of-pipe patents						-4.96**
Average plant size	0.02***	0.02***	0.02***	0.02***	0.02***	0.03***
Share of soft coal	2.02***	1.76***	2.09***	2.13***	1.72***	1.42**
BIC	342.45	335.59	342.82	342.94	337.94	337.29
N	325	325	325	325	325	325

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ based on robust standard errors.

Table 5. Regression estimates of NO_X efficiency

Dependent variable: NO_X efficiency score	(1)	(2)	(3)	(4)	(5)	(6)
Price of coal	-0.03	0.10	0.13	-0.46	-0.15	0.60
Public RD&D intensity	1318.01***	1429.81***	1252.65***	1141.52***	1113.30***	1562.39***
Regulatory stringency	1262.15***	2298.36***	1482.11***	1311.51***	2385.31***	2531.09***
Size differentiation		-2.68***			-2.84***	-2.30***
Fuel differentiation			-8.18**		-10.68***	-14.19***
Age differentiation				-1.48***	-0.94**	-0.94**
Share of end-of-pipe patents						-7.73***
Average plant size	0.01***	0.02***	0.02***	0.02***	0.02***	0.02***
Share of soft coal	2.24***	1.92***	2.26***	2.33***	1.91***	1.51***
BIC	282.66	279.11	286.49	282.22	284.61	282.40
N	325	325	325	325	325	325

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ based on robust standard errors.

Table 6. Regression estimates of coal efficiency

Dependent variable: Coal efficiency score	(1)	(2)	(3)	(4)	(5)	(6)
Price of coal	0.01	-0.05	0.58	0.19	0.59	0.81*
Public RD&D intensity	129.84	106.67	-18.05	91.30	-23.24	0.89
Regulatory stringency	869.17***	730.39*	1615.51***	1065.93***	1581.59***	1689.73***
Size differentiation		0.42			0.15	0.19
Fuel differentiation			-25.53***		-24.89***	-25.52***
Age differentiation				-0.88*	-0.15	-0.36
Share of end-of-pipe patents						-1.95*
Average plant size	0.01***	0.01***	0.02***	0.01***	0.02***	0.02***
Share of soft coal	-5.11***	-5.22***	-4.70***	-4.90***	-4.70***	-4.81***
BIC	222.38	228.09	223.90	227.46	235.46	240.83
N	325	325	325	325	325	325

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ based on robust standard errors.

Furthermore, while increases in regulatory stringency lead to improvements in plants' productive efficiency this does not mean that such increases will generate improvements indefinitely. Indeed, Table 7 shows that there might be "diminishing returns" to regulatory stringency. A quadratic term is included in the regression to examine this hypothesis. Indeed, the results suggest a concave relationship between stringency and efficiency meaning that the positive effect of rising regulatory stringency diminishes (significant at the 1% level for NO_X and coal) and might eventually lead to negative effects at very high levels of stringency. Based on our sample, most countries are in a situation of positive but decreasing marginal effect. For reasons of parsimony, only the results for model specification (5) are reported for SO_X, NO_X and Coal but the findings are robust in the remaining cases. In sum, these results suggest that **while more stringent emission standards encourage firms to search for efficiency improvements, the impact will be diminished if the standards are implemented in a differentiated manner or if the levels of regulatory stringency leap over a certain threshold.**

Table 7. Regression estimates with a quadratic term

	SOx	NOx	Coal
Price of coal	0.854*	-0.55	0.68*
Public RD&D intensity	178.51	1092.44*	-40.98
Regulatory stringency	3076.53***	3009.18***	2041.61***
Regulatory stringency (squared)	-1.42e+05	-2.16e+05***	-1.45e+05***
Size differentiation	-3.13***	-3.20***	-0.23
Fuel differentiation	-16.76***	-9.94***	-23.86***
Age differentiation	-0.35	-0.96**	-0.21
Average plant size	0.025***	0.02***	0.02***
Share of soft coal	1.734***	1.96***	-4.64***
BIC	343.60	290.06	240.92
N	325	325	325

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ based on robust standard errors.

To further explore the role of environmental policy design, we test whether differentiated emission standards induce efficiency in the short run (i.e. contemporaneous effect, without lagging) while in the medium to long run (i.e. 5 to 10 years lag) they might induce inefficient outcomes. Specifically, we investigate the temporal effect of policy design on the models presented in Tables 4-6 using different number of lags of the policy stringency and design variables. Table 8 gives the coefficients of the stringency variable as well as the coefficients of variation for SO_X, NO_X and coal for specification (5) at different lags: 0, 5, and 10-year lag. The four variables are lagged simultaneously.[22]

Table 8. The dynamic of coefficients related to regulation

SOx efficiency	No lag	5-year lag	10-year lag
Stringency variable	1304.05***	2697.63***	2727.13***
Size differentiation	-0.56	-2.92***	-2.04***
Fuel differentiation	-4.00	-17.40***	-21.93***
Age differentiation	0.18	-0.34	-0.26
NOx efficiency	**No lag**	**5-year lag**	**10-year lag**
Stringency variable	935.75***	2385.31***	2881.07***
Size differentiation	-0.67	-2.84***	-2.11***
Fuel differentiation	-2.64	-10.68***	-12.22*
Age differentiation	-0.44	-0.94**	-0.78**
Coal efficiency	**No lag**	**5-year lag**	**10-year lag**
Stringency variable	-1.33	1581.59***	3738.06***
Size differentiation	1.11	0.15	-2.14**
Fuel differentiation	-1.54	-24.89***	-51.69***
Age differentiation	1.73	-0.15	0.37

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$ based on robust standard errors.

We find no contemporaneous effect of regulatory differentiation on SO_X, NO_X and fuel efficiency. However, the stringency of environmental regulation has a contemporaneous effect on both SO_X and NO_X efficiency but not on fuel efficiency. The effect of regulatory stringency also increases over time, suggesting that it takes time for firms to respond to environmental regulation by improving their production process, for example though innovation. At the same time, the effect of regulatory differentiation becomes significantly negative after 5 years, and further increases after 10 years. This is especially true for fuel differentiation. This supports the idea that differentiated standards generate inefficiencies in the longer run because they provide wrong incentives to firms. For example, discrimination based on age or size can induce a sub-optimal investment over time in cleaner generation capacities.

Next, we examine whether the nature of technological innovation plays a role. We find that a higher share of post-combustion abatement technologies is negatively correlated with efficiency in all three cases (SO_X, NO_X and coal efficiency). This means that **integrated approaches are more likely to bring about efficiency improvements than end-of-pipe innovations**, consistent with the theoretical argument presented in section 2.

Finally, results for the control variables show that larger plants tend to be more efficient than smaller facilities (significant at the 1% level, and robust across all models estimated). Countries with a higher use of soft coal tend to achieve lower efficiency in the use of coal (this is expected because of the lower quality of soft coal in terms of the presence of impurities) and higher efficiency in SO_X and NO_X abatement (this latter result is unexpected and might indicate that countries that tend to rely on low-quality coal which generates more emissions also devote more attention to emissions reductions).

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[22] For brevity, only stringency and policy differentiation variables are shown, however, all model specifications are run as in model (5) in tables 4-6.

4. CONCLUSIONS

Depending on their design, environmental regulations can potentially result in increased efficiency in the joint production and use of market goods (electricity and coal) and non-market bads (SO_X and NO_X). That is, if there is a decrease in productive efficiency of market outputs and use of marketed inputs, it may be compensated for by increased productivity in the mitigation of non-market, environmental outputs. This implies that when firms are faced with environmental regulations, they might develop innovative means of dealing with the regulations, thereby shifting out the multi-product production frontier. This paper has sought to investigate the relationship between regulation, innovation and productivity when both desirable and undesirable inputs and outputs are considered.

A general principle of environmental economics is that cost-efficient abatement is realised through the use of measures in which marginal abatement costs are equalised. In the case of local and regional air pollutants (e.g. SO_X and NO_X) the marginal benefits of abatement will differ by location. In addition, there may be administrative barriers to implementing and enforcing those measures which treat sources in an undifferentiated manner. As such in many cases policy measures are implemented across a variety of dimensions through the use of differentiated emission standards. Using data on inputs and outputs, emissions, plant characteristics, patent stocks, and policy characteristics we have explored how innovation and policy design characteristics affect the efficiency of the production of goods and bads.

In this paper we find empirical evidence that while more stringent emission standards encourage firms to search for efficiency improvements, the impact will be diminished if the standards are implemented in a differentiated manner or if the levels of regulatory stringency leap over a certain threshold. We also find that the positive effects of policy stringency and negative effects of differentiation become more important over time. Whereas policy stringency in emission standards has a small and sometimes not significant impact in the short term, the effect is strongly significant and increasing 5 and even 10 years after the regulation has been adopted.

Similarly, the results indicate that when countries discriminate in setting polluting standards, this tends to lead to greater inefficiencies in the longer run. For example, vintage regulations, which might be appealing politically insofar as incumbents are likely to apply pressure for less stringent regulation, show increasingly strong adverse implications over time in terms of productive efficiency. Similarly, discrimination based on plant size, which may arise because operators of large plants are likely to exercise greater political influence, also shows greater negative impact on efficiency over the longer run. Regulatory differentiation can thus generate inefficiencies by inducing a sub-optimal investment over time in cleaner generation capacities.

Next, we find that while reductions in SO_X emissions can be achieved more efficiently through increases in coal prices (which are likely to encourage substitution for cleaner, low-sulphur fuels) reductions in NO_X emission have been achieved more efficiently if they focused on improving the technology rather the type of fuel used. However, the evidence for the role of coal prices is generally rather weak and may reflect the difficulty in capturing such effects through a slow-moving dependent variable.

Finally, we find evidence that the nature of technological innovation plays a role, with integrated approaches more likely to bring about efficiency improvements than end-of-pipe innovations. This is important insofar as these innovations have the potential to decrease the cost of emissions abatement over the longer run by encouraging firms to "mainstream" their efforts to achieve environmental objectives, seeing production of their primary outputs and abatement as joint decisions.

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ANNEX A. CONSTRUCTION OF CAPACITY STOCKS

The IEA Electricity Information database contains country-level data on installed generation capacity. However, there is a large number of missing observations, and while some of these missing observations are in fact ‘true’ zeros (i.e. countries without coal capacity) others could well be ‘false’ zeros, and it is not possible to distinguish the two cases. As such in this paper, we construct country-level coal capacity using micro-level data on energy generation plants. We use the UDI/Platts database of power plants to re-construct the historic stocks of coal capacity.

The database provides a snapshot of the stock of power plants at a given point in time (here we use the December 2012 release) distinguishing between plants that are currently “in operation”, those that have been “retired” or are currently “shutdown” (e.g. for maintenance), have been “deactivated” (mothballed) or whose status is “unknown”. We use data for these plants to re-construct the historic capacity stocks. The remaining plants in the database have either never been in operation (have been “cancelled” or “abandoned”) or are only being “planned” or “under construction” – and as such, we exclude these plants from our calculations.

To re-construct the historic stocks of coal capacity, we need to know for every plant the year when it first went in service (opening date) and, if applicable, when it was retired (closing date). The dataset is only partially complete: while the opening date is known for as many as 97% of the 3189 coal plants that are currently in operation in OECD countries, this is somewhat less (95%) for the 203 coal plants that are currently not in operation (i.e. deactivated, shutdown, or status unknown) and (91%) for the 2347 coal plants that have been retired during 1907-2012. Among the retired plants the closing dates are known for 72% of the sample. We use the subset of retired plants for which both the opening and closing dates are known to estimate the “lifetime” of coal power plants, and then use predicted lifetime to calculate the opening or closing dates of plants for which one of these dates is missing.

First, we regress a plant’s lifetime (i.e. years in operation between opening and closing dates, including any shutdowns for maintenance) on plant size (megawatts of installed capacity), technology characteristics such as steam temperature, steam pressure and fuel type (anthracite, bituminous coal, sub-bituminous coal, lignite), plant vintage (opening date) as well as location (country) dummies. We estimate the regression on a sample of retired plants located in 25 OECD countries that first went in service between 1945 and 2012.

We estimate several alternative models (log-linear least squares, negative binomial, tobit) and they all yield very similar results in terms of goodness-of-fit and distribution of residuals. We select the log-linear least-squares specification because it requires least assumptions about the error term. To maximize the sample for which we can predict plant lifetime, we estimate five alternative specifications of the model with decreasing number of covariates and, as expected, decreasing goodness-of-fit (Table A1).[23] This is because if we used only the base model with maximum number of covariates we would be able to predict the lifetime only for a limited number of plants with missing

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[23] We apply the “Duan” correction to address the “retransformation problem” of prediction in logs (see Cameron and Trivedi 2010, pp. 108-109).

dates. Whenever possible, we use the prediction from the best model to impute the dates. If this is not possible, we use the next best model's prediction, and so on. Using this approach we are able to impute dates for 72% of the 831 plants with missing dates.[24] The only plants that we are not able to impute are those with both the opening and closing dates missing (i.e. 229 plants of 8 GW of combined capacity, representing 1% of total global capacity).

Table A.1 Regression estimates of the lifetime of coal power plants

	REG1	REG2	REG3	REG4	REG5
Capacity (MW)	0.0004***	-0.0002*	-0.0002	-0.0003**	0.0005***
	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0001)	(-0.0001)
Steam temperature	0.0012***	0.0012***	0.0016***	0.0012***	
	(-0.0002)	(-0.0002)	(-0.0002)	(-0.0001)	
Steam pressure	-0.0001***	-0.0001**	-0.0001***		
	(0.000)	(0.000)	(0.000)		
Vintage	-0.0189***				
	(-0.0012)				
Fuel type					
- Anthracite	0.1262	0.099			
	(-0.1257)	(-0.1471)			
- Bituminous coal	0.0606*	0.0488			
	(-0.028)	(-0.0327)			
- Sub-bitum. coal	0.1392***	0.1064*			
	(-0.0391)	(-0.0457)			
- Lignite	(base)	(base)			
Country dummies	Yes	Yes	Yes	Yes	Yes
N	674	674	712	712	1039
Adjusted R-sq.	0.558	0.394	0.308	0.290	0.042
F-test	32.457	17.838	14.187	13.633	2.834
	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)

Note: Standard errors in parentheses. * p<0.05, ** p<0.01, *** p<0.001

Next, we use the predicted lifetimes to calculate the missing opening (or closing) year of each plant. We then combine the three datasets – 3095 plants currently in operation with known opening dates, 193 plants currently not in operation with an imputed closing year (this could be before or after 2012), and 2222 retired plants with an imputed opening or closing year (before 2012). Altogether, we now have opening and closing years for 5510 plants of a combined capacity 796 GW. Finally, we construct time series of capacity stocks as a cumulative sum of the installed capacity (MW) of all coal plants for which we have evidence (observational or econometric) to have been in operation in a given year and country (1990-2010, 30 countries). In order to validate the data we then compare our constructed capacity stocks with those constructed using raw UDI/Platts data for the year – our stocks are slightly higher, as expected, because we also impute closing dates for plants with "unknown" or "shutdown" (e.g. for maintenance) status.

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[24] In fact, the vintage variable has a negative sign what is expected because it is estimated on a sample of retired plants. However, it would be meaningless to use include this variable to predict lifetime of plants that have not yet been retired. Consequently, we only use regression #1 to predict retired plants.

ANNEX B. CONSTRUCTION OF PATENT STOCKS

Technological innovation in emissions abatement

At the macro-economic level, emissions can be reduced by achieving structural changes in the economy either as energy savings on the demand side or as changes in the overall energy mix on the supply side (Managi et al., 2009). At the microeconomic (plant) level, emissions abatement options can be distinguished by the stage of the production process at which they intervene. At the pre-combustion stage, both fuel switching (e.g. using low-sulphur coal instead for high-sulphur coal) and fuel cleaning (e.g. desulphurisation) can reduce emissions. Conversely, at the post-combustion stage, several technologies for treatment of flue gases have been developed, including selective catalytic (or non-catalytic) reduction (for NO_X removal), flue gas desulphurisation (FGD) such as wet scrubbing (for SO_X removal), as well as activated carbon process (for combined NO_X/SO_X removal) or combined catalytic NO_X/SO_X removal.

Pre- and post-combustion options are typically adopted at lower levels of regulatory stringency. However, more far-reaching modifications of the production process (or "integrated" innovations) might be required to meet increasingly stringent emission limits. Among these, fluidised bed combustion (developed to abate primarily SO_X emissions) and other process and combustion modifications such as low-excess air combustion, reduced air preheating, low-NO_X burners, or flue gas recirculation (developed for NO_X reduction). Apart from integrated solutions that target abatement of SO_X and NO_X specifically, other innovations that improve overall fuel efficiency of combustion plants represent complementary options because they might generate additional emission reductions per unit of energy generated. These include technologies for improved output efficiency such as combined heat and power (CHP) and combined cycles.

Identification of abatement technologies in patent data

We aim to construct patent stocks for technologies that mitigate SO_X and NO_X emissions from fuel combustion. To identify the relevant patent applications – and construct frequency counts (EPAT) – we draw on the patent search strategy developed by Popp (2006) (see Tables B1 and B2) and tagging scheme developed by the EPO (Table B3). We extract data from the European Patent Office's Worldwide Patent Statistical Database, known as PATSTAT (EPO 2012) using a search algorithm developed at the OECD.

Table B.1 Patent classifications for post-combustion SOX/NOX abatement

POST-COMBUSTION	*IPC or CPC codes*
Chemical or biological purification of waste gases, e.g. engine exhaust gases, smoke, fumes, flue gases or aerosols; Removing sulfur oxides	B01D53/50
Separation of gases or vapours by absorption; Removing sulfur dioxide or sulfur trioxide	B01D53/1481
Chemical or biological purification of waste gases; Catalytic processes; Removing sulfur oxides	B01D53/8609
Chemical or biological purification of waste gases, e.g. engine exhaust gases, smoke, fumes, flue gases or aerosols; Removing nitrogen oxides	B01D53/56
…by treating the gases with solids	B01D53/565
Chemical or biological purification of waste gases; Catalytic processes; Removing nitrogen oxides	B01D53/8625 B01D53/8628 B01D53/8631
Chemical or biological purification of waste gases, e.g. engine exhaust gases, smoke, fumes, flue gases or aerosols; Simultaneously removing sulfur oxides and nitrogen oxides	B01D53/60
Chemical or biological purification of waste gases; Catalytic processes; Simultaneously removing sulfur oxides and nitrogen oxides	B01D53/8637

Table B.2 Patent classifications for integrated abatement technologies

Integrated technologies targeting SOx/NOx abatement (combustion modification)	*IPC or CPC codes*
Fluidized Bed Combustion (FBC)	
Apparatus in which combustion takes place in a fluidised bed of fuel or other particles	F23C10
Flue gas recirculation (FGR)	
Combustion apparatus characterised by arrangements for returning combustion products or flue gases to the combustion chamber	F23C9
Combustion apparatus characterised by the combination of two or more combustion chambers	F23C6/045-047
Integrated technologies targeting improved output efficiency	
Heat utilisation in combustion or incineration of waste	Y02E20/12
Combined heat and power generation [CHP]	Y02E20/14
Combined cycle power plant [CCPP], or combined cycle gas turbine [CCGT]	Y02E20/16
Integrated gasification combined cycle [IGCC]	Y02E20/18
…Combined with carbon capture and storage [CCS]	Y02E20/185

Construction of patent stock variables

We use the methodology developed in Haščič et al. (2015) to construct ‘coverage weights’ that improve the reliability of the patent counts, especially in regions of the world where coverage of the database is incomplete. This allows us to distinguish observations that are true zeros from those that are truly missing and thus reduces the ‘idiosyncratic bias’ due to incomplete database coverage. While this is a particularly important issue in the developing country context, it is much less important for OECD countries, especially after 1990 (our sample). The exceptions are Chile and countries such Slovakia, Slovenia, the Czech Republic, Iceland and Estonia for whom coverage is incomplete in the early 1990s. Therefore, we use coverage weights to identify those years and then extrapolate from years for which reliable data is available.

The extracted data covers all countries and time series is developed for over 40 years. We then construct frequency counts by patent office (i.e. country or jurisdiction of the patent office), year of application, and technology. We choose to aggregate the counts by patent office because we are interested in what drives innovators’ incentives to diffuse their technologies widely. However, this approach necessitates dealing with regional and international patent filings explicitly, in particular filings at the European Patent Office (EPO) in our case.[25] In the past, the problem of regional or international filings has simply been ignored due to lack of data to properly address it. However, the EPO is an increasingly important route for patent protection and ignoring it would increasingly lead to biases in calculation of "patent stocks". In this paper we follow the methodology developed in Haščič et al. (2015) to account for filings at the EPO using "protection propensities".

In sum, estimation of 'protection propensities' allows apportioning regional patent filings onto national jurisdictions, and thus allows to correct for the drop in national patenting caused by growing tendency to protect inventions at the regional rather than national authorities. This is a significant improvement relative to the standard methodology of constructing knowledge (technology) stocks using patent data. Subject to availability of data, this methodology could be extended to other regional offices. However, in this paper EPO is the only regional office that is of relevance. We generate patent application propensities based on total patent filings (not only environmental) and use such propensities to "apportion" EP filings onto national office jurisdictions. Finally, the apportioned counts are combined with national counts. Now we are ready to proceed to construction of the patent stocks.

We use the perpetual inventory method to construct a cumulative stock of patent applications deposited in a given patent office *i* (i.e. not an inventor country), discounted by the standard 15% rate.[26] Since, by construction, this measures the extent of IP protection – and hence technology diffusion – we refer to this protection-oriented (by office) indicator "patent stock" (not knowledge stock). It is calculated as a discounted stock of patent applications in technology field *k*, registered in year *t* at patent office *i*. We do not use a parameter for average growth rate because the counts are frequently very low, with frequent zeroes, and without a particular increasing or decreasing trend, giving rise to negative growth rates. Instead, we use data spanning the period 1960-1989 to build up the stock and initialize the stock in year 1990.

Neither do we use an explicit rate of diffusion. This is because the patent stock counts applications at patent offices, and hence accounts for technology diffusion 'by construction'. Consequently, there is no need to further adjust for geographic spillovers. Two types of patent stocks are constructed – using patent counts of post-combustion technologies for SO_X/NO_X abatement (PAT_A) and using patent counts of integrated technologies targeting SO_X/NO_X abatement and output efficiency improvements (PAT_B). A stock of all relevant patents (A+B) is generated (PAT_AB) and included in the DEA step of the analysis. The nature of environmental innovation is analysed using the ratio of post combustion patents over all relevant patents (PAT_A / PAT_AB).

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[25] Given that our sample is composed of OECD countries, the EPO is the only regional patent office that matters.

[26] We also apply 5%, 10% and 20% rates for sensitivity analysis.