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ECONOMETRIC ANALYSIS OF THE IMPACTS OF THE UK CLIMATE CHANGE LEVY AND CLIMATE CHANGE AGREEMENTS ON FIRMS' FUEL USE AND INNOVATION ACTIVITY

This paper was prepared by Ralf Martin, London School of Economics, and Ulrich Wagner, Universidad Carlos III de Madrid, as a contribution to the project on Taxation, Innovation and the Environment. It presents an econometric study of impacts of the Climate Change Levy in the United Kingdom on fuel use and innovation.

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FOREWORD

This paper was prepared by Ralf Martin[1], London School of Economics, and Ulrich Wagner[2], Universidad Carlos III de Madrid, as a contribution to the OECD project on *Taxation, Innovation and the Environment*. It presents an econometric study of impacts of the Climate Change Levy in the United Kingdom on fuel use and innovation.[3] [4]

A companion paper by the same authors, *Survey of firms' responses to public incentives for energy innovation, including the UK climate change levy and climate change agreements,* is available at www.oecd.org/env/taxes.

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4 Authors' acknowledgements: This report draws on results from our papers "The impacts of the Climate Change Levy on business: Evidence from microdata" (joint work with Laure de Preux) and "Climate change policies and innovation: Evidence form firm level patent data". Our work has benefitted from comments and suggestions by Michael Ash, Nils Axel Braathen, Nick Johnstone, Tom Jones, Ivan Hascic, and from participants at the 2008 Joint Meetings of Tax and Environment Experts. All remaining errors are our own.

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1. Scope of this Report and Summary

1. As the issue of climate change mitigation has moved to the top of the political agendas, there is now a widespread interest in the effects of different policy instruments designed to reduce greenhouse gas (GHG) emissions from the business sector. Depending on the perspective of the stakeholder, the focus of this interest is either on the environmental effectiveness of such policies, on the magnitude and distribution of the costs and benefits associated with these policies, or on their effects on international competitiveness. However, empirical evidence on the effects of such policies is scarce. This may be in part due to the small number of concrete climate change policies that have been implemented thus far, or to the lack of suitable data study them.

2. The single most important climate change policy that the United Kingdom has imposed unilaterally thus far is the so-called Climate Change Levy (CCL). The CCL is an energy tax levied on the business sector which added approximately 15% to the energy bill of a typical UK business when it was introduced in 2001 (NAO, 2007). The government has sought to reduce the tax burden on energy-intensive firms by offering them an 80% discount on the tax rate if they join a so-called Climate Change Agreement (CCA) and adopt a specific target for energy consumption or carbon emissions. This policy package was expected to contribute more than half of all carbon savings in the business sector under the UK Climate Change Programme (HM Government, 2006).

3. Given its scope and institutional context, the CCL package provides a unique opportunity to study the impacts of large-scale regulations of carbon dioxide emissions in a post-industrial economy. This report draws on the findings of recent and ongoing research of ours (Martin, de Preux and Wagner, 2009; Martin and Wagner, 2009a) to provide a comprehensive empirical analysis of the impacts of the CCL package on energy use, inter-fuel substitution, climate change related innovation, and on economic performance. In contrast to previous research, our analysis is undertaken at the level at the individual plant or firm, drawing upon several new sources of data and on newly matched combinations of existing data bases. The fundamental advantage of using longitudinal microdata for policy evaluation lies in the researcher's ability to clearly distinguish between the effects of the policy and other contemporaneous events.

4. The remainder of this report can be subdivided into two parts. In the first part, we estimate the impacts of an energy tax (the CCL) on the manufacturing sector using panel data from the UK production census. Our identification strategy builds on the comparison of trends in outcomes between plants subject to the full CCL and plants that were granted an 80% discount on the levy after joining a CCA. Since the CCAs stipulate specific targets for energy usage or carbon emissions, this comparison yields a lower bound on the impact of the discount. To address a likely selection endogeneity in CCA participation, we adopt an instrumental variable approach that exploits exogenous variation in pollution discharges that determined eligibility for CCA participation. We find robust evidence that CCA participation had a strong positive impact on growth in both energy intensity and energy expenditures. Specifically, CCA participation is associated with a 15 % increase in the growth in energy expenditures and a more than 20% increase in the growth in energy intensity. An analysis of fuel choices at the plant level reveals that this effect is mainly

driven by a 26% *increase* in electricity consumption in CCA plants. This is consistent with the fact that the levy rate is highest for electricity compared to other fuels. These effects translate into a *positive* effect of CCA participation on carbon dioxide emissions, of at least 5% and at most 26%.

5. An argument often made to justify the CCA tax discount is that the unilateral implementation of a major climate change policy could jeopardize the competitiveness for energy-intensive UK firms. We have investigated this empirically and find neither a discernible loss of jobs, nor a decline in output or productivity for the average plant paying the full tax rate. Hence, we conclude that the tax discount granted to plants in a CCA cannot be justified as a means of avoiding alleged negative impacts on economic performance arising from the climate change levy. In contrast, our results strongly suggest that further cuts in energy use of substantial magnitude could have been achieved without jeopardizing economic performance if the CCL had been implemented at full rate for all businesses.

6. The second part of this report investigates the effects of these policies on innovation, using firm-level data on patent grants for climate change related innovation. We match patent data from the European Patent Office (EPO) to business performance data and analyze the empirical relationship between CCA participation and patenting activity of the firm. To this end, we perform non-linear regressions of the patenting activity and number of patents on CCA participation. Here the selection problem is addressed to the extent that we control for persistent unobserved heterogeneity across firms. The firm level regressions reveal a significant negative correlation between CCA participation and patenting. The numbers suggest that CCA participation leads to a reduction in the propensity to patent of 11 to 16 percentage points after 2001. This appears to be driven by a reduction in innovation related to energy efficiency, but also by patents not related to climate change.

7. In sum, our analysis of the CCL package provides ample evidence for the view that a moderate energy tax such as the CCL is more effective at promoting energy efficiency and hence mitigating climate change than a quantity target negotiated between government and industry. This is true from both a static and a dynamic perspective, since the CCL leads to more energy conservation and fosters more innovation in energy efficiency and other areas. Contrary to concerns about adverse effects on competitiveness, the CCL had no discernable effect on output and employment.

8. The structure of the report is as follows. Section 2 describes the CCL package in detail and provides a critical appraisal of the results obtained in previous studies. A comprehensive summary of analysis of the plant level impacts of the CCL package is contained in section 3. Section 4 reports on our research into the impacts of this policy on climate change related innovation. Section 5 discusses these findings and section 6 concludes.

2. Climate Policy in the UK business sector

2.1 Background

9. The UK signed the Kyoto Protocol in 1998, with a commitment to reduce its GHG emissions by 12.5% from 1990 levels by 2012, as stipulated under the terms of the EU Burden Sharing Agreement. In addition, the Blair administration promised to put the country on a path leading to more ambitious CO_2 reductions in the short and medium run, such as a 19% cut by 2010 (in the 2000 Climate Change Programme) and a 60% reduction by 2050 (in the Energy White Paper 2003). With the passing into law of the Climate Change Bill in November 2008, the commitment to reduce GHG emissions in the UK by at least 80% until 2050 has become legally binding.

10. Of all the policy measures that the British government has adopted in order to achieve its ambitious abatement targets, we focus on the most comprehensive one. The Climate Change Levy package

combines an economy-wide energy tax (the CCL) with a negotiated agreement scheme (the CCAs) by which firms in eligible sectors adopt binding energy (efficiency) targets in exchange for a generous discount on the tax rate. The government estimates that combined carbon savings from the CCL and CCA will amount to 6.6 MtC in 2010, making it the top contributor towards a projected total reduction of 20.8 MtC to be achieved by the Climate Change Programme 2006 (HM Government, 2006). Next we shall explain the fundamental aspects of both policies in more detail.

2.2 The Climate Change Levy

11. The CCL was first announced in March 1999 and came into effect in April 2001. The CCL is a per unit tax payable at the time of supply to industrial and commercial users of energy. Taxed fuels include coal, gas, electricity, and non-transport Liquefied Petroleum Gas (LPG). Table 1 displays, for each fuel type subject to the CCL, the tax rates per kilowatt hour (kWh), the average energy price paid by manufacturing plants in 2001 and the implicit carbon tax. It is evident that energy tax rates vary substantially across fuel types, ranging from 6.1% on coal to 16.5% on natural gas. The tax thus establishes a meaningful price incentive for energy conservation overall.

Table 1. The Climate Change Levy rates

Fuel type	Tax rate	Fuel price	Implicit carbon tax
	Pence per kWh		GBP per tonne carbon
Electricity	0.43	4.25	31
Coal	0.15	2.46	16
Gas	0.15	0.91	30
LPG	0.07	0.85	22

Source: Martin, de Preux and Wagner (2009).

12. However, it is immediately seen that the CCL is *not* a pure carbon tax, as the carbon contained in gas and electricity is taxed at almost twice the rate as carbon contained in coal. According to David Pearce (2006), this can be attributed to political pressures arising from historical ties between the New Labour Party and the coal industry, which had suffered from the dash for gas over the 1990s. Some fuel types are tax-exempt based on their low carbon content, notably electricity generated from renewable sources and from combined heat and power generation. Hence, the CCL is best characterized as an energy tax with non-uniform rates.

13. The revenue generated by the CCL is, for the most part, recycled back to industry in the form of a 0.3% reduction of the employer contribution to National Insurance Contributions (NIC). A small part of the revenues are used to fund the Carbon Trust, an institution set up by the government to foster research and development into energy efficiency schemes and renewable energy resources.

2.3 The Climate Change Levy Agreements

14. In order to address concerns about possible adverse effects of the CCL on competitiveness and economic performance of energy intensive industries, the Government set up a scheme of negotiated agreements, the CCAs. Participation in a CCA entitles facilities in certain energy-intensive sectors to an 80% discount on their tax liability provided that they adopt a binding target on their energy use or carbon emissions. The participation process involved two stages. First, the trade association of an energy intensive sector negotiated a so-called umbrella agreement with the government (represented by DEFRA, the Department of Environment, Food and Rural Affairs) to determine a sector-wide target for energy use or carbon emissions in 2010, as well as interim targets for each two-year milestone period. Targets were defined either in absolute terms or relative to (often physical units of) output. At the second stage, firms in eligible sectors applied for a reduced-rate certificate that entitled them to the discount on the levy paid at a

qualifying site. If the application was approved, these firms entered a so-called underlying agreement with DEFRA which defined the target unit, *i.e.* the facility or group of facilities benefiting from the tax discount, and stipulated a specific reduction to be achieved by the target unit.

15. At the end of each milestone period (*i.e.* 2002, 2004, 2006, 2008), the sector associations report to DEFRA whether the sector-wide target has been met. Only if a sector-wide target has been missed does DEFRA verify compliance at the target unit level. A facility that is found in non-compliance is not "re-certified" for the reduced rate in the following milestone period. If the facility misses the 2010, target it faces the threat to repay all rebates on the levy it has accumulated in previous periods.

16. Eligibility to enter a CCA is limited to facilities in certain energy intensive sectors. For lack of a clear-cut definition of these sectors, the government initially determined eligibility based on existing pollution regulation. In particular, CCAs were open to businesses carrying out activities regulated under part A of the 1999 Pollution Prevention and Control (PPC) Act, which included emission limits and other permit conditions in relation to releases to air, water and land, waste minimization, energy efficiency and site restoration. The eligibility criteria were extended in 2006 to take into account the energy intensity of businesses as defined in the EU Energy Products Directive (NAO, 2007).

17. CCA participants who were in danger of missing their target could buy emission allowances on the UK Emissions Trading Scheme (UK ETS), a market for carbon permits that was launched in 2002 and ended in December 2006. Conversely, excess carbon or energy reductions could be sold in the UK ETS or "ring-fenced" (banked) for use towards future targets. Transfers of permits from the relative sector to the absolute sector are subject to approval by the authority according to a "Gateway" mechanism which only allows such transfers provided that there is no net aggregate flow of permits from the relative sector to the absolute sector.

18. DEFRA originally negotiated 44 umbrella agreements with different industrial sectors, including the ten major energy intensive sectors (aluminium, cement, ceramics, chemicals, food and drink, foundries, glass, non-ferrous metals, paper, and steel) and over thirty smaller sectors. Sector definitions rarely coincide with common economic classification systems. While most sector associations have chosen relative targets for energy, absolute targets were negotiated for the aerospace, steel, supermarkets and wall coverings sectors. Carbon targets were negotiated for the aluminium and packaging (including metal packaging) sectors. Table 2 summarizes the coverage of agreements and sectors throughout the first three target periods.

Table 2. CCA sectors and targets

Sectors	(1) Sector Target	(2) Target Period 1 # TU	(3) Target Period 2 # TU	(4) Target Period 3 # TU
Aerospace	Abs E	11	17	24
Agricultural Supply	Rel E	165	152	137
Aluminium	Rel C	57	34	50
Apparel & Textile I	Rel E	155	131	100
Apparel & Textile II	Rel E			12
Bakers	Rel E	380	328	299
Brewers	Rel E	66	60	48
Calcium Carbonate	Rel E			<10
Cathode Ray Tube	Rel E	<10	.	.
Cement Slag	Rel E		<10	<10
Cement	Rel E	<10	<10	<10
Ceramic	Rel E	124	117	114
Chemical	Rel E	279	243	234
Clay	Abs E			<10
Industrial Gases	Rel E			<10
Dairy	Rel E	152	120	101
Eggs	Rel E	10	<10	<10
Eggs Farming	Rel E	311	174	142
Food & Drink	Rel E	923	896	830
Foundries	Rel E	235	188	174
Geosynthetics	Rel E			<10
Glass Manufacturing	Rel E			15
Gypsum	Rel E	<10	<10	<10
Heat Treatment	Rel E			50
Horticulture	Rel E			121
Leather	Rel E	12	11	<10
Lime	Rel E	<10	<10	<10
Maltsters	Rel E	25	24	21
Metal Forming	Rel E	103	98	84
Metal Packaging	Rel C	20	22	21
Motors	Rel E	12	20	25
Non Ferrous Alliance	Rel E		78	75
Packaging	Rel C			16
Pig Farming	Rel E	612	349	297
Poultry Meat Farming	Rel E	253	182	159
Poultry Meat Production	Rel E	80	71	63
Poultry Farming	Rel E	549	402	359
Printing	Rel E	103	121	150
Red Meat Production	Rel E	145	147	155
Renderers	Rel E	16	12	13
Rubbers	Rel E	<10	<10	<10
Semi Conductor	Rel E	16	23	28
Spirits	Rel E	24	26	25
Steel	Abs E	<10	20	21
Supermarkets	Abs E	<10	<10	<10
Surface Engineering	Rel E	179	191	206
Wallcovering	Abs E	15	10	11
Wood	Rel E	<10	<10	10
Total		5,108	4,319	4,262

Source: Martin, de Preux and Wagner (2009). Notes: Rel=relative target, Abs=absolute target, C=carbon, E=energy, TU=target unit.

3. The impacts of the CCL on energy use, carbon emissions and economic performance: Evidence from manufacturing plants

3.1 Review of previous research on the CCL and CCA

3.1.1 Energy efficiency, carbon emissions and the stringency of CCA targets

19. While the CCL and the CCA share the common objective of enhancing the efficiency of energy use in the business sector, it is important to note that there are fundamental differences between these policy instruments.

- The CCL increased energy prices faced by the typical business in 2001 by approximately 15% (NAO, 2007). If energy demand is price sensitive, the increased relative price of energy should lead to improvements in energy efficiency. Unless there is a strong rebound effect, or an exogenous increase in economic activity, this should reduce energy use in the CCL sector. However, the levy's impact on carbon emissions is ambiguous because even an absolute reduction in energy use could come with a shift towards more carbon-intensive fuels.
- The CCA, by contrast, combines a much more diluted price signal with quantity regulation, mostly in the form of efficiency targets. The CCAs' impact on energy use thus depends critically on whether the target places a binding constraint on a plant's production choices. If not, then the plant has less of an incentive to conserve on energy than it would under have under the full tax rate. Furthermore, since most targets are specified in terms of energy units rather than carbon emissions, there is no guarantee that even a stringent target leads to reductions in GHG emissions.

20. While both the CCA and the CCL have an ambiguous effect on carbon emissions, their price effects on energy use can be ranked if CCA targets are not stringent.

21. Not surprisingly, the stringency of CCA targets has been given particular attention in previous research. Theoretical research by Smith and Swierzbinski (2007) shows that a government with perfect information could have used its bargaining power vis-à-vis firms to extract abatement concessions equal to or in excess of the abatement conducted under the full tax rate. The assumption that government had perfect information about firm-specific abatement cost is unlikely to be true, however. Sharing this information with the government could have compromised a firm's bargaining position in the impending negotiations, so they had no incentive to reveal this to the regulator. Moreover, the government may not have been willing to drive a hard bargain because of concerns about adverse effects on competitiveness and about exacerbating the distortions in marginal abatement cost (de Muizon and Glachant, 2003; Smith and Swierzbinski, 2007).

22. In practice, the negotiations of CCA targets were jointly administered by DEFRA and AEA Technology plc. (AEAT), a consultancy DEFRA hired for practical assistance with this task. AEAT estimated that annual carbon savings from the 10 main CCA sectors at 2.5 million tonnes carbon (MtC) by 2010, holding output fixed at 2000 levels in sectors with relative targets (HMCE, 2000). Measured against this baseline, the combined annual carbon savings in all CCA sectors have been substantially larger than the 2010 target throughout the first three milestone periods. For the first milestone period, CCA sectors reported savings of 4.5 MtC (3.9 MtC and 4.5 MtC in subsequent milestone periods) against baseline emissions, most of which (2.6 MtC) was due to a dramatic decline in steel production. Even without the 4 sectors with absolute targets there was significant over-compliance with carbon savings estimated at 3 MtC (3.9 MtC and 4.3 MtC in subsequent milestone periods).

23. The extent of over-compliance of CCA sectors with their 2010 targets raised suspicions that the targets were indeed closer to business-as-usual than the AEAT analysis would grant. AEAT estimated a mean improvement in energy efficiency of 4.8% between 2000 and 2010. Alternative estimates for this period ranged from 9.5% for all UK industry (the EU Energy Outlook) to 11.5% (DTI Energy Paper 68). The average 11% reduction target to be achieved by CCA sectors falls well into this range.[5]

24. Other aspects also point to the possibility that the negotiated targets were rather lax indeed. The proportion of target units that were re-certified was consistently high, rising from 88% in the first period to 98% and 99% in the second and third target periods, respectively (AEAT 2004, 2005, 2007). As a rule, CCA participants reached their targets or purchased allowances on the UK carbon trading market to ensure compliance at low cost.[6] In fact, a lower bound on compliance cost is zero. This is true for a considerable amount of target units that missed their target but were re-certified due to the sector as a whole being in compliance.

25. A large degree of flexibility was built into the target negotiations both prior and subsequent to the compliance review. Target units could call upon several risk management tools that made it easier to meet their targets. For example, adjustments to targets could be made to reflect a more energy intensive product mix, declining output or relevant constraints arising from other types of regulation. In some sectors, performance was measured against a tolerance band in lieu of a fixed target.[7] Moreover, sectors were permitted to choose their baseline year. More than two thirds of all sectors chose baseline years of 1999 or earlier. Hence, carbon savings that had occurred before the policy package was implemented could be counted towards the target achievement (NAO, 2007). Finally, in some instances, growing companies that belonged to a sector with an absolute target successfully bargained for a relative target (and vice versa) as this made it easier to comply.

26. In sum, there is ample evidence that the negotiated targets are unlikely to have placed binding constraints on energy use by CCA companies.

3.1.2 Evaluation studies of the CCL package

27. In 2000, the Government projected that the CCL element alone to achieve carbon savings of at least 2 MtC in 2010 against business as usual projections (HCME, 2000).[8] The Government also commissioned an official evaluation study at the end of the second commitment period. The study was conducted by Cambridge Econometrics (2005) and used a macroeconometric forecasting model (MDM-E3) of the UK economy that explicitly accounts for energy-environment interactions. The key finding is a reduction in energy demand by the service and public sectors (which excludes manufacturing) following the announcement of the CCL package in March 1999. The authors identify this "announcement effect" in the form of a structural break in quarterly energy demand and further argue that the effect is permanent rather than transitory.[9] Moreover, the authors compare forecasts of business energy use with and

[5] The Association for the Conservation of Energy thus accused the government of double-counting carbon savings from the CCA scheme (ACE, 2005).

[6] Due to significant oversupply of carbon credits, carbon prices remained between GBP 7 and GBP 15 per tonne of carbon for most of the period (Smith and Swierzbinski, 2007), which is lower than most of the implicit carbon tax rates displayed in Table 1.

[7] These risk management tools had to be approved by the Government, and some of them were discontinued in later periods (NAO, 2007).

[8] This estimate came from a model of business energy use based on energy price-elasticities maintained by the Department of Trade and Industry (DTI).

[9] See Agnolucci *et al.* (2004) for details.

without the introduction of different versions of the CCL package. They conclude "that the energy (and therefore carbon) saving and energy-efficiency targets would have been met without the CCAs" (Cambridge Econometrics, 2005, p. 7).

28. Using the same model, Ekins and Etheridge (2006) compared simulated carbon savings from the CCL package as is and from a levy only that is applied at full rate across sectors. They obtained a difference of 0.9 MtC between the scenarios, which is smaller than the excess carbon savings of 1.7 MtC that (AEAT, 2004) computed for the relative target sectors in the first milestone period. Since their model does not account for this difference they conclude that "the CCL package as implemented [...] achieved a greater carbon reduction than a no-rebate CCL would have done by itself" (Ekins and Etheridge, 2006, p. 2079). They attributed this phenomenon to the possibility that managers become aware of cost-effective efficiency enhancement projects only as they start to benchmark their energy use. Another version of the MDM-E3 model was used by Barker, Ekins and Foxon (2007) to simulate the impact of the CCAs on macroeconomic outcome variables such as output, employment, and industrial energy demand. In their exercise, however, a large effect of the CCAs on sector energy demand – averaging a 9.1% reduction in sector energy use by 2010 – was built into the model by assumption rather than estimated from the data.

3.1.3 The case for plant level analysis

29. In sum, previous research on the CCL package illustrates two fundamental difficulties in policy evaluation, namely (i) to determine a valid baseline against which to measure the impact of a policy and (ii) to attribute any measured impact to this policy in a causal fashion.

30. When simulated trajectories of energy use are taken as a baseline against which to measure the impact of the CCL package, the results critically depend on those counterfactual baselines. Since, by definition, counterfactual scenarios cannot be observed, the evaluation results are subject to a large degree of uncertainty. In the case of simulations with macroeconometric models, additional uncertainty derives from the estimation error in the model parameters, from structural changes in those parameters, and from the possibility of changes in the economic environment – not to mention changes to the policy itself.

31. The causality issue arises in econometric studies that use time-series data aggregated at the sector level for evaluation purposes. While aggregate data can provide meaningful clues as to the effects of a policy, they rarely deliver conclusive evidence. This is because they do not allow the researcher to discern the effects of the policy from that of other concurrent events in a dynamically changing economic and political environment. At the time the levy package was introduced, energy markets in the UK had been undergoing fundamental changes that entailed significant and prolonged adjustments to prices, notably declining electricity prices and increasing prices of gas and coal. Furthermore, the levy interacted with a number of pre-existing taxes in the business sector, such as National Insurance Contributions and the Fuel Duty Escalator. Not least, with the Enhanced Capital Allowance and Carbon Trust energy audits, other energy efficiency enhancing measures were introduced simultaneously.

32. Our study (Martin, de Preux and Wagner, 2009) is the first to bring to bear confidential business microdata on the evaluation of the Climate Change Levy package. We use longitudinal observations at the plant level to estimate the impact of the CCAs on energy efficiency, interfuel substitution, and economic performance. The estimate is based on comparisons of plants before and after the introduction of the policy package, and on comparisons between establishments paying the full rate of the levy and those entitled to the 80% rebate. Our approach addresses the baseline problem by comparing changes in actual firm behaviour under two types of policy regimes, thus purging the effect of shocks at the economy, sector or regional level. In our most general specification, we even control for plant specific unobserved trends in the outcome variable that can be correlated with CCA participation in an arbitrary fashion. Moreover, we

identify the causal effect of the tax rebate by exploiting exogenous variation in the eligibility rules for participation in the CCAs.

3.2 Data

33. We have constructed a novel data set by matching two confidential business data sets and augmenting it with publicly available data on participation in the CCA. In particular, we use the following data sources (for further information, see Martin, de Preux and Wagner, 2009).

- The Annual Respondents Database (ARD) from the Office of National Statistics (ONS) has data on output and factor inputs, including energy expenditure, for about 10.000 manufacturing plants between 1999 and 2004.
- The Quarterly Fuels Inquiry (QFI) provided by the ONS, holding energy consumption data (kWh, tonnes etc.) for about 1.000 firms for 1997-2004. This was matched to ARD via the government business registry numbers (IDBR).
- Data on CCA participation for about 5.000 agreements available online from the web pages of DEFRA and HM Revenue & Customs (HMRC). We collected information on the facilities covered and matched this to the ONS data through a mixture of postcode matching in combination with matching via company register numbers.
- Data on pollution emissions by UK facilities reported to the European Pollution and Emissions Register (EPER). We downloaded the data from the European Environmental Agency's web site. The 2001 EPER file contains reporting thresholds and pollution discharges into air and water for 50 pollutants and covers 2,397 facilities in 56 sectors of activity in the UK. We matched this to the ONS data through a mixture of postcode matching in combination with matching via company register numbers.

34. Table 3 summarizes the main variables from the ARD data set, namely age, number of employees, gross output, variable cost, capital stock, energy expenditure, as well as the percentage of energy expenditures in gross output and in variable costs. The data are summarized for the regression sample which runs from 1999 until 2004. The data exhibit a substantial amount of dispersion between plants in energy intensity. For example in terms of energy expenditure over gross output (row 7), a plant at the 90th percentile (column 6) has an energy intensity that is more than 7 times higher than that of a plant at the 10th percentile (column 5).

Table 3. Descriptive statistics -- ARD sample

	(1)	(2)	(3)	(4)	(5)	(6)	(7)
Variables	**mean**	**sd**	**sd, between**	**sd,within**	**p10**	**p90**	**N obs**
Age	14.20	9.58	8.92	1.14	3.00	29.00	54,078
Employment (L)	180.76	489.96	386.16	126.90	8.00	407.00	54,078
Gross Output (GO)	25.44	123.77	95.48	27.28	0.35	45.20	54,078
Variable Costs (Vcost)	21.80	107.15	80.53	26.12	0.26	39.45	54,078
Capital Stock (K)	15.84	86.57	67.60	6.43	0.14	29.16	52,494
Energy Expenditures (EE)	0.41	2.97	2.67	0.63	0.00	0.64	53,650
EE over GO (EE/GO %)	1.58	1.27	1.20	0.43	0.44	3.07	47,559
EE over Vcost (EE/VCost %)	1.95	1.57	1.55	0.51	0.57	3.73	47,559

Source: Martin, de Preux and Wagner (2009). Notes: Descriptive statistics for the ARD pooled sample (1999-2004) The variables GO, K, Vcost and EE are in thousands of pounds.

35. Table 4 and Table 5 show the descriptive statistics of the variables in the QFI sample and for the joint sample of QFI and ARD observations, respectively. The variables are electricity, liquid fuels, gas,

solid fuels such as coal, and total energy use. The tables report both quantities consumed and expenditures paid for all fuel variables. Moreover, the tables list the share of gas in the consumption of both gas and electricity and the corresponding expenditure shares. We compute total CO_2 emissions (in thousands of tonnes) on the basis of the fuel use.

Table 4. Descriptive statistics -- QFI sample

Variables	(1) mean	(2) sd	(3) sd, between	(4) sd,within	(5) p10	(6) p90	(7) N obs
Electricity (El)	13,570.45	50,803.78	58,280.98	8,285.08	350.17	26,274.92	5,521
Electricity Expenditures (ElE)	406.81	1,306.07	1,491.93	205.84	17.30	821.81	5,521
Liquid Fuels (Li)	0.57	7.57	6.73	1.14	0.00	0.00	5,521
Liquid Fuels Expenditures (LiE)	35.78	434.39	414.52	67.03	0.00	0.00	5,521
Gas (Gas)	27,635.74	135,419.71	132,196.10	36,953.70	0.00	47,623.43	5,511
Share of Gas over Gas and El Consumption (Gas/(Gas+El))	0.24	0.20	0.19	0.08	0.00	0.52	5,487
Gas Exp. (GasE)	201.31	939.64	861.76	289.11	0.00	352.16	5,521
Share of Gas over Gas and El Expenditures (GasE/(GasE+ElE))	0.46	0.30	0.29	0.10	0.00	0.82	5,487
Solid Fuels (So)	0.38	5.20	6.79	1.42	0.00	0.36	5,521
Solid Fuels Expenditures (SoE)	51.43	573.91	746.03	144.53	0.00	63.97	5,521
Total kWh (kWh)	49,992.84	219,778.46	240,000.00	41,300.00	929.49	82,506.86	5,521
Total kWh Expenditures (kWhE)	692.13	2,410.12	2,679.24	372.24	26.62	1,331.08	5,521
CO_2 (CO_2)	18,579.60	74,992.96	84,091.85	12,085.18	428.39	32,086.12	5,521
CO_2 over total kWh (CO_2/kWh)	0.45	0.13	0.13	0.05	0.30	0.67	5,521

Source: Martin, de Preux and Wagner (2009). Notes: Descriptive statistics for the QFI pooled sample (1999-2004) GO and all the expenditure variables are in thousands of pounds. Total kWh, Gas and El are in thousands of kWh. So and Li are in thousands of tonnes. The CO_2 variable measures total CO_2 emissions in thousands of tonnes based on fuel use (the conversion factors are from the Entech Utility Service Bureau, for more details see Martin, 2006).

Table 5. Descriptive statistics -- Joint ARD/QFI sample

Variables	(1) mean	(2) sd	(3) sd, between	(4) sd,within	(5) p10	(6) p90	(7) N obs
Electricity (El)	17,411.14	53,354.97	44,439.77	10,111.78	550.61	38,122.57	3,614
Electricity Expenditures (ElE)	518.81	1,364.78	1,150.48	244.60	25.66	1,190.39	3,614
Liquid Fuels (Li)	0.74	8.59	7.42	1.37	0.00	0.00	3,614
Liquid Fuels Expenditures (LiE)	46.41	500.32	466.05	71.99	0.00	0.00	3,614
Gas (Gas)	36,396.56	154,114.30	119,049.80	45,320.24	0.00	65,819.65	3,608
Share of Gas over Gas and El Consumption (gas/(gas+el))	0.25	0.20	0.19	0.07	0.00	0.53	3,597
Gas Expenditures (GasE)	267.71	1,108.01	847.58	352.83	0.00	517.79	3,614
Share of Gas over Gas and El Expenditures (GasE/(GasE+ElE))	0.47	0.30	0.29	0.09	0.00	0.82	3,597
Solid Fuels (So)	0.41	4.99	5.50	1.59	0.00	0.49	3,614
Solid Fuels Expenditures (SoE)	58.13	577.63	638.67	175.92	0.00	78.60	3,614
Total kWh (kWh)	64,265.10	231,896.29	196,818.80	49,477.93	1,490.49	121,507.90	3,614
Total kWh Expenditures (kWhE)	887.35	2,553.34	2,216.24	448.23	40.05	1,890.61	3,614
Total kWh over GO (kWh/GO)	0.02	0.02	0.02	0.00	0.00	0.04	3,034
CO_2 (CO_2)	23,791.86	77,904.14	67,160.30	14,456.08	679.42	46,653.24	3,614
CO_2 over total kWh (CO_2/kWh)	0.45	0.13	0.13	0.05	0.30	0.67	3,614
CO_2 over GO (CO_2/GO)	444.15	678.87	645.06	120.53	48.75	1,071.94	3,614

Source: Martin, de Preux and Wagner (2009). Notes: Descriptive statistics for QFI variables in the joint sample of firms with lnGO not missing, pooled for 1999-2004. All the expenditure variables are in thousands of pounds. Total kWh, Gas and El are in thousands of kWh. So and Li are in thousands of tonnes. The CO_2 variable measures total CO_2 emissions in thousands of tonnes based on fuel use (the conversion factors are from the Entech Utility Service Bureau, for more details see Martin, 2006).

36. Finally, Table 6 shows the descriptive statistics for all samples in the year 2000, broken down by CCA participation status, as well as the results of a *t*-test of equality of the group means. CCA plants are, on average, older, larger and more energy intensive, and for most of these plant characteristics equality is rejected at the 1% significance level. In view of the strong correlation of CCA participation with observable plant characteristics, we cannot rule out the possibility that unobservable plant characteristics also influence selection. In the analysis below we thus adopt an identification strategy that takes due account of the sample selection issue, so as to avoid inconsistent estimation.

Table 6. Descriptive statistics by CCA participation status

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)
Data set	**ARD**			**QFI**			**QFI and ARD**		
Variables	**CCA=0**	**CCA=1**	**diff test**	**CCA=0**	**CCA=1**	**diff test**	**CCA=0**	**CCA=1**	**diff test**
Age	13.55	17.53	***	21.86	22.87	-	21.54	22.84	*
Employment (L)	151.49	536.44	***	372.05	548.98	***	373.14	548.98	***
Gross Output (GO)	19.08	86.08	***	49.07	91.56	***	49.29	91.56	***
Energy Expenditures (EE)	0.22	1.95	***	0.59	3.79	***	0.59	3.79	***
Variable Costs (Vcost)	15.99	75.14	***	42.19	78.46	***	42.39	78.46	***
Capital Stock (K)	9.64	58.17	***	23.12	65.44	***	28.89	72.78	***
EE over Variable Costs (EE/Vcost)	1.92	3.01	***	1.99	3.60	***	1.99	3.60	***
Electricity (El)	8,701.55	38,191.39	***	8,888.03	34,210.84	***	8,701.55	38,191.39	***
Electricity Expenditures (ElE)	306.93	1,162.83	***	292.64	1,050.91	***	306.93	1,162.83	***
Gas (Gas)	14,144.07	75,098.82	***	14,859.74	68,213.13	***	14,144.07	75,098.82	***
Share of Gas over Gas and El Consumption (Gas/(Gas+El))	0.19	0.24	***	0.18	0.25	***	0.19	0.24	***
Solid Fuels (So)	0.01	0.34	-	0.39	1.44	-	0.21	1.66	-
Solid Fuels Expenditures (SoE)	1.91	44.30	*	55.98	191.24	-	36.42	219.43	-
Liquid Fuels (Li)	0.01	0.36	-	0.21	2.02	*	0.28	1.78	-
Liquid Fuels Expenditures (LiE)	0.71	20.45	**	10.74	132.41	**	13.52	101.28	*
Total kWh (kWh)	27,261.95	146,775.90	***	29,834.32	135,378.51	***	27,261.95	146,775.90	***
Total kWh Expenditures (kWhE)	23.23	390.91	***	446.06	1,784.71	***	443.30	1,936.10	***
Total kWh over GO (kWh/GO)	0.01	0.03	***	0.01	0.03	***	0.01	0.03	***
CO_2 (CO_2)	10,673.51	54,239.67	***	11,454.80	50,219.85	***	10,673.51	54,239.67	***
CO_2 over total kWh (CO_2/kWh)	0.45	0.44	-	0.45	0.43	*	0.45	0.44	-
CO_2 over GO (CO_2/GO)	326.82	750.21	***	326.82	750.21	***	326.82	750.21	***
Number of Plants	8,282	1,050		701	251		434	212	

Source: Martin, de Preux and Wagner (2009). Notes: Variables in 2000 by CCA status GO and all the expenditure variables are in thousands of pounds. Total kWh, Gas and El are in thousands of kWh. So and Li are in thousands of tonnes. The CO_2 variable measures total CO_2 emissions in thousands of tonnes based on fuel use (the conversion factors are from the Entech Utility Service Bureau, for more details see Martin, 2006). Columns 3, 6, and 9 report significance levels from a *t*-test of differences in group means with unequal variance, at ≤1% (***), ≤5% (**), ≤10% (*).

37. In the analysis below we focus on the manufacturing sector, because the QFI data only cover manufacturing plants. We examine the first two target periods, running from April 2001 until December 2004. On the one hand, this is dictated by the time coverage in our data set. On the other hand, it

avoids possible complications due to (i) an overlap with the EU ETS which affected about 500 CCA plants from 2005 onwards, (ii) adjustments of CCAs targets for the third milestone period, and (iii) new entry of sectors in 2006 after eligibility had been changed.

3.3 Empirical framework

3.3.1 Identifying the effect of the tax discount

38. Our strategy to identify the impact of the tax discount builds on the comparison of trends in energy intensity and other plant outcomes between facilities in a CCA and others. This approach follows the literature on programme evaluation and treatment effects (*e.g.* Rosenbaum and Rubin, 1983, Angrist, Imbens and Rubin, 1996). There are two fundamental issues that need to be addressed. First, CCA plants receive a tax discount, but they are also subject to quantity regulation which might constrain their production choices. Second, participation in a CCA is voluntary, but not every plant is eligible. This potentially creates a selection problem in the treatment population.[10] We shall discuss both issues in turn.

39. With respect to the first issue, previous evaluations concluded that the CCA targets were unlikely to impose binding constraints on firm behaviour. If this is true, estimated treatment coefficient measures the effect of an 80% reduction in energy taxes, which amounts to an energy price drop on the order of 10% for a typical business. In contrast, the estimate falls short of the true price effect if the CCA target prevents plants from choosing optimal levels of energy under the lower tax rate. Therefore, the empirical framework provides a conservative estimate of the impact of the CCL. Figure 1 illustrates this point.[11]

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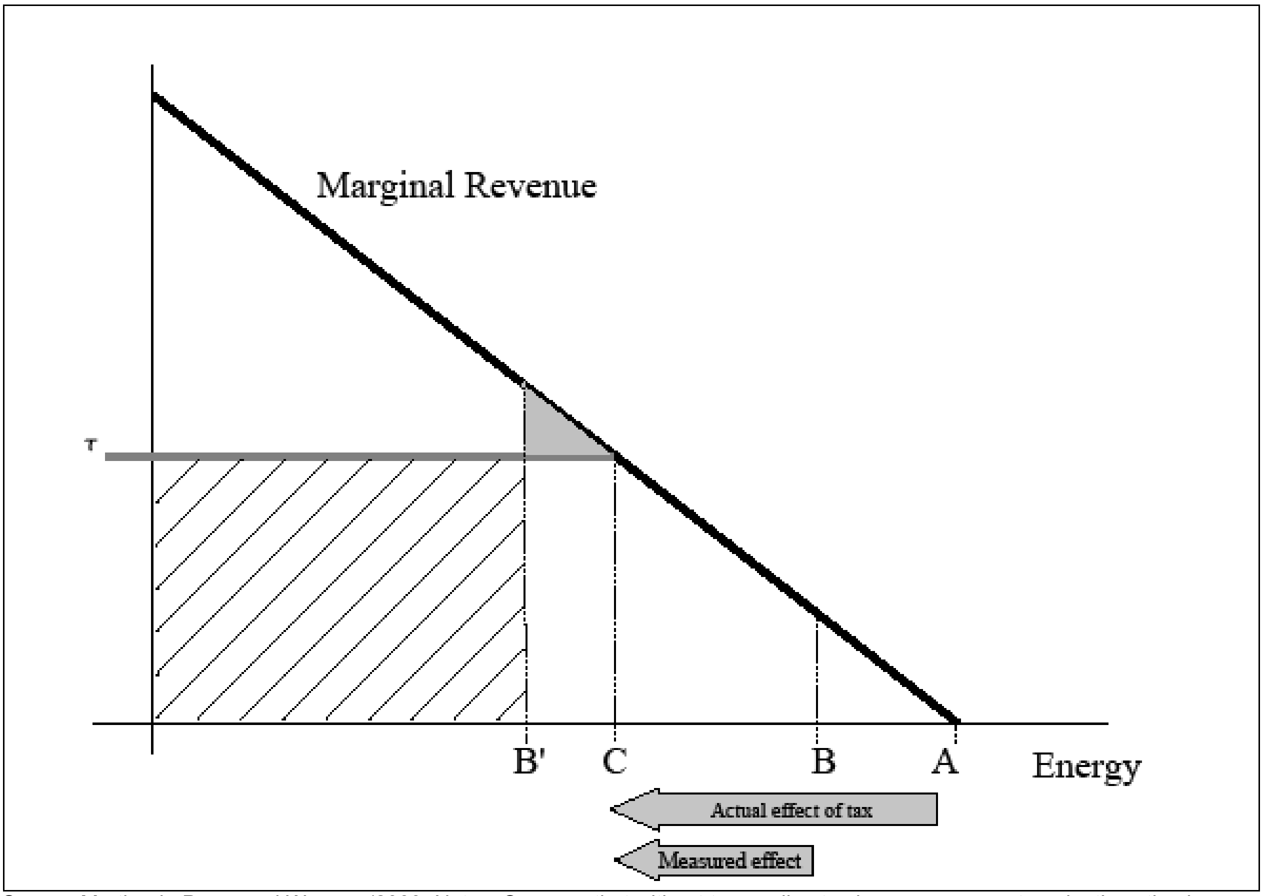
10 A further complication is that the tax impact might vary systematically with treatment status as among the group of treated plants. We discuss these issues in Martin, de Preux and Wagner (2009).

11 The reader should bear in mind that the stringency of CCA targets is only relevant for the interpretation of the estimated effect as a lower bound on the full tax effect. The stringency does not affect the consistency of the procedure we use to arrive at this estimate.

Figure 1. Target vs. tax effect

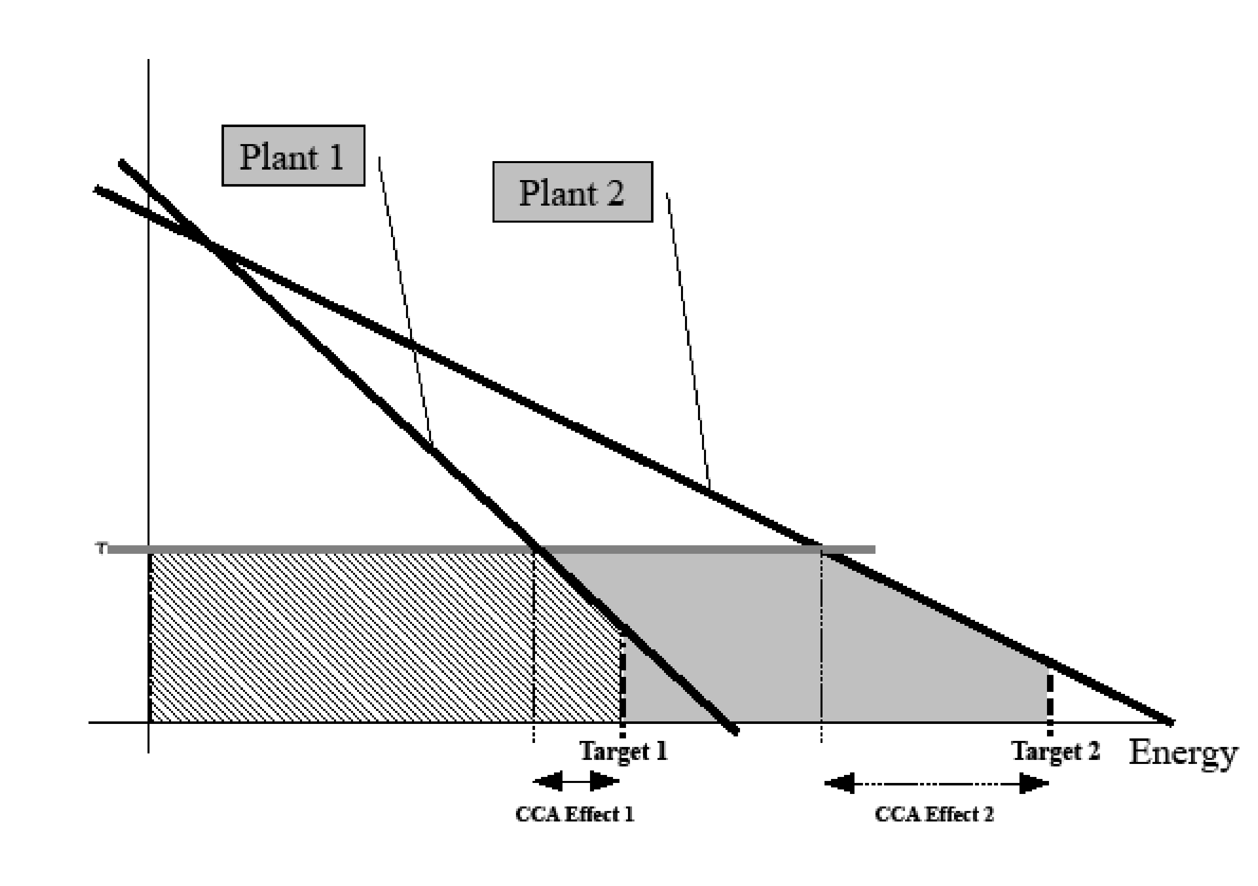


Source: Martin, de Preux and Wagner (2009. Notes: Suppose that without tax or climate change agreement, a plant's optimal energy consumption is at A. With a tax τ, the optimal consumption reduces to C. If the target set by a Climate Change Agreement (CCA) is at an intermediate point such as B, comparing CCA and non CCA plants provides a meaningful lower bound on the impact of the tax. On the other hand, if the target is at B', we would not be able to identify the decrease in energy consumption from A to C due to the tax. For simplicity, we normalized the graph so that the reduced CCA tax rate coincides with the horizontal axis.

40. The issue of non-random selection of plants into agreements arises if plants with different levels of the outcome variable prior to treatment have differing incentives to join a CCA. It is easy to find reasons for why this might be the case. For example, plants using more energy have more to gain – in absolute terms – from a discount on an energy tax than plants with lower levels of energy consumption. If participation in a CCA comes with a fixed cost, the latter might find it more profitable not to join.[12] Figure 2 illustrates this graphically.

[12] In personal communication, representatives of CCA sector associations pointed out multiple sources of fixed costs to us. The main cost drivers are payments to consultants or staff for doing the necessary energy accounting and administrative work, as well as administrative fees charged by the sector associations.

Figure 2. Selection into CCA



Source: Martin, de Preux and Wagner (2009). Notes: Consider two plants with different marginal revenue schedules. Even if both plants have a target that implies the same absolute reduction of energy consumption, the plant with the higher revenue curve (plant 2) has more to gain from joining a CCA. Plant 2's gain equals the sum of grey and diagonally striped areas, whereas plant 1's gain equals the striped area only.

3.3.2 Econometric model

41. Thanks to having longitudinal data, we can control for selection based on persistent heterogeneity across plants by analyzing within-plant changes in outcome variables. We compare the change in an outcome variable y_{it} before and after the introduction of the CCL package in 2001, and between CCA and non-CCA firms. To simplify the discussion that follows, assume that y_{it} stands for a plant's energy consumption, although we consider a variety of different outcome variables in our results below. We estimate the linear model

(1) $$\Delta y_{it} = \alpha \Delta CCA_{it} + x_{it}^{'}\beta + \xi_t + \eta_i + \nu_{it}$$

where x_{it} is a vector of exogenous plant characteristics, such as age controls and dummy variables for region and sector. Second, we include year effects ξ_t and a plant specific fixed effect η_i in the error term. The disturbance term ν_{it} reflects short-term deviations from a plant's idiosyncratic trend in energy consumption. Simultaneity of these shocks and CCA participation would induce bias in the estimate of α. Suppose, for example, that the Government imposes the same reduction target relative to current consumption for all plants. For plants that are planning to expand their energy consumption, this may impose a binding constraint and therefore prevent them from joining the CCA, whereas plants that expect a reduction in consumption may be better off by joining if the fixed cost is not too large. To the extent that such idiosyncratic trends persist throughout the estimation period, they are absorbed into the plant fixed effects.

42. To further address simultaneity arising from transitory shocks, we propose an instrumental variable (IV) approach based on eligibility restrictions for CCA participation. The Government intended to base eligibility upon energy intensity, yet in practice granted eligibility to all qualifying part A activities under the PPC Act. A dummy variable for whether or not a facility carries out such an activity is thus a good predictor of CCA participation. Further, this variable is a valid instrument if the polluting activity does not directly affect energy use. This should be true of plants that are covered by PPC regulations, because they emit pollutants other than those resulting from combustion processes. When this instrument is used in equation (1), the identifying assumption is that being covered by the PPC act must be exogenous to a plant's specific trend deviation v_{it} occurring after 2000.

43. The intuition behind this instrument can be explained using the glass industry as an example. Both the production and the recycling of glass containers are highly energy intensive processes. However, since only the production is pollution-intensive, recycling was not eligible for CCA participation until the eligibility rules were revised in 2006. The eligibility rules for the British Apparel and Textile Confederation were amended in 2006 to include low pollution, high energy users that had previously been excluded from CCA participation. This institutional 'glitch' provides quasi-experimental variation in the probability of treatment.

44. To construct the instrument, we drop all air pollutants from the EPER file for which the European Environmental Agency lists combustion or other energy intensive processes as the main source of emissions, as they might be endogenous to energy use.[13] We define the instrumental variable, *EPER*, as a dummy variable that equals 1 if a facility reports emissions of any of the remaining air pollutants or of the water pollutants regulated under IPPC. We assign a value of zero otherwise. Just like our treatment variable CCA, this variable is zero for all plants before 2001 and does not vary between 2002 and 2004.

45. We perform a two-stage, least squares estimation, where the first stage is a regression of CCA participation on *EPER*

(2)
$$\Delta CCA_{it} = \breve{\alpha}\Delta EPER_{it} + x'_{it}\breve{\beta} + \breve{\xi}_t + \breve{\eta}_i + \breve{v}_{it}$$

and the second stage is a regression of outcome variables on predicted treatment indicators from the first stage

(3)
$$\Delta y_{it} = \alpha\Delta\widehat{CCA}_{it} + x'_{it}\beta + \xi_t + \eta_i + v_{it}$$

3.4 Results

3.4.1 The determinants of CCA participation

46. We first examine the explanatory power of the instrumental variable EPER, which indicates whether a plant is covered by the PPC regulation due to emissions of water pollutants or of air pollutants other than those stemming from combustion activities. While PPC coverage is a legal precondition for CCA participation, it is also one of the formal requirements needed for our instrumental variable approach

[13] For example, combustion of coal is the main source of arsenic emissions, iron and steel production is the main source of cyanide emissions, and so on. We identify 31 air pollutants in this way; see Martin, de Preux and Wagner (2009) for details.

to be valid. Furthermore, we explore how various other plant characteristics correlate with CCA participation.

47. Table 7 reports various regressions of CCA participation. Each regression is run both on the sample with ARD data and on the sample with QFI data. We start in columns 1 and 6 with a simple linear regression of CCA participation on EPER in a cross-section for 2001. We see that PPC coverage proxied by EPER is a significant determinant of CCA participation. Columns 2 and 7 report the marginal effects from a probit regression of the same specification. The coefficients imply that a value of EPER=1 increases a plant's chances of participating in a CCA by 38% in the ARD sample and by 60% in the QFI sample.

Table 7. First-stage regression

	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
Dep.Variable	**CCA participation**									
Sample	**ARD sample**					**QFI sample**				
Time period	**2001**	**2001**	**2000-2004**	**2000-2004**	**2001**	**2001**	**2001**	**1998-2004**	**1998-2004**	**2001**
Method	**OLS**	**Probit**	**OLS**	**FE**	**Probit**	**OLS**	**Probit**	**OLS**	**FE**	**Probit**
EPER	0.411***	0.383***	0.391***	0.480***		0.433***	0.609***	0.414***	0.497***	
	(0.030)	(0.044)	(0.033)	(0.040)		(0.069)	(0.076)	(0.062)	(0.061)	
lnGO(t-1)					-0.014***					-0.043
					(0.004)					(0.067)
lnK(t-1)					0.016***					0.222***
					(0.003)					(0.056)
lnEE(t-1)					0.020***					0.057
					(0.003)					(0.040)
lnL(t-1)					0.011***					-0.031
					(0.003)					(0.059)
Age controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Sector controls	yes	yes	yes	no	yes	yes	yes	yes	no	yes
Region X year controls	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Plant fixed effects	no	no	no	yes	no	no	no	no	yes	no
Observations	9175	8506	17040	17040	8456	922	735	4578	4578	478

Source: Martin, de Preux and Wagner (2009).

48. Next we run the linear regression in the full regression samples we use below. This corresponds to the first stage of the IV regression given by equation (2). The results are reported in columns 3 and 8 (with sector dummies) and in columns 4 and 9 (with plant fixed effects). The positive and significant coefficients in these columns confirm that *EPER* is a strong predictor of CCA participation.

49. Finally, columns 5 and 10 display the results from a probit regression for the 2001 cross-section, including various plant-level controls for 2000. The coefficient estimates largely confirm that the simple correlations we found in Table 6 persist even when controlling for sectoral differences. In particular, plants that are larger in terms of their capital, labour and energy inputs are more likely to participate in a CCA. Interestingly, we obtain a negative coefficient on gross output. A plausible explanation for this is that conditional on size plants that expanded their output in the year before the CCL package was introduced were less inclined to participate in a CCA, as an expansion would make it more difficult to meet their CCA target. In the next section we shall find further evidence for this type of selection bias.

3.4.2 The impacts of CCA participation

50. Table 8 summarizes regression results for various outcome variables (in rows) under different assumptions about the error term (in columns). The first column contains results from a pooled OLS estimation of equation (3) without plant fixed effects. In column 2, we replace the CCA participation

variable with the instrumental variable *EPER* to estimate a reduced-form equation. Column 3 reports results from a pooled two-stage, least squares specification. Columns 4 to 6 repeat this sequence while including plant specific fixed effects. Consequently, column 6 reports the most general estimate of the average treatment effect on the treated. Figure 3 provides a graphical summary of the results we obtained using this specification. Subsequently, we discuss the results in more detail.[14]

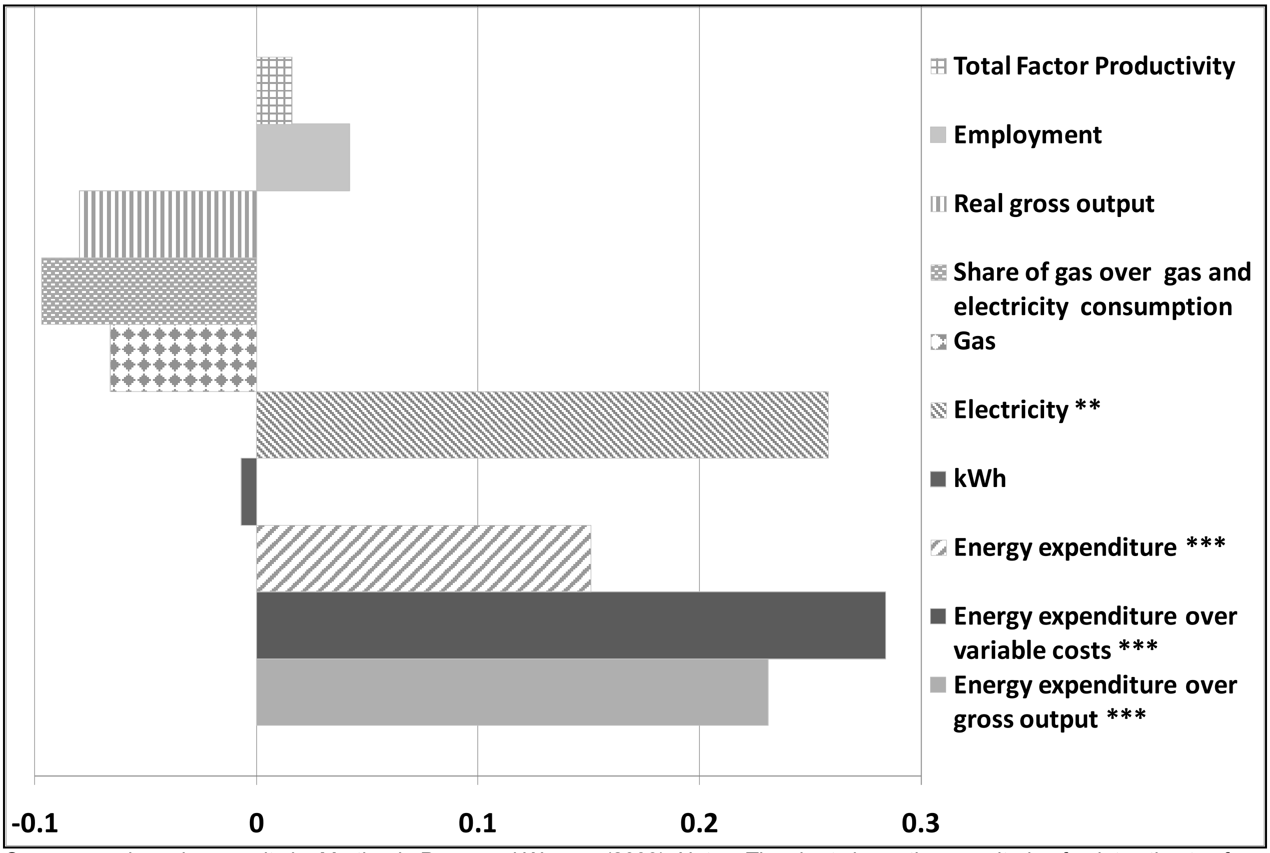
Table 8. The impacts of CCA participation

		(1)	(2)	(3)	(4)	(5)	(6)	(7)
DepVar	**ExpVar**	**OLS**	**Reduced Form (OLS)**	**IV**	**Fixed Effects**	**Reduced Form (FE)**	**Fixed Effects IV**	**Obs./ Plants**
Energy exp. over gross output	CCA/EPER	0.026**	0.086***	0.220***	0.025	0.111***	0.231***	14,336
Δln(EE/GO)		(0.013)	(0.028)	(0.072)	(0.019)	(0.040)	(0.084)	4,209
Energy exp. over variable costs	CCA/EPER	0.026**	0.104***	0.266***	0.015	0.137***	0.285***	14,336
Δln(EE/VCost)		(0.012)	(0.026)	(0.069)	(0.018)	(0.037)	(0.080)	4,209
Energy exp.	CCA/EPER	0.019	0.033	0.085	0.036**	0.075**	0.156**	14,336
Δln(EE)		(0.012)	(0.024)	(0.061)	(0.017)	(0.029)	(0.061)	4,209
Total kWh	CCA/EPER	0.068**	-0.000	-0.001	0.079**	-0.004	-0.007	4,452
Δln(kWh)		(0.027)	(0.049)	(0.115)	(0.035)	(0.068)	(0.135)	928
Electricity	CCA/EPER	0.026	0.085*	0.206*	0.028	0.128**	0.258**	4,452
Δln(El)		(0.021)	(0.046)	(0.118)	(0.024)	(0.058)	(0.127)	926
Gas	CCA/EPER	0.016	0.014	0.036	0.012	-0.035	-0.066	3,602
Δln(Gas)		(0.037)	(0.052)	(0.127)	(0.047)	(0.080)	(0.151)	764
Share of gas over gas & elec. cons.	CCA/EPER	0.018**	-0.044	-0.107	0.022**	-0.048	-0.097	4,435
Δ(Gas/(Gas+El))		(0.008)	(0.031)	(0.078)	(0.009)	(0.039)	(0.084)	926
Share of gas over kWh	CCA/EPER	0.013	-0.007	-0.018	0.018	-0.010	-0.021	4,449
Δ(Gas/kWh)		(0.011)	(0.023)	(0.055)	(0.015)	(0.032)	(0.065)	928
Solid fuels	CCA/EPER	-0.155	-0.226	-0.649	-0.091	-0.290	-0.542	1,467
Δln(So)		(0.101)	(0.224)	(0.597)	(0.115)	(0.266)	(0.486)	344
Solid fuels over kWh	CCA/EPER	0.003	-0.016	-0.039	0.005	-0.022	-0.044	4,452
Δ(So/kWh)		(0.004)	(0.011)	(0.025)	(0.006)	(0.015)	(0.030)	928
CO2	CCA/EPER	0.050**	0.018	0.044	0.053**	0.024	0.048	4,452
Δln(CO2)		-0.021	-0.040	-0.094	-0.026	-0.051	-0.101	928
Employment	CCA/EPER	-0.014	-0.039*	-0.101*	0.021	-0.019	-0.041	14,336
Δln(L)		(0.011)	(0.021)	(0.054)	(0.014)	(0.036)	(0.075)	4,209
Real gross output	CCA/EPER	-0.008	-0.053**	-0.136**	0.011	-0.036	-0.076	14,336
Δln(Real GO)		(0.011)	(0.022)	(0.057)	(0.014)	(0.035)	(0.072)	4,209
Total Factor Productivity	CCA/EPER	-0.002	0.000	0.001	-0.007	0.009	0.018	14,288
		(0.006)	(0.015)	(0.038)	(0.009)	(0.026)	(0.054)	4,194
Δln(GO)	Δln(M)	0.477***	0.477***	0.477***	0.468***	0.469***	0.468***	
		(0.013)	(0.013)	(0.013)	(0.017)	(0.017)	(0.017)	
	Δln(EE)	0.034***	0.034***	0.034***	0.036***	0.036***	0.036***	
		(0.006)	(0.006)	(0.006)	(0.008)	(0.008)	(0.007)	
	Δln(L)	0.257***	0.257***	0.257***	0.237***	0.237***	0.237***	
		(0.013)	(0.013)	(0.013)	(0.018)	(0.018)	(0.018)	
	Δln(K)	0.049***	0.049***	0.049***	0.069***	0.068***	0.068***	
		(0.016)	(0.016)	(0.016)	(0.020)	(0.020)	(0.020)	

Source: Martin, de Preux and Wagner (2009). Dependent variables are first-differenced from 1997 until 2000 and differenced at various intervals thereafter. Column 1 displays OLS coefficient, column 2 displays OLS coefficient on the instrumental variable in the reduced form, and column 3 displays the 2-stage least squares estimate. Columns 4 to 6 have the same setup while including a firm fixed effect. Column 7 reports the number of observations. All regressions include age, age squared, year dummies and region-by-year dummies. Columns 1 to 3 in addition include region and 3-digit industry dummies.

14 The discussion draws upon the discussion in Martin, de Preux and Wagner (2009).

Figure 3. A graphical summary of the main results



Source: own based on results by Martin, de Preux and Wagner (2009). Notes: The chart shows the magnitude of point estimates from instrumental variable (IV) regressions of the growth rates of these variables on participation in a Climate Change Agreement and other plant characteristics. The instrument is a binary indicator of whether a plant reported water or non-combustion air pollutants under the PPC regulation. More intuitively, this is the average deviation from the average growth rate after 2000 which can be causally attributed to a plant's participation in CCA. The regression also controls for plant age, year, and includes region-by-year and plant fixed effects. Asterisks indicate whether a value is statistically different from 0 at significance level 10% (*), 5% (**), and 1% (***).

Energy

51. The first two panels of Table 8 report the results for energy intensity measured as energy expenditures over gross output and as the share of energy expenditures in variable costs (the sum of expenditures on materials, energy and wages), respectively. The results are very similar for both variables. We find that plants in a CCA *increased* their energy intensity by more than 20% relative to plants that paid the full levy after 2000 (the point estimates from the fixed-effects IV regressions are 0.231 for the former measure and 0.284 for the latter). This effect is both economically and statistically significant. The point estimates change very little when moving to the regressions with fixed effects in columns 4 to 6. This suggests that normalizing energy use by some measure of plant size goes a long way to control for unobserved heterogeneity between plants. Further, the importance of controlling for selection is evident from the sizable differences between the OLS and IV estimates. In particular, OLS estimation leads to a downward bias when estimating the effect of CCA membership on the growth in energy intensity. A plausible explanation for this is that plants that expected a negative shock to energy intensity growth following the introduction of the CCL were more prone to seek membership in a CCA, expecting that it would be relatively easy for them to comply with a reduction target. This is consistent with the results from the probit regression presented above.

52. Panel 3 reports the results for energy expenditure. Here we only find a statistically significant and positive effect once we include fixed effects. This is an indication that there may have been declining trends in energy use within some 3-digit industries that are correlated with both CCA participation and EPER coverage. For instance, parts of the steel industry experienced a seminal downturn that coincided with the introduction of the CCL package, yet did not affect all quality tiers in steel production equally. Naturally, this issue disappears when dividing by a size control (as in panels 1 and 2) or when controlling for plant specific fixed effects (as in columns 4 to 6). The point estimate in the IV regression (column 6) implies that participation in a CCA led plants to *increase* their expenditures on energy by more than 15% relative to plants that were subject to the full tax.

Fuel substitution

53. The above results leave open the question whether CCL plants lowered their energy expenditures in a way that would be considered a success for climate change policy. A priori, this is not clear because this measure of energy use lumps together changes in the price and quantity of energy, as well as the effects of substitution between different fuel types. For example, instead of consuming less of all fuel types CCL plants might substitute towards cheaper fuel sources, which might also be more polluting, *e.g.* coal. To investigate this, the next seven panels in Table 8 report results from regressions using quantity changes in energy consumption by fuel type which are available in the QFI sample. Although this sample is smaller than the ARD sample, we find economically and statistically significant evidence that CCA membership led plants to increase their electricity use by about 26%. This is in line with the design of the CCL, which imposes the highest tax rate for electricity. For both gas and solid fuels (*i.e.* coal), we obtain negative point estimates on the CCA coefficient. We also find negative point estimates when looking at the share of these fuels in total kWh consumed. While these coefficients are not different from zero in a statistical sense, they hint at the possibility that some CCL plants switched from electricity to the lower-taxed fuels gas and coal. This would also explain why the overall effect on total kWh is not significant in the IV regressions. If plants switch from electricity to gas or coal they are likely to require more kWhs of primary energy to achieve a given energy service. This could account for at least a partial offset of a tax-induced reduction in the demand for those services.

Carbon emissions

54. A significant increase in electricity consumption by CCA plants should translate into an increase in carbon emissions, given that we did not find a significant decline in the consumption of other fuel types. Next we examine whether we can find this effect when the outcome measure is the total sum of CO_2 emissions across fuel types. The eleventh panel of Table 8 reports that CCA membership is associated with a 5% increase in total CO_2 emissions. The point estimate is very robust across specifications, yet loses statistical significance in the IV regressions. It seems likely that this is due to the noise in the estimated response by fuels other than electricity. In the absence of a larger sample that would enable us to estimate this effect with more precision, we are left with two possible interpretations. On the one hand, we could disregard coefficients that are statistically insignificant at conventional levels altogether and conclude that the unchecked increase of electricity consumption translates into an increase in CO_2 emissions of equal magnitude. On the other hand, a more cautious interpretation of our results would put the impact of CCA participation on carbon dioxide emissions at 5%, which accounts for the possibility that some CCL plants switched into dirtier fuels such as coal. We thus conclude that the full-rate CCL - though not designed as a pure carbon tax - led plants to reduce growth in CO_2 emissions by between 5 and 26% more than the CCA targets did in combination with the discount on the levy.

Economic performance

55. Finally, we investigate whether the impacts on energy consumption and energy efficiency that we find correspond to movements along the production isoquant, or stem from significant shifts in the scale at which plants operate. In the 3 panels at the bottom of Table 8, we look at various plant performance variables such as output, employment and total factor productivity (TFP). When estimating the difference regression without fixed effects, we obtain significantly negative coefficients for both employment and output. However, these effects disappear when we control for plant-specific trends in columns 4 to 6. There are two things worth pointing out. First, a key policy concern with unilateral implementation of energy taxes is that they might jeopardize the competitiveness of domestic industry. If this was the case, we should observe positive employment or productivity effects of CCA participation, because plants that pay the CCL scale down production and employment. Our finding of the opposite effect ought to dissipate such concerns. Second, the fact that the negative coefficients effects lose significance once we include plant fixed effects suggests that they are driven by pre-existing trends, unrelated to the policy intervention. Similar to what occurred in the steel industry, this could be due to plants in industries covered by both CCA and PPC regulations which were on a declining trend even before the arrival of the CCL policy package. The last panel suggests that CCA participation had no discernible effect on total factor productivity. In sum, there is no evidence that the CCL had any adverse effects on economic outcome variables.

3.4.3 Robustness

56. We performed a series of robustness checks on these results (see Martin, de Preux and Wagner, 2009, for details). For example, we interacted the treatment variable with a year dummy, so as to estimate the time-profile of the effect. This exercise confirmed the qualitative findings presented above. On some occasions, we found that the impacts were significant only from 2002 onwards.

57. We also estimated the econometric models in a balanced sample, *i.e.* using only plants for which we have observations in all years. Again this confirmed the qualitative finding, although statistical significance levels were reduced in some instances, as the sample size became smaller.

58. In order to investigate heterogeneous treatment effects among the treated group, we estimated the model in a sample with common support for the treatment and control group, following the method proposed by Blundell *et al.* (2004). This resulted in very similar point estimates and suggests that heterogeneity effects of the tax discount among treated plants are not much of a concern.

3.4.4 Aggregate Effects

59. The values in Figure 1 represent the causal effect of CCA participation on CCA-type plants, *i.e.* the kind of plant that tends to participate in a CCA. When extrapolating these results to the manufacturing sector as whole - where not every plant is of that type - we have to take into account what fraction of an aggregate outcome variable is due to CCA-type plants in our sample. For energy expenditure, we find a value of 59%. For electricity, we have a share of 65% of CCA-type in the sample. Had the lower CCL tax rate been applied indiscriminately across all plants in the manufacturing sector, we estimate an increase in energy expenditures of

$$15.6\% \cdot 0.59 = 9.2\%$$

and an increase in electricity use of

$$25.8\% \cdot 0.65 = 16.8\%.$$

4. Policy impacts on innovation: firm level evidence from a newly matched patent data base

4.1 The role of innovation for climate change mitigation

60. It is not hard to understand why fostering innovation is a highly desirable route in efforts to mitigate GHG emissions. If new inventions allow further emission reductions without sacrifices in consumption behaviour, global warming could be avoided at little cost. It is less clear how much resources should be devoted to producing such innovations, and what kind of role government has to play in this process. On the one hand, it is widely held that environmental innovation is underprovided due to the "double" market failures arising from pollution externalities and technological spillovers (Jaffe, Newell and Stavins, 2005). On the other hand, it is conceivable that heavy-handed government interventions to stimulate climate change related innovations divert resources from other kinds of R&D activity, which could adversely affect economic growth (at least in the short run). In spite of this, the UK Government has been advocating stringent climate change policies with the promise that this will lead to a new period of accelerated growth in output and employment.[15]

61. The CCL package offers a unique opportunity to make progress towards answering these questions. Using a new linked data resource which combines patent counts from the EPO with business performance data, we explore the empirical relationship between CCA participation and the patenting activity of firms.[16] In so doing, we identify, for the first time, a comprehensive set of climate change related patents in the EPO database. In the remainder of this Section 4 we summarize the findings from this exercise. The next subsection reviews previous empirical research on environmental innovation based on patent counts. Subsection 4.3 describes the identification of climate change related patents and the matching to business microdata. Subsection 4.4 explains our econometric framework and subsection 4.5 summarizes the results.

4.2 Review of the literature

62. Obtaining a reliable measure of innovation is one of the key challenges in empirical research on the determinants of innovation. Since data on R&D expenditures or R&D personnel are often available at the firm or sector level, they have been widely used in applied economic research to proxy for innovative activity. An issue is that they measure innovation input, not output. Patent data allow for the construction of superior measures of innovation for several reasons. First, a patent grant is a true output indicator of innovation and can often be linked to industries or even firms (Johnstone, Hascic and Ostertag, 2008). Granted only for novel and nontrivial inventions that have a commercial application, patents must satisfy an objective quality standard that changes only slowly over time. Moreover, analysis of cross-patent citations allow for the construction of a measure of the impact of an innovation (Jaffe and Trajtenberg, 2002). Finally, patent data are readily available and amenable to statistical analysis (*e.g.* Griliches 1990).

63. A potential drawback of patents is that they do not measure all inventions. Apart from rejected patent applications, this includes inventions that the inventor keeps a secret for strategic reasons (Jaffe and Trajtenberg, 2002). It has been argued, however, that there are very few major inventions that have not been patented (Dernis and Guellec, 2001). A fundamental practical problem with the use of patent data in research, however, has been solved with the computerization of major patent data bases which has made millions of patent records available in digital form (Jaffe and Trajtenberg, 2002). Given the recent

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15 See various speeches by Gordon Brown 2007-2008; *e.g.* www.number10.gov.uk/Page13791.

16 In related research, we conduct interviews with managers of randomly selected firms in the UK in order to shed light on the interplay of climate change policies, innovation and management practices (Martin, Muuls, de Preux and Wagner, 2009). We summarize this research in a separate report (Martin and Wagner, 2009b).

advances in computing technology, researchers can now conduct research involving complex patent searches on their PC.

64. While the focus of our work is on climate change related innovation, most existing empirical research in this area has been done with respect to environmental innovation more broadly. This literature uses R&D expenditures, patents counts as well as survey data to shed light on the relationship between environmental policy and environmental innovation. In what follows, we briefly review the results obtained in other studies based on patent counts.[17]

65. A common approach in this literature has been to examine the relationship between the number of patents granted and pollution abatement cost, as a proxy for the stringency of environmental policy. Comparing trends in environmental innovation in US, Japan and Germany between 1971 and 1988, Lanjouw and Mody (1996) found that increases in pollution abatement costs were associated with increases in the number of environmental patents granted. In a more rigorous econometric analysis, using panel data for US industries, Jaffe and Palmer (1995) found no effect of abatement cost on the total number of patents granted. When the outcome variable is limited to environmental patents only, Brunnermeier and Cohen (2003) found that abatement cost had a positive and significant effect on environmental innovation in the US.

66. Several papers have studied patent applications for technology controlling air pollutants such as sulfur dioxide and nitrogen oxides (Taylor, Rubin and Hounshell, 2003, Popp 2003, 2006, de Vries and Withagen, 2005). A common finding in this research is that (domestic) environmental regulation has a positive impact on patent applications, though sometimes this effect is not robust to alternative specifications.

67. More relevant to our research is previous work on energy efficiency improvements, as those are part of an effective strategy to mitigate greenhouse gas emissions. Crabb and Johnson used monthly data on energy prices in the period from 1980 until 1999 to estimate the price effect on innovation in automotive technologies that improve energy efficiency. Their results are consistent with the induced innovation hypothesis, in that increases in wellhead extraction costs led to increased patenting activity. Johnstone, Hascic and Popp (2008) examined the impact of different policy instruments on patent counts for renewable energy technologies. Using a panel of 25 high-income countries over 26 years, they found that public policy has had positive and statistically significant impact on innovation for all renewable energy sources. Their results further indicate that instrument choice matters, with taxes, obligations and tradable certificates having the most significant impact.

4.3 Data

4.3.1 Climate change related patents across countries and over time

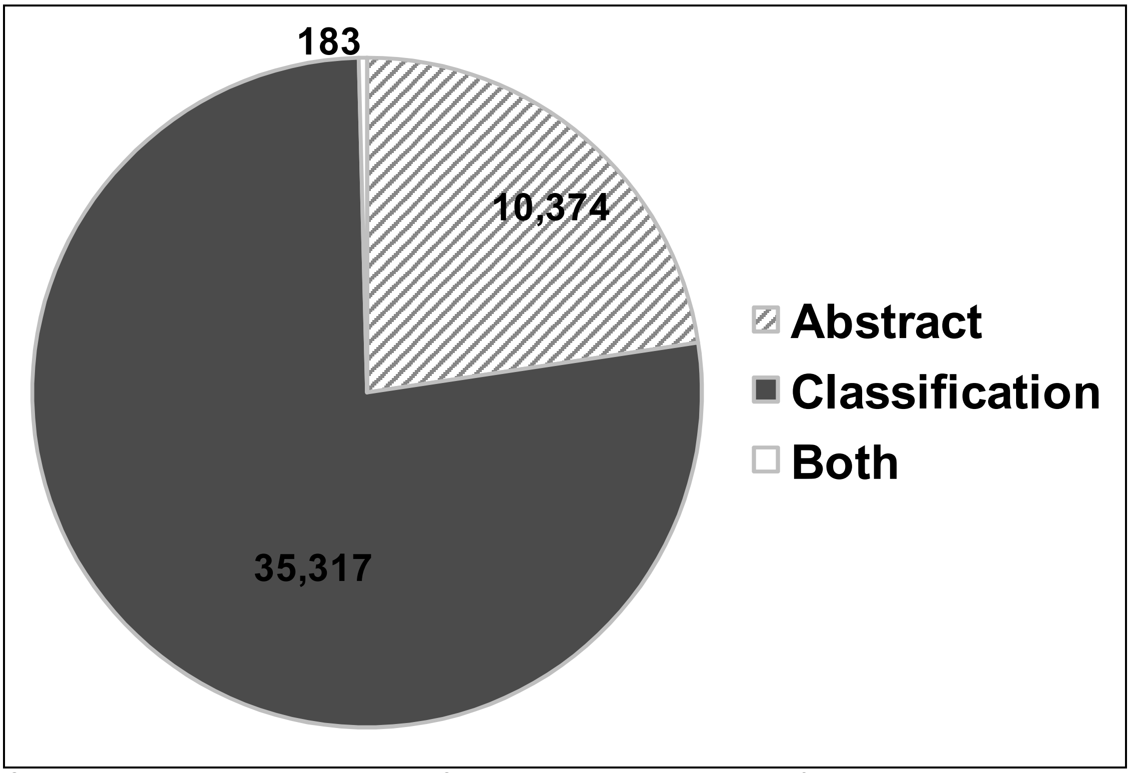
68. There are two ways to identify technological aspects of patents: patent classes and abstract searches. Previous research in the area has primarily relied on patent classes (Lanjouw and Mody 1996; Johnstone *et al.*, 2008; Popp 2002, 2005). Here we combine both approaches. We follow Popp (2002, 2005) in using a list of energy efficiency related patent classifications. In addition, we perform keyword searches within the abstracts of patents. The Appendix provides more details, including a precise list of patent classes and the correspondence between the US and European classification systems, as well as a list of the queries used in the abstract searches.

[17] See Jaffe, Newell and Stavins (2002) for an extensive overview of previous research. See also Arimura, Hibiki and Johnstone (2007), who present evidence on environmental policy and innovation based on a postal survey of managers in seven OECD countries.

69. The principal reason for exploring abstract searches in addition to the energy efficiency patent classes is that climate change mitigation is not only about energy efficiency. Since many economic and non-economic activities contribute directly or indirectly to GHG emissions, it is plausible that innovation in a wide range of areas - not necessarily those classified as "energy saving" - may have an impact on GHG emissions. Consequently, climate change policies might induce innovation in a wide range of areas with a potential for further GHG emission reductions.

70. Using both methods, we identify more than 45,000 climate change related (CCR) patents in the EPO database. Figure 4 shows that the majority of those (about 77%) are identified via the patent classification system. However, there is also a sizeable number (23%) identified through abstract searches. We would therefore ignore a large number of patents if we only relied on identification through classification. The overlap between both types is less than 1%.[18]

Figure 4. Identification of climate change related patents



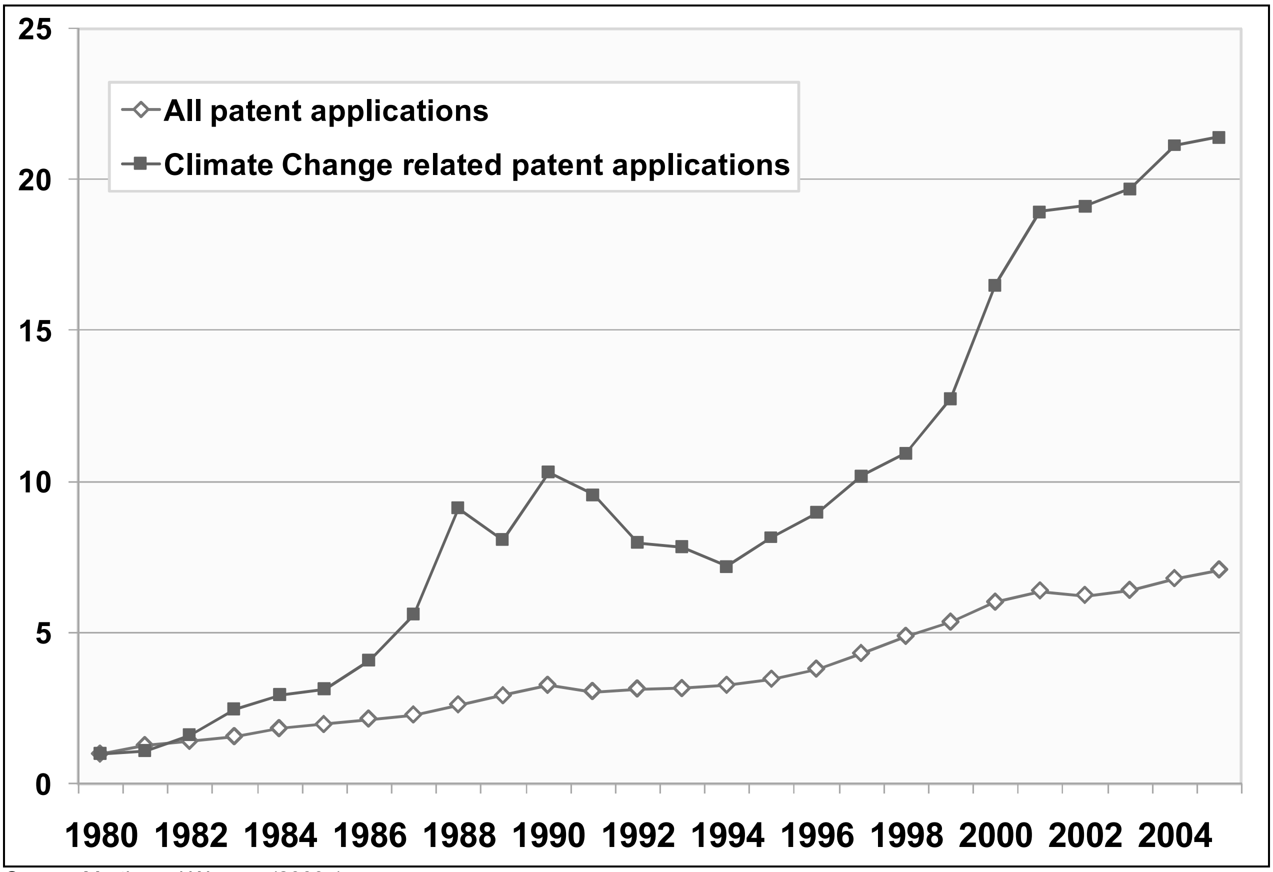
Source: Martin and Wagner (2009a). Notes: Climate change related patents identified via abstract searches, patent classes, or both. The data source is the European Patent Office from 1980 until 2005.

71. Figure 5 examines the evolution of total patents and CCR patents over time. It shows indices of new patent applications each year with base year 1980. Both the number of patents overall and CCR patents have been increasing dramatically since then. The increase in CCR patents was more pronounced and also more volatile. The pace of new applications accelerated at the end of the 1980s as well the end of the 1990s.[19]

18 It is actually somewhat surprising that the overlap is not larger. This issue needs further attention in future research.

19 One can speculate as to whether the earlier acceleration was a lagged response to the energy price shocks of the late 1970s and early 1980s. The second acceleration occurred at the outset of a prolonged increase in

Figure 5. Indices of CCR patents and total patents over time

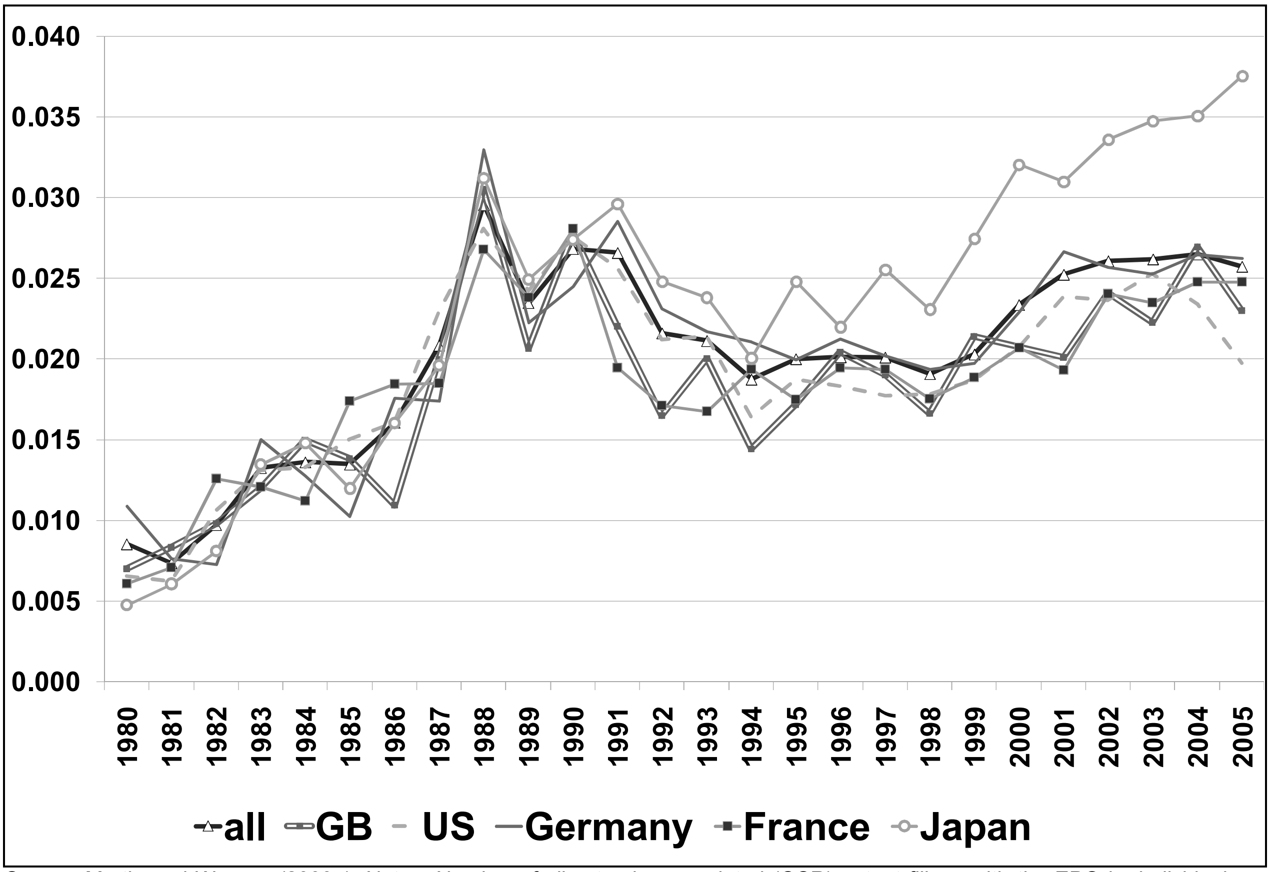


Source: Martin and Wagner (2009a).

72. Figure 6 displays the share of CCR patents in total patent applications between 1980 and 2005 across countries and in the G5 economies in total. It is evident that the relative importance of CCR patents increased in all economies during this period. Among the G5 economies, Japan and Germany are leading in terms of CCR patent shares in more recent years. Innovative output in France, the US and Great Britain is less focused on climate change related patents, although Great Britain is catching up. Notice that Japan has moved from the bottom to the top of the ranking of CCR inventors, whereas in the US inventors have turned away from CCR innovation over the 1990s.

energy prices and may also reflect increasing concern about climate change mitigation following the negotiations of the Kyoto Protocol in 1997.

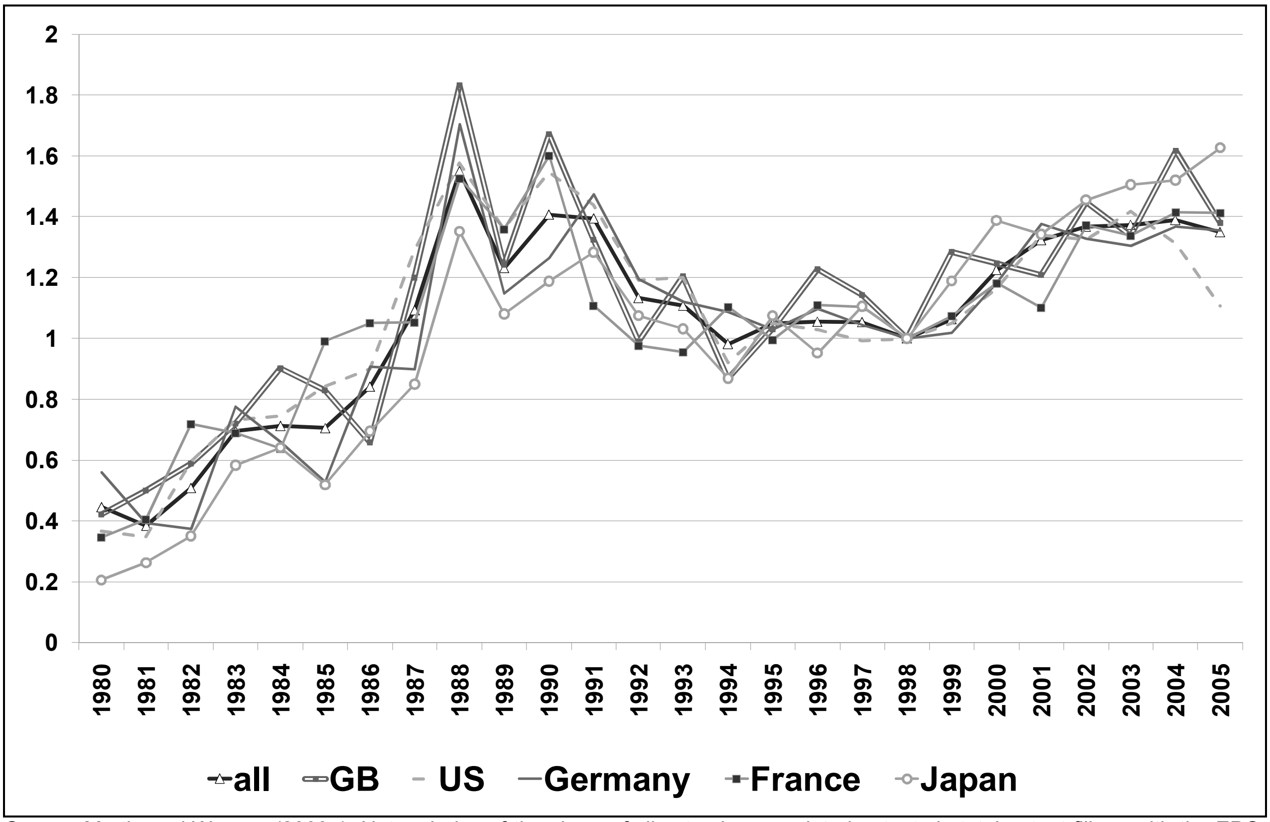
Figure 6. Shares of CCR patent applications across countries and over time



Source: Martin and Wagner (2009a). Notes: Number of climate change related (CCR) patent filings with the EPO by individuals or companies residing in various countries over the total number of filings from each country.

73. Figure 7 examines in more detail the increase in the CCR patent share after 1998 by showing an index of the time series from Figure 6 with base year 1998. This shows that the changes over time in various countries are very similar. Still we can see that Japan had a steeper increase in its CCR patent share both before and after 1998 than the other countries studied (the Japan line is at the bottom before and on top after 1998). Great Britain, on the other hand, has gone from period of reducing its CCR innovative output before 1998 to one of dynamic growth in the importance of CCR patents after that.

Figure 7. Index of the share of CCR patents



Source: Martin and Wagner (2009a). Notes: Index of the share of climate change related patents in total patent filings with the EPO. The base year is 1998.

4.3.2 Linking patent counts to UK firm level data

74. We use the CEP AMAPAT[20] database to establish a match between EPO data to business performance data. The initial link is to the population of firms in the Bureau van Dijk Amadeus[21] dataset. A host of other firm level datasets can be added, once the initial link is established. This means that we can analyze the innovative output of firms in the context of data on firm characteristics and on policy measures that these firms are subject to. Specifically, the matched data set allows us to investigate whether the CCL package introduced in 2001 affected the innovative output of UK firms.

75. Overall, we are able to match 66,479 patents to 10,085 UK firms. Of those patents, we identify 1,196 CCR patents held by 653 firms. Table 9 displays summary statistics for all EPO patents that we can match to UK firms in the Amadeus dataset. The statistics are broken down by patent type and by CCA/EPER treatment status. The difference in the mean number of patents per firm in either of these groups is always statistically significant at the 5% level or more.

20 See Belenzon and Berkovitz (2007) for more details on the matching process.

21 See www.bvdep.com/

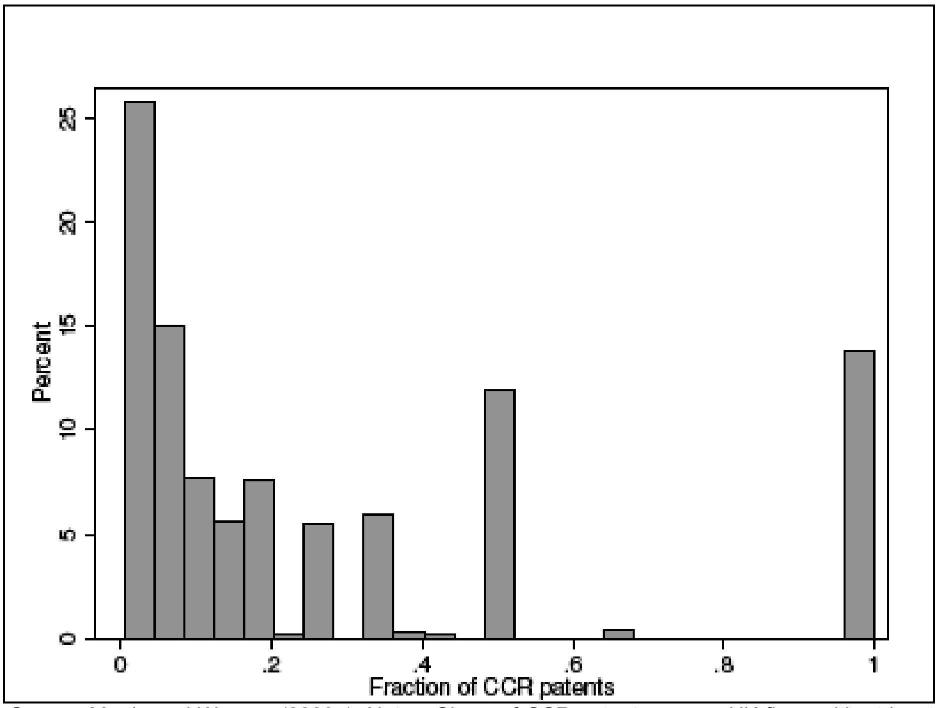
Table 9. Patents held by UK firms in the sample, 1980-2005

Patents type	Sample	Mean		Firms	Patents	p25	p75	p90
All	non CCA	5.92		9,816	58,111	1	3	7
	CCA	31.11	***	269	8,368	1	10	45
	non EPER	5.37		9,931	53,288	1	3	7
	EPER	85.66	***	154	13,191	1	9	73
	Totals			10,085	66,479			
CCR	non CCA	1.72		612	1,051	1	1	2
	CCA	3.54	**	41	145	1	4	8
	non EPER	1.56		623	972	1	1	2
	EPER	7.47	***	30	224	1	4	17
	Totals			653	1,196			

Source: Martin and Wagner (2009a). Notes: The table reports descriptive statistics for the total number of patent applications that were filed by UK firms in the sample during the period from 1980 to 2005. Sample statistics are reported by patent type and by treatment status for the CCA and EPER variables. Asterisks indicate that differences in group means are statistically significant at the 5% (**) or 1% (***) level, respectively.

76. Figure 8 displays the share of CCR patents in total patents filed per firm (rather than absolute numbers as in Table 9). This is a measure of the weight given to CCR patents as part of the firms' innovation activities. We see that the distribution of CCR patent share is multi-modal. There is a concentration of firms with only a small fraction of CCR patents. Next, there is a concentration of firms who are active to about equal degree in CCR and other patenting areas. Finally, there is a type of firm that concentrates all patenting exclusively in CCR areas. This highlights substantial heterogeneity in the innovation portfolio across firms, which needs further explanation.

Figure 8. Distribution of CCR patents in total patents



Source: Martin and Wagner (2009a). Notes: Share of CCR patents among UK firms with at least one CCR patent in 2005.

4.4 Econometric framework

77. Our econometric approach is similar to the one taken by Martin, de Preux and Wagner (2009, see the discussion in Section 3.3) in that we wish to estimate the impact of CCA participation on patenting activity of firms. Due to the discrete nature of patent counts, we need to find appropriate econometric models. We use two different models that are commonly used in econometric analyses of discrete data. The first model performs a conditional logit regression on the binary event of a firm *i* applying for at least one patent in year *t*. Thus we look at

$$\mathbf{Pr}(\mathrm{I}\{\boldsymbol{Patents}_{it} > 0\}) = \boldsymbol{f}(\boldsymbol{\beta}_D \boldsymbol{D}_{it} + \boldsymbol{x}'_{it}\boldsymbol{\beta}_x + \boldsymbol{\alpha}_i) \quad (4)$$

where D_{it} is the treatement indicator, x_{it} is a vector of control variables which includes year dummies, α_{it} is a firm fixed effect and *f* is derived from the extreme value distribution.

78. The issue with binary outcomes is that they provide only an incomplete picture of the intensity of innovative activity. We therefore also implement a Poisson count data model (Hausmann *et al.*, 1984). This model posits that the innovation process follows a stochastic process such that the expected number of patents of a firm *i* in year *t* is given by

$$\mathbf{E}(Patents_{it}) = e^{\alpha_i} e^{\beta_D D_{it} + x'_{it}\beta_x} \quad (5)$$

79. As treatment indicator, D_{it} we use the CCA and EPER variables described in Section 3.2 above. As we have discussed there, CCA participation was contingent on coverage under the Pollution Prevention and Control legislation (PPC). That is, only firms that were releasing polluting substances into air, soil or water could apply for a CCA. In Martin, de Preux and Wagner (2009) we argue in more detail why (conditional on removing fixed firm level differences) this is likely to be an exogenous shifter for CCA participation and thus for the receipt of a tax discount. To measure PPC coverage in practice we combined our firm level data with information from the European Pollution and Emissions Register (EPER).[22]

4.5 Results

80. Table 10 reports the main regression results. Columns 1 and 2 contain coefficient estimates from simple logit and Poisson models, respectively, without controls for firm-specific unobserved heterogeneity in the propensity to apply for patent protection of new inventions. To control for this, columns 3 and 4 display results from a conditional logit model and from a Poisson conditional maximum likelihood estimation (CMLE), respectively.[23] The different panels of Table 10 refer to different types of patents and regressions with different policy variables.

22 In Martin, de Preux and Wagner (2009), we use EPER as an instrument for CCA treatment. This is beyond the scope of the analysis presented here and left as a task for future research.

23 Including fixed effects in this way not only controls for firm-specific differences, but also for sector differences that may exist.

Table 10. Regression of firm-level patent applications

		(1)	(2)	(3)	(4)	(5)
	Model	**Logit**	**Poisson**	**Clogit**	**FE Poisson**	**Observations/**
Patent type	**Policy Variable**	**I(Patent)**	**Patent Count**	**I(Patent)**	**Patent Count**	**firms**
All patents	CCA	0.069***	1.382***	-0.109***	-0.510**	134320
		(0.017)	(0.295)	(0.035)	(0.243)	8395
	EPER	0.055***	1.326***	-0.161***	-0.585***	
		(0.021)	(0.376)	(0.048)	(0.186)	
CCR Patents All	CCA	0.024	0.506**	-0.135	-0.531	8832
		(0.024)	(0.228)	(0.087)	(0.388)	552
	EPER	0.033	0.474	-0.140*	-0.432	
		(0.029)	(0.317)	(0.082)	(0.359)	
CCR Patents Popp	CCA	0.021	0.491*	-0.138	-0.513	8576
		(0.024)	(0.269)	(0.088)	(0.371)	536
	EPER	0.026	0.436	-0.172**	-0.528**	
		(0.029)	(0.304)	(0.076)	(0.221)	
Non-Popp Patents	CCA	0.070***	1.375***	-0.106***	-0.510**	134224
		(0.017)	(0.236)	(0.035)	(0.220)	8389
	EPER	0.056***	1.328***	-0.167***	-0.586**	
		(0.022)	(0.375)	(0.048)	(0.277)	

Source: Martin and Wagner (2009a).

81. The first panel deals with all patents. We see that without controlling for firm-level heterogeneity, treated firms patent significantly more. This result appears regardless of whether CCA or EPER status is used as the treatment variable. Column 1 reports marginal effects instead of coefficients from the binary choice regression. These effects correspond to the marginal effect of the treatment on the propensity to patent. For example, the results imply that treated firms are 5.5. to 6.9 percentage points more likely to apply for a patent than other firms (depending on whether CCA or EPER is used as the treatment variable). Likewise, the Poisson regression indicates that CCA participation has a positive and significant effect on the expected number of patent applications.

82. However, it turns out that this result is not robust. When we control for unobserved heterogeneity, we find that, to the contrary, the propensity of CCA firms to patent innovation is up to 16 percentage point lower than that of non-CCA firms after 2001 (column 3). The Poisson regression in column 4 confirms that the number of patents filed by CCA firms dropped relative to that of non-CCA firms following the introduction of the CCL package in 2001. As was the case with the results in columns 1 and 2, the differences between the results obtained with CCA and EPER are small and well within the margin of error. This demonstrates once more that there are important unobserved differences between treated and non-treated firms which we need to control for in order to gauge the effect of CCA participation.

83. In the subsequent panels, we report results from the same set of specifications but using different dependent variables. In panel two, we use all CCR patents we identified using the combination of abstract searches and patent classifications described above. In panel three, we regressed only the patent classes identified suggested by Popp (2002, 2005). Similar to the regressions with all patents, we find evidence of a relative decline in patenting by CCA firms after 2001. However, the results are statistically significant at the 5% level only for the patents identified in Popp's way.

84. Finally in the last panel we look at non CCR patents which we define as all patents minus the patents identified using Popp's mapping of patent classes. Perhaps not surprisingly, the pattern emerging from this exercise is very similar to what we found for all patents, as non-CCR patents dominate the sample. Column 5 further explores the impact on different types of patents by taking the share of CCR patents in total patents as the dependent variable. We find no significant impacts in this regression.

85. How do these results fit together? As we have argued before, firms in a CCA face less stringent regulation and therefore have lower incentives to respond to the regulation with innovation. This could, in principle, generate the negative coefficient on patenting found in columns 3 and 4. However, we would expect any such innovation responses to be concentrated in areas related to climate change, so that negative effects should only arise in panels 1 to 3 and not in panel 4.

86. There are two possible explanations for the results in panel 4 which we will examine in future research.

87. First, the CCL had indeed an impact on innovation across the board. An explanation for why this could happen is as follows: Suppose there is a known technology that allows the firm to produce a given output using less energy but increasing its labour input. For a firm that shifts to this technology in response to the CCL the eventual effect of the CCL is to increase the incentives for labour saving R&D rather than energy saving R&D. As another example, consider a manufacturing firm that outsources the most energy intensive production processes. This in turn could require innovation in Information Communications Technology (ICT) to co-ordinate production between the firm and its outsourcing partner. Another potential explanation is often referred to as the Porter hypothesis (Porter and van der Linde, 1995). According to this hypothesis, environmental regulation can stimulate innovation in general because it forces firms to re-think their business practices in a fundamental way. Economists are often sceptical about this idea, however, as it implies in its strongest form that firms are not entirely rational and systematically overlook profit opportunities ahead of a regulatory intervention.

88. Second, it might be the case that our measure of climate change related patents is incomplete or subject to measurement error. For instance, there are concerns that the EU and US patent classification systems are too different so that using a concordance table, as we have done above, leads to mis-classifications. To address this we would have to create a list of climate change related patent classes from scratch which was beyond the scope of the current paper but appears to be a worthwhile endeavour in future work.

89. In Table 11 we report results from a regression that interacts the treatment dummy with year dummies, to examine the time-profile of the impacts found in Table 10 more closely. When looking to the most general specification in columns 3 and 4 of the second panel, it appears that the impact emerges primarily from 2002 onwards. This is consistent with there being a short lag between the introduction of a policy (in 2001) and its impact on patenting.

Table 11. Regressions of patent applications with year interactions

	(1)	(2)	(3)	(4)	
Model	**Logit**	**Poisson**	**Clogit**	**FE Poisson**	**Observations/**
Policy Variable	**I(Patent)**	**Patents**	**I(Patent)**	**Patents**	**Firms**
CCAX1998	0.166***	1.754***	0.052	-0.187	134320
	(0.030)	(0.200)	(0.040)	(0.316)	8395
CCAX1999	0.130***	1.998***	0.002	0.057	
	(0.028)	(0.228)	(0.046)	(0.295)	
CCAX2000	0.129***	1.646***	0.008	-0.295	
	(0.027)	(0.211)	(0.044)	(0.359)	
CCAX2001	0.078***	1.302***	-0.078	-0.639*	
	(0.024)	(0.246)	(0.048)	(0.367)	
CCAX2002	0.045**	1.359***	-0.156***	-0.582	
	(0.023)	(0.323)	(0.052)	(0.377)	
CCAX2003	0.081***	1.489***	-0.070	-0.451	
	(0.024)	(0.267)	(0.055)	(0.356)	
CCAX2004	0.068***	1.398***	-0.109**	-0.542	
	(0.024)	(0.272)	(0.055)	(0.370)	
CCAX2005	0.071***	1.340***	-0.106*	-0.601*	
	(0.025)	(0.256)	(0.058)	(0.324)	

EPERX1998	0.194***	1.915***	0.076	-0.022	
	(0.040)	(0.259)	(0.048)	(0.159)	
EPERX1999	0.145***	1.932***	0.010	-0.005	
	(0.037)	(0.275)	(0.058)	(0.186)	
EPERX2000	0.113***	1.756***	-0.034	-0.181	
	(0.035)	(0.314)	(0.059)	(0.235)	
EPERX2001	0.083***	1.540***	-0.086	-0.397	
	(0.032)	(0.342)	(0.065)	(0.293)	
EPERX2002	0.036	1.063***	-0.207***	-0.874**	
	(0.029)	(0.384)	(0.072)	(0.350)	
EPERX2003	0.052*	1.471***	-0.150**	-0.465	
	(0.029)	(0.421)	(0.073)	(0.307)	
EPERX2004	0.056*	1.180***	-0.161**	-0.757**	
	(0.031)	(0.367)	(0.077)	(0.361)	
EPERX2005	0.049	1.241***	-0.182**	-0.696**	
	(0.031)	(0.352)	(0.083)	(0.312)	

Source: Martin and Wagner (2009a). The table reports regressions of indicator and patent count variables on CCA participation and EPER coverage. Column 1 displays results from a logit regression of the binary indicator “the firm applied for at least one patent in a given year”. Column 2 reports a Poisson model on the number of patents. Columns 3 and 4 repeat this but allow for fixed unobserved firm level heterogeneity. The different panels of the table examine different types of patents and different policy variables. All regressions include year dummies.

90. To check the robustness of our regression framework to unobserved trends that might be correlated with the treatment variable(s), we follow the programme evaluation literature and investigate the effects of a “placebo treatment” on our estimation results. To this end, we restrict the dataset to include only years before 2001, and code “placebo” policy variables pretending that the CCAs and CCL were introduced in 1995. The results are reported in Table 12. Like before, CCA firms have a higher propensity to patent when we do not control for firm fixed effects. This disappears in columns 3 and 4 when controlling for firm level heterogeneity, yet no significantly negative coefficients emerge as in our previous tables. This gives us some confidence that our research design is not prone to picking up random shocks to patenting that are correlated with the treatment dummies.

Table 12. Regressions of patent applications with year interactions

	(1)	(2)	(3)	(4)	(5)
Model	**Logit**	**Poisson**	**Clogit**	**FE Poisson**	**Observations/**
Policy Variable	**I(Patent)**	**Patent Count**	**I(Patent)**	**Patent Count**	**firms**
Placebo CCA	0.129***	1.682***	0.019	-0.045	61622
	(0.021)	(0.172)	(0.040)	(0.336)	5602
Placebo EPER	0.155***	1.746***	0.081	0.086	
	(0.030)	(0.319)	(0.052)	(0.184)	

Source: Martin and Wagner (2009a). Notes: The table reports regressions of indicator and patent count variables on Placebo CCA participation and Placebo EPER coverage. We construct the Placebo variables by pretending the introduction of the CCL and CCA was in 1995 and restricting our sample to the pre-2001 period. Each column represents a different model: Column 1 reports results from a logit regression of the binary indicator “the firm applied for at least one patent in a given year”. Column 2 reports a Poisson model on the number of patents. Columns 3 and 4 repeat this but allow for fixed unobserved firm level heterogeneity. The different panels of the table examine different types of patents and different policy variables. All regressions include year dummies. Standard errors account for clustering at the level of a firm.

5. Implications for climate change policy

91. Our results support a strong case for the introduction of moderate energy taxes to encourage electricity conservation, to improve energy efficiency and to curb greenhouse gas emissions in the manufacturing sector. In a wider interpretation of our results, one could reckon that other measures to put a price on GHG emissions may also be adequate to incentivise businesses to factor emissions into their production decisions. A carbon trading system, such as the UK ETS and the EU ETS, could in principle achieve this, provided that the underlying cap on emissions puts binding constraints on business energy use. Both our analysis and previous research on CCA targets show that there is no guarantee that the emission targets that come out of the political bargaining process are stringent. The consistently low prices

in the UK ETS speak to this as well (Smith and Swierzbinski, 2007). In view of this, we prefer a narrow interpretation of our results and maintain that further cuts in energy use of substantial magnitude could have been achieved without negative impacts on economic performance, had the CCL been implemented at full rate for all businesses.

92. One rationale behind the CCA tax discount is that the unilateral implementation of a major climate change policy could jeopardize the economic performance of energy-intensive UK firms. We have investigated this empirically and find neither a discernible loss of jobs, nor a decline in output or productivity for the average plant paying the full tax rate. From this we conclude that the tax discount granted to plants in a CCA cannot be justified as a means to avoid alleged negative impacts on economic performance arising from the climate change levy.

93. Since climate change is a long-term problem, it is often emphasized that climate policy must stimulate technical change that will allow further reductions in GHG emissions in the future. Evidence from an empirical investigation of the impacts of CCA participation on firm-level counts of climate change related patents strongly suggests that a moderate energy tax on the business sector leads to increased innovative activity overall. Pending further refinements of our research design with respect to patent classifications and to the attribution of causal effects, our results indicate that this increase in patenting is most likely driven by patents for energy efficiency equipment, but also for things not related to climate change. Based on these findings, we arrive at the conclusion that more such innovation would have occurred had the CCL been implemented at full rate for all businesses.

6. Conclusion and directions for future research

94. This report summarizes the findings from several research projects in which we link various sources of business microdata to evaluate the impacts of climate policy on the UK business sector (Martin, de Preux and Wagner 2009, Martin and Wagner 2009). Previous research on the impacts of the CCL package on fuel use and energy efficiency suffers from two main weaknesses. First, simulation studies are sensitive to the assumption of counterfactual baselines, against which to calculate energy efficiency improvements attributable to the CCL or CCA. Second, econometric analysis using aggregate data does not allow for the identification of the causal effects of these policies. What is more, no previous research exists on the impacts of the CCL package on climate change related innovation.[24]

95. We have constructed a new dataset by matching data on CCA participation and energy use at the plant level to a large panel of manufacturing plants from the UK production census. The data allow us to circumvent the baseline problem, by comparing changes in plant outcomes both over time and between plants that were subject to different energy tax rates. The baseline is hence given by the contemporaneous outcomes of plants that are not in a CCA. While we can only assess the "relative" effect of the CCA in this way, our strategy offers the benefit that it does not require any of the assumptions made in previous research regarding macroeconomic or sectoral trends in energy use. Moreover, our estimates of the impact of the CCA are purged of confounding factors that affect plant performance at the level of the economy, the region, the sector, and of unobserved differences in plant specific trends. Since we also control for self-selection into CCAs by exploiting exogenous variation in CCA eligibility rules in an instrumental variable regression framework, we can interpret our estimates as the causal effect of CCA participation on plant performance.

96. A similar idea is underlying our approach to evaluating the effects on innovation. We compare patent counts of firms that participate in a CCA to those of firms not in a CCA, and use the panel

[24] In related research, we conduct interviews with managers to shed light on this issue from a different angle, see Martin, Muuls, de Preux and Wagner (2009), Martin and Wagner (2009b).

dimension to control for unobserved heterogeneity in firms' propensity to patent. As a prerequisite for this exercise we have linked patents in the EPO data base to firm level business performance data. We have also adopted a new approach to identifying climate change related patents in this data base which combines abstract searches and patent classifications.

97. Our results support a strong case for the introduction of moderate energy taxes to encourage electricity conservation, to improve energy efficiency and to curb greenhouse gas emissions in the manufacturing sector. This is in contrast to previous research that attributed substantial carbon savings to the CCA scheme, on the basis of comparisons with counterfactual baseline emissions (Ekins and Etheridge, 2006; Barker *et al.*, 2007; AEAT, 2004). Furthermore, we find no evidence of an impact of the CCL on output, employment and total factor productivity. Interestingly, we do find evidence that the CCL induces more innovative activity in firms than the CCA. This raises the question of why we do not find any positive effects on productivity for firms subject to the tax. An explanation for this is that the productivity effects of innovation might take longer to materialize than our current sample period allows us to analyze. Alternatively, it might be the case that the innovative response of firms simply minimizes the extra regulatory burden imposed by the policy, rather than leading to net economic gains. Of course, this would still be a desirable outcome in terms of efforts to address global warming.

98. Our findings beg the question of whether alternative measures of putting a price on carbon emissions would have led to similar results. For example, a carbon trading system, such as the UK ETS or the EU ETS, can in principle sustain carbon prices at meaningful levels if the underlying cap on emissions puts binding constraints on business energy use. However, neither previous research (Cambridge Econometrics, 2005; Smith and Swierzbinski, 2007) nor our own (Martin, de Preux and Wagner 2009) supports the view that the targets negotiated under the CCA were indeed stringent. Therefore, we abide by a narrow interpretation of our results and conclude that further cuts in energy use and carbon emissions of substantial magnitude, as well as accelerated innovative activity could have been achieved without negative impacts on economic performance, had the CCL been implemented at full rate for all businesses.

99. The two research projects we report on here can be seen as first steps towards building an evidence-base using microdata to inform policy-makers about the impacts of climate change policies on the business sector. As more and more such policies are implemented across countries, and as business microdata become more abundant and easier to access, we expect that researchers will exploit the variation in policies and institutional settings to make much-needed contributions to this evidence-base. In the particular context of climate change policy in the UK, there are several issues that deserve attention in future research. First, it seems imperative to gain a better understanding of how plants achieved the substantial reductions in energy use that we measure. Better knowledge of the key drivers - be they technical, economic or managerial - of energy conservation and of the adoption and innovation of energy-efficient technologies will facilitate the design of more sophisticated policies that achieve reductions in carbon emissions at minimal cost to business. In a companion report we describe our efforts to gather this kind of knowledge, using a research design that combines interview responses with hard economic performance data (Martin and Wagner, 2009b).

100. Further research is needed to determine the causal effect of the CCL package on innovation. We are currently looking into the availability of non-linear instrumental variable estimation techniques to address this issue. Moreover, our patent data set will allow us to paint a richer picture of the effects of climate policies on innovation, by investigating the differences in patenting between CCA and non-CCA firms more closely.

101. From a political economy point-of-view, a thorough analysis of the bargaining process in the setting of CCA targets, and of compliance behaviour of individual CCA facilities, should provide important insights for the design of negotiated agreements. In ongoing research we investigate these issues,

using a unique data set on compliance. The data set is administered by DEFRA/DECC and covers all facilities that participated in a CCA between 2001 and 2007.

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APPENDIX: ABSTRACT SEARCHES AND PATENT CLASSES

We use two methods to identify CCR patents. First, we conduct key word searches in the patent abstracts. For example we search for patents which contain the string "energy efficient". This leads for example to EPO patent number 14729353 with the following abstract:

> "The present invention relates to a refrigerator appliance combining a fridge compartment and a freezer compartment. In order to allow an energy efficient operation, the refrigerator appliance comprises a solenoid valve (1) for controlling the flow of cooling liquid in the refrigeration circuit, the solenoid valve (1) having at least three different operating states (S1, S2, S3). Due to the plurality of different operating states, it is possible to achieve an independent operation of each of the evaporators (5a, 5b) of the combirefrigerator appliance, or a simultaneous operation of the evaporators, in accordance with the actual cooling demand in each of the compartments. Also, due to the plurality of operating states it is possible to provide one operating state in which the outlet of the compressor (2) is blocked when the compressor (2) is off, to sustain the pressure in the condensor during periods of compressor inactivity. In this way a cooling overshoot at the end of period of compressor activity can be shifted to the beginning of each period of compressor activity, this resulting in increased energy efficiency."

The following table contains the search strings and Boolean operators we used to identify CCR patents via abstract search.

Abstract keyword search queries

Category	Search Query
Energy Efficiency	("energy" and ("efficiency" or "efficient")) or "waste heat" or "heat exchange" or "stirling engine" or "power factor correct" or "smart meter"
Greenhouse Gas	"greenhouse gas" or " ghg"
Clean Cars	"hybrid car" or "electric vehicle" or "fuel cell" or "hybrid engine" or "hybrid engine" or "fuel-cell" or "fuelcell" or "steam methane reform" or "hydrogen storage"
Clean Coal	"carbon sequestration" or "carbon-sequestration" or "clean coal"
Renewables	"renewable" or "windpower" or "wind power" or "solar" or "photovoltaic" or "geothermal" or "ocean power" or "wave power" or "tidal power"

Source: Martin and Wagner (2009a)

Second, we rely on a list of patent classes suggested by Popp (2002, 2005) as "energy saving". The next table contains those patent classes and their translations.

CCR Patent Classes				
Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
Heat Exchange	165	4 - 5	F23L	15/02
	165	4 - 5	F28D	17/00
	165	6 - 9.4	F23L	15/02
	165	10	F28D	17/00
	165	10	F28D	19/00
	165	11.1	B60H	1/00
	165	11.2	F22B	37/00
	165	41	B60H	1/00
	165	42 - 44	B60H	3/00
	165	42 - 44	B61D	27/00
	165	45	F24J	3/08
	165	46	F28F	7/00
	165	47	F24H	3/00
	165	48.1 - 48.2	F25B	29/00
	165	49	F24D	19/02
	165	49	F24H	9/06
	165	50	F24F	3/00
	165	51	F01N	5/02
	165	52	F02M	31/08
	165	53	F24D	5/10
	165	53	F24D	19/02
	165	53	F24H	9/06
	165	54	F24H	3/02
	165	55	F24D	19/02
	165	55	F24D	19/06

CCR Patent Classes				
Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	165	55	F24H	9/06
	165	56	F24D	3/16
	165	57	F28D	1/02
	165	58	F25B	29/00
	165	59	F24F	7/00
	165	60	F24F	3/14
	165	61	F25B	29/00
	165	62	F25B	13/00
	165	63 - 65	F25B	29/00
	165	66	A23C	3/02
	165	67 - 68	F28F	9/00
	165	69	F28F	7/00
	165	70	F28F	11/00
	165	71	F16F	1/34
	165	72 - 75	F28D	1/06
	165	76 - 83	F28F	7/00
	165	84	F28D	11/06
	165	84	F28G	7/00
	165	85	F24H	3/02
	165	85	F28F	25/10
	165	86	F28D	11/00
	165	86	F28F	5/00
	165	87	F28F	5/06
	165	88	F28D	11/08
	165	89	F28D	11/02
	165	89	F28F	5/02
	165	90 - 91	F28D	11/02
	165	92	B01F	15/06
	165	93	C22B	1/00
	165	94	F28F	17/00
	165	94	F28F	19/00
	165	95	F28G	1/12
	165	96	F28F	27/00
	165	97	F28F	27/02
	165	98 - 99	F01P	7/10
	165	100 - 103	F28F	27/02
	165	104.11 - 104.15	F28D	15/00
	165	104.16	F28D	13/00
	165	104.17 - 104.34	F28D	15/00
	165	108	F28F	13/06
	165	109.1	F28F	13/12
	165	110	F28B	1/00

CCR Patent Classes				
Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	165	111 - 114	F28B	3/00
	165	111 - 114	F28B	9/10
	165	115	A23C	3/04
	165	115	F28D	5/02
	165	116	A23C	3/04
	165	116	B01D	5/00
	165	117	A23C	3/04
	165	117	F28D	3/02
	165	118	A23C	3/04
	165	118	F28D	3/00
	165	119	F28F	13/12
	165	119	F28F	19/00
	165	120	B29C	47/88
	165	120	F24H	3/02
	165	121	F24H	3/02
	165	121	H01L	23/467
	165	122	F24H	3/06
	165	122	F28F	13/12
	165	123	F24F	3/04
	165	123	F28F	13/12
	165	124 - 127	F24B	1/06
	165	124 - 127	F28F	13/12
	165	128	F24H	3/00
	165	128	F24H	9/02
	165	129	F24H	9/02
	165	130	F24H	3/00
	165	130	F28F	9/26
	165	131	F24H	3/00
	165	132	F28D	1/06
	165	133	F28F	13/18
	165	133	F28F	19/02
	165	134.1	F28F	19/00
	165	135 - 136	F28F	13/00
	165	137 - 139	F28F	7/00
	165	140 - 141	F28D	7/10
	165	142	F28D	7/12
	165	143 - 144	F28F	9/26
	165	145	F28F	9/22
	165	146	F28F	13/00
	165	147	F28F	13/08
	165	148 - 150	F28D	1/00
	165	151	F28D	1/04

CCR Patent Classes				
Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	165	152 - 153	F28D	1/02
	165	154	F28D	7/10
	165	155	F28D	7/10
	165	156	F28D	7/12
	165	157	F28D	7/10
	165	158	F28F	9/02
	165	159 - 161	F28D	7/00
	165	159 - 161	F28F	9/22
	165	162	F28D	7/00
	165	162	F28F	9/00
	165	163	F28D	7/02
	165	164 - 165	F28D	7/02
	165	166	F28F	3/00
	165	167	F28F	3/08
	165	168 - 169	F28F	3/12
	165	170	F28F	3/14
	165	171	F28F	1/32
	165	172	F28F	1/10
	165	173 - 175	F28F	9/02
	165	176	F28D	7/06
	165	177	F28F	1/00
	165	178	F28F	9/04
	165	179	F28F	1/42
	165	180	F28F	21/00
	165	181	F28F	1/20
	165	182	F28F	1/30
	165	183 - 184	F28F	1/14
	165	183 - 184	F28F	1/36
	165	185	F28F	7/00
	165	186	A61C	5/06
	165	200	F28F	27/00
	165	201	A47J	39/00
	165	201	F25B	29/00
	165	202 - 204	B60H	1/00
	165	205 - 221	F24F	3/00
	165	222 - 230	F24F	3/14
	165	222 - 230	F24F	6/00
	165	231 - 233	F25B	29/00
	165	231 - 233	F25D	21/00
	165	231 - 233	F28F	17/00
	165	234 - 235	B64D	13/04
	165	234 - 235	B64D	13/08

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Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	165	236	F24D	11/00
	165	236	F28D	20/00
	165	237	F24F	11/00
	165	238 - 239	F24F	11/00
	165	238 - 239	G05D	23/19
	165	240 - 242	F25B	29/00
	165	243 - 247	F24F	11/04
	165	243 - 247	F24F	11/06
	165	248 - 252	F24F	11/04
	165	248 - 252	F25B	29/00
	165	253 - 266	F25B	29/00
	165	267	F25D	23/12
	165	267	F28F	13/00
	165	268	C12Q	1/68
	165	268	F28F	13/00
	165	269	F28F	13/00
	165	269	G05D	23/19
	165	270	F28F	13/00
	165	270	G05D	23/24
	165	271	B60H	1/00
	165	272 - 278	F28F	27/00
	165	279 - 286	G05D	15/00
	165	279 - 286	G05D	16/00
	165	279 - 286	G05D	23/00
	165	287 - 300	G05D	23/00
	165	301 - 302	F28F	27/00
	165	301 - 302	G05D	9/00
	165	303	F24B	13/00
Coal Liquefaction	208	400 - 402	C10G	1/00
	208	403	C10G	1/06
	208	403	C10G	1/08
	208	404 - 407	C10G	1/00
	208	408	C10G	1/08
	208	409 - 411	C10G	1/00
	208	412 - 414	C10G	1/06
	208	412 - 414	C10G	1/08
	208	415	C10G	1/00
	208	416	C10G	1/06
	208	416	C10G	1/08
	208	417	C10G	1/00
	208	418 - 423	C10G	1/06
	208	418 - 423	C10G	1/08

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Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	208	424 - 435	C10G	1/00
Coal	48	71	C10J	3/00
Gasification	48	71	C10J	3/68
	48	71	C10K	3/00
	48	72	C10J	3/30
	48	72	C10J	3/68
	48	72	C10K	3/00
	48	73	C10J	3/20
	48	76 - 81	C10J	3/68
	48	98	C10J	3/20
	48	98	C10J	3/48
	48	99 - 101	C10B	1/00
	48	99 - 101	C10J	3/00
	48	99 - 101	F27B	5/00
	48	200	C10J	3/00
	48	201	C10J	3/68
	48	201	C10J	3/70
	48	201	C10K	3/06
	48	202	C10J	3/16
	48	202	C10J	3/46
	48	202	C10K	3/06
	48	206 - 210	C10J	3/00
	60	641.11 - 641.15	F03G	6/00
Solar Energy	60	641.11 - 641.15	F03G	7/00
	60	641.8	B60K	16/00
	60	641.8	B60L	8/00
	60	641.8	F03G	6/00
	60	641.9	F03G	6/00
	126	561 - 568	F24J	2/42
	126	569	F24J	2/00
	126	570 - 571	F24J	2/46
	126	572	F24J	2/40
	126	573 - 582	F24J	2/38
	126	583 - 599	F24J	2/40
	126	600 - 608	F24J	2/38
	126	609 - 616	F24J	2/42
	126	617 - 620	F24J	2/34
	126	621 - 622	E04D	13/18
	126	623	F24J	2/46
	126	624 - 626	F24J	2/36
	126	627	F24J	2/46
	126	628 - 633	E04D	13/18

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Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	126	634	F24J	2/04
	126	635 - 637	F24J	2/32
	126	638 - 639	F24J	2/44
	126	640 - 642	F24J	2/04
	126	643 - 645	F24J	2/30
	126	646 - 647	F24J	2/04
	126	648 - 650	F24J	2/46
	126	651	F24J	2/24
	126	652	F24J	2/50
	126	653 - 656	F24J	2/24
	126	657	F24J	2/10
	126	658 - 673	F24J	2/24
	126	674	F24J	2/26
	126	675	F24J	2/22
	126	676 - 677	F24J	2/48
	126	678 - 679	F24J	2/04
	126	680 - 682	F24J	2/02
	126	683 - 684	F24J	2/08
	126	683 - 684	F24J	2/10
	126	685	F24J	2/18
	126	686 - 687	F24J	2/16
	126	688 - 689	F24J	2/10
	126	690 - 691	F24J	2/12
	126	692 - 693	F24J	2/10
	126	694	F24J	2/12
	126	695 - 697	F24J	2/10
	126	698 - 700	F24J	2/08
	126	701 - 703	F24J	2/00
	126	704	F24J	2/46
	126	705 - 708	F24J	2/50
	126	709 - 713	F24J	2/46
	136	206 - 207	H01L	35/00
	136	243	H01L	25/00
	136	243	H01L	31/00
	136	243	H02N	6/00
	136	244 - 251	H01L	31/042
	136	244 - 251	H02N	6/00
	136	252 - 265	H01L	31/00
Fuel Cells	429	12 - 13	H01M	8/00
	429	14 - 15	H01M	8/04
	429	16	H01M	8/14
	429	17	H01M	8/04

CCR Patent Classes				
Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	429	18	H01M	8/24
	429	19 - 21	H01M	8/18
	429	22 - 26	H01M	8/04
	429	22 - 26	H01M	8/12
	429	27 - 29	H01M	4/00
	429	30 - 33	H01M	8/10
	429	34	H01M	2/00
	429	34	H01M	2/02
	429	35 - 37	H01M	2/08
	429	38 - 39	H01M	2/14
	429	40 - 45	H01M	4/00
	429	46	H01M	8/08
	429	46	H01M	8/14
Using Waste as Fuel	110	235 - 236	B09B	3/00
	110	235 - 236	F23D	14/00
	110	235 - 236	F23G	5/00
	110	235 - 236	F23G	7/00
	110	237	F23G	7/00
	110	238	F23G	7/04
	110	239 - 241	F23D	3/00
	110	239 - 241	F23D	5/00
	110	239 - 241	F23D	7/00
	110	239 - 241	F23D	9/00
	110	239 - 241	F23D	11/00
	110	242 - 245	F23G	5/00
	110	242 - 245	F23G	7/00
	110	246	A47J	36/00
	110	246	A47J	36/24
	110	247 - 249	F23G	5/00
	110	247 - 249	F23G	7/00
	110	250	F23G	5/00
	110	251	F23G	5/00
	110	251	F23G	5/12
	110	251	F23G	7/00
	110	252	F23G	5/00
	110	253 - 259	F23G	5/00
	110	253 - 259	F23G	7/00
	110	346	F23G	5/00
Waste Heat	122	7A	C21C	5/40
	122	7B	F22B	1/18
	122	7C	F23G	7/04
	122	7D	F22B	1/18

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Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	122	7D	F23G	7/06
	122	7R	F01K	23/10
	122	7R	F22B	1/18
	122	7R	F22B	37/00
	60	597	B60K	6/20
	60	598	F02B	33/44
	60	599	F02B	29/04
	60	600 - 603	F02D	23/00
	60	604	F01K	23/06
	60	604	F01K	23/14
	60	604	F02B	37/16
	60	605.1 - 612	F02B	33/44
	60	613 - 617	F02G	3/00
	60	618	F01K	23/10
	60	619 - 624	F02G	3/00
Heat Pumps	62	238.1 - 238.7	F25B	27/00
	62	324.1 - 324.6	F25B	13/00
	62	325	F25B	29/00
Stirling Engine	60	517 - 529	F01B	29/10
	60	517 - 529	F02G	1/04
Continuous Casting	148	541 - 542	C21D	8/02
	148	549 - 552	C22F	1/04
	164	263	B22D	11/12
	164	268	B22D	11/12
	164	415	B22D	11/00
	164	416	B22D	11/04
	164	417	B22D	11/12
	164	418	B22D	11/00
	164	419	B22D	19/00
	164	420 - 421	B22D	11/00
	164	422	B22D	13/02
	164	423	B22D	11/00
	164	424	B22D	11/12
	164	425 - 426	B22D	11/08
	164	427 - 434	B22D	11/06
	164	435 - 436	B22D	11/04
	164	437 - 440	B22D	11/10
	164	441 - 442	B22D	11/12
	164	443 - 444	B22D	11/124
	164	445 - 446	B22D	11/08
	164	447 - 448	B22D	11/12
	164	449.1 - 450.5	B22D	11/16

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Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	164	449.1 - 450.5	B22D	11/18
	164	451	B22D	11/00
	164	451	B22D	46/00
	164	452	B22D	11/16
	164	453	B22D	11/18
	164	454	B22D	11/20
	164	455	B22D	11/22
	164	459	B22D	11/00
	164	460	B22D	11/126
	164	461 - 465	B22D	11/00
	164	466 - 471	B22D	11/00
	164	466 - 471	B22D	27/02
	164	472	B22D	11/07
	164	473	B22D	11/10
	164	474 - 477	B22D	11/00
	164	478	B22D	11/04
	164	479 - 481	B22D	11/06
	164	482	B22D	11/00
	164	483	B22D	11/08
	164	484	B22D	11/128
	164	485 - 486	B22D	11/124
	164	487	B22D	11/00
	164	488 - 489	B22D	11/10
	164	490	B22D	11/00
	164	491	B22D	11/10
	164	502 - 509	B22D	11/00
	164	502 - 509	B22D	27/02
	164	154.4 - 154.5	B22D	11/16
	164	154.4 - 154.5	B22D	11/18