Climate policy and innovation: Evidence from patent data*

Ralf Martin† Ulrich J. Wagner‡

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Abstract

We examine innovative activity of businesses in the UK following the introduction of the Climate Change Levy (CCL) and Climate Change Agreements (CCA) in 2001. This is facilitated by the CEP AMAPAT database, a new data resource that links European Patent Office patent data with business performance data. The CCL is an energy tax levied on all businesses except those who enter a Climate Change Agreement (CCA) that entitles them to an 80% large discount on the tax. In return CCA participants have to accept specific targets on energy efficiency or total energy consumption which are negotiated between the government, the sector associations and the firm. We find that CCA firms have a higher propensity to patent than non-CCA firms. However, when taking into account persistent unobserved differences across firms that pre-date the introduction of the CCL and CCA, we find the opposite result that patenting decline in CCA firms relative to firms paying the levy at full rate. We interpret this as evidence that the price-based conservation incentive imposed on firms by the CCL gives them stronger incentives to engage in innovative activity than the negotiated targets. We also document, for the first time, major trends across time and countries of a wide range of climate change related (CCR) patenting. This suggests that CCR patenting has increased in recent years and that Japan is leading in this area among the G5 economies.

1 Introduction

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 behavior, 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

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†Centre for Economic Performance (CEP/LSE) and Grantham Research Institute on Climate Change and the Environment, London School of Economics and Political Science, Houghton Street, London WC2A 2AE, United Kingdom. E-mail: r.martin@lse.ac.uk

‡Department of Economics, Universidad Carlos III de Madrid, Calle Madrid 126, 28903 Getafe (Madrid), Spain, and CEP/LSE. E-mail: uwagner@eco.uc3m.es

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 et al., 2005). Pollution regulation may – depending on the policy instrument – create incentives for environmental innovation and could even strengthen the incentives for innovation more broadly (Porter & van der Linde, 1995). 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 and hence adversely affect economic growth.

Notwithstanding such concerns, the UK government has been advocating stringent climate change policies for the business sector with the promise that this will lead to a new period of accelerated growth in output and employment.[1] The principal policy measure implemented thus far is the Climate Change Levy package of 2001 which comprises the Climate Change Levy (CCL) and the Climate Change Agreements (CCA). The CCL is a tax on energy inputs which averages 15% of the energy cost of a typical business (NAO, 2007). The government offers energy intensive firms 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.

The CCL package offers a unique opportunity to empirically estimate the impact of energy taxes on firm-level innovation. Using a novel 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. In so doing, we identify, for the first time, a comprehensive set of climate change related patents in the EPO database. The merged data set allows us to look at a wide range of characteristics of innovating firms and includes information on the specific tax regime they are facing under the CCL package. Our econometric identification strategy exploits the fact that the CCA quotas were hardly binding for many firms (Martin et al., 2009a; NAO, 2007; Cambridge Econometrics, 2005). We can thus use firms in a CCA as a control group to recover a (lower bound) estimate of the impact of an energy or carbon tax (Martin et al., 2009a). Since participation in a CCA is voluntary for eligible firms, self-selection might lead to biased estimates. For example, larger firms with higher levels of patenting might be more likely to join the CCA because it is easier for them to recoup the fixed cost of CCA participation. We account for this in two ways. First, we employ panel data techniques that control for unobserved heterogeneity across firms. Second, we identify the impact of the CCA participation using exogenous variation in elegibility for CCA participation rather than CCA participation itself .

We find robust evidence of a significant decline in patenting by CCA firms relative to other firms. Moreover, we demonstrate that failing to account for unobserved heterogeneity across firms leads to severely biased results; in fact, we obtain teh opposite result that CCA firms have a large propensity to patent when we do not include firm fixed effects. We find no such effect for climate change related patents.

The paper is organized as follows. The next subsection reviews previous empirical research on environmental innovation based on patent counts. Section 4 describes the identification of climate change related patents and the matching to business microdata. Section 5 explains our econometric frame-

[1] see various speeches by Gordon Brown 2007-2008; e.g. http://www.number10.gov.uk/Page13791

work and subsection 6 summarizes the results. Section 7 concludes.

2 Environmental Regulation, Climate Policy, and Innovation

To conduct empirical research on the determinants of innovation one needs a reliable measure of innovative activity. Data on R&D expenditures or R&D personnel at the firm or sector level 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 et al., 2008a). 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 allows an assessment of the impact of an innovation (Jaffe & Trajtenberg, 2002). Finally, patent data are readily available and amenable to statistical analysis (e.g. Griliches, 1990).

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 & Trajtenberg, 2002). It has been argued, however, that there are very few major inventions that have not been patented (Dernis & Guellec, 2001). A fundamental practical problem with the use of patent data has been solved with the computerization of major patent data bases which has made millions of patent records available in digital form (Jaffe & Trajtenberg, 2002). Given the recent advances in computing technology, researchers can now conduct research involving complex patent searches on their PC.

While the focus of our work is on climate change related innovation, most existing empirical research[2] in this area has been done with respect to environmental innovation more broadly. A common approach 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. Lanjouw & Mody (1996) compare trends in environmental innovation in US, Japan and Germany from 1971 until 1988. They find that increases in pollution abatement costs were associated with increases in the number of environmental patents granted. In an econometric analysis using panel data for US industries, Jaffe & Palmer (1997) find no effect of abatement cost on the total number of patents granted. Brunnermeier & Cohen (2003) revisit this study and show that abatement cost had a positive and significant effect on patenting in the US when the dependent variable is a measure of environmental patents.

A series of papers have studied patent applications for technologies suited to controlling air pollutants such as sulfur dioxide and nitrogen oxides (Taylor et al., 2003; Popp, 2003, 2006; De Vries & Withagen, 2005). A common finding in this research is that environmental regulation has a positive impact on patent applications, though sometimes this effect is not robust to alternative specifications. An-

[2] Apart from patent counts, researchers have also used R&D expenditures and survey data to shed light on the relationship between environmental regulation and innovation. For a comprehensive overview of previous research see Jaffe et al. (2003). Arimura et al. (2007) present evidence from a postal survey of managers in seven OECD countries. Martin et al. (2009b) conduct telephone interviews with managers and match the responses to business performance data and to patent counts in order to shed light on the issue.

other recent strand of the literature focuses on innovation for energy efficiency improvements. Crabb & Johnson (2007) use 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 et al. (2008b) examine the impact of different policy instruments on EPO patent counts for renewable energy technologies. Using a panel of 25 high-income countries over 26 years, they find 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.

Our paper extends this literature in two ways. First, we exploit the particularities of a concrete policy measure – the CCL package – to identify the effect of regulation on innovation at the firm level. The issue with abatment costs, which have been used as a measure of environmental stringency in previous research, is the non-monotonic relationship with the stringency of environmental regulation. While sector level abatement cost may increase with regulation initially, it will fall as the dirtiest industries exit or relocate. Second, we identify a comprehensive class of climate change related patents in the EPO data and investigate the effects of the CCL package on this measure of innovation as well as on innovation overall.

3 The Climate Change Levy and Climate Change Agreements

The CCL is a per unit tax payable at the time of supply to industrial and commercial users of energy.[3] The tax was introduced in 2001 and is levied on coal, gas, electricity, and non-transport Liquefied Petroleum Gas (LPG). Table 1 displays the tax rates[4] per kilowatt hour (kWh, column 1), the average fuel price paid by manufacturing plants in 2001 (column 2) and the implicit carbon tax (column 3). Energy tax rates vary substantially across fuel types, ranging from 6.1% on coal to 16.5% on natural gas, and some fuel types are tax-exempt.[5] The government estimates that the tax liability of the average business paying the full rate amounts to 15% of the energy bill.

To minimize 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. By participating in a CCA, facilities in certain energy intensive sectors can reduce their tax liability by 80% provided that they adopt a binding target on their energy use or carbon emissions.[6] Targets are defined either in absolute terms or relative to (often physical units of) output for a series of 2-year compliance or "milestone" periods. 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 final target in 2010 it faces the threat

[3]For more detailed information on the CCL see NAO (2007).

[4]Tax rates were constant between April 2001 and March 2007, and were adjusted for inflation only in April 2007.

[5]Mineral oil is exempt because it is already subject to the "fuel duty escalator". Also exempt are fuels with a low carbon content, notably electricity generated from renewable sources and and from combined heat and power.

[6]This process involves two stages. First, the sector association negotiates 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. Second, the acceding firm adopts an individual target in accordance with the sector association.

to repay all rebates on the levy it has accumulated in previous periods.

CCA participants not in compliance could meet their target by buying 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. All 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.

Eligibility to enter a CCA is confined 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, namely the Pollution Prevention and Control (PPC) Act 1999.[7] CCAs were open to businesses carrying out activities regulated under part A of the 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. In 2006, the eligibility criteria were extended to take into account the energy intensity of businesses following the definition underlying the EU Energy Products Directive NAO (2007).

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.

Early on, critics of the CCA scheme alleged that the CCA targets were equivalent to business-as-usual improvements in energy efficiency and hence not place binding constraints on firm behavior (ACE, 2005). In fact, the first comprehensive evaluation study commissioned by the government concluded that "that the energy (and therefore carbon) saving and energy-efficiency targets would have been met without the CCAs" (Cambridge Econometrics, 2005, p. 7). Apart from lax targets, Martin et al. (2009a) argue that compliance costs have been negligible for most CCA participants due to a number of other design features. For example, non-compliance by individual firms goes unpunished if the sector is in compliance. A firms that is unable to meet its target has several options to renege on them (both ex-ante and ex-post). If none of the previous options worked, firms could buy allowances at rock-bottom prices on the UK carbon market. Using a large panel data set of UK manufacturing plants, Martin et al. (2009a) estimate the impact of CCA participation on growth in plant-level outcomes and interpret this coefficient as a lower bound of the impact of the 80% tax discount granted under the CCAs. They find robust evidence that, compared to firms paying the full rate of the CCL, CCA firms experienced faster growth in energy intensity and energy expenditures, mostly driven by a stronger growth in electricity demand. In what follows, we follow a similar

[7] This act transposed EU Directive 96/61 on Integrated Pollution Prevention and Control also known as the "IPPC Directive" or as Directive 2008/1/EC)

rationale to estimate the impact of the tax discount on patenting activity, paying particular attention to climate change related patents.

4 Data

4.1 Climate change related patents across countries and over time

There are two ways to identify technological aspects of patents: patent classes and abstract searches. Previous research has primarily relied on patent classes (Lanjouw & Mody, 1996; Johnstone et al., 2008b; 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. Appendix C 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.

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.

Using both methods, we identify more than 45,000 climate change related (CCR) patents in the EPO database. Figure 1 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%.[8]

Figure 2 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 and again at the end of the 1990s.

Figure 3 displays the share of CCR patents in total patent applications between 1980 and 2005 across all countries and for each of the G5 economies. 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 U.S. inventors have turned away from CCR innovation over the 1990s.

Figure 4 examines in more detail the increase in the CCR patent share after 1998 by showing an index of the time series from Figure 3 with base year 1998. This shows that the changes over time

[8] The surprisingly small overlap needs further attention in future research.

in various countries are very similar. Still we can see that Japan experienced a steeper increase in its CCR patent share both before and after 1998 than the other countries studied (the Japan line moves from the bottom to the top after 1998). Great Britain, on the other hand, has gone from a period of lowering its CCR innovative output before 1998 to one of dynamic growth in CCR patenting after that.

4.2 Linking patent counts to UK firm level data

We use the CEP AMAPAT database[9] 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[10] 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. Since our goal is to investigate how the introduction of the CCL package in 2001 affected the innovative output of UK firms, we define a binary variable *CCA* that indicates participation in a CCA based on information from DEFRA and HM Revenue & Customs (see Martin et al., 2009a, for details). We also define a binary variable *EPER* that indicates whether or not a firm reported any emissions of water or air pollutants other than those resulting from combustion processes to the European Environmental Agency in 2001. This variable shifts the eligibility for participation in a CCA and is exogenous to the energy use at the firm.[11] We match both treatment variables at the firm level.

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 2 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.

Figure 1 displays the share of CCR patents in total patents filed per firm (rather than absolute numbers as in Table2). 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 2 examines the evolution of patents and climate change related patents over time. It shows an index 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 with an acceleration at the end of the 1980s as well the end

[9] See Belenzon & Berkovitz (2007) for more details on the matching process.

[10] See http://www.bvdep.com/

[11] Full details on the construction of *EPER* are given in Martin et al. (2009a) where we argue that (conditional on removing fixed firm level differences) this is likely to be an exogenous shifter for CCA participation and hence for the receipt of a tax discount, and use this variable as an instrument for *CCA*.

of the 1990s. The earlier acceleration might reflect a lagged response to the energy price shocks of the late 1970s and early 1980s. The second acceleration might be a response to increasing concerns about climate change as well as more recent energy price hikes.

5 Econometric Framework

Our econometric approach is similar to the one taken by Martin et al. (2009a) who estimate the impact of CCA participation on growth in plant level outcome variables using panel IV techniques. Due to the discrete nature of patent counts, some modifications to the econometric model are in order. 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

$$\mathbf{Pr}\left\{Patents_{it} > 0\right\} = F\left(\beta_D D_{it} + \mathrm{x}'_{\mathrm{it}}\beta_X + \alpha_i\right) \tag{1}$$

where D_{it} is the treatment indicator, $\mathbf{x_{it}}$ is a vector of control variables such as year dummies, α_i is a firm fixed effct and $F(\cdot)$ is derived from the extreme value distribution.

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 (Hausman 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

$$\mathbb{E}\left[Patents_{it}\right] = \exp\left(\beta_D D_{it} + \mathbf{X_{it}}\beta_X\right)\exp(\alpha_i)$$

As treatment indicator, D_{it} we use the binary variable *CCA* indicating participation in a CCA. As discussed in Martin et al. (2009a), CCA participation was contingent on coverage under the Pollution Prevention and Control legislation (PPC). That is, only firms that were releasing pollutants regulated under PPC into the air, the soil or water could apply for a CCA. Below we show results from regression where the treatment variable is taken to be the *EPER* variable described above.[12]

6 Regression Results

Table 3 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, present results from a conditional logit model and from a Poisson conditional maximum likelihood estimation (CMLE) in columns 3 and 4, respectively. The four panels in Table 3 report the regression results for different outcome variables, and each panel contains results for both treatment variables.

[12] We are currently exploring non-linear IV techniques that would allow us to use *EPER* as an instrumental variable for *CCA*.

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 apply for a 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). The results from the simple Poisson regression in column 2 corroborate that CCA participation has a positive and significant effect on the expected number of patent applications.

However, it turns out that this result is not robust to controlling for unobserved heterogeneity. To the contrary, results obtained with the conditional logit framework in column 3 show that the propensity of CCA firms to patent is up to 16 percentage point lower than that of non-CCA firms after 2001. The CMLE 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. These results highlight the importance of unobserved differences between treated and non-treated firms which we need to control for in order to gauge the effect of CCA participation.

In the subsequent panels, we report results from the same set of specifications but for 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 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 and when *EPER* is the treatment variable.

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. Moreover, column 5 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.

How do these results fit together? An immediate explanation is that firms in a CCA face less stringent regulation and hence lower incentives to respond to the regulation with innovation. This mechanism could generate the negative coefficient on patenting found in columns 3 and 4. However, it is puzzling that this pattern is absent in innovation related to climate change. Our intutition would be that negative effects should only arise in panels 1 to 3, but not in panel 4.

There are two possible explanations for the results in panel 4 which deserve to be examined more closely in future research. 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 provided by what has become known as the Porter hypothesis (Porter & 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. There is some scepticism about this idea, however, since it implies (in its strongest form) that firms are not entirely rational and were systematically overlooking profitable opportunities before the regulatory intervention.

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 is a formidable task but might still be a worthwhile endeavor.

In Table 4 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 3 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.

To check the robustness of our regression framework to unobserved trends that might be correlated with the treatment variables we follow the program 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 5. 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.

7 Summary and conclusion

This paper adds to a small empirical literature on the impact of climate change policies on patenting and innovation. To the best of our knowledge, it is the first study that does so using longitudinal data at the firm level. We identify climate change related patents in the Europen Patent Office database and examine how the Climate Change Levy package impacted on patent activity at the individual firm. Since 2001, the Climate Change Levy has been the single most important uni-lateral climate change policy instrument adopted by the UK government. Our econometric identification strategy compares the patenting activity of firms that had to pay the full rate of the levy with that of firms who were granted an 80 percent discount on the levy rate. While CCA firms clearly patent more we show that this is driven by pre-treatment differences between these two types of firms. We show that with the introduction of the tax patenting in firms that received a tax discount slowed down relative to fully taxed firms. We suggest that this is driven by the stronger incentives given by the tax as a price-based climate change policy instrument.

We find no statistically significant effect on CCR patents. This could be due either to error in identifying all climate change related patents or to genuine impacts on patentin areas we have not identified as climate change related. Further work is needed to narrow down the set of possible explanations for this pattern. In addition, it might be important to control for self-selection of firms into CCAs. In Martin et al. (2009a) we propose a strategy based on instrumental variables (IV) for that purpose. Implementation of this strategy is complicated by the fact that we are dealing with discrete outcomes for which non-linear models are better suited than linear regression. Instrumental variable procedures for such models are not always readily available. Another concern is that CCA participation might trigger a different behavioral response by the firm even if the target is less stringent than the CCL. For example, the "strong version" of the Porter hypothesis maintains that firms benefit from regulation because it helps them to discover previously un-used innovation potential and forces them to rethink their practices. It is conceivable that the CCA target setting process which involves energy consumption assessments by external experts could lead to more such discoveries than simply paying the levy.[13]

References

ACE (2005). *The Climate Change Levy and the Negotiated Agreements*. Technical Report 05, Association for the Conservation of Energy, London, UK.

Arimura, T. H., Hibiki, A., & Johnstone, N. (2007). An empirical study of environmental r&d: what encourages facilities to be environmentally friendly? In N. Johnstone (Ed.), *Environmental Policy and Corporate Behavior* Cheltenham: Edward Elgar.

Belenzon, S. & Berkovitz, T. (2007). *Innovation in Business Groups*. Technical report, Department of Economics, University of Oxford, Oxford, UK.

Brunnermeier, S. B. & Cohen, M. A. (2003). Determinants of environmental innovation in us manufacturing industries. *Journal of Environmental Economics and Management*, 45, 278–293.

Cambridge Econometrics (2005). *Modelling the initial effects of the Climate Change Levy*. Technical report, Cambridge Econometrics, Cambridge, UK.

Crabb, J. M. & Johnson, D. K. N. (2007). *Fueling the Innovative Process: Oil Prices and Induced Innovation in Automotive Energy-Efficient Technology*. Technical report, Colorado College Department of Economics and Business, Colorado Springs, CO.

De Vries, F. P. & Withagen, C. (2005). *Innovation and Environmental Stringency: The Case of Sulfur Dioxide Abatement*. Technical Report #2005-18, Tilburg University.

[13] We hope to make some progress on these issues trough an in-depth telephone survey among UK manufacturing firms Martin et al. (2009b).

Dernis, H. & Guellec, D. (2001). *Using patent counts for cross-country comparisons of technology output*. Technical report, Organisation for Economic Co-operation and Development, Paris, France.

Griliches, Z. (1990). Patent statistics as economic indicators: A survey. *Journal of Economic Perspectives*, 28(4), 1661–1707.

Hausman, J., Hall, B. H., & Griliches, Z. (1984). Econometric models for count data with an application to the patents-R&D relationship. *Econometrica*, 52(4), 909–938.

Jaffe, A. B., Newell, R. G., & Stavins, R. N. (2003). Technological change and the environment. In K. G. Mäler & J. R. Vincent (Eds.), *Handbook in Environmental Economics*, volume 1 chapter 11, (pp. 461–516). Amsterdam, NL: Elsevier Science.

Jaffe, A. B., Newell, R. G., & Stavins, R. N. (2005). A tale of two market failures: Technology and environmental policy. *Ecological Economics*, 54(2-3), 164–174.

Jaffe, A. B. & Palmer, K. (1997). Environmental regulation and innovation: A panel data study. *The Review of Economics and Statistics*, 79(4), 610–619.

Jaffe, A. B. & Trajtenberg, M. (2002). *Patents, Citations, and Innovations*. Cambridge, MA: MIT Press.

Johnstone, N., Hascic, I., & Ostertag, K. (2008a). Environmental policy, technological innovation and patent activity. In *Environmental Policy, Technological Innovation and Patents*, OECD Studies on Environmental Innovation (pp. 17–62).: Organisation for Economic Co-operation and Development.

Johnstone, N., Hascic, I., & Popp, D. (2008b). *Renewable Energy Policies And Technological Innovation: Evidence Based On Patent Counts*. Technical Report 13760, National Bureau of Economic Research.

Lanjouw, J. O. & Mody, A. (1996). Innovation and the international diffusion of environmentally responsive technology. *Research Policy*, 25(4), 549–571.

Martin, R., de Preux, L., & Wagner, U. (2009a). The impacts of the climate change levy on business: Evidence from microdata. *CEP Discussion Paper*, 917.

Martin, R., Muûls, M., de Preux, L. B., & Wagner, U. J. (2009b). *Climate Change Policy and Management Practices*. Technical report, Centre for Economic Performance, London, UK.

NAO (2007). *The Climate Change Levy and Climate Change Agreements*. Technical report, National Audit Office, London, UK.

Popp, D. (2002). Induced innovation and energy prices. *The American Economic Review*, 92(1), 160–180.

Popp, D. (2003). Pollution control innovations and the clean air act of 1990. *Journal of Policy Analysis and Management*, 22(4), 641–660.

Popp, D. (2005). They don't invent them like they used to: An examination of energy patent citations over time. *NBER working paper*, 11415.

Popp, D. (2006). International innovation and diffusion of air pollution control technologies: the effects of nox and so2 regulation in the u.s., japan, and germany. *Journal of Environmental Economics and Management*, 51, 46–71.

Porter, M. & van der Linde, C. (1995). Toward a new conception of the environment-competetiveness relationship. *Journal of Economic Perspectives*, 9(4), 97–118.

Taylor, M. R., Rubin, E. S., & Hounshell, D. D. (2003). Effects of government actions on technological innovations for SO2 control. *Environmental Science and Technology*, 37, 4527–4534.

A Tables

Table 1: Taxation of energy and implicit carbon by fuel type

fuel type	tax rate $[\frac{pence}{kWh}]$	fuel price $[\frac{pence}{kWh}]$	implicit carbon tax $[\frac{£}{tC}]$
electricity	0.43	4.25	31
coal	0.15	2.46	16
gas	0.15	0.91	30
LPG	0.07	0.85	22

Notes: Average fuel prices in 2001 based on QFI sample.
Carbon prices taken from Pearce (2006).

Table 2: Patents held by UK firms in the sample, 1980-2005

Patents type	Sample	mean	firms	patents	p25	p75	p90
All	non CCA	5.92	9816	58111	1	3	7
	CCA	31.11 ***	269	8368	1	10	45
	non EPER	5.37	9931	53288	1	3	7
	EPER	85.66 ***	154	13191	1	9	73
	Totals		10085	66479			
CCR	non CCA	1.72	612	1051	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	1196			

Notes: The table reports descriptive statistics on the total number of patent applications that are filed by the firms in our UK sample for the period 1980 to 2005. It distinguishes by patent type as well as by which environmental policy a firm holding the patent was subject to.

Table 3: Regressions of firm level patent applications

	Model	(1) Logit	(2) Poisson	(3) Clogit	(4) FE Poisson	(5) FE	Observation
Patent type	**Policy Variable**	**I(Patent)**	**Patent Count**	**I(Patent)**	**Patent Count**	**Share in total Patents**	**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	-0.004	8832
		(0.024)	(0.228)	(0.087)	(0.388)	(0.009)	552
	EPER	0.033	0.474	-0.140*	-0.432	0.032	
		(0.029)	(0.317)	(0.082)	(0.359)	(0.021)	
CCR Patents Popp	CCA	0.021	0.491*	-0.138	-0.513	-0.009	8576
		(0.024)	(0.269)	(0.088)	(0.371)	(0.008)	536
	EPER	0.026	0.436	-0.172**	-0.528**	0.016	
		(0.029)	(0.304)	(0.076)	(0.221)	(0.015)	
Non Popp Patents	CCA	0.070***	1.375***	-0.106***	-0.510**	0.021	134224
		(0.017)	(0.236)	(0.035)	(0.220)	(0.019)	8389
	EPER	0.056***	1.328***	-0.167***	-0.586**	-0.012	
		(0.022)	(0.375)	(0.048)	(0.277)	(0.025)	

Notes: The table reports regressions of indicator and patent count variables on CCA participation and EPER coverage. 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. Column 5 looks at the share of the different patent types in overall patents. All regressions include year dummies.

Table 4: Regressions of patent outcomes 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)	

Notes: The table reports regressions of indicator and patent count variables on CCA participation and EPER coverage.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.

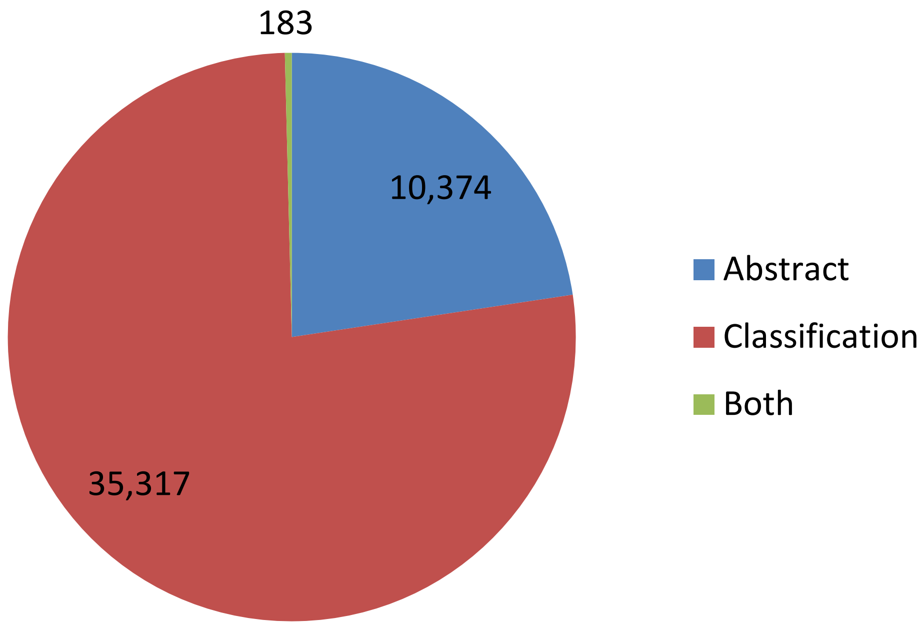
Table 5: Regressions of patent outcomes with year interactions

Patent type	Model Policy Variable	(1) Logit I(Patent)	(2) Poisson Patent Count	(3) Clogit I(Patent)	(4) FE Poisson Patent Count	(5) Observations/ firms
All patents	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)	

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.

B Figures

Figure 1: Identification of climate change related patents

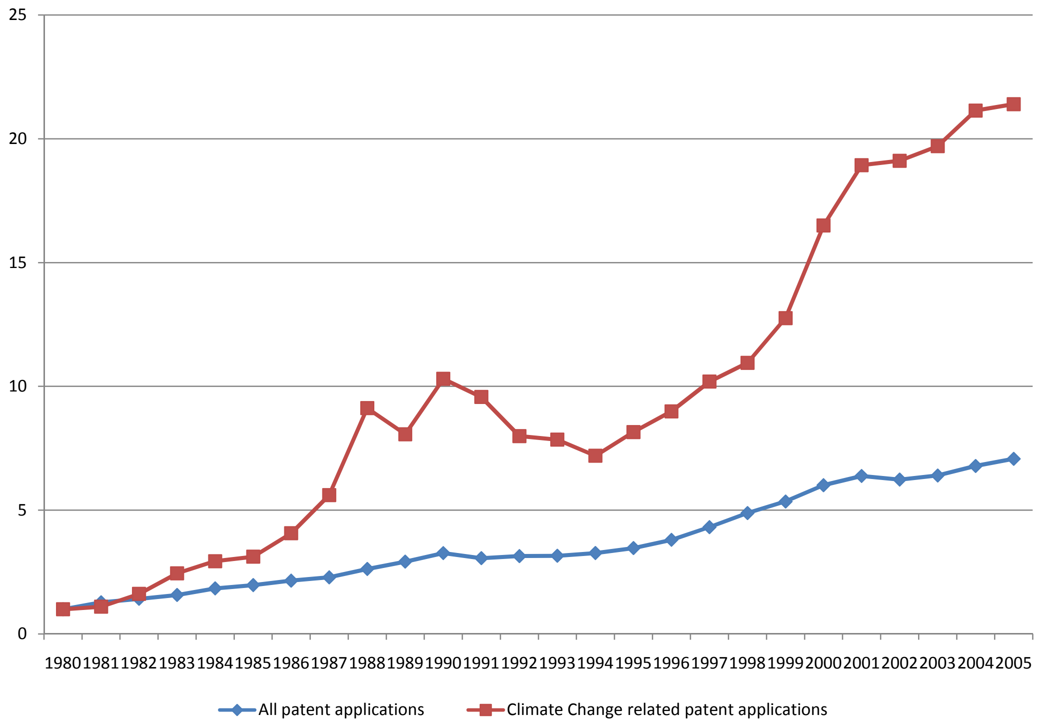


C Abstract searches and patent classes

We use two methods to identify Climate Change related patents. First, we perform key word searches in the abstracts describing patents. For example we search for patents which contain the 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."

Figure 2: Climate change related patents over time

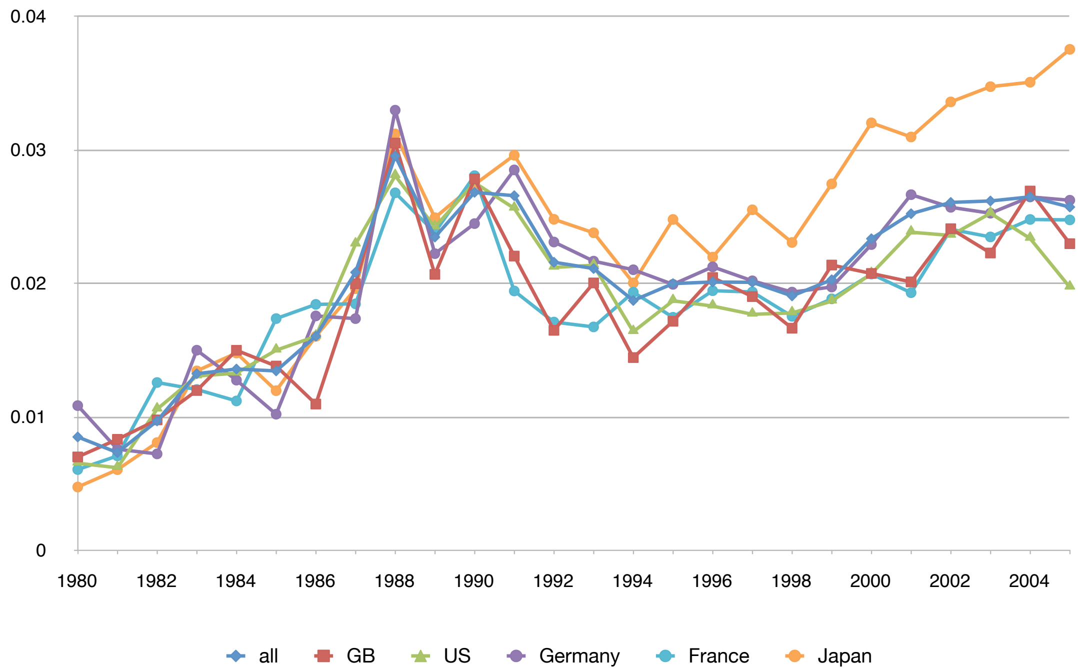


Second, we rely on a list of patent classes suggested in various papers by Popp (2002, 2005) as energy saving. This appendix lists all the keywords used in the abstract search as well as all the categories used in the category search. The following tables detail how we identified climate change related patents both through searching for keywords in the abstracts that describe patents and by using the patent classifications.

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"

Figure 3: Shares of CCR patent applications across countries and time



Notes: The figure reports the number of CCR patent filings with the EPO by individuals or companies residing in various countries over the total number of filings from each country.

Figure 4: Index of the share of CCR patents (baseyear 1998)

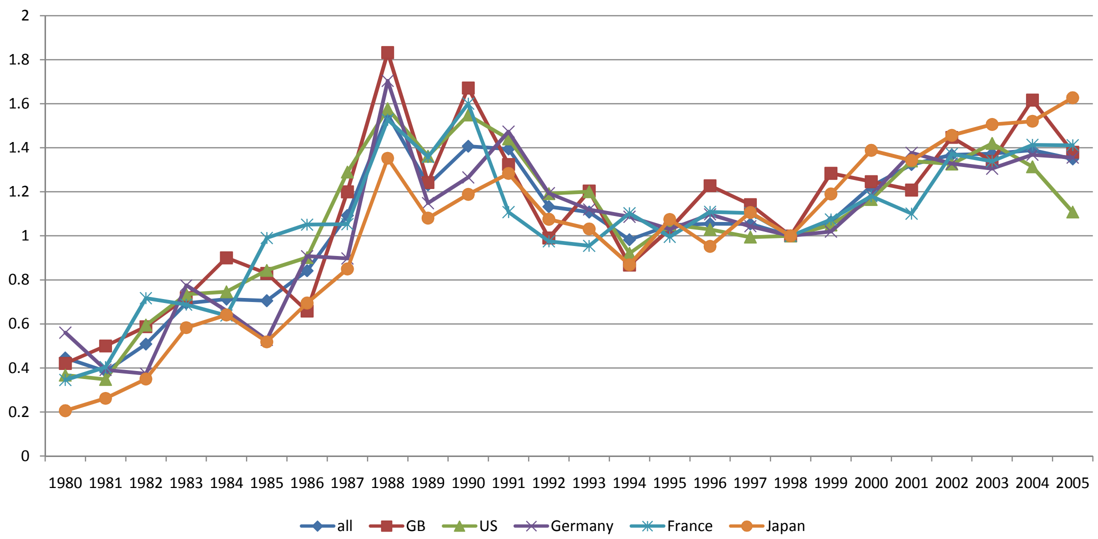
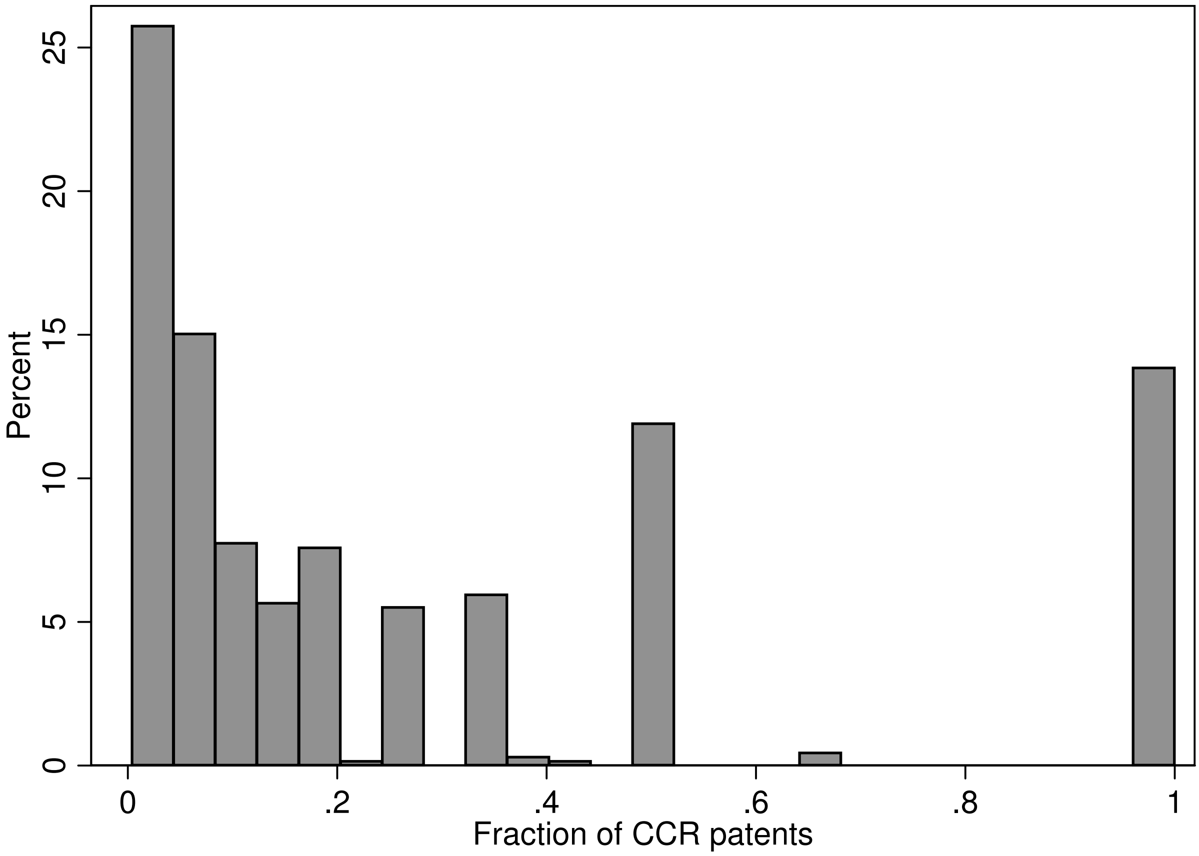


Figure 5: Share of CCR Patents among UK firms with at least one CCR Patent in 2005



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
	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

CCR Patent Classes				
Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	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
	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

CCR Patent Classes				
Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	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

CCR Patent Classes				
Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	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
	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

CCR Patent Classes				
Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	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
	208	424 - 435	C10G	1/00
Coal Gasification	48	71	C10J	3/00
	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
Solar Energy	60	641.11 - 641.15	F03G	6/00
	60	641.11 - 641.15	F03G	7/00

CCR Patent Classes				
Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	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
	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

CCR Patent Classes				
Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	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
	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

CCR Patent Classes				
Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	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
	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

CCR Patent Classes				
Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class
	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

CCR Patent Classes				
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

CCR Patent Classes				
Technology type	US Sub Class	IPC Sub Class	IPC Group	US Class