"Certificate Oversupply in the European Union Emission Trading System and its Impact on Technological Change"

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Abstract

We examine the number of patent applications for climate change mitigation technologies (CCMT) filed at the European Patent Office and seek to relate it to the oversupply of emission allowances under the European Union Emission Trading System (EU ETS). We use a panel count data approach to show that firms covered by the policy take the oversupply into account when determining their level of innovative activity. We also indirectly demonstrate that the "weak" version of the Porter hypothesis holds for the EU ETS, given the sizable oversupply of allowances in the market. Our results suggest that in order to set the European economy firmly on the low-carbon technology pathway, and to ensure that the ambitious EU climate targets are met, serious policy changes must be undertaken.

JEL classification: Q55; Q58; O33; O38
Keywords: Environmental Policy; Emission Trading System; Certificate Oversupply; Technological Change; Patent Count Data

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I. Introduction

Technological change aimed at mitigating the impact of economic activity on climate change is a powerful tool for moving towards a low-carbon economy. To strike out on this path, various policies have been adopted worldwide. One of these is the European Union Emission Trading System (EU ETS), which as a market-based regulation, established the first and largest market for greenhouse gas (GHG) emissions allowing installations in the system to cut their emissions in a flexible and cost efficient way. However, external shocks and a lack of stringency have led to the creation of a sizeable oversupply of allowances in the market potentially hampering the effect of the policy on low-carbon technological change (Sandbag 2013).

Against this backdrop, the primary goal of our study is to determine empirically whether or not an oversupply of allowances in the market has a negative effect on the innovative behavior of firms covered by the policy, measured in terms of the number of patent applications filed at the European Patent Office (EPO). We employ a count data model to estimate the impact of certificate oversupply on climate change mitigation technologies (CCMTs). Secondly, and since the EU ETS falls within the category of market-based regulations that are considered well-designed environmental regulation, we seek to validate the Porter hypothesis (Porter, 1991; Porter & van der Linde, 1995); that is, we aim to determine whether market-based environmental regulations are a suitable tool to spur "green" innovation. With this study we make a twofold contribution to the literature. First, we show how the excess supply of EU emission allowances (EUAs) negatively affects the innovative behavior of firms in the EU ETS. Second, we separate the impact of this oversupply with respect to two CCMTs, namely, technologies or applications for the mitigation of, or adaptation to, climate change; and technologies for the reduction of GHG related to energy generation, transmission or distribution.

The rest of the study is organized as follows. First, the EU ETS and its different phases are briefly outlined and the literature is reviewed. In section 3, we describe the structure of the data and the variables used in the empirical exercise. Next, we present the methodology and the identification approach. The regression outcomes are then presented and discussed along with their implications for the research questions posed. Finally, we draw our main conclusions and highlight policy measures that might put the EU ETS back on the right track.

II. Description & Aims of the Policy

In 2005 the EU ETS came into operation. The trading system can be considered the European Commission's (EC) main policy for reaching its ambitious GHG reduction targets under the 2030 framework for climate and energy policies. To date, the 28 EU Member States, as well as the three EEA-EFTA states (Iceland, Liechtenstein, and Norway) have joined the system, making it the world's largest carbon market. The main principle of the EU ETS can be summed up quite simply as "cap and trade". The first step in the system – "cap" – sees the EC set an EU-wide ceiling for installations under the policy which is then gradually reduced every monitoring period. The GHG ceiling is fixed in such a way that the EC issues so-called EU emission allowances (EUAs), which represent the right of a holder of such a certificate to emit one ton of CO_2, or an equivalent amount of GHG with respect to its climate impact as listed in Annex II of the EC Directive 2003/87/EC (European Commission 2013).

Hence, in order to reduce the EU ETS cap the EC cuts the overall number of EUAs in the market. Firms subject to this policy have to cover, therefore, their emissions by allowances; otherwise, they face heavy fines for every ton of CO_2 emission not covered. The second step – "trade", on the other hand, permits firms in the case of a shortage of allowances to purchase additional EUAs in a common market and, so, avoid penalization for non-compliance. Furthermore, EU ETS companies have the option of covering some of their emissions using international offsets, the so-called "Kyoto-offsets" (KO), stemming from Clean Development

Mechanism or Joint Implementation projects. The principle underpinning the EU ETS is market-based regulation which aims to leave the means of compliance in the hands of the individual. Currently, more than 11,000 installations are subject to the policy, accounting for around 45% of total GHG emissions in the participating countries. Only heavy-emitting sectors are covered by the policy, [1] which includes many manufacturing industries[2] and the power generation sector. The latter, however, is responsible for the lion's share of GHG emissions, accounting for 31% of total GHG emission from the EU 27 (European Environmental Agency 2012).

The EU ETS has been implemented in three phases, each marked by fundamental changes in policy design. The first phase (2005-07) can be considered a trial phase adhering to a "learning by doing" credo. Given that prior to 2005 no reliable emission data for the sectors in the new system were available, the main task was to build an EU-wide data base for GHG emissions for the participating members. Precisely due to this lack of emission data, the first phase was marked by a certificate oversupply that led to EUAs being priced at zero. The default distribution method for the EUAs was that of free allocation in accordance with the national allocation plans. With the second phase (2008-12), the EC sought to improve the EU ETS by cutting total allowances by around 6.5% compared to the 2005 level. To further counter price corrosion, the EUAs from the first phase were not bankable into the second period, while several participants started to auction off some of their allowances as opposed to just giving them away. These actions served to strengthen the policy in its aim to further cut GHG emissions.

However, the start of the second trading period coincided with the onset of the global economic crisis (2008/09) which had a marked impact on production levels and, hence, on GHG emissions in the participating countries. For this motive, installations in the system reduced their

[1] From 2012 on, aviation has also been covered by the EU ETS, so that all the participating countries' flights (within, outgoing, and incoming) are subject to the policy.

[2] Manufacturing sectors covered by the EU ETS are oil refineries, steel works and producers of iron, aluminum, metals, cements, lime, glass, ceramics, pulps, cardboards, acids, and bulk organic chemicals.

emissions by a sizeable volume as a result of the economic recession rather than their abatement efforts (Bel and Joseph 2015). This in turn led to a build-up of a considerable oversupply of allowances in the market, a problem that was exacerbated by the fact that during this second trading phase firms could cover part of their emissions by KOs. All in all, the stringency of the policy was greatly compromised. This is particularly evident if we consider the marked deterioration in price, falling to 0.16€/CER[3] [Commodity Exchange Bratislava (2015)] by 2014, which was equivalent to providing firms with a "free lunch".

The EU ETS is currently in its third phase (2013-2020). A major change with respect to the earlier phases is the introduction of a cap that is reduced each year by 1.74% in an attempt at reaching the emission abatement target of 21% of the 2005 level by 2020. Likewise, the default method for allocating allowances has gradually shifted from a free-of-charge distribution to that of auctioning. The EC has also implemented the "back-loading" of additional allowances, thus postponing the auctioning of 900 million EUAs until 2019-2020 resulting in a reduction of 400 million allowances in 2014, 300 million in 2015, and 200 million in 2016 (European Commission 2014). However, these measures need to prove themselves effective in tightening policy stringency and reducing the oversupply created since 2008 so that the price of EUAs might rise.[4]

III. Induced technological change and the EU ETS

The main drivers of emission abatement under the EU ETS were, and continue to be, fuel switching and the impact of the global recession that hit the EU in 2008/09. Fuel switching has proved to be a valid tool for cutting emissions in a cost efficient manner, especially in the power generation sector (Delarue et al. 2008). But, as Calel & Dechezleprêtre (forthcoming) point out,

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[3] CER are Certified Emission Reductions certificates stemming from the Clean Development Mechanism and are one type of KOs.

[4] Since the introduction of the "back-loading" initiative in 2014, the price of EUAs on the secondary market has increased markedly (c. 4.5€/EUA in January 2014 vs. 7.5€/EUA in May 2015). However, the price is subject to considerable volatility and so no clear trend can be identified (European Energy Exchange 2015)

fuel switching alone cannot provide sufficient emission abatement to meet the ambitious EU target of an 80-95% reduction in 1990 GHG emission levels by 2050. For this reason the EC emphasizes that "the Emissions Trading System is the principal driver of the deployment of new technology, by putting a price on carbon emissions, and so stimulating the development of technologies which avoid them" (European Commission 2015). The idea underpinning this statement is the hypothesis known as "induced innovation", which was first proposed by Hicks (1930) and later reformulated in terms of environmental regulation by Porter (1991) and Porter & van der Linde (1995), where it is known as the Porter hypothesis (PH). One version of this hypothesis states that well-designed environmental policies can foster "green" innovations.[5]

III.1 Market-based regulations and their impact on innovation

Many papers have subsequently sought to provide theoretical as well as empirical validations of the question as to whether environmental regulations *de facto* spur environmental innovation.[6] Few, however, have focused on market-based regulations such as the EU ETS. Popp (2003), for example, compared the innovation impact of a market-based regulation, on the one hand, and a command-and-control regime, on the other. By focusing on the transition from one policy regime to the other, Popp recorded a surprising finding following the introduction of the 1990 Clean Air Act (CAA) in the US. Contrary to theoretical predictions, the overall number of innovations (as measured by patent counts) did not rise. However, he found that the direction of technological change was altered by the policy. Although the overall number of patents decreased during the observation period, the quality of patents with respect to environmental-friendliness

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[5] This is typically referred to as the "weak" version of the PH. The remaining versions identified by Jaffe & Palmer (1997) are the "narrow" and the "strong" version of the PH.

[6]As our study takes an empirical approach to analyze EU ETS –a market-based regulation-, only empirical analyses of such policies are reported here. See Ambec et al. (2011) for a detailed overview of the recent literature in this field.

increased. Accordingly, the shift to a market-based regulation spurred "green" innovation[7], which could be seen as a favorable outcome of the policy regime change.

A second paper to analyze whether "induced innovation" occurs under environmental regulation and if the PH has empirical implications is that of Lanoie et al. (2011). The authors draw on data from a survey conducted in seven OECD countries, giving them a sample size of 4,144 observations. The study empirically tests the different versions of the PH and finds strong evidence in support of its "weak" version. This they claim is unsurprising given that environmental policies affect pollution costs by incorporating them within the production chain. Interestingly, Lanoie et al. (2011), additionally, find some support for the "narrow" version of the PH, meaning that more flexible/market-based regulations can potentially outperform inflexible, classic command-and-control policy regimes.

Evidence that environmental policies can spur innovation is also to be found in Johnstone et al. (2010). Using the patent counts for 1978 to 2003 for renewable energy sources in 25 countries, the authors demonstrated that different environmental policy regimes have different outcomes with regards to technological innovations. For example, market-based regulations promote technological innovations for renewable energy sources that are in competition with fossil fuels and which are less costly to develop (e.g., wind power as opposed to solar power). This is highly plausible given that market-based regulations leave it up to the company to decide how to meet policy goals. Thus, profit-maximizing firms will tend to choose the path with the least costs in order to comply with the regulation. As this brief review of the current literature examining the link between market-based environmental regulations and "induced innovation" shows, innovation does occur under such policy regimes and, hence, they constitute valid tools for putting an economy on a less-polluting technological pathway.

III.2 The EU ETS and its impact on innovation

[7] In the case of the CAA, air quality increased due to more environmentally friendly innovations

In the case of the impact of the EU ETS, the results are far from clear. Although various studies aimed at untangling the impact of the trading system on innovation have been conducted, results remain inconclusive. Anderson et al. (2011) report a moderate stimulating effect of the policy on technological change. Following a survey conducted among EU ETS firms in Ireland, they conclude that nearly half the companies were engaged in the acquisition of new machinery and equipment and two thirds had performed process or behavioral changes. Likewise, Fontini and Pavan (2014) find a positive link when studying the Italian pulp and paper industry; they show a positive relation between the initiation of the second trading period and technological change in the sector. However, the reduction in emissions detected during the study period was due mainly to an overall reduction in output and not to technological change, and so they conclude that the ETS has had only a limited, albeit positive, impact on low-carbon technological change.

Similar impacts of the EU ETS were reported by Rogge and Hoffmann (2010) in an interview-based study of the German electricity sector[8]. The policy was seen to have had an impact on R&D for carbon capture technologies, especially on large-scale, coal-based power generation; however, the authors claim that the impact was limited by the free allocation of EUAs in the market. Further evidence of the positive impact on innovation can be found in Petsonk and Cozijnsen (2007) and Martin et al. (2011), the second of these studies suggesting that the amount of freely allocated allowances hampers innovation incentives under the policy regime.

In contrast, a large number of studies attest to the fact the system has no or little influence on firms' innovative behavior. For example, Borghesi et al. (2012) show that the EU ETS has resulted in few environmental innovations among Italian manufacturing firms and attribute this to the lack of policy stability. Aghion et al. (2009) share this opinion, arguing that in a cap-and-trade system a sufficiently high carbon price is needed to induce technological change

[8] Similar studies by Hoffmann (2007) and Rogge et al. (2011) come to similar conclusions but are more critical of the incentives for innovations under the EU ETS due to a lack of stringency.

and policy stability is essential. However, they show that neither factor was observed during the first few years of the policy, thus hampering the development of "green" innovations.

One of the most ambitious studies, in terms of the number of firms in the system that were examined, is Calel and Dechezleprêtre (forthcoming). As an indicator of technological change, patent counts for CCMTs filed at the EPO were used. At first glance, the data showed a rapid increase in low-carbon patenting with the introduction of the EU ETS in 2005, creating the impression that the policy initiated a surge in CCMT patenting. To verify the true impact of the EU ETS on patenting behavior, firms in the system were matched with other firms of similar characteristics (in terms, for example, of employment and turnover) and a difference-in-differences estimation was performed. This showed that the EU ETS was responsible for just a 2% increase in low-carbon patenting and that the impact of the policy on "green" technological change has been limited to date. Likewise, Martin et al. (2012) performed an evidence review of existing literature regarding various features of the EU ETS such as emission abatement, economic performance but also innovation. In the case of the latter, the study could find no strong evidence that the EU ETS is driving technological change for directly regulated firms.

As shown, the evidence regarding the EU ETS and its impact on innovation is far from clear. However, most of the studies, whether they report a positive impact or no impact at all on induced innovation, state that to incentivize firms to engage in low-carbon technological change the EU ETS has to be more stringent. This point was recognized by Porter and van der Linde (1995) to ensure that well-designed environmental regulations spur innovation. The lack of policy stringency is attributed primarily to the accumulation of EUAs due to external shocks and lax emission caps, but exacerbated by the introduction of KOs into the system. These circumstances would seem to compromise incentives to engage in the innovation of new-to-the-market CCMTs and, at the same time, to undermine the "induced innovation" hypothesis in the case of the EU ETS. However, while this suspicion has been repeatedly voiced, it has yet to be tested empirically.

With this study we seek to contribute to the literature by showing how the innovative behavior of firms in the EU ETS, measured in terms of patent applications for CCMTs to the EPO on a country level, is affected by the excess supply of EUAs. Furthermore, and thanks to the richness of our data, we can separate the impact of this oversupply in relation to two different CCMTs, namely, technologies or applications for the mitigation of, or adaptation to, climate change; and technologies for the reduction of GHG related to energy generation, transmission or distribution. Our study closes a gap in the existing literature with regard to the EU ETS, and more broadly for any cap-and-trade regulation. Moreover, it broadens our understanding of the way in which market failures influence innovative behavior under such policies.

IV. Data Sources and Variables

In order to account properly for the cross-national character of the EU ETS, we constructed a longitudinal data set covering the 27 member states of the EU plus the EFTA-state Norway between 2005 and 2011, thus taking most of the first two trading periods into account. Although the EU ETS is currently operating in a 31 countries, at the time of this analysis a complete set of data was only available for those 28 countries. Croatia only joined the EU (and, hence, the EU ETS) in 2013 and so falls outside the time frame of our analysis. As for the other two EFTA-EEA states in the system, Lichtenstein and Iceland, a full set of all the variables could not be completed. However, the possible distortion created by leaving out these two small countries is likely to be relatively low given their minor role as polluters in the EU ETS. Our final data sample comprises 189 observation pairs.[9] Data for this study have been taken from Eurostat, with the exception the variables related to the EU ETS (allocated allowances and verified emissions), which source was the Community Independent Transaction Log (CITL).

IV.1 The dependent variables: Patent Counts for CCMT

[9] Bulgaria and Romania joined the EU and, thus, the EU ETS, in 2007, and so data for these two countries are only available thereafter. Norway joined the EU ETS in 2008 and so again only a reduced set of data is available.

To measure the innovative activity of firms covered by the policy we use patent counts of CCMTs as a proxy. Advantages and disadvantages of using patents as an output measure of the creative process have been carefully considered (Griliches 1990). The typical drawback of patent data is that they only capture part of the outcome of innovative activities, since not all technological improvements are patented, voluntarily or otherwise, while innovations might also be of an organizational nature. Bearing these shortcomings in mind, patent data are a valid and frequently used measure for the innovative activity of firms, sectors, or countries.

The patent counts used in this study were created originally by the EPO and subsequently aggregated to the country-level by Eurostat. Every newly filed patent at the EPO is classified according to the International Patent Classification (IPC), recently enriched by the introduction of the new patent class, Y02, for patents providing CCMTs[10]. The Y02 class is built from several subclasses, including Y02-B, -C, -E, and -T. Given the focus of this paper, only patents from subclasses Y02C and Y02E are used here, as the other subclasses correspond to technologies that lie outside the scope of the EU ETS. Subclass Y02C includes patents for technologies for the capture, storage, sequestration or disposal of GHG, while subclass Y02E includes technologies for the reduction of GHG emission, related to energy generation, transmission or distribution.

An initial inspection of data for the Y02 patents shows several peculiarities (Figure 1). The most striking is the heterogeneity in the number of patent counts per country. In our sample, twelve countries[11] account for most CCMT patent applications at the EPO and together account for over 60% of overall patent applications. Additionally, we identify a strong outlier –Germany-, which accounts for more than three times the mean number of applications than the country ranked second, France. This is discussed and taken into account when modeling the relationship between innovative behavior and oversupply of certificates. A further interesting observation emerges on separating the Y02 class into its two subclasses, Y02C and Y02E. Over 90% of

[10] Veefkind et al. (2012) and EPO (2013) provide more details for the contents of the Y02 class and its subclasses.

[11] Austria, Belgium, Germany, Denmark, Spain, Finland, France, UK, Italy, The Netherlands, Norway, and Sweden.

patents classified as Y02 fall into the subclass Y02E. In other words, most of the patents in our sample have been developed for the energy sector. This is very interesting since this sector is one of the largest polluters in the trading system and, hence, the sector affected most by the policy.[12]

(Insert figure 1 around here)

IV.2 The explanatory variables

Explanatory variables have to fulfill different tasks in regression equations. In our case, we identify the following groups of explanatory variables so as to address different features of the number of patent applications per country. As we are interested in measuring the impact of the policy on patent counts, our "core" variable is the oversupply of allowances. Furthermore, and in order to specify correctly the impact of this oversupply on patenting behavior and so as not to mistakenly attribute the effects of other influences to these variables, we use a broad set of controls. We employ business enterprise and government R&D spending, measured as percentage of GDP, and the number of workers with tertiary education, given that these variables are known to be highly influential in determining innovation output (Griliches 1984).

An additional set of covariates is introduced to capture the economic performance of countries during the period of observation and respective industry size. These variables are industry indices for the three main sectors -Mining and Quarrying (NACE B), Manufacturing (NACE C), and Energy (NACE D) –covered by the policy and annual GDP growth rates. As shown earlier, energy related patents make up the vast majority of CCMT patents. To incorporate this fact, we introduce the share of energy from renewable sources into the equations as this is an obvious indication of "green" technological change. As the different trading phases are marked by mayor policy changes, a regression equation analyzing these policy shifts needs to take this into account. For this reason, we created a dummy variable equal to 1 for years belonging to the

[12] One shortcoming of our data is the fact that we include all CCMT patents for a selected country. However, as mentioned, most CCMT patents are closely related to the energy sector and since this sector is most affected by the policy, it is quite likely that innovative activities stem mostly from companies subject to the policy.

second trading period and equal to zero for those belonging to the first period. This allows us to identify whether patenting behavior changed during the shift from phase one to two.

Since we are particularly interested in the role of EUA oversupply on patenting behavior, we examine this variable in greater detail. Given that the main principle underpinning the EU ETS is that of 'cap and trade' and the capping is achieved through the allocation of emission allowances, the overall number of allowances on the market determines the degree of stringency of the policy. We would expect a scarcity of allowances to put pressure on firms to cut their emissions and to reduce the costs of compliance by employing cost efficient means. But the reality is somewhat different. External shocks and lax emission caps have resulted in a sizable oversupply during the second and third trading periods, having a negative effect on firms' decisions to engage in low-carbon technological change (measured here in patent counts for CCMTs). In this study, the oversupply is defined as the annual accumulated number of excess EUAs in the market; that is, the difference between the total number of allowances allocated in the market and total emissions in each respective year. We opted for this form of calculation as firms do not only access their own oversupply but also that of the market as whole, given the presence of a common market place. A detailed overview of the variables used, including their descriptive statistics, units of measurement and labels can be found in Table A1 in the Appendix.

V. Methodology and Identification Strategy

V.1 Methodology

In order to measure empirically the impact of the excess supply of EUAs, the following reduced form equations are estimated, employing a count data approach:

$$Patents_{i,t} = \alpha + \beta_1 eua\_ovs_{i,t} + \beta_2 empl_{i,t} + \beta_3 L.BERD_{i,t-1} + \beta_4 L.GORD_{i,t-1} +$$
$$\beta_5 GDP\_growth_{i,t} + \beta_6 nace\_b_{i,t} + \beta_7 nace\_c_{i,t} + \beta_8 nace\_d_{i,t} + \beta_9 renew_{i,t} +$$
$$+\beta_{10} dummy\_ets_{i,t} + \mu_{i,t} + \varepsilon_{i,t} \qquad (1)$$

where the dependent variable *Patents* is a count of patent applications registered at the EPO for different CCMT categories. To avoid stating very similar equations repeatedly, *Patents* is a placeholder for Y02, Y02E and Y02C patent classes. *a* is the constant in the model. The core variable in our estimations is *eua_ovs* which represents the annual accumulated oversupply of EUAs in the market. *empl* is the total number of workers employed in the tertiary sector in the country, *L.BERD* and *L.GERD* are the lagged R&D expenditure by Business Enterprises and by Governments, respectively, measured as a percentage of GDP. The variable *GDP_growth* is the percentage change in GDP on the previous year. The covariates *nace_b*, *-_c*, and *–_d* are economic industry indices for the main sectors covered by the EU ETS: Mining and Quarrying, Manufacturing, and Energy. *renew* represents the percentage share of renewable energies in the gross final energy consumption. The variable *dummy_ets* is a dummy variable with values zero for years belonging to the first trading period, and values 1 for those belonging to the second trading period. $\mu_{i,t}$ is the between-entity error and $\varepsilon_{i,t}$ is the within-entity error term of the random effect specification. The subscripts *i* and *t* define the cross-section and the time dimension of our data.

Count data models, more specifically Poisson and negative binomial regressions abound in the literature (Hausman et al. 1984; Cincera 1997; Cameron and Trivedi 2005; Johnstone et al. 2010), and are suitable for estimating the number of patent counts given their distribution characteristics. We use negative binomial fixed effects estimates on the grounds that an approach that supposes a Poisson distribution is too restrictive for our data. Indeed, one of the requirements to use of a Poisson model is equidispersion; that is, equality of mean and variance:

$$E[Y] = V[Y] = \mu$$

However, the patent counts used here do not satisfy these criteria (see Table A1 for mean and variance relationship). This problem can be overcome using a negative binomial approach, whereby the mean still equals μ but the variance is allowed to increase by parameter $\alpha > 0$, allowing for unobserved heterogeneity across the sample. Hence, the first two moments of the negative binomial distribution are given by:

$$E[y|\mu, \alpha] = \mu$$

$$V[y|\mu, \alpha] = \mu(1 + \alpha\mu)$$

Recall that the variance now exceeds the mean, thereby addressing the problem of over-dispersion of the data and allowing unobserved heterogeneity to alter the mean-variance relationship.[13] Moreover, we use random effects due to short panel properties and the corresponding incidental parameter problem (Cameron & Trivedi 2013, Hilbe 2011, Greene 2007).[14] Furthermore, we use the exposure variable *GDPvol*, because the number of patent applications at the EPO varies significantly from country to country, giving the impression that country size, measured as GDP, matters. We use maximum likelihood as estimation method.

V.2. Identification Strategy

Since we are interested in the effect of the oversupply of allowances on green technology innovations, and as to whether or not the observed relationship is stable, we employ the following identification strategy. We begin with a fairly simple regression equation for the basic relationship between patents and the key variables responsible for the creation of innovations. We then introduce additional covariates into the equation, focused at all times on our variable of interest, *eua_ovs*. Thus, the first equation includes the variable *eua_ovs* and only those covariates known as having an impact on innovation, including *empl*, *L.BERD*, and *L.GERD*. Next, we introduce the variable GDP_growth and the industry indices for the main sectors covered by the EU ETS, *nace_b*, *-_c*, and *–_d*, followed by the variable *renew* in order to control for the possibility that the share of renewable energies in the gross final energy consumption influences the number of patent applications registered at the EPO. Finally, the dummy variable *dummy_ets* designed to differentiate between the two trading phases is introduced. Thus, we end up with four estimations for the Y02, Y02E, and Y02C classes, respectively, where the fourth is equivalent to our main equation (1). The primary aim of this exercise is to verify whether the underlying

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[13] See Cameron & Trivedi (2005) for a more detailed description of Poisson and negative binomial models.

[14] However, note that estimation results using fixed effects are presented in Tables A2 and A3 in the Appendix, since the Hausman test for random and fixed effects could not be estimated properly for all model specifications. These tables show that results using fixed effects do not significantly vary or alter the main outcomes presented in the text.

relationship between oversupply and the number of patent applications is robust across the different specifications even when a broad set of controls is added.

VI. Estimation Results

In line with the above strategy, we performed the four estimations for the Y02 class (Table 1) and its respective subclasses, Y02E and Y02C (Table 2). An initial inspection of the fit of the regressions for the main CCMT class and subclasses leads to a number of observations. First, the overall model fit, given by the χ^2 statistic of the Wald test, can be provided for every equation since it rejects the H_0 of joint statistical insignificance.

(Insert table 1 around here)

(Insert table 2 around here)

Second, by adding variables to the equation, the log-likelihood increases steadily, indicating an overall improvement with each additional step. A likelihood-ratio test is used to check if the panel structure is justified or whether a pooled estimator with constant over-dispersion should be used. In each case we reject the H_0 of constant over-dispersion; hence, the panel structure chosen for our model is valid. Third, we performed a multicollinearity test. This shows that all variance inflation factors are well below five suggesting that there are no problems of multicollinearity in our regressions (all results available upon request). The overall sample included 189 observations; however, due to the use of the lagged variable for *BERD* and *GERD,*[15] the sample size was reduced by 28 observations for the regressions.

Focusing on the different estimates of the Y02, Y02E, and Y02C classes, the variables known to have an impact on innovation are statistically significant for estimations (1) through to (8); hence, for the main class, Y02, and the subclass, Y02E, they positively influence the patenting of CCMTs, as expected. More specifically, tertiary employment (workers with a good academic background) consistently has a positive impact on the number of patent applications. Likewise, business enterprise R&D expenditure has an even higher positive impact, being statistically

[15] The lagged R&D expenditures are used in line with Cameron & Trivedi (2005).

significant at the 1% level for estimations (1) through to (10). However, it is not the case of government R&D expenditure –the coefficient for *L.GERD* being statistically insignificant in all regressions. This suggests that the main driver of green technological change is private, rather than governmental, financing. In the following step, GDP growth rates and industry indices for the main sectors are included in the equations (Table 1, Models 2-4; Table 2, Models 6-8, 10-12).

Interestingly, innovative activity measured in terms of patent counts is not affected by a country's economic performance, indicating that the 2008/09 economic crisis did not directly influence technological change.[16] However, as discussed, the recession played a key role in the build-up of the excess supply of EUAs and, thus, it had an indirect impact on "green" patenting. The coefficient for the mining and quarrying sector (*nace_b*), for example, is statistically insignificant. Hence, higher activity levels in this sector do not seem to result in more patent applications being made at the EPO. The same is true for the coefficient corresponding to the energy sector (*nace_d*), which is not significant across the different model specifications. However, in the case of the manufacturing sector's production levels the opposite holds. Higher levels of activity in this sector have a decreasing impact on the number of patents in the Y02 and Y02E classes. This is attributable to the relationship between the electricity and manufacturing sectors, with the latter being one of the main consumers of electricity. Bearing in mind that more than 90% of patents are taken out by the energy sector, it seems that this sector is more specifically focused on meeting demand than on reducing the costs of compliance. This also explains why patenting behavior is not affected by a higher volume of production in the energy sector.

The introduction of the share of energy from renewable sources into the specifications (Table 1, Models 3-4; Table 2, Models 7-8, 11-12) gives the expected positive coefficient across all estimates; however, the coefficient is statistically insignificant across the board, indicating that

[16] It might be thought that GDP growth rates affect patent counts in a similar way to R&D expenditures, i.e., in a lagged manner. In additional estimations this was taken into account but no statistically significant impact of lagged GDP growth rates was found. Results are available upon request.

it does not affect green patenting in our sample. Finally, we add the dummy variable for the two EU ETS trading periods (*dummy_ets*) into the equations (Table 1, Models 4; Table 2, Models 8, 12). A similar observation to that for renewable energy shares can be made for the dummy variable: it presents the expected positive sign yet it is not significant, once again suggesting that the different trading phases have no impact on "green" patenting in our sample. This outcome is not surprising as the policy with respect to emission caps and the auctioning of parts of the allowances was much stricter in the second phase. Yet, this said, even in the first year of the second phase (2008), the oversupply of allowances was similar to the level recorded in 2007, despite the fact that all allowances from the first phase were canceled with the initiation of the second period. This serves to illustrate the constant oversupply in the market and its impact on "green" technology change.

VI.1 The EUA oversupply: effects and implications

The main purpose of the identification strategy is to verify if the impact of the certificate oversupply is robust even when applying a broad set of controls. If we inspect the estimates corresponding to oversupply (*eua_ovs*), this would appear to be the case. The outcomes show high significance levels (at the 1% level) across the regressions for the Y02 and Y02E classes and moderate significance levels for those of Y02C. Moreover, the coefficients show a low variation across the specifications, highlighting the strong relationship with the number of patent applications for CCMTs made at the EPO. The sign associated with every equation is, as expected, negative, indicating that an increase in market oversupply reduces the overall number of "green" patents. These are the overt conclusions to be drawn from the statistical analysis; however, the implications of these results are complex.

Our results show that "green" technology change is closely related to the EU ETS as a whole, when measured in terms of patent applications registered at the EPO.[17] Yet, the current situation of the EU ETS, characterized by an excess supply of allowances, cannot be considered to be conducive to technology change; on the contrary, it would appear to be discouraging it to some extent. Based on our regression results, firms can be seen to be taking the oversupply of emission allowances into account when deciding what "green" innovative activity needs to be undertaken. This means that the oversupply of allowances in the market, and the consequently low price for certificates, is causing the policy to lose much of its potential for fostering the technological change needed to achieve the EU's ambitious climate goals. This situation is exacerbated by the other modes of compliance available to firms in the system, namely, KOs. These additional certificates of negligible price undermine even further the incentives to innovate by reducing the cost of compliance for firms.

Our findings demonstrate that the EU ETS, as a market-based regulation, has an impact on firms' levels of innovative activity (in terms of number of patents for CCMTs); however, so do market failures. As we have shown, EU policy has been unable to generate a sufficiently high price as a result of oversupply. In addition, this can be seen as indirect verification of the PH and of the circumstances under which environmental policies foster "green" innovation. The firms in the system are not responding to the policy as expected, owing to the negative impact of EUA oversupply on patent applications at the EPO. Thus, in line with Porter & van der Linde's (1995) claim, the stringency of the policy plays a vital role in determining whether an environmental policy will spur technological change. Here, we can assume that a shortage of EUA allowances in the market might serve to encourage innovation, a conclusion that indirectly validates the PH that well-designed market based regulations spur innovation.

[17] Our assumption that most of the innovative activity is undertaken by companies that form part of the EU ETS seems to hold; otherwise, no statistically significant relationship could be expected between oversupply and patent application for CCMTs.

VII. Conclusion

In this study we have used patent count data for CCMTs to evaluate the relationship between the sizable oversupply of EUAs under the EU ETS, on the one hand, and on "green" patenting, on the other. According to our results, the expected negative impact of this oversupply on technological change seems to be confirmed. Thus, the EU ETS, as a market-based regulation, means firms in the system take their emissions into account when determining their innovative activity. However, firms also take market failures, in this case the oversupply of certificates, into account. The latter is clearly apparent in the strong negative impact of the excess supply of EUAs on the number of CCMT patent applications.

From a policy perspective, several actions might be implemented to counter this negative impact. Although the EC introduced the "back-loading" of new allowances in the third trading period, a rigorous cancelling of allowances would help put the policy back on the right track and ensure firms rethink production in a more environmentally friendly way. In addition, given that the market for EUAs adheres to the fundamentals of supply and demand in fixing prices, it is prone to external shocks such as the 2008 economic crisis that seriously hampered the systems credibility as a driver of low-carbon technologies. In order that the market might be less vulnerable to shocks, a price floor could be installed guaranteeing a minimum price for EUAs and, thus, providing the policy with both greater stringency and stability. Such a price floor would have to be sufficiently high to spur innovation, but low enough to avoid a crowding-out of production and a loss of competiveness in the EU. These measures, not unnaturally, would be opposed by the industrial sector, but they would put the policy back on track. From an academic perspective, our results suggest that market-based regulations have an impact on firms' innovative behavior and when they are well-designed such regulations can spur innovation, as firms take the actual price of emissions, resulting from the supply of certificates, into account. Therefore, indirectly we are able to validate the weak version of the PH.

All in all, the results presented in this work are robust for a broad set of controls and show the expected relationship. The main limitation of the study, however, is our data and future research should seek to use firm-level data. More specifically, the matching of single firms by patents and their respective shortage/oversupply of allowances could be used to cross-validate our findings. Likewise, a more detailed differentiation of sectors in the trading system is desirable.

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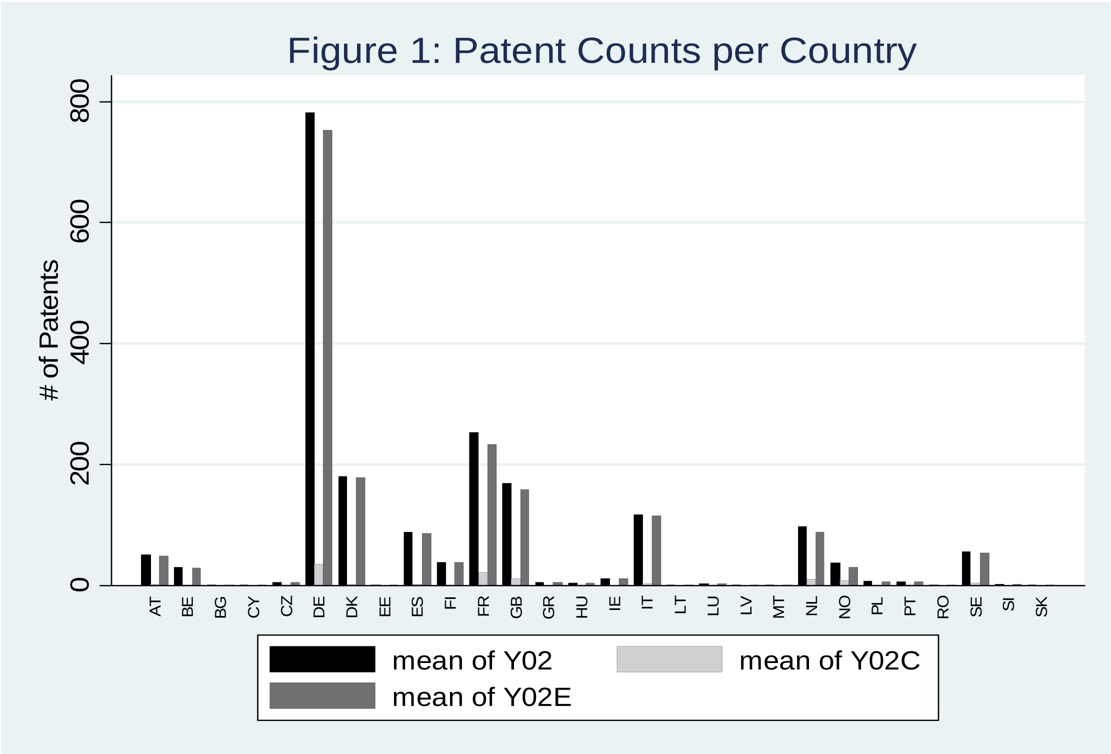
Figure 1: Patent Counts per Country



TABLES

Table1: Estimations Results for the Random Effects Negative Binomial – Y02 category

Random Effects Regression for the Y02 category				
	(1)	(2)	(3)	(4)
eua_ovs	-0.00439***	-0.00398***	-0.00391***	-0.00353***
	(0.000501)	(0.000476)	(0.000479)	(0.000683)
Empl	7.02e-05*	0.000107**	0.000110**	9.89e-05*
	(3.80e-05)	(5.02e-05)	(4.82e-05)	(5.03e-05)
L.BERD	0.964***	0.935***	0.891***	0.913***
	(0.224)	(0.169)	(0.165)	(0.148)
L.GORD	0.0580	0.0294	-0.0493	0.0325
	(0.935)	(1.023)	(1.008)	(0.944)
GDP_growth		0.00396	0.00298	0.00288
		(0.00606)	(0.00589)	(0.00581)
nace_b		0.000727	0.000968	0.00148
		(0.00166)	(0.00153)	(0.00161)
nace_c		-0.00934***	-0.00904***	-0.00910***
		(0.00241)	(0.00241)	(0.00238)
nace_d		0.00873	0.00944	0.00936
		(0.00698)	(0.00635)	(0.00598)
Renew			0.00763	0.00571
			(0.00727)	(0.00712)
dummy_ets				0.0415
				(0.0641)
Constant	-6.693***	-6.717***	-6.923***	-7.345***
	(0.629)	(0.986)	(0.995)	(1.188)
Observations	161	161	161	161
Number of country_id	28	28	28	28
F	155.7	101.8	109.6	133.9
Log-Likelihood	-513.1	-501.7	-501.2	-501.0
Panel vs Pooled	221.9	234.1	227.0	222.5

Note: Robust Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table 2: Estimations Results for the Random Effects Negative Binomial – Y02E and Y02C category

	Random Effects Regression for the Y02E category				Random Effects Regression for the Y02C category			
	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
eua_ovs	-0.00429***	-0.00388***	-0.00384***	-0.00348***	-0.00585**	-0.00570*	-0.00542*	-0.00483*
	(0.000463)	(0.000467)	(0.000462)	(0.000673)	(0.00253)	(0.00313)	(0.00307)	(0.00264)
Empl	6.91e-05*	0.000107**	0.000109**	9.87e-05*	5.84e-05	6.46e-05	0.000112	0.000107
	(3.60e-05)	(4.71e-05)	(4.76e-05)	(4.85e-05)	(6.34e-05)	(6.34e-05)	(9.19e-05)	(9.66e-05)
L.BERD	0.982***	0.955***	0.924***	0.944***	0.902***	0.938***	0.676	0.692
	(0.221)	(0.162)	(0.158)	(0.143)	(0.275)	(0.311)	(0.545)	(0.570)
L.GORD	-0.0580	-0.114	-0.160	-0.0871	2.829	3.035	2.328	2.430
	(0.952)	(1.043)	(1.036)	(0.984)	(1.899)	(2.332)	(2.188)	(2.454)
GDP_growth		0.00411	0.00350	0.00338		-0.00374	-0.00358	-0.00442
		(0.00589)	(0.00577)	(0.00567)		(0.0188)	(0.0183)	(0.0167)
nace_b		0.000588	0.000757	0.00123		0.00136	0.00309	0.00407
		(0.00186)	(0.00183)	(0.00191)		(0.00633)	(0.00770)	(0.0101)
nace_c		-0.00972***	-0.00954***	-0.00959***		0.000749	0.000414	0.000416
		(0.00230)	(0.00233)	(0.00233)		(0.00724)	(0.00644)	(0.00599)
nace_d		0.00927	0.00972	0.00967		0.00275	0.00251	0.00283
		(0.00719)	(0.00683)	(0.00648)		(0.0198)	(0.0216)	(0.0244)
Renew			0.00492	0.00321			0.0268	0.0259
			(0.00786)	(0.00771)			(0.0439)	(0.0451)
dummy_ets				0.0387				0.0590
				(0.0624)				(0.250)
Constant	-6.837***	-6.854***	-6.988***	-7.385***	-7.876***	-8.587*	-9.060*	-9.767**
	(0.585)	(0.972)	(0.961)	(1.142)	(2.333)	(4.571)	(4.751)	(4.076)
Observations	161	161	161	161	161	161	161	161
country_id	28	28	28	28	28	28	28	28
F	165.0	98.52	96.66	114.8	5.798	3.954	5.112	4.402
Log-Likelihood	-509.7	-497.7	-497.4	-497.3	-201.6	-201.5	-199.4	-199.4
Panel vs Pooled	220.3	232.1	222.6	217.6	24.35	22.14	23.44	23.29

Notes: Robust Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

APPENDIX

Table A1: Variable Overview

Variables	Description	N	mean	sd	Min	max
Y02	Number of Patent application at the EPO for the Y02 category	189	71.63	160.1	0	999
Y02C	Number of Patent application at the EPO for the Y02C category	189	3.741	8.357	0	47
Y02E	Number of Patent application at the EPO for the Y02E category	189	68.51	153.8	0	966
GDP_growth	Percentage change of GDP on previous year	189	1.747	4.383	-17.70	11
Renew	Share of renewable energy in gross final energy consumption	189	14.60	13.03	0.300	64.80
nace_b	Volume index of production for the mining and quarrying sector; data adjusted by working days	189	110.2	21.19	75.57	224.8
nace_c	Volume index of production for the manufacturing sector; data adjusted by working days	189	103.4	10.18	65.54	130.0
nace_d	Volume index of production for the energy sector; data adjusted by working days	189	99.17	6.841	75.87	118.4
Empl	Total Employees with tertiary education (levels 5-8) from age 25-64 in thousands	189	2,048	2,737	20	10,889
dummy_ets	Dummy for the shift from phase one to phase two of the EU ETS	189	0.593	0.493	0	1
eua_ovs	Yearly accumulated oversupply of EUA in the market in Mgt.	189	901.8	42.99	851.9	985.2

Table A2: Estimations Results for the Fixed Effects Negative Binomial – Y02 Category

	FE Regression for the Y02 category			
	(1)	(2)	(3)	(4)
eua_ovs	-0.00444***	-0.00386***	-0.00380***	-0.00425***
	(0.000366)	(0.000513)	(0.000496)	(0.000867)
Empl	9.26e-05	0.000177*	0.000151	0.000167
	(0.000162)	(8.76e-05)	(0.000106)	(0.000112)
L.BERD	0.705*	0.589**	0.571**	0.531**
	(0.357)	(0.219)	(0.223)	(0.220)
L.GORD	0.377	0.333	0.159	-0.00907
	(1.765)	(1.268)	(1.438)	(1.481)
GDP_growth		0.00434	0.00188	0.00132
		(0.00702)	(0.00585)	(0.00623)
nace_b		0.00186	0.00172	0.00107
		(0.00284)	(0.00258)	(0.00249)
nace_c		-0.0111***	-0.00962***	-0.00924***
		(0.00211)	(0.00283)	(0.00315)
nace_d		0.0101	0.0112	0.0118
		(0.00879)	(0.00757)	(0.00712)
Renew			0.0172	0.0233
			(0.0290)	(0.0318)
dummy_ets				-0.0531
				(0.0749)
Constant	-6.444***	-6.541***	-6.926***	-6.494***
	(0.622)	(1.176)	(1.051)	(1.398)
Observations	161	161	161	161
# of country_id	28	28	28	28
F	96.35	81.16	61.70	58.99
Ll	-369.8	-355.1	-354.5	-354.2

Note: Robust Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

Table A3: Estimations Results for the Fixed Effects Negative Binomial – Y02E and Y02C Category

	FE Regression for the Y02E category				FE Regression for the Y02C category			
	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
eua_ovs	-0.00435***	-0.00375***	-0.00370***	-0.00426***	-0.00628**	-0.00600**	-0.00584*	-0.00452
	(0.000372)	(0.000508)	(0.000480)	(0.000868)	(0.00241)	(0.00273)	(0.00291)	(0.00424)
Empl	8.97e-05	0.000182**	0.000162	0.000183*	6.80e-05	8.72e-05	5.68e-05	2.47e-05
	(0.000181)	(8.40e-05)	(0.000100)	(9.80e-05)	(0.000234)	(0.000176)	(0.000420)	(0.000257)
L.BERD	0.758**	0.624***	0.606**	0.554**	-0.00951	0.0780	-0.242	0.00180
	(0.340)	(0.223)	(0.230)	(0.228)	(0.820)	(1.580)	(1.042)	(1.813)
L.GORD	0.271	0.185	0.0694	-0.131	3.162	3.453	3.337	3.737
	(1.855)	(1.238)	(1.385)	(1.442)	(2.618)	(3.504)	(4.403)	(6.679)
GDP_growth		0.00448	0.00265	0.00208		-0.00286	-0.00921	-0.00824
		(0.00710)	(0.00574)	(0.00606)		(0.0239)	(0.0279)	(0.0245)
nace_b		0.00184	0.00172	0.000923		0.00176	0.00203	0.00420
		(0.00294)	(0.00276)	(0.00263)		(0.0105)	(0.00909)	(0.0180)
nace_c		-0.0116***	-0.0105***	-0.0101***		-0.000589	0.00219	0.00116
		(0.00238)	(0.00298)	(0.00318)		(0.0109)	(0.0151)	(0.0108)
nace_d		0.0109	0.0117	0.0123		-0.000360	0.00416	0.00299
		(0.00908)	(0.00803)	(0.00765)		(0.0231)	(0.0274)	(0.0404)
Renew			0.0126	0.0191			0.0470	0.0282
			(0.0271)	(0.0296)			(0.0593)	(0.0914)
dummy_ets				-0.0653				0.150
				(0.0684)				(0.551)
Constant	-6.624***	-6.733***	-7.016***	-6.466***	-5.155	-5.751	-7.023	-8.404
	(0.580)	(1.148)	(0.983)	(1.341)	(3.908)	(19.15)	(11.55)	(8.701)
Observations	161	161	161	161	99	99	99	99
country_id	28	28	28	28	17	17	17	17
F	104.9	66.66	54.23	58.67	23.77	8.313	10.94	10.01
Ll	-368.0	-352.4	-352.1	-351.7	-129.5	-129.5	-129.0	-128.9

Note: Robust Standard errors in parentheses. *** p<0.01, ** p<0.05, * p<0.1

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