The Productivity of Environmental Innovations

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Abstract. While recent literature has mainly focused on explaining the determinants of green innovations, it is not well understood how such innovations affect productivity. For this reason, the influence of green inventions on productivity was analysed on the basis of patent data. New industry-level panel data were exploited: these included 12 OECD countries, the whole manufacturing sector and a period of 30 years. The results of the analysis show that green inventions are U-shape related to productivity on an industry level. However, the turning point is quite high and hence only relevant for a few industries. The results indicate that - given the current level of green promotion - market incentives alone are not sufficient to allow the green invention activities of industries to rise considerably.

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1 Introduction

Empirical research on environmental innovations provides us with a good understanding of what leads to investments in research for environmental technologies. Popp (2002) examined the share of environmental patents from the total number of patents in the United States and found that energy prices induce innovation. Newell et al. (1999) looked at the level of product characteristics and found that energy prices had an observable effect on technical features of the products offered for sale. In addition to energy prices, environmental regulation is also likely to increase the total number of patents (see Jaffe and Palmer 1997) as well as the number of environmental patents (see Brunnermaier and Cohen 2003). Popp (2006) used the examples of the emission of two gases (NOx and SO2) and states that inventors respond to domestic regulatory pressure and not to foreign regulatory pressure. However, patent activities of foreigners increase due to regulation in their home market. Lanoie et al. (2011) found a positive relationship between high environmental policy stringency and environmental R&D. Further, Horbach (2008) stated, based on a firm-level study for Germany, that in addition to environmental regulation, technological capabilities and organisational changes are positively related to environmental innovations as well.

These investigations stop at the innovation level and do not examine whether environmental innovations are profitable or when they are profitable. However, after more than 30 years of private investments in green technologies, as well as a number of governmental market interventions in different countries and emission restriction policies (not only on a national but also on a multilateral level), it is time to measure empirically whether – given the regulatory framework in the countries and industries considered – green investments have also contributed to profitability and not only to innovation output.

It is clear that green innovation investments would proceed without further intervention if such investments were already profitable. Consequently, we investigated the profitability of green innovations in order to determine whether green innovation investments are already profitable and whether they will increasingly substitute older, environmentally unfriendly technologies.

We found that green innovation investments have not been profitable for most of the industries so far. Hence, it is unlikely that investments in green innovations will proceed without policy interventions to a level where environmentally unfriendly technologies would be replaced by green technologies in due time. For this reason, we think that the current answer to Popp's (Popp 2005, p. 224) question as to whether environmental innovation will proceed without policy intervention is probably no.

Our research results and policy-relevant conclusions are based on a broad empirical basis. We exploited a new patent data set that is aggregated on an industry level. The use of aggregated data has several advantages. Firstly, it allows us to use the OECD Stan database to estimate a standard Cobb-Douglas production function. Secondly, it allows us to generate a data set on inventions that cover the whole manufacturing sector (22 two and three-digit industries), the most important countries for green invention (12 OECD countries that are responsible for 95% of all green patents and total patents worldwide) and this over a period of 30 years. Furthermore, the balanced data set allows us to control for correlated unobserved heterogeneity between the industries of the different countries.

We used patent data to identify green and non-green inventions. Patent documents considered as covering green inventions were identified according to the OECD Indicator of Environmental Technologies (see OECD 2012). Patents were aggregated to inventions following the patent family definition of Thomson Reuters' Derwent World Patents Index database [systematic]. We only considered patent families that are comprised of at least one PCT (Patent Cooperation Treaty) application indicating significant commercial value of the invention. The use of this patent data allowed us to define a quantitative measure for green inventions and hence to analyse non-linear effects of green inventions on productivity.

The results show that green inventions are U-shape related to productivity on an industry level. The turning point is, however, quite high and thus only relevant for a few industries. The results indicate that industries themselves are probably not willing to increase their investments in green inventions.

The paper is organised as follows: chapter two provides the conceptual background and the hypotheses. Chapter three describes the data. In chapter four we show how we tested the hypotheses empirically. Chapter five presents the results, and in chapter six we present our conclusions.

2 Conceptual Background and Hypotheses

There are a number of empirical investigations (e.g., Crepon et al. 1989) that reveal a positive relationship between inventive output (measured through innovative sales or patent applications) and the productivity of a firm.[1] This standard result in innovation economics cannot be taken for granted if we look at newer technologies, such as green inventions. Especially in an initial phase, there are several reasons why firms are unable to develop green technologies in a profitable way. There are demand-side factors, such as willingness to pay for green products, and supply-side factors referring to firms' technological and organisational capabilities and financial constraints that may prevent productivity gains.

The demand for a product shapes the incentives to innovate (Dasgupta and Stiglitz 1980). Demand is expressed by the willingness to pay for newer products. Green innovative products are likely to be more expensive as compared to traditional ones, and the exclusivity of green product benefits is not given, since they are not fully appropriable (e.g., the benefits of emission reduction in the case of electro cars). In contrast, the greatest benefits are likely to be public rather than private ones. Accordingly, the willingness to pay for green products will be low (Aghion et al. 2009).

[1] Please notice that our conceptual framework refers to the firm level and our empirical investigation is based on more aggregated industry data (see, e.g., Aghion et al. 2005 for a similar practice).

The development of green products and processes also challenges a firm's capability profile in terms of knowledge creation and technology development. To meet these challenges, at least a modification, if not a change, of the firm's resource base is required, since the resource base marks its spectrum of capabilities (Wernerfelt 1984, Barney 1991, Penrose 1995, or Barney et al. 2001) in terms of diversification into the field of green technologies and products (Horbach 2008).[2] This could be a costly task because firms may not have the capacity to alter the technological basis. If they find useful external knowledge, this knowledge may be non-tradable due to its 'tacit' character, or it is only available at a very high price (Teece et al. 1997). Costs could also result from the coordination of technological activities within firms or between firms or institutions if green technologies are investigated or acquired through cooperation in research.

It is not a change in technology alone that increases costs (Danneels 2002). In addition to technology, business processes and working routines also have to be adapted or even newly developed. Moreover, it may be necessary to hire new employees, constitute new departments or acquire specialised firms, as we observed in other sectors that underwent considerable technological changes (e.g., the increase of biotechnology in the pharmaceutical industry). In the light of these challenges, it is not surprising that there is considerable reluctance to change.

Furthermore, investment costs in green technology can be substantial. We learn from transaction cost economics (see Williamson 1975) and also from empirical investigations of R&D financing that internal capital flows (cash flow) are more likely to be used, rather than external capital flows, in order to finance technological activities (see Hall 1992, Himmelberg and Petersen 1994).

Access to external financial means suffers from the 'moral hazard' problem, since the output of R&D activities can never be predicted from the input (see Arrow 1962, p. 172). It is not surprising that a researcher who is familiar with a green technology project assesses the

[2] Modification of the knowledge base should also be timely in order to keep pace with changes in demand (see Newbert 2007).

likelihood of a technological success more optimistically than investors because the latter lack detailed information and experience concerning the investigation processes. Therefore, it is difficult for external investors to distinguish good projects from bad projects (the lemon problem). Hence, there are costly information asymmetries between potential external investors and researchers, and financial markets are not efficient as far as technological investments are concerned.

While the costs of technological diversification in new technology fields can be considerable, the commercialisation of these new technologies is difficult. Prices of green products are unlikely to be competitive, at least in the initial phase when production costs are relatively high. We thus postulate the following hypothesis:

H1: The costs of developing a green knowledge stock are considerably high and they significantly decrease the productivity of a firm or an industry.

As argued in H1, research into new knowledge is expensive. Accordingly, one cannot expect positive marginal returns from such investments right from the beginning. However, positive returns to scale are expected in research (see Henderson and Cockburn 1996, or Figueiredo 2002, for the steel industry), whereupon the impact of green inventions on productivity should increase as the quantity of knowledge increases.

Building up a stock of knowledge involves substantial fixed costs. It takes considerable investment, not only in new technological knowledge, but also in additional training of employees, new equipment, or learning-by-searching (see Malerba 1992). Accordingly, positive returns to scale are expected. The fixed costs only pay off if green research investments exceed a certain limit. If there are positive returns to scale in green research, a firm moves from expensive ’exploration’ of new knowledge to the less expensive ‘exploitation’ of existing knowledge (see March 1991, Quintana-García and Benavides-Velasco 2008), once it decides to further increase its knowledge stock.

The second hypothesis reads as follows:

H2: Industries with a green knowledge stock beyond a certain limit are more likely to show positive productivity effects as compared to industries with a poorer knowledge stock in green technologies.

3 Description of the Data

3.1 Measurement of green inventions based on patent statistics

We used patent statistics in order to measure the green investment activities of an industry. Although patent statistics have many disadvantages in measuring innovation output (see Aghion et al. 2011), they are a rather good proxy for input because there is a strong relationship between the number of patents and R&D expenditure (see Griliches 1990), despite the fact that not all inventions are patentable and smaller firms are more reluctant to patent than larger firms.

For the paper at hand, patent information was gathered in cooperation with the Swiss Federal Institute of Intellectual Property (IPI). Green patents were selected according to the OECD Indicator of Environmental Technologies (see OECD 2012). The OECD definition distinguishes seven environmental areas, i.e. (a) general environmental management, (b) energy generation from renewable and non-fossil sources, (c) combustion technologies with mitigation potential, (d) technologies specific to climate change mitigation, (e) technologies with potential or indirect contribution to emission mitigation, (f) emission abatement and fuel efficiency in transportation, and (g) energy efficiency in buildings and lighting.

In order to identify our proxy for the green knowledge base of an industry, further specifications and clarifications had to be made:

a) In order to assign patents to countries, the applicant's home country or the inventor's home country can be chosen. We assigned patents according to the applicant's address, since this information is generally available for patent applications in all investigated countries except for the USA, for which inventor's information is available generally. Hence, we used the inventor statistics for the USA. Moreover, we collected both the inventor's information and the applicant's information for Germany in order to have an idea of the robustness of our findings for the USA, assuming distortions are similar for all countries. In fact, we did not see any significant differences between the inventor's and applicant's statistics for Germany. Hence, we felt safe to use the inventor's statistics for the USA.

b) We collected inventions (patent families) and not single patents. Patents were grouped into patent families according to the Derwent World Patents Index patent family definition of Thomson Reuters (peer-review procedure). This approach has the advantage that distortions caused by different national granting procedures and different application attitudes (USA: greater number of single applications for one invention compared to Europe) were mitigated.

c) Only inventions which were at minimum filed for patent protection under the PCT (Patent Cooperation Treaty) were considered. Hence, our data set mainly includes inventions with considerable commercial potential.

d) Inventions (patents)[3] were aggregated on an industry level, using the concordance scheme published by Schmoch et al. (2003). They linked technological fields according to the International Patent Classification with 22 two and three-digit manufacturing industries. Aggregating patents on an industry level should reduce potential problems with patent waves within a firm. Furthermore, the usual problem of double counts of patents in different technology fields is mitigated as well, since the probability is lower that one patent refers to technological fields that are linked with different industries.

e) We used patent data from 12 countries (Austria, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom and the United States). These 12 countries account for about 95% of all green inventions as well as other inventions worldwide. The data set includes 22 industries (NACE two/three-digit level of whole manufacturing sector except 'printing and publishing' and 'recycling') and a period of 30 years

[3] In this paper, patents and inventions are largely used synonymously.

(1980 to 2009). This yields a data set of 7920 observations. Because of missing values for the other model variables, the number of observations that could be used for econometric estimations is significantly lower.

Figure 1 shows the aggregated development of green inventions over time. In 1980, the beginning of our sample, only a few green inventions were registered. The number of green inventions remained very low during the following five years. Between 1985 and 1995, the number slightly increased. The increase was, however, not disproportionally high compared with other inventions. A sharp increase in the number of green inventions can be observed since 1995. In 2009, 13397 green inventions were protected worldwide. While the share of green inventions was mostly stable in the initial stage, green inventions have increased disproportionally since 2000. In 2009, nearly 9% of all inventions were classified as green.

Insert Figure 1 about here

Detailed descriptive statistics for our disaggregated patent data is presented in Table 1. Most green inventions are patented in the industries 'machinery' (24%), 'chemicals (excluding pharmaceuticals)' (18%), 'motor vehicles' (12%) and 'electrical machinery and apparatus' (11%). The two industries 'motor vehicles' and 'electrical machinery and apparatus' are at the same time the most green-intensive industries.

Among the twelve countries that are in our sample, the United States (32%), Japan (23%) and Germany (19%) have the highest number of green inventions. Japan and Germany have also high shares of green inventions. The highest shares, however, can be found in Denmark, whereby green inventions represent 11% of all inventions in this country.

Insert Table 1 about here

3.2 OECD Stan data

To analyse the impact of green inventions on productivity, further information on the output, labour input and capital stock of the industries is required. Information for all three variables comes from the OECD STAN database (OECD 2011).

4 Empirical Test of Hypotheses

4.1 Econometric framework

Our model is based on a standard Cobb-Douglas production function for a country *i* and an industry *j* at time *t*:

$$q_{ijt} = A_{ijt} L_{ijt}^{\alpha} K_{ijt}^{\beta}, \tag{1}$$

where *q* is the output, *L* is the labour input and *K* the capital stock. The parameters *α* and *β* are elasticities with respect to labour and physical capital respectively. In our model, we use the industries' total value added in real terms as a proxy for output (*q*). The total number of employees engaged proxies labour (*L*) and the gross fixed capital formation in real terms is used to proxy physical capital (*K*). Ideally, one would use data on the capital stock instead of capital formation. Unfortunately, these data are only available for a few countries in the STAN database. We thus used a flow variable as a proxy for physical capital. Both variables, *L* and *K*, should be positively related with value added.

Expressing (1) in logarithms yields

$$\ln(q)_{ijt} = \ln(A)_{ijt} + \alpha \ln(L)_{ijt} + \beta \ln(K)_{ijt}. \tag{2}$$

To analyse the impact of green inventions, we augmented this specification with a variable that measures an industry's stock in green patents (*Green_stock*). Following Cockburn and Griliches (1988) and Aghion et al. (2011), the patent stock was calculated using the perpetual inventory method. Following this method, the stock was defined as

$$Green\_stock_{ijt} = (1-\delta) Green\_stock_{ijt-1} + Green\_patents_{ijt}, \tag{3}$$

where δ is the depreciation rate of R&D capital.[4] According to most of the literature, we took δ to be equal to 15% (see Keller 2002, Aghion et al. 2011). However, we tested the sensitivity of our results against other depreciation rates (see Table A.5) as well. To capture potential effects of different invention potentials between industries or their patent affinities, we also controlled for the stock of patents within an industry that are not classified as green (*Other_stock*). The stock of other patents is calculated in the same way as the stock of green patents. To identify non-linear relationships between these two patent variables and output, we also included quadratic terms of these variables in our model. The augmented specification is given by:

$$\begin{aligned}\ln(q)_{ijt} &= \ln(A)_{ijt} + \alpha\ln(L)_{ijt} + \beta\ln(K)_{ijt} + \delta_1 Green\_stock\_d_{ijt-1} + \delta_2 Green\_stock_{ijt-1} \\ &\quad + \delta_3 Green\_stock^2_{ijt-1} + \lambda_1 Other\_stock_{ijt-1} + \lambda_2 Other\_stock^2_{ijt-1} + \mu Year_{ijt} + \eta_{ij} + \varepsilon_{ijt},\end{aligned} \tag{4}$$

where δ and λ are the coefficients, η is the individual constant error across time, and ε is the varying error term (across time and industries). All variables dealing with patents are not in logarithmic form, since there are a substantial number of industries with zero values (see Wooldridge 2002, p. 185). This number is substantial especially with respect to the stock of green patents (about 20% of the observations in the whole sample; about 15% in the estimates). To capture econometric effects of these zero values, we included a dummy variable that measures whether there are green inventions within an industry (*Green_stock_d*). The patent variables were introduced with a lag of one year to deal with the potential problem of reverse causality. To control for correlated unobserved heterogeneity, we included country-specific industry fixed effects (η_{ij}). Furthermore, we also included year fixed effects (*Year*) (see Table 2 for variable description).

Insert Table 2 about here

[4] The initial value of the patent stock was set at $Green\_stock_{1980}/(\delta+g)$, where g is the pre-1980 growth in patent stock. In line with Aghion et al. (2011) we assumed g to be 15%. However, as the number of green patents in 1980 was very limited (see Figure 1), the impact of g was small. To test the robustness of our results, we reduced the influence of the initial stock by increasing the lag between the estimation period and the initial stock (see Table 4 for alternative estimates).

4.2 Operationalisation of hypotheses

H1 emphasises the costs of diversifying the knowledge base into green technologies. However, based on the available data, we cannot measure the costs of diversification empirically. Hence, we deduce from a negative relationship between the industries' stock of green patents (*Green_stock*) and productivity that costs are considerably higher than the benefits from investing in green research. Following H1 we expect *Green_stock* to be negatively related to productivity.

H2 indicates positive 'scale effects' and hence learning from green investments in terms of productivity should be detected. This is the case if we see a positive, or at least less negative, correlation between *Green_stock* and the industry's productivity level.

H1 and H2 point at a non-linear relationship between *Green_stock* and productivity. In addressing H1, we expect the effect of *Green_stock* to be negative and in addressing H2, the effect of the quadratic term $Green\_stock^2$ to be positive.

If we take the results from H1 and H2, we can also identify the degree of specialisation required for the green research investments of an industry to show a positive effect on its productivity level. In other words, we can detect at which point an industry benefits from its green research investments.

5 Estimation Results

5.1 Main results

The estimation results are reported in Table 3. The main results are presented in column (1). To test the robustness of this model, columns (2) and (3) show the same model as in column (1) with some modifications. In column (2) the model is estimated for a shorter time period ('early stage'). Column (3) does not include the physical capital variable. In this way, we considerably increase the number of observations, since our proxy for the physical capital has many missing values. For most models, F-test and Hausman-test show that OLS and random-effects GLS, respectively, are not appropriate methods for estimating our production function. We thus conclude that fixed-effects regression is the appropriate method to deal with unobserved heterogeneity in our model. The model of column (3) is an exception. In column (4) we thus alternatively use random-effects GLS to estimate this model. However, the results are very similar.

Insert Table 3 about here

The results for the control variables are on the whole in line with general expectations. Labour input (*L*) and the stock of other patents (*Other_stock*) are both positively correlated with the value added of the industries (*q*). The impact of *Other_stock* is inverted-U shaped – the quadratic term is significantly negative. However, as only very few industries in our sample have a stock of other patents above the turnaround value, the decreasing part of the inverted-U can be ignored. Thus, the marginal effect of other inventions is positive, but it is negatively correlated with invention intensity. Surprisingly, physical capital (*K*) does not significantly affect value added. The expected positive effect of physical capital is significant (at the 1% level) only in the OLS models.[5] Thus, a possible reason for the insignificant effect in the fixed-effects model is that the variation of physical capital is low within the industries over time. Corrections for unobserved heterogeneity cancel this effect out.

Green inventions do significantly affect value added. While the coefficient of *Green_stock* is negative, the coefficient of the quadratic term $Green\_stock^2$ is positive. The relationship between value added and green inventions is U-shaped. Thus hypotheses 1 and 2 are confirmed. Furthermore, a shift from an industry without green inventions to an industry with green inventions (*Green_stock_d*) positively affects the value added of the industry. This effect is just not statistically significant at the 10% test level in our main model, but it becomes statistically

[5] This estimation is not shown in the paper. However, it is available from the authors upon request.

significant when we analyse the impact for the early stage separately (see column 2). In the period 1981-2001, a switch from zero to a certain level of green patent stock increases the value added by about 11%. There seems to be some kind of advertising (image) effect. Industries that start to innovate in green technologies obtain a green touch which positively stimulates productivity. As time passes, fewer industries without any green patent stock can be observed and, accordingly, the advertising (image) effect from a switch to green inventions disappears.

While the effect of a switch to green inventions is positive (*Green_stock_d)*, the total effect of green inventions rapidly decreases with additional investments (*Green_stock)*. At low stocks of green patents, the positive switching effect to green inventions dominates. An increasing stock of green patents reduces the impact of this switching effect, and the overall effect turns negative. Over the whole sample period, the industries' green stocks increased on average by 16 inventions per year. Given the marginal effects in Table 3 (column 1), an increase of the sample average (152 inventions) by 16 inventions would decrease the value added by about 2%.

The marginal effect of green inventions increases with additional green patents. Thus, industries with a higher knowledge stock in green patents have in general lower investment costs for the same amount of invention output. At a stock of 3014 inventions, the increasing negative marginal effect of green inventions on value added turns. Beyond this point, the marginal effect of additional green inventions relates positively to value added. However, only a few industries have a green stock of more than 3014 inventions. In our sample, only 1% of the industries exceed this level.

Information on physical capital in real terms is not available for Japan and Switzerland. Hence, these two countries have not been included in our estimates so far. To test the robustness of our results, we alternatively estimated our model without the physical capital variable. In general, this should not affect our main results, as the effect of physical capital has not been significant in previous estimates. Results are shown in columns (3) and (4) of Table 3. The estimation includes all 12 countries in our sample. Comparing the results in column (4) to those in column (1) shows that the estimates are largely the same.

5.2 Productivity effects over a period of time: comparing earlier periods with later periods of inventions

The impact of green inventions on productivity for the whole sample period is predominantly negative. This indicates that sales markets do not provide sufficient incentives to increase firms' investments in green technologies. One reason for this finding may be the long sample period and different productivity effects in earlier periods as compared to later periods. Especially in early periods of green inventions, the costs of invention were relatively greater and, at the same time, the demand for green inventions was limited. The marginal costs of green inventions should have decreased over time. Furthermore, increasing political pressure may also have stimulated the demand for such inventions in the recent years. We thus expect that the negative impact of green inventions on productivity has declined over time.

To analyse such time-varying effects, we estimated our main model separately for four different time segments. Estimation results are presented in Table 4. Due to a limited number of observations, especially in early periods of green inventions, it is not possible to estimate models without overlapping time segments. Consequently, we estimated the model for overlapping time segments. From one column to the next, we shortened the time segment by five years. Accordingly, the impact of the last years in a time segment increases from one estimate to the next.

Insert Table 4 about here

Because the first years were disregarded, we found that the switching effect (*Green_stock_d*) is not statistically different from zero for all four time segments, which is in line with our previous result in Table 3 (column 1). As expected, the estimation results show that the negative impact of green inventions decreases over time. Figure 2 shows the marginal effect of green inventions for the four different time segments. While the marginal effect for the first two time segments is almost the same, we found that the negative marginal effect of green inventions decreases over time. Furthermore, the decrease seems to accelerate over time. However, there is still a statistically significant negative impact of green inventions on value added for most industries, even in the last period of observation (1999-2009).

Insert Figure 2 about here

5.3 Robustness tests

We made comprehensive tests to check the robustness of our main results presented in column (1) of Table 3 (see Aghion et al. 2011 for a similar approach).

Patent flow instead of stock

Table A.3 shows an alternative estimate of the model that includes patent flows instead of the stock variables. These alternative estimates of green inventions only marginally affect our results. Again, the impact of green inventions is U-shaped and only very few industries have positive returns from additional green inventions. However, in contrast to our previous results, there is now a statistically significant positive switching effect (*Green_patents_d*) for the whole sample period. A reason for this result seems to be that *Green_patents_d* is more likely to vary across time, since one may have green inventions in one period and zero inventions in the following period. In contrast, the *Green_stock* of an industry may be larger than zero, even if the industry has no green inventions in a certain period. Nevertheless, it is worth noting that the size of the impact of the switching effect is comparable to what we found in our previous estimates.

Controlling for country-specific time effects

All our estimates include annual fixed effects, aiming to control for the impact of global shocks. However, we have no control for country-specific shocks. For example, changing political influence within a certain country may affect the demand for green products over time. As this would directly affect productivity, the impact of our measure for green inventions may be biased. To control for such effects, we estimated our main model including country-specific time effects. The results of this estimation are presented in column (1) of Table A.4. Here we see that country-specific time effects only have a marginal impact on our results. The effect of the intensity of *Green_stock* is nearly the same. However, some differences can be observed for the switching effect. While the impact of *Green_stock_d* was just not significant in our main model, it is significantly positive now.

Alternative lags

Another problem may be that the impact of green inventions on productivity has a certain time lag. This problem is even more pronounced when patent waves are observed. As we analysed the impact of green inventions on an aggregated level, the impact of patent waves should be reduced. To further control for this problem, we alternatively estimated our main model using larger lags. Estimation results for a 2-year lag and a 5-year lag respectively are presented in column (2) and (3) of Table A.4. Our main results are robust to such modifications. The differences are the same as when we estimate our model for different time segments (see column (2) of Table 3). As mentioned above, the meaning of the switching effect is greater if green stocks are relatively lower. Since this is observable in earlier times of green inventions and longer lags emphasize earlier periods, we expect a larger switching effect when introducing further lags in our model. Accordingly, it is not surprising to see in our estimations with larger lags a significantly positive switching effect. However, the impact of additional green inventions on value added is still negative for most industries.

Checking for outliers

Column (4) of Table A.4 shows the estimation result with regard to outliers. The distribution of inventions across industries is highly heterogeneous. For this reason, we disregarded the top 1% of the individual industries in both clean and dirty patent stocks.[6] This only marginally affected our results. We thus conclude that our results are not driven by outliers.

Alternative construction of the patent stocks

In literature, different ways of constructing a patent stock are described (see Keller 2002, Aghion et al. 2011, Cockburn and Griliches 1988). The level of the depreciation rate, as well as the construction of the initial stock, may affect estimation results. Regression results for alternative ways of constructing the patent stocks are presented in Table A.5; columns (1) and (2) show the estimates for alternative depreciation rates. Such modifications do not affect our main results. As we have seen in previous estimates, our main results are also valid in the case of higher depreciation rates (patent flows $\rightarrow$ δ=100%).

The influence of the initial green stock on regression decreases with an increasing lag between regression period and initial stock. As we have seen in Table 4, the results are robust for different time segments, which indicates that the impact of the initial stock on our main results is negligible.

6 Conclusions

In this paper, the impact of green inventions on productivity was analysed. Addressing this issue is an important task. On the one hand, the need for green inventions steadily increases. On the other hand, the incentives for firms to invest in green inventions primarily depend on the profitability of such inventions. If green technological investments turn out to be profitable, further policy interventions would be unnecessary.

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[6] Our main estimates presented in column (1) of Table 3 are based on 146 groups. To check for outliers, we excluded all groups with an average clean or dirty patent stock greater THAN or equal to the top 1% of the groups. All in all, we thus dropped two groups that account for 1.6% of the observations.

The relationship between green inventions and productivity was analysed on the basis of industry-level data that include most manufacturing industries, the most relevant countries for green inventions and a time period of 30 years. We found a positive effect of switching to green inventions for earlier years of observation. However, the general relationship between the intensity of green inventions and productivity is U-shaped; for most industries, an increasing level of green inventions negatively affects productivity. With a value of 3014 inventions, the turning point is considerably high. Only industries with a very large stock of green patents are likely to show a positive effect on their productivity. These results are robust for different time segments. As expected, we saw strong negative marginal effects in early periods and, even in the last period of our sample, the marginal effect of green inventions on productivity remained negative for most industries, but to a smaller extent. Consequently, we can answer Popp's (2005, p. 224) question as to whether environmental innovations will proceed without policy interventions with probably no.

These results are of significant policy relevance. As firms direct their R&D resources towards the most profitable ends, the negative marginal effect of additional green inventions, in combination with the high turning point, indicate that firms are probably not willing to increase investment in green technologies by themselves. This finding leads us to formulate the following two conclusions:

a) As the costs of investment in green technologies can be substantial, a free rider problem may occur. A single country probably has no incentives to adjust its political framework to further push green inventions in its country, but will focus on the import of technologies developed abroad. To overcome such "free rider" problems, and to further increase green inventions worldwide, a form of global, or at least multilateral, coordination is required.

b) If some kind of coordination occurs in the future, and an international market for green technologies evolves, there will be incentives for current investments in green technologies. This is especially true if first mover advantages are considerable. However, as Porter and van der

Linde (1995, p. 127) state, “the belief that companies will pick up on profitable opportunities without regulatory push makes a false assumption about competitive reality.” The advantages of current investments in green technologies, and thus the need of some kind of market interventions, strongly depend on the size of early mover advantages. Probably, the disadvantages will be smaller for advanced countries with a well-developed general knowledge stock. Countries with a less developed knowledge stock may persistently lag behind. Latecomers (also on an industry or country level) that stick to resource-wasting technologies and delay green investments run the risk to become and remain uncompetitive (see Porter and van der Linde 1995). To prove this statement, further investments in the analysis of the diffusion of green technologies across industries and countries will be crucial.

References

Aghion, P., Bloom, N., Blundell, R., Griffith, R., Howitt, P. (2005). Competition and innovation: an inverted-U relationship. *The Quarterly Journal of Economics*, May, pp. 701-728.

Aghion, P., Veugelers, R. and Serre, C. (2009). Cold Start for the Green Innovation Machine. *Bruegel Policy Contribution*, 2009/12, Bruegel, Brussels.

Aghion, P., Dechezlepretre, A., Hemous, D., Martin, R. and Van Reenen, J. (2011). Carbon Taxes, Path Dependency and Directed Technical Change: Evidence from the Auto Industry, *Working paper*.

Arrow K.A. (1962). Economic welfare and the allocation of resources to invention, pp. 165-180, in Mirowski P. and Sent E.-M. (eds.), Science bought and sold, Chicago, The University of Chicago Press 2002.

Barney, J. (1991). Firm resources and sustained competitive advantage. *Journal of Management*, Vol. 17, pp. 99–120.

Barney, J., Wright, M. and Ketchen, D.J. (2001). The resource-based view of the firm: ten years after 1991. *Journal of Management*, Vol. 27, pp.625–641.

Brunnermeier, S.B. and Cohen, M.A. (2003). Determinants of Environmental Innovation in US Manufacturing Industries. *Journal of Environmental Economics and Management*, Vol. 45(2), pp. 278-293.

Cockburn, I. and Griliches, Z. (1988). Industry Effects and Appropriability Measures in the Stock Market's Valuation of R&D and Patents, *American Economic Review*, Vol. 78(2), pp. 419-423.

Crepon, B., Duguet, E. and Mairessec, J. (1998). Research, Innovation And Productivity: An Econometric Analysis At The Firm Level, *Economics of Innovation and New Technology*, Vol. 7(2), pp. 115-158.

Danneels, E. (2002). The dynamics of product innovation and firm competences. *Strategic Management Journal*, Vol. (23), pp. 1095-1121.

Dasgupta, P., Stiglitz, J. (1980). Industrial structure and the nature of innovative activity. *The Economic Journal*, Vol. 90(358), pp. 266-293.

Figueiredo, P.N. (2002). Does technological learning pay off? Inter-firm differences in technological capability-accumulation paths and operational performance improvement. *Research Policy*, Vol. 31, pp. 73-94.

Grilliches, Z. (1990). Patent statistics as economic indicators: a survey. *Journal of Economic Literature*, Vol. 28(4), pp. 1661-1707.

Hall, B.H. (1992). Research and development at the firm level: does the source of financing matter?, *NBER Working Paper No. 4096.*

Henderson, R. and Cockburn, I. (1996). The determinants of research productivity in drug discovery. *The RAND Journal of Economics*, Vol. 27(1), pp. 32-59.

Himmelberg, C.P., and Petersen, B.C. (1994). R&D and internal finance: a panel study of small firms in high-tech industries. *Review of Economics and Statistics*, Vol. 76(1), 38-51.

Horbach J. (2008). Determinants of environmental innovation – New evidence from German panel data sources. *Research Policy,* Vol. 37(1), pp. 163-173.

Huber, G.P. (1991). Organizational Learning: The Contributing Processes and the Literatures. *Organization Science,* Vol. 2(1), pp. 88-115.

Jaffe, A.B. and Palmer, K. (1997). Environmental Regulation and Innovation: A Panel Data Study. *The Review of Economics and Statistics*, Vol. 79(4), pp. 610-619.

Keller, W. (2002). Geographic Localization of International Technology Diffusion, *American Economic Review,* Vol. 92(1), pp. 120-142.

Lanoie, P., Laurent-Lucchetti, J., Johnstone, N. and Ambec, S. (2011). Environmental Policy, Innovation and Performance: New Insights on the Porter Hypothesis, *Journal of Economics and Management Strategy,* Vol. 20(3), pp. 803–842.

Malerba, F. (1992). Learning by firms and incremental technical change, *The Economic Journal*, Vol. 102(413), pp. 845-859.

March, J.G. (1991). Exploration and Exploitation in Organizational Learning, *Organization Science,* Vol. 2(1), pp. 71-87.

Newbert, S.L. (2007). Empirical research on the resource-based view of the firm: an assessment and suggestions for future research. *Strategic Management Journal*, Vol. 28, pp. 121-146.

Newell, R.G., Jaffe, A.B. and Stavins, R.N. (1999). The Induced Innovation Hypothesis and Energy-Saving Technological Change. *The Quarterly Journal of Economics*, Vol. 114(3), pp. 941-975.

OECD (2009): Science Technology and Industry Scoreboard, Paris.

OECD (2012): Indicators of Environmental Technologies (ENV-Tech Indicators), OECD, Paris, available at: http://www.oecd.org/dataoecd/4/14/47917636.pdf (accessed February 2012).

OECD (2011). OECD STAN database, STAN Industry 2008 available at: www.oecd.org/sti/stan (accessed Mai 2011).

Penrose, E. (1995). The theory of the growth of the firm. 3rd ed. Oxford University Press: Oxford, New York.

Popp, D. (2002). Induced Innovation and Energy Prices, *American Economic Review*, Vol. 92(1), pp. 160-180.

Popp, D. (2005). Lessons from patents: using patents to measure technological change in environmental models. *Ecological Economics*, 54, pp. 209-226.

Popp, D. (2006). Innovation in climate policy models: Implementing lessons from the economics of R&D, *Energy Economics*, Vol. 28(5-6), pp. 596-609.

Porter, M.E. and van der Linde, C. (1995). Green and Competitive: Breaking the Stalemate, *Harvard Business Review*, September-October 1995.

Quintana-García, C. and Benavides-Velasco, C.A. (2008). Innovative competence, exploration and exploitation: the influence of technological diversification. *Research Poli*cy, Vol. (37), pp. 492-507.

Schmoch U., Laville F., Patel P., Fritsch R. (2003). *Linking technology areas to industrial sectors*. Final Report to the European Commission, DG Research. Karlsruhe, Paris, Brighton.

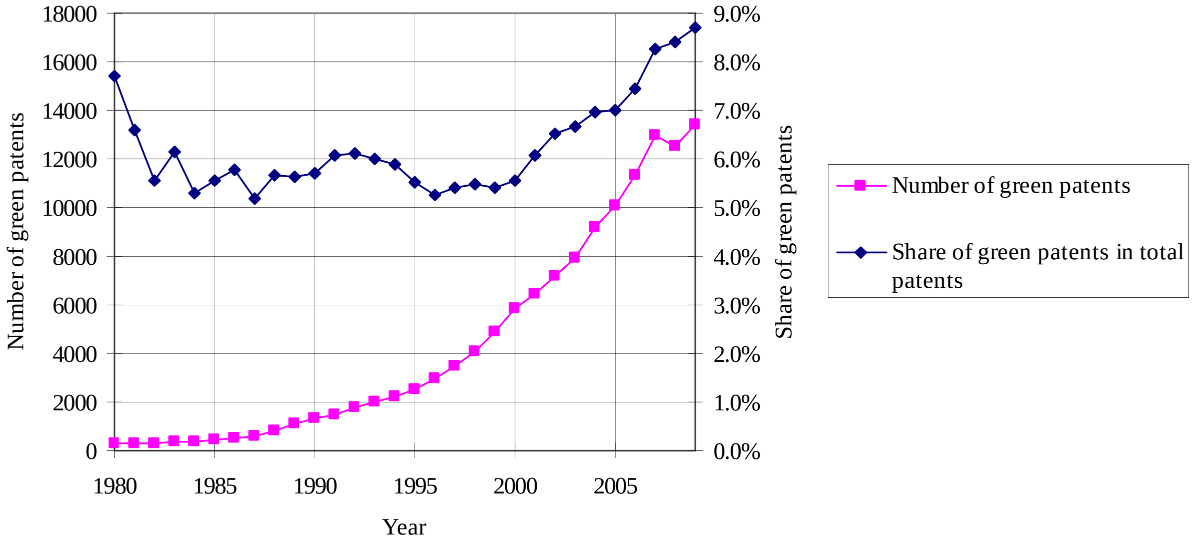
Teece, D.J., Pisano, G. and Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, Vol. 18(7), pp. 507–533

Wernerfelt, B. (1984). A resource-based view of the firm. *Strategic Management Journal*, Vol. 5, pp. 171–180.

Williamson, O.E. (1975). Markets and hierarchies. New York: Free Press.

Wooldridge, J.M. (2002). Introductory Econometrics – A modern approach. South-Western College Pub, 2 ed.

Figure 1: Development of green patents worldwide, 1980-2009



Notes: To reduce the problem of double counts of patents, this information is based on world-aggregated data and is not restricted to countries and industries that are in our estimation sample.

Table 1: Number of green and other patents (inventions) by industry and country

Period	1980-2009			
	Number of other patents	Number of green patents	Relative share in total green patents	Share of green patents in total patents
Industry				
Food, beverages	37,798	1,672	0.65%	4.2%
Tobacco products	2,325	69	0.03%	2.9%
Textiles	16,111	1,070	0.42%	6.2%
Wearing apparel	5,733	75	0.03%	1.3%
Leather articles	3,670	19	0.01%	0.5%
Wood products	4,584	256	0.10%	5.3%
Paper	21,463	1,400	0.54%	6.1%
Petroleum products, nuclear fuel	17,053	3,514	1.37%	17.1%
Rubber and plastics products	102,022	6,485	2.52%	6.0%
Non-metallic mineral products	81,906	8,965	3.48%	9.9%
Basic metals	42,426	6,892	2.68%	14.0%
Fabricated metal products	61,777	8,073	3.14%	11.6%
Machinery	421,085	61,667	23.96%	12.8%
Office machinery and computers	271,075	5,276	2.05%	1.9%
Electrical machinery and apparatus	96,389	28,502	11.08%	22.8%
Radio, television and communication equipment	416,041	23,731	9.22%	5.4%
Medical, precision and optical instruments	464,886	14,898	5.79%	3.1%
Motor vehicles	90,872	29,911	11.62%	24.8%
Other transport equipment	25,742	2,495	0.97%	8.8%
Furniture, consumer goods	47,174	561	0.22%	1.2%
Chemicals (excluding pharmaceuticals)	301,064	46,427	18.04%	13.4%
Pharmaceuticals	322,450	5,382	2.09%	1.6%
Country				
Austria	30,593	3,311	1.29%	9.8%
Switzerland	93,498	5,720	2.22%	5.8%
Germany	414,160	49,795	19.35%	10.7%
Denmark	30,970	3,825	1.49%	11.0%
Finland	43,313	3,004	1.17%	6.5%
France	167,953	14,723	5.72%	8.1%
United Kingdom	194,920	14,829	5.76%	7.1%
Italy	58,198	4,314	1.68%	6.9%
Japan	490,415	59,595	23.16%	10.8%
Netherlands	116,486	9,306	3.62%	7.4%
Sweden	93,741	6,397	2.49%	6.4%
United States	1,119,399	82,521	32.07%	6.9%

Notes: These statistics are based on 30 cross-sections, 12 countries and 22 industries (total of 7920 observations); the relative share in total green patents is calculated as the share of an industry's/country's number of green patents relative to the number of all green patents in our sample (sum of green patents over all industries/countries in the sample); the share of green patents in total patents is defined as an industry's/ country's share of green patents relative to its total number of patents (green patents and other patents).

Table 2: Variable definition and measurement

Variable	Definition/measurement	Source
Dependent variable		
q	Value added, volumes (current price value)	OECD STAN
Independent variable		
L	Number of persons engaged (total employment)	OECD STAN
K	Gross fixed capital formation, volumes (current price value)	OECD STAN
Other_patents	Number of patents that are not classified as green	own calculations
Green_patents	Number of green patents	own calculations
Other_stock	Stock of patents that are not classified as green	own calculations
Green_stock	Stock of green patents	own calculations

Table 3: Estimates of the production function

	$\ln(q)_{ijt}$			
	(1)	(2)	(3)	(4)
Period	1981-2009	1981-2001	1981-2009	1981-2009
Estimation method	Fixed-effects regression	Fixed-effects regression	Fixed-effects regression	Random-effects GLS
Constant_{ijt}	9.6274***	10.337***	12.011***	11.388***
	(2.0202)	(1.823)	(1.594)	(1.1122)
$\ln(L)_{ijt}$	.89323***	.93892***	.9177***	.94631***
	(.16859)	(.1388)	(.1442)	(.11356)
$\ln(K)_{ijt}$	.11018	.04791		
	(.07014)	(.05102)		
$\text{Other\_stock}_{ijt-1}$	.0002**	.00023*	.00016**	.00015**
	(9.7e-05)	(.00012)	(6.5e-05)	(6.3e-05)
$\text{Other\_stock}^2_{ijt-1}$	-5.1e-09**	-1.1e-08*	-3.6e-09**	-3.4e-09**
	(2.5e-09)	(5.9e-09)	(1.5e-09)	(1.5e-09)
$\text{Green\_stock\_d}_{ijt-1}$	.08698	.11222**	.09013	.09136
	(.05791)	(.05507)	(.06584)	(.06616)
$\text{Green\_stock}_{ijt-1}$	-.00122**	-.00183*	-.00099**	-.00094**
	(.00058)	(.00093)	(.00041)	(.00039)
$\text{Green\_stock}^2_{ijt-1}$	2.0e-07**	5.6e-07*	1.4e-07**	1.4e-07**
	(1.0e-07)	(3.2e-07)	(6.3e-08)	(6.1e-08)
Year fixed effects	Yes	Yes	Yes	Yes
Country-specific industry fixed effects	Yes	Yes	Yes	No
Industry fixed effects	No	No	No	Yes
Country fixed effects	No	No	No	Yes
N	2936	1969	4527	4527
Groups	146	146	201	201
R^2 within	0.48	0.51	0.38	0.38
Rho	0.91	0.96	0.96	0.43
F tets of rho=0	41.66***	67.40***	613.77***	
Hausman chi^2	361.53***	63.90***	19.93	19.93
LR test of rho=0				10096***

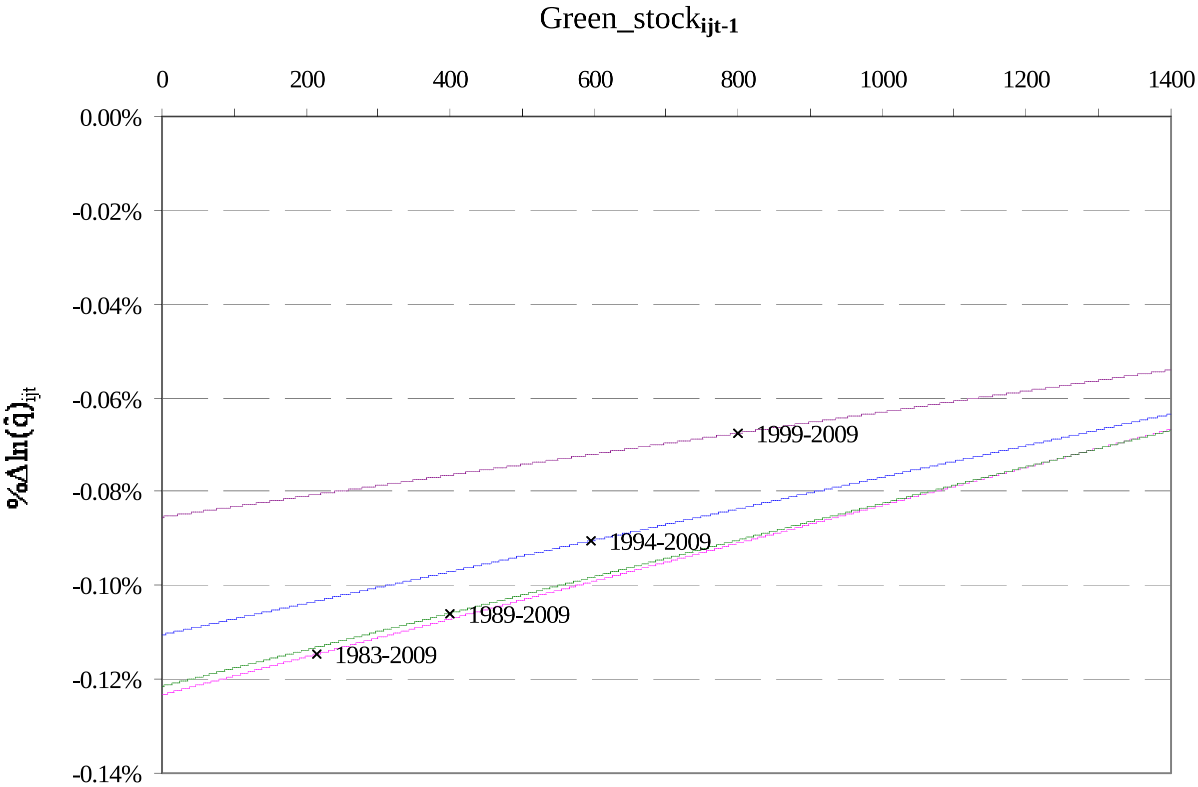
Notes: see Table 2 for the variable definitions; robust standard errors that are adjusted for within-cluster correlation (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denote statistical significance at the 1%, 5% and 10% test level, respectively. F test and Hausman test are based on estimates without robust standard errors.

Table 4: Analysis for different time segments

	$\ln(q)_{ijt}$			
	(1)	(2)	(3)	(4)
Period	1983-2009	1989-2009	1994-2009	1999-2009
Estimation method	Fixed-effects regression	Fixed-effects regression	Fixed-effects regression	Fixed-effects regression
Constant_{ijt}	10.12***	11.083***	12.4***	13.69***
	(2.0414)	(2.0964)	(1.9348)	(2.9622)
$\ln(L)_{ijt}$	.86564***	.79342***	.74074***	.66803**
	(.17596)	(.18623)	(.18152)	(.33648)
$\ln(K)_{ijt}$	.10725	.11037*	.086**	.06117
	(.06579)	(.05814)	(.04202)	(.06401)
$\text{Other\_stock}_{ijt-1}$	.0002**	.0002**	.0002**	.00017**
	(9.6e-05)	(9.5e-05)	(8.5e-05)	(7.0e-05)
$\text{Other\_stock}^2_{ijt-1}$	-5.0e-09**	-4.9e-09**	-4.4e-09**	-3.2e-09**
	(2.4e-09)	(2.4e-09)	(2.0e-09)	(1.5e-09)
$\text{Green\_stock\_d}_{ijt-1}$	.04792	-.04616	-.0948	-.05042
	(.06068)	(.08359)	(.0896)	(.09283)
$\text{Green\_stock}_{ijt-1}$	-.00123**	-.00122**	-.00111**	-.00085**
	(.00057)	(.00056)	(.0005)	(.00043)
$\text{Green\_stock}^2_{ijt-1}$	2.0e-07**	2.0e-07**	1.7e-07**	1.1e-07*
	(9.9e-08)	(9.5e-08)	(8.0e-08)	(6.1e-08)
Year fixed effects	Yes	Yes	Yes	Yes
Country-specific industry fixed effects	Yes	Yes	Yes	Yes
N	2756	2446	2018	1401
Groups	146	146	146	146
R^2 within	0.45	0.40	0.34	0.26
Rho	0.92	0.91	0.93	0.95

Notes: see Table 2 for the variable definitions; robust standard errors that are adjusted for within-cluster correlation (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denote statistical significance at the 1%, 5% and 10% test level, respectively.

Figure 2: Marginal effect of additional *Green_stock* for different time windows (ΔGreen_stock=1)



Notes: This figure is plotted for values of *Green_stock* between 0 and 1400 only because in each time window less than 5% of the observations have a higher *Green_stock*.

APPENDIX

Table A.1: Correlation matrix (based on model (1) of Table 3; 2936 observations)

	$\ln(q)_{ijt}$	$\ln(L)_{ijt}$	$\ln(K)_{ijt}$	$Other\_stock_{ijt-1}$	$Other\_stock^2_{ijt-1}$	$Green\_stock\_d_{ijt-1}$	$Green\_stock_{ijt-1}$
$\ln(L)_{ijt}$	0.83						
$\ln(K)_{ijt}$	0.95	0.79					
$Other\_stock_{ijt-1}$	0.38	0.36	0.33				
$Other\_stock^2_{ijt-1}$	0.17	0.17	0.16	0.86			
$Green\_stock\_d_{ijt-1}$	0.43	0.32	0.44	0.15	0.05		
$Green\_stock_{ijt-1}$	0.36	0.35	0.33	0.90	0.81	0.12	
$Green\_stock^2_{ijt-1}$	0.18	0.18	0.17	0.81	0.95	0.05	0.88

Table A.2: Descriptive statistics (based on model (1) of Table 3; 2936 observations)

Variable	Mean	Std. Dev.	Min	Max
Dependent variable				
$\ln(q)_{ijt}$	21.98	1.82	15.20	25.75
Independent variable				
$\ln(L)_{ijt}$	10.75	1.76	5.72	14.46
$\ln(K)_{ijt}$	19.97	1.93	4.61	23.89
$Other\_stock_{ijt-1}$	1,189.14	3,550.93	0	54,430.81
$Green\_stock\_d_{ijt-1}$	0.83	0.37	0	1
$Green\_stock_{ijt-1}$	152.28	550.89	0	8,492.57

Table A.3: Estimate of the production function based on patent flows

Estimation method	$\ln(q)_{ijt}$ (1) Fixed-effects regression
$Constant_{ijt}$	9.8559***
	(2.0533)
$\ln(L)_{ijt}$	.88***
	(.17097)
$\ln(K)_{ijt}$	.10564
	(.06995)
$Other\_patents_{ijt-1}$	.00071*
	(.00039)
$Other\_patents^2_{ijt-1}$	-8.0e-08*
	(4.3e-08)
$Green\_patents\_d_{ijt-1}$	.10338***
	(.03751)
$Green\_patents_{ijt-1}$	-.00381*
	(.002)
$Green\_patents^2_{ijt-1}$	2.7e-06*
	(1.5e-06)
Year fixed effects	Yes
Country- specific industry fixed effects	Yes
N	2936
Groups	146
R^2 within	0.48
Rho	0.91

Notes: see Table 2 for the variable definitions; robust standard errors that are adjusted for within-cluster correlation (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denote statistical significance at the 1%, 5% and 10% test level, respectively.

Table A.4: Alternative estimates of model (1) of Table 3

	$\ln(q)_{ijt}$			
Estimation method	(1) Fixed-effects regression	(2) Fixed-effects regression	(3) Fixed-effects regression	(4) Fixed-effects regression
Robustness test	Controlling for country-specific time effects	Alternative lags		Checking for outliers
$Constant_{ijt}$	10.451***	9.7434***	9.9895***	9.6908***
	(1.8756)	(2.0354)	(2.1372)	(2.0157)
$\ln(L)_{ijt}$	.75307***	.89216***	.87691***	.88369***
	(.16342)	(.172)	(.18082)	(.16899)
$\ln(K)_{ijt}$	.1651**	.10537	.10857*	.11178
	(.07967)	(.06788)	(.06132)	(.07077)
$Other\_stock_{ijt-1}$	.00026***			.00021*
	(9.2e-05)			(.00011)
$Other\_stock^2_{ijt-1}$	-6.5e-09***			-6.0e-09
	(2.4e-09)			(3.6e-09)
$Green\_stock\_d_{ijt-1}$	.13224**			.09437*
	(.0552)			(.05638)
$Green\_stock_{ijt-1}$	-.00129**			-.00118**
	(.00055)			(.00058)
$Green\_stock^2_{ijt-1}$	2.3e-07**			1.9e-07*
	(9.9e-08)			(9.9e-08)
$Other\_stock_{ijt-2}$		.00021**		
		(1.0e-04)		
$Other\_stock^2_{ijt-2}$		-5.7e-09**		
		(2.7e-09)		
$Green\_stock\_d_{ijt-2}$		.10757**		
		(.05366)		
$Green\_stock_{ijt-2}$		-.00131**		
		(.00061)		
$Green\_stock^2_{ijt-2}$		2.3e-07**		
		(1.1e-07)		
$Other\_stock_{ijt-5}$			.00025**	
			(.00012)	
$Other\_stock^2_{ijt-5}$			-8.4e-09**	
			(3.9e-09)	
$Green\_stock\_d_{ijt-5}$			.14644***	
			(.04703)	
$Green\_stock_{ijt-5}$			-.00162**	
			(.00074)	
$Green\_stock^2_{ijt-5}$			3.7e-07**	
			(1.7e-07)	
Year fixed effects	No	Yes	Yes	Yes
Country-specific year fixed effects	Yes	No	No	No
Country-specific industry fixed effects	Yes	Yes	Yes	Yes
N	2936	2876	2696	2889
Groups	146	146	146	144
R^2 within	0.48	0.48	0.44	0.49
Rho	0.89	0.92	0.92	0.91

Notes: see Table 2 for the variable definitions; robust standard errors that are adjusted for within-cluster correlation (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denote statistical significance at the 1%, 5% and 10% test level, respectively.

Table A.5: Estimates with alternative depreciation rates

	$\ln(q)_{ijt}$	
	(1)	(2)
Depreciation rate	10%	30%
Estimation method	Fixed-effects regression	Fixed-effects regression
$Constant_{ijt}$	9.5957***	9.6752***
	(2.0325)	(2.0068)
$\ln(L)_{ijt}$	.89572***	.88988***
	(.16948)	(.16782)
$\ln(K)_{ijt}$	.11045	.10955
	(.07024)	(.06994)
$Other\_stock_{ijt-1}$	.00016**	.0003**
	(7.9e-05)	(.00015)
$Other\_stock^2_{ijt-1}$	-3.4e-09**	-1.3e-08**
	(1.6e-09)	(6.2e-09)
$Green\_stock\_d_{ijt-1}$	.08512	.08991
	(.05791)	(.05796)
$Green\_stock_{ijt-1}$	-.00103**	-.00181**
	(.00049)	(.00088)
$Green\_stock^2_{ijt-1}$	1.4e-07**	4.8e-07*
	(6.9e-08)	(2.4e-07)
Year fixed effects	Yes	Yes
Country-specific industry fixed effects	Yes	Yes
N	2936	2936
Groups	146	146
R^2 within	0.48	0.48
Rho	0.91	0.91

Notes: see Table 2 for the variable definitions; robust standard errors that are adjusted for within-cluster correlation (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denote statistical significance at the 1%, 5% and 10% test level, respectively.