The Productivity of Environmental Innovations

Christian Soltmann*, Tobias Stucki**, Martin Woerter***

Abstract. While recent literature mainly focused on explaining the determinants of green innovations, it is comparatively not well understood how such innovations affect productivity. We analyze this relationship on the basis of patent data. We exploit new industry-level panel data that includes 12 OECD countries, the whole manufacturing sector and a period of 30 years. The results show that green inventions are U-shape related with productivity on an industry level. The turning point is, however, quite high and thus only relevant for few industries. Hence, there could be a policy issue here. The results indicate that market incentives alone are not sufficient to let industries' activities in green inventions to take off.

Keywords: Innovation; R&D; patents; environment; technological change; productivity

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* Swiss Federal Institute of Intellectual Property, CH-3003 Bern, Phone +41 31 377 70 89, email: christian.soltmann@ipi.ch

** ETH Zurich, KOF Swiss Economic Institute, CH-8092 Zurich, Phone: +41 44 632 63 07, email: stucki@kof.ethz.ch

*** ETH Zurich, KOF Swiss Economic Institute, CH-8092 Zurich, Phone: +41 44 632 51 51, email: woerter@kof.ethz.ch

1 Introduction

Empirical research in environmental innovations provides us with a good understanding about what induces investments in environmental technological research. Popp (2002) found that energy prices induce innovation measured through the share of environmental patents on total patents in the United States. Newell et al. (1999) looked at the level of product characteristics and found that energy prices had an observable effect on technical characteristics of the products offered for sale. In addition to energy prices we learnt that environmental regulation is likely to increase the number of total 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 two gasses (NOx and SO2) and specifies that inventors respond to domestic regulatory pressure and not to foreign regulatory pressures. 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. Moreover, Horbach (2008) stated based on a firm-level study for Germany that in addition to environmental regulation, technological capabilities and organizational changes are positively related with environmental innovations as well.

These investigations stop at the innovation level and they do not ask if environmental innovations are profitable or when they are profitable. However, after more than 30 years of private investments in green technologies and a number of governmental market interventions in different countries and emission restriction policies also on a multilateral level, it is time to look empirically if – given the regulatory framework in the considered countries and industries – green investments have contributed to profitability and not only to innovation output. It is clearly that green innovation investments would proceed without further intervention if such investments are already profitable. Consequently, we investigate the profitability of green innovation in the paper at hand in order to detect if green innovation investments are already sustainable and will more and more substitute older environmental unfriendly technologies.

We find that green innovation investments have not been profitable for most of the industries so far. Thus, it is unlikely that investments in green innovation would proceed without policy interventions to a level that environmental unfriendly technologies would be replaced by green technologies in due time. Hence, we think that the current answer to Popp's (Popp 2005, p. 224) question if environmental innovation would proceed without policy intervention is 'probably not".

Our research results and policy relevant conclusions are based on a broad empirical basis. We exploit a new patent data set that is aggregated on an industry level. The use of aggregated data has several features. 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 covers the whole manufacturing sector (21 two and three digit industries), the most important countries of green invention (12 OECD countries that are responsible for 95% of all green patents and total patents worldwide) and 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 use patent data to identify green and not green inventions. The patent classifications considered as green inventions are identified following the OECD classification (see OECD 2011a). We only consider 'triadic patents". Patents are aggregated to inventions following the Thomson-Reuters systematic. The use of this patent data allows us to define a quantitative measure for green inventions and thus to analyze non-linear effects of green inventions on productivity.

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

The paper is organized as follows. Chapter two provides the conceptual background and the hypotheses. Chapter three describes the data. In chapter four we show how we test the hypotheses empirically. Chapter five presents the results and in chapter six we conclude.

2 Conceptual background and hypotheses

There are a number of empirical investigations (e.g., Crepon et al. 1989) that show 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 can not be taken for granted if we look at newer technologies, like 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, like willingness to pay for green products, and supply side factors referring to firms' technological and organizational capabilities and financial constraints that may prevent productivity gains.

The demand of a product shapes the incentives to innovate (Dasgupta and Stiglitz 1980). Demand is expressed with the willingness to pay for newer products. Green innovative products are likely to be more expensive compared to traditional ones and the exclusivity of benefits of green products 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. Accordingly, the willingness to pay for green products will be low (Aghion et al. 2009).

The development of green products and processes also challenges firm's capability profile in terms of knowledge creation and technology development. To meet those challenges requires at least a modification if not a change of the firm's resource base, since the resource base marks its spectrum of capabilities (Wernerfelt 1984, Barney 1991, Penrose 1995, or Barney et al. 2001)

[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).

also in terms of diversification into the field of green technologies and products (Horbach 2008).[2] That could be a costly task, because firms may lack organization capacities to alter the technological base. If they detect useful external knowledge, it could be simply not tradable because of its tacit character or it is only available at a very high price (Teece et al. 1997). Costs could be also related to coordination of technological activities within firms or between firms or institutions in case green technologies are explored or acquired through research cooperation

It is not technology change alone that increases costs (Danneels 2002). Following the technological phase also business processes and working routines have to be adapted or even newly developed. Moreover, it could be necessary to hire new employees, constitute new departments or to acquire specialized firms, like we observed in other sectors that underwent considerable technological changes (e.g., biotechnology in the pharmaceutical industry). Consequently it is not surprising that there is considerable resistance to change.

Furthermore costs of investment in green technology can be substantial as it is often difficult to finance technological investments. We learn from transaction cost economics (see Williamson 1975) and also from empirical investigations for R&D financing that internal capital flows (cash flow) are more likely to be used compared to 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). Consequently, it is not surprising that a researcher that is familiar with the green technology project asses the likelihood of the technological success more optimistic compared to investors, since the later lack detailed information and experiences with the investigation processes. Therefore it is difficult for external investors to distinguish good projects from bad projects (lemon problem). Hence, there are costly

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

information asymmetries between potential external investors and researchers and financial markets are not efficient in case of technological investments.

While the costs of technological diversification in new technology fields can be considerable, sales of these new technologies are limited. The prices of green products are unlikely to be competitive at least in the initial phase when the production costs are relatively high. We thus posit 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, the exploration of 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 invention on productivity should increase with the size of knowledge stock.

The formation of a knowledge stock involves substantial fixed costs. It takes considerable investments 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 go beyond a certain limit. If there are positive returns to scale in green research, a firm moves from the expensive exploration of new knowledge to the less expensive exploitation of existing knowledge (see March 1991, Quintana-García and Benavides-Velasco 2008), ones it decides to further increase its knowledge stock. The second hypothesis reads as follows:

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

3 Description of the Data

3.1 Measurement of green invention based on patent statistics

We use patent statistics in order to measure the green investment activities of an industry. Although patent statistics has many disadvantages in measuring innovation output (see Aghion et al. 2011), it is a rather good proxy for innovation input, since there is a strong relationship between patent numbers and R&D expenditures (see Griliches 1990). This is the case, 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, patents have been collected in cooperation with the Swiss Federal Institute of Intellectual Property (IGE). Green patents have been selected following the OECD definition for environmental patents (see OECD 2011). The OECD definition comprises four environmental areas, i.e. air pollution control, water pollution control, solid waste management, and renewable energy. 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 one can choose the applicant’s home country or the inventor’s home country. We assigned patents according to the applicant’s address, since this information is compulsory for patent applications in all of the investigated countries, except the USA; there inventor’s information is compulsory. Hence, we used the inventor statistics for the USA. We collected both, the inventor’s information and the applicant’s information for Germany in order to have an idea about the robustness of our findings for the USA, assuming that if there are distortions than they are similar in all countries. In fact, we did not see any significant differences between the inventor’s and applicant’s statistic for Germany. Hence, we feel save to use the inventor’s statistic for the USA.

b) We collected inventions (patent families) and not single patents. Patents are comprised to patent families following the method of Thomson/Reuters (peer-review procedure). Thereby we assure that important inventions are considered. Technologically less important patent applications are not taken into account. Moreover this has the advantage that distortions due to different granting procedures in countries and distortions due to different application cultures (USA: greater number of single applications for one invention compared to Europe) are attenuated.

c) Only patents (inventions) under the PCT (Patent Cooperation Treaty) are considered. Thus, our dataset only includes inventions with a considerable commercial potential.

d) Patents (inventions) have been aggregated on an industry level, using the Schmoch et al. (2003) concordance scheme. Schmoch et al. (2003) links technological fields of the patent statistics with 44 two and three digit manufacturing industries. To aggregate 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 attenuated as well, since the probability is lower that one patent refers to technological fields that are linked with different industries.

e) In sum we have patent (invention)[3] data for 12 countries (Austria, Denmark, Finland, France, Germany, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom and the United States). These 12 countries make up for about 95% of all green patents as well as other patents worldwide. Furthermore, 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 (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 patents over time. In 1980, the beginning of our sample, only a few green inventions were registered. The number of green patents remained very low during five years. Between 1985 and 1995, the number slightly increased. The increase was, however, not over proportional compared with other patents. A sharp increase in the number of green patents can be observed since 1995. In 2009, 13397 green inventions were protected worldwide. While the share of green patents was mostly stable in the first stage, green inventions increased over proportionally since 2000. In 2009, nearly 9% of all patents 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 numbers of green patents. Japan and Germany have also high shares of green patents. The highest shares, however, can be found in Denmark. Green patents represent 11% of all patents in Denmark.

Insert Table 1 about here

3.2 OECD Stan data

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

[3] Patents and inventions are used synonymously.

4 Empirical test of hypotheses

4.1 Econometric framework

Our model is based on a standard Cobb-Dougals 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 labor input and *K* the capital-stock. The parameters α and β are elasticities with respect to labor 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 labor (*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, this information is only available for a few countries in the STAN database. We thus use 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 analyze the impact of green inventions, we augment this specification with a variable that measures an industries' stock in green patents (*Green_stock*). Following Cockburn and Griliches (1988) and Aghion et al. (2011), the patent stock is calculated using the perpetual inventory method. Following this method, the stock is 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 take δ to be equal to 15% (see Keller 2002, Aghion et al. 2011). However, we test the sensitivity of our results to other depreciation rates (see Table A.5) as well. To capture potential effects of different

[4] The initial value of the patent stock is 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 assume *g* to be 15%. However, as the number of green patents in 1980 was very limited (see Figure 1), the impact of *g* is small. To test the robustness of our results, we reduced the influence of the

invention potentials between industries or their patent affinities, we also control 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 nonlinear relationships between these two patent variables and output, we also include quadratic terms of these variables in our model. The augmented specification is given by:

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

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). Especially with respect to the stock of green patents this number is substantial (about 20% of the observations in the whole sample; about 15% in the estimates). To capture econometric effects of these zero values, we include a dummy variable that measures whether there are green patents within an industry (*Green_stock_d*). To deal with the potential problem of reverse causality the patent variables are introduced with a lag of one year. To control for correlated unobserved heterogeneity, we include country specific industry fixed effects (η_{ij}). Furthermore, we also include year fixed effects (*Year*) (see Table 2 for variable description).

Insert Table 2 about here

4.2 Operationalization 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

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initial stock by increasing the lag between the estimation period and the initial stock (see Table 4 for alternative estimates).

(*Green_stock*) and productivity that costs are considerably higher than the benefits from investing in green research. Following H1 we expect that *Green_stock* is negatively related with 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 industry’s productivity level.

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

Taking together the results from H1 and H2 we also identify the sufficient degree of specialization that green research investments of an industry 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. 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 to estimate our production function. We thus conclude that fixed-effects regression is the adequate 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 more or less in line with general expectations. Labor 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 invention 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 invention does 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 invention is U-shaped. Thus hypotheses 1 and 2 are confirmed. Furthermore, a shift from an industry without green invention to an industry with green invention (*Green_stock_d*) does positively affect the value added of the industry. This effect is just not statistically significant at the 10% test level in our main model, but it gets statistically significant when we analyze 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 does increase the value added by about 11%. There seems to be some kind of an advertising (image) effect. Industries that start to innovate in green technologies get a green touch what positively stimulates productivity. As time

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

passes, fewer industries without any green patent stock can be observed and, accordingly, the advertising (image) effect from a switch to green invention disappears.

While the effect of a switch to green invention is positive (*Green_stock_d)*, the total effect of green invention rapidly decreases with additional investments (*Green_stock)*. At low stocks of green patents the positive switching effect to green invention 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 patents per year. Given the marginal effects in Table 3 (column 1), an increase of the sample average (152 patents) by 16 patents would decrease the value added by about 2%.

The marginal effect of green invention 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 patents, the increasing negative marginal effect of green invention on value added turns. Beyond this point, the marginal effect of additional green invention does positively relate to value added. However, only a few industries have a green stock of more than 3014 patents. 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 estimate 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. Now the estimation includes all 12 countries that are in our sample. Comparing the results in column (4) to the ones in column (1) we see that the estimates are pretty much the same.

5.2 Productivity effects across time: comparing earlier periods with later periods of inventions

The impact of green invention 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 compared to later ones. Especially in the initial stage of green invention, costs of invention were substantial greater and, at the same time, the demand for green invention was limited. The marginal costs of green invention should have decreased over time. Furthermore, increasing political pressure may also have stimulated the demand for such invention in the recent years. We thus expect that the negative impact of green invention on productivity has declined over time.

To analyze such time varying effects, we estimate our main model separately for four different time windows. 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 periods. Consequently, we estimate the model for overlapping time windows. From one column to the next, we shorten the time window by five years. Accordingly, the impact of the last years increases from one estimate to the next.

Insert Table 4 about here

Because we dropped the first years, we find that, in line with our previous result, the switching effect is not statistically different from zero for all four time windows. As expected, the estimation results show that the negative impact of green invention decreases over time. To visualize the impact, Figure 2 shows the marginal effect of green invention for the four different time windows. While the marginal effect for the first two periods is nearly the same, we find that the negative impact for the same amount of invention decreases over time. Furthermore, the decrease seems to accelerate over time. However, the impact of green invention on value added remains statistically significant negative for most industries, even in the last period of observation (1999-2009).

Insert Figure 2 about here

5.3 Robustness tests

We made some comprehensive tests to proof 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 invention do only marginally affect our results. Again, the impact of green invention is U-shaped and only very few industries have positive returns of additional green invention. However, in contrast to our previous results, the switching effect (*Green_patents_d*) is now statistically significant positive 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 patents in one period and zero patents in the following one. In contrast, the *Green_stock* of an industry may be larger than zero, even if the industry has not any green patents 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 control for year fixed effects. This should capture 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 invention may be biased. To control for such effects, we estimate our main model including country specific time effects.

Estimation results are presented in column (1) of Table A.4. In general, this modification does only marginally affect our results. The effect of the intensity of *Green_stock* is nearly the same. 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 invention on productivity has a certain time lag. This problem is even more pronounced when patent waves can be observed. As we analyze the impact of green invention 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-years lag and a 5-years 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 windows (see column (2) of Table 3). When we use a larger lag, the impact of previous observations for green patents increases. Accordingly, the impact of the switching effect increases and the marginal effect of additional green invention decreases. Nevertheless, the impact of additional green invention on value added is still negative for most industries.

Checking for outliers

Column (4) of Table A.4 shows the estimation result when we check for outliers. The distribution of patents across industries is highly heterogeneous. For this reason we dropped the top 1% of the industries in both clean and dirty patent stocks. This does only marginally affect our results. We thus conclude that our results are not driven by outliers.

Alternative construction of the patent stocks

In the literature you find different ways to construct a patent stock (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 constructions of the patent stocks are presented in Table A.5. Columns (1) and (2) show the estimates for alternative depreciation rates. This modification does not affect our main results. As we have seen in previous estimates, this is even the case for higher depreciation rates (patent flows → δ=100%).

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

6 Conclusions

In this paper the impact of green invention on productivity is analyzed. This is an important task. On the one side, the political requirement of green invention steadily increases. On the other side, the incentives of the firms to invest in green invention primarily depend on the profitability of these inventions. If green technological investments turn out to be profitable, further policy interventions would be unnecessary. The relationship between green invention and productivity is analyzed on the basis of industry-level data that includes most manufacturing industries, the most relevant countries for green invention and a time period of 30 years. We find a positive effect of switching into green inventions for earlier years of observation. However, the general relationship between the intensity of green invention and productivity is U-shaped; for most industries, an increasing level of green invention does negatively affect productivity. With a value of 3014 patents, the turning point is considerably high. Only industries with a very large stock of green patents are more likely to show a positive productivity effect of green inventions. These results are robust for different time windows. Like expected we saw strong negative marginal effects in early periods and even in the last period of our sample the marginal effect of green invention on productivity remained negative for most industries, but on a lower level. Consequently we can answer Popp's (2005, p. 224) question if environmental innovations would proceed without policy interventions with “probably not”.

These results are of high policy relevance. As firms direct their R&D resources towards the most profitable ends, the negative marginal effect of additional green invention, in combination with the high turning point, indicate that firms are probably not willing by themselves to increase investment in green technologies. This 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 has probably no incentives to adjust its political framework to further push green invention in its country, but will focus on the import of technologies developed abroad. To overcome such free rider problems, and to further increase green invention worldwide, a form of global or at least multilateral coordination is required.

b) Given that some kind of coordination will occur in the future, and consequently an international market for green technologies evolves, there are 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 interactions, 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. Nevertheless Porter and van der Linde (1995, p. 133) are convinced that “developing countries that stick with resource-wasting methods and forgo environmental standards because they are ‘too expensive’ will remain uncompetitive, relegating themselves to poverty.” To proof 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*, Vo. 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 (2011a): Indicators of Environmental Technologies (ENV-Tech Indicators), OECD, Paris.

OECD (2011b). OECD STAN database, STAN Industry 2008 available at: www.oecd.org/sti/stan (accessed 28 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.

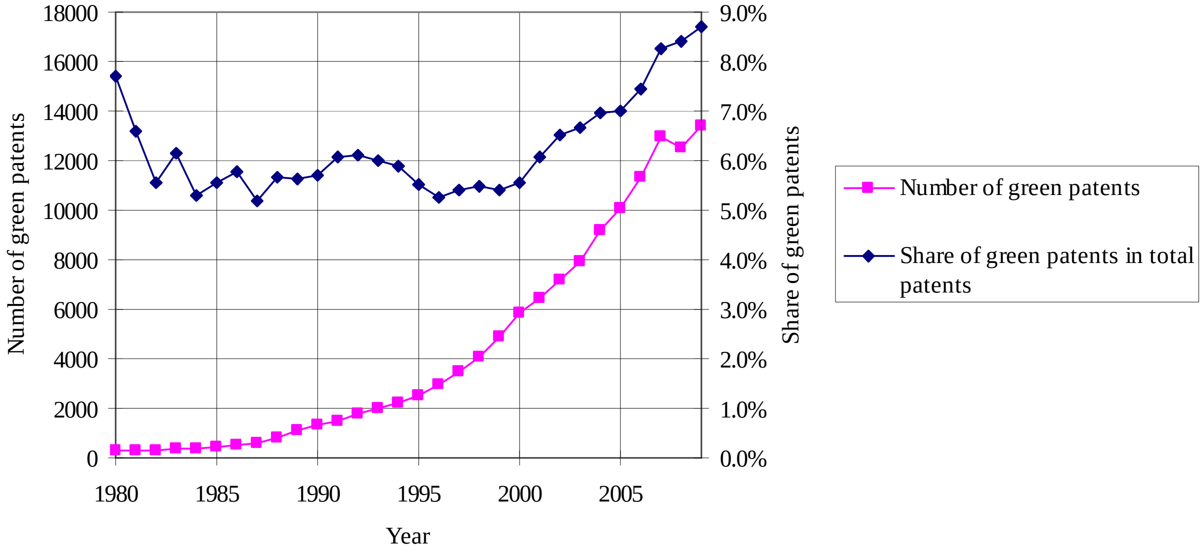
Teece, D.J., Pisano, G. and Shuen, A. (1997). Dynamic capabilities and strategic management. *Strategic Management Journal*, Vol. 18(7), pp. 507–533

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: This 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***

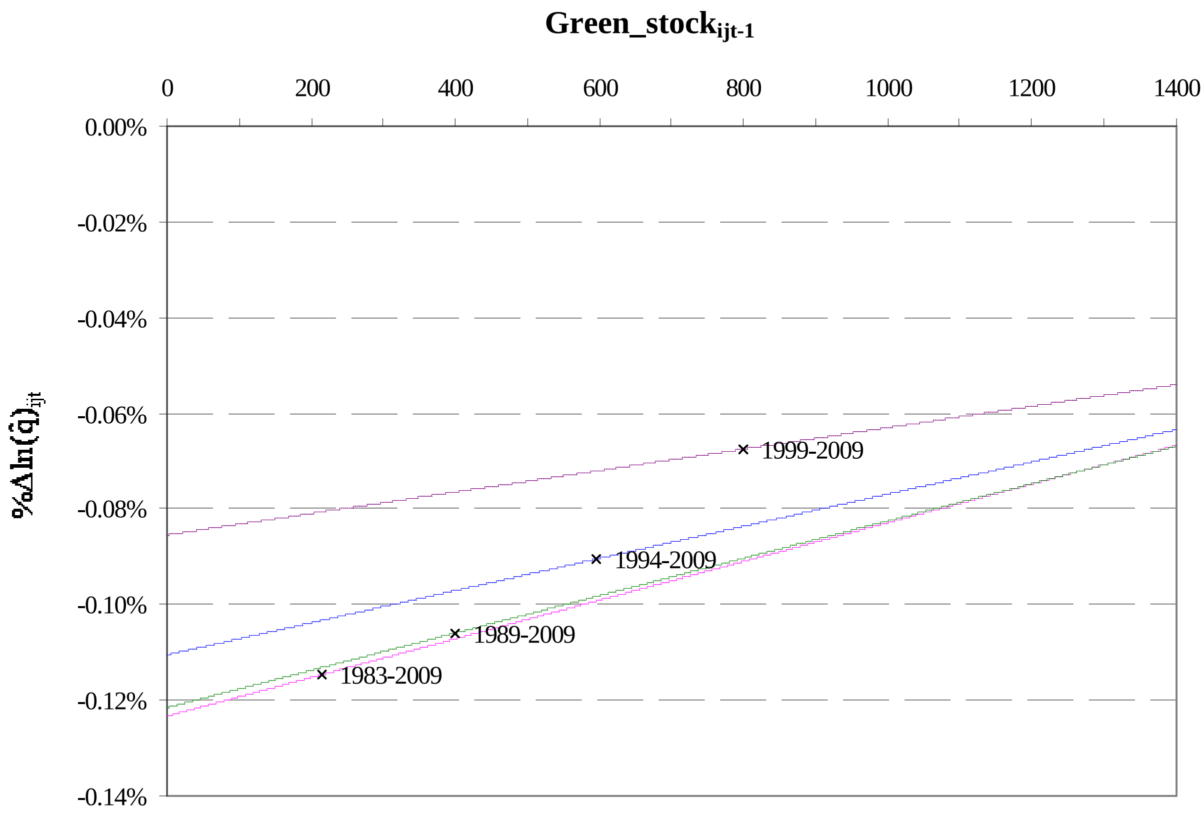
Notes: see Table 2 for the variable definitions; robust standard errors that are adjusted for within-cluster correlation (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively. F test and Hausman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

Table 4: Analysis for different time windows

	$ln(q)_{ijt}$			
	(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)
$Other\_stock_{ijt-1}$	.0002**	.0002**	.0002**	.00017**
	(9.6e-05)	(9.5e-05)	(8.5e-05)	(7.0e-05)
$Other\_stock^2_{ijt-1}$	-5.0e-09**	-4.9e-09**	-4.4e-09**	-3.2e-09**
	(2.4e-09)	(2.4e-09)	(2.0e-09)	(1.5e-09)
$Green\_stock\_d_{ijt-1}$	.04792	-.04616	-.0948	-.05042
	(.06068)	(.08359)	(.0896)	(.09283)
$Green\_stock_{ijt-1}$	-.00123**	-.00122**	-.00111**	-.00085**
	(.00057)	(.00056)	(.0005)	(.00043)
$Green\_stock^2_{ijt-1}$	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; ***, **, * denotes 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

	$\ln(q)_{ijt}$ (1)
Estimation method	Fixed-effects regression
Constant_{ijt}	9.8559***
	(2.0533)
$\ln(L)_{ijt}$	.88***
	(.17097)
$\ln(K)_{ijt}$	.10564
	(.06995)
$\text{Other\_patents}_{ijt-1}$	.00071*
	(.00039)
$\text{Other\_patents}^2_{ijt-1}$	-8.0e-08*
	(4.3e-08)
$\text{Green\_patents\_d}_{ijt-1}$	.10338***
	(.03751)
$\text{Green\_patents}_{ijt-1}$	-.00381*
	(.002)
$\text{Green\_patents}^2_{ijt-1}$	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; ***, **, * denotes 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; ***, **, * denotes 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)
$\text{Other\_stock}_{ijt-1}$	.00016**	.0003**
	(7.9e-05)	(.00015)
$\text{Other\_stock}^2_{ijt-1}$	-3.4e-09**	-1.3e-08**
	(1.6e-09)	(6.2e-09)
$\text{Green\_stock\_d}_{ijt-1}$	.08512	.08991
	(.05791)	(.05796)
$\text{Green\_stock}_{ijt-1}$	-.00103**	-.00181**
	(.00049)	(.00088)
$\text{Green\_stock}^2_{ijt-1}$	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; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively.