# The Performance Effect of Environmental Innovations

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**Abstract.** While recent literature has focused on explaining the determinants of green innovations, it is not well understood how such innovations affect performance. To analyse the relationship between green innovation and performance, new industry-level panel data were exploited: these include 12 OECD countries, the whole manufacturing sector and a period of 30 years. The results show that green inventions are U-shape related to performance. However, the turning point is quite high and hence only relevant for a few industries. This indicates 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 innovation in environmental technologies. In particular, a better understanding of the linkage between green innovation and policy has been a major area of research in environmental economics. Newell et al. (1999) look at the level of product characteristics and find that energy prices have an observable effect on technical features of the products offered for sale. Popp (2002) examine the share of environmental patents from the total number of patents in the United States and find that energy prices induce innovation. 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) uses 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) find a positive relationship between high environmental policy stringency and environmental R&D. Further, Horbach (2008) states 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 innovation have also contributed to performance and not only to general innovation output.

It is clear that green innovation would proceed without further intervention if such innovation were already profitable. Consequently, we investigate the impact of green innovation on

performance (measured as value added) in order to determine whether green innovations are already profitable and whether they will increasingly substitute older, environmentally unfriendly technologies.

Our research is based on a broad empirical basis. We use patent data to identify green and non-green inventions. Patent documents considered as covering green inventions are identified according to the OECD Indicator of Environmental Technologies (see OECD 2012) that 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. If an invention can be assigned to one of these sub-groups (a to g), it is counted as a green invention; otherwise it is counted as a non-green invention. Based on these counts and using the perpetual inventory method, we can define a quantitative measure to analyse non-linear effects of green inventions on performance.

The data used for our analysis 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 that cover the whole manufacturing sector (22 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.

The results show that green inventions are U-shape related to performance on an industry level. The turning point is, however, quite high and thus only relevant for a few industries. Accordingly, green innovation has not been profitable for most of the industries so far. Hence, it is unlikely that green innovation 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.

The paper is organised as follows: Section two provides the conceptual background and the hypotheses. Section three describes the data. In section four we show how we tested the hypotheses empirically. Section five presents the results, and in section 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 performance 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 technological phase, there are several reasons why firms are unable to develop green technologies in a profitable way. The development of green products and processes usually implies investing in technologies that lie beyond the firm's traditional technological scope (see Noci and Verganti 1999) and thus 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. This could be a costly task because firms may not have the capacity to alter the technological basis. If they identify 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 research cooperation.

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[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).

It is not a change in technology alone that increases costs in the initial phase. In addition to technology, business processes and working routines also have to be adapted or even newly developed (Danneels 2002). 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).

Furthermore, financial market imperfections that are normally associated with innovation activities (see Arrow 1962, p. 172) are even more pronounced for green innovation. Due to unclear market developments, green innovations carry a high technical risk and uncertainty (Aghion et al. 2009). 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. As a consequence, access to external capital to finance green innovation is likely to be constrained.

While the discussion above has shown that costs for green innovation can be substantially larger than for traditional innovation activities, there are also demand-side factors that reduce a firm's returns to green innovation compared with traditional innovation activities. 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. As the greatest benefits from green innovation compared with traditional innovation are likely to be public rather than private ones, the exclusivity of green product benefits is not given (e.g., the benefits of emission reduction in the case of electro cars). Accordingly, the willingness to pay for green products will be low (see, e.g., Beise and Rennings 2005, Faber and Frenken 2009, Hall and Helmers 2011).

To sum up, the discussion above has shown that while the costs of technological diversification in green 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 developing of a green knowledge stock does significantly decrease the performance 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 innovation activities right from the beginning. However, increasing 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 performance 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, increasing returns to scale are expected. The fixed costs only pay off if green innovation activities exceed a certain limit. If there are increasing 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 performance 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 use patent statistics in order to measure the green innovation 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, patent counts are still the best available source of data on innovation activities as it is readily available and comparable across countries (Johnstone et al. 2010). This is especially true for green technological activities, since the OECD (2012) provides a definition of green technologies based on the patent classification.

For the paper at hand, patent information is gathered in cooperation with the Swiss Federal Institute of Intellectual Property (IPI). Green patents are a sub-group of patents that are selected according to the OECD Indicator of Environmental Technologies (see OECD 2012). Based on the International Patent Classification, 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 have 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 assign patents according to the applicant's address, since this information - in contrast to the inventor's address - is generally available for patent applications in all investigated countries except for the USA, for which inventor's information is available generally. Hence, we use 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 feel safe to use the inventor's statistics for the USA. In general, these results indicate that the decision whether to use the applicant's or the inventor's country should not affect our main results.

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) are mitigated.

c) Only inventions were considered which were at minimum filed for patent protection under the Patent Cooperation Treaty (PCT). Fees for a PCT patent application are generally higher than for patent applications filed with national or regional patent authorities. Accordingly, applicants are expected to file inventions for patent protection under the PCT if they assume the invention to have enough commercial potential to compensate for the higher fees.

d) Most of our model variables are classified by industrial sectors and not according to the IPC technology classes. On the basis of a concordance table developed by Schmoch et al. (2003) we thus recoded our patent data into 22 manufacturing industry classes either at the NACE two or three-digit level. In comparison with patent data at the firm level, aggregating patents[2] on an industry level should reduce potential problems with patent waves within a firm.

e) Our data set includes 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 (either NACE two or three-digit level of the 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

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

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 performance, 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 $t$:

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

where $q$ is the output, $L$ is the labour input, $K$ the capital stock and $A$ is a constant. The parameters $\alpha$ and $\beta$ 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 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

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

To analyse the impact of green inventions, we augment this specification with a variable that measures an industry's stock in green patents (*Green_stock*; see, e.g., Bloom and Van Reenen 2002 or Guellec and Van Pottelsberghe de la Potterie 2004 for a related approach). 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.[3] 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 against other depreciation rates (see Table A.6) as well. To capture potential effects of different 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 non-linear relationships between these two patent variables and output, we also include quadratic terms of these variables in our model.[4] The augmented specification is given by:

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\begin{aligned}
\ln(q)_{ijt} = \ln(A) + \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_t + \eta_{ij} + \varepsilon_{ijt},
\end{aligned}
\tag{4}
$$

where δ and λ are the coefficients 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 include a dummy variable that measures whether there are green inventions within an industry (*Green_stock_d*). The patent variables are introduced with a lag of one year to deal with the potential problem of reverse causality.

As our model does not directly control for environmental regulation, an omitted variable bias may occur when environmental regulation is correlated with green innovation as well as an industry's performance. To control for correlated unobserved heterogeneity, we include country-specific industry fixed effects ($\eta_{ij}$) and year fixed effects (*Year*) (see Table 2 for variable description). Furthermore, to make sure that our results are not affected by an omitted variable

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[3] 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] The robustness of our results with respect to alternative model specifications (e.g., no quadratic terms) is tested in alternative estimates (see Table A.3).

bias we control in alternative estimates for country-specific time fixed effects (see Table 'A.5). These variables should even capture effects driven by country specific shocks such as changes in a country's environmental regulation system.

*Insert Table 2 about here*

## 4.2 Operationalisation of hypotheses

We deduce from a negative relationship between the industries' stock of green patents (*Green_stock*) and performance that costs are considerably higher than the benefits from investing in green research. Following H1 we thus expect *Green_stock* to be negatively related to performance.

H2 indicates positive 'scale effects' and hence learning from green innovation activities in terms of performance 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 performance level.

H1 and H2 point at a non-linear relationship between *Green_stock* and performance. 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 activities of an industry to show a positive effect on its performance level. In other words, we can detect at which point an industry benefits from its green research activities.

# 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 test the robustness of our results for a considerably larger sample, since our proxy for the physical capital has many missing values (e.g., no information for Japan and Switzerland). 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. The impact of physical capital (*K*) on value added is positive, but just not significant at the 10% level (t-value=1.57). 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.

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

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 (t-value=1.50), but it becomes statistically 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%. Accordingly, additional revenues of green innovation exceed its additional costs at low levels of innovation activities. This effect may be interpreted as a kind of advertising (image) effect. Industries that start to innovate in green technologies obtain a green touch, which positively stimulates performance. Costs are under such circumstances comparatively low, as innovation activities are kept at moderate levels. 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 (combination of the effects of all *Green_stock* variables) rapidly decreases with additional innovation activities (*Green_stock)*. At low stocks of green patents, the positive switching effect to green inventions dominates and thus a positive overall effect of green innovation results. 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 Performance effects over a period of time: comparing earlier periods with later periods of inventions

The impact of green inventions on performance for the whole sample period is predominantly negative. This indicates that sales markets do not provide sufficient incentives to increase firms' green innovation activities. One reason for this finding may be the long sample period and different performance 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 performance 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.

### *Alternative model specifications*

Table A.3 shows the robustness of our results with respect to alternative model specifications. Column (1) shows the results for the standard Cobb-Douglas production function. The model in column (2) additionally includes the linear terms of the innovation variables. Column (3) adds the dummy variable that captures the effect of zero values. Column (4) shows the results for the

model that includes the non-linear terms of the innovation variables but not the correction for zero values. The results of our main model are presented in column (5). The estimates show that our results do only marginally change between model specifications. While the impact of non-green innovation tends to be positive, the effect of green innovation is negative. Furthermore, the estimates show that the significance of the innovation variables increases when we include the non-linear terms. Accordingly, we conclude that our main model that includes the quadratic form is the model that best fit the data.

### *Patent flow instead of stock*

Table A.4 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 performance, 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.5. 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 performance 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.5. 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.5 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.

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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.

*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.6; 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 $\rightarrow \delta$=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 performance 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 performance effect of such inventions. If green innovation activities turn out to be profitable, further policy interventions would be unnecessary.

The relationship between green inventions and performance 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 performance is U-shaped; for most industries, an increasing level of green inventions negatively affects performance. 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 performance. 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 performance 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 green innovation activities by themselves. This finding leads us to formulate the following two conclusions:

a) As the costs of green innovation activities 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 green innovation activities. 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 green innovation activities, 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 innovation activities 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.

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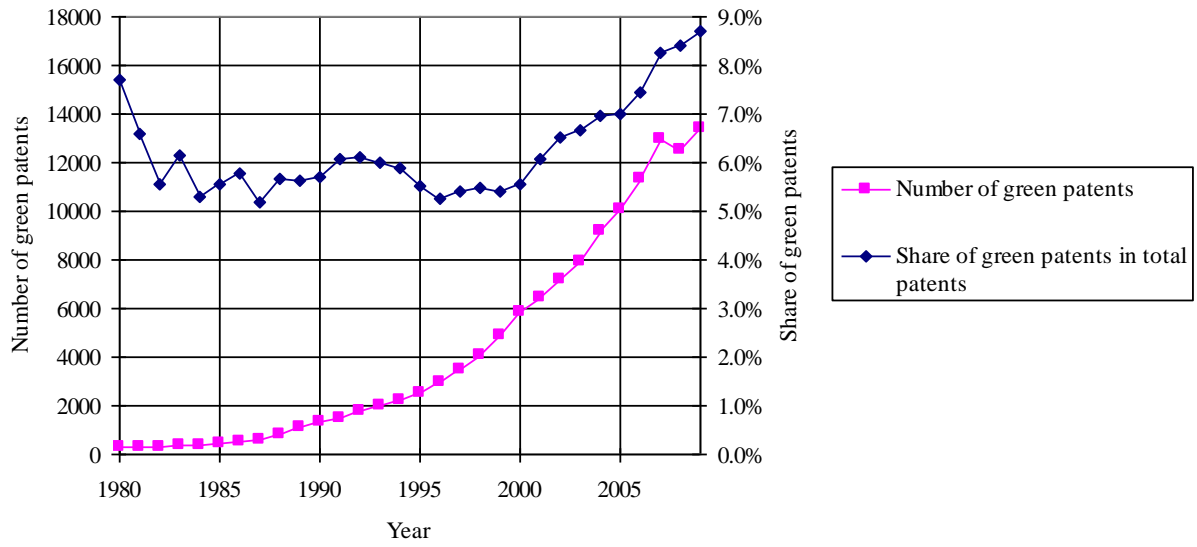


*Notes:* To reduce the problem of double counts of patents, this information is based on world-aggregated data and is not restricted to countries and industries that are in our estimation sample.

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 | 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) | | |
| Other_stock$_{ijt-1}$ | .0002** | .00023* | .00016** | .00015** |
| | (9.7e-05) | (.00012) | (6.5e-05) | (6.3e-05) |
| 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) |
| Green_stock_d$_{ijt-1}$ | .08698 | .11222** | .09013 | .09136 |
| | (.05791) | (.05507) | (.06584) | (.06616) |
| Green_stock$_{ijt-1}$ | -.00122** | -.00183* | -.00099** | -.00094** |
| | (.00058) | (.00093) | (.00041) | (.00039) |
| 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; standard errors that are robust to heteroskedasticity and clustered at the industry-country level (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 | 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; standard errors that are robust to heteroskedasticity and clustered at the industry-country level (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)
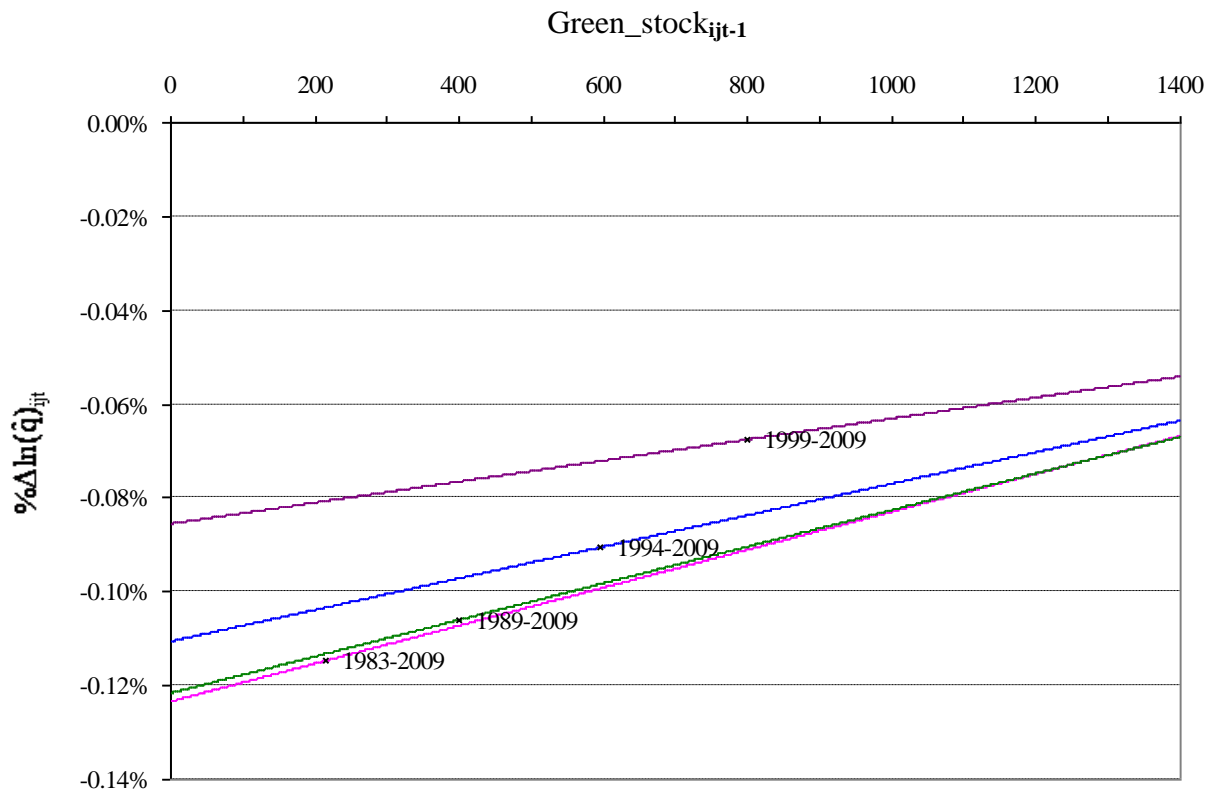


*Notes:* This figure is plotted for values of *Green_stock* between 0 and 1400 only because in each time
window less than 5% of the observations have a higher *Green_stock*.

# 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 for alternative model specifications

| | $\ln(q)_{ijt}$ | | | | |
|---|---|---|---|---|---|
| | (1) | (2) | (3) | (4) | (5) |
| Period | 1981-2009 | 1981-2009 | 1981-2009 | 1981-2009 | 1981-2009 |
| Estimation method | Fixed-effects regression | Fixed-effects regression | Fixed-effects regression | Fixed-effects regression | Fixed-effects regression |
| Constant | 9.2229*** | 9.3893*** | 9.2933*** | 9.7353*** | 9.6274*** |
| | (2.4432) | (2.3212) | (2.3129) | (2.0369) | (2.0202) |
| $\ln(L)_{ijt}$ | .94753*** | .92884*** | .93666*** | .8848*** | .89323*** |
| | (.20337) | (.19147) | (.19264) | (.16787) | (.16859) |
| $\ln(K)_{ijt}$ | .10269 | .10439 | .10384 | .11077 | .11018 |
| | (.06882) | (.06965) | (.06899) | (.07099) | (.07014) |
| Other_stock$_{ijt-1}$ | | 4.8e-05 | 4.9e-05 | .00019** | .0002** |
| | | (3.4e-05) | (3.4e-05) | (9.7e-05) | (9.7e-05) |
| Other_stock$^2_{ijt-1}$ | | | | -5.0e-09** | -5.1e-09** |
| | | | | (2.5e-09) | (2.5e-09) |
| Green_stock_d$_{ijt-1}$ | | | .06898 | | .08698 |
| | | | (.0594) | | (.05791) |
| Green_stock$_{ijt-1}$ | | -.00033* | -.00033 | -.00123** | -.00122** |
| | | (.0002) | (.0002) | (.00058) | (.00058) |
| Green_stock$^2_{ijt-1}$ | | | | 2.0e-07** | 2.0e-07** |
| | | | | (1.0e-07) | (1.0e-07) |
| Year fixed effects | Yes | Yes | Yes | Yes | Yes |
| Country-specific industry fixed effects | Yes | Yes | Yes | Yes | Yes |
| N | 2936 | 2936 | 2936 | 2936 | 2936 |
| Groups | 146 | 146 | 146 | 146 | 146 |
| $R^2$ within | 0.44 | 0.45 | 0.45 | 0.48 | 0.48 |
| Rho | 0.91 | 0.91 | 0.91 | 0.91 | 0.91 |

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

Table A.4: Estimate of the production function
          based on patent flows

| Estimation method | $\ln(q)_{ijt}$ (1) Fixed-effects regression |
|---|---|
| Constant | 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; standard errors that are robust to heteroskedasticity and clustered at the industry-country level (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denote statistical significance at the 1%, 5% and 10% test level, respectively.

Table A.5: Alternative estimates of model (1) of Table 3

| | $\ln(q)_{ijt}$ | | | |
|---|---|---|---|---|
| | (1) | (2) | (3) | (4) |
| Estimation method | Fixed-effects regression | Fixed-effects regression | Fixed-effects regression | Fixed-effects regression |
| Robustness test | Controlling for country-specific time effects | Alternative lags | | Checking for outliers |
| Constant | 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; standard errors that are robust to heteroskedasticity and clustered at the industry-country level (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denote statistical significance at the 1%, 5% and 10% test level, respectively.

Table A.6: Estimates with alternative depreciation rates

| | ln(q)$_{ijt}$ | |
|---|---|---|
| | (1) | (2) |
| Depreciation rate | 10% | 30% |
| Estimation method | Fixed-effects regression | Fixed-effects regression |
| Constant | 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; standard errors that are robust to heteroskedasticity and clustered at the industry-country level (clustered sandwich estimator) are in brackets under the coefficients; ***, **, * denote statistical significance at the 1%, 5% and 10% test level, respectively.