Stucki, Tobias; Woerter, Martin

Working Paper

Determinants of green innovation: The impact of internal and external knowledge

KOF Working Papers, No. 314

Provided in Cooperation with:
KOF Swiss Economic Institute, ETH Zurich

Suggested Citation: Stucki, Tobias; Woerter, Martin (2012) : Determinants of green innovation: The impact of internal and external knowledge, KOF Working Papers, No. 314, ETH Zurich, KOF Swiss Economic Institute, Zurich, https://doi.org/10.3929/ethz-a-007365407

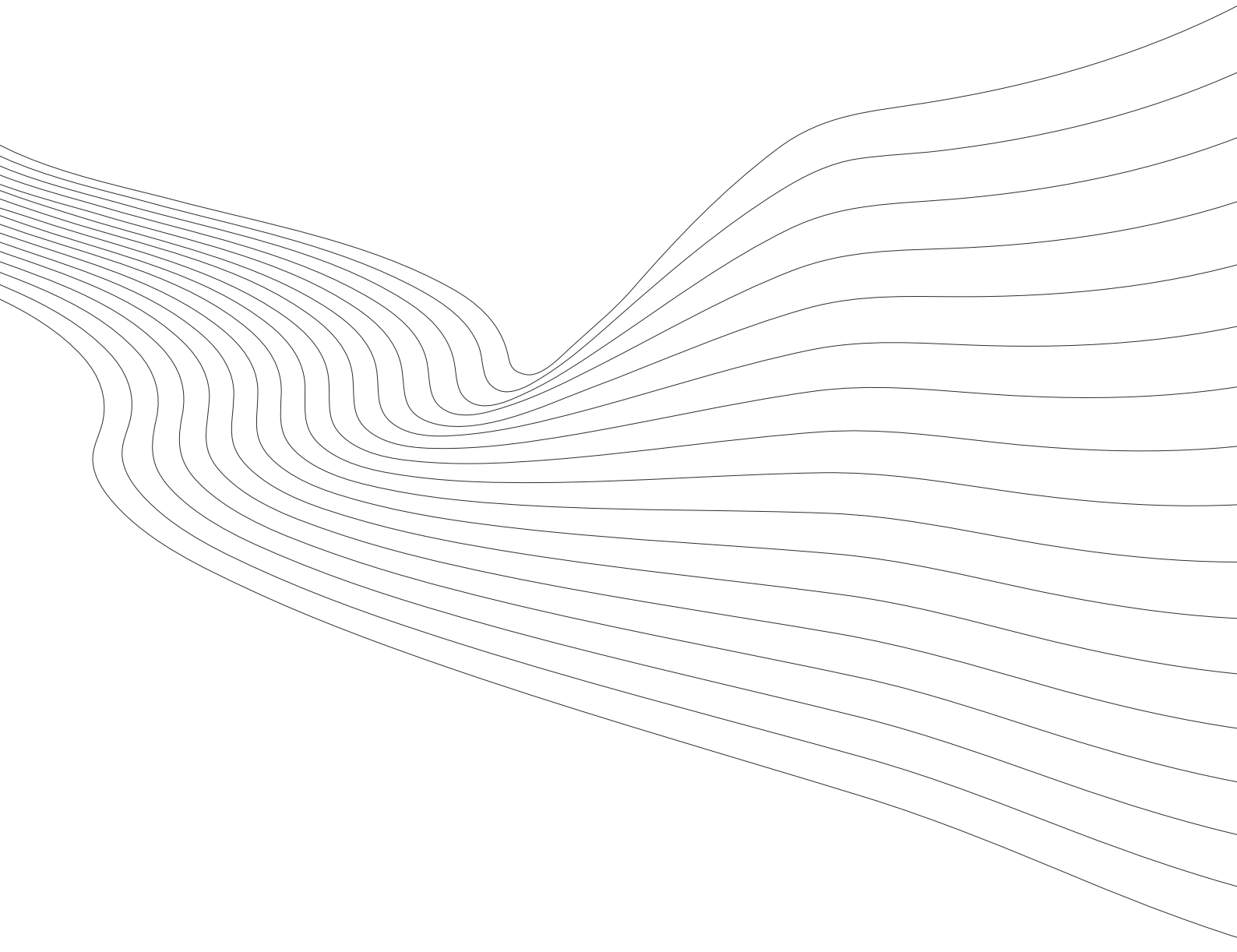
This Version is available at:
https://hdl.handle.net/10419/80815

KOF

KOF Working Papers

Determinants of Green Innovation:
The Impact of Internal and External Knowledge

Tobias Stucki and Martin Woerter



No. 314
September 2012

ETH
Eidgenössische Technische Hochschule Zürich
Swiss Federal Institute of Technology Zurich

KOF

ETH Zurich
KOF Swiss Economic Institute
WEH D 4
Weinbergstrasse 35
8092 Zurich
Switzerland

Phone +41 44 632 42 39
Fax +41 44 632 12 18
www.kof.ethz.ch
kof@kof.ethz.ch

Determinants of Green Innovation: The Impact of Internal and External Knowledge

Tobias Stucki*, Martin Woerter**

This version: September 2012

Abstract. Based on a comprehensive data set comprising 13 countries, 22 industries and a period of 30 years we investigate the impact of internal and external knowledge pools of both green and 'other than green' technologies on green patent activities. It turned out that the internal green knowledge stock is positively related to green patent activities with a considerably large marginal value. The country's green knowledge stock and the green knowledge stock of the same industry in other countries are also positively related with industries' green patent activities, although with a significantly lower marginal value. External 'other than green' knowledge stocks are negatively related with green inventions. The considerable greater marginal value for internal green knowledge stock indicates that a free-riding position on green technology investments of other industries in the same country or the same industry in other countries does not seem to be very promising in terms of green inventions. The negative marginal effect of external 'other than green' knowledge stocks and the positive marginal value of external green knowledge stocks indicate that country level policy measures to promote green knowledge formation would provide additional positive effects for green inventions on an industry level.

Keywords: Innovation; knowledge; patents; environment; technological change; spillovers

JEL classification: O30; O34; Q55.

---

* Corresponding author; ETH Zurich, KOF Swiss Economic Institute, CH-8092 Zurich, Phone: +41 44 632 63 07, fax: +41 44 632 12 18; 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

On the one hand, climate change increases the demand for green technologies. On the other hand, firms have low incentives to invest in green technologies as there is a 'double externality problem' (see, e.g., Beise and Rennings 2005, Faber and Frenken 2009, Hall and Helmers 2011). Firstly, due to the public goods nature of knowledge (see, e.g., Geroski 1995, Popp 2011) and due to financial market imperfections green technology investment decisions are complex and often linked with financial constraints. Secondly, because the greatest benefits from green innovation are likely to be public rather than private, the customers' willingness to pay for these innovations is low. Accordingly, firms would only invest if the revenues outperform the costs of externalities. In fact, firms face not just the question *whether* it is profitable to innovate in green technologies (see Soltmann et al. 2012), but also *when* they should start to innovate. As the demand for green innovation is limited at the current stage and positive knowledge spillovers from green R&D activities of other firms and institutions can be expected, a firm probably prefers to wait with investments in green innovation. However, they also have to consider the costs of permanently lagging behind technologically or even miss the opportunity to enter the market before the gap to the technological frontier gets too large. Latecomers (also on an industry or country level) that stick to resource-wasting technologies and delay green investments run the risk to become and remain uncompetitive (see Porter and van der Linde 1995). Later policy interventions could be costly and country growth effects are likely to be low for a longer transmission phase (see Acemoglu et al. 2012). Whether this prediction will be true is determined in large part by the extent of the innovation effects of available knowledge. For example it could be easier for a firm to technologically catch up, if it has already a well developed traditional knowledge base and if there are synergies with green knowledge.

In the paper at hand we analyze the impact of different type of knowledge stocks on green innovation activities. We distinguish between internal and external stocks, and stocks of green and traditional (other than green) knowledge, respectively. Information about the size of the

effects of the different knowledge stocks should indicate the overall effect of different types of past innovation activities on current innovation activities and thus allow for conclusions about the future development. Accordingly, our study provides insights into the question weather it may be worth for a firm to wait until technologies mature or weather it should start immediately investing in green technologies, conditional on the internal and external technological knowledge currently available.

So far, the impact of different knowledge stocks on green innovation is unclear. Most studies in empirical environmental economics that analyze the determinants of green innovation focus on the impact of environmental policy, so-called policy induced innovation (see Popp et al. 2009 for an overview). To the best of our knowledge, only the study of Aghion et al. (2011) analyzes the impact of available knowledge on current innovation activities. Based on firm-level data for the auto industry, they study the impact of firm knowledge stocks (dirty and clean) on current green innovation activities. Although their main focus is on politically induced innovation, these results allow at least some conclusions about the impact of internal knowledge on green patent applications.

The study at hand is based on a broad set of industry-level patent data (panel). The use of aggregated patent data has several beneficial features. Firstly, it allows us to use the OECD Stan database to control for other than knowledge factors that are likely to be related with current innovation activities. Secondly, it allows us to generate a data set on inventions that covers the whole manufacturing sector (22 two and three digit industries), the most important countries of green invention (13 OECD countries that are responsible for 95% of all green patents and total patents worldwide) and a period of 30 years. Thus, we are able to consider a broad set of knowledge pools (internal, home country, foreign). This allows us to simultaneously analyze the effect of different knowledge pools on green innovation intensity and to draw conclusions about their relative importance for green innovation. Furthermore, the balanced data set enables us to control for correlated unobserved heterogeneity between the industries of the different countries.

The econometric estimations show the expected positive relationship between internal and external 'green knowledge stocks' on green patent applications. Furthermore, we find that external traditional knowledge stocks are negatively related with green patent applications, while the internal traditional knowledge stock is positively related. Internal green knowledge stock has a significantly greater marginal effect compared to other types of knowledge stocks. Consequently, we cannot reject our two hypotheses since we see that green knowledge does positively affect current green innovation activities (H1) and that the marginal effect of green knowledge on current green innovation activities is larger than the marginal effect of traditional knowledge (H2). These results indicate that it seems to be difficult to remain competitive in green technologies without timely accumulating internal green knowledge. Although effects from external green knowledge stocks are positively related with green patent activities of an industry, the effects are quite moderate and they cannot compensate the lack of internal green competences; evidence for the success of a wait-and-see attitude cannot be seen in the results.

2 Conceptual background and hypotheses

2.1 Sources of available knowledge

There are different pools of knowledge that may have an effect on an industry's current green innovation activities. In line with Mancusi (2008) we distinguish between internal knowledge and external knowledge. Internal knowledge refers to the knowledge stock within the industry in the home country. Furthermore, we distinguish two types of external knowledge, namely the knowledge accumulated in the other industries within the home country ('country pool') and knowledge accumulated in the same industry in foreign countries ('industry pool').[1] As we

[1] Actually knowledge accumulated in other industries in foreign countries ('foreign inter-industry pool') is another pool of knowledge that may affect an industry's current green innovation activities. However, due to multicollinearity with the knowledge accumulated in the 'country pool', it is not possible to identify the two effects separately. As knowledge in the 'industry pool' is a more specific type of foreign knowledge, we decided to focus on the identification of the effect of foreign intra-industry knowledge. This decision is supported by the results of previous empirical studies that find significantly stronger effects of foreign intra-industry knowledge than for inter-

analyze the impact on green innovation and not for innovation in general, the available pools of knowledge can furthermore be separated in green specific knowledge and pools related to traditional knowledge. Thus, we define a total of six different pools of knowledge. The aim of this paper is to identify the impact of these knowledge pools on current green innovation activities.

2.2 Impact of available knowledge

Knowledge is a semi public good (non-rival and non-excludable), since not all results from knowledge production activities are appropriable. At least some of the knowledge associated with the invention 'spills over' within firms or industries and also between firms or industries. Such 'knowledge spillovers' are very important for industries operating on advanced technologies like green technologies, since they do not only shape and direct technological progress but also affect market competition and the incentives for innovation activities (see Shapiro 2011). Consequently they are of considerable meaning for explaining and understanding economic processes. They influence innovation activities on several levels (e.g. Peri 2005, Cohen et al. 2002), contribute to the diffusion of new technologies (e.g. Jaffe 1989, Keller 2002), provide opportunities for entrepreneurial activities (e.g. Audretsch 1995, Audretsch and Lehmann 2005), increase productivity (e.g. Griliches 1992, Moretti 2004), and ultimately generate economic growth (e.g. Grossman and Helpman 1991).

On the level of innovation activities *spillovers* from knowledge accumulation are essentially contributing to the innovativeness. On the firm level Blundell et al. (1995) or Crepon et al. (1998) identified a strong positive relationship between knowledge capital on the one hand, and patent activities or innovativeness on the other hand. Also on the industry level, Dosi (1984) convincingly showed for the semiconductor industry that innovation advantages are resulting

industry foreign knowledge on current innovation activities (see Malerba et al. 2007, Mancusi 2008). Malerba et al. (2007) even find that the total effect of foreign knowledge is almost explained by its intra-sectoral component.

from an accumulated knowledge stock. US companies early invested in semiconductors and gained a head start to the European and Japanese competitors and they stayed ahead of competitors even once the technology matured and its commercial perspectives became clearer. Knowledge does not only 'spill over' within firms or industries but also between firms or industries (see, e.g., Jaffe 1986, Jaffe et al. 1993). In line with this literature, we expect that the size of internally and externally available green knowledge is positively correlated with an industry's current innovation activities in green technologies.

Whether the knowledge comes from traditional technologies or from green technologies should not affect the direction of the effect. Since many green technologies are in a rather early phase of development and they are just about to penetrate markets, knowledge and experiences in other fields of advanced technologies are likely to play an important role in their development. It is likely that advanced knowledge in e.g. chemistry or engines increases the propensity of green research activities. This is especially true if there are 'economies of scope' in research activities (see Henderson and Cockburn 1996 for the pharmaceutical industry), i.e. synergies between different R&D projects or lines of research. For instance, an industry with knowledge and experiences in turbine development and production has capability advantages to diversify into steam turbine for biomass energy, solar energy, or energy from abatement. Or the chemical industry has knowledge advantages in order to make the dyeing process of clothes more environmental friendly (save water, energy, and abatement). The availability of knowledge related 'economies of scope' eases the diversification into green technology markets. Such industries can refer to internal knowledge and do not need to begin from scratch in order to develop green technologies. Consequently, we would expect to see a positive effect of expertise in other than green knowledge on green patent activities. In the following we refer to this positive effect of available knowledge, either through spillovers from green or other knowledge, as a 'resource effect'.

Since the work by Jaffe et al. (1993) empirical literature on spillovers is mostly based on patent citation data that allows to track the direction and intensity of spillovers. Empirical evidence for spillovers in environmental economics is scarce. At least some evidence is found in Popp (2006). Based on patent citation data Popp (2006) finds in the case of air pollution control patent activities that the relevant knowledge stock in foreign countries influences the technological activities in the United States and vice versa. This is especially true for early foreign patents. They serve as a building block for green innovations in other countries.

While the spillover literature focuses on the impact of available knowledge on current innovation activities within a certain type of technology, we differ between two types of technologies, i.e. green and traditional technologies. Accordingly, in our framework the formation of green innovation implies not just the investment in knowledge formation, but also to shift resources into the development of a new (green) technology. Thus, the just mentioned positive 'resource effect' of available knowledge has a flip side. Available knowledge in one of the two technology fields (green vs. traditional) represents *opportunity costs* that may lead to 'path dependency' and affect the decision between further investments in green technologies.

Such 'path dependency' or technologically lock-in is a well known phenomenon in the history of technical change. The QWERTY keyboard (see David 1985), the US Ice-Industry, or the typewriter industry (see Utterback 1996) are famous examples of industries that did not change timely their technological basis. The German chemical industry after World War II is a further example that painfully shows the adverse consequences of a technological lock-in (see Stockes 1994). Skills, education, and attitudes that have been developed under the traditional technological regime delay or even prevent a timely change to newer technologies. Also investment in new technologies can be hindered or delayed through 'sunk' investments in traditional technologies. Accordingly we expect that due to the large opportunity costs, firms with a large stock of green (traditional) patents will be more likely to invest in green (traditional) technologies today (see Aghion et al. 2011 for a similar argumentation).

Despite internal pressure, technological change may also be induced by pressure from different external sources such as regulators or customers. An increase in costs of important input factors (e.g. energy prices), or a policy induced increase in demand for green products is likely to foster green technology investments (see Newell et al. 1999, Berkhout 2002, Popp 2002). A firm in an ecologically friendly environment will find it more profitable to invest in green technologies. The availability of knowledge of a certain technology is a proxy for the characteristics of the environment. We thus assume that a firm in an environment with a large stock of green (traditional) patents will be more likely to invest in green (traditional) innovations today.

Literature on opportunity costs in environmental economics mostly focuses on externally induced innovation, analyzing the impact of prices and environmental policy (see Popp et al. 2009 for an overview). In line with our expectation, they find that both higher energy prices and changes in environmental policies do stimulate green innovations.

In sum it is obvious that technical change is a quite complex issue and difficult to frame into clear hypotheses. However, it becomes clear from the literature that *resource (spillover) effects* and *opportunity cost effects* are important forces in order to understand green technology activities. Based on the argumentation above Table 1 arranges the relationship between resource (spillover) effects and opportunity cost effects on the one side and different types of knowledge capital on the other side. This should help to frame our hypotheses.

Insert Table 1 about here

We expect a positive resource effect for all types of knowledge and an ambiguous effect in terms of opportunity costs (Table 1). Opportunity costs are positive in the case of green capital stocks independent of their origin, and opportunity costs operate against green technology innovation in case of traditional capital stocks. Hence, the net effect is positive in case of green

knowledge capital and it is ambiguous in case of traditional knowledge capital. Consequently the hypotheses read like follows:

H1: Green knowledge does positively affect current green innovation activities.

H2: The marginal effect of green knowledge on current green innovation activities is larger than the marginal effect of traditional knowledge.

Empirical evidence for the impact of available knowledge on green innovation activity is rather scarce. In line with hypothesis 1, Aghion et al. (2011) find for the auto industry that the stock of green knowledge is positively related with the number of green patents. In line with hypothesis 2, they also find a stronger effect from green knowledge than from 'dirty' knowledge. Furthermore, they find that the size of a firm's 'dirty' knowledge stock has a positive effect on clean innovation. Consequently, we would also assume for the investigation at hand that internal traditional capital accumulation is positively related with current green patent application. The second study related with our analysis is the work by Popp et al. (2011). Popp et al. (2011) do not analyze the impact of available knowledge on current innovation, but on investment in green technologies. In line with hypothesis 1 they detect a positive influence of world patent applications of certain green technologies on domestic investment activities, respectively. However, the effect of such technology-induced technical progress appears to be moderate.

3 Description of the Data

3.1 Measurement of green invention based on patent statistics

We use patent statistics in order to measure green investment activities of an industry and to detect national and international spillovers. Patent activities are a good measure for innovation input (see Griliches 1990) and widely used for international comparisons. Although patent propensity varies across firm size, across industries (see Pakes and Griliches 1980 and Scherer

1983), and across countries (see Cohen et al. 2002), patents are strongly correlated with R&D expenditures and consequently can be considered as a good proxy for knowledge capital (see, e.g., Aghion et al. 2011).

Since the work of Jaffe et al. (1993) most empirical literature on knowledge effects is also based on patent statistics. Statistical tests showed that patent citations serve as a measure for directed knowledge spillovers (see Jaffe et al. 2000). However, following the reasoning of Bottazzi and Peri (2003), such a 'paper trail' to track the direction of spillovers does not cover the whole amount of R&D externalities. Patent citations do not capture non-codified forms of knowledge, which are also an important part of externalities.

For the paper at hand we use patents as a proxy for knowledge capital of an industry and we do not consider patent citations to track knowledge flows. Instead, we exploit the correlation between green and non-green capital stocks and green innovation activities to detect knowledge effects or R&D externalities within and between countries. Consequently we follow a 'functional approach' to detect R&D externalities. Such an approach has also been used by Bottazzi and Peri (2003) to measure research externalities in generating innovation, Coe and Helpman (1995) to detect the meaning of domestic and foreign R&D capital for total factor productivity, Keller (2002) to estimate the relationship between spillovers from R&D activities on a geographical basis and productivity, and Aghion et al. (2011) to measure internal innovation spillovers from green investments.

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 2012). The OECD definition comprises seven environmental areas, (a) general environmental management, (b) energy generation from renewable and non-fossil sources, (c) combustion technologies with mitigation potential, (d) technologies specific to climate change mitigation, (e) technologies with potential or indirect contribution to emission mitigation, (f) emission abatement and fuel efficiency in transportation

and (g) energy efficiency in buildings and lighting. In order to identify our proxy for the green knowledge base of an industry, further specifications and clarifications had to be made:

a) In order to assign patents to countries 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 were aggregated to inventions following the patent family definition of Thomson Reuters' Derwent World Patents Index database [systematic]. Thereby we assure that important inventions are considered. Technologically less important patent applications are not taken into account, thereby ensuring homogeneity of the data. 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) We only considered patent families that comprise at least one PCT (Patent Cooperation Treaty) application. 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 22 two and three digit manufacturing industries. Aggregating patents on an industry level reduces 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)^2 data for 13 countries (Austria, Denmark, Finland, France, Germany, Ireland, Italy, Japan, the Netherlands, Sweden, Switzerland, the United Kingdom and the United States). These 13 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). To reduce the impact of the initial patents stock, regressions are only based on the period 1986-2009. This yields a data set of 7150 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 disproportional 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 80s and 90s, green inventions increased disproportionally 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 2. 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 13 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 12.4% of all patents in Denmark.

Insert Table 2 about here

3.2 OECD Stan data

In order to control for important industry characteristics beside their stock of knowledge we accessed the OECD STAN database (OECD 2011). We used information on labor input (total employment) and the capital-stock (gross fixed capital formation, volumes (current price value)) of relevant industries for our estimations.

4 Empirical test of hypotheses

As stated by Jaffe and Palmer (1997) it is very difficult to specify a theoretically satisfying structural or reduced-form innovation equation at the industry level. Our model is based on a standard Cobb-Douglas production function for an industry *j*, in country *i* at time *t*:

$$Green\_patents_{ijt} = AL_{ijt}^{\alpha} K_{ijt}^{\beta}, \quad (1)$$

where *Green_patents* is the number of green patents (inventions), *L* is the labor input and *K* the capital-stock, *A* is a constant. The parameters α and β are elasticities with respect to labor and physical capital respectively. In our model we use the industries' total number of employees as a proxy for 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.

[2] Patents and inventions are used synonymously.

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 innovation activity.

Expressing (1) in logarithms yields

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

To analyze the impact of available knowledge on green innovation, we augment this specification with several variables that measure stocks in green patents. *Internal_green_stock* measures the patent stock of an industry *i*, in country *j* at time *t*. *Country_green_stock* is the stock in green patents accumulated in industries other than *i* in the home country. *Foreign_green_stock* is the green stock accumulated in the same industry in other countries than *j*. 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 to other depreciation rates as well (see Table A.4). To capture potential effects of available knowledge in traditional technologies, we also control for the stocks of patents 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. The augmented specification is given by:

$$\begin{aligned} \ln(Green\_patents)_{ijt} = {} & \ln(A) + \alpha \ln(L)_{ijt-1} + \beta \ln(K)_{ijt-1} + \delta_1 \ln(Internal\_green\_stock)_{ijt-1} \\ & + \delta_2 \ln(Country\_green\_stock)_{ijt-1} + \delta_3 \ln(Foreign\_green\_stock)_{ijt-1} \\ & + \lambda_1 \ln(Internal\_other\_stock)_{ijt-1} + \lambda_2 \ln(Country\_other\_stock)_{ijt-1} \\ & + \lambda_3 \ln(Foreign\_other\_stock)_{ijt-1} + \mu Year_t + \eta_{ij} + \varepsilon_{ijt}, \end{aligned} \tag{4}$$

[3] 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, the influence of the initial stock should be small, as we have a lag of five years between the estimation period and the initial stock.

where δ and λ are the coefficients of knowledge stocks and ε is the stochastic error term. As patent variables can take on the value 0, we used ln(1+patents) to avoid problems with the logarithm (see Wooldridge 2002, p. 185). To deal with the potential problem of reverse causality the independent variables are introduced with a lag of one year. To control for correlated unobserved heterogeneity, we include country specific industry fixed-effects (η). Furthermore, we also include year fixed effects (*Year*) (see Table 3 for variable description).

Insert Table 3 about here

5 Estimation results

5.1 Main results

The main results are presented in Table 4. In column (1) and (2) we see the OLS log linear fixed-effects estimations. Column (1) includes a control variable for the capital stock. In column (2) we see the same estimation without capital control, which doubles the number of observations from 2926 to 5853 observations. Since the capital stock variable is insignificant in the model and the results are qualitatively the same, we do not further discuss the results of column (1). Column (3) shows the results for the fixed-effects Poisson model with robust standard errors as recommended by Allison and Waterman (2002) to correct for over-dispersion. Column (4) shows the negative binomial model with a pre-sample mean estimator like it was proposed by Blundell et al. (1995) in order to deal with fixed unobserved heterogeneity in the presence of lagged endogenous variables. In doing so we add the average level of patenting over the pre-sample period 1980-1985 for both, green and other patents (both in logs), as well as a binary variable that measures whether an industry has patent applications at all in the respective period (see, e.g., Mancusi 2008 or Aghion et al. 2011 for a similar approach). Column (5) presents a negative binomial model without pre-sample fixed-effects.

There are some differences if we compare the results of the OLS log linear fixed-effects estimator (column 2) with the negative binomial model with a pre-sample mean estimator (column 4). Here, we see a significant effect for 'country green stock' and 'country other stock' in the OLS model (column 2) and an insignificant effect in the negative binomial model (column 4), respectively. However, when we compare the results of the two negative binomial models of column (4) and column (5) we see that there are hardly any differences between the two models.[4] Consequently, the differences between the OLS log linear fixed-effects estimator and the negative binomial model with a pre-sample mean estimator are not caused by the inclusion of the pre-sample fixed-effects, but due to the exclusion of the individual fixed-effects. There are only minor differences if we compare the results from the OLS log linear fixed-effects estimator (column 2) with the count data (Poisson) fixed-effects estimator (column 3); most importantly the 'foreign other stock' variable gets significant in the Poisson model. The signs of the coefficients are identical and even the relative size of the coefficients is quite similar independent of the applied model. Given these similar results and the fact that the coefficients in the OLS estimation can be interpreted as elasticities, we refer to the results in column (2) for what follows.

The 'internal green stock', 'country green stock', and 'foreign green stock' are significantly positive related with green patent activities. This indicates positive knowledge spillovers not only from the internal green knowledge stock but also from a green technology environment in the country and from the same industry in other countries. Consequently we cannot reject hypothesis 1; green knowledge does positively affect current green innovation activities. It is also remarkable that the marginal effect of the 'internal green' knowledge stock is significantly larger (more than twice) than the effect of 'country green' and 'foreign green' knowledge stocks, respectively.

[4] The impact of the pre-sample fixed effects is even smaller when we increase the pre-sample period to ten years.

Table 4 column (2) also shows that 'internal other stock' is positively related to future green patent activities, which is in line with the findings of Aghion et al. (2011). This indicates that positive spillovers resulting from an accumulated knowledge stock other than green outweighs the negative effect resulting from technological lock-in or great opportunity costs. However, the marginal effect of 'internal green stock' is nearly three times greater than the marginal effect resulting from 'internal other stock'. In contrast, our proxy for the 'country other stock' (significantly) and 'foreign other stock' (insignificantly) are negatively related to green patents. This indicates that a non-green technological environment hinders green patent activities of an industry. In this case the opportunity costs for investing in green activities are greater than possible positive spillovers (resource effect) resulting from technological know-how in other than green technological fields. Consequently, we cannot reject hypotheses 2; the marginal effect of green knowledge on current green innovation activities is larger than the marginal effect of traditional knowledge. The negative results for external knowledge is intuitively understandable if one considers the fact that the positive effect of internal knowledge in traditional technologies is moderate in our model, and that the positive spillover (resource) effects from internal knowledge are expected to be larger than the spillover effects from external knowledge (see, e.g., Keller 2002).

5.2 Robustness tests

We made comprehensive tests to proof the robustness of our main results presented in column (2) of Table 4.

Estimates for alternative regression periods

It cannot be fully excluded that the time window for estimating the initial stock might influence the regression results. In our main models (see Table 4) we have an initial stock period of five years, i.e. we calculate the stock values from 1980 onwards and estimate the models starting with the 1985 values of green patents (see Aghion et al. 2011 for a related procedure). Table A.3

provides a robustness test for the initial stock period. It turns out that the relative size of the coefficients and also the significance of the effects are robust if we increase the initial stock period. However, if we reduce the initial stock period (see Table A.3 column 1 and 2), the internal other stock variable gets insignificant. This result indicates that a longer initial stock period is required in order to distinguish the effects of 'internal green stock' from 'internal other stock'.

Alternative construction of the patent stock

In our main models (Table 4) we applied a depreciation rate of 15% in order to calculate knowledge stocks. Table A.4 (column 1 and 2) presents the results for alternative depreciation rates of 10% and 30%. The results are relatively independent of the chosen depreciation rate. The coefficients are similar and directions of the effects are identical. Only the effect of internal other stock gets insignificant if we reduce the depreciation rate to 10%.

Checking for outliers

Outliers may bias the results in OLS estimations. Consequently we run our estimation excluding the top 1% of performers and the top 5% of the performers, respectively. The results are presented in Table A.4 column 3 and 4. We can see that our main results are not driven by outliers; neither the direction nor the significance of the effects change considerably. The strongest reduction in coefficient we see for 'country green stock', if we skip the top 5%. However, 'country green stock' still remains significant.[5]

6 Conclusions

Based on industry-level panel data the paper at hand investigates the meaning of green knowledge stock and 'other than green' knowledge stock for the green patent applications of an

[5] Our main estimates presented in of Table 4 are based on 262 groups. To check for outliers we excluded all groups with an average clean or 'other than green' patent stock greater than or equal to the top 1% and 5% of the groups,

industry. The data allows us to distinguish between an industry's internal knowledge stock, the knowledge stock of a country, and the knowledge stock of the same industry in other countries. Applying different econometric models and a number of robustness tests show that an industry's internal green knowledge stock shows the largest positive elasticity. The elasticities of country green knowledge stock and the green knowledge stock of the same industry in other countries are also positively related with future green patent applications; however, their elasticities are significantly smaller. Turning to the effects of other than green knowledge stocks, we see a more ambiguous result. 'Internal other knowledge stock' is positively related with future green patent applications, although the elasticity is very moderate. 'Country other knowledge stock' and other than green knowledge stock of the same industry in other countries are negatively related with future green patent applications. These results emphasise the importance of the internal green knowledge base for green technological activities. Potential positive spillovers from other than green existing knowledge bases are moderate and clearly outweighed by negative opportunity cost effects. Consequently we cannot reject our two hypotheses. We see that green knowledge does positively affect current green innovation activities (H1) and that the marginal effect of green knowledge on current green innovation activities is larger than the marginal effect of traditional knowledge (H2).

These results indicate that early knowledge accumulation is likely to payoff in terms of patent applications or innovation performance. The marginal effect of internal green knowledge is much larger than the marginal effects of external green knowledge stocks. Consequently a wait-and-see position of an industry is likely to lead to a relatively moderate green innovation performance, since a lack of internal green knowledge stock can hardly be compensated by positive spillovers from other industries in the same country or the same industry in other countries. A free-riding

respectively. All in all we thus dropped three and 13 groups that account for 1.2% and 5.0% of the observations, respectively.

position on green technology investments of other industries or the same industry in other countries does not seem to be very promising.

Green technology activities on a country level are positively related with industry level green patent applications. Moreover we see a considerable negative effect of other than green knowledge stocks on a country level on industry's green patent applications. This result indicates considerable opportunity costs for green research activities. However, the opportunity costs could be lowered through country level policy measures to create a more green research friendly environment. This implies that research activities in green technologies become more attractive, since profit expectations would be improved. Furthermore, increasing green knowledge stocks on a country level would create positive spillovers for green patent applications on an industry level. Consequently, we would also perceive an indirect positive effect from improving the framework conditions on a country level. Given the moderate impact of foreign green stock on industry's green patent applications a free-riding position on a country level would be also questionable if green technology development has some priority.

Funding:

This paper was supported by the MTEC Foundation in Switzerland.

References

Acemoglu, D., Aghion, P., Busztyn, L., Hemous, D. (2012). The Environment and Directed Technological Change. *American Economic Review*, 102(1): 131–166

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*.

Allison, P. and Waterman, R.P. (2002). Fixed-effects negative binomial regression models. *Sociological Methodology*, 32(1): 247-265.

Audretsch, D.B. (1995). *Innovation and Industry Evolution*. Cambridge: MIT Press.

Audretsch, D.B. and Lehmann, E.E. (2005). Does the Knowledge Spillover Theory of Entrepreneurship Holds for Regions. *Research Policy*, 34(8): 1191-1202.

Beise, M. and Rennings, K. (2005). Lead markets and regulation: a framework for analyzing the international diffusion of environmental innovations. *Ecological Economics*, 52(1): 5-17.

Berkhout, F. (2002). Technological regimes, path dependency and the environment. *Global Environmental Change*, 12(1): 1–4.

Blundell, R., Griffith, R. and Van Reenen J. (1995). Dynamic Count Data Models of Technological Innovation. *The Economic Journal*, 105(March): 333-344.

Bottazzi, L. and Peri, G. (2003). Innovation and spillovers in regions: Evidence from European patent data. *European Economic Review*, 47(4): 687-710.

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*, 78(2): 419-423.

Coe, D.T. and Helpman, E. (1995). International R&D Spillovers. *European Economic Review*, 39(5): 859-887.

Cohen, W.M., Goto, A., Nagata, A., Nelson, R.R. and Walsh, J.P. (2002). R&D Spillovers, Patents and the Incentives to Innovate in Japan and the United States. *Research Policy*, 31(8-9): 1349-1367.

Crepon, B., Duguet, M. and Mairesse, J. (1998). Research, Innovation, and Productivity: an Econometric Analysis at the Firm Level. *Economics of Innovation and New Technology* 7(2): 115-158.

David, P. A. (1985). Clio and the Economics of QWERTY. *The American Economic Review*, 76: 332-337.

Dosi, G. (1984). Technical Chance and Industrial Transformation. The Macmillian Press Ltd. London.

Faber, A. and Frenken, K. (2009). Models in evolutionary economics and environmental policy: Towards an evolutionary environmental economics. *Technological Forecasting and Social Change*, 76(4): 462-470.

Geroski, P. (1995). *Markets for technology: Knowledge, innovation, and appropriability.* In Handbook of the economics of innovation and technological change, ed. Paul Stoneman, 90–131. Oxford: Blackwell Publishers.

Griliches, Z. (1990). Patent Statistics as Economic Indicators: A Survey. *Journal of Economic Literature*, 28(4): 1661-1707.

Griliches, Z. (1992). The Search for R&D Spillovers. *The Scandinavian Journal of Economics,* 94: 29-47.

Grossman, G.M. and Helpman, E. (1991). Trade, Knowledge Spillovers, and Growth. *European Economic Review*, 35(2-3): 517-526.

Hall, B.H. and Helmers, C. (2011). Innovation and Diffusion of Clean/Green Technology: Can Patent Commons Help?. *National Bureau of Economic Research Working Paper No. 16920*.

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

Jaffe, A.B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *American Economic Review*, 76(5): 984-1001.

Jaffe, A.B. (1989). Real effects of academic research. *American Economic Review*, 79(5): 957–970.

Jaffe, A.B., Trajtenberg, M. and Henderson, R. (1993). Geographic Localization of Knowledge Spillovers as Evidenced by Patent Citations. *Quarterly Journal of Economics*, 63(3): 577-98.

Jaffe, A.B. and Palmer, K. (1997), Environmental regulation and innovation: A panel data study, *Review of Economics and Statistics*, 79(4):610-519.

Jaffe, A.B., Trajtenberg, M. and Fogarty, M.S. (2000). Knowledge Spillovers and Patent Citations: Evidence from a Survey of Inventors. NBER/Sloan Project Report: Industrial Technology and Productivity: Incorporating Learning from Plant Visits and Interviews into Economic Research.

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

Malerba, F., Mancusi, M.L. and Montobbio, F. (2007). Innovation, International R&D Spillovers and the Sectoral Heterogeneity of Knowledge Flows. *CESPRI Working Paper No. 204*.

Mancusi, M.L. (2008). International Spillovers and Absorptive Capacity: A Cross-Country Cross-Sector Analysis Based on Patents and Citations. *Journal of International Economics*, 76(2): 155-165.

Moretti, E. (2004). Association Workers' Education, Spillovers, and Productivity: Evidence from Plant-Level Production Functions. *American Economic Review*, 94(3): 656-690

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*, 114(3): 941-975.

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

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

Pakes, A. and Griliches, Z. (1980). Patents and R&D at the Firm Level: A first Look. *Economic Letters*, 5(4): 377-381.

Perri, G. (2005). Determinants of Knowledge Flows and Their Effect on Innovation. *The Review of Economics and Statistics*, 87(2): 308-322.

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

Popp, D. (2006). International innovation and diffusion of air pollution control technologies: the effects of NO_x and SO_2 regulation in the U.S., Japan, and Germany. *Journal of Environmental Economics and Management*, 51(1): 46–71.

Popp, D., Newell, R.G. and Jaffe, A.B. (2009). Energy, the Environment, and Technological Change. *National Bureau of Economic Research Working Paper No. 14832*.

Popp, D., Hascic, I. and Medhi, N. (2011). Technology and the diffusion of renewable energy. *Energy Economics*, 33(4): 648-662.

Porter, M.E. and van der Linde, C. (1995). Green and Competitive: Breaking the Stalemate. *Harvard Business Review*, 73(5): 120-133.

Scherer, F.M. (1983). The Propensity to Patent. International Journal of Industrial Organization, 1(1): 107-128.

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

Shapiro, C. (2011). Competition and Innovation: Did Arrow Hit the Bull's Eye? Draft: 17 January 2011, NBER.

Soltmann, C., Stucki, T. and Woerter, M. (2012). The Productivity of Environmental Innovations. *Working paper*.

Stockes, R.G. (1994). Opting for Oil. The Political Economy of Technical Change in the West German Chemical Industry, 1945-61. Cambridge University Press. Cambridge.

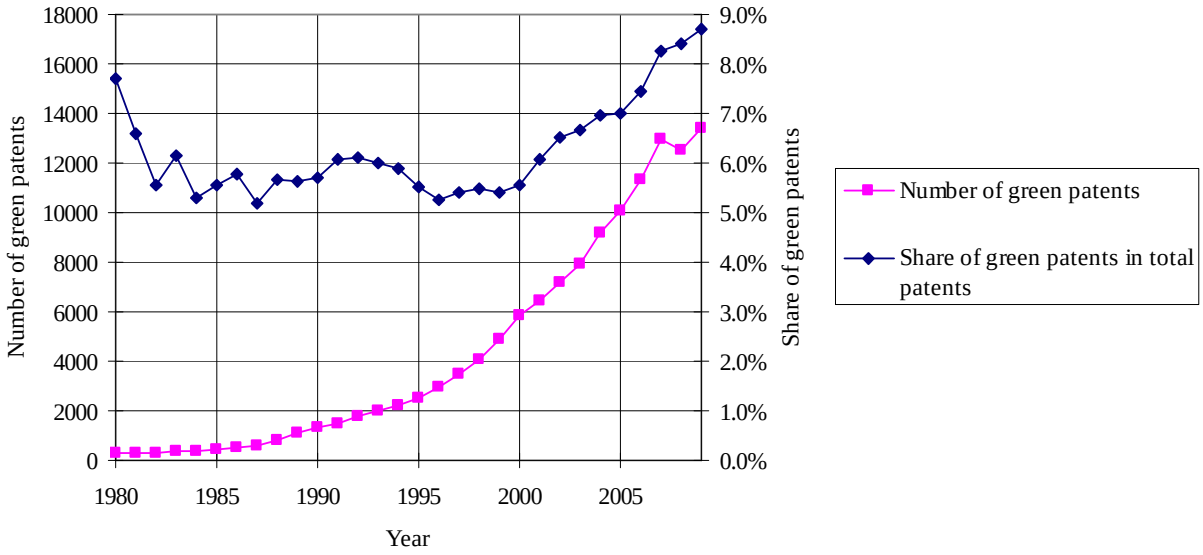
Utterback, J.M. (1996). Mastering the Dynamic of Innovation. Harvard Business School Press, Boston, Massachusetts.

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

Table 1: Expected direction of the knowledge effects by the different sources of knowledge

	Internal knowledge		Country knowledge		Foreign knowledge	
	Green	Traditional	Green	Traditional	Green	Traditional
Resource effect:	+	+	+	+	+	+
Opportunity cost effect:	+	-	+	-	+	-
Net effect:	+	~	+	~	+	~

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 2: 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	37'991	1'674	0.65%	4.4%
Tobacco products	2'336	69	0.03%	3.0%
Textiles	16'147	1'073	0.42%	6.6%
Wearing apparel	5'751	75	0.03%	1.3%
Leather articles	3'682	19	0.01%	0.5%
Wood products	4'607	257	0.10%	5.6%
Paper	21'521	1'402	0.54%	6.5%
Petroleum products, nuclear fuel	17'082	3'539	1.37%	20.7%
Rubber and plastics products	102'379	6'518	2.53%	6.4%
Non-metallic mineral products	82'249	8'998	3.49%	10.9%
Basic metals	42'518	6'906	2.68%	16.2%
Fabricated metal products	62'002	8'120	3.15%	13.1%
Machinery	422'498	61'860	23.97%	14.6%
Office machinery and computers	272'259	5'286	2.05%	1.9%
Electrical machinery and apparatus	96'680	28'546	11.06%	29.5%
Radio, television and communication equipment	417'488	23'782	9.22%	5.7%
Medical, precision and optical instruments	467'133	14'950	5.79%	3.2%
Motor vehicles	91'038	29'949	11.61%	32.9%
Other transport equipment	25'800	2'502	0.97%	9.7%
Furniture, consumer goods	47'429	567	0.22%	1.2%
Chemicals (excluding pharmaceuticals)	301'877	46'550	18.04%	15.4%
Pharmaceuticals	324'108	5'391	2.09%	1.7%
Country				
Austria	30'593	3'311	1.28%	10.8%
Switzerland	93'498	5'720	2.22%	6.1%
Germany	414'160	49'795	19.30%	12.0%
Denmark	30'970	3'825	1.48%	12.4%
Finland	43'313	3'004	1.16%	6.9%
France	167'953	14'723	5.71%	8.8%
United Kingdom	194'920	14'829	5.75%	7.6%
Ireland	10'929	693	0.27%	6.3%
Italy	58'198	4'314	1.67%	7.4%
Japan	490'415	59'595	23.10%	12.2%
Netherlands	116'486	9'306	3.61%	8.0%
Sweden	93'741	6'397	2.48%	6.8%
United States	1'119'399	82'521	31.98%	7.4%

Notes: These statistics are based on 30 cross-sections, 13 countries and 22 industries (total of 8580 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 3: Variable definition and measurement

Variable	Definition/measurement	Source
Dependent variable		
$Green\_patents_{ijt}$	Number of green patents	own calculations
Independent variable		
L_{ijt}	Number of persons engaged (total employment)	OECD STAN
K_{ijt}	Gross fixed capital formation, volumes (current price value)	OECD STAN
$Internal\_green\_stock_{ijt}$	Stock of green patents in industry *i* in country *j*	own calculations
$Country\_green\_stock_{ijt}$	Stock of green patents in industries other than *i* in the home country *j*	own calculations
$Foreign\_green\_stock_{ijt}$	Stock of green patents accumulated in industry *i* in countries other than *j*	own calculations
$Internal\_other\_stock_{ijt}$	Stock of patents that are not classified as green in industry *i* in country *j*	own calculations
$Country\_other\_stock_{ijt}$	Stock of patents that are not classified as green in industries other than *i* in the home country *j*	own calculations
$Foreign\_other\_stock_{ijt}$	Stock of patents that are not classified as green accumulated in industry *i* in countries other than *j*	own calculations

Table 4: Estimation results

	(1)	(2)	(3)	(4)	(5)
Dependent variable	$\ln(\text{Green\_patents})_{ijt}$	$\ln(\text{Green\_patents})_{ijt}$	$\text{Green\_patents}_{ijt}$	$\text{Green\_patents}_{ijt}$	$\text{Green\_patents}_{ijt}$
Estimation method	OLS log linear fixed-effects regression	OLS log linear fixed-effects regression	Fixed-effects Poisson regression	Negative Binomial pre-sample mean estimator	Negative Binomial regression
Period	1986-2009	1986-2009	1986-2009	1986-2009	1986-2009
$\ln(L)_{ijt-1}$	.17865***	.12403**	.31257***	.06947***	.06648***
	(.0653)	(.05176)	(.09491)	(.01942)	(.02004)
$\ln(K)_{ijt-1}$	.03076				
	(.02231)				
$\ln(\text{Internal\_green\_stock})_{ijt-1}$	.4116***	.58207***	.62047***	.75159***	.73738***
	(.04558)	(.02889)	(.07983)	(.03151)	(.03023)
$\ln(\text{Country\_green\_stock})_{ijt-1}$	.1122	.24049***	.39299***	.10258	.11629
	(.10672)	(.07774)	(.13661)	(.08427)	(.08308)
$\ln(\text{Foreign\_green\_stock})_{ijt-1}$	.35862***	.19496***	.38123**	.2085***	.22025***
	(.07204)	(.04611)	(.15775)	(.07927)	(.07856)
$\ln(\text{Internal\_other\_stock})_{ijt-1}$	.0863	.07367*	.26311**	.16557***	.15139***
	(.06033)	(.03891)	(.11866)	(.03724)	(.03375)
$\ln(\text{Country\_other\_stock})_{ijt-1}$	.09922	-.42895***	-.39683*	-.05453	-.03807
	(.15064)	(.0986)	(.22064)	(.12932)	(.12933)
$\ln(\text{Foreign\_other\_stock})_{ijt-1}$	-.02646	-.06231	-.47793***	-.21378**	-.1912**
	(.12657)	(.09281)	(.17856)	(.09337)	(.09196)
Constant	-5.0206***	-.10172		-2.0347**	-2.2145***
	(1.3699)	(.95507)		(.83271)	(.81713)
Year fixed effects	yes	yes	yes	yes	yes
Country specific industry fixed effects	yes	yes	yes	no	no
Country fixed effects	no	no	no	yes	yes
Industry fixed effects	no	no	no	yes	yes
Pre-sample fixed effects	no	no	no	yes	no
N	2926	5853	5527	5853	5853
Groups	166	262	247	262	262
F	44.97***	96.41***			
Wald chi^2			31891.02***	93601.19***	83584.20***
R^2 within	0.55	0.65			
Rho	0.66	0.52			
F test of rho=0	7.65***	7.53***			
Hausman chi^2	100.57***	120.75***			
LogLikelihood			-15161.07	-13864.70	-13873.28
Over-dispersion (alpha)				0.07***	0.07***

Notes: see Table 3 for the variable definitions; Columns (1), (2), (4) and (5): standard errors that are robust to heteroskedasticity and clustered at the industry-country level (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; Column (3): In line with Allison and Waterman (2002) we used robust standard errors to correct for overdispersion; Column (4): Pre-sample mean scaling approach proposed by Blundell et al. (1995) was used to account for fixed unobserved heterogeneity in the propensity to patent in the presence of lagged endogenous variables. Likelihood ratio test that alpha equals zero is based on estimates without robust standard errors.

APPENDIX

Table A.1: Correlation matrix (based on model (2) of Table 4; 5853 observations)

	$\ln(\text{Green\_patents})_{ijt}$	$\ln(L)_{ijt-1}$	$\ln(\text{Internal\_green\_stock})_{ijt-1}$	$\ln(\text{Country\_green\_stock})_{ijt-1}$	$\ln(\text{Foreign\_green\_stock})_{ijt-1}$	$\ln(\text{Internal\_other\_stock})_{ijt-1}$	$\ln(\text{Country\_other\_stock})_{ijt-1}$
$\ln(L)_{ijt-1}$	0.54						
$\ln(\text{Internal\_green\_stock})_{ijt-1}$	0.94	0.54					
$\ln(\text{Country\_green\_stock})_{ijt-1}$	0.55	0.43	0.60				
$\ln(\text{Foreign\_green\_stock})_{ijt-1}$	0.70	0.21	0.77	0.21			
$\ln(\text{Internal\_other\_stock})_{ijt-1}$	0.83	0.56	0.89	0.70	0.69		
$\ln(\text{Country\_other\_stock})_{ijt-1}$	0.56	0.45	0.61	0.99	0.23	0.70	
$\ln(\text{Foreign\_other\_stock})_{ijt-1}$	0.62	0.15	0.68	0.26	0.90	0.76	0.27

Table A.2: Descriptive statistics (based on model (2) of Table 4; 5853 observations)

Variable	Mean	Std. Dev.	Min	Max
Dependent variable				
$\ln(\text{Green\_patents})_{ijt}$	1.85	1.75	0	7.50
Independent variable				
$\ln(L)_{ijt-1}$	10.78	1.80	4.61	14.40
$\ln(\text{Internal\_green\_stock})_{ijt-1}$	2.79	2.09	0	9.05
$\ln(\text{Country\_green\_stock})_{ijt-1}$	6.70	1.81	0.48	10.48
$\ln(\text{Foreign\_green\_stock})_{ijt-1}$	5.75	2.28	0	10.24
$\ln(\text{Internal\_other\_stock})_{ijt-1}$	5.21	2.25	0	11.36
$\ln(\text{Country\_other\_stock})_{ijt-1}$	9.15	1.78	3.02	13.03
$\ln(\text{Foreign\_other\_stock})_{ijt-1}$	8.53	1.85	2.90	12.19

Table A.3: Estimates of model (2) of Table 4 for alternative time windows

	(1)	(2)	(3)	(4)	(5)	(6)
Dependent variable	$\ln(\text{Green\_patents})_{ijt}$	$\ln(\text{Green\_patents})_{ijt}$	$\ln(\text{Green\_patents})_{ijt}$	$\ln(\text{Green\_patents})_{ijt}$	$\ln(\text{Green\_patents})_{ijt}$	$\ln(\text{Green\_patents})_{ijt}$
Estimation method	OLS log linear fixed-effects regression	OLS log linear fixed-effects regression	OLS log linear fixed-effects regression	OLS log linear fixed-effects regression	OLS log linear fixed-effects regression	OLS log linear fixed-effects regression
Period	1984-2009	1985-2009	1986-2009	1988-2009	1989-2009	1990-2009
$\ln(L)_{ijt-1}$	.13685***	.12556**	.12403**	.13218**	.13633**	.13498**
	(.05009)	(.0502)	(.05176)	(.05393)	(.0566)	(.05947)
$\ln(\text{Internal\_green\_stock})_{ijt-1}$	.60626***	.59486***	.58207***	.54591***	.52525***	.46676***
	(.02724)	(.02804)	(.02889)	(.03073)	(.03219)	(.03492)
$\ln(\text{Country\_green\_stock})_{ijt-1}$	.2047***	.22877***	.24049***	.24264***	.21497***	.19928**
	(.07527)	(.07723)	(.07774)	(.07611)	(.07755)	(.07694)
$\ln(\text{Foreign\_green\_stock})_{ijt-1}$	.16316***	.18653***	.19496***	.2071***	.20982***	.22804***
	(.04179)	(.04357)	(.04611)	(.04993)	(.05226)	(.05473)
$\ln(\text{Internal\_other\_stock})_{ijt-1}$	.04897	.05634	.07367*	.08996**	.10999**	.13574***
	(.03483)	(.03676)	(.03891)	(.04411)	(.04609)	(.05191)
$\ln(\text{Country\_other\_stock})_{ijt-1}$	-.39006***	-.41406***	-.42895***	-.40194***	-.37121***	-.27681**
	(.09294)	(.09638)	(.0986)	(.09824)	(.10547)	(.11301)
$\ln(\text{Foreign\_other\_stock})_{ijt-1}$	-.02489	-.04458	-.06231	-.07938	-.07992	-.06302
	(.08469)	(.08843)	(.09281)	(.1079)	(.11614)	(.13456)
Constant	-.45043	-.14137	-.10172	-.20787	-.37225	-1.1219
	(.86759)	(.90322)	(.95507)	(1.057)	(1.1658)	(1.3862)
Year fixed effects	yes	yes	yes	yes	yes	yes
Country specific industry fixed effects	yes	yes	yes	yes	yes	yes
N	6239	6046	5853	5458	5247	4825
Groups	262	262	262	262	262	262
F	99.02***	99.57***	96.41***	84.17***	82.09***	66.95***
R^2 within	0.68	0.66	0.65	0.61	0.59	0.53
Rho	0.49	0.51	0.52	0.52	0.53	0.53

Notes: see Table 3 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; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively.

Table A.4: Alternative estimates of model (2) of Table 4

	(1)	(2)	(3)	(4)
Dependent variable	$\ln(\text{Green\_patents})_{ijt}$	$\ln(\text{Green\_patents})_{ijt}$	$\ln(\text{Green\_patents})_{ijt}$	$\ln(\text{Green\_patents})_{ijt}$
Estimation method	OLS log linear fixed-effects regression	OLS log linear fixed-effects regression	OLS log linear fixed-effects regression	OLS log linear fixed-effects regression
Period	1986-2009	1986-2009	1986-2009	1986-2009
Robustness test	Depreciation rate=10%	Depreciation rate=30%	Checking for outliers: drop top 1%	Checking for outliers: drop top 5%
$\ln(L)_{ijt-1}$	.12852**	.11318**	.12432**	.12652**
	(.05625)	(.04476)	(.0517)	(.05052)
$\ln(\text{Internal\_green\_stock})_{ijt-1}$	.5793***	.57424***	.57579***	.54868***
	(.03135)	(.02625)	(.02916)	(.02865)
$\ln(\text{Country\_green\_stock})_{ijt-1}$	.22144**	.20371***	.22895***	.14213*
	(.09397)	(.05361)	(.07805)	(.0734)
$\ln(\text{Foreign\_green\_stock})_{ijt-1}$	.21977***	.15393***	.19869***	.18423***
	(.0555)	(.03458)	(.04619)	(.04627)
$\ln(\text{Internal\_other\_stock})_{ijt-1}$	.06041	.09688***	.07516*	.08664**
	(.04422)	(.03049)	(.03909)	(.03859)
$\ln(\text{Country\_other\_stock})_{ijt-1}$	-.42871***	-.32017***	-.41746***	-.31909***
	(.12584)	(.06128)	(.09916)	(.09446)
$\ln(\text{Foreign\_other\_stock})_{ijt-1}$	-.04541	-.05894	-.04977	-.05404
	(.10001)	(.08008)	(.09388)	(.09705)
Constant	-.28851	-.36834	-.22981	-.46072
	(1.0974)	(.78155)	(.95283)	(.95298)
Year fixed effects	yes	yes	yes	yes
Country specific industry fixed effects	yes	yes	yes	yes
N	5853	5853	5781	5560
Groups	262	262	259	249
F	39.06***	132.51***	92.81***	81.99***
R^2 within	0.54	0.67	0.65	0.62
Rho	0.57	0.41	0.52	0.48

Notes: see Table 3 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; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively.