The Impact of Energy Prices on Environmental Innovation

Marius Ley*, Tobias Stucki**, Martin Woerter***

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Abstract. Based on patent data and industry specific energy prices for 18 OECD countries over 30 years we investigate on an industry level the impact of energy prices on green innovation activities. Our econometric models show that energy prices and green innovation activities are positively related and that energy prices have a significantly positive impact on the share of green innovations in non-green innovations. More concretely, our main model shows that a 10% increase of the average energy prices of the previous five years results in a 2.7% and 4.5% increase of the number of green patents and the share of green patents on non-green patents, respectively. We also find that the impact of energy prices increases with an increasing lag between energy prices and innovation activities. Robustness tests confirm the main results.

Keywords: Innovation; patents; environment; technological change; energy prices.

JEL classification: O30; O34; Q55.

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* ETH Zurich, KOF Swiss Economic Institute, CH-8092 Zurich, Phone: +41 44 632 60 08, email: ley@kof.ethz.ch

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

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

1 Introduction

Despite the fact that climate change should ideally increase the demand for green technologies, firms have still 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. In line with this literature a study by Soltmann et al. (2012) shows that economic performance is negatively affected by green inventions. This result indicates that – given the current level of green promotion – free market incentives alone are not sufficient to allow the green invention activities of industries to rise considerably. However, technological innovations are needed to solve environmental problems. "Without significant technological development of both existing low-carbon technologies and new ones, climate change is unlikely to be limited to anything like 2ºC" (see Helm 2012, p. 213). Accordingly, a kind of intervention is required to stimulate green innovation activities.

The paper at hand focuses on energy prices as a measure for environmental policy and investigates if energy prices are likely to contribute to increase the probability of 'clean' innovations. More concretely, we investigate if the effects of energy prices are different for 'clean' innovations than for 'other than clean' innovations.

Empirical research linking environmental policy and innovation is related to a small but increasing literature. A first group of studies uses pollution abatement control expenditures (PACE) to proxy for environmental regulation stringency. Brunnermeier and Cohen (2003) found for the US that PACE is positively related to environmental innovation. Based on a data set that includes 17 countries Lanjouw and Mody (1996) also found a positive correlation between PACE and environmental innovation. However, the use of PACE as a measure for policy stringency in a cross-country study is questionable due to the heterogeneity in the definitions and sampling strategies (see Johnstone et al. 2012, p. 2161). To overcome this problem Johnstone et al. (2012) used survey data. Based on this data they again found that environmental innovation is positively affected by environmental policy stringency.

Most other studies overcome the problem of comparability by using energy prices as proxy for environmental regulation. Most of them focus on a single industry. Aghion et al. (2012) investigated the significance of energy prices for technological change by looking at the car industry based on patent data over a long period in time (1978 - 2007). They found that higher energy prices increase the propensity of 'clean' innovation in the car industry. Moreover they stated that the price effect is stronger for firms with a great stock of 'dirty' patents. Newell et al. (1999) looked at the level of product characteristics in the air-conditioning industry and found that energy prices had an observable effect on energetic features of the products offered for sale. Lanzi and Sue Wing (2011) found a positive relationship between energy prices and innovations in renewable technologies in the energy sector of 23 countries.

Popp (2002) did not focus on a single industry but a single country. He looked for the USA at 11 different technologies including supply (e.g. solar energy, fuel cells) and demand technologies (e.g. recovery of waste heat for energy, heat pumps) and found that energy prices and the existing knowledge stock have a strong and significant positive effect on innovation.

In all these studies it is unclear whether the results also hold for other industries and/or countries. Only a few studies are based on data for more than one country and more than one industry. Johnstone et al. (2010) analyzed for five different renewable energy technologies how different policies (among others energy prices) did affect innovation on a certain technology. Verdolini and Galeotti (2011) investigated the impact of energy prices on technological innovation (12 technologies like in Popp 2002) for a panel of 17 countries and found a positive sign. However, as both studies are based on data that is either aggregated on country-level or technology-level, there is a concern that there may be other macro-economic shocks correlated with both innovation and the energy price (see Aghion et al. 2012, p.5).

In the study at hand we extend the existing literature in many respects. Firstly, we use energy prices as a proxy for environmental regulation. This allows us to generate an industry-level data set that covers the whole manufacturing sector (grouped into 10 industries), the most important countries for green invention (18 OECD countries that are responsible for more than 95% of all green patents and total patents worldwide) and this over a period of 30 years. Secondly, 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. By using the Schmoch et al. (2003) concordance scheme we switch from the technology level to the industry level. This allows us to include control variables on the aggregation level of an industry (e.g., capital and number of employees). Furthermore, we reduce the potential problem of an omitted variable bias by controlling for industry/country specific fixed effects. Thirdly, we calculate industry specific energy prices what allows us to include country specific time fixed-effects. Compared with previous studies on a more aggregated level (e.g. country level) there is no concern that there could be macro-economic shocks correlated with both innovation and the energy prices that bias our results (see Aghion et al. 2012, p.5).

With respect to our main variable we find that energy prices do stimulate both the intensity of green innovation as well as the propensity of green innovation. In our model, a 10% increase of the average energy prices of the previous five years results in a 2.7% and 4.5% increase of the number of green patents and the share of green patents on other patents, respectively. Knowledge about potential political instruments to stimulate innovation in this area is of large importance. As our study shows, energy prices may serve as such an instrument. An increase in energy prices may stimulate the building of a green knowledge stock that (a) would help to achieve a country's climate targets and (b) may serve as an important fundament to establish an industry in the cleantech market for which long-term growth is predicted.

2 Conceptual Background and Hypotheses

The idea that an increase in the relative price of a production factor will direct innovation efforts towards technologies that are less intensive in the production factor becoming more expensive can be attributed to Hicks (1932): "A change in the relative prices of the factors of production is itself a spur to invention, and to invention of a particular kind—directed to economising the use of a factor which has become relatively expensive."

This intuitively appealing assertion has been known as the induced innovation hypothesis. Subsequent research attempted to provide microeconomic foundations for this claim and to assess its relevance for traditional welfare economics (Binswanger et al., 1978, ch. 4). Induced innovation is generally thought to exacerbate the effects of externalities not properly taken into account. In particular, the exploitation of fossil fuels has undesirable side effects as CO_2 emissions negatively affect global climate. Two harmful mechanisms are at work as a result of not having adequately priced these energy resources (by failing to take into consideration their negative externalities, e.g. by charging a CO_2 tax): price signals not only affect entrepreneurs' choice of input combinations, given the production techniques currently available; but they also affect their choice of which production technologies to develop for future use.

Taking the opposite perspective, it can be argued that taking into account induced innovation renders market-based policies to tackle climate change more efficient (or, more precisely, less costly). This is because such policies not only motivate profit-seeking firms to switch to less energy-demanding technologies that are available as of today, but these policies will induce firms to strengthen their efforts to develop such technologies for the future (see, e.g., Carraro and Siniscalco (1994) for a consideration of this point).

Porter and van der Linde (1995) even go as far as claiming that well-designed environmental regulation may bring about a net benefit to firms subject to such regulation. According to their argument, technological advances in process and product design triggered by such regulation often result not only in a decrease of harmful emissions (or of other undesirable ecological consequences), but also in new modes of production which are altogether more efficient, bringing about competitive gains that offset the initial private costs of complying with environmental policy. A controversial debate has subsequently been triggered about the general validity of their claims, which became to be known under the name of the Porter hypothesis. While we do not provide an empirical test for it in the present study, it should be noted that the Porter hypothesis implicitly relies on the induced innovation hypothesis. Thus, finding support for induced innovation can be regarded as a necessary but not sufficient condition for validating the claims made by Porter and van der Linde.

We therefore formulate the two following hypothesis to be tested empirically:

H1: Energy prices are positively related to the number of 'clean' innovations (i.e., the intensity to patent in green technologies).

H2: Energy prices are positively related to the number of green patents relative to other patents (i.e., the propensity to patent 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. 2012), 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 output of an industry, further specifications and clarifications have to be made:

a) In order to assign patents to countries, the applicant’s country of residence or the inventor’s country of residence may be chosen. We assigned patents according to the applicant’s address. Since only those inventions were selected for which at least one PCT (Patent Cooperation

Treaty) application was filed, the applicant's address was generally available.[1] Patent applications are costly. Hence, it is very plausible that countries for which patent applications were filed are also target markets of the invention. Accordingly, there should be a direct link between these countries and the expected market performance.

b) We used PATSTAT patent data in order to collect inventions (patent families). We did not look at single patents. Patents were grouped into patent families instead according to the PATSTAT 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. Schmoch et al. (2003) developed a concordance scheme that links technology fields of the patent statistics to industry classes.[2] On the basis of this concordance table we thus recoded our patent data into 10 manufacturing industry classes either at the NACE two or three-digit level for which also energy price data were available.[3] In comparison with

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[1] We may also have used the inventor's address instead. However, there may be a risk of distorting the analysis, especially for smaller countries, because the inventor may not live in the country where the invention occurs. Conversely, by using the applicant's address the analysis may be biased by patent applications from multinationals for which the country of residence of the applicant possibly differs from the country where the invention occurred. In order to investigate if there are considerable differences, we took both the inventor's information and the applicant's information for Germany. In fact, we did not see any significant differences between the analysis based on the inventor's and applicant's address for that country.

[2] Lybbert and Zolas (2012), suggest new methods for constructing concordances. In comparing different concordance, they confirmed that on a relatively coarse level (e.g., 2 digit), the Schmoch et al. (2003) concordance enable a useful empirical policy analysis.

[3] The concordance scheme is based on patent classification and also the OECD Indicator of Environmental Technologies (see OECD 2012) is based on the patent classification, hence, we can easily distinguish green from non-green patents on the industry level. This way we can identify for each industry class the total number of green and non-green patents.

patent data at the firm level, aggregating patents[4] on an industry level should reduce potential problems with patent waves within a firm.

e) Our data set includes patent data from 18 countries (Australia, Austria, Belgium, Canada, Denmark, Finland, France, Germany, Ireland, Italy, Japan, Korea, the Netherlands, Spain, Sweden, Switzerland, the United Kingdom and the United States). These 18 countries account for more than 95% of all green inventions as well as all other inventions worldwide. The data set includes 10 industries that capture the whole manufacturing sector (chemicals; food and tobacco; machinery; basic metals; non-metallic minerals; paper, pulp and print; textile and leather; transport equipment; wood and wood products; non-specified industry). The patent data is available from 1975 onwards.[5]

Figure 1 shows the aggregated development of green inventions over time. In 1975, the beginning of our sample period, only a few green inventions were registered. The number of green inventions remained very low during the following ten 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, 29’444 green inventions were protected worldwide. Due to generally low patent activity, the share of green inventions was quite instable in the beginning of our sample period. In a second stage, the share stabilized between 6-8%. A disproportional increase of green inventions can be observed after 2000. By 2009, the relative importance of green inventions compared with other inventions had increased to 11.6%.

Detailed descriptive statistics for our disaggregated patent data is presented in Table 1. Nearly half of all green inventions are patented in the ‘machinery’ sector (49%). Furthermore, a considerable share is patented in the two industries ‘chemicals’ (24%) and ‘transport equipment’

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

[5] Actually the EPO (European Patent Office) was created in 1977/78. However, patent data are already available from 1975 onwards. The reason is that we use PCT applications, which can contain patents that are filed before 1977. Hence PCT applications can be found in PATSTAT before EPO was created.

(16%). The industry ‘transport equipment’ (35%) is at the same time the most green-intensive industry, followed by the two industries ‘basic metals’ (14%) and ‘non-metallic minerals’ (11%).

Among the eighteen countries that are in our sample, the United States (29%), Japan (21%) and Germany (18%) have the highest number of green inventions. Japan (12%) and Germany (11%) have also high shares of green inventions. In addition, Denmark and Canada (both 11%) can also be found among the countries with the highest share of green inventions.

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 labour input (total employment) and the capital stock (gross fixed capital formation, volumes at current prices) of industries relevant for our estimations.

3.3 IEA energy data

To analyse the impact of energy prices on innovation, we use information on energy prices available from the International Energy Agency’s (IEA) Energy Prices and Taxes Statistics (IEA 2012a) for all 18 countries that are included in our sample. The price information is available for different energy products on a country level from 1978 onwards. To get internationally comparable information, we use total end-use prices (per toe[6] including taxes) for the manufacturing sector in USD (PPP). This information is available for different energy products, such as electricity, light fuel oil,[7] natural gas and different coal products. Descriptive information on energy prices by country and year can be found in Figures 2 and 3, respectively.

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[6] Tonne of oil equivalent; unit of energy for the practical expression of energy quantities (e.g., 1 MWh = 0.086 toe).
[7] The IEA does also collect price information for other oil products, such as motor gasoline. However, as the number of observations is very low for these variables, we could not use this price information to construct our industry specific energy price. Our energy price should nevertheless be representative, as the energy products that could be taken into account (electricity, light fuel oil, natural gas and different coal products) make up more than 70% of total energy consumption (on average over all industries and the whole time period; see Figure 4). This figure is quite impressive, as the remaining 30% do not only include motor gasoline, but also the consumption of energy products for which no price information is collected, such as energy from biogases or heat.

Besides the energy prices, the IEA collects data on consumption of the different energy products (in ktoe) on the industry level. This information is available for 10 different industries of the manufacturing sector and comes from the IEA World Energy Statistics and Balances (IEA 2012b). This allows us to calculate the relative importance of a certain energy product compared with other products on the industry level. Information on the aggregated importance of the different energy products and the relative importance by industry is presented in Figures 4 and 5, respectively.

To get industry specific energy prices, we finally multiply the energy prices with the relative importance within the industry. The industry specific energy price, is formulated as follows:

$$energy\_price_{ijt} = \sum_{i=1}^{s} w\_E_{ijt} * \ln(electricity\_price)_{its}$$

where;

$$w\_E_{ijt} = \frac{s}{\sum_{i=1}^{s} electricity\_use_{ijt}}$$

and

$$s \in [electricity, light\ fuel\ oil, natural\ gas, steam\ coal, coking\ coal]$$

The information on energy consumption as well as on energy prices is available for electricity, light fuel oil, natural gas, steam coal, and cooking coal. However, due to missing values for some of the price variables, the prices used in our main model are based on the three products, i.e. electricity, LFO and natural gas. Besides the fact that there are fewer missing values for these three products than for the other products, these are also the three products that show the largest relative importance in our sample (see Figure 4). However, we test the sensitivity of our results to prices that are based on other baskets of energy products as well (see Table A.7).

3.4 Combining the data

As only very few patent counts could be registered in the years before 1980, we restrict the patent sample used for regression analysis to the years 1980-2009. Accordingly, the final data set includes 18 countries, 10 industry classes and a period of 30 years. This yields a data set of 5400 observations. Because of missing values for the other model variables, the number of observations that could be used for econometric estimations is significantly lower.

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. Hence, we follow the framework of a knowledge production function as it was formulated by Griliches (1979) and implemented in form of a modified Cobb-Douglas model by Jaffe (1986, 1989). Similar to Jaffe (1989) we look at patents as the outcome variable but we differ in two respects, first we investigate the industry level and secondly we can distinguish between different types of knowledge inputs. We formulate the following knowledge production function for an industry *j*, in country *i* at time *t*:[8]

$$Green\_patents_{ijt} = AL^{\alpha}_{ijt}K^{\beta}_{ijt}, \tag{1}$$

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

[8] Other functional forms, like e.g., a translog function, would require more detailed data to describe the production process (see Griliches 1979).

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 (3) in logarithms yields

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

Besides the standard input factors, the current flow of green patents should also be affected by an industry's stock of knowledge. To capture this effect we augment our specification with a variable that measures an industry's stock in green patents (*Green_stock*).[9] Following Cockburn and Griliches (1988) and Aghion et al. (2012), the patent stock is calculated using the perpetual inventory method. Following this method, the stock is defined as

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

where δ is the depreciation rate of R&D capital.[10] According to most of the literature, we take δ to be equal to 15% (see Keller 2002, Hall et al. 2005). However, we test the sensitivity of our results to other depreciation rates as well (see Table A.8). To capture potential effects of available knowledge in other than green 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. In line with previous literature (see, e.g., Aghion et al. 2012, Stucki and Woerter 2012) we expect that both green specific knowledge and other than green (henceforth: "traditional") knowledge do stimulate current green innovation activities.

Finally, to test the impact of energy prices, a variable that measures the industry specific energy prices (*Energy_price*) is included in this innovation model. The augmented specification is given by:

[9] Popp (2002) finds empirical evidence that failing to properly take into account measures for existing knowledge stocks may severely bias estimates of the innovation inducing effect of energy prices.

[10] Due to the low number of patents before 1980, we restricted our sample period to the years 1980-2009. However, patent applications before 1980 were used to calculate the patent stocks. The initial value of the patent stock is set at $Green\_stock_{1975}/(\delta+g)$, where *g* is the pre-1975 growth in patent stock that is assumed to be 15%.

$$\ln(Green\_patents)_{ijt} = \ln(A) + \alpha \ln(L)_{ijt-1} + \beta \ln(K)_{ijt-1} + \varphi \ln(Green\_stock)_{ijt-1}$$
$$+ \lambda \ln(Other\_stock)_{ijt-1} + \phi \ln(Energy\_price)_{ijt-1} + \mu_{it} + \eta_{ij} + \varepsilon_{ijt}, \quad (4)$$

where φ and λ are the coefficients of knowledge stocks, ϕ is the coefficient of energy prices and ε is the stochastic error term. As patent variables may contain a value of zero, 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 test the robustness of the price effect we use different dynamic specifications for energy prices, i.e. we use alternative lags (2-5 year lag), we construct a weighted average of past prices as proposed by Popp (2002)[11] and we calculate a moving average of the energy prices of the previous five years.

To control for correlated unobserved heterogeneity, we include country specific industry fixed effects (η). Furthermore, to reduce the risk of an omitted variable bias from country specific shocks, we include country specific time fixed effects (μ). As stated in Aghion et al. (2012), the increase of energy prices, e.g., might be correlated with country specific subsidies for green innovation. Accordingly, the effect of energy prices may represent an indirect effect of subsidies on green innovation, and not a direct effect of prices as suggested above. The fixed effect μ captures such country specific shocks.

As we are not just interested in the effect of energy prices on the total number of green patents (i.e., the intensity of green patent activities; see H1), but also in the effect on the development of the number of green patents relative to other patents (i.e., the propensity to patent in green technologies; see H2), we alternatively estimate our innovation model with a different dependent

[11] As in Popp (2002), this energy price is based on an adaptive expectation model, in which expected future energy prices are a weighted average of past prices: $P_{ijt} = \sum_{k=0}^{n} \psi^k P_{ijt-k}$, where ψ, the adjustment coefficient that represents the weights placed on past observations, is 0.83, and k takes the values 1 to n, while n represents the period under investigation (see Aghion et al. 2012 for a similar procedure).

variable that measures the difference between the logarithms of the number of green patents and other patents (share of green patents on other patents). Our second model thus reads as follows:

$$\begin{aligned}\ln(Green\_patents)_{ijt} - \ln(Other\_patents)_{ijt} &= \ln(A) + \alpha \ln(L)_{ijt-1} + \beta \ln(K)_{ijt-1} \\ &+ \varphi \ln(Green\_stock)_{ijt-1} + \lambda \ln(Other\_stock)_{ijt-1} + \phi \ln(Energy\_price)_{ijt-1} \\ &+ \mu_{it} + \eta_{ij} + \varepsilon_{ijt}.\end{aligned} \tag{5}$$

5 Estimation Results

5.1 Main results

The main results are presented in Tables 3 and 4. Table 3 shows OLS log linear fixed-effects estimations for the number of green patents.[12] The columns with uneven numbers show the results of the full model as specified in equation 6 for different dynamic specifications of the price variable. The columns with even numbers show the results for the same estimations without capital control (reduced model), which significantly increases the number of observations. To test whether this modification does lead to an omitted variable bias, Table A.3 shows the results for the reduced models based on the same observations that are available in the full model. As the results for the energy price variable do only marginally differ between these two models, we conclude that at least the result for the energy price should not be affected by an omitted variable bias in the reduced models. Table 4 shows the results for the model with the log share of green patents as dependent variable, as specified in equation 7.

On the whole, the results for the control variables are in line with general expectations. Labour input (L) and physical capital (K) tend to be positively correlated with the number of green patents. However, we cannot observe a significant effect for these two variables with respect to the share of green patents. The propensity to patent in green technologies is neither affected by labour input nor by physical capital input. As expected a larger stock of green knowledge does stimulate current activities in green innovation. Furthermore, we find in Table 3 that knowledge

[12] Our dependent variable is the natural logarithm of the number of green patents and the number of green patents is a count variable. Accordingly, robustness tests using count data models are appropriate. Such alternative estimates are presented in Table A.9.

in other than green technologies serves as a resource for green innovation as well – the effect of *Other_stock* on the number of green patents is significantly positive. The positive effect of green knowledge on current green innovation activities is, however, significantly larger than the positive effect of traditional knowledge. The effect of *Other_stock* on the share of green patents is significantly negative (see Table 4). Thus, it seems that due to opportunity costs, the relative impact of *Other_stock* on green innovation is smaller than the impact on other than green innovation.

We turn attention now to the main focus of our paper, the impact energy prices have on green innovation. In line with hypothesis H1 we find that larger energy prices do stimulate current green innovation activities. The impact of energy prices increases with an increasing lag between energy prices and innovation activities.[13]

Hypothesis H2 is confirmed as well, as energy prices have a significantly positive impact on the relative share of green innovation (see Table 4). Accordingly, energy prices do positively affect both, the intensity and the propensity of green innovation. In our model, a 10% increase of the average energy price of the previous five years results in a 2.7% and 4.5% increase of the number of green patents and the share of green patents, respectively. Does this increase in the propensity of green innovation come at the cost of other than green innovation? This is what the relatively large elasticity with respect to the share of green invention (4.5% vs. 2.7%) indicates. And in fact, we find for most specifications a significant negative effect of energy prices on other than green innovation (see Table A.5).

As described in the introduction, our model is based on a broader data set than most previous studies. It would thus be interesting to analyse how this fact does affect the impact of the energy prices. As previous models either include different control variables or even use different

[13] To test whether the differences arising from different time lags for the price variable in Table 3 are driven by the different lag structure or the different samples, Table A.4 shows the results for the same estimates, but with the same observations across the models. As these results do only marginally differ from previous results, we conclude that differences across models are driven by dynamic effects.

measures for green innovation, a direct comparison of the marginal effects of energy prices is hardly possible. Nevertheless, a comparison can show evidence for the question whether the impact of energy prices differs substantially among countries and industries. Based on US-data Popp (2002) identifies an effect of energy prices on the share of green patents in total patents of 3.4% (long run elasticity). Though we defined our share variable differently, the size of the effect is quite similar to the 5.2% that we find with respect to the share of green innovation in other innovation when using comparable energy prices[14] (see columns 11 and 12 of Table 4). As our result is based on a data set that includes 13 countries, we thus conclude that the effect found for the U.S. by Popp (2002) is representative for the group of countries we consider here. Aghion et al. (2012) analyze the effect of fuel prices on different innovation variables for the auto industry. Based on a slightly different model specification that also controls for other types of knowledge stocks, they identified elasticities of 0.97 and -0.57 for the number of green and dirty patents, respectively. These elasticities are considerably larger than the figures we find for the total manufacturing sector (based on a lag structure of one year we find elasticities of 0.12 and -0.14, respectively). Accordingly, it seems that the dependency on energy prices in the auto industry is larger than the dependency in the other manufacturing industries. To sum up, the comparison of our results with the results of these two studies indicate that variation in price elasticities is larger across industries than across countries.s

5.2 Robustness tests

We made comprehensive tests to check the robustness of our main results presented in Tables 3 and 4. All these tests are based on the models without the capital flow variable and using moving averages of the energy prices of the previous five years.

Estimates for different subcategories of green innovation

[14] Estimates based on a weighted average energy price with an adjustment coefficient of 0.83.

Our estimates are so far based on a quite broad definition of green inventions. Obviously, energy price shocks should, however, primarily affect inventions that are somehow related to energy reduction. To deal with this assertion, we estimate our previous model (column 14 of Table 3) separately for the seven environmental areas that are included in the OECD definition (see OECD 2012). The respective estimates are presented in Table A.6. The estimation results show that elasticities are larger for categories that we would suppose are more directly related to energy. Accordingly, the elasticity is largest for innovations in 'technologies with potential or indirect contribution to emission mitigation' (e.g., energy storage) and 'energy generation from renewable and non-fossil sources'. More general green innovation such as innovation dealing with 'technologies specified to climate change mitigation' (e.g., CO_2 capturing) is not significantly affected by energy price shocks. Nevertheless, our overall results seem to be quite representative, as the effect of energy prices is significantly positive for all other subcategories, and does only marginally vary across the different groups (elasticities between 0.24 and 0.38 for the other six categories).

Alternative price variables

Despite the fact that our price variable includes the prices of the three most important energy products, the construction of this variable may affect the results of our estimates. To test the robustness of our results with respect to the construction of the price variable, we alternatively estimated our main model of Tables 3 and 4 with price variables that are based on alternative baskets of energy products. As there are missing values for some product-specific energy prices, enlarging the price basket significantly reduces the number of observations that is available for the model estimation.[15] To get comparable results for the different price baskets, we estimate all models for the same set of observations. The respective estimation results are presented in Table

[15] While 3'448 observations are available when only the two products electricity and light fuel oil are included in the price basket, only 1'203 observations are available when we additionally include the three products natural gas, steam coal and coking coal.

A.7. To be able to compare these results with previous results, columns (2) and (8) show the results for the previous estimates based on the smaller sample. The fact that the price elasticities of these estimates only marginally differ from previous estimates (0.36 vs. 0.34 for green intensity and 0.55 vs. 0.48 for green propensity) indicates that the reduction of the sample size does not significantly affect our results.

The estimates for the different price baskets show that the elasticities of our main models represent the lower limit. For all other price baskets the price elasticities are significantly larger. The largest elasticities can be observed for prices based on the three products electricity, light fuel oil and steam coal. Based on this basket we identify elasticities of 0.98 and 1.25 for the number of green patents and the share of green patents, respectively (see columns 3 and 9). The elasticities are lowest when natural gas prices are included in the basket. Due to the relatively low prices of natural gas (see Figure 3) and its relatively high weight compared with other energy products (see Figure 4), the price mixes that include natural gas tend to be lower. Accordingly, a relative increase in these prices does lead to a lower absolute increase in energy costs than an increase in other price mixes. Other factors that may affect the different elasticities across the different price mixes may be different factor substitutabilities. For example it may be comparatively difficult for an industry to replace electricity by another product when electricity prices increase.

Testing the robustness of the stock variables

In our main models (Tables 3 and 4) we applied a depreciation rate of 15% in order to calculate knowledge stocks. Table A.8 (columns 1 to 4) 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.

Checking for outliers

Columns (5) to (8) of Table A.8 show the estimation results with regard to outliers. The distribution of inventions across industries is highly heterogeneous. Consequently we run our estimation excluding the top 1% of performers and the top 5% of the performers, respectively.[16] This only marginally affected our results. We thus conclude that our results are not driven by outliers.

Dealing with special characteristics of our data

To deal with the count data characteristics of the green innovation variable, column (1) of Table A.9 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. Unfortunately, this procedure does not allow the inclusion of country specific time fixed effects. However, the estimation results with respect to energy prices is only marginally affected by this alternative estimation procedure. The effect of energy prices on green innovation remains statistically significant and positive, and the coefficient is only slightly smaller (0.20 vs. 0.34).

Column (2) of Table A.9 shows an OLS model that includes pre-sample fixed effects as proposed by Blundell et al. (1995) in order to deal with unobserved heterogeneity in the presence of lagged endogenous variables. In doing so we add the average level of patenting over the pre-sample period 1975-1985 for both, green and other patents (both in logs), as well as two binary variables that measure whether an industry had any patent applications at all in the respective period. This procedure does again slightly reduce the size of the effect of energy prices (0.15 vs. 0.34); the effect remains, however, statistically significant and positive.

[16] Our main estimates presented in Tables 3 and 4 are based on 144 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% and 5% of the groups, respectively. All in all, we thus dropped two and ten groups that account for 1.5% and 6.6% of the observations, respectively.

6 Conclusions

Based on industry-level panel data, the paper at hand investigates the determinants of green patent applications of an industry. While the main focus is on the impact of energy prices, our model shows several other interesting results. Firstly, we find that an available knowledge stock serves as innovation relevant resource for green innovation independent whether it is green specific knowledge or knowledge in traditional technologies. Secondly, as a large knowledge stock in traditional technologies represents larger opportunity costs with respect to green innovation, the effect of traditional knowledge on current green innovation is significantly smaller than the effect of green knowledge. Furthermore, the effect of traditional knowledge on the share of green patents is significantly negative. With respect to our main variable we find that energy prices do stimulate both, the intensity of green innovation as well as the propensity of green innovation. In our model, a 10% increase of the average energy prices of the previous five years results in a 2.7% and 4.5% increase of the number of green patents and the share of green patents, respectively. This is not a new result. Certain previous empirical studies came to a quite similar finding. However, in contrast to previous studies, our results are more general, as they are based on a broader basis. While most previous studies focused on certain industries or countries, our data set includes the whole manufacturing sector and the most important countries for green innovation. Furthermore, in contrast to studies that are based on aggregated data, we reduced the problems of an omitted-variable bias by calculating industry-specific energy prices.

Despite a large future market potential, firms are probably not willing by themselves to invest in green technologies, as green innovation is still negatively related to economic performance (see Soltmann et al. 2012). Furthermore, free-riding possibilities in green technologies seem to be limited (see Stucki and Woerter 2012). Accordingly, knowledge about potential policy instruments to stimulate innovation in this area is of large importance. As our study shows, energy prices may serve as such an instrument. An increase in energy prices may stimulate the building of a green knowledge stock that (a) would help to achieve a country's climate targets and (b) may serve as an important fundament to establish an industry in the cleantech market for which long-term growth is predicted. Even more in Switzerland an increase in energy prices may be an important instrument. Despite the strong performance in general innovation activities (see, e.g., SECO 2012), the green innovation machine has not been activated so far. The share of green patents in other patents is just 5.3% for the years 1975-2009 (see Table 1). This is among the lowest values among all 18 countries in our sample.

When comparing our results with the results of previous studies, we found that price elasticities seem to vary across industries. Accordingly, energy prices do not seem to be equally suitable as an instrument to stimulate green innovation in different industries. Due to the limited number of observations that is available in our data set, it was unfortunately not possible for us to compare price elasticities across industries. However, to increase the efficiency of energy price regulations it seems to be an interesting task for future research to identify such difference across industries.

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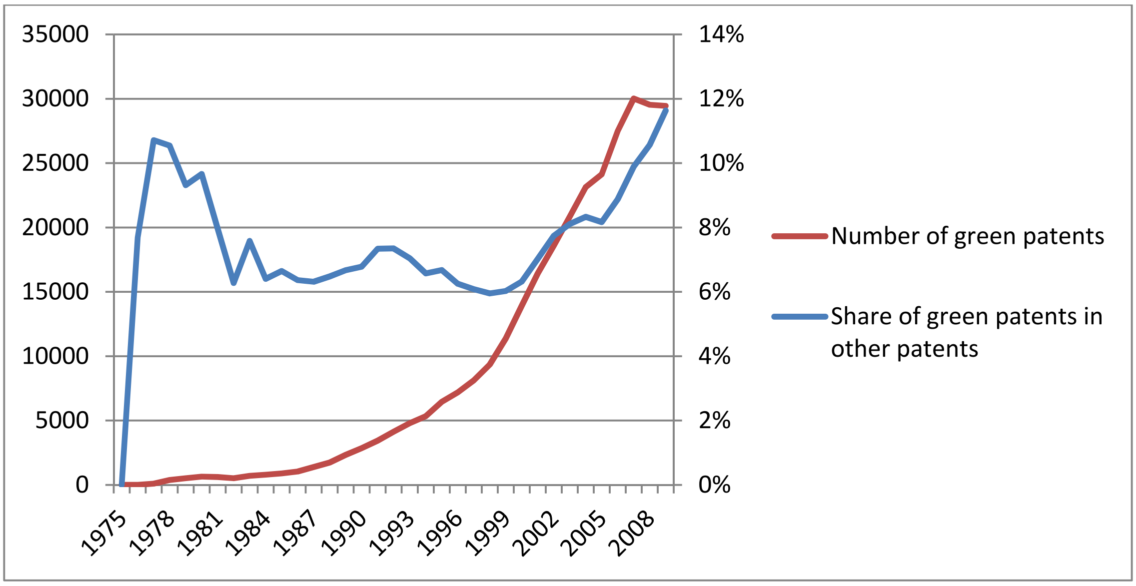
Figure 1: Development of green patents worldwide, 1975-2009



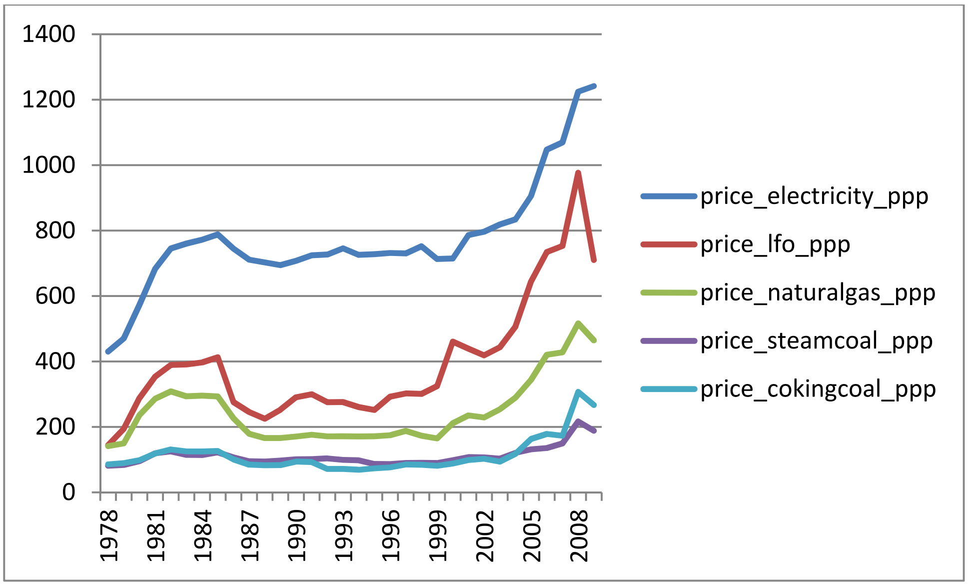
Source: Own calculations.

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

Period	1975-2009				
Type of patent	Other		Green		Green vs. Other
	Number of other patents	Relative share in total other patents	Number of green patents	Relative share in total green patents	Share of green patents in other patents
Industry					
Chemicals	1174189	30.7%	75005	24.3%	6.4%
Food and tobacco	57745	1.5%	2299	0.7%	4.0%
Machinery	2057737	53.8%	151000	49.0%	7.3%
Basic metals	51937	1.4%	7058	2.3%	13.6%
Non-metallic minerals	90436	2.4%	9936	3.2%	11.0%
Paper, pulp and print	23630	0.6%	1439	0.5%	6.1%
Textile and leather	28133	0.7%	949	0.3%	3.4%
Transport equipment	145020	3.8%	50350	16.3%	34.7%
Wood and wood products	5213	0.1%	189	0.1%	3.6%
Non-specified industry	190613	5.0%	10103	3.3%	5.3%
Country					
Australia	62475	1.6%	5720	1.9%	9.2%
Austria	35787	0.9%	3479	1.1%	9.7%
Belgium	40323	1.1%	2586	0.8%	6.4%
Canada	85872	2.2%	8978	2.9%	10.5%
Switzerland	114720	3.0%	6042	2.0%	5.3%
Germany	490347	12.8%	55373	18.0%	11.3%
Denmark	38944	1.0%	4276	1.4%	11.0%
Spain	28403	0.7%	2520	0.8%	8.9%
Finland	50947	1.3%	3440	1.1%	6.8%
France	203523	5.3%	17130	5.6%	8.4%
United Kingdom	226841	5.9%	15172	4.9%	6.7%
Ireland	12425	0.3%	637	0.2%	5.1%
Italy	65926	1.7%	4640	1.5%	7.0%
Japan	565774	14.8%	65906	21.4%	11.6%
Korea	86305	2.3%	7267	2.4%	8.4%
Netherlands	130982	3.4%	8794	2.9%	6.7%
Sweden	111130	2.9%	6977	2.3%	6.3%
United States	1473929	38.5%	89391	29.0%	6.1%
Total	3824653	100%	308328	100%	8.1%

Notes: Data is based on own calculations; these statistics are based on 35 cross-sections, 18 countries and 10 industries (total of 6'300 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 other patents is defined as an industry's/ country's share of green patents relative to its number of other patents.

Figure 2: Energy prices (PPP adjusted) for electricity, light fuel oil, natural gas, steam coal and coking coal (per toe) by year, 1978-2009

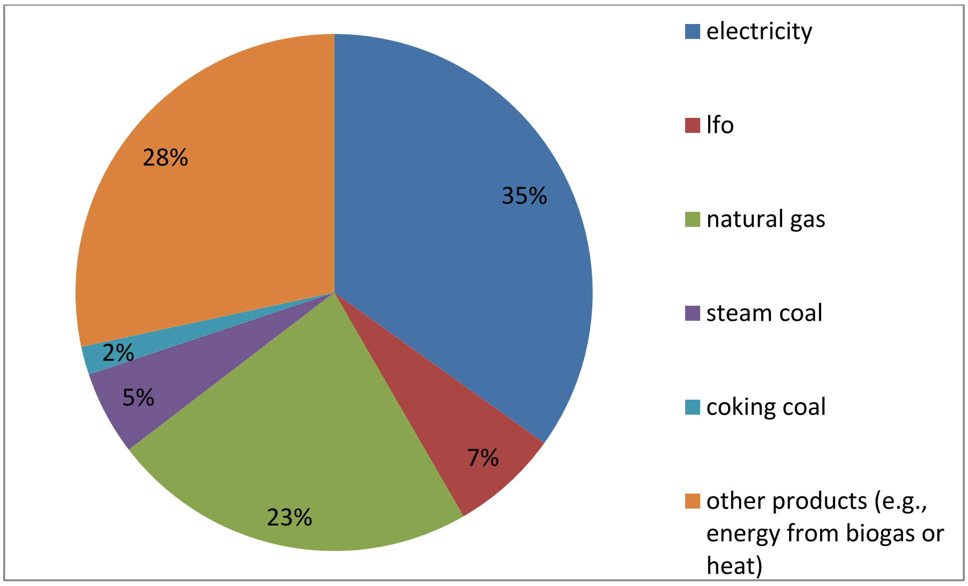


Source: IEA (2012a).

Figure 3: Average energy prices (per tonne of oil equivalent, PPP adjusted) for the three most used energy products electricity, light fuel oil and natural gas (see Figure 4) by country, 1978-2009

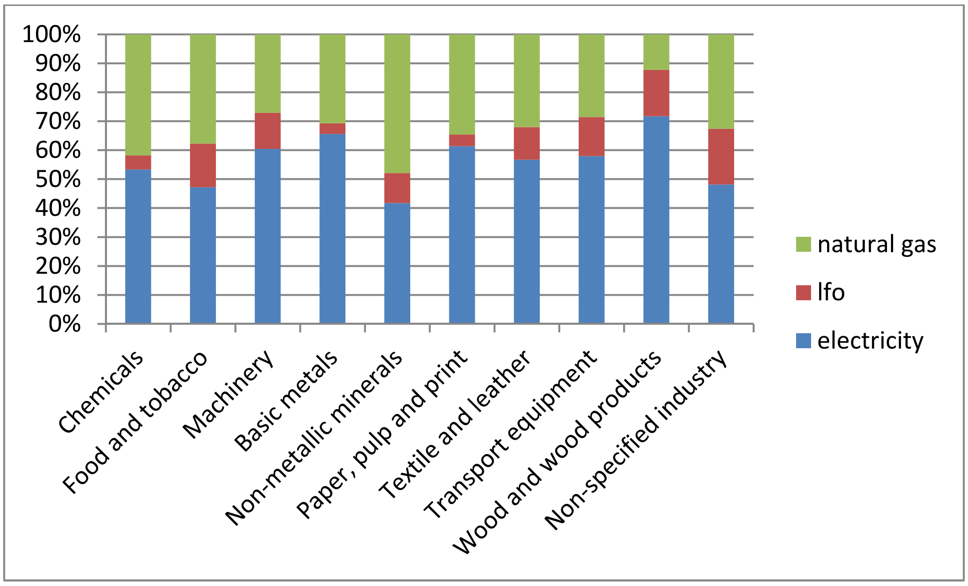
Notes: As the different price information is not available for all countries over the whole sample period, some of the figures are not directly comparable across countries and products. Natural gas prices for Sweden are for example only available for the years 2007-2009, and are thus not directly comparable with the respective prices for light fuel oil that are available for the whole sample period. Other prices averages with few observations are: Australian LFO price (6 years), Danish natural gas price (4 years) and Korean natural gas price (6 years); Source: IEA (2012a).

Figure 4: Share of total energy consumption by product, 1978-2009



Source: IEA (2012b).

Figure 5: Relative share of top three energy products by industry, 1978-2009



Source: IEA (2012b).

Table 2: Variable definition and measurement

Variable	Definition/measurement	Source
Dependent variable		
$Green\_patents_{ijt}$	Number of green patents	own calculations
$Other\_patents_{ijt}$	Number of patents that are not classified as green	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
$Green\_stock_{ijt}$	Stock of green patents	own calculations
$Other\_stock_{ijt}$	Stock of patents that are not classified as green	own calculations
$Energy\_price_{ijt}$	Industry specific energy price based on electricity, light fuel oil and natural gas prices, PPP	IEA
$Popp\_energy\_price_{ijt}$	Weighted average energy prices as in Popp (2002) for the whole sample period from 1978 onwards with an adjustment coefficient of 0.83 (see Aghion et al. 2012 for a similar procedure).	IEA
$Moving\_average\_energy\_price_{ijt}$	Moving average of the energy prices of the previous five years.	IEA

Table 3: Estimation results for green patent flow

Estimation method	OLS log linear fixed-effects regression													
Period	1981-2009												1984-2009	
Dependent variable	$\ln(\text{Green\_patents})_{ijt}$													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
$\ln(L)_{ijt-1}$	0.068	0.096	0.072	0.101	0.077	0.111*	0.081	0.130*	0.055	0.117*	-0.030	0.035	0.028	0.098
	(0.080)	(0.067)	(0.078)	(0.065)	(0.083)	(0.065)	(0.082)	(0.067)	(0.079)	(0.066)	(0.088)	(0.072)	(0.084)	(0.068)
$\ln(K)_{ijt-1}$	0.125**		0.113**		0.111**		0.118**		0.117**		0.132**		0.119**	
	(0.052)		(0.052)		(0.056)		(0.058)		(0.056)		(0.054)		(0.059)	
$\ln(\text{Green\_stock})_{ijt-1}$	0.617***	0.613***	0.603***	0.599***	0.579***	0.580***	0.567***	0.564***	0.551***	0.552***	0.590***	0.591***	0.550***	0.551***
	(0.035)	(0.034)	(0.035)	(0.035)	(0.036)	(0.035)	(0.040)	(0.037)	(0.040)	(0.037)	(0.041)	(0.039)	(0.047)	(0.043)
$\ln(\text{Other\_stock})_{ijt-1}$	0.150***	0.147***	0.158***	0.155***	0.139***	0.147***	0.151***	0.154***	0.180***	0.174***	0.172***	0.164***	0.158***	0.164***
	(0.047)	(0.041)	(0.047)	(0.043)	(0.050)	(0.045)	(0.057)	(0.047)	(0.065)	(0.052)	(0.051)	(0.044)	(0.059)	(0.050)
$\ln(\text{Energy\_price})_{ijt-1}$	0.115	0.205**												
	(0.089)	(0.087)												
$\ln(\text{Energy\_price})_{ijt-2}$			0.119	0.200**										
			(0.091)	(0.087)										
$\ln(\text{Energy\_price})_{ijt-3}$					0.164*	0.223**								
					(0.091)	(0.087)								
$\ln(\text{Energy\_price})_{ijt-4}$							0.201**	0.222***						
							(0.084)	(0.080)						
$\ln(\text{Energy\_price})_{ijt-5}$									0.277***	0.265***				
									(0.100)	(0.087)				
$\ln(\text{Popp\_energy\_price})_{ijt-1}$											0.286	0.391**		
											(0.174)	(0.162)		
$\ln(\text{Moving\_average\_energy\_price})_{ijt-1}$													0.268*	0.342**
													(0.143)	(0.141)
Constant	-4.475***	-2.812***	-4.483***	-2.920***	-4.657***	-3.179***	-5.073***	-3.436***	-5.307***	-3.540***	-4.296***	-2.984***	-4.985***	-3.880***
	(1.054)	(0.893)	(1.037)	(0.878)	(1.061)	(0.878)	(1.133)	(0.886)	(1.154)	(0.870)	(1.146)	(1.121)	(1.190)	(1.092)
Country specific time fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country specific industry fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	2293	3142	2227	3051	2181	2969	2146	2899	2099	2829	1920	2725	1962	2669
Groups	126	174	126	174	116	164	116	154	116	154	105	143	116	144
R^2 within	0.77	0.80	0.75	0.79	0.73	0.78	0.72	0.77	0.70	0.75	0.76	0.80	0.71	0.76

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; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively.

Table 4: Estimation results for relative patenting

Estimation method	OLS log linear fixed-effects regression													
Period	1981-2009												1984-2009	
Dependent variable	$\ln(\text{Green\_patents})_{ijt} - \ln(\text{Other\_patents})_{ijt}$													
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)	(13)	(14)
$\ln(L)_{ijt-1}$	-0.052	-0.117	-0.045	-0.112	-0.045	-0.106	-0.039	-0.080	-0.066	-0.097	-0.158	-0.185*	-0.093	-0.111
	(0.103)	(0.088)	(0.101)	(0.088)	(0.100)	(0.084)	(0.096)	(0.081)	(0.095)	(0.076)	(0.116)	(0.095)	(0.102)	(0.085)
$\ln(K)_{ijt-1}$	0.040		0.021		0.023		0.018		0.004		0.039		0.022	
	(0.070)		(0.069)		(0.072)		(0.070)		(0.070)		(0.068)		(0.068)	
$\ln(\text{Green\_stock})_{ijt-1}$	0.377***	0.365***	0.363***	0.350***	0.342***	0.338***	0.326***	0.320***	0.303***	0.305***	0.346***	0.333***	0.295***	0.292***
	(0.044)	(0.042)	(0.043)	(0.042)	(0.043)	(0.044)	(0.046)	(0.045)	(0.047)	(0.045)	(0.049)	(0.046)	(0.051)	(0.051)
$\ln(\text{Other\_stock})_{ijt-1}$	-0.313***	-0.368***	-0.302***	-0.356***	-0.280***	-0.337***	-0.227***	-0.300***	-0.231***	-0.294***	-0.301***	-0.359***	-0.227***	-0.297***
	(0.061)	(0.054)	(0.060)	(0.056)	(0.064)	(0.057)	(0.074)	(0.063)	(0.082)	(0.065)	(0.067)	(0.058)	(0.080)	(0.068)
$\ln(\text{Energy\_price})_{ijt-1}$	0.265**	0.345***												
	(0.131)	(0.123)												
$\ln(\text{Energy\_price})_{ijt-2}$			0.253*	0.323***										
			(0.130)	(0.122)										
$\ln(\text{Energy\_price})_{ijt-3}$					0.305**	0.361***								
					(0.134)	(0.123)								
$\ln(\text{Energy\_price})_{ijt-4}$							0.358***	0.367***						
							(0.131)	(0.114)						
$\ln(\text{Energy\_price})_{ijt-5}$									0.408***	0.367***				
									(0.142)	(0.116)				
$\ln(\text{Popp\_energy\_price})_{ijt-1}$											0.519**	0.615**		
											(0.257)	(0.238)		
$\ln(\text{Moving\_average\_energy\_price})_{ijt-1}$													0.450**	0.481**
													(0.213)	(0.194)
Constant	-3.007**	-1.823	-3.007**	-1.887	-3.210**	-2.160*	-3.709**	-2.683**	-3.469**	-2.524**	-2.986*	-2.241	-3.810**	-3.101**
	(1.401)	(1.172)	(1.387)	(1.169)	(1.387)	(1.107)	(1.427)	(1.093)	(1.499)	(1.045)	(1.649)	(1.524)	(1.580)	(1.408)
Country specific time fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country specific industry fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	2293	3142	2227	3051	2181	2969	2146	2899	2099	2829	1920	2725	1962	2669
Groups	126	174	126	174	116	164	116	154	116	154	105	143	116	144
R^2 within	0.50	0.50	0.48	0.48	0.47	0.47	0.43	0.44	0.43	0.43	0.51	0.51	0.43	0.44

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; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively.

APPENDIX

Table A.1: Identification of a possible omitted variable bias (estimates of Table 3 without capital variable but same observations)

Estimation method	OLS log linear fixed-effects regression						
Period	1981-2009						1984-2009
Dependent variable	$\ln(\text{Green\_patents})_{ijt}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(L)_{ijt-1}$	0.150*	0.145*	0.148*	0.156*	0.123	0.054	0.103
	(0.079)	(0.076)	(0.080)	(0.083)	(0.080)	(0.087)	(0.085)
$\ln(\text{Green\_stock})_{ijt-1}$	0.622***	0.607***	0.584***	0.573***	0.557***	0.597***	0.557***
	(0.034)	(0.034)	(0.036)	(0.040)	(0.040)	(0.040)	(0.046)
$\ln(\text{Other\_stock})_{ijt-1}$	0.154***	0.163***	0.144***	0.157***	0.189***	0.179***	0.166***
	(0.047)	(0.047)	(0.051)	(0.057)	(0.066)	(0.051)	(0.059)
$\ln(\text{Energy\_price})_{ijt-1}$	0.104						
	(0.089)						
$\ln(\text{Energy\_price})_{ijt-2}$		0.112					
		(0.091)					
$\ln(\text{Energy\_price})_{ijt-3}$			0.161*				
			(0.091)				
$\ln(\text{Energy\_price})_{ijt-4}$				0.202**			
				(0.084)			
$\ln(\text{Energy\_price})_{ijt-5}$					0.283***		
					(0.099)		
$\ln(\text{Popp\_energy\_price})_{ijt-1}$						0.274	
						(0.173)	
$\ln(\text{Moving\_average\_energy\_price})_{ijt-1}$							0.269*
							(0.141)
Constant	-2.884***	-3.013***	-3.190***	-3.604***	-3.786***	-2.519**	-3.384***
	(1.034)	(0.998)	(1.004)	(1.062)	(1.034)	(1.159)	(1.123)
Country specific time fixed effects	yes	yes	yes	yes	yes	yes	yes
Country specific industry fixed effects	yes	yes	yes	yes	yes	yes	yes
N	2293	2227	2181	2146	2099	1920	1962
Groups	126	126	116	116	116	105	116
R^2 within	0.77	0.75	0.73	0.72	0.70	0.76	0.71

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; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively.

Table A.2: Identification of pure dynamic effects (same observations for all models)

Estimation method	OLS log linear fixed-effects regression						
Period	1981-2009						1984-2009
Dependent variable	$\ln(\text{Green\_patents})_{ijt}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(L)_{ijt-1}$	0.085	0.086	0.083	0.082	0.079	0.067	0.077
	(0.075)	(0.075)	(0.075)	(0.074)	(0.074)	(0.075)	(0.074)
$\ln(\text{Green\_stock})_{ijt-1}$	0.553***	0.553***	0.552***	0.551***	0.550***	0.546***	0.548***
	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)	(0.046)
$\ln(\text{Other\_stock})_{ijt-1}$	0.174***	0.176***	0.179***	0.181***	0.185***	0.190***	0.185***
	(0.058)	(0.058)	(0.057)	(0.058)	(0.058)	(0.058)	(0.058)
$\ln(\text{Energy\_price})_{ijt-1}$	0.164						
	(0.100)						
$\ln(\text{Energy\_price})_{ijt-2}$		0.152					
		(0.102)					
$\ln(\text{Energy\_price})_{ijt-3}$			0.185*				
			(0.096)				
$\ln(\text{Energy\_price})_{ijt-4}$				0.192**			
				(0.084)			
$\ln(\text{Energy\_price})_{ijt-5}$					0.240***		
					(0.089)		
$\ln(\text{Popp\_energy\_price})_{ijt-1}$						0.460**	
						(0.226)	
$\ln(\text{Moving\_average\_energy\_price})_{ijt-1}$							0.331**
							(0.153)
Constant	-2.602**	-2.464**	-2.698***	-2.674***	-2.879***	-3.672***	-3.562***
	(1.008)	(0.983)	(0.958)	(0.922)	(0.925)	(1.301)	(1.173)
Country specific time fixed effects	yes	yes	yes	yes	yes	yes	yes
Country specific industry fixed effects	yes	yes	yes	yes	yes	yes	yes
N	2299	2299	2299	2299	2299	2299	2299
Groups	125	125	125	125	125	125	125
R^2 within	0.76	0.76	0.76	0.76	0.76	0.76	0.76

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; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively.

Table A.3: Estimation results for other patent flow

Estimation method	OLS log linear fixed-effects regression						
Period	1981-2009						1984-2009
Dependent variable	$\ln(Other\_patents)_{ijt}$						
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(L)_{ijt-1}$	0.213***	0.213***	0.216***	0.210***	0.214***	0.220***	0.209***
	(0.057)	(0.062)	(0.063)	(0.066)	(0.062)	(0.064)	(0.071)
$\ln(Green\_stock)_{ijt-1}$	0.248***	0.248***	0.242***	0.243***	0.247***	0.258***	0.259***
	(0.026)	(0.028)	(0.031)	(0.033)	(0.034)	(0.030)	(0.036)
$\ln(Other\_stock)_{ijt-1}$	0.515***	0.511***	0.484***	0.454***	0.467***	0.522***	0.462***
	(0.036)	(0.039)	(0.041)	(0.046)	(0.043)	(0.038)	(0.051)
$\ln(Energy\_price)_{ijt-1}$	-0.140*						
	(0.071)						
$\ln(Energy\_price)_{ijt-2}$		-0.123*					
		(0.067)					
$\ln(Energy\_price)_{ijt-3}$			-0.138**				
			(0.068)				
$\ln(Energy\_price)_{ijt-4}$				-0.144**			
				(0.066)			
$\ln(Energy\_price)_{ijt-5}$					-0.102*		
					(0.060)		
$\ln(Popp\_energy\_price)_{ijt-1}$						-0.224*	
						(0.132)	
$\ln(Moving\_average\_energy\_price)_{ijt-1}$							-0.139
							(0.091)
Constant	-0.989	-1.034	-1.019	-0.753	-1.016	-0.744	-0.779
	(0.701)	(0.746)	(0.795)	(0.869)	(0.821)	(0.906)	(0.972)
Country specific time fixed effects	yes	yes	yes	yes	yes	yes	yes
Country specific industry fixed effects	yes	yes	yes	yes	yes	yes	yes
N	3142	3051	2969	2899	2829	2725	2669
Groups	174	174	164	154	154	143	144
R^2 within	0.91	0.91	0.91	0.90	0.90	0.91	0.90

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; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively.

Table A.4: Estimates for different types of green innovation

Estimation method	OLS log linear fixed-effects regression						
Period	1984-2009						
Dependent variable	$\ln(\text{Specific\_green\_patents})_{ijt}$						
Type of green patents:	General environmental management	Energy generation from renewable and non-fossil sources	Combustion technologies with mitigation potential	Technologies specific to climate change mitigation	Technologies with potential or indirect contribution to emission mitigation	Emission abatement and fuel efficiency in transportation	Energy efficiency in buildings and lighting
	(1)	(2)	(3)	(4)	(5)	(6)	(7)
$\ln(L)_{ijt-1}$	0.053	0.149	0.036	-0.006	-0.001	-0.007	0.031
	(0.070)	(0.103)	(0.044)	(0.039)	(0.075)	(0.080)	(0.061)
$\ln(\text{Specific\_green\_stock})_{ijt-1}$	0.460***	0.526***	0.461***	0.593***	0.580***	0.547***	0.554***
	(0.044)	(0.054)	(0.044)	(0.050)	(0.040)	(0.039)	(0.042)
$\ln(\text{Specific\_other\_stock})_{ijt-1}$	0.198***	0.097**	0.037	0.034**	0.072*	-0.012	0.078**
	(0.052)	(0.041)	(0.029)	(0.017)	(0.039)	(0.041)	(0.037)
$\ln(\text{Moving\_average\_energy\_price})_{ijt-1}$	0.239*	0.379***	0.328***	0.074	0.382***	0.342***	0.255**
	(0.135)	(0.133)	(0.103)	(0.087)	(0.115)	(0.116)	(0.120)
Constant	-2.851**	-4.429***	-2.558***	-0.638	-2.746**	-1.851	-2.442**
	(1.099)	(1.369)	(0.734)	(0.699)	(1.111)	(1.185)	(1.008)
Country specific time fixed effects	yes	yes	yes	yes	yes	yes	yes
Country specific industry fixed effects	yes	yes	yes	yes	yes	yes	yes
N	2669	2669	2669	2669	2669	2669	2669
Groups	144	144	144	144	144	144	144
R^2 within	0.68	0.70	0.52	0.64	0.70	0.65	0.67

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; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively.

Table A.5: Estimates based on alternative price variables (same observations for all models)

Estimation method	OLS log linear fixed-effects regression											
Period	1984-2009											
Dependent variable	$\ln(\text{Green\_patents})_{ijt}$						$\ln(\text{Green\_patents})_{ijt}$ - $\ln(\text{Other\_patents})_{ijt}$					
Products included in price basket	electricity, light fuel oil	electricity, light fuel oil, natural gas	electricity, light fuel oil, steam coal	electricity, light fuel oil, natural gas, steam coal	electricity, light fuel oil, steam coal, coking coal	electricity, light fuel oil, natural gas, steam coal, coking coal	electricity, light fuel oil	electricity, light fuel oil, natural gas	electricity, light fuel oil, steam coal	electricity, light fuel oil, natural gas, steam coal	electricity, light fuel oil, steam coal, coking coal	electricity, light fuel oil, natural gas, steam coal, coking coal
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)	(11)	(12)
$\ln(L)_{ijt-1}$	-0.059	-0.069	-0.092	-0.116	-0.080	-0.104	-0.173	-0.192	-0.212	-0.251	-0.193	-0.232
	(0.170)	(0.157)	(0.167)	(0.147)	(0.165)	(0.146)	(0.208)	(0.191)	(0.200)	(0.181)	(0.199)	(0.182)
$\ln(\text{Green\_stock})_{ijt-1}$	0.437***	0.448***	0.429***	0.439***	0.431***	0.441***	0.277***	0.292***	0.270***	0.281***	0.274***	0.284***
	(0.068)	(0.070)	(0.069)	(0.070)	(0.070)	(0.070)	(0.087)	(0.089)	(0.089)	(0.088)	(0.090)	(0.088)
$\ln(\text{Other\_stock})_{ijt-1}$	0.170	0.182	0.170	0.194*	0.160	0.190	-0.118	-0.100	-0.119	-0.086	-0.131	-0.093
	(0.116)	(0.115)	(0.108)	(0.114)	(0.111)	(0.115)	(0.113)	(0.111)	(0.105)	(0.107)	(0.108)	(0.109)
$\ln(\text{Moving\_average\_energy\_price})_{ijt-1}$	0.716**	0.364**	0.984**	0.675**	0.944**	0.650**	1.014*	0.553*	1.251***	0.929**	1.125**	0.871**
	(0.350)	(0.182)	(0.376)	(0.274)	(0.384)	(0.267)	(0.516)	(0.284)	(0.446)	(0.379)	(0.452)	(0.363)
Constant	-4.066	-1.672	-5.054*	-2.825	-4.868*	-2.809	-6.891*	-3.793	-7.902**	-5.375*	-7.184**	-5.175*
	(2.681)	(2.143)	(2.868)	(2.325)	(2.890)	(2.304)	(3.720)	(2.878)	(3.143)	(3.029)	(3.141)	(2.958)
Country specific time fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
Country specific industry fixed effects	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes	yes
N	1203	1203	1203	1203	1203	1203	1203	1203	1203	1203	1203	1203
Groups	89	89	89	89	89	89	89	89	89	89	89	89
R^2 within	0.80	0.80	0.80	0.80	0.80	0.80	0.31	0.31	0.32	0.32	0.31	0.32

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; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively.

Table A.6: Estimates based on alternative depreciation rates and controlling for outliers, respectively

Estimation method	OLS log linear fixed-effects regression							
Period	1984-2009							
Dependent variable	$\ln(Green\_patents)_{ijt}$		$\ln(Green\_patents)_{ijt} - \ln(Other\_patents)_{ijt}$		$\ln(Green\_patents)_{ijt}$		$\ln(Green\_patents)_{ijt} - \ln(Other\_patents)_{ijt}$	
Depreciation rate	10%	30%	10%	30%	15%	15%	15%	15%
Checking for outliers	no	no	no	no	drop top 1%	drop top 5%	drop top 1%	drop top 5%
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)
$\ln(L)_{ijt-1}$	0.101	0.089	-0.114	-0.103	0.097	0.091	-0.111	-0.118
	(0.072)	(0.062)	(0.086)	(0.080)	(0.069)	(0.068)	(0.085)	(0.084)
$\ln(Green\_stock)_{ijt-1}$	0.551***	0.539***	0.276***	0.321***	0.551***	0.548***	0.292***	0.288***
	(0.044)	(0.040)	(0.052)	(0.047)	(0.043)	(0.043)	(0.051)	(0.051)
$\ln(Other\_stock)_{ijt-1}$	0.161***	0.177***	-0.293***	-0.299***	0.163***	0.157***	-0.297***	-0.301***
	(0.054)	(0.041)	(0.072)	(0.058)	(0.050)	(0.048)	(0.068)	(0.067)
$\ln(Moving\_average\_energy\_price)_{ijt-1}$	0.356**	0.309**	0.491**	0.458**	0.352**	0.321**	0.486**	0.463**
	(0.146)	(0.127)	(0.199)	(0.182)	(0.143)	(0.139)	(0.199)	(0.195)
Constant	-4.103***	-3.302***	-3.122**	-3.176**	-3.862***	-3.558***	-3.047**	-2.871**
	(1.144)	(0.960)	(1.446)	(1.292)	(1.100)	(1.057)	(1.432)	(1.400)
Country specific time fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
Country specific industry fixed effects	yes	yes	yes	yes	yes	yes	yes	yes
N	2669	2669	2669	2669	2629	2494	2629	2494
Groups	144	144	144	144	142	134	142	134
R^2 within	0.76	0.77	0.44	0.45	0.76	0.74	0.44	0.44

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; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively.

Table A.7: Models dealing with the count data characteristics of the green innovation variable and the endogeneity of the stock variables, respectively

Estimation method	Fixed-effects Poisson regression	OLS pre-sample mean estimator
Period	1984-2009	
Dependent variable	$Green\_patents_{ijt}$	ln(Green_patents)ijt
	(1)	(2)
$\ln(L)_{ijt-1}$	0.046	0.056*
	(0.121)	0.056*
$\ln(Green\_stock)_{ijt-1}$	0.798***	(0.033)
	(0.094)	(0.033)
$\ln(Other\_stock)_{ijt-1}$	0.035	0.085**
	(0.119)	(0.036)
$\ln(Moving\_average\_energy\_price)_{ijt-1}$	0.202**	0.148**
	(0.096)	(0.069)
Constant		-2.216***
		(0.715)
Year fixed effects	yes	no
Country specific industry fixed effects	yes	no
Country specific time fixed effects	no	yes
Country fixed effects	no	no
Industry fixed effects	no	yes
Pre-sample fixed effects	no	yes
N	2610	2669
Groups	137	144
Wald chi2	72782.29***	
R^2		0.94
Log Likelihood	-7674.11	

Notes: see Table 2 for the variable definitions; standard errors that are in brackets under the coefficients; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively; Column (1): In line with Allison and Waterman (2002) we used robust standard errors to correct for overdispersion; Column (2): 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; standard errors are robust to heteroskedasticity and clustered at the industry-country level (clustered sandwich estimator).