The Impact of Energy Prices on Green Innovation

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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 ratio of green innovations to non-green innovations. More concretely, our main model shows that a 10% increase of the average energy prices over the previous five years results in a 3.4% and 4.8% increase of the number of green innovations and the ratio of green innovations to non-green innovations, 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, Environment, Energy prices

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1. INTRODUCTION

Despite the fact that climate change should ideally increase the demand for green technologies, firms still have little incentive 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, financial market imperfections that are normally associated with innovation activities (see Arrow 1962, p. 172) are even more pronounced for green innovation. Green innovations carry a large technical risk as they often imply investing in technologies that lie beyond the firm’s traditional technological scope. Additional commercial uncertainty arises from unclear market developments (Aghion et al. 2009). Hence, potential external investors are hardly willing to invest in such projects and financial markets are usually not ready to finance such risky technological investments. As a consequence, access to external capital to finance green innovation is likely to be constrained. Secondly, because the greatest benefits from green inventions are likely to be public rather than private, the customers’ willingness to pay for these innovations is low. In line with this literature, recent studies have shown at the firm and industry levels that green innovations currently have lower returns than non-green innovations (see Marin 2014, Soltmann et al. 2014). These results indicate that—given the current level of green promotion—free market incentives alone are not sufficient to allow the green innovation 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

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to be limited to anything like 2°C" (see Helm 2012, p. 213). Accordingly, policy intervention is required to stimulate green innovation activities.

This paper focuses on energy prices and investigates whether energy prices increase the probability of producing green inventions. More concretely, we investigate whether the effects of energy prices are different for 'green' inventions than for 'non-green' inventions. The fluctuation of energy prices has a price component and a policy component. As the price component is primarily driven by international market prices and we control for between-country variation, the remaining variation in the energy price in our model is mainly due to energy taxes. Consequently, energy prices can be interpreted as an environmental policy instrument (see Aghion et al. 2012 for a similar argumentation). Nevertheless, as we cannot fully capture the price component, the econometric results of this paper cannot be interpreted as a 'pure' policy effect. Our results refer to fluctuation of the end-use price including taxes.[1]

Empirical research linking environmental policy and innovation is related to a small but growing literature. A first group of studies uses pollution abatement control expenditures (PACE) as a 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 using patent data between 1978 and 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 large 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.

Rather than focusing on a single industry, Popp (2002) focused on a single country. He looked 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) for the USA and found that energy prices and the existing knowledge stock have a strong and significant positive effect on innovation.

It is unclear in all these studies 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 how different policies (among others energy prices) affect innovation for five different renewable energy technologies. Verdolini and Galeotti (2011) inves-

1. Aghion et al. 2012 separated the tax component of the energy price and found that tax fluctuation show a similar effect as energy price fluctuation (including taxes) on green inventions in the car industry. For this paper we also see that energy prices are highly correlated with taxes. Industry specific taxes and prices for the three products electricity, light fuel oil, and natural gas, respectively, show a correlation coefficient of 0.72. Unfortunately, the large number of missing values with respect to the tax data for the different energy products does not allow for an econometric identification of the pure tax effect.

tigated 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 to the country-level or technology-level, there is a concern that there may be other country-specific shocks correlated with both innovation and the energy price (see Aghion et al. 2012, p. 5).

This study contributes to the existing literature primarily in two respects. First, the breadth of our data set allows us to draw much more general conclusions than was possible in previous studies, which have focused on single industries or countries. This enables us to generate an industry-level data set that covers the whole manufacturing sector (grouped into 10 industries), the most important countries for green innovation (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, in contrast to previous studies, we greatly reduce the probability of omitted variable bias, which makes our results more reliable.

In line with previous studies, we use patent data to identify green and non-green inventions according to the OECD Indicator of Environmental Technologies (see OECD 2012),[2] however, we switch from the technology level to the industry level by using the Schmoch et al. (2003) concordance scheme. In contrast to studies that stay on the technology-level, this approach allows us to include industry-level control variables (e.g., capital and number of employees). Furthermore, we reduce the potential problem of omitted variable bias by controlling for industry and country fixed effects. Additionally, we calculate industry specific energy prices, which allow us to include country-specific time fixed effects. Compared with previous studies on a more aggregated level (i.e. country level), country-specific shocks that are correlated with both innovation and the energy prices (see Aghion et al. 2012, p.5) do not bias the results in this particular study. An important concern here is that national governments may have introduced policies directly supporting green innovation (such as research subsidies) simultaneously with higher energy taxes. In such a scenario, not controlling for country-specific attributes would tend to bias estimates for the price effect on innovation.[3]

With respect to our main variable, green inventions, we find that energy prices stimulate both the level of green invention as well as the share of green invention. In our model, a 10% increase in the average energy prices over the previous five years results in a 3.4% and 4.8% increase of the number of green inventions and the ratio of green inventions to non-green inventions, respectively. Knowledge about potential political instruments to stimulate invention in this area is of great importance. This study shows that 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 help to establish a cleantech market for which long-term growth is predicted.

2. The OECD Indicator of Environmental Technologies distinguishes 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. 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.

3. As the policy effects may simultaneously interact with other country-specific shocks, (e.g., macroeconomic shocks) it is not possible to make a clear prediction about the direction of the bias that is captured by the country-specific time fixed effects.

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, as quoted e.g. in Binswanger et al. 1978): "A change in the relative prices of the factors of production is itself a spur to innovation, and to innovation of a particular kind - directed to economizing 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 induced innovation into account leads to market-based policies that tackle climate change more efficiently (or, more precisely, in a less costly manner). This is because such policies not only motivate profit-seeking firms to switch to less energy-demanding technologies, which are currently available, 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).

In line with the induced innovation hypothesis, Porter and van der Linde (1995) go as far as to claim 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 in harmful emissions (or 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 has become to be known as 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 implies that regulation triggers innovation. 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.

Subsequent theoretical research based on the Porter hypotheses supports what is known as the "weak" version of the Porter hypotheses, i.e. that energy prices are positively related with green innovation. Mohr (2002) showed that environmental regulation, like higher energy prices, are encouraging firms to invest in clean technologies. Also Mohr and Saha (2008) showed that environmental taxes trigger green innovation. Schmutzler (2001) chose an owner-manager model and confirmed that environmental taxes lead to innovation activities if some restrictive conditions are fulfilled. Hence, we formulate the following hypothesis:

H1: Energy prices are positively related to the number of 'green' innovations (i.e., the *level* of green technology inventions).

Econometric estimations (see, e.g., Popp 2002 (for different technologies), Aghion et al. 2012 (for the car industry)) confirm the fact that energy prices are positively related with the green innovation activities. Van Leeuwen and Mohnen (2013) found strong evidence that energy prices are positively related with green innovation investments.[4]

While the effect of energy prices on the incentive to invent green technologies is certainly relevant to policy, their effect on the *share* of inventions (i.e. a *relative* measure of patenting in green technologies in relation to other technologies) is also of interest because it can imply a diversion from other R&D activities. In line with theoretical models of green innovation (see e.g. Aghion et al. 2012) we expect a negative effect of energy prices on non-green innovation.[5] As a consequence of this and in combination with the positive effect of energy prices on green innovation proposed in hypothesis 1, the energy price effect on the share should be positive. Hence our second hypothesis is as follows:

H2: Energy prices are positively related to the number of green innovations relative to non-green innovations (i.e., the *share* of green technology inventions).

3. DESCRIPTION OF THE DATA

3.1 Measurement of Green Inventions Based on Patent Statistics

We use patents in order to measure the green invention activities of an industry. Patent statistics have many disadvantages in measuring innovation output (see Aghion et al. 2012, Griliches 1990). However, despite the fact that not all innovations 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.

The patent information in this paper has been 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.[6]

4. Horbach et al. (2012) found that cost savings are an important driver for green innovations. This implies that higher energy prices stimulate green innovation.

5. In some cases an increase in energy prices could lead firms to try to reduce costs by increasing innovation activities in technologies other than those increasing energy efficiency. However, even when the total effect of energy prices on non-green innovation may be positive (unlike suggested by Aghion et al. 2012), the direction of the price effect on the share of green technologies does not have to be positive as well, as on average of all companies the positive impact on green innovation proposed in hypothesis 1 may be larger than the impact on non-green innovation.

6. While there are energy related patent classifications included in all these categories, some of the categories may be less related to energy prices than others (e.g., technologies specific to emission mitigation). To deal with this fact we additionally estimated our main model separately for each of the seven categories (see Table A.8 and discussion in Section 5.3).

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

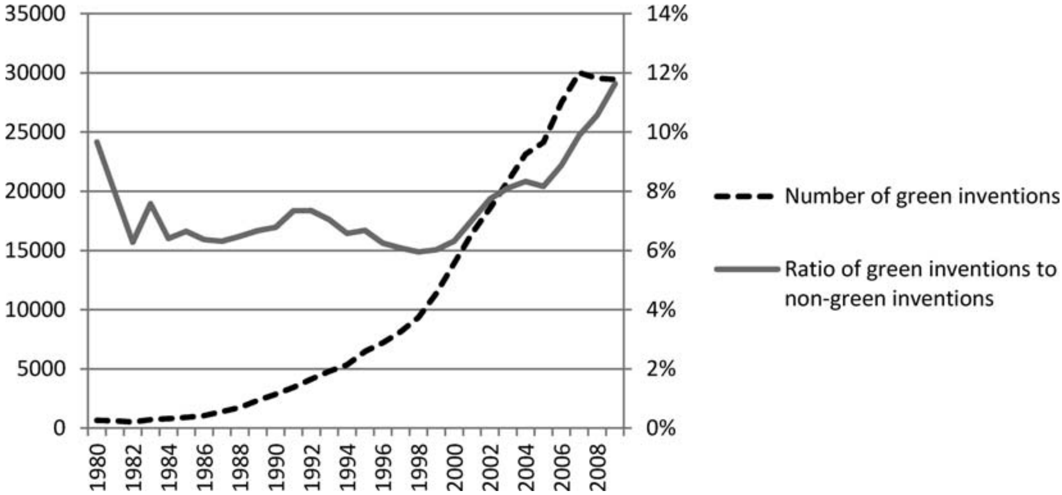
(a) In order to assign patents to countries, the applicant's country of residence or the inventor's country of residence may be chosen. We assigned patents according to the applicant's address. Since only those inventions were selected for which at least one PCT (Patent Cooperation Treaty) application was filed, the applicant's address was generally available.[7] Patent applications are usually costly. Moreover, the fees for an international patent application under the PCT are generally higher than those for a national or regional patent application. It seems likely that companies only use the PCT application route if they expect the inventions in question to have a significant commercial potential on the international level.
(b) We collected inventions (patent families) rather than single patents. The patent data stem from the EPO (European Patent Offices) World Patent Statistical database (PATSTAT). Patents were grouped into patent families according to the PATSTAT procedure (INPADOC). 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) 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.[8] Based on this concordance table we thus recoded our invention data into 10 manufacturing industry classes at the NACE two-digit level for which also energy price data were available.[9] In comparison with invention data at the firm level, aggregating inventions on an industry level should reduce potential problems with invention cycles within a firm.
(d) Our data set includes invention 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' and 'non-green' 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 refer to the period 1980–2009.

7. 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.

8. 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.

9. 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.

Figure 1: Development of Green Inventions Worldwide, 1980–2009



Source: Own calculations.

Figure 1 shows the aggregated development of green inventions over time. In 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 non-green 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 invention activity, the share of green inventions was quite instable at the beginning of our sample period and later stabilizes between at 6–8%. A disproportional increase in green inventions can be observed after 2000. By 2009, the overall share of green inventions had increased to 11.6%.

Detailed descriptive statistics for our disaggregated invention data are presented in Table 1. Nearly half of all green inventions are patented in the 'machinery' sector (48.8%). Furthermore, a considerable share is invented in the two industries 'chemicals' (24.3%) and 'transport equipment' (16.3%). The industry 'transport equipment' (34.8%) is at the same time the most green-intensive industry, followed by the two industries 'basic metals' (13.6%) and 'non-metallic minerals' (11.0%).

On the country level (see Table 1) we see larger shares of non-green inventions being generated by larger countries. The USA, Japan, and Germany hold 38.4%, 14.8%, and 12.8% respectively.

Concerning the respective shares in total green inventions (see column 4 in Table 1), we see a different picture. Although the USA (28.8%), Japan (21.4%), and Germany (17.9%) also show the greatest green shares, the country rankings change further down the line.

The last column in Table 1 shows the ratio of green inventions to non-green inventions. Japan (11.7%), Germany (11.3%) and Denmark (11.0%) show the highest degree of specialization in green invention activities, followed by Canada (10.5%) and Austria (9.7%). In sum, we see from these descriptive statistics that green invention activities show a great heterogeneity across industries and across countries.

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

Table 1: Number of Green and Non-green Inventions by Industry and Country

Period	1980–2009				
Type of invention	Non-green		Green		Green vs. non-green
	Number of non-green inventions	Relative share in total non-green inventions	Number of green inventions	Relative share in total green inventions	Ratio of green inventions to non-green inventions
Industry					
Chemicals	1172396	30.7%	74774	24.3%	6.4%
Food and tobacco	57592	1.5%	2288	0.7%	4.0%
Machinery	2051964	53.7%	150514	48.8%	7.3%
Basic metals	51632	1.3%	7032	2.3%	13.6%
Non-metallic minerals	90085	2.4%	9900	3.2%	11.0%
Paper, pulp and print	23549	0.6%	1429	0.5%	6.1%
Textile and leather	28032	0.7%	948	0.3%	3.4%
Transport equipment	144272	3.8%	50200	16.3%	34.8%
Wood and wood products	5193	0.1%	189	0.1%	3.6%
Non-specified industry	189730	5.0%	10046	3.3%	5.3%
Country					
Australia	62303	1.6%	5701	1.8%	9.2%
Austria	35719	0.9%	3466	1.1%	9.7%
Belgium	40310	1.1%	2586	0.8%	6.4%
Canada	85859	2.2%	8978	2.9%	10.5%
Switzerland	113971	3.0%	5995	1.9%	5.3%
Germany	489542	12.8%	55284	17.9%	11.3%
Denmark	38724	1.0%	4254	1.4%	11.0%
Spain	28392	0.7%	2520	0.8%	8.9%
Finland	50888	1.3%	3439	1.1%	6.8%
France	202914	5.3%	17071	5.5%	8.4%
United Kingdom	226064	5.9%	15076	4.9%	6.7%
Ireland	12421	0.3%	637	0.2%	5.1%
Italy	65896	1.7%	4639	1.5%	7.0%
Japan	564861	14.8%	65844	21.4%	11.7%
Korea	86305	2.3%	7267	2.4%	8.4%
Netherlands	130798	3.4%	8789	2.9%	6.7%
Sweden	110091	2.9%	6847	2.2%	6.2%
United States	1469387	38.4%	88927	28.8%	6.1%
Total	3814445	100%	307320	100%	8.1%

Notes: Data is based on own calculations; these statistics are based on 30 cross-sections, 18 countries and 10 industries (total of 5,400 observations); the relative share in total green inventions is calculated as the share of an industry's/country's number of green inventions relative to the number of all green inventions in our sample (sum of green inventions over all industries/countries in the sample); the ratio of green inventions to non-green inventions is defined as an industry's/ country's ratio of green inventions relative to its number of non-green inventions.

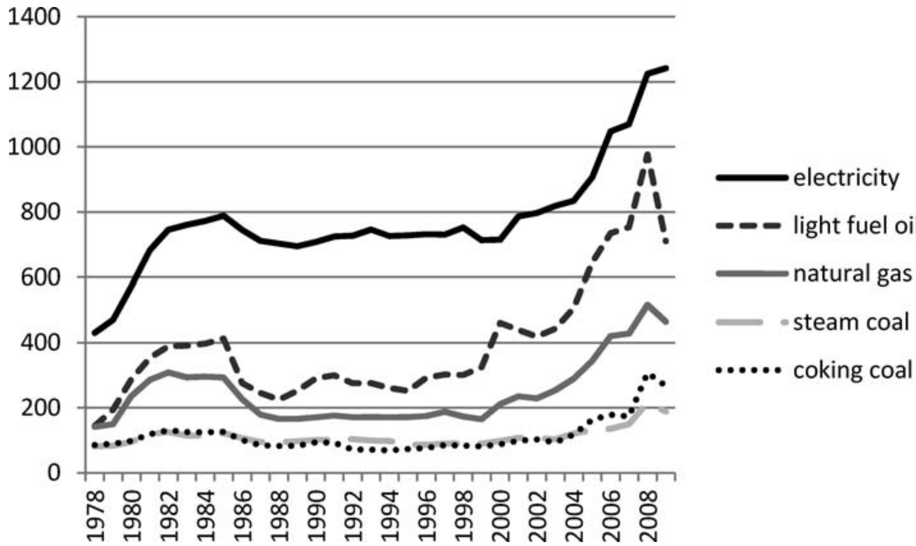
employment) and the capital input (gross fixed capital formation, volumes at current prices) of industries relevant for our estimations.[10]

3.3 IEA Energy Data

To analyse the impact of energy prices on invention, we use information on energy prices available from the International Energy Agency's (IEA) Energy Prices and Taxes Statistics (IEA

10. For the descriptive statistics of variables from the STAN data and other model variables see also Table 2.

Figure 2: Nominal Energy Prices for Electricity, Light Fuel Oil, Natural Gas, Steam Coal and Coking Coal (per tonne of oil equivalent (toe); PPP adjusted) by Year, 1978–2009



Source: IEA (2012a).

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[11] including taxes) for the manufacturing sector in USD (PPP).[12] This information is available for different energy products, such as electricity, light fuel oil,[13] natural gas and different coal products. Figure 2 shows the development of the energy prices since 1978. We see a parallel development of the energy prices of the respective sources. Several of these products show a sharp increase at the beginning of the 1980s and again from 2000 onwards. While the price of light fuel oil remarkably dropped in 2008, electricity prices increased. Electricity is the most expensive energy source at all times, followed by light fuel oil, natural gas, steam coal, and coking coal. With the exception of electricity, energy prices have doubled since 2000.

11. Tonne of oil equivalent; unit of energy for the practical expression of energy quantities (e.g., 1 MWh = 0.086 toe).

12. We refrain from producing estimates based on taxes alone (instead of total end-use prices including taxes) as the main explanatory variable. It is not clear why changes in taxes alone should drive innovation behavior, rather than changes in total prices (imagine a petroleum tax increase of 5 % and a contemporaneously decrease of the crude oil prices of 6%, ceteris paribus). Moreover, tax rates are either not available or zero for a large number of energy products and observations in our data, which makes the estimation of tax elasticities not only imprecise but also questionable.

13. The IEA also collects 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 waste heat.

At the country level (see Figure 3), we see that electricity is most expensive in Italy, followed by Japan, Korea, and Spain. Light fuel oil is most expensive in Korea followed by Italy, Spain, and Ireland. Natural gas is most expensive in Korea, followed by Sweden, Denmark, and Japan. However, the meaning of such a descriptive comparison of these prices is very limited, since prices are not available for all countries for all times. Hence, the average might be biased due to the fact that energy prices are only available at later times. This is the case for Sweden in terms of natural gas, for example.

Besides 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. Electricity (35%) followed by other products (28%) and natural gas (23%) are the most important sources of energy. Light fuel oil, steam coal and coking coal are of minor importance in the countries we looked at (see Figure 4). If we compare natural gas, light fuel oil and electricity on an industry level across all countries and all times, we see that in most industries, electricity is the most important energy source (see Figure 5). Only in the non-metallic minerals industry natural gas is more important. Natural gas is also relatively important in chemicals, food and tobacco, and in unspecified industries.

To get industry-specific energy prices, we multiply the energy prices with their relative importance within the industry.[14] The industry-specific energy price for an industry j, in country i at time t is defined as follows:

$$Energy\_price_{ijt} = \sum_{k \in S} w\_E_{ijtk} * \ln(Energy\_price_{itk}), \tag{1}$$

where

$$w\_E_{ijtk} = \frac{Energy\_use_{ijtk}}{\sum_{l \in S} Energy\_use_{ijtl}}, \tag{2}$$

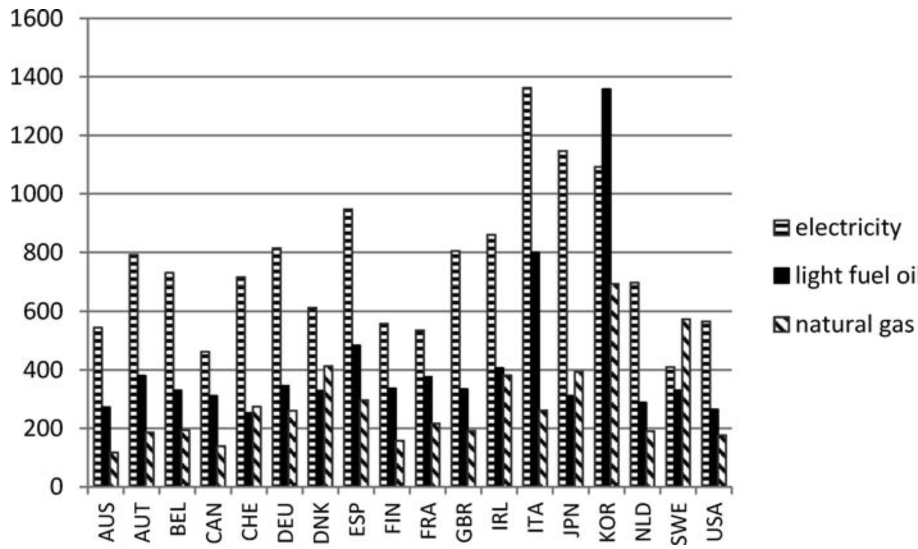
and

$$S = \{electricity, light\,fuel\,oil, natural\,gas, steam\,coal, coking\,coal\}. \tag{3}$$

The information on energy consumption as well as on energy prices is available for electricity, light fuel oil, natural gas, steam coal, and coking coal. However, due to missing values for some of the price variables, the industry-specific prices used in our main model are based on the three products electricity, light fuel oil (LFO) and natural gas, i.e. S includes only 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.3).

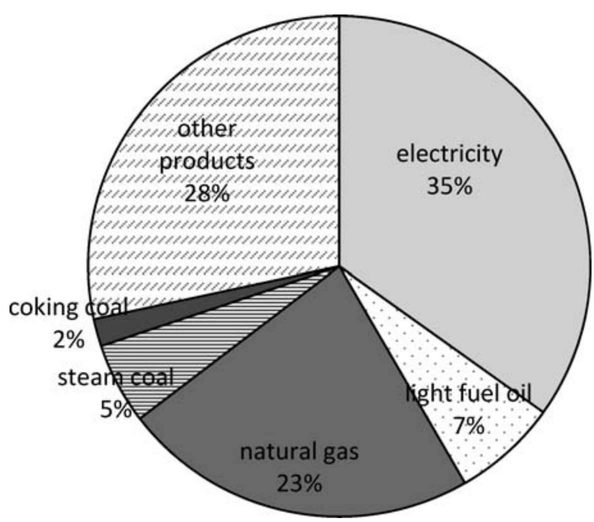
14. The appendix includes some additional notions and the results of related robustness checks on the construction of the composite industry-specific energy prices.

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



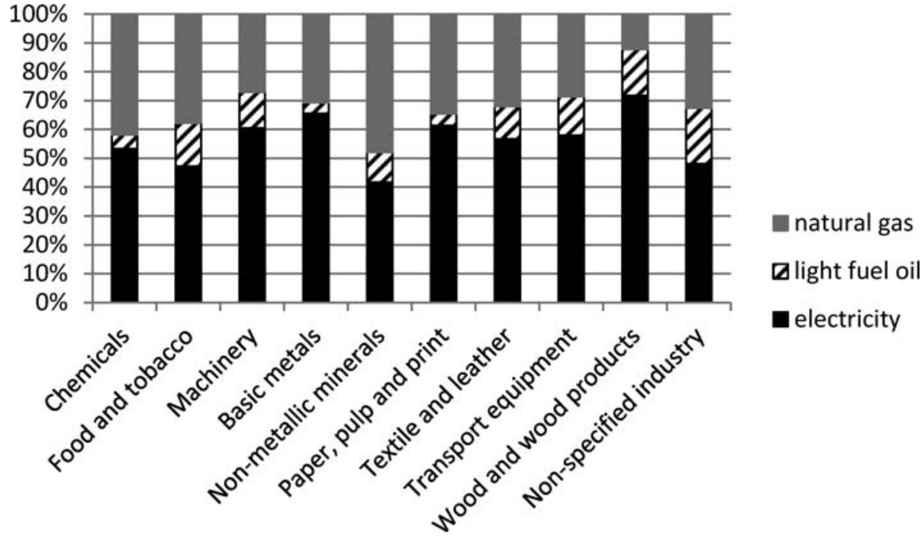
Notes: As the different price information is not available for all countries over the whole sample period, some of the figures are not directly comparable across countries and products. Natural gas prices for Sweden are for example only available for the years 2007–2009, and are thus not directly comparable 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



Other products: e.g., energy from biogas or heat.
Source: IEA (2012b).

Figure 5: Relative Share of Top Three Energy Products by Industry, 1978–2009



Source: IEA (2012b).

3.4 Combining the Data

As only very few invention counts could be registered in the years before 1980, we restrict the 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 5,400 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 formulated by Griliches (1979) and also applied by Jaffe (1986, 1989). Similar to Jaffe (1989), we look at innovations (i.e. patentable inventions) 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. Our dependent variable is *Green_inventions*, which is measured by the number of green patent families (inventions). Firm labor and capital are two important determinants. Specifically, we operationalize labor (*L*) as the industries' total number of employees, and the gross fixed capital formation per employee is used to proxy capital intensity (*K/L*).[15] Ideally, one would use data on the capital stock instead of capital formation. Unfortunately, this information is only available for a few countries in the STAN data-

15. Given that capital flow also has a size component, we measure capital as the ratio of capital/labor. With this formulation we lower the multi-collinearity between our measures for labor and capital in our main model. We thank an anonymous referee for this suggestion.

base. We thus use a flow variable as a proxy for capital intensity. Both variables, *L* and *K/L*, should be positively related with invention activity.

Besides the standard input factors, the current flow of green inventions 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 inventions (*Green_stock*).[16] Following Cockburn and Griliches (1988) and Aghion et al. (2012), the invention stock is calculated using the perpetual inventory method. Following this method, the stock is defined as

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

where δ is the depreciation rate of R&D capital.[17] 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.5). To capture potential effects of available knowledge in non-green technologies, we also control for the stocks of inventions that are not classified as green (*Non_green_stock*). The stock of non-green inventions is calculated in the same way as the stock of green inventions. In line with previous literature (see, e.g., Aghion et al. 2012, Stucki and Woerter 2012) we expect that both green-specific knowledge and non-green knowledge do stimulate current green invention 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 specification of our model is given by:

$$\begin{aligned} \ln(Green\_inventions_{ijt}) &= \ln(A) + \alpha\ln(L_{ijt-1}) + \beta\ln(K/L_{ijt-1}) + \varphi\ln(Green\_stock_{ijt-1}) \\ &+ \lambda\ln(Non\_green\_stock_{ijt-1}) + \phi\ln(Energy\_price_{ijt-1}) + \mu_{it} + \eta_{ij} + \varepsilon_{ijt}, \end{aligned} \tag{4}$$

where φ and λ are the coefficients of knowledge stocks, ϕ is the coefficient of energy prices, μ and η are two dimensions of fixed effects (see below), and ε is the stochastic error term (see Table 2 for variable definition). As invention variables may contain a value of zero, we used $\ln(1 + inventions)$ to avoid problems with the logarithm (see Wooldridge 2002, p. 185).[18] 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 time lags for energy prices (2–5 year lag), we construct a weighted average of past prices as proposed by Popp (2002) and we calculate a moving average of the energy prices over the previous five years.

To control for correlated unobserved heterogeneity, we include country-specific industry fixed effects (η). This way we control for the general policy climate of countries in terms of industry-specific policy measures.[19] Furthermore, to reduce the risk of an omitted variable bias from country

16. 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.

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

18. Alternative estimates that either exclude observations where the dependent variable takes a value of 0 or are based on count data models in order to avoid such a transformation are discussed in the robustness section.

19. More concretely, we control for policies that are industry specific and do not change across time. These fixed effects do not control for industry specific policy shocks.

Table 2: Variable Definition and Measurement

Variable	Definition/measurement	Source	Mean	Std. Dev.	Min	Max
Dependent variable						
Green_inventions$_{ijt}$	Number of green inventions	own calculations	75.09	309.92	0	4015
Non_green_inventions$_{ijt}$	Number of inventions that are not classified as green	own calculations	1049.61	5002.95	0	66161
Independent variable						
L$_{ijt-1}$	Number of persons engaged (total employment)	OECD STAN	424714.50	771460.70	2676	6036188
K/L$_{ijt-1}$	Gross fixed capital formation (volumes at current price value) per employee	OECD STAN, and own calculation	8981.49	6317.22	933.67	126731.40
Green_stock$_{ijt-1}$	Stock of green inventions	own calculations	280.60	1240.17	0	18692.86
Non_green_stock$_{ijt-1}$	Stock of inventions that are not classified as green	own calculations	4314.71	22570.66	0	321222.30
Energy_price$_{ijt-1}$	Industry-specific energy price based on electricity, light fuel oil and natural gas prices, PPP	IEA	550.06	267.12	90.05	2921.94
Popp_energy_price$_{ijt-1}$	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	241.23	182.44	47.02	1365.05
Moving_average_energy_price$_{ijt-1}$	Moving average of the energy prices over the previous five years	IEA	470.53	175.16	103.71	1173.78

Notes: The descriptive statistics for most variables is based on the estimation sample of column (4) of Table 3 (1,962 observations); exceptions are the statistics for the variables Popp_energy_price$_{ijt-1}$ that is based on the estimation sample of column (3) of Table A.4 (2,725 observations) and Energy_price$_{ijt-1}$ that is based on the estimation sample of column (1) of Table A.6 (3,142 observations).

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 estimates for energy prices may be biased. The fixed effect μ captures such country specific shocks.[20]

As the time series dimension of our data is quite long and the patent data series are likely to be persistent, the results for our patent stock variables may be driven by non-stationarity. In order to deal with this issue, we perform unit root tests for the patent stock variables included in the regressions. We employ three different tests proposed by Levin et al. (2002), Im et al. (2003) and Pesaran (2003), respectively. Based on all three tests we can reject the unit root assumption for any of the patent variables (test results are available on request).

As we are not just interested in the effect of energy prices on the total number of green inventions (i.e., the level of green invention activities; see H1), but also in the effect on the development of the number of green inventions relative to non-green inventions (i.e., the share of green technology inventions; see H2), we alternatively estimate our innovation model with a different dependent variable that measures the difference between the logarithms of the number of green inventions and non-green inventions (ratio of green inventions to non-green inventions). Our second model is:

$$\begin{aligned}\ln(Green\_inventions_{ijt}) - \ln(Non\_green\_inventions_{ijt}) &= \ln(A) + \alpha\ln(L_{ijt-1}) + \beta\ln(K/L_{ijt-1}) \\ &+ \varphi\ln(Green\_stock_{ijt-1}) + \lambda\ln(Non\_green\_stock_{ijt-1}) + \phi\ln(Energy\_price_{ijt-1}) \\ &+ \mu_{it} + \eta_{ij} + \varepsilon_{ijt}.\end{aligned} \tag{5}$$

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 inventions (alternative estimation methods that, e.g., deal with the count data characteristics of the green invention variable are discussed in the robustness section).[21] Table 4 shows the estimates for the models with the log ratio of green to non-green inventions as dependent variable, as specified in Equation 4. Our baseline specifications include a moving average of the energy prices over five years, as we believe that innovation decisions are primarily linked to longer time trends. Estimates based on alternative price variables are presented in Tables A.4, A.6 and A.7.

In columns (1) and (2) we estimate a basic model that includes neither a variable controlling for capital, nor country-specific time fixed effects. In these specifications, the price effect goes in

20. The remaining variance in the price variable comes from both (a) changes in the individual energy mix of the industries and (b) changes in the prices of the different energy products, given an industry's energy mix.

21. Our dependent variable is the natural logarithm of the number of green inventions, which is a count variable. Accordingly, count data models would be appropriate. However, these models turned out to be incapable of incorporating both dimensions of fixed effects (μ and η) at the same time, which is one of the main contributions of our paper. We thus decided to present as a baseline specification the OLS fixed-effects regressions. Nevertheless, we present robustness tests using count data models based on slightly simplified specifications in Table A.1.

Table 3: Estimation Results for the Green Invention Level

Estimation method	OLS log linear fixed-effects regression				
Period	1984–2009				
Dependent variable	$\ln(\text{Green\_inventions}_{ijt})$				
	(1)	(2)	(3)	(4)	(5)
$\ln(L_{ijt-1})$	0.056	−0.001	0.098	0.147*	0.103
	(0.045)	(0.075)	(0.068)	(0.080)	(0.085)
$\ln(K/L_{ijt-1})$				0.119**	
				(0.059)	
$\ln(\text{Green\_stock}_{ijt-1})$	0.791***	0.642***	0.551***	0.550***	0.557***
	(0.030)	(0.041)	(0.043)	(0.047)	(0.046)
$\ln(\text{Non\_green\_stock}_{ijt-1})$	0.034	0.013	0.164***	0.158***	0.166***
	(0.035)	(0.043)	(0.050)	(0.059)	(0.059)
$\ln(\text{Moving\_average\_energy\_price}_{ijt-1})$	0.037	0.144	0.342**	0.268*	0.269*
	(0.074)	(0.111)	(0.141)	(0.143)	(0.141)
Constant	−1.013	−0.774	−3.880***	−4.903***	−3.384***
	(0.736)	(1.138)	(1.092)	(1.190)	(1.123)
Time fixed effects	yes	yes	no	no	no
Country fixed effects	yes	no	no	no	no
Industry fixed effects	yes	no	no	no	no
Country-specific time fixed effects	no	no	yes	yes	yes
Country-specific industry fixed effects	no	yes	yes	yes	yes
N	2669	2669	2669	1962	1962
Groups	144	144	144	116	116
R^2 within		0.69	0.76	0.71	0.71
R^2	0.92				

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.

the expected direction, but is statistically insignificant. However, the price effect doubles in magnitude and becomes statistically significant positive at the 5% level, when we include country-specific time fixed effects (see column 3). Accordingly, the price effect is downward biased when we do not control for country specific shocks. These results empirically emphasize the importance of such controls that have been neglected in previous studies. In column (4) we finally add a capital control variable that slightly reduces the price effect. However, as the capital variable has many missing values, the inclusion significantly reduces the available number of observations from 2,669 to 1,962. Accordingly, the reduction in the price effect may be driven by a selection bias. To test whether this is the case, column (5) shows the results for the reduced model based on the same observations that are available in the full model. As the results for the energy price variable only marginally differ between these two models, we conclude that the capital control does not affect the price effect. Accordingly, the minor differences in the price effect between model (3) and (4) seem to be driven by a selection bias. Accordingly, we take model (3) as our baseline specification for which we conduct a number of further robustness checks. In this model, a 1% increase of the average energy price of the previous five years results in a 0.34% increase of the number of green inventions. This result is in line with hypothesis H1 that states that higher energy prices stimulate current green innovation activities.

In line with Hypothesis H2, the green invention share is positively related to energy prices (see Table 4). Like for the green invention level, the price effect on green invention share is also

Table 4: Estimation Results for the Green Invention Share

Estimation method	OLS log linear fixed-effects regression				
Period	1984–2009				
Dependent variable	$\ln(Green\_inventions_{ijt}) - \ln(Non\_green\_inventions_{ijt})$				
	(1)	(2)	(3)	(4)	(5)
$\ln(L_{ijt-1})$	−0.060	−0.234***	−0.111	−0.071	−0.079
	(0.049)	(0.077)	(0.085)	(0.100)	(0.096)
$\ln(K/L_{ijt-1})$				0.022	
				(0.068)	
$\ln(Green\_stock_{ijt-1})$	0.563***	0.372***	0.292***	0.295***	0.296***
	(0.031)	(0.043)	(0.051)	(0.051)	(0.052)
$\ln(Non\_green\_stock_{ijt-1})$	−0.592***	−0.506***	−0.297***	−0.227***	−0.225***
	(0.038)	(0.051)	(0.068)	(0.080)	(0.080)
$\ln(Moving\_average\_energy\_price_{ijt-1})$	0.127	0.210*	0.481**	0.450**	0.450**
	(0.081)	(0.120)	(0.194)	(0.213)	(0.212)
Constant	−0.323	1.169	−3.101**	−3.745**	−3.480***
	(0.789)	(1.201)	(1.408)	(1.569)	(1.310)
Time fixed effects	yes	yes	no	no	no
Country fixed effects	yes	no	no	no	no
Industry fixed effects	yes	no	no	no	no
Country-specific time fixed effects	no	no	yes	yes	yes
Country-specific industry fixed effects	no	yes	yes	yes	yes
N	2669	2669	2669	1962	1962
Groups		144	144	116	116
R^2 within		0.31	0.44	0.43	0.43
R^2	0.63				

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. Alternatively we inserted the ratio of green to non-green knowledge stock as an independent variable and omitted the variable for the level of the green knowledge stock and the level of the non-green knowledge stock. The ratio also has a significant positive effect.

downward biased when we do not control for country specific shocks. Furthermore, the price effect is not affected by the inclusion of the capital control variable. In our baseline specification, a 1% increase in the average energy price over the previous five years results in a 0.48% increase of the ratio of green to non-green inventions (see column 3).

The results for the control variables are in line with general expectations. Labor input (*L*) and physical capital intensity (*K/L*) are positively correlated with the number of green inventions. However, we cannot observe a significant effect for these two variables with respect to the share of green inventions. The green invention share is neither affected by labor input nor by physical capital intensity. As expected a larger stock of green knowledge does stimulate current activities in green invention. Furthermore, we find in Table 3 that knowledge in non-green technologies serves as a resource for green invention as well—the effect of *Non_green_stock* on the number of green inventions is significantly positive. The positive effect of green knowledge on current green invention activities is, however, significantly larger than the positive effect of non-green knowledge. The effect of *Non_green_stock* on the share of green inventions is significantly negative (see Table 4).[22]

22. The *Non_green_stock* and the *Green_stock* have an elasticity of similar magnitude with opposite signs. Hence, we conducted a t-test on the "equal and opposite" effects of the green knowledge stock and the non-green knowledge stock and we see that the sum of both is not significantly different from zero, e.g., for equation 4 in Table 4 we get $p = 0.9365$.

Yet, the relative impact of *Non_green_stock* on green invention is smaller than the impact on non-green invention, which would seem to indicate differentiated opportunity costs.

5.2 Robustness Tests

We made comprehensive tests to check the robustness of our main results discussed before. All these tests are based on the models without the capital flow variable and using moving averages of the energy prices over the previous five years (as appearing in column 3 of Tables 3 and 4, respectively). Moreover, we present some additional notions and robustness checks on the construction of the composite industry-specific energy prices (see Appendix).

Dealing with special characteristics of our data

Adding 1 before taking the logarithm is often used in order to avoid a significant drop in the number of observations. However, such a transformation may bias the results (see Wooldridge 2002, p. 185). This is especially true if the data contain many zeros. In our data set about one third of the industries do not have green inventions. Accordingly, our baseline results could be biased.

To deal with this potential problem, we estimate our baseline models in a next step when we drop the observations where the dependent variables take a value of 0. The respective estimation results are presented in columns (1) and (2) of Table A.1. In both models, the price effect is smaller than that found in previous estimates. The effect on the green invention level decreases from 0.34 to 0.22 and the effect on the green invention share decreases from 0.48 to 0.29, and becomes statistically insignificant.

A drawback of dropping the zeros is that we probably introduce a selection problem. An appropriate solution to overcome the problem is thus to avoid taking the logarithm and instead estimate a count data model. 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. Unfortunately, this procedure does not allow for the inclusion of country-specific time fixed effects, thus time fixed effects only have been included as the nearest best alternative specification. The estimation results with respect to energy prices are only marginally affected by this alternative estimation procedure. While still statistically significant, the effect of energy prices on green inventions decreases from 0.34 to 0.20 compared with the baseline model. However, this decrease in the coefficient estimate for energy prices seems to be driven by the different specification of fixed effects, rather than due to applying a count data model: when estimating a log-linear OLS model with time fixed effects only and on the same sample as was used for column (3) in Table A.1, the coefficient drops from 0.34 to 0.15 (see column 4).

Column (5) of Table A.1 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 inventions over the pre-sample period 1975–1985 for both, green and non-green inventions (both in logs), as well as two binary variables that measure whether an industry had any inventions at all in the pre-sample period. This procedure does again slightly reduce the size of the effect of energy prices (0.15 vs. 0.34); however, the effect remains statistically significant and positive.

In sum we thus find some evidence that our baseline results may overestimate the price effect. However, as the alternative estimation methods do not allow us to control for country-specific shocks that turned out to be econometrically relevant, we chose these models not to be our baseline specification.[23]

Alternative price baskets

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 presented in Tables 3 and 4 with price variables that are based on more detailed baskets of energy products, i.e. S in equations 1 and 2 was extended to additional energy products (for descriptive information about these variables see Table A.2). 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.[24] 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 A.3. To be able to compare these results with previous results, columns (1) and (4) 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 invention level and 0.55 vs. 0.48 for green invention share) 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 four products electricity, light fuel oil, natural gas, and steam coal. Based on this basket we identify elasticities of 0.68 and 0.93 for the number of green inventions and the ratio of green vs. non-green inventions, respectively (see columns 2 and 5). Consequently, the robustness test shows that more energy products, which better reflects the "real" product mix of an industry, tend to increase the price effect compared to our baseline model.

Alternative clustering level

So far, standard errors were clustered at the industry/country level. However, as our control variables do not control for a potential industry specific shock, we alternatively cluster at the industry level. In columns (1) and (2) of Table A.4 we thus present the baseline regressions based on standard errors that are clustered at the industry level. The alternative clustering level even slightly decreases the standard errors compared with previous estimates.

Alternative construction of the price variable

In our baseline specification of the energy price was included as a moving average of the energy prices over the previous five years. Popp (2002) proposed an alternative price variable that is based on a weighted average of past prices.[25] Estimations based on such an alternative price

23. Furthermore, the Blundell et al. (1995) procedure mainly corrects for the endogeneity of the lagged dependent variable, which is a control variable in our model.

24. 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.

25. 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: where ψ, the adjustment coefficient that represents the weights placed on past

variable are presented in columns (3) and (4) of Table 4. While the price effect on the green invention level only marginally increases by this alternative construction (0.39 vs. 0.34), the increase in the price effect on the green invention share is more pronounced (0.61 vs. 0.48).

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.5 (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 magnitude, significance, and sign of the coefficients remain essentially unchanged.

Checking for outliers

Columns (5) to (8) of Table A.5 show the estimation results with regard to outliers. The distribution of inventions across industries is very heterogeneous. Consequently we run our estimation excluding the top 1% of performers and the top 5% of the performers, respectively.[26] This only marginally affected our results. We thus conclude that our results are not driven by outliers.

5.3 Extensions

Estimates based on different time lags

In Tables A.6 and A.7 we analyze the dynamics of the price effects based on alternative lags. The estimation results indicate that the impact of energy prices increases with an increasing time lag between energy prices and invention activities. To be able to properly identify the time trends, we alternatively estimate the models for similar samples (columns 6 to 10 of the respective tables). With respect to the green invention level, the price effect increases from 0.14 to 0.24 when we extend the time lag from 1 to 5 years (see Table A.6). The effect of energy prices on the green invention share increases from 0.24 to 0.35 (see Table A.7).

Estimates for different subcategories of green invention

Our estimates are so far based on quite a 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 baseline model for the green invention level separately for the seven environmental areas that are included in the OECD definition (see OECD 2012). To make a prediction about the relative size of the price effects, we first have to get an understanding of what is really included in the different categories. Based on the OECD Patents statistics we can identify the relative importance of the different patent fields that are included in the seven environmental areas (see OECD 2013). 'General environmental management' primarily includes technologies dealing with air or water pollution abatement. 'Energy generation from re-

observations, is 0.83 (see Popp 2002 for a similar procedure), and at the beginning of the sample period where no price data for previous time periods was available, price expectations have been set to current prices.

26. 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 invention 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.

newable and non-fossil sources' primarily includes solar photovoltaic energy generation. 'Combustion technologies with mitigation potential' primarily includes combined cycles for improved output efficiency. 'Technologies specific to climate change mitigation' mostly refers to CO_2 capture and storage (CCS). 'Technologies with potential or indirect contribution to emission mitigation' mostly deal with energy storage or fuel cells. 'Emission abatement and fuel efficiency in transportation' primarily include technologies that control the emissions produced by internal combustion. Finally, most patents in 'energy efficiency in buildings and lightings' deal with lighting.

Based on this information we would expect that the two categories 'general environmental management' and 'technologies specific to climate change mitigation' are not directly energy related. Accordingly, innovation in these areas should primarily be related to general emission costs (e.g., CO_2 prices) rather than specific energy prices.

The estimation results for the different categories are presented in Table A.8. 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 inventions in 'technologies with potential or indirect contribution to emission mitigation' (0.38) and 'energy generation from renewable and non-fossil sources' (0.38).[27] A smaller impact can be observed for more general green inventions dealing with 'general environmental management' (0.24). Inventions dealing with 'technologies specified to climate change mitigation' are not even significantly affected by energy price shocks. This result may also be driven by the fact that these technologies are not mature yet, and thus probably respond more to technology-push policies than to demand pull policies.

However, overall we have to state, that the variation in the elasticities between the different categories is relatively small. With the exception of technologies dealing with 'climate change mitigation' the effects vary between 0.24 and 0.38. As we have seen in the robustness section, we should not over interpret this variation.

5.4 Discussion

Our results indicate that energy prices positively affect both, the level and the share of green invention. Although we do not explicitly investigate crowding out effects of green innovation activities (see van Leeuwen and Mohnen 2013, Marin 2014 for crowding out investigations on the firm-level), the relatively large difference in the price effects for the green invention level (0.34) and for the price effects for the green share (0.48) indicates some tendency to crowd out non-green invention; this because the *share* of green invention responds more to energy prices than the *number* of green inventions. Indeed, we find a significantly negative effect of energy prices on non-green invention in all but one model specification (see Table A.9).[28]

27. Somewhat surprising is the relatively strong positive effect for "transport patents", as such technologies should primarily be stimulated by end-user prices and not by industry specific prices. However, we would expect that some of these inventions are used in the industry, and are thus also affected by industry-specific energy prices. Another explanation is that innovation activities in a certain field of green innovation are induced by innovation activities in other fields (e.g., due to knowledge spillovers). Accordingly, even when innovation activities in a certain field are not directly affected by energy prices, there may be an indirect effect via other green innovation activities. Some evidence for such interrelations is the fact that the developments of the number of inventions in the different areas are relatively strongly correlated with each other (these correlations are not presented here but are available on request).

28. The impact of energy prices on total invention activity is negative but only small in size and not statistically significant (these estimates are not presented here but are available on request). This finding is not surprising, given that to a large degree, innovation activities are financed by firms' cash flow (rather than through external funding). Thus, by raising total costs of production, higher energy prices are likely to diminish firms' capacities to finance overall innovation activities.

As described in the introduction, our model is based on a broader data set than most previous studies. It would thus be interesting to analyze how the breadth of the panel affects the estimated impact of energy prices. Since previous models either include different control variables or even use different measures for green innovation, we attempt to draw some comparisons of the effects of energy prices, yet we stress that these can only be of limited scope.

Crabb and Johnson (2011) focus on energy-efficient automotive patents in the USA and find a price elasticity of 0.36 (with the retail price of gas as the explanatory variable), which is only slightly larger than what we find in our best corresponding estimation. Based on a lag structure of one year we find for the reduced model a price elasticity of 0.20.

Aghion et al. (2012) also focus on the auto industry and analyze the effect of fuel prices on different innovation variables based on firm-level data across 80 countries. They identify elasticities of 0.97 and -0.57 for the number of 'clean' 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 for the reduced model elasticities of 0.20 and -0.14, respectively (see Tables A.7 and A.9). In line with our results, they also find that the impact of energy prices increases with an increasing lag between energy prices and innovation activities.

Popp (2002) analyses the impact of energy prices on energy-related technologies in the USA and identifies an effect of energy prices on the share of energy-efficient innovations in total innovations. Though we look at the ratio of green innovations to non-green innovations, the long run elasticity of 0.34 identified by Popp is similar to the 0.52 that we find when using comparable energy prices[29] for 13 countries (see columns 3 and 4 of Table A.4).

In sum we observe that our results are more similar to studies that focus on a single country (i.e. Popp 2002 for the USA) than to studies that focus on a single industry (i.e. Aghion et al. 2012 for the auto industry). While the price effect in the USA is somewhat smaller than what we find in our cross-country study (0.34 vs. 0.52), the effect for the auto industry is significantly larger than what we find on average of all industries (0.94 vs. 0.20 and -0.57 vs. -0.14). Accordingly, it seems that the dependency on fuel prices in the auto industry is larger than the dependency on energy prices in other manufacturing industries. Furthermore, the dependency on energy prices in the USA seems to be slightly smaller than in other countries. The result by Crabb and Johnson (2011) that are based on both, the auto industry and the USA, lies somewhere in the middle (0.36 vs. 0.20). However, further investigations are necessary to identify the factors that drive the observed differences in price elasticities between countries and/or industries.[30]

Probably more related to our study are the results by Verdolini and Galeotti (2011) that are based on a panel of 17 countries and 12 technologies. They analyze the impact of country-specific energy prices (IEA real index for end-use energy prices for industry obtained estimates for the elasticity of energy prices) on the number of energy-related patents on the technology level. They obtained estimates for the elasticity of energy prices on the number of energy-related patents in a range between 0.4 and 0.6, depending on model specification; thus slightly higher than our best corresponding (in terms of model specification) estimate of 0.2 (Table A.6, column 1). These differences are likely to be driven by different model specifications. While Verdolini and Galeotti

29. Estimates based on a weighted average of lagged energy prices with a discount factor of 0.83.

30. In additional estimates we separately estimated our main model for high energy intensive and low energy intensive industries. Due to the much lower number of observations, we could not identify statistically significant price effects in the two models. However, the effect of energy prices turned out to be positive in both models, and the effect of energy prices was slightly larger for energy-intensive industries.

(2011) stay on the technology level, we refer to the industry level, and we can thus control for industry characteristics. Moreover they work with country-level energy prices, while we have industry-specific prices, which enable us to control for country-specific shocks.

6. CONCLUSIONS

Based on industry-level panel data, this paper investigates the determinants of green invention activities of an industry. We find that energy prices do stimulate both, the level of green invention as well as the share of green invention. In our model, a 10% increase of the average energy prices over the previous five years results in a 3.4% and 4.8% increase of the number of green inventions and the ratio of green to non-green inventions, respectively. While the main focus is on the impact of energy prices, our model shows several other interesting results. Firstly, we find that available knowledge stocks serve as an invention-relevant resource for green invention independent of whether available knowledge is green-specific knowledge or knowledge in non-green technologies. Secondly, as a large knowledge stock in non-green technologies represents larger opportunity costs with respect to green invention, the effect of non-green knowledge on current green invention is significantly smaller than the effect of green knowledge. Furthermore, the effect of non-green knowledge on the share of green inventions is significantly negative.

In contrast to previous studies, our results are more general because they are based on a broader set of industries and countries. 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 invention. Furthermore, we have reduced the probability of an omitted-variable bias by calculating industry-specific energy prices. When comparing our results with the results of previous studies, we found that price elasticities seem to vary primarily across industries and not across countries. Accordingly, energy prices do not seem to be an equally suitable instrument to stimulate green invention across different industries. Due to the limited number of observations in our data set, it was unfortunately not possible to compare price elasticities across industries. In order to improve energy policy, it would be a worthwhile task for future research to identify such inter-industry differences in innovation response to energy prices.

Despite a large future market potential, firms are probably not willing by themselves to invest in green technologies, as green innovations currently show lower returns than non-green innovations (see Marin 2014, Soltmann et al. 2014). Furthermore, as green inventions are primarily related to green-specific knowledge, industries and countries will have to build up their own green knowledge when they want to be competitive in this market, even when it is financially not very attractive at the moment (see Stucki and Woerter 2012). Accordingly, knowledge about potential policy instruments to stimulate inventions 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; (b) may serve as an important foundation to establish a cleantech market for which long-term growth is predicted.

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REFERENCES

Aghion, P., A. Dechezleprêtre, D. Hemous, R. Martin and J. Van Reenen (2012). "Carbon taxes, path dependency and directed technical change: Evidence from the auto industry." NBER Working Paper, No. 18596.

Allison, P. and R.P. Waterman (2002). "Fixed-effects negative binomial regression models." *Sociological Methodology* 32(1): 247–265. http://dx.doi.org/10.1111/1467-9531.00117.

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

Beise, M. and K. Rennings (2005). "Lead markets and regulation: a framework for analyzing the international diffusion of environmental innovations." *Ecological Economics* 52(1): 5–17. http://dx.doi.org/10.1016/j.ecolecon.2004.06.007.

Binswanger, H.P. and V.W. Ruttan (1978). *Induced Innovation*. The Johns Hopkins University Press, Baltimore.

Blundell, R., R. Griffith and J. Van Reenen (1995). "Dynamic Count Data Models of Technological Innovation." *The Economic Journal* 105(March): 333–344. http://dx.doi.org/10.2307/2235494.

Brunnermeier, S.B. and M.A. Cohen (2003). "Determinants of Environmental Innovation in US Manufacturing Industries." *Journal of Environmental Economics and Management* 45(2): 278–293. http://dx.doi.org/10.1016/S0095-0696(02)00058-X.

Carraro, C. and D. Siniscalco (1994). "Environmental policy reconsidered: The role of technological innovation." *European Economic Review* 38(1): 545–554. http://dx.doi.org/10.1016/0014-2921(94)90090-6.

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

Crabb, J. M. and D.K.N. Johnson (2010). "Fueling Innovation: The impact of oil prices and CAFE standards on energy-efficient automotive technology." *The Energy Journal* 31(1): 199–216. http://dx.doi.org/10.5547/ISSN0195-6574-EJ-Vol31-No1-9.

Faber, A. and K. Frenken (2009). "Models in evolutionary economics and environmental policy: Towards an evolutionary environmental economics." *Technological Forecasting and Social Change* 76(4): 462–470. http://dx.doi.org/10.1016/j.techfore.2008.04.009.

Griliches, Z. (1979). "Issues in Assessing the Contribution of Research and Development to Productivity Growth." *Bell Journal of Economics* 10(1): 92–116. http://dx.doi.org/10.2307/3003321.

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

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.

Hall B.H., A. Jaffe and M. Trajtenberg (2005). "Market value and patent citations." *Rand Journal of Economics* 36(1): 16–38.

Helm, D. (2012). *The Carbon Crunch*. Yale University Press, New Haven and London. http://dx.doi.org/10.12987/yale/9780300186598.001.0001.

Horbach, J., C. Rammer and K. Rennings (2012). "Determinants of eco-innovations by type of environmental impact - The role of regulatory push/pull, technology push and market pull." *Ecological Economics* 78: 112–122. http://dx.doi.org/10.1016/j.ecolecon.2012.04.005.

IEA (2012a). "IEA Energy Prices and Taxes Statistics." available at: www.oecd-ilibrary.org/energy/data/iea-energy-prices-and-taxes-statistics_eneprice-data-en (accessed December 2012).

IEA (2012b). "IEA World Energy Statistics and Balances, Extended world energy balances." available at: www.oecd-ilibrary.org/energy/data/iea-world-energy-statistics-and-balances_enestats-data-en (accessed December 2012).

Im, K.S., M.H. Pesaran and Y. Shin (2003). "Testing for unit roots in heterogeneous panels." *Journal of Econometrics* 115: 53–74. http://dx.doi.org/10.1016/S0304-4076(03)00092-7.

Jaffe, A.B. (1986). "Technological Opportunity and Spillovers of R&D: Evidence from Firms' Patens, 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. and K. Palmer (1997). “Environmental regulation and innovation: A panel data study.” *Review of Economics and Statistics* 79(4): 610–519. http://dx.doi.org/10.1162/003465397557196.

Johnstone, N., I. Haščič. and D. Popp (2010). “Renewable energy policies and technological innovation: Evidence based on patent counts.” *Environmental and Resource Economics* 45(1): 133–55. http://dx.doi.org/10.1007/s10640-009-9309-1.

Johnstone, N., I. Haščič, J. Poirier, M. Hemar and C. Michel (2012). “Environmental policy stringency and technological innovation: evidence from survey data and patent counts.” *Applied Economics* 44(17): 2157–2170. http://dx.doi.org/10.1080/00036846.2011.560110.

Keller, W. (2002). “Geographic Localization of International Technology Diffusion.” *American Economic Review* 92(1): 120–142. http://dx.doi.org/10.1257/000282802760015630.

Lanzi, E. and Sue Wing, I. (2011). “Directed Technical Change in the Energy Sector: An Empirical Test of Induced Directed Innovation.” Paper presented at the WCERE 2010 Conference, mimeo.

Lanjouw, J.O. and A. Mody (1996). “Innovation and the international diffusion of environmentally responsive technology.” *Research Policy* 25(4): 549–571. http://dx.doi.org/10.1016/0048-7333(95)00853-5.

Levin, A., C.F. Lin and C.S.J. Chu (2002). “Unit root tests in panel data: Asymptotic and finite-sample properties.” *Journal of Econometrics* 108: 1–24. http://dx.doi.org/10.1016/S0304-4076(01)00098-7.

Lybbert, T. and N.J. Zolas (2012). “Getting Patents and Economic Data to Speak to Each Other: An ‘Algorithmic Links with Probabilities’ Platform for Joint Analyses of Patenting Trade and Industrial Activity.” Working Paper, University of California, Davis.

Marin, G. (2014). “Do Eco-Innovations harm productivity growth through crowding out? Results of an extended CDM model for Italy.” *Research Policy* 43(2): 301–317. http://dx.doi.org/10.1016/j.respol.2013.10.015.

Mohr, R.D. (2002). “Technical Change, External Economies, and the Porter Hypothesis.” *Journal of Environmental Economics and Management* 43: 158–168. http://dx.doi.org/10.1006/jeem.2000.1166.

Mohr, R.D., and S. Saha (2008). “Distribution of Environmental Costs and Benefits, Additional Distortions, and the Porter Hypothesis.” *Land Economics* 84(4): 689–700.

Newell, R.G., A.B. Jaffe and R.N. Stavins (1999). “The Induced Innovation Hypothesis and Energy-Saving Technological Change.” *The Quarterly Journal of Economics* 114(3): 941–975. http://dx.doi.org/10.1162/003355399556188.

OECD (2011). “OECD STAN Database for Structural Analysis (ISIC Rev. 3) .” available at: www.oecd.org/sti/stan (accessed December 2012).

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

OECD (2013). “OECD Patents statistics, Main Science and Technology Indicators full database.” available at: http://www.oecd.org/sti/msti.htm (accessed April 2014).

Pesaran, H. (2003). “A Simple Panel Unit Root Test in the Presence of Cross Section Dependence.” Cambridge Working Papers in Economics 0346, Faculty of Economics (DAE), University of Cambridge.

Popp, D. (2002). “Induced Innovation and Energy Prices.” *The American Economic Review* 92(1): 160–180. http://dx.doi.org/10.1257/000282802760015658.

Popp, D. (2011). “International Technology Transfer, Climate Change, and the Clean Development Mechanism.” *Review of Environmental Economics and Policy* 5(1): 131–152. http://dx.doi.org/10.1093/reep/req018.

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

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

Schmutzler, A. (2001). “Environmental Regulations and Managerial Myopia.” *Environmental and Resource Economics* 18: 87–100. http://dx.doi.org/10.1023/A:1011113106055.

Soltmann, C., T. Stucki and M. Woerter (2014). “The Impact of Environmentally Friendly Innovations on Value Added.” *Environmental and Resource Economics*, forthcoming. http://dx.doi.org/10.1007/s10640-014-9824-6.

Stucki, T. and M. Woerter (2012). “Determinants of Green Innovation: The Impact of Internal and External Knowledge.” KOF Working Paper, No. 314.

Van Leeuwen, G., and P. Mohnen (2013). “Revisiting the Porter hypothesis: an empirical analysis of green innovation for the Netherlands.” CIRANO Working Paper, No. 2013s-02. Montreal.

Verdolini, E. and M. Galeotti (2011). “At home and abroad: An empirical analysis of innovation and diffusion in energy technologies.” *Journal of Environmental Economics and Management* 61(1): 119–134. http://dx.doi.org/10.1016/j.jeem.2010.08.004.

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

APPENDIX

A Note on the Construction of Composite Industry-specific Energy Prices

A profit maximizing firm that is exposed to a positive price shock specific to a certain energy source can be expected to seek technical opportunities for switching to other energy sources which have, as a result of this price shock, become relatively cheaper. If such substitution opportunities are abundant in the short run (i.e. they manifest themselves within the same calendar year), our calculation of industry-specific prices may be criticized on the ground that we weight prices with consumption shares that are measured at the same time period and thus depend on current prices themselves. Conventionally, price indices are constructed in a manner to avoid incorporating such substitution effects, for instance by relying on weights that have been fixed to reflect the relative importance of different inputs prior to subsequent price changes. For the analysis in the paper at hand, however, we argue that the composite energy price that firms face *after* they have exploited any substitution opportunities is more relevant than the composite energy price they would observe while holding their energy mix constant. This is motivated by the simple reasoning that if, in a given industry, technological opportunities exist that would allow a firm to perfectly offset a price shock for a certain energy source by immediately switching to other energy sources, there is no financial motive for increased innovation in energy efficiency. What matters for firms' decisions to strengthen their efforts in green innovation is the total energy bill they face at the end of each year, having made use of potential substitution opportunities, rather than the annual energy expenditure level they would hypothetically face while holding their energy input mix constant.

Nevertheless, we have conducted estimations of equation (3) of Table 3 incorporating energy prices that have been calculated on weights based on lagged (by lags of one up to five years) instead of contemporaneous energy consumption shares. The estimated coefficients for energy prices do only show a slight tendency to decrease as the lag increases; yet they remain, with one exception, statistically significant at the 5% level. These results are available from the authors upon request.

Table A.1: Models Dealing with the Count Data Characteristics of the Green Invention Variables and the Endogeneity of the Stock Variables, Respectively

Estimation method	OLS log linear fixed-effects regression	OLS log linear fixed-effects regression	Fixed-effects Poisson regression	OLS log linear fixed-effects regression	OLS pre-sample mean estimator
Period			1984–2009		
Dependent variable	ln(Green_inventions$_{ijt}$)	ln(Green_inventions$_{ijt}$)− ln(Non_green_inventions$_{ijt}$)	Green_inventions$_{ijt}$	ln(Green_inventions$_{ijt}$)	ln(Green_inventions$_{ijt}$)
	(1)	(2)	(3)	(4)	(5)
ln(L$_{ijt-1}$)	0.042	−0.168	0.046	0.012	0.056*
	(0.115)	(0.120)	(0.121)	(0.079)	(0.069)
ln(Green_stock$_{ijt-1}$)	0.449***	0.343***	0.798***	0.638***	0.647***
	(0.069)	(0.065)	(0.094)	(0.043)	(0.033)
ln(Non_green_stock$_{ijt-1}$)	0.256**	−0.263**	0.035	0.010	0.085**
	(0.105)	(0.129)	(0.119)	(0.045)	(0.036)
ln(Moving_average_energy_price$_{ijt-1}$)	0.223	0.285	0.202**	0.145	0.148**
	(0.151)	(0.188)	(0.096)	(0.112)	(0.069)
Constant	−2.895*	−1.603		−0.887	−2.216***
	(1.480)	(1.653)		(1.154)	(0.715)
Year fixed effects	no	no	yes		no
Country specific industry fixed effects	yes	yes	yes		no
Country specific time fixed effects	yes	yes	no		yes
Industry fixed effects	no	no	no		yes
Pre-sample fixed effects	no	no	no		yes
N	1913	1902	2610	2610	2669
Groups	137	137	137	137	144
Wald chi2			72782.29***		
R^2					0.94
R^2 within	0.79	0.32		0.69	
Log Likelihood			−7674.11		

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; Column (1): We drop the observations where the green invention flow takes a value of 0; Column(2): We drop the observations where the green or non-green invention flow takes a value of 0; Column (3): In line with Allison and Waterman (2002) we used robust standard errors to correct for over-dispersion; Column (5): Pre-sample mean scaling approach proposed by Blundell et al. (1995) was used to account for fixed unobserved heterogeneity in the propensity to invent in the presence of lagged endogenous variables; standard errors are robust to heteroskedasticity and clustered at the industry-country level (clustered sandwich estimator).

Table A.2: Descriptive Statistics for the Variable Moving_average_energy_price$_{ijt-1}$ Based on Alternative Price Baskets

Products included in price basket	Mean	Std. Dev.	Min	Max
electricity, light fuel oil, natural gas	519.07	246.09	103.71	1216.79
electricity, light fuel oil, natural gas, steam coal	471.97	224.32	102.49	1216.79
electricity, light fuel oil, natural gas, steam coal, coking coal	456.75	214.98	102.42	1216.79

Notes: Descriptive statistics is based on same sample for all price variables (1,203 observations).

Table A.3: Estimates Based on Alternative Price Baskets (same observations for all models)

Estimation method	OLS log linear fixed-effects regression					
Period	1984–2009					
Dependent variable	ln(Green_inventions$_{ijt}$)			ln(Green_inventions$_{ijt}$) − ln(Non_green_inventions$_{ijt}$)		
Products included in price basket	electricity, light fuel oil, natural gas	electricity, light fuel oil, natural gas, steam coal	electricity, light fuel oil, natural gas, steam coal, coking coal	electricity, light fuel oil, natural gas	electricity, light fuel oil, natural gas, steam coal	electricity, light fuel oil, natural gas, steam coal, coking coal
	(1)	(2)	(3)	(4)	(5)	(6)
ln(L$_{ijt-1}$)	−0.069	−0.116	−0.104	−0.192	−0.251	−0.232
	(0.157)	(0.147)	(0.146)	(0.191)	(0.181)	(0.182)
ln(Green_stock$_{ijt-1}$)	0.448***	0.439***	0.441***	0.292***	0.281***	0.284***
	(0.070)	(0.070)	(0.070)	(0.089)	(0.088)	(0.088)
ln(Non_green_stock$_{ijt-1}$)	0.182	0.194*	0.190	−0.100	−0.086	−0.093
	(0.115)	(0.114)	(0.115)	(0.111)	(0.107)	(0.109)
ln(Moving_average_energy_price$_{ijt-1}$)	0.364**	0.675**	0.650**	0.553*	0.929**	0.871**
	(0.182)	(0.274)	(0.267)	(0.284)	(0.379)	(0.363)
Constant	−1.672	−2.825	−2.809	−3.793	−5.375*	−5.175*
	(2.143)	(2.325)	(2.304)	(2.878)	(3.029)	(2.958)
Country specific time fixed effects	yes	yes	yes	yes	yes	yes
Country specific industry fixed effects	yes	yes	yes	yes	yes	yes
N	1203	1203	1203	1203	1203	1203
Groups	89	89	89	89	89	89
R^2 within	0.80	0.80	0.80	0.31	0.32	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.4: Estimates Based on Alternative Clustering Level and Price Variable, Respectively

Estimation method	OLS log linear fixed-effects regression			
Period	1984–2009		1981–2009	
Dependent variable	ln(Green_inventions$_{ijt}$)	ln(Green_inventions$_{ijt}$)− ln(Non_green_inventions$_{ijt}$)	ln(Green_inventions$_{ijt}$)	ln(Green_inventions$_{ijt}$)− ln(Non_green_inventions$_{ijt}$)
Clustering level	Industry (1)	Industry (2)	Industry/country (3)	Industry/country (4)
ln(L$_{ijt-1}$)	0.098	−0.111	0.035	−0.185*
	(0.121)	(0.082)	(0.072)	(0.095)
ln(Green_stock$_{ijt-1}$)	0.551***	0.292***	0.591***	0.333***
	(0.058)	(0.059)	(0.039)	(0.046)
ln(Non_green_stock$_{ijt-1}$)	0.164**	−0.297***	0.164***	−0.359***
	(0.071)	(0.084)	(0.044)	(0.058)
ln(Moving_average_energy_price$_{ijt-1}$)	0.342**	0.481**		
	(0.106)	(0.167)		
ln(Popp_energy_price$_{ijt-1}$)			0.391**	0.615**
			(0.162)	(0.238)
Constant	−3.880*	−3.101**	−2.984***	−2.241
	(1.821)	(1.333)	(1.121)	(1.524)
Country specific time fixed effects	yes	yes	yes	yes
Country specific industry fixed effects	yes	yes	yes	yes
N	2669	2669	2725	2725
Groups	144	144	143	143
R^2 within	0.76	0.44	0.80	0.51

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 Depreciation Rates and Controlling for Outliers, Respectively

Estimation method	OLS log linear fixed-effects regression							
Period	1984–2009							
Dependent variable	ln(Green_inventions$_{ijt}$)		ln(Green_inventions$_{ijt}$)− ln(Non_green_inventions$_{ijt}$)		ln(Green_inventions$_{ijt}$)		ln(Green_inventions$_{ijt}$)− ln(Non_green_inventions$_{ijt}$)	
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(Non_green_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.6: Estimation Results for the Green Invention Level Based on Different Lags

Estimation method	OLS log linear fixed-effects regression									
Period	1981–2009									
Dependent variable	$\ln(\text{Green\_inventions}_{ijt})$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln(L_{ijt-1})$	0.096	0.101	0.111*	0.130*	0.117*	0.092	0.093	0.090	0.087	0.083
	(0.067)	(0.065)	(0.065)	(0.067)	(0.066)	(0.073)	(0.073)	(0.073)	(0.072)	(0.072)
$\ln(\text{Green\_stock}_{ijt-1})$	0.613***	0.599***	0.580***	0.564***	0.552***	0.544***	0.544***	0.544***	0.543***	0.541***
	(0.034)	(0.035)	(0.035)	(0.037)	(0.037)	(0.044)	(0.044)	(0.043)	(0.043)	(0.043)
$\ln(\text{Non\_green\_stock}_{ijt-1})$	0.147***	0.155***	0.147***	0.154***	0.174***	0.166***	0.167***	0.170***	0.172***	0.177***
	(0.041)	(0.043)	(0.045)	(0.047)	(0.052)	(0.055)	(0.055)	(0.055)	(0.055)	(0.055)
$\ln(\text{Energy\_price}_{ijt-1})$	0.205**					0.144				
	(0.087)					(0.094)				
$\ln(\text{Energy\_price}_{ijt-2})$		0.200**					0.130			
		(0.087)					(0.097)			
$\ln(\text{Energy\_price}_{ijt-3})$			0.223**					0.159*		
			(0.087)					(0.090)		
$\ln(\text{Energy\_price}_{ijt-4})$				0.222***					0.186**	
				(0.080)					(0.080)	
$\ln(\text{Energy\_price}_{ijt-5})$					0.265***					0.235***
					(0.087)					(0.084)
Constant	−2.812***	−2.920***	−3.179***	−3.436***	−3.540***	−2.402**	−2.319**	−2.516***	−2.575***	−2.960***
	(0.893)	(0.878)	(0.878)	(0.886)	(0.870)	(0.965)	(0.940)	(0.911)	(0.888)	(0.890)
Country-specific time fixed effects	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
N	3142	3051	2969	2899	2829	2504	2504	2504	2504	2504
Groups	174	174	164	154	154	136	136	136	136	136
R^2 within	0.80	0.79	0.78	0.77	0.75	0.75	0.75	0.75	0.75	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.7: Estimation Results for the Green Invention Share Based on Different Lags

Estimation method	OLS log linear fixed-effects regression									
Period	1981–2009									
Dependent variable	$\ln(Green\_inventions_{ijt}) - \ln(Non\_green\_inventions_{ijt})$									
	(1)	(2)	(3)	(4)	(5)	(6)	(7)	(8)	(9)	(10)
$\ln(L_{ijt-1})$	−0.117	−0.112	−0.106	−0.080	−0.097	−0.119	−0.119	−0.123	−0.128	−0.131
	(0.088)	(0.088)	(0.084)	(0.081)	(0.076)	(0.086)	(0.086)	(0.085)	(0.084)	(0.084)
$\ln(Green\_stock_{ijt-1})$	0.365***	0.350***	0.338***	0.320***	0.305***	0.285***	0.284***	0.284***	0.282***	0.280***
	(0.042)	(0.042)	(0.044)	(0.045)	(0.045)	(0.051)	(0.051)	(0.051)	(0.051)	(0.051)
$\ln(Non\_green\_stock_{ijt-1})$	−0.368***	−0.356***	−0.337***	−0.300***	−0.294***	−0.303***	−0.300***	−0.296***	−0.291***	−0.287***
	(0.054)	(0.056)	(0.057)	(0.063)	(0.065)	(0.070)	(0.070)	(0.070)	(0.070)	(0.071)
$\ln(Energy\_price_{ijt-1})$	0.345***					0.238*				
	(0.123)					(0.130)				
$\ln(Energy\_price_{ijt-2})$		0.323***					0.224*			
		(0.122)					(0.130)			
$\ln(Energy\_price_{ijt-3})$			0.361***					0.271**		
			(0.123)					(0.126)		
$\ln(Energy\_price_{ijt-4})$				0.367***					0.317***	
				(0.114)					(0.116)	
$\ln(Energy\_price_{ijt-5})$					0.367***					0.348***
					(0.116)					(0.116)
Constant	−1.823	−1.887	−2.160*	−2.683**	−2.524**	−1.392	−1.337	−1.486	−1.791	−2.045*
	(1.172)	(1.169)	(1.107)	(1.093)	(1.045)	(1.120)	(1.070)	(1.065)	(1.092)	(1.095)
Country-specific time fixed effects	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
N	3142	3051	2969	2899	2829	2504	2504	2504	2504	2504
Groups	174	174	164	154	154	136	136	136	136	136
R^2 within	0.50	0.48	0.47	0.44	0.43	0.43	0.43	0.43	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.8: Estimates for Different Types of Green Invention

Estimation method	OLS log linear fixed-effects regression						
Period	1984–2009						
Dependent variable	$\ln(\text{Specific\_green\_inventions}_{ijt})$						
Type of green inventions:	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)
$\ln(\text{Specific\_non\_green\_stock}_{ijt-1})$	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	0.7	0.52	0.64	0.7	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 using the sandwich estimator) are in brackets under the coefficients; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively.

Table A.9: Estimation Results for Non-green Invention Level

Estimation method	OLS log linear fixed-effects regression						
Period	1981–2009						1984–2009
Dependent variable	$\ln(Non\_green\_inventions_{ijt})$						
	(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)
$\ln(Non\_green\_stock_{ijt-1})$	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.