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KOF Working Papers

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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 share of green innovations in non-green innovations. More concretely, our main model shows that a 10% increase of the average energy prices of the previous five years results in a 2.7% and 4.5% increase of the number of green innovations and the share of green innovations in 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.

JEL classification: O30; O34; Q55.

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1 Introduction

Despite the fact that climate change should ideally increase the demand for green technologies, firms have still low incentives to invest in green technologies as there is a ‘double externality problem’ (see, e.g., Beise and Rennings 2005, Faber and Frenken 2009, Hall and Helmers 2011). Firstly, due to the public goods nature of knowledge (see, e.g., Geroski 1995, Popp 2011) and due to financial market imperfections green technology investment decisions are complex and often linked with financial constraints. Secondly, because the greatest benefits from green inventions are likely to be public rather than private, the customers’ willingness to pay for these innovations is low. In line with this literature a study by Soltmann et al. (2013) shows that economic performance is negatively affected by green innovations. This result indicates 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 to be limited to anything like 2°C” (see Helm 2012, p. 213). Accordingly, a kind of intervention is required to stimulate green innovation activities.

The paper at hand focuses on energy prices as a measure for environmental policy¹ and investigates if energy prices are likely to contribute to increase the probability of green inventions. More concretely, we investigate if the effects of energy prices are different for ‘green’ inventions than for ‘other than green’ inventions.

Empirical research linking environmental policy and innovation is related to a small but increasing literature. A first group of studies uses pollution abatement control expenditures

¹ Energy prices can be seen as a measure for environmental policy, since energy prices are mainly driven by international markets and their variations between countries are mainly due to taxes or other policy measures (see Aghion et al. 2012). This is also what we see in our data. The energy prices are highly correlated with the taxes (correlation coefficient between industry specific taxes and prices, respectively, for the three products electricity, light fuel oil and natural gas of 0.72). Unfortunately, restrictions with respect to the tax data for the different energy products do not allow an econometric identification of the pure tax effect.

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

Most other studies overcome the problem of comparability by using energy prices as proxy for environmental regulation.² Most of them focus on a single industry. Aghion et al. (2012) investigated the significance of energy prices for technological change by looking at the car industry based on patent data over a long period in time (1978 - 2007). They found that higher energy prices increase the propensity of ‘clean’ innovation in the car industry. Moreover they stated that the price effect is stronger for firms with a great stock of ‘dirty’ patents. Newell et al. (1999) looked at the level of product characteristics in the air-conditioning industry and found that energy prices had an observable effect on energetic features of the products offered for sale. Lanzi and Sue Wing (2011) found a positive relationship between energy prices and innovations in renewable technologies in the energy sector of 23 countries.

Popp (2002) did not focus on a single industry but a single country. He looked for the USA at 11 different technologies including supply (e.g. solar energy, fuel cells) and demand

² Following the findings in other fields (consumer behavior), it is likely that the elasticity effects of energy prices and energy taxes (policy instrument) have the same direction, although they are different in magnitudes. Li et al. (2012) showed that gasoline taxes reduce gasoline consumption stronger than a tax-exclusive price increase in gasoline. Davis and Kilian (2011) find that tax elasticity is much larger than price elasticity. Ghalwash (2007) compares environmental tax elasticities with traditional price elasticities and found that the effects depend on the type of energy good. Scott (2012) finds that consumers are twice as responsive to tax-driven price changes as to market-driven price changes and also Baranzini et al. (2009) find for Switzerland that consumers’ reaction depend on the source of price variation. They found that the Swiss mineral oil tax increase in 1993 decreases gasoline demand by about 3.5% in addition to its direct impact through the price increase. This additional effect may result from the consumer’s understanding that taxes are not a market driven variation or that gasoline tax changes receive a great deal of attention from the media, which could contribute to reinforce consumers’ reaction (Li et al. 2012).

technologies (e.g. recovery of waste heat for energy, heat pumps) and found that energy prices and the existing knowledge stock have a strong and significant positive effect on innovation.

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

In the study at hand we contribute to the existing literature in many respects. Firstly, we use energy prices as a proxy for environmental regulation. This allows us to generate an industry-level data set that covers the whole manufacturing sector (grouped into 10 industries), the most important countries for green 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, we use patent data to identify green and non-green inventions. Patent documents considered as covering green inventions are identified according to the OECD Indicator of Environmental Technologies (see OECD 2012) that distinguishes seven environmental areas, i.e. (a) general environmental management, (b) energy generation from renewable and non-fossil sources, (c) combustion technologies with mitigation potential, (d) technologies specific to climate change mitigation, (e) technologies with potential or indirect contribution to emission mitigation, (f) emission abatement and fuel efficiency in transportation, and (g) energy efficiency in buildings and lighting. If an invention can be assigned to one of these sub-groups (a to g), it is counted as a green invention; otherwise it is counted as a non-green invention. By using the Schmoch et al. (2003) concordance scheme we switch from the technology level to the industry

level. This allows us to include control variables on the aggregation level of an industry (e.g., capital and number of employees). Furthermore, we reduce the potential problem of an omitted variable bias by controlling for industry/country specific fixed effects. Thirdly, we calculate industry specific energy prices what allows us to include country specific time fixed-effects. Compared with previous studies on a more aggregated level (e.g. country level) there is no concern that there could be macro-economic shocks correlated with both innovation and the energy prices that bias our results (see Aghion et al. 2012, p.5).

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

2 Conceptual Background and Hypotheses

The idea that an increase in the relative price of a production factor will direct innovation efforts towards technologies that are less intensive in the production factor becoming more expensive can be attributed to Hicks (1932, 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 economising the use of a factor which has become relatively expensive.”

This intuitively appealing assertion has been known as the induced innovation hypothesis. Subsequent research attempted to provide microeconomic foundations for this claim and to assess its relevance for traditional welfare economics (Binswanger et al. 1978, ch. 4). Induced

innovation is generally thought to exacerbate the effects of externalities not properly taken into account. In particular, the exploitation of fossil fuels has undesirable side effects as CO₂ 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 CO₂ tax): price signals not only affect entrepreneurs' choice of input combinations, given the production techniques currently available; but they also affect their choice of which production technologies to develop for future use.

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

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

- H1:** Energy prices are positively related to the number of ‘green’ innovations (i.e., the *intensity* to invent in green technologies).
- H2:** Energy prices are positively related to the number of green innovations relative to other innovations (i.e., the *propensity* to invent in green technologies).

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.³

3 Description of the Data

3.1 Measurement of green inventions based on patent statistics

We use inventions in order to measure the green invention activities of an industry. Although patent statistics have many disadvantages in measuring innovation output (see Aghion et al. 2012), they are a rather good proxy for input because there is a strong relationship between the number of patents and R&D expenditure (see Griliches 1990). Despite the fact that not all 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

³ Horbach et al. (2012) found that cost savings are an important driver for green innovations. This implicates that higher energy prices stimulate green innovation.

and comparable across countries (Johnstone et al. 2010). This is especially true for green technological activities, since the OECD (2012) provides a definition of green technologies based on the patent classification.

For the paper at hand, patent information is gathered in cooperation with the Swiss Federal Institute of Intellectual Property (IPI). Green patents are a sub-group of patents that are selected according to the OECD Indicator of Environmental Technologies (see OECD 2012). Based on the International Patent Classification, the OECD definition distinguishes seven environmental areas, i.e. (a) general environmental management, (b) energy generation from renewable and non-fossil sources, (c) combustion technologies with mitigation potential, (d) technologies specific to climate change mitigation, (e) technologies with potential or indirect contribution to emission mitigation, (f) emission abatement and fuel efficiency in transportation, and (g) energy efficiency in buildings and lighting.

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

(a) In order to assign patents to countries, the applicant's country of residence or the inventor's country of residence may be chosen. We assigned patents according to the applicant's address. Since only those inventions were selected for which at least one PCT (Patent Cooperation Treaty) application was filed, the applicant's address was generally available.⁴ 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.

⁴ 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.

(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. 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.⁵ On the basis of 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.⁶ In comparison with invention data at the firm level, aggregating inventions on an industry level should reduce potential problems with invention waves 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 inventions as well as all other inventions worldwide. The data set includes 10 industries that capture the whole manufacturing sector (chemicals; food and tobacco; machinery; basic metals; non-metallic minerals; paper, pulp and print; textile and

⁵ 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.

⁶ 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.

leather; transport equipment; wood and wood products; non-specified industry). The patent data is available from 1975 onwards.⁷

Insert Figure 1 about here

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 disproportionately high compared with other inventions. A sharp increase in the number of green inventions can be observed since 1995. In 2009, 29'444 green inventions were protected worldwide. Due to generally low invention activity, the share of green inventions was quite instable in the beginning of our sample period. In a second stage, the share stabilized between 6-8%. A disproportional increase of green inventions can be observed after 2000. By 2009, the relative importance of green inventions compared with other inventions had increased to 11.6%.

Insert Table 1 about here

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 (49%). Furthermore, a considerable share is invented in the two industries 'chemicals' (24%) and 'transport equipment' (16%). The industry 'transport equipment' (35%) is at the same time the most green-intensive industry, followed by the two industries 'basic metals' (14%) and 'non-metallic minerals' (11%).

⁷ Actually the EPO (European Patent Office) was created in 1977/78. However, patent data are already available from 1975 onwards. The reason is that we use PCT applications, which can contain patents that are filed before 1977. Hence PCT applications can be found in PATSTAT before EPO was created.

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 38.5%, 14.8%, and 12.8% respectively. Switzerland has a remarkable share of 3.0%, which is about three times that of Austria or Denmark, and still about twice the share of Italy. In sum Switzerland is ranked 7th in terms of the share of other inventions.

Concerning the respective shares in total green inventions (see column 4 in Table 1), we see a different picture. Although the USA (29.0%), Japan (21.4%), and Germany (18.0%) also show the greatest green shares, the country ranking further down the line changes. Switzerland has 2.0% of all green inventions and is ranked on the 10th position, followed by Australia (1.9%), Italy (1.5%), Denmark (1.4%), and Austria (1.1%). Compared to the ranking in other inventions, Switzerland shows the greatest drop and Austria or Denmark the greatest improvement in the ranking.

The last column in Table 1 shows the ratio of green inventions to non-green inventions. Japan (11.6%), Germany (11.3%) and Denmark (11.0%) show the highest degree of specialisation in green invention activities, followed by Canada (10.5%) and Austria (9.7%). Switzerland (5.3%) is ranked on the 17th position just before Ireland (5.2%). In sum we see from this 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 labour input (total employment) and the capital stock (gross fixed capital formation, volumes at current prices) of industries relevant for our estimations.⁸

⁸ For the descriptive statistics of variables from the STAN data and other model variables see also Table A.1 in the appendix.

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 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 toe⁹ including taxes) for the manufacturing sector in USD (PPP).¹⁰ This information is available for different energy products, such as electricity, light fuel oil,¹¹ 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 80s and again from 2000 onwards. While the price of light fuel oil remarkably dropped in 2008, the electricity price further 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 doubled since 2000.

Insert Figure 2 about here

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,

⁹ Tonne of oil equivalent; unit of energy for the practical expression of energy quantities (e.g., 1 MWh = 0.086 toe).

¹⁰ 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.

¹¹ The IEA does also collect price information for other oil products, such as motor gasoline. However, as the number of observations is very low for these variables, we could not use this price information to construct our industry specific energy price. Our energy price should nevertheless be representative, as the energy products that could be taken into account (electricity, light fuel oil, natural gas and different coal products) make up more than 70% of total energy consumption (on average over all industries and the whole time period; see Figure 4). This figure is quite impressive, as the remaining 30% do not only include motor gasoline, but also the consumption of energy products for which no price information is collected, such as energy from biogases or heat.

Spain, and Ireland. Natural gas is most expensive in Korea, followed by Sweden, Denmark, and Japan. However, the descriptive comparisons 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 e.g. for Sweden in terms of natural gas.

Besides the energy prices, the IEA collects data on consumption of the different energy products (in ktoe) on the industry level. This information is available for 10 different industries of the manufacturing sector and comes from the IEA World Energy Statistics and Balances (IEA 2012b). This allows us to calculate the relative importance of a certain energy product compared with other products on the industry level. Electricity (35%) followed by other products (28%) and natural gas (23%) are the most important energy sources. 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 the non-specified industry.

Insert Figures 3,4 and 5 about here

To get industry specific energy prices, we finally multiply the energy prices with the relative importance within the industry.¹² The industry specific energy price for an industry j , in country i at time t is defined as follows:

$$Energy_price_{ijt} = \sum_{i=1}^s w_{ijts} * \ln(Energy_price_{its})$$

¹² The appendix includes some additional notions and the results of related robustness checks on the construction of the composite industry-specific energy prices.

where

$$w_{-E_{ijts}} = \frac{Energy_use_{ijts}}{\sum_{k=1}^{N(s)} Energy_use_{ijk}}$$

and

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

The information on energy consumption as well as on energy prices is available for electricity, light fuel oil, natural gas, steam coal, and coking coal. However, due to missing values for some of the price variables, the prices used in our main model are based on the three products 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.6).

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 (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. We formulate the following knowledge production function for an industry j , in country i at time t :¹³

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

where $Green_inventions$ is the number of green inventions, L is the labour input and K the capital-stock, A is a constant. The parameters α and β are elasticities with respect to labour and physical capital respectively. In our model we use the industries' total number of employees as a proxy for labour (L) and the gross fixed capital formation in real terms is used to proxy physical capital (K). Ideally, one would use data on the capital stock instead of capital formation. Unfortunately, this information is only available for a few countries in the STAN database. We thus use a flow variable as a proxy for physical capital. Both variables, L and K , should be positively related with invention activity.

Expressing (3) in logarithms yields

$$\ln(Green_inventions_{ijt}) = \ln(A) + \alpha \ln(L_{ijt}) + \beta \ln(K_{ijt}). \quad (2)$$

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 ($Green_stock$).¹⁴ 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

$$Green_stock_{ijt} = (1 - \delta)Green_stock_{ijt-1} + Green_inventions_{ijt}, \quad (3)$$

where δ is the depreciation rate of R&D capital.¹⁵ 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.7). To capture potential effects of

¹³ Other functional forms, like e.g., a translog function, would require more detailed data to describe the production process (see Griliches 1979).

¹⁴ 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.

¹⁵ Due to the low number of patents before 1980, we restricted our sample period to the years 1980-2009. However, patent applications before 1980 were used to calculate the 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%.

available knowledge in other than green technologies, we also control for the stocks of inventions that are not classified as green (*Other_stock*). The stock of other 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 other than 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 augmented specification is given by:

$$\begin{aligned} \ln(\text{Green_patents}_{ijt}) = & \ln(A) + \alpha \ln(L_{ijt-1}) + \beta \ln(K_{ijt-1}) + \varphi \ln(\text{Green_stock}_{ijt-1}) \\ & + \lambda \ln(\text{Other_stock}_{ijt-1}) + \phi \ln(\text{Energy_price}_{ijt-1}) + \mu_{it} + \eta_{ij} + \varepsilon_{ijt}, \end{aligned} \quad (4)$$

where φ and λ are the coefficients of knowledge stocks, ϕ is the coefficient of energy prices and ε is the stochastic error term (see Table 2 for variable definition). As invention variables may contain a value of zero, we used $\ln(1+\text{inventions})$ to avoid problems with the logarithm (see Wooldridge 2002, p. 185). To deal with the potential problem of reverse causality the independent variables are introduced with a lag of one year.

Insert Table 2 about here

To test the robustness of the price effect we use different dynamic specifications for energy prices, i.e. we use alternative lags (2-5 year lag), we construct a weighted average of past prices as proposed by Popp (2002)¹⁶ and we calculate a moving average of the energy prices of the previous five years.

¹⁶ As in Popp (2002), this energy price is based on an adaptive expectation model, in which expected future energy prices are a weighted average of past prices: $P_{ijt}^* = (1-\psi) \sum_{k=0}^{\infty} \psi^k P_{ijt-k}$, where ψ , the adjustment coefficient that represents the weights placed on past 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.

To control for correlated unobserved heterogeneity, we include country specific industry fixed effects (η). This way we control for the general policy attitude of countries in terms of industry specific policy measures.¹⁷ Furthermore, to reduce the risk of an omitted variable bias from country specific shocks, we include country specific time fixed effects (μ). As stated in Aghion et al. (2012), the increase of energy prices, e.g., might be correlated with country specific subsidies for green innovation. Accordingly, the effect of energy prices may represent an indirect effect of subsidies on green innovation, and not a direct effect of prices as suggested above. The fixed effect μ captures such country specific shocks.

As we are not just interested in the effect of energy prices on the total number of green inventions (i.e., the intensity of green invention activities; see H1), but also in the effect on the development of the number of green inventions relative to other inventions (i.e., the propensity to invent in green technologies; 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 thus reads as follows:

$$\begin{aligned} \ln(\text{Green_inventions}_{ijt}) - \ln(\text{Other_inventions}_{ijt}) &= \ln(A) + \alpha \ln(L_{ijt-1}) + \beta \ln(K_{ijt-1}) \\ &+ \varphi \ln(\text{Green_stock}_{ijt-1}) + \lambda \ln(\text{Other_stock}_{ijt-1}) + \phi \ln(\text{Energy_price}_{ijt-1}) \\ &+ \mu_{it} + \eta_{ij} + \varepsilon_{ijt}. \end{aligned} \quad (5)$$

5 Estimation 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.¹⁸ The columns with uneven numbers show the results of the full model as specified in equation 4 for different dynamic specifications of the

¹⁷ 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.

¹⁸ 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 do not allow to control for country specific time fixed effects, which is one of the main contributions of our paper. We thus decided to present as a baseline specification the OLS fixed effects regressions. Robustness tests using count data models are presented in Table A.8.

price variable. The columns with even numbers show the results for the same estimations without capital control (reduced model), which significantly increases the number of observations. To test whether this modification does lead to an omitted variable bias, Table A.2 shows the results for the reduced models based on the same observations that are available in the full model. As the results for the energy price variable do only marginally differ between these two models, we conclude that at least the result for the energy price should not be affected by an omitted variable bias in the reduced models. Table 4 shows the results for the model with the log ratio of green to non-green inventions as dependent variable, as specified in equation 5.

Insert Tables 3 and 4 about here

Our econometric estimations show that energy prices are significantly positively related with green invention. This result is in line with hypothesis H1 which states that larger energy prices stimulate current green innovation activities. Moreover, the impact of energy prices increases with an increasing time lag between energy prices and invention activities (see Table 3).¹⁹ If we take a 5-year lag we get significant coefficients of 0.28 (full specification) and 0.27 (reduced model); if we take the moving average of energy prices over five years we see significant coefficients of 0.27 and 0.34 for the full specification and the reduced model, respectively.

Hypothesis H2 is confirmed as well, as energy prices have a significantly positive impact on the ratio of green innovations to non-green innovations (see Table 4). Accordingly, energy prices do positively affect both, the intensity and the propensity of green invention. In our model, a 1% increase of the average energy price of the previous five years results in a 0.45% (full

¹⁹ To test whether the differences arising from different time lags for the price variable in Table 3 are driven by the different lag structure or the different samples, Table A.3 shows the results for the same estimates, but with the same observations across the models. As these results do only marginally differ from previous results, we conclude that differences across models are driven by dynamic effects.

model) and 0.48% (reduced model) increase of the ratio of green to non-green inventions. Although we do not investigate crowding out effects of green innovation activities explicitly (see van Leeuwen and Mohnen 2013, Marin 2013 for crowding out investigations on the firm-level), the relatively large difference in elasticities (0.27 in the green invention equation vs. 0.45 in the green share equation) indicates some crowding out tendencies, since the share of green invention is more strongly affected than the number of green inventions. Indeed, we find a significantly negative effect of energy prices on non-green invention for all but one model specification (see Table A.4).²⁰

As described in the introduction, our model is based on a broader data set than most previous studies. It would thus be interesting to analyse how this fact does affect the impact of the energy prices. As previous models either include different control variables or even use different measures for green innovation, a direct comparison of the marginal effects of energy prices is hardly possible. Nevertheless, a comparison can provide evidence on the question whether the impact of energy prices differs substantially among countries and industries. Popp (2002) identifies an effect of energy prices on the share of green innovations in total innovations of 0.34 (long run elasticity) for the USA. Though we defined our share variable differently, the size of the effect is quite similar to the 0.52 that we find with respect to the share of green inventions in non-green inventions when using comparable energy prices²¹ for 13 countries (see columns 11 and 12 of Table 4). Aghion et al. (2012) analyse the effect of fuel prices on different innovation variables for the auto industry. Based on a slightly different model specification that also controls for other types of knowledge stocks, they identified elasticities of 0.97 and -0.57 for the number of ‘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). Accordingly, it seems

²⁰ 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).

²¹ Estimates based on a weighted average of lagged energy prices with a discount factor of 0.83.

that the dependency on energy prices in the auto industry is larger than the dependency in the other manufacturing industries. In line with our finding, they also find that the impact of energy prices increases with an increasing lag between energy prices and innovation activities. These comparisons indicate that the differences of price elasticities across countries are smaller than the respective differences across industries. However, further investigations are necessary to clarify this point.

The results for the control variables are in line with general expectations. Labour input (L) and physical capital (K) tend to be positively correlated with the number of green inventions. However, we cannot observe a significant effect for these two variables with respect to the share of green inventions. The propensity to invent in green technologies is neither affected by labour input nor by physical capital input. As expected a larger stock of green knowledge does stimulate current activities in green invention. Furthermore, we find in Table 3 that knowledge in other than green technologies serves as a resource for green invention as well – the effect of *Other_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 *Other_stock* on the share of green inventions is significantly negative (see Table 4). Thus, it seems that due to opportunity costs, the relative impact of *Other_stock* on green invention is smaller than the impact on other than green invention.

5.1 Robustness tests

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

Estimates for different subcategories of green invention

Our estimates are so far based on a quite broad definition of green inventions. Obviously, energy price shocks should, however, primarily affect inventions that are somehow related to energy reduction. To deal with this assertion, we estimate our previous model (column 14 of Table 3) separately for the seven environmental areas that are included in the OECD definition (see OECD 2012). The respective estimates are presented in Table A.5. 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’ (e.g., energy storage) and ‘energy generation from renewable and non-fossil sources’. More general green invention such as invention dealing with ‘technologies specified to climate change mitigation’ (e.g., CO₂ capturing) is not significantly affected by energy price shocks. Nevertheless, our overall results seem to be quite representative, as the effect of energy prices is significantly positive for all other subcategories, and does only marginally vary across the different groups (elasticities between 0.24 and 0.38 for the other six categories).

Alternative price variables

Despite the fact that our price variable includes the prices of the three most important energy products, the construction of this variable may affect the results of our estimates. To test the robustness of our results with respect to the construction of the price variable, we alternatively estimated our main model of Tables 3 and 4 with price variables that are based on alternative baskets of energy products. As there are missing values for some product-specific energy prices, enlarging the price basket significantly reduces the number of observations that is available for

the model estimation.²² 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.6. To be able to compare these results with previous results, columns (2) and (8) show the results for the previous estimates based on the smaller sample. The fact that the price elasticities of these estimates only marginally differ from previous estimates (0.36 vs. 0.34 for green intensity and 0.55 vs. 0.48 for green propensity) indicates that the reduction of the sample size does not significantly affect our results.

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

Testing the robustness of the stock variables

In our main models (Tables 3 and 4) we applied a depreciation rate of 15% in order to calculate knowledge stocks. Table A.7 (columns 1 to 4) presents the results for alternative depreciation

²² 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.

rates of 10% and 30%. The results are relatively independent of the chosen depreciation rate. The coefficients are similar and directions of the effects are identical.

Checking for outliers

Columns (5) to (8) of Table A.7 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.²³ This only marginally affected our results. We thus conclude that our results are not driven by outliers.

Dealing with special characteristics of our data

To deal with the count data characteristics of the green invention flow variable, column (1) of Table A.8 shows the results for the fixed-effects Poisson model with robust standard errors as recommended by Allison and Wateran (2002) to correct for over-dispersion. Unfortunately, this procedure does not allow 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. The effect of energy prices on green invention remains statistically significant and positive, and the coefficient is only slightly smaller (0.20 vs. 0.34).

Column (2) of Table A.8 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 inventing over the pre-sample period 1975-1985 for both, green and other inventions (both in logs), as well as two binary variables that measure whether an industry had any inventions at all in the pre-sample

²³ 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.

period. This procedure does again slightly reduce the size of the effect of energy prices (0.15 vs. 0.34); the effect remains, however, statistically significant and positive.²⁴

²⁴ We chose these models not to be our baseline specification due to the fact that the count data model does not allow to control for country time fixed effects, and the Blundell et al. (1995) procedure mainly corrects for the endogeneity of the lagged dependent variable, which is a control variable in our model.

6 Conclusions

Based on industry-level panel data, the paper at hand investigates the determinants of green invention activities of an industry. We find that energy prices do stimulate both, the intensity of green invention as well as the propensity of green invention. In our model, a 10% increase of the average energy prices of the previous five years results in a 2.7% and 4.5% increase of the number of green 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 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, as they are based on a broader empirical basis. While most previous studies focused on certain industries or countries, our data set includes the whole manufacturing sector and the most important countries for green innovation. Furthermore, we have reduced the problems 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 equally suitable as an instrument to stimulate green invention in different industries. Due to the limited number of observations that is available in our data set, it was unfortunately not possible to compare price elasticities across industries. However, it seems to be an interesting task for future research to identify such difference across industries in order to increase the efficiency of energy price regulations.

Despite a large future market potential, firms are probably not willing by themselves to invest in green technologies, as green innovation is still negatively related to economic performance (see Soltmann et al. 2013). Furthermore, free-riding possibilities in green technologies seem to be limited (see Stucki and Woerter 2012). Accordingly, knowledge about potential policy instruments to stimulate innovation in this area is of large importance. As our study shows, energy prices may serve as such an instrument. An increase in energy prices may stimulate the building of a green knowledge stock that (a) would help to achieve a country's climate targets and (b) may serve as an important fundament to establish a cleantech market for which long-term growth is predicted.

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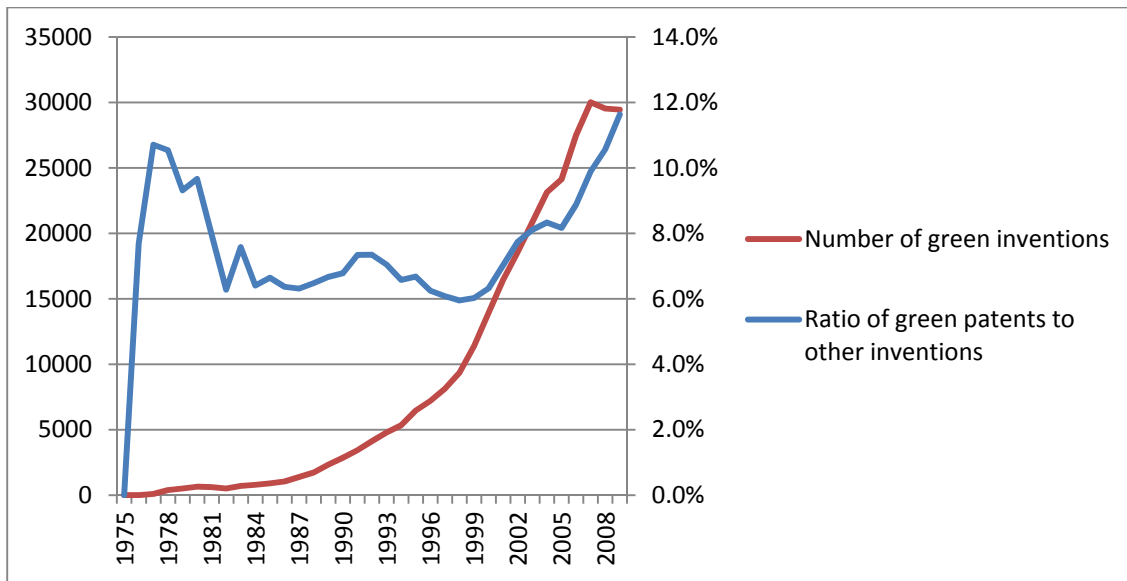
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Figure 1: Development of green inventions worldwide, 1975-2009



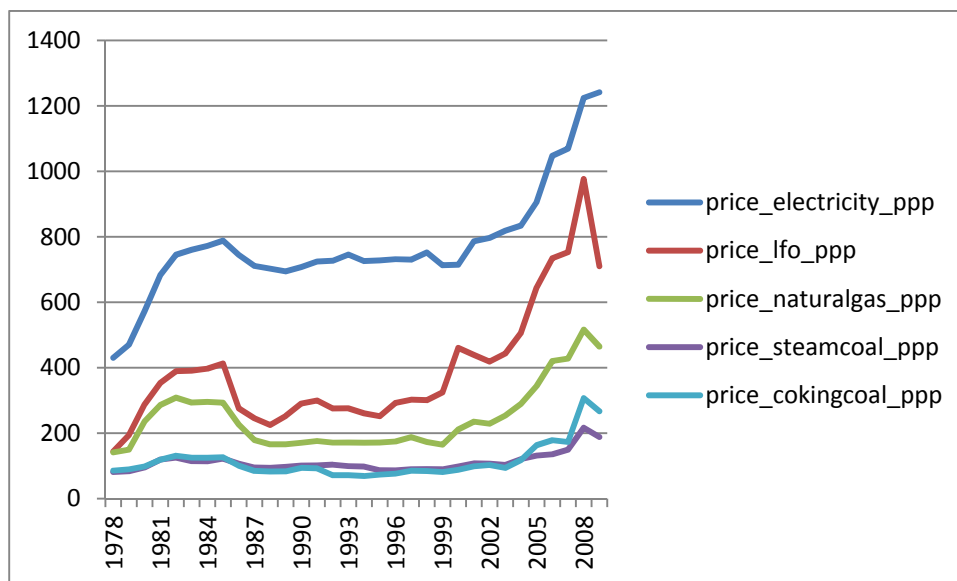
Source: Own calculations.

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

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

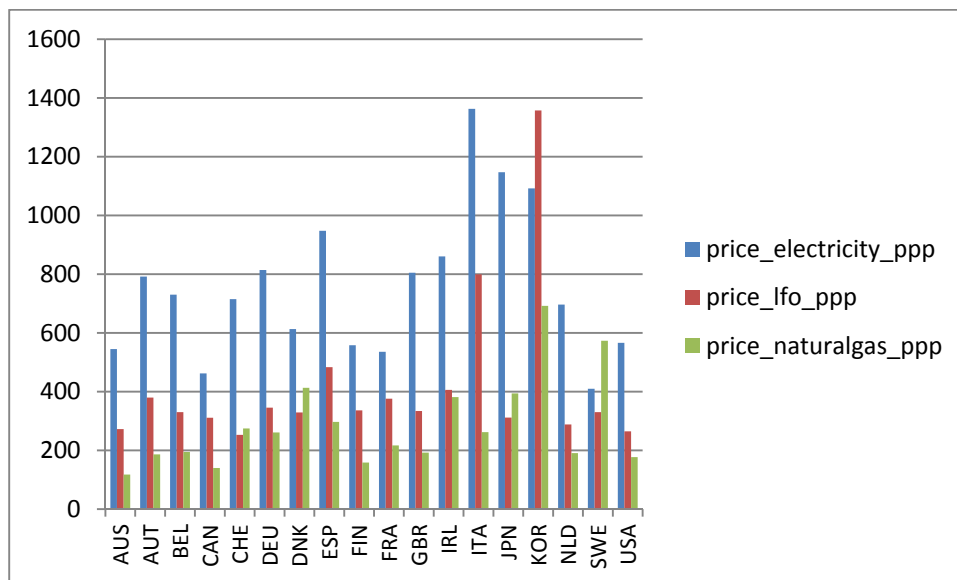
Notes: Data is based on own calculations; these statistics are based on 35 cross-sections, 18 countries and 10 industries (total of 6'300 observations); the relative share in total green inventions is calculated as the share of an industry's/country's number of green inventions relative to the number of all green inventions in our sample (sum of green inventions over all industries/countries in the sample); the ratio of green inventions to other inventions is defined as an industry's/ country's ratio of green inventions relative to its number of other inventions.

Figure 2: 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



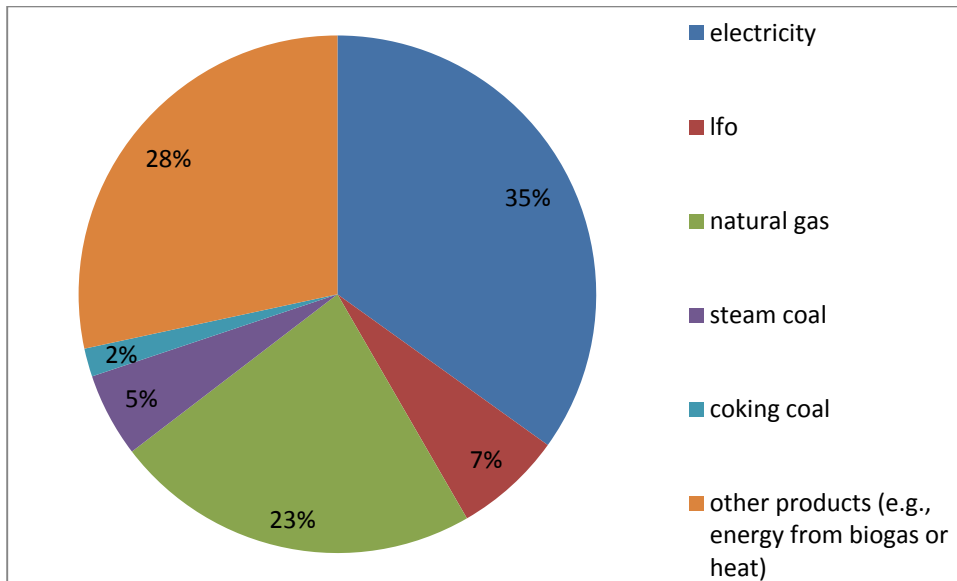
Source: IEA (2012a).

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



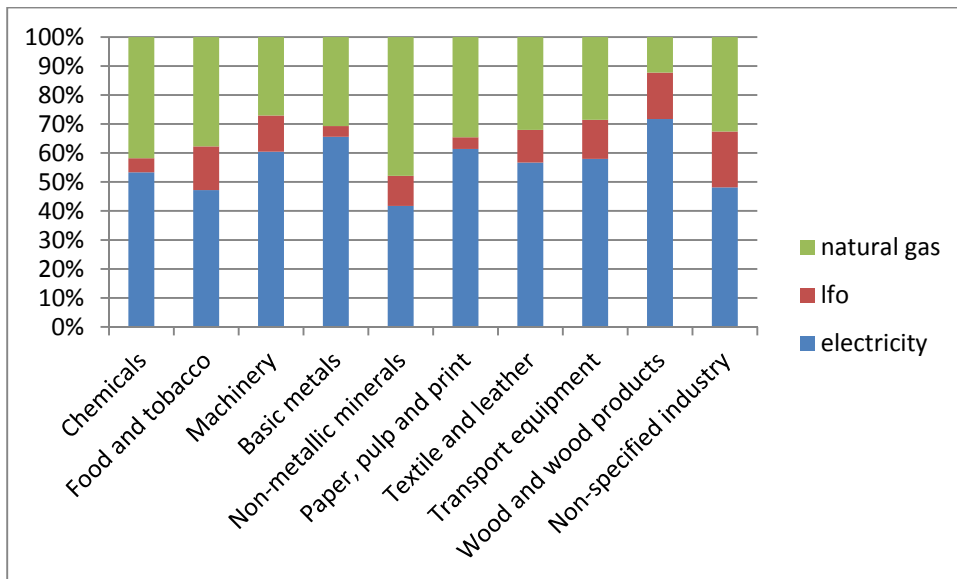
Notes: As the different price information is not available for all countries over the whole sample period, some of the figures are not directly comparable across countries and products. Natural gas prices for Sweden are for example only available for the years 2007-2009, and are thus not directly comparable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

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



Source: IEA (2012b).

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



Source: IEA (2012b).

Table 2: Variable definition and measurement

| Variable | Definition/measurement | Source |
|--|---|------------------|
| <i>Dependent variable</i> | | |
| Green_inventions _{ijt} | Number of green inventions | own calculations |
| Other_inventions _{ijt} | Number of inventions that are not classified as green | own calculations |
| <i>Independent variable</i> | | |
| L _{ijt} | Number of persons engaged (total employment) | OECD STAN |
| K _{ijt} | Gross fixed capital formation, volumes (current price value) | OECD STAN |
| Green_stock _{ijt} | Stock of green inventions | own calculations |
| Other_stock _{ijt} | Stock of inventions that are not classified as green | own calculations |
| Energy_price _{ijt} | Industry specific energy price based on electricity, light fuel oil and natural gas prices, PPP | IEA |
| Popp_energy_price _{ijt} | Weighted average energy prices as in Popp (2002) for the whole sample period from 1978 onwards with an adjustment coefficient of 0.83 (see Aghion et al. 2012 for a similar procedure). | IEA |
| Moving_average_energy_price _{ijt} | Moving average of the energy prices of the previous five years. | IEA |

Table 3: Estimation results for green flow of inventions

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

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

Table 4: Estimation results for relative inventing

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

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

Appendix

A note on the construction of composite industry-specific energy prices

A profit maximising 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 criticised 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 allowing 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 equations (2) and (14) 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 not show any clear tendency in equation (2), and a slight tendency to decrease in equation (14) 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: Descriptive statistics

| Variable | Mean | Std. Dev. | Min | Max |
|---------------------------------|-----------|-----------|----------|-----------|
| Green_inventions _{ijt} | 74.4 | 305.2 | 0 | 4'015 |
| Other_inventions _{ijt} | 1'011.6 | 4'768.9 | 0 | 66'161 |
| Energy_price _{ijt-1} | 511.5 | 239.1 | 90.0 | 2'463.5 |
| Green_stock _{ijt-1} | 280.0 | 1'216.9 | 0 | 18'692.9 |
| Other_stock _{ijt-1} | 4'154.9 | 21'367.7 | 0 | 321'222.3 |
| K _{ijt-1} | 3.47E+09 | 7.09E+09 | 1.22E+07 | 8.51E+10 |
| L _{ijt-1} | 426'469.4 | 772'114 | 2'676 | 6'395'273 |

Notes: see Table 2 for the variable definitions; the set of observations is identical to that used for (1) in Table 3 (2'293 observations).

Table A.2: Identification of a possible omitted variable bias (estimates of Table 3 without capital variable but same observations)

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

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

Table A.3: Identification of pure dynamic effects (based on the same observations for all models)

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

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

Table A.4: Estimation results for “other” invention flow

| Estimation method Period Dependent variable | OLS log linear fixed-effects regression | | | | | | |
|---|---|---------------------|---------------------|---------------------|---------------------|---------------------|---------------------|
| | 1981-2009 | | | | | 1984-2009 | |
| | ln(Other_inventions _{ijt}) | | | | | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) |
| ln(L _{ijt-1}) | 0.213*** (0.057) | 0.213*** (0.062) | 0.216*** (0.063) | 0.210*** (0.066) | 0.214*** (0.062) | 0.220*** (0.064) | 0.209*** (0.071) |
| ln(Green_stock _{ijt-1}) | 0.248*** (0.026) | 0.248*** (0.028) | 0.242*** (0.031) | 0.243*** (0.033) | 0.247*** (0.034) | 0.258*** (0.030) | 0.259*** (0.036) |
| ln(Other_stock _{ijt-1}) | 0.515*** (0.036) | 0.511*** (0.039) | 0.484*** (0.041) | 0.454*** (0.046) | 0.467*** (0.043) | 0.522*** (0.038) | 0.462*** (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 (0.701) | -1.034 (0.746) | -1.019 (0.795) | -0.753 (0.869) | -1.016 (0.821) | -0.744 (0.906) | -0.779 (0.972) |
| Country specific time fixed effects | yes | yes | yes | yes | yes | yes | yes |
| Country specific industry fixed effects | yes | yes | yes | yes | yes | yes | yes |
| N | 3142 | 3051 | 2969 | 2899 | 2829 | 2725 | 2669 |
| Groups | 174 | 174 | 164 | 154 | 154 | 143 | 144 |
| R ² within | 0.91 | 0.91 | 0.91 | 0.90 | 0.90 | 0.91 | 0.90 |

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

Table A.5: Estimates for different types of green invention

| Estimation method Period Dependent variable Type of green inventions: | OLS log linear fixed-effects regression 1984-2009 ln(Specific_green_inventions _{ijt}) | | | | | | |
|--|---|---|---|--|---|--|---|
| | 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 (0.070) | 0.149 (0.103) | 0.036 (0.044) | -0.006 (0.039) | -0.001 (0.075) | -0.007 (0.080) | 0.031 (0.061) |
| ln(Specific_green_stock _{ijt-1}) | 0.460*** (0.044) | 0.526*** (0.054) | 0.461*** (0.044) | 0.593*** (0.050) | 0.580*** (0.040) | 0.547*** (0.039) | 0.554*** (0.042) |
| ln(Specific_other_stock _{ijt-1}) | 0.198*** (0.052) | 0.097** (0.041) | 0.037 (0.029) | 0.034** (0.017) | 0.072* (0.039) | -0.012 (0.041) | 0.078** (0.037) |
| ln(Moving_average_energy_price _{ijt-1}) | 0.239* (0.135) | 0.379*** (0.133) | 0.328*** (0.103) | 0.074 (0.087) | 0.382*** (0.115) | 0.342*** (0.116) | 0.255** (0.120) |
| Constant | -2.851** (1.099) | -4.429*** (1.369) | -2.558*** (0.734) | -0.638 (0.699) | -2.746** (1.111) | -1.851 (1.185) | -2.442** (1.008) |
| Country specific time fixed effects | yes | yes | yes | yes | yes | yes | yes |
| Country specific industry fixed effects | yes | yes | yes | yes | yes | yes | yes |
| N | 2669 | 2669 | 2669 | 2669 | 2669 | 2669 | 2669 |
| Groups | 144 | 144 | 144 | 144 | 144 | 144 | 144 |
| R ² within | 0.68 | 0.70 | 0.52 | 0.64 | 0.70 | 0.65 | 0.67 |

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

Table A.6: Estimates based on alternative price variables (same observations for all models)

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

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

Table A.7: Estimates based on alternative depreciation rates and controlling for outliers, respectively

| Estimation method | OLS log linear fixed-effects regression | | | | | | | |
|---|---|----------------------|---|----------------------|--------------------------------------|----------------------|---|----------------------|
| | 1984-2009 | | | | | | | |
| | ln(Green_inventions _{ijt}) | | ln(Green_inventions _{ijt}) - ln(Other_inventions _{ijt}) | | ln(Green_inventions _{ijt}) | | ln(Green_inventions _{ijt}) - ln(Other_inventions _{ijt}) | |
| | 10% | 30% | 10% | 30% | 15% | 15% | 15% | 15% |
| Depreciation rate | | no | | drop top 1% | | drop top 5% | | |
| Checking for outliers | | no | | drop top 1% | | drop top 5% | | |
| | (1) | (2) | (3) | (4) | (5) | (6) | (7) | (8) |
| ln(L _{ijt-1}) | 0.101 (0.072) | 0.089 (0.062) | -0.114 (0.086) | -0.103 (0.080) | 0.097 (0.069) | 0.091 (0.068) | -0.111 (0.085) | -0.118 (0.084) |
| ln(Green_stock _{ijt-1}) | 0.551*** (0.044) | 0.539*** (0.040) | 0.276*** (0.052) | 0.321*** (0.047) | 0.551*** (0.043) | 0.548*** (0.043) | 0.292*** (0.051) | 0.288*** (0.051) |
| ln(Other_stock _{ijt-1}) | 0.161*** (0.054) | 0.177*** (0.041) | -0.293*** (0.072) | -0.299*** (0.058) | 0.163*** (0.050) | 0.157*** (0.048) | -0.297*** (0.068) | -0.301*** (0.067) |
| ln(Moving_average_energy_price _{ijt-1}) | 0.356** (0.146) | 0.309** (0.127) | 0.491** (0.199) | 0.458** (0.182) | 0.352** (0.143) | 0.321** (0.139) | 0.486** (0.199) | 0.463** (0.195) |
| Constant | -4.103*** (1.144) | -3.302*** (0.960) | -3.122** (1.446) | -3.176** (1.292) | -3.862*** (1.100) | -3.558*** (1.057) | -3.047** (1.432) | -2.871** (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.8: Models dealing with the count data characteristics of the green flow of invention variable and the endogeneity of the stock variables, respectively

| Estimation method Period Dependent variable | Fixed-effects Poisson regression | OLS pre-sample mean estimator |
|---|----------------------------------|--------------------------------------|
| | 1984-2009 | |
| | Green_inventions _{ijt} | ln(Green_inventions _{ijt}) |
| | (1) | (2) |
| ln(L _{ijt-1}) | 0.046 (0.121) | 0.056* (0.069) |
| ln(Green_stock _{ijt-1}) | 0.798*** (0.094) | 0.647*** (0.033) |
| ln(Other_stock _{ijt-1}) | 0.035 (0.119) | 0.085** (0.036) |
| ln(Moving_average_energy_price _{ijt-1}) | 0.202** (0.096) | 0.148** (0.069) |
| Constant | | -2.216*** (0.715) |
| Year fixed effects | yes | no |
| Country specific industry fixed effects | yes | no |
| Country specific time fixed effects | no | yes |
| Industry fixed effects | no | yes |
| Pre-sample fixed effects | no | yes |
| N | 2610 | 2669 |
| Groups | 137 | 144 |
| Wald chi2 | 72782.29*** | |
| R ² | | 0.94 |
| Log Likelihood | -7674.11 | |

Notes: see Table 2 for the variable definitions; standard errors that are in brackets under the coefficients; ***, **, * denotes statistical significance at the 1%, 5% and 10% test level, respectively; Column (1): In line with Allison and Waterman (2002) we used robust standard errors to correct for overdispersion; Column (2): Pre-sample mean scaling approach proposed by Blundell et al. (1995) was used to account for fixed unobserved heterogeneity in the propensity to invent in the presence of lagged endogenous variables; standard errors are robust to heteroskedasticity and clustered at the industry-country level (clustered sandwich estimator).