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Invention in Energy Technologies: Comparing Energy Efficiency and Renewable Energy Inventions at the Firm Level

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Invention in Energy Technologies: Comparing Energy Efficiency and Renewable Energy Inventions at the Firm Level*

Sascha Rexhäuser† *and Andreas Löschel*‡

Abstract - Many countries, especially in Europe, have ambitious goals to transform their national energy systems towards renewable energies. Technological change in both renewable production and efficient use of energy can help to make these targets come true. Using a panel of German firms linked to the PATSTAT patent data, we study invention in both types of energy technologies and how their inventors differ in terms of central firm-specific characteristics. More importantly, we study the relation between conventional (i.e. non-energy) invention and energy invention within the firms. The results from dynamic count data models point to a stimulating effect of conventional inventions for energy efficiency technologies but have no effect on inventions in renewable energies.

Keywords - Innovation, invention, renewable energy, energy efficiency, dynamic count data.
Date - May 26, 2014

1 Introduction

In light of increasing prices for energy and increasing problems of climate change due to the extensive use of fossil fuels, many countries pursue a transition of their national energy systems towards renewable energies. In these countries—for instance Denmark, Spain, and recently Germany, invention and innovation in renewable energy technologies can help to achieve these targets at lower costs. In addition, also innovation in energy efficiency is central to the realisation of the energy transition. Technological change in this area has been identified as the central driver of reducing aggregate energy intensity (Voigt et al., 2014). Moreover, in countries where the share of total energy consumption due to energy-intensive manufacturing increased in the last years—as for instance in Germany or Taiwan

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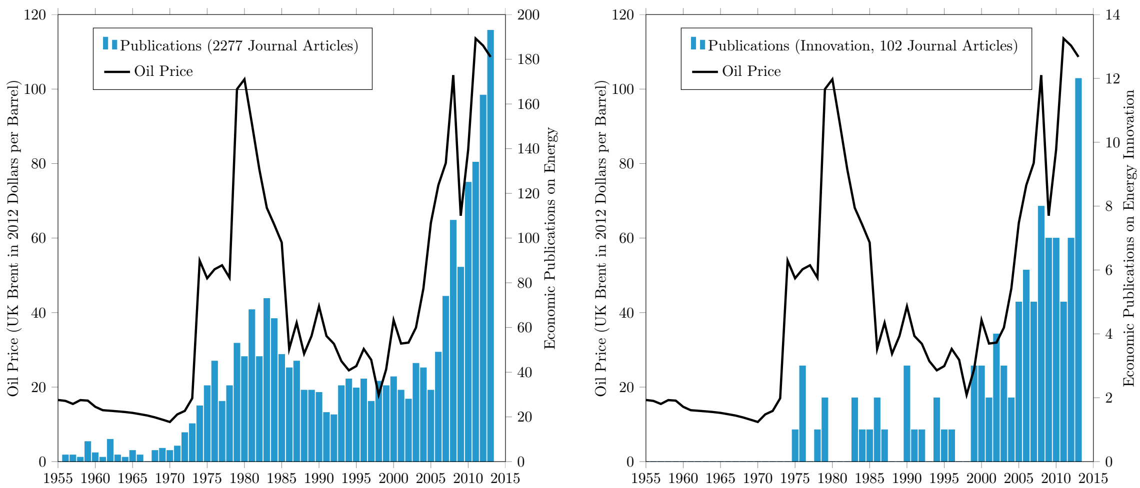
(Voigt et al., 2014)—technological change is even more important to economise energy costs.

For a long time—when energy prices (relative to other input prices)—where rather low, energy and technical change related to energy did not receive much, if any, attention by economists. The situation changed completely in the late 1970s and early 1980s, a time in which the oil price increased dramatically due to the two oil crises. In this sense, economic research on energy issues seems to be induced by energy prices, similar to energy price-induced innovation as documented by Lichtenberger (1986), Newell et al. (1999), Popp (2002). Figure 1 below supports this view by illustrating the development of the energy economics (and business) literature and the oil price over time. More robust support comes from time series regressions documented in Appendix A, which point to a significant effect of the oil price's development on the one for publications.

Figure 1: Research in Energy Economics

(a) All Publications (b) Studies on Innovation



The underlying data for publications in the energy economics literature comes from the Thompson and Reuters Web of Science[1]. Overall, more than 2277 studies where identified and plotted by publication year in Figure 1a. Of much more importance for this study is Figure 1b illustrating the strand of the energy economic literature dealing with R&D, innovation, and issues of technical changes. As this strand of the literature contains more than 100 scientific journal articles, the following survey is necessarily highly selective. The selection criteria that applies

[1]See Appendix A.1 for a comprehensive description of the underlying publication data and how the respective publications were identified.

here is the focus on the micro level.

A growing body of empirical literature studies the drivers of energy inventions. Most of the existing research typically relies on the concept of induced inventions—based on Hicks (1932). Energy price-induced technical change is documented in several studies, such as Lichtenberger (1986), Newell et al. (1999), Popp (2002), or more recently Crabb and Johnson (2010). In addition, regulation is identified as a key driver of energy technologies, see Newell et al. (1999) amongst many others[2]. For regulation-driven[3] energy innovation, especially for renewable energy technologies, much less empirical evidence exist. In the case of renewable energy technologies, Johnstone et al. (2010, p. 146) conclude that: "In general, policy, rather than prices, appears to be the main driver of innovation in these technologies." Moreover, most of this evidence is based on country-level or sector-level data, whereas there is much less micro-economic evidence, such as Aghion et al. (2012). They find that firms engaged in the automobile sector, innovate more in electric or hybrid engine technologies in the presence of higher fuel prices. Considering also conventional technologies on fossil fuel combustion engines, they find that firms' past innovation activities are a central determinant of current innovation in either "clean", i.e. electric or hybrid or "dirty", i.e. combustion engine technologies.

Another strand of literature the present paper takes a closer look at is dealing with the sources of energy R&D within firms. An early study by Mansfield and Switzer (1984) demonstrates that firms reduce their own energy R&D expenditures if governmental energy R&D funding is reduced. However, the authors do not find evidence for a crowding out, i.e. that government funded energy R&D replaces firms' own energy R&D spending. A much more recent contribution by Popp and Newell (2012) points to the fact that energy R&D for alternative energy (or patents measuring the outcomes of renewable energy R&D) comes at the expense of other types of R&D within firms. However, the authors note that this is

[2]Most of the regulation-induced literature deals rather with environmental innovation in general, see Jaffe et al. (2002) and Popp et al. (2010) for comprehensive reviews of this literature. Policy stimulated demand for renewable energy technologies (feed-in-tariffs), however, is not found to be a significant driver of related innovation; see Braun et al. (2010) and especially Böhringer et al. (2014) for German evidence.

[3]Note that there is also literature analysing the effect of deregulation on energy R&D. Nakada (2005) set up a theoretical model and arrives at the conclusion that deregulation of an energy market can foster innovation if the market structure is concentrated before the deregulation. Conversely, Jamasb and Pollitt (2011) find that liberalisation in the United Kingdom's electricity sector has reduced its R&D spending but, on the other hand, led to more patents for renewable and non-nuclear energy technologies in the time after the liberalisation. A more recent contribution by Nesta et al. (2014) finds that deregulation complements environmental policies in stimulating innovation in renewable energy technologies.

not due to financial constraints, and thus not due to a crowding out, but changing market opportunities.

We aim at contributing to this research by providing evidence for energy conservation inventions and compare the results to renewable energy inventions and their relation to conventional (i.e. any other) inventions. This evidence is based on a panel of German firms for the period 1992-2009. Given intensive regulation for renewable energies (in particular feed-in tariffs) and energy and oil taxation, there are strong invention incentives to be expected for both types of energy technologies in Germany. We find that inventors with more conventional inventions (patents) have—holding any other factors (especially size and R&D expenditures) fixed—on average more energy conservation patents. Conversely, for renewable energy technologies, this relationship does not exist. To put it otherwise, energy conservation technologies may complement firms' conventional technology portfolio. That is, firms with a larger amount of technological knowledge (accounted for by conventional patents) produce at the same time more energy efficiency patents and not less. Understanding in much more detail how energy invention is related (or not related in the case of renewable inventions) to conventional invention at the firm level is crucial for policymakers to set properly incentives for invention and innovation.

Moreover, in contrast to previous research, we study invention in energy technologies in both firms located in manufacturing and firms located in service sectors. This is of central importance as the overwhelming number of energy conservation patent holders come from manufacturing sectors, especially from the sectors of manufacturing computers and electrical equipment as well as the automotive sectors. Conversely, the sector contributing most to the overall number of renewable energy patents is the scientific research and development sector. By jointly studying manufacturing and service sectors, our study allows to draw a more comprehensive picture of invention activities in energy technologies.

The remainder of the paper is organised as follows. Section 2 describes the underlying data sources of this paper and presents descriptive statistics on the history of renewable energy and energy conservation technologies. The empirical model is presented in Section 3 followed by a discussion of our results in Section 4. Section 5 concludes.

2 Data and Descriptive Statistics

To investigate this papers' central research questions, we link two data bases—the Worldwide Patent Statistical Database (PATSTAT) from the European Patent Office (EPO) and the Mannheim Innovation Panel (MIP). The latter is a representative firm-level data set based on the German Community Innovation Survey (CIS). In contrast to CIS data for other EU member countries, the German Innovation Panel has been conducted annually from 1992 on. It is a random, stratified (by firm size, region, and sector), and representative sample of the German economy covering mostly manufacturing and service sectors. We exclude the sectors mining and quarrying as well as public administration from our analysis. As the sample is representative and as the German economy consists of a larger number of rather small firms, the firm in our sample observed at the median has only 37 employees, whereas the mean firm has 474 employees. The Innovation Panel data is highly unbalanced. However, we refrain from using a balanced sub-sample as we would necessarily restrict the sample to rather old (surviving) and rather large incumbent firms. Note that we cannot distinguish between firms being not sampled in a period and firms that exit the market in this period.

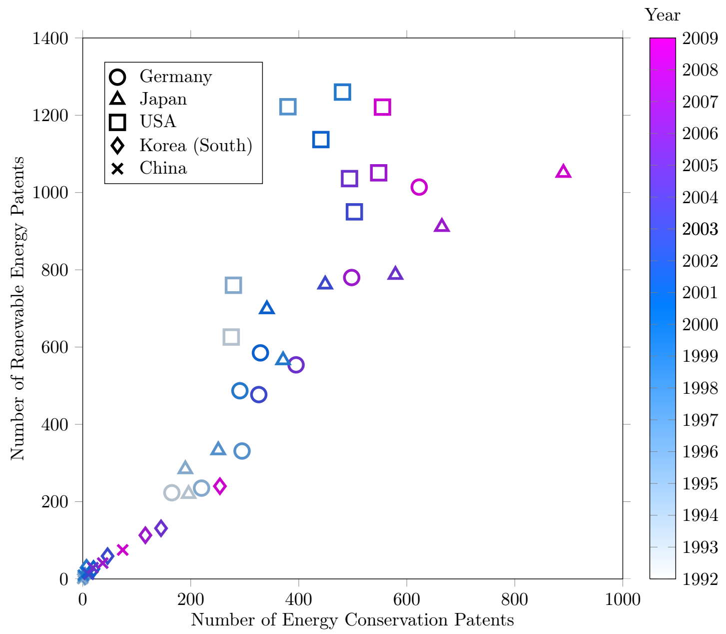
The MIP data provides basic firm level information like the number of employees and R&D expenditures, as well as firm age and sector affiliation. This database is merged with the firms' number of granted patents per year (priority year) from the PATSTAT data based on firm name and address data. The PATSTAT data provides ipc (international patent classification) codes that are used to identify energy patents. Based on ipc codes listed in the WIPO Green Inventory[4] classification, we distinguish between energy efficiency (conservation) and renewable energy technologies.

2.1 Descriptive Statistics at an Aggregate Level

Germany is one of the world's leading countries in terms of energy technologies which justifies the application of German firm level data. For the whole PATSTAT data and for a selection of countries, Figure 2 below presents the development for energy conservation and renewable energy patents over time for the same years (1992-2009) as we have firm level information in the Innovation Panel.

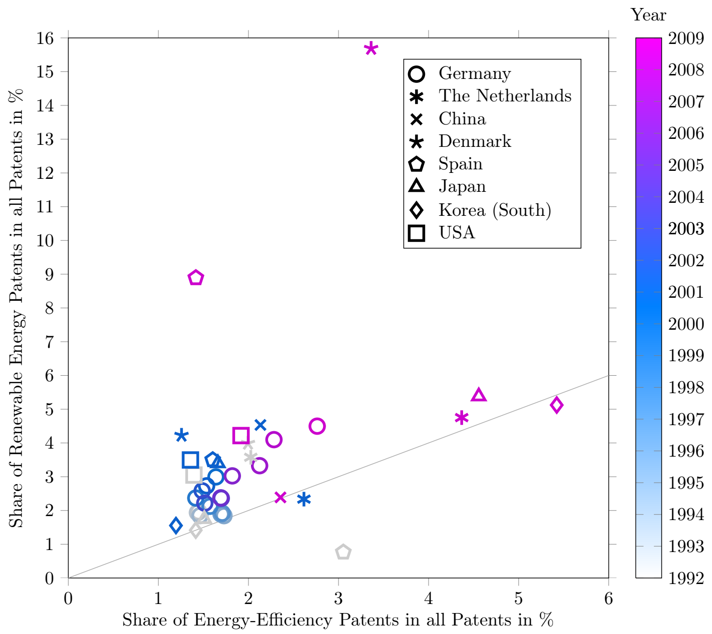
[4] See World Intellectual Property Organization (WIPO): http://www.wipo.int/classifications/ipc/en/est/.

Figure 2: International Comparison of Energy Patents



The world's most important countries with respect to energy technologies are the United States (USA), Japan, and Germany. However, other countries like South Korea have high growth rates for energy efficiency and renewable energy patents in more recent times. In absolute numbers, China does not seem to play a major role in energy technologies. Figure 3 plots the share of countries' renewable energy and energy conservation patents in all patents assigned by patent holders from the respective country at the EPO. This allows us to study the change in patenting activities for the two energy patent types relative to overall patenting activities in the countries. For all countries, the years 1992, 2001, and 2009 are presented, whereas the whole period 1992-2009 is plotted for Germany.

Figure 3: International Comparison of Energy Patents

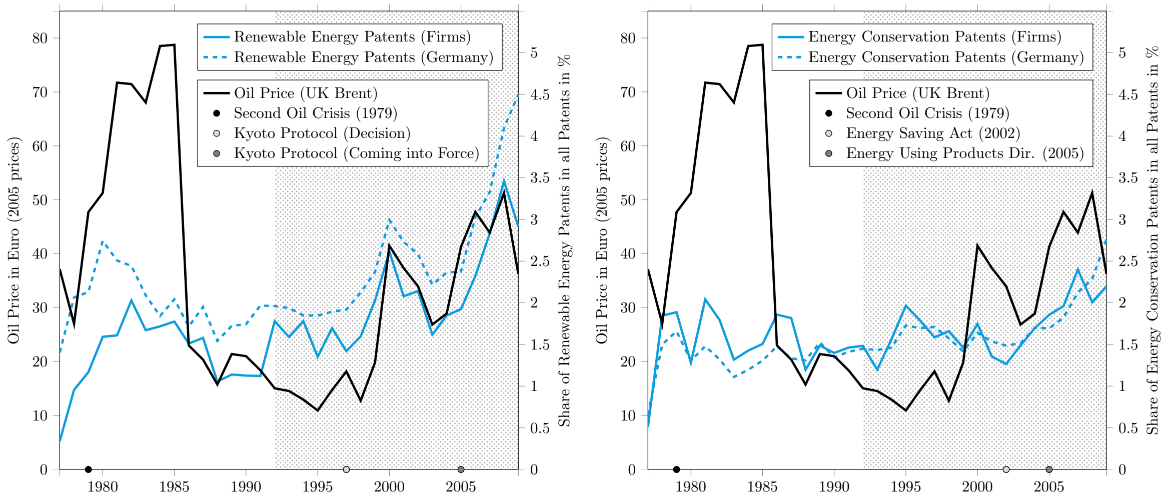


For some countries like Spain and Denmark, we can observe a focus on renewable energy technologies over time. In general, the share of renewable energy patents in all patents in 2009 is higher than the one for energy efficiency technologies for every country (but South Korea in 2009). For Germany as well as for other countries like Japan, there was a stronger increase in renewable energy patents' share in all patents compared to the one for energy conservation patents in early years. In more recent years, however, this trend is not observable as the share of both patent classes was growing according to a similar pattern. Figure 4 below illustrates this development in much more detail for Germany.

Figure 4 below illustrates the relative importance of energy patents in the whole invention process over time. In particular, Figure 4a documents the case of renewable energy patents while Figure 4b illustrates the case for energy conservation technologies.

Figure 4: Patent Activities in Germany

(a) Renewable Energy (b) Energy Conservation



In both graphs, i.e. in Figure 4a and 4b, the share of the patents for the respective energy type in all patents is shown for both the set of all German patents granted by the European Patent Office (EPO) and for the set of the firms in the Innovation Panel (MIP). For renewable energy patents, there is a large gap between the line indicating the patents of firms in the MIP and all German patents. The case for energy conservation patents reveals a different picture. The respective lines for the firm sample and the set of all German patents are rather close to each other. In this sense, energy conservation seems to be relatively more important to firms than it is the case for renewable technologies. In contrast to renewable energy patents, the energy conversation patents' time series seem to be less correlated with oil price (UK Brent in 2010 euros)[5] that serves as a proxy for the energy price and there is relatively less variation over time. In particular, for the early years from 1978-2002, there seems to be no long-run upward tendencies. However, from 2002 on, Figure 4b reveals a long-run (and for Germany as a whole a steady) increase in the share of energy conservation patents in all patents.

2.2 *Descriptive Statistics for the Firm Panel*

In total, we identified 733 energy conservation patents (836 renewable energy patents) of the firms in our (representative) Innovation Panel data set. This corresponds to about 9.54% (7.23%) of all energy-efficiency (renewable energy patents) patents by German patent holders. Figure 4b shows that the share of energy-

[5]The oil price data is obtained from the Association of the German Petroleum Industry.

efficiency patents in all patents for the firm sample is fits pretty well to the one for all German patents. Interestingly, 39.84% of the energy-efficiency patents held by German firms come from the information technology and electronic and optical products sector (Nace 26). Another 12.28% come from the electronic equipment sector (Nace 27). That is most of the energy-efficiency patents come from the electronic industry. For the 10 most important sectors, their contribution of energy conservation patents is documented in Table 1 below, as well as for renewable energy patents.

Table 1: Share of Energy Conservation Patents by Sectors

Sector	**Nace 2 /ISIS 4**	**Type of Energy Patents: Conservat.**	**Renewable**
Manufacture of computer, electronic, and optical products	26	39.84%	11.36%
Manufacture of electrical equipment	27	12.28%	2.51%
Manufacture of motor vehicles, trailers, and semi-trailers	29	8.05%	5.86%
Manufacture of machinery, and equipment n.e.c.	28	5.05%	7.42%
Manufacture of basic metals	24	3.55%	0.01%
Scientific research and development	72	3.41%	16.03%
Wholesale trade, except of motor vehicles, and motorcycles	46	3.27%	2.03%
Office administrative, office support, and other business support activities	82	2.87%	4.90%
Manufacture of chemicals and chemical products	20	2.86%	15.19%
Manufacture of other non-metallic mineral products	23	2.59%	2.27%

In general, the distribution of energy patents over sectors differs largely between the two patent types (energy conservation patents and renewable energy patents). The most important sector with respect to renewable energy patents is the science sector. Also the chemical industry as well as the electronic sectors contribute a significant number of renewable energy patents to the overall number of renewable energy patents.

At the firm level, there is a very large number of firms with zero patents, neither energy nor non-energy patents. That is, only 10% of the firms in the entire innovation panel are observed to have at least one or more patents granted by the EPO in 1992-2009. Only the top percentile of the firms are observed to be holders of at least one energy patent, while the remaining 99% are not active in energy technologies. In what follows, we restrict our attention to this top percentile, i.e. to firms engaged in energy technologies (patents), which are firms with at least one energy conservation or at least one renewable energy patent granted by the EPO in the sample period (i.e. between 1992 and 2009)[6]. Also in this sample of

[6]Note that restricting the sample in this fashion leaves the results largely unaffected. However, if the sample is not restricted, there is a large amount of firms that are never observed to have

380 firms observed between 1992 and 2009, only for 10% of the firm-year observations, we detect non-zero energy patents. In contrast to cross-sectional data where an excessive number of zero counts would require the use of zero-inflated count data models, "panel data [...] provide a more robust alternative as allowing explicit examination of the dynamic feedback" (Blundell et al., 1995, p.333f). In what follows, we discuss such a panel data estimation approach that is robust to a larger number of zero patent counts.

3 Model and Estimation Strategy

Let p_{it} represent firm i's number of patents observed in year t and assume that $\boldsymbol{x}_{it}$ is a vector of variables that may explain observed patents. In this sense, we are interested in how the conditional mean $E[p_{it}|\boldsymbol{x}_{it}]$ changes due to changes in $\boldsymbol{x}_{it}$. In count data models it is frequently assumed that p_{it} given $\boldsymbol{x}_{it}$ is Poisson distributed, where the mean parameter of the resulting density in log-linear form is given by $\mu = e^{(\boldsymbol{x}'_{it}\boldsymbol{\beta})}$. $\boldsymbol{\beta}$ is a vector of parameters[7]. Assume that there is a firm specific constant c_i which accounts for differences in the propensity to patent inventive output across firms, so that $E[p_{it}|\boldsymbol{x}_{it}, c_i] = e^{(\boldsymbol{x}'_{it}\boldsymbol{\beta}+c_i)}$. The resulting regression model is

$$p_{it} = \mu_{it} v_i + u_{it}, \tag{1}$$

where $\mu_{it} = e^{(\boldsymbol{x}'_{it}\boldsymbol{\beta})}$, $v_i = e^{(c_i)}$, and u_{it} is a random error term that account for instance for differences in organisational structures, creativity of the workforce, motivation and other factors explaining success in inventive processes. Typically, it is assumed that new inventive output (accounted for by p_{it}) is produced in a production process where technological knowledge is the only production factor. Existing technological knowledge is assumed to be a representation of past and current R&D expenditures (r_{it}, r_{it-1}, r_{it-2}, ...). In this sense, the vector $\boldsymbol{x}_{it}$ includes past and current R&D expenditures. The functional form of the "technology" in which past and current R&D expenditures are transformed into invective output and thus patents is traditionally assumed to be of the Cobb-Douglas type, where past R&D expenditures enter the model as a (distributed) lag function, see Pakes and Griliches (1980) among others. Since p_{it-1} itself is also produced by the same "technology" that use (r_{it-1}, r_{it-2}, ...) as inputs, we can replace (r_{it-1}, r_{it-2}, ...)

non-zero patents so these observations do not contribute to the coefficient estimates but increase the number of observations and thus the level of significance.

[7] See Cameron and Trivedi (2013) for a general introduction into count data models.

in $\boldsymbol{x}_{it}$ by p_{it-1}[8]. That is p_{it-1} is a noisy measure of the input factor technological knowledge.

There are three challenging issues in estimating the parameters of equation 1. First of all, strict exogeneity of the regressors in $\boldsymbol{x}_{it}$ is unlikely to hold in a dynamic panel model because some regressors might be predetermined. That is, as successful invention process in the past may give rise to current R&D expenditures, r_{it} (included $\boldsymbol{x}_{it}$) is likely to be correlated with u_{it} through a possible correlation with u_{it-1} (Blundell et al., 2002). Of course, p_{it-1} is also predetermined because of a correlation with past errors. Secondly, including the lagged dependent variable p_{it-1} in the exponential model 1 can lead to explosive series (Blundell et al., 2002). Finally, the remaining issue is how to deal with the firm specific fixed effects v_i.

To start with the latter issue, different methods have been proposed. Chamberlain (1992) and Wooldridge (1997) suggest GMM estimation techniques that make use of quasi-first-differences to eliminate firm specific fixed effects. As an alternative, Blundell et al. (1995) proposed to measure firm specific effects directly by using pre-sample means of the dependent variable. The pre-sample mean is the mean of the dependent variable before the sample period. In this sense, unobserved firm-specific heterogeneity (in patent counts) is assumed to be only due to differences in knowledge stocks across firms, which itself can be approximated using (pre-sample) patent information (Blundell et al., 1995). The estimation technique suggested by Blundell et al. (2002) also proposes the use of pre-sample means and provides a solution to the problem of predetermined regressors as their approach does not require strict exogeneity of the regressors[9]. Moreover, they suggest to exclude the lagged dependent variable from the vector $\boldsymbol{x}_{it}$ and include it in a linear form in the model (the so-called linear feedback model). The corresponding regression model reads as

$$p_{it} = (1-\delta)p_{it-1} + e^{(\alpha + \boldsymbol{x}'_{it}\boldsymbol{\beta} + \phi \ln \bar{p}_i)} + u_{it}, \tag{2}$$

where the parameter δ is the rate at which technological knowledge (represented

[8]The key advantage of using lagged patents to account for all lagged values of R&D expenditures is that we do not lose so much observations later in the estimation due to this lag structure. See also Griliches (1979) for a general discussion on the lag structure of R&D expenditures to account for firms' knowledge stocks.

[9]The reason is that the pre-sample mean—dated earlier than the other regressors—control for any systematic and firm-specific differences in invention success so that the error term is likely the represent only pure random success and failure in the invention process. The error term is therefore expected to be uncorrelated with potentially pre-determined regressors in the presence of pre-sample means.

by the noisy indicator patents) depreciates. α denotes a constant and $\ln \bar{p}_i$—the (logged) pre-sample mean—is the measure for c_i. According to Blundell et al. (2002), the moment condition for this model to be solved by the method of moments estimator reads in the just identified case as

$$\sum_{i=1}^{N} \sum_{t=2}^{T} \boldsymbol{z}_{it} \Big(p_{it} - (1-\delta) p_{it-1} - e^{(\alpha + \boldsymbol{x}_{it}' \boldsymbol{\beta} + \phi \ln \bar{p}_i)} \Big) = 0, \tag{3}$$

where $\boldsymbol{z}_{it} = (1, p_{it-1}, \boldsymbol{x}_{it}, \bar{p}_i)$ denotes the vector of instruments. Amongst R&D expenditures, the vector $\boldsymbol{x}_{it}$ includes further controls going to be discussed at length in the next subsection. A focus will lie on the inclusion of conventional (non-energy) patents and its relation to energy patents.

3.1 Variables of the Model

Dependent Variable — Energy efficiency inventions are accounted for by the number of patents classified as energy conservation technology based on the respective WIPO ipc-codes by priority year. Renewable energy patents are identified in the same fashion. To reduce the number of zero patent counts and to make the firms more comparable, we restrict the sample only to firms that are active in energy technologies. That is, firms that have at least one renewable or energy conservation patent granted by the European Patent Office (EPO) (regardless in which year)[10]. Moreover, as a further robustness check, we restrict the sample in a later step to firms with non-zero overall patents for each (observed) year. The rational behind this exercise is to exclude firms no longer active in patenting at all so that we can rather explain the number of patents in energy technologies for patent holders and exclude firms that do not patent their inventions or are not innovative at all.

Independent Variables — A key explanatory variable in the model is the pre-sample mean of the dependent variable. In this paper, it measures the mean of granted energy patents (by priority year) for the five years before a firm was sampled the first time. Thus, the pre-sample period differs between firms as the panel is highly unbalanced. If a firm being sampled the first time in later years (say in 2000) is an entrant, we cannot observe any pre-sample patents (for 1995-1999) because no patents in prior years exist. In this case, the pre-sample mean is

[10]Restricting the sample in this fashion comes at the consequence that the firms are on average much bigger (i.e. have on average 4328 employees, the median is 500) compared to the unrestricted sample (where the average is only 474 employees and the median is 37).

necessarily zero. However, the average firm was 25.13 years old when sampled for the first time, the median firm was 12 years old. Note that the pre-sample mean accounts for *any* firm-specific differences in the propensity to patent so that other controls for sector affiliation are not necessarily required. However, we control for firms' affiliation in computer and electrical equipment sectors (NACE 26, 27) and in science and engineering sectors (NACE 71, 72) as we are interested in estimates of the conditional mean of energy patents of firms in these special sectors. Including these two sector dummies leaves other coefficient estimates of other variables largely unaffected. Figures 4a and 4b, respectively, reveal differences in energy patenting activities over time which motivates controlling for year-specific effects that are common across all cross-sectional units. However, as the number of 17 year dummies included in the model caused computational difficulties so that no convergence could be achieved[11], we control for six three-year period dummies, where the period 1992-1994 serves as the reference category.

The control for firm size is constructed as the log of the number of employees. Firms' R&D-intensity is measured by R&D expenditures (in euros and 2010 prices[12]), scaled by the number of employees, and enters the model in logarithms. As R&D information is not reported for some firms, we set R&D expenditures for these firms to zero to avoid possible sample selection bias due to item non-response. To control for an impact of this manipulation on our results, we follow Hall and Ham Ziedonis (2001) by including a dummy variable that takes the value of one if missing R&D information was replaced by a zero.

Moreover, $\boldsymbol{x}_{it}$ includes the (logged) firm age and squared logged firm age allowing for a possible non-linear relationship between age and the number of energy patents. Especially young firms or entrants are seen as responsible for inventions, especially more radical ones[13]. In this sense, we would expect that younger firms have ceteris paribus more energy patents while older ones have less. That is older firms are expected to improve existing conventional technologies rather

[11]This was rather the case for the restricted sample and for the models using the number of renewable energy patents as dependent variable. For the basic model and for energy conservation patents, the model including the 16 year dummies (1992 served as control group) reports almost identical coefficient estimates for the other explanatory variables compared to the model using the three-year period dummies. This is likely due to the fact that coefficient estimates for the year dummies where not significant nor are they for the three-year dummies.

[12]Price deflator information is taken from the German Statistical Office, destatis.

[13]Henderson (1993) provides first empirical evidence that incumbent (and thus older) firms spend more on R&D for incremental technical change while entrants, i.e. younger firms, are responsible for rather radical innovation. Using German firm-level data, Schneider and Veugelers (2010) find that younger and smaller firms are more likely to introduce radical innovation compared to larger ones.

than to become active in energy technologies.

Due to a different historical and especially economic development in the Eastern (former communist) part of Germany, we expect firms located there to differ in terms of inventive output from firms located in the Western part. This may also be due to extensive subsidies to foster economic development in the Eastern part after the reunification of Germany. Consequently, a dummy variable takes the value of one if a firm is located in the Eastern part and zero otherwise.

Finally and most important, we control for the (logged) number of conventional patents in $t-1$ scaled by the number of employees. Scaling is important as the number of conventional patents is—similarly to R&D expenditures—highly correlated with firm size. This variable allows us to study whether a firm of equal size, age, and so on produces more energy efficiency patents when it produces at the same time more conventional patents. In this way, energy conservation technologies would be a valuable component in these firms' technological portfolio where possible complementarities among conventional and energy efficiency technologies could exist. For renewable energy patents, we do not expect this relationship to exist as we expect at least a part (those firms that provide renewable energy production equipment) of the holders of renewable energy patents to be firms specialized in providing such technology. For the other part, for instance firms in the chemical sectors, a positive relationship as for energy efficiency patents could exist so that the overall effect is unclear.

Finally, Table 2 below presents the summary statistics for all variables.

Table 2: Summary Statistics of the Model's Variables

Variables*	**Obs.**	**Mean**	**Std. Dev.**	**Min.**	**Max.**
number of energy conservation patents	2469	0.292	1.919	0.000	>40.000
number of renewable energy patents	2469	0.321	1.423	0.000	>40.000
number of conventional patents	2469	11.160	43.098	0.000	>1000.000
ln(R&D-intensity$_t$) (R&D/no. of employees)	2469	0.387	7.566	-12.388	12.717
dummy for missing R&D information	2469	0.490	0.500	0.000	1.000
number of employees	2469	4826.836	19716.920	1.000	>200000.000
firm age (median: 26 years)	2469	43.507	43.512	0.500	>150.000
dummy for location in East Germany	2469	0.120	0.325	0.000	1.000
pre-sample mean (energy conservation patents)	2469	0.103	1.123	0.000	34.600
pre-sample mean (renewable energy patents)	2469	0.129	0.729	0.000	13.400

* For some variables, we do not report (for reasons of confidentiality) the maximum values as these information would allow to identify the respective firms.

4 Results

The results obtained from the method of moments (and GMM) regressions are discussed in the following.

4.1 Basic Results

Table 3 below presents the results for our basic models, i.e. the models not restricted to firms that have non-zero (overall) patents in each observed year. Models 1a and 2a, respectively, report estimated based on the just identified moment condition in Equation 3, whereas the Models 1b and 2b, respectively, provide GMM estimates using one over-identification restriction. We use the logged one year lagged oil price (UK Brent in 2005 euros) as an additional instrument that is very likely to be completely exogenous to the number of patents. Exogeneity of the instruments is tested for using a Sargan test. In both Model 1b and Model 2b, respectively, we cannot reject the Null that the vector of instruments is orthogonal to the residuals. As the orthogonality condition applies, the instruments are exogenous and the models are well specified. Moreover, the coefficient estimates of both just-identified models differ from those two models using one over-identification restriction only at the margin.

Table 3: Results from the Basic Model

Dependent Variable: number of energy patents in t	**Energy Conservation**		**Renewable Energy**	
	(1a) *just ident.*	*(1b)* *overident.*	*(2a)* *just ident.*	*(2b)* *overident.*
Linear Feedback Part				
number of energy conservation patents in $t-1$	0.485***	0.486***	-	-
	(0.148)	(0.158)		
number of renewable energy patents in $t-1$	-	-	0.672***	0.668***
			(0.075)	(0.075)
Log-Link Part				
constant	-6.068***	-6.196***	-3.610***	-3.629***
	(1.101)	(1.051)	(0.808)	(0.801)
ln(R&D-intensity in t) (R&D/no. of employees)	0.077	0.074	-0.004	-0.003
	(0.078)	(0.076)	(0.039)	(0.039)
dummy for missing R&D information in t	1.375	1.237	0.324	0.341
	(1.272)	(1.226)	(0.621)	(0.623)
ln(firm size in t) (no. of employees)	0.315***	0.314***	0.295***	0.298***
	(0.070)	(0.072)	(0.081)	(0.079)
ln(firm age in t)	0.759**	0.804**	-0.106	-0.109
	(0.325)	(0.341)	(0.220)	(0.217)
ln(firm age in t)^2	-0.139***	-0.140***	-0.018	-0.017
	(0.049)	(0.051)	(0.054)	(0.053)
dummy for location in East Germany in t	-0.680	-0.586	-0.412	-0.418
	(0.506)	(0.501)	(0.639)	(0.633)
sectors computer and electrical equipment (NACE 26, 27)	1.075***	1.018***	-0.187	-0.195
	(0.272)	(0.282)	(0.387)	(0.386)
engineering and science sector (NACE 71, 72)	0.037	0.129	1.069**	1.072**
	(0.532)	(0.505)	(0.423)	(0.418)
ln(pre-sample mean) (energy conservation patents)	1.427***	1.527***	-	-
	(0.256)	(0.241)		
ln(pre-sample mean) (renewable energy patents)	-	-	1.205***	1.187***
			(0.214)	(0.213)
Observations	2469	2469	2469	2469
Hansen J-test statistic	-	0.902	-	0.209
Hansen J-test [p-value]		[0.342]		[0.647]

† The model includes 5 insignificant three-year period dummies.
* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

In general, the estimates reveal important differences between energy conservation and renewable energy patents. First of all, the coefficient estimate for the lagged dependent variable, i.e. for $(1-\delta)$, differs quite a lot. In model 1a, the coefficient estimate that, following Blundell et al. (2002), represents in some way the yearly "depreciated rate" of patents with respect to energy conservation technologies is very high, namely 51.5 per cent per year. However, as we do not measure patent stocks, the coefficient estimate of the lagged dependent variable, can also be seen as to account for a correlation of current and past patents due to patents clusters (for instance one good invention can give rise to many others in the future) or because the lagged dependent variable picks up some individual effects not entirely captured by other controls. For the case of renewable energy technologies, the respective "depreciation rate" in model 2a is much lower, namely 32.8 per cent per year[14]. Note that the present analysis does not allow to identify the reasons for these findings. A possible explanation could be that in the case of energy efficiency technologies, the average firm is not a specialised supplier of such technologies and develops it rather occasionally to complement the core technologies and to provide further value to their customers in times of high energy prices. As we expect providers of renewable energy technologies (at least the equipment suppliers) to be rather specialised in these technologies, the much lower estimate of 35.6 percent per year could be seen support in favor of this argument.

The impact of firm size on inventive activities does not differ in a significant way between energy conservation and renewable energy technologies. However, the impact of firms' age does. That is, for energy conservation patents, the results point to a significant inverted U-shaped relationship between firm age and patenting activities, where, ceteris paribus, the maximum of patenting activities is estimated to occur at an age of 15.336 years. Inventors that are more active in energy conservation technologies are (ceteris paribus) much younger than the average firm that is 43.507 years old (the median is 26). For renewable energy patents, there is a negative, however, not significant relationship between age and patenting activities.

Firms in the computer and electronic equipment sector have on average (and holding any other factors fixed) 1.075 more energy conservation patents compared to the control group of firms in any other sector but the science and engineering sector. Moreover, a firm affiliated in the science and engineering service sector (NACE71 and 72) is observed to have on average 1.069 renewable energy patents more than firms in the reference group, holding any other factors fixed. While this number seems to be rather small at the first glance, it is quite a lot given that the average firm in our sample (of energy patenting active firms) has only 0.321 new renewable energy patents in a certain year.

[14]Both estimated depreciation rates differ largely from those the literature provides. See Griliches (1990) for more details and an overview on the literature that typically assumes a depreciation rate of knowledge (capital) of 15 per cent.

4.2 Extension: Relationship with other Technologies

In the following, we are interested in the relationship between conventional technologies and energy technologies within firms' inventive processes. Thus, we include the (logged) number of conventional patents in $t-1$, i.e. patents of any technology class but energy classes, scaled by the number of employees to avoid possible size effects and multicollinearity with firm size. One year lagged information on conventional patents is used to avoid (potential) simultaneity with energy patents. Please note that we do not claim causality here as its direction is per se unclear. For energy conservation patents, we would expect causality to run rather from conventional technology to energy conservation if firms use energy conservation technologies to complement their conventional ones by offering the customers a further value in terms of reduced energy use. If, however, a firm is rather specialised in energy technologies (no matter whether in energy conservation or renewable energy), as for instance a manufacturer of solar panels, causality is likely to run in the opposite direction. Therefore, for our sample of different firms across different sectors, the direction of causality is per se hard to judge so that the "effect" of conventional inventive activities on energy patents is likely to represents (conditional) correlation rather than causality. Using one year lagged information of conventional innovative activities does not necessarily solve this problem. In addition, we are interested in the relationship between invention of energy conservation and renewable energy technologies so that the logged and one year lagged number of the other energy patents (scaled by employees) is included.

Moreover, the sample is restricted to firms with at least one patent, no matter of its technology class, for an observed year. As most of the firms report zero patents for both energy and conventional technologies, including the logged number of conventional (and the other energy type) patents in $t-1$ would result in a strong correlation with the lagged dependent variable and thus to multicollinearity problems. Restricting the sample to firms with non-zero patents in an observed year avoids this problem.

Restricting the sample in this fashion leaves the central results largely unaffected, except of the estimates for firm size that appear to be much smaller than before[15]. The models 3a and 4a reproduce the basic regressions for the models 1b

[15]Recall that restricting the sample to firms with non-zero patents in an observed year comes with a large increase in the average number of employees from 4826 to 7037. That is, the restricted sample is composed of rather large firms so that much less variation in firm size exists leading to a smaller, if any, impact of size on patenting activities.

and 2b (the over-identified models), respectively, based on the restricted sample. In another step, we include our measure of conventional inventive activities in Models 3b and 4b, see the Tables 4 and 5 below.

Table 4: Extensions: Results for Energy Conservation Patents

Dependent Variable: number of energy patents in t	**Energy Conservation**			
	(3a)	*(3b)*	*(3c)*	*(3d)*
	overident.	*overident.*	*overident.*	*overident.*
Linear Feedback Part				
number of energy conservation patents in $t-1$	0.513***	0.529***	0.540***	0.546***
	(0.148)	(0.143)	(0.141)	(0.140)
Log-Link Part				
constant	-3.688***	-3.544***	-3.412***	-3.346***
	(0.929)	(0.905)	(0.883)	(0.866)
ln(R&D-intensity in t) (R&D/no. of employees)	0.019	0.021	0.023	0.024
	(0.047)	(0.047)	(0.048)	(0.048)
dummy for missing R&D information in t	0.300	0.328	0.369	0.373
	(0.731)	(0.741)	(0.747)	(0.747)
ln(firm size in t) (no. of employees)	0.125	0.372	0.250**	0.383
	(0.087)	(0.278)	(0.124)	(0.288)
ln(firm age in t)	0.662**	0.695**	0.740**	0.756**
	(0.292)	(0.325)	(0.343)	(0.370)
ln(firm age in t)^2	-0.119***	-0.126**	-0.137**	-0.140**
	(0.046)	(0.051)	(0.054)	(0.059)
ln(no. of renew. energy pat. in $t-1$/no. of employees in t)	-	0.275	-	0.157
		(0.258)		(0.274)
ln(no. of convent. patents in $t-1$/no. of employees in t)	-	-	0.240**	0.225**
			(0.111)	(0.113)
dummy for location in East Germany in t	-0.295	-0.324	-0.384	-0.397
	(0.416)	(0.425)	(0.442)	(0.445)
sectors computer and electrical equipment (NACE 26, 27)	0.850***	0.885***	0.857***	0.885***
	(0.250)	(0.254)	(0.255)	(0.255)
engineering and science sector (NACE 71, 72)	-0.058	-0.191	-0.156	-0.224
	(0.464)	(0.456)	(0.466)	(0.460)
ln(pre-sample mean) (energy conservation patents)	1.413***	1.217***	1.167***	1.071***
	(0.206)	(0.233)	(0.221)	(0.234)
Observations	1552	1552	1552	1552
Hansen J-test statistic	0.424	0.696	0.296	0.425
Hansen J-test [p-value]	[0.515]	[0.404]	[0.586]	[0.514]

† The model includes 5 insignificant three-year period dummies.
* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

Table 5: Extensions: Results for Renewable Energy Patents

Dependent Variable: number of energy patents in t	**Renewable Energy**			
	(4a) *overident.*	*(4b)* *overident.*	*(4c)* *overident.*	*(4d)* *overident.*
Linear Feedback Part				
number of renewable energy patents in $t-1$	0.694***	0.651***	0.699***	0.662***
	(0.093)	(0.088)	(0.107)	(0.097)
Log-Link Part				
constant	-1.353**	-1.450**	-1.368**	-1.510**
	(0.638)	(0.600)	(0.629)	(0.598)
ln(R&D-intensity in t) (R&D/no. of employees)	-0.031	-0.019	-0.031	-0.018
	(0.029)	(0.026)	(0.029)	(0.026)
dummy for missing R&D information in t	-0.342	-0.241	-0.341	-0.236
	(0.406)	(0.379)	(0.409)	(0.384)
ln(firm size in t) (no. of employees)	0.079	0.537**	0.062	0.536**
	(0.071)	(0.242)	(0.135)	(0.247)
ln(firm age in t)	-0.041	-0.033	-0.038	-0.024
	(0.198)	(0.190)	(0.197)	(0.192)
ln(firm age in t)^2	-0.026	-0.020	-0.027	-0.021
	(0.048)	(0.046)	(0.049)	(0.047)
ln(no. of energy conv. pat. in $t-1$/no. of employees in t)	-	0.465**	-	0.512**
		(0.227)		(0.241)
ln(no. of convent. patents in $t-1$/no. of employees in t)	-	-	-0.025	-0.070
			(0.130)	(0.123)
dummy for location in East Germany in t	0.226	0.300	0.227	0.315
	(0.294)	(0.283)	(0.296)	(0.289)
sectors computer and electrical equipment (NACE 26, 27)	-0.438	-0.873**	-0.424	-0.866**
	(0.322)	(0.417)	(0.341)	(0.425)
engineering and science sector (NACE 71, 72)	0.612*	0.664**	0.600*	0.642**
	(0.333)	(0.295)	(0.355)	(0.310)
ln(pre-sample mean) (renewable energy patents)	1.374***	1.104***	1.400***	1.151***
	(0.220)	(0.253)	(0.300)	(0.284)
Observations	1552	1552	1552	1552
Hansen J-test statistic	0.150	0.127	0.146	0.116
Hansen J-test [p-value]	[0.698]	[0.721]	[0.701]	[0.734]

† The model includes 5 insignificant three-year period dummies.
* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors in parentheses.

First of all, including the measure of conventional inventive activities or patents of the other energy technology seem to have no large effect on the coefficient estimates for the other variables, with firm size being the only exception. That is, although the number of conventional patents and other energy patents is scaled by the number of employees, it is likely to pick up at least some size effects.

In Models 3b and 3d, there is no significant relationship of the measure of lagged renewable energy inventions on inventive activities of energy conservation technologies. Conversely, there is a significant positive relationship in the

Models 4b and 4d. Thus, invention of energy conservation technologies are positively related to the number of renewable energy patents within firms. A reason could be that energy efficiency technologies seem to complement renewable energy inventions but not the other way round.

The (logged) number of conventional patents scaled by employees is significantly (and positively) associated with energy conservation patents holding any other factors (especially size) fixed, see Models 3c and 3d. In this sense, an increase in conventional inventive activities do not come at the expense of energy conservation technologies, it rather stimulates them. This result does not come at a surprise. Very roughly speaking, whenever there is technological progress in areas where new goods or products use energy, there is also some room for technological change to improve energy efficiency. While these results seem to be rather obvious they have some implications for economic policy. As energy efficiency inventions come jointly with conventional inventions at the firm level, incentives fostering energy efficient technical change exist and work out. In this sense, technological progress with respect to more efficient use of energy would come also as a side-effect of unspecific (or non-technology specific) R&D subsidies to promote technological change in general.

Model 4c and 4d point out, that no such relationship between conventional inventions and renewable inventions is found to exist. As pointed out earlier, renewable energy inventions are generated in rather different sectors including manufacturing sectors and also the science service sector. In this sense, inventors differ strongly and are therefore hard to compare. However, one argument in favour of these results would be that a non-trivial share of inventors of renewable energy technology is rather specialized in this technology. If willing to promote technological progress in renewable energy, policymakers should therefore set more specific incentives in order to promote related technical change, for instance R&D subsidies specific to clean renewable energy production techniques.

5 Conclusion

Technological progress in both renewable energy and energy conservation technologies is key to ensure a secure and sustainable provision of energy at competitive costs. This is of special interest for countries willing to increase their share of energy produced using renewable resources such as Denmark, Spain, and recently Germany. In this paper, we shed some more light on related technological inventions at the level of inventors comparing renewable and energy conservation inventions by the use of patent data for a panel of German firms.

As a first result, we find that renewable energy and energy conservation inventions are generated in very different sectors, where most of the energy conservation patents come from the computer and electrical equipment as well as from the automotive sector. Given that the most important contributions to the overall number of renewable energy patents have been made by sectors others than those we would expect to matter most—i.e. manufacturing of wind turbines, solar panels, etc.—policy makers should set properly and rather general incentives to foster technological change in this area. That is policymakers should provide unspecific R&D support with respect to sector affiliation of subsidy receivers as a significant fraction of necessary technological knowledge required for renewable energy innovation comes from other sectors. In this light, a feed-in-tariff alone, for instance, is expected to foster technological change at the level of manufacturers of renewable energy production equipment (for instance for more efficient production technologies) rather than in the science service sectors. A mix of instruments seems to be more effective to stimulate technical change in all areas and sectors. Moreover, as a large fraction of renewable energy patents comes from the science service sector, a part of renewable energy technologies seems to represent basic research, rather than applied research. Conversely, the overwhelming majority of energy conservation patents comes from manufacturing sectors and represents therefore rather applied research. Policymakers should also consider this finding by setting appropriate incentives to foster technological development.

As a second result, we find that the two types of energy inventions do not differ much with respect to certain firm-specific characteristics, except for firm age. A negative but not significant relationship is found for renewable energy patents and a significant inverted U-shaped relationship for energy conservation inventions, where the most active inventors are on average much younger than the average firm (inventor) in our data set.

Finally and most importantly, the results indicate that energy conservation inventions are positively associated with conventional inventions at the firm level whereas no such relationship is found for the case of renewable energy inventions. With respect to this finding, several policy implications have been addressed earlier in the paper. Future research should overcome the limitations of this paper in a way as to study in much more detail the underlying mechanism in which energy technologies are related to other types of technology at the firm level. Moreover, future research should study the impact of firm-specific drivers of invention on this relationship, especially using information on R&D subsidies (in general and specifically for energy technologies) to provide more detailed and more robust evidence. Moreover, the use of a data set including firms from different (European) countries would allow to study the impact of country-specific differences, for instance due to differences in regulation, on inventive processes in the area of energy technologies.

Appendix A: Energy Prices and Publications

A.1 Description of the Data

For the year 1955 until 2013, information on publications and oil prices is available so that the sample consists of 59 observations. Three time series are available: 1) the oil price, i.e. the UK Brent[16] in 2012 US Dollars. 2) scientific publications included in the Thompson and Reuters Web of Science database with key words on energy issues as well as on energy innovation issues in the title[17] and classified as economic article publications.

Overall, 2277 economic publications on energy are included in the analysis, whereas the number of publications belonging to the innovation strand of the literature is much smaller, i.e. only 102 publications.

A.2 Time Series Regression

In what follows, we consider a simple dynamic (first-order autoregressive, AR(1)) model of the form:

$$\begin{aligned} \ln(publications_t) &= \beta_0 + \beta_1 \ln(publications_{t-1}) + \beta_2 \ln(oil\ price_{t-1}) \\ &\quad +\beta_3 time + u_t, \quad \text{where} \qquad (4) \\ u_t &= \rho u_{t-1} + \varepsilon_t \qquad (5) \end{aligned}$$

That is, the error term (u_t) is likely to follow an autocorrelated process of the first order, with unknown ρ. Whether ρ is zero or not will be tested for in a later step. Logged publications at time t are assumed to depend on publications in $t-1$ that are a result of several factors other beyond the econometrician's con-

[16]The oil price date is taken from the BP historical oil price database.

[17]In detail, the keywords are: "Energy*" or "Wind Industry" or "Solar Industry" or "Photovoltaic Industry" or "Biomass Industry" or "Wind Sector" or "Solar Sector" or "Photovoltaic Sector" or "Biomass Sector" for the field of energy economics and "Inventi*" or "Innovati*" or "Techn* Change" or "Research and Development" or "R&D" or "Technology" for the strand of the energy economics literature dealing with technical change.

trol. Such factors are the number of energy economic departments, availability of public research funds and so on. A linear time trend variable may catch up influential factors such as the propensity to publish in economics at all as well as the growth of the whole economic research field—at least to some extent. As a positive side effect, the time trend may reduce possible problems of autocorrelation and—more importantly—possible spurious regression. Note that spurious regression is not a problem here. Augmented Dickey-Fuller tests do not allow to reject the Null that both time series ($\ln(publications_t)$ and $\ln(oil\ price_t)$) have a unit root. Moreover, an Engel-Granger test allows to reject (t-statistic is -4.506) the Null that both time series are *not* cointegrated. Provided that cointegration very likely exists, a regression of $\ln(publications_t)$ on $\ln(oil\ price_{t-1})$ is very likely to be not spurious. The results from estimating model 4 appear in Table 6 below, next to results from an estimation in logged differences (growth rates) to eliminate autocorrelation and reduce possible problems of spurious regressions.

Table 6: Results from Time Series Regressions (OLS)

	All Energy Publications		**Energy Innovation Publications**	
Dependent Variable	$\ln$**(publications)**	$\Delta(\ln$**(publicat.))**	$\ln$**(publications)**	$\Delta(\ln$**(publicat.))**
	(1)	**(2)**	**(3)**	**(4)**
$\ln$(all publications$_{t-1}$)	0.352***			
	(0.130)			
$\ln$(innovation publications$_{t-1}$)			0.330*	
			(0.177)	
$\ln$(oil price$_{t-1}$)	0.567***		0.117	
	(0.132)		(0.127)	
linear time trend	0.020***		0.022***	
	(0.005)		(0.008)	
Δ(ln(oil price))		0.302***		0.247
		(0.109)		(0.223)
Constant	-0.491	0.081	-0.612*	0.036
	(0.322)	(0.071)	(0.307)	(0.068)
R^2	0.869	0.022	0.702	0.016
Observations	58	58	58	58

* p<0.10, ** p<0.05, *** p<0.01. Robust standard errors are in parentheses.

In Model 1, the energy price (oil price) has a significant effect on economic publications on energy issues. A one percent increase in the (lagged) oil price is associated with a 0.567 percent increase in publications. Results for Models 3 and 4 are for the strand of the energy economics literature on innovation issues. The impact of the oil price in Model 3 is much below of the one for the whole literature but not significant. A straightforward reason is the data, i.e. the respective publication time series is highly volatile as there are only a few articles observed every year (1.729 on average over the 59 years).

A Breusch-Pagan test allowed to reject the Null of constant variance of error the error term with a p-value of 0.000 in Model 1. In the presence of heteroscedasticity and possible endogeneity because of including a lagged dependent variable the standard Durbin-Watson test for autocorrelation as well as the Breusch-Godfrey test cannot be applied here. Instead, Durbin (1970)'s h-statistics is applicable (although the number of observations is pretty small) and does not allow to reject the Null that ρ is zero in Model 1 (p = 0.633)[18].

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[18]When ignoring heteroscedasticity, the Breusch-Godfrey test provides similar results (p = 0.618). In Model 2, we cannot reject the Null of constant variance of the error terms so heteroscedasticity is not a problem. In this sense, the Breusch-Godfrey test can be applied and does allows, however, to reject the Null that ρ is zero with p = 0.009. The Durbin h-statistics supports this result as the respective p-value is 0.007.

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