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THE IMPACT OF GREEN INNOVATION ON ENERGY INTENSITY: AN EMPIRICAL ANALYSIS FOR 14 INDUSTRIAL SECTORS IN OECD COUNTRIES

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The Impact of Green Innovation on Energy Intensity: An Empirical Analysis for 14 Industrial Sectors in OECD Countries

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Abstract

This paper analyses the impact of green innovation on energy intensity in a set of 14 industrial sectors in 17 OECD countries over the 1975-2005 period. We create a stock of green patents for each industrial sector and estimates a translog cost function to measure the impact of green innovation on energy intensity, next to other factors such as input substitution and autonomous technical change. We find that green innovation has contributed to the decline in energy intensity in the majority of sectors: the median elasticity of energy intensity with respect to green patenting is estimated at -0.03 in our sample. Hence, a 1% increase in green patenting activities in a given sector is associated with a 0.03% decline in energy intensity. The magnitude of the effect is larger in energy-intensive sectors and in more recent years. We also find that the impact of an additional green patent on energy intensity is larger than an average non-green patent. Our results are robust to alternative definitions of patents.

Keywords: Energy intensity, Green innovation; Patents; Technology; Cost function

JEL Codes: Q41; O33

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1 Introduction

Reducing the energy intensity[1] of production processes is a core objective of climate policies since it is an important mean to reduce carbon emissions. According to recent estimates of the International Energy Agency, 31% of emissions reductions necessary to halve emissions by 2050 compared to 2009 levels can be achieved through this lever (IEA, 2012). In addition, decreases in energy intensity contribute to the competitiveness of industries facing higher energy prices, which makes energy efficiency a 'win-win' objective for policymakers and the private sector (Porter and Van der Linde, 1995). Finally, the decoupling of economic growth from energy use may also contribute to improve energy security and the resilience of economies depending on energy imports.

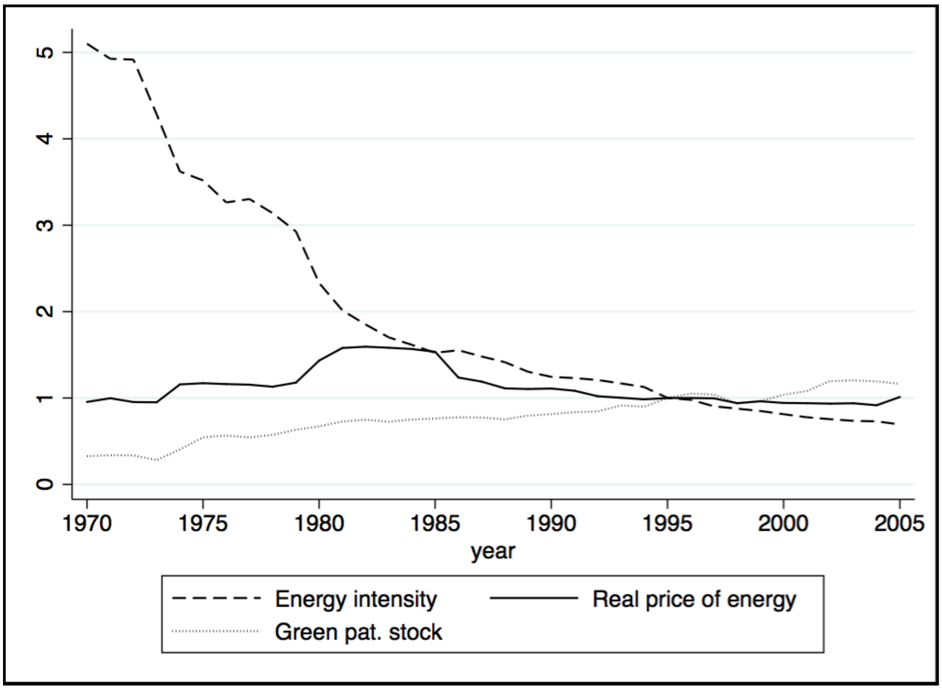
Over the last decades, industrialized countries have witnessed a significant decrease in the energy intensity of their economies. As shown in Figure 1, energy intensity, i.e. the quantity of energy used per unit of production value, declined by a factor of 5 over the 1970-2005 period. According to recent studies (e.g. Mulder and de Groot, 2012; Voigt et al., 2014), this decline is mainly explained by improvements within sectors, rather than across sectors. In other words, the decrease in energy intensity at the aggregate level is not explained by a composition effect, i.e. a shift to cleaner sectors in the economy, but rather the result of a more efficient use of energy within industries. There are two main *within industry* sources of improvements, namely input substitution – whenever firms substitute energy by using more labour or capital for instance, or technological innovation – whenever firms save on energy by using new energy-efficient production techniques. As an illustration, Figure 1 shows that the stock of green technologies, as proxied by the cumulative number of green patenting activities over time in our set of 17 OECD countries[2], has been steadily increasing over time since the 1980s. Since an increase in energy prices can trigger both a substitution of inputs away from energy and innovation in green technologies, Figure 1 also plots the evolution of the prices of energy over time. While energy intensity seem to be negatively correlated with energy prices until mid-1980s, the relationship is less clear for the second part of the period.

The objective of the current study is to clarify empirically the role of green technologies for

[1] Energy efficiency is defined as a technical measure, i.e. a ratio of input and output, whereas energy intensity refers to the quantity of energy used over the value of production.

[2] The precise definition of the stock of green patents is given in Section 3.

Figure 1: Energy Intensity, Energy Prices and Green Patent Stocks: OECD average



Notes: All data have been normalized so that 1995 = 1 and are averaged across sectors. Energy intensity is the ratio of an index of quantity of energy to value of output. Green patent stock is the average of the sector-specific stock of energy efficient patents. Real prices of energy are indexes of constant 1995 USD.

the decline in energy intensity for a set of 14 industrial sectors in 17 OECD countries over the 1975-2005 period. Green technologies are defined as technologies impacting energy usage, such as insulation or heat exchange apparatuses. Using the OECD Triadic Patent Families database, we identify green patenting activities using International Patent Classification (IPC) codes (Johnstone et al., 2010; Popp, 2001) and match patents to industrial sectors by applying a recently developed concordance table (Lybbert and Zolas, 2014). This allows us to compute the stock of relevant green innovation for each industrial sector in our set of OECD countries. Using production data at the industry level from the EU-KLEMS database, we estimate a translog production function following the (widely-used) framework developed by Berndt and Wood (1975) (see for example Haller and Hyland, 2014; Kim and Heo, 2013; Arnberg and Bjorner, 2007) to measure the impact of green patents on energy intensity per sector. We find that an increase in green patenting activities is associated with a reduction in energy intensity in most of the sectors in our sample, with a median elasticity of -0.04. Hence, a 1% increase in green patenting activities in a given sector is associated with a 0.04% decline in energy intensity at the median. We also find that the magnitude of the effect for green patents is larger in energy-intensive sectors and also larger than an average non-green patent.

Our study is related to an extensive literature which has used input demand functions to identify substitution patterns, in particular between energy and capital, since the 1970's (Binswanger, 1974; Berndt and Wood, 1975; Apostolakis, 1990). This literature has mainly focused on the role of energy prices on the demand for energy and capital inputs. Instead, the impact of technology has been neglected as the latter is often simply modelled as a time trend in the demand equations (for example in Jorgenson and Fraumeni, 1981; Welsch and Ochsen, 2005; Ma et al., 2008). This presents important drawbacks. First, it does not allow to cater to the induced innovation literature, which states that when energy prices are high, firms will tend to innovate in order to develop energy-saving technologies (Hicks, 1932; Ahmad, 1966; Jaffe and Palmer, 1997; Newell et al., 1999; Acemoglu, 2002; Popp, 2002). Second, the use of a time trend allows to observe only aggregate technical change without pinning down the specific effect of energy-saving technologies. The major reasons for this simplification in the energy input demand functions were first the absence of global datasets on innovation, and second the need for concordance tables to relate technologies to their potential sector of use to bridge the gap between patents and industrial sectors.

Some recent papers have circumvented the lack of specific measure of technology by using past energy prices as a proxy for biased technical change (Sue Wing, 2008; Mulder et al., 2014). Sue Wing (2008), for example, finds that within-sector gains in energy intensity in the U.S. occur through price-induced substitution of variable inputs, adjustments in quasi-fixed inputs, and, to a limited extent, through price-induced innovation. However, the use of past energy prices as a proxy for biased technical change requires the *ex-ante* assumption that energy prices are indeed an incentive to innovate. In contrast, Popp (2001) presents an unique study on the role of energy-efficient innovation on sectoral energy intensity where technology is measured using patent data. He uses a concordance table based on Canadian industries, the Yale Concordance Table, to match technologies to their potential sectors of use and finds an estimate of -0.06 for the short run elasticity between green technology and energy intensity averaged across all sectors. Overall, his results suggest that price-induced input substitution and induced innovation decreased energy consumption by a factor of two-thirds and one-third respectively. However, his study is limited to the U.S. and to the 1972-1991 period, which leaves out an important time period in terms of green innovation. By contrast to Popp (2001)'s analysis which was limited to the US, our study brings novel insights on the impact of green innovation on energy intensity for a large set of OECD countries. This helps to uncover whether the US results can be generalized more broadly. In addition, our analysis is original as it covers three decades of data up to 2005, while Popp (2001)'s study was limited to the beginning of the 1990s.

The remainder of this paper is structured as follows. Section 2 describes our empirical methodology. Section 3 provides a discussion of our data sources as well as some descriptive statistics. Section 4 presents the estimation results. Section 5 concludes.

2 Theoretical Framework

There is a large body of literature estimating energy demand using a cost function approach following the pioneering work of Berndt and Wood (1975).[3] We consider an industry's production function:

$$Y = f(K, L, E, M, T) \tag{1}$$

where $f(\cdot)$ represents an industry's technology that produces output Y using the four input factors: capital K, labor L, materials M and energy E, and T the level of technology. We transform Equation (1) into a cost function by using the duality theorem between production and cost functions (Shephard, 1953):[4]

$$C = g(P_K, P_L, P_M, P_E, Y, T)$$

where C is the minimum cost required to produce Y and P_i is the i-th input price. This allows to circumvent the issue of production functions with endogenous choice of inputs (Binswanger, 1974). As the level of inputs is a choice variable for firms, estimating econometrically a production function potentially violates the assumption of strict exogeneity of regressors, as there could be numerous factors affecting simultaneously the output level and the choice of inputs. By us-

[3]Recent studies include Welsch and Ochsen (2005); Arnberg and Bjorner (2007); Ma et al. (2008); Kim and Heo (2013); Haller and Hyland (2014).

[4]Under the duality theorem, if the production function is twice differentiable, then there is a corresponding cost function that is also twice differentiable.

ing input prices in a cost function framework, this particular problem is most likely avoided, as prices can be considered exogenous provided that sectors are small. In addition, for the purpose of estimation, a flexible functional form imposing no a priori restrictions on the elasticities of substitution is preferred to estimate $g(\cdot)$. We thus employ a translog cost function, which makes no restrictive assumptions on the estimated substitution elasticities and on the optimal path of input factor adjustments induced by price changes (Christensen et al., 1973), expressed as: [5]

$$
\begin{aligned}
lnC &= \beta_0 + \sum_i \beta_i lnP_i + \beta_Y lnY + \beta_T lnT \\
&+ \frac{1}{2}\beta_{YY}(lnY)^2 + \frac{1}{2}\beta_{TT}(lnT)^2 + \frac{1}{2}\sum_i\sum_j \beta_{ij} lnP_i lnP_j \\
&+ \sum_i \beta_{iY} lnY lnP_i + \sum_i \beta_{iT} lnT lnP_i
\end{aligned} \tag{2}
$$

with $i, j = K, L, M, E$. Slutsky symmetry condition is imposed by setting $\beta_{ij} = \beta_{ji}$. Because of the collinearity problem, an estimation of the first derivatives of (2) is preferred to a direct estimation of the cost function. Cost minimization w.r.t. input prices implies the following:

$$\frac{\partial lnC}{\partial lnP_i} = \beta_i + \frac{1}{2}2\beta_{iK} lnP_K + \frac{1}{2}2\beta_{iL} lnP_L + \frac{1}{2}2\beta_{iE} lnP_E + \beta_{iY} lnY + \beta_{iT} lnT \tag{3}$$

Under Shephard's lemma, assuming cost minimization, the demand functions for input i are equal to the derivative of expenditures with respect to price (i.e the cost shares for each input). Equation (3) equals the energy cost share:

$$\frac{\partial lnC}{\partial lnP_i} = \frac{\partial C}{\partial P_i}\frac{P_i}{C} = Q_i\frac{P_i}{C} = \frac{P_iQ_i}{C} = s_i \tag{4}$$

where s_i is the cost share of the i-th input. Hence, the cost share for each input is defined as:

$$s_i = \beta_i + \sum_j \beta_{ij} lnP_j + \beta_{iY} lnY + \beta_{iT} lnT \tag{5}$$

The inclusion of β_{iY} measures potential scale effects in production, or whether the size of the sector changes the cost share of inputs (for example if an increase in the output of the sector shifts

[5] See Thompson (2006) for a discussion of the specification of the translog cost function.

the production function towards, say, more capital). The coefficient β_{iT} measures shifts due to technical change. To ensure homogeneity of degree one in prices (a doubling of all prices results in a doubling of total costs), the following restrictions are imposed:

$$\sum_i \beta_i = 1 \quad \text{and} \quad \sum_i \beta_{ij} = \sum_i \beta_{iY} = \sum_i \beta_{iT} = 0$$

Since cost shares sum up to unity, the disturbance terms sum up to one, making the covariance matrix singular. The estimation procedure involves dropping one of the equations from the equation system and normalizing all input prices.[6] Since the objective of our paper is to measure the contribution of green technologies in particular, we decompose the technology variable between green technology (G) and autonomous technical change captured by a time trend t:[7,8]

$$s_i = \beta_i + \beta_{iL} ln \frac{P_L}{P_M} + \beta_{iE} ln \frac{P_E}{P_M} + \beta_{iK} ln \frac{P_{Kt}}{P_M} + \beta_{iY} lnY + \beta_{iG} lnG + \beta_{it} t + \varepsilon_i \tag{6}$$

for $i = K, L, E$ with cross-equation symmetry imposed. We estimate this equation using iterated three-stage least squares (Berndt, 1991) such that results are not sensitive to the choice of the omitted equation. We take advantage of our panel data structure to estimate the system of Equations (6) sector-by-sector while controlling for unobserved heterogeneity at the country level.

We measure the impact of green technology by computing the elasticity of energy intensity with respect to green technology. To obtain this elasticity, the first step is to derive energy intensity from the cost share functions as defined in Equation (6). Using the zero profit condition stating that $TC = p_Y Y$ and substituting into the definition of s_E, we are able to recover energy intensity E/Y (Welsch and Ochsen, 2005). We simply multiply s_E by $\frac{P_Y}{P_E}$:

$$s_E = \frac{P_E E}{TC} = \frac{P_E E}{P_Y Y}; \quad \frac{E}{Y} = \frac{P_Y}{P_E} s_E \tag{7}$$

[6]The choice of numeraire should not affect the estimated elasticities. Here, following Welsch and Ochsen (2005), we use material input as numeraire.

[7]Obviously, different empirical specifications are possible, each answering different research questions related to innovation. For instance, one could focus on overall technical change and thus use total patents, or on directed technical change and use the share of green patents. In this paper we are primarily interested in measuring the impact of green technologies, among other because green and non-green patent stocks are highly correlated, and because the share of green patents does not vary much through time.

[8]This framework measures the input bias of technological change (a potential shift in the isoquant structure or slope), and thereby ignore Hicks neutral technological change affecting all inputs simultaneously. Empirical studies testing for evidence of neutrality of technological change usually reject it (Hesse and Tarkka, 1986; Hunt, 1986).

The elasticity of energy intensity w.r.t. green technology is:[9]

$$\epsilon_{EG} = \frac{\partial ln(E/Y)}{\partial lnG} = \frac{\hat{\beta}_{EG}}{\hat{s}_E} \tag{8}$$

with $\hat{\beta}_{EG}$ and $\hat{s}_E$ the estimated coefficients on green technological change in the energy demand equation and the predicted cost share of energy.

3 Data and Descriptive Statistics

3.1 Patent data

Technological innovation is measured using patent counts. Besides being readily available, patents present the advantage of being a good indicator of innovative activity and tend to be highly correlated with a large number of alternative measures of innovation (see Acs and Audretsch, 1989; Comanor and Scherer, 1969; Griliches, 1990; Hagedoorn and Cloodt, 2003; Popp, 2005). We extract patent data for 17 countries from the OECD Triadic Patent Families (TPF) database (Dernis and Khan, 2004), over the 1975-2005 period.[10] Triadic patents families are patents filed at the European, Japanese and US patent offices (respectively, EPO, JPO and USPTO) to protect the same invention.[11] These technologies tend to be of much higher economic value than patents filed only at a single national authority, as firms would only be willing to bear the substantial costs involved with filing a patent at the EPO, JPO and USPTO, if they expect their invention to be of high commercial value (Nesta et al., 2014). This quality hurdle thus removes low-value inventions, reducing the variance in patent quality (Johnstone et al., 2010), identified as one of the main challenges of methodologies using simple patent counts (Griliches, 1990; Popp, 2001). The use of triadic patents also has the advantage to reduce the home bias (Griliches, 1990): applicants tend to apply for patent protection in their home country more than in other countries, overestimating the stock of patent of domestic applicants compared to foreign applicants when relying on data from a single patent office.

Following Jaffe et al. (1993) (see also the OECD patent manual, 2009), we allocate patents to

[9] Derivation can be found in Appendix A.

[10] We consider the following countries: Austria, Belgium, Germany, Denmark, Spain, Finland, France, Great Britain, Italy, Japan, South Korea, Luxembourg, the Netherlands, Portugal, Sweden, Slovenia and the United States.

[11] For a typology of patent families, please refer to Dernis and Khan (2004) or Martinez (2010).

countries using the address of the inventor. When a patent is invented by multiple inventors located in different countries, we disaggregate them using fractional counts. We count patents per priority year, which is the date closest to the date of invention (see OECD, 2009, chapter 4).

3.1.1 Identification of green patents by sector

Our identification of the relevant green technologies uses the following strategy. In a first step, we start from the broadest possible list of green patented technologies – identified using International Patent Classification (IPC) codes. We use the extensive list of climate change mitigation technologies provided in Dechezlepretre et al. (2011) and expand it with the list of technologies more specifically relevant to energy-efficiency selected by Popp (2001). This gives us a list of 1,529 technology classes defined at the 6-digit IPC code.[12] We use fractional counts for patents with several IPC codes. If a given patent specifies two technological fields, among them only one relevant for our analysis, 0.5 patent will be allocated to the prevailing country/year.

In a second step, we relate patents (coded in IPC) to their sectors of use (coded in ISIC or NACE), i.e. sectors in which these specific technologies are used in the production process. We rely on the recently released ALP ('Algorithmic Links with Probabilities') concordance table developed by Lybbert and Zolas (2014) together with the World Intellectual Property Organization (WIPO). This table makes it possible to link patents and economic data through technology-industry associations. The authors use a text analysis software and keyword extraction programs to develop a probability distribution of possible industries with which a patent in a given technology field may be associated. For each patent, the table provides us with a list of economic sectors with a corresponding probability.[13] In essence, these probability weights blend two types of links, namely *usage* and *production* of technologies (Lybbert and Zolas, 2014), reflecting the fact that technologies are allocated to industries either because they are used therein, or because the technology was developed by this industry. Yet, in their robustness analysis, Lybbert and Zolas (2014) find that there are only negligible differences between their estimated weights and the

[12] The complete list of IPC codes can be provided upon request.

[13] Several modifications are made. First, because the concordance table developed by Lybbert and Zolas (2014) provide the sectors of use in ISIC 3.1 code, while our production data is provided in Nace rev.1.1, we use the concordance table from the United Nations Statistical Division to match sector codes (available at http://unstats.un.org/unsd/cr/registry). Second, the output from the concordance table is provided in disaggregated Nace sectors (1.11, 1.12, 1.13), while EU-KLEMS data is provided only in aggregated Nace (11). We thus simply add up the weights provided by the table for each of the aggregated Nace codes.

weights of other methodologies distinguishing between sector of use and industry of manufacture (Lybbert and Zolas, 2014, p. 537). While the concordance table allows us to screen out green patents that are not being used in a given sector (e.g. solar technologies in the pulp-and-paper industry), we may be concerned about two remaining sources of measurement errors.

First, some patents identified as green could still be unrelated to energy consumption. For instance, end-of-pipe technologies, such as a pollution filter, may be selected as green patents but are not likely to affect energy usage. This could result in an overestimation of the stock of patents compared to energy-efficient patents narrowly defined, thereby adding statistical noise and blurring our estimations. To check the relevance of this concern, we identified the 'sectors of use' as provided by the concordance matrix for renewable energy patents (wind, solar, hydro, marine and biomass) for which the energy-saving characteristics are the least obvious. Most of these technologies are allocated to the sector Nace 40 (Generation of electricity), as expected, but also fall in other industrial sectors with a small probability. As an illustration, wind technologies are allocated with a 0.72 probability to electricity production, but also with a probability of 0.125 to Nace 29 (Machinery nec).

In consequence, we choose to keep these patents in our sample selection. An overestimation of the stock of patents could increase the risk finding no statistically significant coefficient when the true parameter value in fact is significant, but does not prevent us to make conclusive arguments on parameters found significant as long as these are uncorrelated with the error term.

An additional measurement error can arise as, although we use the most comprehensive list of green IPC codes available, in theory there might exist additional energy-efficient technologies excluded from our selection. In this case, we might be underestimating the stock of green knowledge, implying that our estimates may be only a lower bound. Again, this does not prevent us from making conclusive arguments on parameters found significant.

Table 1 summarizes the list of IPC classifications related to each sector and the associated concordance weight from Lybbert and Zolas (2014), for a selection of industries: Nace sectors 21 (Pulp and Paper), 24 (Chemicals), 27 (Basic metals) and 28 (Fabricated Metals). For example, the probability weight between the green IPC class D21C11 (Regeneration of pulp liquors) and the Nace sector 21t22 (Pulp & Paper) is 85%. In words, this technology has a probability of 85% of being used in this sector. We then count the number of patents allocated to each sector of use weighted by the corresponding probabilities. For example, if there are 10 patents in this IPC classification in a given year (each with only a single inventor and a single IPC code), a flow of 8.5 patents will be allocated to this industrial sector. Note that weights for each technology class sum up to one, such that the total count of patents remains unchanged after being split between sectors of use.

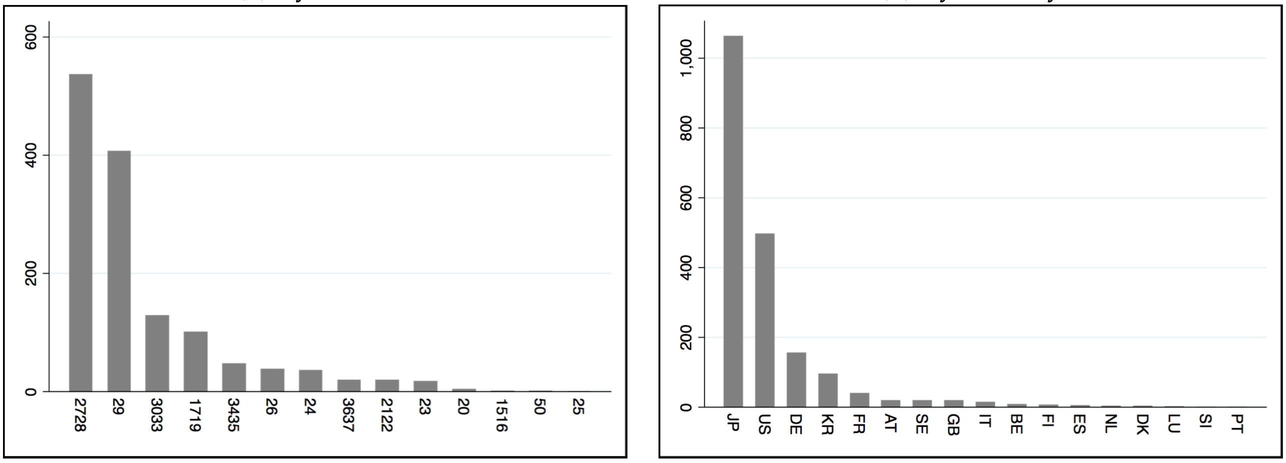
Table 1: Sectors and technologies (selection)

Nace code	Sector name	IPC	Category	Conc. weight
21	Pulp and Paper	D21C11	Regeneration of pulp liquors	0.8463
24	Chemicals	C25D13	Processes for the Electrolytic Production of Coatings	0.3767
24	Chemicals	C23C16	Coating Metallic Material	0.1990
24	Chemicals	C23C22	Coating Metallic Material	0.1325
24	Chemicals	C12M1	Methane capture	0.1235
24	Chemicals	C02F11	Methane capture	0.1200
24	Chemicals	H01L25	Semiconductor devices	0.0897
24	Chemicals	C02F11	Methane capture	0.0782
24	Chemicals	D21C11	Regeneration of pulp liquors	0.0721
24	Chemicals	C25D9	Processes for the Production of Coatings	0.0698
24	Chemicals	C10L1	Waste	0.0641
27	Basic Metals	C25C3	Coating Metallic Material	0.9315
27	Basic Metals	C25C1	Refining of Metals	0.8373
27	Basic Metals	C21D8	Methods or devices for heat treatment	0.8167
27	Basic Metals	B22D21	Casting of Metals	0.7585
27	Basic Metals	C21D6	Methods or devices for heat treatment	0.7380
27	Basic Metals	C25C5	Coating Metallic Material	0.7030
27	Basic Metals	C25D11	Processes for the Production of Coatings	0.6741
28	Fabr. Metals	C25D2	Processes for the Production of Coatings	0.7524
28	Fabr. Metals	C23C30	Coating Metallic Material	0.6722
28	Fabr. Metals	C23C18	Coating Metallic Material	0.6122
28	Fabr. Metals	C25D7	Processes for the Production of Coatings	0.6085
28	Fabr. Metals	C23C28	Coating Metallic Material	0.5876

Figure 2: Average green patent stocks

(a) By sector

(b) By country

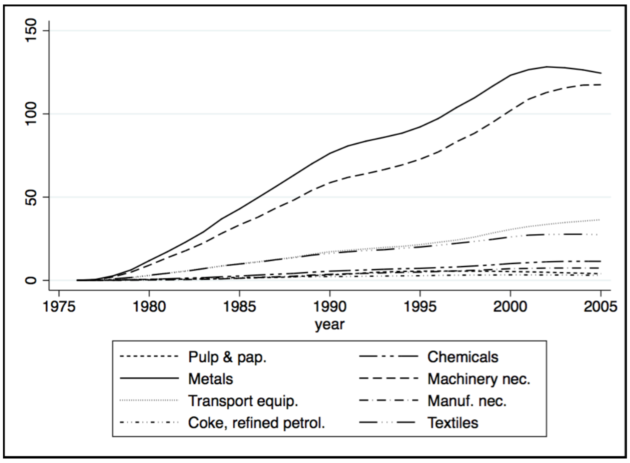


3.1.2 Descriptive statistics of patent stocks

We compute cumulative green patent stocks over the 1970–2005 period for our set of 17 OECD countries using the perpetual inventory method with a 10% yearly depreciation rate (Verdolini and Galeotti, 2011) to the counts of patents per sector/country/year. Figure 2a shows the average patent stock allocated to each sector across countries.[14] Sectors with the largest stocks of green patenting activities are sector 27t28 (Metals), 29 (Machinery nec), 30t33 (Office and accounting; electrical engineering; medical, precision and optical instr.) and 17t19 (Textiles, textile products, leather and footwear). In contrast, some sectors have a very low number of green patents throughout the sample, namely: 15t16 (Food, beverages and tobacco), 25 (Rubber and plastics) and 50 (Sale, maint. and repair of motor vehicles; retail sale of fuel). Figure 2b gives the total number of green patents per country (aggregated over all sectors). Green innovation appears to be highly concentrated geographically: most innovation is performed by inventors in Japan, but also in the United States, Germany and South Korea, as commonly found in the literature. Finally, Figure 3 shows the evolution of the stock of green patents over time (averaged across all 17 OECD countries in our sample) for a selection of industrial sectors. Patent stocks broken down by industry increase steadily through time in most cases.

[14]Effective green patents are green patents weighted by the inventor fractional counts, and allocated to sectors by the concordance table.

Figure 3: Green patent stocks (OECD average)



3.2 Input demand functions

We use production data at the industry level from the EU-KLEMS database, March 2008 version.[15] This dataset is developed from supply-and-use tables to recover energy, materials and services from total intermediate inputs as provided by National Accounts, and is widely used to estimate input demand functions (see for example Mulder and de Groot, 2012; Kim and Heo, 2013; Steinbuks and Neuhoff, 2014).[16] Data on input quantities and volumes per industrial sector over the 1970-2005 period are available for the following inputs: energy, material, labor and capital. Sectoral implicit prices of inputs are recalculated from input expenses (CAP, LAB, IIE and IIM) and volume indexes (CAP_QI, LAB_QI, IIE_QI and IIM_QI) available in the the 2008 version of EU-KLEMS. We normalize expenses and divide them by volume indexes ($1995 = 100$) to obtain current energy purchaser's price indexes.[17] Table 2 lists the industries included in our

[15] Available at www.euklems.net.

[16] O'Mahony and Timmer (2009) provide a complete description of the methodologies used to build the EU-KLEMS dataset.

[17] Many observations in this dataset (approx. 14%) have negative value for capital. This occurs because capital is measured as the difference between value added and labor inputs, and because in some sectors, an important fraction of labor is self-employed. As the wage rate for self-employed is typically unobserved, authors proxy it by using the wage rate of employed workers. In sectors where the latter is greater than the former, this results in negative values for capital when the value of employment exceeds the value added. We could simply drop sectors/countries with negative capital, but this would assume an arbitrary threshold for dropping observations, because industries with a high rate of self-employment, even with a positive value for capital, still suffer from this estimation bias. We thus choose to constrain the value of capital compensation to be strictly positive, and replace all negative values by zero. This does not change the results qualitatively, but makes them more significant.

Table 2: Sectors

Nace Rev. 1	sector name
15t16	Food, beverages and tobacco
17t19	Textiles, textile products, leather and footwear
20	Wood and products of wood and cork
21t22	Pulp, paper and paper products, printing and publishing
23	Manufacture of coke, refined petroleum products and nuclear fuel
24	Chemicals
25	Rubber and plastics
26	Non-metallic minerals
27t28	Metals
29	Machinery nec
30t33	Office and accounting; electrical engineering; medical, precision and optical instr.
34t35	Transport equipment
36t37	Manufacturing nec; recycling
50	Sale, maint. and repair of motor vehicles; retail sale of fuel

sample.[18]

Figure 4 presents the share of each input (capital, labor, materials, energy) in total costs, our main dependent variable. Figure 5 plots the evolution of the cost share attributable to energy input over time for various industries. The cost share of energy tends to decrease through time and this decline is particularly strong over the first sample period (1980-1995).[19] Figure 4 shows that sector 23 (Manufacture of coke, refined petroleum products and nuclear fuel) is by far the most intensive in energy as a proportion of total input costs, followed by sectors 26 (Non-metallic minerals), 24 (Chemicals), 25 (Rubber and plastics) and 27t28 (Metals). Summary statistics of our dataset are presented in Table B1 in Appendix B.

[18]Some sectors are aggregated to maximize sample size, while others are removed due to missing observation.

[19]One needs to bear in mind that being a share, this variable can also be affected by movements in the consumption of other inputs. An increase in the use of, say, labor, will mechanically affect the cost share of other inputs. A simple graphical analysis is thus limited in this respect.

Figure 4: cost shares by sector: OECD, all sectors

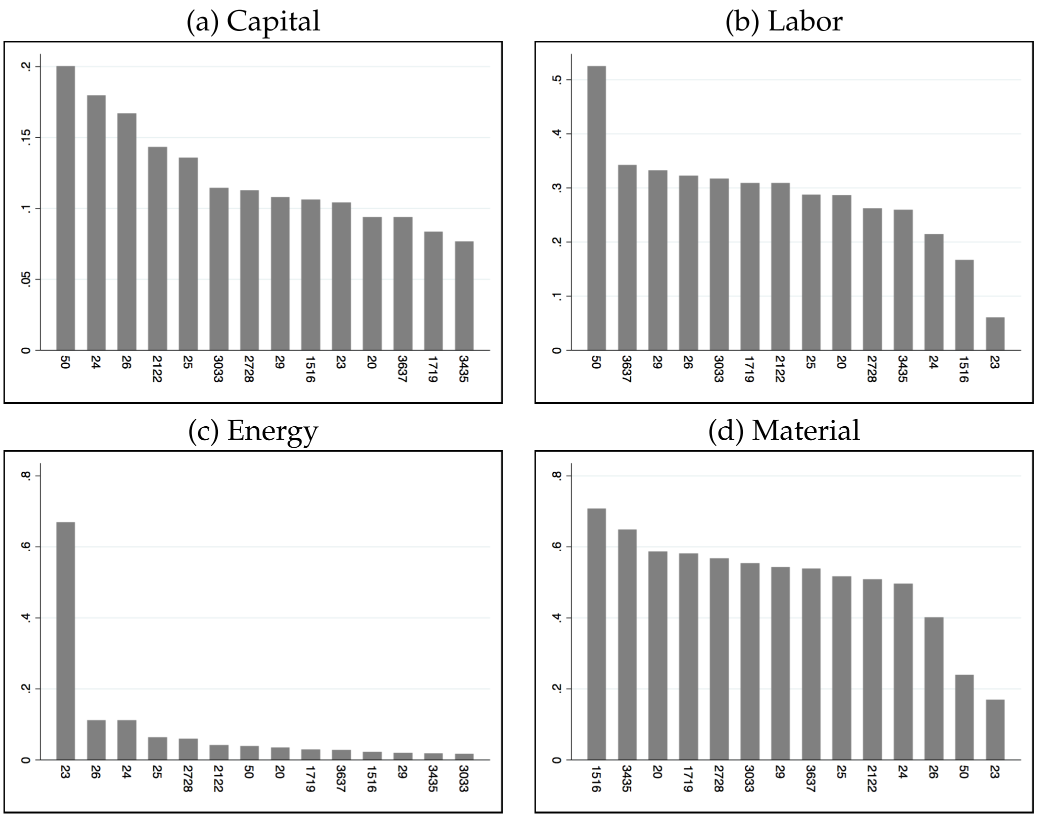
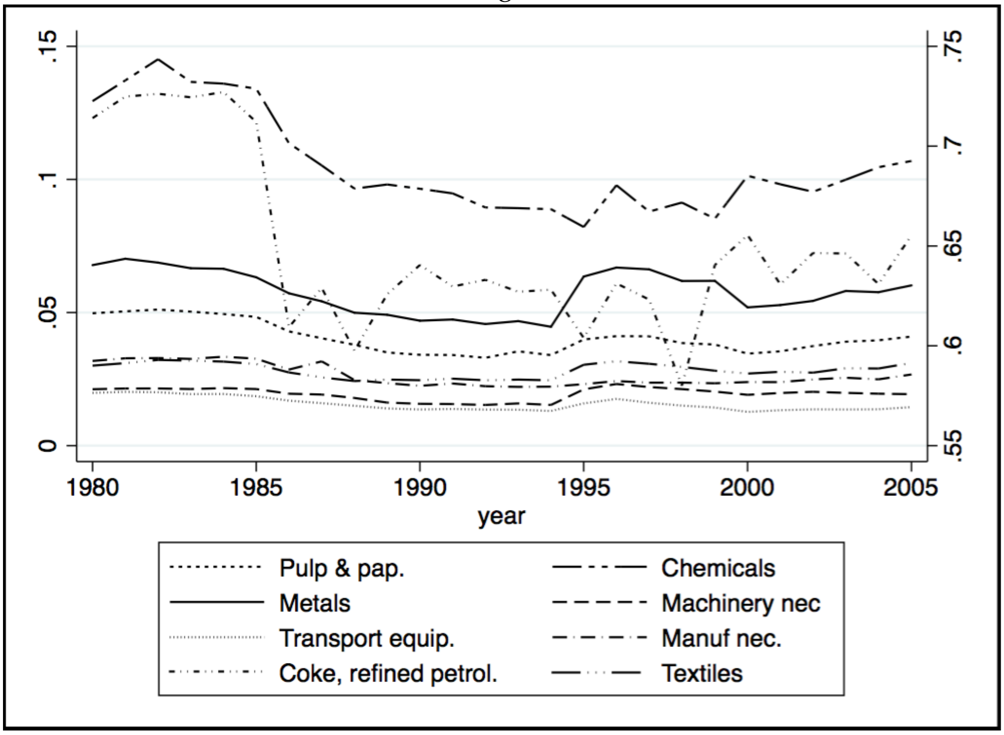


Figure 5: Cost share of energy

OECD average, 1975-2005



4 Econometric Results

In this section, we present our main results. We estimate the system of equations (6) from Section 2 sector-by-sector, and recover parameters and corresponding elasticities w.r.t. technology as defined in Equation (8). We use a one-period lag for knowledge stocks to account for potential reverse causality between green innovation and energy intensity, which simultaneously allows for a time lag between disclosure of patented innovation and effective implementation in industrial sectors. Table 3 shows the estimates of the coefficients for the cost share of energy (β_{EG} and β_{Et}), the corresponding own-price elasticity ($\eta_{E,PE}$), and the elasticity of energy intensity w.r.t. green knowledge stocks ($\epsilon_{E,G}$).[20,21] For a given sector, our sample includes 17 countries followed through 31 years. Because previous literature highlighted important differences across countries (Voigt et al., 2014), all our equations include country fixed effects to account for country-specific unobserved heterogeneity.[22]

As can be seen in Table 3, the coefficients on green knowledge stocks (β_{EG}) are negative in 10 out of 14 sectors. These results are somewhat consistent with the findings of Popp (2001), where a negative elasticity of energy w.r.t. energy-efficient technology is observed for 8 out of 13 industrial sectors, though precise cross-study comparison is limited due to differences in the definition of sectors and aggregation levels. In terms of magnitude, our median estimate for the elasticity of green knowledge stocks ($\epsilon_{E,G}$) is -0.027. In other words, a 1% change in the green knowledge stock decreases the energy intensity by approx. 0.03% in the next period, with a maximum value of 2.07% found for sector 25 (Rubber and plastics), where the decrease in energy intensity throughout our sample period is close to the sample average but with the smallest patent stock in our sample, as highlighted in Figure 2.

Interestingly, industries with the highest average cost share of energy, i.e. with the highest potential economic gains from energy productivity improvements – 23 (Man. of coke, refined

[20] Appendix D shows estimated coefficients for additional regressors. Complete parameter estimates for other factor shares, sector by sector, are provided upon request.

[21] For price variables, elasticities are reported because coefficients as such provide little interpretation (Binswanger, 1974): the coefficient on the price of energy for the cost share of energy ($P_e * E$), for example, mixes a direct effect (the initial increase in price increases the factor share) and a substitution effect (the subsequent decrease in quantity lowers the factor share), having thus an ambiguous effect.

[22] An important aspect to consider is that although excluding control variables for energy subsidies, energy export restrictions, or any exogenous shocks on energy demand, our econometric framework implicitly controls for factors impacting input prices.

petroleum prod. and nuclear fuel), 24 (Chemicals), 25 (Rubber and plastics), 26 (Non-metallic minerals) and 27t28 (Metals) – all present negative and significant impact of green innovation.[23] In contrast, some sectors seem less sensitive to green innovation, despite a large number of patents throughout our sample, as shown previously in Figure 2, namely sectors 17t19 (Textiles, textile products, Leather), 29 (Machinery nec), 30t33 (Office, account.; electric., medic. and precis. engin.) and 34t35 (Transport equipment). This could again be related to the potential gains from energy-saving innovation. Indeed, the cost share of energy in all of these sectors is lower than 2%.[24]

The coefficient associated with the time trend variable is negative and statistically significant in 8 out of 14 industries. This result suggests that autonomous technical change could play a role for the decrease in energy usage in some industries.

Table 3 and Table E1 in Appendix E present the estimates of respectively own- and cross-price elasticities for energy. The negative elasticities of energy consumption w.r.t. the price of energy, and, to a lesser extent, the price of capital, suggest that price induced input substitution also affects energy consumption in most sectors. Furthermore, the estimated values of the own-price elasticities ($\eta_{E,PE}$) presented in Table 3 provide us with a way to verify the properties of our cost functions.[25] In Table 3, one can see that the own-price elasticity of energy is negative for all sectors, confirming that energy usage responds negatively to price changes, as expected. The magnitude of the estimated elasticities are respectively -0.538 and -0.610 for the mean and median values. A 1% change in the price of energy decreases energy demand by 0.610% at the median, close to the range of estimates previously found in the literature.[26]

[23]The average cost share of energy for these sectors amounts respectively 67%, 11%, 6%, 10% and 5%, whereas the average for the rest of the sample is 2.6%.

[24]The positive and significant impact in Nace 29 could be caused by the vague definition of industrial activities. As this sector is defined as a residual of machinery and equipment technologies not elsewhere classified, we expect it to cover a large number of very heterogenous activities. This could affect both the dynamic of energy intensity, as well as its corresponding allocation of patents.

[25]A cost function concave in input price reflects non-zero input substitution. This property of concavity of input demand is not necessarily verified in the case of the translog functional form. Derivation of input price elasticities are also provided in Appendix A.

[26]See for example Berndt and Wood (1975), or Popp (2001), who finds an average of -0.680.

Table 3: Baseline results

Sector	N	β_{EG}	β_{Et}	$\eta^{\mathbf{a}}_{E,PE}$	$\epsilon^{\mathbf{b}}_{E,G}$
Food, beverages and tobacco	405	-0.0016***	0.0002***	-0.765	-0.066
		(0.0005)	(0.0001)		
Textiles, textile products, Leather	388	-0.0002	0.0006	-0.331	-0.006
		(0.0005)	(0.0001)		
Wood and products of wood and cork	393	-0.0095***	0.0010***	-0.656	-0.267
		(0.0027)	(0.0002)		
Pulp, paper and paper prod., print. and publish.	405	-0.0024***	-0.0004***	-0.512	-0.053
		(0.0009)	(0.0001)		
Man. of coke, refined petr. prod. and nucl. fuel	353	-0.0299***	-0.0001	-0.209	-0.044
		(0.0054)	(0.0005)		
Chemicals	405	-0.0064***	-0.0010***	-0.548	-0.056
		(0.0023)	(0.0004)		
Rubber and plastics	403	-0.1394***	0.0008***	-0.472	-2.066
		(0.0402)	(0.0002)		
Non-metallic minerals	405	-0.0029*	-0.0004	-0.452	-0.027
		(0.0016)	(0.0002)		
Metals	405	-0.0023***	-0.0003**	-0.418	-0.040
		(0.0006)	(0.0001)		
Machinery nec	405	0.0006**	-0.0003***	-0.643	0.031
		(0.0003)	(0.0001)		
Office, account.; electric., medic. and precis. engin.	399	0.0000	-0.0001**	-0.610	-0.001
		(0.0003)	(0.0001)		
Transport Equipment	392	0.0002	-0.0004***	-0.845	0.011
		(0.0004)	(0.0001)		
Manufacturing nec; recycling	400	-0.0007	0.0007***	-0.625	-0.027
		(0.0008)	(0.0001)		
Sale, maint. of motor vehic.; retail sale of fuel	388	0.0078	0.0007***	-0.440	0.215
		(0.0197)	(0.0001)		
Median		-0.0016	-0.0001	-0.610	-0.027
Mean		-0.0133	0.0001	-0.538	-0.171
Coeff. < 0		10	8		
Coeff. > 0		4	6		

Notes: [a] Own-price elasticity of energy. [b] Short run elasticity of energy intensity w.r.t. green knowledge stock. Elasticities calculated using mean levels of inputs by sector. All estimations are by sector, based on the spec. with domestic stocks of green Triadic patents, with country FE. Standard errors in parentheses. p***$\leq$ 0.01, p**$\leq$0.05, p*$\leq$0.1.

4.1 Alternative specifications

In this section we present three alternative specifications. First, hinging upon the difference in the trend of energy intensity through time observed in Figure 1, we distinguish between the 1975-1990 and the 1991-2005 period by interacting our variables for technology with an indicator variable for each of the periods. Results are presented in Table 4. As can be seen by the magnitude of the coefficients and their statistical significance, green patented innovation seems to have a stronger effect in more recent years, with a median elasticity of -0.057, than in earlier periods, with a corresponding elasticity of -0.011. We also find a negative, statistically significant impact of green innovation in the same subset of industries as our baseline specification, for both time periods.

Second, we include the stock of patents not identified as green, calculated by subtracting the stock of green patents from the total stock of patents. This affords an indirect mean to control for the robustness of our identification of patents expected to affect energy intensity, as well as to account for potential cyclical trends in the number of general patent applications. Estimates are presented in Table 5. Although multicollinearity could reduce the statistical significance of some estimated coefficients, this does not prevent us to make conclusive arguments on parameters that are found significant. We observe that non-green patents do not decrease energy intensity as consistently as green patents.[27] In terms of magnitude, the median impact of non-green patents is estimated at -0.01, roughly a third of the corresponding statistic for green innovation. Furthermore, estimates for green innovation remain close to our baseline specification: here, the median elasticity of energy intensity w.r.t. green patents amounts -0.030, compared to -0.027 estimated previously.

Finally, we present the result of estimations with patent stocks composed only by the subset of technologies identified as directly related to energy consumption technologies by Popp (2001), in order to control the robustness of our definition of green patents. Results, presented in Table 6, show that our estimates are robust to this alternative specification, with a median elasticity of -0.043, of slightly greater magnitude than in our baseline.

[27] The correlation between the log of the stock of green and non-green patents, as included in our regressions, equals 0.8.

Table 4: 1975-1990 vs. 1991-2005

Sector	N	$\beta_{EG,1}$	$\beta_{EG,2}$	$\beta_{Et,1}$	$\beta_{Et,2}$	$\epsilon^{\mathbf{a}}_{E,G1}$	$\epsilon^{\mathbf{b}}_{E,G2}$
Food, bev. and tob.	405	-0.0004	-0.0014***	0.0001	0.0004***	-0.019	-0.060
		(0.0007)	(0.0004)	(0.0001)	(0.0001)		
Text, text. prod, Leath.	388	0.0024***	0.0013***	-0.0003***	0.0007***	0.079	0.045
		(0.0005)	(0.0004)	(0.0001)	(0.0001)		
Wood and prod. of wood	393	-0.0008	-0.0048**	-0.0003**	0.0008***	-0.022	-0.135
		(0.0037)	(0.0022)	(0.0001)	(0.0002)		
Pulp, pap., print. and publ.	405	-0.0029***	-0.0039***	-0.0002	-0.0002	-0.065	-0.086
		(0.0011)	(0.0008)	(0.0001)	(0.0002)		
Man. of coke & petr.	353	-0.0276***	-0.0372***	-0.0001	0.0019**	-0.041	-0.055
		(0.0051)	(0.0043)	(0.0005)	(0.0007)		
Chemicals	405	-0.0080***	-0.0132***	0.0002	0.0017***	-0.070	-0.115
		(0.0025)	(0.0019)	(0.0003)	(0.0004)		
Rubber and plastics	403	0.0110	-0.1208***	0.0003*	0.0015***	0.162	-1.779
		(0.0463)	(0.0387)	(0.0002)	(0.0003)		
Non-metal. minerals	405	-0.0039**	-0.0085***	-0.0005**	0.0010***	-0.035	-0.076
		(0.0017)	(0.0013)	(0.0002)	(0.0003)		
Metals	405	-0.0024***	-0.0039***	-0.0002*	0.0005***	-0.041	-0.066
		(0.0006)	(0.0005)	(0.0001)	(0.0002)		
Machinery nec	405	0.0003	-0.0003	-0.0001*	0.0000	0.019	-0.017
		(0.0003)	(0.0003)	(0.0001)	(0.0001)		
Office, acc.; elec. eng.	399	-0.0001	-0.0004	-0.0001*	0.0001	-0.004	-0.026
		(0.0004)	(0.0003)	(0.0001)	(0.0001)		
Transport Equipment	392	0.0001	-0.0008**	0.0000	-0.0001	0.004	-0.047
		(0.0005)	(0.0003)	(0.0001)	(0.0001)		
Manuf. nec; recycl.	400	0.0005	0.0007	0.0000	0.0007***	0.021	0.026
		(0.0010)	(0.0007)	(0.0001)	(0.0001)		
Sale & maint. of mot. vehic.	388	0.0213	0.0333*	0.0003**	0.0008***	0.589	0.922
		(0.0222)	(0.0200)	(0.0001)	(0.0002)		
Median		-0.0003	-0.0026	-0.0001	0.0007	-0.011	-0.057

Notes: [a] Short run elasticity of energy intensity w.r.t. green knowledge stock, 1975-1990. [b] Short run elasticity of energy intensity w.r.t. green knowledge stock, 1991-2005. $\beta_{EG,1}/\beta_{t,1}$ and $\beta_{EG,2}/\beta_{t,2}$ correspond to the first (1975-1990) and second (1991-2005) period respectively. Elasticities calculated using mean levels of inputs by sector. All estimations are by sector, based on the spec. with domestic, green stocks of Triadic patents, with country FE. Standard errors in parentheses. p***≤ 0.01, p**≤0.05, p*≤0.1.

Table 5: Green vs. non-green patents

Sector	β_{EG}	β_{ENG}	β_{Et}	$\epsilon^{\mathbf{a}}_{E,G}$	$\epsilon^{\mathbf{b}}_{E,NG}$
Food, bev. and tob.	-0.0014***	-0.0003	0.0002***	-0.061	-0.011
	(0.0005)	(0.0003)	(0.0001)		
Text, text. prod, Leath.	-0.0009	0.0006	0.0006***	-0.030	0.022
	(0.0010)	(0.0008)	(0.0001)		
Wood and prod. of wood	-0.0073**	-0.0015	0.0010***	-0.205	-0.042
	(0.0031)	(0.0012)	(0.0002)		
Pulp, pap., print. and publ.	-0.0036***	0.0014**	-0.0004***	-0.079	0.031
	(0.0011)	(0.0007)	(0.0001)		
Man. of coke & petr.	-0.0139*	-0.0119***	0.0004	-0.020	-0.017
	(0.0079)	(0.0043)	(0.0005)		
Chemicals	-0.0016	-0.0046**	-0.0012***	-0.014	-0.041
	(0.0031)	(0.0020)	(0.0004)		
Rubber and plastics	-0.2638***	0.0068***	0.0004**	-3.937	0.101
	(0.0443)	(0.0012)	(0.0002)		
Non-metal. minerals	0.0014	-0.0039***	-0.0004*	0.013	-0.036
	(0.0024)	(0.0015)	(0.0002)		
Metals	-0.0017	-0.0006	-0.0003**	-0.029	-0.010
	(0.0018)	(0.0016)	(0.0001)		
Machinery nec	-0.0002	0.0007	-0.0002***	-0.010	0.040
	(0.0007)	(0.0006)	(0.0001)		
Office, acc.; elec. eng.	-0.0006	0.0006	-0.0001**	-0.039	0.037
	(0.0006)	(0.0005)	(0.0001)		
Transport Equipment	-0.0011*	0.0014***	-0.0004***	-0.065	0.080
	(0.0006)	(0.0005)	(0.0001)		
Manuf. nec; recycl.	-0.0002	-0.0006	0.0007***	-0.006	-0.024
	(0.0010)	(0.0008)	(0.0001)		
Sale & maint. of mot. vehic.	0.0415*	-0.0039**	0.0008***	1.145	-0.107
	(0.0240)	(0.0016)	(0.0001)		
Median	-0.0013	-0.0004	0.0000	-0.030	-0.010

Notes: [a] Short run elasticity of energy intensity w.r.t. green knowledge stock. [b] Short run elasticity of energy intensity w.r.t. non-green knowledge stock. β_{EG} and β_{ENG} correspond to green and non-green technologies respectively. Elasticities calculated using mean levels of inputs by sector. All estimations are by sector, based on the spec. with domestic, green stocks of granted patents, with country FE. Standard errors in parentheses. p***$\leq$ 0.01, p**$\leq$0.05, p*$\leq$0.1.

Table 6: Robustness check: alternative patent counts

		Missing[a] (1)		Triadic[b] (2)	
		β_{EG}	$\epsilon_{E,G}$	β_{EG}	$\epsilon_{E,G}$
Food, beverages and tobacco	428	-0.0016*	-0.069	-0.0015***	-0.062
		(0.0009)		(0.0005)	
Textiles, textile products, Leather	410	-0.0031***	-0.104	-0.0009*	-0.030
		(0.0005)		(0.0005)	
Wood and products of wood and cork	411	-0.0019	-0.055	-0.0094***	-0.268
		(0.0016)		(0.0025)	
Pulp, paper and paper prod., print. and publ.	428	0.0005	0.011	-0.0016*	-0.036
		(0.0010)		(0.0009)	
Man. of coke, ref. petr. prod. and nucl. fuel	371	-0.0285***	-0.042	-0.0307***	-0.045
		(0.0044)		(0.0046)	
Chemicals	428	-0.0080***	-0.071	-0.0060***	-0.053
		(0.0022)		(0.0020)	
Rubber and plastics	426	-0.0322**	-0.492	-0.1713***	-2.618
		(0.0137)		(0.0391)	
Non-metallic minerals	428	-0.0047***	-0.044	-0.0039***	-0.036
		(0.0014)		(0.0015)	
Metals	428	-0.0027***	-0.046	-0.0018***	-0.030
		(0.0005)		(0.0005)	
Machinery nec	428	-0.0009***	-0.050	0.0009	0.055
		(0.0003)		(0.0002)	
Office, account.; electric., medic. and prec. eng.	422	-0.0004	-0.024	0.0002	0.011
		(0.0003)		(0.0003)	
Transport Equipment	411	0.0017***	0.103	0.0007**	0.040
		(0.0004)		(0.0003)	
Manufacturing nec; recycling	423	-0.0012*	-0.048	-0.0006	-0.025
		(0.0007)		(0.0007)	
Sale, maint. of motor vehic.; retail sale of fuel	411	-0.0069**	-0.189	0.0010	0.027
		(0.0031)		(0.0191)	
Mean		-0.0064	-0.0800	-0.0161	-0.2194
Median		-0.0023	-0.0490	-0.0015	-0.0330
Coeff. < 0		12		10	
Coeff. > 0		2		4	

Notes: [a] Missing countries in this spec. are removed from sample. [b] Uses counts of Triadic Patent Families. Estimates by sector, based on the spec. with domestic, green stocks of granted patents, with country FE. Standard errors in parentheses. p***≤ 0.01, p**≤0.05, p*≤0.1.

5 Conclusion

This paper aimed to quantify the impact of green innovation on energy intensity of industries using patent statistics in a multi-sector, multi-country setting. By matching sector-specific green knowledge stocks based on Triadic Patent Families with input cost functions using EU-KLEMS data, we have found green innovation to be energy-saving in a majority of industries, with a median elasticity of -0.03. In other words, Hence, a 1% increase in green patenting activities in a given sector is associated with a 0.03% decline in energy intensity. We find a statistically significant impact in all energy intensive industries. Over the years 1991-2005, the impact of green innovation also appears to be stronger than in the earlier period. In addition, we find that non-green patenting activities are found to have an effect of smaller magnitude – roughly a third – than green patenting ones. In parallel, our estimates for own- and cross-price elasticities suggest a role for price induced input substitution for the observed decrease in energy intensity. Our findings are robust to a more restrictive set of patents.

The main purpose of our results is to inform policymakers about the magnitude of the impact of green innovation on energy intensity across industrial sectors, thereby contributing to the empirical body of evidence in favour of policies supporting green R&D. However, our empirical estimates of the impact of technological change on energy intensity could also serve as an input for forecasting energy consumption and carbon emissions in CGE models. Our findings could thus contribute to reduce the existing gap between the empirical and the modeling sub-stream of the literature on technological change and the environment (Pizer and Popp, 2008; Fisher-Vanden et al., 2014).

We close by suggesting several extensions for future work. First, future contributions could include more factors potentially affecting energy consumption, such as energy policies for example. Although these are implicitly captured by the price variables in our estimated equations, inasmuch as they influence input demand, incorporating explicitly variables measuring energy policies could help identifying the role of policymaking more clearly. Second, our measure of elasticity captures the direct impact of green patents. Long term elasticities are likely to be of greater magnitude as effects accumulate through time. A more complete analysis of these long term effects remains an important research question, but would require to measure adequately spillover effects, both across industries and time, for example in a general equilibrium setting.

Appendix A Parameter Derivation

Appendix A.1 Elasticities of energy intensity w.r.t. technology

$$\begin{aligned}\epsilon_{E,G} &= \frac{\partial ln(E/Y)}{\partial lnG} = \frac{\partial(E/Y)}{\partial lnG}\frac{Y}{E} = \frac{\partial((P_Y/P_E)s_E)}{\partial lnG}\frac{Y}{E} \\ &= \frac{\partial s_E}{\partial lnG}\frac{Y}{E}\frac{P_Y}{P_E} = \beta_{EG}\frac{P_Y Y}{P_E E} = \beta_{EG}\frac{1}{s_E} = \frac{\beta_{EG}}{s_E}\end{aligned}$$

Appendix A.2 Standard error of elasticities

$$V(\eta_{ij}) = V\left(\frac{\beta_{ij}}{S_i} + S_j\right) = \frac{1}{S_i^2}V(\beta_{ij})$$

$$SE(\eta_{ij}) = \sqrt{V(\eta_{ij})} = \frac{1}{S_i}SE(\beta_{ij})$$

$$SE(\eta_{ii}) = \sqrt{V(\eta_{ii})} = \frac{1}{S_i}SE(\beta_{ii})$$

$$V(MES_{ii}) = V(\eta_{ij}) + V(\eta_{jj}) - 2cov(\eta_{ij}, \eta_{jj})$$

Following Koetse et al. (2008), we approximate the covariance term by $rx\sqrt{V(\beta_{ij})}x\sqrt{V(\beta_{jj})}$ and assume that $r = 0$, i.e. that there is no systematic bias in the estimation of the covariance. We obtain:

$$SE(MES_{ii}) = \sqrt{\frac{1}{S_i^2}V(\beta_{ij}) + \frac{1}{S_j^2}V(\beta_{jj})} = \frac{1}{S_i}SE(\beta_{ij}) + \frac{1}{S_j}SE(\beta_{jj})$$

Appendix B Sample Statistics

Table B1: Descriptive statistics of the dataset

Variable	Code	Units	Obs	Mean	Std. Dev.	Min	Max
Green patent stocks							
Year			12'409	1987.7	10.4	1970	2005
Pat Stock (H)	PATSTAT	Patent number	8'532	164.1	911.9	0.00	15'131
Pat Stock (F)	PATSTAT	Patent number	8'532	100.4	411.52	0.00	7'397
Pat Stock (H)	Triadic	Patent number	8'532	18.8	90.35	0.00	1'339
Value of output and input compensation							
Y	GO	cst. mil. LCU	8'490	2'142'898	9'649'104	0.00	$1.92*10^8$
K	CAPNIT	cst. mil. LCU	8'490	267'804	1'250'149	0.00	$2.80*10^7$
L	LAB	cst. mil. LCU	8'490	364'597	1'518'297	0.00	$2.46*10^7$
E	IIE	cst. mil. LCU	6'922	167'778	1'146'254	0.00	$3.00*10^7$
M	IIM	cst. mil. LCU	6'922	1'348'215	5'869'449	0.00	$1.07*10^8$
Input quantity indexes							
Y_QI	GO_QI	Index	8'490	.895	.363	0.006	5.09
K_QI	CAPNIT_QI	Index	8'028	.889	.846	0.003	48.99
L_QI	LAB_QI	Index	6'748	1.050	.311	0.054	4.77
E_QI	IIE_QI	Index	6'341	.999	.468	0.008	63.54
M_QI	IIM_QI	Index	6'341	.926	.412	0.006	9.12
Price indexes							
py		Index	8'608	.797	.359	0.026	4.435
pk		Index	8'104	1.049	184.06	0.00	36.24
pl		Index	6'888	.832	60.35	0.03	5.537
pe		Index	6'484	.993	101.87	0.12	27.88
pm		Index	8'952	.935	2.404	0.07	97.32
Total costs and cost shares							
TC		cst. mil. LCU	9'635	2'290'811	9'293'264	0.0000	$1.6*10^8$
sk		Percentage	6'911	0.121	0.065	0.0000	0.589
sl		Percentage	6'911	0.286	0.123	0.0080	0.788
se		Percentage	6'911	0.087	0.180	0.0002	0.973
sm		Percentage	6'911	0.505	0.164	0.0002	0.858

Notes: Input compensation and Value of output are in constant mill. local currency. Quantities are indexes (1995 = 1). Price are calc. from normalized input compensation and indexes of quantities (1995 = 1). Cost shares are calculated from Total Costs (TC), calc. as the sum of all input compensation

Appendix C Additional Parameter Estimates

Table C1: Coefficient on price indexes and output level, cost share of energy

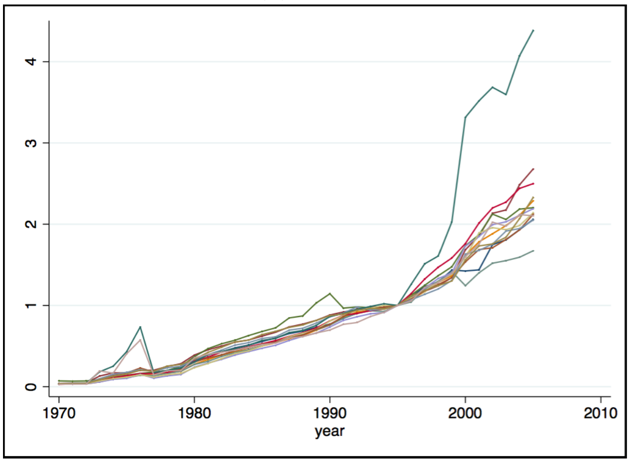
Sector	β_{EE}	β_{EK}	β_{EL}	β_{EY}
Food, beverages and tobacco	0.0061***	-0.0031***	-0.0029***	0.0001
	(0.0008)	(0.0008)	(0.0008)	(0.0007)
Textiles, textile products,leather	0.0173***	-0.0004	-0.0169***	0.0011
	(0.0014)	(0.0007)	(0.0013)	(0.0010)
Wood and products of wood and cork	0.0098***	-0.0042***	-0.0056***	0.0036**
	(0.0021)	(0.0009)	(0.0020)	(0.0018)
Pulp, paper and paper prod., print. and publish.	0.0199***	-0.0115***	-0.0084***	0.0032**
	(0.0018)	(0.0014)	(0.0020)	(0.0014)
Man. of coke, refined petrol. prod. and nucl. fuel	0.0651***	-0.0433***	-0.0218***	0.0531***
	(0.0035)	(0.0027)	(0.0020)	(0.0049)
Chemicals	0.0389***	-0.0244***	-0.0146***	0.0217***
	(0.0028)	(0.0019)	(0.0019)	(0.0038)
Rubber and plastics	0.0368***	-0.0146***	-0.0221***	0.0012
	(0.0033)	(0.0017)	(0.0032)	(0.0025)
Non-metallic minerals	0.0477***	-0.0266***	-0.0211***	0.0110***
	(0.0026)	(0.0021)	(0.0023)	(0.0025)
Metals	0.0314***	-0.0107***	-0.0207***	0.0083***
	(0.0018)	(0.0011)	(0.0018)	(0.0013)
Machinery nec.	0.0059***	-0.0015***	-0.0044***	0.0038***
	(0.0009)	(0.0006)	(0.0010)	(0.0006)
Office, account.; electric., medic. and precis. engin.	0.0056***	-0.0038***	-0.0018**	0.0014**
	(0.0007)	(0.0005)	(0.0007)	(0.0006)
Transport equipment	0.0030***	-0.0025***	-0.0005	0.0023***
	(0.0005)	(0.0003)	(0.0006)	(0.0007)
Manufacturing nec; recycling	0.0092***	0.0014*	-0.0106***	-0.0055***
	(0.0013)	(0.0008)	(0.0013)	(0.0013)
Sale, maint. of motor vehic.; retail sale of fuel	0.0170***	-0.0055***	-0.0115***	-0.0092
	(0.0016)	(0.0009)	(0.0016)	(0.0015)
Mean	0.0224	-0.0108	-0.0116	0.0069
Median	0.0171	-0.0049	-0.0110	0.0027

Notes: Estimates by sector, based on the spec. with domestic, green stocks of granted patents, with country FE. Sectors 51, 52, 60t63, 64, 70, 71t74 missing because of zero green capital stock (see conc. table for details). Standard errors in parentheses. p***$\leq$ 0.01, p**$\leq$0.05, p*$\leq$0.1.

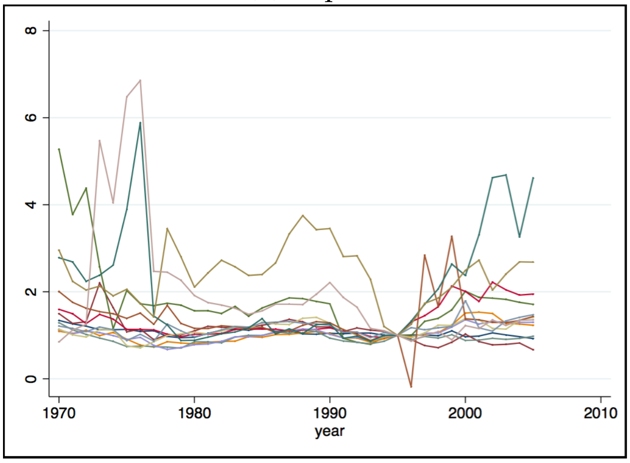
Appendix D Additional Figures

Figure D1: Input price indexes

(a) Labor



(b) Capital



Appendix E Elasticities of Substitution

We first derive Allen partial elasticities of substitution (σ_{ii} and σ_{ij}) from the coefficients estimated in equation (6):

$$\sigma_{ij} = \sigma_{ji} = 1 + \frac{\beta_{ij}}{s_i s_j}, \quad i \neq j \tag{E1}$$

$$\sigma_{ii} = \frac{\beta_{ii} + s_i^2 - s_i}{s_i^2} \tag{E2}$$

Since AES cannot be easily interpreted in the case of more than two inputs (Blackorby and Russell, 1989; Thompson and Taylor, 1995), we calculate cross- and own-price elasticities from the estimated AES, following (Berndt, 1991):[28]

$$\eta_{ij} = \sigma_{ij} s_j = \frac{\beta_{ij} + s_i s_j}{s_i} = \frac{\beta_{ij}}{s_i} + s_j, \quad i \neq j \tag{E3}$$

$$\eta_{ii} = \sigma_{ii} s_i = \frac{\beta_{ii} + s_i^2 - s_i}{s_i} = \frac{\beta_{ii}}{s_i} + s_i - 1 \tag{E4}$$

The cross-price elasticity measures the change in the quantity of input x_i caused by a change of the price of input j (for instance, in the case of energy and labor, $\eta_{E,PL} = \frac{\partial lnE_i}{\partial lnp_L}$ where E is energy demand) and thus has a direct economic interpretation. Substitutability/complementarity between inputs can be interpreted as follows. Based on cross-price elasticities, input i is a substitute (complement) for input j if $\eta_{ij} > (<)$ 0. Standard errors for the estimated parameters have been reconstructed following Binswanger (1974) or Koetse et al. (2008) by using the Delta method (Greene, 2000).[29]

In Table E1, we detail our estimates of the elasticity of energy demand w.r.t. to changes in the price of other inputs. Substitution elasticities found in the (extensive) literature can vary both in signs and in magnitude, depending on methodological choices on the number of inputs considered as well as the input used as numeraire (Koetse et al., 2008): there seems to be no clear consensus on complementarity/substitutability. Estimates of our cross-price elasticities show that energy demand decreases in response to an increase in the price index of capital in 9/14 sectors,

[28]The computation of the variance of each elasticity can be found in Appendix A.
[29]Derivation can be found in the Appendix A.

Table E1: Cross Price elasticities of substitution (η_{Ej})

	Energy	Capital	Labor
Food, beverages and tobacco	-0.716	-0.004	0.072
	(0.035)	(0.033)	(0.036)
Textiles, textile products, leather	-0.380	0.087	-0.248
	(0.047)	(0.023)	(0.045)
Wood and products of wood and cork	-0.686	-0.009	0.142
	(0.059)	(0.025)	(0.058)
Pulp, paper and paper prod., print. and publish.	-0.511	-0.108	0.145
	(0.040)	(0.031)	(0.044)
Man. of coke, refined petrol. prod. and nucl. fuel	-0.229	0.065	0.024
	(0.005)	(0.004)	(0.003)
Chemicals	-0.541	-0.023	0.092
	(0.025)	(0.017)	(0.017)
Rubber and plastics	-0.372	-0.079	-0.033
	(0.051)	(0.027)	(0.050)
Non-metallic minerals	-0.451	-0.072	0.140
	(0.024)	(0.019)	(0.021)
Metals	-0.402	-0.064	-0.069
	(0.031)	(0.018)	(0.031)
Machinery nec	-0.656	0.038	0.104
	(0.048)	(0.031)	(0.057)
Office, account.; electric., medic. and precis. engin.	-0.627	-0.106	0.222
	(0.045)	(0.032)	(0.047)
Transport equipment	-0.805	-0.055	0.238
	(0.031)	(0.020)	(0.036)
Manufacturing nec; recycling	-0.617	0.166	-0.052
	(0.050)	(0.031)	(0.051)
Sale, maint. of motor vehic.; retail sale of fuel	-0.502	0.053	0.216
	(0.042)	(0.024)	(0.045)
Mean	-0.535	-0.008	0.071

Notes: Elasticities are calculated at the mean of each cost share

and only 4/14 in the case of labor. This suggests that, on average, energy and capital are gross economic complements, while energy and labor are gross substitutes. Moreover, Table E1 shows that energy demand is more sensitive to changes in its own price than in the price of other inputs, and that the average response of energy demand to the price of labor is greater in magnitude than to the price of capital, probably because the cost share of labor exceeds the cost share of capital.

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