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In this article, I empirically analyze and compare the impact of innovation in green and non-green energy technologies on the economic performance of firms. My analysis is conducted on a panel of 8,619 patenting firms including 968 green energy patenters from 22 European countries over the period 2003 to 2010. I measure economic firm performance in terms of productivity and use a panel data model based on an extended Cobb-Douglas production function. My results show that green energy innovation has a statistically significant negative impact on economic firm performance. In contrast, non-green energy innovation is shown to have a statistically significant positive impact on economic firm performance. These findings suggest that private economic returns in terms of productivity are lower for green energy than for non-green energy innovation.

Key words: green energy technologies, innovation, performance, patents, technological change

JEL codes: C33, L25, O31, Q40, Q55

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1 Introduction

Recent empirical economic literature has focused to a great extent on the determinants and inducement mechanisms of innovation in green energy (GE) (or environmental, or eco-) technologies. A large number of contributions provides a robust understanding of factors determining and policies inducing GE innovation (see, for example, Jaffe and Palmer, 1997; Popp, 2002; Johnstone et al., 2010; Verdolini and Galeotti, 2011). However, little attention has been devoted to the economic effects of GE innovation, especially to the relationship between innovating in GE technologies and the economic performance of the innovating firms. Understanding this relationship helps to answer the widely debated question whether firms gain (forgo) economic opportunities by innovating (not innovating) in GE technologies.

This article empirically investigates the impact of innovation in GE technologies on the economic performance of firms. In addition, the impact of GE innovation is compared to the one of non-GE innovation. I analyze a panel of 8,619 patenting firms from 22 European countries over a period of 8 years from 2003 to 2010. Economic firm performance is measured in terms of productivity. Using productivity as performance indicator has several advantages. First, results from production function approaches are easily interpretable and comparable to other studies (Bloom and Van Reenen, 2002). Second, firm performance is mainly driven by productivity trends which are closely linked to innovation dynamics (Cainelli et al., 2011). Furthermore, compared to data on market valuation, data on productivity is available for a large number of firms including medium- and small-sized ones. I specify a panel data model based on an extended Cobb-Douglas production function in which productivity is a function of capital, labor, and innovation output. Firm accounts data is taken from the AMADEUS database provided by Bureau van Dijk (BvD). Innovation at the firm level is measured using patent data from the Organisation for Economic Co-operation and Development (OECD) REGPAT database.

My work is related to two strands of empirical literature on innovation and economic firm performance. The link between innovation and economic performance at the firm level has been analyzed in a large number of empirical economic articles (see, for example, Scherer, 1965; Comanor and Scherer, 1969; Griliches, 1981; Griliches et al., 1991; Blundell et al., 1999; Ernst, 2001; Bloom and Van Reenen, 2002; Lanjouw and Schankerman, 2004; Hall et al., 2005). The majority of these investigations identifies a positive relationship between innovative output and economic performance. However, since these studies focus on general innovation, the results cannot be simply transferred to GE innovation. There are fewer articles exploring the relationship between GE (or environmental or eco) innovation and economic firm performance. Ayari et al. (2012) investigate the impact of renewable energy innovation (patents) on firm performance (return on assets, stock market return) using a panel of 154 firms from 14 European countries (1987-2007). They find evidence that renewable energy innovation has a significant positive impact on both measures of firm performance. Marin (2014) analyzes the effect of environmental and non-environmental innovation (patents) on firm performance (value added) for a panel of 5,905 Italian firms (2000-2007). He shows that environmental innovation in most cases has no significant effect on firm performance, while non-environmental innovation has a positive effect. In a very similar study Marin and Lotti (2016) analyze the same relationship using a larger and longer panel of 11,938 Italian firms (1996-2006). They find positive impacts of both environmental and non-environmental patenting, while observing a substantially lower return for environmental ones. Wörter et al. (2015) examine the link between environmental innovation (patents) and performance (value added) on the industry-level. Their analysis is conducted on a panel of 22 manufacturing industries from 12 OECD countries (1980-2009). In contrast to Ayari et al. (2012) and Marin and Lotti (2016), they find that green innovation is negatively related to performance for most industries. Overall, the empirical evidence concentrating on GE innovation can thus be described as ambiguous.

This study contributes to the existing literature in three respects. First, I provide new evidence on the unsolved question how innovation in GE technologies impacts firms' economic performance. Second, the impact of GE and non-GE innovation on performance is compared. Moreover, as robustness check I distinguish two subgroups of GE technologies: (a) Renewable Energy Sources (RES) and (b) Energy Efficiency (EE) technologies. Third, I base my analysis on a comparatively large panel of 8,619 European patenting firms including 968 GE patenters from 22 countries over an estimation period of 8 years (2003-2010) and a patent count period of 32 years (1977-2010).

The remainder of the article is structured as follows. Section 2 outlines the theoretical background my analysis is based on. Section 3 presents and discusses the data. Section 4 describes the empirical strategy employed. Section 5 discusses the results of the econometric estimations and of the robustness tests. Finally, Section 6 summarizes the main findings and concludes.

2 Theoretical Background

Innovative activity in market economies to large parts exists because private profit-maximizing firms allocate resources to the research and development (R&D) of new products and processes, for which they see innovation opportunities and market success and consequently expect a positive impact on future economic performance, that is positive private returns (Dosi, 1988). The resulting innovation output of private firms is widely believed to be an important source of economic wealth and growth in economies (see, for example, Romer, 1986, 1990). In addition, innovation in the subgroup of GE technologies is acknowledged to be a crucial factor for handling climate change while maintaining reasonable economic growth (so called green growth) (see, for example, Jaffe et al., 2002; Popp et al., 2010; Acemoglu et al., 2012).

Private profit-maximizing firms decide about R&D investments solely on the basis of private returns. Therefore, a firm deciding about two R&D investment projects, one a GE option and one a non-GE option, would always choose the option with the higher private return, even though the GE option might have higher social returns (the sum of both private and non-private returns). Higher social returns for a GE compared to a non-GE option can result from higher non-private economic returns due to positive innovation spillovers and the internalization of negative environmental externalities (Dechezleprêtre et al., 2014). As a consequence, private R&D investments in GE technologies depend on the private return of these investments compared to the private return of non-GE investments.

In economic theory, arguments can be found in favor and against higher private returns of GE compared to non-GE innovation. Higher returns may be expected because: (a) GE technologies are newer and less explored than other technology fields. Therefore, research in GE technologies builds on a lower knowledge stock than research in more mature technologies. This could imply greater development perspectives and opportunities for high marginal private returns (Popp and Newell, 2012). (b) GE technologies bear the potential of having an impact on many sectors and becoming general purpose technologies. General purpose technologies are expected to generate large economic gains (Helpman, 1998). (c) Markets are increasingly shaped by strict environmental regulations. This induces a larger demand for GE technologies and hence increases the probability of higher private returns from GE innovation (Colombelli et al., 2015).

Contrariwise, lower returns could arise because: (a) GE technologies aim at internalizing negative environmental externalities resulting from energy production and use. As far as policies have not completely internalized these externalities, the benefits from GE compared to non-GE innovation are public rather than private. Accordingly, the willingness to pay and, in turn, the demand for GE technologies will be low. Consequently, the demand will be highly dependent on political developments which are unstable and can change unexpectedly. These circumstances lead to uncertain private returns from GE innovation (Beise and Rennings, 2005). (b) GE technologies often are new to a firm and lie outside their traditional technological scope. In addition, adjustments of business processes, working routines, employment, and organizational structures may be necessary. This could lead to large adjustment costs (Noci and Verganti, 1999). (c) Financial markets are usually imperfect with regard to technological innovation. These market imperfections are even more pronounced for GE innovation due to the higher technical risk and uncertainty about market developments. This may imply high costs of capital (Wörter et al., 2015).

Thus, I derive two rival hypotheses: H1: Private economic returns measured in terms of productivity are higher for GE than for non-GE innovation, and H2: Private economic returns measured in terms of productivity are lower for GE than for non-GE innovation. This work aims to find out which of these hypotheses is right.

3 Data

3.1 Data Sources

To analyze the impact of GE innovation on the economic performance of firms, I combine two different databases and construct a unique firm-level data set that matches patent applicants at the European Patent Office (EPO) to firm accounts.

The first performance-related database is BvD's AMADEUS which contains annual financial data taken from the registries of approximately 19 million firms from 44 Western and Eastern European countries (Bureau van Dijk, 2015). It covers all sectors with exception of the financial one and contains up to ten recent years of information per firm. The database includes firm-level financial information in a standardized format for 26 balance sheet items, 26 profit and loss items and 26 financial ratios.[1] First, I use information on sales as a measure of economic performance respectively productivity. Second, I collect information on the number of employees as a measure of labor input and information on total assets as a measure of capital input. A GDP deflator from the World Bank's World Development Indicators (The World Bank, 2015) is used to

[1] The coverage of the items varies across countries and time.

deflate all nominal values. To avoid double-counting firms and subsidiaries, I consider only firms that report unconsolidated statements.

In order to measure innovation activities at the firm level, I extend the financial data with patent data from the OECD REGPAT database (OECD, 2015).[2] The REGPAT database covers patent applications filed at the EPO from 1977 to 2011, derived from the EPO's Worldwide Patent Statistical Database (PATSTAT, Autumn 2014). To avoid a truncation downward bias towards the end of the sample period, I consider only patents filed until 2010. Using EPO patent applications ensures that applications for low-value inventions are excluded from the analysis. Application costs for multinational EPO patent applications are generally higher than for applications filed at national institutions. Accordingly, patent applications filed at the EPO often constitute innovations of high value that are expected to be commercially profitable and thus justify the relatively high application fees (Johnstone et al., 2010).

The financial data is combined with the EPO patent information using the OECD Harmonised Applicants' Names (HAN) database (OECD, 2014). This database provides a grouping of patent applicants' names constructed by harmonising names and matching them against company names from business register data. The business register data stems from the ORBIS database from BvD. Since AMADEUS is a component of the ORBIS database, the HAN database allows me to match EPO patent information to AMADEUS company names. The intersection of the AMADEUS and REGPAT databases then results in a panel of 11,001 firms from 27 countries[3] over a period of 34 years (1977 to 2010) who applied for at least one patent at the EPO during this period.

I count GE and non-GE (all patents except GE ones) patent applications filed by these firms at the EPO over the period 1977 to 2010.[4] I date the patents based on their priority date which refers to the first filing date of the invention worldwide since this date is strongly related to R&D activities and closest to the date of invention as well as to the decision to apply for a patent (Griliches, 1990; OECD, 2009). The GE patents are

[2] The advantages and disadvantages of using patents as a measure of innovation have been discussed at length in the literature. See, for example, Griliches (1990), Dernis et al. (2002), and OECD (2009).

[3] The countries are (sorted by country code): Austria (AT), Belgium (BE), Switzerland (CH), Czech Republic (CZ), Germany (DE), Denmark (DK), Estonia (EE), Spain (ES), Finland (FI), France (FR), United Kingdom (GB), Greece (GR), Hungary (HU), Ireland (IE), Iceland (IS), Italy (IT), Liechtenstein (LI), Luxembourg (LU), Latvia (LV), Netherlands (NL), Norway (NO), Poland (PL), Portugal (PT), Romania (RO), Russian Federation (RU), Sweden (SE), and Slovenia (SI).

[4] If a single patent is filed by multiple firms, I count it fractionally. That is, if a patent is filed by more than one firm, the patent count is divided by the number of firms and each firm receives equal shares of the patent. This avoids giving a higher weight to a patent filed by multiple firms compared to one filed by just one firm.

identified by using International Patent Classification (IPC) codes from the "IPC Green Inventory" (WIPO, 2015*a*,*b*). The inventory provides IPC codes for patents relating to so-called Environmentally Sound Technologies. Combining these codes with the energy technology structure developed at the IEA (IEA, 2011), I count GE patents from two groups: RES and EE. The RES group contains five RES technologies: solar energy, wind energy, geothermal energy, ocean energy, and fuel cells. The EE group contains three EE technologies: energy efficiency in residential and commercial buildings, appliances and equipment, energy efficiency in transport, and other energy efficiency[5]. Table 1 provides an overview on the considered technologies.

Table 1: Green energy technologies.

Renewable energy sources technologies
Wind energy
Solar energy
Geothermal energy
Ocean energy
Fuel cells
Energy efficiency technologies
Energy efficiency in residential and commercial buildings, appliances and equipment
Energy efficiency in transport
Other energy efficiency

To investigate the effect of firms' GE and non-GE knowledge, I construct a GE knowledge stock (GKS) and a non-GE knowledge stock (NKS) for firm i at time t using the perpetual inventory method following Cockburn and Griliches (1988) and Peri (2005):

$$GKS_{it} = GPAT_{it} + (1 - \delta)\, GKS_{it-1} \quad and \tag{1}$$

$$NKS_{it} = NPAT_{it} + (1 - \delta)\, NKS_{it-1}, \tag{2}$$

where $GPAT_{it}$ (respectively $NPAT_{it}$) is the number of GE (respectively non-GE) patent applications and δ is a depreciation rate accounting for the fact that knowledge becomes

[5] Following the IEA energy technology structure, the other energy efficiency group includes waste heat recovery and utilization, heat pumps, and measurement of electricity consumption.

obsolete as time goes by. The depreciation rate is set to 10% as is often assumed in the literature (see, for example, Verdolini and Galeotti, 2011).[6] [7]

The availability of the AMADEUS financial firm information is limited. The first available year is 2003. Since I count patents filed until 2010, I use AMADEUS data from 2003 to 2010. For approximately 22% of the matched firms I have no information on sales, employment, and/or total assets. For the remaining firms, there are missing values for some years. Because of these missings, the number of firms and years and, by this, the number of observations that can be used for the econometric estimations is lower than in the base sample with 11,002 firms and 34 years. The resulting estimation data set is an unbalanced panel of 8,619 firms from 22 countries[8] over a period of 8 years (2003 to 2010), who have filed at least one EPO patent between 1977 and 2010. In total, these 8,619 firms filed 3,021 GE patents and 100,835 non-GE patents at the EPO between 1977 and 2010. The GE patents were filed by a subset of 968 firms from 17 countries[9] since not every firm in the full sample applied for a GE patent. The non-GE patents were filed by a subset of 8,345 firms from 22 countries which shows that almost every firm in the full sample filed a non-GE patent.

Table 2 reports summary statistics for the full sample of 8,619 patenting firms. The mean values of sales and total assets suggest the presence of some major firms as the means lie well above the threshold for the AMADEUS classification of a very large firm. The knowledge stock values demonstrate the difference in patent counts between GE and non-GE technologies, reflecting that just about 11% of the sampled firms are GE patenters. The standard deviations of the knowledge stock of GE and non-GE technologies have a similar level of about 10% of the mean value. The last row shows that I have on average almost 6 years of data for each firm.

Table 3 reports correlations between the variables sales, employees, and total assets as well as GKS and NKS. The highest correlation persists between GKS and NKS (0.552). This shows that the development of GKS is positively related to those of the significantly larger group of NKS. The two knowledge stocks are all only weakly correlated to the measure of firms' performance, labor, and capital input. As expected, there is also a

[6] The initial knowledge stock GKS_{it_0} (respectively NKS_{it_0}) is given by $GKS_{it_0} = GKS_{it_0}/(g+\delta)$ (respectively $NKS_{it_0} = NKS_{it_0}/(g+\delta)$) where $GPAT_{ijt_0}$ (respectively $NPAT_{ijt_0}$) is the number of patent applications in 1977, the first year observed. The growth rate g is the pre-1977 growth in patent stock, assumed to be 15%, and δ again represents depreciation of 10%.

[7] I test the robustness of the regression results against the utilization of different depreciation rates in the calculation of the knowledge stocks in Section 5.2, Table 10.

[8] The countries are AT, BE, CH, CZ, DE, DK, EE, ES, FI, FR, GB, GR, HU, IT, LI, LU, LV, NL, NO, PL, SE, and SI.

[9] The countries are AT, BE, CH, CZ, DE, DK, ES, FI, FR, GB, IT, LU, LV, NL, NO, PL, and SE.

Table 2: Summary statistics.

	Mean	Std. dev.	Min.	Max.
Sales (million EUR)	186.83	2526.82	0.00	323387
Employees (100s)	3.56	38.85	0.01	2888
Total assets (million EUR)	335.96	4091.64	0.00	310898
GE knowledge stock	0.15	1.35	0.00	108
Non-GE knowledge stock	6.11	63.92	0.00	3627
Observations per firm	5.70	1.93	1.00	8

Note: Sales and total assets are both in 2006 million. The knowledge stock variables are calculated using the patent data from 1977 to 2010.
Source: Authors' calculations, based on AMADEUS and REGPAT databases.

positive correlation between the firm indicators themselves, the one between sales and total assets (0.621) being the highest.

Table 3: Correlation matrix.

	Sales	Employees	Total assets	GKS	NKS
Sales	1				
Employees	0.202	1			
Total assets	0.621	0.282	1		
GKS	0.101	0.101	0.121	1	
NKS	0.080	0.106	0.131	0.552	1

Source: Authors' calculations, based on AMADEUS and REGPAT databases.

3.2 Descriptive Statistics

Figure 1 shows the development of yearly GE and non-GE patenting activities of all firms during 1977 and 2010. GE patent applications are shown on the left axis and non-GE applications on the right axis. Both variables show an increasing trend from 1977 to 2010. The number of yearly non-GE patent applications increases monotonically and it can be seen that the yearly increases become significantly larger since the beginning of the 1990s. Yearly non-GE patent applications peak after a small drop at about 8,000 in 2009. The development of the yearly number of GE patents in my sample is characterized by two periods of growth. While they remain fairly stable well below 100 at the beginning, there is a steep increase to over 100 yearly GE patents at the end of the 1990s. After a phase of stagnation at the beginning of the 2000s, again an increase to over 300 yearly GE patents from 2005 to 2008 can be observed. Overall, the development of GE patents is less steady than the one of non-GE patents.

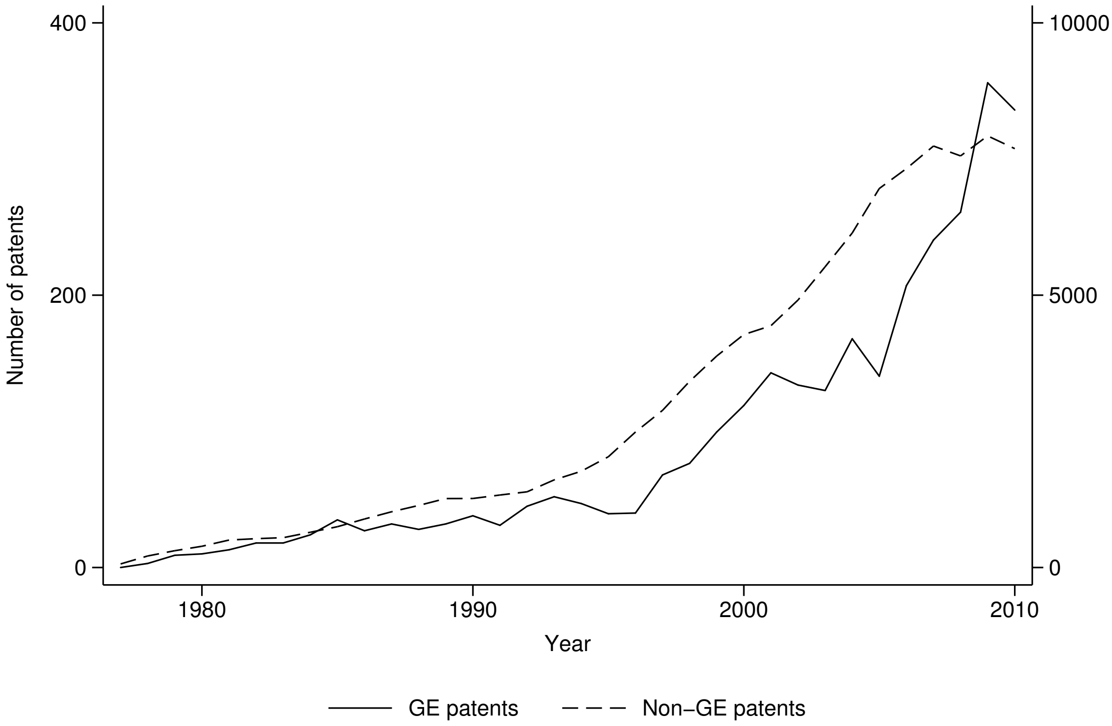

Figure 1: Number of yearly GE (left axis) and non-GE (right axis) patent applications filed at the EPO by all firms. *Source:* Authors' calculations, based on AMADEUS and REGPAT data.

Table 4 shows the distribution of firms by GE and non-GE patents. In the range from one to 1,000 or more patents, it can be seen how many firms have filed at least a certain number of patents. As stated before, the sample contains 8,619 firms of which 968 firms have filed at least one GE and 8,345 firms at least one non-GE patent. Only about 13% (1,059) of the non-GE firms have filed ten or more non-GE patents while the respective figure lies at 5% (51) for GE patents, that is the majority of firms has filed less than ten patents, even more so with regard to GE patents. There are some particularly innovative firms in the sample as 439 firms have filed 25 non-GE patents or more, 121 firms 100 or more and still 51 firms 250 or more. Finally, 12 firms have filed 1,000 or more non-GE patents. Concerning GE patents, there are 15 firms which have filed 25 or more patents and 2 firms which have filed 100 or more patents.

Table 4: The distribution of firms by GE and non-GE patents.

	1 or more	10 or more	25 or more	100 or more	250 or more	1,000 or more
Firms (GE)	968	51	15	2	0	0
Firms (Non-GE)	8,345	1,059	439	121	51	12

Source: Authors' calculations, based on AMADEUS and REGPAT data.

Table 5 gives complementary information on the distribution of the firms with regard to technology, firm size[10], industry[11], and country. The GE patenters in the sample are more involved in EE than RES innovation as 73% of GE firms have patented in the field of EE technologies and only 41% in RES technologies. GE firms tend to be larger compared to the non-GE sample. While 31% of GE firms are categorized as very large, only 17% of the non-GE sample are. The distribution among industries and countries is very similar between GE firms and the non-GE sample. 50% and 54% respectively are classified as manufacturers which is thus the most prominent industry group. Other well represented groups are professional, scientific and technical activities, wholesale and retail trade as well as construction. Concerning the country distribution of the non-GE firms, Germany (32%) and France (30%) dominate the sample followed by Spain (11%) and Italy (10%). It is interesting to note that GE patenters disproportionately come from Germany (38%).

[10] AMADEUS groups firms into the three size categories very large, large, and medium. For firms to be classified as very large, they have to satisfy at least one of the following criteria: Operating revenue of at least 100 million EUR, total assets of at least 200 million EUR, at least 1000 employees, or the firm has to be publicly listed. The respective criteria for large companies are: at least 10 million EUR operating revenue, at least 20 million EUR total assets, or at least 150 employees. For medium sized firms these criteria are: at least 1 million EUR operating revenue, at least 2 million EUR total assets, or at least 15 employees.

[11] AMADEUS assigns firms to industries using NACE (for the French term "nomenclature statistique des activités économiques dans la Communauté européenne"), the standard European industry classification system.

Table 5: Distribution of firms by technology, size, industry, and country.

Technology	RES	EE	GE
No. of GE firms	399	704	968
% in GE firms	41%	73%	100%

Size	Very Large	Large	Medium	All
No. of GE firms	296	305	367	968
% in GE firms	31%	32%	38%	100%
No. of non-GE firms	1,399	2,684	4,262	8,345
% in non-GE firms	17%	32%	51%	100%

Industry	Manu-facturing	Professional, scientific and technical activities	Wholesale and retail trade	Construction	Other	All
No. of GE firms	485	159	126	70	128	968
% in GE firms	50%	16%	13%	7%	13%	100%
No. of non-GE firms	4,559	977	1,357	346	1,106	8,345
% in non-GE firms	54%	12%	16%	4%	13%	100%

Country	DE	FR	ES	IT	Other	All
No. of GE firms	369	290	72	65	172	968
% in GE firms	38%	30%	7%	7%	18%	100%
No. of non-GE firms	2,630	2,542	894	834	1,445	8,345
% in non-GE firms	32%	30%	11%	10%	17%	100%

Source: Authors' calculations, based on AMADEUS and REGPAT data.

4 Empirical Strategy

To empirically evaluate the impact of GE innovation on firm performance, I follow the approach by Bloom and Van Reenen (2002) who measure firm performance by productivity. I use a panel data model based on a standard Cobb-Douglas production function for firm i at time t, extended by innovation respectively knowledge as an additional input:

$$Q_{it} = AL_{it}^{\alpha} K_{it}^{\beta} I_{it}^{\gamma}, \tag{3}$$

where Q is the output, L is the labor input, K is the capital input, I is the knowledge stock, and A is a constant. The parameters α, β, and γ are elasticities with respect to labor, capital, and knowledge respectively.

The elasticity with respect to labor accounts for the effect on output caused by growth in labor input. The elasticity with respect to capital accounts for the effect in output caused by growth in capital input. These parameters measure the corresponding single factor productivity (SFP) growth. The elasticity with respect to knowledge measures the total factor productivity (TFP) by accounting for the effect in output not caused by the growth in labor and capital input. This is in line with the conventional view that TFP is the measure of the rate of technical change (Krugman, 1996). Precisely, since I will use sales as a proxy for output, I measure revenue productivity which includes both changes in factor productivity as well as in markups as firms are able to raise prices for new innovations (Bloom and Van Reenen, 2002).

Expressing 3 in logarithms yields:

$$ln\left(Q\right)_{it} = ln\left(A\right) + \alpha ln\left(L\right)_{it} + \beta ln\left(K\right)_{it} + \gamma ln\left(I\right)_{it}. \tag{4}$$

In the empirical application, I use sales as a proxy for output Q, the number of employees engaged as a proxy for labor L, and total assets as a proxy for capital K. The knowledge stock I is proxied by the firm's GE knowledge stock (GKS), capturing GE specific knowledge, and the respective non-GE knowledge stock (NKS), capturing non-GE knowledge. This allows a separate assessment of the productivity impact of GE and non-GE innovation. Including the non-GE knowledge stock also controls for differences in the firms' overall propensity to patent innovations. The knowledge stocks are included in levels and not in logarithmic form since a substantial number of firms have knowledge stocks of zero (Wooldridge, 2002). In the complete sample of 8,619 firms the share of zero observations is 91% for the GE and 17% for the respective non-GE knowledge stock. Thus, this share is substantial especially with respect to the GE knowledge stock.[12] In order to mitigate any reverse causality problems and to account for the fact, that the impact of innovation on productivity is dynamic and comes with a certain time lag (Bloom and Van Reenen, 2002), the knowledge stock variables are

[12] In a robustness test, I address this approach. I use an alternative specification that includes the logged total knowledge stock instead of the separated GE and non-GE stocks in levels. Therefore, the problem of zero knowledge stocks is less pronounced. Using the total knowlege stock in logs does not change the sign and significance of the coefficients so that I continue to use the knowledge stocks in levels in the main specification.

lagged by two years.[13] To control for correlated unobserved heterogeneity, I include year fixed effects T_t and firm-specific fixed-effects η_i. The baseline specification to be estimated then is given by:

$$\begin{aligned} ln\,(Q)_{it} = {} & ln\,(A) + \alpha ln\,(L)_{it} + \beta ln\,(K)_{it} + \gamma_1\,(GKS)_{it-2} + \gamma_2\,(NKS)_{it-2} \\ & + T_t + \eta_i + u_{it}, \end{aligned} \tag{5}$$

where u_{it} is a standard varying error term (across time and firms). I estimate (5) using OLS and fixed-effects (within) regression (least-squares dummy-variable regression) with standard errors cluster-robust to heteroscedasticity (Section 5.1). To test the robustness of the baseline model, I use alternative specifications with modifications (Section 5.2).

5 Results

5.1 Baseline Results

The baseline results of estimating the Cobb-Douglas production function (5) are presented in Table 6. Initially, the full sample of 8,619 firms is used. Column (1) gives the OLS estimates of the production function. As the independent variables employment and total assets enter the estimations in log form, the estimated coefficients can be interpreted as elasticities. The coefficients on employment and total assets are both positive and statistically significant at the 1% level. This result is in line with general expectations. As one would also expect, the sum of the coefficients is close to unity suggesting constant returns to scale. Column (2) has the results of the fixed-effects estimator which controls for time-invariant unobserved heterogeneity between firms by including firm-specific fixed effects. Again the coefficients on employment and total assets are both positive and statistically significant while slightly smaller for employment and slightly higher for total assets. The estimated elasticities of 0.639 and 0.469 suggest that a 10% increase in employment or capital is associated with a 6.4 and 4.7% increase in productivity respectively.

Column (3) reports the results from adding the firm's GE knowledge stock and the corresponding non-GE stock as proxies for a firm's knowledge. As the knowledge stocks enter the estimation in levels, the estimated coefficients have a percentage interpretation when they are multiplied by 100, commonly called semi-elasticity. The GE knowledge stock is negative and significant at the 5% level. The coefficient suggests that an increase

[13] I test the robustness of my results against other lag structures in Section 5.2, Table 9.

Table 6: Estimated coefficients of the Cobb-Douglas production function. Estimation time span: 2003-2010. Dependent variable: Sales (log).

	(1)	(2)	(3)	(4)
Firms	All	All	All	GE patenters
Employees (log)	0.700***	0.639***	0.643***	0.441***
	(0.029)	(0.055)	(0.055)	(0.094)
Total assets (log)	0.408***	0.469***	0.469***	0.730***
	(0.027)	(0.047)	(0.046)	(0.167)
GE knowledge stock$_{t-2}$			−0.036**	−0.031**
			(0.014)	(0.012)
Non-GE knowledge stock$_{t-2}$			0.001***	0.001***
			(0.000)	(0.000)
Year dummies	yes	yes	yes	yes
Firm dummies	no	yes	yes	yes
Adj. R-Squared	0.581	0.896	0.896	0.915
No. observations	39152	39152	39152	4482
No. firms	8619	8619	8619	968

Note: Column (1), (2), and (3) present the results using the population of all patenting firms. Column (4) presents the results for the subset of firms with GE patents. The knowledge stock variables are calculated using the patent data from 1977 to 2010. Robust standard errors clustered by firm are in parantheses. ***, **, and *: Significant at the 1%, 5%, and 10%-level.

of the stock by 1 would lead to a 3.6% decrease in productivity. A doubling of the stock with respect to its sample average (0.15) would lead to a 0.5% decrease in productivity. In contrast, the corresponding non-GE stock is positive and significant at the 1% level. Here an increase of the stock by 1 would result in a 0.1% increase in productivity. A doubling of the stock with respect to its sample average (6.11) would result in a 0.6% increase in productivity. Thus, the marginal effect of GE innovation is negative while the marginal effect of non-GE innovation is positive indicating that sales markets do not provide sufficient incentives to increase firms' GE innovation activities but do provide enough incentives to increase firms' non-GE innovation activities. The results suggest that, while there is a positive return in terms of productivity for non-GE innovation, a negative return is found for GE innovation. Thus, hypothesis H2 can be confirmed: Private economic returns measured in terms of productivity are lower for GE than for non-GE innovation. The findings are in line with the aforementioned examinations by Marin (2014), Marin and Lotti (2016), and Wörter et al. (2015).

The last column (4) gives the results of the previous specification for the subset of the 968 GE patenters. Using this specification, I test if the results in column (3) are robust or mainly driven by the shift from a firm without any GE patents to a firm with GE patents. Again the estimate on the GE knowledge stock is negative and significant although slightly smaller than in column (3). Likewise the coefficient on the respective stock in non-GE patents is still positive and significant but slightly lower. The lower estimates on employment and higher estimates on total assets indicate that the GE patenting firms are on average more capital intensive than the non-GE patenting firms. In fact the GE patenters have on average a 37% higher capital to labor ratio compared to the complete sample.

5.2 Robustness Tests

In order to test the sensitivity of the baseline results presented in Table 6, I conduct a number of robustness tests based on the main model in column (3).

First, I repeat the main specification differentiating between two subgroups of GE technologies: RES and EE technologies. Column (1) and (3) in Table 7 present results using the population of all patenting firms. Overall, the estimated coefficients are similar but show differences between the two technology groups. The negative coefficients of the RES and EE knowledge stocks are higher compared to the coefficient of the GE knowledge stock, even more so for the RES knowledge stock. Thus, patents in the field of RES have a more pronounced negative impact on productivity than EE patents. This finding may be explained by different maturity levels of RES and EE markets. Again in contrast, the corresponding coefficient of the non-RES and non-EE knowledge stocks are small, but positive and significant.

Column (2) and (4) give the results for the subset of firms with RES respectively EE patents. Doing this, I test again if the results in column (1) and (3) are robust or mainly driven by the shift from non-RES respectively non-EE patenters to RES- respectively EE patenters. The coefficient on the RES knowledge stock is negative and significant and increases slightly in absolute terms compared to column (1). Contrary, the coefficient on the EE knowledge stock decreases slightly compared to column (3) but still remains negative and significant. The coefficients on the respective stocks in non-RES and non-EE patents do not change compared to columns (1) and (3). The estimates on employment and total assets show that both RES and EE patenters are on average more capital intensive than non-GE firms, with EE patenters having the highest capital-intensity. The sum of the coefficients is 1.22 in column (2) and 1.05 in column (2), suggesting higher returns to scale in tangible factors for RES than EE patenters.

Table 7: Differentiating by technology group. Estimation time span: 2003-2010. Dependent variable: Sales (log).

	(1)	(2)	(3)	(4)
Firms	All	RES patenters	All	EE patenters
Employees (log)	0.643***	0.508***	0.642***	0.343***
	(0.055)	(0.165)	(0.055)	(0.100)
Total assets (log)	0.469***	0.714***	0.469***	0.707***
	(0.046)	(0.174)	(0.046)	(0.238)
RES knowledge stock$_{t-2}$	−0.055*	−0.061**		
	(0.031)	(0.025)		
Non-RES knowledge stock$_{t-2}$	0.001**	0.001***		
	(0.000)	(0.000)		
EE knowledge stock$_{t-2}$			−0.044**	−0.029*
			(0.022)	(0.016)
Non-EE knowledge stock$_{t-2}$			0.001**	0.001**
			(0.001)	(0.000)
Year dummies	yes	yes	yes	yes
Firm dummies	yes	yes	yes	yes
Adj. R-Squared	0.896	0.896	0.896	0.937
No. observations	39152	1816	39152	3344
No. firms	8619	399	8619	704

Note: Estimations are based on the same specification as in column (3) of Table 6. Column (1) and (3) present the results using the population of all patenting firms. Column (2) and (4) present the results for the subset of firms with RES respectively EE patents. The knowledge stock variables are calculated using the patent data from 1977 to 2010. Robust standard errors clustered by firm are in parantheses. ***, **, and *: Significant at the 1%, 5%, and 10%-level.

The relationship between innovation and productivity may be dependent on a firm's size. Therefore, I conduct a second robustness test differentiating between the size of the investigated firms. Table 8 reports estimated coefficients of the main model for very large, large, and medium sized firms. The coefficient on the GE knowledge stock, which has been significant in all previous specifications, is only significant for very large firms. For very large firms it also has the same size as in the main specification. The coefficient on the non-GE knowledge stock, likewise always significant before, is highly significant for medium sized firms only, significant at the 10% level for very large firms and insignificant for large firms. Overall, the results are very similar in size but not always statistically significant. The results suggest that the (negative) impact of GE innovation on productivity tends to be more pronounced for larger firms whereas the (positive) productivity effect of non-GE innovation seems to be more important for smaller firms. Possible reasons for the lower levels of significance are that the sample sizes are smaller and the variation of the knowledge stocks is lower between firms of similar size.

Table 8: Differentiating by firm size. Estimation time span: 2003-2010. Dependent variable: Sales (log).

	(1)	(2)	(3)
Firms	Very large	Large	Medium
Employees (log)	0.686***	0.652***	0.606***
	(0.140)	(0.066)	(0.063)
Total assets (log)	0.530***	0.541***	0.412***
	(0.105)	(0.063)	(0.070)
GE knowledge stock$_{t-2}$	−0.031*	−0.039	−0.056
	(0.017)	(0.040)	(0.113)
Non-GE knowledge stock$_{t-2}$	0.001*	0.000	0.004***
	(0.001)	(0.001)	(0.001)
Year dummies	yes	yes	yes
Firm dummies	yes	yes	yes
Adj. R-Squared	0.870	0.846	0.814
No. observations	8109	13956	17087
No. firms	1428	2775	4416

Note: Estimations are based on the same specification as in column (3) of Table 6. Column (1) presents the results for the subset of very large, column (2) for the subset of large, and column (3) for the subset of medium sized firms. The knowledge stock variables are calculated using the patent data from 1977 to 2010. Robust standard errors clustered by firm are in parantheses. ***, **, and *: Significant at the 1%, 5%, and 10%-level.

As noted before, in the baseline specification I lag the knowledge stock variables by two years in order to mitigate any reverse causality problems and to account for the fact that innovative output does not immediately have an effect on a firm's productivity. In order to test the sensitivity of the knowledge stock results to other lag structures, I conduct a third robustness test and re-estimate the main model with the current knowledge stocks and with knowledge stocks lagged one, two (as used in the baseline specification depicted in Table 6), and three years. The results are given in Table 9. Overall, the results are robust to these modifications. The impact of additional GE innovation on productivity is still negative and the impact of additional non-GE innovation still positive. The higher point estimates on the two- and three-year lag compared to the zero- and one-year lag for both knowledge stocks[14] support the hypothesis of a time lag between innovation and its effect on performance. In other words, patented innovations take some time to enter the production function. Another explanation for the stronger negative impact of additional GE innovation for longer lags might be that marginal costs of GE innovation were higher and demand for GE innovation was lower in earlier periods (for a similar result and reasoning see Wörter et al., 2015).

Table 9: Different lags for the knowledge stocks. Estimation time span: 2003-2010. Dependent variable: Sales (log).

	(1)	(2)	(3)	(4)
Firms	All	All	All	All
Employees (log)	0.643***	0.643***	0.643***	0.642***
	(0.055)	(0.055)	(0.055)	(0.055)
Total assets (log)	0.469***	0.469***	0.469***	0.469***
	(0.046)	(0.046)	(0.046)	(0.046)
GE knowledge stock	−0.029**	−0.028*	−0.036**	−0.034**
	(0.013)	(0.015)	(0.014)	(0.017)
Non-GE knowledge stock	0.001***	0.001***	0.001***	0.001**
	(0.000)	(0.000)	(0.000)	(0.001)
Year dummies	yes	yes	yes	yes
Firm dummies	yes	yes	yes	yes
Adj. R-Squared	0.896	0.896	0.896	0.896
No. observations	39152	39152	39152	39152
No. firms	8619	8619	8619	8619

Note: Estimations are based on the same specification as in column (3) of Table 6. Column (1), (2), (3), and (4) present the results for the current knowledge stocks and for knowledge stocks lagged one, two, and three years, respectively. The knowledge stock variables are calculated using the patent data from 1977 to 2010. Robust standard errors clustered by firm are in parantheses. ***, **, and *: Significant at the 1%, 5%, and 10%-level.

The final robustness test is done by utilizing different depreciation rates in the calculation of the knowledge stocks. Table 10 reports the main model estimates for depreciation rates of 5%, 10% (as used in the baseline estimation depicted in Table 6), 15%, and 20%. The higher the depreciation rate, the lower the importance of past knowledge. A depreciation rate of 100% would mean that the knowledge stock becomes a flow variable, that is only the patents from the current period contribute to a firm's productivity. For all specifications, the coefficients on the GE and non-GE knowledge stocks are significant at

[14] For the non-GE coefficients, the increase concerns the fourth decimal place and cannot be seen in the presented output table.

least at the 5% level. While the coefficient of the non-GE knowledge stock does not vary in size, the coefficient of the GE stock becomes more negative using higher depreciation rates. Hence, the negative effect of GE knowledge on productivity becomes larger when firms can rely on less previous GE knowledge. In other words, a larger GE knowledge stock mitigates the negative effect that an increase in GE knowledge has on productivity. An explanation might be that firms with a larger knowledge stock in GE technologies have lower R&D costs for the same amount of inventive output than firms with a lower knowledge stock.

Table 10: Different depreciation rates for the knowledge stocks. Estimation time span: 2003-2010. Dependent variable: Sales (log).

	(1)	(2)	(3)	(4)
Firms	All	All	All	All
Employees (log)	0.642***	0.643***	0.643***	0.643***
	(0.055)	(0.055)	(0.055)	(0.055)
Total assets (log)	0.469***	0.469***	0.469***	0.468***
	(0.046)	(0.046)	(0.046)	(0.047)
GE knowledge stock$_{t-2}$	−0.026**	−0.036**	−0.042***	−0.046***
	(0.012)	(0.014)	(0.016)	(0.017)
Non-GE knowledge stock$_{t-2}$	0.001**	0.001***	0.001***	0.001***
	(0.000)	(0.000)	(0.001)	(0.001)
Year dummies	yes	yes	yes	yes
Firm dummies	yes	yes	yes	yes
Adj. R-Squared	0.896	0.896	0.896	0.896
No. observations	39152	39152	39152	39152
No. firms	8619	8619	8619	8619

Note: Estimations are based on the same specification as in column (3) of Table 6. Columns (1), (2), (3), and (4) present the results for knowledge stock depreciation rates of 5%, 10%, 15%, and 20%, respectively. The knowledge stock variables are calculated using the patent data from 1977 to 2010. Robust standard errors clustered by firm are in parantheses. ***, **, and *: Significant at the 1%, 5%, and 10%-level.

6 Conclusions

In this article, I studied the effect of innovation in GE technologies on the economic performance of firms and compared it to the effect of non-GE innovation. I based my study on a panel of 8,619 patenting firms including 968 GE patenters from 22 European countries over the period 2003 to 2010. To construct the panel, I combined firm accounts data with data on firms' patent applications. My results show that, all else equal, innovation in GE technologies has a negative impact on the economic performance of firms while innovating in non-GE technologies positively affects firms' economic performance. This confirms the hypothesis H2 that private economic returns in terms of productivity are lower for GE than for non-GE innovation, which corresponds to previous results found by Marin (2014), Marin and Lotti (2016), and Wörter et al. (2015). I also find evidence for different performance effects across GE technologies. My results reveal that the negative effect on firm performance is more pronounced for RES than for EE technologies. Moreover, my findings suggest that the negative relationship between GE innovation and performance is stronger for larger firms. Furthermore, the negative impact of GE innovation on performance is found to be stronger with a larger time lag between both. On the one hand, this supports the hypothesis of a time lag between innovation and its impact on performance. On the other hand, it indicates that marginal costs of GE innovation decreased and demand for GE innovation increased over time. Finally, the use of different knowledge depreciation rates shows that the negative impact of new GE patents on performance is less pronounced when firms can build on an existing stock of GE knowledge.

Given these results, the initial research question can be answered: since GE innovation guarantees lower private returns than non-GE innovation, firms forgo economic opportunities by innovating in GE technologies and gain economic opportunities by concentrating on innovation in non-GE technologies. However, as one can observe in the data, firms nevertheless have invested in GE technologies. Since the resources that firms can allocate to R&D investment projects are limited and since firms always choose the project with the highest private return, this observation evidences a potential crowding out of GE innovation at the expense of (more rewarding) non-GE innovation. Thus it seems that there where factors (for example political expectations, environmental regulation) that somewhat forced firms to use their scarce R&D funds for projects with comparatively low returns (Marin, 2014). Assuming that the non-private returns for the GE and the non-GE project are the same, this crowding out would be welfare decreasing. However, if the GE project has higher social returns (that is combined private and non-private returns) compared to the non-GE project, this crowding out would be welfare increasing. This then would be an argument for policy intervention aiming to increase private returns of GE innovation in order to promote socially beneficial green growth.

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Appendix

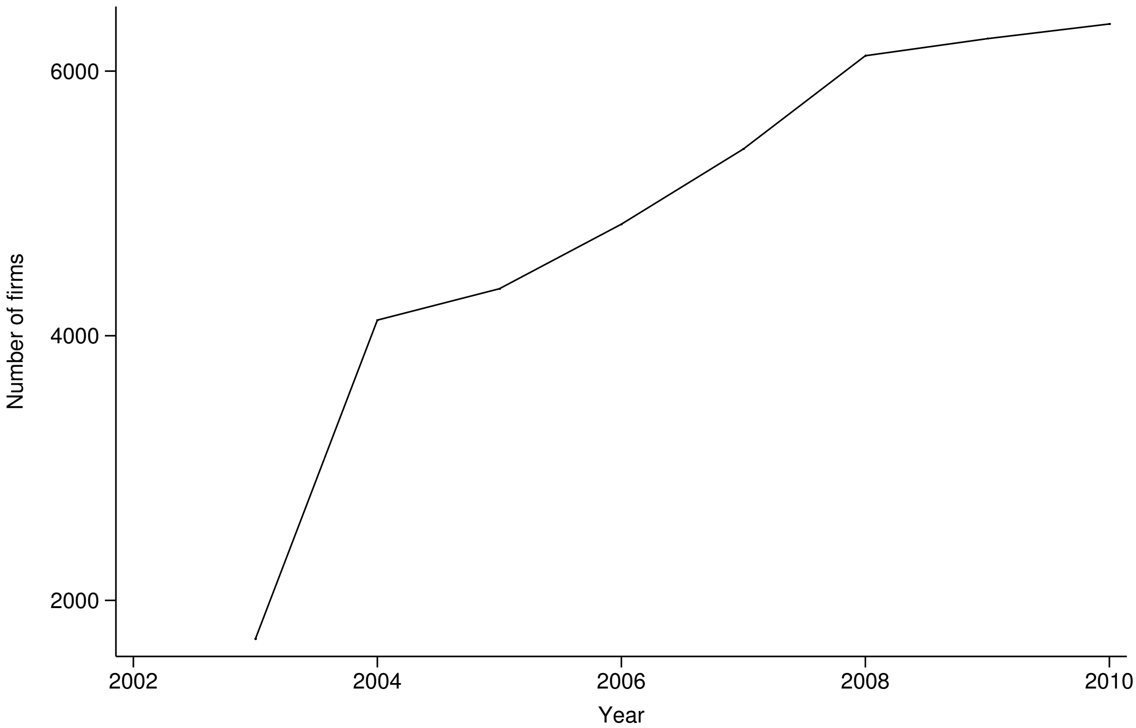

Figure A1: Number of firms, 2003-2010. *Source:* Authors' calculations, based on AMADEUS and REGPAT data.

Table A1: Number of yearly patent applications filed at the EPO by all firms by technology group.

Year	RES	EE	GE	Non-GE
1977	0	0	0	66
1978	0	3	3	212
1979	2	7	9	309
1980	1	9	10	390
1981	1	12	13	504
1982	4	14	18	530
1983	5	16	18	548
1984	7	20	24	647
1985	3	32	35	749
1986	7	26	27	891
1987	4	28	32	1,024
1988	3	25	28	1,140
1989	11	30	32	1,267
1990	5	33	38	1,268
1991	3	29	31	1,331
1992	5	40	45	1,390
1993	10	45	52	1,609
1994	8	42	47	1,768
1995	12	35	40	2,034
1996	11	33	40	2,487
1997	20	57	68	2,886
1998	25	62	77	3,419
1999	26	88	100	3,883
2000	41	108	119	4,278
2001	59	101	143	4,440
2002	51	94	134	4,911
2003	46	94	130	5,522
2004	63	110	168	6,142
2005	54	89	141	6,959
2006	82	142	207	7,324
2007	106	168	241	7,739
2008	132	181	261	7,558
2009	195	192	356	7,925
2010	189	207	336	7,691
Total	1,190	2,171	3,021	100,835

Source: Authors' calculations, based on AMADEUS and REGPAT data.

Table A2: Country distribution of GE firms.

Country	No.	%
DE	369	38.12
FR	290	29.96
ES	72	7.44
IT	65	6.71
SE	49	5.06
AT	46	4.75
BE	24	2.48
NO	23	2.38
FI	6	0.62
CH	5	0.52
PL	5	0.52
GB	4	0.41
DK	3	0.31
LU	3	0.31
CZ	2	0.21
LV	1	0.10
NL	1	0.10
Total	968	100.00

Source: Authors' calculations, based on AMADEUS and REGPAT data.

Table A3: Country distribution of non-GE firms.

Country	No.	%
DE	2630	31.51
FR	2542	30.46
ES	894	10.71
IT	834	9.99
SE	502	6.02
AT	313	3.75
NO	234	2.80
BE	184	2.20
FI	45	0.54
PL	37	0.44
CH	32	0.38
DK	25	0.30
GB	22	0.26
LU	17	0.20
EE	9	0.11
NL	9	0.11
CZ	6	0.07
HU	4	0.05
LV	3	0.04
GR	1	0.01
LI	1	0.01
SI	1	0.01
Total	8345	100.00

Source: Authors' calculations, based on AMADEUS and REGPAT data.