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From less promising to green? Technological opportunities and their role in (green) ICT innovation

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ABSTRACT

This article aims to shed light on the role of technological opportunities for green innovation by studying the case of Green ICT innovation. We test whether firms active in low-opportunity technological areas are less likely to be innovative and whether they are more likely to change their direction of technical change. To do so, we construct a firm-level panel data set for the years 1992–2009 combining patent data from the European Patent Office with firm-level data from the German Innovation Panel (Mannheim Innovation Panel). The results are based on dynamic count data estimation models applying General Methods of Moments estimators. Our results support our hypotheses: firms active in low-opportunity technological areas are less innovative but are more likely to switch from pure ICT innovation to Green ICT innovation.

KEYWORDS

Technological opportunities; innovation; information and communication technology (ICT); green ICT; firm-level patent data; dynamic count data model

JEL CLASSIFICATION

D22; L63; O31; Q55

1. Introduction

Innovation in environment-friendly, ‘green’, technologies is crucial to ensure sustainable growth. A large literature studies potential drivers of green innovation (for surveys see e.g. Jaffe, Newell, and Stavins 2003; Barbieri et al. 2016). However, despite the well known fact that technology push factors, such as technological opportunities and path dependencies, are important determinants of innovation behavior in general (Klevorick et al. 1995; Breschi, Malerba, and Orsenigo 2000), the literature studying environmental innovation has mainly focused on price- and regulation-induced innovation (see e.g. Jaffe and Palmer 1997; Newell, Jaffe, and Stavins 1999; Popp 2002; Brunnermeier and Cohen 2003; Johnstone, Hascic, and Popp 2010). Some evidence with respect to the role of path dependencies for green innovation exists (Acemoglu et al. 2012; Rexhäuser and Löschel 2015; Aghion et al. 2016), but there is nearly no empirical work which examines the role of technological opportunities for green innovation. We provide such evidence to help closing this gap in the literature.

Technological opportunities, which describe the ease of innovative activities in a technological domain (Malerba and Orsenigo 1996; Corrocher, Malerba, and Montobbio 2007), have been shown to affect the efficiency of R&D and thus the rate of innovation (see e.g. Klevorick et al. 1995; Kumar and Siddharthan 1997). We test this relationship in the context of green innovations. In addition, we test the hypothesis that firms which are active in low-opportunity technologies are more likely than firms active in high-opportunity technologies to change their direction of technical change. We study those two hypotheses in the context of innovation in green and non-green information and communication technologies (ICT). ICT are an interesting field of investigation since they are characterized by rapid, disruptive technical change and short technology life cycles resulting at

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the same time in both many high- and low-opportunity technologies (Corrocher, Malerba, and Montobbio 2007). Also, ICT are a highly relevant field for studying green innovations, given ICT's ubiquity as a general purpose technology (Bresnahan and Trajtenberg 1995), and given that the use of ICT is shown to be closely related to energy use (see e.g. Schulte, Welsch, and Rexhäuser 2016).

To implement our study empirically, we construct a firm-level panel data set for the years 1992–2009 which combines information on patents from the European Patent Office (EPO) and data from the Mannheim Innovation Panel (MIP). The main results are based on dynamic count data estimation models applying General Method of Moments (GMM) estimators. Controlling for size, age, R&D intensity, the degree of competition and past innovation performance, we find that technological opportunities indeed play an important role for the rate and direction of technical change. Firms active in low-opportunity fields are less likely to innovate but are more likely to switch technological fields, i.e. they switch from pure ICT to green ICT innovation. Our work provides first empirical evidence on the role of technological opportunities in green innovation and at the same time offers valuable insights for policy interventions which aim at stimulating green innovation (in the ICT sector). Our results show that such policy interventions are more effective, i.e. they can be realized at lower costs, in low opportunity technology areas since firms there anyway have a tendency to change the direction of technical change and thus just have to be incentivized choosing their new area of research in a green technology field.

The rest of the paper is organized as follows. Section 2 reviews and summarizes the related literature. Section 3 describes our data set and presents descriptive evidence. Section 4 introduces the empirical framework and describes the econometric methods used. Section 5 presents the results, including various robustness checks. Section 6 concludes.

2. Previous research

A large literature studies potential drivers of environmental innovation (for surveys see e.g. Jaffe, Newell, and Stavins 2003; Barbieri et al. 2016). Most studies are focused on understanding the role of prices and regulation for innovation (see e.g. Jaffe and Palmer 1997; Newell, Jaffe, and Stavins 1999; Popp 2002; Brunnermeier and Cohen 2003; Johnstone, Hascic, and Popp 2010). Technology push factors, such as technological opportunities and path dependencies, despite the well-known fact that these are important determinants of innovation behavior in general (Klevorick et al. 1995; Breschi, Malerba, and Orsenigo 2000), are hardly analyzed in the context of environmental innovation. Some evidence exists with respect to the role of path dependencies (Acemoglu et al. 2012; Rexhäuser and Löschel 2015; Aghion et al. 2016), but there is, to our knowledge, no empirical work which examines the role of technological opportunities for environmental innovation.

Both empirical and theoretical literature have underlined the importance of technological opportunities for the development of innovation. Technological opportunities describe the ease of innovative activities in a technological domain (Malerba and Orsenigo 1996; Corrocher, Malerba, and Montobbio 2007). They are considered to be exogenous to the firm (Kumar and Siddharthan 1997; Barge-Gil and López 2014) and have been shown to influence the productivity of R&D and thus are important determinants of firms' research decisions (Klevorick et al. 1995). High technological opportunities are associated with a high innovation potential within a technological domain. Despite these insights there is no evidence on the role of technological opportunities for the development of environmental innovations, especially not with respect to green general purpose technologies (GGPT) such as Green ICT.¹

To study the role of technological opportunities for the development of environmental innovations and green ICT, we rely on the framework of technological push factors (Rosenberg 1994). We derive two research hypotheses. In a first step, in line with the key finding from the general innovation literature showing the positive relationship between technological opportunities and innovative success, we aim to replicate this finding in the context of environmental innovations and ICT. We hypothesize that, if there are limited or no technological opportunities within a

subdomain of ICT, firms will have low invention output relative to the amount they invest into R&D. In contrast, in areas where there are more opportunities, firms are expected to produce *ceteris paribus* more ICT patents given an investment into R&D. Thus, the first research hypothesis we want to test, is:

Hypothesis I: Higher technological opportunities are associated with more innovative output.

Testing this hypothesis contributes on the one hand to the literature concerned with understanding drivers of environmental innovation and provides insights useful for determining optimal R&D levels necessary to reach desired levels of green growth. On the other hand, such evidence also contributes to the general innovation literature by providing alternative empirical evidence on the role of technological opportunities which is based on an empirical context not studied before.

In a second step of our analysis, we study the consequences of technological opportunities for the direction of technical change, i.e. for the choice of the technological field inventors decide to become active in. With respect to this relationship, to our knowledge, no studies exist. Some studies analyze the role of path dependencies for the direction of technical change - their findings suggest that changing the direction of technical change is costly (Dosi 1982; David 1985). As technological knowledge is by nature cumulative, as noted by Rosenberg (1994), major innovations constitute new building blocks which provide a basis for subsequent technologies indicating that path-dependency is an important driver of both the number of inventions (as well as current R&D expenditures) and the direction of technical change. Changing the direction of technical change implies costs through the need to abandon some of the previously acquired knowledge in technology domains which are left behind. The role of path dependencies has also been shown in the context of environmental innovations, where some studies, e.g. (Acemoglu et al. 2012; Rexhäuser and Löschel 2015; Aghion et al. 2016) confirm that both path-dependencies and cumulativeness of knowledge are potential drivers of the direction of technical change.² Despite the costs which come with changing the direction of technical change, we expect firms active in low opportunity areas to be more likely to adjust the direction of technical change. If the benefits of adjusting research efforts from a low to a high opportunity technological field (where such benefits should increase in the low-to-high opportunity differential) exceed the cost of adjustment (from abandoning existing know-how), we would expect firms and innovators to adjust research efforts, but otherwise would expect them to remain in their technological domain. In the case of ICT and Green ICT innovation, we hypothesize that firms active in low opportunity ICT domains are more likely to adjust their research efforts into new technological areas, such as Green ICT technological domains, which allow those firms reusing some of their existing knowledge (on ICT) to create innovations in new, less researched technological areas such as Green ICT. More precisely, we expect firms active in high opportunity ICT domains to have *ceteris paribus* more pure ICT patents and less green ICT patents, whereas firms active in low opportunity ICT domains are expected to have *ceteris paribus* less patents in pure ICT domains but relatively more ones in green ICT. Our second research hypothesis is:

Hypothesis II: Low technological opportunities are associated with a higher likelihood of a change in the direction of technical change.

3. Data, definitions, and descriptive statistics

In this section we describe our data (Section 3.1) and provide descriptive evidence on our research questions (Section 3.2).

3.1. Data and definitions

To study the effect of technological opportunities on the rate and direction of technological change we use longitudinal data of German firms linked to patent data from the EPO as well as from the Worldwide Patent Statistical Database (PATSTAT). Germany is an interesting country to look at as it

is one of the leading technological countries in the world and in particular heavily active in environmentally-friendly technologies. Our data set merges the MIP, covering firm-level observations from 1992 onwards, with patent data. The former is a representative panel stratified by firm size and sector affiliation where the target group is firms with at least five employees, however, also smaller firms are in the data set but the number is considerably small.³ The MIP is based on the Community Innovation Survey (CIS) for Germany and is, in contrast to most other European countries, conducted annually so that a yearly unbalanced data set of approximately 50,000 companies exists.⁴ We match the MIP to patent data from the PATSTAT database by using firm names and locations. Finally, in a last step, we add industry-level data related to the R&D expenditure data collected by the OECD ANBERD database as well as ICT capital services information published by the EU KLEMS database. Based on this information we construct our main variables of interest: measures of innovation and technological opportunities as well as several control variables.

Estimation sample: For our estimation sample we restrict our sample to firms that have at least one ICT patent granted by the EPO (since 1978).⁵ This subset of firms is hereinafter denoted as ICT-active firms. After the elimination of incomplete records and outlier observations, the final unbalanced panel dataset consists of 8653 observations for 1837 ICT-active companies. Note that most of the 50,000 firms in the MIP, 87.65%, do not have patents granted by the EPO. Of the remaining 12.35% of firms that show up as patent holders, only approximately 31.86% are holders of patents in the ICT area. Thus, these 1837 ICT-active firms account for 3.95% of all firms in the MIP but for 31.86% of all patent holders in this representative dataset. On average, firm-level data for these firms is observed for 4.7 years.

Measuring innovation: Patent data is a good and frequently used indicator to measure (environmental) technological inventions (Oltra, Kemp, and de Vries 2010), which allow us to investigate innovation at the technology area level and especially to analyze the rate and direction of technical change over time.⁶ The classification of patents by technological domains is done using International Patenting Classification (IPC) codes. The identification of ICT technologies follows the OECD list of IPC codes in the ICT field (OECD 2016). In a similar way, environmentally-friendly technologies, which in this study are referred to as 'green technologies', are also measured using the patents' IPC codes. We define a green technology as any technology with a direct or indirect beneficial effect on the environment, such as energy- and resource-saving inventions or technologies that reduce waste, replace hazardous materials in products and so on. Similar to for example Albino et al. (2014), we use IPC codes to identify green technologies which are listed in the WIPO Green Inventory defined by the World Intellectual Property Organization (WIPO). We define an invention (patent) as a green ICT one if the respective patent has at least one IPC code in the ICT area and at least one IPC code in the area of green technologies.⁷ Figure 1 illustrates this definition.

Measuring technological opportunities: To measure the strength of technological opportunities, we follow the longstanding empirical literature which aims to measure them. Although the importance of this concept is uncontroversial, there is a lack of a clear and precise understanding of how to measure technological opportunities empirically. Several proxies have been proposed and applied. For an overview over the literature and the empirical measures used to study technological opportunities, see Cohen (2010). Starting with Scherer (1965), who shows that innovation activities differ across sectors and who relates this finding to differences in technological opportunities, mainly two types of empirical measures have been applied to measure technological opportunities: survey-based measures and measures based on patents. Levin, Cohen, and Mowery (1985), Zahra (1996) and Crépon, Duguet, and Mairesse (1998) make use of survey data to identify technological opportunities. They measure variables thought to represent an industry's technological opportunities, such as the contribution of basic and applied sciences, suppliers, users, governments etc. to the industry's technological knowledge. Some of such measures, as Cohen (2010) summarizes, performed well in explaining industry's innovation activity. However, this approach requires specific survey questions and could be prone to response- and survey-bias as well as to measurement error. Alternatively, other studies such as Scherer (1967) or Jaffe (1986) apply cluster methods on

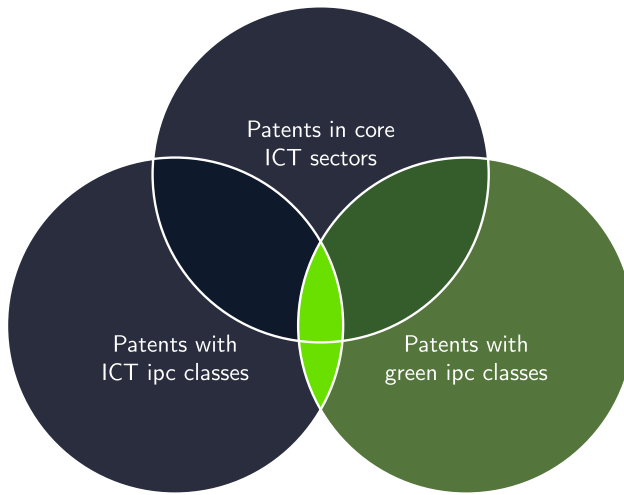


Figure 1. Definition of green ICT inventions.

data capturing realized innovations to define high- and low-opportunity areas. For example, Scherer (1967) argues that technological opportunities are sector-specific and thus distinguished low- and high-technological opportunity sectors. Jaffe (1986) uses data on the distribution of patents across patent classes to assign firms to technological opportunity classes, i.e. to classify firms into high- and low-opportunity technological domains; see also Jaffe (1989). A similar approach was pursued by Corrocher, Malerba, and Montobbio (2007), who measure technological opportunities in the ICT sector using the growth rate of innovative activities observed through patent data. Another example is Geroski (1990) who used industry-specific innovation counts in previous periods as a measure of technological opportunities.

To keep our analysis in line with the literature applying innovation-based measures of technological measures and to keep it as traceable as possible, we abstain from performing a cluster analysis as a means of identifying high- and low-opportunity fields but instead derive an alternative proxy of technological opportunities which is more transparent. Following Breschi, Malerba, and Orsenigo (2000) and Corrocher, Malerba, and Montobbio (2007), a technology can be considered a high-opportunity technology as long as there are positive growth rates of the number of inventions in this technological field. We consider technological fields as high-opportunity fields as long as the maximum annual number of patents in this class has not been reached and consider it a low-opportunity field afterwards. To account for changes in world-wide patenting trends, which vary a lot as illustrated by Figure 2, we weight the number of patents in a technology group by the total number of patents in the given year.⁸

Technically, we conduct our analysis at the technology group level (such as H04L 1) where 288 classes exist and base our opportunity measure on patents from all countries filed at the EPO.⁹ Thus, a technology class is considered a high-opportunity one as long as the share of patents from this class in total patents in all IPC classes has not reached its maximum. Formally, the high-/low-opportunity status ($h_{c,t}$) of a technology class c in year t is defined as:

$$h_{c,t} = \begin{cases} (\text{high} = 1) & \forall t \leq t(\max_t(s_{c,t})) \\ (\text{low} = 0) & \text{otherwise} \end{cases} \quad (1)$$

where $s_{c,t}$ denotes the share of patents filed at the EPO in year t in the technological class c . The following graphs provide some examples of such classes and illustrate our definition of high- and low-opportunity periods. In Figures 3 and 4, low-opportunity periods are marked by the gray shaded area.

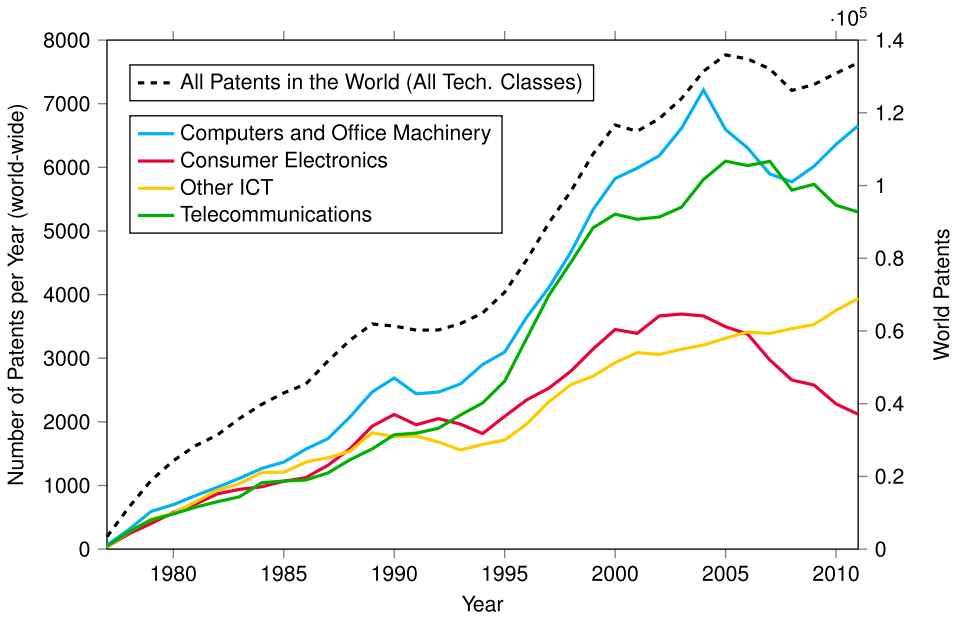


Figure 2. World patents (by technology).

To measure technological opportunities at the firm-level we match the group-level indicators with our firm-level data. We compute the share of IPC classes of all patents of firm i in year t in technologically high-opportunity areas ($opp_{i,t}$) as:

$$opp_{i,t} = \left(\sum_c h_{c,t} \cdot IPC_{i,c,t} / \sum_c IPC_{i,c,t} \right) \cdot 100. \quad (2)$$

Finally, as our main measure of firms' technological opportunities, based on this share, we construct a dummy which is equal to one if a firm has a positive share ($opp_{i,t}$) of high-opportunity IPC classes and

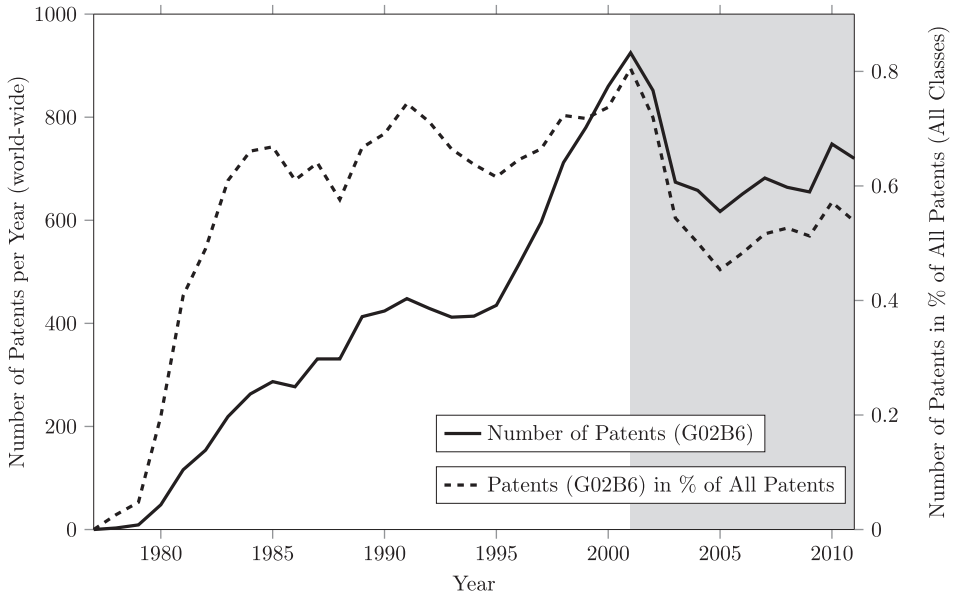


Figure 3. IPC class G02B6: light guides; structural details of arrangements comprising light guides, etc.

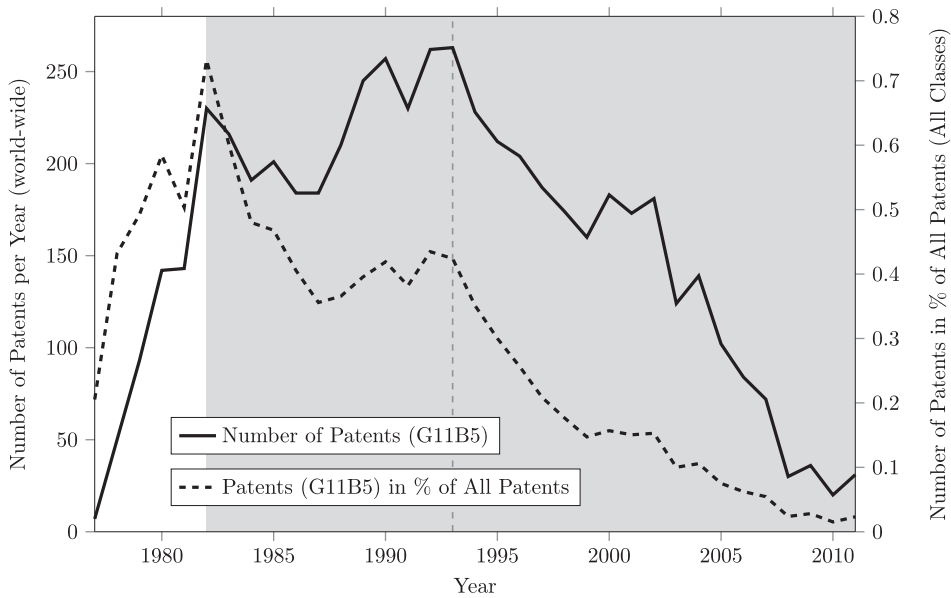


Figure 4. IPC class G11B5: recording by magnetization or demagnetization of a record carrier; reproducing by magnetic means; record carriers, etc.

which is zero if it has none of such patents. This dummy is our main measure for technological opportunities which we use in the empirical analysis. However, in a set of robustness checks, as an alternative, we use the share itself as our measure of technological opportunities.

3.2. Descriptive statistics

This section offers descriptive statistics on core firm-level indicators and patents held by firms as well as a sectoral breakdown. Table 1 below reports summary statistics for the 8653 observations of our estimation sample.

The average firm in this dataset has around 2847 employees which is surprisingly large compared to the average German firm, which has on average around 12 employees (Eurostat 2015). This is because, on the one hand, the sampling procedure does not automatically target small start-up companies as target firms have at least five employees. On the other hand, restricting the sample to firms that have at least one patent filters out small and innovative firms that have no patent so far as the patenting procedure usually takes some time and is expensive. In addition, it filters out firms without

Table 1. Summary statistics.

| Variables | Mean | Std. Dev. | Min. | Max. |
|--|---------|-----------|-------|----------|
| Number of green ICT patents | 0.09 | 1.14 | 0.00 | 48.00 |
| Number of ICT patents | 1.01 | 10.60 | 0.00 | 781.00 |
| $\ln(\text{R\&D-intensity})$ (R\&D/no. of employ.) | 5.81 | 7.22 | 0.00 | 23.96 |
| Dummy for missing R\&D information | 0.53 | 0.50 | 0.00 | 1.00 |
| Number of employees ^a | 2847.96 | 18410.36 | 1.00 | >200,000 |
| Share high opportunity IPC cls in $t-1$ | 9.51 | 28.35 | 0.00 | 100.00 |
| Dummy for no ICT patents in $t-1$ | 0.88 | 0.33 | 0.00 | 1.00 |
| Herfindahl index | 1023.27 | 1061.57 | 56.57 | 10,000 |
| \ln R\&D expenditures in NACE 2-dig. sect. | 20.99 | 1.85 | 0.00 | 23.45 |
| Firm age ^a (median: 26 years) | 38.23 | 44.91 | 0.50 | >300 |
| Dummy for location in East Germany | 0.18 | 0.38 | 0.00 | 1.00 |

^aFor reasons of confidentiality, maximum values are not reported.

ICT patents which are also on average rather small. Taking also into account that the average firm in the dataset is relatively old (38.23 years), this implies that the results of this study do not necessarily hold for the average population of firms but rather for established innovative firms. One reason why the average firm in our dataset is relatively old compared to what we would expect an ICT firm to be becomes clearer when looking at Table 2. A non-trivial share of all the ICT patents does not come from the core ICT sector such as computers and electric equipment. Instead, the automobile sector and the machinery as well as the equipment sector highly contribute to the total number of ICT patents.

Another interesting finding from Table 1 is that 53% of the firms do not report R&D expenditures, meaning that they do not formally do R&D. However, only recently Rammer, Czarnitzki, and Spielkamp (2009) show that firms that do not do formal R&D might be nevertheless innovative. This finding also corresponds to Acs and Audretsch (1990), who argue that smaller firms are on average more innovative but the likelihood that a firm is engaged actively in formal R&D processes and has R&D labs increases significantly with firm size.

4. Empirical model and estimation strategy

Scholars interested in explaining the number of inventions generated by firms typically rely on the concept of the knowledge production function (Griliches 1979; Pakes and Griliches 1980, 1984; Jaffe 1986). It assumes that the existing stock of knowledge of firms is the main production factor of new knowledge, which is often measured by patents granted.¹⁰ Following this approach, in our empirical model the dependent variable is the firm i 's number of (pure) ICT or green ICT patents in year t , respectively (hereinafter $p_{i,t}$).¹¹ In line with the knowledge production function approach, we assume that knowledge creation is explained by a vector of variables $x_{i,t}$ which includes the knowledge stock $k_{i,t}$. $p_{i,t}$ given $x_{i,t}$ is assumed to be Poisson distributed, so that the mean parameter of the resulting density in log-linear form is given by $\mu = e^{(x'_{i,t}\beta)}$, where β is a vector of coefficients to be estimated. Allowing for a firm-specific constant c_i , which accounts for differences in the propensity to patent, leads to the following Poisson regression model:¹²

$$p_{i,t} = \mu_{i,t} v_i + \varepsilon_{i,t}, \quad (3)$$

where $\mu_{i,t} = e^{(x'_{i,t}\beta)}$, $v_i = e^{(c_i)}$, and $\varepsilon_{i,t}$ is a random disturbance term. The most important component in $x_{i,t}$ is the existing stock of knowledge ($k_{i,t}$), which depends on past and current levels of R&D inputs ($r_{i,t}$). As $p_{i,t-1}$ is produced by the input $k_{i,t-1}$ and the same 'production technology' as $p_{i,t}$, several authors (such as Blundell, Griffith, and Van Reenen 1995) propose to replace $k_{i,t}$ by the lagged dependent variable $p_{i,t-1}$ which can be considered a noisy measure of lagged inputs.¹³

Including the lagged dependent variable into $x_{i,t}$, however, comes with several econometric problems where the most obvious one is a violation of the assumption of strict exogeneity.¹⁴ Several

Table 2. Share of ICT patents by sectors (10 most important ones).

| Sector | Nace 2/ISIS 4 | Type of ICT | |
|---------------------------------------|---------------|--------------|-------------|
| | | All ICT | Green ICT |
| Manuf. of computers and optical prod. | 26 | 32.21% (171) | 40.71% (32) |
| Telecommunications | 61 | 9.14% (8) | 6.11% (3) |
| Manuf. of machinery and equip. n.e.c. | 28 | 5.77% (123) | 2.55% (12) |
| Manuf. of motor vehicles, trailers | 29 | 5.31% (21) | 7.00% (7) |
| Printing and recorded media | 18 | 5.16% (3) | 1.15% (3) |
| Manuf. of pharmaceutical products | 21 | 4.49% (16) | 0.76% (2) |
| Installation and repair of machinery | 33 | 4.49% (11) | 1.27% (5) |
| Manuf. of electrical equipment | 27 | 4.48% (61) | 6.23% (14) |
| Wholesale trade | 46 | 4.24% (32) | 2.42% (2) |
| Scientific research and development | 72 | 4.05% (75) | 5.34% (22) |

Notes: Number of patent holders by sector in parentheses.

solutions to this problem have been proposed, such as the use of quasi-first-differenced GMM estimation techniques (see Chamberlain 1992; Wooldridge 1997). However, Blundell, Griffith, and Windmeijer (2002) argue that including the lagged dependent variable in the exponential term in equation (3) can result in computational difficulties due to explosive series. They therefore suggest to exclude it from $\mu_{i,t} = e^{(\alpha'_{i,t}\beta)}$ and to include it in a linear form. The resulting linear feedback regression model reads as:

$$p_{i,t} = \lambda p_{i,t-1} + e^{(\alpha + \alpha'_{i,t}\beta + \phi \ln \bar{p}_i)} + \varepsilon_{i,t}, \quad (4)$$

where α is a constant and the vector $\alpha_{i,t}$ includes, amongst other controls, the R&D input $r_{i,t}$ and the spillover pool $\sum_{j \neq i}^n r_{j,t}$ which are not controlled for by the lagged dependent variable. Moreover, most importantly, $\alpha_{i,t}$ includes the variable of interest, $a_{d,t}$, which measures technological opportunities. Blundell, Griffith, and Van Reenen (1995) and Blundell, Griffith, and Windmeijer (2002) further suggest including the pre-sample mean of the dependent variable, $\ln \bar{p}_i$, to deal with both the presence of firm-specific effects and with the violation of the strict exogeneity assumption. The pre-sample mean is the mean of the dependent variable before the sample period and shall catch up any firm-specific differences in the propensity to patent. As a side-effect, it also eliminates the potential source of endogeneity bias arising from the inclusion of the lagged dependent variable and the pre-determined regressor. This is because the pre-sample means are dated earlier than the other regressors and control for any systematic firm-specific differences in the success of the invention process. If the pre-sample means can rule out systematic differences in invention success, what remains in the error term is pure random success and failure in invention activities. Thus, if this assumption holds, the error term is uncorrelated with potentially pre-determined regressors (Blundell, Griffith, and Windmeijer 2002). Blundell, Griffith, and Windmeijer (2002) propose to estimate model (4) by method of moment (GMM) estimation techniques where the resulting sample moment conditions read as:

$$\sum_{i=1}^N \sum_{t=2}^T \mathbf{z}_{it} (p_{i,t} - \lambda p_{i,t-1} - e^{(\alpha + \alpha'_{i,t}\beta + \phi \ln \bar{p}_i)}) = 0, \quad (5)$$

where $\mathbf{z}_{i,t} = (1, p_{i,t-1}, \alpha_{i,t}, \bar{p}_i)$ denotes the vector of instruments.¹⁵ The exogeneity of $\mathbf{z}_{i,t}$, i.e. orthogonality of $\mathbf{z}_{i,t}$ and $\varepsilon_{i,t}$, will be tested by using a Sargan test. Next to this econometric specification we provide additional results based on Pooled OLS, LPM and a Fixed-Effects panel specification.

Control variables: To implement our specification empirically, next to our two main variables of interest (those for innovation and for technological opportunities), we construct several additional control variables. In line with our model, we control for the current year's contribution to the knowledge stock by including firms' total R&D expenditures scaled by the number of total employees (to avoid multi-collinearity with firm size). This R&D intensity variable enters the model in the same year as patent output is observed. We consider R&D intensity as a control for differences in relative R&D spending across firms and time, rather than as a variable of primary interest.¹⁶

Another factor we control for is the contribution of other firms to a common spillover pool. This contribution is accounted for by NACE2 2-digit sector-level R&D data provided by the OECD Structural Analysis Database for very broadly defined sectors. Subtracting firm i 's own R&D spending from the sector-level R&D allows excluding internal R&D that is still controlled for and allows the external R&D information to vary also in the cross-sectional dimension. The resulting purely external R&D expenditures are multiplied by the share of the sectors' ICT patents in all patents to have a measure for the sectors' R&D expenditures directly related to ICT.¹⁷ The effect of external knowledge from previous years on current inventions is assumed to be captured by a lagged dependent variable.

The pre-sample means, as outlined in the empirical model, are constructed as the means of the respective dependent variable (either ICT or green ICT patents) over a period of five years before the firm appears for the first time in our database.¹⁸

Next to variables directly related to our model, we also control for additional innovation drivers. Market structure is an important determinant of innovation and innovation opportunities. We include a self-constructed measure of the Herfindahl Index as an additional control variable.¹⁹ This measure is not based on the firms in the panel dataset used for the empirical analysis but is based on the underlying sampling database which consists of around 130,000 firms. This sampling base is representative and stratified by sector and size and allows us to construct unbiased measures of market concentration based on these firms sales numbers. The final Herfindahl-Index numbers are constructed as the sum of the squared market shares of the firms in their own NACE Rev. 2.0 four-digit sector.²⁰

A control variable for firm size is included, too. It is measured as the full-time equivalent number of employees.²¹ In addition to size, also firm age may be an important predictor of innovative outputs.²² We add a linear and a quadratic age term to control for any non-linear relationship between firm age and innovative output. A final control variable addresses the fact that firms located in the eastern part of Germany received high amounts of subsidies to foster their economic development. Given that and a different economic history in this area, we include a dummy variable that is set to one if a firm is located in the Eastern part of Germany and zero otherwise.

5. Results

The results we obtain from applying the outlined empirical framework are discussed in the following.

5.1. Main results

In this section we report our baseline results where we study the role of technological opportunities in Green ICT innovation by using our baseline proxy for technological opportunities. The subsequent section then provides robustness checks where we apply alternative econometric methods and alternative measures of technological opportunities.

In Table 3 we show the results we obtain by applying the outlined GMM estimator. All three specifications have the number of patents in period t as the dependent variable. In specification (1) it is the number of all ICT patents, in specification (2) it is the number of Green ICT patents and in specification (3) it is the number of pure ICT patents, i.e. the number of non-green ICT patents. The variable of interest, our measure of technological opportunities, is the dummy equal to one if the firm has at least one patent with a high-opportunity ICT IPC class in $t-1$. In specification (1), we find a positive and significant effect of technological opportunities. This result, in combination with our findings from the robustness checks section, supports hypothesis I, stating that firms active in high-opportunity areas in period $t-1$ are more efficient in terms of innovation and thus are more likely to innovate in period t . Quantitatively, *ceteris paribus*, we expect firms which are active in high-opportunity technology areas to have 0.68 patents more in the year after.

Specification (2) and (3) are concerned with hypothesis II which deals with the direction of technical change and which states that firms being active in high-opportunity ICT technologies are less likely to switch to Green ICT technologies but are more likely to go on innovating in pure ICT technologies. Indeed, our results support this idea: in specification (2) we find an insignificant negative effect of technological opportunities, whereas in specification (3) we find a positive significant one. This indicates that past innovation in high-opportunity ICT IPC classes increases the likelihood of subsequent innovation in pure ICT technologies relative to subsequent innovation in Green ICT technologies. Firms without past innovation in areas of high technological opportunities have a lower likelihood to stay in pure ICT innovation relative to Green ICT innovation, i.e. they are more likely to switch technological areas. Thus, the results are in line with hypothesis II and can be considered first evidence that technological opportunities affect the direction of technical change, i.e. high-opportunity firms stay in their technological domain, whereas low-opportunity firms switch technological domains.

Table 3. Technological opportunities (weighted) and innovation.

| Dependent variable: number of patents _{<i>t</i>} | All ICT 1 | Green ICT 2 | Pure ICT 3 |
|---|---------------------|----------------------|---------------------|
| <i>Linear Feedback Part</i> | | | |
| Number of patents in $t-1$ | 0.661*** (0.117) | 0.531*** (0.120) | 0.681*** (0.112) |
| <i>Log-Link Part</i> | | | |
| Constant | -4.798** (1.941) | -6.832** (2.925) | -5.636** (2.437) |
| ln(R& D-intensity in t) (R& D/employ.) | 0.011 (0.024) | 0.021 (0.044) | 0.014 (0.029) |
| Dummy for missing R& D information in t | 0.263 (0.314) | 0.216 (0.749) | 0.323 (0.373) |
| ln(firm size in t) (no. of employees) | 0.398*** (0.094) | 0.304*** (0.082) | 0.422*** (0.108) |
| Dummy for weigh. high-opp. ICT IPC $t-1$ | 0.684* (0.377) | -0.203 (0.343) | 1.071* (0.650) |
| Dummy for no patents in $t-1$ | -0.427 (0.682) | -2.056*** (0.321) | 0.059 (1.072) |
| ln(Herfindahl $t-1$) | 0.185** (0.088) | 0.382* (0.199) | 0.166* (0.095) |
| ln(external R& D, NACE 2-dig. sector) | 0.042 (0.067) | -0.037 (0.114) | 0.056 (0.073) |
| ln(firm age in t) | -0.151 (0.157) | 0.698* (0.405) | -0.203 (0.161) |
| ln(firm age in t) ² | 0.025 (0.030) | -0.153** (0.062) | 0.040 (0.031) |
| Dummy for location in East Germany in t | -0.079 (0.278) | -0.523 (0.846) | 0.004 (0.301) |
| ln(pre-sample mean) (of the dependent var.) | 0.613*** (0.091) | 1.491*** (0.308) | 0.603*** (0.100) |
| Observations | 8653 | 8653 | 8653 |
| Hansen <i>J</i> -test statistic | 0.975 | 2.855 | 0.771 |
| Hansen <i>J</i> -test [<i>p</i> -value] | [0.614] | [0.240] | [0.680] |

Notes: [†]The model includes 5 insignificant three-year period dummies and 13 sector dummies. [‡]The quantity index of ICT capital services (EU KLEMS) by sectors serve as additional instruments. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

To a large extent, the remaining variables show signs one would expect or coefficients which are insignificant. Larger firms are more likely to have new innovations. This effect is larger for pure ICT patents than for Green ICT patents. The R&D-intensity has a positive but insignificant effect. The Herfindahl-Index shows a positive and significant coefficient, indicating that firms are the more innovative, the lower the degree of competition, a finding which is not against previous results (see e.g. Aghion et al. 2005). Finally, firm age shows for Green ICT innovation an inverted u-shaped relationship. Very young and very old firms are less likely to innovate compared to middle-aged firms. For non-green ICT innovations both the age and the age-squared variable are insignificant.

5.2. Robustness checks

To test the robustness of our results we apply alternative econometric methods as well as alternative measures of technological opportunities and of the direction of technical change. In Table A1 we provide results based on a simple and transparent Pooled OLS estimator. It yields similar results as our baseline specification: we find positive significant effects for technological opportunities in the specification with all patents and in the one with only pure ICT patents. For Green ICT innovations we again find a negative, insignificant effect. In addition, in this table we provide a specification where the dependent variable is the difference between the number of pure ICT patents and the number of green ICT patents (pure minus green ICT patents). In this latter specification the dummy for high opportunity patents is positive and significant which illustrates the effect of technological opportunities on the direction of technical change in an alternative way. Firms having patents

in high technological opportunity ICT areas proceed innovating in pure ICT research areas whereas those which do not have such patents change their direction of innovation and innovate relatively more often in Green ICT areas.

Table A2 applies a Fixed-Effects panel estimator, which allows controlling directly for firm-specific unobserved heterogeneity.²³ With it, we again find similar results as before. We find a positive albeit insignificant effect of technological opportunities on all patents and still find a positive significant effect on pure ICT patents. The specification with Green ICT patents again shows a negative but insignificant effect. Specification 4, which studies the difference between pure and green ICT patents, again shows a positive significant effect. Taken together, these results also support the idea that technological opportunities affect the direction of technical change.

Table A3 provides evidence based on another empirical specification, namely a linear probability model (LPM). The dependent variable in specifications 1–3 is a dummy equal to one if firm i has in year t at least one patent, green ICT or pure ICT patent. In specification 4 the dependent variable is a dummy equal to one if the firm has more pure ICT patents than green ICT patents. A LPM model can be advantageous in a setting such as ours since it is less sensitive to observations with extremely high or extremely low values of the dependent variable, a typical feature of patent data. Since the distribution of patents among firms is extremely skewed, which is one reason for the choice of the poisson model, it is reassuring that our LPM results support our baseline findings. In all four specifications we find a positive significant effect of technological opportunities. Thus, our findings again support hypothesis 1 stating that high technological opportunities come with a higher subsequent innovation likelihood. In a similar way specifications 2, 3 and 4 support the second hypothesis. Although specification 2 shows a positive significant effect, the effect is around 60% smaller than the one in specification 3, again supporting the idea that high opportunities come with a higher subsequent likelihood to stay in the technological field the firm has been active before. Column 4 corroborates this latter finding directly by showing again the positive relationship between high opportunity claims and a relatively high subsequent innovation activity in pure ICT.

Finally, **Table A4** contains another set of results based on our baseline econometric approach where we however use an alternative measure of technological opportunities. Instead of a dummy which is equal to one if a firm has any high opportunity claims, in these specifications we use the share of high opportunity claims as a measure of firms' activity in high opportunity technology fields. These results show again a positive significant effect for all patents, but show no significant effect for the subgroups of green and pure ICT patents. However, these weak results could be due to the fact that the share measure is quite noisy since we here do not directly control for the total number of claims.

6. Conclusion

Technological opportunities are a central element in the innovation process. The present article aims to fill a gap in the literature on green innovation by assessing the role of technological opportunities for the development of green ICT innovation. Green ICT are important since they are a key enabler of economic growth and can enhance the environmental performance of other sectors which has important consequences for climate policy.

We study the role of technological opportunities for green innovation by testing two research questions: (1) whether technological opportunities affect the efficiency of research, i.e. the rate of innovation, and (2) whether firms which are relatively active in low-opportunity technologies are more likely to switch from non-green to green technological areas than firms relatively active in high-opportunity areas. We study those research questions for the case of Green ICT. To implement our study empirically, we construct a firm-level panel data set for the years 1992–2009 which combines information on patents from the EPO and data from the Mannheim Innovation Panel. The results are based on dynamic count data estimation models applying GMM estimators as well as several robustness checks. We find that, controlling for path dependency, size, age, R&D intensity,

the degree of competition and further relevant factors, technological opportunities indeed play an important role for the rate and direction of technical change. Firms active in low opportunity fields are less likely to innovate but are relatively more likely to change their direction of technical change by becoming Green ICT inventors.

Our work provides first empirical evidence on the role of technological opportunities in green innovation and at the same time offers valuable insights for policy interventions which aim at stimulating green innovation (in the ICT sector). Our results show that such policy interventions are more effective, i.e. can be realized at lower costs, in low opportunity areas, since firms there have a tendency to change the direction of technical change. However, our work is descriptive in scope and can only be seen as first, but important evidence regarding this topic. Our article has important implications for environmental policy as it suggests that policy interventions are needed to reach certain levels of green growth in particular when technological opportunities are low. Future research should aim at corroborating our findings, especially those with respect to the role of technologies for the direction of technical change.

Notes

1. Green general purpose technologies are environmentally-friendly technologies that can affect a wide array of economic processes within an economy. They play an important role for economic growth (Cecere et al. 2014). Drivers of their development have been studied, for example by Ardito, Petruzzelli, and Albino (2016) who find that the search breadth across knowledge domains is related to an invention's technological generality. Green ICT represent an interesting example of GGPT (Pearson and Foxon 2012). Two strands of literature analyze Green ICT. On the one hand, several studies try to quantify ex-post the effect of the increasing use of ICT in production and consumption processes on environmental quantities such as energy use (Collard, Fève, and Portier 2005; Bernstein and Madlener 2010; Schulte, Welsch, and Rexhäuser 2016). This literature shows varying evidence regarding the direction of the effect but is united by the assessment that ICT is closely related to energy use developments. A second strand, smaller but more closely related to our work, focuses on potential drivers of green innovation in ICT. Faucheux and Nicolai (2011) provide a first overview over the area of Green ICT (innovation) but do not conduct an analysis of potential innovation drivers. Using patent data, Cecere et al. (2014) show that innovative activity in green ICT is associated with high levels of technological pervasiveness.
2. See e.g. Aghion et al. (2016) who study how previous innovation influences future innovative activities in the automotive industry. Their results show that the process of technological development is path dependent, thus firms that have inventions in dirty technologies will find it more profitable to continue innovating in dirty technologies instead of switching to clean technologies.
3. Note that this property of the data likely comes at the expense of losing some very young and innovative start-up companies in the IT sector. In other words, the results of this study refer to rather established firms.
4. The yearly response rate to the German CIS survey is approximately 25%, which is relatively high when taking into account that participating in the survey is – in contrast to some other European countries – not mandatory. The underlying sampling base of firms used for these surveys consists of 130,000 firms and is drawn from the official Creditreform database that covers almost all of the 3.6 million German firms.
5. The logic behind this restriction of the sample is obvious. Using all firms instead of the firms that have at least one patent in the ICT technological domain would dramatically increase the sample size, however, these firms would always show up as having no patents. In terms of a regression analysis this means that for these firms, the dependent variable is always zero in each year of the panel. Thus, these observations would not help identifying the effects of interest and would only increase the sample size and thus the degrees of freedom with the obvious consequence of increasing the level of significance. For this reason, the sample is restricted to firms that have at least one ICT patent granted by the EPO – no matter in which year.
6. Of course, as is well known, patent data are not without drawbacks. For example, not all inventions are applied for patent protection or get it granted and the importance of patent protection varies significantly across different sectors (Mansfield 1986; Levin et al. 1987). Another disadvantage of using patent data is that patent protection is perceived a more useful way to protect intellectual property for product innovations rather than for process technology (Levin et al. 1987). Moreover, the process of applying for patent protection and receiving a grant usually takes some time. In the area of information technologies where there are short technology and product life cycles, other possibilities to protect inventions may therefore be used too, such as secrecy and leading time, see Friedman, Landes, and Posner (1991) for an extensive discussion on that issue.
7. Alternatively, one could identify ICT inventions not by making use of IPC classes but by focusing on the ICT sector affiliation of patent holders that hold green technologies (based on the WIPO IPC codes). The advantage of such a

less strict definition would be that one can focus on firms in the ICT sector no matter whether they have ICT patents or not. As not all inventions receive patent protection – especially software inventions – this definition allows considering all green inventions from the ICT sector as green ICT inventions. Conversely, a more strict definition would be to restrict the ICT inventions as defined before on IPC codes for both ICT and green technologies to the ICT sector. This, however, comes at the expense of excluding green ICT technologies from other sectors such as the automotive sector.

8. An increasing number of world-wide patents can signal economic growth, higher spendings for R&D, and so on. In other words, it is important to look at the number of ICT patents in a certain technological area relative to the development of the number of patents in all other areas.
9. According to the OECD definition of ICT IPC codes, more than 10,000 different technology classes exist at the full detail (subgroup) level (e.g. H04L 1/02), such that only very few patents per class and year exist, resulting in highly volatile time series, which makes a classification based on it not very informative.
10. Pakes and Griliches (1980) find that there is a strong correlation between the input factor R&D and patents. In other words, patents serve as a good output indicator for inventions. What makes it especially appealing for the purpose of this study is that it allows associating inventive output with several technological fields. However, the use of patents to protect intellectual property varies largely between sectors (Mansfield 1986; Levin et al. 1987). In addition, it varies also across types of innovations: patent protection is identified to play a more important role for the protection of product innovations than of process innovations (Levin et al. 1987). Note further that not all inventions can be registered for patent protection, as e.g. software in case of the EPO. See also Griliches (1990) for a more detailed discussion on the use of patents as an indicator for inventions.
11. This is a strictly non-negative integer variable with a considerable number of the firm-year observations being zero.
12. See Cameron and Trivedi (2013) for a general introduction into count data models.
13. In our case, this procedure is advantageous as there is a lot of missing information in firms' R&D data for observations dated earlier than t which would lead to a smaller sample and potential sample selection issues if a distributed lag model would be applied. Using a lagged dependent variable helps overcome this problem as typically it is assumed that $k_{i,t}$ can be replaced by $p_{i,t-1}$, $r_{i,t}$, and $\theta_{i,t} \sum_{j \neq i} r_{j,t}$, where $\theta_{i,t} = \theta(k_{i,t-1})$ is a measure of absorptive capacities. The absorptive capacity in t , $\theta_{i,t}$, itself is often assumed to be a function of firm i 's knowledge stock and highly correlates with $p_{i,t-1}$ such that $p_{i,t-1}$ can be regarded as to catch up this effect. What then would remain is $\sum_{j \neq i} r_{j,t}$ (all other firms' contribution in t to the spillover pool) that is time-invariant but does hardly vary between firms.
14. This problem in dynamic panel data models is due to the fact that $p_{i,t-1}$ is likely to be correlated with $\varepsilon_{i,t}$, because $\varepsilon_{i,t}$ is likely to be serially correlated with $\varepsilon_{i,t-1}$. In other words, $p_{i,t-1}$ is a predetermined regressor which makes the standard Poisson model likely to be inconsistent.
15. Note that $\mathbf{z}_{i,t}$ does not include an instrument (excluded in the main equation) for $p_{i,t-1}$ as endogeneity is assumed to be ruled out in the presence of pre-sample means. This assumption is rather strong as systematic firm-specific differences in invention activities and success are assumed to be time-invariant.
16. Note that the causality can also run in the opposite direction so that successful innovation can give rise to more R&D as this 'productive' factor should be used more intensively (Arora, Ceccagnoli, and Cohen 2008; Czarnitzki, Kraft, and Thorwarth 2009).
17. Note that the sectors are defined very broadly to allow for 'inter-sectoral' spillovers across similar sectors. We abstain from estimating spillovers from close competitors, i.e. firms in the same technological area defined by proximity of patents as for instance done by Jaffe (1989). This is because we have a representative sample of rather small firms having only few patents and because the spillover effects are assumed to be accounted for by including the lagged number of patents.
18. As the first year in the database is 1992 and as patent data is available from 1978 onwards, this is no problem. Note that the firm panel is highly unbalanced which means that the pre-sample period necessarily varies across firms.
19. Official data for market concentration exists and is provided by the German Monopoly Commission. However, the most recent data is provided only for the NACE Rev. 2.0 industry classification. In contrast, for earlier years a different sector classification is used and for even earlier years in the 1990s a completely different classification is the base for the concentration measures. It was not possible to create a concordance between the different sector classification schemes at a sufficient level of sectoral desegregation which would allow deriving reliable measures of market concentration.
20. For the market share, we assume that total sales of all firms in a four-digit level sector are a good proxy for the total sales in this sector and that there are no systematic differences with respect to the true sales numbers across sectors.
21. It enters the regression model in natural logarithms and is included in the non-linear (log-link) part of the regression equation.
22. Note that there is a long history of scientific economic work on this issue, which is not the core subject of this study. We therefore refer to the excellent survey by Cohen (2010).

23. In this specification we neglect the lagged dependent variable since it is well known that a Fixed-Effects estimator applied to a dynamic model is biased with a high likelihood.

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References

- Acemoglu, Daron, Philippe Aghion, Leonardo Burszty, and David Hemous. 2012. "The Environment and Directed Technical Change." *American Economic Review* 102 (1): 131–166.
- Acs, Zoltan J., and David B. Audretsch. 1990. *Innovation and Small Firms*. MIT Press.
- Aghion, Philippe, Nicholas Bloom, Richard Blundell, Rachel Griffith, and Peter Howitt. 2005. "Competition and Innovation: An Inverted-U Relationship." *Quarterly Journal of Economics* 120: 701–728.
- Aghion, Philippe, Antoine Dechezlepretre, David Hemous, Ralf Martin, and John Van Reenen. 2016. "Carbon Taxes, Path Dependency and Directed Technical Change: Evidence from the Auto Industry." *Journal of Political Economy* 124 (1): 1–51.
- Albino, Vito, Lorenzo Ardito, Rosa Maria Dangelico, and Antonio Messeni Petruzzelli. 2014. "Understanding the Development Trends of Low-carbon Energy Technologies: A Patent Analysis." *Applied Energy* 135: 836–854.
- Eurostat. 2015. Annual Enterprise Statistics for Special Aggregates of Activities (NACE Rev. 2) (sbs_na_sca_r2).
- Ardito, Lorenzo, Antonio Messeni Petruzzelli, and Vito Albino. 2016. "Investigating the Antecedents of General Purpose Technologies: A Patent Perspective in the Green Energy Field." *Journal of Engineering and Technology Management* 39: 81–100.
- Arora, Ashish, Marco Ceccagnoli, and Wesley M. Cohen. 2008. "R&D and the Patent Premium." *Research Policy* 26 (5): 1153–1179.
- Barbieri, Nicolò, Claudia Ghisetti, Marianna Gilli, Giovanni Marin, and Francesco Nicolli. 2016. "A Survey of the Literature on Environmental Innovation Based on Main Path Analysis." *Journal of Economic Surveys* 30 (3): 596–623.
- Barge-Gil, Andrés, and Alberto López. 2014. "R&D Determinants: Accounting for the Differences Between Research and Development." *Research Policy* 43 (9): 1634–1648.
- Bernstein, Ronald, and Reinhard Madlener. 2010. "Impact of Disaggregated ICT Capital on Electricity Intensity in European Manufacturing." *Applied Economics Letters* 17 (17): 1691–1695.
- Blundell, Richard, Rachel Griffith, and John Van Reenen. 1995. "Dynamic Count Data Models of Technological Innovation." *Economic Journal* 105 (429): 333–344.
- Blundell, Richard, Rachel Griffith, and Frank Windmeijer. 2002. "Individual Effects and Dynamics in Count Data Models." *Journal of Econometrics* 108 (1): 113–131.
- Breschi, Stefano, Franco Malerba, and Luigi Orsenigo. 2000. "Technological Regimes and Schumpeterian Patterns of Innovation." *Economic Journal* 110 (463): 388–410.
- Bresnahan, Timothy F., and Manuel Trajtenberg. 1995. "General Purpose Technologies: 'Engines of Growth?'" *Journal of Econometrics* 65 (1): 83–108.
- Brunnermeier, Smita B., and Mark A. Cohen. 2003. "Determinants of Environmental Innovation in US Manufacturing Industries." *Journal of Environmental Economics and Management* 45 (2): 278–293.
- Cameron, A. Colin, and Pravin K. Trivedi. 2013. *Regression Analysis of Count Data*. 2nd ed. New York: Cambridge University Press.
- Cecere, Grazia, Nicoletta Corrocher, Cedric Gossart, and Muge Ozman. 2014. "Technological Pervasiveness and Variety of Innovators in Green ICT: A Patent-Based Analysis." *Research Policy* 43 (10): 1827–1839.
- Chamberlain, Gary. 1992. "Comment: Sequential Moment Restrictions in Panel Data." *Journal of Business & Economic Statistics* 10 (1): 20–26.

- Cohen, Wesley M. 2010. "Fifty Years of Empirical Studies of Innovative Activity and Performance." Chap. 4 in *Handbook of the Economics of Innovation*, edited by B. H. Hall, and N. Rosenberg, 129–213. Amsterdam: North-Holland.
- Collard, Fabrice, Patrick Fève, and Franck Portier. 2005. "Electricity Consumption and ICT in the French Service Sector." *Energy Economics* 27 (3): 541–550.
- Corrocher, Nicoletta, Franco Malerba, and Fabio Montobbio. 2007. "Schumpeterian Patterns of Innovative Activity in the ICT Field." *Research Policy* 36 (3): 418–432.
- Crépon, Bruno, Emmanuel Duguet, and Jacques Mairesse. 1998. "Research, Innovation and Productivity: An Econometric Analysis at the Firm Level." *Economics of Innovation and New Technology* 7 (2): 115–158.
- Czarnitzki, Dirk, Kornelius Kraft, and Susanne Thorwarth. 2009. "The Knowledge Production of 'R' and 'D'." *Economics Letters* 105 (1): 141–143.
- David, Paul A. 1985. "Clio and the Economic of QWERTY." *American Economic Review* 75 (2): 332–337.
- Dosi, Giovanni. 1982. "Technological Paradigms and Technological Trajectories: A Suggested Interpretation of the Determinants and Directions of Technical Change." *Research Policy* 11 (3): 147–162.
- Faucheux, Sylvie, and Isabelle Nicolai. 2011. "IT for Green and Green IT: A Proposed Typology of Eco-Innovation." *Ecological Economics* 70 (11): 2020–2027.
- Friedman, David D., William M. Landes, and Richard A. Posner. 1991. "Some Economics of Trade Secret Law." *Journal of Economic Perspectives* 5 (1): 61–72.
- Geroski, Paul A. 1990. "Innovation, Technological Opportunity, and Market Structure." *Oxford Economic Papers* 42 (3): 586–602.
- Griliches, Zvi. 1979. "Issues in Assessing the Contribution of Research and Development to Productivity Growth." *Bell Journal of Economics* 10 (1): 92–116.
- Griliches, Zvi. 1990. "Patent Statistics as Economic Indicators: A Survey." *Journal of Economic Literature* 28 (4): 1661–1707.
- Jaffe, Adam B. 1986. "Technological Opportunity and Spillovers of R & D: Evidence from Firms' Patents, Profits, and Market Value." *American Economic Review* 76 (5): 984–1001.
- Jaffe, Adam B. 1989. "Characterizing the 'Technological Position' of Firms, with Application to Quantifying Technological Opportunity and Research Spillovers." *Research Policy* 18 (2): 87–97.
- Jaffe, Adam B., Richard G. Newell, and Robert N. Stavins. 2003. "Technological change and the Environment." In *Handbook of Environmental Economics*. Vol. 1., edited by Karl-Göran Mäle, and Jeffrey R. Vincent, 416–516. Elsevier. "Technological Change and the Environment." In *Handbook of Environmental Economics*. Vol. I, 461–516.
- Jaffe, Adam B., and Karen Palmer. 1997. "Environmental Regulation and Innovation: A Panel Data Study." *Review of Economics and Statistics* 79 (4): 610–619.
- Johnstone, Nick, Ivan Hascic, and David Popp. 2010. "Renewable Energy Policies and Technological Innovation: Evidence Based on Patent Counts." *Environmental and Resource Economics* 45 (1): 133–155.
- Klevorick, Alvin K., Richard C. Levin, Richard R. Nelson, and Sidney G. Winter. 1995. "On the Sources and Significance of Interindustry Differences in Technological Opportunities." *Research Policy* 24 (2): 185–205.
- Kumar, N., and N. S. Siddharthan. 1997. *Technology, Market Structure and Internationalization*. London: UNU Press.
- Levin, Richard C., Wesley M. Cohen, and David C. Mowery. 1985. "R & D Appropriability, Opportunity, and Market Structure: New Evidence on Some Schumpeterian Hypotheses." *American Economic Review* 75 (2): 20–24.
- Levin, Richard C., Alvin K. Klevorick, Richard R. Nelson, Sidney G. Winter, Richard Gilbert, and Zvi Griliches. 1987. "Appropriating the Returns from Industrial Research and Development." *Brookings Papers on Economic Activity* 1987 (3): 783–831.
- Malerba, Franco, and Luigi Orsenigo. 1996. "Schumpeterian Patterns of Innovation are Technology Specific." *Research Policy* 25 (3): 451–478.
- Mansfield, Edwin. 1986. "Patents and Innovation: An Empirical Study." *Management Science* 32 (2): 173–181.
- Newell, Richard G., Adam B. Jaffe, and Robert N. Stavins. 1999. "The Induced Innovation Hypothesis and Energy-Saving Technological Change." *Quarterly Journal of Economics* 114 (3): 941–975.
- OECD. 2016. OECD Patent Databases: Identifying Technology Areas for Patents. <https://protect-us.mimecast.com/s/g5YZBRF3xxwMVtx?domain=oe.cd.org>.
- Oltra, Vanessa, René Kemp, and Frans de Vries. 2010. "Patents as a Measure for Eco-Innovation." *International Journal of Environmental Technology and Management* 13 (2): 130–148.
- Pakes, Ariel, and Zvi Griliches. 1980. "Patents and R&D at the Firm Level: A First Report." *Economics Letters* 5 (4): 377–381.
- Pakes, Ariel, and Zvi Griliches. 1984. "Patents and R&D at the Firm Level: A First Look." Chap. 3 in *R&D, Patents, and Productivity*, edited by Zvi Griliches, 55–72. National Bureau of Economic Research, Inc.
- Pearson, Peter J. G., and Timothy J. Foxon. 2012. "A Low Carbon Industrial Revolution? Insights and Challenges from Past Technological and Economic Transformations." *Energy Policy* 50: 117–127.
- Popp, David. 2002. "Induced Innovation and Energy Prices." *American Economic Review* 92 (1): 160–180.
- Rammer, Christian, Dirk Czarnitzki, and Alfred Spielkamp. 2009. "Innovation Success of Non-R&D-Performers: Substituting Technology by Management in SMEs." *Small Business Economics* 33: 35–58.
- Rexhäuser, Sascha, and Andreas Löschel. 2015. "Invention in Energy Technologies: Comparing Energy Efficiency and Renewable Energy Inventions at the Firm Level." *Energy Policy* 83: 206–217.

- Rosenberg, Nathan. 1994. *Exploring the Black Box: Technology, Economics, and History*. Cambridge, MA: Cambridge University Press.
- Scherer, Frederic M. 1965. "Firm Size, Market Structure, Opportunity, and the Output of Patented Inventions." *American Economic Review* 55 (5): 1097–1125.
- Scherer, Frederic M. 1967. "Market Structure and the Employment of Scientists and Engineers." *American Economic Review* 57 (3): 524–531.
- Schulte, Patrick, Heinz Welsch, and Sascha Rexhäuser. 2016. "ICT and the Demand for Energy: Evidence from OECD Countries." *Environmental and Resource Economics* 63 (1): 119–146.
- Wooldridge, Jeffrey M. 1997. "Multiplicative Panel Data Models Without the Strict Exogeneity Assumption." *Econometric Theory* 13 (5): 667–678.
- Zahra, Shaker A. 1996. "Governance, Ownership, and Corporate Entrepreneurship: The Moderating Impact of Industry Technological Opportunities." *Academy of Management Journal* 39 (6): 1713–1735.

Appendix: Tables

Table A1. Technological opportunities (weighted) and innovation (pooled OLS).

| Dependent variable: number of patents _{<i>t</i>} | All ICT 1 | Green ICT 2 | Pure ICT 3 | P/G ICT 4 |
|---|---------------------|---------------------|---------------------|---------------------|
| <i>Linear Feedback Part</i> | | | | |
| Number of patents in $t-1$ | 0.821*** (0.061) | 0.699*** (0.101) | 0.813*** (0.071) | 0.784*** (0.073) |
| <i>Log-Link Part</i> | | | | |
| Constant | −0.648 (0.513) | −0.036 (0.150) | −0.663 (0.474) | −0.725 (0.495) |
| ln(R& D-intensity in t) (R& D/employ.) | 0.010 (0.009) | −0.001 (0.002) | 0.011 (0.008) | 0.012 (0.009) |
| Dummy for missing R& D information in t | 0.103 (0.075) | −0.006 (0.021) | 0.117 (0.073) | 0.135* (0.075) |
| ln(firm size in t) (no. of employees) | 0.116*** (0.034) | 0.020** (0.009) | 0.107*** (0.032) | 0.104*** (0.031) |
| Dummy for weigh. high-opp. ICT IPC $t-1$ | 0.632* (0.366) | −0.059 (0.105) | 0.787** (0.352) | 1.059*** (0.359) |
| Dummy for no patents in $t-1$ | 0.227 (0.217) | −0.117** (0.046) | 0.294 (0.208) | 0.330* (0.190) |
| ln(Herfindahl $t-1$) | 0.050* (0.029) | 0.008 (0.006) | 0.048* (0.028) | 0.049* (0.028) |
| ln(external R& D, NACE 2-dig. sector) | −0.009 (0.021) | −0.001 (0.008) | −0.008 (0.019) | −0.005 (0.020) |
| ln(firm age in t) | 0.043 (0.064) | 0.008 (0.013) | 0.037 (0.061) | 0.030 (0.062) |
| ln(firm age in t) ² | −0.009 (0.014) | −0.003 (0.003) | −0.008 (0.014) | −0.007 (0.014) |
| Dummy for location in East Germany in t | 0.032 (0.057) | 0.004 (0.016) | 0.030 (0.053) | 0.035 (0.055) |
| Observations | 5597 | 5597 | 5597 | 5597 |

Notes: [†]The model includes 5 insignificant three-year period dummies and 13 sector dummies. [‡]The quantity index of ICT capital services (EU KLEMS) by sectors serve as additional instruments. Robust standard errors in parentheses. * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$.

Table A2. Technological opportunities (weighted) and innovation (panel).

| Dependent variable: number of patents _{<i>t</i>} | All ICT 1 | Green ICT 2 | Pure ICT 3 | P/G ICT 4 |
|---|-------------------|--------------------|--------------------|--------------------|
| <i>Linear Feedback Part</i> | | | | |
| Constant | −1.163 (4.513) | 1.145 (0.843) | −2.308 (4.115) | −3.453 (3.862) |
| ln(R& D-intensity in <i>t</i>) (R& D/employ.) | −0.008 (0.014) | −0.002 (0.002) | −0.006 (0.014) | −0.005 (0.014) |
| Dummy for missing R& D information in <i>t</i> | −0.060 (0.110) | −0.022* (0.013) | −0.038 (0.110) | −0.016 (0.111) |
| ln(firm size in <i>t</i>) (no. of employees) | 0.801 (0.543) | −0.016 (0.017) | 0.817 (0.553) | 0.834 (0.562) |
| Dummy for weigh. high-opp. ICT IPC <i>t</i> −1 | 0.857 (0.573) | −0.130 (0.144) | 0.987** (0.495) | 1.116** (0.451) |
| Dummy for no patents in <i>t</i> −1 | −0.094 (0.244) | −0.115* (0.061) | 0.021 (0.209) | 0.136 (0.188) |
| ln(Herfindahl <i>t</i> −1) | −0.093 (0.072) | −0.003 (0.007) | −0.089 (0.071) | −0.086 (0.070) |
| ln(external R& D, NACE 2-dig. sector) | −0.098 (0.126) | −0.041 (0.038) | −0.057 (0.091) | −0.016 (0.058) |
| ln(firm age in <i>t</i>) | −0.131 (0.181) | 0.055 (0.037) | −0.187 (0.157) | −0.242* (0.139) |
| ln(firm age in <i>t</i>) ² | −0.027 (0.057) | −0.017 (0.014) | −0.011 (0.046) | 0.006 (0.036) |
| Observations | 8653 | 8653 | 8653 | 8653 |

Notes: [†]The model includes 5 insignificant three-year period dummies and 13 sector dummies. [‡]The quantity index of ICT capital services (EU KLEMS) by sectors serve as additional instruments. Robust standard errors in parentheses. **p* < 0.10, ***p* < 0.05, ****p* < 0.01.

Table A3. Technological opportunities (weighted) and innovation (LPM).

| Dependent variable: dummy for a patent _{<i>t</i>} | All ICT 1 | Green ICT 2 | Pure ICT 3 | P/G ICT 4 |
|--|---------------------|----------------------|----------------------|----------------------|
| <i>Linear Feedback Part</i> | | | | |
| Number of patents in <i>t</i> −1 | 0.246*** (0.022) | 0.292*** (0.035) | 0.248*** (0.023) | 0.220*** (0.023) |
| <i>Log-Link Part</i> | | | | |
| Constant | −0.083 (0.095) | −0.069 (0.042) | −0.103 (0.093) | −0.090 (0.093) |
| ln(R& D-intensity in <i>t</i>) (R& D/employ.) | 0.004*** (0.001) | 0.000 (0.001) | 0.004*** (0.001) | 0.004*** (0.001) |
| Dummy for missing R& D information in <i>t</i> | 0.036** (0.017) | 0.002 (0.007) | 0.039** (0.016) | 0.038** (0.016) |
| ln(firm size in <i>t</i>) (no. of employees) | 0.032*** (0.004) | 0.014*** (0.002) | 0.031*** (0.003) | 0.029*** (0.003) |
| Dummy for weigh. high-opp. ICT IPC <i>t</i> −1 | 0.163*** (0.035) | 0.060** (0.027) | 0.167*** (0.035) | 0.177*** (0.035) |
| Dummy for no patents in <i>t</i> −1 | −0.083** (0.032) | −0.054*** (0.015) | −0.084*** (0.032) | −0.088*** (0.032) |
| ln(Herfindahl <i>t</i> −1) | 0.011** (0.005) | 0.007*** (0.002) | 0.011** (0.005) | 0.010* (0.005) |
| ln(external R& D, NACE 2-dig. sector) | 0.001 (0.004) | −0.000 (0.002) | 0.002 (0.004) | 0.003 (0.004) |
| ln(firm age in <i>t</i>) | −0.006 (0.012) | 0.003 (0.006) | −0.001 (0.012) | −0.003 (0.012) |
| ln(firm age in <i>t</i>) ² | −0.001 (0.002) | −0.001 (0.001) | −0.002 (0.002) | −0.001 (0.002) |
| Dummy for location in East Germany in <i>t</i> | −0.008 (0.013) | 0.005 (0.006) | −0.010 (0.013) | −0.009 (0.013) |
| Observations | 5597 | 5597 | 5597 | 5597 |

Notes: [†]The model includes 5 insignificant three-year period dummies and 13 sector dummies. [‡]The quantity index of ICT capital services (EU KLEMS) by sectors serve as additional instruments. Robust standard errors in parentheses. **p* < 0.10, ***p* < 0.05, ****p* < 0.01.

Table A4. Technological opportunities (weighted) and innovation (share).

| Dependent variable: number of patents _{<i>t</i>} | All ICT 1 | Green ICT 2 | Pure ICT 3 |
|---|---------------------|----------------------|---------------------|
| <i>Linear Feedback Part</i> | | | |
| Number of patents in <i>t</i> –1 | 0.654*** (0.120) | 0.540*** (0.124) | 0.674*** (0.116) |
| <i>Log-Link Part</i> | | | |
| Constant | –5.007** (2.134) | –6.959** (3.006) | –5.825** (2.642) |
| ln(R& D-intensity in <i>t</i>) (R& D/employ.) | 0.008 (0.024) | 0.022 (0.043) | 0.011 (0.028) |
| Dummy for missing R& D information in <i>t</i> | 0.211 (0.309) | 0.208 (0.739) | 0.260 (0.366) |
| ln(firm size in <i>t</i>) (no. of employees) | 0.409*** (0.092) | 0.295*** (0.083) | 0.437*** (0.110) |
| Weigh. share of high-opp. ICT IPC cl. in <i>t</i> –1 | 0.009* (0.006) | –0.001 (0.004) | 0.012 (0.008) |
| Dummy for no patents in <i>t</i> –1 | –0.456 (0.808) | –1.994*** (0.312) | –0.097 (1.105) |
| ln(Herfindahl <i>t</i> –1) | 0.196** (0.087) | 0.379* (0.205) | 0.182* (0.094) |
| ln(external R& D, NACE 2-dig. sector) | 0.048 (0.068) | –0.034 (0.117) | 0.064 (0.075) |
| ln(firm age in <i>t</i>) | –0.150 (0.153) | 0.731* (0.424) | –0.200 (0.157) |
| ln(firm age in <i>t</i>) ² | 0.024 (0.029) | –0.157** (0.066) | 0.038 (0.030) |
| Dummy for location in East Germany in <i>t</i> | –0.100 (0.275) | –0.541 (0.882) | –0.034 (0.296) |
| ln(pre-sample mean) (of the dependent var.) | 1.498*** (0.321) | 0.667*** (0.083) | 0.680*** (0.085) |
| Observations | 8653 | 8653 | 8653 |
| Hansen <i>J</i> -test statistic | 1.100 | 2.841 | 0.892 |
| Hansen <i>J</i> -test [<i>p</i> -value] | [0.577] | [0.242] | [0.640] |

Notes: [†]The model includes 5 insignificant three-year period dummies and 13 sector dummies. [‡]The quantity index of ICT capital services (EU KLEMS) by sectors serve as additional instruments. Robust standard errors in parentheses. **p* < 0.10, ***p* < 0.05, ****p* < 0.01.