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Abstract - This paper aims to shed light on the role of technological opportunities for green innovation by studying the case of Green ICT innovation. We test two hypotheses: (1) Firms active in low-opportunity technological areas are less innovative; (2) Firms active in low-opportunity technological areas 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.
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1 Introduction

Innovation in environment-friendly, 'green', technologies is crucial to ensure sustainable growth. A large literature studies potential drivers of green innovation (for a survey see e.g. Jaffe et al., 2003). However, despite the well known fact that technology push factors, such as technological opportunities and path dependencies, are important determinants of innovation behaviour in general (Klevorick et al., 1995; Breschi et al., 2000), the literature studying environmental innovation has mainly focused on price- and regulation-induced innovation (see e.g. Jaffe and Palmer, 1997; Newell et al., 1999; Brunnermeier and Cohen, 2003; Popp, 2002; Johnstone et al., 2010). Some evidence with respect to the role of path dependencies for green innovation exists (Acemoglu et al., 2012; Aghion et al., forthcoming; Rexhäuser and Löschel, 2015), 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 tech-

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nological domain (Malerba and Orsengio, 1996; Corrocher et al., 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, i.e. in our case to switch from non-green to green technological areas. 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 the same time in both many high- and low-opportunity technologies (Corrocher et al., 2007). Also, ICT are a highly relevant field for studying green innovations, given ICT's ubiquity as a general purpose technology (GPT) (Bresnahan and Trajtenberg, 2002), and given that the use of ICT is shown to be closely related to energy use (see e.g. Schulte et al., 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 German Innovation Panel (Mannheim Innovation Panel). The 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

In order to study the role of technological opportunities for the development of green ICT we rely on the framework of technological push factors (Rosenberg, 1994). Technological opportunities describe the ease of innovative activities in a technological domain

(Malerba and Orsengio, 1996; Corrocher et al., 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. Cohen and Levinthal (1989) show that science based research and external sources of knowledge are important determinants of the technological opportunities. The empirical literature identifies different measures of technological opportunities. Scherer (1967) argues that technological opportunities are sector specific and thus distinguished low and high technological opportunity sectors. Using patent data, Jaffe (1986, 1989) identifies the pattern of technological opportunities applying cluster analysis. Levin et al. (1985) used a questionnaire to measure technological opportunities. Analyzing patenting activity, Corrocher et al. (2007) measure technological opportunities in the ICT sector using the growth rate of innovative activities. They show that internal technological knowledge plays a more prominent role for inventions in low opportunity technology ICT fields. The literature shows that high opportunity, i.e. fast growing, ICT fields are characterized by a high degree of diversification. For more details, see section 4.3.

We build on the established literature concerned with environmental innovation. This literature has identified several drivers of green innovation. In particular, regulation and induced technological change have been shown to have an important role in R&D investment decisions. In contrast, among technological push factors only the role of path-dependencies has been studied empirically. The induced innovation hypothesis, based on Hicks (1932), focuses on the impact of factor prices on the direction of innovation, relying on an innovation possibility frontier (Popp, 2002). Energy price-induced technical change is documented in several studies, such as Lichtenberg (1986), Newell et al. (1999), Popp (2002), or more recently Crabb and Johnson (2010). Among them, especially Popp (2002) shows that the increase in energy prices is positively associated with the production of energy-saving innovations (measured by patents) and thus provides evidence in favour of directed technical change. In addition, regulation is identified as a key driver of research in energy technologies (Jaffe and Palmer, 1997; Newell et al., 1999; Brunnermeier and Cohen, 2003; Popp, 2002; Johnstone et al., 2010). Jaffe and Palmer (1997) find no significant impact of regulatory compliance costs on patent applications but they corroborate the existence of the narrow version of the Porter hypothesis which states that stringency of regulation spurs innovation. Brunnermeier and Cohen (2003) provide evidence that environmental regulation and especially pollution abatement regulation induce environmental innovation. The literature of path dependency applied to green innovation (Acemoglu et al., 2012; Aghion et al., forthcoming; Rexhäuser and Löschel, 2015) suggests that both path-dependency and cumulativeness of knowledge are potential drivers of technical change (along a trajectory). Aghion et al. (forthcoming) 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.

The pervasiveness of certain types of green general purpose technologies (GPT), such as energy technologies and green ICT, are more and more considered a valuable mean to increase the usage of more environmentally-friendly technologies. In particular, ICT are defined as general purpose technologies as they can be used in different sectors and are the basis for several further innovations (Antonelli, 1998; Cardona et al., 2013). Green ICT represent an interesting example of green GPT (Pearson and Foxon, 2012; Cecere et al., 2014). With respect to Green ICT, two strands of literature exist. 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 et al., 2005; Bernstein and Madlener, 2010; Schulte et al., 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 Nicolaï (2011) provide a first overview over the area of Green ICT (innovation) but do not conduct an analysis of potential innovation drivers. Røpke (2012) explores the environmental directionality of the broadband transition focusing on energy impacts. She argues that innovation in ICT is directed into an unsustainable direction. Using patent data, Cecere et al. (2014) show that innovative activity in green ICT is associated with high levels of technological pervasiveness.

3 Data, Definitions, and Descriptive Statistics

The effect of technological opportunities on the rate and direction of technological change is studied using longitudinal data of German firms linked to patent data from the European Patent Office (hereinafter 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. Patent data is a good and frequently used indicator to measure technological inventions, not necessarily innovations. However, 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 et al. (1991) for an extensive discussion on that issue. Despite all these concerns, patent data allow us to investigate innovation at the technology area level and especially to analyze the rate of technical change over time.

3.1 Data and Definitions

Our empirical work is based on an original data set which merges the Mannheim Innovation Panel, 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. 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. The MIP is based on the Community Innovation Survey (CIS) for Germany and is conducted by the Centre for European Economic Research (ZEW), Mannheim, Germany. In contrast to most other European countries, the CIS is conducted annually in Germany so that a yearly unbalanced dataset of approximately 50,000 companies exists.[1]

This firm-level data from the MIP is matched to patent data from the PATSTAT database based on firm names and locations. In addition, all patents filed at EPO (from all countries) are used in a different step to derive measures of technological opportunities. More details on this issue will be given in Section 4.3. Note that most of the firms do not have patents granted by the European Patent Office (EPO), namely 87.65 percent of the 50,000 firms in the unbalanced panel dataset. Of the remaining 12.35 percent of firms that show up as patent holders, only approximately 31.86 percent are holders of patents in the ICT area. The classification of patents by technological domains is done using ipc codes (International Patenting Classification) for ICT technologies reported by the OECD.[2]

Throughout this study, environmentally-friendly technologies are referred to as "green technologies" and are measured using the patents' ipc codes. A green technology is defined in this study 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. All IPC code identifying green technologies are listed in the Green Inventory defined by the World Intellectual Property Organization (hereinafter WIPO).

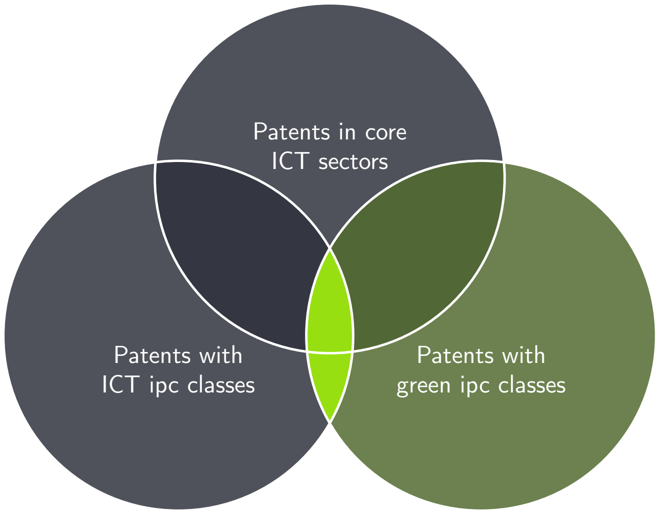
We define an invention as a green ICT if one single patent has at least one IPC code in the ICT area and at least one IPC code in the area of green technologies. The following

[1]The yearly response rate to the German CIS survey is approximately 25 percent, 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.

[2]See OECD (2016).

figure illustrates this definition.

Figure 1: Definition of Green ICT Inventions



For robustness checks, other definitions can be considered. One is to 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). Firms in core ICT sectors are defined as firms in the ICT manufacturing, trade and service industries (NACE codes 26, 465, 61, 62, 63 and 951). The advantage of this less strict definition is that we 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.

Having classified all patents in the sample as either ICT patents, green patents, green ICT patents or any other patents (corresponding to any other technological areas), the sample can be restricted to those firms that have at least one patent granted by the European Patent Office (EPO) (since 1978). 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. 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 8,653 observations for 1,837 ICT-active companies. On average, firm-level data for these firms is observed for 4.7 years. These 1,837 ICT-active firms account for 3.95 percent of all firms in the Mannheim Innovation Panel (MIP) but for 31.86 percent of all patent holders in this representative dataset. In addition, 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.

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. More descriptive details on patent information at the technology level are provided in section 4.3. Table 1 below reports summary statistics for the 8653 observations.

Table 1: Summary Statistics

Variables	**Mean**	**Std. Dev.**	**Min.**	**Max.**
Number of green ICT patents	0.090	1.144	0.000	48.000
Pre-sample mean (green ICT patents)†	0.039	0.682	0.000	40.4
Number of ICT patents	1.012	10.595	0.000	781.000
Pre-sample mean (ICT patents)†	0.552	7.672	0.000	443.8
ln(R&D-intensity$_t$) (R&D/no. of employees)	5.812	7.221	0.000	23.963
Dummy for missing R&D information	0.534	0.499	0.000	1.000
Number of employees*	2847.962	18410.360	1.000	>200000
Share high opportunity IPC cl.s in $t-1$	9.509	28.351	0.000	100.000
Dummy for no ICT patents in $t-1$	0.876	0.330	0.000	1.000
Herfindahl index	1023.269	1061.565	56.586	10000
ln R&D expenditures in NACE 2-dig. sectors	20.994	1.854	0.000	23.45
Firm age* (median: 26 years)	38.231	44.914	0.5	>300
Dummy for location in East Germany	0.175	0.380	0.000	1.000

Notes: * For reasons of confidentiality, maximum values are not reported. † Pre-sample mean: Mean of no. of patents for the 5 years before a firm was sampled for the first time.

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). The reasons for this property of the data are twofold. On the one hand, the sampling procedure does not automatically target small start-up companies as target firms have at least five employees. Moreover, 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 ICT patents which are also on average rather small. Taking further into consideration that the average firm in the dataset is relatively old (38.23 years) 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.

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.

Another interesting finding from Table 1 is that 53 percent of the firms do not report R&D expenditures, meaning that they do not formally do R&D. However, only recently Rammer et al. (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

4.1 Theoretical Considerations and Assumptions

The knowledge production function — Scholars interested in explaining the number of inventions generated by firms typically rely on the concept of the knowledge production function. This concept was introduced by Griliches (1979) and was implemented by many others such as Pakes and Griliches (1980, 1984) or Jaffe (1986) to mention only the earliest contributions. Assume that there is only one output of the knowledge production process —

new technological knowledge, i.e. inventions. Assume further that this inventive output can be measured by the number of patents[3] (hereinafter $p_{i,t}$) granted to firm i by a patent office in year t. According to Griliches (1979), there is only one single production factor — the existing stock of knowledge of firms, hereinafter $k_{i,t}$. It is assumed to represent all current and past R&D expenditures r_{it}, r_{it-1}, r_{it-2}, ..., r_{it-s} of firm i where the subscript s denotes the number of previous years. $k_{i,t}$ incorporates an element of path-dependency of previous invention activities. Here we follow Rosenberg (1994, p. 15) who states that "[t]echnological knowledge is by nature cumulative: major innovations constitute new building blocks which provide a basis for subsequent technologies, but do so selectively and not randomly.", 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. In addition to internal knowledge, external knowledge inflows may add to the knowledge stock. External knowledge is created by the sum of all other inventors' $j \neq i$ R&D expenditures which Jaffe (1986) calls the "spillover pool". The absorptive capacity to receive and make use of technological spillovers crucially depends on firm i's own R&D investments, allowing them to understand received technical knowledge (Cohen and Levinthal, 1989). The resulting knowledge stock reads as

$$k_{i,t} = \sum_{s=0}^{S} \Big((1-\delta)^s r_{i,t-s} + \theta_{i,t} (1-\delta)^s \sum_{j \neq i}^{n} r_{j \neq i,t-s} \Big), \tag{1}$$

where δ is the rate of depreciation[4]. $\theta_{i,t}$ measures absorptive capacities of firms. It depends on firms' own existing technological knowledge (Cohen and Levinthal, 1989), such that $\theta_{i,t} = \theta(k_{i,t-1})$. As the stock of existing technical knowledge $k_{i,t}$ is assumed to be the only production factor, the resulting knowledge (patent) production function is

$$p_{i,t} = f(a_{d,t}, k_{i,t}, c_i, \varepsilon_{i,t}), \tag{2}$$

where $\varepsilon_{i,t}$ represents random success and failure in the uncertain invention process. Assume that $\varepsilon_{i,t}$ is distributed with a zero mean and simply adds "white noise" to the invention production process. c_i is a firm-specific constant accounting for the fact that some firms are simply more successful in creating inventions than others for reasons unknown to us but assumed to be time-invariant. $a_{d,t}$ accounts for factors that determine the productivity

[3]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 various 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 European Patent Office (EPO). See also Griliches (1990) for a more detailed discussion on the use of patents as an indicator for inventions.

[4]The literature typically assumes a depreciation rate of 15 percent; see Griliches and Mairesse (1984).

of the knowledge production process. Needless to say, technological opportunities, which may differ across different technological domains d and across time t, are one of those factors.[5] If there are limited or not technological opportunities, firms will have no invention output regardless of how much they invest into R&D. In contrast, in areas where there are more opportunities, firms are expected to produce ceteris paribus more patents given an investment into R&D.

Finally, aside from technological opportunities and path-dependencies, we account for the market structure which is an important determinant of innovation behavior. Recent empirical evidence by Aghion et al. (2005) points to an inverted u-shaped relationship between competition and innovation incentives.[6]

Hypotheses — We summarize the theoretical thoughts in the following hypotheses. First, according to Corrocher et al. (2007), we expect firms active in high-opportunity ICT domains to have ceteris paribus a higher innovation output than those active in low-opportunity domains. Assuming a continuous measure of technological opportunities, our first hypothesis equals:

$$\frac{\partial p_{i,t}}{\partial a_{d,t}} > 0. \qquad \text{(Hypothesis I)}$$

Secondly, we expect firms active in high-opportunity domains to stay in these domains and not to change their technological field. We expect this since we assume that path dependencies make changing technological domains costly. Thus, 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. The second hypothesis reads as:

$$\frac{\partial p_{i,t}^{\text{pure ICT}}}{\partial a_{d,t}} > \frac{\partial p_{i,t}^{\text{green ICT}}}{\partial a_{d,t}}. \qquad \text{(Hypothesis II)}$$

4.2 Empirical Implementation

The dependent variable(s) - firm i's (pure) ICT or green ICT patents, respectively - is a strictly non-negative integer variable with a considerable number of the firm-year observations being zero. Assume that $\boldsymbol{x}_{i,t}$ is a vector of variables that may explain observed patents and includes $k_{i,t}$ among other controls. Typically, $p_{i,t}$ given $\boldsymbol{x}_{i,t}$ is assumed to be Poisson distributed, so that the mean parameter of the resulting density in log-linear form is given by $\mu = e^{(\boldsymbol{x}'_{i,t}\boldsymbol{\beta})}$, where $\boldsymbol{\beta}$ is a vector of coefficients to be estimated. Moreover, allowing for the aforementioned firm-specific constant c_i, which accounts for differences in

[5]Note that the concept of technological domains is very different from the one of sectors as argued by Jaffe (1986, 1989).

[6]For an overview over the literature concerned with this issue, see Cohen (2010).

the propensity to patent, leads to the following Poisson regression model[7]:

$$p_{i,t} = \mu_{i,t} v_i + \varepsilon_{i,t}, \tag{3}$$

where $\mu_{i,t} = e^{(x'_{i,t}\boldsymbol{\beta})}$, $v_i = e^{(c_i)}$, and $\varepsilon_{i,t}$ is a random disturbance term. The most important component in $\boldsymbol{x}_{i,t}$ is the input factor of existing knowledge ($k_{i,t}$). 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 et al. (1995), among others) propose to replace $k_{i,t}$ by the lagged dependent variable $p_{i,t-1}$ that can itself be considered a noisy measure of lagged inputs. 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. Thus, using a lagged dependent variable helps overcome this problem as $k_{i,t}$ can be replaced by $p_{i,t-1}$, $r_{i,t}$, and $\theta_{i,t}\sum_{j\neq i}^{n} r_{j,t}$, where $\theta_{i,t} = \theta(k_{i,t-1})$. As the absorptive capacity in t, $\theta_{i,t}$, itself is a function of firm i's knowledge stock, it highly correlates with $p_{i,t-1}$ so that $p_{i,t-1}$ can be regarded as to also catch up this effect, however not perfectly. What remains is $\sum_{j\neq i}^{n} r_{j,t}$ (all other firms' contribution in t to the spillover pool) that is time-variant but does hardly vary between firms. However, ICT inventors may be affiliated to different sectors where spillovers from the same sector may be stronger than inter-sectoral spillovers. To allow for inter-sectoral spillovers between rather similar sectors, a control for the sum of all other firms' R&D expenditures in year t from very broadly defined sectors will be included.

As the vector $\boldsymbol{x}_{i,t}$ now includes the lagged dependent variable, several econometric problems arise with the most obvious one being a violation of the assumption of strict exogeneity. This standard 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. Several solutions to this problem have been proposed, such as the use of quasi-first-differenced GMM estimation techniques(see Chamberlain (1992) and Wooldridge (1997)). This approach allows to solve the problem of firm-specific differences in the propensity to patent. However, Blundell et al. (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 $\mu_{i,t} = e^{(x'_{i,t}\boldsymbol{\beta})}$ and to include it in a linear form. The resulting linear feedback regression model reads as

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

where α is a constant and the vector $\boldsymbol{x}_{i,t}$ includes, amongst other controls, the components $r_{i,t}$ and $\sum_{j\neq i}^{n} r_{j,t}$ from the knowledge stock $k_{i,t}$ that are not controlled for by the lagged dependent variable. Moreover $\boldsymbol{x}_{i,t}$ includes the variable of interest, $a_{d,t}$, which measures

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

technological opportunities. $\ln \bar{p}_i$ is the pre-sample mean of the dependent variable. Blundell et al. (1995) and Blundell et al. (2002) suggest including it to deal with both the presence of firm-specific effects and 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. The pre-sample mean serves as a direct control for firm-specific heterogeneity with respect to patenting behavior. 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 et al., 2002). Blundell et al. (2002) propose to estimate model 4 by method of moment (GMM) estimation techniques where the resulting sample moment conditions read as:

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

where $\boldsymbol{z}_{i,t} = (1, p_{i,t-1}, \boldsymbol{x}_{i,t}, \bar{p}_i)$ denotes the vector of instruments. Note that $\boldsymbol{z}_{i,t}$ 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. The exogeneity of $\boldsymbol{z}_{i,t}$, i.e. orthogonality of $\boldsymbol{z}_{i,t}$ and $\varepsilon_{i,t}$, will be tested by using a Sargan test. Amongst firm i's own R&D expenditures in t and the sum of all other firms' R&D in t, the vector $\boldsymbol{x}_{i,t}$ includes further controls that will be discussed at length in the next subsection.

4.3 Variables of the Model

Technological Opportunities — Although the importance of this concept is uncontroversial, there is a lack of a clear and precise understanding of how to measure it empirically. Several proxies of technological opportunities have been proposed and applied. As one of the first, Schmookler (1966) shows that innovation activities differ across sectors and relates this finding to differences in technological opportunities. Levin et al. (1985), Zahra (1996) and Crépon et al. (1998) make use of survey data to identify technological opportunities. Jaffe (1986) applies cluster analysis to patent data in order to classify high- and low-opportunity technological domains; see also Jaffe (1989). A similar approach is pursued by Corrocher et al. (2007) for the case of ICT technologies. To keep our analysis 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 et al. (2000), 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. However, implementing this concept empirically proves problematic. 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. To reduce the volatility, we restrict our analysis to the group level (such as H04L 1) where only 288 classes exist. Still, focusing on the growth rate of patents remains difficult since even at that level there is much volatility. Therefore, we propose an alternative, more robust criterium: technological fields are considered high-opportunity fields as long as the maximum annual number of patents in this class has not been reached and is considered low-opportunity afterwards. The following graphs provide some examples of such classes and illustrate our definition of high- and low-opportunity periods. In the three figures, low-opportunity periods are marked by the grey shaded area.

Figure 2: IPC Class G02B6: Light guides; Structural details of arrangements comprising light guides ...

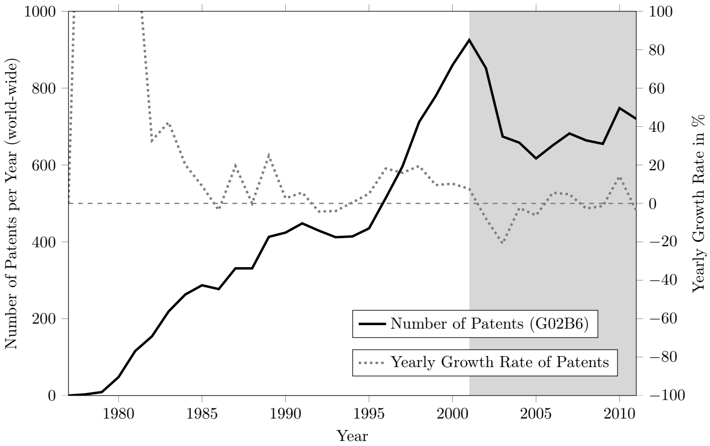


Figure 3: IPC Class G11B5: Recording by magnetisation or demagnetisation of a record carrier; Reproducing by magnetic means; Record carriers ...

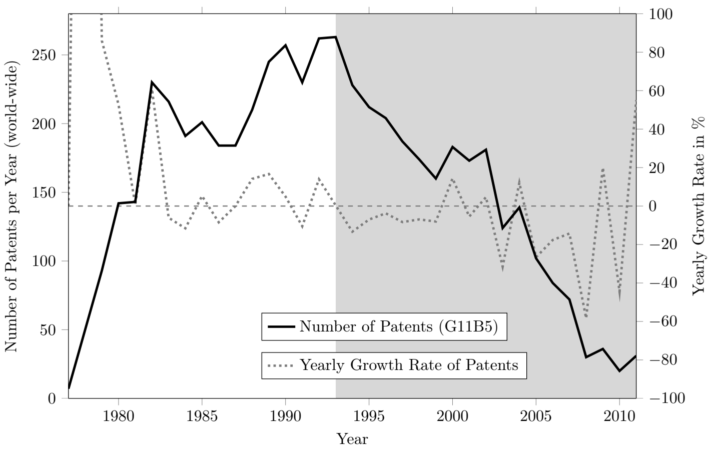
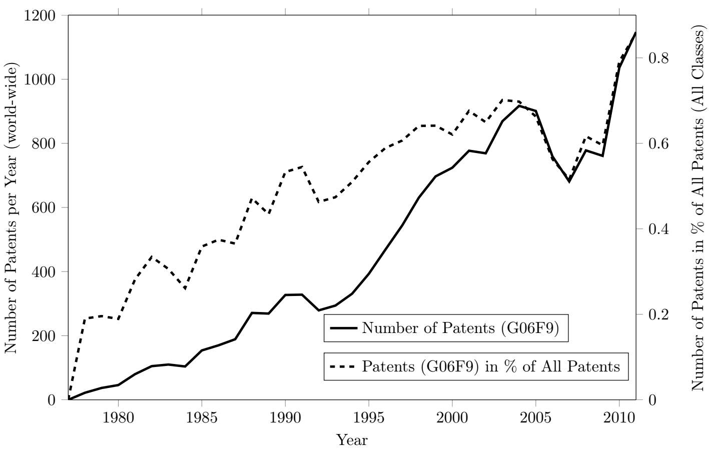


Figure 4: IPC Class G06F9: Arrangements for programme control, e.g. control unit (programme control for peripheral devices)



Formally, the high/low-opportunity status ($h_{c,t}$) of a technology class (ipc group level) c in year t is defined as:

$$h_{c,t} = \begin{cases} (high = 1) & \forall\ t \leq t(\max_t(p_{c,t})) \\ (low = 0) & \text{otherwise} \end{cases} \tag{6}$$

where $p_{c,t}$ denotes the number of patents filed at the EPO in year t in the technological class c. This binary indicator of high/low opportunity status of a certain ipc class, which is computed using all existing EPO patents, is matched with firm-level data at the ipc group level. To measure technological opportunities at the inventor-level ($opp_{i,t}$), we consider the share of IPC classes of all patents of firm i in year t in technological high-opportunity areas, i.e.:

$$opp_{i,t} = \Big(\sum_c h_{c,t} \cdot IPC_{i,c,t} / \sum_c IPC_{i,c,t}\Big) \cdot 100. \tag{7}$$

This way of measuring opportunities relies on the past so it is not clear whether the number of patents in a certain area will increase in the future or even will exceed the maximum. In addition, this measure could be sensitive to changes in world-wide patenting research trends. For the latter concern, we construct an alternative measure where we weight the number of patents in a technology group by the total number of patents in the given year (see section 5.1).

Control Variables One variable we control for is the contribution of all other firms $j \neq i$ to the common spillover pool in year t. The effect of external knowledge from all previous years on current inventions is assumed to be captured by the lagged dependent variable. 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. 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.

The current year's contribution to the knowledge stock is controlled for 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. 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 et al., 2008; Czarnitzki et al., 2009). We therefore 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.

The pre-sample means are defined 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. 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.

As discussed before, 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.[8] 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. 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.

A control variable for firm size is included, too. It is measured as the full-time equivalent number of employees and enters the regression model in natural logarithms and is included in the non-linear (log-link) part of the regression equation. In addition to size, also firm age may be an important predictor of innovative outputs. 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). Note that the age variable is measured in natural logarithms too and a quadratic term is added 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.

[8] 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.

5 Results

The results we obtain from applying the outlined empirical framework are discussed in the following. Table 3 reports 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 measures of technological opportunities and of the ICT patents. In Table 3, 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 share of high-opportunity ICT IPC classes in $t-1$.

In specification (1), we find a positive but insignificant 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[9]. A second variable of interest, the lagged number of patents, representing path-dependency, shows, as expected, a positive significant coefficient. It equals 0.64, indicating that one more patent in $t-1$ increases the expected number of patents in t by 0.64 patents holding all other influencing factors fixed. Note that the coefficient estimate of the lagged-dependent variable accounts for the cumulativeness of technological knowledge. A successful invention meaning new technical usable knowledge in a certain area (here ICT in general) gives rise to additional inventions in the following years. Seen in this light, the effect of the lagged-dependent also accounts for a path dependency in an existing technology with respect to new inventions.

Specification (2) and (3) are concerned with hypothesis II which deals with the direction of technical change and 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 a significant negative effect of technological opportunities, whereas in specification (3) we find a positive, however insignificant one. This indicates that a higher share of high-opportunity ICT IPC classes comes with a lower probability of innovation in Green ICT, but with no effect or even with a higher probability to innovate in pure ICT technologies. Thus, both results together 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. Interestingly, comparing the lagged dependent variable for the two

[9] Or in other words, firms active in high-opportunity areas are observed to have ceteris paribus more patents than firms in low-opportunity areas so that the invention process is more efficient. A one percentage point increase in the share of high-opportunity ICT IPC classes comes with an increase of 0.015 patents in the year after.

specifications, the one of the Green ICT specification shows the lowest coefficient (0.473 vs. 0.654), indicating that path-dependencies are smaller in this relatively new technology area.

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.

5.1 Robustness Checks

To test the robustness of the results which we have obtained using our baseline proxy, as a first robustness check we account for global trends in patenting. This is important to look at as increasing numbers of patents in a certain ICT area do not necessarily signal high technological opportunities if also the number of patents in all other fields (not necessarily ICT) are increasing too. As Figure 5 illustrates, the global number of patents varies strongly. 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. To account for this concern, we apply an alternative proxy for technological opportunities, which weighs the number of patents in an IPC class by the total number of patents (in all IPC classes) in a year. Figures 6 and 7 illustrate how this affects our measure of technological opportunities. Table 4 in the Appendix provides the estimation results we obtain in doing so. In analogy to our baseline results, the same three specifications, now using the alternative proxy, are provided. The direction of the main effects remains unchanged. Specification (1), which studies the effect onto the group of all ICT patents shows a positive, significant effect of the technological opportunity measure, which again supports hypothesis I. Specification (2) and (3) also show the same, albeit insignificant coefficient signs for the effect of technological opportunities on Green ICT and pure ICT innovation: a higher share of high-opportunity ICT IPC classes comes with a lower innovation probability in Green ICT, but with a higher innovation probability in pure ICT. That is, all three specifications again are in line with hypotheses I and II.

In a second set of robustness checks we make use of an alternative definition of ICT innovations by restricting our sample to firms affiliated to the ICT sector (as defined by their NACE code). That is, we study whether technological opportunities affect the rate and direction of ICT innovations within the ICT sector. Doing so reduces our sample to only 1661 observations. Still, using this reduced sample, the direction of the effects remains unchanged, although coefficient estimates become insignificant (see Table 5 in the Appendix).

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. Since green ICT can be considered to be general purpose technologies, innovating in them can enhance the environmental performance of other sectors and has important consequences for a better 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 European Patent Office (EPO) and data from the German Innovation Panel (Mannheim Innovation Panel). The results are based on dynamic count data estimation models applying General Method of Moments (GMM) estimators. 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 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.

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Figure 5: World Patents (by Technology)

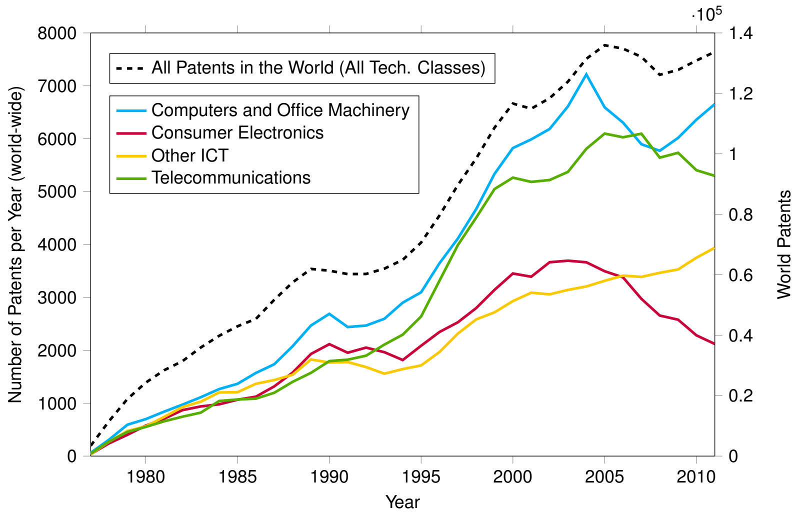

Figure 6: IPC Class G02B6: Light guides; Structural details of arrangements comprising light guides ...

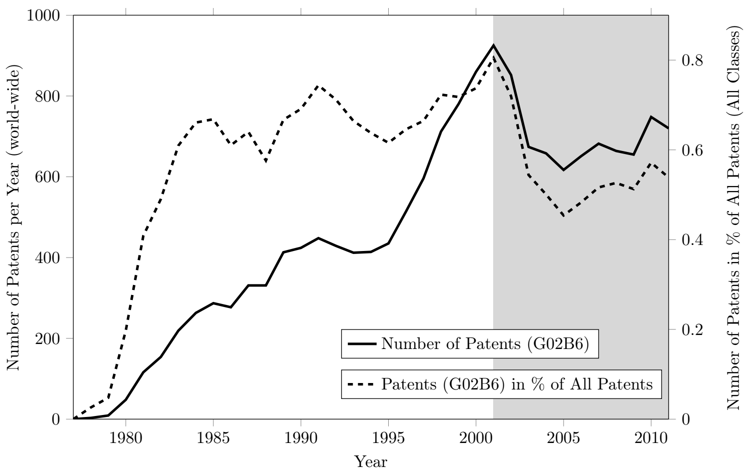

Figure 7: IPC Class G11B5: Recording by magnetisation or demagnetisation of a record carrier; Reproducing by magnetic means; Record carriers ...

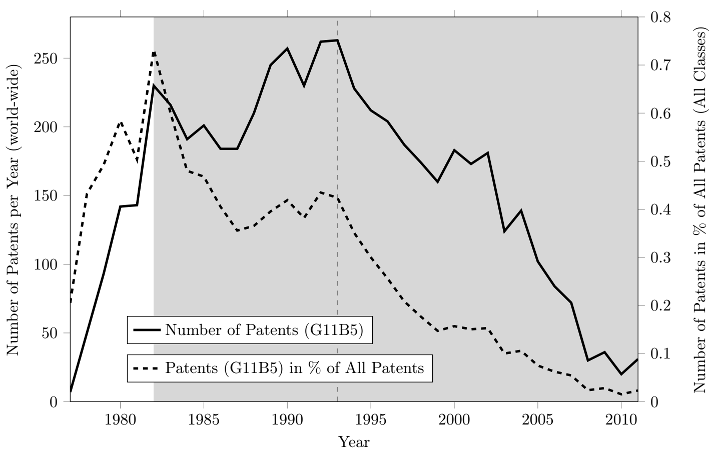

Table 3: Technological Opportunities and Innovation

Dependent Variable: number of patents$_t$	**All ICT** *coef.*	**Green ICT** *coef.*	**Pure ICT** *coef.*
Linear Feedback Part			
number of patents in $t-1$	0.640***	0.473***	0.654***
	(0.127)	(0.123)	(0.138)
Log-Link Part			
constant	-5.778	-5.794**	-7.857
	(3.588)	(2.479)	(9.185)
ln(R&D-intensity in t) (R&D/no. of employ.)	0.011	0.021	0.013
	(0.024)	(0.039)	(0.028)
dummy for missing R&D information in t	0.229	0.301	0.272
	(0.316)	(0.678)	(0.375)
ln(firm size in t) (no. of employees)	0.411***	0.306***	0.444***
	(0.100)	(0.072)	(0.152)
share of high-opportunity ICT IPC cl. in $t-1$	0.015	-0.007*	0.030
	(0.022)	(0.004)	(0.074)
dummy for no patents in $t-1$	0.342	-2.484***	1.966
	(2.477)	(0.369)	(7.686)
ln(Herfindahl $t-1$)	0.197**	0.362**	0.185*
	(0.082)	(0.176)	(0.097)
ln(external R&D, NACE 2-dig. sector)	0.043	-0.055	0.054
	(0.063)	(0.096)	(0.068)
ln(firm age in t)	-0.140	0.660*	-0.177
	(0.149)	(0.347)	(0.168)
ln(firm age in t)^2	0.021	-0.142***	0.032
	(0.029)	(0.054)	(0.033)
dummy for location in East Germany in t	-0.063	-0.408	0.014
	(0.260)	(0.687)	(0.274)
ln(pre-sample mean) (of the dependent var.)	0.651***	1.464***	0.665***
	(0.270)	(0.088)	(0.080)
Observations	8653	8653	8653
Hansen J-test statistic	0.680	3.205	0.442
Hansen J-test [p-value]	[0.712]	[0.201]	[0.802]

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 4: Technological Opportunities (Weighted) and Innovation

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

Table 5: ICT Sector Technological Opportunities and Innovation

Dependent Variable: number of patents$_t$	**All ICT**	**Green ICT**	**Pure ICT**
	coef.	*coef.*	*coef.*
Linear Feedback Part			
number of patents in $t-1$	0.457*	0.361	0.638***
	(0.236)	(0.224)	(0.121)
Log-Link Part			
constant	5.510	-8.185	-8.739
	(8.863)	(6.852)	(10.930)
ln(R&D-intensity in t) (R&D/no. of employ.)	-0.050	-0.005	-0.046
	(0.042)	(0.059)	(0.037)
dummy for missing R&D information in t	-0.475	0.094	-0.534
	(0.647)	(0.992)	(0.425)
ln(firm size in t) (no. of employees)	0.184	0.315***	0.599***
	(0.130)	(0.093)	(0.155)
share of high-opportunity ICT IPC cl. in $t-1$	-0.006	-0.006	0.049
	(0.006)	(0.004)	(0.063)
dummy for no patents in $t-1$	-1.969***	-2.264***	4.260
	(0.720)	(0.518)	(6.506)
ln(Herfindahl $t-1$)	0.456	0.625***	0.018
	(0.318)	(0.241)	(0.215)
ln(external R&D, NACE 2-dig. sector)	-0.538	0.035	0.038
	(0.355)	(0.260)	(0.363)
ln(firm age in t)	1.057*	0.405	0.052
	(0.631)	(0.442)	(0.430)
ln(firm age in t)^2	-0.222**	-0.145**	-0.048
	(0.093)	(0.070)	(0.080)
dummy for location in East Germany in t	-0.331	-0.629	-0.251
	(0.959)	(0.714)	(0.466)
ln(pre-sample mean) (of the dependent var.)	1.137***	1.796***	0.658***
	(0.308)	(0.522)	(0.206)
Observations	1661	1661	1661

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.