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Breakthrough Innovations and Productivity: An International Perspective

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Abstract

In this paper, we shed new light on the productivity impact of breakthrough patents, as well as their role in the variability of productivity across countries. We use text analysis and machine learning–based estimates of the number of breakthrough patents and show that there was a significant drop in quantity in the early 2000s. According to our econometric analysis, the slowdown in innovation activity has a clear temporal connection with the later slowdown in productivity in the 2010s. Breakthrough patents increased productivity on a large scale until the beginning of the 2010s, in particular in industrial information and communications technology (ICT) industries. In sectors other than ICT, productivity growth was more differentiated so that productivity growth is observed in industries that invested significantly in R&D after the emergence of breakthrough patents. We also identify large differences across countries in the link between productivity and breakthrough patents.

Tiivistelmä

Läpimurtoinnovaatiot ja tuottavuus: kansainvälinen näkökulma

Tässä artikkelissa arvioimme läpimurtopatenttien tuottavuusvaikutuksia sekä niiden roolia eri maiden tuottavuuden vaihtelussa. Käytämme tekstianalyysiin ja koneoppimiseen perustuvia arvioita läpimurtopatenttien määrästä. Osoitamme, että määrässä tapahtui merkittäviä muutoksia 2000-luvun alussa. Ekonometrisen analyysimme perusteella läpimurtojen tekemisen hidastumisella on selkeä ajallinen yhteys tuottavuuden myöhempään hidastumiseen 2010-luvulla. Tarkastelemillamme teollisuusaloilla läpimurtopatentit ovat lisänneet tuottavuutta laajasti 2010-luvun alkuun asti erityisesti tieto- ja viestintätekniikan (ICT) alalla. Muilla aloilla tuottavuuden kasvu on eriytyneempää niin, että sitä havaitaan enemmän toimialoilla, jotka ovat investoineet merkittävästi tutkimukseen ja kehitykseen läpimurtopatentointien jälkeen. Havaitsemme suuria maiden välisiä eroja tuottavuuden ja läpimurtopatenttien välisessä yhteydessä.

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FT **Tero Kuusi** on Elinkeinoelämän tutkimuslaitoksen tutkimusjohtaja.

KTM **Jenni Nevavuo** on Suomen Pankin ekonomisti.

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Keywords: Productivity, Innovation, Breakthroughs, Patents

Asiasanat: Tuottavuus, Innovaatiot, Läpimurrot, Patentit

JEL: D24, O31, O33

1. Introduction

Breakthroughs at the frontier of innovation are considered key determinants of economic growth, as the process by which innovative discoveries replace older technologies is at the heart of Schumpeter's notion of creative destruction (Aghion et al. 2014). These breakthroughs are distinguished from other innovations because they build on and advance new ideas rather than conventional technologies. Although innovations that recombine conventional ideas are also useful, the willingness to try out novel ideas as inputs in the innovation process is crucial to technological progress and in that way, to productivity growth. Without novel ideas as inputs in the innovation process, the frontier eventually stops advancing—and innovation stagnates.

In this paper, we shed new light on the productivity impact of breakthrough innovations, as well as their role in the variability of productivity across countries. This work is motivated by the fact that in the last two decades, developed countries have not been as effective as previously in promoting long-term productivity growth (Hall 2016; Gordon 2000, 2012; Gordon and Sayed 2019). There is reason to believe that the slowdown is, at least partly, due to weakness in how useful new innovations have been discovered and adopted (Bloom et al. 2019; Bhattacharya and Packalen 2020).

Although the theoretical arguments for the important role of breakthroughs are undoubtedly strong, a key challenge of the analysis is the measurement of breakthroughs in practice. Previous researchers used the number of patents or citation counts to measure the importance of innovation, but they have some significant disadvantages (Kelly et al. 2021). Without quality adjustments, the number of patents provides little information about the importance of the innovations. Although citations can be used as a proxy for quality, they are based on discretionary views regarding the patent links, and their availability is limited. Moreover, although citations are a definite sign of impactful patents, they provide only limited information about the patents' novelty.

Thus, we use an alternative method to measure technological progress: Kelly et al.'s (2021) breakthrough patent indicator. This indicator identifies important patents that are novel and impactful at the same time and exemplify technological progress over time. The indicator was created from U.S. patent data and therefore focuses on U.S. technological progress, but we use it as an indicator of the current pace of technological progress globally. In particular, we analyze how different countries respond to changes in the indicator.

Interestingly, the data show that there is a significant drop in the number of breakthrough patents in the early 2000s, coinciding with the slowdown of productivity growth. This decline is visible in particular in information and communication technology (ICT), although it can be observed in other sectors. We analyze how breakthrough patents have affected labor productivity in an international panel of industries and examine regional differences in economic responses to the emergence of breakthrough patents.

2. Literature review

A large amount of economic literature has aimed at identifying breakthrough patents and their economic impacts. Previous work suggests that economically valuable patents are also cited more often (Hall et al. 2005). More recently, Kogan et al. (2017) show that patent-level estimates of economic value are strongly and positively correlated with forward citations and that the correlation is robust to a number of patent- and firm-level controls. Abrams et al. (2013) examine how different types of innovative effort are linked to connection between patents and economic value, and argues that the relationship might be non-linear.

This paper focuses on examining technological explanations for recent productivity dynamics. After the 2008 financial crisis, many modern economies suffered from persistent economic stagnation. A decrease in productivity-enhancing investment and R&D due to the crisis may have at least partly been the reason for the stagnation (Hall 2016). Moreover, this period coincides with the ICT revolution. Relative to other industrial revolutions (Gordon 2000), it may have created only a short productivity revival between 1996 and 2004, although the showdown coincided with other economic headwinds (Gordon 2012). They arose from demography, the overhang of consumer and government debt, education, inequality, energy/environment, and globalization.

Previous work suggests that the slowdown may be rooted in breakthrough innovations and their dynamism (see Bloom et al. 2019; Bhattacharya and Packalen 2020). The slowdown may be related to the availability of potential breakthrough ideas and to incentives for creating them. In terms of the latter, Porter and stern (2000) argue that there seems to be a gap between the production of ideas and the ability to translate these ideas into productivity growth in advanced economies. Most research projects fail to produce groundbreaking results, and only a few generate impactful breakthrough scientific discoveries (Machado 2021). This may lead to insufficient scientific funding. Rzhetsky et al. (2015) find that scientists pursue progressively less risk, as riskier research leads to more failures, and this reduces publications. However, the authors find that publication of failures leads to speed of discovery and in that way, breakthrough innovations. Thus, science policies could improve discoveries by subsidizing riskier strategies, encouraging the publication of failed experiments, and incentivizing strategy diversity, as a record of failures provides an understanding of research behavior and improves its efficiency.

Finally, the analysis is also related to cross-country differences in productivity growth. The positioning of countries and industries in terms of the novelty of innovations and their market structure are central economic mechanisms for innovation and economic growth (Aghion et al., 2014), and several models attempt to capture the roles of countries in contributing to breakthrough innovations (see, e.g., Acemoglu et al. 2012). In particular, our data period reflects a period when European productivity growth fell behind U.S. growth. Previously, this pattern has been argued to reflect the failure of European Union (EU) countries to reap the benefits of ICT (Inklaar et al. 2007; Timmer et al. 2011; Gordon and Sayed 2019).

3. Methodology

In this paper, we follow Kelly et al.'s (2021) novel method to identify breakthrough patents and use it to quantify the role of breakthroughs in economic growth[1]. These breakthrough patents represent the most important patents and improvements in the technological frontier. Following Kelly et al.'s methodology, U.S. patents are used as a proxy for the global innovation pool at the industry and aggregate levels.

The core quantitative measure, a breakthrough indicator, is defined in terms of the similarity between patents. The similarity metric calculates the similarity of texts by measuring the number of text occurrences in two patent documents while appropriately weighing words by their importance.

First, this approach must identify words that are common, and thus, their occurrence in both texts is not sufficient to indicate similarity, and on the other hand, informative words that are most diagnostic of a document's topical content. Following Kelly et al. (2021), we use the so-called "term-frequency-inverse-document-frequency" (TFIDF) transformation of word counts:

$$TFIDF_{pw} = TF_{pw} IDF_{w},$$

where the first term counts how many times term *w* appears in patent *p,* adjusted for the patent's length. The second term is the inverse document frequency (IDW) of term *w*, which is defined as the (log of) ratio of all documents in the sample and documents that include term w. Kelly et al. (2021) augment the IDW by considering the log frequency of all patents containing *w* in any patent granted *before* patent *p*, yielding a modified version of the TFIDF. The similarity between the pair of patents (i,j) can be characterized for *i* (the same for *j*) as

$$TFBIDF_{wit} = TF_{wi} BIDF_{wt}, t \ \equiv \min{(i, j)}.$$

Finally, the overall similarity between two patents is described in terms of a vector ($TFBIDF_{it}$), where each element corresponds to individual similarity $TFBIDF_{wit}$, and the dimension of the vector equals the number of terms that exist in either application (union set). After each vector is normalized to have a unit length, the cosine similarity between the normalized vectors of the two patents (*i* and *j*) is taken,

[1] Note that alternative approaches have been proposed for example by Blit and Packalen (2019).

$$\rho_{ij} = V_{it} \cdot V_{jt},$$

where the normalized vector corresponding to the vector $TFBIDF_{it}$ is denoted as V_{it}. ρ_{ij} lies in the interval [0,1]. When there are exactly the same words with the same proportions, the value is 1. When there is no overlap, the value is 0.

3.1. Breakthrough patents

Breakthrough patents are defined as those for which the content is novel (5 years backward) with respect to previous patents but are impactful in terms of future patents (10 years forward), thus influencing future scientific advances. The measurement is conducted by analyzing the links between each new invention and the set of existing and subsequent patents in patent documentation. The links used in the importance measure are created by using textual similarity, and the similarity metric is constructed by weighing words by their importance in a pair of text documents.

Kelly et al.'s (2021) breakthrough patent indicator identifies important patents that are novel and impactful at the same time and exemplify technological progress over time.

The novelty of patent *j* is defined as its backward similarity over a 5-year period ($\tau = 5$):

$$BS_j^\tau = \sum_{i \in \mathrm{B}_{\mathrm{j}\tau}} \rho_{ij},$$

where ρ_{ij} is a pairwise similarity of patent *i* and *j,* and $\mathrm{B}_{\mathrm{j}\tau}$ represents the set of previous patents filed in τ calendar years before *j*'s filing. Correspondingly, FS_j^τ measures a patent's impact by its forward similarity:

$$FS_j^\tau = \sum_{i \in \mathrm{B}_{\mathrm{j}\tau}} \rho_{ij},$$

where *Fjt* represents the set of patents filed in the next τ years following *j*'s filing.

Kelly et al. (2021) form a patent importance indicator by combining the two metrics as a ratio:

$$\frac{FS_j^{\tau=10}}{BS_j^{\tau=5}}.$$

After constructing a breakthrough indicator, Kelly et al. (2021) remove cohort issue year fixed effects and choose the most important patents to be those that fall within the top 10% of the unconditional distribution of the importance indicator.

3.2. Economic modeling

We examine the links between breakthrough patents and labor productivity growth by using an international panel dataset of breakthrough patents and economic variables. We also consider the U.S. patent dataset to provide an indicator of the global technological frontier.

Model 1 explains variation in labor productivity in country *c*, industry *i*, and year *t* with lagged values of the breakthrough patent index

$$\ln\left(\frac{Y_{c,i,t}}{L_{c,i,t}}\right) = \beta * \text{breakthrough patent index}_{\,i,t-10} + controls_{c,i,t} + \epsilon_{c,i,t},$$

where $\text{breakthrough patent index}_{\,i,t-10}$ is the Kelly et al. (2021) index lagged by 10 years, and $controls_{c,i,t}$ includes country-year and industry-country fixed effects. The error terms $\epsilon_{c,i,t}$ are allowed to be clustered across the panel unit's (industry-country) observations.

The multiplier β shows how industries react to a technological breakthrough, either by introducing technology or with new further innovations. To provide additional insights, we augment the baseline model by investigating how R&D investments jointly affect labor productivity (Model 2):

$$\ln\left(\frac{Y_{c,i,t}}{L_{c,i,t}}\right) = \beta * \text{breakthrough patent index}_{\,i,t-10} * + \beta^{R\&D} * \text{breakthrough patent index}_{\,i,t-10} * \ln\left(R\&D_{i,c,t-1}\right) + controls_{c,i,t} + \epsilon_{c,i,t}.$$

In this case, the multiplier $\beta^{R\&D}$ shows how R&D investments in industries affect readiness to respond to (previous) breakthrough patents.

Note that squared terms of $\ln\left(R\&D_{i,c,t-1}\right)$ and $\text{breakthrough patent index}_{\,i,t-10}$ are included as control variables. We use lagged values of $R\&D$ in order to avoid reverse causality from productivity toward $R\&D$. As another variation of this model, we also examine whether breakthrough patents *in ICT* have a special role in other sectors.

Finally, we consider a model in which the ability of individual countries to benefit from the breakthrough patents is examined. In this case, we use Model 3:

$$\ln\left(\frac{Y_{c,i,t}}{L_{c,i,t}}\right) = \beta^{c} \times \text{breakthrough patent index}_{\,i,t-10} \times Indicator[country = c] + controls_{c,i,t} + \epsilon_{c,i,t},$$

where the variable $Indicator[country = c]$ has a value of 1 if the productivity observation belongs to country c and 0 otherwise. The multiplier can be interpreted as a country's β^{c}overall capability to respond to breakthrough technologies.

4. Data

4.1. Dataset

The data consist of three datasets: i) U.S. patent data from Kelly et al.'s (2021) research paper, ii) productivity data, and iii) R&D data. The ii) and iii) data from the OECD database. The datasets include time-series data across industries; consequently, we can link the datasets and construct panel data.

Kelly et al.'s (2021) data consist of more than nine million U.S. patents from 1840 to 2010. The patents are collected from two sources: the UPSTO and Google's patent search engine. With these data, it is possible to construct the importance measure of the per-capita number of breakthrough patents in the US across industries and at the aggregate level. Industries are defined by NAICS codes[2]. The final breakthrough patent data are valid until 2002.

The OECD database includes productivity and R&D data. The productivity data consist of OECD STAN Industrial Analysis 2020 edition data. The industrial analysis database provides annual data across countries and industries.[3] This allows us to measure productivity. Productivity is constructed by dividing *Value added (volume)* variable by *Hours worked (by employees)*. The data are collected from the years 1970–2019, and the ISIC Rev. 4[4] classification is used. Because there are so few values for the year 2019, we drop that year, and the final data are collected for the years 1970–2018. The second dataset is the OECD Business enterprise R-D personnel by industry and R-D investments (BERD). It consists of data from the years 1987–2018 across industries and includes OECD countries as well as some non-member economies[5]. The dataset uses the ISIC Rev. 3.1 classification.

4.2. Descriptive statistics

Next, we present Kelly et al.'s (2021) results for the breakthrough patent indicator at the aggregate and sectoral levels, and then how productivity and the breakthrough patent index are related. To give a perspective on the results, we take a longer view on innovation. When considering the major technological breakthroughs of the 19th and 20th centuries, Kelly et al. (2021) find that the indicator of patent significance performs quite well. They construct a time series index of breakthrough patents by dividing the number of breakthrough inventions granted each year by the U.S. population.

Figure 1 presents the index at the aggregate level. There are three breakthrough innovation waves at the aggregate level from 1840 to 2010. The first wave (1870–1880) occurs during the second industrial revolution. The second wave is between 1920 and 1935, and advances in manufacturing breakthrough

[2] NAICS = North American Industry Classification System
[3] A list of analyzed industries can be found in Figure 3 and a list of countries in Table 3.
[4] International Standard Industrial Classification (Revision 4)
[5] These are Argentina, China, Romania, the Russian Federation, Singapore, South Africa, and Chinese Taipei.

patents are the core technological innovations of this period. The third wave, from 1985 to the present, is larger than the two previous waves in terms of the number of patents, and it corresponds to the revolution in ICT.

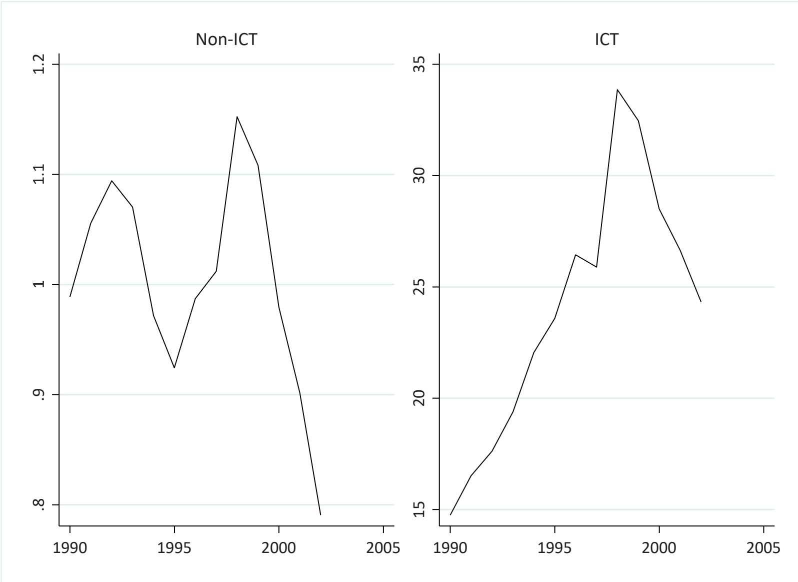
The number of breakthrough patents also varies considerably across sectors. In the 1840–1870 period, the most important innovations are in engineering, consumer goods, construction, and manufacturing. After 1870, patents related to electricity and telephone score high on the breakthrough patent indicator, and between 1860 and 1910, patents related to transportation, such as airplanes and improvements in railroads, as well as innovations in construction score high. After 1900, important patents are related to chemistry, for example, synthetic plastics and different drugs. In the 1950s, patents related to nuclear energy for civilian purposes and electronics score high, and between 1980 and 1990, patents related to computer networks emerge. Genetics also emerges at the end of this time period (Kelly et al., 2021).

In addition, Kelly et al. (2021) compare the timing of citations and the breakthrough indicator and find that the breakthrough indicator provides a more timely assessment of patent quality than citation counts.

Figure 1. Breakthrough index at the aggregate level: Three breakthrough innovation waves at the aggregate level from 1840 to 2010.

Note: Kelly et al. (2021). The time series index of breakthrough patents is constructed by dividing the number of breakthrough inventions granted each year by the U.S. population.

Figure 2. Average number of breakthrough patents in the ICT sector and other sectors (non-ICT).

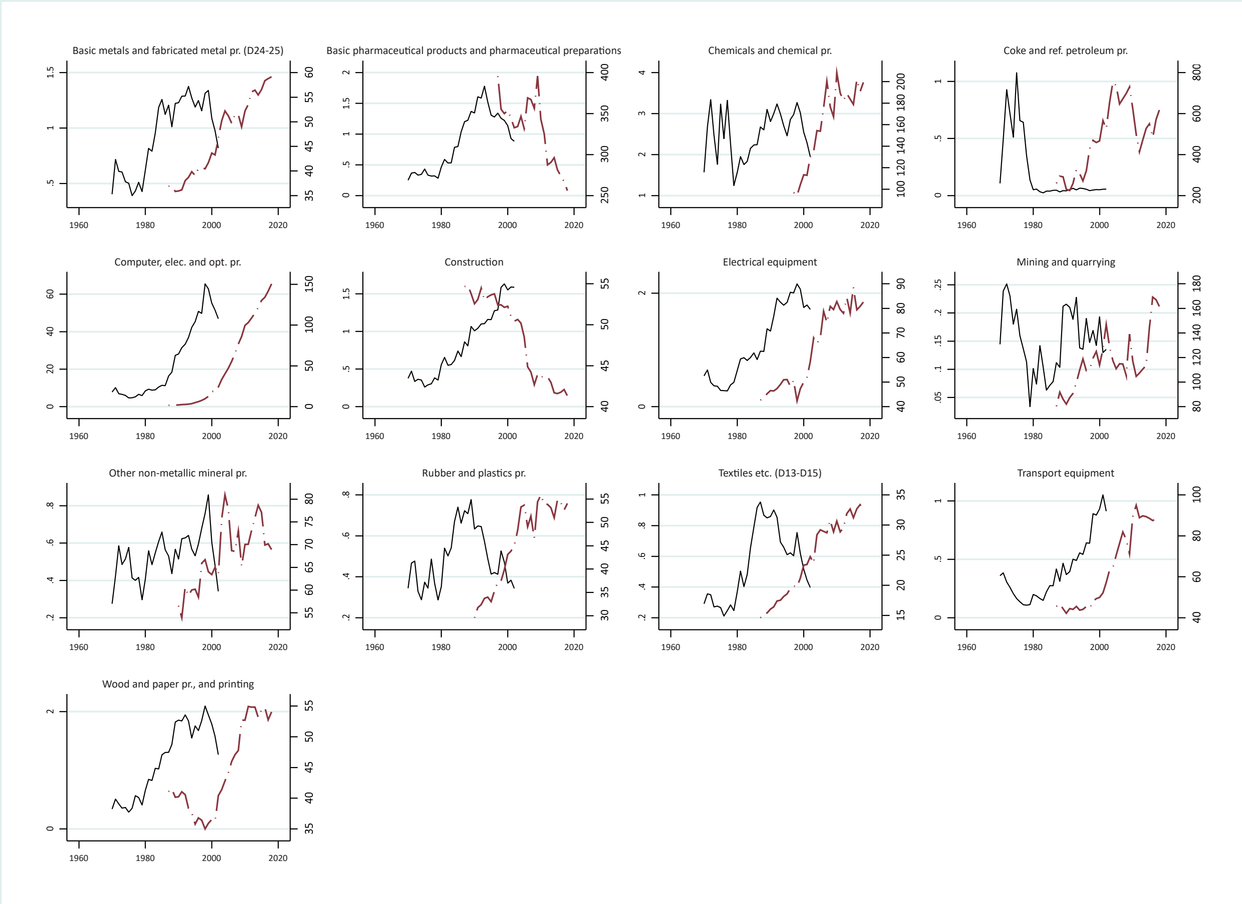


Note: Kelly et al. (2021) and the authors' calculations.

Focusing on the analysis period and comparing the average number of breakthrough patents in the ICT sector and other sectors, we can clearly see that the number of breakthrough patents in the ICT sector is large compared to those for other sectors (Figure 2). From 1980 onward, the number in the ICT sector increases until it declines in the early 2000s.

In Figure 3, we present Kelly et al.'s (2021) breakthrough patents and OECD STAN productivity data for the US at the sector level. In the figure, productivity is related to the breakthrough index in almost all sectors. This can be seen especially in the Transport, Electrical equipment, and Computer and electronics sectors. As can be seen, productivity follows the breakthrough index with a delay of several years. However, for example, construction sector productivity is not related to the breakthrough index.

Figure 3. Breakthrough innovation across industries and labor productivity in U.S. data.



Note: Kelly et al. (2021) and the authors' calculations.

5. Results

First, we analyze the association between breakthrough patents and productivity growth using Model 1. The specifications include the baseline model, which we estimate with fixed-effects panel regression while controlling for country-year fixed effects. The error terms are allowed to be clustered across panel observations and are heteroskedasticity robust. The results are presented in Table 1.

The baseline model indicates that there is a statistically significant relationship between relative (ln) changes in labor productivity and an increase in the number of breakthrough patents. In 10 years, productivity is 2.35% higher when the initial number of breakthrough patents increases by 1.

We also consider many alternative specifications. First, we adjust the propagation time from 10 years to 5 years. Second, we use the baseline model but estimate it without data for years after the onset of the global financial crisis in 2008. Third, we allow clusterization of the error terms for the entire country. Fourth, we introduce the initial level of productivity of the panel unit 10 years before, thus controlling for the dependency of the explained variable on trends in the productivity variable itself. Fifth, we omit ICT industries[6] and finally, allow for linear industry trends at the global level.

We find that the results are robust to different kinds of potential identification problems. However, we find that the results depend on the inclusion of the ICT sector. This implies that the broad-based spillovers from breakthrough patents are limited to the ICT sector when we do not take into account differences in R&D investments across the panel units.

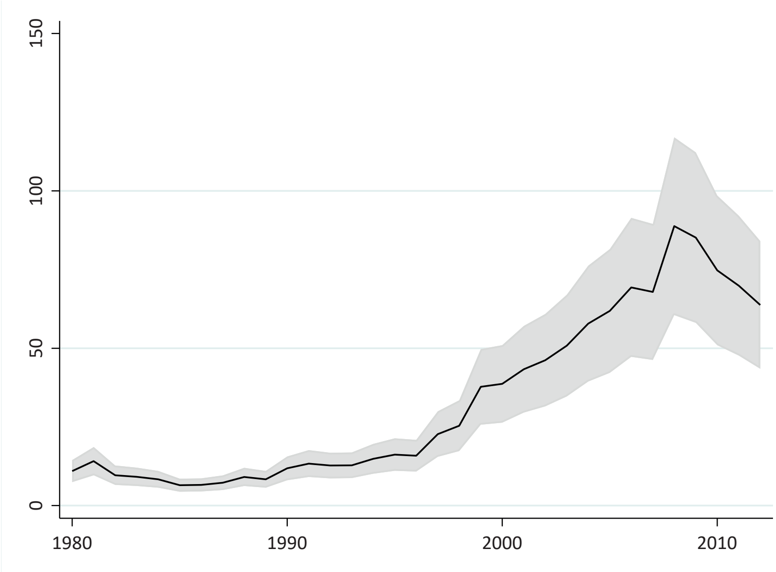
Table 1. Econometric results for the response of labor productivity to previous breakthrough patents.

	Baseline	5-year impact	Baseline, but data until 2007	Baseline, but clustered ε at country level	Baseline, but with (t-10) productivity	Baseline, but no ICT sector	Baseline, but only EU	Baseline, but with linear industry trends
Response of (ln) labor productivity on breakthrough patents after 10 years (β)	**0.0262*****		**0.0285*****	**0.0262*****	**0.0180*****	**-0.0412**	**0.0260*****	**0.0066***
Standard error	*0.0042*		*0.0053*	*0.0046*	*0.0031*	*0.0588*	*0.004*	*0.0038*
Response of (ln) labor productivity on breakthrough patents after 5 years (β)		**0.0250*****						
Control variables								
Initial (ln) labor productivity (10 years ago)					0.3499***			
Country-industry fixed effects	x	x	x	x	x	x		x
Country-year fixed effects	x	x	x	x	x	x		x
Industry-level (global) linear trends								x
Statistics								
Number of observations	6569	5287	4988	6569	4088	5565	5299	6569
Number of groups	323	297	297	323	279	274	250	323
R2 (within)	0.5516	0.6125	0.5942	0.5516	0.5649	0.4412	0.549	0.5969
Clustered error terms	Industry-country	Industry-country	Industry-country	Country	Industry-country	Industry-country	Industry-country	Industry-country
Note: Significance levels *** = 0.1%, ** = 1%, * = 5%.								

Note: The authors' calculations.

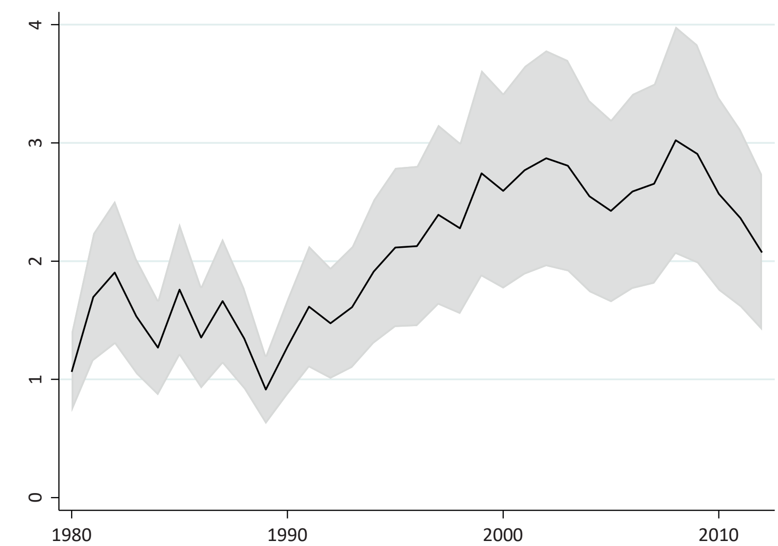
[6] They include industries D26 and D27 (computer, electronic and optical products; electrical equipment) in our data.

Figure 4. Average impact of breakthrough patents on productivity growth in the ICT sector after 10 years, prediction of the baseline model.



Note: The authors' calculations.

Figure 5. Average impact of breakthrough patents on productivity growth in non-ICT sectors after 10 years, prediction of the baseline model.



Note: The authors' calculations.

In Figures 4 and 5, we provide a prediction for the model for labor productivity. The data show that there is a significant drop in the number of breakthrough patents in the early 2000s. After strong growth in previous decades, a drop is seen in particular in ICT, although it can also be observed in other sectors. Based on the econometric analysis, the slowdown in innovation activity has a clear temporal connection with the later slowdown in productivity in the 2010s in the sectors in which the number of breakthrough patents decreased.

Next, we further examine how R&D investments affect readiness to respond to (previous) breakthrough patents, as measured with the multiplier $\beta^{R\&D}$. We aim to answer whether breakthrough patents have increased labor productivity in different ways across industries, and in particular, whether productivity growth can be observed in particular in the industries that invest significantly in R&D after the emergence of breakthrough patents.

We use previous year values of $R\&D$ in order to avoid reverse causality from productivity toward $R\&D$. Again, we consider different specifications that take into consideration potential problems in the statistical inference. The results are reported in Table 2.

Table 2. Econometric results for how R&D investments in industries affect readiness to respond to (previous) breakthrough patents.

	R&D = ln(BERD), all countries				R&D = ln(BERD), EU				R&D = ln(research personnel), all countries			
	Baseline	Baseline, sector-VA weighted	No ICT sector	No ICT, sector-VA weighted	Baseline	Baseline, sector-VA weighted	No ICT sector	No ICT, sector-VA weighted	Baseline	Baseline, sector-VA weighted	No ICT sector	No ICT, sector-VA weighted
Response of (ln) labor productivity on breakthrough patents (10 yrs ago) x R&D (1 yrs ago)	**0.002**	**0.004***	**0.029***	**0.088*****	**-0.001**	**0.001**	**0.018**	**0.078*****	**0**	**0.001**	**0.031**	**0.080*****
Standard error	*0.002*	*0.002*	*0.017*	*0.019*	*0.001*	*0.002*	*0.02*	*0.022*	*0.002*	*0.002*	*0.026*	*0.027*
Control variables												
Breakthrough patents (10 yrs ago)	0.022*	0.024*	-0.179*	-0.439***	0.037***	0.038***	-0.121	-0.451***	0.040**	0.039*	-0.249	-0.576***
R&D (1 year ago)	0.046	0.026	0.043	-0.044	0.046	0.005	0.034	-0.057	0.102*	0.110**	0.098*	0.07
Squared breakthrough patents (10 years ago)	-0.000**	-0.000***	0.005	-0.01	-0.000*	-0.000**	0.01	0	-0.000*	-0.000**	0.005	0.003
Squared R&D (1 year ago)	0	-0.002	-0.002	-0.004	0.003	0.003	0.002	0	-0.005	-0.007*	-0.008	-0.009
breakthrough patents in ICT (10 years ago) x R&D (1 year ago)	0	0	0	0	0	0.000**	0	0	0	0	0	0
Initial (ln) labor productivity (10 years ago)												
Country-industry fixed effects	x	x	x	x	x	x	x	x	x	x	x	x
Country-year fixed effects	x	x	x	x	x	x	x	x	x	x	x	x
Statistics												
Number of observations	3611	3611	3060	3060	2914	2914	2466	2466	2900	2900	2461	2461
Number of groups	291	291	246	246	226	226	190	190	278	278	235	235
R2 (within)	0.604	0.628	0.470	0.521	0.592	0.608	0.470	0.523	0.575	0.596	0.447	0.51
Clustered error terms	Industry-country	Industry-country	Industry-country	Industry-country	Industry-country	Industry-country	Industry-country	Industry-country	Industry-country	Industry-country	Industry-country	Industry-country

Note: Significance levels *** = 0.1%, ** = 1%, * = 5%.

Note: The authors' calculations.

Overall, we find that the effect of previous breakthrough patents on the impact of R&D on labor productivity is positive, but the effect seems to concentrate on non-ICT industries. In industrial ICT industries, breakthrough patents increase productivity on a large scale until the beginning of the 2010s. That is, breakthrough patents remain a statistically and economically significant determinant of labor productivity.

In sectors other than ICT, however, productivity growth is more differentiated so that productivity growth can be observed especially in industries that invest significantly in R&D after the emergence of breakthrough patents. When an industry has invested heavily in R&D, and new breakthrough patents have been observed, there is an increase in the returns to R&D, when measured as changes in labor productivity. It is notable that these returns become higher when the estimation is done while weighting observations based on their value-added weight in the domestic economy (nominal value added of the industry / overall value added of the country).

Variation at the country level

We also assess the ability of different countries to respond to the productivity growth potential created by breakthrough patents. That is, we analyze with Model 3 how breakthrough patents are linked to labor productivity at the country level. The multiplier β^c can be interpreted as a country's overall capability to respond to breakthrough technologies: How has country *c* productivity responded to a technological breakthrough (either by adopting technology or by subsequent innovations)?

The results are shown in Table 3. We separately consider the relationship between productivity and breakthrough patents for all OECD countries and the EU. Moreover, we consider the relationship separately for different sectors, namely, the ICT and non-ICT sectors. In Figure 6, we further illustrate the findings by showing the covariation between productivity and breakthrough patents for the EU.

According to the results, the EU countries that have the strongest correlation between breakthrough patents and labor productivity are in Eastern Central Europe and the Nordic countries (Figure 6). In the case of the Nordics, the positive relationship is concentrated in the ICT sector, as indicated by the fact that the multiplier is negative and statistically insignificant for non-ICT industries. In the case of Eastern Central Europe, however, larger multipliers may be related to non-ICT industries, as the multiplier for these industries alone is often positive, albeit not typically statistically significant.

Similarly, for non-EU countries, the greatest variation in the size of the response tends to be related to non-ICT industries. However, the US, similarly to Sweden and Finland, has a high response estimate, although it is concentrated on the ICT sector. That is, the estimates for the non-ICT sector are negative.

As a related question, we also investigate whether in different countries there is a systematic relationship between previous breakthrough patents and changes in R&D (ln BERD). A systematic relationship would indicate that countries would shift their R&D resources toward (or away from) industries where breakthrough patents have been detected. As breakthrough patents with the current methodology are visible only with a 10-year lag, the correlation between breakthrough patents and R&D 10 years later indicates whether investment activities follow breakthrough patents within a time range that allows the identification of breakthrough patents, at least in principle.

Based on the results shown on the right side of Table 3, the link between productivity growth and breakthrough sectors tends to be stronger in countries where R&D investments move toward the breakthrough sectors. The results indicate that the productivity gains from breakthrough patents may be due not only to the larger responses of individual industries but also to the shifting emphasis of R&D across industries at the country level. While this result is tentative, it suggests that there may be room for active policies to identify breakthrough patents and allocate resources according to their productivity potential.

Table 3. Response of productivity and R&D to previous breakthrough patents at the country level.

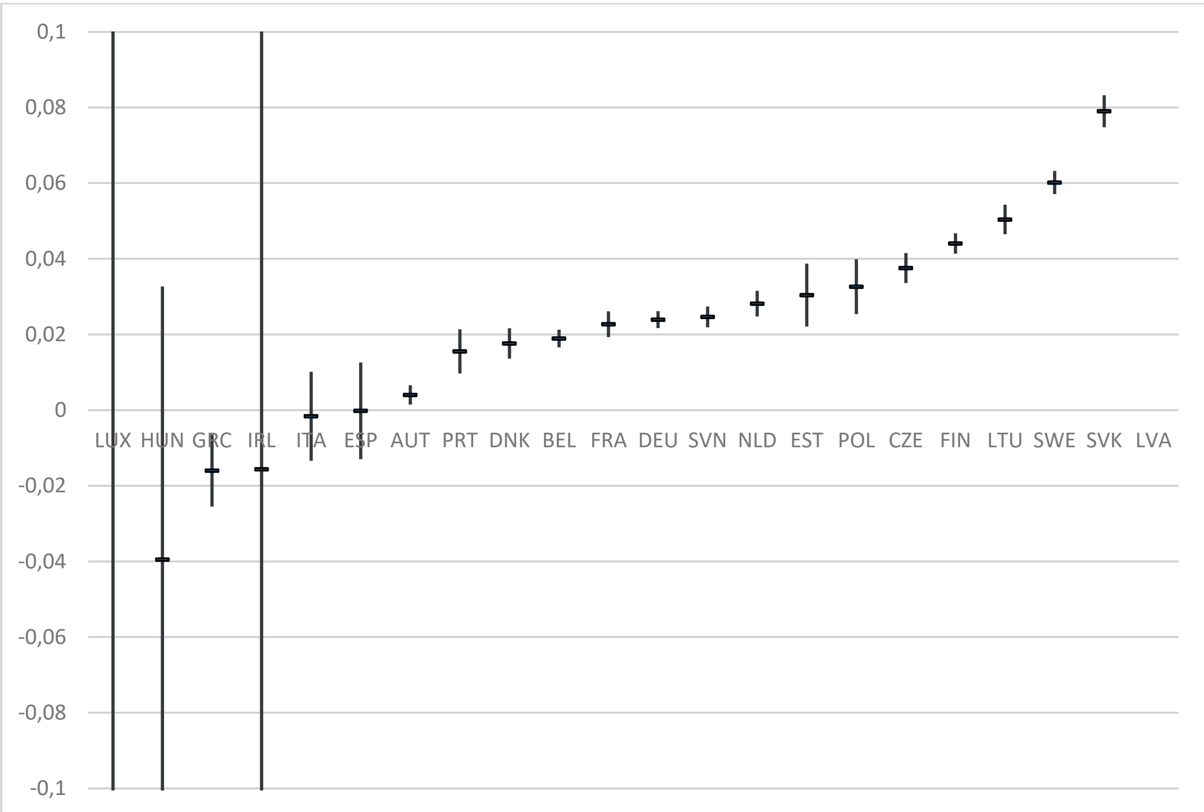
	Response of (ln) labor productivity to breakthrough patents after 10 years (β^c)			**Response of (ln) BERD to breakthrough patents after 10 years**		
	All countries	**Only EU**	**All, but without ICT**	**All countries**	**All, but without ICT**	**All, after 1995**
AUS	**-0.092**		**-0.193**	**-0.042**	**0.836**	**-0.034**
	0.042		*0.038*	*0.009*	*0.834*	*0.011*
AUT	**0.005**	**0.004**	**-0.186**	**0.008**	**0.107**	**-0.007**
	0.001	*0.001*	*0.134*	*0.002*	*0.314*	*0.001*
BEL	**0.02**	**0.019**	**-0.03**	**-0.014**	**-0.001**	**-0.012**
	0.001	*0.001*	*0.034*	*0.002*	*0.062*	*0.002*
CAN	**0.004**		**-0.004**	**-0.005**	**-0.038**	**0.01**
	0.001		*0.025*	*0.006*	*0.204*	*0.008*
CHE	**-1.018**		**-0.546**	**0.024**	**-7.544**	**0.024**
	0.236		*0.242*	*0.019*	*0*	*0.019*
CHL	**2.363**		**2.2**	**-0.215**	**-6.071**	**-0.215**
	0.748		*0.596*	*0.269*	*0.63*	*0.269*
COL	**-1.157**		**-0.685**			
	0.236		*0.242*			
CRI	**0.166**		**0.09**			
	0.05		*0.055*			
CZE	**0.039**	**0.038**	**0.096**	**0.018**	**0.567**	**0.025**
	0.002	*0.002*	*0.399*	*0.007*	*0.553*	*0.006*
DEU	**0.025**	**0.024**	**-0.065**	**-0.008**	**-0.32**	**-0.002**
	0.001	*0.001*	*0.15*	*0.006*	*0.265*	*0.005*
DNK	**0.018**	**0.018**	**-0.203**	**0.016**	**0.357**	**0.007**
	0.002	*0.002*	*0.148*	*0.007*	*0.321*	*0.004*
ESP	**0.002**	**0**	**-0.356**	**-0.032**	**1.13**	**-0.038**
	0.006	*0.006*	*0.127*	*0.01*	*0.529*	*0.015*
EST	**0.032**	**0.03**	**0.233**	**-0.077**	**-0.252**	**-0.077**
	0.005	*0.004*	*0.148*	*0.011*	*1.309*	*0.011*
FIN	**0.045**	**0.044**	**-0.023**	**0.023**	**0.168**	**0.017**

	0.001	*0.001*	*0.21*	*0.006*	*0.313*	*0.003*
FRA	**0.023**	**0.023**	**-0.128**	**0.001**	**-0.092**	**0.01**
	0.001	*0.002*	*0.149*	*0.004*	*0.183*	*0.005*
GBR	**0.006**		**-0.129**	**-0.003**	**0.44**	**-0.007**
	0.001		*0.107*	*0.003*	*0.25*	*0.002*
GRC	**-0.014**	**-0.016**	**-0.128**	**0.014**	**0.359**	**0.018**
	0.004	*0.005*	*0.138*	*0.009*	*0.555*	*0.009*
HUN	**-0.033**	**-0.039**	**-0.227**	**0.016**	**1.342**	**0.014**
	0.027	*0.037*	*0.065*	*0.007*	*0.287*	*0.008*
IRL	**0.038**	**-0.016**	**-0.159**	**-0.012**	**1.7**	**-0.021**
	0.203	*0.211*	*0.074*	*0.009*	*0.507*	*0.006*
ISL	**-0.093**		**-0.205**	**-0.033**	**-0.049**	**-0.045**
	0.048		*0.052*	*0.007*	*0.543*	*0.011*
ISR	**-0.083**		**-0.133**	**-0.015**	**0.1**	**-0.024**
	0.06		*0.066*	*0.004*	*0.136*	*0.004*
ITA	**0**	**-0.002**	**-0.341**	**-0.026**	**-0.163**	**-0.03**
	0.006	*0.006*	*0.191*	*0.009*	*0.591*	*0.008*
JPN				**0.005**	**-0.106**	**0.001**
				0.004	*0.189*	*0.004*
KOR				**0.016**	**-0.43**	**0.016**
				0.003	*0.124*	*0.003*
LTU	**0.052**	**0.05**	**0.189**			
	0.002	*0.002*	*0.168*			
LUX	**-0.095**	**-0.148**	**-0.145**			
	0.187	*0.203*	*0.188*			
LVA	**0.568**	**0.498**	**0.518**			
	0.06	*0.052*	*0.066*			
MEX				**0.021**	**-0.233**	**0.021**
				0.007	*0.3*	*0.007*
NLD	**0.029**	**0.028**	**-0.158**	**-0.019**	**-0.206**	**-0.019**
	0.001	*0.002*	*0.182*	*0.007*	*0.219*	*0.007*
NOR	**0.01**		**-0.228**	**-0.007**	**0.53**	**-0.011**
	0.002		*0.102*	*0.005*	*0.243*	*0.002*
NZL	**0.611**		**0.187**	**0.062**	**0.45**	**-0.018**
	0.149		*0.163*	*0.013*	*0.753*	*0.036*
POL	**0.034**	**0.033**	**-0.295**	**0.015**	**-0.378**	**0.014**
	0.003	*0.004*	*0.267*	*0.008*	*0.618*	*0.008*
PRT	**0.017**	**0.016**	**-0.242**	**-0.049**	**0.694**	**-0.046**
	0.003	*0.003*	*0.145*	*0.016*	*0.744*	*0.014*
SVK	**0.08**	**0.079**	**0.21**	**0.029**	**-0.838**	**0.024**
	0.002	*0.002*	*0.216*	*0.004*	*0.39*	*0.005*
SVN	**0.026**	**0.025**	**-0.112**	**0.007**	**-0.971**	**0.002**
	0.001	*0.001*	*0.144*	*0.012*	*1.172*	*0.011*
SWE	**0.061**	**0.06**	**-0.115**	**0.009**	**-0.311**	**0.003**
	0.001	*0.002*	*0.103*	*0.003*	*0.311*	*0.005*
TUR				**-0.014**	**2.073**	**-0.015**

				0.014	*1.161*	*0.018*
USA	**0.064**		**-0.312**	**0.008**	**0.404**	**0.006**
	0.001		*0.155*	*0.004*	*0.206*	*0.005*

Note: The authors' calculations. Countries: AUS - Australia AUT - Austria BEL - Belgium CAN - Canada CHE - Switzerland CHL - Chile COL - Colombia CRI - Costa Rica CZE - Czech Republic DEU - Germany DNK - Denmark ESP - Spain EST - Estonia FIN - Finland FRA - France GBR - United Kingdom GRC - Greece HUN - Hungary IRL - Ireland ISL - Iceland ISR - Israel ITA - Italy JPN - Japan KOR - South Korea LTU - Lithuania LUX - Luxembourg LVA - Latvia MEX - Mexico NLD - Netherlands NOR - Norway NZL - New Zealand POL - Poland PRT - Portugal SVK - Slovakia SVN - Slovenia SWE - Sweden TUR - Turkey USA - United States of America

Figure 6. Response of productivity to breakthrough patents at the country level (β^c).



Note: The authors' calculations.

6. Conclusion

This study assessed the quantity and economic impact of new innovations using data on so-called breakthrough patents. Based on text analysis and machine learning (Kelly et al. 2021), patents were identified that differ from previous patents (novel) but are broadly similar to later patents (impactful). The most relevant patents were selected for this study. These patents represent clear improvements in technology, and new innovations have been built on them. Therefore, it is justified to talk about breakthrough patents.

The data show that there is a significant drop in the number of breakthrough patents in the early 2000s. After strong growth in previous decades, the drop is seen in particular in the ICT sector, although it can be observed in other sectors. Based on an econometric analysis, the slowdown in innovation activity has a clear temporal connection with the later slowdown in productivity in the 2010s in sectors where the number of breakthrough patents decreased. Based on the analysis, one breakthrough patent is linked to an increase of about 2% in labor productivity in the corresponding industry after 10 years.

A more detailed industry analysis shows that breakthrough patents increase labor productivity in different ways across industries. In industrial ICT industries, breakthrough patents increase productivity on a large scale until the beginning of the 2010s. In sectors other than ICT, productivity growth is more differentiated so that productivity growth can be observed especially in industries that invest significantly in R&D after the emergence of breakthrough patents.

The study also assessed the ability of different countries to respond to the productivity growth potential created by breakthrough patents. In the EU, the countries that have the strongest correlation between breakthrough patents and labor productivity are in Eastern Central Europe and the Nordic countries. Overall, a link between productivity growth and breakthrough sectors tends to be stronger in countries where R&D investments are more located in breakthrough sectors.

The identification of breakthrough patents can help better target innovation and innovation policy in the future, as sectors experiencing breakthrough patents may have more productive investments in R&D than in other sectors long after the breakthrough. While the extent of innovation across countries and technology areas has been quantified by many, to date there is little quantitative work on what type of invention each innovation represents—novel innovation, or more conventional innovation. Estimates of frontier innovations can be valuable inputs to designing microeconomic and macroeconomic policies that seek, on one hand, to eliminate the barriers to frontier innovation and, on the other hand, help take advantage of the areas that do well in frontier innovation.

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