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R&D, innovation and productivity

Pierre Mohnen

Maastricht Economic and social Research institute on Innovation and Technology (UNU-MERIT)
email: info@merit.unu.edu | website: http://www.merit.unu.edu

Boschstraat 24, 6211 AX Maastricht, The Netherlands
Tel: (31) (43) 388 44 00

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R&D, innovation and productivity

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Pierre Mohnen

Maastricht University and UNU-MERIT

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Abstract

This chapter reviews various technological indicators from innovation inputs to innovation outputs, pointing out their strengths and weaknesses and the consequent caution that is in order when using these data for economic analysis. It briefly explains the theoretical link between innovation and productivity growth and then compares the estimated magnitudes of that relationship using the different innovation indicators.

Keywords: innovation, productivity, indicators

JEL classification: D24, O3

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1. Introduction

In the short run labour productivity (output per hour worked), capital productivity (output per unit of capital stock) or total factor productivity (a weighted sum of outputs divided by a weighted sum of inputs) varies over the business cycle because of inflexibilities of various sorts: hiring and firing costs, labour regulations, time to build or adjustment costs leading to variations in capacity utilisation. In the long run, however, changes in technology alter technical coefficients – the amount of a certain input needed per unit of output - augmenting the marginal productivity of certain factors of production or saving on some of them and thereby affect total factor productivity (TFP).

For a long time, technological change was considered as exogenous or simply measured by a time trend. In the last 50 years, various theories have been developed to try and explain the phenomenon of technological change and its impact on economic growth. Various indicators have been collected in order to better understand how it occurs and what effect it has on the level and the growth rate of TFP.

This chapter goes over various technological indicators - R&D expenditure, patents, patent citations, innovation expenditure, the share of innovative sales, count data of innovations and various measures of purchased technologies - pointing out their strengths and weaknesses and the consequent measures of caution to be taken when using these data for economic analysis. It briefly explains the theoretical link between innovation and productivity growth and then compares the estimated magnitudes of that relationship using the different innovation indicators.

The rest of the paper is organised as follows. First, it reviews the most frequently used indicators of technology and discusses their pros and cons. It then examines how they have been used to explain changes in productivity, what econometric challenges are posed by each indicator, and what have been the major results obtained. It concludes with some reflections on the merits of indicators and on the state of knowledge regarding the link between innovation and total factor productivity.

2. Technological indicators

It is useful to start with a description of the data sources available to study the link between innovation and productivity. I shall cover in detail three types of data, which are available in most countries: R&D surveys, patent statistics and innovation surveys. I shall say a few words about other data sources, less frequently used or only available sporadically in a limited number of countries[1].

2.1 Research and Development surveys

According to the Frascati Manual (OECD, 2015), "Research and experimental development (R&D) comprises creative work undertaken on a systematic basis in order to

[1] For a more extended discussion on innovation indicators, see Kleinknecht, Van Montfort and Brouwer (2002), Hagedoorn and Cloodt (2004), Gault (2010), Gault (2013) and Hall and Jaffe (2018).

increase the stock of knowledge, including knowledge of man, culture and society, and the use of this stock of knowledge to devise new applications." It excludes things like routine testing, the analysis of materials, feasibility studies, routine software development and general purpose data collection. R&D can be decomposed into basic research, applied research and experimental development. It can be performed and/or funded by the business enterprise sector, government, higher education and private non-profit organisations.

Starting with the pioneering work of Griliches and Mansfield in the late 50s and early 60s (Griliches, 1964; Mansfield, 1965), a large literature has developed in which R&D expenditures are considered as investments in a stock of knowledge, which depreciates because of physical disappearance (e.g. death of a scientist in case of tacit knowledge, fire in case of codified knowledge) or because of obsolescence (as new knowledge replaces old knowledge). A large literature has considered this stock of knowledge as a determinant of productivity (for surveys of this literature, see for example Griliches (1995), Hall (1996), Hall, Mairesse, Mohnen (2010)).

Besides serving as a measure of innovation input, R&D can also be considered as a way to assimilate knowledge so as to be better able to absorb outside knowledge. In this regard it is like an investment in education to increase the absorption capacity. This dual aspect of R&D investment has been articulated by Cohen and Levinthal (1989).

It is not always crystal-clear what is, and what is not, considered as R&D. In the (2015) version of the Frascati Manual, five conditions are stated to characterise R&D: it has to be aimed at new findings, it has to be based on original concepts and hypotheses, it has to be uncertain about the final outcome, it has to be planned and budgeted, and it has to lead to results that can be reproduced. For a long time the inclusion or not of software in R&D was a matter of discussion. In the new version of the Manual, software is included if it satisfies the five criteria just mentioned. Another limitation of R&D is that more inputs are needed to innovate than just doing R&D. The Oslo Manual (the latest version of which is OECD, 2018) has made a serious attempt in this direction by enlarging the scope of innovation expenditure.

The R&D surveys are, unlike the innovation surveys, supposed to cover all R&D performers in a country, past observed R&D performers as well as new suspected R&D performers because they have for instance applied for R&D tax credits, subsidies, or other forms of government support for innovation. R&D statistics are regularly collected on a yearly basis. Small firms are underrepresented: first of all, R&D surveys are often limited to firms above a certain size in terms of number of employees; second, often a more concise questionnaire is sent to small firms; third, in some countries like Canada R&D from small firms are provided to the statistical offices by the tax department; and fourth, in other countries like the Netherlands the R&D statistics are collected in tandem with the innovation surveys in the years the innovation surveys take place - to avoid different numbers from two separate surveys – and they only cover so-called core R&D performers in the years between two innovation surveys. Moreover, the R&D statistics only cover formal R&D. Small firms without a formal R&D department might be doing some informal R&D and not bother reporting it to the statistical office.

2.2 Patent statistics

In parallel to the literature on the returns to R&D, another branch of studies has explored the estimation of a knowledge production function, linking knowledge inputs in the form of R&D with knowledge outputs in the form of patents. Patents are used as a measure of knowledge output, which can then be inserted in the explanation of other economic variables like productivity or market value. The output measured here is closer to the notion of invention than to the notion of innovation. Patenting is a measure of protection of intellectual property. It may help in bringing new products or processes on the market, but it is not a requisite for it, nor is it sufficient to be successful in innovating. Moreover patents may be applied for strategic reasons to create entry barriers (e.g. patent thickets), to be able to cross-license, or as signals of capability in order to attract outside funding.
Although some earlier studies had already tried to investigate the link between patents and productivity, the literature of patents as indicators of inventive performance really took off with the NBER work under the direction of Zvi Griliches (see in particular the 1984 NBER conference volume and his 1990 paper in the JEL).

Patents contain a lot of extra information besides the recording of a patent grant, the date and the technology class: applicant, assignee, inventor, number of claims, citations to previous patents and publications, priority application date, family information and many more (see Nagaoka, Motohashi, Goto, 2010). It is well known that the distribution of patent values is highly skewed. Therefore it makes more sense to weigh the number of patents somehow, for instance by giving more weight to patents that receive many forward citations.

When performing inter-industry comparisons one should be aware that in some fields it is more difficult to patent, and that some firms prefer not to patent. The 1987 Yale Survey on Industrial Research and Development (Levin, Klevorick, Nelson and Winter, 1987) and the Carnegie-Mellon University R&D Survey of 1994 (Cohen, Nelson and Walsh, 2000) have clearly shown that patents are widely used in fields such as chemicals, drugs and computer and not so much in other fields, where firms prefer alternative means to appropriate the returns from investing in knowledge, such as being the first on the market or developing complex technologies. Similar results of patent concentration in a few sectors are reported by Arundel and Kabla (1998) for Europe. Applying for patents and especially defending one's patents against infringement can be costly and discourage many firms, especially small firms, from applying for patents.

Patent data have the advantage that they are easily available, for long periods of time, and that they contain lots of information on the content of the patented invention, the timing of introduction, renewals and termination, the name and the location of the assignee and references to prior knowledge. All these pieces of information can be useful to infer the private and social value of a patent. The weakness of patent data is the selectivity of patenting, the difficulty of merging patent data with other firm-level data (technology classification versus industry classifications, disambiguation for matching on the basis of firm names).

2.3 Innovation surveys[2]

The innovation surveys follow the guidelines of the Oslo Manual. They collect three types of information on innovation: innovation inputs, outputs and modalities.

The latest version of the Oslo Manual (OECD, 2018) defines innovation as "a new or improved product or process (or combination thereof) that differs significantly from the unit's previous products or processes and that has been made available to potential users (product innovation) or brought into use by the unit (process innovation)". Product innovations encompass goods or services that have undergone significant improvements in one or the other functional characteristic such as quality, affordability, durability to name just a few. Process innovations refer to improvements in the business functions such as increased efficiency, meeting regulatory requirements or cost reductions. The Oslo Manual (OECD, 2018) recognises 6 types of business processes: production of goods and services, distribution and logistics, marketing and sales, information and communication systems, administration and management, and product and business process developments. Organisational and marketing innovations, which were identified separately in the third version of the Oslo Manual, are now considered as part of process innovations. In contrast to patents, innovation measures the implementation and not just the invention of something new. Here also there may be disagreements about what is included in this definition. Price changes due to external circumstances, seasonal and routine changes in the type of products sold, mere colour changes or customisation are not considered as innovations. Some scholars consider that any change in the way business is done is an innovation. There subsists thus a grey area in the definition of innovation.

Innovation surveys collect data on innovation expenditure, which comprises besides the intramural and extramural R&D expenditure already collected in the R&D surveys, engineering, design and other creative activities, marketing and brand equity activities, IP-related activities, employee training activities, software developments and database activities, activities related to the acquisition of lease of tangible assets, and innovation management activities (OECD, 2018). Unfortunately, many of these items are not (yet) collected regularly by all firms, and therefore difficult to quantify and very likely subject to substantial measurement errors. Think of employee training activities specifically for the production of new products or the use of new machines, not employee training activities in general.

The innovation surveys also collect information about the modalities of innovation, such as research collaborations, obstacles to innovation, sources of information, innovation objectives, presence of government support, or environmental innovations.

Innovation surveys are supposed to be representative regarding size, industry, and in some countries even regional distribution, based on stratified random sampling, above a

[2] Since 2009 in the United States, the Business R&D and Innovation Survey, conducted jointly by the National Science Foundation/Science Resources Statistics (NSF/SRS) and the U.S. Census Bureau, replaces the Survey of Industrial Research and Development by adding to the R&D survey some questions related to innovation. It is more an R&D survey than an innovation survey.

certain minimal size threshold. They are conducted every two years now in EU countries (every four years previously) and on a more irregular basis in many other countries. A few countries have yearly data (Germany since 1993[3], Spain since 1990[4], U.S. since 2009).

The innovation survey data have certain characteristics that are important to keep in mind when using them in empirical research. First, they are to a large extent subjective data: the definition itself of what is an innovation leaves room for interpretation, whether a product is new to the firm or new to the market depends on the perception of what the relevant market is, some data asked in the surveys are not systematically collected by firms (such as training for innovation or the share of sales due to new products) and therefore more guestimates than hard data. The likely presence of errors in variables in the innovation survey data and the ensuing attenuation bias in the estimation of the relationship between innovation and productivity has been formally shown in Mairesse, Mohnen and Kremp (2005) and Mairesse and Robin (2017).

Second, contrary to the R&D and patent statistics, few of the data are quantitative to reveal something about the extent of the innovation success. Among the various types of innovation, there is a quantitative measure only for product innovation, the share of total sales due to new products. A few countries have quantitative measures for process innovation, namely the share of cost reduction due to new processes. For most countries, though, only dichotomous information exists for process innovation. While binary variables are less informative than continuous variables, it can, however, be argued that the errors in variables problem is less distorting with binary information.

Third, there is a timing problem, in the sense that innovation refers to a three year period, whereas the few quantitative variables refer only to the last of the three years. It makes for instance little sense to explain the fact that a firm has innovated sometime over a three-year timespan by the amount it spent on R&D in the last year of that period. Fourth, there is a potential selectivity issue as some variables are collected only for innovators. For example, no data on R&D are collected for firms that do not declare to have been innovative. Fifth, it is difficult to conduct panel data analysis with the innovation survey data because of the stratified random sampling. Only large firms (e.g. above 250 employees; the threshold depends on the country) will be approached in every wave. Smaller firms might randomly not be included in every wave. This systematic inclusion of larger firms may create a selection bias in the results obtained. Sixth, the structure of the questionnaire of the innovation surveys, the wording of the questions, the sampling and the mere mandatory nature of these surveys differ across countries more than the R&D surveys, rendering the innovation surveys less comparable internationally than the R&D surveys.

A general problem faced when relating innovation indicators to innovation or economic performance is the endogeneity of innovation. Some variables that drive innovation efforts also drive directly economic performance, and there may be a two-way

[3] The German Mannheim Innovation Panel is managed by the ZEW-Leibniz Center for European Economic Research.

[4] The Spanish ESSE (Encuesta sobre Estrategias Empresariales) Survey on Business Strategies has been conducted since 1990 by the Ministry of Industry and the SEPI Foundation.

relationship between the two variables. Many other variables contained in the innovation surveys may also be subject to endogeneity. Hence, unless the innovation survey data can be merged with other statistics or be made into a longitudinal dataset, there will be a problem of instrumenting the endogenous variables.

Contrary to patent data, R&D and innovation survey micro data are not as easily accessible for reasons of confidentiality. It is therefore difficult to merge innovation survey data from different countries to conduct international comparisons, unlike what can be done with business register data like ORBIS/AMADEUS from Bureau van Dijk, the Business Environment and Enterprise Performance Survey (BEEPS) database from the World Bank and the European Bank for Reconstruction and Development or the EU Industrial R&D Investment Scoreboard database managed by the Joint Research Centre of the European Commission.

Despite this long list of challenges that the user of innovation survey data should be aware of, these data contain new statistics, which have enlarged our understanding of the determinants and the effects of innovation on economic performance, as we shall see in section 3.

2.4 Other data

Literature-based innovation counts

Another measure of innovation output is the literature-based innovation output (LIBO) indicator, which counts innovation announcements that are published in trade and technical journals (Coombs, Naradren, Richards, 1996, Santarelli and Piergiovanni, 1996). One of the first to introduce it were Kleinknecht, Reijnen and Smits (1993).This indicator offers some advantage compared to the innovations surveys: it is less subjective than the innovation outputs from the innovation surveys since it is based on published material and verifiable, it gets recorded soon after the introduction on the market and not one or two years afterwards, in can cover the small firms better than the innovation surveys (as shown by Kleinknecht, 1987), and in principle it could provide more details about the innovation itself. It has, however, the disadvantage that announcements are to some extent subject to self-selection, confined to product innovations, cover tangible goods more than intangible services, focus more on inputs and capital goods, are often biased towards major innovations, and are not systematically collected and readily available for all countries.

Actually a forerunner of the LIBO count data was the Science Policy Research Unit (SPRU) innovation database. This dataset was set up as follows. Experts from industry were asked to identify significant technical innovations that were commercialised in the U.K. between 1945 and 1983. Firms producing these innovations were then approached to provide information about the innovation and characteristics of the firm (Robson, Townsend and Pavitt, 1988). This database ultimately led to the development of the Innovation Surveys, which are no longer based on specific innovations but on firms that innovate or not. In other words, the Innovation Surveys follow the *subject* approach, collecting information about a particular firm, instead of the *object* approach, where the basic statistical unit is an innovation.

Bibliometrics/scientometrics
There is a branch of research called bibliometrics/scientometrics that uses publications and citations from databases such as Google Scholar, Scopus or Web of Science to measure the quantity and the impact of scientific research. These indicators are used for monitoring scientific research output and for measuring productivity of scientific research in universities, research labs, individual researchers and scientific fields, or for measuring technology transfer or collaborations between research institutes and enterprises, more than for explaining the role of innovation in explaining productivity variations within and between firms. These indicators can, however, be helpful as indirect indicators of the connectivity between researchers or the quality of other indicators. To cite one example, Callaert, van Looy, Verbeek, Debackere and Thijs (2006) have looked at backward citations to non-patent references in patent applications to assess the science-intensity of patents.

Inventor surveys
The inventor surveys collect data on the inventors obtained from the patent databases, e.g. the PatVal Survey for six European countries (Giuri et al, 2007), the RIETI-Georgia Tech inventor survey (Walsh and Nagaoka, 2009) for the US and Japan. The aim of those surveys is primarily to gather information about inventors such as profiles, motivations, mobility, performance, and perceived value of the inventions. Inventor survey data have been used as an alternative to patent citations for measuring the value of a patent, sources of knowledge and knowledge spillovers.

Market for Technology
Instead of conducting their own R&D, firms may decide to buy knowhow instead on the market for technology. The innovation surveys contain some binary and continuous data on the purchase of patents and investments related to new technologies among the innovation expenditures. Licensing is another way to purchase outside technologies. No systematic data on licensing deals exist. The European and Japanese Patent Offices (EPO and JPO) organised a survey of licensing among patent holders in 2007 (Zuniga and Guellec, 2009). Arqué-Castells and Spulber (2018) use data on patent trades from USPTO, licensing deals from the SEC (Securities and Exchange Commission) filings (ktMINE's licensing database), and cross-licensing data from the SEC forms, as well as Google searches, to construct connections in the market for technology. They find that when the returns on the markets for technology, which diffuse technological change, are internalised, the private and social rates of return on R&D increase substantially, by as much as 50% and 100% respectively.

Technology adoption and diffusion
One way to foster technological change is to develop new products, services or technologies, another one is to adopt existing technologies and ensure their diffusion throughout the economy. Surveys on the adoption of advanced technologies in manufacturing have been conducted in a number of countries. They do not identify transactions and amounts paid, but they identify whether a firm has used a range of advanced technologies. Empirical studies examining the link between the adoption of advanced technologies and productivity growth in manufacturing conclude that there is a

positive link between the two variables (e.g. Baldwin and Sabourin, 2004 for Canada, Bartelsman, van Leeuwen and Niewenhuijsen, 1998 for the Netherlands).

User innovation
Firms are user innovators if they develop a process innovation for their own use or if they adopt a process and adapt it for their own use. A sizeable proportion of firms are user innovators, as high as 54% in high-tech Dutch small and medium enterprises (de Jong and von Hippel, 2013). User innovators are more prone than commercial innovators to share their findings and the adoption rate of user innovations is also higher than adoption rates in general.

3. **Innovation and productivity**[5]

In this section, we shall examine what we have learned from R&D, patents, innovation surveys and innovation count data regarding the link between innovation and productivity.

3.1 Studies based on R&D data

The various indicators of innovation that have been listed above have been used in various ways to measure their impact on economic performance at the firm, sector or country level. In endogenous growth models productivity growth is in part due to R&D efforts that are only undertaken if the costs of engaging in R&D (those can be variable, fixed or even sunk costs) do not exceed the returns from doing R&D. R&D generates innovation in the form of new intermediate inputs or new consumer goods, the variety of which increases productivity or consumer utility. In parallel to this love for variety approach, a Schumpeterian creative destruction approach has been developed in which new products replace old products because of superior quality instead of just increasing the range of products in the market and diminishing the margins made on old products (see Aghion and Howitt, 1998, Barro and Sala-i-Martin, 2004). There is also a debate in this literature between the contenders of the semi-endogenous and the fully-endogenous R&D-based growth models, the former arguing that the returns to R&D are decreasing, the latter defending the assumption of constant returns to R&D. Ha and Howitt (2007) show evidence in favour of the Schumpeterian fully-endogenous growth models, whereas Bloom, Jones, Van Reenen and Webb (2017) illustrate the declining productivity of R&D in a number of research fields. Nonetheless, so they argue, endogenous growth can survive because of the non-rival nature of knowledge.

Spillovers play an important role in R&D-based growth models. They can be positive as knowledge gets transmitted between agents or over generations or when rents occur because of imperfect price discrimination or network externalities. They can also be negative because of decreasing returns, duplication, obsolescence or market stealing. A number of macro studies based on assumptions regarding these various forces have

[5] Part of this section is based on Mohnen (2018), « The role of research and development in fostering economic performance. A survey of the macro-level literature and policy implications for Finland", report submitted to OECD, February 2018.

simulated the societal effects of R&D on economic growth. Depending on whether the positive or the negative externalities dominate, there is private underinvestment or overinvestment in R&D (see Montmartin and Massard, 2005).

Even before these theoretical developments in the modelling of endogenous economic growth took place, empirical studies were devoted to estimate the returns to R&D starting with Griliches (1964) and Mansfield (1965). The underlying model is an extended production function with as additional input the stock of knowledge obtained from R&D expenditure. The stock of knowledge depreciates when tacit knowledge gets lost for instance with the death of a scientist[6] or when through obsolescence new knowledge supersedes old knowledge. The idea is to estimate the increment in production or value added due to a marginal increase in the stock of knowledge. If this marginal productivity remains constant over time, it can also be interpreted as the internal rate of return that equates costs and revenues gross of the depreciation rate of the stock of knowledge. When multiplying this marginal productivity by the R&D over output ratio one gets the elasticity of output with respect to R&D, which multiplied by the growth rate of the R&D stock measures the contribution of R&D to output or total factor productivity growth in growth accounting.

Spillovers are captured by including as an additional argument in the production function the R&D stock accumulated outside of the firm. This is usually done by constructing a weighted average of the R&D stocks of other R&D performers (plants, firms, sectors, regions or countries depending on the level of aggregation), unless one wants to estimate separate spillover sources, which can quickly become difficult to identify as the allowed number of sources increases. Various weighting schemes have been experimented with depending on the assumed channel of transmission of the spillovers: geographical proximities, R&D collaborations, co-patenting, correlations of positions in the patent classes or in the lines of business, patent citations, interindustry transactions, international trade, foreign direct investment, to name the most popular ones. If the outgoing R&D externalities are added to the private rate of return to R&D, one obtains a social rate of return to R&D, that is, the return to society at large.

The rate of return to R&D has been estimated in a variety of ways. We briefly list below several of the major differences in specification and the possible effects they could have on the estimated returns to R&D. For a more thorough and detailed discussion of these issues, the reader is referred to the initial presentation of the whole framework in Griliches (1979) and to the survey by Hall, Mairesse and Mohnen (2010).

Regarding the specification, most studies have used a Cobb-Douglas production function. Some have used a translog or other second-order approximations of a general production function, which allow for complementarities or substitutions between R&D and other inputs. Some studies have preferred assuming a constant elasticity of output with respect to productivity rather than a constant marginal productivity of R&D. Estimates seem to

[6] Recent work on team capital confirms this loss of tacit knowledge. Azoulay, Graff Zivin and Wang (2010) find that the premature death of a superstar scientist reduces by 5% to 8% the quality-adjusted publication record of his (her) collaborators. In the same vein, Jaravel, Petkova and Bell (2018) find that the unexpected death of an inventor decreases the co-inventors' earnings by 4% and their citation-weighted patents by 15% after 8 years.

be more stable with a constant elasticity specification, implicitly assuming a declining marginal productivity of R&D. Some studies have favoured a dual representation of technology, conditional on variable factor prices and, maybe more contentiously, on the exogenous level of production in lieu of the input levels. A system of demand equations can then be estimated, which increases the number of degrees of freedom. Sometimes a mixture of variable and quasi-fixed inputs is allowed for. A few studies have opted for an intertemporal model of decision-making to derive the optimal path of knowledge accumulation, which yields the specification of the demand for R&D equation.

Regarding the data, the earlier studies used sector or aggregate country data. Nowadays, the majority of studies are based on firm data or even on establishment data. At a higher level of aggregation, one would expect higher rates of return because of internalised spillovers, but this is not systematically the case. Ideally, the traditional inputs should be cleared of their R&D component to avoid R&D double-counting (Schankerman, 1981). This is rather rarely done at the cost of yielding underestimates of the returns to R&D. A crucial element in the estimation of the rate of return to R&D is the assumed depreciation rate. At the beginning of this literature, when time-series on R&D were still relatively short, a zero rate of depreciation was often assumed to obviate the need to construct a stock of knowledge. Later studies constructed R&D stocks assuming constant - over time and space - R&D depreciation rates. The latest studies obtain time- and industry-specific R&D depreciation rates (Li and Hall, 2017).

The production function or the dual representation of technology has been estimated in levels or in growth rates. Estimates are generally higher, more stable and more likely to be significant when based on levels rather than growth rates. Most studies are based on time-series data, exploiting only the temporal variation, some use only cross-sectional data, the more recent studies exploit panel data, where both temporal and cross-sectional variations can be exploited and individual effects can be controlled for. Typically, lower returns are obtained in the within than in the between variation. Some studies have controlled for other factors that may affect productivity, such as human capital, organisational capital, ICT equipment, R&D spillovers or sector-specificities. The returns to R&D tend to drop when these other variables are introduced.

Over the last 50 years, many empirical papers have been devoted to the estimation of the private and the social rates of return to R&D (see the survey by Hall, Mairesse and Mohnen (2010) and the meta-analyses by Wieser (2005), Koopmans and Donselaar (2015) and Ugur, Trushin, Solomon and Guidi (2016)). Despite the large heterogeneity in the results obtained, the following seem to be reasonable orders of magnitude. The private rate of return on R&D exceeds the normal rate of return and is the 10% to 30% range. Estimates of the elasticity of output with respect to R&D are largely consistent with those of the rates of return and hover around 0.10. Given these estimates and the growth in R&D stock, the contribution of R&D to TFP growth is expected to be in the range of 10 to 15%. The social rate of return exceeds the private rate of return by a factor of 50% to 100%. Rates of return are found to be heterogeneous. They are generally found to be higher for private than for public R&D and for basic R&D than for applied R&D or development. The estimated elasticities are generally higher in high-tech, i.e. R&D-intensive, than in low-tech sectors (e.g. Ortega-Argilés, Piva and Vivarelli, 2015) but according to the results reported by Wieser (1979) and Ugur et al. (2016), the associated rates of return are not necessarily different between the two sectors. Rates of return may differ across countries because of differences in distance to the frontier (Griffith, Redding and Van Reenen, 2004), industrial structure or national innovation systems (Kokko, Gustavsson Tingvall and Videnord, 2015). Countries may benefit from international R&D spillovers. As shown in Mancusi (2008) laggard countries are mainly the beneficiaries, depending on their absorptive capacity, whereas technological leaders are mainly the source of international R&D spillovers.

The 2008 revision of the National Income and Product Accounts treats R&D as an investment and no longer as an expenditure. Fraumeni and Okubo (2005) have focused on the contribution of R&D in the new national income accounting. For the United States over the period 1961-2000, they arrive, on the expenditure side, at a contribution of R&D investment to corrected GDP between 2% and 7% depending on the scenarios, and on the income side, at a contribution of the returns on R&D to corrected GDP between 4% and 15%. Corrado, Haskel, Jona-Lasinio and Iommi (2013) follow the approach of Corrado, Hulten and Sichel (2009) and consider three types of intangible assets: (i) computerised information (software, databases), (ii) innovative property (research and development, mineral exploitation, copyright and license costs and other product development, design and research expenses), and (iii) economic competences (brand equity, firm-specific human capital and organisational structure). They have capitalised the investments in these intangibles under some assumptions regarding deflators and depreciation rates. They find that innovative property (including R&D) accounts for a proportion of labour productivity growth that ranges from 4.5% in the UK to 12.5% in the US.

Besides the extended production function approach, there are at least three other approaches that are worth signalling: the stochastic efficiency frontier, the market value and the stochastic productivity residual. The stochastic efficiency frontier estimates both the outward shift of the frontier and changes of positions with respect to the frontier. Kumbhakar et al. (2012) estimate a parametric stochastic efficiency frontier instead of a production function. For a sample of top European R&D investors between 2000 and 2005 they show that in high-tech sectors R&D mainly shifts out the frontier, whereas in low-tech sectors its role is mainly to bring firms closer to the frontier. Many studies have also looked into whether valuations of firms in the stock market are related to the volume of their R&D capital stocks in publicly traded firms. The underlying model is a market value equation that depends on the replacement value times Tobin's q, which depends on knowledge capital (see Griliches, 1990 and Hall, 2000). Although, this method can only be applied for publicly traded firms, it has the advantage of including expected future returns. Positive effects of R&D have been estimated for many countries, although these estimated coefficients are lower than one, suggesting overinvestment, insufficient shareholder protection or too low R&D depreciation rates used in the construction of the R&D capital stocks (see Hall and Oriani, 2006). The last approach that we want to mention models R&D no longer as a capital stock, which affects productivity in a linear and deterministic fashion, but as an investment that affects the distribution of total factor productivity. Using this kind of framework, Doraszelski and Jaumandreu (2013) find that in most Spanish industries the return to R&D is higher, the higher is past productivity, and that the mean expected productivity is higher for R&D-performing than for non-R&D-performing firms. The net rate of return to R&D varies across industries but averages around 40%, being higher in industries where the uncertainty is higher.

3.2 Studies based on patent data[7]

In principle, the methods used in the previous section could be applied to the stock of patents as a measure of the stock of knowledge in lieu of the R&D stock. In this way the patent stock could be related to productivity, market value, movements to the efficiency frontier or the Markov process governing the stochastic productivity residual. The fact that the distribution of patent values is highly skewed, with very few patents being worth a lot, militates in favour of using R&D instead of patents to explain TFP or market value, because the errors in variable problem is higher for patents than for R&D. Hall, Jaffe and Trajtenberg (2005) have compared the effect of R&D, patents and citations on the market value of firms and found that a percentage point increase in the R&D/assets ratio leads to a 0.8% increase in market value, that an extra patent per million $ of R&D boosts market value by about 2%, and an extra citation per patent boosts it by over 3%. They also find that the market values are particularly correlated with citations that cannot be predicted from past citations. Hence patents count, and especially citations. Although they are not as good predictors of market value as R&D, they nevertheless add to the understanding of market values.

What has also been examined is the link between patents and R&D, one version of the so-called knowledge production function (Griliches, 1990). It has been found that patents are correlated with R&D and that there is hardly any lag between the two. Here again the relationship is less visible in the within temporal dimension. In the cross-sectional dimension, the relationship between patents and R&D is higher for small than for large firms, because of selectivity (observing the best small firms) and more frequent use of informal IP protection in large firms and informal R&D in small firms.

Patents can be very useful for estimating R&D spillovers. There are two ways in which this can be done. The first is to measure a spatial correlation of firms in the patent space, i.e. the vector positions of firms in patent classes. This idea goes back to Jaffe (1986). The idea is that the more firms patent in the same or in close patent classes, the more they perform similar research and benefit from each other's research. The second way patents can be used in connection to R&D spillovers is by way of patent citations. Citations to previous patents can be considered as proxies for knowledge flows between firms. This approach had been used to estimate spillovers across industries (Scherer, 1982), countries (Jaffe, Trajtenberg and Henderson, 1993; Verspagen, 1997) or regions (Peri, 2005). Patent citations tend to be localised and therefore, if they are supposed to reflect knowledge flows, they point to geographical spillovers that decrease with distance to the origin. Peri (2005) finds that only 20% of the knowledge generated in a region flows out of it even though knowledge flows are much less localised than trade flows.

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[7] Patent data have been used for other topics than their link to R&D and productivity, like the strategic use of patents (pre-emptive patenting, patent trolls, patent litigations, patent thickets), or policies for protecting intellectual property (patent length, patent breath, patentability); see Hall and Harhoff, 2012. We shall limit ourselves to the use of patents as indicators of innovation and their link to variations in productivity.

Using the Google Patent database, Kogan, Papanikolaou, Seru and Stoffman (2017) infer the value of patents from the stock market reactions three days after patents are issued. A firm's innovation is measured as the sum of the values of all the patents granted to a firm normalised by its size. The authors find that a one standard deviation increase in a firm's innovation is associated with a 2.4% increase in a firm's revenue-based productivity, whereas a one standard deviation increase in innovation by a firm's competitors is followed by a 1.7% drop in productivity over five years. At the macro level, they find that a one standard deviation increase in macro innovation leads to a 3.4% increase in TFP growth in the next 5 years.

3.3 Studies based on innovation survey data

With the advent of the innovation surveys, which started to be collected in many countries in the early 1990s, it became possible to relate productivity with measures of implemented innovation output instead of just innovation inputs. Actually, the production function relating productivity to innovation output could be combined with a knowledge production function relating innovation input (R&D or innovation expenditure) with innovation output. This structural model was first proposed by Pakes and Griliches (1984) using patents as innovation outputs, and later implemented by Crépon, Duguet and Mairesse (1998), using patents and the share of innovative sales as alternative measures of innovation output, in what has come to be known as the CDM model. It treats the endogeneity of R&D and innovation output by having an equation explaining the amount of R&D, one that explains the intensity of innovation and one that explains productivity in growth rates or in levels. Moreover, some firms happen to do no R&D and many are not innovative. This selectivity issue is also handled in the CDM model using tobit models or Heckman's two-step approach. The CDM framework allows for the use of binary and continuous data for innovation inputs and or outputs, and in principle for multiple sources of innovation.

The original CDM model is a recursive model without feedback from productivity to R&D or innovation. It may well be that productive firms are more innovative because they can afford to finance innovation projects. Several attempts have been made to let this happen by introducing past productivity in the innovation input or output equations (Baum, Lööf, Nabavi and Stephan, 2017; Raymond, Mairesse, Mohnen and Palm, 2015; Cainelli, Evangelista and Savona, 2006). Another generalisation of the CDM model consists in allowing for lags in the relationships among R&D, innovation and productivity, as well as for persistence in innovation and productivity. It is important in that case to allow for unobserved heterogeneity so as to avoid spurious persistence. Persistence seems to be correlated with the intensity of innovation as it is found to be more pronounced for R&D performing innovative firms (Peters, 2009), in high-tech industries (Raymond, Mohnen, Palm and Schim van der Loeff, 2010) and for radical innovators (Zhen, 2018).

When continuous measures of innovation output are used, the typical orders of magnitude of the elasticities of output with respect to innovation are between 0.10 and 0.25, indicating that a 10% increase in innovation output (sales of new products per employee) increases labour productivity by 1 to 2.5 % (Mohnen and Hall, 2013). The elasticity of productivity with respect innovation output declines when other factors like capital stock or human capital are controlled for. As was also mentioned for R&D, lower elasticities are found when the regression is in growth rates rather than levels of productivity. The innovation survey allows for various levels of novelty of product innovations by distinguishing products new to the firm and products new to the market. With continuous data, no major differences are found regarding the level of novelty. When only binary data on innovation output are available, innovation generally increases productivity significantly, whatever kind of innovation is considered. Peters et al. (2017) report that in German high-tech industries it is product innovation that increases productivity, in low-tech industries it is process innovation. As Jaumandreu and Mairesse (2017) actually argue and show, it is difficult to identify separately the effect of different types of innovation, partly because we know too little to instrument each type of innovation output by different exogenous variables, and partly because different types of innovation are often introduced simultaneously.

On French data, Mairesse, Mohnen and Kremp (2005) have shown that the rates of return to R&D calculated from the CDM model are consistent with those obtained from the reduced form model where R&D enters the production function directly. What these innovation surveys have also revealed is that especially for low and medium technology firms, small and medium sized firms and firms in developing countries, non-R&D is an important input in the innovation process besides formal R&D. Instead of relying on their own R&D, these firms buy outside technologies and invest in advanced manufacturing technologies, licensing and training to advance their state of knowledge (Santamaría, Nieto and Barge-Gil, 2009; Huang, Arundel and Hollanders, 2010). The CDM model has recently been generalised by Peters, Roberts, Vuong and Fryges (2017) in the direction of making the effect of R&D on innovation and of innovation on productivity stochastic. Their model allows for firms to be innovative without doing R&D; as a matter of fact, on German data they find that this is the case for 22% of the firms. Firms that do R&D are more likely to be innovative, but R&D is not a sufficient condition for being innovative: the probability of turning out not to be innovative is 10% in low-tech industries and 20% in high-tech industries. The long-run rate of return to R&D is calculated as the relative difference in the expected firm value between firms that do and those that do not do any R&D. In the high-tech industries the median rate of return to R&D is 6.7%. In low-tech industries the corresponding figure is 2.8%. They also find a lot of heterogeneity between firms and thereby rejoin Baum, Lööf, Navari, Stephan (2017), who report that the relationship between innovation and productivity differs across industries. The international comparison study performed on 18 OECD countries also found heterogeneity across countries, types of sectors, and sizes of firms with generally larger effects of innovation on productivity in manufacturing than in services (OECD, 2009). The positive links between innovation input, innovation output and productivity are also obtained on Latin American data, but the semi-elasticity of productivity with respect to dichotomous measures of innovation tend to be higher in Latin American than in European countries, reflecting a greater productivity gap that could be overcome by innovation in the former countries (Crespi and Zuniga, 2012).

There is mixed evidence regarding the existence of any complementarity between different types of innovation, meaning that the return from one type would increase in the presence of the other type. Ballot, Fakhfakh, Galia, Salter (2015) find some complementarity between product and process innovation in France and in the UK, but only complementarity between product (not process) and organisational innovation in France (not the UK). Peters et al. (2017) find no sign that the simultaneous introduction of product and process innovation has any additional effect in German firms, whereas Schmidt and Rammer (2007) conclude that product and process innovations lead to higher cost reductions or more novel (new-to-market) product innovations when combined with both organisational and marketing innovations.

3.4 Innovation count data

One of the first studies using counts of new products is by Comanor and Scherer (1969). They used two measures of new product counts corresponding to the notions of new to the market and new to the firm: the number of new chemical entities introduced by each pharmaceutical firm from 1955 to 1960, with each new product weighted by its sales during the first two calendar years following introduction, and a similar broader measure that includes combinations of active ingredients, new dosage forms and products that merely duplicate those already introduced by competing firms as well as new chemical entities. They found significant positive correlations between the three measures even after controlling for firm size.

Acs and Audretsch (1988) exploit count data on announced innovations compiled by the U.S. Small Business Administration from listings in hundreds of trade journal. They report a higher correlation between innovation counts and patents than between innovation counts and R&D. When controlling for other determinants, they obtain an elasticity of innovation counts with respect to corporate R&D close to 0.5. Using the SPRU innovation count database, Geroski (1991) and Sterlachinni (1989) find a positive correlation between the number of innovations used in an industry and its productivity growth.[8]

4. Conclusion and discussion

Whatever the innovation indicator, there will always be the problem that part of the variation of productivity reflects mismeasured prices. Few micro datasets contain product prices. To the extent that industry deflators incorrectly measure firm-specific price changes on the input or on the output side productivity gets over- or underestimated. This problem is magnified when it comes to innovation. First, prices of new products are hard to measure, secondly quality changes are difficult to dissociate from pure price changes, and third, part of revenue productivity growth can be due to market power instead of efficiency in the production of goods or services.

[8] Sjöö (2016) examines whether there was an industrial renewal in Sweden between 1970 and 2007 in terms of degree of novelty, volume, firm size, concentration, and industrial origin on the basis of some 4000 innovations introduced in Sweden during this time period. She does not relate innovations to productivity growth.

Over the last 50 years, efforts have been made to collect indicators of innovation inputs and outputs in a systematic and standardised way. R&D surveys are conducted in almost all countries and innovation surveys are conducted on a regular basis in more and more countries. Patent applications have soared, thereby collecting useful data on inventions in technology classes, citations and patent renewal fees to infer the value of patents and to measure knowledge spillovers. With progress in digital technology, information on patents and other IP tools like trademarks, licenses and utility models, can be easily stored and made available worldwide. In the future, big data will allow the examination of innovation from other angles, such as consumption patterns and networks.

The choice between indicators depends on the purpose of their use. In this paper we confined ourselves to explaining TFP growth. They could also be used to assess domestic and international competitiveness, employment, standard of living, development or inequality in the distribution of income. Policy makers tend to concentrate on a particular indicator for monitoring and benchmarking innovative capabilities, for instance the R&D over GDP ratio. This rather narrow view of technological capabilities neglects at least three facts: first, some industries are more R&D intensive than others, and a country might be specialised in low R&D-intensive industries; secondly, what matters is not just R&D generation but rather R&D use and a country may decide to buy knowledge in the technology market rather than doing R&D itself; and third, many digitally-based innovations are services, which do not require much R&D but developments of connectivity, multi-sided markets and integration of technologies.

Even when it comes to explaining TFP growth, there is not one best indicator. As we have seen, every indicator has its specificities, strengths and weaknesses. Some measure the inputs, others measure the outputs of technological of innovation; some are easily available, others require special permissions; some are collected regularly, others only occasionally; some present themselves as panel data, others only as cross-sections. They may be biased towards large firms or publicly-listed firms. They may pertain to a particular date or to a longer period. They may reflect a verifiable transaction or they may represent guestimates. And the list goes on. One solution is to construct an index based on these various indicators. While it may do a good job in terms of monitoring and benchmarking, it does not exploit the full information contained in multiple indicators, which would lead to a better understanding of the links between them and the ultimate performance measure one seeks to explain.

Improvements will be made in the future thanks to the ease of sharing and storing information. New indicators will be developed such as the tracing of the value chains for many goods, data on functionalities rather than services, integration of worldwide operations of multinational firms. As much as possible we should try to strive for longitudinal data that can be merged with other data.

The present state of knowledge confirms Schumpeter's and long before him John Rae's vision of innovation as driver of economic growth. Whatever innovation indicator we select, the evidence overwhelmingly shows that in the long run innovation is correlated with total factor productivity growth whether at the firm or at the aggregate level.

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