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INNOVATION AND PRODUCTIVITY: THE RECENT EMPIRICAL LITERATURE AND THE STATE OF THE ART

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CS
2025s-03
WORKING PAPER

ISSN 2292-0838 (online version)

Innovation and productivity: the recent empirical literature and the state of the art

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Abstract/Résumé

This paper reviews the empirical work that has been done over the period 2013-2023 on the topic of innovation and productivity. A visual graph based on keywords shows the main areas that have been investigated. The literature review is organized around the way the link between innovation and productivity has been analyzed, the data that have been used, and the evidence that has been obtained. The paper ends with suggestions of future research on the topic.

Ce document passe en revue les travaux empiriques réalisés au cours de la période 2013-2023 sur le thème de l'innovation et de la productivité. Un graphique visuel basé sur des mots-clés montre les principaux domaines qui ont été étudiés. La revue de littérature est organisée autour de la manière dont le lien entre l'innovation et la productivité a été analysé, des données qui ont été utilisées et des preuves qui ont été obtenues. Le document se termine par des suggestions de recherches futures sur le sujet.

Keywords/Mots-clés: literature review, productivity, innovation, micro data / Revue de littérature, productivité, innovation, données microéconomiques

JEL Codes/Codes JEL: D24, O30, O31, O32

Acknowledgement: We thank Marco Vivarelli and two referees for their constructive comments.

Pour citer ce document / To quote this document
Mairesse, J., Mohnen, P., & Notten, A. (2025). Innovation and productivity: the recent empirical literature and the state of the art (2025s-03, Working Papers, CIRANO.) https://doi.org/10.54932/OBKC2057

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1. Introduction

This paper takes stock of what has been done over the period 2013-2023 on the topic of innovation and productivity emphasizing the direction in which research has been going, what has been found and what could be done in the future. It is by presenting what has been found and how it has been done that we get a clearer picture of what needs to be done in the future.

We shall build up on the reviews by Hall et al. (2010), Mairesse and Mohnen (2010), Hall (2011), Mohnen and Hall (2013), Mohnen (2019) and Ugur and Vivarelli (2021). We shall circumscribe the unavoidable overlap with the previous reviews by restricting this one to papers published over the period 2013-2023, by not reviewing the literature that relates R&D to productivity without considering innovation output, and by not covering any theoretical papers. To clearly delimit the scope of this literature review, we only cover empirical work using micro data. As such, we do not cover papers dealing essentially with the effectiveness of policy interventions like environmental regulations, subsidies or tax incentives, nor papers looking at determinants of productivity or innovation without making the link between the two variables, nor agent-based models replicating stylized facts of industrial dynamics. We have also deliberately eliminated papers on particular technologies, like agricultural technologies, digitization, automation, or artificial intelligence, unless they are related to the link between innovation and productivity.

We have certainly missed some contributions to this literature. We apologize for that. The main point was not to include each and every paper written in this area, but mainly to indicate the directions in which the literature has been developing in the last ten years. We started by collecting papers in a systematic way using a multi-pronged approach. Our search strategy first focused on peer-reviewed papers that cite the 1998 paper by Crépon, Duguet and Mairesse (Crépon et al.,1998), a paper also known by the acronym CDM. In parallel we also collected peer-reviewed papers studying innovation and productivity using micro-data through a general keyword search in the title, abstract and keyword fields. This search was delimited by a selection of peer-reviewed journals and working paper series, i.e. a "journal set"[1], which is a well-accepted way of delineating a research area (Milojevic, 2020, p.184). Then, in a third stage we looked at specific citations in the list of references of the papers we reviewed, taking on board those papers that matched the earlier search criteria. In all, more than a thousand papers were collected for initial review.

Productivity essentially means producing more output with less input, but it can be measured in different ways: single factor productivity like output per hours worked, total factor productivity,

[1] Journals and (working) paper series usually serve as an outlet for specific research communities. Authors, editors, reviewers and readers of these outlets are an integral part of these communities and view particular journals as "core" to their community, research area and discipline.

which is the output not explained by the inset of all factors of production, revenue productivity, where output is expressed in nominal prices and therefore captures both the total factor productivity and the price markup, and efficiency, which measures the distance to the best practice frontier. Because of the paucity of good statistical data, like the unavailability of capital stock, materials or output prices, productivity is often measured by labour productivity or revenue productivity and therefore measures only imperfectly total factor productivity. Besides the difficulties related to the data needed to measure productivity, another major challenge is to estimate the marginal productivities or output elasticities of the various inputs. Under some stringent assumptions like perfectly competitive markets, constant returns to scale and optimal factor holdings, total factor productivity can be computed by the index method. Alternatively, it can be estimated econometrically from a production function, especially if some of these assumptions are not imposed. Another problem that many studies have tried to tackle recently is the endogeneity of certain inputs. Recent studies have tackled this difficulty by assuming that the productivity shock that is known to the firm but unobserved by the econometrician can be proxied by another observed variable and follows a first-order Markov process that can be approximated by a polynomial function, see Olley and Pakes (1996), Levinsohn and Petrin (2003) and Ackerberg et al. (2015). Generally, levels of productivity are considered, but sometimes also growth rates, firm levels relative to sector means or quintiles of the productivity distribution (Audretsch and Belitski, 2020; Coad et al., 2016).

Innovation can be measured in different ways as well. On the input side, you have R&D expenditure or the purchase of patents and licenses. On the output side, you have patents, new products/services, new processes, new ways of organizing production or of marketing the products. Given the huge literature on R&D and productivity, which has been reviewed many times already (see Hall et al., 2010; Kokko et al., 2015; and Ugur et al., 2016), we shall disregard these studies and concentrate on the literature of innovation output and productivity. Innovation inputs are only examined in so far as they affect innovation output.

There has been a proliferation of new survey data that allow for more control variables, more sources of heterogeneity, more countries, longer time series and the examination of innovation in particular technologies like ICT (Information and Communication Technologies), robotization, digitization, artificial intelligence or environmental innovations. New waves of the Innovation Surveys, which follow the guidelines of the Oslo Manual (OECD-Eurostat, 2018), have been conducted in many countries, including developing countries. The World Bank Enterprise Surveys (WBES) conducted by the World Bank in many developed and developing countries, and the Business Environment and Enterprise Performance Surveys (BEEPS) conducted by the European Bank for Reconstruction and Development and the World Bank in countries from Eastern and Central Europe and from Central Asia and the Caucasus, allow international comparisons and links with many other variables besides innovation and productivity. The survey data have the disadvantage to be self-reported and subjective (see Cirera and Muzzi, 2016 for a critical view of the innovation surveys in developing countries). There is ongoing work attempting to measure innovation in a more timely fashion using web-based data. As an example, Nathan and Rosso (2022) use event data on the launch of a new product or service as a new metric of innovation and combine these data with data from the UK companies register. Their new product/service launch data are obtained with the help of machine learning routines from events reported in 3740 news sources.

On the modeling side, there are still some studies, but few of them, that regress productivity on innovation considering the latter to be exogenous (Carvalho and de Avellar (2017) for Brazil, Long and Ahn (2017) for Vietnam, Liao (2020) for Spain, Nathan and Rosso (2022) for the UK). The CDM model has clearly been the workhorse of the empirical literature on innovation and productivity in the last 10 years. The model has the particularity that (1) it handles the endogeneity of R&D and innovation in the productivity equation due to measurement errors, reverse causality or common dependence with third factors; (2) it deals with the selection into R&D and innovation, i.e. it models the non-occurrence of those two variables; and (3) it proposes a causality running from R&D to innovation to productivity (more on this later).[2] Actually, the authors of the original CDM paper had in mind a framework more than a model in which to incorporate R&D, innovation and productivity. As we shall document, the original CDM model has indeed been extended in different directions. A new approach introduces stochasticity in the relationships between R&D, innovation and productivity: not all R&D projects lead to innovation, and new products or processes do not necessarily increase productivity. Finally, some studies have tested for a causal relationship between innovation and productivity by using randomized or quasi-random experiments.

As a way of scoping the current "innovation and productivity landscape", we have collected all the keywords contained in the final selection of papers and classified them, somewhat arbitrarily, into twelve classes as shown in Table 1 below. For instance, "collaboration" would be classified under innovation characteristics, "firm size" under firm characteristics and "general propensity score" under econometric techniques. "Emerging countries" regroups all the countries that are not classified as advanced economies in the IMF classification.

Table 1. Twelve Classes of keywords

1. Data	7. Innovation Characteristics
2. Econometric Techniques	8. Modeling
3. Emerging Countries	9. Performance
4. Firm Characteristics	10. Policy Measures
5. Industrial Countries	11. Technological Characteristics
6. Industries	12. Technologies

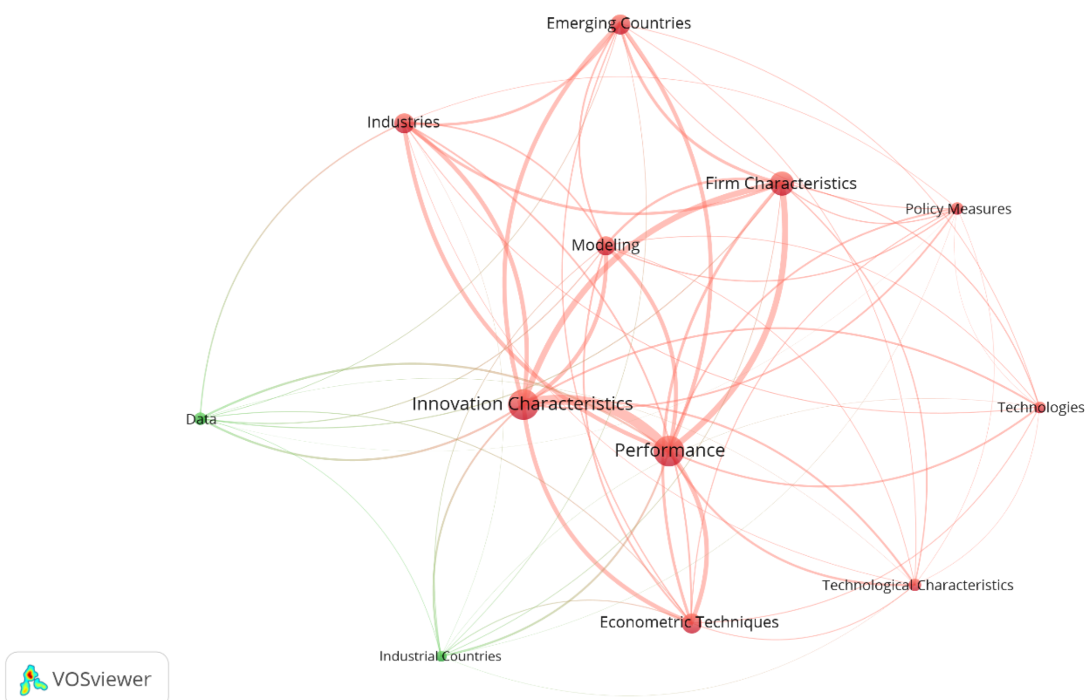
[2] A special issue of the Economics of Innovation and New Technology was devoted to the 20th anniversary of the CDM model (see Lööf et al., 2017).

Note: Author's own interpretation

Using this scoping exercise, we try to understand which are the areas of the literature that are well researched, and which areas are less popular in terms of research conducted. The main benefit of this method is that it has given us a feeling for "the lay of the land".

In order to visualize this classification, we have used network analytical tools such as Pajek (Batagelj and Mvar, 2002) and VOSviewer[3]. The visualization in Figure 1 shows that the literature focuses foremost on Innovation Characteristics and Performance, as well as Firm Characteristics. The literature also focuses on Emerging Countries and, obviously, on Modeling and Econometric Techniques. Although we have not used this classification as a guidance tool for our literature review, some of the classes are consistent with some of the review's headings. For instance, the class "Emerging Countries" reappears under heading 2.1 "Extension to more countries", the class "Econometric Techniques" under heading 2.2 "Alternative estimation methods", and "Innovation Characteristics" under heading 2.3 "Additional endogenous innovation inputs".

Figure 1.Innovation and Productivity: A visualization of the classification



Note: Network calculations using Pajek and visualized using VOSviewer.

[3] See: VOSviewer: Visualizing Scientific Landscapes, https://www.vosviewer.com/

In the end, we have chosen to organize the literature along the models used to analyze the relationship between innovation and productivity. First, we go over the extensions brought to the original CDM model and present the results obtained regarding complementarity between types of innovation, causality, links with other endogenous variables on the input or the output side of innovation, and heterogeneity regarding innovation types and business environments. Secondly, we review the studies that have introduced stochastic elements in the CDM model. Thirdly, we present some estimates of the average treatment effect of innovation from studies that look at causality through other methods than instrumental variables. We close by discussing avenues of future research.

2. CDM model

The original purpose of the CDM model was to enrich the estimation of the rate of return to R&D – a return in terms of productivity - by estimating a recursive model where R&D leads to innovation output (using patent count data or data on sales of innovative products from Innovation Surveys), and innovation output affects productivity. Over the last ten years the original CDM model was generalized in different directions: extension to more countries and to panel data (2.1), alternative estimation methods (2.2), additional endogenous innovation inputs besides R&D (2.3), introduction of different types of innovation output (2.4), additional endogenous determinants of productivity besides innovation output (2.5), heterogeneity in the links between innovation output and productivity (2.6), and the inclusion of spillovers (2.7).

2.1 Extension to more countries and to panel data

Thanks to new innovation surveys, especially in developing countries, the model has been estimated on countries or regions hitherto not examined. Moreover, the World Bank Enterprise Surveys and the BEEPS[4] datasets jointly set up by the World Bank and the European Bank for Reconstruction and Development contain many additional statistics on the business environment, which can be used as instrumental or control variables and allow for larger economic models (with additional endogenous variables). These data are, however, essentially cross-sections or repeated cross-sections of firm data in different countries. In other countries, additional innovation surveys have allowed for panel data analysis or the estimation of dynamic models (Raymond et al., 2015; Demmel et al., 2017; Van Leeuwen and Mohnen, 2017; Morris, 2018; Taveira et al., 2019; Audretsch and Belitski, 2020; Audretsch et al., 2020; Edeh and Acedo, 2021; Hoang et al., 2021; García-Pozo et al. (2021); Broome et al., 2023).

In general, the positive link between innovation and productivity has been confirmed (more on this later). However, in studies based on cross-sectional data it is hard to speak of causality. As Morris (2018) illustrates, cross-sectional data, which do not allow to correct for individual effects, tend to

[4] Business Environment and Enterprise Performance Surveys

overestimate the link between innovation and productivity. A few studies have used lagged innovation and current productivity to test whether there is at least a Granger causality from innovation to productivity. Raymond et al. (2015) on Dutch and French data conclude that past innovation Granger causes contemporaneous productivity, but past productivity does not Granger cause contemporaneous innovation. Evidence of self-selection into innovation on the basis of past productivity is, however, reported by Demmel et al. (2017) for Argentina and Mexico, confirming earlier studies by Máñez et al. (2009) and Rochina-Barrachina et al. (2010) for Spain.

While the first studies on CDM models were conducted on data from advanced countries, the advent of innovation survey data from emerging countries enabled the estimation of the CDM model in countries with lower levels of development and different institutional setups. For Latin America, we have Crespi et al. (2016) for 17 Latin American countries, Demmel et al. (2017) for Argentina, Mexico, Colombia, and Peru; Aboal and Garda (2016) and Aboal and Tacsir (2018) for Uruguay, Busom and Vélez-Ospina (2017) and Gallego et al. (2015) for Colombia; on data from Eastern and Central Europe, Central Asia and the Caucasus we have Tevdovski et al. (2017), Bartz-Zuccala et al. (2018), Toshevska-Trpchevska et al. (2019), Disoska et al. (2020), and Vujanović et al. (2022) for Serbia and Tuncel and Oktay (2022) for Turkey; ; for Africa, we have Fu et al. (2018) for Ghana and Kasongo et al. (2023) for South Africa; for Asia, Wadho and Chaudhry (2018) for Pakistan and Calza et al. (2019), Hoang et al. (2021) and Tran et al. (2022) for Vietnam.

2.2 Alternative estimation methods

The initial CDM model was a recursive model with three parts: first, a Tobit type II or Heckman selection model for R&D, second, an intensity of innovation output equation with R&D as a determinant, where the output was either the patent count or the share of sales due to new products, and third, a productivity equation with innovation output as a determinant. The model was estimated by the method of asymptotic least squares or minimum distance estimator. The identification of all the parameters rested on a set of exclusion restrictions. Later studies, in part depending on data availability, estimated only selection models for R&D and/or innovation or multivariate probits in the first or second stage of the model, as we shall document later on.

As already mentioned in Mohnen and Hall (2013) the CDM models have been estimated in different ways: asymptotic least squares (Crépon et al., 1998; Bartz-Zuccala et al., 2018), maximum likelihood or generalized structural equation modeling (Raymond et al., 2015; Cirera et al., 2016; Baum et al., 2017; Kijek and Kijek, 2019; Gogokhia and Berulava, 2021; Segarra-Blasco et al. 2022), sequential 2SLS (Brown and Guzmán, 2014; Morris, 2018; Audretsch et al., 2020; Tuncel and Oktay, 2022), 3SLS (Hashi and Stojčić, 2013; Friesenbichler and Peneder, 2016; Toshevska-Trpchevska et al., 2019; Disoska et al., 2020; Mason et al., 2020), LIML (Véganzonès-Varoudakis and Plane, 2019). On the one hand, estimating a system of equations is more efficient than estimating individual equations since it takes into account the correlations between the error terms of the various equations and possible cross-equational parameter restrictions. On the other hand, it is more easily affected by specification errors. Attention should be paid to the correct estimation of standard errors of the estimates when predicted variables are used as explanatory variables, possibly by bootstrapping. A somewhat different model is followed by Crowley and McCann (2018) and Hoang et al. (2021). They estimate an endogenous switching regression model with labor productivity as an outcome equation and the decision to innovate as a selection equation.

One major difficulty in the structural equations modeling is the choice of exclusion restrictions (which variables to exclude in which equations?). Theory is often of little help in solving this conundrum. In the end, the choice will depend on which variables we want and can, given the data, estimate significantly the direct and indirect effects on the endogenous variables of the model.

A second challenge, not unrelated to the previous one, is to find valid and strong instrumental variables. The quality of the instruments should be tested, as much as possible, and be theoretically founded. Panel data can help in finding acceptable instrumental variables.

A third difficulty is the possible simultaneity between innovation and productivity. Whereas the original CDM model was a recursive model, Hashi and Stojčić (2013) allow for a contemporaneous feedback from productivity to innovation and estimate the innovation and productivity equations by 3SLS (although it is not quite clear whether they are able to identify all the parameters given the apparent absence of exclusion restrictions). A feedback from lagged productivity to innovation, as done in Demmel et al. (2017) is probably more realistic.

A fourth difficulty is the measurement errors problem. As Jaumandreu and Mairesse (2017) show, product and process innovation are likely to be mismeasured, especially when measured as dummy variables. But even with quantitative measures of innovation the errors in variables issue does not disappear: they are subjective, not always clearly defined, and the timing of their effects is difficult to capture when innovation is defined over a three-year period. The authors try to find sufficiently good instrumental variables that capture the expected effects of each type of innovation, product innovation shifting the demand curve and process innovation shifting the marginal cost curve. Mairesse and Robin (2017) estimate the magnitude of the measurement errors of R&D and innovation by estimating by OLS different specifications of the innovation and productivity equations using levels and first differences, controlling or not for fixed effects, and controlling for other explanatory variables. Their results on French innovation survey data show that measurement errors exist in both variables, more so for innovation than for R&D, that these measurement errors are unrelated to those pertaining to the capital stock, and that other sources of endogeneity besides errors in variables are present.

2.3 Additional endogenous innovation inputs besides R&D

Other endogenous variables have been added in parallel to R&D or in place of R&D as innovation inputs: innovation expenditure, ICT, management practices, methods of appropriability, collaboration and public support for innovation.[5]

Innovation-related expenditures, including R&D but also patenting, the purchase of licenses, training or investment for innovation - or simply the presence of innovation activities in the case of dichotomous variables - have often replaced R&D as the innovation input (Álvarez et al., 2015; Aboal and Garda, 2016; Hall and Sena, 2017; Kahn et al., 2022). Taveira et al. (2019) use the total quantity of scientific-technical workers as an input measure of innovation. They obtain for Brazilian firms a significant effect of innovation input on innovation output when using this variable and not when using R&D expenditure. This result may indicate that it is a capital of knowledge rather than a flow of knowledge which should enter the productivity equation. Indeed, R&D expenditure can lead to innovations in the current period but also in the future, and likewise past R&D can still affect innovation in the current period. Hence the correct measure of R&D would be a stock of accumulated past and present R&D expenditure. The expenditure might be a convenient proxy to net investment in knowledge if productivity growth is the variable to be explained. Many studies use the expenditure variable even if the level of productivity is the dependent variable because of insufficient long time series data to construct a stock of knowledge capital. Moreover, the quantity of technical workers also incorporates tacit knowledge and may include knowledge from outside the firm.

Hall et al. (2013) add ICT besides R&D in the standard CDM model. They find that R&D contributes more to innovation than ICT, and ICT more to productivity than R&D. They find no significant complementarity between ICT and R&D on Italian firm panel data. Aboal and Tacsir (2018) put software and hardware investments besides innovation investments in a CDM model for Uruguay. They report that ICTs are more linked to innovation and productivity in services than in manufacturing. Grazzi and Jung (2016) on data from Latin America and the Caribbean conclude that different forms of ICT are positively linked to innovation, but only some of them (e.g. broadband) directly to productivity. Cirera et al. (2016) add ICT as an additional equation besides R&D on data of 6 African countries. The authors also find that ICT is a facilitator of innovation, a relationship robust across countries and types of ICT, but that productivity is facilitated only by radical innovation.

Czarnitzki et al. (2023) have introduced the use of artificial intelligence (AI) besides continuous R&D in the production function and instrumented AI use or intensity of use by the frequency of AI use at the sector level, the average past innovation expenditure per employee and the perceived resistance to innovation by employees. They find that productivity is positively and significantly related to the use of AI in German firms. Their measure of AI includes various AI methods (such

[5] Not quite in the spirit of the CDM model, some studies have included additional determinants of innovation but treated them as exogenous: Gaglio et al. (2022) and Lo et al. (2023) for digital technologies , Kijek and Kijek (2019) for ICT, training and investment in machinery and equipment, Rammer et al. (2022) for artificial intelligence.

as language understanding, image recognition, machine learning, knowledge-based systems) and is not restricted to AI methods developed internally. They model AI as an intangible capital rather than as an innovation, but in an early companion paper (Rammer et al., 2022) they found evidence of a positive correlation between the use of AI and various measures of innovation, predominantly world-first innovations.

Bartz-Zuccala et al. (2018) introduce management practices besides R&D as determinants of innovation. They find that management practices are also important determinants of innovation and productivity. They have actually a greater impact on productivity than innovation in lower-income economies. Calza et al. (2019) look at the effect of the possession of a certified management standard besides innovation on SME panel data of Vietnam. They find that the possession of an ISO management standard has a significant positive effect on productivity, especially for innovation-intensive firms.

Audretsch and Belitski (2020) add sources of collaboration to R&D in the first stage of the CDM model. The types of collaboration that are significantly related to innovation depend on the type of innovation, for instance the enterprise group and customers for self-made innovations and competitors for purchased or imitated innovations.

Busom and Vélez-Ospina (2017) add the incidence and the intensity of public support for innovation in the innovation equations. Public support in Colombian firms is significantly related with the incidence of innovation, but with the intensity of innovation only in knowledge-intensive industries. Czarnitzki and Delanote (2017) introduce public support for innovation in the innovation input and output equations for Flemish firms and conclude that public support stimulates R&D but has no indirect additional effect on innovation output.

Hall and Sena (2017) consider that firms decide simultaneously whether to innovate and whether to use formal or informal methods of appropriation. The first stage of the CDM model is thus a trivariate probit model. They find that firms that innovate and use formal methods of appropriability in the UK are more productive than those that innovate with informal methods of appropriability.

2.4 Different types of innovation output

Following the Oslo Manual (OECD/Eurostat, 2018) data have been collected for different types of innovation: technological innovations (product, process), and non-technological innovations (organizational and marketing). Within the category of product innovations, some authors have distinguished product innovations by their degree of novelty, i.e. first-to-the-firm or first-to-the-market (e.g., Cozzarin et al., 2017). Finally, at some point innovation surveys also enquired about environmental innovation targets, which can be categorized as resource-saving and pollution-reducing eco-innovations (van Leeuwen and Mohnen, 2017). New products can improve productivity if there is a strong demand for these products creating increasing returns to scale, or if thanks to the demand enthusiasm for these products consumers are ready to pay a price that exceeds marginal cost, producing price-cost margins that increase revenue productivity. By introducing new products firms may create new domestic or foreign markets and benefit from spillovers if these products are complementary to existing products or services. However, if new products do not meet a strong demand, or require a period of learning-by-doing before reaching a productivity level comparable with that of the old products, or if new products simply replace old products, the impact of new product introduction on productivity may be small and even negative. Process innovations are likely to increase productivity because they are generally input-saving and incorporate technological progress. Moreover, by saving on costs process innovation may create increased demand and improved productivity via returns to scale. Non-technological innovations may increase productivity by re-organizing production or distribution, e.g. through internet sales. Environmental innovations primarily target environmental concerns, but can also according to the Porter hypothesis increase productivity by developing an early comparative advantage in this area. Another type of innovation that has been examined recently in relationship to productivity is artificial intelligence. AI can offer new products and services that are suited to the individual based on information on habits and preferences retrieved from the individual; it can also increase the productivity of research such as large scale experiments on combinations of chemical compounds in the pharmaceutical industry or fasten the communication of information across production teams and firms. Two main questions have been addressed namely (i) which type of innovation output, and indirectly which type of innovation input, affects productivity most[6], and (ii) whether there is any complementarity between different types of innovation.

On the limited sample of UK small and medium sized enterprises (SMEs) Nathan and Rosso (2022) regress revenue productivity (in levels, growth rates and episodes) on the number of new product launches. For the level equation, they obtain a positive and statistically significant coefficient for new product launches: each additional launch is linked to a 1.7% increase in revenue productivity. The link seems to be driven by important launches.

Siedschlag and Zhang (2015) for Ireland find that innovation is positively and significantly linked to productivity for process and organizational innovation, not for product innovation, a conclusion shared by Baumann and Kritikos (2016) on German micro firms and SMEs. Cozzarin et al. (2017) for South Korean manufacturing also obtain a positive effect of organizational and process innovation on productivity but a negative effect for product innovations, and even more negative for new-to-the-market than for new-to-the-firm product innovations. Bartz-Zuccala et al. (2018) on data from Eastern and Central Europe, Central Asia and the Caucasus report that process innovation is a stronger predictor of labor productivity than product innovation, and that management practices affect productivity indirectly more via process than via product innovations. Segarra-Blasco et al. (2022) for seven European countries also report that R&D is positively

[6] Other performance measures besides productivity have also been examined, such as exports (Becker and Egger, 2013; D'Attoma and Pacei, 2018), profitability (D'Attoma and Pacei, 2018) , growth (Dalgiç and Fazlioğlu, 2021), and firm survival (Zhang and Mohnen, 2022).

related to product and process innovation, whereas productivity is positively related to process innovation but negatively to product innovation. Tello (2015) for Peru finds no significant effect for either technological or non-technological innovation on productivity. This could partly be due to the rather small number of observations underlying his study. Taveira et al. (2019) for Brazil find no significant marginal effect of new-to-market product innovations and even a negative effect of non-technological innovation on productivity, suspecting a missing link.

Differences in the returns to types of innovation could be sector-specific. Gallego et al. (2015) for Colombia, and Aboal and Garda (2016) and Aboal and Tacsir (2018) for Uruguay find that non-technological innovations contribute more to firm productivity in the services sector than in the manufacturing sector. Kasongo et al. (2023) also find that non-technological innovation has more of an impact on productivity than technological innovation in South African services. Morris (2018) finds that product innovation has a greater impact on productivity than process innovation in manufacturing whereas process innovation has a greater impact in services. He also finds that innovation has a greater effect on productivity in Latin American countries than in other countries in his sample (or at least for countries under the LACES[7] way of conducting the survey). Fu et al. (2018) obtain a higher effect of technological than of non-technological innovation on Ghanaian manufacturing firms.

Marin (2014) examines the effect of environmental and non-environmental innovations on productivity in Italy. Environmental innovations are measured by patents pertaining to specific IPC classes following the classification of environmental innovations on the basis of IPC classes by WIPO and the OECD. Non-environmental patents yield a higher return than environmental patents. Van Leeuwen and Mohnen (2017) construct a green CDM model with three types of eco-investments and two types of eco-innovation outputs: resource-saving and pollution-reducing eco-innovations. On Dutch firm-level panel data they find that the former are positively, the latter negatively related to productivity. On Norwegian manufacturing firm data Børing (2019) finds that innovations with an environmental purpose decrease productivity and those intended to provide health and safety for the employees are not significantly correlated with productivity at least in the short run. Damioli et al. (2021) on a worldwide panel dataset of 5257 firms active in AI-patenting report a positive relationship between AI-patent applications and labor productivity. They use GMM-SYS techniques to account for the endogeneity of AI-patenting instead of additional equations.

There is less agreement across studies regarding complementarities. Van Leeuwen and Mohnen (2017) find that the two types of eco-innovations reinforce each other. Cozzarin et al. (2017) find signs of substitutability between R&D and organizational innovation when the latter is considered as an innovation input. Peters et al. (2017b) find no complementarity between product and process innovation in Germany. Aldieri et al. (2021) consider the 4 types of innovation (product, process,

[7] Latin American and Caribbean Enterprise Survey.

organizational and marketing) and various combinations of them, but do not really test for complementarity between them. Instead, they concentrate on possible complementarities between innovation types and human capital, physical capital or ICT. Mohnen et al. (2021) estimate a model that simultaneously determines productivity growth and the binary choices of R&D, organizational innovation and ICT that lead to that productivity growth on Dutch firm panel data. They find signs of complementarity between R&D and organizational innovation and between ICT and R&D, but not between ICT and organizational innovation. Various reasons can explain these divergent results. First, the fact that often different types of innovation are conducted simultaneously does not necessarily imply that the joint innovations lead to better performance. Second, complementarities may differ depending on the performance one is focusing on. Third, complementarities are often examined on the basis of occurrence or non-occurrence of an innovation instead of innovation intensities. Fourth, the analysis of complementarity gets complicated by the fact that the innovation choices are themselves endogenous. In the future it would certainly help to have larger datasets with sufficient variations in the combinations of innovation types to reach more significant conclusions.

2.5 Additional endogenous determinants of productivity besides innovation output

Besides these different innovation outputs, some other endogenous variables (i.e. with a separate equation explaining their determinants) have been introduced in the productivity equation.[8]

Friesenbichler and Peneder (2016) add to the CDM model a competition equation, with competition depending on innovation and affecting productivity and innovation expenditures. They find that there is an inverted-U relationship between innovation and R&D, that innovation reduces competition and that both competition and innovation are positively related to productivity.

Segarra-Blasco et al. (2022) add two export equations to the CDM model, one that explains the share of exports in total sales and the other one the number of markets in which the firm exports. On data from 7 European countries, the authors find that firms with a more extensive and intensive presence on foreign markets are more likely to do R&D and to innovate and are more R&D-intensive. The authors also confirm the selection hypothesis according to which more productive firms are the ones that are more intensively and extensively active on foreign markets.

Mason et al. (2020) estimate by 3SLS on a panel dataset of seven industries in 8 countries a recursive system of three equations: openness to foreign trade and FDI, the growth of patents per

[8] Bartelsman et al. (2019) have added the proportion of employees with broadband internet connection to the various innovation outputs in explaining total factor productivity. On evidence from 10 European countries, they find that ICT is an important contributor to productivity and diminishes the significance of the correlation of innovations and productivity. But they do not handle the endogeneity of either innovation outputs or of broadband connections. Gogokhia and Berulava (2021) construct a business environment index on the basis of perceived constraints by firms for doing business in 28 transition economies. An improved business environment is found to be correlated significantly with R&D, innovation output and productivity, but the index is treated as exogenous.

hour worked, and multifactor productivity growth. Skills and their interactions with openness and proximity to the frontier enter resp. the second and third equation. In general, skills are positively related to patent flows and directly and indirectly to productivity growth, while patent flows are positively related to productivity growth. Siedschlag and Zhang (2015) compare for Ireland the impact on innovation and on productivity of domestic non-exporter, domestic exporting firms and foreign-owned firms. Firms that operate internationally are more innovative than domestic non-exporting firms. Foreign-owned firms are more productive than domestic firms.

Ramírez et al. (2020) enlarge the CDM model by adding an endogenous human capital variable, measured by the number of R&D workers in the total number of workers, in the R&D and innovation equations. On Colombian data they obtain significant marginal effects of human capital on R&D and innovation. They also use two specific kinds of human capital, namely the percentage of technicians and professionals, respectively postgraduates, working in R&D. Whereas the proportion of technicians and professionals has a greater impact than the proportion of postgraduates on R&D and innovation, innovation has a greater effect on productivity with the postgraduates.

Crespi et al. (2016) introduce IPR not among the conditions leading to an innovation, but directly as a measure of innovation output. On Latin-American firm data they find that firms that apply for IPR have a higher productivity than those that do not.

These additional links between the endogenous variables enrich the models by introducing direct and indirect effects and feedback loops. The difficulty is to find exogenous variables that drive the endogenous variables and exclusion restrictions or other ways to identify the structural form parameters. More work in this direction would provide a deeper understanding of the economic forces at play, a possible testing of different causality structures and a tool for conducting simulations of the effects of policy measures or unexpected systemic shocks on innovation and productivity.

2.6 Heterogeneity in the links between innovation and productivity

The CDM model has also been estimated on different kinds of specific datasets such as micro firms (Audretsch et al., 2020; Gaglio et al., 2022), small and medium-sized enterprises (Edeh and Acedo, 2021; Hoang et al., 2021), service sectors (Kasongo et al., 2023), high-tech/low tech sectors, manufacturing/services (Álvarez et al., 2015; Busom and Vélez-Ospina, 2017), emerging and transition countries (Bartz-Zuccala et al., 2018), as well as specific regions (Garcia-Pozo et al., 2021) and industries (Wadho and Chaudhry, 2018; Frick et al., 2019). As is often the case when working with firm data, there is a lot of heterogeneity in the link between innovation and productivity, which is not allowed for if the same coefficients hold for all observations. Baum et al. (2017) test formally the homogeneity across different industries on Swedish panel firm data. In all three parts of the CDM model they reject the homogeneity of key coefficients. The same is found by Frick et al. (2019) on data from four European countries and three different industries. Here are a few examples of allowed for heterogeneities.

Hashi and Stojčić (2013) compare the innovation-productivity link between Western European and Central and East European countries and do not find a statistically significant difference, except for the influence of organizational innovation, which is positively related to productivity in Western Europe and not significant in Central and East European countries. Demmel et al. (2017) find a self-selection into innovation on the basis of past productivity only for the two upper-middle-income countries in their sample and only for product innovation and an innovation to productivity effect again driven by product innovation and only for the upper-middle-income countries. They conclude that the level of development plays a mediating role in the link between innovation and productivity. Crowley and McCann (2018) separate their sample of firms of thirteen European countries into innovating countries and countries still in transition between efficiency seeking and innovating. They find in general a positive link between innovation and productivity except in the manufacturing sectors of countries in transition between efficiency seeking and innovation. Bartz-Zuccala et al. (2018) compare low-income countries (in terms of gross national income per capita) with high-income countries. In both groups innovation and management practices are positively related to productivity, but in the former group the marginal effect of management quality is at least three times as high as the marginal effect of innovation, whereas in the latter group innovation has a larger marginal effect on productivity than management. R&D has a significant indirect effect only in the latter group. In developing countries, a great deal of GDP and employment occurs in the informal sector. Fu et al. (2018) compare the role of innovation on productivity in formal and informal firms in Ghana. They find that formal firms do not tend to be more productive than informal firms are, but innovation tends to be more important for productivity in formal firms.

Busom and Vélez-Ospina (2017) on Colombian firm data run a quantile regression of productivity. They find that innovation affects productivity below the median of the productivity distribution in service industries and more pervasively across the productivity distribution in manufacturing. According to their results, innovation affects productivity more in the bottom of the productivity distribution. Crespi et al. (2016) come to the opposite conclusion on pooled data from 16 Latin American countries. Liao (2020) on firm panel data from Spain reports that for firms located in the lower quantiles of their labor productivity distribution imitative sales (i.e. sales of new-to-the-firm products) have a greater marginal effect on productivity than innovative sales (sales of new-to-the-market products) and the opposite holds for firms in the upper quantiles of their productivity distribution.

Baumann and Kritikos (2016) conclude from their study on German micro, small and medium-sized firms, using a CDM model, that "overall, the link between R&D, innovation, and productivity in micro firms does not largely differ from their larger counterparts". Hall and Sena (2017) find that firms that innovate and use formal IP are more productive, and this is the case more in services, trade and utility sectors than in manufacturing. Hoang et al. (2021) report that in Vietnamese SMEs innovators are 23% more productive than non-innovators. Tran et al. (2022) add nine indicators of open innovation as determinants of innovation inputs and outputs, and two measures of economic performance (total factor productivity and profitability). On Vietnamese firm data they confirm that open innovation knowledge management has a positive effect on innovation capabilities, which in turn affect positively productivity and profitability. For SMEs though there are hurdles in the acquisition of capabilities to enhance economic performance. Ramírez et al. (2020) also obtain a much higher impact of innovation on productivity for large compared to small firms in Colombia. Piekkola and Rahko (2020) distinguish between high-market-share and low-market-share firms in Finland. Product and process innovations increase productivity more in low-market-share firms than in high-market-share firms, but they are more profitable in high-market share firms. The impact of the financial crisis on innovation and productivity was also different for small and large firms. From a field survey conducted in Greece in 2011 and 2013, Giotopoulos et al. (2023) report that the crisis discouraged small firms to engage in R&D, while it increased the willingness to engage in R&D activities among the larger ones. Knowledge production was not affected but the innovation output seemed to improve the productivity for larger firms only.

Despite differences in results across studies and samples, productivity is related to innovation in developing and emerging countries as it is in advanced countries, and in micro firms as in large and middle-sized firms. Differences in significance or magnitude can be due to differences in sampling, the sample compositions, the number of observations, or the environments in which firms operate. It would be advisable to investigate what the differences are due to, when they occur, and conduct sensitivity analyses to find out whether the differences are due to the data, econometric problems like selectivity or endogeneity (errors in variables, simultaneity or omitted variables), or differences in the environment in which firms operate, maybe by performing a meta-analysis.

2.7 Inclusion of spillovers

A couple of studies have incorporated spillovers in the CDM model. Spillovers are considered as exogenous. They can be spillovers in innovation, training, R&D and FDI, they can be inter-industry or international spillovers.

A positive role of innovation spillovers is reported in the study of Crespi et al. (2016): firms benefit from product (but not process) innovations and from IPR applications of other firms in the same country/industry. Research by Giovannetti and Piga (2017), on UK firm data, find that intersectoral R&D and training spillovers, in what they call passive sources of collaboration as opposed to active sources of collaboration with customers, universities, suppliers, competitors and so on, influence positively mostly process innovation, slightly organizational innovation and not significantly product innovation, which all three have a positive influence on the gross value added and gross profit margins. The spillovers have hardly any effect on innovation inputs (internal R&D, external

R&D, training and advertising expenditure over sales). Howell (2018) adds learning variables (learning by doing, learning by exporting, absorption capacity and mediating institutions) at the various stages of the CDM model and finds that for Chinese firms learning spillovers reduce the incentives to do R&D but increase the innovation output and productivity.

Audretsch and Belitski (2020) look at complementarity between R&D and R&D spillovers in producing innovation. Knowledge spillovers measured using sectoral R&D and input-output weights increase co-created innovation, but not those made internally and those bought externally, contributing positively to productivity. R&D spillovers are a better predictor of productivity than innovation. Vujanović et al. (2022) add FDI spillovers as additional sources of knowledge and direct determinants of innovation and productivity. They estimate their enlarged CDM model on Serbian firm data. They find positive foreign spillover effects from foreign firms in the same industry and from industry sales to foreign suppliers mostly at the innovation level and more so for firms that rely on external knowledge (knowledge users) than for firms that do R&D themselves (knowledge creators).

3 Stochastic returns to R&D and innovation

In the tradition of Olley and Pakes (1996), an alternative to the extended production function approach, where R&D and/or some measure of innovation is inserted as an additional input, was proposed by Doraszelski and Jaumandreu (2013). They model productivity as a stochastic shock known to the firm but not observable by the econometrician. It follows a first-order Markov process and depends on the R&D investment in the previous period. In this way, R&D no longer affects productivity in a linear and deterministic manner. Applying their model to Spanish data, the authors find that the return to R&D is higher, the higher is past productivity; between 25% and 75% of productivity is unpredictable; the mean expected productivity is higher for R&D-performing than for non-R&D-performing firms; productivity is more persistent in industries where there is less uncertainty; the net (of depreciation) rate of return to R&D is higher in industries where the uncertainty (the variance of the stochastic part of the productivity) is higher, hence part of the return to R&D compensates for the inherent uncertainty.

Peters et al. (2017b) combine the CDM model and the Doraszelski and Jaumandreu (2013) model. Instead of having R&D affecting productivity directly, they let R&D affect productivity through innovation output but introduce uncertainty in the effects of R&D on innovation and of innovation on productivity. There are three sources of stochasticity in their model: one relates to the cost of doing R&D, one regards the probability of having combinations of product and process innovations depending on the choice of R&D, and one relates to the evolution of productivity. Their model allows firms to be innovative without doing R&D, and actually on German data they find that this is the case for 22% of the firms. The decision to invest in R&D or not is endogenous. Firms invest in R&D if the difference in expected future profits by investing in R&D or not is higher than the startup or maintenance costs of doing R&D. They find that 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 not turning out to be innovative is 10% in low-tech industries and 20% in high-tech industries. The success rate is higher for product than for process innovations. The most likely outcome is the simultaneous introduction of new products and new processes. In high-tech industries it is product innovation that increases productivity, whereas in low-tech industries it is process innovation that matters. There is no sign that the simultaneous introduction of product and process innovation has any additional effect on productivity. There is a high persistence in productivity, which implies that productive firms are more likely to invest in R&D. There is a lot of heterogeneity between firms.

Chen, Zhang and Zie (2021) generalize Peters et al. (2017b) in having innovation depend on both R&D (a continuous variable representing tacit knowledge) and patents (binary variables representing codified knowledge). R&D affects productivity directly and in combination with two types of patents: inventions and utility models. They estimate their model on Chinese patent and firm data for high-tech manufacturing firms. They find that for their sample of Chinese firms; 1) the rate of return on R&D in terms of increase in firm value is low: 0.22%; 2) the largest part of that return comes from tacit knowledge, i.e. not through patenting; 3) on average an invention patent causes a 0.76 percent increase in firm value, a utility model a 0.66 percent increase; 4) the start-up costs of R&D are around ten times as large as the maintenance R&D costs.

Peters et al. (2022) apply the Peters et al. (2017b) structural R&D/product and process innovations/productivity model for German exporting and non-exporting firms separately. They obtain a higher rate of return on R&D for exporting firms, which may explain the higher R&D investments for exporting firms. The persistently higher impact of innovation on productivity for exporting firms explains their higher rate of return to R&D. In another application of the Peters et al. (2017b) model, Peters et al. (2017a) make the cost of doing R&D depend on the financial strength of the firm. The find that “financially strong firms have a higher probability of generating innovations from their R&D investment, and the innovations have a larger impact on productivity and profits”.[9]

4 Causality of innovation based on randomized or quasi-randomized experiments

In many areas of economics, quasi-experiments are run to assess the causality of certain treatments on measures of economic performance. This approach has also started to be followed in the empirical literature on innovation and productivity.

[9] Roth et al. (2023) do not quite estimate the Peters et al. (2017b) model but add various intangible investments in the Markov process determining stochastic productivity. They show that in Germany intangibles have a positive effect on productivity, often far above the effect of only R&D. Intangibles include, besides R&D, training, advertising and marketing, design and licenses, and software and databases.

Bloom et al. (2013) run a randomized experiments with 17 large Indian textile firms providing consulting on management practices for 6 randomly chosen firms, the other ones being the control group. The authors find that the firms that adopted the management practices, a form of organizational innovation, are 17% more productive in the first year than their counterparts in the control group and increase in size three years after the experiment. Multidimensional propensity score matchings are used by Coad et al. (2016) to investigate the non-innovation and productivity link. They match firms by the probability to encounter multiple barriers to innovation and find that the average treatment effect on the treated in terms of productivity are negative and significant for most barriers. In other words, barriers to innovation prevent firms from innovating and affect negatively their productivity. D'Attoma and Pacei (2018) use the EU-EFIGE/Bruegel-Unicredit dataset for 7 European countries and a generalized propensity score approach to attest the effect of product innovation intensity on productivity. They do not find a statistically significant effect of innovation intensities on productivity. Dai and Sun (2021) obtain an average treatment effect of innovation on productivity for firms in China on the basis of a propensity score matching with difference in difference. Innovating firms are matched to non-innovating firms with similar propensity scores of being innovative and then first differences of productivity are compared for the treated firms and the control group. The authors find that innovating firms are 11% more productive than comparable non-innovating firms. Asiedu et al. (2023) use a cross-section of five Central American countries (Ecuador, El Salvador, Guatemala, Honduras, and Nicaragua) and compare the productivity of firms with and without product and process innovations on the basis of a propensity score matching. Productivity is the outcome variable, product and process innovation are the treatment variables. They report that innovative firms are more productive: "firms that did not introduce significantly new products in the last 3 years are 23.3% less productive than firms that did. Also, firms that did not introduce new technology in the past 3 years are 25.2% less productive than firms that introduced significantly improved technology". For a particular type of innovation, namely AI patents, Alderucci et al. (2020) find that AI-patenting firms are more productive. They reach this conclusion after matching AI patenting firms with non-AI patenting firms in the U.S. (by age, multi-unit status, primary industry, primary state, size) and performing an event study.

5 Discussion and conclusion

The evidence gathered in the studies published over the time span 2013-2023 reaches the following conclusions. Productivity is positively related to innovation, be it in small or in large firms, formal or informal firms, advanced and emerging countries. Besides R&D, other innovation expenditures, ICT, AI, management practices, public support for innovation, collaborations, and protection of intellectual property have been shown to stimulate innovation at the firm level. Product innovations are not always positively associated with productivity, except in the most advanced countries, high-tech sectors and productive firms. Many studies conclude that productivity depends more on process than on product innovations. But the relative effects of different types of innovation are also sector-specific. It seems that in services non-technological innovations have more of an effect on productivity than technological innovations and process innovations more than product innovations. Environmental innovations do not always increase productivity, but AI seems to be an important driver not just of innovation but also of productivity. There is not much sign of complementarity between the different kinds of innovation, but more between innovation and outside conditions such as human capital, a favorable investment climate and competition.

It is hard to rank the strength of the relationship between innovation and productivity across firm size, levels of development, the formal and informal nature of firms, and industrial sectors, especially when these characteristics interact. Yet, it seems that product innovation, especially drastic product innovation, and organizational innovation are more strongly linked to productivity in advanced countries, high-tech industries and in firms of the formal sector. In low-tech industries process innovations are more important than product innovations and in emerging countries imitative innovations more than drastic innovations.

The studies we have examined in this survey were not centered on the effectiveness and efficacy of particular innovation policies. If any policy conclusion can be drawn from the evidence we have gathered it would be to encourage innovation since it is related to productivity (possibly in a bi-causal way), develop the capacities to innovate, remove barriers to innovation such as regulations and access to finance, accept the possibility that innovations can fail, and pursue an open-door policy, as foreign trade transmits knowledge and at the same time creates a competitive environment, where only the best can survive.

On the modeling side, it has been a period of consolidation of the CDM model as roughly three quarters of the work has adopted or extended the CDM model. Extensions include other innovation inputs besides R&D, other determinants of productivity besides innovation, granularity in the types of innovation and their complementarity and extension to emerging countries and micro firms. An important generalization of the CDM model has been the incorporation of uncertainty in getting innovation output from R&D and in getting productivity improvements from innovation. Finally, some recent papers have used experiments or quasi-experiments instead of instruments to uncover a possible causality between innovation and productivity.

To wrap up our review of the state of the art of the literature on innovation and productivity we discuss a few directions in which we think progress could be made.

Innovation Survey data are still useful for benchmarking, but for the advancement of our understanding of innovation new surveys, maybe surveys specific to certain sectors of the economy, ought to be conducted. As more data become available for particular industries, geographical regions and technological trajectories, studies can be conducted at a more granular level. In this way, we could uncover the reasons for heterogeneity between innovation and productivity across sectors, technologies, regions and types of firms. The links between innovation and productivity could be different for particular technologies.

As the Innovation Surveys are repeated, larger panel datasets will become available. The use of panel data allows to account for unobserved individual effects - without which the productivity effects of innovation are probably overestimated -, to soften some of the endogeneity problems by using lagged explanatory variables - although the use of lagged variables is not the ubiquitous solution to endogeneity - and to allow for dynamics in the link between innovation and productivity.

More use could be made of available web-based data. More and more information on research endeavors, new technologies, techniques and codified know-how is available on the web. These data would have to be formatted, standardized in some way, but with the advent of artificial intelligence this should be increasingly easy to do. These data would be more timely than survey data from statistical agencies.

As we have mentioned, the CDM model has been extended to other measures of economic performance. It has, for instance, been noticed that exports, the use of ICT, AI, and innovation spillovers are facilitators of innovation and indirectly of productivity. Especially in emerging countries, innovation operates not just through R&D but very much through imported technologies, imitation and technology adoption, in other words the "buy" besides the "make". Innovation may go hand in hand with a shift in the composition of employment, outsourcing and offshoring of certain activities. Only larger models can take these nuances into account.

Adding uncertainty in the relationship between innovation and productivity has been maybe the most innovative aspect of the literature in the last 10 years. More work could, and probably will, be done extending the Peters et al. (2017b) model to continuous variables and to other dimensions of innovation. Especially in the area of innovation, it is important to incorporate the stochastic element and its effect on decision-making. Linked to the imperfect information is the role of competition between incumbents and newcomers, especially in the world of digital technologies. How much further we can build up structural models depends on the data available.

A major difficulty with the micro data available from R&D, production and innovation surveys is the endogeneity of many, if not most, of the variables, such as exporting, collaboration, training, and public support for innovation. Consequently, it is difficult to find truly exogenous explanatory variables and sound instrumental variables to treat the endogeneity problem. An alternative that has started to be developed also in this literature is the use of quasi-experiments or even natural experiments to be able to assess causalities. A last word of caution to end this survey. It has often been stated that innovation leads to higher productivity. Strictly speaking it is daring to make such a claim when working with cross-sectional data or even with panel data and static models.

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Annex 1. Search strategy and Journal Set

Search strategy:

1st stage: Search for Reference title "Research, Innovation and Productivity" AND Reference publication year "1998".

2nd stage: Search Keywords "innovation" AND "productivity" AND Publication year > 2019 AND Source title (see journal set below).

Searches conducted in Scopus and Web of Science.

Journal set definition:

Journals

- Economics of Innovation and New Technology
- Research Policy
- Journal of Technology Transfer
- Industry and Innovation
- Structural Change and Economic Dynamics
- Industrial and Corporate Change
- Technovation
- Journal of Productivity Analysis
- Eurasian Business Review
- American Economic Review
- Review of Economics and Statistics
- Journal of the European Economic Association
- International Journal of Industrial Organization
- Journal of Industrial Economics
- RAND Journal of Economics
- Quarterly Journal of Economics
- Journal of Political Economy
- Journal of Economic Literature
- American Economic Journal: Applied Economics
- Small Business Economics
- World Development
- Journal of Economic Perspectives
- Journal of Economic Surveys
- Journal of Development Economics
- Journal of Evolutionary Economics
- European Economic Review

- Technological Forecasting and Social Change
- Cambridge Journal of Economics
- Economic Journal
- Management Science
- Review of Income and Wealth

Working paper series

- ZEW
- NBER
- CEPR