

EMPIRICAL MODELS OF FIRMS' R&D

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1. Introduction

During the last few decades, economists have paid increasing attention to the role played by R&D in modern economies. The origins of this research agenda are often placed in Solow's (1957) work on the importance of the total factor productivity growth as a measure of technological change, and in Nelson's (1959) and Arrow's (1962) works on the economics of knowledge creation (Encaoua et al., 2013). From a theoretical point of view, the tools of new game theory were applied to analyze the behavior and interactions of firms undertaking R&D. From an empirical point of view, some authors began the task of measuring and understanding the determinants and outcomes of R&D.

Nowadays, the empirical literature on R&D is abundant and still growing because of the increasing availability of micro-data. Taking this fact into account, the main purpose of this chapter is to provide a general view of three of the main topics covered by this literature: the determinants of firms' R&D investments, the link between R&D, innovation and productivity, and the studies trying to open up and examine the contents of the black box of R&D. To this aim, we build on already existing reviews, and complete them with some recent works. In addition, we pay special attention to some new lines of research not covered in previous reviews. For reasons of space, our analysis does not address other topics that appear to be worthwhile, like the relationship between R&D and employment, the outsourcing and/or offshoring of R&D, or R&D spillovers.

In the second section of the chapter, we review studies on the determinants of R&D, which are generally supported on Dorfman-Steiner-type (1954) models. In these models, profit-maximizing firms choose the level of R&D investment that equalizes the marginal revenue effect and the marginal cost effect of R&D expenditure. Regarding specific determinants of revenues and costs, most of the literature has focused on testing the so-called Schumpeterian hypotheses, which predict a positive relationship between size and R&D investment on the one hand, and between market power and R&D investment on the other. A related line of research also focuses on industry determinants of R&D: demand pull, technological opportunity and appropriability.

Much attention has recently been devoted to the role of public funding as a determinant of business R&D investment. There is considerable agreement that R&D activities suffer from market failures. First of all, the presence of information asymmetries and moral hazard increases the cost of financing R&D relative to other investments. Secondly, the main output of R&D activities is knowledge, which shows some 'public good' characteristics that make its full appropriation difficult. As a consequence, the amount of public funding for R&D is of considerable magnitude in most countries, and many studies have aimed to evaluate its effect. Despite the profusion of empirical literature about this subject (see David et al., 2000, Becker, 2013, and Zúñiga-Vicente et al., 2014, for a review), only a few papers propose structural models describing firms' decisions as the analytical framework for their estimations. We pay special attention to these papers in our assessment.

In the third section of the chapter, we deal with studies analyzing the relationship between R&D, innovation and productivity. In this regard, we take into account three main approaches:

the knowledge capital model, the model proposed by Crèpon, Duguet and Mairesse (1998) and subsequently known as the CDM model, and a group of recent structural models.

In most early studies, an augmented production function with R&D capital (or R&D expenditures) is used to estimate the returns to R&D at the firm level. Later, this approach was improved by using a more complex modelization in which a demand equation is also included to control the bias generated in the estimation of a firm-level production function where output is proxied by deflated sales. In this case, the firm's knowledge capital also affects the demand by improving product quality. Hall et al. (2010) review the literature on returns to R&D based on different specifications of the production function at the plant, firm, industry, and country levels since the 1960s. We summarize their review and include some new papers.

A second approach refers to the CDM model, which takes into account the fact that it is not innovation inputs but innovations outputs that increases productivity. Specifically, under this approach, productivity is explained by technological outputs and the latter by technological effort. Revisions of this approach have already been provided by Hall (2011) and Mohnen and Hall (2013). However, most papers included in these revisions use cross-sectional data and do not take into account dynamic linkages between innovation and economic performance or persistence in R&D activities. The availability of longer time series and new econometric methods has generated some recent empirical evidence that considers the timing of innovation and other dynamics aspects. There are different explanations for persistent behavior in R&D activities: sunk costs associated with the performance of R&D activities, the "success breeds success" hypothesis and the existence of dynamic increasing returns, among others. We summarize this empirical evidence, which has not been reviewed before.

Finally, we revise the results obtained in recent papers that develop structural models to relate productivity and R&D. In these studies, productivity is assumed to be unobservable and is modeled as a Markov process which depends on R&D expenditure or other endogenous firms' decisions. In addition, to deal with the simultaneity problem, instead of estimating a production function, these authors model and estimate the firm's dynamic decision to invest in R&D. Specifically, they propose a dynamic structural model of R&D demand where the expected benefit to the firm's investment in R&D is inferred from the rational decision of R&D investment.

The forth section of this chapter concerns itself with studies aimed at opening up the black box of R&D. In particular, we examine two lines of research. The first one distinguishes between the components of R&D, while the second analyzes the complementarities among different types of R&D activities.

One common drawback of much of the literature is that R&D is considered a single activity. However, the black box of R&D is composed of basic research, applied research and development activities. These activities are different in purposes, knowledge bases, the people involved and management styles, so their determinants and outcomes may be quite different. While some seminal studies were carried out on this topic in the 1980s, it has gained renewed attention in the last decade. To our knowledge, no systematic empirical review addresses this subject.

A related topic is that internal R&D is not carried out in isolation. On the contrary, in-house R&D activities should be understood as part of a more general strategy of the firm. In this regard, one important topic of the recent literature has focused on the analysis of the complementarities of internal R&D with other firm decisions related to technological activities. From an empirical point of view, the analysis of complementarities involves some specific challenges. We briefly summarize both the methodologies developed to address these challenges and the main empirical studies on complementarity in R&D activities.

Finally, in section 5, we provide the main conclusions of our analysis and suggest some avenues for further research.

2. R&D determinants

The study of Research and Development (R&D) determinants is a classic topic in industrial organization. From a theoretical point of view, these studies are generally supported on Dorfman-Steiner-type (1954) models, in which profit maximizing firms choose the level of R&D investment that equalizes the marginal revenue effect and the marginal cost effect of R&D expenditure (Needham, 1975; Scherer, 1980; Kamien and Schwartz, 1970, 1976, 1978, 1982).¹ The specific relation among the key variables depends on whether the R&D investment is considered a demand-increasing strategy and/or a cost-reducing strategy. In particular, Cohen and Levin (1989) emphasize that the impact of price elasticity of demand will be ambiguous in empirical studies that do not distinguish between product and process innovation: the gains from process innovation, which is associated with cost-reducing strategies, will be larger the more elastic demand is (Kamien and Schwartz, 1970), while the gains from product innovation, which is related to demand-increasing strategies, will be larger the more inelastic demand is, given that inelastic demand could amplify the gains from a rightward shift in the demand curve (Spence, 1975).

With the emergence of new firm-level and project-level databases at the end of the twentieth century, the study of the determinants of R&D investment faced a revival. As in previous works, most of the authors tended to distinguish between demand-side effects and cost-side effects of R&D. The implicit framework in these analyses assumes that, for each planning period and R&D project, the level of R&D expenditure is the result of equalizing the marginal cost of R&D, MCR , and the marginal revenue of R&D, MRR . Following David et al. (2000), we can represent this setting through the equations:²

$$MRR = f(R, \mathbf{X}) \quad [2.1]$$

$$MCR = g(R, \mathbf{Z}) \quad [2.2]$$

¹ For instance, following Needham (1975), the profit maximizing R&D expenditure condition can be written as follows: $\frac{R}{PY} = \frac{\varepsilon_R + \varepsilon_{conj} \cdot \varepsilon_{Rr}}{\varepsilon_d}$, where ε_d is the price elasticity of demand for the firm's product, ε_R is the elasticity of the quantity demanded of the firm's product with respect to the firm's R&D expenditure, ε_{conj} is the elasticity of the rival's R&D expenditure respect to the firm's own R&D expenditure and ε_{Rr} is the elasticity of demand for the firm's product with respect to the rival's R&D expenditure.

² Throughout the chapter we slightly change the original notation in reference papers to keep the notation as homogeneous as possible in all sections.

where R is the level of R&D expenditures. In this simplified model \mathbf{X} stands for the vector of other variables that can affect the distribution of project rates of return, like technological opportunities and appropriability conditions, while \mathbf{Z} represents the vector of other variables that determine the marginal cost of R&D, such as those related to access to bank financing or venture capital, to macroeconomic conditions or to technological public policy.³

Where MRR and MCR are equal, we find the firm's profit maximizing level of R&D investment, R^* :

$$R^* = h(\mathbf{X}, \mathbf{Z}) \quad [2.3]$$

Departing from this kind of model, the use of a micro-level perspective in empirical analysis allows the testing of new hypotheses. One of the most relevant during the last few decades is the complementarity or substitutability relation between public R&D and private R&D. This concern about the effect of public aid on business R&D points out the relevance of taking into account not only the determinants of R&D intensive margins, but also the determinants of extensive margins, that is, the propensity to perform R&D (González et al., 2005; Takalo et al., 2013a; Arqué-Castells, 2013; Arqué-Castells and Mohnen, 2015). The evidence obtained about extensive margins supports the existence of sunk costs of R&D that act as a barrier to entering R&D markets, especially for small firms. This would be one of the explanations for R&D persistence, and justifies the interest in dynamic approaches to model R&D decisions. Some of these topics will be analyzed in more detail in the following sections.

There are several estimation issues involved in the estimation of the R&D equation: unobservable heterogeneity, dynamics and persistence, endogeneity and parameter heterogeneity.

First, a number of unobservable characteristics, such as managerial ability or culture, usually exist. This issue is dealt with by using some kind of transformation (within or differencing) that wipes out individual (time-invariant) effects.

Second, R&D is an investment that should be analyzed in a dynamic framework because it shows high adjustment costs. Accordingly, firms tend to smooth their R&D investment over time (Lach and Schankerman, 1989). Most R&D studies use standard investment equation methodology to incorporate adjustment cost dynamics into the static R&D model. The main approach is a neoclassical accelerator model with ad-hoc dynamics (Mairesse et al., 1999), introducing a lagged dependent variable. This model is sometimes expressed in error correction form in order to take explicit account of short term versus long-term effects (Bond et al, 2005). Recent developments distinguish adjustment costs of those firms starting R&D from adjustment costs of those firms already investing in R&D (Peters et al., 2013).⁴

Third, R&D endogeneity may take place for a number of reasons: (i) it may be correlated with unobserved time-variant effects, (ii) it may respond to expectations regarding future technological shocks, (iii) the random shocks to current R&D (ε_{it}) may affect the future values

³ Prior antecedents to this model can be found in Anderson (1967) and Howe and McFetridge (1976). See also a reference to this model in Martin (2010).

⁴ This issue will be addressed in detail in Section 3.4.

of the explanatory variables; or, (iv) it may be determined simultaneously with other firm characteristics included in X_{it} . These problems have usually been addressed using GMM-IV methods, where the model is estimated in first differences and the lagged levels are used as instruments and system-GMM where the equation in levels is added and the lagged differences are used as instruments (Bond et al, 2005).

Fourth, the models usually assume that the effect of the different determinants is homogeneous across firms. If one believes they are heterogeneous, then the estimated coefficients reflect average effects within the sample. Some authors have explored whether the effect of R&D determinants may differ across different types of firms (e.g., small vs large, low-tech vs high-tech or young vs mature).

The rest of this section is organized as follows. First, we review the literature on the classical determinants of R&D. Second, we summarize the more recent structural studies focusing on the role played by public funding.

2.1 Classical determinants

The main classical determinants of R&D investment are firm size, market power and industry determinants, such as appropriability, demand pull and technological opportunity. The role played by size and market power in firm investment has been analyzed since Schumpeter (1939, 1942) while the focus on industry determinants was raised by a series of papers in the 1980s (Levin et al., 1985; Cohen et al., 1987; Cohen and Levin, 1989).

2.1.1 Size

There are several arguments which support a positive relationship between firm size and R&D investment. The main one is related to the availability of R&D funding. Larger firms are usually able to generate larger cash flows to internally finance R&D investment, and they have better access to imperfect capital markets. In addition, R&D investment usually shows scale and scope economies.

The empirical analysis of the size-R&D relationship has been a matter of interest for decades leading to the development of some stylized facts (Cohen and Klepper, 1996; Cohen, 2010): (i) the likelihood of performing R&D increases with firm size, (ii) R&D rises monotonically, and typically proportionally, with firm size (within industries and among R&D performers, (iii) small firms account for a larger share of innovations and patents than expected according to their R&D investment.

More recent studies focus on directly analyzing the relationship between R&D and the motives behind the importance of size. Many studies focus on indicators of internal and external availability of funding, usually concluding that availability of funding is positively related with R&D investment effect (Bloch, 2005; Brown et al, 2009; Czarnitzki and Hottenrott, 2011; Borisova and Brown, 2013)⁵. Some evidence has been developed that this relationship is stronger in the US and the UK than in continental Europe (Hall, 2002; Bond et al, 2005), because of a different structure of capital markets and different corporate attitudes towards

⁵ Some studies have not found a significant effect (Bond et al., 2005).

uncertainty. In turn, Henderson and Cockburn (1996) find strong evidence of the existence of scale and scope economies using program level data from the pharmaceutical industry.

2.1.2 Market power

The relationship between market competition and R&D investment is less straightforward. Theory postulates two different effects. On the one hand, a decrease in market power may reduce the incentive to invest in R&D because the firm would be less able to extract the rent resulting from innovation output (Grossman and Helpman, 1991; Aghion and Howitt, 1992). On the other hand, innovation could partially displace oligopolistic rents, thus reducing R&D incentives for firms with high market power (Arrow, 1962), or it may be used as a strategic variable to face increased competition (Spencer and Brander, 1983). The theoretical controversy has stimulated empirical research. Some authors have obtained a positive influence of market power on innovation (Crèpon et al., 1998; Blundell et al., 1999), while others authors have found a negative one (Geroski, 1990; Harris et al., 2003). As a third possibility, Aghion et al. (2005) find that the relationship between product market competition and innovation is an inverted U-shape. All in all, Cohen (2010) concludes that what emerges from previous empirical evidence is that market power does not seem to play an important, independent role in affecting R&D.⁶

2.1.3 Industry determinants

Since the late 1980s some studies (Levin et al., 1985; Cohen et al., 1987; Cohen and Levin, 1989; Geroski, 1990) have placed great attention on industry-specific determinants of R&D, such as appropriability, demand and technology opportunity.

Appropriability issues have received most of the attention. Firms should be able to appropriate returns sufficient to make their investment worthwhile (Levin et al., 1987). Appropriability may take place using formal or informal methods. Although most of the studies have focused on the role played by the patenting system, empirical evidence suggests that lead time, secrecy and complementary assets are the most employed methods to appropriate innovation results, especially outside some specific industries, such as pharmaceuticals or medical equipment (Hall et al., 2014). However, the idea that more appropriability is related to more innovation effort has been questioned (Bessen and Maskin, 2009; Lerner, 2009). The reason is that knowledge spillovers and own R&D may be complements. That is, higher appropriability means a decrease of spillovers, which may lead to a net decrease of own R&D (Hall et al., 2014). Empirical evidence is not conclusive. On the one hand, firms in industries with high formal appropriability are found to invest more in R&D (Hall and Sena, 2014). On the other, the increase in formal property rights has been found to increase only patents but not R&D in the semiconductor industry (Hall and Ziedonis, 2001), while a strengthening of legal protection of trade secrets has been found to reduce R&D in manufacturing firms (Png, 2015).

⁶ In a recent study, Beneito et al. (2015) argue that these contradictory results are driven by the impossibility of finding an accurate measure of market power. Instead, they use indicators of the fundamental determinants of competitive pressure (product substitutability, size of the market and ease of entry) and distinguish between product and process innovation. They conclude that greater product substitutability and higher costs of entry induce greater process innovation and lower product innovation, while market enlargement spurs both types of innovation.

Some studies qualify these results. Arora and Ceccagnoli (2006) show that stronger patent protection helps firms lacking complementary assets to appropriate from innovation output through licensing. Arora et al. (2008) find that patenting is a net cost for the typical invention but very valuable for a subset of inventions and, consequently does provide an incentive for R&D. Czarnitzki and Toole (2011) find that patents increase R&D in German firms through a reduction in market uncertainty, and Duguet and Lelarge (2012) find that patents clearly promote R&D and product innovations but not process innovations in French firms.

Regarding the role of demand and technology opportunity, they are the subjects of an old debate: the seminal works by Schmookler (1962) pointed out the critical importance of demand as a driver of innovation. The underlying assumption is that a common pool of knowledge and capabilities is available to all industries, and therefore large and growing markets provide higher incentives to invest in innovation as these markets offer higher returns for the investment (Cohen and Levin, 1989). On the other hand, some authors supported the view that technological opportunities were the driving force of technological change. Technological opportunities comprise the set of possibilities for advancing the knowledge frontier and may be measured in terms of the distribution of values of improved production-function or product-attribute parameters that may be attained through R&D or, alternatively, as the distribution of returns to R&D, given demand conditions and the appropriability regime (Klevorick et al., 1995). That is, at prevailing input prices, innovation is “easier” (less costly) in some industries than in others (Cohen and Levin, 1989), so more R&D is found in these industries. Technological opportunities are usually considered exogenous to a firm’s decisions. Some authors, however, argue that its influence over technological input is not clear. The reason is that technological opportunity may raise the average product of R&D without raising its marginal product, and therefore may not increase R&D investment (Klevorick et al., 1995).

Empirical studies support the importance of demand pull (Cohen et al., 1987; Acemoglu and Linn, 2004), although this support is not as strong as Schmookler thought (Geroski and Walters, 1995). On the other hand, empirical studies have usually agreed that technological opportunities are very influential in driving technological change (Raymond et al., 2010; Graevenitz et al., 2013). Accordingly, the old debate has been solved, concluding that both are important determinants of R&D investments, although the fraction of variance explained by technological opportunity seems larger.

2.2 The role of public funding

The main justification for public support of R&D activities is the correction of market failures. Because of the presence of information asymmetries and moral hazard, innovating firms usually face a higher cost of R&D finance with respect to ordinary investment and show a lower level of private external financing (Hall, 2002; Hall and Lerner, 2010). In addition, the ‘public good’ nature of knowledge prevents full appropriation, which pushes private R&D investment below the socially optimal level.

Taking this into account, there is abundant literature analyzing whether public R&D spending complements or displaces private R&D spending. When public support consists of subsidies or loans, testing for complementarity relies on determining whether public R&D induces additional private R&D investment beyond the level that would have been performed anyway.

The spectrum of empirical methodologies for performing this analysis is wide, including specific techniques to control for potential endogeneity of public support, firm heterogeneity or non-linearities, among other issues. Interested readers are referred to the reviews by David et al. (2000), Becker (2013) and Zúñiga-Vicente et al. (2014). As these reviews point out, the evidence is ambiguous, with results supporting both a (total or partial) crowding-out and a crowding-in (additionality) effect of public subsidies on private R&D investments.

Despite this wealth of empirical literature about the impact of public R&D funding on business R&D, only a few papers propose structural models describing firms' decisions as the analytical framework for their estimations. Outstanding exceptions are the works by González et al. (2005), Takalo et al. (2013a, 2013b) and Arqué-Castells and Monen (2015).

González et al. (2005) model firms' decisions about R&D extensive and intensive margins when some government support can be expected. In their model, each firm is a product-differentiated competitor capable of shifting the demand for its product by enhancing product quality through R&D. To decide the level of R&D expenditures, the firm maximizes expected profits, $E[N(R) - (1-s)^\beta R]$, where firm net revenue, N , is a function of R&D expenditures, R , with s being the subsidized fraction of these R&D expenditures. In the equilibrium, the optimal non-zero R&D effort can be expressed as follows:

$$e^* = \frac{R^*}{P^* Y^*} = \frac{R}{Y} \frac{\partial Y}{\partial R} \left/ \left(-\frac{P}{Y} \frac{\partial Y}{\partial P} E[(1-s)^\beta] \right) \right., \quad [2.4]$$

where E denotes the expectation over s values and β stands for the level of expenditure efficiency of public funds.

This Dorfman-Steiner (1954) type expression reflects both the optimal effort of performing and non-performing firms. It will only be observed if it surpasses a threshold effort \bar{e} that corresponds to the level of expenditure which makes the firm indifferent between performing R&D or not. Below this threshold, R&D costs are not completely recovered by means of the sales increment. Notice that, as expected subsidies reduce the cost of R&D, they affect both the decision to undertake innovative activities and the size of planned R&D expenditures of performing firms.

As González et al. (2005) explain, this framework naturally leads to a Tobit-type modelling of a censored variable for estimating the model parameters and, particularly, the effect of subsidies. The econometric model consists of the following equations:

$$e^* = -\beta \ln(1-s^e) + z_1 \beta_1 + u_1 \quad [2.5]$$

$$\bar{e} = z \beta_2 + u_2 \quad , \quad [2.6]$$

where e^* is only observed when $e^* - \bar{e} > 0$. z (which contains at least all variables in z_1), stands for the vector of variables that determine the spending profitability threshold, that is, demand characteristics, technological opportunities and set-up costs of R&D projects. The error term u_1 is assumed to be auto-correlated, while the error term u_2 is supposed to be independent and identically distributed over time. s^e is the expectation for s , which is

unobservable and must be previously estimated. To do so, the expectation is decomposed in the product of the conditional expectation of receiving a grant, $P(s > 0 | z_p)$, and the expected value of the subsidy conditional on z_p and its granting, $E(s | z_p, s > 0)$. These two components are estimated using, respectively, a probit and an OLS specification.

Given that subsidies are presumably granted by agencies according to the effort and performance of firms, for the estimation of this model González et al. (2005) apply methods for dealing with selectivity and endogeneity in a context which allows for auto-correlated errors. One of the main conclusions of their analysis is that subsidies can stimulate non-R&D-performing firms to start investing in R&D.

Takalo et al. (2013b) complement the framework of González et al. (2005) with the structural modelling of the subsidy-application decision of firms, each one with a unique R&D project, and the subsidy-granting decision of the public agency. In particular, the subsidy program is modelled as a four-stage game of incomplete information between both players. In stage 0, the players' types (denoted by ε and η , respectively, for the project/firm and the agency) are determined.⁷ In stage 1, the firm decides whether or not to apply for a subsidy. In stage 2, the agency grades the proposal and learns its type. Finally, in stage 3, the firm chooses the R&D investment with or without the subsidy. As in González et al. (2005), the optimal R&D investment (intensive margin) is obtained through the first order condition of the firm's profit-maximizing problem.

As Takalo et al. (2013b) point out, given that the goal of their approach is to derive equations that could be empirically estimated, they "model the players' payoffs by more specific functional forms that would be necessary from a purely theoretical point of view" (page. 257). In particular, the objective function of the firm and the agency's expected utility from an applicant's project are expressed, respectively, as:

$$\Pi(R(s), s, X, \varepsilon) = \exp(X\beta + \varepsilon) \ln R(s) - (1-s)R(s) \quad [2.7]$$

$$U(R(s), s, X, Z, \varepsilon, \eta) = V(R(s), Z, \eta) + \Pi(R(s), s, X, \varepsilon) - gsR(s) - F \quad , \quad [2.8]$$

where s stands for the subsidy rate. In equation [2.8], the first term, $V(\cdot)$, captures the (domestic) spillovers of the project beyond the firm's profits, the direct costs of the subsidy ($gsR(s)$) and the fixed costs of applying and processing the application (F). g denotes the constant opportunity cost of agency resources, while X and Z stand for vectors of observable firm characteristics.⁸

Under this framework, Takalo et al. (2013b) prove that there is a unique perfect Bayesian equilibrium of the game. The econometric implementation of this model relies on the estimation of four types of equations regarding the firms' application and R&D investment decisions, the agency's subsidy rate decision and the grading process. The estimation of this multi-equational system with project-level data from Finland allows them to quantify the

⁷ The type of project and the agency's type corresponding to each project are drawn from common knowledge (joint) distributions and constitute the unobservables of the econometric model.

⁸ See the complete set of equations in the original paper.

benefits and costs of the R&D subsidy program. They report four main findings: first, the expected effects of subsidies are very heterogeneous; second, estimated application costs vary greatly, and shocks to application costs and marginal profitability of R&D are positively correlated. Third, spillover effects of subsidies are somewhat smaller than effects on firm profits; and, fourth, the expected rate of return on the subsidy program is about 30% to 50%.

Two strong assumptions in the depicted model are the lack of fixed R&D costs and the absence of credit rationing. Takalo et al. (2013a) specifically extend this model by including a cost of external funding and fixed costs of R&D projects. To overcome liquidity problems and given that public subsidies are paid ex-post, these authors assume that the firm can raise funding from financial markets, which are competitive with free entry of identical financiers and an unlimited supply of funds. Therefore, the contract between the firm and the financier can be defined as the one that maximizes the firm's payoff subject to a financier's zero profit condition. In this framework, the presence of fixed costs of R&D allows us to determine the effects of R&D subsidies at the extensive margin, where the firms decide whether or not to invest in R&D. In addition, the cost of external finance reduces the optimal subsidy rate at the intensive margin, while the association is the opposite at the extensive margin. Takalo et al. (2013a) also derive necessary and sufficient conditions for the existence of additionality effects of public support to private R&D. In particular, they show that additionality at the intensive margin inversely depends on the spillover rate. As a consequence, the relationship between additionality and welfare may be ambiguous.

Focusing explicitly on the firm's optimal R&D decisions, Arqué-Castells and Mohnen (2015) consider an additional dimension: the existence of sunk entry costs of R&D. The firm would incur these costs only the first time that it engages in R&D. Classical subsidy granting schemes consist of subsidies seeking to increase the intensive margin, i.e., to promote the R&D effort of regular R&D performers. The existence of sunk costs also provides a justification for the use of 'extensive' subsidies, i.e., subsidies seeking to expand the base of R&D performers through the coverage of these costs.

The model framed by Arqué-Castells and Mohnen is similar to the ones in González et al. (2005) and Takalo et al. (2013a, 2013b). However, they consider a dynamic model in which firms decide whether to start, continue or stop performing R&D depending on R&D 'intensive' or 'extensive' subsidies. Through this model, they characterize the firm's optimal participation strategy in terms of two subsidy thresholds, which determine R&D entry and continuation. Using firm-level data on Spanish manufacturing firms, Arqué-Castells and Mohnen (2015) are able to compute these thresholds through the estimation of a dynamic panel data type-2 Tobit model with two equations: the R&D participation equation and the R&D investment equation. Simulation on this estimated model suggests that one shot trigger subsidies positively affect the share of R&D performers and average R&D expenditures. In addition, extensive subsidies might induce permanent effects, as R&D performers in a given period are more likely than non-performers to undertake R&D activities in the next period.

3. R&D, innovation and productivity

The analysis of productivity growth and its determinants is a classic topic in industrial economics. There is a large number of papers that study this question from an empirical point of view, pointing out the performance of technological activities as an essential source of firms' growth. Specifically, many authors have analyzed the relationship between R&D activities and productivity, finding, in general, a positive and significant effect of R&D on productivity, although with different magnitudes depending on the methodology employed and the level of analysis. In this respect, as Mairesse and Sassenou (1991) point out, the issue is not so much the question of whether or not such a relationship exists, but whether or not econometric studies can characterize such a relationship in a satisfactory and useful manner.

R&D activity can affect productivity in different ways. It can reduce the production costs or increase the quality of the goods that exist in the markets. But it can also generate new goods. These effects can cause price reductions, margins increases and reallocations, not only in terms of factors, but also in terms of firm entry and exit in the market. In this sense, it is difficult to accurately measure the impact of R&D because it affects both supply and demand of products. In addition, R&D undertaken by other firms in the own sector (or different sectors and countries) can generate positive spillovers in other firms of the same sector (or different sectors or different countries) and should also be taken account. In our revision, we are going to distinguish between three main approaches: the knowledge capital model, the CDM model⁹ and recent structural models.

Most early studies follow Griliches (1979) using an augmented production function with R&D capital (or R&D expenditure) to estimate the returns to R&D at the firm level. They focus on the supply side estimating a Cobb-Douglas production¹⁰ in levels or in log differences, which allows them to compute the impact of R&D capital on the level or the growth of the productivity. In this context, under the assumptions of constant returns to scale and perfect competition, some papers use the growth accounting framework, which allows relating the growth of total factor productivity (TFP) to R&D in a non-parametric way. This framework will be known as the knowledge capital model.

Later, following Hall (1988), Klette (1996) proposes a combination of non-parametric and parametric productivity analysis to take into account not only the existence of markups as in Hall (1988) but also the treatment of scale economies. In addition, and as in Klette and Griliches (1996), he tries to control the bias generated in the estimation of firm-level production functions when output is proxied by deflated sales, based on a common deflator across firms. In this case, biases occur in situations where firms compete in an imperfectly competitive environment in which prices will reflect idiosyncratic differences in cost and in market power across firms. Some of these differences are generated by the innovation in creating and/or increasing that market power. To control this, they add a model of product demand to the model of producer behavior. The firm's knowledge capital affects the demand

⁹ The model proposed by Crèpon, Duguet and Mairesse (1998) and subsequently known as the CDM model.

¹⁰ A smaller number of papers estimates a system of factor demand equations derived from a dual (cost function) representation of technology.

through improved product quality. They rewrite the production function in terms of revenue rather than real output assuming an isoelastic demand function and combining the production function with the demand equation.

In the previous approach, the variable which measures the technological activity and enters in both supply and demand equations is R&D capital (or R&D expenditures), which is an input measure. Recently, the idea that the growth of firms is more related to the results of technological activities than to the inputs used in them has generated some studies that directly analyze the impact of technological outputs (process, product or organizational innovations, patents, etc.) on firms' productivity. Specifically, Crèpon et al. (1998) developed a multiequational model that explains productivity by technological outputs and the latter by technological effort (innovation input). Since the appearance of this seminal paper, many researchers have applied the same methodology to different European countries, using essentially cross-sectional data from Community Innovation Surveys (CIS Data). Most of them estimate the equations of this model in a recursive way, although some recent papers estimate the equations simultaneously.

More recently, some authors developed structural models to relate productivity and R&D. Specifically, they assume that productivity is unobservable and model it as a Markov process which depends on the R&D expenditure or other endogenous decisions of the firms (Aw et al., 2011; Doraszelski and Jaumandreu, 2013). In this context, Aw et al. (2011), Roberts and Vuong (2013) and Peters et al. (2013) propose a dynamic structural model of R&D demand where the expected benefit to the firm's investment in R&D is inferred from the rational decision of R&D investment.

In sections 3.1 and 3.2, the general theoretical framework of the classical approach is summarized as the empirical results derived of it. In sections 3.3 and 3.4, the CDM model and the new papers taking into account the persistence inside the structure of this model are depicted. Finally, section 3.5 presents some recent structural models that relate R&D and productivity.

3.1 The knowledge capital model

Griliches (1979) introduced a basic framework where the production function is augmented with a knowledge capital term. In this case, the productivity equation starts by assuming a production function for firm i in year t of the type:

$$Y_{it} = A_{it} F(L_{it}, K_{it}, M_{it}, G_{it}), \quad [3.1]$$

where Y denotes the quantity of output, L , K and M are, respectively, the quantities of labor, physical capital and materials, G denotes the quantity of knowledge capital, and A represents the level of efficiency reached by the firm (or a productivity shifter). Griliches (1979) proposed computing the knowledge capital from the accumulation of R&D expenditures over time, i.e., to construct a variable that measures the stock of R&D capital owned by a firm. Specifically, he used the perpetual inventory method, and this method remains the most widely used.

Assuming a Cobb-Douglas production function for equation [3.1] and taking logarithms, we obtain two alternative linear regressions (in levels and first differences) to be estimated:

$$y_{it} = a_{it} + \alpha_l l_{it} + \alpha_k k_{it} + \alpha_m m_{it} + \gamma g_{it} + u_{it} \quad [3.2]$$

$$\Delta y_{it} = \Delta a_{it} + \alpha_l \Delta l_{it} + \alpha_k \Delta k_{it} + \alpha_m \Delta m_{it} + \gamma \Delta g_{it} + \Delta u_{it} , \quad [3.3]$$

where lower case letters denote logarithms of the variables and Δ denotes first differences of the variables. The parameters α_l , α_k and α_m measure the output elasticities with respect to the traditional inputs, and γ is the output elasticity with respect to the knowledge capital of the firm. In this context, γ is the main parameter of interest and it may reflect the impact of process innovation. In this sense, the knowledge capital is expected to have a direct positive effect on productivity because new processes reduce production costs. In addition, process innovations can also have indirect effects: if cost reductions are translated to prices, a big enough increase in sales to compensate price decreases can generate additional productivity improvements in the presence of returns to scale. However, the translation to the price depends on the competition in the market.

Estimation of firm-level production functions (such as equations [3.2] and [3.3]) involves a number of econometric issues, including simultaneity (endogeneity of the firm's input choices) and selection bias (endogenous exit)¹¹. Apart from these econometric issues, the estimation of production functions is full of challenges, especially related to data problems and, in particular, to measurement error in inputs and output. In the context of the knowledge capital model, the construction of R&D capital stock is problematic. As we said before, this capital is usually computed using the perpetual inventory method, but this method has major drawbacks in practice.¹² First, the depreciation rate is unknown and usually considered to be constant over time. Second, there is a problem related to the initial conditions for R&D capital stock.

Other measurement issues are related to quality changes in both inputs and output. If the prices used to deflate nominal inputs do not include quality adjustment, the real input would be undervalued and the TFP would be overestimated. This problem is clear in the case of ICT equipment but can also be applied to labor input, whose productivity can be increased over time. In this regard, if inputs are quality-adjusted, they can capture the effects of innovation on them. With respect to the output, if the price doesn't incorporate the quality changes, the real output is undervalued when an industry output deflator is used. Instead, the quality improvement is reflected as an increase in the nominal revenue.

For the output measure, there is an additional problem related to non-competitive pricing. Market power across firms can be different and the differences are associated with the innovator behavior of firms: product innovations give a market-power position to the firms that allow them to sell at prices higher than competitive prices¹³. As in the case of quality

¹¹ Van Beveren (2012) provides a detailed overview of both the econometric issues that arise when estimating total factor productivity in a production function framework at the firm level, and the existing (parametric and semi-parametric) techniques designed to overcome them.

¹² See Van Beveren (2012) for a detailed discussion.

¹³ In Dobbelaere and Mairesse (2010, 2013), they also consider monopsonistic competition, which allows firms to hire some of their inputs below competitive prices.

improvement, if there are no firm prices, the use of industry output deflators implies that part of the estimated productivity reflects price effects.

A second way to calculate Total Factor Productivity (TFP) growth is the accounting growth approach, which assumes some assumptions that allow calculating the elasticities from observables. Specifically, under assumptions of constant returns to scale with respect to L , K and M and competitive markets, the inputs elasticities are the shares of revenue received by each of the factors. Even in the context of imperfect markets, cost minimization implies that input elasticities equal cost shares, s_i . Therefore, the Solow residual can be rewritten as:

$$\tilde{\theta}_{it} = y_{it} - (s_l \cdot l_{it} + s_k \cdot k_{it} + s_m \cdot k_{it}) \quad [3.4]$$

The main problems of this methodology are the non-fulfillment of the previous assumptions associated with this kind of model (constant returns to scale, instant adjustment of the inputs, competitive markets) and the interpretation of TFP. Note that it picks up everything not captured by the labor productivity, capital intensity, materials as changes in the firms' efficiency, capacity utilization or measurement errors of the variable (output and inputs). Nevertheless, some papers use this approach to estimate TFP, including some variables reflecting the non-fulfillment of the assumed assumptions, x_{it} , along with other control variables like the cycle. In this context, to estimate the impact of knowledge capital on TFP, equation [3.3] can be replaced by¹⁴:

$$\tilde{\theta}_{it} = \lambda \cdot g_{it} + x_{it}' \beta + v_{it} \quad [3.5]$$

Hall et al. (2010) review the literature on returns to R&D based on different specifications of the production function previously revised at the plant, firm, industry, or country levels since the 1960s. Most papers refer to pooled (or temporal) estimates on firm data which use the level production function, although they also consider estimates from growth rates regressed on R&D intensity. When the production function is estimated in first-differenced form, they find a substantial downward bias to the R&D coefficient. This bias can be mitigated by imposing constant returns. They find that research elasticities range from 0.01 to 0.25. The cross-sectional estimates are higher than the panel data estimates, which in some cases are statistically non-significant. One explanation might be that measurement errors have a much more serious impact on growth rates than on the levels of variables. The rate of return is obtained by multiplying the estimated elasticity by the average output–R&D capital ratio in the sample. The R&D rates of return in developed economies during the past half century have been strongly positive and are more likely to be in the 20–30% range.

Wieser (2005) surveys the empirical literature on firm-level R&D and productivity at the firm level using a production function approach, but also taking into account the impact of R&D spillovers. He finds a significant impact of R&D on firm performance on average. A meta-analysis on the studies surveyed shows that the estimated rates of return do not significantly

¹⁴ Klette (1996), following Hall (1988), develops a model to take into account the possibility of the existence of scale economies in addition to imperfect competition in the product market (markup different from one) considered by Hall (1988). He proposes an expanded equation of [3.2], which allows estimating the markup and the scale elasticity.

differ among countries, whereas the estimated elasticities do. Furthermore, the estimated elasticities are significantly higher in the 1980s and consistently higher in the 1990s compared with the 1970s.

3.2. Interaction with the demand side

When equations [3.2] and [3.3] are estimated using firm data with sectoral deflators, the output measure (deflated nominal sales) also captures the impact of product innovation. Klette & Griliches (1996) deal with the problem of unobservable output prices including a demand equation. They consider that with an appropriate specification of the demand system, there is identification: the omitted price variable can be expressed in terms of the firm's output growth relative to industry output, and eventually in terms of observables and parameters already present in the production (or cost) function¹⁵. In this regard, the supply side approach can be improved by considering a demand function as follows:

$$Y_{it} = Y(P_{it}, G_{it}, D_{it}) , \quad [3.6]$$

where Y denotes the quantity of demanded output and P , G and D refer to price, knowledge capital and other demand shifters, respectively.

Technological capital affects firms' demand through the improvement of product quality or product innovations. The introduction of a new product on the market generates a new source of demand. The new product can replace the old product and in this case can cannibalize the revenues and the profits made from producing the old products. However the new product can also be complementary to the old product. In this case, selling both products can generate economies to scale in the distribution of the goods on the market.

Assuming a Cobb-Douglas specification for equation [3.6] and taking log differences, we obtain:

$$\Delta y_{it} = \eta \Delta p_{it} + \xi \Delta g_{it} + \Delta d_{it} \quad [3.7]$$

where lower-case letters denote logarithms of the variables and Δ denotes first differences of the variables. As in Klette and Griliches (1996), Klette (1996) uses the relationship between output and sales (revenue), $S_{it} = p_{it} Y_{it}$ to rewrite the TFP equation in terms of revenue rather than real output, under the assumption of an isoelastic demand equation. Klette (1996) assumes that each firm produces differentiated products and therefore faces its own downward sloping demand curve, that the number of firms is large and that oligopolistic aspects of price setting behavior are negligible. Because firms have idiosyncratic output prices, real revenue instead of an actual output measure is generated when revenue is deflated by an industry deflator. Taking log differences in the sales, $\Delta s_{it} = \Delta p_{it} + y_{it}$, and substituting in equation [3.7], the demand equation can be rewritten as:

¹⁵ Nevertheless, Mairesse & Jaumandreu (2005) do not find big differences estimating the revenue function or the production function (using a real output measure) for French and Spanish firms. They point out that biases due to other sources of specification errors are probably more important.

$$\Delta y_{it} = \frac{\eta}{1+\eta} \Delta s_{it} + \frac{\xi}{1+\eta} \Delta g_{it} + \frac{1}{1+\eta} \Delta d_{it} \quad [3.8]$$

where $\frac{\eta}{1+\eta} = \mu$ is the price-marginal cost markup¹⁶. Combining, [3.3] and [3.8], the revenue production function can be expressed as:

$$\Delta s_{it} = \frac{\Delta a_{it}}{\mu} + \frac{\alpha_l}{\mu} \Delta l_{it} + \frac{\alpha_k}{\mu} \Delta k_{it} + \frac{\alpha_m}{\mu} \Delta m_{it} + \left(\frac{\gamma}{\mu} - \frac{\xi}{\eta} \right) \Delta g_{it} - \frac{1}{\eta} \Delta d_{it} + \frac{\Delta u_{it}}{\mu} \quad [3.9]$$

Equation [3.9] combines supply and demand effects, which that implies that the parameter associated with R&D capital captures the effects of process innovations (cost reduction) and product innovations (demand increase)¹⁷. Because demand elasticity is negative, the parameter associated with this variable is positive. However, as the dependent variable is the revenue, the R&D elasticity is a combination of output and price elasticity. Identification is only possible with individual prices that allow us to estimate η and ξ separately.¹⁸

There are only a few papers that incorporate the demand side. In these studies, the impact of R&D on revenues is usually higher than the impact on physical output. See Hall et al. (2010) for a review of this literature.

3.3 The CDM model

For the last two decades, the most commonly used model to analyze the effect of innovation on productivity has been proposed by Crèpon, Duguet and Mairesse (1998), subsequently known as the CDM model. It takes into account the fact that not innovation inputs but innovation outputs increase productivity. Firms decide to invest in R&D in order to obtain some innovation outputs (product, process, organizational innovations, patents, etc.) which positively affect their productivity (or productivity growth) and other performance variables. In this regard, this model consists of a recursive system of three sets of equations. The first set of equations describes whether a firm undertakes R&D and, if so, how much, as a function of firm and industry characteristics.¹⁹ The second one takes the form of a knowledge production function, that is, explains innovation outcomes as a function of R&D intensity and other firm/industry characteristics. Finally, a productivity equation is considered where innovation outputs are factors among other inputs.

The first set explains the probability of undertaking R&D and the intensity of the R&D expenditure. The R&D effort R_{it}^* can be measured by the intensity of the R&D expenditure R_{it} only if the firm makes (and reports) that expenditure. The decision to perform R&D expenditures is represented by:

¹⁶ Alternatively, the demand equation can also be expressed in levels.

¹⁷ This equation can also be estimated in levels.

¹⁸ Van Leeuwen (2002) estimates this equation and, apart from including process innovation, he parameterizes the demand shifter by the share of new (or new and improved) sales in total sales. The basic assumption of this model is that innovation is predominantly "demand driven," and therefore its contribution to productivity growth should be measured according to quality or product variety.

¹⁹ Sometimes this first block involves just one equation when the sample refers to innovative firms.

$$dR_{it} = \begin{cases} 1 & \text{if } dR_{it}^* = x_{1it}'\beta_1 + \varepsilon_{1it} > 0 \\ 0 & \text{if } dR_{it}^* = x_{1it}'\beta_1 + \varepsilon_{1it} \leq 0 \end{cases} \quad [3.10]$$

where dR_{it} is a binary variable that takes the value 1 when the firm invests in R&D, and 0 otherwise. If the latent variable dR_{it}^* is bigger than a constant threshold (which can be zero), we then observe that the firm engages in R&D activities. x_{1it} is a vector of observable explanatory variables (time-variant and time-invariant variables). Conditional on the performance (and report) of R&D activities, the second equation refers to the quantity of resources allocated to this purpose:

$$R_{it} = \begin{cases} R_{it}^* = x_{2it}'\beta_2 + \varepsilon_{2it} & \text{if } dR_{it} = 1 \\ 0 & \text{if } dR_{it} = 0 \end{cases} \quad [3.11]$$

where x_{2it} is a vector of determinants of the innovative effort, which can differ from those determinants that explain the decision to perform R&D expenditures. Finally, ε_{1it} and ε_{2it} are idiosyncratic errors (which refer to other unobservable time-variant determinants). Most papers assume that the error terms ε_{1it} and ε_{2it} follow a bivariate normal distribution with a mean equal to 0, variances $\sigma_1^2 = 1$ and σ_2^2 , and correlation coefficient ρ_{12} . For this reason, both equations are usually estimated as a generalized Tobit model by maximum likelihood (Heckman 1976, 1979). In the original paper, the innovative effort is approached by the research-technological capital per employee. Posterior empirical evidence usually considers the R&D expenditure per employee a proxy of technological effort.

The third equation of the model corresponds to the estimation of the new knowledge production function, g_{it} , generated from firms' innovative effort. The model assumes that the investment intensity is a public good within the firm that can be used to produce different outputs without depletion. Therefore, g_{it} can be modeled as a vector of technological outputs that can take several forms:

$$g_{it} = \lambda R_{it}^* + x_{3it}'\beta_3 + \varepsilon_{3it}, \quad [3.12]$$

where latent investment intensity R_{it}^* appears as an explanatory variable with the vector x_{3it} , which includes other determinants of knowledge production (time-variant and time-invariant variables).

In the original paper, new knowledge is measured by two variables: the number of patents and the percentage share of firm innovative sales (products launched in the market in the last five years). In the first case, the patent equation is specified as a heterogeneous count data process. In the second one, since the share is only known by intervals, the equation is specified as an ordered probit model. The choice of the dependent variable is conditioned by the availability of data in Community Innovation Surveys (CIS), which are the data bases most frequently used to estimate the CDM model with European data. Subsequent studies complement these indicators with dummy variables that capture the achievement of product and process innovation and, recently, organizational innovation.

Finally, the last equation refers to the productivity equation. Most papers consider an augmented Cobb-Douglas production function with physical capital, employment, innovation outputs and other control variables. In addition, they usually assume constant returns to scale (in standard inputs). The functional form that has been used more frequently following the original CDM is:

$$y_{it} - l_{it} = \delta g_{it} + x_{4it}' \beta_4 + \varepsilon_{4it}, \quad [3.13]$$

where $y_{it} - l_{it}$ is labor productivity (added value or output per worker, expressed in log), innovative output g_{it} appears as an explanatory variable with the vector x_{4it} , which includes other determinants like physical capital per employee (in log) and skill composition, among others. However, recent empirical evidence considers other augmented Cobb-Douglas production functions like equations [3.2] and [3.9] of the previous section²⁰.

In the original paper (Crèpon et al., 1998), all equations ([3.10]-[3.13]) are estimated jointly by asymptotic least squares or a minimum distance estimator. In the first stage, they estimate the reduced form equations parameters by M-estimation, and in the second stage, ALS-estimation to retrieve consistent estimates of structural parameters. However, successive empirical evidence uses a sequential approach: the predicted value of the dependent variable of each set enters as a determinant in the next equation.

Specifically, after the estimation of equations [3.10] and [3.11] of the first set, the predicted value for all firms is used as a proxy of the innovation effort and included as a determinant in equation [3], the knowledge production function. This implies that the model assumes that all firms make some innovative effort even if they do not report this effort. That is, below a certain threshold, the firm is not capable of picking up explicit information about this effort and will not report on it. In this regard, equation [3.12] is estimated for all firms and not only for the sub-sample of those reporting R&D expenditures. In addition, the predicted value instead of the observed value dR_{it}^* is used as an explanatory variable to take into account the potential endogeneity of this variable in the knowledge production function: some unobservable characteristics of firms can generate both innovative effort and technological outputs increases. In the last step, the productivity equation is estimated by using the predicted values of g_{it} to take care of the endogeneity of this variable in equation [3.13]. In this regard, the CDM model takes into account the endogeneity of R&D effort and innovation outputs in the knowledge and productivity equation, respectively. However, there is no feedback from productivity to innovative activities.

Revisions of this literature have been provided by Hall (2011) and Mohnen and Hall (2013). The empirical evidence shows that productivity is positively related to both innovative sales and the binary indicator for product innovations and that the association is higher for high

²⁰ Klomp and van Leeuwen (2001) also have exploited the CIS data in a structural modelling approach. But in contrast to Crèpon et al. (1998), they do not use a production function framework.

technology sectors²¹. However, regarding process innovation, results vary a lot and, in some cases, are even negative. Two possible explanations have been provided (Hall, 2011): (i) firms operate in the inelastic portion of their demand curve so that revenue productivity is not affected by efficiency improvements in the production process and (ii) there is so much measurement error in the innovation variables that only one of the two is positive and significant when added to the productivity equation²².

3.4 Persistence in technological inputs and outputs

Although there is ample empirical evidence that tests the CDM model, most of it is based on cross-sectional data. This fact does not permit the estimations to take into account persistence in R&D activities, dynamic linkages between innovation and economic performance or unobserved firm heterogeneity. Recently, some studies have begun to consider the timing of innovation and dynamics aspects.

There are papers that show persistence in economic performance (profits and productivity) of firms. For example, Cefis and Ciccarelli (2005) find long-run persistence in profit differentials among UK manufacturing firms. In addition, their results show a positive difference in profitability between innovators (firms which apply for patents) and non-innovators, which is greater when the comparison is between persistent innovators and non-innovators. Bartelsman and Dhrymes (1998) and Fariñas and Ruano (2005) give evidence of persistence in the differences in productivity across firms for US and Spanish manufacturing firms, respectively. The static version of the CDM model shows that output innovation is related to productivity and, in this regard, persistence in innovation activity can explain the persistence in firm economic performance.

More recently, the availability of new data allows estimating the growth of labor productivity or TFP by using panel data and introducing dynamics in the CDM model or, at least, in the equations for the decisions on technological inputs or outputs. There are two main explanations for persistent behavior: true state dependence and spurious dependence. The first one implies a real causal effect: the probability of investing in $t-1$ increases the probability of investing in t . Explanations for this real true dependence in the case of innovation activities are the sunk costs associated with the performance of R&D activities, the “success breeds success” hypothesis and the existence of dynamic increasing returns, among others (see, for example, Peters, 2009; Mañez-Castillejo et al., 2009; and Raymond et al., 2010).

Sunk costs represent a barrier to both entry into and exiting from R&D activities. If a firm decides to undertake R&D investment, it has to incur start-up expenditures to build an R&D department. These costs are an entry barrier because potential entrants have to take them into account in their profit maximization behavior. They also are a barrier to exiting because

²¹ The effect tends to be lower when growth rather than level of productivity is estimated and when skilled labor is controlled for, suggesting an identification problem between innovation and other measures of knowledge and physical capital.

²² Van Leeuwen and Klomp (2006) present a structural model similar to the CDM model but they use revenue per employee growth as the measure of firm performance instead of the level of value added per employee in the performance equation (equation [3.9] of section 3.2.).

they are not recovered when the firm stops R&D activity and it has to incur them (maybe in a smaller quantity) again if it decides to re-enter.

Another explanation is the “success breeds success” hypothesis, which is based on different arguments in the literature. Firstly, and following Schumpeter, if there is a positive relationship between market power and innovation, incumbents have more to lose by not innovating than potential new entrants do and this causes incumbents to innovate persistently. In addition, a firm’s innovation success broadens its technological opportunities, which make subsequent innovation success more likely. Another argument is the existence of financial constraints. Innovation projects entail a high risk and, because of information asymmetry between the innovator and the lender, firms have problems obtaining external funds. Profits that are generated by past successful innovations provide firms with increased internal funding that can be used to finance further innovations.

The last explanation, as Peters (2009) points out, is based on the idea that knowledge accumulates over time (Nelson and Winter, 1982). Evolutionary theory states that technological capabilities are a decisive factor in explaining innovation. Experience in innovation is associated with dynamic increasing returns in the form of learning effects which enhance knowledge stocks and, hence, technological capabilities. In addition, evolutionary theory defines the notion of technological trajectory. Along a trajectory, radical innovations are followed by a succession of incremental innovations. Consumers are inclined to buy new generations of products, increasing the demand for innovation.

According to these theoretical explanations for real state dependence, it is not clear whether persistence is more related to technological inputs or outputs. Under the sunk cost hypothesis, R&D decisions are modeled on a long-term horizon, given that sunk costs could represent a barrier not only to entry for new firms, but also a barrier to exiting for incumbent firms that have not recovered their investments. In this case, an input measure would be desirable. However, the “success breeds success” and the “learning by doing” hypotheses are more associated with technological results. Additionally, if we assume that innovation outputs are in part determined by innovation inputs, input persistence should be partially translated into output persistence.

From an empirical point of view, there is a lower number of papers focused on innovation inputs (R&D expenditure) than on technological outputs (patents or process and product innovations). As for the first, two outstanding studies are the ones developed by Mañez-Castillejo et al. (2009) and Peters (2009). Both obtain evidence in favor of a high degree of persistence regardless of the methodology. In particular, Mañez-Castillejo et al. (2009) estimate a multivariate dynamic discrete choice model of R&D decisions using firm-level data of Spanish manufacturing for 1990–2000. Conditional on firm heterogeneity and serially correlated unobservable factors, they find that R&D history matters. They interpret this true dependence as the existence of sunk R&D costs associated with performing R&D. They deal

with econometric problems (error term serially correlated because of permanent firm-specific component and the initial conditions problem) following Heckman (1981).²³

Peters (2009) analyzes the persistence of firms' innovation for German manufacturing and service firms for the period 1994–2002. She estimates a dynamic random effects discrete choice model and uses the estimator proposed by Wooldridge (2005). The econometric results show that past innovation experience is an important determinant for manufacturing and for service sector firms alike, and hence confirm the hypothesis of true state dependence. She defines an innovator as a firm with positive innovation expenditure in a given year. In this regard, the paper analyzes persistence in innovation input.

With respect to innovation outputs, apart from patents, the empirical evidence is also consistent with the existence of high persistence. Duguet and Monjon (2004) show that persistence in (process or product) innovation is strong for a sample of French manufacturing firms. Using data on Australian firms, Rogers (2004) also finds that there is some degree of persistence in innovative activities defined in terms of product and organizational innovations. However, neither study controls for unobserved individual heterogeneity. Flaig and Stadler (1994) deal with this problem and examine persistence in process and product innovations using a panel of manufacturing firms in West Germany in the 1980s. They estimate a dynamic panel probit model that accounts for unobserved firm-specific characteristics following Heckman's (1981) approach. For both types of innovation, their results suggest the existence of true state dependence, which implies a positive impact of innovative success on further innovations in the following years.

In the case of patents, most papers find a low level of persistence (see, Malerba and Orsenigo, 1999; Cefis and Orsenigo, 2001; and Cefis, 2003). This result is confirmed by Geroski et al. (1997) using a duration model for granted patents for a sample of US firms to test the "success breeds success" idea: very few innovative firms are persistently innovative. This low persistence when innovation activity is measured with patents can be explained because not all inventions are patented. In addition, as Duguet and Monjon (2004) point out, patenting involves both innovating and being the first to innovate. In this regard, patent data could measure the persistence of innovative leadership rather than the persistence of innovation. With a panel of French manufacturing firms, Crèpon and Duguet (1997) also use patent data to measure innovation. They estimate a dynamic count data model that links the current number of patents to both the previous year's number of patents and the amount invested in R&D. They find that the effect of lagged patents on the current number of patents is significantly positive, which suggests a persistence in innovation among formal R&D performers, but the effects slowly vanish as the number of innovations increases.

Previous empirical evidence analyzes persistence in the R&D activities in just a single equation without considering the links among technological inputs and outputs and productivity. Recent papers provide evidence about the relevance of taking persistence into account when examining these links. In particular, Raymond et al. (2009) consider the possibility of dynamics

²³ Heckman (1981) suggests starting on the joint distribution of the dependent variable in all periods conditioned to the permanent component of the residual and the mean of the explanatory variables. He also proposes specifying the distributions of the initial condition and the permanent component to the error term to integrate out the unobserved effect.

in the first two equations of the CDM model for Dutch manufacturing, using an unbalanced panel from five waves of the CIS during 1994-2004. They consider not only the persistence of innovation input and innovation output, but also the lag effect of innovation input on innovation output and the feedback effect of innovation output on innovation input.²⁴ They find persistence of innovation input and innovation output, a lag effect of the former on the latter and a feedback effect of the latter on the former.

Van Leeuwen (2002) analyzes the dynamics of R&D intensity and links it to that of innovative sales using two waves of the Dutch CIS data. The results show that innovation persistence is smaller when measured from the output side than when judged from R&D intensities. As in Van Leeuwen and Klomp (2006), he also includes a productivity equation in terms of revenue growth. In this last equation, the returns of the current R&D endeavor are more significant if the dynamic specification is relaxed, and a restricted and static model is applied to all available CIS data.

Huergo and Moreno (2011) specifically take into account persistence in R&D activities and technological outputs inside the CDM model for a sample of Spanish manufacturing firms between 1990 and 2005. For the first two equations, they estimate a Heckman model with a dynamic pooled probit for the decision whether to engage in R&D activities or not, where the individual heterogeneity is parameterized as in Wooldridge (2005). In the third equation (new knowledge generation), the lagged dependent variable is added as an explanatory variable to reflect whether the firm has previously generated new knowledge capturing the innovation output experience. Because of the binary character of innovation measures, this equation is estimated as an RE dynamic probit model. The last equation of this paper is a TFP growth equation, where TFP is calculated as a Solow residual, imposing the usual assumptions. In the estimation, the authors assume a recursive model where feedback from productivity growth to technological effort is not allowed, and therefore a three-stage estimation procedure is applied. The results reflect the existence of true state dependence both in the decision of R&D investment and in the production of innovations. The omission of this persistence leads to an overestimation of the current impact of innovations on productivity growth.

The previous paper does not take into account the potential correlation of the error terms across equations or the dynamics in the productivity equation. Raymond et al. (2015) deal with these challenges and introduce dynamics in the R&D-to-innovation and innovation-to-productivity relationships. They consider four nonlinear dynamic simultaneous equations and estimate them by full information maximum likelihood using two unbalanced panels of Dutch and French manufacturing firms from three waves of the CIS.²⁵ The results provide evidence of robust unidirectional causality from innovation to productivity and of stronger persistence in

²⁴ To do so, a dynamic panel data bivariate tobit with double-index sample selection accounting for individual effects is estimated by maximum likelihood.

²⁵ Specifically, they take care of the initial conditions problem using Wooldridge's (2005) approach and they handle multiple integration due to the correlations of firm effects and idiosyncratic errors across equations by using Gauss-Hermite quadrature sequentially (Raymond et al., 2007).

productivity than in innovation. Specifically, they only find true persistence in product innovation in French manufacturing.²⁶

Using an alternative approach, Deschryvere (2014) analyzes what role persistence of innovation output plays in the growth of firms. Specifically, he applies a vector auto-regression model to Finnish firm-level data. He finds that only continuous product and process innovators show positive associations between R&D growth and sales growth. In the case of process innovations, occasional innovators are the ones that exhibit a stronger association between sales growth and subsequent R&D growth.

3.5 Recent structural models

Previous empirical analyses on the effect of R&D at the firm level are based on the estimation of the relationship between technological input (or technological outputs as in the CDM model) and the level of output. The marginal product of the knowledge input (technological capital) in the production function provides a measure of the return of the firm's R&D expenditure.

An alternative way to incorporate R&D in the firm's production process has been developed by Aw et al. (2011) and Doraszelski and Jaumandreu (2013). Instead of building a knowledge capital, like Griliches (1979), they assume that productivity is unobservable and model it as a Markov process which depends on the R&D expenditure. That is, productivity is affected by the firm's endogenous decision to invest in R&D. In the case of Aw et al. (2011), the export choice also endogenously affects the path of productivity²⁷. Specifically, from the standard Cobb-Douglas production function in logarithms:

$$y_{it} = a_0 + \alpha_t t + \alpha_l l_{it} + \alpha_k k_{it} + \alpha_m m_{it} + w_{it} + u_{it} \quad [3.14]$$

Doraszelski and Jaumandreu (2013) assume that actual productivity, w_{it} , can be decomposed into expected productivity and a random shock²⁸:

$$w_{it} = E[w_{it} | w_{it-1}, R_{it-1}] + \xi_{it} = G(w_{it-1}, R_{it-1}) + \xi_{it} \quad [3.15]$$

where R_{it-1} is R&D expenditures in t-1. That is, the firm anticipates the effect on R&D productivity in period t when making the decision about investment in knowledge in period t-1. Using an unbalanced panel of Spanish manufacturing firms during the 1990s, they found that R&D expenditures determine the differences in productivity across firms and the evolution of firm-level productivity over time. They also provide evidence of the non-linearities and uncertainty in the R&D process.

²⁶ In a previous paper, using the same estimation technique, Raymond et al. (2010) study the persistence of product or process innovation and of innovative sales. They estimate a dynamic type 2 Tobit model and find that the intensity of past innovation output affects current intensity in high-tech activities, but there is no effect in low-tech activities.

²⁷ To deal with the endogeneity, following Olley and Pakes (1996), the econometric literature models productivity as an exogenous first-order Markov process.

²⁸ As in Olley and Pakes (1996), the conditional expectation function $G(\cdot)$ is not observed by the econometrician and must be estimated non-parametrically along with the parameters of the production function.

Aw et al. (2011) use a model of firm revenue in domestic and export market instead, but instead of using equation [3.14] from a standard production function, they consider a short-run marginal cost function and firms operating in monopolistic competitive markets (domestic and foreign) that apply a markup to the marginal cost. The firm's revenue in each market depends on the aggregate market conditions, the capital stock, the vector of variable inputs prices and the firm-specific productivity that they model as:

$$w_{it} = G(w_{it-1}, dR_{it-1}, dX_{it-1}) + \xi_{it} \quad , \quad [3.16]$$

where dR_{it-1} and dX_{it-1} , are the firm's R&D and export market participation in t-1, respectively. As in Doraszelski and Jaumandreu (2013), they assume that the firm can affect the evolution of its productivity by investing in R&D, but now, they also consider the possibility of learning-by-exporting. That is, being an exporter is a source of knowledge and can improve future productivity. Using plant-level data for the Taiwanese electronics industry, they obtain that both activities, R&D and export, positively affect the future productivity of the plants. Nevertheless, R&D marginal effect varies a lot with productivity; it is much higher for high productivity plants, and it is higher for non-exporting firms (although the magnitudes of these second results are quite small).

Some recent articles complement the previous papers and take a different approach to deal with the simultaneity problem by modelling and estimating the firm's dynamic decision to invest in R&D instead of estimating just a production function (Roberts and Vuong, 2013; Peters et al, 2013). They elaborate a dynamic structural model of R&D demand so that the expected benefit to the firm's investment in R&D is inferred from the rational decision of R&D investment. One important advantage of these models is that they allow the change of parameters in the firm environment²⁹ and the quantification of the effect of these changes on the firm's decision to invest in R&D, productivity and the long-run impact on profitability.

The antecedents of these models can be found in Rust's (1987) model for discrete investment decision by firms and have been applied to a wide range of a firm's choices, for example, export decisions in international trade (Das et al., 2007) or entry and exit choices in industrial organization (Aguirregabiria and Mira, 2007; Collard-Wexler, 2013).

The starting point of the dynamic structural models for R&D demand is that R&D investment is an inherently dynamic decision because the firm must incur costs in the present period for an anticipated gain in profits in future periods. This gain shows several important features: (i) there is a time lag between investment and output, (ii) R&D is unlikely to have a one-time impact and (iii) the magnitude of the gains is surrounded by uncertainty. Structural models accounts for these features.

We will present a summarized version of this kind of model, following Robert and Vuong (2013)³⁰. A more complex version can be found in Peters et al. (2013). They consider a single firm, l that makes input choices at the beginning of time period t and faces a logarithmic production function as equation [3.14].

²⁹ For example, the degree of competition in the output market or the introduction of R&D subsidies.

³⁰ In their paper, Robert and Vuong (2013) relate the equations of their model to the CDM model.

As in previous papers, they consider w_{it} to be a firm-specific productivity level that the firm observes and u_{it} a random shock that the firm does not control and does not observe in advance.

In the simplest version, the firm chooses l (and other variable inputs) that maximizes the profit function, $\pi(w_{it})$. The important point here is that the future firm productivity level (w_{it}) directly impacts profit and can be affected through R&D investments³¹.

Accordingly, the firm must decide whether to invest in R&D (R_{it}) to improve the level of its future productivity. This decision is based on the comparison of costs and benefits of R&D.

On the one hand, costs of R&D, $c(r_{it})$ include not only expenditures on R&D inputs but also adjustment costs. Adjustment costs will be higher for those firms not performing R&D in the previous period than for those firms already developing R&D activities, reflecting the existence of an entry cost to R&D. It is also acknowledged that some R&D costs (such as capital costs) will not be observed by the research and should be estimated within the model.

On the other hand, the benefits of R&D are treated in two steps. First, the firm's choice of R&D affects the probability of realizing an innovation in the next period, $F(g_{it+1}|R_{it})$, where n_{t+1} stands for innovations in $t+1$. This function recognizes that there is uncertainty in the innovation process, so some R&D efforts may fail. In addition, it allows innovation without any formal R&D spending³². In the Peter et al. (2013) paper, R_{it} is measured as a discrete variable, dR_{it} , and the innovations, g_{it+1} , are also defined as discrete variables.

Second, innovations can lead to improvements in the firm's future productivity, which is represented by a distribution function $G(w_{it+1}|w_{it}, n_{it+1})$, that depends on both the firm's current productivity and its realized innovation³³. This specification recognizes the persistence of firm-level productivity and that innovations have a lasting effect on productivity:

$$w_{it+1} = G(w_{it}, g_{it+1}) + \xi_{it+1} \quad [3.17]$$

That is, Peters et al. (2013) and Roberts and Vuong (2013) include the innovation process in the model (the first step) instead of linking R&D to productivity like Aw et al. (2011) and Doraszelski and Jaumandreu (2013). Combining both steps, they capture not only the endogeneity of the productivity process but also the uncertainty of the innovation process. In addition, that allows them to analyze whether R&D expenditure improves productivity through the demand side (product innovations) or cost side of the firm's operations (process innovations). These features of the model allow for an explicit formulation of the firm's dynamic demand for R&D that is absent from the knowledge capital or CDM model.

The firm i chooses its sequence of R&D expenditures (R_{it}) to maximize the discounted sum of expected future profits net of the costs of R&D. Its value function can be written as:

³¹ The profit function will also depend on the fixed inputs (k) and the exogenous input prices (the firms apply a markup on the short marginal cost like Aw et al. (2011)). The more complex model incorporates exogenous state variables in the specification (Peters et al., 2013) and explicit equations for firm cost and demand, so that the profit function is derived from them.

³² Innovation without R&D is quite widespread and it could be driven by other innovation inputs, such as design, training or hiring of new people.

³³ This is analogous to the third equation in the CDM model.

$$V(w_{it}) = \pi(w_{it}) + \max_{r_{it}} [\beta EV(w_{it+1} | w_{it}, R_{it}) - c(R_{it})], \quad [3.18]$$

where β is the discount factor, and the firm's value function, V , is the sum of the current period profit, π , and the maximized discounted future expected value net of the cost of investment. The term $EV(w_{it+1} | w_{it}, R_{it})$ is important because it captures all future payoffs to the firm from R&D investment and it can be written as:

$$EV(w_{it+1} | w_{it}, R_{it}) = \int V(w_{it+1}) dG(w_{it+1} | w_{it}, g_{it+1}) dF(g_{it+1} | R_{it}), \quad [3.19]$$

where the three terms on the right hand side of the equation identify the three steps: (i) from R&D to innovation, (ii) from innovation to future productivity and (iii) from future productivity to future long-run profits.

As previously mentioned, empirical papers have focused on the discrete choice of R&D, so the R&D variable is given as $dR_{it}=1$ if the firm invests in R&D and $dR_{it}=0$ if it does not. Therefore, the long-run payoff of R&D is defined as:

$$\Delta EV(w_{it}) = EV(w_{it+1} | w_{it}, dR_{it} = 1) - EV(w_{it+1} | w_{it}, dR_{it} = 0) \quad [3.20]$$

The term ΔEV is simply the increment to the expected (long-term) future value of the firm if it chooses to invest in R&D in period t ³⁴.

When deciding to invest in R&D the firm weighs this expected gain in future profits against the current cost of R&D so that the final element to complete the model is the specification of the cost function for R&D. Like Aw et al. (2011), Peters et al. (2013) treat firm costs as independent draws, ψ_{it} , from an underlying cost distribution, $C(\psi)$, and estimate parameters describing this distribution as part of the model.

In the discrete framework, the firm's demand for R&D is simply the probability that they choose to invest in R&D, that is, the probability that $\Delta EV \geq \psi_{it}$.

Peters et al. (2013) estimate the model using firm-level data from the Manheim Innovation Panel for German manufacturing results. The main results show that, expressed as a proportion of firm value, the net benefit for the median firm with prior R&D experience varies from 2.4 to 3.2 percent across five high tech industries but varies from -4.6 to 0.6 percent for firms without previous R&D experience. This negative value implies that the median unexperienced firm would not find it profitable to invest in R&D. Given unexperienced firms find R&D profitable, the net benefit of starting R&D varies from 2.0 to 2.4 percent of firm value. In low-tech industries the net benefits are substantially smaller. In addition, they simulate how changes in the R&D cost affect the firm's choice and, consequently, future productivity. For example, in high-tech industries a 20% reduction in fixed R&D cost leads after 5 years to an average increase of 7 percentage points in the probability of investing in R&D and a 4% increase in productivity.

³⁴ A higher level of productivity would imply a higher return on the investment, thus making it more likely that the firm will invest in R&D in the future.

Robert and Vuong (2013) estimate a simplified version of the model estimated in Peters et al. (2013) for German data. They find similar results: the expected benefit of R&D investment varies positively with the firm's productivity, and is substantially larger in a group of high-tech industries than in a group of less R&D-intensive industries. As a share of a firm's value, the expected benefit of R&D net of R&D costs varies from -0.6% to 1.6% across firms with different productivity levels in high-tech industries, and from -3.3% to 0.8% in low-tech industries. Firms with negative net benefits would choose not to invest in R&D.

4. Inside the R&D black box

The literature reviewed so far is generally constrained by a lack of information on and analysis of R&D specificities. This section is aimed at summarizing two strands of literature that seek to open up and examine the contents of the R&D black box. First, there is literature that has attempted to open up the R&D black box by explicitly taking into account that research and development are two different activities, and therefore may differ in terms of their determinants and effects. Second, firms often adopt a number of innovation strategies simultaneously, and this coexistence of strategies suggests the existence of complementarities. Here we focus on empirical studies aimed at identifying complementarity relationships in R&D activities.

4.1. R&D composition

One limitation of previous literature is that R&D has been assumed to be a homogeneous activity. However, research and development are two different activities that differ in purposes, knowledge bases, the people involved and management styles (Barge-Gil and López, 2015). More precisely, the main purpose of research is to acquire new knowledge, while the main purpose of development is directed to the introduction of new or improved products or processes (OECD, 2005). Research is more theoretical in nature (although frequently oriented to some practical objective) and is based on analytical knowledge. Development is essentially applied and based on synthetic knowledge (Asheim and Coenen, 2005). Research needs specialized human capital which works relatively independently of the rest of the organization and without much hierarchy, while development shows clear hierarchy and needs generalists able to coordinate with other functions of the organization (Leifer and Triscari, 1987). As a consequence, research and development are increasingly carried out in different departments, even located in distant places (Chiesa, 2001).

The issue of heterogeneity in R&D was addressed in seminal works by Mansfield (1980, 1981), Link (1981, 1982, 1985), Griliches (1986) and Lichtenberg and Siegel (1991). However, these authors themselves point out the limitations of their studies and stress that their results should be viewed as preliminary. The reason is that they use small samples of very large US firms and usually were not able to address issues of simultaneity and endogeneity. Two main topics were addressed: R&D determinants and R&D effect.

Regarding the first topic, Mansfield (1981) uses a survey of 108 large US firms to analyze the determinants of the composition of R&D expenditures and the effect of this composition on innovative output. Four types of R&D expenditures are distinguished: (i) devoted to basic

research, (ii) devoted to relatively long-term projects (five or more years), (iii) aimed at entirely new products and processes, and (iv) devoted to relatively risky projects (less than a fifty-fifty estimated chance of success). He finds that these four dimensions of R&D are not related much (when comparing firms within industries) and that larger firms are more oriented towards basic research. In addition, there is some correlation between the number of innovations and the proportion of basic research on total R&D expenditures. Link (1982) analyzes the determinants of basic research, applied research and development for a sample of 275 firms belonging to the Fortune 1000 list in the US. He finds that orientation to development is higher for firms operating in more concentrated markets and receiving more public funding, while firms with a higher level of profits are more oriented to applied research. Finally, orientation to basic research increases with diversification and profits and was higher for owner-managed firms. In a later work, Link (1985) adopts a dynamic perspective. He finds that orientation to basic and long-term research is decreasing, so he analyzes the determinants of this change for 146 very large US firms. He finds that managerial issues are important as firms with a more offensive strategy and central R&D labs are also those more increasingly oriented towards basic and long-term research.

Regarding the second topic, Mansfield (1980) uses data from 119 US firms to analyze the effect of R&D composition on productivity. He finds that there is a positive relationship between the amount of basic research and productivity, after holding constant other R&D expenditures (which do not show an effect on productivity). Griliches (1986) analyzes the relationship between R&D and productivity growth in approximately 1,000 large US firms from 1957 to 1977. He finds that basic research appears to be more important as a productivity determinant than other types of R&D and that privately-financed R&D expenditures are more effective than federally-financed ones³⁵. These results hold when individual firm effects are dropped out. Finally, Lichtenberg and Siegel (1991) use an improved dataset, with more than 2,000 firms (including some small ones) accounting for 84% of the R&D performed in the US in 1976. The data allow them to control for firm diversification so that efficiency of estimation is improved. They find that only investment in basic research shows a positive effect on productivity (neither applied research nor development show effects different from zero) and that company-funded R&D shows a positive effect on productivity, but not federally-funded R&D³⁶.

However, to our knowledge, in spite of the relevance of these papers and claims by their authors about the importance of studying the composition of R&D, this topic has not received much attention for a long period. In the last few years, however, interest has been renewed, driven by the availability of new data from CIS surveys. Three main topics have been addressed: the relationship between public funding and the composition of R&D, the different determinants of R&D components and the different effect of these components on innovation outputs.

Regarding the first topic, Aerts and Thorwarth (2009) use a sample of 521 Flemish firms from two waves of the R&D survey (2004 and 2006) and find that additionality of public funding

³⁵ Confirming at the firm level, the results obtained at the industry level by Griliches and Lichtenberg (1984).

³⁶ In an appendix of their work, Hall and Mairesse (1995) explore the compositional effects of R&D in a sample of 197 firms during 8 periods. They find that the fraction of R&D devoted to basic research reduces overall productivity by 5-9 percent (standard error of 2-3 percent) and government funded research does not seem to have much effect until it raises over 20% of the firm's R&D budget. At this point, its effect is positive.

exists in development but not in research. Clausen (2009) uses a sample of 1019 firms in Norway and distinguishes between subsidies for research and subsidies for development and finds that there is additionality for research but not for development subsidies. Czarnitzki et al. (2011) use an unbalanced panel (1999-2007) including 952 Belgian firms. These authors analyze financial constraints associated with research and development activities. They find a higher effect of financial constraints on research (this activity is performed by firms showing more liquidity and less debt than those performing development). In a related work, Czarnitzki and Hottenrot (2011) use an unbalanced panel (1993-2002) of 352 German firms for ten years and distinguish between 'routine' vs 'cutting edge' R&D investment and conclude that financial constraints exist for 'cutting edge' R&D but not for 'routine' R&D.

Regarding the second topic³⁷, Barge-Gil and López (2014) use a sample of more than 4,000 firms per year in the period 2005-2009, accounting for the correlation between error terms from a research and development equation. They find that demand pull and appropriability have a higher effect on development activities while technological opportunity has a higher effect on research activities. Additionally, for larger firms the effect of size is usually higher on development than on research and no important effect is achieved for market power. The work by Czarnitzki and Hottenrot (2011) controls for the Herfindahl index of market concentration and finds a positive effect of this index on routine R&D but not on cutting-edge R&D.

Regarding the third topic, Lim (2004) analyzes the different impact of basic and applied research in firms from pharmaceutical and semiconductor industries. His sample is composed of an unbalanced panel (1981-1997) containing 1,129 observations for the semiconductor industry and 571 for the pharmaceutical industry. He finds that applied research shows a much higher effect on the number of patents than basic research (actually, basic research shows a negative effect in the semiconductor industry). Czarnitzki et al. (2009) analyze the different impact of research and development on patents. They use an unbalanced panel of 122 Flemish firms from 1993 to 2003. They find that the patent-R&D relationship exhibits a premium for the portion of R in R&D although they warn about the explorative nature of the result due to the small size of the sample used. In a later work, Czarnitzki and Thorwall (2012) argue that previous studies do not control for technological opportunity and appropriability, so they analyze the different impact of basic research in low-tech and high tech industry, using a sample of 353 Flemish firms observed in three periods. They find that there is a premium for investment in basic research in high tech industries but no premium (or discount) exists in low-tech industries. Additionally, they find that the premium for basic research increases with firm size. They interpret these results as showing that appropriability conditions for basic research are lower in low-tech industries and in small firms. Finally, Barge-Gil and López (2015) use a sample of 4,024 Spanish firms for the years 2005-2008 to estimate the differentiated effect of research and development in several innovation outputs: patents, new products and processes and sales from new products. The main findings show that both activities contributes to each

³⁷ Some theoretical works have also been developed in this line. Cabral (1994) proposes that market power is associated with development (rather than research) activities in a static framework. In a later work, Cabral (2003) extends this result to a dynamic framework, using a model with a leader and a laggard. In this case, he finds that the optimal choices are pursuing safer (development) projects for leaders and pursuing riskier (research) projects for laggards. The model proposed by Kwon (2010) suggests that lower market power leads to riskier and longer-term projects (research).

innovation output, but the contribution of research is higher for process innovation, while the contribution of development is higher for new products, and especially for sales from new products. On an industry level, they also find that research shows a greater effect of sales from new products in low-tech sectors.

4.2. Complementarity in R&D activities

In its more general definition, complementarity between practices is understood to exist if the returns to adopting one practice are greater when the other practices are present. Literature on Empirical Industrial Organization has long been interested in the analysis of complementarity between practices or decisions. Researchers in the field of Economics of Innovation, and in particular those interested in R&D activities, are not indifferent to this tendency.

The objectives of this section are twofold. First, we summarize the main econometric approaches used for testing for complementarity. Second, we review the main contributions to the empirical literature on complementarity in R&D activities.

4.2.1. Empirical methods for testing complementarity

The formal study of complementarity relies on analyzing the interactions among pairs of decisions and it can be traced back to Topkis (1978). Topkis (1978) formulated the concept of complementarity within the mathematical theory of lattices, while Milgrom and Roberts (1990) and Vives (1990) first applied this approach to economics. For a recent review of the precise mathematical treatment of complementarity, interested readers are referred to Brynjolfsson and Milgrom (2013). These authors summarize the theory about decision problems with complementarities in ten theorems based on the results by Topkis (1978), Milgrom and Roberts (1995, 1996), Milgrom and Shannon (1994), and Milgrom et al. (1991).

This section is focused on the empirical analysis of complementarity. Literature has proposed two principal ways in which complementarities reveal themselves empirically. First, complementary practices are often more likely to be adopted jointly rather than separately (i.e., clustering of practices across firms). Second, complementary practices are often more productive when adopted together than when adopted separately. These two empirical predictions are the basis for the statistical methods used to assess the existence of complementarities (the review of these different approaches done by Athey and Stern (1998) remains a cornerstone of this literature).

There are two main approaches for testing the existence of complementarities. The first approach, the so-called adoption or correlation approach, consists of estimating correlations and demand equations. The second approach, the so-called productivity, production or performance approach, consists of estimating performance differences.

For simplicity in the exposition, in what follows, we consider a case with two potential complements, y_1 and y_2 . We will refer to the generalization to the case of more than two complements when necessary. Here, we closely follow the arguments and the notation used by Brynjolfsson and Milgrom (2013).

Adoption approach

This approach is based on the *revealed preference principle*: under the assumption of optimizing behavior of the firm, the joint adoption of practices is potentially informative about the joint returns generated by them. This approach has been popular among researchers because of its simplicity. It does not require data on the objective function, only availability of data on the practices themselves. In this regard, this approach is referred to as an “indirect” approach.

Two types of methodologies have been used to implement this approach. The first methodology relies on the idea that correlation between two practices can be interpreted as the first evidence of complementarities. This suggests a simple test for complementarities measuring the correlation coefficient κ_C . A large value of κ_C provides evidence in favor of the existence of complementarities.

The second methodology relies on measuring correlations among error terms of equations representing the demands of practices. The adoption of the respective practices is regressed conditionally on assumed exogenous control variables, given by Z (we drop firm subscript for simplicity):

$$y_1^* = \alpha_1 Z + \varepsilon_1, \quad y_1 = 1 \text{ if } y_1^* > 0 \text{ and } 0 \text{ otherwise,} \quad [4.1]$$

$$y_2^* = \alpha_2 Z + \varepsilon_2, \quad y_2 = 1 \text{ if } y_2^* > 0 \text{ and } 0 \text{ otherwise,} \quad [4.2]$$

The error terms ($\varepsilon_1, \varepsilon_2$) are assumed to be normally distributed with zero mean ($E[\varepsilon_1] = E[\varepsilon_2] = 0$), variances equal to one ($Var[\varepsilon_1] = Var[\varepsilon_2] = 1$), and the covariance equal to ρ ($Cov[y_1, y_2] = \rho$).

Equations [4.1] and [4.2] can be jointly estimated by using a bivariate probit approach. In this case, a statistically significant covariance coefficient between the error terms of the regressions would imply a complementary relationship.

The adoption approach can be implemented to test complementarity among three or more practices by using a multivariate framework (Arora and Gambardella, 1990; Schmiedeberg, 2008).

Productivity approach

This approach starts out with a performance equation (for example, a production function). In this case, testing for complementarities relies on regressing a measure of firm performance on interactions (i.e., combinations) of the potential complements. In practice, the implementation of this approach differs depending on whether we use dichotomous (discrete) practices or continuously measured practices.

For dichotomous practices the analysis of complementarity builds on the concept of supermodularity introduced by Topkis (1978). In this case, to test the complementarity hypothesis, we need to derive an inequality restriction as implied by the theory of supermodularity and test whether this restriction is accepted by the data. For a two-

dimensional function $f(y_1, y_2)$, where $y_1 = \{0,1\}$ and $y_2 = \{0,1\}$, practices y_1 and y_2 are (strictly) complementarity if:

$$f(1,1) - f(0,1) > f(1,0) - f(0,0) \quad [4.3]$$

Equation [4.3] means that the difference in the performance function, f , that arises from starting to implement one practice (for example, from changing y_1 from 0 to 1) is greater if the other practice is also implemented (for example, greater if $y_2 = 1$ than if $y_2 = 0$).

To implement this approach empirically, the performance function is typically estimated in a multivariate regression framework as a function of four mutually exclusive combinations of the practices of interest and other exogenous factors that may affect performance (we drop firm subscript for simplicity):

$$\begin{aligned} f(y_1, y_2, Z) = & \theta_{00}(1 - y_1)(1 - y_2) + \theta_{10}y_1(1 - y_2) + \theta_{01}(1 - y_1)y_2 \\ & + \theta_{11}y_1y_2 + \theta_Z Z + \varepsilon \end{aligned} \quad [4.4]$$

where Z is a vector of exogenous variables and $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. The test statistic for complementarity between y_1 and y_2 now corresponds to:

$$\kappa_p \equiv \theta_{11} - \theta_{01} - \theta_{10} + \theta_{00} \quad [4.5]$$

A value of κ_p significantly greater than zero indicates that we can reject the null hypothesis of no complementarity.

The productivity approach using dichotomous practices can be generalized to the case of three or more practices. However, no simple testing procedures are available since, in this case, testing for complementarity involves adopting a multiple inequality restrictions framework. Mohnen and Röller (2005) derive the set of inequality constraints that need to be satisfied for the case of four practices. These authors proceed by testing each pair of practices separately, which implies jointly testing four inequality constraints by using a distance or Wald test proposed by Kodde and Palm (1986). Leiponen (2005) and Belderbos et al. (2006) use a similar specification. Aral et al. (2012) and Tambe et al. (2012) use a graphical framework (the *Cube View*) to understand the complementarities among three practices, where each axis represents one of the practices and there are eight potential combinations of practices. These authors propose four tests for complementarities: three specific tests of pair-wise complementarities and a full test of three-way complementarities (the *System Test*). The *System Test* determines whether the gains from implementing the full system of practices are greater than the sum of gains from adopting any one of the three practices in isolation.

The productivity approach can also be implemented when practices y_1 and y_2 are measured as continuous variables. Complementarity between two continuous variables means that the incremental effect of one variable on the performance function increases conditionally on increasing the other variable. In this case, the test for complementarity relies on using a cross-term specification of the performance function. Now the performance function is estimated in a multivariate regression framework as a function of the continuous versions of the practices of interest along with an interaction term between these practices and other exogenous factors (we drop firm subscript for simplicity):

$$f(y_1, y_2, Z) = \alpha_1 y_1 + \alpha_2 y_2 + \alpha_{12} y_1 y_2 + \alpha_z Z + \varepsilon \quad [4.6]$$

where Z is a vector of exogenous variables and $\varepsilon \sim N(0, \sigma_\varepsilon^2)$. The cross-derivative $\frac{\partial^2 f}{\partial y_1 \partial y_2}$ is equal to α_{12} . This implies that there is evidence for complementarity between practices y_1 and y_2 if α_{12} is significantly greater than zero.

Again, this approach can be generalized to the case of three or more practices measured as continuous variables. As in the case of dichotomous practices, difficulties arise from the need to test multiple inequality restrictions. The first studies are focused on estimating all pair-wise interaction effects in one equation (see, for example, Caroli and Van Reenen, 2001), but do not consider the effect of additional cross-terms (for example, a three-way term in the case of three practices). Recent empirical studies deal with this issue. Aral et al. (2012) and Tambe et al. (2012) are also concerned with complementarities between three practices measured as continuous variables. These authors point out that a positive coefficient of the three-way term is not sufficient for complementarity. In this case, to establish the conditions for complementarity, it is necessary to evaluate the terms and cross-terms over the sample range for each practice. Carree et al. (2011) introduce an alternative test for complementarity in the general case of n practices. These authors focus on explaining for three and four practices, and claim that their procedure is also applicable to the case of dichotomous practices. Carree et al. (2011) propose a separate induced test for complementarity. In this case, the separate induced procedure accepts the null hypothesis of complementarity (which is a combined hypothesis) if and only if the separate hypotheses are all accepted. These authors derive the separate hypotheses to be held in the context of a linear regression (the number of separate hypotheses depends on the number of practices, n).

Unobserved Heterogeneity

Up to this point, we have omitted the discussion of the problems created by unobserved heterogeneity. Firms' practices are typically endogenous decisions, and it is precisely (unobserved) firm heterogeneity in the determinants of firms' practices that is one of the main problems in identifying complementarities. The existence of firms' unobserved heterogeneity can bias the tests for complementarities based on both the adoption and productivity approaches we described above. For example, a positive correlation between two practices or residuals cannot serve as a definite test for complementarity, as it might be the result of unobserved heterogeneity. Athey and Stern (1998) carefully discuss the problem of unobserved heterogeneity in the context of cross-section data, while Brynjolfsson and Milgrom (2013) present a recent review of the principal approaches to mitigating the effects of unobserved heterogeneity.

Athey and Stern (1998) propose using a system of equations approach, estimating the demand and the performance equations simultaneously. Kretschmer et al. (2012) is the first example that implements this approach. These authors adopt the setup of Miravete and Pernías (2006) to distinguish the complementarity and correlation caused by unobserved heterogeneity. However, integrating the adoption approach and the productivity approach in a single estimation procedure is challenging. In the context of cross-section data, a two-step regression can also be estimated by using instrumental variables (Brynjolfsson and Milgrom, 2013).

Moreover, if panel data are available, we can look to panel data techniques for tools to control for unobserved heterogeneity. For example, if we assume that unobserved heterogeneity does not change over time, we can control for it by including fixed effects or taking first differences (Brynjolfsson and Milgrom, 2013). Panel data also allow us to control for the simultaneity in the choices of output and inputs (Leiponen, 2005).

As pointed out by Brynjolfsson and Milgrom (2013), there are alternative approaches for mitigating the effects of unobserved heterogeneity which are not based on econometric techniques. A leading example is the use of homogeneous populations. The idea behind this approach is to eliminate as much unobserved heterogeneity as possible by identifying a narrow performance function that can be modelled empirically. In practice, this approach is typically implemented by limiting the analysis to firms in a narrow industry. The rationale is that firms in the same industry are expected to be similar in terms of the performance function. The obvious drawback of this approach is that the results may not be generalizable to other contexts.

To sum up, the study of complementarity is challenging. There are two main approaches for testing the existence of complementarities, although in practice, both tests are often useful. Moreover, unobserved heterogeneity can seriously affect both tests. One empirical strategy followed in some studies is to use both approaches to present as much evidence consistent with the complementarity hypothesis as possible (Bresnahan et al., 2002; Cassiman and Veugelers, 2006; Ichniowski et al., 1997). This evidence, considered as a whole, may strongly suggest the existence of such complementarity.

4.2.2. Empirical studies of complementarity in R&D activities

In what follows, we present examples of empirical studies focused on identifying complementarity relationships in R&D activities. This revision does not aim to be comprehensive, and we restrict our attention to those studies which we think are the most relevant to understanding the scope of this literature. Moreover, we are interested in the evidence based on the approaches we described above.

Before starting, it is important to notice that we focus on complementarity between practices when at least one of these practices is related to R&D. Inevitably, our review is limited, since complementarity has been empirically explored in many fields related to industrial organization, economics of innovation and strategy literature. Brynjolfsson and Milgrom (2013) and Ennen and Richter (2010) present comprehensive reviews of this broad literature. For example, empirical studies of complementarity include the relationship between new organizational practices and the use of ICTs (see Brynjolfsson and Hitt, 2000, for a review of this literature), human resource management practices (see, for example, Ichniowski et al., 1997, and Ichniowski and Shaw, 2003, for a review of this literature), different types of innovations (Ballot et al., 2015; Martínez-Ros and Labeaga, 2009; Miravete and Pernías, 2006), and obstacles to innovation (Galia and Legros, 2004; Mohnen and Röller, 2005; Mohnen and Rosa, 2002).

Researchers in the R&D literature have focused mainly on the analysis of complementarity between internal R&D and different types of external technology sourcing. Other examples of

studies of complementarity in R&D activities are the relationship between partners in R&D cooperation, R&D cooperation and other practices, R&D and ICT investments, domestic and foreign R&D, R&D and human capital, and components of R&D.

Complementarity between internal R&D and external technology sourcing

The view of in-house R&D as a major factor in explaining technological innovation and productivity growth is widespread. However, firms typically combine this internal activity with external sources, including, among others, R&D contracting, R&D licensing, and hiring away personnel. As we explained before, the joint adoption of such internal and external activities suggests that these activities are complementary, and most of the empirical evidence supports this result. Literature has proposed a number of reasons for complementarity between internal R&D and external technology sources. These factors are related mainly to the concepts of absorptive capacity and economies of scope (see Schmiedeberg, 2008, for a detailed discussion).

One of the more detailed analyses of complementarity between internal R&D and external technology sources comes from Cassiman and Veugelers (2006). They examine 269 Belgian firms from the Community Innovation Survey (CIS)³⁸ conducted in 1993 and characterize the firm's innovation practices (internal R&D and external technology acquisition) using dichotomous variables. From a methodological point of view, Cassiman and Veugelers (2006) present evidence using both the adoption and the productivity approaches. The performance measure they use is the percentage of sales due to new or substantially improved products. Moreover, they propose a two-step procedure for correcting for unobserved heterogeneity. In the first step (i.e., the adoption approach), the predicted values of the innovation practices are calculated. In the second step (i.e., the productivity approach), the predicted values of the first step regressions are used as instruments. However, they are aware of the difficulty of finding perfectly exogenous instruments. Their two main conclusions are that (i) their results are consistent with the existence of complementarity between firms' internal R&D and external technology acquisition, and (ii) the degree of complementarity is context specific and depends on the use of "basic" R&D.

Schmiedeberg (2008) runs a similar analysis using German CIS data. However, there are two main differences with Cassiman and Veugelers (2006). First, this author does not use a two-step procedure combining the adoption and the productivity approaches. Second, this author tests for complementarity between internal R&D and externally contracted R&D, but also between internal R&D and R&D cooperation. The results of this study are twofold: (i) there is evidence of complementarity between internal R&D and R&D cooperation, but (ii) the evidence for complementarity between internal R&D and externally contracted R&D is rather weak.

Lokshin et al. (2008) is a representative application of the productivity approach using continuous variables. Using a panel of Dutch manufacturing firms, the authors test for complementarity between internal and external R&D in determining labor productivity. Panel

³⁸ CIS data are widely used in the empirical literature (see Mairesse and Mohnen, 2010, for a review). This is also the data source used in many of the studies we review in this section.

data estimation techniques allow them to control for unobserved heterogeneity and potential endogeneities. As its main result, this paper finds evidence of complementarity between internal and external R&D, but only when allowing for diseconomies of scale in internal and external R&D. In this case, the positive impact of external R&D is conditional upon a sufficient level of internal R&D. More recently, Hagedoorn and Wang (2012) find similar results in their study of pharmaceutical firms. They find evidence of complementarity (substitutability) between internal and external R&D if the level of internal R&D investment is high (low).

In a recent study, and going beyond the existence of complementarity, Ceccagnoli et al. (2014) focus on the conditions under which internal R&D and external technology sources are complements (i.e., the study of “complementarity drivers”). As pointed out by these authors, there is little research evidence on this issue (Cassiman and Veugelers, 2006, is one exception). Similar to Lokshin et al. (2008), Ceccagnoli et al. (2014) apply panel data estimation techniques to a panel of 94 pharmaceutical firms to study whether internal R&D investments and in-licensing expenditures are complementary in determining the firm’s product pipeline. Using the whole sample of firms, they find that internal R&D and in-licensing expenditures are neither complements nor substitutes. However, and more interestingly, this result does not hold when analyzing the impact of three potential drivers of complementarity: (i) absorptive capacity, (ii) economies of scope, and (iii) licensing experience. The idea is to separately analyze subsamples of firms with low and high levels of the examined drivers. Doing this, they find a complementary relationship between internal R&D and in-licensing for firms that have a larger value (to 25%) of two of the drivers (economies of scope and licensing experience).

The literature we have reviewed so far uses data from developed countries. However, a number of empirical studies have also analyzed the complementarity between internal R&D and external technology sourcing in developing countries (see Hou and Mohnen, 2013, for a review of this literature). As a leading example of this literature, Hu et al. (2005) analyze the complementarity among three continuous variables (internal R&D and expenditures on disembodied technology from foreign and domestic providers) in determining firm productivity. One limitation of this study is that it estimates three pair-wise interaction effects in one equation (a production function), but does not consider the effect of a three-way term. Using a panel of approximately 10,000 Chinese firms, these authors find evidence of complementary relationships between internal R&D and both the domestic and foreign technology transfer variables.

Other topics in the literature of R&D complementarity

The determinants and the effects of R&D cooperation with different partners have been widely investigated. However, little evidence exists on the complementarity effect between R&D cooperation with different partners. Using Dutch CIS data, Belderbos et al. (2006) are the first in exploring the complementarity effects of four types of R&D cooperation on labour productivity³⁹. This is an example of the application of the productivity approach using dichotomous variables (in this case, four dummies for R&D cooperation with competitors,

³⁹ Veugelers and Cassiman (2005) analyze the relationship between R&D cooperation between firms (customers and/or suppliers) and universities. However, as they pointed out, they do not test for complementarity as such. In terms of the empirical approaches reviewed above, they only present pair-wise correlations between R&D cooperation with firms and R&D cooperation with universities.

customers, suppliers, and universities and research institutes). Their empirical results on complementarities are mixed. On the one hand, they find evidence of complementarity between R&D cooperation with competitors and with customers, and between R&D cooperation with customers and with universities and research institutes. On the other hand, they find evidence, especially for small firms, of substitutability between three pairs of practices (supplier cooperation combined with either competitor or university and research institute cooperation, and competitor cooperation combined with university and research institute cooperation).

A number of studies have also analyzed R&D cooperation, but in terms of its potential complementarity with other practices (in this line, we have already cited the paper by Schmiedeberg, 2008). Using Finnish CIS data, Leiponen (2005) finds a significant complementarity effect between R&D cooperation and technical skills (measured by educational levels and fields of employees) in determining a firm's profits. More recently, Harhoff et al. (2014) analyze technology sourcing activities of German firms in the United States. They find a complementarity effect between R&D cooperation with suppliers located in Germany (United States) and the R&D stock in Germany (United States) at the industry level (R&D stocks are used as a proxy for the local knowledge pools). Finally, Arvanitis et al. (2015) use Swiss and Dutch CIS data to analyze the complementarity between external R&D and R&D cooperation in the presence of internal R&D. These authors find little evidence supporting this hypothesis.

Other examples of studies of complementarity in R&D activities are the relationship between R&D and ICT investments (Hall et al., 2013), domestic and foreign R&D (Belderbos et al., 2015), R&D and human capital (Ballot et al., 2001), and components of R&D (Barge-Gil and López, 2013).

5. Conclusions

The objective of this chapter has been to provide a general view of three of the main topics in current empirical literature about firms' R&D: the determinants of R&D investments, the link between R&D, innovation and productivity, and the studies trying to open up and examine the contents of the black box of R&D. Regarding research questions, our selection of subjects indicates that classical topics such as the role of size and market power in determining R&D or the effect of R&D on productivity still receive considerable attention. However, nowadays there is a tendency to focus on other issues: the role played by public funding as an R&D determinant, the channels (for example, new products and processes) through which R&D influences productivity, the importance of R&D composition and the complementarities of internal R&D with other activities, such as external R&D, cooperation, ICT investments or human capital. Other topics that fall beyond the scope of the present chapter are also receiving increasing attention: the relationship between R&D and employment, the causes and effects of international R&D sourcing or, in association with the recent economic crisis, the response of R&D investment to economic cycles.

Our review also points out that there is a tendency towards a higher use of structural theoretical models to support empirical analysis. These models have made it possible: i) to

distinguish between the determinants of R&D extensive margin (the decision to undertake R&D activities) and those of R&D intensive margin (the magnitude or intensity of R&D expenditures); ii) to reveal the problems of uncertainty and incomplete information that are usually present in R&D markets; iii) to link additionality effects of public support of private R&D (when they exist) with social welfare; iv) to take into account the persistence and the dynamic nature of R&D decisions and their effects (as long as there is a time lag between R&D investment and output, R&D is unlikely to have a one-time impact and the gains in profits derived from R&D are surrounded by uncertainty); v) to quantify the effect of changes in the firm's environment on its decision to invest in R&D and long-run profitability.

An important question remains open: Where should empirical research on business R&D go now? There are at least two related areas in which this research may be extended: methodology and data availability. Regarding the first, although there has been significant progress in the use of structural modeling, this is still an emerging line of work. A second methodological issue concerns the exploitation and design of controlled field experiments. The experimental approach may complement what we learn from more sophisticated modeling. On the data side, one interesting opportunity is the use of longer panels that would allow for a more appropriate analysis of the relationship between R&D and the dynamics of entry and exiting of firms, and also of the persistence in firms' behavior differences. The availability of more quantitative data would also improve qualitative analyses that are frequently conditioned by the categorical character of innovation outputs in public databases.

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