Journal of Economic Behavior and Organization 194 (2022) 1–23

Contents lists available at ScienceDirect

Journal of Economic Behavior and Organization

journal homepage: www.elsevier.com/locate/jebo

Division of labor in R&D? Firm size and specialization in corporate research

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ARTICLE INFO

Article history:
Received 15 July 2020
Revised 12 October 2021
Accepted 5 December 2021

JEL classification:
L11
014
031
032

Keywords:
Corporate research
R&D
Firm size
Specialization
Comparative advantage
Productivity

ABSTRACT

Corporate research and development constitutes one of the main sources of innovation. Recent research, however, discusses a decline in corporate research and its implications for technological progress. The contribution of this study is to model research & development (R&D) decisions in an R&D investment model that allows the analysis of firms' engagement in research (R) as compared to development (D) activities. The model predicts higher investments in both activities for larger firms, but it also shows that research intensity, i.e. the R-share in R&D, declines with firm size. We test these propositions using data of R&D-active firms over the period from 2000 to 2015. While larger firms invest indeed more in both research and development, results from panel model estimations that account for unobserved heterogeneity across firms show that the relative focus on research decreases with firm size. In addition, the empirical results suggest that, since the returns to research in terms of productivity gains decline with firm size, specialization maximizes overall returns to R and D.

1. Introduction

Investments in corporate R&D are important for economic development since R&D intensity has been shown to be a driver of productivity growth (Griliches, 1987; Romer, 1990; Doraszelski and Jaumandreu, 2013). Policy makers and economists are therefore interested in firms' incentives to invest in R&D in order to design regulations and conditions that promote such activities. However, recent studies document a decline in corporate research measured by the number of scientific articles published by companies (Arora et al., 2017; 2018; Bloom et al., 2020). This may be a cause for concern since basic research activities, in particular, have been shown to drive firm-level productivity (Griliches, 1980; Mansfield, 1980; Czarnitzki and Thorwarth, 2012). At the same time, research-intensive and science-based industries such as artificial intelligence, biotechnology, nanotechnology, and renewable energy emerged. This trend is also reflected in data from the Organisation for Economic Co-operation and Development (OECD), reporting the growth of research expenditures relative

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https://doi.org/10.1016/j.jebo.2021.12.006

to development expenditures over the past 30 years. While development expenditures have doubled from 1985 to 2015, research expenditures have almost tripled in real terms (see Appendix Fig. A.1).

These two trends may seem paradoxical at first sight. However, earlier studies on corporate research tended to focus on large firms, thereby overlooking the contribution of small firms to overall research activities. Traditionally, it has been argued that larger firms possess an absolute advantage over smaller firms in terms of R&D due to economies of scale and scope, market reach, and access to financial resources (Schumpeter, 1942; Teece, 2010; Czarnitzki and Hottenrott, 2011a). It is essential to stress that while R&D is often seen as one activity, it consists of two distinct components: research and development (OECD, 2015). As illustrated in earlier research, both activities respond to different drivers, pursue different goals and result in different outcomes (Czarnitzki et al., 2009; 2011; Barge-Gil and López, 2015; Hottenrott et al., 2017). Research typically involves analyzing fundamental principles and phenomena, and it often aims at generating new ideas and testing hypotheses without a specific application in mind (Martinez-Senra et al., 2015). Development activities encompass the application of knowledge, usually start from an existing 'proof of concept' and aim at improving specific products, processes or services (OECD, 2015). This implies that when cost-spreading and complementary assets are important, larger firms may have higher incentives and better preconditions for conducting both, research as well as product or process development activities (Cohen and Klepper, 1996a; Rothaermel and Hill, 2005). Moreover, firm size comes with advantages in appropriating the returns to R&D because larger firms may possess greater abilities to find commercial applications for research outcomes and may benefit from internalizing spillovers between multiple products or R&D projects (Henderson and Cockburn, 1996; Belenzon and Patacconi, 2014). On the other hand, prior research documents innovation advantages for small firms in emerging, research-intensive sectors (Acs and Audretsch, 1987) which indicates that they may have an comparative advantage in research-intensive activities.

Drawing from the concept of comparative advantages, Baumol (2002) refers to a 'David-Goliath symbiosis' in which smaller firms provide breakthrough discoveries and heterodox ideas, whereas larger firms create value from developing those innovations further and thereby contribute to their usefulness. In this symbiosis, 'Markets for Ideas' (Gans et al., 2002; Gans and Stern, 2003) and 'Markets for Technology' (Arora et al., 2001; Arora and Gambardella, 2010) enable smaller firms to sell research outcomes to other (larger) companies rather than developing the final goods themselves. Thus, the related but yet distinct properties of R versus D suggest that firms may have comparative advantages in one or the other activity, with firm size being a factor determining the relative returns to each activity. While the absolute advantage of larger firms may result in higher expenditures for R and D than in smaller firms, smaller firms may have a higher research share in their total R&D. Larger firms may gain more per unit of investment if they devote it to D instead of R. If the returns to product development positively depend on a firm's size measured in its existing customer base (or simply sales), larger firms' relative returns to D may outweigh those to R, resulting in lower research intensities of larger firms.

Building on these considerations, this study addresses the question whether the incentives to invest in R versus D depend on firm size and whether the returns to each activity vary with firm size. A comparative advantage of larger corporations in development could explain their decreasing engagement in research, resulting in a division of labor in R&D between smaller and larger firms. This study's contribution to the analysis of corporate R&D is to theoretically illustrate firms' research and development spending decisions in an R&D investment model and to show analytically firms' relative engagement in R versus D activities, with each activity contributing differently to productivity. The model accounts for the relative returns to R and D as well as for the interdependence of both activities.

The model predicts higher R&D investments of larger firms but demonstrates that development becomes relatively more (and research relatively less) profitable the larger the firm is, resulting in lower optimal research intensities (R-share of R&D) in larger firms. We test this proposition using firm-level data of R&D-active firms which range from very small firms to large corporations observed during the period 2000–2015. Unlike previous research, our analysis does not need to rely on scientific publications as a proxy of research intensity. The detailed data allow us to distinguish between firms' research and development expenditures and to account for other firm-level characteristics driving R&D decisions. Results from panel model estimations show that the relative focus on research declines with firm size. In addition, the results reveal that specialization is explained by the returns to each activity in terms of total factor productivity (TFP) with the returns to R declining (and the returns to D increasing) with firm size. In other words, focusing on product and process development pays a greater productivity premium to larger firms compared to research. These results have implications for the discussion on the role of corporate research in knowledge-based economies.

2. Corporate research and development

R&D comprises two related but yet distinct activities: research and product & process development (OECD, 2015). While these activities are typically considered jointly, each has different drivers and pursues different goals. Consequently, it seems important to distinguish between the R and D component of R&D when investigating firms' innovation efforts (Czarnitzki et al., 2009; 2011; Barge-Gil and López, 2015). Research is concerned with exploring fundamental principles and phenomena often driven by curiosity (Martinez-Senra et al., 2015). It aims at generating and pioneering revolutionary ideas and concepts, formulates and tests hypotheses, theories or laws, and ultimately broadens the knowledge base (OECD, 2015). It is important to stress that research is often carried out without a specific application or use in mind. The lack of a predefined goal has an upside as well as a drawback. As a positive aspect, conducting research without targeting a specific application or use supports the application of possible findings to a spectrum of different fields, which the researcher potentially did not take into account (Levy, 2011). However, the lack of a clear target also raises the risk of not generating any commercially viable outcome (Rosenberg, 1989; Pavitt, 1991).

Firms also conduct research activities for building absorptive capacity in order to make better use of external knowledge (Cohen and Levinthal, 1989; 1990; Gambardella, 1992). Research may also serve in enhancing a firm's reputation helping to attract customers and investors as well as pleasing regulators (Hicks, 1995; Belenzon and Patacconi, 2014). In addition, firms may have incentives to invest in (basic) research which can be published in scientific journals in order to signal high-skilled scientists and inventors their science-promoting working conditions (Audretsch and Stephan, 1996; Stern, 2004). In contrast, development activities encompass the application of established knowledge, e.g. gained through basic and applied research (OECD, 2015). It often directly aims at improving existing products or at creating new products and services based on the knowledge derived from research. The linear innovation model (Rosenberg, 1989) as well as the chain-linked model (Kline and Rosenberg, 2009) acknowledge that R and D are interdependent activities with both contributing to innovation outcomes (Griliches, 1985; David et al., 1992; Fleming and Sorenson, 2004).

While this argues in favor of any firm to perform at least some R and some D, there are important aspects affecting the role of research in smaller versus larger firms. Prior research has largely focused on the question whether smaller or larger firms are more likely to produce innovative output rather than differentiating between the returns to research versus development spending and how these returns depend on firm size (Henderson, 1990; Henderson and Cockburn, 1996; Macher and Boerner, 2006; Arora et al., 2009).

An exception is the study by Belenzon and Patacconi (2014). They investigate to which extent large and small firms differ in their ability to benefit from different types of research. They distinguish between basic and applied research with the outputs of basic research being scientific publications versus applied research resulting in patents. They find that large firms profit more from publishing, whereas smaller firms appear to benefit more from patenting. However, they also argue that publications seem to complement large firms' marketing and sales efforts which is less relevant for smaller firms due to their smaller customer base or market share. While not including development activities into their analysis and by using (output) proxies for research rather than expenditures, this study hints at varying returns to research activities depending on firm size. The higher returns to patenting for smaller firms may reflect the important role of research in these firms and point to an underlying mechanism similar to the one suggested by Baumol (2002). The same reasoning also suggests that engaging in the activity for which a firm can exploit a higher relative return increases the overall returns to innovation efforts. For these reasons, studying firms' relative engagement in R and D seems therefore crucial for understanding the division of labor by firms of different sizes in the innovation process.

2.1. Firm size and heterogeneity of R&D

In line with the preceding arguments, when studying incentives for R&D as well as the returns to such activities, it is important to take the relative returns to one or the other individual component – R and D – into account. It seems furthermore important to consider firms in their competitive environment as their incentives to invest in one or the other activity also depends on the corresponding investments of other firms in the market.

Smaller firms may then possess a comparative advantage in doing research as compared to product development, since the latter is often capital-intensive and requires substantial investments for which smaller firms may not be able to reap the benefits of economies of scale (Arrow, 1993; Baumol, 2002). These properties may result in a relatively stronger orientation of larger firms towards development, despite holding an absolute advantage in both. Whereas smaller firms may be overall more constrained in their ability to invest in R&D due to its riskiness and due to fewer assets that can serve as collateral for debt (Czarnitzki and Hottenrott, 2011a; 2011b), they could still obtain higher relative returns to research than to development. Baumol (2002) argues that the routinization of innovation processes in larger firms is particularly beneficial for improvements of existing inventions rather than for creating heterodox breakthrough innovation. The routinized R&D processes in larger firms are therefore (better) designed for development rather than for green-field research activities. Thus, it is the *relative* return of development that is higher for larger firms and lower for smaller ones.

Making a similar point in a study on publicly traded US-based firms during the 1970–1989 period, Dhawan (2001) argues that the higher efficiency of smaller firms results from their leaner organizational structure which allows them to exploit opportunities in new markets. Being less entrenched in existing technology, smaller firms can engage in more fundamental R&D, although this is achieved at the cost of increasing these firms' riskiness. Larger firms, on the other hand, may outsource or spin-off research activities to other (smaller) firms or entities. By the organizational separation of knowledge creation from product development, firms free capacities to specialize in the activity which is relatively most profitable to them, which Arora et al. (2001) coined 'division of innovative labor'. This organizational detachment can also occur within the same enterprise group, leading to the vertical disintegration of R and D, with research activities being delegated to smaller entities (Williamson, 1971; Monteverde, 1995).

In some industries, such as biotechnology, a division of labor in R and D has long been present (Danzon et al., 2005; Arora et al., 2009). Small research-intensive firms carry out much of the work related to exploring new active substances needed for drug development. Developing novel drugs is however extremely resource-intensive. Clinical trials are costly and may eventually fail, requiring even higher investments. While drug-related research is likewise costly and risky, the relative returns for smaller firms when focusing on this activity (and leaving drug development to larger pharmaceutical firms) is relatively higher compared to development.

Larger firms with the necessary infrastructure may find it more profitable to focus on development benefiting from routinization and economies of scale in production and sales. The drug development process is an example of a very pronounced labor division in R and D, where the transmission of research through collaboration and the market for technology appears to be well-functioning. However, these patterns are not exclusive to this industry as similar observations can be made in software development and (digital) product commercialization (Lee and Berente, 2012).

In the context of innovative output rather than return to investments in terms of productivity, previous studies already documented comparative innovation advantages for small firms in research-intensive industries (Acs and Audretsch, 1987; Henderson, 1990; Henderson and Cockburn, 1996; Macher and Boerner, 2006; Arora et al., 2009; Belenzon and Patacconi, 2014). Moreover, firm asymmetry in size has been shown to explain differences in patent output, with smaller firms being more productive per US dollar spent (Cohen and Klepper, 1996b). This may be explained by research rather than development activities contributing to relatively higher patenting numbers (Czarnitzki et al., 2009).

With respect to specialization, earlier studies typically analyzed the relationship between firm size and product or process innovation, observing that larger firms find it relatively more profitable to invest in process improvements rather than in new products (Cohen and Klepper, 1996a; 1996b; Yin and Zuscovitch, 1998; Plehn-Dujowich, 2009). With regard to the innovation degree, larger firms innovate more incrementally compared to smaller firms (Corsino et al., 2011). This previous research does, however, not provide an analysis of specialization in R or D and the theoretical arguments may not be directly transferable from the product versus process innovation framework. If research and development activities differ in determination, scaling and effects, the relative intensity of both (the respective expenditure component over total R&D expenditures) can be seen as a function of firm properties of which many vary with firm size (Barge-Gil and López, 2015). The purpose of the following section is therefore to derive insights from an R&D investment model that incorporates both research and development explicitly as strategic firm decisions.

3. An R and D investment model

3.1. Model set up

Assume the production function for firm i is of the standard form

$$q_i = \omega_i K_i^{\alpha_i} L_i^{\beta_i} R_i^{\gamma_i} D_i^{\delta_i} \tag{1}$$

where q_i denotes the output of firm i, K_i represents the firm's assets, L_i is the number of employees in non-R&D tasks, R_i is the research expenditure, D_i is the development expenditure, and ω_i denotes the Total Factor Productivity (TFP). The parameters α_i, β_i, γ_i, δ_i are the output elasticities of capital, non-R&D labor, research expenditure, and development expenditure, respectively. Marginal products of research and development expenditures are $\gamma_i q_i/R_i$ and $\delta_i q_i/D_i$, respectively. Suppose, the profit of firm i from the product market is given by

$$\pi_i = p(q_i)q_i - c_i(q_i)$$

where $p = a - bq_i$ denotes the inverse market demand and $c_i(q_i) = c_{i0} + c_{i1}q_i + c_{i2}q_i^2$ is the firm's quadratic cost function.[1]

The profit accruing exclusively from the existing product market is rewritten as

$$\pi_i = (a - bq_i - c_{i1} - c_{i2}q_i)q_i - c_{i0} = (a - c_{i1})q_i - (b + c_{i2})q_i^2 - c_{i0} \tag{2}$$

$$= (A_i - B_i q_i)q_i - c_{i0}, \quad \text{where} \quad A_i = a - c_{i1}, B_i = b + c_{i2}. \tag{3}$$

Put simply, A_i and B_i are the coefficients of the linear and quadratic components in the profit function. Furthermore, in line with the assumption of increasing but diminishing returns to R&D expenditure from the literature on product and process innovation (Cohen and Klepper, 1996b; Yin and Zuscovitch, 1998; Fritsch and Meschede, 2001; Plehn-Dujowich, 2009), we assume that $A_i = f(D_i)$ with $f'(D_i) > 0$ and $f''(D_i) < 0$. That is, the per-unit price-cost margin itself can be increased by investing more in development. Development may, for instance, improve product quality or reduce cost of production, both resulting in a higher price-cost margin (Dorfman and Steiner, 1954; Grabowski, 1970). We define quality improvement in the sense of "any alteration in quality which shifts the demand curve to the right over the relevant range" (Dorfman and Steiner, 1954, p.831). This definition is based on Grabowski (1970, p.218) who notes "... firms in oligopolistic market structures prefer to compete by demand-shifting strategies like new product development, advertising, and the like, rather than trying to influence demand directly by price". Alternatively and equivalently, one could assume that B_i is a decreasing function of development expenditure. In graphical terms, this would imply a flattening of the demand curve with higher development activity, enabling the firm to charge a higher price for every unit sold, or the costs becoming less convex. Assuming either A_i or B_i to be a function of D_i serve similar purposes with regards to the scope of this model. We proceed with the first one for the sake of analytical simplicity and further assume that $f(D_i) = D_i^{\theta_D}$, where $\theta_D \in (0, 1)$ is the elasticity of the price-cost margin with respect to the development expenditure, and $f'(D_i) > 0$, $f''(D_i) < 0$.

[1] A quadratic cost function is assumed for the sake of higher generalizabiliy but is not necessary for the model.

Additionally, we assume that research activity undertaken by the firm can potentially open up a new product market, for instance by winning a patent race and licensing the technology, or through selling in the product market directly. That is, carrying out research has a benefit on two levels. On one hand, it enhances firm's output level as is apparent from the production function in Eq. (1). On the other hand, research activities can contribute to a firm's revenue independently of the firm's existing production activities. Such additional gains provide incentives to increase research expenditures (Byrski et al., 2021). Using a simple functional construct similar to the innovation production function in Cassiman et al. (2002) or Plehn-Dujowich (2009), we define the additional net gains from research as $f(R_i) = \mu_i R_i^{\theta_R}$, where $\theta_R \in (0, 1)$ is the elasticity of the additional net gains with respect to research expenditure. These additional gains are also increasing at a diminishing rate.

Considering that research can be uncertain with regard to success, the above function can alternatively be interpreted as the expected net return from a Bernoulli process. If success in research is a binomially distributed random variable, $\tilde{\mu}$ is the estimated average probability of success in a single project, and $R_i^{\theta_R}$ is the number of projects that can be carried out from R_i, the amount of research expenditure, then expected success from research will be given by $\tilde{\mu} R_i^{\theta_R}$. If net gains upon success in research are denoted by M_i, then $\mu_i R_i^{\theta_R}$, where $\mu_i = \tilde{\mu} M_i$, will represent the expected net gains from research alongside the gains from the product market. Such net gains may include patent earnings in the form of licensing fees or returns from selling know-how. It is crucial to point out that these gains are parallel to the firm's primary product market. Even though the returns from research and development may not be precisely separable in practice, this is the primary distinction that we draw between research and development: Research is a more exploratory process and can generate parallel gains when successful, whereas development activities are more goal-oriented and focused at improving the prevailing price-cost margin. Development activities, especially in certain industries such as pharmaceuticals, expand the market significantly, whereas market size does not affect research effort (Byrski et al., 2021).

It is important to note that unlike Cohen and Klepper (1996b), Fritsch and Meschede (2001), Plehn-Dujowich (2009), we do not simply subtract the expenditures on research and development from the firm's revenue. As development expenditure is assumed to be tied to production, the cost of development is entirely accounted for through $c_i(q_i)$. The cost of research can have components which depend on the level of output and components which are independent of the output level. The former is included in $c_i(q_i)$. To take the latter into account, $\mu_i R_i^{\theta_R}$ is defined as the expected *net* gains from research upon success.

The firm's expected profit from both R and D activities can then be written as

$$\pi_i^e = (D_i^{\theta_D} - B_i q_i) q_i + \mu_i R_i^{\theta_R} - c_{i0}. \tag{4}$$

Firm i's profit thereby depends on both R_i and, and the firm maximizes this expected profit by deciding on research and development expenditures. We assume θ_D and θ_R to be similar across firms within an industry.

3.2. Analysis of R and D choices

To focus on the relationship between firm size and the emphasis on research vis-à-vis development activity, we assume that firms choose their research and development expenditures while holding the other factor inputs constant. Costs for any additional employee employed in research and development tasks and investments in R&D-related equipment are captured through the R&D expenditures. Adjustments in non-R&D labor and non-R&D capital inputs may eventually be needed in the production technology. However, those are not assumed to be instantaneous changes and, therefore, ignored in our static analysis. We are interested in firms' decision regarding research and development expenditures at a given point in time. The non-R&D labor and non-R&D capital stock at that particular point in time are treated as parameters indicating the firm size. This approach helps with distinctly focusing on the contribution of R&D activities to the firm's profit maximization, independently of other factor choices.

Maximizing the expected profit function with respect to R_i and D_i require

$$\frac{\partial \pi_i^e}{\partial R_i} = D_i^{\theta_D} \frac{\gamma_i q_i}{R_i} - 2B_i \frac{\gamma_i q_i^2}{R_i} + \mu_i \theta_R R_i^{\theta_R - 1} \tag{5}$$

$$\text{and} \quad \frac{\partial \pi_i^e}{\partial D_i} = (\theta_D + \delta_i) D_i^{\theta_D - 1} q_i - 2B_i \frac{\delta_i q_i^2}{D_i}. \tag{6}$$

The first order conditions for profit maximization are obtained by setting these first derivatives equal to zero.

Setting (5) equal to zero, we obtain

$$\mu_i \theta_R R_i^{\theta_R} = \gamma_i q_i (2B_i q_i - D_i^{\theta_D}). \tag{7}$$

Setting (6) equal to zero, we obtain

$$q_i = \frac{\delta_i + \theta_D}{2B_i \delta_i} D_i^{\theta_D}. \tag{8}$$

Plugging the expression for q_i from Eq. (8) into Eq. (7) and simplifying, we obtain

$$R_i^{\theta_R} = g_i D_i^{2\theta_D}, \quad \text{where} \quad g_i = \frac{\gamma_i \theta_D (\delta_i + \theta_D)}{2B_i \mu_i \delta_i^2 \theta_R}. \tag{9}$$

Further, plugging in the production function from Eq. (1) into Eq. (8), we can write

$$D_i = h_i^{\frac{1}{\theta_D-\delta_i}} R_i^{\frac{\gamma_i}{\theta_D-\delta_i}}, \quad \text{where} \quad h_i = \left(\frac{2B_i\delta_i\omega_i}{\delta_i+\theta_D} K_i^{\alpha_i} L_i^{\beta_i}\right). \tag{10}$$

Note that both g_i and h_i are arbitrary parametric constructs used for the exclusive purpose of representational simplification. Incorporating Eq. (10) into Eq. (9) and simplifying we get the following:

$$R_i = g_i^{\frac{\delta_i-\theta_D}{\theta_R(\delta_i-\theta_D)+2\gamma_i\theta_D}} h_i^{\frac{-2\theta_D}{\theta_R(\delta_i-\theta_D)+2\gamma_i\theta_D}}. \tag{11}$$

The second order conditions for profit maximization requires $\delta_i - \theta_D > 0$. Note that, a lower μ_i implies a higher g_i and therefore a higher R_i. That is, ceteris paribus, a firm with lower expected returns from research has to spend relatively more in research to maintain the competitive edge. Inserting the profit-maximizing value of R_i, the profit-maximizing value of D_i is immediately determined from Eq. (10).

The total R&D expenditure is given by

$$R_i + D_i = R_i + h_i^{\frac{1}{\theta_D-\delta_i}} R_i^{\frac{\gamma_i}{\theta_D-\delta_i}} = R_i\left(1 + h_i^{\frac{-1}{\delta_i-\theta_D}} R_i^{\frac{-\gamma_i-(\delta_i-\theta_D)}{(\delta_i-\theta_i)}}\right). \tag{12}$$

Consequently, the R-share of firm i's total R&D expenditures can be expressed as

$$\frac{R_i}{R_i+D_i} = \frac{1}{1 + h_i^{\frac{-1}{\delta_i-\theta_D}} R_i^{\frac{-\gamma_i-(\delta_i-\theta_D)}{(\delta_i-\theta_D)}}} \tag{13}$$

$$= \frac{1}{1 + g_i^{\frac{-\gamma_i-(\delta_i-\theta_D)}{\theta_R(\delta_i-\theta_D)+2\gamma_i\theta_D}} h_i^{\frac{(2\theta_D-\theta_R)}{\theta_R(\delta_i-\theta_D)+2\gamma_i\theta_D}}}. \tag{14}$$

Based on the above deductions, we can claim the following:

Proposition 1. *If output elasticities of research and development (γ_i and δ_i) are sufficiently comparable across firms, then for $2\theta_D > \theta_R$, a profit-maximizing firm with a higher L_i (or higher K_i) will incur a lower R-share compared to another firm with lower L_i (or, lower K_i).*

Proof. Ceteris paribus, a higher L_i or K_i, or both, implies a higher value of h_i. The profit-maximizing $R_i/(R_i + D_i)$ is lower for a higher value of h_i when $2\theta_D > \theta_R$. Given θ_D and θ_R both lie in the (0,1) interval, this implies that, with other parameter values sufficiently comparable across firms, when the elasticity of the price-cost margin with respect to development expenditure (as captured by θ_D) is larger or at least not too small in comparison with the elasticity of expected additional gains from research expenditure (as captured by θ_R), the optimal R-share is associated inversely with the firm size as measured by its number of non-R&D employees L_i, or accumulated fixed assets K_i. □

3.3. Intuition

To elaborate further on the mechanism behind the above proposition, we reformulate Eqs. (5) and (6) as below.

$$\frac{\partial \pi_i^e}{\partial R_i} = D_i^{\theta_D}\frac{\gamma_i q_i}{R_i} - 2B_i\frac{\gamma_i q_i^2}{R_i} + \mu_i\theta_R R_i^{\theta_R-1} \tag{15}$$

$$\Rightarrow \quad \frac{\partial \pi_i^e}{\partial R_i} \Big/ \frac{\partial q_i}{\partial R_i} = D_i^{\theta_D} - 2B_i q_i + \frac{\theta_R}{\gamma_i}\frac{\mu_i R_i^{\theta_R}}{q_i} since \frac{\partial q_i}{\partial R_i} = \frac{\gamma_i q_i}{R_i} \tag{16}$$

$$\text{and} \quad \frac{\partial \pi_i^e}{\partial D_i} = (\theta_D + \delta_i)D_i^{\theta_D-1}q_i - 2B_i\frac{\delta_i q_i^2}{D_i} \tag{17}$$

$$\Rightarrow \quad \frac{\partial \pi_i^e}{\partial D_i} \Big/ \frac{\partial q_i}{\partial D_i} = \frac{\theta_D+\delta_i}{\delta_i} D_i^{\theta_D} - 2B_i q_i since \frac{\partial q_i}{\partial D_i} = \frac{\gamma_i q_i}{D_i} \tag{18}$$

The left hand side of Eq. (16) is the marginal gain in profit from research over the marginal gain in output from research. Similarly the left hand side of Eq. (18) is the marginal profit from development over the marginal output from development. In our model, both research and development directly contribute to production. But they also have additional contributions toward the firm's revenue; research might open up additional sources of revenue, such as patents, and development increases the per-unit price-cost margin. The higher the ratio of the marginal gain in profit to marginal gain in output resulting from a unit increase in some input factor, the higher is this factor's exclusive contribution (i.e., contribution over and above the increase in output) in the firm's revenue.

By construction, both the measures decrease as q_i increases, but Eq. (16) falls faster. That is, the ratio of marginal profit to marginal output from research falls faster for a firm with a higher q_i. This is because the additional gains from R_i are independent of the firm's ex-ante output level and therefore the bigger firm does not have any additional advantage there. More specifically, comparing the right hand sides of Eqs. (16) and (18), we see that the ratio of marginal profit to marginal output from development is higher than the ratio of marginal profit to marginal output from research when

$$\frac{\theta_D + \delta_i}{\delta_i} D_i^{\theta_D} > D_i^{\theta_D} + \frac{\theta_R}{\gamma_i} \frac{\mu_i R_i^{\theta_R}}{q_i} \tag{19}$$

$$q_i > \frac{(\theta_R/\gamma_i)\mu_i R_i^{\theta_R}}{(\theta_D/\delta_i) D_i^{\theta_D}}. \tag{20}$$

In other words, the marginal gain in profit over output from development is higher than the same from research when the ex-ante output is above a certain threshold determined by the ex-ante R&D expenditures and the model parameters. Increasing the development expenditure is profitable as long as this threshold condition holds. We can further observe from this equation that even if the ex-ante R&D ratios are similar for larger and smaller firms, and the output elasticities of research and development are also comparable, a higher μ_i would raise this threshold output. So, when expected additional gains from success in research is higher – either due to a higher $\tilde{\mu}_i$ or a higher M_i – smaller firms are more likely to find development less profitable compared to the larger ones.

On the other hand, if the additional net gains from research are minimal or non-existent, i.e. $\mu_i = 0$, the model would not give us a closed-form solution for the profit-maximizing levels of R or D. The main result from proposition 1 that a profit-maximizing firm with a higher L_i (or, higher K_i) will incur a lower R-share compared to another firm with a lower L_i (or lower K_i, or both) will still be valid, however.

Another potential concern about the model structure could be our assumption that research involves a certain level of uncertainty in outcome, while development activities have sure-shot outcomes. This may look like a limiting assumption at the outset, especially with reference to Mansfield and Wagner (1975)s' arguments that any kind of R&D involves some sort of risk. However, note that the function $f(D_i) = D_i^{\theta_D}$ is very similar to the research success function $f(R_i) = \mu_i R_i^{\theta_R}$. So technically, $f(D_i)$ can be interpreted in the exact same way as $f(R_i)$ is interpreted, that is, as a Bernoulli process with a given expected success probability. The implications of the model will not change as long as $2\theta_D > \theta_R$.

Regarding the modelling of the innovation process, as mentioned in Section 2, the classic Rosenberg (1989) model suggests a linear relationship between R and D activities, while the Kline and Rosenberg (2009) model proposes recurring feedback loops. Our assumptions about R and D do not contradict these either. The interdependence of R and D is apparent from the first order conditions (Eqs. (7) and (6)). Yet, given the static nature of the model and for the sake of tractability, we do not consider feedback loops between R and D activities that may occur over time.

In the following empirical analysis, we measure firm size by the number of employees (L_i), resulting in the hypothesis that the R-share declines with L_i. Finally, it should be noted that a relatively higher R-share among smaller firms can happen because of multiple reasons, including different sizes of the non-R&D activities (as reflected in L_i or K_i), or asymmetric additional returns from research activity (as captured by μ_i). Proposition 1 shows that, ceteris paribus, the R-share varies with firm size. Alternatively, focusing on g_i in Eq. (14), one can see that g_i decreases in μ_i, which in turn implies that the R-share falls. So, ceteris paribus, a firm with a higher μ_i spends relatively less in research. Given that the larger firms may often have a higher average success rate (i.e., higher $\tilde{\mu}_i$), or a higher scope of appropriating the fruits of research activity (i.e. higher M_i) thanks to their reach and reputation, a higher μ_i may as well induce a lower R-share.

4. Data and estimation strategy

4.1. Data description

The empirical study builds on data from three main sources: a) the Flemish part of the Belgian OECD R&D survey, b) the Thomson/Reuters Belfirst database, and c) the European Patent Office's (EPO) PATSTAT database. The OECD R&D survey is harmonized across OECD countries and follows the guidelines in the Frascati Manual. It is conducted biannually and each wave collects information for the years covered in order to compose the OECD Main Science and Technology Indicators. The collected data is based on the permanent inventory of all R&D-active companies[2] in Flanders and hence covers a large proportion[3] of all R&D activity in the region. A firm is considered R&D-active in the following if it spent at least some money on R&D in at least one year during the sample period.

[2] Firms are considered to be part of the R&D-active firm population (about 12,000 for each wave) stemming from information based on previous surveys, accounting reports as well as based on government information about the application for R&D grants and tax credits. The response rate varies by year at around 75% across all firms and up to 98% for the top-200 R&D firms. For details, see https://www.vlaamsindicatorenboek.be/2.2.1/methodologie. Further information on each wave is documented here: https://www.vlaamsindicatorenboek.be/vorige-edities.

[3] According to the documentation, it is estimated that the included firms are responsible for around 90% of all R&D spending in the region.

Table 1
Sample details.

	Observations	Firms	**Share** (%)
SME (<250 employees)	12,447	3948	84.28
Large firms (≥250 employees)	2322	425	15.72
All	14,769	4373	100.00
Sectors	14 manufacturing sectors, 3 service sectors		

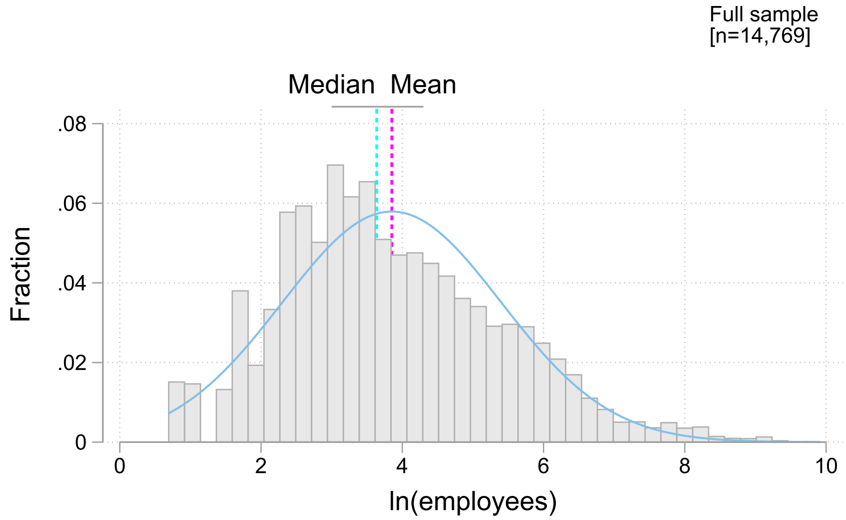


Fig. 1. Distribution of firm size.

Information on R&D expenditures and on shares devoted to research and development as well as the number of R&D employees are taken from the OECD survey. To capture a firm's financial situation and in order estimate firm-level productivity, the survey data is complemented with accounting and balance sheet data from the Thomson/Reuters Belfirst database. It comprises financial information even for small, non-listed firms, since in Belgium all limited liability firms (except for financial institutions, insurance companies, exchange brokers and hospitals) had been legally required to file annual accounts with the National Bank during our period of analysis. We furthermore construct the patent application stock of each company based on information in the PATSTAT data.[4]

The sample covers the years from 2000 to 2015 and includes firms in the manufacturing and knowledge-intensive service sectors. Table 1 illustrates that the final data set consists of 14,769 observations from 4373 unique firms in 17 different sectors. The majority of firms in the sample can be classified as SME following the definition of the European Commission which applies an employment threshold of 250 employees.

Figure 1 depicts the sample distribution in terms of firm size based on the logged number of employees.[5] Key descriptive statistics for the full sample are presented in Table 2.

Research and development expenditures as well as all monetary variables are indicated in thousands of Euros. The data confirm that compared to external R&D, internal R&D plays a more important role in firms' innovation investments. It is also visible that the average research expenditure is lower than the average development expenditure. Firms in the sample are on average 27 years old and 66 percent of the firms belong to an enterprise group.

Table 3 shows the average R-share and D-share[6] in the full sample as well as in the subsample of firm-year observations with positive R&D expenditures. The overall average R-share is 28% whereas the average value is 56% when we only consider firm-year observations in which there were positive R&D expenditures (referred to as R- or D-active subsample in the following). All 17 industries show positive average R and D expenditures. There are differences in the amount as well as the shares between sectors with the chemical and, in particular, the pharmaceutical industry, showing the highest expenditures. High average R-shares (≥40%) can be observed in the latter, but also in the sector including computers, electronics and optical products. See Table A.2 for details.

[4] We match invention patent applicants based on names and addresses and account for patent families in order to avoid double counting of patents filed at several patent offices worldwide. The patent data is available as a time series for each firm, since we retrieve all patents of a firm dating back to its first application included in the data base.

[5] The sample distribution over sectors and size classes can be found in Appendix Table A.1. Figure A.2 delineates the distribution of the logged number of employees for the subsample of R- or D-active firm-year observations.

[6] The R-share is calculated as the share in total R&D expenditures devoted to research activities. The D-share is the remaining share in the total.

Table 2
Descriptive statistics of control variables.

	Mean	P50	Sd	Min	Max
Internal R&D[1]	1,887.77	0	17,626.75	0	858,104
External R&D[1]	695.10	0	14,823.20	0	695,000
Research[1]	829.75	0	6,838.47	0	390,866
Development[1]	1,057.73	0	13,000.10	0	686,483
# total employees	195.81	37	678.01	1	20,132
# R&D employees	11.94	0	65.98	0	1662
Age	27.28	23	18.74	1	144
Fixedassets[1]	42,755.44	1073	364,157.88	0	14,374,981
Workingcapital[1]	9,431.60	1237	47,947.05	−289,570	1,795,746
Long − termdebt[1]	11,542.39	10	145,766.71	0	6,771,719
Short − termdebt[1]	13,451.38	429	104,824.01	0	5,129,187
Patent stock	3.33	0	37.33	0	1342
Enterprise group dummy	0.66	1	0.47	0	1
Observations			14,769 (full sample)		

Measured in € 1000.

Table 3
Descriptive statistics of share variables.

	Count	Mean	P50	Sd	Min	Max
Full sample						
R-share	14,769	0.28	0.00	0.38	0	1
D-share	14,769	0.22	0.00	0.33	0	1
R- or D-active subsample						
R-share	7373	0.56	0.60	0.35	0	1
D-share	7373	0.44	0.40	0.35	0	1

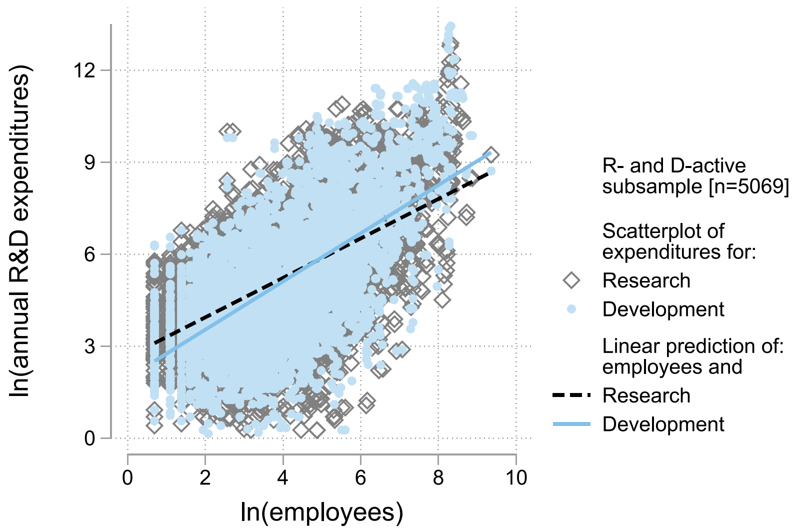


Fig. 2. Correlation between firm size and R and D expenditures.

Figure 2 shows within-sample correlations between R as well as D expenditures and firm size. For both R and D, there is a strong positive correlation with firm size, supporting the idea that larger firms can afford to spend more. The slope of the linear prediction line is steeper for D than for R. Departing from this evident relationship, it is therefore interesting to consider relative amounts, i.e. the research share in R&D.

Figure 3 illustrates the evolution over time of (a) the R-activity of all firms (fraction of observations with a positive R-share, i.e. the extensive margin), and (b) the size of the R-share in the R-active subsample (intensive margin). For a more fine-grained understanding of the attribution of effects to differently sized firms, we distinguish four size classes: tiny firms (< 50 employees), small firms (≥ 50 employees and < 150 employees), medium firms (≥ 150 employees and < 250 employees), and large firms (≥ 250 employees). As can be seen in the left panel, the R-active fraction of observations experienced a sharp decline in 2012. Due to the spending horizon of R&D budgets which stretches over longer cycles, this may be accountable to the aftermath of the global financial and the Euro crisis with firms quitting R or D activities altogether. The

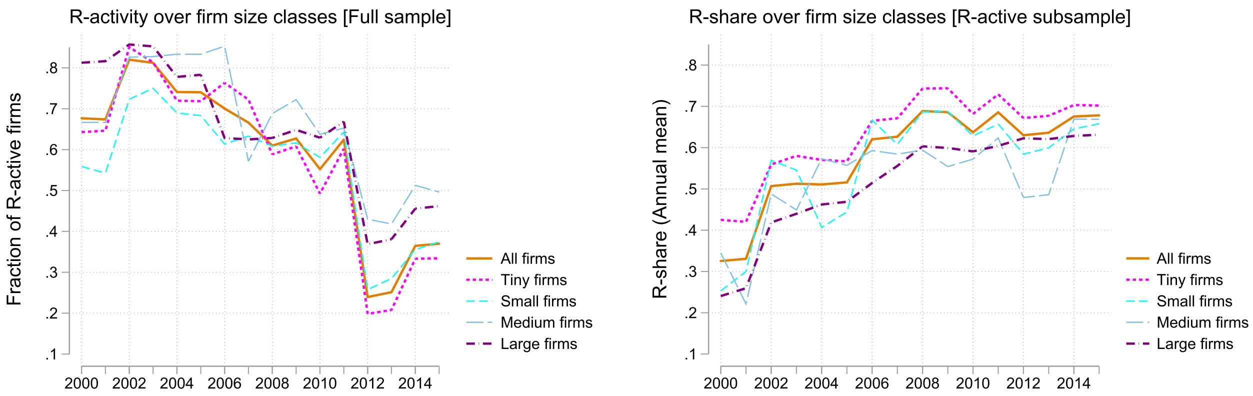


Fig. 3. Development of the extensive and intensive margin for R-activity.

right panel visualizes that the R-share of the R-active subsample over all four firm size classes grew over time. However, this growth was particularly strong in tiny and small firms.[7]

Thus, unlike studies that proxy research activity with scientific publications, we cannot confirm that the average research focus – within the R-active subsample – is declining. Rather, we observe that the fraction of research-performing firms is considerably lower at the end of our sample period. This suggests a rise in the concentration of research activities in fewer firms across the economy considered here over time. This is compatible with conclusions from a study for the German economy by Rammer and Schubert (2018) which highlights that the concentration of innovation spending in a smaller number of firms has increased over time, to the context of research activities. Figure A.4 shows the corresponding information for D-activity, depicting that the average D-share among D-active firms diminished over time, reflecting the opposite evolution for the R-share. Yet, also for development the proportion of D-active firms has fallen, pointing to a growing concentration of R and D activities in fewer firms.

4.2. Analysis of research intensity

To investigate the relationship between firm size and the share of R&D expenditures devoted to research when controlling for other firm characteristics, the variable research share (R-share) is used as the dependent variable. Besides firm size measured by the logged[8] number of employees [ln(employees)] as the main variable of interest, we control for the firm's age [ln(age)] in order to not confound size effects with the firm's maturity[9]. Moreover, we account for the level of internal and external R&D expenditures [ln(internal R&D+1), ln(external R&D+1)], and enterprise group association (dummy indicating whether the firm is a single company or associated to a group). A firm's financial situation is likely to affect research efforts and hence we control for liquidity and debt (working capital, long-term debt and short-term debt). We further include the patent application stock as a measure of the firm's knowledge stock (Patent stock). We follow the standard approach based on Griliches and Mairesse (1984) and compute the stock of each firm and year as a perpetual inventory of past and present patent applications with a constant depreciation rate (δ) of 15 percent:

$$\textit{Patent stock}_{i,t} = (1-\delta)\ \textit{Patent stock}_{i,t-1} + \textit{Patent applications}_{i,t}.$$

Sector fixed effects enter as a set of industry dummies, and year dummies capture business cycle effects that are common for all firms and industries.

4.2.1. Estimation of the R-share in R&D

We estimate Ordinary Least Squares models with firm-fixed effects (OLS FE), Generalized Least Squares models with random effects (GLS RE), as well as models for limited dependent variables. The Tobit model accounts for the censoring of the R-share at zero and one, as well as random effects. The fractional response (FR) model directly takes into account that the dependent variable is non-continuous, i.e. a share with limits at zero and one (Papke and Wooldridge, 1996). The log-likelihood function to be maximized in the FR model is

$$\ln L = \sum_{j=1}^{N} w_j y_j \ln\left\{G(x_j'\boldsymbol{\beta})\right\} + w_j(1-y_j)\ln\left\{1-G(x_j'\boldsymbol{\beta})\right\}$$

[7] Appendix Fig. A.5 accounts for firm characteristics and time trends by including a firm size-year-interaction of the observation period. The rising trend of the predicted R-share over time is still especially strong for tiny and small firms. This is in line with Fig. 3(b) where firms with fewer than 150 employees as well took the lead in high R-shares.

[8] We applied the natural logarithm. All logged variables with non-negative values were transformed by adding 1 before taking the log.

[9] It should be noted that age and size are not perfectly correlated in our data. There is a considerable fraction of young and large firms as well as old and small firms. See Figure A.3 for the distribution of firm age over size classes.

Table 4
Estimations of R-share.

	(1) OLS FE	(2) GLS RE	(3) Tobit RE	(4) FR	(5) FR MC
ln(employees)	0.002	−0.022**	−0.073***	−0.204***	−0.247***
	(0.029)	(0.011)	(0.020)	(0.052)	(0.093)
ln(employees) × ln(employees)	−0.005	−0.001	−0.006**	−0.023***	−0.016**
	(0.003)	(0.001)	(0.002)	(0.006)	(0.006)
ln(age)	0.047	0.013	0.039	0.554***	0.459**
	(0.142)	(0.036)	(0.060)	(0.172)	(0.219)
ln(age) × ln(age)	−0.017	−0.003	−0.004	−0.090***	−0.076***
	(0.036)	(0.006)	(0.010)	(0.028)	(0.029)
ln(internal R&D)	0.096***	0.093***	0.218***	0.596***	0.703***
	(0.003)	(0.002)	(0.003)	(0.008)	(0.018)
ln(external R&D)	0.000	−0.007***	−0.007***	−0.072***	0.002
	(0.003)	(0.002)	(0.002)	(0.009)	(0.014)
Patent stock	−0.000	−0.001***	−0.001***	−0.004***	−0.001
	(0.000)	(0.000)	(0.000)	(0.001)	(0.002)
Working capital ratio*	0.000*	−0.000	−0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Long-term debt ratio*	0.000***	0.000*	−0.000	−0.000	0.001***
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Short-term debt ratio*	−0.000	0.000	−0.000	−0.000	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Enterprise group dummy	−0.000	−0.016**	−0.034***	−0.236***	−0.222***
	(0.014)	(0.007)	(0.012)	(0.043)	(0.043)
MC ln(employees)					−0.000
					(0.081)
MC ln(age)					−0.003
					(0.188)
MC ln(internal R&D)					−0.111***
					(0.019)
MC ln(external R&D)					−0.115***
					(0.018)
MC patent stock					−0.002
					(0.002)
MC working capital ratio*					−0.000
					(0.000)
MC long-term debt ratio*					−0.001***
					(0.000)
MC short-term debt ratio*					0.000
					(0.000)
Sector FE	Yes	Yes	Yes	Yes	Yes
Year FE	Yes	Yes	Yes	Yes	Yes
Pseudo R^2				0.341	0.345
R^2 *within*	0.323				
R^2 *between*	0.604	0.631			
Wald $\chi^2(42)$		5,558.57	6,569.94	8,912.99	8,956.78
F (42, 4372)	28.980				
Observations	14,769 *(full sample)*				

* Ratio uses fixed assets in the denominator. All values are rounded; 0.000 indicates a value of < 0.001.
Standard errors in parentheses (clustered at sector level) $^*p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.010$

with the functional form for $G(x_j'\beta)$ corresponding to a logit function $\exp(x_j')/1 + \exp(x_j')$. To additionally capture unobserved firm-specific effects in the FR model, we follow the Mundlak-Chamberlain (FR MC) approach (Mundlak, 1978; Chamberlain, 1982) which relaxes the assumption that covariates must be independent of individual unobservable effects (strict exogeneity). Modelling the dependence of unobserved heterogeneity on explanatory variables allows for an arbitrary correlation which is why such models are also called correlated random effects models (Wooldridge, 2010). Thus, we augment the specification by inserting the within-sample means of all time-varying covariates as a Mundlak-Chamberlain device (Wooldridge, 2019).

The results from these estimations are shown in Table 4. The random effects models (columns 2 and 3) suggest that the R-share indeed declines with the first order term of the variable ln(employees), holding other firm parameters – including the level of R&D expenditures – constant.

That is, larger firms are less research-intensive than smaller ones. The second order term is likewise negative and statistically significant, indicating that the association is negative over the entire firm size distribution in the sample. This negative relationship is similarly pronounced in the fractional response models for both specifications, without (column 4) and with

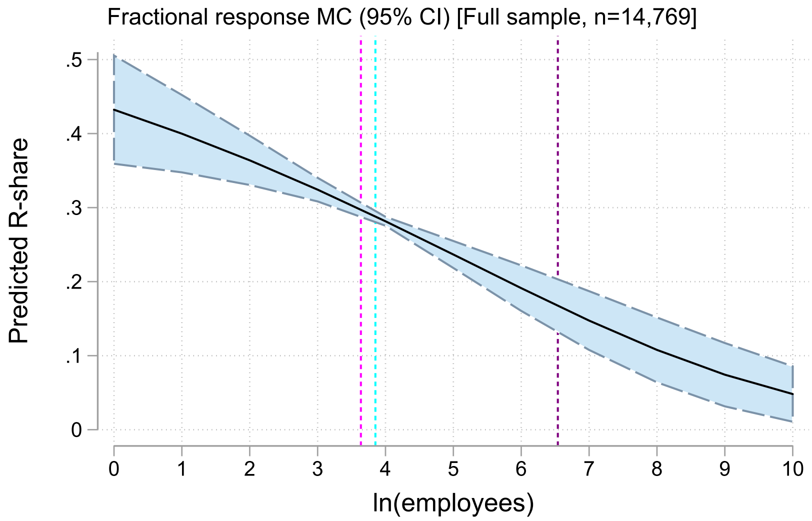


Fig. 4. Adjusted predictions of R-share over firm size. The vertical dashed lines indicate the sample mean, the median and the 95th percentile.

Mundlak-Chamberlain within-sample means (column 5).[10] The fixed effects model (column 1) is less precisely estimated, suggesting that the models capture between-firm variation rather than within-firm variation. Note that there is in fact little within-firm variation in both firm size as well as the research intensity so that we should interpret these findings in terms of between-firm effects.[11]

Since the properties of fractional response model match the nature of the dependent variable best, the FR MC method serves as the basis for the visualization of the main effect in Fig. 4. Figure 4 illustrates the main results graphically by displaying the predicted R-share (adjusted predictions) at different values of ln(employees).

4.3. Analysis of productivity

In order to analyze the link between firms' R-share and productivity, we estimate the firms' total factor productivity (TFP) based on a production function approach. The production function is specified as in Eq. (1). Output is measured as the natural logarithm of the firms' annual value added [q]. Note that we do not use accounting profits as a measure for profitability due to their sensitivity to reporting, depreciation and losses carried forward, for instance, which make annual values incomparable over time and between firms. Instead, we estimate TFP using the same set of input factors used to produce a certain value added. One should, however, keep in mind that the added value (i.e. mark-up) that a firm creates also depends on its market power (De Loecker and Warzynski, 2012) which we do not explicitly account for in the following, assuming that the competitive environment is captured by the sector fixed effects.

Capital input is measured by the natural logarithm of firms stock of fixed assets [k], and labor input by the logged number of employees in non-R&D jobs [l] in a given year. As an augmentation to the classical production function, we add R&D activity to the production function which has been shown to explain productivity differences between firms (Doraszelski and Jaumandreu, 2013). More precisely, we differentiate between logged research and development expenditures [research = r, development = d]. Because a large proportion of R&D expenditures is typically labor costs, the use of non-R&D employees as the labor variable allows us to measure R&D input without double counting of R&D expenditures that reflect wages of R&D employees.

A central challenge in the estimation of production functions is the correlation between unobservable productivity shocks and input levels (Griliches and Mairesse, 1998), i.e. productivity beliefs which influence the firm's input decisions. The approach by Ackerberg et al. (2015) [ACF] – which we adopt in the following – addresses the potential collinearity problem in earlier productivity estimators like the one by Olley and Pakes (1996) [OP], or Levinsohn and Petrin (2003) [LP] by proposing a functional dependence correction. In the ACF method, firms are no longer assumed not to adjust their labor input immediately when subject to productivity shocks. The input demand function is then conditional on the choice of both labor and capital inputs. Whereas the OP framework uses investment as a proxy for productivity in the control function, LP and ACF use intermediate inputs (materials) instead because investment decisions tend to be implemented in blocks which violates the monotonicity assumption underlying the framework. Not only are intermediate inputs less costly to adjust, they are

[10] The test of joint significance of the within-sample means (MC variables) is highly significant ($\chi^2(8) = 111.49^{***}$).

[11] Note that the FR MC model and the OLS FE model differ conceptually. The MC model is a correlated random effects model which includes an approximation of a fixed effect in the sense that it controls for the portion of the variance correlated with the average of all time-varying variables rather than having a fixed parameter for each firm. See chapter 10 in Wooldridge (2010) for details.

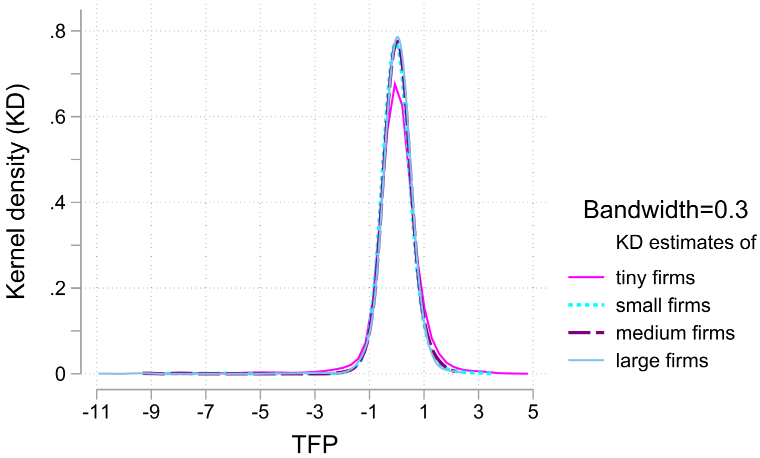


Fig. 5. Kernel density of TFP by firm size class.

also more responsive to the entire productivity term and provide a simple link between theory and the estimation strategy because intermediate inputs are not typically state variables. By taking the natural logarithm of the Cobb-Douglas function in Eq. (21), the factor inputs relate in an additive manner. The error term in Eq. (21) has two components: the transmitted productivity component ω_{it}, and u_{it}. The component u_{it} is an unobservable error term that is uncorrelated with input choices, whereas ω_{it} is observable or predictable by firms when making input decisions.

Furthermore, β_0 is the mean efficiency level across firms and over time:

$$q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \gamma r_{it} + \delta d_{it} + \omega_{it} + u_{it}. \tag{21}$$

Since ω_{it} as a prior productivity belief gives rise to endogeneity (factor choices will depend on it, resulting in a correlation between inputs and ω_{it}), the control function based on intermediate inputs $m_{it} = f(\omega_{i,t}, k_{it}, l_{it}, rd_{it})$ is introduced as a first stage estimation. Inverting this function for $\omega_{i,t}$ and substituting into the production function yields

$$q_{it} = \beta_0 + \beta_k k_{it} + \beta_l l_{it} + \gamma r_{it} + \delta d_{it} + f^{-1}(m_{it}, k_{it}, l_{it}, r_{it}, d_{it}) + u_{it}. \tag{22}$$

This provides an estimate of the composite term $\hat{\Phi}_{it}$ which can be expressed as
$\Phi_{it}(m_{it}, k_{it}, l_{it}, r_{it}, d_{it})$ so that a measure for total factor productivity (TFP) can be derived from

$$\hat{\omega}_{it} = \hat{\Phi}_{it} - \beta_k k_{it} - \beta_l l_{it} - \gamma r_{it} - \delta d_{it}. \tag{23}$$

The empirical strategy used here consists of two sequential steps. In the first, we estimate productivity equations on major factor inputs (*K, L, R&D*) which are instrumented as suggested by Ackerberg et al. (2015).[12] This stage serves to obtain $\hat{\omega}_{it}$ while netting out the unobserved part of the error term, u_{it}.

In a second step, we estimate the effect of variation in the R-share on the estimated TFP. We further interact the R-share with firm size to test the hypothesis that the return to research varies with firm size. Because we expect the research orientation to have a delayed impact on TFP, we apply a two-year lag for the R-share. Firm size is measured in contemporaneous values to capture output effects at the firms' current size. Since past productivity has been shown to be a reliable predictor of future productivity (Doraszelski and Jaumandreu, 2013), we also add lags of TFP to the model.[13] In addition, we control for firm characteristics to account for remaining observed firm-level heterogeneity. Unobserved firm heterogeneity is captured by the fixed or random effects. The equation to be estimated can be described as:

$$\hat{\omega}_{it} = f(R\text{-}share_{it-2}, ln(empl)_{it}, R\text{-}share_{it-2} \times ln(empl)_{it}, controls) \tag{24}$$

4.3.1. Estimation of TFP and its relation to the R-share

Figure 5 depicts the estimated TFP for the four firm size classes and visualizes that there is no strong relationship between firm size and TFP after having accounted for both K and L in the TFP estimation, except for very small firms with less than 50 employees.[14] Appendix Table A.3 displays the results from the sector-wise productivity estimations in detail.[15]

[12] As a robustness check, we apply the LP estimation method and compare the resulting TFP distributions.
[13] Note that we apply the same lag structure as for the R-share by adding a two-year lag and to capture TFP prior to the included R-share by adding a three-year lag.
[14] A pairwise correlation coefficient of 0.0172, however, significant at the 5% level, indicates that larger firms are more productive when not controlling for further firm characteristics.
[15] Separate estimations by sector are standard in the productivity literature and can, for instance, be found in Hottenrott et al. (2016).

Table 5
Panel estimations of TFP on R-share.

	OLS FE	GLS RE	GLS RE	GLS RE	GLS RE	GMM
R-share$_{t-2}$	0.082	0.206***	0.199***	0.283***	0.224***	4.118***
	(0.063)	(0.062)	(0.062)	(0.097)	(0.062)	(1.144)
ln(employees)	−0.352**	−0.034**	−0.024*	−0.012	−0.034**	0.085
	(0.165)	(0.015)	(0.013)	(0.008)	(0.014)	(0.319)
R-share$_{t-2}$ × ln(employees)	−0.018	−0.038***	−0.035***	−0.043***	−0.041***	−0.802***
	(0.014)	(0.013)	(0.014)	(0.016)	(0.013)	(0.268)
ln(age)	−0.163	0.371*	0.195	0.189	0.361*	−22.718**
	(0.592)	(0.192)	(0.134)	(0.151)	(0.196)	(11.425)
ln(age) × ln(age)	0.094	−0.047*	−0.023	−0.024	−0.047*	3.544**
	(0.124)	(0.026)	(0.019)	(0.019)	(0.027)	(1.717)
ln(external R&D)	0.011	0.012	0.010	0.011*	0.011	0.023
	(0.013)	(0.010)	(0.008)	(0.006)	(0.009)	(0.111)
Patent stock	−0.000	−0.000	−0.000	0.000	−0.000	0.005
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.004)
Working capital ratio⋆	−0.000	0.000	0.000	0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Long-term debt ratio⋆	0.000***	0.000***	0.000***	0.000**	0.000***	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Short-term debt ratio⋆	−0.000	0.000	0.000	0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.002)
Enterprise group dummy	−0.063	0.055	0.044	0.041	0.056	−0.309
	(0.050)	(0.047)	(0.039)	(0.025)	(0.041)	(0.345)
TFP ACF$_{t-2}$			0.242***	0.206***		0.102
			(0.025)	(0.064)		(0.077)
TFP ACF$_{t-3}$				0.106*		−0.005
				(0.061)		(0.073)
Sector FE	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	No	No
Arellano-Bond AR(2)						−0.66
						$Pr > z = 0.51$
Hansen [$\chi^2(102)$]						2.06
						$Pr > \chi^2 = 1.0$
Observations	4847	4847	4840	3379	4847	3379

⋆ Ratio uses fixed assets in the denominator. All values are rounded; 0.000 indicates a value of < 0.001.
Cluster-robust standard errors in parentheses. $^{*}p < 0.10$, $^{**}p < 0.05$, $^{***}p < 0.010$

Note that the average productivity in our sample is relatively low. This may be due to several factors: First, we have a high fraction of small firms in the data and these are all comparatively R&D-intensive firms which likely excludes firms that are producing at a large scale (and low cost). Besides this, our sample period covers the financial and economic crisis 2008/2009.[16] Another reason may be the relatively high degree of foreign ownership in Belgium leading to profit shifting within company groups which we account for in the regressions by including a group indicator. The resulting productivity distribution is very similar when we replicate the TFP estimation using the LP method. Figure A.6 compares the TFP distributions based on both methods.

Table 5 presents the results from the linear estimation of Eq. (24) using different estimation methods. The R-share significantly contributes to TFP in the random effects specifications as well as in the General Method of Moments (GMM) model.

Consistent with prior research, the direction of the effect is such that a higher research share results, on average, in higher productivity (Czarnitzki and Thorwarth, 2012). Considering the interaction term between the R-share and ln(employees), we see however that the incremental research premium declines significantly with firm size.[17]

We include past productivity (lags of TFP) to capture the path dependency of productivity. The GMM estimator takes into account the potential endogeneity of these regressors, but does lead to different conclusions with regard to the main variables. The p-value of the test statistics AR(2) is 0.51 which suggests that the error terms are not serially correlated. Overidentification is also not a concern since the p-value of the Hansen test is 1.0. Note that because of differencing, the coefficients are not quite comparable between GLS and GMM; yet the results are similar in terms of direction and significance of the estimated coefficients. The main difference is that the lagged values of TFP are no longer significant likely due to the unbalanced nature of the panel data and the structure of the survey which is not ideal for GMM estimation. Rather than interpreting the results only at the mean of the variables, we look at the average marginal effects of the R-share at

[16] The annual average values of TFP show the pattern of a "double dip" reaction to the financial crisis. Average TFP is positive in the years right before (2005 to 2008) and then turn negative until 2010. After positive values in 2010 and 2011, we estimate again TFP values that are on average negative in 2012. Average TFP remains positive thereafter until the end of our sample period.

[17] Note that we employ a two-year lag between the R-share and TFP which leads to a drop in observations to 4847.

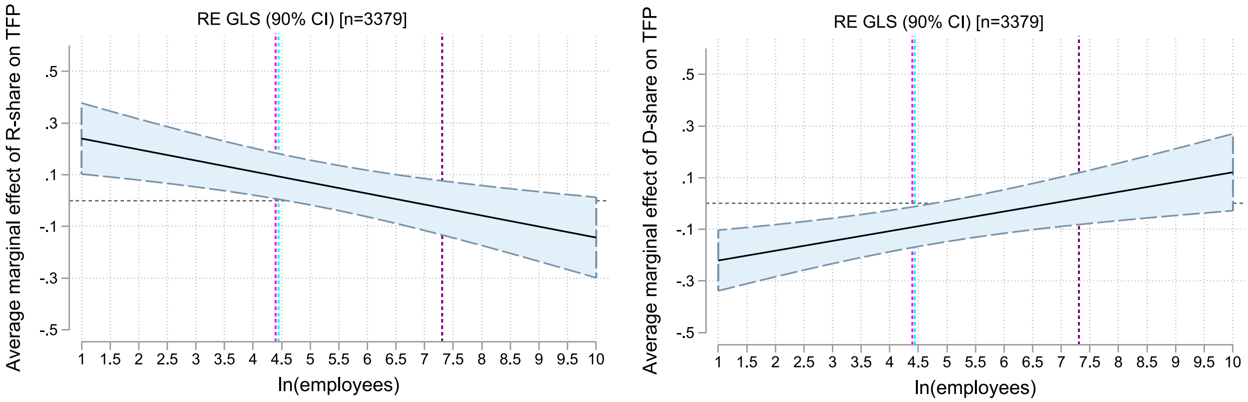


Fig. 6. Average marginal effects of R- and D-share on TFP over firm size. The vertical dashed lines indicate the subsample mean, median and 95th percentile.

different values of firm size. Figure 6 illustrates that the returns to increasing the R-share are positive but declining up to the mean firm size in the sample (left panel). Beyond the mean, the returns to increasing the research intensity are negative on average, but the marginal effect is not statistically different from zero, indicating no significant harm to productivity. Yet, this also suggests that for medium-sized and larger firms, an additional percentage point devoted to research (rather than to development) is no longer beneficial for productivity.

The opposite holds true for the D-share (Fig. 6(b)).[18] The returns to increasing the D-share are lowest for very small firms and the returns increase up to the mean value of the firm-size distribution. While the returns to D do not continue to decrease for the largest firms as compared to median-sized once, they are still significantly larger beyond the median than below the median. Both results are in line with Proposition 1 derived in Section 3.2, i.e. that larger firms find it more profitable than small firms to devote relatively more resources to development activities (and vice versa).

5. Conclusions

This study investigated the link between firm size, research orientation and productivity. While previous research discussed the comparative advantages of small versus large firms with regard to product or process innovation, the role of investments in research versus development as drivers of productivity-enhancing innovations remained little explored.

Our empirical results confirm our theoretical conjecture presented in Section 3 that a firm's optimal research focus, i.e. the share of the R&D budget devoted to R, declines with firm size. While larger firms spend more on both R and D in absolute terms, we find that the optimal R-share falls with firm size. Our analysis based on total factor productivity estimations moreover strengthens previous findings that research is a key driver of productivity. However, they further show that the incremental research premium from increasing the research share in R&D is higher for smaller firms. The results therefore suggest that a division of labor between smaller and larger firms with larger firms focusing on development may indeed be efficient in terms of expected aggregate productivity gains. This finding supports Baumol's (2002) idea of a 'David-Goliath symbiosis' in which small and large firms contribute at different stages of the innovation process. The study thereby extends prior work that focused solely on research activities (Belenzon and Patacconi, 2014), or shed light on specialization in terms of innovative outputs rather than the returns on investment (Acs and Audretsch, 1987; Henderson, 1990; Henderson and Cockburn, 1996; Macher and Boerner, 2006; Arora et al., 2009).

It remains, however, to be examined in future research how much these results are affected by activities not accounted for in the analysis, like outsourcing of R or D in the form of collaborations or licensing. The possibility to conduct collaborative R&D, i.e. in cooperation with other firms like suppliers and joint R&D with universities, may be a factor that explains the declining returns to carrying out research in-house for larger firms. Furthermore, the possibilities of licensing-in or licensing-out technology have not been explicitly accounted for in our analysis but may affect the modelling of the returns to research for both smaller and larger firms. In this context, we may overlook the role played by opportunities for external knowledge sourcing and therefore over- or underestimate the benefits of labor division. Finally, the results may be context-specific in the sense that they originate from an industry landscape with a high proportion of (very) small firms and a substantial fraction of firms that are part of enterprise groups.

The results may still provide insights for innovation policy. Facilitating labor division appears to be crucial for maximizing overall productivity gains from private sector R&D operations. The analysis also highlights the important role of small, research-intensive firms in innovation systems. Policy instruments may be best designed to strengthen firms' comparative advantages. R&D support programs, for instance in the form of direct grants, may be more effective if targeted at research

[18] The underlying regression results are presented in Table A.4.

in small firms, thereby increasing the returns to public funding of industrial R&D. In light of the debate about the decline in productivity growth in developed economies, this study aims to constitute a starting point for further research on division of labor in R&D between firms and between firm and public research organizations or universities. One of the key side-findings of this study is that there is an increasing concentration of both R and D activities in fewer firms. This development deserves further attention and calls for future studies exploring the extensive rather than the intensive margin of R&D efforts. Finally, this study also aims to draw attention to the role of firm size heterogeneity in the analysis of productivity development.

Acknowledgments

The authors thank ECOOM at KU Leuven for access to the R&D survey data. They also would like to thank participants of the Economics research seminar at TUM, the INNOPAT 2019 conference, the EARIE 2019 conference, the G-Forum 2019 Conference, the 2019 Innovation, Competition & Entrepreneurship workshop at the University of Luxembourg as well as two anonymous reviewers for helpful comments. Research support by Julian Schwierzy is highly appreciated.

Appendix A

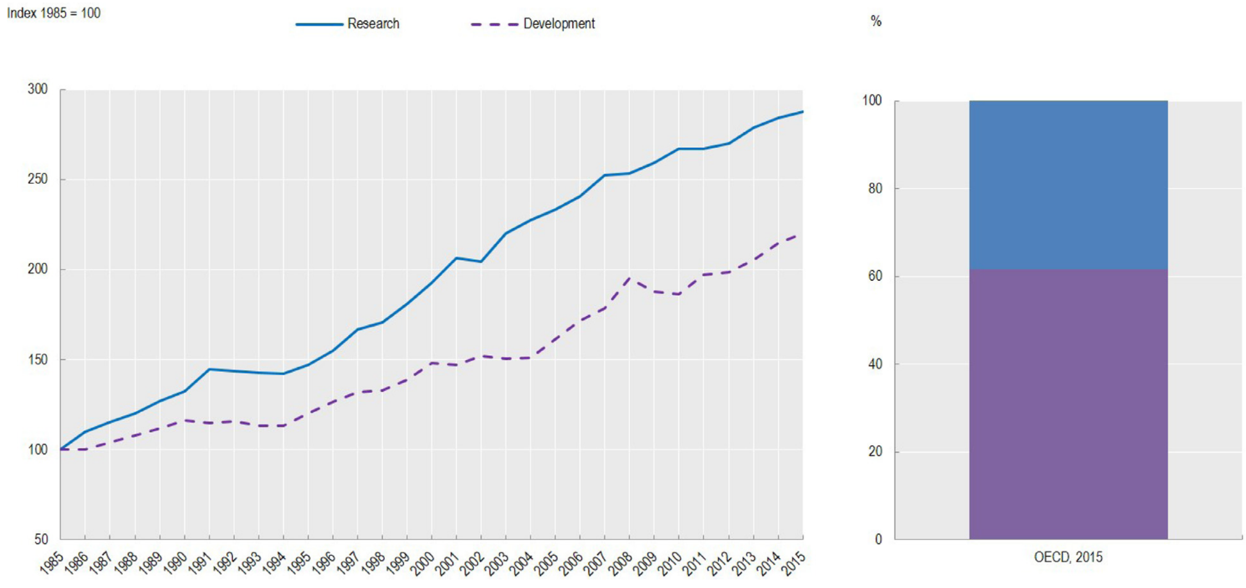


Fig. A.1. Trends in research and development in the OECD Area, 1985–2015. Source: OECD (2017).

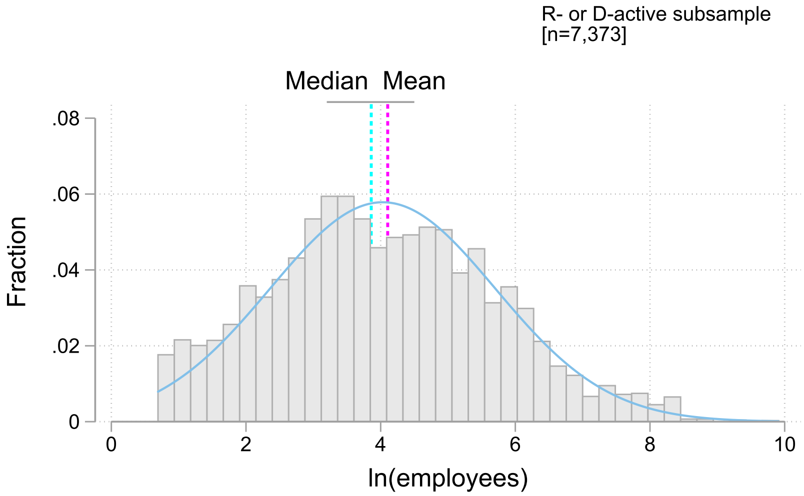


Fig. A.2. Distribution of firm size in the subsample of R- or D-active firm-year observations.

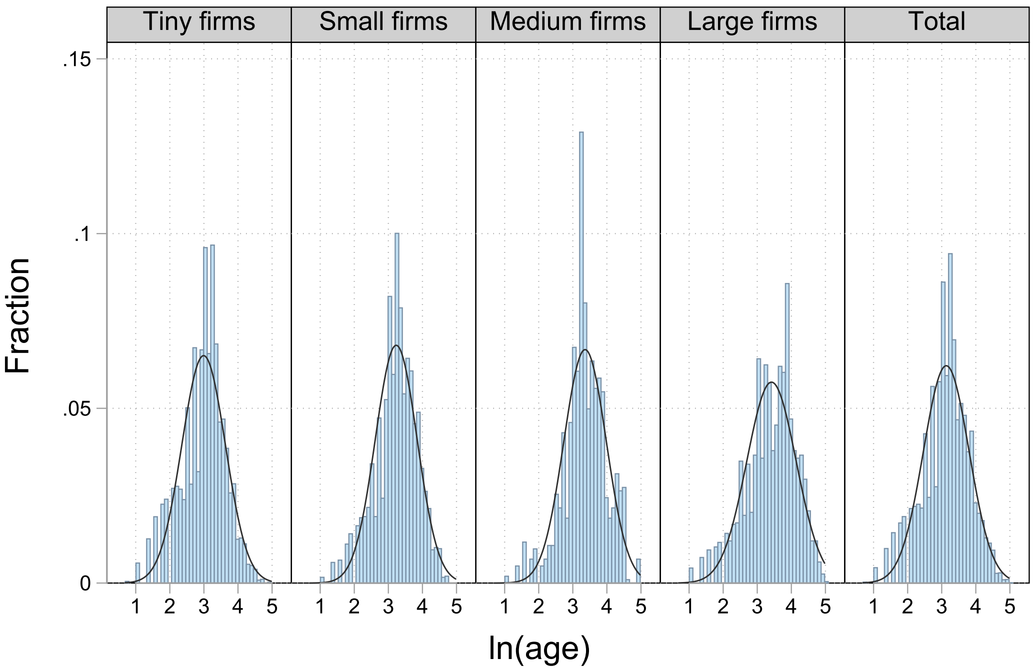
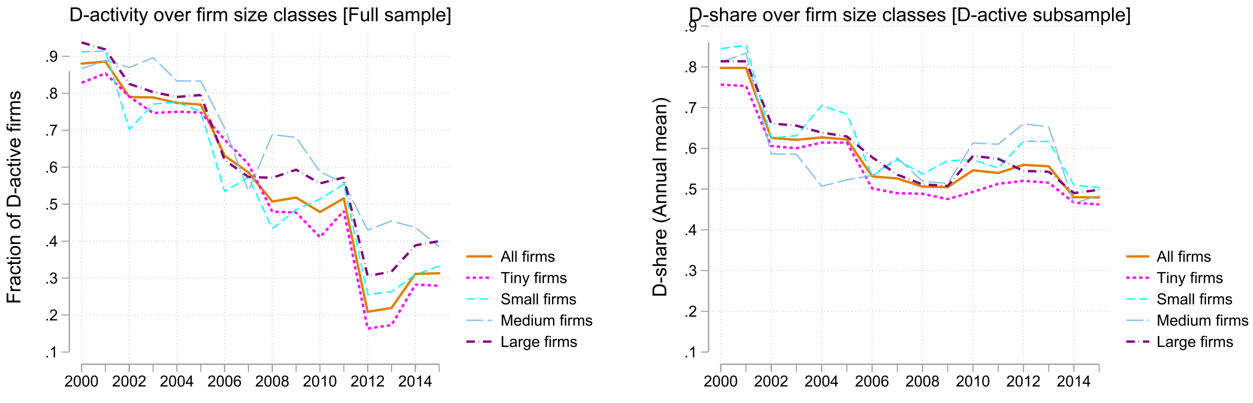


Fig. A.3. Distribution of firm age in different firm size classes.



(a) Extensive margin **(b)** Intensive margin

Fig. A.4. Development of the extensive and intensive margin for D-activity.

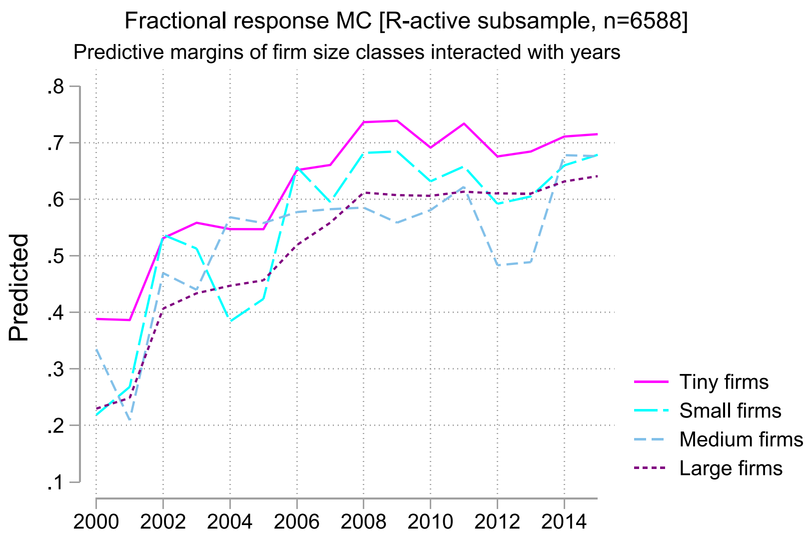


Fig. A.5. Interaction of firm size classes with years.

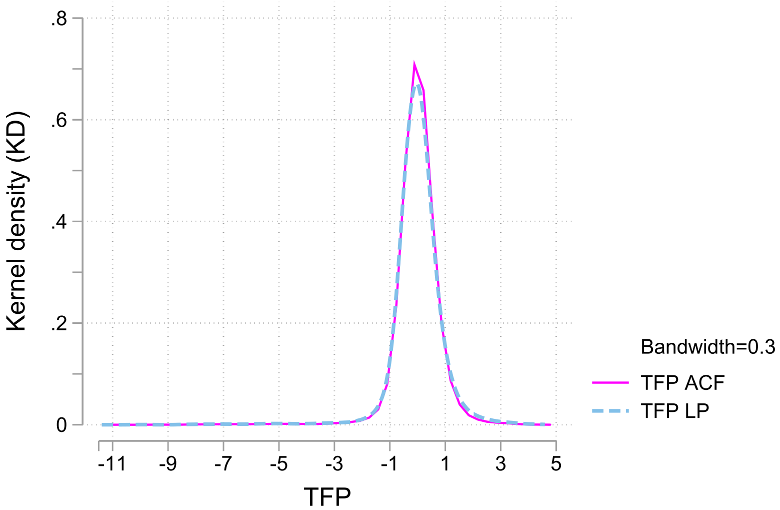


Fig. A.6. Kernel density of TFP by estimation method.

Table A.1
Distribution of sectors by firm size.

#	Sector	SME		Large firms		All firms	
		Count	%	Count	%	Count	%
1	Food,fishery & tobacco	674	5.41	148	6.37	822	5.57
2	Textile	438	3.52	99	4.26	537	3.64
3	Forestry & furniture	266	2.14	13	0.56	279	1.89
4	Paper	261	2.10	78	3.36	339	2.30
5	Chemicals	371	2.98	134	5.77	505	3.42
6	Pharmaceuticals	128	1.03	56	2.41	184	1.25
7	Rubber, plastic & materials	477	3.83	109	4.69	586	3.97
8	Natural resource extraction & waste man.	907	7.29	282	12.14	1189	8.05
9	Machines & equipment	760	6.11	133	5.73	893	6.05
10	Computer, electronic & optical products	365	2.93	73	3.14	438	2.97
11	Transport manufacturing	381	3.06	149	6.42	530	3.59
12	Building & construction	772	6.20	94	4.05	866	5.86
13	Miscellaneous industry	170	1.37	41	1.77	211	1.43
14	Commerce, storage & transport	2743	22.04	403	17.36	3146	21.30
15	Financial & other services	2282	18.33	325	14.00	2607	17.65
16	ICT & software	1286	10.33	136	5.86	1422	9.63
17	Education, health & public personal service	166	1.33	49	2.11	215	1.46
	Total	12,447	100.00%	2322	100.00%	14,769	100.00%

Table A.2
Descriptive statistics of R&D variables by sector.

Sector	Mean	P50	Sd	Min	Max
1					
Research	192.13	0	765.18	0	12,240
Development	148.47	0	587.23	0	6950
R-share	0.30	0	0.39	0	1
D-share	0.20	0	0.32	0	1
2					
Research	254.95	25	842.14	0	8956
Development	238.57	15	566.26	0	3900
R-share	0.33	0	0.36	0	1
D-share	0.30	0	0.35	0	1
3					
Research	56.85	0	164.30	0	1080
Development	38.42	0	115.88	0	978
R-share	0.22	0	0.34	0	1
D-share	0.15	0	0.28	0	1
4					
Research	148.97	0	453.49	0	4860
Development	180.46	0	486.30	0	4400
R-share	0.19	0	0.32	0	1
D-share	0.26	0	0.37	0	1
5					
Research	865.49	38	2,642.51	0	25,064
Development	938.24	35	3,329.95	0	30,569
R-share	0.35	0	0.37	0	1
D-share	0.33	0	0.36	0	1
6					
Research	12,419.48	28	50,990.12	0	390,866
Development	23,796.43	15	102,553.92	0	686,483
R-share	0.40	0	0.41	0	1
D-share	0.35	0	0.39	0	1
7					
Research	344.96	3	1,111.24	0	10,450
Development	487.19	0	1,983.87	0	19,000
R-share	0.30	0	0.36	0	1
D-share	0.27	0	0.34	0	1
8					

(*continued on next page*)

Table A.2 (*continued*)

Sector	Mean	P50	Sd	Min	Max
Research	749.86	0	4,300.76	0	65,268
Development	958.92	0	5,922.70	0	142,200
R-share	0.27	0	0.36	0	1
D-share	0.25	0	0.34	0	1
9					
Research	1,277.96	40	4,865.00	0	50,050
Development	1,726.34	24	6,992.49	0	88,336
R-share	0.38	0	0.37	0	1
D-share	0.34	0	0.36	0	1
Observations	5334				
10					
Research	1,688.08	181	3,922.12	0	29,972
Development	2,736.22	42	12,175.06	0	104,936
R-share	0.46	0	0.39	0	1
D-share	0.32	0	0.35	0	1
11					
Research	1,377.14	36	5,455.25	0	72,000
Development	1,289.82	15	4,149.85	0	47,879
R-share	0.35	0	0.39	0	1
D-share	0.37	0	0.40	0	1
12					
Research	154.35	0	1,160.93	0	25,000
Development	60.22	0	327.24	0	3750
R-share	0.12	0	0.29	0	1
D-share	0.07	0	0.20	0	1
13					
Research	4,125.20	108	11,551.64	0	104,030
Development	6,859.20	70	28,027.67	0	232,133
R-share	0.44	1	0.37	0	1
D-share	0.36	0	0.35	0	1
14					
Research	221.84	0	1,745.10	0	45,907
Development	283.68	0	2,480.89	0	54,000
R-share	0.17	0	0.32	0	1
D-share	0.14	0	0.29	0	1
15					
Research	1,035.14	0	4,917.37	0	97,705
Development	1,049.82	0	6,190.53	0	90,000
R-share	0.31	0	0.39	0	1
D-share	0.20	0	0.32	0	1
16					
Research	580.41	18	2,471.36	0	34,100
Development	289.79	0	2,609.63	0	90,877
R-share	0.38	0	0.42	0	1
D-share	0.21	0	0.33	0	1
17					
Research	1,120.51	0	3,872.06	0	31,724
Development	265.38	0	906.85	0	5627
R-share	0.28	0	0.40	0	1
D-share	0.17	0	0.32	0	1
Observations	9435				

Table A.3
Production function estimations by sector.

	1	2	3	4	5	6	7	8	9
ln(non-R&D employees)	0.648***	0.786***	0.738***	1.042***	0.863***	1.122***	0.904***	0.863***	0.721***
	(0.019)	(0.060)	(0.027)	(0.020)	(0.041)	(0.051)	(0.012)	(0.064)	(0.010)
ln(research expenditures)	0.056***	0.106***	−0.065**	−0.029	−0.017	0.056	0.048*	0.012	0.080***
	(0.012)	(0.025)	(0.026)	(0.037)	(0.051)	(0.039)	(0.027)	(0.040)	(0.018)
ln(development expenditures)	0.034	0.030	−0.015	−0.039	−0.039	0.069	0.012	−0.004	0.022*
	(0.025)	(0.026)	(0.022)	(0.037)	(0.029)	(0.123)	(0.027)	(0.042)	(0.011)
ln(fixed assets)	0.199***	0.114	0.123***	0.083***	0.262***	−0.037	0.165***	0.203***	0.180***
	(0.040)	(0.075)	(0.019)	(0.028)	(0.032)	(0.042)	(0.053)	(0.040)	(0.037)
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Observations	819	535	279	338	503	183	575	1171	888
	10	11	12	13	14	15	16	17	
ln(non-R&D employees)	0.447***	0.736***	0.884***	0.517***	0.900***	0.793***	0.878***	1.024***	
	(0.029)	(0.018)	(0.017)	(0.045)	(0.010)	(0.049)	(0.027)	(0.047)	
ln(research expenditures)	0.140***	0.018	0.001	0.190***	0.044***	0.129**	0.075***	0.003	
	(0.019)	(0.014)	(0.016)	(0.039)	(0.014)	(0.061)	(0.022)	(0.112)	
ln(development expenditures)	0.090***	−0.018	0.074***	0.020	0.014	0.050**	0.015	0.022	
	(0.018)	(0.027)	(0.009)	(0.034)	(0.011)	(0.023)	(0.015)	(0.082)	
ln(fixed assets)	0.183***	0.203***	0.189***	0.327***	0.123***	0.192***	0.113***	0.126*	
	(0.031)	(0.023)	(0.046)	(0.046)	(0.015)	(0.021)	(0.021)	(0.075)	
Year FE	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes	
Observations	436	529	861	211	3105	2542	1410	208	

Bootstrapped standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

Table A.4
Panel estimations of TFP on D-share.

	OLS FE	GLS RE	GLS RE	GLS RE	GLS RE	GMM
D-share $_{t-2}$	−0.264*	−0.146	−0.165*	−0.259***	−0.138	−3.944***
	(0.136)	(0.100)	(0.088)	(0.083)	(0.101)	(0.867)
ln(employees)	−0.378**	−0.055***	−0.046***	−0.042***	−0.056***	−0.426*
	(0.161)	(0.016)	(0.012)	(0.007)	(0.015)	(0.219)
D-share $_{t-2}$ × ln(employees)	0.053*	0.027	0.031	0.038***	0.024	0.616***
	(0.029)	(0.025)	(0.023)	(0.014)	(0.026)	(0.161)
ln(age)	−0.120	0.349*	0.176	0.172	0.334*	−16.623*
	(0.576)	(0.184)	(0.133)	(0.144)	(0.187)	(9.548)
ln(age) × ln(age)	0.081	−0.045*	−0.020	−0.022	−0.044*	2.559*
	(0.123)	(0.025)	(0.019)	(0.019)	(0.026)	(1.415)
ln(external R&D)	0.010	0.011	0.010	0.013*	0.011	0.013
	(0.013)	(0.010)	(0.009)	(0.007)	(0.010)	(0.095)
Patent stock	−0.000	−0.000	−0.000	0.000	−0.000	0.005**
	(0.001)	(0.000)	(0.000)	(0.001)	(0.000)	(0.002)
Working capital ratio⋆	−0.000	0.000	0.000	0.000***	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
Long-term debt ratio⋆	0.000***	0.000***	0.000***	0.000*	0.000***	−0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Short-term debt ratio⋆	−0.000*	0.000	0.000	0.000	0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.001)
Enterprise group dummy	−0.063	0.055	0.044	0.041	0.056	−0.255
	(0.052)	(0.047)	(0.039)	(0.026)	(0.041)	(0.303)
TFP ACF_{t-2}			0.242***	0.206***		0.081
			(0.025)	(0.063)		(0.077)
TFP ACF_{t-3}				0.106*		−0.026
				(0.060)		(0.061)
Sector FE	Yes	Yes	Yes	Yes	No	No
Year FE	Yes	Yes	Yes	Yes	No	No
Arellano-Bond AR(2)						−1.93
						$Pr > z = 0.054$
Hansen $[\chi^2(102)]$						3.77
						$Pr > \chi^2 = 1.0$
Observations	4847	4847	4840	3379	4847	3379

⋆Ratio uses fixed assets in the denominator. All values are rounded; 0.000 indicates a value of < 0.001.
Cluster-robust standard errors in parentheses.
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.010$

References

Ackerberg, D.A., Caves, K., Frazer, G., 2015. Identification properties of recent production function estimators. Econometrica 83 (6), 2411–2451. doi:10.3982/ecta13408.

Acs, Z.J., Audretsch, D.B., 1987. Innovation, market structure, and firm size. Rev. Econ. Stat. 69 (4), 567–574. doi:10.1186/1479-5868-10-22.

Arora, A., Belenzon, S., Patacconi, A., 2018. The decline of science in corporate r&D. Strategic Manage. J. 39 (1), 3–32. doi:10.1002/smj.2693.

Arora, A., Belenzon, S., Sheer, L., 2017. Back to Basics: Why Do Firms Invest in Research? NBER Working Paper Series 23187.

Arora, A., Fosfuri, A., Gambardella, A., 2001. Markets for Technology: The Economics of Innovation and Corporate Strategy. MIT Press, Cambridge.

Arora, A., Gambardella, A., 2010. The market for technology. In: Hall, B.H., Rosenberg, N. (Eds.), Handbook of the Economics of Innovation, Vol. 1. Elsevier B.V., Amsterdam, pp. 641–678. doi:10.1016/S0169-7218(10)01015-4. chapter 15.

Arora, A., Gambardella, A., Magazzini, L., Pammolli, F., 2009. A breath of fresh air? Firm type, scale, scope, and selection effects in drug development. Manage. Sci. 55 (10), 1638–1653. doi:10.1287/mnsc.1090.1055.

Arrow, K.J., 1993. Innovation in large and small firms. J. Small Bus. Finance 2 (2), 111–124.

Audretsch, D.B., Stephan, P.E., 1996. Company-scientist locational links: the case of biotechnology. Am. Econ. Rev. 86 (3), 641–652. doi:10.4337/9781786432797.00019.

Barge-Gil, A., López, A., 2015. R versus D: estimating the differentiated effect of research and development on innovation results. Ind. Corp. Change 24 (1), 93–129. doi:10.1093/icc/dtu002.

Baumol, W.J., 2002. Entrepreneurship, innovation and growth: the David-Goliath symbiosis. J. Entrepreneurial Finance 7 (2), 1–10. http://digitalcommons.pepperdine.edu/jef%5Cn http://digitalcommons.pepperdine.edu/jef/vol7/iss2/2.

Belenzon, S., Patacconi, A., 2014. How does firm size moderate firms' ability to benefit from invention? Evidence from patents and scientific publications. Eur. Manage. Rev. 11 (1), 21–45. doi:10.1111/emre.12021.

Bloom, N., Jones, C.I., Reenen, J.V., Webb, M., 2020. Are ideas getting harder to find? Am. Econ. Rev. 110 (4), 1104–1144. doi:10.1257/aer.20180338.

Byrski, D., Gaessler, F., Higgins, M.J., 2021. Market Size and Research: Evidence from the Pharmaceutical Industry. NBER Working Paper Series 28858.

Cassiman, B., Pérez-Castrillo, D., Veugelers, R., 2002. Endogenizing know-how flows through the nature of R&D investments. Int. J. Ind Organiz 20 (6), 775–799. doi:10.1016/S0167-7187(01)00084-4.

Chamberlain, G., 1982. Multivariate regression models for panel data. J. Econom. 18 (1), 5–46. doi:10.1016/0304-4076(82)90094-X.

Cohen, W.M., Klepper, S., 1996. A reprise of size and R&D. Econ. J. 106 (437), 925–951. https://www.jstor.org/stable/2235365?seq=1

Cohen, W.M., Klepper, S., 1996. Firm size and the nature of innovation within industries: the case of process and product R&D. Rev. Econ. Stat. 78 (2), 232–243. https://www.jstor.org/stable/2109925?origin=crossref.

Cohen, W.M., Levinthal, D.A., 1989. Innovation and learning: the two faces of R&D. Econ. J. 99 (397), 569–596. doi:10.2307/2233763.

Cohen, W.M., Levinthal, D.A., 1990. Absorptive capacity: a new perspective on learning and innovation. Adm. Sci. Q. 35 (1), 128–152. doi:10.2307/2393553.

Corsino, M., Espa, G., Micciolo, R., 2011. R&D, firm size and incremental product innovation. Econ. Innov. New Technol. 20 (5), 423–443. doi:10.1080/10438599.2011.562354.

Czarnitzki, D., Hottenrott, H., 2011. Financial constraints: routine versus cutting edge R&D investment. J. Econ. Manage. Strategy 20 (1), 121–157. doi:10.1111/j.1530-9134.2010.00285.x.

Czarnitzki, D., Hottenrott, H., 2011. R&D investment and financing of small and medium-sized firms. Small Bus. Econ. 36 (1), 65–83. doi:10.1007/s11187-009-9189-3.

Czarnitzki, D., Hottenrott, H., Thorwarth, S., 2011. Industrial research versus development investment: the implications of financial constraints. Cambridge J. Econ. 35 (3), 527–544. doi:10.1093/cje/beq038.

Czarnitzki, D., Kraft, K., Thorwarth, S., 2009. The knowledge production of 'R' and 'D'. Econ. Lett. 105 (1), 141–143. doi:10.1016/j.econlet.2009.06.020.

Czarnitzki, D., Thorwarth, S., 2012. Productivity effects of basic research in low-tech and high-tech industries. Res. Policy 41 (9), 1555–1564. doi:10.1016/j.respol.2012.04.009.

Danzon, P.M., Nicholson, S., Pereira, N.S., 2005. Productivity in pharmaceutical biotechnology R&D: the role of experience and alliances. J. Health Econ. 24 (2), 317–339. doi:10.1016/j.jhealeco.2004.09.006.

David, P.A., Mowery, D., Steinmueller, W.E., 1992. Analysing the economic payoffs from basic research. Econ. Innov. New Technol. 2 (1), 73–90. doi:10.1080/10438599200000006.

De Loecker, J., Warzynski, F., 2012. Markups and firm-level export status. Am. Econ. Rev. 102 (6), 2437–2471. doi:10.1257/aer.102A2437.

Dhawan, R., 2001. Firm size and productivity differential: theory and evidence from a panel of US firms. J. Econ. Behav. Organ. 44 (3), 269–293. doi:10.1016/S0167-2681(00)00139-6.

Doraszelski, U., Jaumandreu, J., 2013. R&D and productivity: estimating endogenous productivity. Rev. Econ. Stud. 80 (4), 1338–1383. doi:10.1093/restud/rdt011.

Dorfman, R., Steiner, P.O., 1954. Optimal advertising and optimal quality. Am. Econ. Rev. 44 (5), 826–836. doi:10.1007/978-3-642-51565-1_53.

Fleming, L., Sorenson, O., 2004. Science as a map in technological search. Strategic Manage. J. 25 (89), 909–928. doi:10.1002/smj.384.

Fritsch, M., Meschede, M., 2001. Product innovation, process innovation, and size. Rev. Ind. Organ. 19 (3), 335–350. doi:10.1023/A:1011856020135.

Gambardella, A., 1992. Competitive advantages from in-house scientific research: the US pharmaceutical industry in the 1980s. Res. Policy 21 (5), 391–407. doi:10.1016/0048-7333(92)90001-K.

Gans, J.S., Hsu, D.H., Stern, S., 2002. When does start-up innovation spur the gale of creative destruction? Rand J. Econ. 33 (4), 571–586. doi:10.2307/3087475.

Gans, J.S., Stern, S., 2003. The product market and the market for "ideas": commercialization strategies for technology entrepreneurs. Res. Policy 32 (2), 333–350. http://www.mbs.edu/home/jgans/research.htm.

Grabowski, H.G., 1970. Demand shifting, optimal firm growth, and rule-of-thumb decision making. Q. J. Econ. 84 (2), 217. doi:10.2307/1883010.

Griliches, Z., 1980. R&D and the productivity slowdown. Am. Econ. Rev. 70 (2), 343–348. doi:10.2307/1815495.

Griliches, Z., 1985. Productivity, R&D, and Basic Research at the Firm Level in the 1970s. NBER Working Paper Series 1547.

Griliches, Z., 1987. R&D and productivity: measurement issues and econometric results. Science 237 (4810), 31–35. doi:10.1126/science.237.4810.31.

Griliches, Z., Mairesse, J., 1984. Productivity and R&D at the firm level. In: Griliches, Z. (Ed.), R&D, Patents, and Productivity. University of Chicago Press.

Griliches, Z., Mairesse, J., 1998. Econometrics and Economic Theory in the 20th Century. Cambridge University Press, Cambridge.

Henderson, R.M., 1990. Underinvestment and Incompetence as Responses to Radical Innovation: Evidence from the Photolithographic Alignment Equipemnt Industry. Working Paper Alfred P. Sloan School of Management 3163-90. https://doi.org/10.1016/j.cirp.2016.06.001.

Henderson, R.M., Cockburn, I., 1996. Scale, scope, and spillovers: the determinants of research productivity in drug discovery. Rand J. Econ. 27 (1), 32–59. doi:10.2307/2555791.

Hicks, D., 1995. Published papers, tacit competencies and corporate management of the public/private character of knowledge. Ind. Corp. Change 4 (2), 401–424. doi:10.1093/icc/4.2.401.

Hottenrott, H., Hall, B.H., Czarnitzki, D., 2016. Patents as quality signals? The implications for financing constraints on R&D. Econ. Innov. New Technol. 25 (3), 197–217. doi:10.1080/10438599.2015.1076200.

Hottenrott, H., Lopes-Bento, C., Veugelers, R., 2017. Direct and cross scheme effects in a research and development subsidy program. Res. Policy 46 (6), 1118–1132. doi:10.1016/J.RESPOL.2017.04.004.

Kline, S.J., Rosenberg, N., 2009. An overview of innovation. In: Rosenberg, N. (Ed.), Studies on Science and the Innovation Process:Selected Works of Nathan Rosenberg. World Scientific Publishing Co., pp. 173–203. doi:10.1142/9789814273596_0009. chapter 9.

Lee, J., Berente, N., 2012. Digital innovation and the division of innovative labor: digital controls in the automotive industry. Organ. Sci. 23 (5), 1428–1447. doi:10.1287/orsc.1110.0707.

Levinsohn, J., Petrin, A., 2003. Estimating production funct using inputs to control for unobservables. Rev. Econ. Stud. 70 (2), 317–341. https://about.jstor.org/terms

Levy, H., 2011. The transformation of basic research into commercial value: economics aspects and practical issues. J. Entrepreneurship Manage. Innov. (7) 4–15. https://papers.ssrn.com/sol3/papers.cfm?abstract_id=2010577.

Macher, J.T., Boerner, C.S., 2006. Experience and scale and scope economies: trade-offs and performance in development. Strategic Manage. J. 27 (9), 845–865. doi:10.1002/smj.540.

Mansfield, E., 1980. Basic research and productivity increase in manufacturing. Am. Econ. Rev. 70 (5), 863–873. doi:10.1158/0008-5472.CAN-06-0356.

Mansfield, E., Wagner, S., 1975. Organizational and strategic factors associated with probabilities of success in industrial R&D. J. Bus. 48 (2), 179. doi:10.1086/295734.

Martinez-Senra, A.I., Quintas, M.A., Sartal, A., Vazquez, X.H., 2015. How can firms' basic research turn into product innovation? The role of absorptive capacity and industry appropriability. IEEE Trans. Eng. Manage. 62 (2), 205–216. doi:10.1109/TEM.2014.2386614.

Monteverde, K., 1995. Technical dialog as an incentive for vertical integration in the semiconductor industry. Manage. Sci. 41, 1624–1638. doi:10.2307/2632742.

Mundlak, Y., 1978. On the pooling of time series and cross section data. Econometrica 46 (1), 69–85. https://about.jstor.org/terms.

OECD, 2015. Frascati Manual: Guidelines for Collecting and Reporting Data on Research and Experimental Development. Technical Report. http://oe.cd/frascati

Olley, G.S., Pakes, A., 1996. The dynamics of productivity in the telecommunications equipment industry. Econometrica 64 (6), 1263–1297. doi:10.2307/2171831.

Papke, L.E., Wooldridge, J.M., 1996. Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. J. Appl. Econom. 11 (6), 619–632. doi:10.1002/(SICI)1099-1255(199611)11:6<619::AID-JAE418>3.0.CO;2-1.

Pavitt, K., 1991. What makes basic research economically useful? Res. Policy 20 (2), 109–119. doi:10.1016/0048-7333(91)90074-Z.

Plehn-Dujowich, J.M., 2009. Firm size and types of innovation. Econ. Innov. New Technol. 18 (3), 205–223. doi:10.1080/10438590701785850.

Rammer, C., Schubert, T., 2018. Concentration on the few: mechanisms behind a falling share of innovative firms in Germany. Res Policy 47 (2), 379–389. doi:10.1016/j.respol.2017.12.002.

Romer, P.M., 1990. Endogenous technological change. J. Polit. Economy 98 (5, Part 2), 71–102. https://www.jstor.org/stable/2937632?seq=1

Rosenberg, N., 1989. Why do firms do basic research (with their own money)? Res Policy 19 (2), 165–174. https://www.worldscientific.com/doi/abs/10.1142/9789814273596_0011

Rothaermel, F.T., Hill, C.W.L., 2005. Technological discontinuities and complementary assets: a longitudinal study of industry and firm performance. Organ. Sci. 16 (1), 52–70. doi:10.2307/25145948.

Schumpeter, J.A., 1942. Capitalism, Socialism, and Democracy. Routledge, New York. https://eet.pixel-online.org/files/etranslation/original/Schumpeter, Capitalism, Socialism and Democracy.pdf.

Stern, S., 2004. Do scientists pay to be scientists? Manage. Sci. 50 (6), 835–853. doi:10.2307/30046122.

Teece, D.J., 2010. Technological innovation and the theory of the firm: the role of enterprise-level knowledge, complementarities, and (dynamic) capabilities. In: Hall, B.H., Rosenberg, N. (Eds.), Handbook of the Economics of Innovation, Vol. 1. Elsevier B.V., Amsterdam, pp. 679–730. doi:10.1016/S0169-7218(10)01016-6. chapter 16

Williamson, O.E., 1971. The vertical integration of production: market failure considerations. Am. Econ. Rev. 61 (2), 112–123. doi:10.2307/1816983.

Wooldridge, J., 2010. Econometric Analysis of Cross Section and Panel Data, second ed. MIT Press.

Wooldridge, J.M., 2019. Correlated random effects models with unbalanced panels. J. Econom. 211 (1), 137–150. doi:10.1016/j.jeconom.2018.12.010.

Yin, X., Zuscovitch, E., 1998. Is firm size conducive to R&D choice? A strategic analysis of product and process innovations. J. Econ. Behav. Organ. 35 (2), 243–262. doi:10.1016/s0167-2681(98)00057-2.