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The effect of technological relatedness on firm sales evolution through external knowledge sourcing

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Abstract

This paper analyzes the impact of knowledge spillovers on firm performance measured through total sales, the percentage of innovative sales and a categorical variable that classifies firms into three different groups depending on the stage of their sales growth evolution: upturn, downturn, or transition. We specifically focus on whether there are asymmetric spillover effects depending on the intermediary role of firms' technological relatedness, which we proxy by the use of external sources of knowledge. Using data on 5900 Spanish firms for the period 2004–2016, we find that spillover effects from intra-sector and upstream knowledge pools are—in general—positive, although with some differences depending on the measure of firm performance and on the moderating role of technological networking. Our results also suggest the presence of a "business stealing effect" in environments with a high proportion of knowledge-based gross added value. Furthermore, we find that spillover effects are asymmetric depending on the firm's size and intensity of R&D employment. Knowledge spillovers seem to play a more significant role in the case of SMEs than in large companies, and firms with high intensities of R&D employment benefit more from upstream spillovers and less from horizontal spillovers than firms with low intensities.

Keywords Asymmetric knowledge spillovers · Technological relatedness · Firm sales evolution · Cooperation in R&D · R&D providers · Tacitness of knowledge

JEL Classification L24 · L25 · O33 · R11

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1 Introduction

The literature on evolutionary economics, innovation systems and knowledge spillovers argues that the effect of such spillovers on the evolution of firms depends on technological relatedness. Specifically, it depends on the sharing of complementary technological experiences and knowledge bases between organizations (Boschma & Frenken, 2009), and on the suitability of the existing knowledge pool for firms' needs. As knowledge spillovers are conditioned by firms' absorptive capacity (their technical capabilities, business management and entrepreneurial insights) and their interaction with external agents, spillover effects are expected to be asymmetric.

The rich empirical literature on relatedness indicators has studied knowledge spillover effects on growth, productivity and knowledge generation mainly with regional or sectoral data (see, for instance, Frenken et al., 2007; Neffke et al., 2011; Boschma & Iammarino, 2015; Balland et al., 2019).[1] The objective of this paper is to contribute to this literature by analyzing the effect of external knowledge sourcing on the dynamics of firms' performance in terms of sales after controlling for the aggregate economic cycle. In our model, external knowledge sourcing through cooperation or outsourcing occupies the place of technological relatedness as moderator of knowledge spillovers.

The novelty of our paper is threefold. First, we analyze whether there are asymmetric knowledge spillover effects depending on the joint role played by firms' absorption capacity and use of external sources of knowledge through cooperation or outsourcing. Where knowledge becomes more tacit, hybrid forms of technological activities—like cooperation in R&D—are more important because they allow firms to better internalize external knowledge (Dumont & Meeusen, 2000). Tojeiro-Rivero and Moreno (2019) provide evidence that the knowledge endowment of the region influences the returns of firms' networking activities (technological cooperation agreements and R&D outsourcing) in terms of innovation performance. In order to shed some additional light on this subject, we also consider that the effects on firms' performance may differ between national and international external knowledge sourcing.

Second, although many recent papers have studied the impact of regional or sectoral spillovers on firms' productivity or innovation performance (see, among others, López-García & Montero, 2011; Carreira & Lopes, 2018; Tojeiro-Rivero & Moreno, 2019; Audretsch & Belitski, 2020), we focus on the effects on a firm's sales, which has been less analyzed in the literature (Cappelli et al., 2014; Choi & Williams, 2014; Goya et al., 2016; Grillitsch & Nilsson, 2017). Our specific contribution is that we also consider that knowledge spillover effects may be different in the different stages of a company's evolution in terms of sales. This allows us to analyze whether such spillovers could favor the firms in maintaining their good results or help them recover their sales in bad times. In addition, we focus on knowledge spillover effects on the part of the sales associated with the introduction of new-to-the-firm or new-to-the-market products. This analysis could not be undertaken with data on productivity, as this is an indicator of the global performance of the firm.

Finally, we use several measures of knowledge pools that capture different channels of knowledge transmission. Among them, we include a measure of the relative economic value of knowledge in the region-sector. This indicator is based on the decomposition of the gross

[1] See Whittle and Kogler (2020) for a survey of the literature on technological relatedness.

value added in each sector and region, isolating the part directly related to all the inputs that incorporate knowledge in the production process. As we explain in more detail in the following sections, the advantage of this indicator is that it takes into account the market value of the inputs based not only on codified knowledge but also on tacit knowledge. Therefore, it can also be used to control for the "tacitness" of knowledge in the firm's neighboring context.

For our analysis, we combine firm-level data with sectoral and regional data for Spain. Firm- level data for the period 2004–2016 come from the Panel of Technological Innovation (PITEC), which contains varied information about Spanish firms' technological activities. In particular, the PITEC includes detailed information about a firm's different partners for technological cooperation and providers of R&D services. With this information, we develop firm-level measures of absorptive capacity and domestic and foreign external knowledge sourcing.

Firm-level information has been complemented with sector- and regional-level indicators that measure knowledge pools. A first group of sector-level indicators is computed from the data on trade flows of intermediate and investment goods reflected in national input–output tables. Such trade flows within the value chain imply a transfer of "embodied knowledge" and therefore are related to inter-sectoral spillovers. As in other studies (Hauknes & Knell, 2009; Medda & Piga, 2014; Goya et al., 2016; Audretsch & Belitski, 2020), we use sectoral R&D expenditures to weight inter-sectoral trade flows. Secondly, from the database of the Valencian Institute of Economic Research, we take the knowledge-based gross value added in Spain. This represents the market value of the inputs that incorporate knowledge into the production process and which is available at a regional level with a sectoral breakdown of 21 sectors according to the NACE Rev-2 for the period 2000–2013. Our final sample consists of an unbalanced panel of 47,575 observations. This panel structure permits us to treat potential selection issues and endogeneity problems.

As expected from evolutionary economic geography (Boschma & Frenken, 2007, 2009; Boschma & Martin, 2010), our results suggest that technological spillover effects on firms' evolution are heterogeneous. First, knowledge spillovers from upstream and intra-sectoral knowledge pools stimulate firm sales, increasing the probability of switching to an upturn stage of sales evolution. Second, horizontal spillover effects are greater the more the firm uses domestic knowledge sourcing. This qualifying effect of domestic technological linkages is especially relevant for increasing the share of innovative sales. Third, foreign knowledge sourcing appears to favor only the part of the sales associated with the most radical innovations. Fourth, the intensity of sectoral-regional knowledge-based value added has a counter-cyclical impact on firm sales, which might reflect the existence of a kind of business stealing effect. Finally, spillover effects also depend on firms' absorption capacities as low-tech firms benefit in general less from supplier-based spillovers than high-tech firms.

The outline of the paper is as follows. Section 2 provides the theoretical framework. Section 3 presents the databases and the main variables used for our analysis. In Sect. 4, we describe the empirical model. In Sect. 5, we summarize the main results. Finally, in Sect. 6, we offer some conclusions and final remarks.

2 The measure of knowledge spillover effects on firm performance

The analysis of spillover effects is crucial for understanding the diffusion of knowledge, and also for explaining how a firm's performance evolves over time. Spillover effects arise because of the "public good" nature of innovations, which prevents the full appropriability of their benefits (Arrow, 1962). Therefore, part of the innovative effort of a firm may be profitable for other firms. From the point of view of the firm that receives the spillover, its gains will depend on whether this new knowledge is used for product and/or process innovations. In the case of product innovations, which are related to demand-increasing strategies, profits will be larger the more inelastic demand is, because inelastic demand may amplify the gains from a rightward shift in the demand curve (Spence, 1975). The introduction of process innovations, associated mainly with cost-reducing strategies, will be reflected in productivity improvements that will turn into higher profits the more elastic the demand is (Kamien & Schwartz, 1970). In fact, many empirical studies about the impact of knowledge spillovers on firm performance follow a production function approach that relates R&D to factor productivity (Wieser, 2005). Unfortunately, in most analyses, as Wieser (2005) points out in his review of the empirical evidence on R&D productivity and spillovers at the firm level, data restrictions prevent adequate differentiation between process and product R&D.

In addition to the problem mentioned above, some other challenges appear when we want to measure spillover effects specifically on a firm's sales dynamics. In a market already saturated with dominant designs, productivity improvements associated with process innovations may help reduce prices, making the product more competitive, but not necessarily increase firm sales. On the other hand, horizontal knowledge spillovers may have a non-significant or even negative effect on a firm's performance if there is a "business stealing effect" based on product rivalry. If rival competitors invest heavily in R&D, it may happen that, despite the increasing sectoral knowledge pool, the focal firms suffer a business stealing effect (Bloom et al., 2013; Goya et al., 2016; Hall et al., 2009). As Hall et al. (2009) state, this business stealing "happens when new products render old products obsolete (creative destruction) and/or are used as a mere strategy to preempt competition or when patent races lead to duplicative R&D" (Hall et al., 2009, p. 28). Such a business stealing effect has been detected especially in emerging markets and in high-tech sectors where the introduction of new products is an important commercial strategy (Goya et al., 2016). Firms in these sectors usually protect their innovations through patents and the continuous introductions of incremental innovations. These strategies decrease the level of outgoing spillover towards competitors. In particular, the duplication of R&D costs would make it difficult for smaller firms to keep the pace of a patent race.

In this regard, the literature distinguishes between "imitation enhancing knowledge spillovers" and "idea creation spillovers." In the first case, firms try to copy or imitate existing technologies, introducing very similar products or services that compete directly with existing ones, while in the second case, firms develop new technologies that imply radical or incremental improvements (Los, 2000). This differentiation is important also because less cognitive knowledge may be required in order to introduce marginally improved products, while the development of radical innovations requires not only higher technological or cognitive capabilities, but also better commercial and entrepreneurial insights. From an empirical point of view, these different effects may be reflected in the firm's sales from new-to-the-firm or new-to-the-market product innovations, which are usually associated with incremental and radical innovations, respectively. However, the effects are difficult to dissociate when firms introduce both types of innovations simultaneously. In this context, the use of information about firm sales and, specifically, the share of sales that corresponds to new-to-the-firm or new-to-the-market product innovations represent an advantage over productivity data that reflect the performance of the company from a global perspective.

The measure of the effects of knowledge spillovers on a firm's performance is also complex because knowledge transmission mechanisms are very broad (worker mobility, technological cooperation, outsourcing, trade related embodied and disembodied knowledge transfers, etc.), and the different dimensions are difficult to disentangle in empirical analyses. For instance, Griliches (1979) distinguishes two ways to channel the effects of a firm's knowledge to the rest of the production structure: rent and knowledge spillovers. Pure knowledge spillovers may consist of non-market transfers of knowledge that will be used for free by other agents in order to enhance their innovative capacity to improve their efficiency, effectivity and speed of technological progress. Griliches emphasizes that such spillovers should be separated from pure rent spillovers in which the receiving firms absorb part of the added value or benefits of an innovation purchased on the market for a price below its market value. However, as stated by Hall et al. (2009), "in practice the two types of spillover are hard to dissociate, because, on the one hand, knowledge flows are often concomitant with user-producer transactions and the capture of rents, and on the other hand, knowledge gains can be used to reap economic rents" (Hall et al., 2009, p. 28). In addition, internal R&D is basically financed with a firm's own funds (Hall & Lerner, 2010; Spielkamp & Rammer, 2009). Therefore, rent spillovers could be used to raise the R&D efforts of the focal firm, and such an indirect effect may be considered a knowledge spillover. This interaction between both types of spillovers makes it difficult to quantify their separate effects in empirical analyses.

An additional problem is associated with the concept and measurement of "available knowledge pool," i.e., the absolute amount of publicly available knowledge in the innovation system where the firm operates. Although the potential of the knowledge pool should be equal for all agents in the innovation system, in practice, not all firms have the same possibility to take advantage of the opportunities offered by the pool. The literature recognizes two main drivers for the creation of spillovers. The first one is the suitability of the knowledge pool for the needs of the firm, which also depends on technological relatedness. The second one is the firm's absorption capability, which is associated with its technical, business management and entrepreneurial competences.

Regarding technological relatedness, innovative efforts made by companies are available to other firms only to the extent that these firms are technologically close enough to recognize and understand the outside opportunities. As Boschma (2005) and Nooteboom et al. (2007) remark, the firm needs sufficient distance to assure the existence of complementary novel knowledge, but also requires a certain proximity in order to understand the incoming external knowledge. On the one hand, pure knowledge spillovers based on knowledge with a strong tacit character often require geographical proximity (Audretsch, 1998; Audretsch & Feldman, 1996; Boschma, 2005; Jaffe, 1986). However, this is less important in the case of spillovers from technologies based on codified information with a strong "public good" character. The fact that the diffusion of complex cognitive knowledge is regionally bounded (Howells, 2002; Jaffe, 1986) implies that the direct business environment is an important determinant for incoming spillovers and should be taken into account in empirical studies.

On the one hand, the final intensity of existing spillovers will depend on the firm's proximity in terms of cognitive capacity (Boschma, 2005; Nooteboom, 2000), industrial activity (Neffke et al., 2011) or skilled employment (Neffke & Henning, 2013), which may be strongly interconnected with the firm's networking scope and intensity. The basic principle behind the concept of technological relatedness is that new knowledge will generate synergies only if complementarities exist between the knowledge of different agents, allowing its recombination in new products or other types of innovation for which a (latent) demand exists. These complementarities frequently materialize in the form of agreements with other agents to obtain external knowledge through cooperation or outsourcing. Such a mutual learning process will be generated only if firms offer useful technological knowledge to each other. This "matching" process of reciprocal demand and supply of knowledge implies a certain level of technological relatedness (Angue et al., 2014; Martínez Ardila et al., 2020).

Firms that have a broad scope of external knowledge sources—cooperating continuously or interacting with a broad number of agents—are more involved in searching for external ideas and technologies (Chiang & Hung, 2010; Flor et al., 2018). Firms may enhance the absorption of technological spillovers through cooperation because they are able to obtain crucial resources, information and ideas for products and services (Chapman et al., 2018; Nieto & Rodríguez, 2011). In this line, the number of partners acquires an important dimension, since a wide range of partners could facilitate the complementarity of knowledge and lead to better innovative results. In addition, the presence of scale economies might force cooperation in order to obtain the resources necessary to undertake innovative projects.

Moreover, interacting with very different kinds of agents—each with its own technical and entrepreneurial insights and view of the direct context—implies a symbiosis of spillovers coming from different sources. External knowledge can enter the focal firm through the concurrency of spillovers that reach cooperation partners or R&D providers. These agents may be acting as eye-openers. External knowledge sourcing may also facilitate the use of more advanced technologies without incurring the high indivisible costs derived from them. These knowledge-based links imply not only direct access to external knowledge but also a learning and accumulation of experience, which enhances the firm's absorption capability (Ferreras-Méndez et al., 2015; Flor et al., 2018).

This might be especially relevant in the case of technological cooperation, which is often based on a long-standing relationship built on mutual trust (Enkel et al., 2018). As Ter Wal and Boschma (2011) point out, when firms engage in cooperative activity, collective economies, which are external to the firm but internal to the network, require the active involvement of firms. This set of relational linkages in regionally and institutionally embedded networks would be at the core of regional innovation systems.

Based on these arguments, we propose the following hypotheses:

Hypothesis 1 Positive spillovers from intra-sectoral knowledge pools on firm sales will be greater the higher the use of external knowledge sourcing is (1a), especially on sales associated with radical innovations (1b).

Hypothesis 2 The greater the firm scope of external knowledge sourcing is, the higher its probability of favorable sales evolution based on incoming spillovers.

Previous empirical studies on knowledge spillover effects relate a firm's absorption capacity mainly to the firm's innovation effort, although another essential aspect is the role of entrepreneurial insight and creativity (Audretsch & Caiazza, 2016; Cohen & Levinthal, 1990; Griliches, 1979). The most innovative firms of each sector learn more and faster from their R&D projects, therefore increasing their cognitive, organizational and technical capabilities (Heijs, 2004, 2012). In addition, firms with high intensities of R&D employment may have better or more appropriate cognitive capabilities to fish in their specific knowledge pools, while firms with low intensities may have a greater need to assimilate external knowledge, but also fewer capabilities to take advantage of knowledge pools.

Furthermore, firm absorption capacity implies not only cognitive capabilities and the ability to identify novel external knowledge, but also commercial insights about the relevance of new knowledge to satisfying existing demands and especially opportunities for non-obvious latent needs in the markets. As Agarwal et al. (2010) point out, spillovers not only depend on the technical capacity to combine internal and external knowledge, although a key element is the identification of new business opportunities in already existing knowledge combined with the firm capabilities. Spillovers also depend on the recognition of new market opportunities to make money out of knowledge by new combinations. In fact, the knowledge spillover theory of entrepreneurship considers firm creation an endogenous process in response to the availability of unused knowledge (Audretsch & Lehman, 2006). According to Lane et al. (2006), "the notion of the absorption capabilities has been extended to business management related knowledge, including managerial techniques, marketing expertise and manufacturing know-how." (Lane et al., 2006, p. 37).

In this regard, the empirical literature suggests that large firms may have better management skills to detect, assimilate and commercialize external knowledge and have more occasions to use external knowledge because of their broader scope in terms of product lines (Goya et al., 2016; Penrose, 1959). Moreover, their assimilation of external knowledge will be relatively cheaper because of their critical mass and scope advantages (Kamien & Schwartz, 1982). However, SMEs may counteract the lack of these capacities through cooperative behavior which enables them to exploit collective economies of scale as a mechanism to gain access to business services, technology and capital on competitive terms (Oughton & Whittam, 1997).

Notice, in addition, that the capabilities required to turn knowledge into innovations and innovations into sales clearly differ for the introduction of new-to-the-firm or new-to-the-market products. Therefore, spillover effects—moderated by technical and business absorption capabilities—also would differ. In the case of new-to-the-market products, a first ability would be the entrepreneurial insight to identify the new business opportunities offered by incoming knowledge. Once the "new product" is identified, the firm requires the technological capability to develop it at an acceptable cost level, the managerial capability to design the production process and the marketing capability to successfully promote the innovation in the market (Agarwal et al., 2010; Audretsch & Lehmann, 2006, 2017). In this sense, interaction with other agents to obtain external knowledge may speed up innovation times and reduce production costs (Rodríguez et al., 2017; Audretsch & Belitsky, 2020). In the case of new-to-the-firm products, technological capabilities would be more relevant than entrepreneurial abilities because the firm imitates or innovates around existing technologies with an already established market.

Based on the foregoing information, we formulate the following hypothesis:

Hypothesis 3 The moderating role of external knowledge sourcing in intra-sectoral knowledge spillovers on the evolution of firm performance depends on the firm's absorption capacities.

On the other hand, the absorption of external knowledge may change dramatically with the level of "tacitness" of the relevant knowledge pool. As mentioned by the evolutionary theory on technological change, tacit knowledge is much more difficult to copy or imitate (Dosi & Nelson, 2010). In the case of codified information, absorption capability will be less relevant to assimilating external knowledge because spillovers spread more equally among firms and generate fewer comparative advantages. This is because codified information and tacit knowledge play different roles in the existence of knowledge spillovers. In traditional sectors often based largely on codified information, firms can more easily take advantage of the technologies developed by their competitors or suppliers. This will also be the case of sectors where tacit knowledge plays a minor role, markets are uncertain and financial risk is low because of the existence of a dominant design and standardized yardsticks. However, in sectors based on tacit knowledge, new knowledge will be more difficult to understand and innovation will be—in the absence of a dominant design—a highly risky activity.

Moreover, in environments with high levels of tacit knowledge, spillover effects for technological followers might be quite different from those for the leading innovative enterprises. The latter would tend to protect their core technologies by developing them basically through in-house R&D activities and would only outsource non-core activities that involve less technical and/or codified knowledge (Spithoven & Teirlinck, 2015). On the contrary, technological followers and imitators would try to screen all the agents of the innovation system to obtain access to knowledge of novel entrepreneurial ideas available in the knowledge pool.

As a consequence, incoming spillovers from regional environments with high levels of tacitness might be quite heterogeneous among firms. On the one hand, some firms might benefit from highly advanced technologies in order to complement their own technological lags. In this case, both highly innovative firms and highly innovative environments might complement each other and generate a self-reinforcing circle (Malmberg & Maskell, 2006; Nieto & Santamaria, 2010).

On the other hand, environments with large intensity of knowledge and, in particular, high levels of tacit knowledge may imply a greater degree of rivalry among firms through product innovation, in which only a small percentage of the firms succeed (Tojeiro-Rivero & Moreno, 2019). This may push firms to undertake riskier R&D activities that, if successful, may result in a higher proportion of radical innovations, as imitation would be more difficult and expensive. Therefore, we may expect firms in these environments to show a lower percentage of sales from incremental innovations in favor of an increase in the percentage of sales from radical innovations. Based on these arguments, we propose the following hypothesis:

Hypothesis 4 Firms located in environments with a relatively higher content of knowledge in value added will show a higher percentage of sales based on radical innovations (4a) and a lower percentage of sales based on incremental innovations (4b).

3 Data and variables

For our analysis, we combine firm-level data with sectoral and regional data for Spain. Firm- level data come from the Panel of Technological Innovation (*Panel de Innovación Tecnológica*, PITEC) for the period 2004–2016.[2] This database is constructed by the Spanish Institute of Statistics using the annual Spanish responses to the Community Innovation Survey. The PITEC includes representative samples of innovative Spanish firms from manufacturing and services sectors and offers data on some companies' economic variables and ample information about firms' technological activities. Although the PITEC includes

[2] The most recent data in the PITEC available for researchers correspond to the year 2016.

Scheme 1 Stages of a firm's change in sales (ΔY_i)

	$\Delta Y_{i,t-1} > 0$	$\Delta Y_{i,t-1} < 0$
$\Delta Y_{i,t} > 0$	Upturn	Transition
$\Delta Y_{i,t} < 0$	Transition	Downturn

a sample of firms without technological activities, for our study, we focus on innovatively active firms, that is, firms with positive innovation expenditures during the period.[3]

We complement this firm-level information with sector- and regional-level indicators of knowledge pools that are obtained from the database of the Valencian Institute of Economic Research (*Instituto Valenciano de Investigaciones Económicas*, IVIE) or elaborated from the information from national input–output tables. These indicators are described in detail in Subsect. 3.2.

After merging all data sources, our final sample consists of an unbalanced panel of 47,575 observations for the period 2004–2016. These observations correspond to innovative companies with at least four consecutive observations with complete information on all variables considered in our empirical models. The panel structure of our data allows us to treat potential selection issues and endogeneity problems.

In what follows, we describe the main variables that we use for the empirical analysis.

3.1 The dependent variables: evolution of a firm's economic performance

Given the information available in the PITEC, to characterize firms' performance, we focus on two different measures of economic performance: a firm's annual sales and the percentage of "innovative" sales, that is, the percentage of total sales associated specifically with the introduction of new products.[4]

In addition, with the information about the rate of change in the firm's total sales in 2 consecutive years, we define three stages in a firm's *sales evolution*: upturn, downturn and transition (see Scheme 1).[5]

Therefore, we consider that the firm may be in a stage of upturn if its economic performance has been increasing in the last 2 years, and that it may be in a stage of downturn if its economic performance has been decreasing in the last 2 years. The "transition" category may include the rest of the alternatives in the evolution of firms' performance.

As can be seen in Fig. 1, the percentage of firms in our sample in an upturn stage follows a pro-cyclical pattern when compared with the annual growth rate of Spanish GDP,

[3] In the PITEC, non-innovative active firms do not have to answer the whole questionnaire, and information about partners for technological cooperation is missing. In addition, only innovative firms declare the regional distribution of their R&D expenditures. We use the information about the region in which the firm undertakes the highest percentage of R&D expenditures to link the data from the PITEC with the regional-level indicators of knowledge pools that we take from other databases.

[4] We use Spanish GDP deflators to express all monetary variables in our database in euros in the year 2010.

[5] We have also tried with this variable to refer to 3 consecutive years, but the results do not differ substantially.

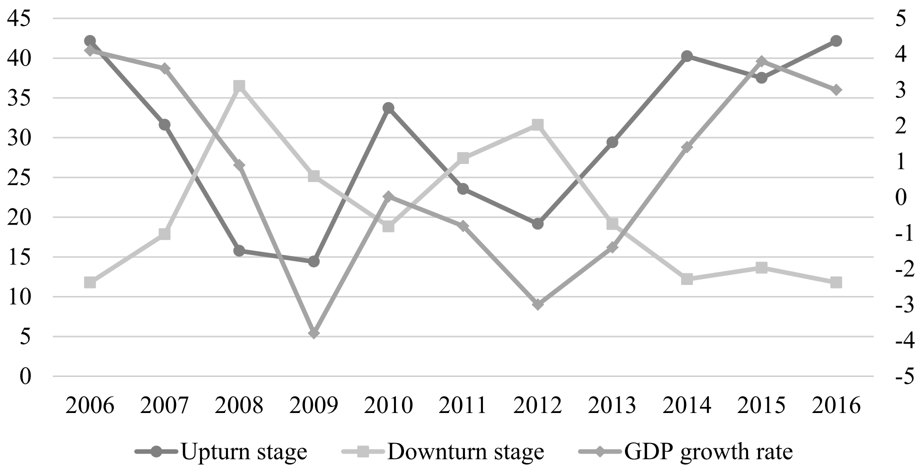

Fig. 1 Firm sales evolution and macroeconomic business cycle. On the left axis, we represent the percentage of firms in our sample in upturn or downturn stages, while on the right axis, we show the annual growth rate of Spanish GDP

while the opposite happens with the percentage of firms in a downturn stage.[6] However, it is remarkable that, even during recession years, there are still firms that show an upturn stage of their sales. As this countercyclical behavior of the performance of some companies might be associated with a different absorption capacity for external knowledge, one aspect that we examine in this paper is whether the dynamic of firm sales is affected by technological spillovers once we control for the aggregate economic cycle.

In the case of innovative sales, the information in the PITEC allows us to distinguish between sales due to new-to-the-firm products and sales due to new-to-the-market products. The most radical product innovations are supposed to be captured by new-to-the-market products. As explained in the previous section, knowledge spillover effects on firm sales are difficult to disentangle because these spillovers may affect the sales from mature or new products differently. This is also true for sales from new products related to radical or incremental product innovations. Having information about the share of sales that corresponds to the introduction of new-to-the firm and new-to-the market products may help us shed some light on this issue.

3.2 External knowledge sourcing and knowledge pools

As Whittle and Kogler (2020) explain in their review of the literature on technological relatedness, the construction of empirical measures of relatedness has usually been based on the hierarchy of industry classifications (Frenken et al., 2007), the notion of co-occurrence (Hidalgo et al., 2007) or the similarity of resources used between industries (Neffke & Henning, 2013). In the context of the knowledge space, most indicators of technological

[6] We can compute the stages of a firm's change in sales only from the year 2006. Notice that, for the construction of the stages in year *t*, we need information from year *t*-2 to *t*, and the first year of data in our sample period is 2004.

relatedness have a regional dimension and require detailed information on patent classes and citations (Balland et al., 2019).

Unfortunately, the data in the PITEC are anonymized, so firms cannot be identified. Therefore, we cannot link firm-level data with the information in patent databases.[7] In addition, measures of technological relatedness based on revealed comparative advantages are less representative when they refer to regions and sectors with a very low number of patents, which is the case of Spain (OECD, 2021). This will make these measures more unstable over time, because a new patent in a specific region-sector may drastically change the value of the indicator.

In the absence of this type of information in our database, we cannot introduce in our model a direct measure of technological relatedness in the knowledge space. Alternatively, we use two indicators of the intensity with which firms actively interact with domestic or foreign agents to obtain external knowledge. As Boschma and Frenken (2009) point out, relatedness and networks are strongly interconnected. Cognitive proximity affects the probability of networking, and networking in turn can increase technological relatedness between firms because of a learning process. External knowledge sourcing is a firm strategy with which firms intentionally look for the support of external agents for the identification, assimilation and conversion of new knowledge and related technologies when they are by themselves not aware of their existence or lack the capabilities for their integration within the firms' internal R&D activities.

Regarding sources of external knowledge, the PITEC offers information about which types of agents are cooperation partners or providers of R&D services. In particular, firms in the survey may choose six different types of partners for technological cooperation: (1) other firms within the business group; (2) suppliers of equipment, materials, components, or software; (3) clients or customers; (4) competitors or other enterprises in the same sector; (5) universities or other higher education institutions; and (6) consultants, commercial labs, or private or public R&D institutes. External suppliers of R&D services may be: (1) firms of the same group; (2) other firms outside the group; (3) research associations or technology centers; (4) public administration organizations; (5) private non-profit institutions; and (6) universities.

Based on these data, we develop two firm-level measures of the use of external knowledge sourcing (scope of networking). Specifically, as firms in the PITEC identify the external agents' domestic or foreign character, we define two separate indicators for *domestic knowledge sourcing* (*DomKSource*) and *foreign knowledge sourcing* (*ForKSource*). These indicators are computed, respectively, as the number of different domestic or foreign types of agents that interact with the firm for external sourcing relative to the maximum (six types of partners for technological cooperation plus six types of providers of R&D services). Therefore, each indicator takes values between 0 (no interaction with external agents) and 1 (the firm interacts with the twelve potential different types of external agents). We use these indicators as indirect proxies of the degrees of domestic and foreign technological relatedness. Compared with the usual measures of sectoral technological relatedness, the advantage of our proxies is that they have a firm-level dimension.

In addition, to capture the existence of knowledge spillovers, firm-level information from the PITEC has been combined with several sectoral- and regional-level indicators. In

[7] This would have allowed the measure of knowledge spillovers using, for example, patent citations (Jaffe et al., 1993; Thompson & Fox-Kean, 2005).

the construction of these indicators, we take into account that not all firms are able to benefit from the whole "knowledge pool" in the economy.

The ability to benefit from knowledge spillovers may be greater among firms that belong to the same industry and the same region. In this sense, using the information about R&D expenditures in the PITEC, we define the following measure of the intra-sectoral knowledge pool available in sector s for a firm i at year t:

$$IntraKPool_{is,t} = \sum_{\forall j \neq i} RD_{js,t},$$

where $RD_{js,t}$ denotes the R&D expenditures of firm j in sector s at time t.[8] This indicator is an unweighted sum, which in principle implies that all companies in the same region and sector benefit in the same way from the knowledge pool. However, in the empirical model, we interact this variable with our measure of domestic external sourcing, as we expect the spillovers from intra-sectoral knowledge pools to be higher for firms with a greater scope of domestic technological networking. In fact, we will test our Hypothesis 1 in this way.

In addition, firms can benefit from the knowledge generated in other sectors to the extent that they have links to those sectors. In particular, to capture the potential spillover effect from sectors that supply inputs to the firm (upstream links), we define a sector-level indicator from the data on trade flows of intermediate and investment goods reproduced in national input–output tables. Such trade flows within the value chain imply a transfer of "embodied knowledge" and therefore may be related to inter-sectoral spillovers. Specifically, as is usual in the literature, the indicator of the *upstream knowledge pool* is constructed as a weighted average of the R&D effort in all providing sectors:

$$UpstreamKPool_{is,t} = \sum_{\forall m \neq s} \sigma_{sm} RD_{m,t},$$

where σ_{sm} represents the share of purchases of inputs that industry s obtains from industry m and which are obtained from the symmetric input–output tables. Therefore, this measure reflects the relative importance that other sectors have as suppliers of knowledge-based inputs of sector s.

Finally, we also use the measure of *knowledge-based gross added value* (*KB-GVA*) provided by the *Instituto Valenciano de Investigaciones Económicas* (IVIE).[9] The IVIE estimates the value of knowledge-based economic activities in terms of the costs of the inputs that incorporate knowledge into the production process (skilled work, ICT, intangible assets and machinery and equipment) and calculates the relative importance of this value on the total gross added value in the same sector and region, which is our measure of interest. This relative indicator is available at a regional level with a sectoral breakdown of 21 sectors according to the NACE Rev-2 (see Table 8 in the Appendix) for the period 2000–2013.

Notice that, while our measures of *intra-sectoral* and *upstream knowledge pools* provide information on the magnitude of knowledge pools in each specific region-sector in terms of R&D expenditures, the relative *KB-GVA* indicates how much of the value added of the

[8] The correspondence between the sectoral breakdown in the PITEC and the NACE Rev.2 can be found in Table 7 of the Appendix.

[9] https://www.ivie.es/en_US/bases-de-datos/economia-del-conocimiento/valor-economico-del-conocimiento/.

Table 1 Descriptive statistics of main variables (2004–2016)

	Mean	Std. Dev	Min	Max
Measures of firms' economic performance				
Sales (log.)	16.09	2.13	0	23.39
% Sales from new-to-firm products (log.)	1.27	1.62	0	4.62
% Sales from new-to-market products (log.)	1.55	1.65	0	4.62
Stage in evolution of sales	0.59	0.78	0	2
Measures of external knowledge sourcing and knowledge pools				
DomKSource	0.13	0.16	0	1
ForKSource	0.04	0.09	0	0.92
IntraKPool (log.)	18.85	1.15	0	21.02
UpstreamKPool (log.)	18.36	2.74	0	20.89
KB-GVA	0.65	0.12	0	0.94
Other variables				
R&D employment (%)	2.51	6.14	0	100
Innovation intensity (log.)	8.41	1.57	0.77	14.91
Physical capital intensity (log.)	6.91	3.42	0	16.50
Age (log.)	2.98	0.78	0	5.74
Exporter (0/1)	0.64	0.48	0	1
Group (0/1)	0.43	0.50	0	1
Large firm (0/1)	0.23	0.42	0	1
No. Observations	47,575			

(0/1) denotes dummy variable. Spanish GDP deflators are used to express all monetary variables in euros in the year 2010

production in the region-sector remunerates the knowledge accumulated in the factors that contribute to that production. In this sense, we interpret the relative *KB-GVA* as a measure of the average intensity with which firms in the region-sector incorporate knowledge in the production.

One advantage of this indicator is that, as it takes into account the remunerations to the knowledge accumulated in all the factors (labor, capital and intermediate inputs) that contribute to the production, besides codified knowledge, it also captures the presence of tacit knowledge. As we explained in Sect. 2, knowledge spillovers may be partially geographically bounded, among other reasons because of the presence of tacit knowledge. Such tacit knowledge makes it difficult to transfer technologies more than an arm's length away and may also hinder their absorption even from agents nearby. Therefore, a higher presence of tacit knowledge in a region-sector could imply a more competitive and complex environment. In this sense, the introduction of the relative *KB-GVA* in our analysis is an indirect way to control also for knowledge "tacitness" in the firm's neighboring productive context (same region and sector).

Descriptive statistics and a pairwise correlation matrix of the measures of external knowledge sourcing and knowledge pools are displayed, respectively, in Tables 1 and 2. As can be seen in the tables, the average use of domestic knowledge sources in our sample roughly triples that of foreign sources, while the correlation coefficient shows a moderate positive relationship between both strategies of external sourcing. We will take this correlation into account when interpreting the results of our estimates. Regarding the measures

Table 2 Pairwise correlation matrix of main explanatory variables

		[1]	[2]	[3]	[4]	[5]	[6]	[7]	[8]	[9]	[10]	[12]	[11]
[1]	*IntraKPool* (log.)	1.000											
[2]	*UpstreamKPool* (log.)	**− 0.218**	1.000										
[3]	*KB-GVA*	**0.264**	**− 0.103**	1.000									
[4]	*DomKSource*	**0.123**	**− 0.107**	**0.034**	1.000								
[5]	*ForKSource*	**0.140**	**− 0.138**	**0.079**	**0.542**	1.000							
[6]	*R&D employment (%)*	**0.113**	**− 0.055**	**0.093**	**− 0.047**	**− 0.067**	1.000						
[7]	*Innovation intensity* (log.)	**0.290**	**− 0.185**	**0.159**	**0.267**	**0.215**	**0.341**	1.000					
[8]	*Physical capital intensity* (log.)	0.005	0.004	**− 0.088**	**0.140**	**0.129**	**− 0.095**	**0.121**	1.000				
[9]	*Age* (log.)	**− 0.124**	**0.021**	**− 0.090**	0.004	**0.036**	**− 0.292**	**− 0.270**	**0.028**	1.000			
[10]	*Exporter* (0/1)	− 0.005	**− 0.024**	**− 0.016**	**0.028**	**0.116**	**− 0.171**	**− 0.036**	**0.112**	**0.236**	1.000		
[11]	*Group* (0/1)	0.007	**0.030**	0.009	**0.189**	**0.199**	**− 0.199**	**− 0.095**	**0.123**	**0.144**	**0.122**	1.000	
[12]	*Large firm* (0/1)	**− 0.031**	**0.044**	**− 0.040**	**0.177**	**0.201**	**− 0.213**	**− 0.283**	**0.148**	**0.254**	**0.064**	**0.427**	1.000

(0/1) denotes dummy variable. In bold when the correlation is significantly different from zero at 99%

of knowledge pools, average sizes of intra-sectoral and upstream pools are quite similar. However, correlation coefficients between them, and with *KB-GVA*, are lower than 0.3 (in absolute value), which suggests that multicollinearity among them is not generating a significant bias in our estimates.

3.3 Other explanatory variables

As is common in the literature about the determinants of firm performance (Coad & Holzl, 2012), in our model we also consider some additional explanatory variables. We include *physical capital intensity*, measured as the logarithm of a firm's physical investment over employment, and *innovation intensity*, measured as the logarithm of a firm's innovation expenditures over employment. In addition, we take into account the *age* of the firm (number of years since creation) and whether the firm is *large* (with more than 200 employees), belongs to a business *group* or is an *exporter.* We also control for regional, sectoral and time dummies. With the inclusion of year-fixed effects, we account for the effect of the macroeconomic business cycle in our model.

Finally, to proxy firms' absorptive technological capabilities, we use the information in the PITEC about R&D employment. In particular, we classify firms as having low or high internal R&D resources depending on whether their percentage of R&D employment (over total employment) is below or above the median percentage of R&D employment in the same sector and year, respectively.

4 Empirical model

To quantify the impact of external knowledge sourcing and knowledge spillovers on the dynamics of firms' performance, we estimate three different models, one for each measure of economic performance depicted in Sect. 3. In the three cases, the empirical model is inspired by a production function framework in which productivity growth relates to firm R&D expenditures and R&D spillovers (Griliches, 1979; Wieser, 2005), although instead of using a measure of productivity growth, we focus on sales growth.

In the first model, in which the dependent variable is firms' sales, we estimate the following equation:

$$\begin{aligned} Sales_{i,t} = {} & \alpha_1\ UpstreamKPool_{is,t-1} + \alpha_2\ IntraKPool_{is,t-1} \\ & + \alpha_3\ IntraKPool_{is,t-1} DomKSource_{i,t-1} \\ & + \alpha_4\ ForKSource_{i,t-1} + \alpha_5\ KB{-}GAV_{rs,t-1} \\ & + \mathbf{X}_{i,t-1}\boldsymbol{\alpha} + \eta_t + \mu_i + \varepsilon_{i,t}, \end{aligned} \tag{1}$$

where *Sales* denotes total sales (in logarithms), $\boldsymbol{X}$ is a vector of other observable explanatory variables (time-variant and time-invariant variables) and η_t stands for year fixed effects that are included to control for the effect of the macroeconomic business cycle. The permanent unobserved heterogeneity is captured by μ_i. Finally, ε is an idiosyncratic error that refers to other unobservable time-variant determinants. Taking into account the panel nature of our database, we estimate the determinants of total sales (in logarithms) with a fixed effects linear model.[10]

In Eq. (1), estimated coefficients for intra-sectoral and inter-sectoral knowledge pools (α_1 and α_2) are supposed to be positive in case of positive spillovers. The estimation of coefficient α_3 will allow us to analyze whether there are asymmetric knowledge spillover effects on performance depending on the firm's technological relatedness in terms of its external domestic knowledge sourcing. A positive α_3 will give support to our Hypothesis 1. We also expect a positive coefficient for foreign knowledge sourcing under our Hypothesis 2.[11]

Secondly, we focus on analyzing whether the intensity of sectoral or regional knowledge spillovers is more relevant for firms that are—in terms of economic performance—in a stage of crisis or boom. As we explained in the previous section, we define three different stages in the evolution of a firm's performance: upturn, downturn and transition (between upturns and downturns). In this case, our empirical strategy consists of the estimation of the following multinomial logit model (Green, 1997):

$$\Pr(D_{i,t} = d) = \frac{\exp\left(Y_{i,t}^{d}\right)}{\sum_{r=1}^{3} \exp\left(Y_{j,t}^{r}\right)}, \quad d = 1\,(\text{transition}),\ 2\,(\text{upturn}),\ 3\,(\text{downturn}),$$

where

$$Y_{i,t}^{d} = \alpha_0 + \mathbf{Z}_{i,t-3}\alpha^{d}, \tag{2}$$

with the set of coefficients $\alpha^1 = 0$, so that the remaining coefficients α^2 and α^3 would measure the change relative to category 1 (transition). The vector of variables $\mathbf{Z}_i$ stands for all the factors that may explain the change among categories, and is also equivalent to the set of explanatory variables in Eq. (1), that is:

$$\mathbf{Z}_i = (UpstreamKPool_{is}, IntraKPool_{is}, IntraKPool_{is} \times DomKSource_i, ForKSource_i, KB{-}GAV_{rs}, \mathbf{X}_i, \eta)$$

Among these variables, we are especially interested in the effects of the interaction of *IntraKPool* with *DomKSource*. Under our Hypothesis 1, we would expect a positive (negative) effect of this interaction on the probability of switching from a transition to an upturn (downturn) stage.

Finally, we examine the determinants of the percentages of innovative sales from new-to-the-firm or new-to-the-market products conditional on having product innovation. In this case, we use Tobit models, where two equations are estimated simultaneously for maximum likelihood. The first equation refers to the firm's probability of having product innovation (selection equation) and is formally expressed as follows:

$$DProdinn_{i,t} = \begin{cases} 1 & \text{if } Prodinn_{i,t}^{*} = F(\mathbf{Z}_{i,t-1}\boldsymbol{\beta} + \mu_i + u_{i,t}) > 0 \\ 0 & \text{otherwise} \end{cases}, \tag{3}$$

[10] We also tried a random effects linear model, but the Hausman specification test rejected the null hypothesis of un-correlation between individual effects and regressors.

[11] Notice that, in this case, there is no measure of international intra-sectoral knowledge pools with which to interact the indicator of foreign knowledge sourcing.

where *DProdinn* represents the achievement of product innovations as a binary variable that takes the value of 1 when the firm attains product innovations in the current year and 0 otherwise. *Prodinn** is a latent variable that can be interpreted as the new knowledge needed to generate new products, and $\mathbf{Z}$ is the vector of explanatory variables, which includes the same set of explanatory variables as in Eq. (1).

Conditional on the achievement of product innovations, we can observe innovative sales; that is:

$$Innsales_{i,t} = \begin{cases} Innsales^{*}_{i,t} = \mathbf{Z}_{i,t-1}\boldsymbol{\beta} + \mu_i + e_{it} & \text{if } dinnprod_{i,t} = 1 \\ 0 & \text{if } dinnprod_{i,t} = 0 \end{cases}, \tag{4}$$

where *Innsales* represents, alternatively, the percentages of sales associated with new-to-the-firm or new-to-the-market products (in logarithms).[12] We assume that the error terms u and e follow a bivariate normal distribution with mean zero, $\sigma_u = 1$ and σ_e, and coefficient of correlation ρ.

Given the non-linearity of the Tobit modeling, to estimate these equations, we prefer in this case to use a random effects model. However, we are aware that estimated coefficients of the random effects model would be inconsistent if observed explanatory variables are correlated with the unobserved heterogeneity, μ_i. Following Wooldridge (1995, 2010), to face this potential endogeneity problem, we model unobserved heterogeneity in terms of the mean values of the exogenous time-variant variables, $\overline{\mathbf{Z}}_i$:

$$\mu_i = \delta_0 + \overline{\mathbf{Z}}_i\boldsymbol{\delta} + a_i, \quad a_i \cong i.i.d.\ N\left(0, \sigma_a^2\right), \tag{5}$$

under the assumption that $a_i \perp \overline{\mathbf{Z}}_i$.[13]

Under our Hypothesis 2, we expect a higher positive effect of the measures of external knowledge sourcing on innovative sales when they refer to the most radical product innovations (new-to-the-market products) than in the case of incremental product innovations (new-to-the-firm products). In addition, if the more competitive environment associated with a higher *KB-GVA* induces the firm to introduce more radical innovations, we expect the effect of *KB-GVA* to be positive on new-to-the-market innovative sales and negative on new-to-the-firm innovative sales. This would give support to our Hypothesis 4.

Notice that, to alleviate the usual endogeneity problem associated with the production function approach, all explanatory variables are included with one lag in Eqs. (1), (3) and (4) and with three lags in Eq. (2). The reason for the 3-year lag in Eq. (2) is associated with the definition of the dependent variable. As explained in Sect. 3, the construction of the categorical variable that reflects the stage of sales evolution requires information about firm sales in 3 consecutive years. Therefore, to mitigate endogeneity concerns, in this case explanatory variables should be included lagged at least three periods.[14]

[12] Barge-Gil (2013) and Capelli et al. (2014) use the same logarithm transformation in similar innovation contexts. As a robustness check, we have also performed the estimates using the shares of innovative sales without the transformation. The results, which are available from the authors upon request, are substantially the same.

[13] Tojeiro-Riveiro et al. (2019) make the same assumption in a similar context when using time-invariant regressors.

[14] Bellemare et al. (2017) characterize two conditions under which lagging explanatory variables addresses endogeneity concerns: (i) serial correlation in the potentially endogenous explanatory variable and (ii) no serial correlation among the unobserved sources of endogeneity.

This use of lagged variables will condition the period analyzed in each estimate. Although the information in the PITEC goes up to the year 2016, in estimations of Eq. (1), the results will refer to the period 2004–2014 because the explanatory variable *KB-GVA* that we take from the IVIE is available only until the year 2013. However, in estimations of Eq. (2), we can take advantage of the PITEC data registered for the years up to 2016 to construct the dependent variable.

Besides the estimation of the three models for the whole sample, given that spillover effects can be conditioned by the firm's absorption capability, to test our Hypothesis 3, we also undertake the estimation of the same models for different subsamples of firms that differ in their levels of internal resources devoted to R&D activities. We use two different measures to proxy these internal resources. First, we split the sample between small and medium-sized firms (SMEs) and large firms, under the assumption that the bigger the firm is, the more absorption capacities it has. Secondly, we distinguish between the subsamples of firms with high and low intensities of R&D employment. To classify the firms into these two groups, we use the median of the percentage of R&D employment over total employment in the same sector and year. Firms with a percentage of R&D employment above/below (or equal to) the median are assigned to the subsample of firms with high/low intensity of R&D employment.

Finally, as a robustness check, we analyze whether the patterns that we find for the whole sample are different between manufacturing and services firms. In the service sector, the difference between product and process innovation is not always clear and the contribution of organizational knowledge and non-technological elements in the innovation process is very important (Hipp & Grupp, 2005). Therefore, spillover effects from knowledge pools might also be different among activity sectors.

5 Results

To quantify the impact of knowledge spillovers on the dynamics of a firm's performance, we estimate three different specifications, each one adapted for a different measure of performance. Firstly, we consider total sales (in logarithms) and estimate Eq. (1) by fixed effects OLS. Secondly, we consider the categorical variable that classifies firms into three different groups depending on the stage of their sales growth evolution: upturn, downturn, or transition. In this case, we estimate a multinomial logit, considering the transition stage as the reference category. Finally, we focus on the percentage of innovative sales (in logarithms) conditional on having product innovations. We undertake two separate estimations for sales from new-to-the-firm and new-to-the-market product innovations. In these cases, we use random effects Tobit models where unobserved heterogeneity is modeled in terms of the mean values of the exogenous time-variant variables. As mentioned above, to lessen potential endogeneity problems, all explanatory variables are included with one lag in the first and third specifications and with three lags in the second one. In addition, all specifications include time dummies to control for the effect of the aggregate business cycle.

Besides the estimations for all firms in our sample, since absorption capacities may be decisive in capturing knowledge spillovers, in all tables we repeat the estimation for different sub-samples of firms that differ in their levels of internal resources devoted to R&D activities. First, we distinguish between SMEs and large firms, as the latter are expected to have more financial resources to devote to R&D activities. Then, we differentiate between firms with high and low intensities of R&D employment relative to the median firm in

Table 3 Effects of knowledge spillovers and external knowledge sourcing on firm sales (in logs.) Fixed effects linear model

	All firms	SMEs	Large firms
	(1)	(2)	(3)
A			
UpstreamKPool (log.)	0.010** (0.004)	0.012** (0.005)	− 0.013* (0.008)
IntraKPool (log.)	0.007 (0.010)	− 0.001 (0.010)	0.033* (0.019)
IntraKPool (log.) × *DomKSource*	0.005** (0.002)	0.005* (0.003)	0.002 (0.003)
ForKSource	0.118* (0.071)	0.195** (0.097)	− 0.007 (0.082)
KB-GVA	− 0.224** (0.087)	− 0.260** (0.101)	− 0.054 (0.123)
Innovation intensity (log.)	− 0.016*** (0.005)	− 0.020*** (0.005)	− 0.001 (0.007)
Physical capital intensity (log.)	0.012*** (0.001)	0.013*** (0.002)	0.005** (0.002)
Exporter (0/1)	0.054*** (0.014)	0.052*** (0.015)	0.017 (0.022)
Age (log.)	0.359*** (0.044)	0.433*** (0.051)	0.022 (0.063)
Large firm (0/1)	0.313*** (0.035)		
Group (0/1)	0.064*** (0.021)	0.073*** (0.025)	0.007 (0.029)
Wald test—Times dummies	86.2***	61.8***	27.6***
Overall F-test	55.1***	40.2***	14.9***
R^2	0.041	0.037	0.038
No. firms	5690	4638	1527
No. observations	43,470	32,967	10,503

Table 3 (continued)

	Firms with low R&D employment	Firms with high R&D employment	Services firms	Manufacturing firms
	(4)	(5)	(6)	(7)
B				
UpstreamKPool (log.)	0.001 (0.006)	0.020*** (0.007)	0.005 (0.005)	0.028*** (0.008)
IntraKPool (log.)	0.024* (0.013)	− 0.013 (0.015)	0.015 (0.013)	0.005 (0.013)
IntraKPool (log.) × *DomKSource*	− 0.000 (0.002)	0.007* (0.004)	0.006 (0.004)	0.003* (0.002)
ForKSource	0.060 (0.075)	0.125 (0.139)	0.182 (0.148)	0.073 (0.060)
KB-GVA	− 0.103 (0.087)	− 0.406*** (0.145)	− 0.227* (0.125)	0.250*** (0.097)
Innovation intensity (log.)	− 0.000 (0.005)	− 0.024** (0.009)	− 0.032*** (0.010)	− 0.003 (0.004)
Physical capital intensity (log.)	0.007*** (0.002)	0.015*** (0.002)	0.011*** (0.003)	0.011*** (0.001)
Exporter (0/1)	0.031** (0.015)	0.053** (0.021)	0.088*** (0.027)	0.018 (0.013)
Age (log.)	0.172*** (0.060)	0.476*** (0.066)	0.376*** (0.069)	0.298*** (0.046)
Large firm (0/1)	0.281*** (0.027)	0.260*** (0.056)	0.386*** (0.099)	0.282*** (0.024)
Group (0/1)	0.018 (0.020)	0.074** (0.036)	0.088** (0.041)	0.048** (0.020)
Wald test—Times dummies	47.0***	36.5***	18.7***	105.8***
Overall F-test	30.6***	25.7***	13.8***	63.9***
R^2	0.039	0.042	0.031	0.079
No. firms	4229	4032	2400	3607
No. observations	21,675	21,795	16,270	27,200

(0/1) denotes dummy variable. All regressions include the constant and time dummies. All independent variables are lagged one period. We report estimated coefficients

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

the same sector and year. Firms with high intensities of R&D employment, which usually imply a greater presence of skilled labor, are supposed to have more technical and entrepreneurial absorption capacities than companies with low intensities.[15] Finally, we distinguish between service and manufacturing firms because their way of innovation is often quite different (Castellacci, 2008; Hipp & Grupp, 2005).

5.1 Effects on firm total sales

The results in column (1) of Table 3 show that, when we analyze the spillovers along the vertical supply chain (*UpstreamKPool*), the effect in total sales for the whole sample is positive. However, in the case of *IntraKPool*, which would be associated with the existence of horizontal spillovers, the effect exists only through the interaction with the indicator of domestic knowledge sourcing (*DomKSource*). This result confirms the mediating role of the firm's technological relatedness in terms of cooperation or outsourcing in determining the existence of horizontal spillover effects and gives partial support to our Hypotheses 1a and 1b.

Besides knowledge pools, we also include in the specification a measure of the scope of international networking in terms of foreign knowledge sourcing (*ForKSource*). As previously discussed, in the same way that firms' national networks tend to favor the capture of externalities from domestic knowledge pools, the relationships with foreign actors may improve economic results because of the complementarity of foreign knowledge. Given that our database does not have any measure of international knowledge pools to be interacted with *ForKSource*, we just add this variable to our models. The estimated coefficient is positive for the whole sample, which is consistent with the assumption that firms operating in foreign markets need to search for novel knowledge not available in the domestic business environment in order to maintain their competitiveness. Moreover, firms that maintain foreign networks show better results.

Regarding our regional-sector indicator of knowledge-based value added *(KB-GVA*), its impact is negative, which is coherent with a higher difficulty of gaining sales from old products in sectors where competeviness is based on knowledge to overcome business stealing effects.

The coefficients of the rest of the explanatory variables have, in general, the expected sign. Being a large firm, belonging to a group, and operating in international markets stimulate firms' sales. Age and the intensity of physical capital also show a positive effect. The exception is innovation intensity, which displays a negative estimated coefficient. This result is in line with the results of Audrestch et al. (2019), who find a negative effect of R&D expenditure on firm performance in German firms and is coherent with the idea that current R&D expenditures may not have an effect until several years later (Griliches, 1979). In fact, we will see that, when we consider the medium-term effects in terms of the stages in the evolution of firm sales, our results are consistent with this idea, as we obtain a positive impact of innovation intensity on the probability of switching to an upward stage.

Analyzing the results by sub-samples, estimated coefficients in columns (2) and (3) confirm the existence of asymmetries in spillover effects by firm size. The results obtained for the whole sample are confirmed in the subsample of SMEs, while large firms show

[15] We obtain similar results when we use the intensity of internal R&D expenditures as an alternative measure of absorptive capacity. The results are available from the authors upon request.

a different pattern. The effect of the upstream knowledge pool remains positive only for SMEs, as it becomes negative for large companies. SMEs depend heavily on their suppliers and may be driven to take advantage of the spillovers that come from this channel. However, the greater levels of both physical and human capital of large firms appear to make them less dependent on the knowledge generated from supplier sectors. In addition, the supplier's spillover may create a catching up effect or business stealing effect by helping SMEs diminish the technological gap with respect to larger firms (Nieto & Santamaria, 2010) or technological leaders (Grillitsch & Nilsson, 2017).

As for horizontal spillovers, domestic knowledge sourcing becomes indispensable only for SMEs to benefit more from the knowledge pool. Such firms might lack sufficient internal technical and entrepreneurial capabilities to recognize the importance of new knowledge and technical capabilities to assimilate and develop applications based on external knowledge. Therefore, external agents might be more important in supporting these firms through that process of external knowledge sourcing. These results are consistent with our Hypothesis 3.

Something similar happens for knowledge-based gross added value and foreign knowledge sourcing. The estimations for SMEs confirm the negative effect of *KB-GVA* obtained for the whole sample, while it does not seem to affect the sales of large firms. Regarding the scope of international networking, our indicator of foreign knowledge sourcing keeps its positive impact for SMEs, while the effect for large firms is not statistically significant.

Spillover effects also differ substantially depending on the firm intensity of R&D employment [columns (4) and (5) of Table 3]. The intra-sectoral knowledge pool seems to play a more positive role for firms with low intensities of R&D employment,[16] while the upstream knowledge pool is more relevant for firms with high proportions of R&D employment. This evidence supports the idea that firms can benefit from the knowledge from providing sectors only if they have a certain level of human skills to capture and utilize the external knowledge, while these skills are not that necessary in the case of knowledge generated within the same activity sector. However, *ForKSource* is not statistically significant in any of the subsamples by relative intensity of R&D employment. This might be in part because the moderate correlation between our indicators of domestic and foreign knowledge sourcing increases in these subsamples.

Finally, we also see some interesting differences between services and manufacturing firms. Knowledge pools only generate positive spillovers in the case of manufacturing firms, while such pools have no effect on services firms. In addition, while in this latter group of firms the negative effect of the intensity of the economic value of knowledge in the sector-region (*KB-GVA*) is confirmed, the effect is the contrary for manufacturing firms. This suggests that services and manufacturing firms have different needs and capabilities when they access external knowledge in order to increase their sales.

We complement these results by analyzing the role of spillovers for the switch between stages in the evolution of firm sales. The results of the multinomial logit in Table 4 consider the transition stage to be the reference category and include time dummies in the specification. Therefore, estimated coefficients for upturn and downturn stages should be interpreted in terms of the effect of explanatory variables on the probability of switching from a transition to an upturn or a downturn stage once we control for the effect of the aggregate business cycle. Notice that, in the case of the transition to a downturn situation,

[16] This result is in line with Grillitsch and Nilsson (2017), who find that Swedish firms with weak internal knowledge grow faster in knowledge-intensive regions.

Table 4 Effects of knowledge spillovers and external knowledge sourcing on the stages of firm sales evolution

Stage of firm sales evolution	All firms	
	Upturn	Downturn
	(1)	(2)
A		
UpstreamKPool (log.)	0.033*** (0.005)	− 0.015*** (0.006)
IntraKPool (log.)	0.109*** (0.015)	− 0.022 (0.015)
IntraKPool (log.) × *DomKSource*	0.010** (0.005)	0.011** (0.005)
ForKSource	− 0.004 (0.157)	0.007 (0.173)
KB-GVA	− 0.463*** (0.146)	1.003*** (0.163)
Innovation intensity (log.)	0.042*** (0.010)	0.007 (0.010)
Physical capital intensity (log.)	0.024*** (0.004)	− 0.006 (0.004)
Exporter (0/1)	0.147*** (0.030)	− 0.031 (0.031)
Age (log.)	− 0.086*** (0.018)	0.114*** (0.020)
Large firm (0/1)	0.122*** (0.035)	0.153*** (0.037)
Group (0/1)	0.002 (0.028)	0.001 (0.030)
Wald test—Time dummies	1091.5***	782.5***
Wald test—Sectoral dummies	71.2***	85.7***
Wald test—Regional dummies	75.4***	29.5**
Overall Wald test	χ^2 (86) = 3180.6***	
No. observations	39,070	

Table 4 (continued)

Stage of firm sales evolution	SMEs		Large firms	
	Upturn	Downturn	Upturn	Downturn
	(3)	(4)	(5)	(6)
B				
UpstreamKPool (log.)	0.035*** (0.006)	− 0.023*** (0.006)	0.032** (0.016)	0.028 (0.018)
IntraKPool (log.)	0.095*** (0.018)	− 0.026 (0.019)	0.145*** (0.029)	− 0.016 (0.028)
IntraKPool (log.) × *DomKSource*	0.011* (0.006)	0.004 (0.007)	0.006 (0.008)	0.017* (0.009)
ForKSource	0.357* (0.205)	0.014 (0.244)	− 0.307 (0.251)	− 0.174 (0.259)
KB-GVA	− 0.447** (0.174)	0.848*** (0.190)	− 0.389 (0.286)	1.275*** (0.328)
Innovation intensity (log.)	0.035*** (0.012)	− 0.017 (0.013)	0.083*** (0.018)	0.067*** (0.019)
Physical capital intensity (log.)	0.020*** (0.004)	− 0.007 (0.005)	0.034*** (0.009)	0.003 (0.009)
Exporter (0/1)	0.180*** (0.034)	− 0.045 (0.036)	0.046 (0.064)	0.009 (0.065)
Age (log.)	− 0.121*** (0.021)	0.150*** (0.024)	− 0.041 (0.033)	0.025 (0.035)
Large firm (0/1)				
Group (0/1)	0.075** (0.031)	− 0.015 (0.034)	− 0.363*** (0.065)	0.055 (0.073)
Wald test—Time dummies	789.1***	574.0***	311.3***	207.9***
Wald test—Sectoral dummies	40.3***	34.3***	47.7***	62.8***
Wald test—Regional dummies	60.2***	25.2*	27.4**	24.5*
Overall Wald test	χ^2 (84) = 2337.6***		χ^2 (84) = 997.7***	
No. observations	29,210		9860	

Table 4 (continued)

Stage of firm sales evolution	Firms with low R&D employment		Firms with high R&D employment	
	Upturn	Downturn	Upturn	Downturn
	(7)	(8)	(9)	(10)
C				
UpstreamKPool (log.)	0.030*** (0.007)	− 0.011 (0.008)	0.036*** (0.008)	− 0.020** (0.008)
IntraKPool (log.)	0.124*** (0.021)	− 0.003 (0.022)	0.087*** (0.021)	− 0.048** (0.022)
IntraKPool (log.) × *DomKSource*	0.011* (0.006)	0.025*** (0.007)	0.008 (0.007)	− 0.007 (0.008)
ForKSource	− 0.108 (0.199)	− 0.130 (0.214)	− 0.021 (0.266)	− 0.020 (0.319)
KB-GVA	− 0.303 (0.207)	0.922*** (0.230)	− 0.590*** (0.209)	1.012*** (0.231)
Innovation intensity (log.)	0.074*** (0.013)	0.031** (0.014)	− 0.004 (0.017)	− 0.045** (0.018)
Physical capital intensity (log.)	0.024*** (0.006)	− 0.010 (0.006)	0.023*** (0.005)	0.001 (0.005)
Exporter (0/1)	0.077* (0.043)	− 0.011 (0.045)	0.199*** (0.042)	− 0.063 (0.044)
Age (log.)	− 0.057** (0.025)	0.078*** (0.028)	− 0.148*** (0.026)	0.148*** (0.029)
Large firm (0/1)	0.134*** (0.042)	0.193*** (0.044)	0.160* (0.084)	− 0.024 (0.092)
Group (0/1) (0/1)	− 0.063 (0.041)	0.013 (0.043)	0.060 (0.040)	0.000 (0.043)
Wald test—Time dummies	556.9***	388.9***	551.31***	399.1***
Wald test—Sectoral dummies	47.9***	62.8***	22.8***	31.9***
Wald test—Regional dummies	55.6***	43.3***	37.2***	20.3
Overall Wald test	χ^2 (86) = 1730.9***		χ^2 (86) = 1606.6***	
No. observations	19,788		19,282	

Table 4 (continued)

Stage of firm sales evolution	Services firms		Manufacturing firms	
	Upturn	Downturn	Upturn	Downturn
	(11)	(12)	(13)	(14)
D				
UpstreamKPool (log.)	0.018*** (0.006)	− 0.003 (0.006)	0.062** (0.025)	0.053* (0.028)
IntraKPool (log.)	0.102*** (0.023)	0.022 (0.023)	0.176*** (0.023)	− 0.087*** (0.023)
IntraKPool (log.) × *DomKSource*	0.013* (0.008)	0.017** (0.008)	0.006 (0.006)	0.004 (0.007)
ForKSource	0.140 (0.247)	− 0.278 (0.269)	− 0.068 (0.206)	0.229 (0.229)
KB-GVA	− 0.194 (0.216)	0.441* (0.246)	− 0.344 (0.228)	1.141*** (0.240)
Innovation intensity (log.)	− 0.005 (0.015)	0.033** (0.016)	0.081*** (0.013)	− 0.011 (0.014)
Physical capital intensity (log.)	0.034*** (0.006)	0.007 (0.007)	0.014*** (0.005)	− 0.013** (0.005)
Exporter (0/1)	0.177*** (0.043)	− 0.075 (0.047)	0.142*** (0.043)	0.015 (0.043)
Age (log.)	− 0.091*** (0.029)	0.111*** (0.033)	− 0.076*** (0.023)	0.102*** (0.025)
Large firm (0/1)	0.149** (0.065)	0.171** (0.067)	0.092** (0.042)	0.173*** (0.045)
Group (0/1) (0/1)	− 0.013 (0.047)	0.080 (0.049)	0.005 (0.036)	− 0.031 (0.038)
Wald test—Time dummies	257.1***	242.9***	985.0***	753.4 ***
Wald test—Sectoral dummies	22.8***	32.7***	58.8***	26.3***
Wald test—Regional dummies	36.3***	15.5	48.9***	27.7**
Overall Wald test	χ^2 (80) = 1075.1***		χ^2 (80) = 2706.7***	
No. observations	14,398		24,672	

Multinomial logit model (Base = Transition)

(0/1) denotes dummy variable. All regressions include the constant and time, sectoral and regional dummies. All independent variables are lagged one period. We report estimated coefficients

Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

a negative coefficient for a knowledge pool in fact implies a positive incoming spillover effect, as it reduces the probability of entering a downturn stage.

As observed in Table 4, in the case of the spillovers along the vertical supply chain, we find the expected positive coefficient for *UpstreamKPool* in the transition to an upturn stage. However, there is a symmetry in the effect, that is, a negative coefficient of this variable in the transition to a downturn stage, in the whole sample and the subsamples of SMEs and high-tech firms within their sector. Something similar happens with horizontal spillovers. The coefficient for *IntraKPool* in isolation appears to be positive on the probability of switching to an upturn stage in all samples, while it is negative only in the subsamples of firms with high R&D employment intensity and manufacturing firms. This suggests that knowledge spillovers from these pools are more relevant for entering an upturn stage than for avoiding a downturn stage.

The asymmetry is even clearer when considering the intermediating role of the scope of external knowledge sourcing. In the case of the whole sample, firms with low intensities of R&D employment and services firms, the interaction of the intra-sectoral knowledge pool with the external networking indicator yields a positive coefficient in both upturn and downturn stages, which does not match the expected relationship. This would mean that certain firms may move towards a downturn stage with a higher probability when interacting with more domestic agents of the innovation system. The positive effect of foreign knowledge sourcing, observed in Table 3 for SMEs, also remains positive on the probability of switching to an upturn stage, but disappears in the case of the downturn stage. This may suggest that external knowledge sourcing is not enough to generate permanent positive effects on firm performance. Further research is required to explain this pattern.

Regarding the rest of the explanatory variables, the indicator of *knowledge intensity in sectoral-regional value added* in all samples shows a negative, although not always significant, coefficient on the transition towards an upturn stage, and a positive and greater magnitude coefficient on the change to a downturn phase. This is consistent with the idea that the higher the presence of knowledge in a region-sector is, the more competitive and complex the firm's environment is, generating a kind of business stealing effect.[17]

Finally, control variables show effects similar to the ones in Table 3 for the whole sample in the case of the upturn swing, but are in general not significant for the downturn swing. The exception is the age of the firm, which has a negative effect on evolution of sales, maybe because older firms are more embedded in old routines which impede the required changes in their behavior. Although these differences in the effects of control variables are interesting, we leave them for future research, as they are marginal elements for the specific focus of this paper.

5.2 Effects on innovative sales

Now we turn to the specific analysis of innovative sales, that is, the share of sales associated with the introduction of new products. As can be seen in Tables 5 and 6, our two measures of knowledge pools (*UpstreamKPool and IntraKPool*) show different effects on the relative importance of innovative sales. In the case of *UpstreamKPool*, which would be

[17] A similar argument is used by Audretsch et al. (2019), who state that high local concentrations of innovation activity imply high levels of competition. This would force the firms to invest more in R&D, and increased investments then would lower firms' operating income.

Table 5 Effects of knowledge spillovers and external knowledge sourcing on percentage of sales from new-to-firm products (in logs.). Random effects Tobit model

	All firms	SMEs	Large firms
	(1)	(2)	(3)
A			
UpstreamKPool (log.)	0.019** (0.009)	0.016* (0.010)	0.027 (0.018)
IntraKPool (log.)	− 0.052 (0.033)	− 0.089** (0.042)	0.027 (0.051)
IntraKPool (log.) × *DomKSource*	0.027*** (0.008)	0.024** (0.010)	0.025** (0.012)
ForKSource	0.113 (0.257)	− 0.361 (0.352)	0.548 (0.355)
KB-GVA	− 0.528* (0.291)	− 0.684** (0.338)	− 0.263 (0.586)
Innovation intensity (log.)	0.079*** (0.018)	0.039* (0.023)	0.158*** (0.030)
Physical capital intensity (log.)	0.006 (0.005)	0.010* (0.006)	− 0.015 (0.012)
Exporter (0/1)	0.137*** (0.041)	0.147*** (0.048)	0.144* (0.083)
Age (log.)	− 0.092** (0.041)	− 0.156*** (0.050)	0.102 (0.065)
Large firm (0/1)	0.045 (0.068)		
Group (0/1)	0.059 (0.053)	0.092 (0.060)	− 0.108 (0.110)
Wald test—Time dummies	191.9***	174.4***	29.2***
Wald test—Sectoral dummies	61.2***	47.4***	27.7***
Wald test—Regional dummies	43.7***	44.2***	23.9*
Wald test—Mundlak mean values	28.7***	31.1***	3.6
Overall Wald test	561.7***	451.1***	245.9***
No. observations	43,470	32,967	10,503

Table 5 (continued)

	Firms with low R&D employment	Firms with high R&D employment	Services firms	Manufacturing firms
	(4)	(5)	(6)	(7)
B				
UpstreamKPool (log.)	0.011 (0.011)	0.023* (0.014)	0.014 (0.010)	0.086** (0.040)
IntraKPool (log.)	− 0.010 (0.042)	− 0.116** (0.051)	− 0.092* (0.048)	− 0.030 (0.065)
IntraKPool (log.) × *DomKSource*	0.039*** (0.010)	0.012 (0.012)	0.040*** (0.013)	0.017* (0.010)
ForKSource	0.118 (0.298)	− 0.194 (0.469)	− 0.109 (0.471)	0.286 (0.298)
KB-GVA	− 0.154 (0.407)	− 0.798* (0.424)	− 1.022** (0.409)	− 0.421 (0.459)
Innovation intensity (log.)	0.114*** (0.023)	0.020 (0.032)	0.096*** (0.033)	0.071*** (0.022)
Physical capital intensity (log.)	− 0.005 (0.008)	0.013* (0.007)	0.011 (0.010)	0.002 (0.006)
Exporter (0/1)	0.172*** (0.057)	0.120** (0.057)	0.120* (0.068)	0.129** (0.052)
Age (log.)	0.062 (0.050)	− 0.168*** (0.054)	− 0.174** (0.072)	− 0.050 (0.048)
Large firm (0/1)	− 0.000 (0.076)	0.303** (0.132)	0.115 (0.139)	0.038 (0.078)
Group (0/1)	− 0.030 (0.068)	0.137* (0.073)	0.093 (0.097)	0.065 (0.063)
Wald test—Time dummies	79.2***	133.4***	79.6***	122.9***
Wald test—Sectoral dummies	31.6***	48.9***	5.9	23.8***
Wald test—Regional dummies	29.7**	34.2***	16.1	30.4**
Wald test—Mundlak mean values	18.2**	18.1**	40.5***	11.1
Overall Wald test	371.2***	348.5***	273.3***	274.2***
No. observations	21,675	21,795	16,270	27,200

(0/1) denotes dummy variable. All regressions include the constant, Mundlak means and time, sectoral and regional dummies. All independent variables are lagged one period. We report estimated coefficients

Robust standard errors in parentheses. ***$p < 0.01$, **$p < 0.05$, *$p < 0.1$

Table 6 Effects of knowledge spillovers and external knowledge sourcing on percentage of sales from new-to-market products (in logs.). Random effects Tobit model

	All firms	SMEs	Large firms
	(1)	(2)	(3)
A			
UpstreamKPool (log.)	0.010 (0.010)	0.008 (0.011)	0.008 (0.020)
IntraKPool (log.)	− 0.022 (0.037)	− 0.055 (0.046)	0.050 (0.057)
IntraKPool (log.) × *DomKSource*	0.058*** (0.008)	0.065*** (0.010)	0.047*** (0.011) 0.040*** (0.014)
ForKSource	0.576** (0.262)	0.959*** (0.348)	− 0.053 (0.391)
KB-GVA	− 0.387 (0.325)	− 0.480 (0.371)	− 0.201 (0.684)
Innovation intensity (log.)	0.149*** (0.020)	0.149*** (0.026)	0.134*** (0.033)
Physical capital intensity (log.)	0.016*** (0.006)	0.014** (0.007)	0.016 (0.013)
Exporter (0/1)	0.178*** (0.045)	0.218*** (0.052)	0.055 (0.091)
Age (log.)	− 0.057 (0.048)	− 0.046 (0.058)	− 0.042 (0.080)
Large firm (0/1)	0.254*** (0.086)		
Group (0/1)	− 0.065 (0.064)	− 0.082 (0.072)	− 0.107 (0.136)
Wald test—Time dummies	126.3***	164.3***	20.2**
Wald test—Sectoral dummies	34.0***	29.9***	5.94
Wald test—Regional dummies	81.6***	71.8***	32.3***
Mundlak means fixed effect χ^2 (7)	184.6***	124.6***	67.0***
Overall Wald test	1201.3***	919.5***	371.5***
No. observations	43,470	32,967	10,503

Table 6 (continued)

	Firms with low R&D employment	Firms with high R&D employment	Services firms	Manufacturing firms
	(4)	(5)	(6)	(7)
B				
UpstreamKPool (log.)	0.003 (0.012)	0.025 (0.016)	0.001 (0.011)	0.107** (0.047)
IntraKPool (log.)	0.028 (0.050)	− 0.088 (0.055)	− 0.080* (0.047)	0.090 (0.083)
IntraKPool (log.) × *DomKSource*	0.047*** (0.011)	0.068*** (0.013)	0.074*** (0.013)	0.045*** (0.011)
ForKSource	0.188 (0.313)	1.119** (0.443)	1.042** (0.418)	0.224 (0.337)
KB-GVA	0.424 (0.469)	− 1.152** (0.451)	− 0.581 (0.418)	0.212 (0.564)
Innovation intensity (log.)	0.167*** (0.026)	0.105*** (0.036)	0.178*** (0.034)	0.134*** (0.026)
Physical capital intensity (log.)	0.003 (0.009)	0.025*** (0.008)	0.016* (0.009)	0.016** (0.008)
Exporter (0/1)	0.214*** (0.061)	0.185*** (0.063)	0.287*** (0.067)	0.078 (0.061)
Age (log.)	− 0.003 (0.061)	− 0.036 (0.063)	− 0.145* (0.078)	0.023 (0.060)
Large firm (0/1)	0.286*** (0.092)	0.215 (0.178)	0.283* (0.153)	0.300*** (0.103)
Group (0/1)	− 0.141* (0.079)	− 0.014 (0.087)	− 0.070 (0.104)	− 0.018 (0.080)
Wald test—Time dummies	68.1***	116.1***	81.3***	100.5***
Wald test—Sectoral dummies	24.3***	32.6***	6.47*	41.0***
Wald test—Regional dummies	53.6***	64.6***	27.7**	62.2***
Mundlak means fixed effect χ^2 (7)	115.2***	108.2***	90.13***	103.4***
Overall Wald test	763.4***	720.4***	743.3***	599.4***
No. observations	21,675	21,795	16,270	27,200

(0/1) denotes dummy variable. All regressions include the constant, Mundlak means and time, sectoral and regional dummies. All independent variables are lagged one period. We report estimated coefficients

Robust standard errors in parentheses. ***p < 0.01, **p < 0.05, *p < 0.1

associated with the existence of vertical spillovers, the effect for the whole sample appears to be positive for sales from new-to-the-firm products in both the whole sample and the subsamples of SMEs, firms with high intensities of R&D employment and manufacturing companies. However, its impact on sales from radical innovations is not significant in almost any of the estimates. This result might imply that the incorporation of innovative products from suppliers in the productive process allows firms to obtain small incremental innovations based on imitation rather than more radical innovations or substantially improved products.

When we analyze the spillovers within the same sector (*IntraKPool*)*,* for both types of innovative sales, the effect becomes positive only when it is interacted with our proxy of domestic technological relatedness. It is worth noting the positive effect of the interaction is quite robust in most subsamples and is greater for the sales related to radical innovations,[18] supporting our Hypothesis 1b. This result suggests that firms interact voluntarily only with partners that can offer complementary assets useful for the focal firm and participate in such a network if they have enough cognitive proximity and technological capacity to make this interaction profitable. This might imply that the level of technical relatedness and complementary cognitive knowledge is more relevant for radical innovations.

Regarding foreign knowledge sourcing (*ForKSource*), a positive effect is found for sales related to products new to the market in the whole sample and, specifically, in the case of SMEs, firms with low intensities of R&D employment and those which develop their activities in services sectors. However, there is no statistically significant impact of this variable on sales from new-to-the-firm products in any of the samples. This might be related to the fact that firms involved in international markets need to be more innovative in order to be competitive, as a result having a higher influence of external knowledge on sales associated with the most radical innovations. In addition, the different results obtained in the impacts of *ForKSource* on sales from new-to-the-market products by subsamples based on the relative innovative capacity of firms suggest that the degree of novelty of foreign knowledge requires more human skills so that this knowledge can be absorbed and turned into new, marketable products.

The indicator that we use to measure the intensity of knowledge in the firm's environment (*KB-GVA*) has a negative effect on sales from new-to-the-firm products in the whole sample and is confirmed for the subsamples of SMEs, firms with low intensities of R&D employment and companies that carry out their activities in services sectors. This is consistent with the idea that the higher the presence of tacit and codified knowledge in a region-sector is, the lower the importance of imitation sales will be, and gives support to our Hypothesis 4b. However, we do not find any evidence in favor of our Hypothesis 4a with regard to sales from radical innovations. In this case, the estimated coefficients for *KB-GVA* are non-statistically different from zero in most samples. The exception is the group of firms with high intensities of R&D employment, where in fact we obtain an unexpected negative effect.

[18] Rodriguez et al. (2017) and Tojeiro-Rivero and Moreno (2019) find similar results, although in a different methodological setting.

6 Conclusions and final remarks

This paper analyzes the existence of asymmetric knowledge spillovers in the dynamics of firm performance, with special emphasis on the role of external knowledge sourcing as an indirect proxy of technological relatedness in a firm's environment. In particular, we contribute to the literature in three aspects. First, although some recent papers have studied the impact of regional spillovers on firm productivity or innovation performance, we specifically assess their importance for a company's performance in terms of sales. Second, we use several measures of sectoral and regional knowledge pools that capture different channels of knowledge transmission. Third, to qualify the impact of knowledge spillovers, we analyze whether there are asymmetric effects depending on the firms' absorption capacity and technological relatedness in terms of the use of external sources of knowledge through cooperation or outsourcing.

For our analysis, we use firm-level information on innovative Spanish firms for the period 2004–2016. This information has been combined with sector- and regional-level indicators of knowledge pools. We estimate three different specifications, each one adapted for a different measure of performance: total sales, a categorical variable for the stages of upturn, downturn or transition in sales growth evolution, and the percentage of innovative sales conditional on having product innovations. In the case of innovative sales, we undertake two separate estimations for sales from new-to-the-firm and new-to-the-market product innovations. In all specifications, we include year fixed effects, which allow us to interpret our results as impacts after controlling for the effect of the macroeconomic business cycle.

The results from our estimations can be summarized as follows:

Firstly, spillover effects from domestic intra-sector and upstream knowledge pools are, in general, positive, although they display some differences depending on the measure of firm performance. Both types of spillovers positively condition the change to an upturn stage of a company's evolution, although the magnitude of the effect seems to be smaller in the case of spillovers that come from the knowledge pool of supplier sectors. Horizontal spillovers seem to be more relevant for increasing sales that come from the most radical innovations, while vertical spillovers stimulate sales from incremental innovations to a greater extent.

Secondly, we find evidence of the mediating role of external knowledge sourcing in determining the existence and magnitude of horizontal spillovers. Spillover effects from the domestic intra-sectoral knowledge pool increase with the use of domestic external sources of knowledge. In fact, the effects on sales from new-to-the-firm products are significant only when the firm interacts with external agents through technological cooperation or R&D outsourcing. This result suggests that firms interact voluntarily only with partners that can offer complementary assets useful for the focal firm and participate in such a network if they have enough cognitive proximity and technological capacity to make this interaction profitable. Moreover, we find that horizontal spillovers, either in isolation or in interaction with domestic external sourcing, are more intense in the case of sales from new-to-the-market products than from new-to-the-firm products. This might imply that the level of technical relatedness and complementary cognitive knowledge is more relevant for radical innovations.

Additionally, we obtain that foreign external sourcing also positively affects total sales, although the effect disappears when we focus on the probabilities of switching between upturn, downturn and transition phases. This may suggest that foreign knowledge sourcing in isolation is not enough to generate permanent positive effects on firm performance. However, we find that a firm's international networking positively affects the most radical innovations, which suggests that the environment of the partners, and not only that of the focal company, leads to a differentiated effect in this case.

Fourthly, spillover effects appear to be asymmetric depending on the firm's absorption capabilities, which are associated with the firm's size or intensity of R&D employment. As for size, knowledge spillovers play a more significant role in the case of SMEs than in large companies. In particular, spillovers from the upstream knowledge pool are especially relevant for SMEs, which implies that SMEs depend more heavily on their suppliers' knowledge. Regarding intensity of R&D employment, firms with relatively high intensities benefit more/less from upstream/horizontal spillovers than firms with relatively low intensities. This is coherent with the idea that firms with low intensities of R&D employment within their own sector are mainly technology imitators or followers with less technical competences, while the group of firms with relatively high intensities includes the technical leaders. Therefore, each group of firms might look for different types of technologies available in the knowledge pool.

Finally, sectors with greater intensities of knowledge-based gross value added within the region are associated with reductions in firm sales and a higher probability of switching to a downturn stage in sales evolution. In contrast to traditional indicators of knowledge pools, usually constructed on information about R&D expenditures or innovation outcomes, the relative knowledge-based gross value added measures how much of the value added of the production in the region-sector remunerates the knowledge accumulated in all factors used in the production process. Therefore, it reflects the intensity of knowledge in the regional environment and indirectly captures the regional level of tacit knowledge within the sector, which usually implies a more competitive and complex domestic environment. To the extent that innovation renders existing technologies obsolete, this would generate a situation where the "business stealing" effect is a dominant strategy. This negative effect seems to be especially relevant for the sales from old products and new-to-the-firm products, while it is non-significant in the case of new-to-the-market products.

Our results about the role of domestic and foreign knowledge sourcing as drivers of firm performance have important policy implications in the current context of slowdown in productive activity as a consequence of the pandemic. However, limitations and future lines of research should be outlined. Looking at the asymmetric panorama of spillover effects, there is still a large number of interactions between facilitating and blocking elements to be analyzed. Further research should explore other alternatives of interdependent and mutual reinforcing mechanisms. Moreover, the analysis of the evolution of firm sales, which becomes much more complex in times of economic turmoil, may be enriched with the inclusion of variables that reflect the degree of market competition. Looking at market shares or the presence of dominant firms that act as innovation leaders may be useful for gaining a more comprehensive view of the importance and role of agents' interactions for the evolution of firms. Finally, because of data restrictions, our sample is limited to innovative firms. This makes our results conditional on the firms having innovation expenditures. However, the potential effects of external knowledge go beyond the innovation effort and performance of already innovative active firms. It may also induce non-innovative active firms to invest in R&D, also with consequences on their performance. We also leave this question for future research.

Appendix

See Tables 7 and 8.

Table 7 Sectoral classification in PITEC and its correspondence with NACE Rev. 2

PITEC sectoral classification		NACE-Rev.2
00	Agriculture, forestry and fishing	01–03
01	Mining and quarrying	05–09
02	Coke and refined petroleum products	19
03	Food products, beverages and tobacco products	10–12
04	Textiles	13
05	Wearing apparel	14
06	Leather and related products	15
07	Wood and products of wood and cork, except furniture	16
08	Paper and paper products	17
09	Printing and reproduction of recorded media	18
10	Chemicals and chemical products	20
11	Pharmaceutical products	21
12	Rubber and plastic products	22
13	Other non-metallic mineral products	23
14	Manufacture of basic metals	24
15	Fabricated metal products, except machinery and equipment	25
16	Computer, electronic and optical products	26
17	Electrical equipment	27
18	Machinery and equipment n.e.c	28
19	Motor vehicles, trailers and semi-trailers	29
20	Building of ships and boats	301
21	Air and spacecraft and related machinery	303
22	Other transport equipment	30 (except 301, 303)
23	Furniture	31
24	Other manufacturing	32
25	Repair and installation of machinery and equipment	33
26	Electricity and water supply	35–36
27	Sewerage, waste management and remediation activities	37–39
28	Construction	41–43
29	Wholesale and retail trade, repair of motor vehicles and motorcycles	45–47
30	Transportation and storage	49–53
31	Accommodation and food service activities	55–56
32	Telecommunications	61
33	Computer programming, consultancy and related activities	62
34	Other services of information and communication	58–60, 63
35	Financial and insurance activities	64–66
36	Real estate activities	68
37	Scientific research and development	72
38	Other professional, scientific and technical activities	69–71, 73–75
39	Administrative and support service activities	77–82
40	Education	85 (except 854)
41	Human health and social work activities	86–88
42	Arts, entertainment and recreation	90–93
43	Other service activities	95–96

Table 8 Regional industry classification of *KB-GVA* and its correspondence with NACE Rev. 2

Regional industry classification of *KB-GVA*	NACE Rev.2
1. Agriculture, forestry and fishing	01–03
2. Mining and quarrying; Electricity and water supply	05–09; 35–39
3. Manufacture of food products, beverages and tobacco products	10–12
4. Manufacture of textiles, apparel, leather and related products	13–15
5. Manufacture of wood and paper products, and printing	16–18
6. Refined petroleum, chemical and pharmaceutical products	19–21
7. Manufacture of rubber and plastics products, and other non-metallic mineral products	22–23
8. Manufacture of basic metals and fabricated metal products, except machinery and equipment	24–25
9. Machinery and equipment	26–28
10. Manufacture of transport equipment	29–30
11. Other manufacturing, and repair and installation of machinery and equipment	31–33
12. Construction	41–43
13. Wholesale and retail trade, repair of motor vehicles and motorcycles	45–47
14. Transportation and storage	49–53
15. Accommodation and food service activities	55–56
16. Information and communication	58–63
17. Financial and insurance activities	64–66
18. Real estate activities	68
19. Professional, scientific, technical, administration and support service activities	69–82
20. Public administration, defense, education, human health and social work activities	84–88
21. Other services	90–99

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References

Agarwal, R., Audretsch, D., & Sarkar, M. B. (2010). Knowledge spillovers and strategic entrepreneurship. *Strategic Entrepreneurship Journal, 4*(4), 271–283.

Angue, K., Ayerbe, C., & Mitkova, L. (2014). A method using two dimensions of the patent classification for measuring the technological proximity: An application in identifying a potential R&D partner in biotechnology. *Journal of Technology Transfer, 39*, 716–747.

Arrow, K. J. (1962). Economic welfare and the allocation of resources for innovation. In R. Nelson (Ed.), *The rate and direction of inventive activity.* Princeton: NBER book, Princeton University Press.

Audretsch, D. B. (1998). Agglomeration and the location of innovative activity. *Oxford Review of Economic Policy, 14*(2), 18–29.

Audretsch, D. B., & Belitski, M. (2020). The role of R&D and knowledge spillovers in innovation and productivity. *European Economic Review, 123*, 103391.

Audretsch, D., & Caiazza, R. (2016). Technology transfer and entrepreneurship: Cross-national analysis. *The Journal of Technology Transfer, 41*(6), 1247–1259.

Audretsch, D. B., & Feldman, M. P. (1996). R&D spillovers and the geography of innovation and production. *American Economic Review, 86*, 630–640.

Audretsch, D. B., & Lehmann, E. (2006). Entrepreneurial access and absorption of knowledge spillovers: Strategic board and managerial composition for competitive advantage. *Journal of Small Business Management, 44*(2), 155–166.

Audretsch, D. B., & Lehmann, E. E. (2017). The knowledge spillover theory of entrepreneurship and the strategic management of places. *The Wiley handbook of entrepreneurship.* London: Wiley.

Audretsch, D. B., Lehmann, E. E., Menter, M., & Seitz, N. (2019). Public cluster policy and firm performance: Evaluating spillover effects across industries. *Entrepreneurship & Regional Development, 31*(1–2), 150–165.

Balland, P. A., Boschma, R., Crespo, J., & Rigby, D. L. (2019). Smart specialization policy in the European Union: Relatedness, knowledge complexity and regional diversification. *Regional Studies, 53*(9), 1252–1268.

Barge-Gil, A. (2013). Open strategies and innovation performance. *Industry and Innovation, 20*(7), 585–610.

Bellemare, M. F., Masaki, T., & Pepinsky, T. B. (2017). Lagged explanatory variables and the estimation of causal effects. *Journal of Politics, 79*(3), 949–963.

Bloom, N., Schankerman, M., & Van Reenen, J. (2013). Identifying technology spillovers and product market rivalry. *Econometrica, 81*, 1347–1393.

Boschma, R. (2005). Proximity and innovation: A critical assessment. *Regional Studies, 39*, 61–74.

Boschma, R., & Frenken, K. (2007). Applications of evolutionary economic geography. In K. Frenken (Ed.), *Applied evolutionary economics and economic geography* (pp. 1–24). Elgar.

Boschma, R., & Frenken, K. (2009). Technological relatedness and regional branching. In H. Bathelt, M. P. Feldman, & D. F. Kogler (Eds.), *Dynamic geographies of knowledge creation and innovation.* Routledge, Taylor and Francis.

Boschma, R., & Iammarino, S. (2015). Related variety, trade linkages, and regional growth in Italy. *Economic Geography, 85*(3), 289–311.

Boschma, R., & Martin, R. (2010). The aims and scope of evolutionary economic geography. In R. Boschma & R. Martin (Eds.), *The Handbook of evolutionary economic geography* (pp. 3–39). Edward Elgar.

Cappelli, R., Czarnitzki, D., & Kraft, K. (2014). Sources of spillovers for imitation and innovation. *Research Policy, 43*(1), 115–120.

Carreira, C., & Lopes, L. (2018). Regional knowledge spillovers: A firm-based analysis of non-linear effects. *Regional Studies, 52*(7), 948–958.

Castellacci, F. (2008). Technological paradigms, regimes and trajectories: Manufacturing and service industries in a new taxonomy of sectoral patterns of innovation. *Research Policy, 37*(6–7), 978–994.

Chapman, G., Lucena, A., & Afcha, S. (2018). R&D subsidies & external collaborative breadth: Differential gains and the role of collaboration experience. *Research Policy, 47*(3), 623–636.

Chiang, Y. H., & Hung, K. P. (2010). Exploring open search strategies and perceived innovation performance from the perspective of inter-organizational knowledge flows. *R&D Management, 40*(3), 292–299.

Choi, S. B., & Williams, C. (2014). The impact of innovation intensity, scope, and spillovers on sales growth in Chinese firms. *Asia Pacific Journal of Management, 31*(1), 25–46.

Coad, A., & Hölzl, W. (2012). Firm growth: Empirical analysis. In M. Dietrich & J. Krafft (Eds.), *Handbook on the economics and theory of the firm, chapter 24.* Edward Elgar Publishing.

Cohen, W. M., & Levinthal, D. A. (1990). Absorptive capacity: A new perspective on learning and innovation. *Administrative Science Quarterly, 35*, 128–152.

Dosi, G., & Nelson, R. R. (2010). Technical change and industrial dynamics as evolutionary processes. *Handbook of the economics of innovation* (pp. 51–127). Elsevier.

Dumont, M., & Meeusen, W. (2000). *Knowledge spillovers through R&D cooperation*. Workshop Paper. Retrieved from http://www.oecd.org/sti/innovationinsciencetechnologyandindustry/2093436.pdf

Enkel, E., Groemminger, A., & Heil, S. (2018). Managing technological distance in internal and external collaborations: Absorptive capacity routines and social integration for innovation. *The Journal of Technology Transfer, 43*(5), 1257–1290.

Ferreras-Méndez, J. L., Newell, S., Fernández-Mesa, A., & Alegre, J. (2015). Depth and breadth of external knowledge search and performance: The mediating role of absorptive capacity. *Industrial Marketing Management, 47*, 86–97.

Flor, M. L., Cooper, S. Y., & Oltra, M. J. (2018). External knowledge search, absorptive capacity and radical innovation in high-technology firms. *European Management Journal, 36*(2), 183–194.

Frenken, K., Van Oort, F., & Verburg, T. (2007). Related variety, unrelated variety and regional economic growth. *Regional Studies, 41*, 685–697.

Goya, E., Vayá, E., & Suriñach, J. (2016). Innovation spillovers and firm performance: Micro evidence from Spain (2004–2009). *Journal of Productivity Analysis, 45*(1), 1–22.

Green, W. H. (1997). *Econometric analysis*. Prentice-Hall.

Griliches, Z. (1979). Issues in assessing the contribution of R&D to productivity growth. *Bell Journal of Economics, 10*, 92–116.

Grillitsch, M., & Nilsson, M. (2017). Firm performance in the periphery: On the relation between firm-internal knowledge and local knowledge spillovers. *Regional Studies, 51*, 1219–1231.

Hall, B. H., Mairesse, J., & Mohnen, P. (2009). *Measuring the returns to R&D*. NBER Working Papers 15622, National Bureau of Economic Research, Inc.

Hall, B. H., & Lerner, J. (2010). *The financing of R&D and innovation*. NBER Working Papers 15325, National Bureau of Economic Research, Inc.

Hauknes, J., & Knell, M. (2009). Embodied knowledge and sectoral linkages: An input-output approach to the interaction of high- and low-tech industries. *Research Policy, 38*, 459–469.

Heijs, J. (2004). Innovation capabilities and learning: A vicious circle. *International Journal of Innovation and Learning, 5*, 263–278.

Heijs, J. (2012). Innovation capabilities and learning. In M. D. Parrilli & B. T. Asheim (Eds.), *Interactive learning for innovation: A key driver within clusters and innovation systems* (pp. 206–233). Palgrave Macmillan.

Hidalgo, C. A., Klinger, B., Barabási, A. L., & Hausmann, R. (2007). The product space conditions the development of nations. *Science, 317*, 482–487.

Hipp, C., & Grupp, H. (2005). Innovation in the service sector: The demand for service-specific innovation measurement concepts and typologies. *Research Policy, 34*(4), 517–535.

Howells, J. R. (2002). Tacit knowledge, innovation and economic geography. *Urban Studies, 39*(5–6), 871–884.

Jaffe, A. B. (1986). Technological opportunity and spillovers of R&D: Evidence from firms' patents, profits, and market value. *American Economic Review, 76*(5), 984–1001.

Jaffe, A. B., Trajtenberg, M., & Henderson, R. (1993). Geographic localization of knowledge spillovers as evidenced by patent citations. *Quarterly Journal of Economics, 108*(3), 577–598.

Kamien, M. I., & Schwartz, N. L. (1970). Market structure, elasticity of demand, and incentive to invent. *Journal of Law and Economics, 13*, 241–252.

Kamien, M. I., & Schwartz, N. L. (1982). *Market Structure and Innovation*. Cambridge University Press.

Lane, P. J., Koka, B. R., & Pathak, S. (2006). The reification of absorptive capacity: A critical review and rejuvenation of the construct. *Academy of Management Review, 31*(4), 833–863.

López-García, P., & Montero, J. M. (2011). Spillovers and absorptive capacity in the decision to innovate of Spanish firms: The role of human capital. *Economics of Innovation and New Technology, 21*(7), 589–612.

Los, B. (2000). The empirical performance of a new inter-industry technology spillover measure. In P. P. Saviotti & B. Nooteboom (Eds.), *Technology and knowledge* (pp. 118–151). Edward Elgar.

Malmberg, A., & Maskell, P. (2006). Localized learning revisited. *Growth and Change, 37*(1), 1–18.

MartínezArdila, H. E., Mora Moreno, J. E., & Camacho Pico, J. A. (2020). Networks of collaborative alliances: The second order interfirm technological distance and innovation performance. *Journal of Technology Transfer, 45*, 1255–1282.

Medda, G., & Piga, C. A. (2014). Technological spillovers and productivity in Italian manufacturing firms. *Journal of Productivity Analysis, 41*(3), 419–434.

Neffke, F., & Henning, M. (2013). Skill relatedness and firm diversification. *Strategic Management Journal, 34*(3), 297–316.

Neffke, F., Henning, M., & Boschma, R. (2011). How do regions diversify over time? Industry relatedness and the development of new growth paths in regions. *Economic Geography, 87*(3), 237–265.

Nieto, M. J., & Rodríguez, A. (2011). Offshoring of R&D: Looking abroad to improve innovation performance. *Journal of International Business Studies, 42*, 345–361.

Nieto, M. J., & Santamaría, L. (2010). Technological collaboration: Bridging the innovation gap between small and large firms. *Journal of Small Business Management, 48*(1), 44–69.

Nooteboom, B. (2000). *Learning and innovation in organizations and economies*. Oxford University Press.

Nooteboom, B., Van Haverbeke, W., Duysters, G., Gilsing, V., & Van den Oord, A. (2007). Optimal cognitive distance and absorptive capacity. *Research Policy, 36*(7), 1016–1034.

OECD. (2021). *Main science and technology indicators, volume 2020 issue 2*. OECD Publishing. https://doi.org/10.1787/0bd49050-en

Oughton, C., & Whittam, G. (1997). Competition and cooperation in the small firm sector. *Scottish Journal of Political Economy, 44*(1), 1–30.

Penrose, E. (1959). *The theory of the growth of the firm* (4th ed.). Oxford University Press.

Rodriguez, M., Doloreux, D., & Shearmur, R. (2017). Variety in external knowledge sourcing and innovation novelty: Evidence from the KIBS sector in Spain. *Technovation, 68*, 35–43.

Spence, A. M. (1975). Monopoly, quality, and regulation. *Bell Journal of Economics, 6*, 417–429.

Spielkamp, A., & Rammer, C. (2009). Financing of innovation—Thresholds and options. *Management & Marketing, 4*(2), 3–18.

Spithoven, A., & Teirlinck, P. (2015). Internal capabilities, network resources and appropriation mechanisms as determinants of R&D outsourcing. *Research Policy, 44*, 711–725.

Ter Wal, A. L. J., & Boschma, R. (2011). Co-evolution of firms, industries and networks in space. *Regional Studies, 45*(7), 919–933.

Thompson, P., & Fox-Kean, M. (2005). Patent citations and the geography of knowledge spillovers: A reassessment. *The American Economic Review, 95*(1), 450–460.

Tojeiro-Rivero, D., & Moreno, R. (2019). Technological cooperation, R&D outsourcing, and innovation performance at the firm level: The role of the regional context. *Research Policy, 48*(7), 1798–1808.

Tojeiro-Rivero, D., Moreno, R., & Badillo, E. R. (2019). Radical innovations: The role of knowledge acquisition from abroad. *Review of Industrial Organization, 55*(2), 173–207.

Whittle, A., & Kogler, D. F. (2020). Related to what? Reviewing the literature on technological relatedness: Where we are now and where can we go? *Papers in Regional Science, 99*(1), 97–113.

Wieser, R. (2005). R&D, productivity and spillovers: Empirical evidence at firm level. *Journal of Economic Surveys, 19*(4), 587–621.

Wooldridge, J. M. (1995). Selection corrections for panel data models under conditional mean independence assumptions. *Journal of Econometrics, 68*(1), 115–132.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data* (2nd ed.). The MIT Press.