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Essays on R&D, knowledge spillovers and firm performance

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Julkaisun nimike

Esseitä t&k-toiminnan ja tiedon leviämisen vaikutuksista yritysten menestykseen

Tiivistelmä

Tässä väitöskirjassa tarkastellaan tutkimus- ja kehitystyön (t&k), organisaatioinvestointien sekä tiedon leviämisen vaikutuksia yritysten menestykseen. Yritysten menestystä arvioidaan markkina-arvon, tuottavuuden, keksintöjen määrän, laadun sekä teknologisen monipuolisuuden kannalta. Ensimmäinen essee tarkastelee suomalaisten yritysten aineettoman pääoman ja markkina-arvon yhteyttä. Tulokset osoittavat, että t&k-investoinneilla, yritysten patentti- ja patenttiviittausmäärillä sekä erityisesti organisaatiopääomalla on positiivinen yhteys yritysten markkina-arvoon.

Toisessa esseessä analysoidaan, kuinka kansainvälinen tutkimustoiminta vaikuttaa eurooppalaisten yritysten keksintöjen määrään, teknologiseen monipuolisuuteen ja laatuun. Tutkimuksessa selvitetään, pystyvätkö vain muita innovatiivisemmat yritykset maksamaan kansainväliseen t&k-toimintaan liittyvät kustannukset vai parantaako kansainvälisyys yritysten tiedon hankintaa ja innovatiivisuutta. Analyysi paljastaa, että innovatiivisemmat yritykset kansainvälistävät todennäköisemmin tutkimustoimintaansa. Lisäksi kansainvälinen t&k lisää näiden yritysten keksintöjen määrää ja monipuolisuutta, muttei kuitenkaan laatua. Kolmas essee analysoi, kuinka t&k-investointien kansainvälistyminen vaikuttaa näiden investointien tuottavuuteen. Tulosten perusteella kansainvälistä tutkimustoimintaa harjoittavien yritysten t&k-investointien tuottavuus on korkeampi ja tämä johtuu erityisesti kansainvälisestä tutkimustoiminnasta teknologian edelläkävijämaissa.

Neljännessä esseessä tarkastellaan keksijöiden liikkuvuuden roolia tiedon siirtymisessä yritysten välillä. Esseessä analysoidaan työntekijän ja hänen edellisen työnantajansa ominaisuuksien merkitystä tiedon leviämisessä. Empiiristen tulosten mukaan keksijöiden siirtyminen ei lisää yritysten patentointia, elleivät siirtyvät keksijät ole keskimääräistä tuottavampia tai tuo yritykseen eri tekniikan alan osaamista. Keksijöiden lähteminen yrityksestä johtaa merkittävästi pienempään patenttihakemusten määrään tulevaisuudessa.

Asiasanat

t&k, aineeton pääoma, tiedon leviäminen, kansainvälistyminen, työvoiman liikkuvuus

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Abstract
This thesis analyzes how research and development (R&D), organizational investments and knowledge spillovers affect firm performance. The performance of firms is examined by analyzing their market value, productivity and the quantity, quality and diversity of innovations. The first essay analyzes the market valuation of Finnish firms and its dependence on firms' knowledge and organizational assets. The results indicate that R&D, patents and patent citations all have positive relationships with market value, while for organizational capital the relationship appears especially strong.

The second essay examines how the innovation performance of European firms is influenced by the internationalization of their R&D activities. The aim of the essay is to determine whether firms with overseas R&D are initially more innovative and are thus able to cover the additional costs of internationalization or whether overseas R&D further improve firms' innovativeness. The results show that firms with more previous innovations are more likely to start international R&D activities. Moreover, engaging in overseas R&D activities further increases their innovative output and the technological diversity of innovations but not their quality. The third essay analyzes how international R&D activities affect the R&D returns. International R&D activities are shown to be associated with higher returns to R&D, and this result is driven by overseas R&D in technologically leading countries.

The fourth essay analyzes knowledge spillovers through inventor mobility. The prior literature recognizes labor mobility as a channel of knowledge spillovers. This essay analyzes how the characteristics of inventors and source firms affect these spillovers. The empirical results suggest that inventor mobility does not increase a firm's future patenting unless the hired inventors have high prior productivity or bring different kinds of technological expertise to the firm. Outbound inventor mobility is shown to decrease the source firm's patenting.

Keywords
R&D, intangible capital, knowledge spillovers, R&D internationalization, labor mobility

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Vaasa, August 2016

Jaana Rahko

Contents

Abbreviations

EPO	European Patent Office
FDI	Foreign direct investments
ICT	Information and communications technology
LEED	Linked employer-employee data
PATSTAT	EPO Worldwide Patent Statistical Database
R&D	Research and development
SGA	Selling, general and administrative
TFP	Total factor productivity

This dissertation consists of an introductory chapter and the following four essays:

1. Rahko, J. (2014). Market value of R&D, patents, and organizational capital: Finnish evidence. *Economics of Innovation and New Technology* 23: 4, 353-377.

2. Rahko, J. (2016). Internationalization of corporate R&D activities and innovation performance. Forthcoming in *Industrial and Corporate Change*.

3. Rahko, J. (2016). Internationalization of R&D and the returns to R&D activities in European firms.

4. Rahko, J. (2016). Knowledge spillovers through inventor mobility: the effect on firm-level patenting. Forthcoming in *The Journal of Technology Transfer*.

1 INTRODUCTION

Growth theories place innovation and knowledge diffusion at the center when they explain long-term growth and welfare in the economy (Aghion & Howitt 1992; Romer 1990). The important roles of research and development (R&D) and other intangible investments in innovation, productivity improvement and economic growth are also empirically documented at the country- and industry-level. Furthermore, large differences in productivity and other measures of firm performance are recognized to depend on the intangible assets of firms. In addition to R&D, these assets include, e.g., patents, brands, trademarks, information and communications technology (ICT), as well as organizational assets and competences. Technological innovations and investments in R&D have been long studied in empirical economics, and the theoretic literature also acknowledges the importance of non-technological intangible investments and innovations; however, the empirical research on their effects is more recent and sometimes fragmental due to quite restrictive data sets (Cardona, Kretschmer & Strobel 2013; Hall, Mairesse & Mohnen 2010; Schautschick & Greenhalgh 2016).

R&D and other intangible investments not only affect the investing firm and country's economic performance, but the innovations and new knowledge created through these investments can also affect the performance of other firms, regions and countries. Such positive externalities, known as knowledge spillovers, occur because of the nonrivalrous and partially public good nature of knowledge, which allows the same knowledge to be simultaneously used by many individuals or firms. Due to incomplete patent protection, reverse engineering, imitation and other reasons, firms can keep only part of their knowledge and the results of R&D to themselves. This leaves room for knowledge spillovers, which can support continuous economic growth (Romer 1990). The importance of knowledge spillovers for firm performance is also documented in empirical studies (Hall, Mairesse & Mohnen 2010; Wieser 2005). However, while empirical research has identified labor mobility and other channels of knowledge spillovers, the extant literature has yet to analyze comprehensively the prerequisites of spillovers and the exact mechanisms through which these spillovers occur.

Because of positive externalities, the social returns to R&D often exceed the private returns to R&D, thus inducing governments to promote and subsidize private R&D investments. The importance of R&D investments and innovations is also highlighted in European Union policy. The EU's Europe 2020 strategy aims to create growth through education, research and innovation. The strategy aims for R&D investment totaling 3% of the EU's GDP. Thus, the productivity and growth effects of R&D and their magnitudes are of great economic, social and political importance.

At the firm-level, gains from R&D and intangible investments do not depend merely on the amount of such investments, but it is crucial to organize these activities in a way that allows the efficient use of resources and enables both knowledge sourcing and access to external knowledge spillovers. In this context, e.g., the interplay between ICT and organizational practices has been studied (Bloom, Sadun & Van Reenen 2012; Brynjolfsson & Hitt 2003). Furthermore, the economic research has identified important interdependencies among R&D and exporting (Bustos 2011; Lileeva & Trefler 2010), foreign direct investment (FDI) (Añón Higón & Manjón Antolín 2012; Aw, Roberts & Xu 2011), research cooperation (Belderbos, Carree & Lokshin 2004), external R&D (Lokshin, Belderbos & Carree 2008) and absorptive capacity (Griffith, Redding & Van Reenen 2004). In addition, the international organization of R&D activities influences the possibilities for knowledge sourcing and thus the R&D performance of firms. Because knowledge spillovers are typically geographically bounded (Audretsch & Feldman 1996), both manufacturing FDI and R&D FDI are considered important to improve access to foreign technological knowledge. However, the extant empirical research on the effects of R&D internationalization on firm performance has provided somewhat mixed results.

In this context, this doctoral thesis aims to extend our understanding of the mechanisms through which R&D and other intangible investments impact firm performance and the size of these effects. The performance of firms is examined by analyzing market value and productivity, as well as the quantity, quality and technological diversity of firms' innovations. The first essay empirically analyzes the effects of intangible assets – patents, patent citations, R&D and organizational investments – on the market value of Finnish firms. The second and third essays study how the benefits of R&D investments depend on the organization of these activities, specifically, how the international distribution of corporate R&D activities affects firms' innovation performance and R&D returns. Finally, the fourth essay of this dissertation studies labor mobility as a mechanism of knowledge spillovers and, especially, how and under which circumstances inventor mobility can impact the innovation performance of firms.

The remainder of this introductory chapter is organized as follows. The next section provides a brief overview of the theoretical foundations and the empirical literature on intangibles and knowledge spillovers. The third section summarizes the four essays that constitute this dissertation. The fourth and final section discusses and concludes.

2 OVERVIEW OF THE LITERATURE

2.1 Theoretical foundation

Economic theories cannot explain sustained economic growth using physical capital investment alone; instead, they emphasize the roles of R&D investments, technological progress and knowledge spillovers in economic growth. This insight is not new, and the R&D literature was already pioneered by authors such as Griliches (1958), Schmookler (1966) and Mansfield (1968). Endogenous growth theories formalize the roles of R&D investments and knowledge spillovers in explaining economic growth (Aghion & Howitt 1992; Romer 1986; Romer 1990). According to these theories, technological progress is driven by conscious investments in research and technology, which are largely conducted by private firms. These investments lead to innovations, i.e., ideas for new products, materials and services as well as new ways to produce, design and use them. This technological change motivates continued capital accumulation, which together drive economic growth. Through two different channels, technological change is also reflected in higher firm productivity, i.e., the efficiency with which firms convert production inputs into outputs. First, improved technologies allow firms to produce existing products more efficiently. Second, firms can develop new or improved products that they can sell at higher prices. The economic literature has typically discussed and analyzed R&D investments and technological innovations; however, the same logic also applies to non-technological innovations, such as organizational innovations.

Firms have incentive to invest in R&D as long as the expected benefits outweigh the costs of R&D. Thus, in order to support private R&D investment, innovators need to be able to keep at least part of the benefits of their innovations and make profit. Thus, to be able to appropriate the returns of innovation, innovating firms need to have some degree of market power, e.g., through temporary patent monopoly or lead time. However, competition between firms may also encourage private R&D investments and innovations because innovating enables firms to escape competition at least partially and temporarily (Aghion et al. 2005; Aghion et al. 2009).

Many technologies and non-technological innovations have general applicability and therefore they can benefit many other firms besides the innovating firm. New technology or a piece of knowledge is a nonrival good, i.e., many individuals can use the same piece of knowledge simultaneously without interference to others.

However, knowledge is also partly excludable, e.g., through patent protection, trade secrets or lead time. Thus, the inventor or the innovating firm can capture some but typically not the whole value of the new technology. When new technologies are not or cannot be patented or otherwise protected, other firms cannot be excluded from utilizing these innovations. Therefore, other firms may use them as inputs in their own production or innovation processes. Therefore, new knowledge has positive externalities in the economy. Knowledge externalities and spillovers allow the rest of the economy to benefit from new knowledge. When knowledge spillovers are strong enough, they can create increasing returns to scale and sustain long-term economic growth. Thus, the social returns to innovation and R&D often[1] exceed the private returns and the level of private R&D investments may be socially suboptimal. This discrepancy motivates governments to support private R&D investments. (Romer 1990)

However, even when patent rights and other legal restrictions are absent, the knowledge spillovers are not perfect but subject to considerable frictions as evidenced by large and persistent differences in firm- and country-level productivity and technology (Syverson 2011). This finding leads to crucial questions: Why do some firms and regions benefit from knowledge spillovers while others do not? When do knowledge spillovers occur? What are their channels and mechanisms? Overall, knowledge spillovers are argued to require some kind of proximity between the firms, regions or countries in question. This proximity can be achieved in many forms including geographical, cognitive, technological and relational proximity. Specifically, it can be attained through, e.g., international trade or other market transactions, labor mobility, research collaboration, communication at technical conferences, scientific publications, and so on. Four aspects of knowledge spillovers have received considerable research interest in this context: the channels of international knowledge spillovers, the role of geographical proximity, the importance of absorptive capacity created through own R&D investments and the spillovers produced through labor mobility.

International knowledge spillovers are positive externalities that occur across national borders. They are knowledge flows that are not automatic or instantaneous but occur through channels such as international trade contacts, FDI and economic integration, as modeled theoretically by Grossman & Helpman (1990; 1991), Rivera-Batiz & Romer (1991) and Eaton & Kortum (1999) and

[1] The social returns to R&D do not always exceed private returns. Due to creative destruction, innovators may spend too much on R&D because they do not consider the negative effect of products and knowledge that become useless after an innovation (Aghion and Howitt 1992).

shown empirically by, e.g., Coe & Helpman (1995) and Keller (2002b; 2004). Moreover, geographic distance increases the communication and trade costs, hinders face-to-face contacts and thus also diminishes the occurrence of both intranational and international knowledge spillovers (Jaffe, Trajtenberg & Henderson 1993; Keller 2002a). At the country-level, openness to international trade and FDI mediate cross-country knowledge spillovers and technological progress (Lichtenberg & de la Potterie 1998). At the firm-level, international presence through exporting, FDI and foreign R&D laboratories improve access to knowledge possessed by foreign competitors, as well as to the skills and expertise of foreign labor markets (Belderbos, Lykogianni & Veugelers 2008; De La Potterie & Lichtenberg 2001; Griffith, Harrison & Van Reenen 2006).

Geographical or trade proximity does not remove all knowledge spillover frictions. Cohen & Levinthal (1989; 1990) and Eaton & Kortum (1996) argue that absorptive capacity is critical at the firm- and country-level for them to benefit from the knowledge and R&D investments of others. Aghion & Howitt (2009) refer to this same process as devoting resources to innovation. R&D-related technological knowledge is often tacit and cannot be directly or costlessly copied. Absorptive capacity forms the cognitive basis that allows firms to recognize, assimilate and apply valuable new external knowledge. Absorptive capacity depends on related technological expertise, i.e., own in-house R&D at the firm-level and the level of education at the country-level. Also, at the country-level, R&D intensity explains the speed of knowledge transfer from technological frontier to non-frontier countries (Griffith, Redding & Van Reenen 2004).

The link between labor mobility and knowledge spillovers has been understood at least since Arrow (1962). Workers can acquire firms' tacit R&D knowledge through job tenure. Such R&D knowledge cannot be easily codified or protected by patents, and thus, when workers move, they can carry this acquired knowledge with them to their new employers (for theoretical contributions see, e.g., Cooper (2001), Fosfuri, Motta & Rønde (2001) and Kim & Marschke (2005)). Labor mobility can thus explain part of the occurrence of intranational and international knowledge spillovers and why some firms and regions are able to benefit from spillovers while others are not (Almeida & Kogut 1999; Saxenian 1994). Therefore, labor mobility can be considered socially desirable, like also other knowledge spillover transmission mechanisms. However, labor mobility and other similar mechanisms may also decrease private R&D investment or increase patenting and the use of other intellectual property protections, as firms struggle to protect the results of their investments (Kim & Marschke 2005).

2.2 R&D, intangibles and firm performance

R&D's role as a driver of growth and productivity is predicted by theoretical work and supported by a substantial empirical literature at the firm-, industry- and country-level (see, e.g., Hall, Mairesse & Mohnen (2010) for a survey). The two most common approaches to analyze the effects of R&D on firm performance evaluate the effect of R&D investments on firms' market value and their effect on firms' production function. Other approaches are also summarized by Hall, Mairesse & Mohnen (2010).

To estimate the returns to R&D investments, firm-level Cobb-Douglas production functions augmented with R&D stock are often estimated. It is assumed that R&D investments create a firm-level stock of knowledge that will yield economic returns. The R&D stock is often constructed using the perpetual inventory method, which assumes that the current level of R&D knowledge depends on present and past depreciated R&D investments. However, the perpetual inventory method entails the problem of choosing a correct depreciation rate. Depreciation rate of R&D is not constant across firms or over time and thus the available empirical estimates vary from zero up to 100 percent (Hall 2007; Li & Hall 2016). However, most of the literature has adopted a constant 15% depreciation rate following early studies by Zvi Griliches. Sometimes R&D intensity, that is, the R&D investment to output ratio, is used in a differenced production function. Another common approach is to first calculate total factor productivity (TFP) and then regress TFP or its change on R&D investments. The empirical estimates of the R&D elasticity of output range from 0.01 to 0.25 but center around 0.08 (Hall, Mairesse & Mohnen 2010).

R&D investments are an input measure of innovation. Their wide use is supported by the fact that R&D investments have clear and easily comparable economic values, whereas innovation output measures, such as the number of granted patents or product and process innovations, have often highly heterogeneous economic values. Moreover, the use of patent-based measures has well-known limitations because not all inventions are patentable and because patents are not the only way to protect inventions. The propensity to patent also varies greatly across firms, industries and countries. However, input and output measures of innovation are shown to be closely related, and thus, patent data are also extensively used, as they are available as long time series and across most of the world. Empirical studies show that patents have a significant impact on firm productivity (Balasubramanian & Sivadasan 2011; Bloom & Van Reenen 2002; Crépon, Duguet & Mairesse 1998). The studies also find that product innovations have a significant positive effect on the revenue productivity of firms, whereas the positive effect of process innovations is somewhat more ambiguous. For survey of studies on the relationship between output measures of innovation and productivity, see Syverson (2011), Hall (2011) and Mohnen & Hall (2013).

Measuring the effect of intangibles on productivity can be problematic, as R&D and other intangible investments are expected to increase firm productivity in the future and the time lag can be long and difficult to predict. Market value is a forward-looking measure of firm performance that should capture the increase in future profitability without a time lag. Hence, empirical studies have attempted to determine the marginal value of R&D and other intangible assets by analyzing how the market value of firms depends on intangible assets, as well as other firm characteristics. The market value model was introduced by Griliches (1981) to analyze the economic value of R&D and patents. In this model, a firm is considered a bundle of assets. The aim is to measure the effect of each asset on the market value, which makes the approach comparable to the hedonic price models. The market value model relies on the assumptions that financial markets are efficient and that the market value equals the present value of discounted expected future dividends (Hall 2000). E.g. Hall, Jaffe & Trajtenberg (2005) have studied the market valuation of R&D and patents in the US stock market. Hall, Thoma & Torrisi (2007) report that European stock markets significantly value the R&D investments, patents and patent citations[2] of European firms. R&D investments appear more important for stock market valuation than patents, with a reported elasticity of Tobin's q with respect to the R&D-asset ratio of approximately 20%.

R&D, patents, product and process innovations describe mainly technological innovations and improvements. Data on R&D and patents have been more easily available, and hence, they have been at the center of empirical research. The importance of many non-technological intangible investments and innovations, e.g., organizational and marketing investments, is also recognized; however, the empirical research on their effects is more recent and less comprehensive. In the literature, ICT and software investments are often discussed along with intangible investments, although part of them, e.g., hardware investments, are tangible.

[2] The empirical literature has often used patent citations as a patent quality indicator. A patent application may be referenced by other applications if the later inventions are based on or related to the earlier invention. Additionally, the patent office conducts a search during the patent-granting procedure and may also add relevant citations to the application. Consequently, if a patent receives many citations, it is likely that the underlying invention is important and of high quality.

The empirical literature on intangible assets and their effect on firm performance has grown considerably in recent years. The existing studies generally find that non-R&D intangible assets have grown over time and have a positive effect on firm- and country-level productivity growth, although the studies are sometimes based on limited data (Hall 2011; Mohnen & Hall 2013; Syverson 2011). Empirical studies show that ICT and computer investments significantly improve firm productivity and that these investments are complementary to organizational changes (Bloom, Sadun & Van Reenen 2012; Brynjolfsson & Hitt 2003). ICT is also argued increases the variance of firm performance (Syverson 2011). At the macro-level, these investments can also partially explain the difference in the productivity growth rates of the US and Europe over the last two decades (Bloom, Sadun & Van Reenen 2012). For a survey of the literature on the effect of ICT investments on firm-, industry- and country-level performance, see Syverson (2011) and Cardona, Kretschmer & Strobel (2013).

Firm-level organizational assets have been studied using many different measures. Some studies analyze firms' selling, general and administrative (SGA) expenses and find that these expenses contribute to higher firm productivity and stock market returns (Chen & Inklaar 2016; Eisfeldt & Papanikolaou 2013; Lev & Radhakrishnan 2005). Other studies show that certain organizational and management practices can cause higher firm productivity (Bloom et al. 2013; Bloom & Van Reenen 2007; Syverson 2011). Prior studies also discuss how advertising expenditure and trademarks can positively affect a firm's market value; see, e.g., Joshi & Hanssens (2010) and Sandner & Block (2011). For a survey of the empirical literature on trademarks and firm performance, see Schautschick & Greenhalgh (2016). The coverage and measurement of non-technological intangible assets varies greatly across studies, and consequently, the magnitudes of the estimated effects vary similarly. The relative importance of different intangible investments has been explored on at the macro-level (Borgo et al. 2013; Corrado, Hulten & Sichel 2009); however, at firm-level, few studies have been able to compare different types of intangibles. In addition, intangibles and market value have mostly been studied in the US and UK contexts and fewer studies have analyzed other countries.

As discussed above, a substantial empirical literature shows that R&D and other intangible investments are important determinants of firm-level productivity growth and market value. However, the returns to R&D are not constant across firms or industries and depend on many firm-specific and environmental factors (Hall, Mairesse & Mohnen 2010; Syverson 2011). In the following, the empirical literature on themes related to this dissertation is shortly reviewed. Many other topics, such as industry characteristics, are covered in a survey by Cohen (2010).

The relationship between firm size and R&D has been an important theme in the extant literature. After decades of research, the general findings are that larger firms appear better able to appropriate the returns of their innovations, but studies have failed to find systematic differences in the relative innovativeness of large and small firms (Cohen 2010). Also related with firm size, exporting has long been recognized as related to firm productivity, mostly because larger and more productive firms self-select into export markets and FDI (De Loecker 2007; Syverson 2011). Moreover, exporting is also understood as related to firms' R&D investments. Access to larger markets may help firms to better appropriate the returns to their innovations and, moreover, firms can exploit returns to scale in R&D by spreading the costs of research investments across several markets and thus better cover its investment costs. Lileeva & Trefler (2010) show that access to larger markets through exporting increases the returns to firms' R&D investments and may further increase firms' investments in R&D and productivity growth. The findings of Aw, Roberts & Xu (2011) and Bustos (2011) point to the same conclusion. In addition, multinational firms are also observed to enjoy higher returns to their R&D investments through their access to larger markets (Añón Higón & Manjón Antolín 2012).

2.3 Knowledge spillovers and firm performance

Knowledge spillovers represent one mechanism through which the characteristics of a firm's environment affect its performance. When analyzing spillovers, we are interested in the effect of other firms, universities or countries' R&D and technological knowledge on firm's own productivity and innovation performance. Knowledge spillovers occur when other firms can utilize previous innovations and knowledge as inputs in their production and innovation activities. Knowledge spillovers refer to unpaid flow of knowledge, whereas technology transfer refers to trade in technology, licensing and other directly paid activities. Rent spillovers occur through purchases of R&D-incorporated goods when the price of the goods does not reflect their entire user value (Griliches 1992). In empirical studies, these different spillovers are not always precisely specified.

Spillovers can also affect firm performance in two counteracting ways. Knowledge spillovers allow firms to access new knowledge; however, competitors investing in R&D may gain market share and thus weaken the performance of its rivals (business stealing effect). Overall, the effect of knowledge spillovers is assessed to dominate (Bloom, Schankerman & Van Reenen 2013).

To measure knowledge spillovers and analyze their effects, it needs to be assumed either that the benefits are in some way localized or that it is possible to detect the channel of spillovers (Griliches 1992). Early empirical studies often analyzed localized knowledge spillovers. These studies included a firm's own R&D stock and a measure of outside R&D available to the firm, i.e. the spillover pool, in its production or innovation production function (Wieser 2005). The available spillover pool is usually assumed to consist of the R&D stocks of other proximate firms. R&D stocks are implicitly assumed to contain transferable knowledge, and different proximity measures describe the transferability of knowledge between firms. In its simplest form, the spillover pool is the stock of R&D conducted by other firms in the same industry (Bernstein & Nadiri 1989). Other studies form the spillover pool by weighting the R&D stocks using a measure of technological, geographical or social proximity between firms. Many studies also use patent citation patterns as evidence of knowledge spillovers and the technology classes of firms' patents to measure the technological proximity between firms (Griliches 1992; Jaffe 1986). Furthermore, Jaffe, Trajtenberg & Henderson (1993) and Audretsch & Feldman (1996) argue and show that knowledge spillovers are geographically concentrated. More recently, e.g., Aldieri & Cincera (2009) and Lychagin et al. (2010) also show how knowledge spillovers decay with geographic distance.

Empirical studies applying the above-described methods usually find that the estimated firm-level output elasticities of R&D spillovers are positive and statistically and economically significant. However, the point estimates vary across studies even more than the estimates of R&D elasticity. (Hall, Mairesse & Mohnen 2010; Wieser 2005)

Non-technological intangible assets can also create spillovers, although these spillovers have not been equally widely studied. Cardona, Kretschmer & Strobel (2013) survey the literature on ICT related spillovers and conclude that their existence and magnitude remains ambiguous. Similarly, the results with respect to the spillovers of organizational capital remain mixed and inconclusive (Chen & Inklaar 2016; Corrado, Haskel & Jona Lasinio 2014).

While many empirical studies find that firms benefit from strong, positive R&D spillovers, the above mentioned studies do not directly specify the exact mechanisms through which knowledge spillovers occur. Many recent studies attempt to analyze and clarify the exact channels of these spillovers.

International trade and FDI transmit the trade in technology but knowledge externalities are also argued to spill over via trade or FDI flows (Keller 2010). On one hand, local firms close to sites, where foreign firms locate and invest, benefit from knowledge spillovers because geographic proximity increases the important face-to-face contacts and reduces the costs of learning[3]. These spillovers can explain substantial part of firm- and country-level productivity improvements (Haskel, Pereira & Slaughter 2007; Javorcik 2004; Keller & Yeaple 2009). On the other hand, while FDI increases the risk of outward spillovers from firms conducting FDI, the local knowledge also spills over to the multinational firms (Keller 2010). This implies that both local knowledge sourcing and knowledge protection considerations affect the location decisions of FDI, including R&D FDI (Alcácer & Chung 2007; Belderbos, Lykogianni & Veugelers 2008; Le Bas & Sierra 2002). Overall, inward knowledge spillovers to the multinational firms can often exceed the outward spillovers to host country firms (Singh 2007). Due to the need for plant-level absorptive capacity, firms may also need to establish overseas R&D facilities to fully utilize the knowledge spillovers obtained through FDI.

While the prior literature has quite extensively discussed the effects of exporting and FDI on R&D returns and productivity, the role of international R&D activities is not equally well covered. With respect to the motives of international R&D activities, it is widely recognized that firms establish overseas R&D units to gain access to local knowledge spillovers, as well as new resources, expertise and technologies, which may improve firms' innovativeness (Alcácer & Chung 2007; Audretsch & Feldman 1996; Moncada-Paternò-Castello, Vivarelli & Voigt 2011). Access to a highly qualified workforce is also identified as an important motive for locating R&D activities abroad (Ambos & Ambos 2011; Lewin, Massini & Peeters 2009; Thursby & Thursby 2006). International R&D investments are also partly motivated by improved access to foreign markets (Kuemmerle 1999; Le Bas & Sierra 2002; von Zedtwitz & Gassmann 2002). Local R&D activities may improve the speed to market and adaptation of domestically developed products to the tastes and regulations of foreign markets. Thus, international R&D activities may improve the returns to corporate R&D through the same mechanisms as export market participation as well as benefit firms through improved local knowledge spillovers.

Few empirical studies have directly analyzed the effect of international R&D activities on firm productivity and R&D returns. Todo & Shimizutani (2008) analyze Japanese firms and find that overseas innovative R&D has a weak, positive effect on a parent firm's productivity growth but not on the rate of return on R&D. In contrast, Fors (1997) finds that international R&D has no effect on parent firm productivity growth. Belderbos, Lokshin & Sadowski (2014) find that

[3] Similarly, international trade also creates new contacts and facilitates learning and knowledge flows.

foreign R&D investments complement domestic R&D in Dutch firms but only in industries that are lagging behind the world technology frontier. Empirical findings on the innovation performance effects of R&D internationalization are generally positive; however, these findings depend on firm characteristics and cannot be interpreted as causal evidence. Iwasa & Odagiri (2004) and Penner-Hahn & Shaver (2005) study the internationalization of R&D activities in Japanese firms and find that it is associated with increased innovative output, at least for some firms. Chen, Huang & Lin (2012) and Hsu, Lien & Chen (2014) study Taiwanese high-tech firms and the geographic diversity of their overseas R&D investments and find that overseas R&D activities positively affect the average quality of innovations, although this finding is contingent on several firm-level characteristics.

The geographic concentration of knowledge spillovers is argued to be largely due to geographically concentrated labor markets, suggesting that labor mobility and personal contacts of researchers as important channels of knowledge spillovers (Breschi & Lissoni 2001; 2009; Hall, Mairesse & Mohnen 2010). While firms pay wages to compensate hired employees for their skills, the work contracts do not always fully compensate for the technology transfer, which allows the hiring firms to benefit from knowledge externalities (Fosfuri, Motta & Rønde 2001; Stoyanov & Zubanov 2014). Therefore, recent studies have focused on the mobility of employees and inventors and on how their mobility contributes to knowledge spillovers and firm performance. These studies analyze the mobility of patent inventors (Agrawal, Cockburn & McHale 2006; Almeida & Kogut 1999), R&D workers (Maliranta, Mohnen & Rouvinen 2009; Moen 2005), highly educated employees (Parrotta & Pozzoli 2012), multinational company employees (Balsvik 2011; Poole 2013) and employees from more productive firms (Stoyanov & Zubanov 2012). Also, spillovers from the ICT investments of other firms are argued to be transmitted by ICT worker mobility (Tambe & Hitt 2013).

Overall, labor mobility and hiring of highly educated employees is found to act as a channel of knowledge spillovers, thus affecting the hiring firm's productivity performance. The growth and innovativeness of regions are also partly attributed to labor mobility (Almeida & Kogut 1999; Miguélez & Moreno 2013; Saxenian 1994). However, some prior studies have found a negative association between employee turnover and firm productivity, as well as innovation performance (Hancock et al. 2013; Ilmakunnas, Maliranta & Vainiomäki 2005; Michie & Sheehan 2003; Zhou, Dekker & Kleinknecht 2011). While insightful, the prior results on labor mobility are thus not unambiguous and it remains to be further clarified, what are the firm or worker characteristics that are the prerequisites for knowledge spillovers. Moreover, many existing studies have emphasized learning by hiring; however, outbound mobility is equally important, as workers who leave a firm produce a knowledge leak and skill losses but may simultaneously act as a channel of reverse knowledge spillovers to the firm (Corredoira & Rosenkopf 2010).

Other knowledge spillover channels have also been explored. For example, Belderbos, Carree & Lokshin (2004) and Crespi et al. (2008) find that firm productivity is related to knowledge flows from competitors, customers and suppliers. Monjon & Waelbroeck (2003) and Audretsch, Lehmann & Warning (2005), among others, have explored the role of university collaboration and location near universities as a mechanism of knowledge spillovers.

3 SUMMARY OF THE ESSAYS

This doctoral thesis consists of four essays. The essays analyze how R&D and intangible investments, as well as how these activities are organized, affect the economic performance of firms. The essays also discuss how firms benefit from knowledge spillovers, that is, from the R&D investments and knowledge of other firms. The following sub-chapters summarize each essay in turn.

3.1 Essay 1: Market value of R&D, patents, and organizational capital: Finnish evidence

The first essay of this dissertation studies how knowledge and organizational capital affect the market valuation of firms. While the market value of knowledge assets has been covered in many prior studies, the literature on organizational investments and market value is less extensive. Yet, organizational expenditures reduce a firm's current profits to increase its value and profits in the future in a similar manner as investments in tangible capital. Therefore, organizational expenditures qualify as investments and should receive the same treatment as tangible investments. This paper contributes to the current empirical literature using detailed Finnish linked employer-employee data (LEED) to measure the production costs of the organizational investments of Finnish firms. The measure of organizational capital used in this study includes both management and marketing investments. Management work aims to establish efficient organizational structures, strategies, employee compensation systems, and working practices within the firm. Marketing and sales personnel create and strengthen the firm's brands and customer relationships. In the empirical part of this paper, I measure these investments using the number of managers and marketing personnel in the firm and their wages.

Then, I examine the relationship between the market value of firms and their organizational capital, also analyzing the firms' knowledge assets – patents, patent citations and R&D investments – in publicly listed Finnish firms during the time period 1995-2008. Thus, this essay provides evidence of the relative importance of different intangible assets to firm market value. I apply the market value model used by Hall, Jaffe & Trajtenberg (2005) and extend it by including organizational capital. The inclusion of the organizational capital is similar to how the accumulated R&D investments are included. A non-linear least squares regression is used to investigate the contribution of these variables to the market value of Finnish firms. The results show that organizational capital, R&D, patents and patent citations all have positive and significant effects on market value. A particularly interesting finding is that the estimated elasticities of Tobin's q with respect to organizational capital are in the range of 10-12%, while the estimated elasticities with respect to R&D are in the range of 3-6%. Thus, by concentrating the analysis on a firm's knowledge assets, we appear to be ignoring an equally or even more important element of its intangible capital.

The study also contributes to the literature on the market value of R&D and patents by reporting results from a Scandinavian stock market. Whereas the relation between the market value of R&D and patents has been extensively studied in the US and the UK, fewer studies have used European data (Czarnitzki, Hall & Oriani 2006). The results indicate that in Finland, the market valuation of R&D, but not patents, is lower than in the US and many European countries.

3.2 Essay 2: Internationalization of corporate R&D activities and innovation performance

The second essay of this dissertation studies how the innovation performance of medium-sized and large European firms is affected when firms internationalize their R&D activities. Despite the prevalence of international R&D activities, previous empirical studies fail to provide conclusive evidence of its effects on the innovation performance of firms. These studies also raise the question of whether the observed relationship between international R&D and innovation performance is due to firms' self-selection into international R&D or to improvements in firms' knowledge sourcing.

There are two alternative, but not mutually exclusive, reasons why international R&D may be linked to the innovation performance of firms. First, firms self-select to conduct R&D abroad. Thus, firms with overseas R&D may be either more innovative firms that are able to cover the additional fixed costs of internationalization or less innovative firms that go abroad to catch up and compensate for their technological weaknesses. Second, internationally distributed R&D activities can improve the innovation performance of firms by providing improved access to local scientists, knowledge spillovers and universities (Alcácer & Chung 2007; Belderbos, Lykogianni & Veugelers 2008; Florida 1997; von Zedtwitz & Gassmann 2002). Alternatively, the increased coordination and communications costs may also cause international R&D to weaken the firms' innovation performance (Argyres & Silverman 2004). Prior empirical studies on R&D internationalization typically employ panel models that control for bias caused by time-invariant, omitted variables; however, these methods do not properly account for the endogenous self-selection by the firms. Therefore, we cannot interpret the prior results as causal. This essay contributes to the literature by accounting for the self-selection process and offering more reliable results on the causal effect that the start of international R&D activities has on the innovation performance of firms. This essay applies propensity score matching and difference-in-differences (DID) methods to control for the endogenous self-selection process. First, a probit model is used to estimate a propensity score, the probability that a firm begins international R&D activities. Then, firms with similar starting probabilities are matched to determine how international R&D affects firm performance in comparison to similar firms that do not engage in international R&D activities.

Obtaining data on the geographic location of firms' R&D activities is not straightforward. Many studies on R&D internationalization rely on patent data because patent information is available for a long period and across nearly all countries. Following these prior studies, patent inventor data from EPO PATSTAT (European Patent Office's Worldwide Patent Statistical Database) is used to track the locations of corporate R&D activities. While the patent applicant may be either the subsidiary or the parent firm, the inventor's address provides better approximation of the locations of corporate research activities. To obtain a comprehensive picture of corporate patenting, the worldwide priority patent filings of each firm are used. The sample covers 850 medium-sized and large European firms during the time period 2003-2009. Information on patent applications, the technological fields of patents, patent citations and the technological fields of citations received are used to measure innovation output, diversity, quality and breadth of technological impact, respectively.

The results indicate that firms with greater numbers of previous innovations and higher quality of innovations are more likely to start international R&D activities, which explains 35% to 100% of the observed quantitative differences in innovation performance between international and domestic firms in my sample. Moreover, beginning R&D internationalization further increases the innovative output of firms. The results imply that firms that begin to internationalize their R&D activities subsequently file more patent applications and receive more citations. At the median, sample firms file few patents per year, and thus, the results imply an increase of approximately 2 patents per year. The results also indicate a weaker increase in the technological diversity and breadth of impact of innovation activities, which implies that international R&D activities allow firms to diversify their innovation activities to new fields of technology.

In contrast to some previous studies, the difference in the average quality of innovations in favor of international firms is shown to be due to self-selection. This and other findings of the essay indicate that empirical research must account for the self-selection of firms to reliably assess the causal innovation performance effects of R&D internationalization. For firms, the results imply that they can improve their innovation performance, in terms of quantity and technological diversity, by engaging in international R&D activities. However, these benefits are not necessarily as large as initially envisaged due to the self-selection process.

3.3 Essay 3: Internationalization of R&D and the returns to R&D activities in European firms

The third essay continues to analyze the effects of international R&D activities on firm performance. The empirical evidence on the contribution of international R&D to firm productivity is scarce and somewhat mixed. Thus, this essay analyzes how international R&D activities affect the R&D returns to productivity, especially how the returns depend on the relative technological strengths of home and R&D host countries.

This essay studies whether European manufacturing firms with international R&D activities obtain higher returns to their R&D investments than firms with domestic R&D. Furthermore, in distinction to prior study by Belderbos, Lokshin & Sadowski (2014) and others, I also track the distribution of R&D host countries and measure their technological strengths. I rely on the address information of patent inventors to determine the locations of corporate R&D activities. To analyze how the relative technological strengths of home and R&D host countries affect the relationship between international R&D and R&D returns, I classify countries as technologically leading and lagging by comparing the number of patent applications at the industry- and country-level in the home and host countries.

Prior empirical studies indicate that R&D internationalization is driven by market-seeking objectives as well as knowledge-seeking motives that aim to improve the innovation performance of a firm (Kuemmerle 1999; von Zedtwitz & Gassmann 2002). Nevertheless, overseas R&D is also associated with high entry costs, loss of economies of scale and additional coordination and communication costs which may in some cases outweigh the benefits (Argyres & Silverman 2004). Because international knowledge sourcing and access to both knowledge spillovers and skilled local workers are important drivers of international R&D

investments, I argue that the benefits of international R&D depend on the relative levels of technology in the home and R&D host country. Because of more limited knowledge sourcing opportunities and the increased risk of knowledge outflows, firms have fewer incentives to engage in international R&D in countries that are technologically weaker than their home countries. These investments may still improve the R&D returns by increasing a firm's capacity to appropriate the returns of R&D investments due to access to larger markets and in some cases diversifying firm's knowledge sourcing and bringing cost advantage. In contrast, when overseas R&D is located in technologically more advanced countries, the returns to R&D are expected to improve due to access to more diversified and more advanced technological knowledge and improved appropriation capacity.

In the empirical part of this essay, I assume that the share of international R&D activities can have a direct effect on firm productivity, as well as an indirect effect by affecting the returns to R&D. Thus, the empirical approach resembles that in the study by Griffith, Harrison & Van Reenen (2006). An augmented production function is then estimated using ordinary least squares and System GMM (Generalized Method of Moments) methods. The results indicate that the R&D elasticity of output is significantly higher in firms with international R&D activities. For firms that conduct 20% of their R&D abroad (the average share in the sample firms), this implies an R&D elasticity of output that is approximately 2 percentage points higher. The results also show that the higher R&D elasticity of output is associated with R&D investments targeted at more technologically advanced countries, whereas overseas R&D in countries that technologically lag behind the firm's home country do not significantly boost the R&D returns. In general, the results suggest that access to more advanced technology is the source of higher R&D returns. An improved access to larger international markets or diversified knowledge sourcing appears to be enough to compensate for the higher costs associated with international R&D, but they cannot significantly improve the R&D returns.

The industry-specific results indicate that both high- and low-tech firms benefit from international R&D, although on average, the gains are larger for low-tech firms. However, the level of technology in host countries is more important for high-tech firms and their technology sourcing. Moreover, the results show that there are significant fixed costs associated with international R&D that smaller or less R&D-intensive firms may not be able to cover. Thus, while large European firms can significantly benefit from international knowledge sourcing, this essay's results might not apply to smaller firms.

3.4 Essay 4: Knowledge spillovers through inventor mobility: the effect on firm-level patenting

The fourth essay of this dissertation analyzes knowledge spillovers through inventor mobility and their effects on the innovation performance of firms. I analyze the effect of inventor mobility on corporate patenting by studying a sample of R&D-investing European firms and use patent data to track inventor mobility. The essay contributes to the literature by shedding light on the role of mobile inventors and source firms' characteristics in enabling knowledge transfer. The essay most closely relates to a study by Kaiser, Kongsted & Rønde (2015), who use Danish linked employer-employee data to show that R&D worker mobility is positively related to the number of patent applications in Danish firms. In distinction to Kaiser, Kongsted & Rønde (2015) and other prior studies, the present study analyzes the prior technological expertise of mobile inventors and the characteristics of their previous employers to discover their effect on knowledge transfer between firms. The prior literature has emphasized learning by hiring; however, outbound mobility is equally important and needs to be considered. Therefore, I also analyze the outbound mobility of inventors and whether its effects depend on the characteristics of inventors and their new employers.

In the empirical part of this study, a patent production function is estimated using negative binomial estimation with pre-sample means to account for unobservable time-invariant firm effects. The results suggest that mobile patent inventors can act as a channel for knowledge spillovers; however, in general, hired patent inventors are not more productive than staying inventors in terms of firm's future patent output. Instead, the gains depend on the characteristics of hired inventors and their source firms, with the latter apparently being more important. Hiring inventors with many prior patents contributes to the patenting activity of hiring firms. Moreover, I find that hiring inventors from firms with many patents contributes to patent output. This implies that these mobile inventors possess more valuable skills and expertise and are able to transfer valuable technological knowledge from their previous employers. Furthermore, I find that firms' future patenting benefits from hiring inventors who bring different kinds of technological expertise to the firm or who move from firms that are technologically related but not too similar. This finding is also in line with earlier results on labor mobility and firm productivity growth (Boschma, Eriksson & Lindgren 2009).

At the same time, inventors who leave a firm are shown to contribute negatively to that firm's future patenting. Separation of inventors with many patents or experience in the firm's core technological area is especially detrimental to patenting. These inventors appear to possess skills that are central to firms' innovation activities; thus, leaving leads to deteriorating innovation performance. Inventors possessing non-core technological expertise and inventors leaving to technologically different firms do not have significantly negative effect on future patenting, although the point estimates remain negative. The lack of a strong negative effect may be explained by the less firm specific, and thus more easily replaceable, knowledge that these inventors possess. Moreover, leavers to high-patenting firms should imply greater potential for reverse knowledge spillovers. Instead, I find that when inventors leave to a high-patenting firm, the negative effect is strongly significant, whereas leavers to low-patenting firms do not have significant effect on future patenting. This finding is in clear contrast to the reverse knowledge spillover hypothesis that has been put forth in prior studies. Moreover, this finding may indicate that firms that systematically engage in R&D and patenting are able to hire better inventors than firms with less intensive patenting activities. Overall, my results do not support the view that reverse knowledge spillovers compensate for the loss of skills and inventor expertise that is associated with outbound mobility. In this respect, my results differ from some previous studies, most notably from the results of Kaiser, Kongsted & Rønde (2015).

Some caution is required when interpreting the causality of the results. Firms can choose who they hire, and even though we can observe and measure inventors and firms' past patenting productivity, it is possible that positive assortative matching on unobservable characteristics could bias our results for the effects of mobility.

These results have practical implications for firms and the entire economy. I show that employee mobility can be beneficial for firm-level innovativeness, and it may thus improve firm productivity and economic growth, as has already been argued in the prior literature. Nevertheless, the negative effect of outbound mobility may also cause firms to reduce investments in R&D and in their employees because these investments are lost if employees leave the firm.

4 CONCLUSIONS

R&D, other intangible investments and knowledge spillovers play important roles in explaining economic growth and firm performance. This dissertation studies how these factors affect firm performance, particularly the implications of the international organization of R&D activities and employee mobility for firm performance.

The results of the first essay indicate that both knowledge and organizational assets are positively related to firms' market value, and, at least in Finland, the effect of organizational capital is even stronger than that of R&D investments. This implies that excluding organizational and other forms of intangible capital and concentrating the study of intangible capital on R&D and patents leads much of the empirical research to ignore an equally or even more important element of a firm's intangible capital. In doing so, we also risk misinterpreting the market value effects of R&D and patents. The essay also shows that linked employer-employee data can be useful in estimating corporate investments in intangible assets, which are not well covered in the ordinary balance sheet data. This kind of data would also allow us to study and compare several types of intangible assets, which is not possible with commonly used SGA expense information.

The second and third essays show that firms can significantly benefit from overseas R&D activities. The benefits of R&D internationalization appear to be driven by improved access to more advanced technological knowledge, and thus, the findings support R&D internationalization as a channel of knowledge spillovers. At the firm-level, my results suggest that firms can improve the returns to their R&D investments and extend and diversify their innovation activities by locating some of their R&D activities abroad and by sourcing new technological knowledge internationally. However, the choice of target locations and countries must be carefully considered because knowledge sourcing opportunities are dependent on the technological level of the overseas R&D location. The essays also leave room for further research. Firm characteristics and motives for engaging in R&D internationalization differ and may affect how the gains from such activities materialize and are divided among firms. Interesting avenues for further research include the effects on imitative innovation and catching up, which cannot be studied using patent data alone. The results of the second essay also indicate that the apparent benefits of R&D internationalization may be inflated by the self-selection of firms into international R&D. This means that the empirical research must account for firm self-selection to reliably assess the causal firm performance effects of R&D internationalization, which has not been properly considered in previous empirical studies.

From an economic policy perspective, the results of second and third essays suggest that increasing relocation of R&D activities abroad does not necessarily weaken the home country's competitiveness and welfare, as improved firm productivity and innovativeness also benefit the home country. Instead, international R&D collaboration and knowledge sourcing by firms is beneficial and improves the innovativeness and growth of European firms.

The fourth essay of this dissertation analyzes inventor mobility as a channel of knowledge spillovers. The empirical results suggest that mobile patent inventors can transfer knowledge between firms, which is also in line with previous literature. Inventor mobility in general does not increase patenting significantly; however, the characteristics of inventors and their previous employers matter greatly. In addition, outbound mobility is related to weaker firm patenting performance in the future, especially, if inventors leave to high-patenting firms, which is in contrast to the reverse knowledge spillover hypothesis presented in prior studies.

The results of fourth essay have practical implications for firms and the entire economy. Employee mobility can be beneficial for firm-level innovativeness, and it may improve firm productivity and growth in the economy as already argued in the prior literature. Nevertheless, the strong negative effect of outbound mobility may also cause firms to reduce investment in R&D and in their employees because these investments are lost if employees leave the firm. This essay analyzes firm-level performance effects and ignores the national level benefits of creative destruction. More innovative firms are likely to gain market shares and grow in size, which can further improve overall productivity in the economy. This implies that labor market flexibility should be considered a tool to facilitate knowledge transfer between firms.

A limitation of all the essays is that they mostly analyze relatively large manufacturing firms, which are well covered by stock market, R&D and patent data. Therefore, the results cannot be directly generalized to service sector or small firms. Further research is needed to explore whether the results also apply to other types of firms, industries and countries. Furthermore, while the first essay also analyzes the role of organizational investments, the other three essays mainly analyze R&D investments and technological innovations.

Finally, labor mobility and international R&D activities, as analyzed in this dissertation, constitute only two channels of knowledge spillovers. Moreover, the spillovers from other intangible assets have been only scarcely explored in the extant literature. Because the potential importance of knowledge diffusion for economic growth is vast, the future empirical research ought to explore both labor mobility and other mechanisms of knowledge spillovers in more detail to provide answers about which tools best support knowledge spillovers and economic growth.

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Market value of R&D, patents, and organizational capital: Finnish evidence

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This paper studies how knowledge and organizational capital (OC) affect the market valuation of firms. Detailed occupational information from Finnish linked employer–employee data is used to form new estimates of firms' organizational investments. The market value of OC is analyzed together with research and development (R&D) and patent variables. A nonlinear least-squares regression is used to investigate the contribution of these variables to the market value of Finnish firms during the period 1995–2008. The results show that OC, R&D, patents, and patent citations all have positive and significant effects on market value. A particularly interesting finding is that the effect of OC appears to be even stronger than the effect of R&D investments. This study also provides internationally comparable results on the market valuation of knowledge assets that indicate that in Finland, the market valuation of R&D, but not patents, is lower than in the USA and many European countries.

Keywords: organizational capital; R&D; patents; intangible assets; market value

JEL Classification: O30; O34; M12; G32

1. Introduction

The performance of firms has become increasingly dependent on knowledge and other intangible assets. These assets include, for example, research and development (R&D), patents, brands, customer relationships, software, and organizational capital (OC). Despite their importance, intangible assets are not fully considered in our current accounting system, and we have few systematic methods to value them. These intangible assets are one likely reason why we so often observe that publicly listed firms have much higher market values than their book values would suggest. In this study, we apply a new method developed by Görzig, Piekkola, and Riley (2011) (later GPR) and use the work force composition of a firm to estimate its organizational investments. Then, we examine the relationship between firm's market value and OC, also analyze patents and R&D investments, in publicly listed Finnish firms during the period 1995–2008.

Intangible investments aim to increase firm productivity and profitability in the future, but the time lag may be long and difficult to predict. Market value is a forward-looking measure of firm performance and should capture the increase in future profitability without a time lag. The market value approach has been used to study the economic value of patents

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and R&D expenditures for a long time (Chan, Lakonishok, and Sougiannis 2001; Griliches 1981; Megna and Klock 1993; Toivanen, Stoneman, and Bosworth 2002). More recent studies such as those by Hall, Jaffe, and Trajtenberg (2005), Coad and Rao (2006), Hall, Thoma, and Torrisi (2007), and Sandner and Block (2011) have extended the literature by analyzing different markets, adding new intangible capital variables, and using different estimation methods. However, the literature on organizational investments and market value is not as extensive, even though organizational investments have experienced significant growth (Corrado, Hulten, and Sichel 2009). The few existing studies on OC, including those by Brynjolfsson, Hitt, and Yang (2002), Hulten and Hao (2008), and Piekkola (2013), find that OC is associated with higher market value. This paper contributes to the current literature by using detailed Finnish linked employer–employee data (LEED) to measure organizational investments. In contrast to earlier studies, we include OC symmetrically into the same market value model with R&D and patents, which allows us to analyze the relative importance of these assets for firm's market value.

Studying intangible investments in the Finnish context is especially interesting for several reasons. First, by studying Finland, we can utilize the detailed Finnish LEED, which allow us to observe the occupational composition, wages, and other characteristics of the workforce and use them to estimate the firm's organizational investments. Second, whereas the market value of R&D and patents has been extensively studied in the USA and UK, fewer studies have used European data (see Czarnitzki, Hall, and Oriani 2006 for a survey). Moreover, Finland and Scandinavian countries in general have a different stock market and legal environment than continental Europe or the USA (La Porta et al. 1998). These factors, such as investor protection, the role of institutional investors and bank financing, and other institutional differences, have been shown to affect the market valuation of firms (Booth et al. 2006; La Porta et al. 2002). Therefore, it is important to improve our understanding of the market valuation of knowledge assets in different environments. The Scandinavian case has been studied by Bloch (2008), who studies the R&D investments and their effect on firm's market value in Denmark. However, while that study covers R&D investments, it does not consider patent variables, which are often included in this type of analysis. By including these variables and using the same modeling approach as Hall, Jaffe, and Trajtenberg (2005) and Hall, Thoma, and Torrisi (2007), we obtain results that are easy to compare with the earlier European and US studies. With this approach, we contribute to the literature on the market value of R&D and patents by reporting comparable results from a Scandinavian stock market.

Our measure of OC includes both management and marketing investments. Management work aims to establish efficient organizational structures, strategies, employee compensation systems, and working practices within the firm. Marketing and sales personnel create and strengthen the firm's brands and customer relationships. Hiring managers and building up brands are costly activities from which the rewards materialize over a long time period. In the empirical part of this paper, we measure these investments using the number of managers and marketing personnel in the firm and their wages. This expenditure-based approach developed by GPR (2010) is similar to country-level estimates presented previously by Corrado, Hulten, and Sichel (2005). This approach uses employees' wages and the cost structures of consulting and market research service firms to estimate the total production costs associated with organizational investments (GPR 2010).

We also analyze firms' investment in knowledge assets, i.e. R&D and patents. R&D expenditures provide an input measure of firm's innovation activities, while patents are outputs of innovation activities. Patents and accumulated R&D investments are valuable assets and therefore should contribute to firm performance and market value. However, not all inventions are patented, and while some patents are extremely valuable, others may have no commercial application at all. The analysis in this paper includes forward patent citations to control for the quality of a firm's patent stock, as has been done in many previous studies (Hall, Jaffe, and Trajtenberg 2005; Harhoff et al. 1999).

Our results indicate that OC, R&D, patent stock, and patent citations have positive and significant relationships with market value. Based on the results, OC seems to have an even larger effect on the market value than R&D investments. Our results with respect to R&D and patents are mostly in line with earlier findings from the US and European countries, although R&D seems to have a lower effect on market value in the Finnish stock market, while patent variables have a slightly higher effect.

The remainder of this paper is organized as follows. The next section reviews some earlier literature on intangible assets and market value and presents the market value model. The third section describes the data and the main variables, the fourth section presents the empirical results, and the fifth section concludes the paper.

2. Intangible assets and market value

2.1. Organizational capital

In recent years, researchers have become increasingly interested in OC and its effects on firm performance. Organizational expenditures reduce a firm's current profits to increase the firm's value and profits in the future in a similar way as investments in tangible capital. Therefore, organizational expenditures should qualify as investments and should receive the same treatment as tangible investments (Corrado, Hulten, and Sichel 2005, 2009). However, the definition and measurement of OC vary considerably among studies. Corrado and coauthors refer to OC as economic competencies, which include the competence of management, employee training, brands and marketing competencies, as well as organizational structure. Brynjolfsson, Hitt, and Yang (2002) define OC as good management practices, whereas Cummins (2005) defines OC as business models and practices that create value from IT. In the present study, OC includes management and marketing investments.

One strand of the OC literature uses survey data to identify firms with high OC. These studies, for example, Brynjolfsson, Hitt, and Yang (2002) and Bloom and Van Reenen (2007, 2010), find that certain management practices are associated with better firm performance, better firm survival, and higher Tobin's q. Another method of estimating OC is used by Lev and Radhakrishnan (2005), who estimate OC as a residual term of the production function and then relate this residual to sales, general, and administrative (SGA) expenses. They analyze the effect of OC on market value and find a positive relationship. Other authors have also measured the OC as a residual term of firm's market value (for example, Hall 2000b) or production function. Antonelli and Colombelli (2011) use total factor productivity (TFP) as a measure of the firm's capability to generate and exploit technological and organizational innovations and find that TFP has a strong positive effect on market value. However, the use of market value or production function residuals to measure OC is somewhat problematic. The residuals do not directly measure innovation or OC, and they may also contain many other factors, as noted by Bresnahan (2005).

Production cost-based estimation methods are another commonly used approach to estimate OC, and a similar approach has also been used to study the market value of advertising (Chauvin and Hirschey 1993; Joshi and Hanssens 2010). Corrado, Hulten, and Sichel (2005) measure OC investments using advertising expenditures, executive compensation, purchased management consultancy services, and employee training costs. For example, they assume that 20% of managers' time, and hence wages, is invested to improve the organization and its business practices. Many other studies have used SGA expenses as a proxy for OC investments. Hulten and Hao (2008) and Tronconi and Vittucci Marzetti (2011) capitalize 30% and 20% of SGA expenses to measure a firm's OC stock. De and Dutta (2007) capitalize 20% of the administrative expenses (part of SGA). While the other two studies estimate a production function, Hulten and Hao (2008) estimate a market value model. They find that R&D and OC can explain about one-half of the market value in their sample of US firms, although their OC estimate is not significant in all models, and the relative importance of OC and R&D depends on the model specification. Moreover, as the authors themselves (Tronconi and Vittucci Marzetti 2011) have noted, SGA expenses may be a too wide measure of OC.

The study by GPR (2010) presents a novel way to estimate OC investments. OC investments are often measured using the cost of production, and GPR follow this approach by taking the wages of organizational workers as the key input in the production of OC.[1] They present both an expenditure-based and a performance-based approach to estimate these investments using occupational information. In this paper, we follow the expenditure-based approach. GPR suggest using 20% of organizational workers' wages to estimate OC investment and adding intermediate and capital costs, which results in a total multiplier of 35%. As a large part of OC investments is human labor, wage costs represent a natural starting point to estimate these investments. Moreover, organizational workers' wage costs and domestic SGA expenses, which are available for a small subset of our sample firms, are fairly closely correlated. Furthermore, analyzing organizational workers provides a narrower and more precise measure of OC because the SGA expenses include several items that are not associated with management or marketing work and, on average, these expenses are more than two times larger than the organizational workers' wage costs.

Applying the GPR approach, Piekkola (2013) uses LEED to estimate OC investments and a joint variable capturing R&D and IT investments. He finds that OC has a positive relationship with market value in Finland. However, he uses a different modeling approach and excludes patent variables, so these results are not comparable to the present study. Moreover, in this study, the LEED are only used to estimate the organizational investments, and we follow the established practice of using firm-reported R&D expenditures to estimate the R&D stock in order to provide internationally comparable results.

2.2. R&D and patents

The economic returns to R&D and patents are perhaps the best studied facet of intangible capital. Because the returns to R&D do not occur immediately, a common approach has been to study the market value. The seminal paper by Griliches (1981) is one of the early papers to study this issue, and many others have followed. Czarnitzki, Hall, and Oriani (2006) provide a survey of this literature.

R&D expenditures are inputs to innovation activities, but as the outcomes of these activities are quite uncertain, R&D expenditures provide an incomplete picture. By including patent applications as a measure of R&D output, we can improve our measurement of a firm's knowledge capital (Czarnitzki, Hall, and Oriani 2006). However, the use of patent applications has some limitations as well because not all inventions are patentable and because patents are not the only way to utilize inventions. Moreover, the value distribution of patents is highly skewed (Harhoff et al. 1999; Harhoff, Scherer, and Vopel 2003; Schankerman and Pakes 1986). Therefore, it is common to include some indicators of a patent's value. These indicators include forward and backward citations, patent renewals, patent family size, opposition (Harhoff, Scherer, and Vopel 2003; van Zeebroeck 2011), and even patent filing strategies (van Zeebroeck and Van Pottelsberghe de la Potterie 2011). All these indicators could be used as controls for patent value, although the most common approach has been to use forward citations (Hall, Jaffe, and Trajtenberg 2005; Harhoff et al. 1999; Trajtenberg 1990). A patent application may be referenced by other patent applications if the later inventions are based on or related to the earlier invention. Moreover, the patent office conducts a search during the patent-granting procedure and may add relevant citations to the application. Consequently, if a patent receives many citations, it is likely that the underlying invention is important and of high quality. Therefore, counting the number of citations of a firm's patents tells us about the quality and economic value of a firm's patent stock.

Most studies show a positive relationship between market value and R&D, which is measured either by current R&D expenditures or accumulated R&D stock. Additionally, patents and patent citations contain valuable information and contribute to the firm's market value (Hall, Jaffe, and Trajtenberg 2005). However, despite the use of patent citations, R&D investments are usually found to contribute more to a firm's market value than patents. The studies have also found that the market value of R&D has decreased over time (Czarnitzki, Hall, and Oriani 2006) and it varies significantly between high market value and low market value firms (Coad and Rao 2006). Most of the above-mentioned studies analyze either US or UK stock markets. Fewer studies use continental European data, and these are more recent. European data are less extensive than US data because the reporting of R&D expenditures is usually voluntary and the stock markets are smaller compared with those of Anglo-Saxon countries. The results indicate that the valuation of R&D is lower in continental European countries than in the USA and the UK, but this gap is not very large (Booth et al. 2006; Czarnitzki, Hall, and Oriani 2006; Hall and Oriani 2006). The valuation of R&D in Denmark, which as a Scandinavian country is similar to Finland in many respects, is at the same level as in the UK (Bloch 2008). The results for the patent variables are relatively similar in the USA and Europe (Hall, Jaffe, and Trajtenberg 2005; Hall, Thoma, and Torrisi 2007), although some studies also report insignificant or negative coefficients for patents (Toivanen, Stoneman, and Bosworth 2002).

2.3. Market value model

This section presents the market value model, which has frequently been used to study the market value of knowledge and other intangible assets. If we aim to study the effect of intangible assets on firm performance, we can either study the market value or the firm's profits or TFP. A profit- or productivity-based analysis has advantages but also some weaknesses in the context of intangible assets. R&D and organizational investments aim to increase the firm productivity and profitability in the future, but their effects come after a time lag that may be long and uncertain (Griliches 1981). Furthermore, measuring the returns to investments in intangible capital requires careful attention to the timing and measurement of other inputs, which may be intangible as well (Hall 2000a). The market value approach enables a forward-looking evaluation of firm performance and avoids the problem with the timing of productivity effects.[2]

The market value model was initially introduced by Griliches (1981) to analyze the economic value of R&D and patents. In this model, the firm is considered to be a bundle of assets. These assets can include tangible capital, such as plants and equipment, knowledge assets, such as patents and R&D, brands, customer relationships, software, and OC. The aim is to measure the effect of each of those assets on the market value, which makes this approach comparable to hedonic price models. The model relies on the assumption that financial markets are efficient and that the market value equals the present value of discounted future dividends. It is well known that anomalies occur in financial markets and that investors are not always rational. Thus, the market value model should be applied with these limitations in mind.

Because the general functional form of the value function for an intertemporal maximization program with many asset types is difficult to derive, we follow the literature and assume that a firm's assets enter the market value equation additively. We apply the model used by Hall, Jaffe, and Trajtenberg (2005) and extend it by including OC. The inclusion of the OC is similar to how the accumulated R&D investments are included. An alternative approach to incorporate OC into the model would be through the valuation coefficient because it reflects a firm's monopoly power and market structures (Griliches 1981). OC is clearly an instrument for building monopoly power and affecting market structures; however, we want to treat all intangible investments symmetrically and hence we adopt the first approach. We can write the market value equation as follows:

$$V_{it} = q_{it}(K_{it} + \gamma_{\mathrm{R\&D}}\mathrm{R\&D}_{it} + \gamma_{\mathrm{OC}}\mathrm{OC}_{it})^{\sigma} \tag{1}$$

and

$$q_{it} = \exp(y_t + m_k + u_{it}). \tag{2}$$

In Equation (1), V_{it} is the market value of firm i at time t, and K_{it} is the total tangible assets of the firm. The organizational and R&D assets are represented by OC_{it} and $\mathrm{R\&D}_{it}$, respectively. The current valuation coefficient q_{it} includes year (y_t) and industry (m_k) effects as well as an individual disturbance (u_{it}). We could also model the valuation coefficient to capture other factors that affect the valuation multiplicatively. σ measures the returns to scale. If $\sigma = 1$, there are constant returns to scale (CRS), and $\gamma_{\mathrm{R\&D}}$ and γ_{OC} are the shadow values of the ratios of R&D assets to total assets and organizational assets to total assets, respectively (Hall and Oriani 2006). The shadow values show the effect of intangible assets relative to tangible assets on the firm's market value. The shadow values are an equilibrium outcome in financial markets reflecting firms' investments and investors' expectations of future cash flows, and these values should not be given a structural interpretation. Furthermore, the shadow values are not necessarily constant over time, although for convenience, we do not allow them to vary in our analysis.

Next, after taking the logarithm of Equation (1) and subtracting the logarithm of K_{it} from both sides, we can write the equation as follows:

$$\log \frac{V_{it}}{K_{it}} = \log q_{it} + (\sigma - 1) \log K_{it} + \sigma \log\left(1 + \gamma_{\mathrm{R\&D}}\frac{\mathrm{R\&D}_{it}}{K_{it}} + \gamma_{\mathrm{OC}}\frac{\mathrm{OC}_{it}}{K_{it}}\right). \tag{3}$$

Equation (3) includes the log of Tobin's q on the left-hand side and total assets and intangible capital intensities with respect to total assets on the right-hand side. The next step is to modify the model to include patents and patent citations following the example of Hall, Jaffe, and Trajtenberg (2005) and Hall, Thoma, and Torrisi (2007). This formulation includes patent applications as an output and a quality indicator of the R&D stock, and the patent citations as a quality indicator of the patent stock. The estimating equation is the following:

$$\begin{aligned}\log \frac{V_{it}}{K_{it}} &= \log q_{it} + (\sigma - 1) \log K_{it} \\ &\quad + \sigma \log\left(1 + \gamma_{\mathrm{R\&D}}\frac{\mathrm{R\&D}_{it}}{K_{it}} + \gamma_{\mathrm{PAT}}\frac{\mathrm{PAT}_{it}}{\mathrm{R\&D}_{it}} + \gamma_{\mathrm{CIT}}\frac{\mathrm{CIT}_{it}}{\mathrm{PAT}_{it}} + \gamma_{\mathrm{OC}}\frac{\mathrm{OC}_{it}}{K_{it}}\right) + \varepsilon_{it}.\end{aligned} \tag{4}$$

This equation is extended with a set of control variables, which enter through the current valuation coefficient. We include year dummies to control for possible time trends and

12 industry dummies to control for industry-specific heterogeneity, as well as dummies for zero reported R&D and no patents. Some firms report their R&D expenditures but report zero expenditures in which case the patent-intensity variable ($\mathrm{PAT}_{it}/\mathrm{R\&D}_{it}$) is coded as zero. These observations are indicated by a dummy variable. Firms that do not report R&D expenditures at all are dropped from the sample. Furthermore, the no patent dummy is included because in the case of no patent applications, the citations-intensity variable ($\mathrm{CIT}_{it}/\mathrm{PAT}_{it}$) needs to be coded as zero. Moreover, if we observe that a firm has no patent applications, it does not follow that the firm has not made any inventions. The innovations in some industries may not meet patentability requirements, and some firms may choose not to patent their inventions. These firms may find it more profitable to utilize their innovations through trade secrecy or lead time. Therefore, the observation of no patents may result from a strategic decision or an industry characteristic. Another control dummy is included to control for the fragmented R&D or OC investment histories in some firms.

The firms are categorized into industry classes using Standard Industrial Classification codes at the one-digit level except for software and manufacturing industries, where greater detail was needed.[3] This approach results in 12 industry categories including electronics, paper industry, software, trade, and services. The industry classes and their characteristics are presented along with other descriptive statistics.

2.4. Estimation

In the early literature, Equation (4) was typically simplified with a logarithmic approximation. The approximation would lead to a simple estimation and analysis, but the approximation is not preferable because it becomes inaccurate as the ratio of intangible assets to total assets grows. Table 1 shows that the intangible assets make up a notable share of capital in Finnish firms. Therefore, the equation should be estimated using nonlinear least-squares (NLS) estimation. Because the model is nonlinear, the estimated coefficients cannot be compared in a straightforward manner. Therefore, in addition to the coefficients, it is necessary to calculate the elasticity of Tobin's q with respect to the regressors. The elasticities also facilitate the interpretation of the coefficients because the variables are measured in different units.

NLS estimation does not consider the unobserved firm-specific heterogeneity. However, part of the heterogeneity is accounted for by using industry and year controls. For robustness, we also estimate the market value equation using ordinary least-square (OLS) and fixed-effect estimation to test the importance of firm-specific effects. However, the firms' intangible capital investments are part of a long-term strategy, and R&D investments have been observed to be persistent in many studies (e.g. Hall, Griliches, and Hausman 1986). This persistency is present in our sample as well. Both R&D and OC intensities ($\mathrm{R\&D}_{it}/K_{it}$ and OC_{it}/K_{it}) are quite persistent within firms, on average growing slowly over time. In these circumstances, the intangible capital intensities are likely to be highly correlated with firm-specific effects, with the result that the fixed-effect estimation may miss a large part of the explanatory power of these variables, decreasing the efficiency and reliability of the estimator. Therefore, NLS estimation is our preferred estimation strategy.

3. Data and descriptive statistics

3.1. Data sources

The empirical analysis in this paper is based on market value, employee, patent, and balance sheet data. OC stock is estimated using the Finnish LEED, obtained from the Confederation of Finnish Industries. LEED covers approximately 8 million person-year observations and over 56,000 firm-year observations for the 1995–2008 period. The data include a rich set of variables covering compensation, education, and occupation in the business sector. The occupational classification is specific to the data from the Confederation of Finnish Industries, and the classification is available for all employees in the firms considered here. R&D expenditure, consolidated balance sheet, and market value data come from Thomson Reuters Worldscope. The variables used here are each firm's total assets, R&D expenditures, total debt, sales, and market value, which are measured at the end of each year. The financial variables have been deflated to real 2000 prices using the Ameco database.

Patent and citation data are constructed using the EPO PATSTAT database. In this study, the analysis includes the firm's patent applications to the European Patent Office (EPO). EPO patents are a good indicator of R&D quality because they have been found to be more valuable than national patents (Deng 2007). Our patent variable includes all patent applications, although only granted patents could be used instead. The use of patent applications is supported by the fact that the information about the applications is made available more quickly. The use of EPO patent applications is also eased by databases maintained by the OECD. The OECD Harmonised Applicants' Names (HAN) database is used to facilitate the linking of balance sheet and patent data (OECD 2013)

3.2. Variables

The dependent variable in the market value equation is the natural logarithm of Tobin's q. Tobin's q is defined as the ratio of a firm's market value to its book value. The book value of the firm is the total value of its assets reported on the balance sheet. The market value is the stock market value of the firm at the end of the year plus the market value of its debt. As the market value of a firm's debt is difficult to obtain, we follow the previous literature and use the nominal value of long-term and short-term debt instead (Hall, Thoma, and Torrisi 2007).

Organizational expenditures should be counted as investments but these investments are difficult to measure and they usually do not enter the official balance sheets. To overcome the measurement problem, we use the LEED to estimate organizational investments. As mentioned above, our estimate of OC investments includes both marketing and management investments. The GPR approach assumes that OC is created by employees in the following occupational categories: management, marketing, supervisors in financial administration, and superior administration positions in the service sector. These occupations include, for example, advertising and public relations department managers, production operations department managers, business service agents and trade brokers, and legal professionals.[4] In the LEED, approximately 6% of employees are reported to work in these occupations. We assume that these managers and specialists make and implement strategic decisions that have long lasting effects on a firm's organization and customer relationships, and thus their work efforts build up a firm's OC. GPR (2010) assume that 20% of organizational workers' time is devoted to activities that form OC, with the rest of their effort devoted to current production. Thus, we can use their wage costs to estimate the production costs of OC within a firm.

In contrast to Corrado, Hulten, and Sichel (2005), the GPR approach calculates the total production costs of new intangible capital, which also requires the evaluation of the intermediate and capital costs that are related to the organizational work. These costs consist of conventional inputs needed to produce services such as electricity or office space. These additional costs are evaluated using the cost structure of firms that produce and sell comparable intangible goods in the market. The organizational activities within firms are assumed to have the same cost structure as the EU average of firms in the business service sector (Nace 74). The cost structure indicates the magnitude by which the wage costs need to be multiplied to account for intermediate and capital costs. Adding these additional costs results in a combined multiplier of 35%, which is then applied to the wage costs (GPR 2010). This multiplier is a rather rough measure, but for our purposes, choosing a different multiplier would only have a scaling effect on our estimate of OC. Furthermore, the earlier studies that have attempted to measure OC using different production cost-based methods have usually capitalized 20–30% of production costs to form the OC stock (Corrado, Hulten, and Sichel 2005, 2009; De and Dutta 2007; Lev and Radhakrishnan 2005). Hence, the multiplier estimate suggested by GPR (2010) falls in the same range as these earlier estimates.

The final organizational investment data have a few short gaps because of issues with the data. However, counting the OC stock requires uninterrupted investment data series, and hence the firm-year observations with missing OC investment information are treated with simple linear interpolation when the gap in the investment data is not longer than three years. In the estimation, a dummy variable is included for those firm-year observations that are based either on interpolated OC or R&D investment values. No other correction measures are conducted aside from interpolation across gaps. Once the organizational investments have been estimated, we can form the OC stocks. Because the employer–employee data are not available for a long time period, the initial capital stocks must be estimated. The starting values at the beginning of the observation period are estimated using the investments in the first observation year. The formula for initial intangible capital stock is shown below. In the formula, IC refers to intangible capital categories, which in this case is the OC:

$$\mathrm{IC}_{i0}^{\text{stock}} = \frac{\mathrm{IC}_{i0}^{\text{invest}}}{\delta + g}. \tag{5}$$

In estimating the initial capital stock, we assume a constant depreciation rate (δ) and a constant investment growth rate (g) prior to the observation period. However, the choice of depreciation and growth rate is not obvious. Different approaches have been used to estimate the depreciation rate of R&D, and while intangible assets are typically found to depreciate faster than tangible assets, the estimates of R&D depreciation rate can vary from 0% to 40% (Hall 2005). The recent literature has typically assumed a depreciation rate of 15% for R&D, and we follow this convention. However, there is less established convention on the depreciation rate of OC. Corrado, Hulten, and Sichel (2009) use 40% for 'firm-specific resources' and 60% for brands and marketing. De and Dutta (2007) use both 20% and 10% depreciation rates, and Sandner and Block (2011) even assume a depreciation rate of zero for trademarks. In their survey, Awano et al. (2010) find that the benefit lives of 'business process improvements' are over five years in the production sector, but only four years in the service sector. Marketing and employee training investments have shorter benefit lives in both sectors. Based on these findings, we set the depreciation rate of OC somewhat arbitrarily in the middle. We set the depreciation rate to 20% for the manufacturing sector and 25% for the service sector because firms in the service sector also engage more intensively in branding and advertising investments (Awano et al. 2010; GPR 2010; Piekkola 2013). The prior growth rate (g) is set to 8%, which follows the literature on the estimation of initial R&D stocks. However, note that the main results are not sensitive to small changes in the assumed growth and depreciation rates.[5]

After the initial values are calculated, the OC stock is formed. The intangible capital stock can be calculated as follows:

$$\mathrm{IC}_{it}^{\mathrm{stock}} = (1-\delta) \times \mathrm{IC}_{i,t-1}^{\mathrm{stock}} + \mathrm{IC}_{it}^{\mathrm{invest}}. \quad (6)$$

This methodology only estimates the own-account production of OC, and it remains unclear how these investments are related to the purchased intangible assets. Moreover, the OC estimates do not include offshore organizational investments because the estimates are formed based on Finnish employer–employee data. However, GPR (2010) argue that at least based on the UK businesses included in the Annual Business Inquiry, the purchases of intangible goods are complementary to firms' own-account production. The authors report that while there is some variation across intangible capital categories, for example, the purchase of advertising services is positively correlated with intra-firm expenditures on marketing across firms in all industries. These findings suggest that intra-firm investments provide reasonable indicators of overall organizational investments. Moreover, it is not clear how the observed increase in the offshoring of business activities should affect the management personnel in the home country. There is evidence (Becker, Ekholm, and Muendler 2012; Head and Ries 2002) that the offshoring of business activities may increase the skill intensity of work in the home country, particularly if some activities are offshored to low-income countries. In any case, we find it plausible that a major share of organizational investment is performed at the headquarters and is therefore included in our estimate. However, the unobserved offshore investments are causing attenuation bias to our estimate.

The firm's R&D capital stock cannot be directly obtained from the firm's balance sheet, but the income statements often include annual R&D expenditure. We follow the previous literature and capitalize these expenses and compute the R&D stock in the same way as the OC stock is formed. Counting the R&D stock also requires that the starting value of the R&D stock is estimated using Equation (5). The initial value is counted using the R&D expenditures in the first year and assuming that investments have grown 8% annually (Hall, Thoma, and Torrisi 2007; Sandner and Block 2011). The depreciation rate is set to 15% to allow an easy comparison to earlier studies. We also check that small changes in the R&D depreciation and growth rate do not significantly alter the main results. To allow the calculation of R&D stock, short gaps in the R&D expenditure histories are treated with linear interpolation when the gaps are not longer than three years. No other corrections are made.

The initial value of the patent stock does not need to be estimated because the patent data begin from 1978. However, the time period is limited because the EPO publishes applications with some time lag, and we also need time to observe the forward patent citations. The forming of the patent stock is simple once we know the depreciation rate. The previous literature uses the same depreciation rate for both R&D and patents (Hall, Jaffe, and Trajtenberg 2005; Hall, Thoma, and Torrisi 2007), and the same approach is adopted here. The patent stock is formed using the same declining balance formula as for OC stock and using a depreciation rate of 15%. The patent flow is the number of patent applications filed by the firm during year t. Some patents have several applicants, which we consider by using fractional counting. The economic value of the patent is assumed to be uniformly distributed, meaning that if a patent has two applicants, one-half of the patent is allocated to each applicant. If there are three applicants, each is allocated one-third of the patent, and so on.

Using the patent stock as a quality indicator for R&D can be problematic because patents do not cover all inventions and because the value distribution of patents is skewed

(Harhoff et al. 1999; Harhoff, Scherer, and Vopel 2003; Schankerman and Pakes 1986). A common solution has been to extend the analysis with patent citations (Hall, Jaffe, and Trajtenberg 2005; Trajtenberg 1990). We follow this convention. We assume that the value of the patent when it is applied is proxied by the number of citations it receives. The value then depreciates over time. The citations emerge over a long time period that can stretch to decades in some cases (Hall, Jaffe, and Trajtenberg 2005; Hall, Thoma, and Torrisi 2007). Computing a complete citation stock for all the patents in this study is not possible. Alternative approaches include correcting for the truncation of the data or using the number of citations received within a shorter time period. Using a long time period to observe the citations would improve the accuracy of the quality control, but at the cost of decreasing the sample size. Here, we use citations received within three years of publication because this time frame allows us to use recent data and is long enough to observe a notable amount of citations (Marco 2007; Metha, Rysman, and Simcoe 2010). Another difficulty with the use of citations is that the patents may be applied in several countries, which leads to several publications that can be cited in subsequent applications. This problem can be solved by using information about patent families. Here, we consider all citations, which the patent application filed at the EPO receives either as a European (EP) or an international (WO) patent publication.[6] The citation count also includes self-citations, which come from a patent application filed by the same firm or its subsidiary. Previous studies (Bessen 2008; Hall, Jaffe, and Trajtenberg 2005) have found that self-citations are even more valuable than other citations, particularly for small firms, and therefore self-citations do not need to be excluded. The citation stock is formed in the same way as the patent stock. The depreciation rate is again set to 15%. New citations in year t are those citations that the firm's patent applications filed in year t receive within three years after publication of the patent applications.

In the market value estimation, intangible capital stocks are used as ratios. R&D and OC assets are divided by the book value of a firm's total assets. The patent stock is divided by the accumulated R&D stock and the citation stock is divided by the patent stock because the ratios are used as quality measures for the R&D and patent stock, respectively.

3.3. Descriptive statistics

The market value and balance sheet data consist of 122 firms listed in the Helsinki stock exchange at the end of 2011. Of those firms, 90 have reported R&D investments after 1995. For 71 firms, we observe both the firm-reported R&D and the OC stock, resulting in 519 firm-year observations for the years 1995–2008.[7] The data end in 2008 because we need time to observe the forward citations. The sample firms cover over 84% of the total market capitalization of the Helsinki stock exchange in 2008. Thus, the sample provides a comprehensive picture of the largest Finnish firms.

Table 1 presents descriptive statistics of the key variables in the final data. Market value and other financial figures have been deflated to real 2000 prices using the GDP deflator and are expressed in millions of euros. The average real market value of the sample firms is 3.4 billion euros. The R&D assets are on average 21% of total assets. The R&D intensity in our sample firms is roughly at the same level as in Denmark (Bloch 2008) but lower than in the USA or Germany (Hall, Jaffe, and Trajtenberg 2005; Hall and Oriani 2006). The firms' investments in organizational assets are considerably lower than their investments in R&D. The organizational assets are on average 2.8% of the total assets, but the variation is large. The variation is also high for the patent and citation variables. For 15% of observations there are no patent applications, whereas the largest patent stock includes over 4000 patents and

Table 1. Descriptive statistics.

Variable	Mean	SD	Min.	Median	Max.
Market capitalization	3255.8	16,651.2	0.645	343.3	222,980.6
Tobins's q	1.279	1.159	0.305	0.937	14.8
Total assets	2511.3	4879.3	5.940	442.5	33,640.5
R&D stock	324.4	1623.0	0	51.3	18,085.4
R&D stock/assets	0.210	0.348	0	0.094	4.372
Patent stock	110.8	533.9	0	9.602	4758.5
Patent stock/assets	0.052	0.107	0	0.012	0.695
Patent stock/R&D stock	0.267	0.318	0	0.159	2.085
Citation stock	127.1	679.1	0	5.397	5352.1
Citation stock/patent stock	0.607	0.492	0	0.530	3.398
OC stock	20.745	38.616	0	6.259	318.8
OC stock/assets	0.028	0.042	0	0.014	0.383
Zero R&D (dummy)	0.029	0.168	0	0	1
No patent (dummy)	0.152	0.360	0	0	1

Notes: 519 observations. Financial variables are in millions of euros, in year 2000 real prices. Patent stock/R&D stock is reported as patents per million euros in R&D stock.

the largest citation stock includes over 5000 citations. The patent intensity of Finnish firms is fairly similar to that of European firms (Hall, Thoma, and Torrisi 2007). The observations with no patent applications are indicated by a dummy variable, and the ratio of citation stock to patent stock is coded as zero for these observations. The descriptive statistics for the ratio of citations to patents are computed conditional on a non-zero patent stock.

Table 2 reports the correlations between the main variables. Statistically significant correlations are noted with asterisks. The intangible assets are positively correlated with Tobin's q, although the correlation with the patents–R&D ratio is not significant. OC and R&D intensities are negatively correlated with total assets. This result suggests that smaller or less capital-intensive firms invest relatively more in intangible assets than other firms. The inverse relationship between intangible assets and firm size also holds for the whole linked employer–employee data set, which includes all firms with a turnover above 1.5 million euros.

Table 3 divides all non-financial firms into two categories based on their decision of whether to report R&D expenditures during the period from 1995–2008. The table shows that concentrating on firms that report R&D expenditures excludes some of the smaller firms in the stock exchange. The firms that report R&D expenditures are typically manufacturing or software firms. The firms that do not report R&D are often engaged in the service, trade, or transportation sectors. The firms that do not report R&D have grown faster than the firms

Table 2. Correlation matrix.

	1	2	3	4	5
1. Tobin's q					
2. Total assets	0.126*				
3. R&D stock/assets	0.218*	−0.120*			
4. Patent stock/R&D stock	0.086	−0.017	−0.029		
5. Citation stock/patent stock	0.200*	0.221*	0.058	0.196*	
6. OC stock/assets	0.153*	−0.240*	0.275*	−0.048	−0.142*

Note: 519 observations.
$^{*}p < .05$.

Table 3. Firm characteristics of R&D reporting and non-reporting firms.

	Reporting R&D		Not reporting R&D	
Variable	Mean	SD	Mean	SD
Market capitalization	2679.1	15,028.2	205.9	411.8
Tobins's q	1.412	1.308	1.561	3.114
Total assets	2100.1	4482.6	281.1	538.5
Sales	2073.8	4845.6	421.1	1115.6
Sales growth	0.068	0.257	0.137	0.416
Debt	574.1	1241.1	63.3	128.4
Debt leverage	0.263	0.212	0.213	0.159
Investments/assets	0.016	0.230	0.058	0.240
Patent stock	91.0	482.1	1.2	5.6
Patent stock/assets	0.055	0.122	0.022	0.088
Citation stock	103.7	612.9	0.7	3.5
Citation stock/patent stock	0.617	0.544	0.702	1.922
OC stock	20.745	38.616	10.694	20.127
OC stock/assets	0.028	0.042	0.042	0.043
No patent (dummy)	0.195	0.397	0.628	0.484

Notes: Reporting R&D group includes 641 observations from 1995 to 2008, for which we observe R&D expenditures. For 519 of these observations, we also observe the OC investment. The R&D non-reporting group includes 506 observations, of which 347 have OC investment.

in the sample, and despite reporting no R&D, almost 40% of these firms have filed patent applications. Patent filings indicate that although these firms do not report their research expenditures, they are indeed active in R&D. Furthermore, these firms are slightly more intensive in OC than R&D reporting firms.

Table 4 presents the industry classification and some summary information for the industries. Because we concentrate only on the firms that report R&D expenditures, some industries are missing or are thinly presented in our sample. Machinery, electronics, and software are the largest industry categories in our sample. There are clear differences in the intangible capital intensities and Tobin's q across industries. On average, Tobin's q is the highest in electronics, manufacturing of controlling and other instruments, and software firms. Those firms also have above-average R&D intensities. Tobin's q is the lowest in the food and paper industries, which are also less intensive in intangible investments. The OC intensity is by far the highest in the manufacturing of control and other instruments industry, while the lowest intensity is found in the paper industry, which is highly intensive in tangible capital. Otherwise, OC is quite evenly distributed across industries.

4. Results

4.1. Main results

This section presents the results from the estimation of the market value equation. The dependent variable is the same, log of Tobin's q, in all models. Table 5 presents the results of the basic NLS models. Because of the model's nonlinearity and the differing units of measurement, the interpretation of the coefficients is not straightforward, and it is more informative to examine the mean elasticities. These elasticities are reported at the end of the table. The first column in Table 5 presents the results from the baseline model specification (model 0) excluding all the intangible capital variables but including year and industry controls. Model 1 is estimated with knowledge capital and includes R&D, patent, and citation variables. This specification is comparable to the earlier studies estimating the

Table 4. Industry characteristics.

Industry	Observations	Observations (%)	Tobin's q	Total assets	R&D stock/ total assets	OC stock/ total assets	Patent stock/ R&D stock	Citation stock / patent stock
Food and kindred products	42	8.09	0.739	409.400	0.075	0.018	0.114	0.962
Chemicals	32	6.17	1.221	1190.148	0.244	0.039	0.595	0.543
Paper and allied products	45	8.67	0.738	10,307.930	0.025	0.005	0.204	0.658
Metal industries	53	10.21	0.964	2052.317	0.070	0.012	0.273	0.363
Machinery and computer equipment	85	16.38	1.185	1352.198	0.145	0.027	0.371	0.432
Electronics and components	54	10.40	2.125	4832.054	0.405	0.013	0.166	0.802
Measuring, analyzing, and controlling instruments	21	4.05	1.804	109.913	0.560	0.145	0.246	0.484
Rubber and miscellaneous plastic products	28	5.39	1.458	723.008	0.103	0.013	0.400	0.542
Transportation, communications & utilities	22	4.24	1.153	8365.156	0.029	0.011	0.433	0.690
Software	54	10.40	1.778	134.307	0.700	0.054	0.231	0.738
Trade and services	17	3.28	0.782	847.062	0.032	0.026	0.070	0.344
Other industries	66	12.72	1.216	1080.791	0.081	0.025	0.156	0.744
Total	519	100	1.279	2511.267	0.210	0.028	0.267	0.607

Notes: Financial variables are in millions of euros, in year 2000 real prices. Patent stock/R&D stock is reported as patents per million euros in R&D stock.

Table 5. Results of NLS regressions.

Dependent variable: log Tobin's q	0	1	2	3
Constant	−0.768***	−0.475	−1.297***	−1.690***
	(0.361)	(0.382)	(0.388)	(0.398)
log Total Assets	0.025	0.003	0.037**	0.063***
	(0.017)	(0.017)	(0.017)	(0.019)
R&D/assets		0.224*	0.416**	0.407***
		(0.122)	(0.163)	(0.142)
Patents/R&D		0.206*	0.324**	
		(0.112)	(0.128)	
Citations/patents		0.266**	0.236**	
		(0.106)	(0.103)	
OC/assets			7.140***	5.803***
			(2.185)	(1.835)
Zero R&D		0.287*	0.255	0.194
		(0.156)	(0.168)	(0.165)
No patent		0.026	−0.021	
		(0.102)	(0.100)	
Adj. R^2	0.288	0.336	0.365	0.333
Observations	519	519	519	519
Elasticities				
R&D/assets		0.035**	0.052***	0.062***
		(0.018)	(0.018)	(0.018)
Patents/R&D		0.040**	0.056***	
		(0.021)	(0.020)	
Citations/Patents		0.102***	0.083***	
		(0.034)	(0.031)	
OC/assets			0.116***	0.113***
			(0.026)	(0.028)

Notes: All equations include the full set of year and industry dummies and a dummy for interpolated values. Robust standard errors are noted in parentheses. Reference year: 2008. Reference industry class: Other industries.
*$p < .10$.
**$p < .05$.
***$p < .01$.

market value of knowledge assets. The model is estimated using the same sample for which OC can also be calculated. In the next column, Model 2 includes the OC variable. The last model excludes the patent variables and includes only R&D and OC.

The results in the second column of Table 5 show that knowledge assets can explain a significant part of the variation in Tobin's q. The adjusted R^2 increases from 0.288 to 0.336 when knowledge assets are included. The estimated elasticities show that R&D stock, patents, and patent citations are positively and significantly related to the firm's market value. The results of model 1 are comparable to the results reported in Hall, Jaffe, and Trajtenberg (2005), Hall, Thoma, and Torrisi (2007), and Sandner and Block (2011). In contrast to the studies by Hall and coauthors, we do not assume CRS, but as the results of model 1 show, the coefficient of total assets is close to zero and so the CRS assumption would not significantly change our results.[8] Our results with respect to patents and citations are in the same range as those reported in earlier studies, although the estimated elasticities, 4.0% and 10.2%, seem quite high in international comparison. Some earlier studies have also reported insignificant or even negative coefficients for patents (Sandner and Block 2011; Toivanen, Stoneman, and Bosworth 2002), which is clearly not the case in Finland.

However, the elasticity of Tobin's q with respect to R&D is 3.5%, lower than the value found by Hall, Thoma, and Torrisi (2007) in their set of European countries[9] and much lower than that found by Hall, Jaffe, and Trajtenberg (2005) in the USA. The results also somewhat surprisingly indicate that despite the institutional similarities, the market valuation of R&D is clearly lower in Finland than it is in Denmark (Bloch 2008) and closer to the market valuations in continental Europe (Hall and Oriani 2006). In some respects, the Scandinavian legal and stock market environment can be considered an intermediate case between the Anglo-Saxon and continental European financial systems (La Porta et al. 1998), but our results do not seem to reflect this situation. However, the low R&D elasticity that we find may partly result from the fact that the market value of R&D has decreased over time in many countries (Czarnitzki, Hall, and Oriani 2006), and our data are quite recent.

The coefficient of R&D is also clearly below unity, indicating that financial markets value R&D investments less than conventional tangible investments, and suggesting inefficient or excessively large investments in R&D. At the same time, the low R&D coefficient could also be interpreted to indicate that the actual depreciation rate of R&D investments is higher than the 15% used here (Czarnitzki, Hall, and Oriani 2006). However, if we exclude the industry dummies, the coefficient of R&D is close to or above one, which would indicate equal valuation.

Model specifications 2 and 3 in Table 5 also include the OC variable. The inclusion of OC increases the adjusted R^2 from 0.336 to 0.365. The OC is positively related to Tobin's q, and the very high coefficient value indicates large returns on organizational investments. Moreover, the elasticity of Tobin's q with respect to OC intensity is approximately 11%, higher than the elasticities of R&D or patents. Moreover, the inclusion of OC increases the elasticities of R&D and patents by 1.5%, while the elasticity of citations is now a bit lower. This effect remains, even when we extend the model with more control variables. The omission of OC would lead us to underestimate the importance of R&D and patents and overestimate the impact of patent citations. Unfortunately, the OC results cannot be compared with earlier studies in as straightforward a manner as the results for R&D because of differences in measurement and estimation methods. However, our results add to the growing literature that finds OC to have a significant effect on the market value.

We also estimate the market value using linear approximation and panel estimation methods. Table 6 presents the results of these estimations. Models 1–3, which were estimated with NLS, are now estimated with OLS and fixed-effect estimation. The OLS results show that all categories of intangible capital are again significantly related to higher market value. After controlling for firm-specific effects, the coefficients are lower and the patent and OC coefficients are no longer significant even though they remain positive. These results indicate that year-to-year changes in these intangible assets are quite unimportant for the market valuation. As noted earlier, intangible assets are strategic investments that change only slowly over time. In particular, organizational practices are usually highly persistent. In fixed-effect estimation, the OC intensity is thus likely to be highly correlated with firm fixed effects, with the result that the estimation misses a large part of the explanatory power of the OC variable.

The market value model can also be estimated with the random-effect estimation method, which is consistent and efficient if the firm-specific effects are uncorrelated with other right-hand side variables. To test this assumption, we estimated both the fixed-effect and random-effect models and run the Hausman specification test (1978). The Hausman test showed that the differences between the fixed-effect and random-effect models are statistically significant, and thus we rejected the random-effect model in favor of the fixed-effect model. Therefore, we do not report the random-effect results in Table 6. In any case, the

Table 6. Results of the panel models.

Dependent variable: log Tobin's q	OLS[a]			Fixed effects[b]		
	1	2	3	1	2	3
Constant	−0.045	−0.633*	−0.737**	−0.338	−0.979	−0.950
	(0.339)	(0.366)	(0.358)	(1.215)	(1.378)	(1.343)
log Total Assets	−0.022	0.003	0.016	−0.007	0.022	0.029
	(0.016)	(0.017)	(0.017)	(0.059)	(0.066)	(0.065)
R&D/assets	0.421***	0.391***	0.432***	0.199**	0.199**	0.173*
	(0.098)	(0.085)	(0.095)	(0.099)	(0.099)	(0.098)
Patents/R&D	0.268***	0.280***		0.095	0.113	
	(0.071)	(0.070)		(0.154)	(0.155)	
Citations/patents	0.165**	0.174**		0.230***	0.228***	
	(0.076)	(0.072)		(0.071)	(0.071)	
OC/assets		2.621***	2.499***		1.518	1.629
		(0.752)	(0.741)		(1.540)	(1.549)
Zero R&D	0.306*	0.265	0.201	0.453*	0.457*	0.489**
	(0.181)	(0.180)	(0.184)	(0.259)	(0.259)	(0.190)
No patent	0.046	0.079		0.332***	0.331***	
	(0.089)	(0.089)		(0.110)	(0.110)	
Adj. R^2	0.199	0.227	0.186	0.157	0.180	0.153
Observations	519	519	519	519	519	519

Note: All equations include the full set of year dummies and a dummy for interpolated values.
[a]Robust standard errors in parentheses.
[b]Standard errors in parentheses. Reference year: 2008.
*$p < .10$.
**$p < .05$.
***$p < .01$.

results from the random-effect model were similar to the fixed-effect results, and the only notable contrast was that the OC had a larger and significant coefficient.

4.2. Robustness

We check the robustness of our results in several ways. First, models 1 and 3 are estimated with a larger sample. The larger sample can be obtained by extending the time period when we drop either the patent variables or the OC from the model. Models 1B and 3B in Table 7 present the results from these models. Model 1B is estimated for knowledge capital for the years 1988–2008, and model 3B is estimated for R&D and OC for the years 1995–2011. The results again show a positive and significant relationship between intangible capital intensities and market value, although the citation elasticity is now somewhat lower. For R&D, the relationship appears to be slightly stronger, which is in line with previous findings of decreasing market value of R&D over time. Extending the time period does not change the OC results.

Second, the last two columns in Table 7 represent models 1 and 2 extended with additional control variables, which may systematically affect the market value. The control variables include the ratio of net investments to total assets, the growth of sales as a control for future growth prospects, and debt leverage. As the results show, adding more control variables increases the R&D elasticity and does not otherwise change the main results.

Third, we want to determine whether the voluntary reporting of R&D expenditures affects our results. The reporting of R&D expenditures is not compulsory, and many firms choose not to report their R&D investments. Therefore, reporting R&D is an endogenous

Table 7. Results of regressions with larger samples and more control variables.

Dependent variable: log Tobin's q	1B	3B	1C	2C
Constant	0.212	−1.617***	0.116	−0.677*
	(0.372)	(0.332)	(0.395)	(0.396)
log Total Assets	−0.032*	0.058***	−0.016	0.014
	(0.017)	(0.015)	(0.016)	(0.016)
R&D/assets	0.512***	0.408***	0.352*	0.589**
	(0.119)	(0.107)	(0.204)	(0.272)
Patents/R&D	0.237***		0.176*	0.290**
	(0.090)		(0.100)	(0.120)
Citations/patents	0.191**		0.284***	0.273**
	(0.091)		(0.106)	(0.106)
OC/assets		6.182***		6.563***
		(1.382)		(2.037)
Zero R&D	−0.029	0.199	0.300*	0.273*
	(0.153)	(0.150)	(0.156)	(0.165)
No patent	0.020		0.033	−0.001
	(0.086)		(0.100)	(0.098)
Debt leverage			−0.683***	−0.568***
			(0.172)	(0.173)
Sales growth			0.471***	0.464***
			(0.171)	(0.173)
Investments/total assets			0.030	0.114
			(0.197)	(0.197)
Adj. R^2	0.382	0.321	0.401	0.429
Observations	717	719	516	516
Elasticities				
R&D/assets	0.085***	0.064***	0.052**	0.069***
	(0.016)	(0.014)	(0.026)	(0.026)
Patents/R&D	0.038***		0.033*	0.048***
	(0.013)		(0.018)	(0.018)
Citations/patents	0.068**		0.104***	0.091***
	(0.028)		(0.032)	(0.030)
OC/assets		0.120***		0.104***
		(0.210)		(0.024)

Notes: All equations include the full set of year and industry dummies and a dummy for interpolated values. Robust standard errors are given in parentheses. Reference year: 2008. Reference industry class: Other industries.
*$p < .10$.
**$p < .05$.
***$p < .01$.

variable, which may cause a sample selection bias. Furthermore, some of the firms that report R&D expenditure do so with interruptions and their R&D histories are fragmented. Moreover, in addition to R&D reporting, our sample is also limited because we are not able to estimate OC for all publicly listed firms. Hence, to test the robustness, we estimate the model with all non-financial firms, replace the missing intangible capital values with zero, and add dummy variables to indicate no R&D and no OC information. About half of the observations have no reported R&D, while one-quarter have no OC information.

We estimate models 1 and 2 for all firms and separately for manufacturing and non-manufacturing firms, because the share of non-manufacturing firms is now much higher than in our original sample, and this increased proportion may affect the results. These results are reported in Table 8. As the table shows, the estimated elasticities for R&D and patent variables are now somewhat lower, although they remain statistically significant except for patents in the non-manufacturing sector. As for OC, the elasticity of OC is clearly

Table 8. Results of regressions with all non-financial firms.

Dependent variable: log Tobin's q	All 1	All 2	Manufacturing 1	Manufacturing 2	Non-manufacturing 1	Non-manufacturing 2
Constant	0.621**	0.221	−0.057	−0.390	1.621***	1.004**
	(0.266)	(0.272)	(0.282)	(0.292)	(0.454)	(0.489)
log Total Assets	−0.056***	−0.038***	−0.017	−0.006	−0.105***	−0.078***
	(0.012)	(0.013)	(0.013)	(0.013)	(0.021)	(0.022)
R&D/assets	0.322***	0.302***	0.336**	0.336**	0.267*	0.253*
	(0.112)	(0.102)	(0.152)	(0.154)	(0.148)	(0.133)
Patents/R&D	0.402***	0.419***	0.413***	0.463***	−0.163	−0.081
	(0.132)	(0.130)	(0.118)	(0.126)	(0.130)	(0.164)
Citations/patents	0.239***	0.222***	0.270***	0.278***	0.130*	0.128**
	(0.067)	(0.063)	(0.098)	(0.101)	(0.067)	(0.065)
OC/assets		1.945**		3.757**		0.404
		(0.923)		(1.475)		(1.064)
No R&D report	0.070	0.056	0.300***	0.287***	−0.206***	−0.164**
	(0.049)	(0.050)	(0.066)	(0.066)	(0.074)	(0.074)
Zero R&D	0.080	0.084	−0.045	−0.050	0.211	0.257
	(0.147)	(0.149)	(0.222)	(0.221)	(0.166)	(0.162)
No OC		0.208***		0.065		0.217**
		(0.054)		(0.068)		(0.094)
No patent	−0.013	−0.032	−0.122	−0.117	−0.016	−0.048
	(0.052)	(0.052)	(0.075)	(0.077)	(0.080)	(0.084)
Adj. R^2	0.304	0.314	0.329	0.341	0.341	0.351
Observations	1147	1147	713	713	434	434
Elasticities						
R&D/assets	0.025***	0.024***	0.027**	0.026**	0.022**	0.021**
	(0.007)	(0.007)	(0.011)	(0.010)	(0.010)	(0.009)
Patents/R&D	0.035***	0.036***	0.050***	0.053***	−0.008	−0.004
	(0.010)	(0.010)	(0.012)	(0.012)	(0.008)	(0.009)
Citations/patents	0.059***	0.055***	0.076***	0.075***	0.030**	0.030**
	(0.013)	(0.013)	(0.023)	(0.023)	(0.012)	(0.012)
OC/assets		0.034**		0.058***		0.008
		(0.015)		0.019)		(0.022)

Notes: All equations include the set of year and industry dummies and a dummy for interpolated values. Robust standard errors are given in parentheses. Reference year: 2008. Reference industry class: Other industries.
*$p < .10$.
**$p < .05$.
***$p < .01$.

lower in these estimations, and this result seems to be primarily driven by the large number of non-manufacturing firms that are now included in the sample.[10] The elasticity is now lower in the manufacturing sector as well, but it remains strongly significant. However, the separate non-manufacturing results show that the OC intensity does not have a significant coefficient. This result is surprising, because although the non-manufacturing firms are less intensive in R&D, they do not seem to rely on OC investments either. However, it may be that our OC depreciation rate assumption is too modest for the non-manufacturing sector. Higher depreciation rate significantly increases the OC elasticity estimate in the non-manufacturing sector but does not have similar effect in the manufacturing sector. This result may reflect the short benefit lives of brand investments in the service sector (Awano et al. 2010). In general, it appears that the formation of OC and its relationship with market value is somewhat different in the non-manufacturing sector, which was thinly presented in our original sample.

Furthermore, the coefficient of the no R&D report dummy variable is also interesting, as it is positive in the manufacturing sector but negative in the non-manufacturing sector. This indicates that R&D reporting status has different implications in different industries. A positive coefficient can be interpreted to indicate that many manufacturing firms are active in R&D, and the stock market recognizes this, even if firms do not report R&D expenditures. Similarly, the positive coefficient of the no OC dummy variable can be interpreted to indicate that firms make organizational investments although the investments are not observed. The interpretation of the negative coefficient in the non-manufacturing sector is less clear. However, the negative coefficient seems to be partly due to the fact that our industry classification is perhaps not sufficiently detailed. Furthermore, the results for the non-manufacturing sector should be interpreted with caution, as a high number of intangible capital values are missing, approximately 40% for OC and almost 70% for R&D.

Another robustness test for the sample selection is the estimation of the market value of knowledge assets using the Heckman two-step estimator, where the first step is a probit estimation of whether the firm reports R&D. The second step is to estimate the market value model including the inverse Mill's ratio as an explanatory variable. Because the availability of OC information could affect the estimation, we exclude OC variable from the estimation. The results are reported in Appendix 2 and show that the coefficient of the inverse Mill's ratio is not significant and that the choice of R&D reporting should not cause a bias to the results. However, the above-mentioned results for all non-financial firms are somewhat in contrast, and the first step in our sample selection model may not contain all the necessary explanatory variables.

Finally, further robustness checks are conducted by estimating the model for different subsamples.[11] The original sample is divided into large and small firms based on sales, and high and low market value firms based on Tobin's q. The smaller firms are more intensive in R&D and OC but not in patents. The intangible capital intensities also vary more in the smaller firms than in the larger firms. When the market value model is estimated, the results show that the market value reacts more strongly to the R&D intensity in small firms, while the patent variables do not have significant effects. For the larger firms, both patent citations and R&D have statistically significant effects on the market value. The elasticity of Tobin's q with respect to OC is similar for large and small firms, although it is slightly higher for large firms. We also divided the sample into high and low market value groups. Coad and Rao (2006) find that the market valuation of R&D is much higher in firms with high Tobin's q than in firms with low Tobin's q. This result also applies to our Finnish data, for OC as well as for R&D.

5. Conclusions

This study has investigated the relationship between intangible capital and the stock market valuation of Finnish firms during the period 1995–2008. This paper provides new evidence on the market value of OC, which is studied along with the more frequently analyzed knowledge assets. Firms invest in OC by building and managing brands, hiring managers, and improving working practices. These investments have increased in recent years, but it remains difficult to measure these activities. We have used a rich Finnish linked employer–employee data set to estimate firms' OC using the occupational composition of the workforce and the wage costs of organizational workers. Our results show that this novel method, developed by GPR (2010), is able to measure firm-level OC in a way that is relevant for firm's market valuation. This result is interesting and suggests that a firm's workforce composition can also be used to study other aspects of intangible capital investments.

This study has analyzed organizational investments together with knowledge assets, thus providing evidence of their relative importance to the firm's market value. The results with respect to OC indicate large returns on these investments. The estimated elasticities of Tobin's q with respect to OC are in the range of 10–12% and they are significantly higher than the estimated R&D elasticities. The results indicate that when concentrating the study of intangible capital on R&D and excluding OC, we ignore an equally or even more important element of a firm's intangible capital. In doing so, we also risk misinterpreting the market value effects of R&D and patents.

While most of the existing literature on the market value of knowledge assets analyzes US or UK stock markets, this study extends the literature by studying a Scandinavian market. The Finnish results obtained in this study mostly confirm the earlier US and European results on the market valuation of R&D and patents. Financial markets value R&D assets, patents, and patent citations. However, the market value of R&D appears to be lower in Finland compared with the USA, Denmark, or other European countries. In contrast, the market value of patents and patent citations is slightly higher in Finland than in other countries. The results that institutional differences matter and that the valuation of R&D tends to be higher in Anglo-Saxon countries are not new (Booth et al. 2006; Hall and Oriani 2006). However, the institutional differences do not entirely explain our R&D results, and the results also imply that institutional differences do not seem to have the same effect on the valuation of patents.

Our estimation results are robust after adding more control variables and estimating the model for a longer time period. However, our robustness tests also show that while the relationship between intangible capital and market value is robust in the manufacturing sector, the relationship seems to be somewhat different in the non-manufacturing sector. Unfortunately, our sample contains few non-manufacturing firms for which we observe the intangible investments. However, the industry-specific differences in intangible capital investments and their firm performance effects would represent an interesting topic for further research. Furthermore, the current literature on OC uses widely varying methods to estimate the organizational investments and their effects on market value, which makes it extremely difficult to compare the results. As our estimation results and other studies underline the importance of OC for a firm's market value and performance, more systematic measurement and analysis of OC are clearly needed to enable a better comparison and improve our understanding of intangible capital.

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Notes

1. Measuring organizational investments with employee wage costs or any other production cost-based measurement naturally raises the question of whether production costs are actually investments in better management and organizational practices or simply high expenditure resulting from inefficiencies. However, the established practice of using R&D expenditures to measure R&D capital could be criticized for the same reason.
2. For results on the productivity effects of patents, see Bloom and Van Reenen (2002). For results on other intangible assets and productivity, see Ilmakunnas and Piekkola (2010), who use a LEED-based measurement of intangibles.
3. Manufacturing accounts for 81% of the observations in our sample, and thus it is disaggregated further. Among non-manufacturing firms, half of the firms that report R&D are software firms (SIC 737), and as a distinctive group, they are placed in a separate industry category.
4. The complete list of occupations can be found in GPR (2010).

5. We estimated the model using a depreciation rate of 20% for all firms, which did not change the results. We also used depreciation rates of 30% and 15% for OC. The choice of depreciation rate has a scaling effect on the estimated coefficients, but only a small effect on the estimated elasticities.
6. Patent applications filed at the European Patent Office may also be filed internationally under the Patent Cooperation Treaty. Later patent applications may cite either of these publications.
7. For the remaining firms, the employer–employee data could not be reliably linked. The exact list of firms included in the sample can be found in Appendix 1.
8. As a robustness check, we also tested CRS assumption. This assumption had only minor effects on the results in models 1–3.
9. This may be partly due to the large number of UK firms in their sample. According to Hall and Oriani (2006), the market value of R&D is clearly higher in the UK than in continental Europe.
10. Baseline models 1–3 were also estimated using a sample that excluded the non-manufacturing firms. This restriction slightly increased the patent elasticity but otherwise the results remained unchanged.
11. These results are available upon request.

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Appendix 1. Sample firms

Table A1. List of sample firms.

1	Affecto Oyj	37	Metsä Board Oyj
2	Ahlstrom Oyj	38	Metso Oyj
3	Aldata Solution Oyj	39	Neste Oil Oyj
4	Alma Media Oyj	40	Nokia Oyj
5	Amer Sports Oyj	41	Nokian Renkaat Oyj
6	Aspo Oyj	42	Nurminen Logistics Oyj
7	Aspocomp Group Oyj	43	Okmetic Oyj
8	Atria Oyj	44	Olvi Oyj
9	Basware Oyj	45	Orion Oyj
10	Biohit Oyj	46	Outokumpu Oyj
11	Cargotec Oyj	47	Outotec Oyj
12	Cencorp Oyj	48	Panostaja Oyj
13	Componenta Oyj	49	PKC Group Oyj
14	Comptel Oyj	50	Pohjois-Karjanlan Kirjapaino Oyj
15	Digia Oyj	51	Ponsse Oyj
16	Dovre Group	52	Raisio Oyj
17	Elecster Oyj	53	Rapala VMC Oyj
18	Elisa Oyj	54	Rautaruukki Oyj
19	Exel Composites Oyj	55	Raute Oyj
20	Fiskars Oyj	56	Sanoma Oyj
21	Fortum Oyj	57	Solteq Oyj
22	F-Secure Oyj	58	SSH Communications Security Oyj
23	GeoSentric Oyj	59	Stonesoft Oyj
24	Glaston Oyj	60	Stora Enso Oyj
25	HKScan Oyj	61	Suominen Oyj
26	Honkarakenne Oyj	62	Talentum Oyj
27	Incap Oyj	63	Tecnotree Oyj
28	Kemira Oyj	64	Teleste Oyj
29	Keskisuomalainen Oyj	65	Tieto Oyj
30	Kesko Oyj	66	Tulikivi Oyj
31	Kesla Oyj	67	UPM-Kymmene Oyj
32	Kone Oyj	68	Uponor Oyj
33	Konecranes Oyj	69	Vaisala Oyj
34	Lassila & Tikanoja Oyj	70	Wärtsilä Oyj
35	Lännen Tehtaat Oyj	71	YIT Oyj
36	Martela Oyj		

Appendix 2. Sample selection model

The probability of a firm reporting R&D is explained by the firm's log sales, the industry R&D intensity (sum of industry R&D expenditures divided by industry total sales), the firm's capital intensity (total assets divided by sales), and year dummies. The model is estimated for all non-financial firms for the period 1988–2008.

Table A2. Sample selection model.

Observations	1265
Number reporting R&D	714
Share reporting R&D	56.44%
Probit for reporting R&D	
log Sales	0.333*** (0.023)
Industry R&D intensity	20.373*** (1.697)
Capital intensity	0.076*** (0.022)
Pseudo-R^2	0.218
NLS regression	
Dependent variable: log Tobin's q	
Constant	−0.271 (0.787)
log Total Assets	−0.013 (0.033)
R&D/assets	0.449*** (0.112)
Patents/R&D	0.239*** (0.088)
Citations/patents 0.167* (0.086)	
Zero R&D	−0.099 (0.151)
No patent	0.006 (0.088)
Mill's ratio	0.168 (0.188)
Adj. R^2	0.369
Observations	714

Notes: The Probit equation includes the full set of year dummies. The NLS equation includes the full set of year and industry dummies and a dummy for interpolated values. Robust standard errors are given in parentheses. Reference year: 2008. Reference industry class: Other industries.
*$p < .10$.
**$p < .05$.
***$p < .01$.

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Internationalization of corporate R&D activities and innovation performance

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Abstract

The internationalization of corporate research and development (R&D) activities is a growing phenomenon, but previous empirical studies provide inconclusive evidence of its effects on the innovation performance of firms. This article examines how the innovation performance of European firms changes when they begin to internationalize their R&D activities. Propensity score matching and difference-in-differences methods are applied to control for self-selection and to estimate the causal effect of R&D internationalization. Patent inventor data are used to track the locations of corporate R&D activities. Information on patent applications, patent citations, and technological fields is used to measure innovation output, quality, and diversity, respectively. The results indicate that firms with a greater number of previous innovations are more likely to begin international R&D activities. Moreover, beginning R&D internationalization further increases the innovative output of firms. The results also indicate a weaker increase in the technological diversity of innovation activities. In contrast, the difference in the average quality of innovations in favor of international firms is shown to be due to self-selection.

JEL classification: O32, F23, L25

1. Introduction

The internationalization of corporate research and development (R&D) activities is a prevalent phenomenon that has grown considerably over recent decades (Moncada-Paternò-Castello *et al.*, 2011; European Commission, 2012). International R&D investments are considered to be driven not only by the market-seeking objectives of firms but also by knowledge-seeking motives and improved access to new technological knowledge (Kuemmerle, 1999; Chung and Alcácer, 2002; Le Bas and Sierra, 2002). Consequently, the innovation performance effects of international R&D have begun to receive attention in recent empirical studies. However, the results obtained thus far are inconclusive. Some studies, e.g., Penner-Hahn and Shaver (2005) and Chen *et al.* (2012), report that R&D internationalization has a positive effect on the innovation performance of firms, but contrary findings have also been reported (Singh, 2008).

There are two alternative but not mutually exclusive explanations for why international R&D may be linked to the innovation performance of firms. First, firms self-select into conducting R&D abroad. Thus, firms that engage in overseas R&D could either be more-innovative firms that are able to cover the additional fixed costs of internationalization or less-innovative firms that go abroad to catch up and compensate for their technological weaknesses. Second, internationally distributed R&D activities can improve the innovation performance of firms by providing improved access to local scientists, knowledge spillovers, and universities (Florida, 1997; von Zedtwitz and Gassmann, 2002).[1] Prior empirical studies typically employ panel models that control for bias caused by time-invariant omitted variables (e.g., Chen *et al.*, 2012 and Hsu *et al.*, 2014); however, these methods do not properly account for the endogenous self-selection of firms. Therefore, we cannot interpret prior results as causal. The aim of the present article is to account for the self-selection process and offer more reliable results on the causal effect of the start of international R&D activities on firm innovation performance. This study contributes to the literature by applying propensity score matching and difference-in-differences (DID) methods to control for the endogenous self-selection process. The combination of these methods has been used by De Loecker (2007), Greenaway and Kneller (2008), Hanley and Monreal Pérez (2012), and others to estimate the causal effect of exporting on firm performance. However, to the best of our knowledge, this method has not been applied in the context of R&D internationalization. This combination of methods does not necessarily eliminate all endogeneity problems (Dehejia, 2005; Smith and Todd, 2005). Nevertheless, by considering only firms that begin internationalization and by controlling for the self-selection process, this approach can account for endogeneity better than the previous studies have done. Several robustness tests are conducted to further narrow down remaining endogeneity concerns.

This study analyzes European firms and their international R&D investments. European firms have exhibited a higher level of R&D internationalization than their American or Japanese competitors (European Commission, 2012), and therefore, the innovation performance effects of R&D internationalization should be especially important for European firms. The extant literature, however, has mostly analyzed US and Asian firms. In the present article, the analysis concentrates on medium-sized and large European firms, and their R&D activities are studied by analyzing their worldwide priority patent applications. Following previous studies, patent inventor addresses are used to track the international distribution of corporate R&D activities. Again, consistent with prior studies, we use information on patent applications, patent citations, and technological fields of patents to measure innovation output, quality, and diversity, respectively.

Our findings suggest that more-innovative firms in the lead-up are more likely to begin overseas R&D operations. Thus, we find evidence of positive self-selection. This self-selection explains 35–100% of the observed differences in innovation performance between domestic firms and firms that start international R&D. After controlling for self-selection using propensity score matching, the start of overseas R&D activities has a statistically significant positive effect on innovative output and on the technological diversity of innovation activities. In contrast, the difference in the innovation quality in favor of international firms is shown to be entirely due to self-selection. This result diverges from some earlier studies that find international R&D to have a positive effect on innovation quality. Thus, our results imply that self-selection does matter, and it needs to be accounted for when estimating the effects of international R&D activities.

The remainder of this article is organized as follows. The second section reviews prior literature discussing the internationalization of R&D activities. The third section presents the data and main variables. The fourth section presents the descriptive statistics. The fifth section discusses the empirical model and results. The sixth section analyzes the sensitivity of the results, and the seventh section concludes the article.

2. Previous literature

The literature indicates that since the 1980s, R&D activities have rapidly become more internationally dispersed (OECD, 2008; Picci, 2010). This is especially the case in Europe. One reason for this dispersion is that firms from small European countries have needed to internationalize their R&D activities due to the pressures of international demand and limited resources in their home countries (von Zedtwitz and Gassmann, 2002). Moreover, many European firms source knowledge and offset home country technological weaknesses by establishing R&D units in the United States and other countries (Almeida, 1996; Florida, 1997). Increasingly prevalent international R&D investments can also have a considerable influence on the innovation performance of firms and countries. The majority of empirical studies have focused on the drivers of R&D internationalization and how countries should adjust their policies to attract foreign R&D investment (e.g., Hegde and Hicks, 2008; Athukorala and Kohpaiboon, 2010). However, the effects on firm performance have also begun to receive attention.

1 In contrast, Argyres and Silverman (2004) argue that by centralizing R&D activities, firms can achieve economies of scale and avoid coordination and communication costs.

2.1 Benefits of R&D internationalization

The market-seeking, or existing capabilities exploiting, view of foreign direct investment suggests that R&D internationalization may be used to gain access to new markets and utilize the innovations developed in the home market internationally (Kuemmerle, 1999; von Zedtwitz and Gassmann, 2002). International R&D facilities may be necessary to adapt existing, domestically developed innovations to the conditions and legal regulations of foreign markets. In addition, local R&D units may allow a quicker introduction of new products to local markets (Lewin *et al.*, 2009). Thus, this view implies that more-innovative firms are more likely to establish overseas R&D units to gain access to foreign markets; however, the view does not predict subsequent changes in innovation performance.

Studies suggest that R&D internationalization is also driven by knowledge-seeking motives that aim to improve firm innovation performance. These studies argue that internationally distributed R&D provides firms with access to a wide range of new resources (Chung and Alcácer, 2002; Le Bas and Sierra, 2002). Having a local presence in different countries provides improved access to local scientists, informal knowledge networks and universities, and it may thus improve innovation performance (von Zedtwitz and Gassmann, 2002). Knowledge spillovers from competitors, customers, and other parties are another way firms may benefit from international R&D activities (Granstrand *et al.*, 1993; Kuemmerle, 1999). Spillovers are typically national or even local in scope due to factors such as the tacitness of knowledge bases and specialization of local labor markets (Jaffe *et al.*, 1993; Branstetter, 2001; Breschi and Lissoni, 2001). Thus, to access these spillovers, R&D units must be located near knowledge sources. Therefore, R&D activities benefit from collocation with industry peers more than many other corporate activities (Alcácer, 2006; Audretsch and Feldman, 1996). A local presence may also enable firms to improve their cooperation with customers. As customers can serve as an important source of new ideas and product development (von Hippel, 2005) and these ideas may not be easily transferable, a local presence can be crucial. Moreover, an internationally distributed R&D organization allows a firm to create a diverse knowledge base within the firm, which can facilitate innovation and lead to new ideas and combinations of existing knowledge (Patel and Pavitt, 1997). Thus, the more internationalized corporate R&D activities are, the larger the knowledge pools and potential spillovers that a firm can access and the greater the potential improvement of firm innovation performance.

However, R&D internationalization may involve the imitation of competitors rather than increasing original, in-house knowledge production. If this is the main driver of international R&D investments, there may be a negative self-selection process, whereby initially less-innovative firms engage in international R&D to catch up their competitors.

International R&D may also enable a firm to reduce the costs of R&D by utilizing country-specific cost advantages, such as hiring scientists or buying inputs in a low-cost country (von Zedtwitz and Gassmann, 2002). R&D activities may also be located abroad to exploit country-specific R&D subsidies or patent boxes. Whether this type of strategy affects the overall quantity and quality of firms' innovations remains unclear.

2.2 Costs of R&D internationalization

Internationally distributed R&D activities also generate additional costs which may weaken the innovation performance of firms. R&D activities have a potential for economies of scale, but if a firm's R&D facilities are spread out too wide and thin, the firm cannot achieve such economies (Argyres and Silverman, 2004). R&D activities are also subject to economies of scope, as research projects in different technological fields may support one another (Henderson and Cockburn, 1996). Absent proper coordination, these benefits may be lost in distributed R&D organization and lead to weaker innovation performance.

Overseas R&D units often require a certain degree of autonomy to be able to access local knowledge networks and create innovations (Ghoshal and Bartlett, 1988); however, this creates problems for firm-level coordination. Coordination failures may lead to duplicated research efforts and wasted resources. Coordination problems in distributed organizations may be exacerbated by the communication problems that internationalization may create. Geographic and cultural distances make communication and interunit learning more time-consuming and difficult. This is especially true for R&D units because communicating R&D-related information often includes transferring tacit knowledge that requires face-to-face meetings, which become more infrequent as geographic distance increases (von Zedtwitz and Gassmann, 2002). The risk of intellectual property infringements and knowledge spillovers from the firm may also increase with R&D internationalization (Sanna-Randaccio and Veugelers, 2007; Schmiele, 2013).

2.3 Previous empirical studies

As discussed above, we can identify both significant benefits and costs that stem from international R&D activities. Thus, the overall effect of international R&D activities on firm performance remains an empirical question. Furthermore, there are indications that previous innovation performance and other firm characteristics affect which firms engage in international R&D. This selection needs to be considered in the empirical methodology. Next, we will briefly summarize the findings of previous empirical studies and the methodologies they employ.

Using patent data, Iwasa and Odagiri (2004) and Penner-Hahn and Shaver (2005) study the internationalization of R&D activities in Japanese firms and find that it is associated with increased innovative output, at least for some firms. Chen *et al.* (2012) and Hsu *et al.* (2014) study Taiwanese high-tech firms and the geographic diversity of their overseas R&D investment and find that international R&D activities have a nonlinear but positive effect on the average quality of innovations. R&D offshoring is also shown to be associated with higher probability of innovation (Nieto and Rodriguez, 2011). Finally, R&D internationalization is shown to be linked to improved firm productivity (Todo and Shimizutani, 2008; Belderbos *et al.*, 2014), although not all studies confirm this finding (Fors, 1997). Other studies have analyzed the effects of geographically distributed R&D activities within countries rather than across national borders. For example, Singh (2008) studies the innovation quality effects of geographically distributed R&D using US patent data and finds that patents resulting from distributed R&D are of lower quality. Studies by Argyres and Silverman (2004) and Furman *et al.* (2006) suggest that decentralized and geographically distributed R&D is associated with lower innovation performance. On the contrary, Lahiri (2010) and Leiponen and Helfat (2011) find that geographically distributed R&D has a positive effect on the number of patent citations and on imitative innovation. To sum up, the majority of studies find that international R&D improves the innovation performance of firms, but the results with respect to nationally distributed R&D are somewhat contradictory.

Most of the above-mentioned papers on R&D internationalization use patent data to measure the innovation performance of firms. Patent inventor addresses are also often used to determine the R&D locations. The studies have typically employed panel models with firm random effects (e.g., Lahiri, 2010; Chen *et al.*, 2012; Hsu *et al.*, 2014) or firm fixed effects (e.g., Singh, 2008) to control for unobserved firm-specific heterogeneity. Nevertheless, if there exists unobserved firm-specific time-variant heterogeneity that affects both R&D location decisions and innovation performance, then neither random nor fixed effects model can solve the endogeneity problem. Moreover, simultaneity can also cause endogeneity in this setting. The extant research typically lags independent variables by one period, which is said to mitigate the problem. However, this method does not consider that firms' past innovation performance is likely to affect which firms engage in international R&D. Therefore, the methods employed in previous studies can suffer from endogeneity problems, and the results cannot be considered causal.

3. Data and main variables

3.1 Using patent data to determine the R&D locations

Patent data have been used in numerous firm- and country-level studies to examine the reasons for and effects of R&D internationalization, and the present study follows the same approach. Patent application data are obtained from the European Patent Office (EPO) PATSTAT database (2013). The data are aggregated at corporate group level under the assumption that the parent firm is the ultimate owner of its subsidiaries' patents. The Organization for Economic Co-operation and Development (OECD) HAN database (2013) and manual matching and firm ownership information from Bureau van Dijk's Orbis database are used to match subsidiary patents to parent firms.

Patent data are useful in studying R&D internationalization and innovation performance, as patent information is available for a long period and across nearly all countries. Technology classifications added by independent patent examiners also provide information on the technological field of inventions. Moreover, a patent application can be assigned to a country based on the address of patent's inventor. The addresses of inventors provide an accurate picture of where a firm's inventions are developed, and thus, we use this information to track the locations of corporate R&D activities.[2] If all inventors listed on a firm's patent applications in a given year are located in a single country, we conclude that the firm only engages in domestic R&D activities. If the firm's inventors reside in several countries

2 The inventor address can be misleading if, e.g., the inventor recently moved to another country. Nevertheless, according to Bergek and Bruzelius (2010), inventor information provides a fairly reliable picture of the location of R&D activities.

or in one country that changes from year to year, we conclude that the firm has internationally distributed R&D activities.

The treatment variable in our empirical models is the start of international R&D activities. This is a dummy variable that takes the value 1 if a firm begins to engage in international R&D in a given year and 0 otherwise. When we construct this variable, we require that the firm has not conducted international R&D during the preceding 2 years, and that it continues international R&D activities in the next 2 years after the start. Thus, to reliably measure the beginning of international R&D activities, we want to measure the geographic scope of firm's past innovation activities during the sample period and 5 years before it. Only firms that have applied for at least 10 patents during that time period are included in the sample. Patents that are co-applied by several firms are excluded in the determination of R&D locations because we wish to track the locations of firms' in-house R&D activities; however, in other patent-based innovation variables, these patents are included using fractional counting, i.e., a patent is assumed to be uniformly distributed among co-applicants.

To avoid home country bias in the patent data, the worldwide priority patent filings of each firm are counted. By using priority filings from every national patent office, we cover more inventions than by using EPO or Patent Cooperation Treaty (PCT) patent counts (de Rassenfosse *et al.*, 2013). A problem with this approach is that the PATSTAT database has missing inventor information for many national patent offices. The missing inventor country information can, nevertheless, be retrieved by following the steps suggested by de Rassenfosse *et al.* (2013), which recover the missing information with 97% accuracy.

3.2 Innovation performance variables

Firm innovation performance is analyzed using several variables that capture different aspects of innovation activity. The variables are following: number of patent applications as a measure of innovative output, number of citations as a measure of quality-weighted innovative output, number of citations per patent as a measure of the average quality of innovations, technological diversity index as a measure of the technological diversity of innovations, and technological diversity of citing patents as a measure of the breadth of technological impact. Next, we describe how these variables are constructed.

First, the innovation output measure is log $(Patents_{it} + 1)$. $Patents_{it}$ refers to the number of worldwide priority patent applications filed by firm i in a given year t.[3] Different measures of patent output are used as a robustness check.

After the patent application is published, the application may be referenced by other patent applications when subsequent inventions are based on or related to the earlier invention. The number of citations a patent receives is associated with several aspects of patent quality, such as the economic and social value of the patent, firm's market value, and patent renewal rate (Hall *et al.*, 2005; Harhoff *et al.*, 2003; Trajtenberg, 1990). The value distribution of patents is highly skewed, and hence, prior research has often used patent citations to better capture the economic value of firms' patents (Harhoff *et al.*, 1999; Trajtenberg, 1990). Thus, our second innovation performance measure, the quality weighted innovation output, is log $(Citations_{it} + 1)$. $Citations_{it}$ refers to the number of citations that a firm's patent applications filed in year t receive during our observation period. Third, the average quality of firm's innovations is measured using the following ratio: $Citations_{it}/Patents_{it}$. Again, we test the robustness of our results by using different citation measures.

We count the citations that a patent receives directly and as non-priority applications (i.e., subsequent applications that are filed in a different patent office and cover the same invention). The citation information in the PATSTAT database is imperfect for many national patent offices. Thus, we consider citations made in EPO, US, and PCT patents, which are reliably covered in PATSTAT. A patent can receive citations over decades, which we do not have time to observe. This means that some of patents in our sample have a longer period over which to receive citations than do other patents. To avoid this bias, the empirical approach compares citations to patents that are applied in the same year; and therefore, the truncated citation period treats all compared patents equally.

Fourth, we measure the technological diversity of innovation activities. If international R&D is used to source new technologies, firm's technological diversity may increase. Moreover, diversity can improve firm performance (Miller, 2006). Technological diversity is measured using patent technology codes (IPC) at the three-digit level. Using IPC classes, the technological diversity of firm's innovations is calculated as 1 − the Herfindahl index. Using this

3 We add one to the number of patent applications to retain firms with zero patents in our sample.

index in a patent context is suggested by Trajtenberg *et al.* (1997). However, Hall (2002) notes that the index is biased in the case of few patents, and an adjusted index should be employed. Thus, the bias-adjusted technological diversity index is written as follows:

$$\text{Adj. technological diversity index} = \left(1 - \sum_k \left(\frac{N_k}{N}\right)^2\right)\left(\frac{N}{N-1}\right), \tag{1}$$

where N is the number of IPC codes in a firm's patent applications, and N_k is the number of patent applications assigned to technology class k. The index takes values between 0 and 1, where high values indicate a high degree of technological diversity. If several IPC codes are assigned to a patent, we assume that an identical fraction of the patent is assigned to each class. Missing values (i.e., observations with no patent applications or single technology class) are replaced by zeros.

Finally, we measure the breadth of technological impact, i.e., the diversity of citations received. The number of citations describes the quality of a patent and the magnitude of its impact on later inventions. The technological diversity of citations describes patent's generality or breadth of impact (Henderson *et al.*, 1998; Argyres and Silverman, 2004). If the citations come from few technological fields, the invention is likely to be incremental, whereas citations from many different fields indicate an invention with wide applicability. Using the IPC technology codes of each citing patent, the breadth of impact is calculated using the above-described Herfindahl index. Now, N_k is the number of forward citations from patents assigned to class k, and N is the number of IPC codes in citations. Missing values are again replaced by zeros.

Using patents to measure innovation activities is subject to some well-known limitations. Patents only protect technological inventions, and hence, many other inventions are excluded. Furthermore, many firms choose to use trade secrecy or lead-time and do not patent their inventions. Thus, the propensity to patent varies considerably across industries. Moreover, patents can only be used to measure and analyze new-to-market inventions. The advantages and disadvantages of patent data for our purposes have been discussed in detail, e.g., in Patel and Pavitt (1991) and Le Bas and Sierra (2002).

3.3 Control variables

We use several firm-level control variables that are based on firm balance sheet data. These data are obtained from Bureau van Dijk's Orbis database. We expect that, in addition to the innovation variables, the decision to engage in international R&D activities is affected by similar firm characteristics as the decision to enter export markets. Thus, we refer to the literature on export market participation to select the control variables (Wagner, 2007, 2012). Firm turnover is used to control for firm size, and the growth of turnover is used to control for growth performance. We also control for R&D intensity by including the ratio of R&D investment to turnover. Missing R&D expenditure figures are replaced by zeros, and a dummy variable is created to indicate these observations. The control variables also include dummy variables for years, industries, and countries. Industry classification uses NACE codes at the two-digit level. In categories with few firms, the one-digit codes are used instead.

We include one further important control variable for previous long-run innovativeness of firm. Past patent stock is counted using the number of patent applications as follows:

$$Patentstock_{it} = (1-\delta) \times Patentstock_{i,t-1} + Patents_{it}, \tag{2}$$

where the depreciation rate δ is set to 15% following the prior literature (e.g., Hall *et al.*, 2005). The patent stock includes patents since 1995.

4. Descriptive statistics

Our sample covers over 850 medium-sized and large firms in 23 European countries during the period 2003–2009. The sample includes all independent or stock-listed firms that have consolidated balance sheet data available in the Orbis database, have a turnover of over 10 million Euros, and have applied for at least 10 patents. This means that our sample is restricted to relatively large firms, and the results may not directly apply to small firms. Table 1 presents selected descriptive statistics for the sample firms. The financial variables have been deflated to year 2005 real prices using a gross domestic product deflator. On average, our sample firms have annual sales of 6500 million

Table 1. Descriptive statistics

Variable	Mean	Median	SD
International R&D status	0.572	1	0.495
Patents per year	52.936	7	202.846
Patent stock	260.767	32.790	1024.546
Citations	98.947	5	491.567
Citations/Patents	1.417	0.621	2.438
Technological diversity	0.570	0.681	0.342
Breadth of impact	0.526	0.644	0.350
Turnover	6515.671	824.760	18663.320
Growth of turnover	0.052	0.026	0.187
R&D intensity	0.048	0.013	0.143
R&D missing	0.294	0	0.456
Firm age	59.037	39	57.395

Notes: A total of 3598 observations. Financial variables deflated to year 2005 prices and are expressed in millions of Euros.

Table 2. Descriptive statistics by international R&D status

	Domestic firms		Starters		Firms with international R&D	
Variable	Mean	SD	Mean	SD	Mean	SD
Patents per year	4.845	5.899	12.120	19.787	100.000	281.213
Patent stock	22.854	24.391	50.104	75.310	496.663	1421.613
Citations	4.230	12.025	14.648	28.713	193.012	687.904
Citations/Patents	0.826	1.906	1.466	2.784	1.803	2.551
Technological diversity	0.416	0.391	0.590	0.323	0.669	0.268
Breadth of impact	0.372	0.384	0.515	0.334	0.634	0.285
Turnover	2104.17	7672.94	3831.37	10449.82	10462	24457.64
Growth of turnover	0.045	0.214	0.070	0.205	0.051	0.158
R&D intensity	0.058	0.212	0.027	0.046	0.048	0.101
R&D missing	0.484	0.500	0.305	0.461	0.160	0.367
Firm age	43.935	41.274	73.545	57.471	64.250	64.205
Number of firms	419		121		409	
Number of observations	1207		620		1771	

Notes: Financial variables deflated to year 2005 prices and are expressed in millions of Euros.

Euros, and R&D expenditures represent approximately 4.8% of turnover, while the medians are much lower. The mean number of patent applications that firms file each year is 53, while the median is lower, at 7 patents. On average, each patent receives 1.4 citations during the observation period.

The sample firms can be divided by their R&D internationalization status as follows: domestic firms, firms that begin international R&D activities, and firms that engage in international R&D throughout the observation period. Table 2 represents the main characteristics of the different groups. The table indicates that firms conducting a share of their R&D abroad are larger, more R&D intensive, file more patent applications, and receive more citations per patent than firms with domestic R&D activities. International firms also have a higher degree of technological diversity, and their innovations have a greater breadth of impact than those of domestic firms. The firms that begin to internationalize their R&D have intermediate characteristics and are, in general, more similar to domestic firms than to larger firms with uninterrupted international R&D. Thus, the table suggests that R&D internationalization is associated with higher quantity and quality of innovations. These characteristics are in line with abundant evidence that exporting firms are, on average, larger, more productive, and more innovative than are non-exporting firms (Wagner, 2007, 2012). In the R&D literature, the results of, e.g., Lahiri (2010) and Penner-Hahn and Shaver (2005) also point to the same conclusion.

However, Table 2 is uninformative of whether international R&D improves innovation performance or whether observed differences are due to self-selection. As discussed in the literature review, we can expect both effects to be significant. In the next section, we separate the selection effects and analyze how the start of international R&D activities affects innovation performance. Firms that conduct international R&D throughout the observation period are excluded in the following analysis.

5. Estimation and results

To control for the self-selection process and discover the causal effect of international R&D activities on the innovation performance of European firms, we use propensity score matching with DID estimation. This methodology estimates the causal effect by matching the firms that begin international R&D activities to similar firms that engage only in domestic R&D activities. Matching on propensity scores allows us to control for the endogenous self-selection into international R&D, and DID estimation and matching within years remove time-invariant firm-specific differences and common shocks. The treatment variable in our model is the start of international R&D activities.

Let us denote time periods such that a firm begins overseas R&D in period t. Following Heckman *et al.* (1997), the average effect of starting overseas R&D on innovation performance at time period $t+s$ is defined as follows:

$$E\{y^1_{i,t+s} - y^0_{i,t+s}|start_{it} = 1\} = E\{y^1_{i,t+s}|start_{it} = 1\} - E\{y^0_{i,t+s}|start_{it} = 1\}. \quad (3)$$

In the equation above, y denotes the performance variable of interest, and the superscripts denote international R&D status. The difficulty with this expression is that the last term of the above equation is not observable. This term is the performance that a treated firm would have had, had it not started international R&D. To capture this term, each treated firm is matched to one or more similar firms that do not receive the treatment using propensity score matching (Rosenbaum and Rubin, 1983).

The first step of propensity score matching is to estimate a probit model that captures how beginning to engage in R&D internationalization depends on observable pretreatment characteristics of the firm.[4] The dependent variable takes the value 1 when a firm begins international R&D and 0 otherwise. The explanatory variables are either lagged by one period or constant over time. The probability model explaining the decision to internationalize R&D is represented as follows:

$$\Pr\,(start_{it} = 1) = \Phi(y_{i,t-1}, X_{i,t-1}), \quad (4)$$

where $\Phi(.)$ is the normal cumulative distribution function, $y_{i,t-1}$ denotes the lagged innovation performance measure, and $X_{i,t-1}$ denotes all other lagged explanatory variables.[5] Because the innovation performance of firms is measured using several outcome variables, the probit model is estimated separately for each variable. Not including the respective lagged outcome variable in the propensity score estimation could lead to insufficient covariate balance in the matched sample, and the remaining self-selection could bias the results. Moreover, the coefficients of the lagged outcome variables provide evidence of underlying self-selection process. All the propensity score estimations control for the scale and scope of firm's past innovation activities by including the following variables: number of patent applications in the previous year, past patent stock, and past technological diversity index. Two of these variables are also outcome variables, and hence, we estimate four different probit models. Further explanatory variables are included as discussed in Section 3.3.

The number of observations in the probit estimations is smaller than in Table 2, because observations after the start of international R&D as well as all firms with continuous international R&D are excluded from the estimations. The results of the probit models presented in Table 3 show that firms that are older, have higher growth, and have applied for more patents in the past are more likely to start international R&D activities. Moreover, higher past innovation quality increases the probability of engaging in international R&D (column 3). In other words, there is positive self-selection, and firms with superior innovation performance in the past are more likely to engage in international R&D. This result indicates that at least a part of the difference between the groups reported in Table 2 is

4 Logit estimation yields very similar results as well.

5 We also estimated probit models in which 2- and 3-year lags of innovation performance were included. This had only minor effects on our results.

Table 3. The results of propensity score estimation. Firm's probability to start international R&D

	1.	2.	3.	4.
Constant	−2.819***	−2.767***	−2.856***	−2.831***
	(0.390)	(0.391)	(0.392)	(0.389)
log(Patents+1)	−0.004	−0.085	−0.019	0.057
	(0.107)	(0.119)	(0.107)	(0.111)
log(Patent stock)	0.204**	0.214**	0.225**	0.196**
	(0.100)	(0.100)	(0.100)	(0.100)
Technological diversity	0.133	0.131	0.133	0.198
	(0.154)	(0.155)	(0.155)	(0.157)
log(Citations+1)		0.086		
		(0.054)		
Citations/Patents			0.039**	
			(0.019)	
Breadth of impact				−0.347**
				(0.165)
log(Turnover)	0.066	0.061	0.063	0.069
	(0.042)	(0.042)	(0.042)	(0.042)
Growth of turnover	0.525**	0.518**	0.533**	0.542**
	(0.257)	(0.258)	(0.257)	(0.258)
Growth missing	0.090	0.089	0.094	0.094
	(0.220)	(0.221)	(0.221)	(0.220)
R&D intensity	−0.654	−0.695	−0.674	−0.627
	(0.795)	(0.819)	(0.806)	(0.798)
R&D not reported	−0.234*	−0.224*	−0.222*	−0.239*
	(0.133)	(0.133)	(0.133)	(0.133)
log(Firm age)	0.133**	0.134**	0.133**	0.132**
	(0.055)	(0.055)	(0.055)	(0.055)
Pseudo R squared	0.138	0.141	0.142	0.144
Obs	1496	1496	1496	1496

Notes: All explaining variables are lagged by 1 year. All estimations include country, industry, and year dummies.
*Significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

due to self-selection. However, with respect to breadth of impact (column 4), we find evidence of negative self-selection, indicating that R&D activities that are general and relevant to a broad range of technologies are more likely to remain centralized.

Next, each treated firm is matched with similar untreated firms using the propensity scores. The matching is conducted within years and restricted to the area of common support. We apply several different matching estimators: radius matching, one-to-one nearest neighbor matching and kernel matching. There are over 12 times more control observations in our sample than there are treated observations. This ensures that there are many good matches available for most of the treated observations. However, a few observations with very high propensity scores may be poorly matched, although a common support restriction is applied. Therefore, our preferred model is radius matching, which can use many comparison observations while avoiding bad matches. The other matching estimators are discussed in the robustness analysis. Radius matching requires setting a radius size (i.e., the allowed distance between treated and control observations). We use a radius of 0.01 in our preferred model and discuss alternative radii in the robustness analysis.

To verify that the estimated propensity scores balance the covariates in our model, we calculate standardized bias in the covariates between the treated and matched control firms. The covariate means in treated and matched control group are reported in Appendix. Unfortunately, no clear guidelines exist on what level of remaining bias is acceptable. However, following Rosenbaum and Rubin (1985), the remaining bias should be smaller than 20%. Overall, radius matching significantly reduces bias for most variables. The remaining mean bias after radius matching varies slightly across the different propensity scores; however, it is always between 3.1% and 3.7%. Furthermore, the

Table 4. The results of DID estimation. Radius matching, $r = 0.01$

	ATT	SE	Obs
Log(Patents+1)			
t	0.557***	(0.086)	1480
t+1	0.556***	(0.122)	1480
t+2	0.560***	(0.128)	1480
Log(Citations+1)			
t	0.540***	(0.143)	1434
t+1	0.421***	(0.138)	1406
t+2	0.379**	(0.150)	1397
Citations/Patents			
t	−0.034	(0.367)	1216
t+1	0.051	(0.360)	1060
t+2	0.097	(0.384)	1021
Technological diversity			
t	0.145***	(0.049)	1480
t+1	0.063	(0.052)	1480
t+2	0.079	(0.052)	1480
Breadth of impact			
t	0.093	(0.057)	1481
t+1	0.145**	(0.060)	1481
t+2	0.031	(0.055)	1481

Notes: Bootstrapped standard errors with 200 repetitions.
*Significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

largest remaining biases for individual variables are always below 20%. Comparing the pseudo-R^2 values of the propensity score estimation before and after matching reveals a decline in explanatory power from approximately 0.10 to 0.025. These results indicate that propensity score matching balances the observable covariates between treated and control firms and the balancing property is satisfied.[6]

Next, the innovation performance of the treated and matched control group is compared using the DID methodology which, in combination with matching, improves the quality of nonexperimental evaluation studies (Blundell and Costa Dias, 2000; Smith and Todd, 2005). This estimator uses the change in the outcome variable relative to the pretreatment value and estimates the difference in the changes between the treated and non-treated groups. The treatment effect is estimated for the year of the treatment (t), year after ($t+1$), and 2 years after the treatment ($t+2$). The results of the radius matching are reported in the table below. The table also reports bootstrapped standard errors and the number of observations in the area of common support. Only few observations with very high propensity scores fall outside the area of common support.

Table 4 presents the average treatment effects on treated (ATT). The results indicate that after controlling for self-selection, beginning R&D internationalization increases innovative output whether measured by the number of patents or the number of citations. The ATT on the number of patents and citations is approximately 0.55 in the first year, but the effect decreases somewhat over time with respect to the citations outcome. This implies an over 50% increase in the number of patent applications per year, which seems very large effect indeed. However, note that the median of patent applications in the year before start is only 3, and thus, the implied increase is only two patents per year. The median of citations is 2, and thus, the ATT implies increase of one or two citations.

Moreover, the ATTs reveal that the number of citations per patent does not change significantly, although the ATTs are positive in period $t+1$ and $t+2$. This finding indicates that the difference in the citations-patent ratio that

6 The covariate balance was also tested using alternative matching methods. Kernel matching and larger radius ($r = 0.05$) produced approximately similar balance; however, nearest neighbor matching and smaller radius ($r = 0.005$) performed worse.

we observe in the descriptive statistics in Table 2 is entirely due to self-selection and that beginning overseas R&D activities does not improve the average quality of innovations, at least not within 3 years. This result is in contrast to some earlier studies that do not control for self-selection (e.g., Chen *et al.*, 2012). However, the firms that engage in international R&D throughout the observation period have even higher average quality of innovations than beginning firms. Therefore, we cannot entirely exclude the possibility that innovation quality would improve after the 3-year period that we analyze.

The technological diversity of patents and the breadth of impact also increase after beginning overseas R&D. Thus, international knowledge sourcing helps firms to diversify their innovation activities to new fields of technology; and moreover, their inventions have wider applicability. The increase in the indexes varies between 0.031 and 0.145, and the estimated effects are not statistically significant for every lag. Regarding the technological diversity index, the positive effect is the strongest during the first year, whereas for breadth of impact, it is strongest in the second year. The ATT estimates for these variables are always positive, which differs from the results of Argyres and Silverman (2004) that centralized R&D activities lead to greater breadth of impact. The difference is again explained by self-selection because we found evidence of significant negative self-selection with respect to the breadth of impact variable.

Because the skewness of outcome variables and thus the validity of t-tests is a possible concern, we use Wilcoxon signed-ranks test as an additional check. This does not change the results with respect to number of patents, citations, technological diversity, or breadth of impact. However, with respect to the citations-patent ratio, the test indicates a positive and significant effect in period $t+1$ and $t+2$. Thus, there is some indication of improvement in innovation quality as also implied by the ATT estimates. However, the standard errors of ATT estimates are high, and thus the estimates with respect to innovation quality do not enable precise prediction.

Overall, the ATT estimates indicate that the quantity and diversity of firm's innovations increase when the firm engages in international R&D, but the improvement in quality is not statistically significant. Thus, we not only find positive self-selection but also observe a positive effect after start. The effect with respect to the number of patents and citations is highly significant, whereas the results on technological diversity and breadth of impact are not as strong. The change in innovation performance occurs during the first year of internationalization, and the difference compared to domestically operating firms persists in the later years. As observed in Table 2, firms with a long history of international R&D have clearly superior innovation performance than do firms just beginning to engage in international R&D activities. However, we did not find statistically significant improvement in innovation performance over time. Nevertheless, it is possible that the 3-year period we analyze is too short to capture long-run learning and changes. Firms with long international R&D experience might also be quite different from beginning firms in many other ways, which could explain our findings.

The descriptive statistics in Table 2 show that firms beginning international R&D have over two and half times more patents and patent citations than firms with only domestic R&D. They have almost twice as many citations per patent and are more technologically diversified. If we compare them to the firms that conduct international R&D during the whole sample period, the differences are greater still. To obtain a better grasp of the magnitudes of the selection effect and ATT, we can compare the ATTs to unmatched differences between the treated and control firms in observations within common support. The unmatched differences and mean-comparison test results are reported in Table 5. Compared to the unmatched differences, the ATT estimates are approximately 35% lower for the patent and citation variables and up to 65% lower for the technological diversity and breadth of impact variables. The unmatched differences also show a statistically significant difference in citations per patent. The differences with the ATT estimates are significant, and thus, the selection effect forms roughly one-half of the difference in innovation diversity and a somewhat smaller portion of the difference in innovation output outcomes.

6. Robustness analysis

6.1 Firms that increase their R&D spending

The key assumption in estimating the causal effect in the model above is that the differences between treated and non-treated firms are captured by observable characteristics. We calculate the propensity score using several observable firm characteristics, including past innovation performance, and we also use the DID approach and matching within years. Nevertheless, a change in innovation performance could be driven by unobservable shocks

Table 5. The unmatched difference in outcomes between treated and control groups

	Unmatched difference	SE	Obs
Log(Patents+1)			
t	0.897***	0.083	1480
t+1	0.871***	0.094	1480
t+2	0.890***	0.102	1480
Log(Citations+1)			
t	0.784***	0.132	1434
t + 1	0.660***	0.124	1406
t + 2	0.526***	0.115	1397
Citations/Patents			
t	0.035	0.122	1216
t + 1	0.127*	0.092	1060
t + 2	0.186**	0.109	1021
Technological diversity			
t	0.263***	0.027	1480
t + 1	0.168***	0.034	1480
t + 2	0.201***	0.033	1480
Breadth of impact			
t	0.147***	0.036	1481
t + 1	0.235***	0.037	1481
t + 2	0.090**	0.036	1481

Notes: *Significant at 10% level, **significant at 5% level, and ***significant at 1% level.

that are correlated with the start of R&D internationalization. For example, it seems possible that beginning international R&D activities is related to a general expansion of R&D activities. Therefore, a potentially more accurate control group is firms that expand their R&D activities domestically. Unfortunately, due to the patchy availability of inventor addresses, the R&D locations within countries cannot be reliably tracked. To assess this concern in another manner, we limit our sample to firms that increase their R&D spending in real terms, which we take as an indication of expanding R&D activities.[7] Within this limited sample, we again estimate the treatment effect of R&D internationalization and also use the increase in R&D investments to compute the propensity scores.[8] Thus, we now match firms that increase their R&D investments and begin international R&D with firms with similar growth in their R&D investments but who keep their R&D activities domestic. This limits our sample considerably because many firms do not report their R&D investments, and only approximately one-half of the firms report increases.

The results of these estimations are presented in Table 6. We used radius matching with both 0.05 and 0.01 radii, where the larger radius is our preferred choice because the significantly smaller sample reduces the number of possible matches and leads to significantly higher standard errors. Therefore, the estimates with $r = 0.01$ are mostly statistically insignificant, although the point estimates are similar to our original estimates in Table 4. Overall, the ATT estimates with respect to patents, citations, and citations per patent are similar, albeit somewhat weaker than in our baseline model. The ATT estimates (with $r = 0.05$) for the number of patents and citations in period t are approx. 0.51 and lower for the following periods. The standard errors are clearly higher, which leads to weaker statistical significance. With respect to technological diversity and breadth of impact, the ATTs are similar and even slightly higher than in our baseline model. Therefore, we are confident that our main results are not driven by unobservable firm-specific shocks that induce firms to expand their R&D activities.

7 We excluded firms that more than tripled their R&D investments from year to year. These outliers weakened the estimation of propensity scores and led to weaker balancing of covariates after matching.

8 Probit results are available upon request.

Table 6. The results of DID estimation. Radius matching, $r = 0.05$ and $r = 0.01$. Sample restricted to firms that increase their R&D expenditures

	Radius 0.05			Radius 0.01		
	ATT	SE	Obs	ATT	SE	Obs
Log(Patents + 1)						
t	0.511***	0.145	419	0.577**	0.233	413
$t+1$	0.390*	0.218	419	0.680**	0.309	413
$t+2$	0.290	0.241	419	0.495	0.358	413
Log(Citations + 1)						
t	0.508*	0.260	410	0.522	0.415	400
$t+1$	0.465*	0.270	406	0.545	0.421	396
$t+2$	0.166	0.275	402	0.120	0.448	392
Citations/Patents						
t	−0.097	0.560	366	−0.401	0.875	354
$t+1$	0.128	0.552	336	0.167	0.878	324
$t+2$	0.160	0.565	319	0.166	0.946	307
Technological diversity						
t	0.199**	0.099	419	0.155	0.168	413
$t+1$	0.044	0.108	419	0.045	0.172	413
$t+2$	0.051	0.100	419	0.097	0.154	413
Breadth of impact						
t	0.076	0.094	419	0.096	0.176	405
$t+1$	0.167*	0.087	419	0.142	0.150	405
$t+2$	0.052	0.099	419	0.097	0.148	405

Notes: Bootstrapped standard errors with 200 repetitions.
*Significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

6.2 Sensitivity to selection on unobservables

As discussed above, our results are robust to controlling for the expansion of R&D activities, which is one way to test selection on unobservables. Nevertheless, there may exist other unobservables that induce firms to engage in international R&D and improve innovation performance. The presence of such unobservables cannot be directly tested. However, we can test how large the impact of such unobservables would have to be in determining selection to invalidate our main results. Rosenbaum (2002) and DiPrete and Gangl (2004) discuss a method to identify the bounds for the ATT estimates in the presence of unobservables.

According to Rosenbaum (2002), two matched observations with the same observable characteristics should have an identical probability of receiving treatment, i.e., the odds ratio (Γ) should equal 1. For example, if $\Gamma = 2$, then matched firms with the same observable characteristics are actually two times more likely to receive treatment due to unobservables. At each hypothetical value of Γ, the P-values of Wilcoxon signed rank test can be calculated, and assuming additive treatment effects, the Hodges-Lehmann point estimates can also be counted. We then calculate how large Γ, i.e., the magnitude of unobserved heterogeneity, is needed to make the ATT estimates statistically insignificant at the 10% level. These critical levels of Γ are reported in Table 7 for estimates that were statistically significant in Tables 4 and 6. It should be noted that these present the worst-case scenarios assuming an unobservable that has a strong effect on both treatment assignment and outcome. If an unobservable has a strong effect on the assignment but only a weak effect on the outcome, the ATT would remain statistically significant even at the reported levels of Γ. The critical values do not tell us whether unobservables exist; they only measure how sensitive our estimates are to potential unobservables.

Table 7 shows that the robustness to unobservables varies across outcome variables. With respect to the number of patents, the critical Γs are high, which indicates that the results are robust with respect to unobservable heterogeneity. With respect to citations, technological diversity, and breadth of impact outcomes, the critical values in Wilcoxon test

Table 7. Rosenbaum bounds. Critical Γ with cutoff $P = 0.10$

	Baseline model			Firms that increase R&D investments		
	Wilcoxon sign rank	Hodges-Lehmann	Obs	Wilcoxon sign rank	Hodges-Lehmann	Obs
Log(Patents + 1)						
t	5.18	4.57	1480	3.00	2.54	419
$t+1$	3.19	2.87	1480	1.53	1.34	419
$t+2$	3.52	3.16	1480	–	–	419
Log(Citations + 1)						
t	2.08	1.90	1434	2.18	1.88	410
$t+1$	1.61	1.48	1406	2.12	1.83	406
$t+2$	1.49	1.37	1397	–	–	402
Technological diversity						
t	1.50	1.37	1480	1.56	1.36	419
$t+1$	–	–		–	–	
$t+2$	–	–		–	–	
Breadth of impact						
t	–	–		–	–	
$t+1$	1.81	1.66	1481	1.41	1.21	419
$t+2$	–	–		–	–	

range from 1.49 to 2.08 in the baseline model, which are also relatively good values. This means that the results remain statistically significant even if an unobservable covariate causes the odds ratio of treatment assignment to differ by 50% between treated and control firms. However, in the smaller sample of firms that increase R&D investment, the Γs are lower for several outcome variables. Overall, the innovation quantity outcomes appear less sensitive to unobservable heterogeneity than innovation diversity, which again supports the main finding that the start of international R&D appears to have a stronger effect on innovative output and a weaker effect on innovation diversity.

6.3 Alternative specifications

In our baseline estimation, the treatment effect of R&D internationalization is estimated using radius matching. Next, we assess whether these results are sensitive to the choice of matching estimator. The choice of matching algorithm can be important, and there is typically a trade-off between bias and variance (Caliendo and Kopeinig, 2008). First, we estimate the baseline model using different radii: 0.05 and 0.005. Selecting a larger versus a smaller radius involves a similar trade-off between bias and variance as in the choice of matching estimators. Next, kernel matching and one-to-one nearest neighbor matching are considered as alternative matching estimators. If all matching approaches produce similar results, we can be fairly satisfied with our estimation approach.

Matching is conducted within years using the propensity scores estimated in Section 5. In the kernel matching model, we use an Epanechnikov kernel with a bandwidth of 0.06. The results of these alternative estimators are presented in the Appendix.[9] Summarizing these findings, we note that changing the matching estimator or radius has little effect on the estimated treatment effects. The most notable difference is that the results with respect to technological diversity and breadth of impact appear stronger when either kernel matching or a larger radius is used.

Next, we test different specifications of our innovation performance variables. In the baseline model, the logarithm of the number of patents or citations plus one is used due to frequent zero observations in the data. However, this choice may have an impact on the results. Next, we define the patent and citation variables as simply the

9 Huber *et al.* (2013) suggest that propensity score matching could be improved by using Mahalanobis matching and matching also on covariates that are good predictors of outcome. In our context, such covariates are, e.g., past innovation performance or increase in firm's R&D expenditure. The treatment effects were estimated using this approach; however, this did not materially change the results.

Table 8. The results of DID estimation with alternative innovation performance measures. Radius matching, $r = 0.01$

	ATT	SE	Obs
Log(Patents)			
t	0.556***	0.101	1211
$t+1$	0.476***	0.121	1190
$t+2$	0.508***	0.136	1151
Log(Citations)			
t	0.373	0.335	401
$t+1$	0.839**	0.363	341
$t+2$	−0.008	0.380	275
Log(Corrected Citations)			
t	0.716***	0.140	1431
$t+1$	0.699***	0.169	1428
$t+2$	0.787***	0.181	1422
Corrected Citations/Patents			
t	−0.070	0.394	1212
$t+1$	0.143	0.406	1191
$t+2$	0.194	0.455	1153

Notes: Bootstrapped standard errors with 200 repetitions.
*Significant at 10% level, ** significant at 5% level, and *** significant at 1% level.

logarithm of number of patents and the logarithm of citations received. This specification leads to a lower number of observations, especially for citations. The results are presented in Table 8. The results with respect to patent outcome are hardly affected by the specification change, but for the citation variable, the standard errors are now clearly larger. The estimates also vary considerably; however, the point estimates for the first 2 years are similar to our baseline results. The estimate for 2 years after the start of internationalization is close to zero. The number of observations is nevertheless quite low, which makes inference somewhat problematic.

Another computation of the citation counts is also tested. Patents may receive citations over a long time period, which we only partially observe. The truncation of the citation period may affect patents in different technological fields differently. In some fields, knowledge diffusion may be slower and citations may take longer to arrive than in others. To test whether truncation affects our results, we correct for the truncation using the method suggested by Hall *et al.* (2000) and applied in Hall *et al.* (2007). We allow for different knowledge diffusion processes in eight technological fields[10] and calculate the expected citation lag distribution for each field. Then, we estimate the expected number of citations in 10 years, given the citations observed thus far. The results for the truncation-corrected citation figures are reported in Table 8. Correcting for the truncated citation period leads to higher treatment effect estimates. The results now indicate that beginning international R&D activities increases the number of citations by over 70%. Regardless, after the truncation correction, the average quality of innovations, i.e., number of citations per patent, does not exhibit significant changes. Thus, the main implications remain unchanged although the truncated citation period may produce a slight downward bias in the ATTs.

6.4 Limitations of the study

In this study, we have not attempted to explore whether the gains from R&D internationalization depend on firm characteristics. However, previous studies suggests that the benefits and costs of internationally distributed R&D activities may depend on a firm's capability to integrate new knowledge and other firm characteristics (Singh, 2008; Lahiri, 2010). We also realize that the motivations of firms to engage in international R&D are likely to vary, and these differences may affect how and which firms benefit from international operations (Arvanitis and Hollenstein, 2011). Thus, there can be treatment effect heterogeneity that would be worth studying in further research.

10 The one-digit IPC classes are following: human necessities, performing operations and transporting, chemistry and metallurgy, textiles and paper, fixed constructions, mechanical engineering, physics, and electricity.

Furthermore, innovation performance is only analyzed at the firm level, and possible differences between overseas R&D units are not considered. This question provides interesting and relevant avenues for further research as well.

The key data used in this study are patent data, which only capture new-to-market inventions. Therefore, we are unable to measure the part of R&D internationalization that is conducted to absorb existing knowledge and create imitative innovations that are only new to an individual firm. This type of knowledge sourcing is undoubtedly important to the innovation strategies of many firms; however, it must be addressed with different types of data.

7. Conclusions

Despite the importance of international knowledge sourcing to the innovation strategies of firms, studies on the innovation performance effects of R&D internationalization have been scarce and provided mixed results. They also raise the question of whether the observed relationship between international R&D and innovation performance is due to self-selection into international R&D or to improvements in firms' knowledge sourcing. This question is the main interest of the present study. To provide an answer, this study has analyzed the internationalization of corporate R&D activities among European firms by applying matching and DID methods. Through this analysis, this study has provided novel evidence regarding the self-selection and causal effect of R&D internationalization on the innovation performance of firms.

The results indicate that more-innovative firms self-select to internationalize their R&D activities, which, in our sample, explains 35–100% of the observed quantitative differences in innovation performance between international and domestic firms. After we control for self-selection using matching methods, we observe that firms that begin to internationalize their R&D activities subsequently file approximately 50% more patent applications and receive more citations. At the median, sample firms file only a few patents per year, and thus, the implied increase is approximately two patents per year. R&D internationalization is also found to have a somewhat weaker positive effect on the technological diversity of firms and the breadth of technological impact. This implies that international R&D activities allow firms to diversify their innovation activities to new fields of technology. In contrast to some previous studies, we do not find a statistically significant effect on the average quality of innovations, and in that case, the self-selection process explains the higher average quality of innovations in international firms. The robustness of these results to selection on unobservables is assessed, and the results with respect to quantity of innovations appear strong, whereas the results with respect to technological diversity and breath of technological impact are somewhat more sensitive to possible unobservables. The sensitivity of the results to different matching methods and outcome variable specifications is also tested.

Our findings indicate that empirical research must account for the self-selection of firms to reliably assess the causal innovation performance effects of R&D internationalization. The results also have clear implications for organizing the R&D activities of firms. The innovation performance of firms significantly benefits from international R&D activities in terms of quantity and technological diversity. However, these benefits are not necessarily as large as initially envisaged due to the self-selection process. Moreover, our findings suggest that firms cannot expect improvements in innovation quality during the first years of R&D internationalization; however, firms with long histories of international R&D activities have significantly higher innovation quality, which may imply qualitative improvements later on. Unfortunately, the time frame of the present study does not allow us to analyze potential long run effects.

Moreover, our results relate to the body of literature on drivers of R&D internationalization. The findings indicate that international R&D activities help firms to increase and diversify their innovative output; thus, the results support the knowledge-seeking view of R&D internationalization. The results also show that firms with more innovations and higher innovation quality in the past are more likely to engage in international R&D activity, which is consistent with the capabilities-exploiting view of R&D internationalization. Therefore, both of these views offer important insights into the relationship between the internationalization of R&D and innovation performance of European firms.

This study represents only one step in understanding the causal effects of R&D internationalization. Firm characteristics and motives for engaging in R&D internationalization differ and may affect how the gains from such an activity materialize and are divided among firms. Interesting avenues for further research include the effects on firm productivity and imitative innovation, which cannot be studied using patent data alone.

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APPENDIX

Table A1. Balancing test. Covariate means after matching

	1.			2.			3.			4.		
Variable	Treated	Control	*P*-value	Treated	Control	*P*-value	Treated	Control	*P*-value	Treated	Control	*P*-value
log(Patents + 1)	1.742	1.802	0.615	1.732	1.851	0.785	1.774	1.828	0.642	1.747	1.772	0.836
log(Patent stock)	3.129	3.179	0.700	3.149	3.260	0.313	3.175	3.242	0.591	3.137	3.137	0.999
Technological diversity	0.543	0.524	0.700	0.537	0.551	0.764	0.554	0.547	0.879	0.552	0.550	0.958
log(Citations + 1)				1.300	1.351	0.785						
Citations/patents							1.411	1.460	0.899			
Breadth of impact										0.412	0.409	0.941
log(Turnover)	0.082	0.070	0.707	0.081	0.079	0.952	0.084	0.082	0.963	0.082	0.067	0.616
Growth of turnover	0.168	0.179	0.843	0.179	0.163	0.752	0.170	0.175	0.922	0.167	0.176	0.851
Growth missing	6.285	6.305	0.937	6.315	6.363	0.836	6.333	6.268	0.778	6.345	6.328	0.946
R&D intensity	0.030	0.030	0.957	0.030	0.033	0.804	0.030	0.032	0.877	0.031	0.028	0.793
R&D not reported	0.364	0.380	0.810	0.348	0.336	0.850	0.348	0.373	0.698	0.352	0.378	0.686
log(Firm age)	3.815	3.813	0.987	3.857	3.787	0.628	3.849	3.815	0.815	3.820	3.821	0.992

Notes: Covariate balance after the four separate propensity score estimations. *P*-values of tests for equality of means are reported.

Table A2. The results of DID estimation using alternative radii, kernel, and nearest neighbor matching

	Radius 0.05[a]			Radius 0.005[a]			Kernel matching[a]			Nearest neighbor matching[b]		
Log(Patents + 1)	ATT	SE	Obs	ATT	SE	Obs	ATT	SE	Obs	ATT	SE	Obs
t	0.620***	0.071	1492	0.578***	0.092	1469	0.616***	0.077	1492	0.628***	0.081	1492
$t+1$	0.496***	0.093	1492	0.567***	0.125	1469	0.499***	0.092	1492	0.537***	0.088	1492
$t+2$	0.540***	0.095	1492	0.605***	0.136	1469	0.541***	0.093	1492	0.710***	0.093	1492
Log(Citations + 1)												
t	0.486***	0.118	1442	0.588***	0.149	1427	0.494***	0.112	1443	0.422***	0.122	1443
$t+1$	0.397***	0.123	1414	0.527***	0.170	1399	0.397***	0.116	1415	0.456***	0.129	1415
$t+2$	0.316***	0.120	1405	0.421**	0.172	1390	0.322**	0.125	1406	0.385***	0.122	1406
Citations/Patents												
t	−0.076	0.266	1224	0.108	0.374	1204	−0.128	0.255	1224	0.530*	0.308	1224
$t+1$	−0.120	0.251	1067	0.072	0.325	1048	−0.110	0.231	1068	0.244	0.229	1068
$t+2$	−0.013	0.304	1028	0.413	0.381	1008	−0.008	0.259	1029	0.401	0.250	1029
Technological diversity												
t	0.152***	0.041	1492	0.180***	0.060	1469	0.148***	0.039	1492	0.124***	0.045	1492
$t+1$	0.045	0.041	1492	0.086	0.063	1469	0.043	0.038	1492	−0.001	0.045	1492
$t+2$	0.085**	0.040	1492	0.091	0.062	1469	0.083**	0.038	1492	0.031	0.046	1492
Breadth of impact												
t	0.088*	0.052	1490	0.111*	0.062	1476	0.088**	0.042	1490	0.078*	0.045	1490
$t+1$	0.161***	0.048	1490	0.163***	0.058	1476	0.156***	0.039	1490	0.175***	0.044	1490
$t+2$	0.038	0.047	1490	0.067	0.055	1476	0.036	0.040	1490	0.063	0.043	1490

Notes: [a]Bootstrapped standard errors with 200 repetitions.
[b]Subsampling standard errors with 200 draws.
*Significant at 10% level, **significant at 5% level, and ***significant at 1% level.

INTERNATIONALIZATION OF R&D AND THE RETURNS TO R&D ACTIVITIES IN EUROPEAN FIRMS

Jaana Rahko[1]

Abstract

Previous studies indicate that international R&D activities can improve the innovation performance of firms. However, evidence is scarcer on the contribution of international R&D activities to firm productivity and which factors drive the possible effects. This study empirically examines whether European firms with international R&D activities obtain higher returns to their R&D investments than firms with domestic R&D. Estimating an R&D augmented production function shows that the R&D elasticity of output is significantly higher in firms with international R&D activities. Particularly, the increase is associated only with R&D investments in technologically stronger host countries, which implies that international knowledge sourcing is a central mechanism behind the gains. Low-tech firms are shown to gain more from international R&D than high-tech firms, while the host country's level of technology is more important for high-tech firms.

JEL codes: O32, D24, F23

Keywords: R&D internationalization, R&D returns, knowledge sourcing

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1 INTRODUCTION

International research and development (R&D) investments have grown in recent decades and now form a significant share of total R&D investments in many firms and countries (European Commission 2012). For example, German pharmaceutical firms now conduct over 60% of their R&D investments overseas, and the share of foreign R&D can be even higher in many smaller countries such as Sweden and Switzerland. The literature indicates that the overseas R&D activities are motivated by access to new markets and technological knowledge (Alcácer & Chung 2007; Kuemmerle 1999; von Zedtwitz & Gassmann 2002). In line with this evidence and prior theoretical literature, recent empirical studies show that geographically (Lahiri 2010; Singh 2008) and internationally distributed R&D activities can improve the innovation performance of firms (Chen, Huang & Lin 2012; Hsu, Lien & Chen 2014; Penner-Hahn & Shaver 2005). However, these innovation performance effects are not uniform but depend heavily on a number of firm characteristics. Moreover, these studies have not analyzed whether international R&D activities increase the productivity or R&D returns of firms.

A few recent studies indicate that multinational firms can obtain higher returns to their R&D investments than domestic firms (Añón Higón & Manjón Antolín 2012; Cincera & Ravet 2014) and foreign R&D investments can complement domestic R&D in industries that are lagging behind the world technology frontier (Belderbos, Lokshin & Sadowski 2014). The present paper extends this literature and analyzes how international R&D activities affect the returns to R&D in European firms. Especially, this paper analyzes the distribution R&D host countries and how the relative technological strengths of foreign R&D locations and firm's home country affect the gains from international R&D, which has not been covered in the extant literature. We argue that more advanced knowledge sourcing opportunities in the R&D host countries are a central determinant of the gains from international R&D and test this hypothesis in our empirical analysis.

We analyze the contribution of international R&D activities to firm productivity by estimating a Cobb-Douglas production function, which is augmented with R&D investments and estimated using ordinary least squares and System GMM (Generalized Method of Moments) estimation methods. Our interest is on whether the R&D returns — measured with R&D elasticity of output in our empirical approach — depend on the country distribution of firms' innovative activities. As in many previous studies, we rely on the address information of patent inventors to determine the locations of corporate R&D activities. To analyze how countries' relative technological strengths affect the relationship between overseas R&D and R&D returns, we classify countries as technologically stronger and weaker by comparing the number of patent applications at the industry- and country-level.

Our empirical results show that the R&D elasticity of output is significantly higher in firms with international R&D activities, which is also in line with prior studies. In firms that conduct 20% of their R&D abroad, the R&D elasticity of output is approximately 2 percentage points higher than in firms with domestic R&D. As a novel contribution to extant literature, we also show that international R&D activities improve the R&D returns only if these activities are located in countries that are technologically more advanced than firms' home country. In contrast, overseas R&D in technologically lagging countries does not significantly boost the returns to R&D.

The remainder of the paper is organized as follows. In the second section, we discuss the literature background and develop our research hypotheses. The third section presents our empirical framework. The fourth section discusses data and variable construction. The fifth section reports and discusses the results. Finally, the sixth section concludes the paper.

2 BACKGROUND AND RESEARCH HYPOTHESES

The growth of international R&D investments and its drivers are well documented in the academic literature. Prior studies indicate that R&D internationalization is driven by market-seeking objectives as well as knowledge-seeking motives that aim to improve the innovation performance of a firm (Kuemmerle 1999; von Zedtwitz & Gassmann 2002).

The importance of knowledge-seeking overseas R&D is particularly emphasized in more recent work (Alcácer & Chung 2007; Belderbos, Lokshin & Sadowski 2014; Todo & Shimizutani 2008). According to this view, firms establish overseas R&D units to obtain access to resources, expertise and technologies that are new to the firm or complement its existing technological capabilities. Because knowledge spillovers from other firms or universities are typically national or even local in scope, foreign firms need to establish overseas R&D facilities to access local technological knowledge (Griffith, Harrison & Van Reenen 2006; Harhoff, Mueller & Van Reenen 2014; Jaffe, Trajtenberg & Henderson 1993). International R&D can improve learning and technology sourcing from foreign competitors, customers, universities and other parties, and moreover, it provides better access to local informal knowledge networks (von Zedtwitz & Gassmann 2002). Furthermore, an improved access to a highly qualified work force is also a central motive for locating R&D activities abroad (Ambos & Ambos 2011; Thursby & Thursby 2006). At the same time, international R&D may enable a firm to reduce the costs of R&D by utilizing country-specific cost advantages and exploiting R&D subsidies or patent boxes, although these are not reported among the most important drivers of international R&D (Moncada-Paternò-Castello, Vivarelli & Voigt 2011; Thursby & Thursby 2006). In line with these arguments, empirical studies reveal that internationally or geographically distributed R&D activities increase the number of patent applications (Penner-Hahn and Shaver 2005) and patent citations for some firms (Lahiri 2010, Chen, Huang, and Lin 2012, Hsu, Lien, and Chen 2014, Singh 2008).

International R&D investments are also motivated by improved access to foreign markets (Le Bas & Sierra 2002; von Zedtwitz & Gassmann 2002). In this case, international R&D activities may be a by-product of exports and foreign direct investments (FDI). Local R&D activity may be needed to improve speed to market and adapt domestically developed products to the tastes and regulations of foreign markets. This view implies no clear improvement in innovation performance of firms. However, improved access to larger international markets may help the firm to better appropriate the returns to its innovations, thus improving the returns to R&D. Firms can spread the costs of research investments across several markets and thus better cover its investment costs, which also explains why multinational and exporting firms can obtain higher returns to their R&D investments (Añón Higón & Manjón Antolín 2012; Aw, Roberts & Xu 2011). Therefore, international R&D can increase the returns to firms' R&D investments by improving the productivity of innovation activities and the appropriation capacity of firms.

While the literature has often highlighted the benefits of international R&D, such activities are also associated with significant costs. First, establishing overseas R&D facilities involves entry costs, thus restraining many smaller or less productive firms from entering (Bernard & Jensen 2004; Rahko 2016). Second, an internationally dispersed R&D organization may hinder the firms from reaching economies of scale and scope in R&D activities and it can create additional coordination and communication costs within the organization (Argyres & Silverman 2004). Third, R&D activities and knowledge sourcing benefit from strong embeddedness in the local innovation system, which foreign firms may find costly or time consuming to establish (Añón Higón & Manjón Antolín 2012; Belderbos, Leten & Suzuki 2013; Meyer, Mudambi & Narula 2011). Finally, firms may wish to avoid foreign R&D, because the knowledge outflows can increase with international R&D (Sanna-Randaccio & Veugelers 2007; Schmiele 2013). However, the prior literature suggests that the benefits in terms of R&D returns or productivity growth outweigh the costs, although not for all firms or industries (Belderbos, Lokshin & Sadowski 2014; Fors 1997; Harhoff & Thoma 2010; Todo & Shimizutani 2008). Therefore, we propose a following hypothesis to be tested in our empirical setting:

> H1: Firms with international R&D activities obtain higher returns to their R&D investments than firms with domestic R&D activities.

However, firm characteristics such as capability to integrate knowledge (Lahiri 2010; Singh 2008), previous innovation experience and absorptive capacity (Penner-Hahn & Shaver 2005) and previous international experience (Hsu, Lien & Chen 2014) affect how a firm can utilize its overseas R&D activities. Such interdependencies may also explain why prior studies report partly mixed results with respect to international R&D and firm productivity.

In addition to firm characteristics, firms differ with respect to their technological operating environment in their home and R&D host countries. Sourcing more advanced technological knowledge is an important factor underlying international R&D investment decisions, and local knowledge sourcing opportunities are recognized to be important in determining the location and extent of international knowledge sourcing (Alcácer & Chung 2007; Chung & Alcácer 2002; Shimizutani & Todo 2008; Song & Shin 2008). Multinational firms are more likely to source knowledge in countries that have a high level of R&D investments and patents or that are specialized in the firm's industry and technological field (Song, Asakawa & Chu 2011; Song & Shin 2008). Moreover, locations with academic innovative activity attract R&D investments, especially from technologically advanced firms (Alcácer & Chung 2007). Technological capabilities also affect which type of R&D activity, innovative or adaptive, is attracted to the location (Frost 2001). Thus, the host country level of technology appears to be an important determinant of the gains from international R&D.

While technologically less advanced countries are less desirable host countries for knowledge sourcing, these countries may provide access to growing markets and attract R&D investments with market-seeking motives (Kuemmerle 1999; Todo & Shimizutani 2008). Moreover, these countries may provide educated workforce and country-specific cost advantages that may compensate for their weaker knowledge sourcing environment, although labor arbitrage is typically not among the most important motives for international R&D (Lewin, Massini & Peeters 2009; Moncada-Paternò-Castello, Vivarelli & Voigt 2011; Thursby & Thursby 2006).

However, the host country characteristics should not be analyzed in isolation, because the knowledge sourcing characteristics of the home country matter as well. A firm from a technologically advanced country has abundant knowledge sourcing opportunities available in the domestic operational environment and only few host destinations may provide a better knowledge sourcing opportunities. If the home country is more advanced than the R&D host country in firm's industry, the potential for within industry learning is naturally limited. However, even in this case the firm may wish to engage in knowledge seeking international R&D to diversify its knowledge base (Chung & Alcácer 2002; Phene, Fladmoe-Lindquist & Marsh 2006; Song & Shin 2008). In contrast, when a firm's home country and industry are technologically weaker than the R&D host country, the firm has much to learn from foreign competitors both in terms of catching up and knowledge diversification and thus the firm can gain more through international R&D (Awate, Larsen & Mudambi 2015; Belderbos, Lokshin & Sadowski 2014).

Home country and industry level of technology matter also for the disadvantages of international R&D. Firms from more advanced countries may have more to lose through international R&D and associated knowledge leakages (Sanna-Randaccio & Veugelers 2007; Schmiele 2013). Especially in technologically less advanced countries the knowledge outflows from multinational firms can exceed the knowledge inflows (Singh 2007). Thus, technologically advanced firms may wish to distance themselves from their foreign competitors by not engaging in international R&D in technologically weaker countries (Alcácer & Chung 2007). Alternatively, these firms can employ intellectual property protection tools or adopt internal mechanisms to protect themselves from knowledge outflows and still reap the benefits of the international operations (de Faria & Sofka 2010; Zhao 2006). However, these tools often limit external knowledge sourcing activity or increase the costs of R&D and thus limit the lucrativeness of overseas R&D for technologically advanced firms (de Faria & Sofka 2010; Liebeskind 1997).

Finally, firms need absorptive capacity, i.e. ability to identify and acquire external knowledge, to be able to benefit from international knowledge sourcing (Cohen & Levinthal 1990; Zahra & George 2002). A strong domestic technology base can give firms an advantage in terms of absorptive capacity, although firm-level absorptive capacity through, e.g., prior R&D investments and organizational routines appears to be more important (Penner-Hahn & Shaver 2005; Salomon & Jin 2008; 2010).

To sum up, the gains of overseas R&D activities are argued to depend on the industry level of technology both in the R&D host and home country. Because of more limited knowledge sourcing opportunities and increased risks of knowledge outflows, firms gain less in terms of knowledge sourcing when the R&D host countries are technologically weaker than their home countries. These investments may still improve the R&D returns by increasing firms' appropriation capacity, knowledge diversification and in some cases bringing cost advantages. In contrast, when overseas R&D is located in technologically more advanced countries, the returns to R&D are expected to improve due to improved knowledge sourcing, knowledge diversification and appropriation capacity. Because knowledge sourcing considerations are highlighted as central drivers of international R&D investments

(Moncada-Paternò-Castello, Vivarelli & Voigt 2011), we end up with our second hypothesis to be tested:

> H2: The improvement in R&D returns is larger when the R&D host country is technologically stronger in firm's industry than the firm's home country.

3 EMPIRICAL STRATEGY

To assess how international R&D investments affect the returns to R&D, we use a Cobb-Douglas production function extended to include the R&D stock. This approach is common in empirical studies that examine the returns to R&D investments (Hall, Mairesse & Mohnen 2010). The approach captures that R&D returns can increase due to both cost reductions in R&D activities and price increases resulting from improved product quality, new product developments or increased demand. The Cobb-Douglas production function is written as follows:

$$Y_{it} = A_{it} K_{it}^{\beta_K} L_{it}^{\beta_L} C_{it}^{\beta_C} \tag{1}$$

In the above equation, output Y_{it} is real value added, K_{it} is physical capital and L_{it} is the number of employees in firm i at time t. C_{it} denotes the knowledge capital stock, which is constructed using R&D expenditure information. β_C reflects the elasticity of output with respect to the R&D stock, i.e. the returns to R&D. A_{it} is a productivity shifter that captures other factors affecting the value added.

Our key variable of interest is the share of international R&D activities, denoted $\text{int}\, R\,\&\,D_{it}$. We are interested in whether the firm's R&D productivity depends on the country distribution of firm's innovative activity. If foreign R&D helps firms to produce better products that sell with higher price, brings cost savings or leads to higher prices through increased international demand, our approach will reveal it as higher R&D returns. We assume that the share of international R&D activities can have both a direct effect on the productivity shifter and an indirect effect by affecting the returns to R&D and thus our approach resembles Griffith, Harrison & Van Reenen (2006). The elasticity of value added with respect to R&D stock is assumed to have the following linear form:

$$\beta_C = \gamma_0 + \gamma_1 \,\text{int}\, R\,\&\,D_{it} \tag{2}$$

We also allow international R&D to have an effect on A_{it}. Empirical evidence suggests that multinational firms are more productive than domestic firms (Tomiura 2007; Yeaple 2009). Therefore, we also allow A_{it} to be affected by a firm's non-R&D FDI and include a variable that measures the number of countries in which the firm has subsidiaries.

$$\ln A_{it} = a_i + \theta_1 \operatorname{int} R\&D_{it} + \delta' \mathrm{z}_{it} + \varepsilon_{it} \tag{3}$$

In equation (3), a_i is a firm-specific productivity term and z_{it} are other observable variables affecting productivity: the number of countries in which the firm is active, time, country and country-time interactions. In the ordinary least squares (OLS) estimation, we also use industry dummies based on NACE codes at the 2-digit level. ε_{it} is an error term. Next, we take the logarithm of the production function and denote logarithmic variables with lower case letters. Together with the above assumptions, this leads us to the following equation to be estimated[2]:

$$\begin{aligned} y_{it} = {} & \beta_K k_{it} + \beta_L l_{it} + \gamma_0 c_{it} + \theta_1 \operatorname{int} R\&D_{it} \\ & + \gamma_1 \left(\operatorname{int} R\&D_{it} \times c_{it} \right) + a_i + \delta' \mathrm{z}_{it} + \varepsilon_{it} \end{aligned} \tag{4}$$

To estimate this equation, we must address several problems, such as unobserved firm-specific heterogeneity and simultaneity, which may bias the estimation results. Unobservable heterogeneity is likely to occur in this setting because we do not observe all characteristics of the firms. Moreover, simultaneity bias arises if unobserved firm productivity and a firm's input choices are correlated. Nevertheless, our first step is to estimate the equation by pooled OLS. Then, we apply the System GMM approach, which uses lagged values of input variables, as well as lagged values of the dependent variable, as instruments to address the above-mentioned problems (Blundell & Bond 2000). The System GMM estimates the production function in both levels and differences. The levels equation is instrumented with lagged differences, and the differenced equation is instrumented with lagged levels[3]. Endogenous variables can be instrumented with variables lagged two periods or more and predetermined variables with variables lagged once or more. This entails the assumption that the two-period lagged differences in the levels equation and the two-period lagged levels in the differenced equation are uncorrelated with the error term. The validity of this assumption and the instruments is tested using the Hansen test. In the levels equation, the instruments are also assumed to be exogenous to

[2] We also considered normalizing the production function with respect to labor, i.e., the output and input variables were denoted in per-employee terms. This did not alter our main findings. A translog production function also produced similar results.

[3] In the differences equation, we use orthogonal deviations proposed by Arellano and Bover (1995) rather than first differencing, because the orthogonal deviations can preserve sample size in panels with gaps.

firm fixed effects and other constant firm-level variables. Time and country dummies and country-time interactions are used to control for country-specific trends.

Difference GMM could be used instead of System GMM (Arellano & Bond 1991). Difference GMM estimates only the differenced equation using lagged levels as instruments. However, the advantage of System GMM is that it allows us to estimate the coefficients of time-invariant variables provided that we are willing to assume that they are exogenous. Moreover, the Difference GMM suffers from the weak instruments problem (Blundell & Bond 1998). Other popular approaches to solving the simultaneity problem include, e.g., methods suggested by Olley & Pakes (1996) and Ackerberg, Caves & Frazer (2006). However, for the purposes of this paper, the advantage of System GMM estimation over such alternative methods is that System GMM allows us to include interaction terms in a simple and flexible manner. Moreover, the related previous studies have most frequently applied System GMM and thus following the same approach allows an easy comparison of the R&D elasticity estimates.

4 DATA

4.1 Data sources

This study combines firm-level financial data from Bureau van Dijk's Orbis database and patent data from the EPO PATSTAT patent database[4]. PATSTAT covers more than 90 million patent documents from over 180 patent offices worldwide. From Orbis, we include manufacturing firms that have consolidated balance sheet data available and report R&D expenditures at least once during time period 2004-2011. We also require information on all variables needed to estimate the production function. Our sample includes firms from Germany, the United Kingdom, France and Italy. These four countries are similar in size, and therefore, the motives for of R&D internationalization are expected to be similar in these countries[5]. Analyzing the internationalization of R&D activities in these European countries appears worthwhile because European firms have exhibited a higher level of R&D internationalization than, e.g., their American or Japanese competitors (European Commission 2012). Thus, we expect that the effects of R&D internationalization may be especially important for European firms.

Obtaining data on the geographic location of firms' R&D activities is not straightforward. Patent information is available for a long period and across nearly all countries. Therefore, inventor location information is employed in many previous studies to explore the effects of internationally or geographically distributed R&D activities (for example Griffith, Harrison & Van Reenen (2006), Singh (2008), and Laurens et al. (2015)). According to Bergek and Bruzelius (2010), the inventor information contains some mistakes, but it nevertheless provides a fairly reliable picture of the locations of R&D activities. Thus, we use this information to track the geographic locations of corporate R&D activities. Patent data have well known weaknesses as a measure of research output. However, in this paper, we do not use patents to measure the output of firm's R&D efforts, but we assume that a firm's patent applications are correlated with its R&D activities and that the country

[4] European Patent Office Worldwide Patent Statistical Database, October 2013.

[5] Firms in small European countries are more open to international trade and FDI, and the benefits of R&D internationalization may differ in these countries (European Commission, 2012). In our sample, the German firms have on average the lowest level of R&D internationalization.

distribution of inventors proxies the country distribution of a firm's R&D activities. The patent data only covers new-to-market inventions and we are not able to track R&D activities that do not result in patents.

To obtain as comprehensive a picture of a firm's R&D activities as possible, we count the worldwide priority patent filings of each firm. By using priority filings from every national patent office, we can cover more inventions than by using EPO (European Patent Office) or US patent counts (de Rassenfosse et al. 2013). Using priority filings is also important for avoiding bias arising from the fact that firms from different countries differ in their probability to rely on, e.g., EPO patents (de Rassenfosse et al. 2013). A problem with the priority filings is that the PATSTAT has missing inventor information for many national patent offices. However, missing inventor country information can be retrieved by following the steps suggested by de Rassenfosse et al. (2013), which recover the missing information with 97% accuracy. A further problem is that there may be gaps in the patent data at some smaller national patent offices. However, if a firm later files the same patent at another patent office, these patents are still included in the sample. Moreover, international R&D activities are primarily concentrated in developed countries, which are typically well represented in PATSTAT database.

The patents are matched to firms based on applicant names. The OECD HAN database, which corrects names from punctuation, accents, abbreviations and legal information, is used for name matching (the methodology is described in Thoma et al. (2010)). Additional manual checks are also conducted to correct variations in applicants' names. The patent data are aggregated at the corporate group level under the assumption that the parent firm (ownership over 50%) is the ultimate owner of its subsidiaries' patents. This aggregation is performed using firm ownership information obtained from the Orbis database and manually checking the year of merger or acquisition in cases when subsidiaries are observed to file patents.

4.2 Variables

To estimate the production function, we need data on a firm's turnover, capital stock, costs of goods sold, number of employees and R&D expenditure. Turnover and costs of goods sold are used to calculate value added, which is the dependent variable in our estimations. Capital stock is measured using tangible fixed assets by their book value. The R&D stock measure is constructed using R&D expenditures and the perpetual inventory method with a depreciation rate of 15%, as is typical in the literature (Hall, Mairesse, and Mohnen 2010). Again following the prior literature, we form the initial value of the R&D stock by using the R&D expenditure in the first year and scaling it up using the depreciation rate and assumed steady-state growth rate (5%).

The financial variables are deflated to year 2010 prices using country-level manufacturing producer price index, investment price index and intermediate goods price index obtained from OECD Statistics. Turnover is deflated with the manufacturing PPI, capital with investment PPI, and costs of goods sold and R&D expenditure with the intermediate goods price index. Using common price indices makes an implicit assumption that all firms face a perfectly competitive market environment. If some firms have more market power and obtain higher prices than others, this may bias the estimated production function coefficients. However, Mairesse and Jaumandreu (2005) argue that availability of firm-level output prices does little to change the estimated production function coefficients.

We use value added as the output variable in the production function estimation. This is constructed by subtracting deflated costs of goods sold from deflated firm turnover. Thus, value added is counted using double deflating, because otherwise changes in input prices would be incorrectly interpreted as changes in firm productivity (Eberhardt and Helmers 2010).

Our key variable of interest is the share of international R&D activities. We construct this measure for each firm and year by taking a firm's all priority patent applications within the previous 10 years and counting the share of inventors that are located outside firm's home country. Shorter time windows of 5 and 3 years were also tested, which confirmed our findings. However, a shorter time window leads to more imprecise measurement of R&D locations in firms that file only few patents and more gaps in the data because of firms that do not file patents every year. Therefore, the longer time window is preferred.

Some patents in our data are co-applied by several firms. Thus, the $\text{int}\,R\,\&\,D_{it}$ variable includes not only in-house R&D but also international R&D cooperation that results in a patent filing. We consider all inventors listed in the applications and the different number of inventors in patents is considered by weighting the data, such that each patent application has the same weight in the construction of the $\text{int}\,R\,\&\,D_{it}$ variable.

The gains from international R&D are expected to depend on the relative technological strengths of firm's home and R&D host countries. Because countries can be specialized in certain industries and technologies, we wish to measure technological capabilities at the industry-level. To measure the technological strength of each industry and country, we follow previous studies and use patent data (Song, Asakawa, and Chu 2011, Alcácer and Chung 2007, Song and Shin 2008, Furman, Porter, and Stern 2002). Because patent technology classifications (IPC codes) do not directly translate to industry classifications, we use a concordance table developed by Schmoch et al. (2003). The table links over 600 patent technology codes to corresponding manufacturing sectors[6]. Using this concordance, we count the number of priority patent applications in each industry and country. Patents are assigned to countries based on inventor addresses. We consider all priority patent applications[7] over the past 10 years and relate their number to the number of inhabitants in a country to obtain a measure of the technological strength of the country[8]. Next, we compare the technological strength of each R&D host country to the firm's home country. If an R&D host country has more patents per capita in firm's industry than the firm's home country, we classify the host country as technologically stronger in the firm's industry. If the country has fewer patents, it is considered technologically weaker. We then separately count the share of international R&D in technologically stronger and weaker countries.

Although patents are only one way to measure the technological capabilities of an industry, Schmoch et al. (2003) show that a country's specialization in patenting is generally correlated with specialization in industry value added and exporting. Thus, patents can also convey more general information on industry competitiveness. In the robustness section, we will consider other ways to measure the technological capabilities of countries.

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[6] All other manufacturing sectors are covered except for NACE 18: Printing and reproduction of recorded media.

[7] The propensity to patent and patentability requirements vary across countries, which could bias our measure based on priority filings. However, when triadic patent families were used instead of priority filings, the results did not change. Triadic patents are patents that are filed at the European Patent Office, the US and Japan.

[8] Patents per population type of measure is used e.g. by Furman, Porter, and Stern (2002). Some prior studies, e.g. Le Bas and Sierra. (2002), use an index of revealed technological advantage (RTA). However, RTA index better describes the technological specialization of countries rather overall technological strength.

Access to international markets may also affect firm productivity, as discussed above. Therefore, we need to control for firms' non-R&D FDI. For this purpose, we use information contained in Orbis on firms' subsidiaries and their locations. Because not only owning foreign subsidiaries but also the scale of international activities is likely to be related to firm productivity (Yeaple 2009), we construct a control variable to measure the scale of international activities. We count the number of countries in which a firm has subsidiaries and use the logarithm of this figure as a control for a firm's international activities[9]. The information on firm subsidiaries is only available in a single cross-section using the most recent information, and therefore, our control variable for a firm's non-R&D FDI is time invariant.

Table 1 presents the main descriptive statistics of our sample. Our final dataset is an unbalanced panel for the period 2004-2011. We remove outliers from the sample. First, we drop all observations with negative value added or capital. We also drop the 1st and 99th percentiles of the distribution of the ratio of value added per employee, value added per capital and value added per R&D stock, as well as in the growth of employment and value added. After cleaning the data, we are left with 546 firms and 2855 observations. This is an unbalanced sample, because there are gaps in some variables, mostly R&D investments or number of employees. Some firms also start patenting during the sample period and thus enter the sample. Our sample primarily consists of relatively large firms with a median turnover of 332 million euros because many smaller firms do not report R&D or have missing data for other items needed to calculate the production function. Moreover, the required patent data further restricts our sample to larger firms. Therefore, our results reflect the situation in large firms and may not apply to smaller firms.

[9] Ideally, we would like to measure firm sales or employment in each country, but unfortunately these figures are missing for many subsidiaries.

Table 1. Descriptive statistics

	Mean	SD	Median	Min	Max	Obs
Turnover	4453.149	15593.478	332.319	0.069	275554.200	2855
Value added	1690.321	4715.951	145.728	0.040	48671.050	2855
Capital	1209.181	4918.017	62.594	0.002	106743.300	2855
Employees	16188.519	43734.227	1752.000	4.000	472500	2855
R&D stock	910.812	3464.186	49.865	0.028	33014.500	2855
International R&D intensity	0.206	0.267	0.091	0	1	2855
International R&D in strong host countries	0.121	0.226	0.001	0	1	2842
International R&D in weak host countries	0.086	0.162	0.013	0	1	2842
Multinational firm	0.914	0.280	1	0	1	2855
Subsidiary countries	17.935	20.672	10	0	114	2855

Notes. 546 firms in 2004-2011. Monetary values are in millions in 2010 prices.

Our sample mostly consists of multinational firms. Table 1 shows that 91% of the firms own at least one foreign subsidiary. Most firms also engage in international R&D activities, with an average international R&D intensity, that is, the share of inventors located overseas, of 20.6%. However, the median of the share of international R&D is 9.1%. These shares have also remained roughly similar throughout the observation period. Thus, even in multinational firms, R&D activities remain mostly concentrated in the home country[10]. According to Table 1 European firms locate R&D activities both in countries that are technologically stronger and in countries that lag behind. This indicates that knowledge-seeking as well as market-seeking and other motives may motivate international R&D investments. However, technologically stronger countries appear to attract more R&D investments than technologically weaker countries.

Many firms enter or exit the sample during observation period, primarily because they start or stop reporting their R&D expenditure information. These changes are likely to be endogenous and may therefore cause selection bias. However, previous studies do not report large differences in the rate of return on R&D between firms that report and those that do not report R&D (Hall, Mairesse, and Mohnen 2010). Thus, we do not expect the selection to significantly impact the R&D elasticity estimates, which are the primary interest of this study.

[10] The overseas R&D activities in our sample are mainly confined to European countries and the US. The distribution of host countries and its trends over time are analyzed in more detail e.g. in Laurens et al. (2015).

5 RESULTS

5.1 Main results

We proceed to estimate the augmented Cobb-Douglas production function. We first use pooled OLS estimation and then apply System GMM estimation. Table 2 presents the OLS estimates. Standard errors clustered at the firm level are presented in parentheses. First, we estimate the production function and include only labor, capital and R&D stock (column 1). The coefficients of labor and capital, 0.647 and 0.306, respectively, are close to the values we can expect based on typical income shares. The output elasticity of R&D in our OLS estimation is 0.073, which is in line with elasticities reported in previous studies (Hall, Mairesse & Mohnen 2010)[11]. In fact, the estimates indicate constant returns to scale, as the coefficients sum close to unity.

Next, we include the share of international R&D and also control for a firm's non-R&D FDI. These results are presented in column 2. The number of subsidiary countries has a positive coefficient, 0.285, which implies that a higher level of international activities is associated with higher productivity. However, international R&D does not appear to have an additional effect on productivity. In column 3, we include the interaction term of international R&D and the R&D stock in the regression. When the interaction term is included, the coefficient of international R&D becomes negative suggesting that there are costs associated with overseas R&D activities. However, the coefficient of the interaction term is 0.104 and statistically significant, suggesting that the R&D elasticity of output is significantly higher in firms that have international R&D activities. This finding supports our first hypothesis. The average share of international R&D is 20.6% in our sample, and thus our results imply that in these firms the R&D elasticity of output is approximately 2 percentage points higher than in firms with no international R&D. This is a

[11] The production function is estimated using present R&D stock. This can be problematic because the results of R&D activity may reach the market only after a lag. However, we use an R&D stock measure that includes past R&D investments as well as current investments. Moreover, using lagged R&D stock in the estimation did not affect the main results but cost in sample size; thus, the present R&D stock is used in the estimations.

substantial increase in the productivity of R&D investments because, as we can see, the R&D elasticity estimates are approximately 5-7%[12].

Table 2. OLS results

Dependent variable ln(Value added)	1.	2.	3.	4.
ln(L)	0.647***	0.520***	0.509***	0.509***
	(0.048)	(0.050)	(0.050)	(0.050)
ln(K)	0.306***	0.317***	0.322***	0.324***
	(0.035)	(0.033)	(0.033)	(0.033)
ln(C)	0.073***	0.062***	0.046*	0.047*
	(0.024)	(0.023)	(0.024)	(0.024)
IntR&D		-0.082	-1.216**	
		(0.092)	(0.500)	
IntR&D*ln(C)			0.104**	
			(0.044)	
IntR&D, strong host				-1.801***
				(0.668)
IntR&D, strong host*ln(C)				0.149***
				(0.058)
IntR&D, weak host				-0.137
				(0.794)
IntR&D, weak host*ln(C)				0.020
				(0.071)
ln(Subsidiary countries)		0.285***	0.285***	0.287***
		(0.044)	(0.044)	(0.044)
Constant	2.944***	3.198***	3.389***	3.339***
	(0.171)	(0.163)	(0.178)	(0.179)
Adj. R-squared	0.940	0.945	0.945	0.945
Obs	2855	2855	2855	2842

Notes. * p<0.10, ** p<0.05, *** p<0.01. All regressions include country, industry and year dummies as well as country-year interactions. Firm-clustered standard errors are presented in parenthesis.

[12] Coordination, communication and other costs may increase with the degree of R&D internationalization implying an inverted U-shape relationship between internationalization and firm performance. However, we do not find evidence of that. Therefore, only the linear interaction of R&D internationalization and R&D stock is included.

Next, we divide the overseas R&D investments based on the relative technological strength of R&D host countries (column 4). The results indicate that when firms locate their R&D in countries that are technologically more advanced than the home country in the firm's industry, the gains from overseas R&D are higher than average. The coefficient of the interaction term is 0.149. At average international R&D intensity, this implies a 3% higher R&D elasticity. In contrast, if the R&D investments are located in relatively weaker countries, the change in R&D returns is not statistically significant, although the coefficient estimate is positive. These findings support our second hypothesis.

Now, we proceed to estimate the production function using the System GMM approach[13]. System GMM results are reported in Table 3. We assume that the time-variant firm-level variables are endogenous. The number of countries in which the firm is active is assumed to be an exogenous variable[14]. Diagnostic tests are presented at the bottom of Table 3. The Arellano-Bond serial correlation tests find no evidence of second-order serial correlation in the differenced residuals. Thus, we can use 2-3 period lags as instruments. Further lags are excluded to avoid instrument proliferation. The Hansen test is a test of instrument validity, but a rejection may also indicate that important input variables are omitted. The p-values of these tests are reported at the bottom of Table 3 and suggest that the instruments are valid. The robustness of results and instrument validity are discussed in section 5.3.

The System GMM results in Table 3 show that the coefficient of R&D stock is clearly higher than in the OLS results, but the standard errors are also higher, and thus the coefficient is not statistically significant. The coefficient of capital stock is now lower, while the coefficient of labor is higher. The results of the model without interactions (column 2) are similar to the OLS estimates.

When the interaction between international R&D and R&D stock is included (column 3), the results are again close to the OLS estimates. Firms with international R&D activities obtain higher returns to their R&D investments (0.105), while the

[13] We also tested the Arellano-Bond Difference GMM estimation. However, it performed poorly, and the moment conditions for the levels equation were not rejected in the Difference-in-Hansen tests. The Difference-in-Hansen test p-values for the levels equation instruments were in the range of 0.199-0.497. Therefore, System GMM is the preferred estimation method.

[14] This is clearly choice variable for the firm and could be correlated with unobserved productivity shocks. Unfortunately, the firm subsidiary information is not available as a time series. Absent other proper instruments, this does not allow us to treat it as an endogenous variable.

coefficient of international R&D is negative (-1.269). In column 4, we divide the international R&D investments based on the relative technological strength of R&D host countries. The System GMM results again confirm the findings of the OLS estimates. Only when the R&D host country is technologically more advanced in the firm's industry, the R&D elasticity of output is statistically significantly higher.

Table 3. System GMM results

Dependent variable ln(Value added)	1.	2.	3.	4.
L.ln(Value added)	0.720***	0.707***	0.697***	0.700***
	(0.080)	(0.080)	(0.079)	(0.064)
ln(Labor)	0.694**	0.666***	0.635***	0.456**
	(0.276)	(0.250)	(0.232)	(0.231)
L.ln(Labor)	-0.522**	-0.464**	-0.406*	-0.358*
	(0.251)	(0.229)	(0.231)	(0.207)
ln(Capital)	0.201*	0.183*	0.167*	0.204**
	(0.114)	(0.105)	(0.098)	(0.093)
L.ln(Capital)	-0.163	-0.166	-0.161	-0.134
	(0.112)	(0.102)	(0.105)	(0.095)
ln(R&D stock)	0.197	0.184	0.162	0.114
	(0.193)	(0.168)	(0.153)	(0.102)
L.ln(R&D stock)	-0.133	-0.162	-0.158	-0.095
	(0.185)	(0.159)	(0.142)	(0.099)
IntR&D		0.003	-1.269	
		(0.131)	(0.774)	
IntR&D*ln(C)			0.105*	
			(0.063)	
IntR&D, strong host				-1.500***
				(0.531)
IntR&D, strong host*ln(C)				0.134***
				(0.044)
IntR&D, weak host				-0.431
				(0.555)
IntR&D, weak host*ln(C)				0.039
				(0.049)
ln(Subsidiary countries)		0.120*	0.121*	0.180***
		(0.068)	(0.065)	(0.051)
Constant	0.945***	1.269***	1.523***	1.465***
	(0.272)	(0.363)	(0.419)	(0.336)
Observations	2252	2252	2252	2243
Firms	481	481	481	478
Instruments	96	114	131	165
AR1, p-value	0.000	0.000	0.000	0.000
AR2, p-value	0.493	0.465	0.454	0.493
Hansen test, p-value	0.424	0.276	0.316	0.365
Hansen test, df	61	77	93	125

Notes. * p<0.10, ** p<0.05, *** p<0.01. All regressions include year and country dummies and country-year interactions. All time-varying firm level variables are assumed endogenous. Other variables are assumed exogenous. Endogenous variables are instrumented with 2 and 3 period lags. Two-step robust standard errors are presented in parenthesis.

These findings indicate that costs advantages, knowledge diversification and improved access to foreign markets can compensate for the loss of efficiency in R&D activities caused by coordination costs and loss of economies of scale and scope associated with overseas R&D. However, these gains are not large enough to significantly improve the R&D returns. On top of these benefits the firms appear to need access to more advanced technological knowledge to significantly improve their R&D productivity. When we re-estimated the model with an additional interaction term between R&D stock and the number of countries in which the firm is active, we did not observe a significant effect. This also points to international technology sourcing as the source of higher R&D returns. Unfortunately, the present study cannot identify the exact mechanisms through which these benefits arrive. However, prior studies point to access to qualified workforce and knowledge spillovers from other firms as important mechanisms.

In both OLS and System GMM estimation the coefficient of $\text{int}\,R\,\&\,D_{it}$ variable was negative. This indicates that there are also costs associated with overseas R&D investments; however, firms with overseas R&D obtain higher R&D returns, which compensates for these costs. The median log R&D stock is approximately 11 in our sample (the nominal value is in thousands). Therefore, the increase in the R&D returns is sufficient to compensate for the additional costs of overseas R&D for firms with above-median R&D investments, but not for firms below the median.

5.2 Industry-specific results

Next, industry-specific results are discussed. The estimation is repeated separately for the largest industry categories. The industry categories are the following: chemicals (NACE 19 and 20), pharmaceuticals (NACE 21), computers, electronic and optical products (NACE 26), machinery and electrical equipment (NACE 27 and 28), other high-tech industries and low-tech industries. The category of other high-tech industries includes, e.g., manufacturing of motor vehicles, other transport equipment and medical instruments. The final category includes low-tech and medium-low-tech firms such as manufacturers of food, basic metals, rubber and plastic products, etc.

The number of observations per industry is low in comparison to the number of instruments and thus System GMM estimation is not viable. Therefore, industry-specific OLS results are presented in Table 4. Specification 1 estimates the model with all international R&D activities and specification 2 separates the R&D investments in technologically stronger and technologically lagging countries. The industry-specific means of R&D variables are shown at the bottom of the table.

The industry-specific results mirror our main results for most of the industries; however, the results vary somewhat from industry to industry. The largest gains from international R&D appear in the low-tech industries. Thus, the R&D activities of low-tech firms can gain more from overseas R&D activities than R&D in high-tech firms. Moreover, two clear outlier industries emerge from the tables, namely manufacturing of computers, electronic and optical products and other high-tech industries. In the former, the relationship between international R&D and R&D elasticity is significantly negative except for leading R&D host countries. However, this may be explained by the fact that this category includes, on average, smaller firms that may not be able to cover the costs of R&D internationalization[15]. In the latter category, the relationship between international R&D and firm performance is insignificant overall but highly positive for technologically stronger countries and negative for weaker countries. In addition to the other high-tech category, the host country's technological strength is particularly important for pharmaceutical firms. In general, the level of technology in the host countries appears to affect high-tech firms more than low-tech firms. This result is intuitive, as knowledge sourcing is likely to be more important for the competitiveness of high-tech firms. It may also explain the result that, on average, low-tech firms benefit more from international R&D.

[15] Further analysis showed that the negative coefficient was indeed driven by the firms with low R&D investments, while the results for firms with high R&D investments mirrored our main findings.

Table 4. Industry specific results

Dependent variable	Chemicals		Pharmaceuticals		Computers	
ln(Value added)	1.	2.	1.	2.	1.	2.
ln(L)	0.739***	0.743***	0.488***	0.507***	0.499***	0.501***
	(0.095)	(0.098)	(0.115)	(0.115)	(0.040)	(0.040)
ln(K)	0.181***	0.178***	0.305***	0.294***	0.207***	0.213***
	(0.051)	(0.052)	(0.067)	(0.068)	(0.037)	(0.037)
ln(C)	-0.048	-0.047	0.057	0.053	0.197***	0.197***
	(0.041)	(0.049)	(0.037)	(0.037)	(0.030)	(0.030)
IntR&D	-0.812		-1.150		1.080*	
	(0.580)		(0.745)		(0.649)	
IntR&D*ln(C)	0.098*		0.117*		-0.107*	
	(0.053)		(0.060)		(0.057)	
IntR&D, strong host		-1.193		-2.658**		0.792
		(0.907)		(1.144)		(0.745)
IntR&D, strong host*ln(C)		0.137		0.266***		-0.088
		(0.088)		(0.086)		(0.067)
IntR&D, weak host		-0.411		-0.028		4.999***
		(1.965)		(0.877)		(1.037)
IntR&D, weak host*ln(C)		0.059		0.010		-0.428***
		(0.142)		(0.073)		(0.091)
ln(Subsidiary countries)	0.326***	0.320***	0.522***	0.525***	0.308***	0.311***
	(0.079)	(0.086)	(0.089)	(0.088)	(0.043)	(0.043)
Constant	4.312***	4.324***	3.173***	3.215***	3.017***	2.914***
	(0.274)	(0.353)	(0.361)	(0.357)	(0.224)	(0.227)
Adj. R-squared	0.969	0.969	0.946	0.947	0.902	0.903
Obs	294	294	332	332	618	618
R&D stock	595.886		2358.158		270.141	
% International R&D intensity	0.190		0.234		0.202	
% International R&D in leading country	0.122		0.089		0.153	
% International R&D in lagging country	0.068		0.145		0.049	

Notes. * p<0.10, ** p<0.05, *** p<0.01. All regressions include country and year dummies as well as country-year interactions. Robust standard errors are presented in parenthesis.

Table 4. Continued

Dependent variable	Machines and equipment		Other high-tech		Low-tech	
ln(Value added)	1.	2.	1.	2.	1.	2.
ln(L)	0.448***	0.450***	0.559***	0.496***	0.440***	0.441***
	(0.082)	(0.081)	(0.079)	(0.079)	(0.046)	(0.047)
ln(K)	0.302***	0.301***	0.360***	0.383***	0.418***	0.421***
	(0.047)	(0.046)	(0.058)	(0.056)	(0.035)	(0.036)
ln(C)	0.013	0.011	0.078*	0.105**	-0.008	-0.010
	(0.030)	(0.031)	(0.041)	(0.041)	(0.021)	(0.021)
IntR&D	-1.906**		-1.111		-2.120***	
	(0.788)		(1.263)		(0.371)	
IntR&D*ln(C)	0.188***		0.083		0.202***	
	(0.068)		(0.097)		(0.034)	
IntR&D, strong host		-1.979**		-4.927***		-2.874***
		(0.818)		(1.529)		(0.512)
IntR&D, strong host*ln(C)		0.178**		0.369***		0.267***
		(0.070)		(0.117)		(0.045)
IntR&D, weak host		-1.351		5.881***		-1.360***
		(1.624)		(1.678)		(0.476)
IntR&D, weak host*ln(C)		0.174		-0.508***		0.137***
		(0.128)		(0.147)		(0.043)
ln(Subsidiary countries)	0.323***	0.328***	-0.070	-0.018	0.232***	0.240***
	(0.057)	(0.058)	(0.058)	(0.056)	(0.039)	(0.040)
Constant	4.277***	4.258***	2.941***	2.773***	3.385***	3.353***
	(0.187)	(0.205)	(0.250)	(0.254)	(0.197)	(0.203)
Adj. R-squared	0.931	0.932	0.961	0.964	0.946	0.946
Obs	534	534	349	349	641	628
R&D stock	601.248		2823.431		255.124	
% International R&D intensity	0.136		0.173		0.281	
% International R&D in leading country	0.074		0.113		0.155	
% International R&D in lagging country	0.062		0.060		0.131	

Notes. * p<0.10, ** p<0.05, *** p<0.01. All regressions include country and year dummies as well as country-year interactions. Robust standard errors are presented in parenthesis.

5.3 Robustness

Above, we measured the technological strength of countries using patent data. Nevertheless, patents are only one way to measure the technological strength of countries, and using them may ignore important aspects of countries' technological capabilities. The propensity to patent also varies across industries and countries, and thus a patent-based measure of technological strength may provide an inaccurate picture of certain industries or countries. Therefore, we test whether our findings are robust to different measures of technological strength. As an alternative, we measure the technological competitiveness of countries using the innovation index contained in the Global Competitiveness Report, which is published annually by the World Economic Forum (WEF). This index analyzes countries by their R&D investments, quality of research institutions, university-industry collaboration and availability of scientists and engineers. Unfortunately, the index is at the country- rather than the industry-level. The composition of the report has also changed over time, and the innovation index is unavailable for the earliest years, and thus we have to rely on a more general technology index for the two earliest years. While the innovation index measures technology and innovativeness more broadly than patents, it does not cover all countries. However, most developed countries are included throughout our sample period. In addition, we also measure the technological strength of countries using their R&D intensities (aggregate R&D investments divided by GDP), following, e.g. Shimizutani & Todo (2008). The data on R&D intensities are obtained from the OECD Statistics. The data primarily cover developed countries, and thus we assume that excluded countries are technologically weaker.

Table 5 represents summary statistics on overseas R&D locations using these alternative measures of country-level technological strength. First, we rank as leading countries those that rank in the top ten on the WEF ranking. As Table 5 indicates, the top ten countries already attract a clear majority of the overseas R&D investments of our sample firms. This further illustrates how geographically concentrated international R&D investments are. We tried categorizing technological leaders as countries with WEF scores higher than that of the firm's home country; however, this led to an even more unbalanced distribution than in Table 5, and thus we dropped it. Second, we categorize technologically leading countries as those with a higher R&D intensity than the firm's home country. The variables in Table 5 are correlated with the patent-based technological strength variables presented in Table 1. Correlation coefficients between the variables measuring international R&D in technologically stronger countries are over 0.8, whereas the correlations are somewhat lower for the variables measuring R&D in technologically weaker countries. Therefore, it appears that patent-based measures also relate to the general technology and innovation competitiveness of countries.

Table 5. Overseas R&D location using alternative measures of technological strength

	Mean	SD	Median	Min	Max	Obs
International R&D in strong host countries (WEF)	0.128	0.214	0.025	0	1	2855
International R&D in weak host countries (WEF)	0.078	0.151	0.011	0	1	2855
International R&D in strong host countries (R&D)	0.143	0.232	0.031	0	1	2855
International R&D in weak host countries (R&D)	0.063	0.135	0.002	0	1	2855

Notes. 546 firms in 2004-2011.

Table 6 presents results using the alternative measures of host country technological strength. The table reveals that the main results do not change when we use the WEF rankings. The estimates are quite close to the results in Table 3. The gains from international R&D are positive when firms locate overseas R&D in technologically leading countries. When we use the country-level R&D intensities as a measure, the coefficients are no longer statistically significant. However, the signs and magnitudes of the coefficient estimates again support our main findings.

The robustness of System GMM results was also tested with respect to the assumptions about the instrument lag structure. A large instrument count weakens the Hansen test and it may not detect whether the instruments are valid. At the same time, using longer lags can increase the precision of estimation. Thus, the models were re-estimated with all available lags and only 2-period-lagged values as instruments[16]. However, changing the instrument set did not change the main findings.

Above, we compare firms with differing levels of international R&D to each other and to firms with only domestic R&D. These firms may differ with respect to many other characteristics besides R&D locations, which could question our results. Thus, we excluded all firms that never conduct international R&D and re-estimated the model; however, the GMM results were identical to Table 3. We also experimented by including firm size dummies and their interactions with R&D stock to test whether our findings are driven by size effects. While this did indicate higher R&D returns in larger firms, it did not change our findings with respect to international R&D.

[16] The results are available upon request.

Table 6. System GMM results using alternative measures of technological strength

Dependent variable ln(Value added)	WEF rankings	R&D intensity
L.ln(Value added)	0.679***	0.703***
	(0.071)	(0.064)
ln(Labor)	0.516**	0.603**
	(0.206)	(0.241)
L.ln(Labor)	-0.272	-0.367*
	(0.186)	(0.218)
ln(Capital)	0.176*	0.213**
	(0.093)	(0.091)
L.ln(Capital)	-0.171*	-0.198**
	(0.097)	(0.095)
ln(R&D stock)	0.190	0.117
	(0.124)	(0.106)
L.ln(R&D stock)	-0.203*	-0.131
	(0.116)	(0.097)
IntR&D, strong host	-1.743***	-1.172
	(0.638)	(0.916)
IntR&D, strong host*ln(C)	0.154***	0.095
	(0.057)	(0.083)
IntR&D, weak host	-0.985	-0.654
	(0.658)	(0.768)
IntR&D, weak host*ln(C)	0.080	0.054
	(0.060)	(0.068)
ln(Subsidiary countries)	0.139**	0.109*
	(0.056)	(0.060)
Constant	1.771***	1.518***
	(0.372)	(0.376)
Observations	2252	2252
Firms	481	481
Instruments	165	165
AR1, p-value	0.000	0.000
AR2, p-value	0.490	0.492
Hansen test, p-value	0.379	0.334
Hansen test, df	125	125

Notes. * $p<0.10$, ** $p<0.05$, *** $p<0.01$. All regressions include year dummies and country and country-year interactions. All time-varying firm level variables are assumed endogenous. Other variables are assumed exogenous. Endogenous variables are instrumented with 2 and 3 period lags. Two-step robust standard errors are presented in parenthesis.

6 CONCLUSIONS

International R&D activities may improve firm productivity and R&D returns by improving a firm's knowledge sourcing, providing different kind of technological knowledge, bringing cost savings or giving a better access to foreign markets which, in turn, helps the firm to better appropriate the returns to its innovations. At the same time, overseas R&D activities may increase coordination, communication and other costs. Despite the growth in international R&D investment flows, few empirical studies have analyzed how these investments affect the productivity of R&D investments. The present study analyzes how the international R&D activities affect firm productivity through returns to R&D and especially contributes to the literature by analyzing how the relative technological strengths of home and R&D host countries moderate this effect.

In our empirical analysis, we estimate a production function that is augmented with a firm's R&D stock and the share of international R&D investments. The empirical results show that the R&D elasticity of output is significantly higher in those European firms that conduct a part of their R&D activities abroad. For firms that conduct 20% of their R&D abroad, this implies an approximately 2 percentage point higher R&D elasticity of output.

Based on the prior literature on knowledge sourcing and spillovers, the gains from international R&D activities are hypothesized to depend on the relative technological strengths of a firm's home country and foreign R&D locations. When the R&D host country is more advanced in comparison to the home country, the technology sourcing opportunities are expected to be larger. The estimation results support our hypothesis. When firms locate overseas R&D in countries that are technologically more advanced than their home country the R&D elasticity is approximately 3% higher with average international R&D intensity. In contrast, when the overseas R&D is located in technologically weaker countries, the returns to R&D do not improve statistically significantly. Possible cost savings, knowledge diversification and an improved access to foreign markets in technologically weaker countries appear to compensate the additional coordination costs and loss of economies of scale associated with internationally distributed R&D activities; however, they are not large enough to significantly improve the R&D returns. Moreover, R&D investments in technologically weaker countries may have market-seeking or other motives and these investments may, e.g., increase firms' market share in those countries, which is not revealed in our analysis. Our industry-specific results indicate that both high- and low-tech firms benefit from international R&D, while the level of technology in the host countries appears more important for the high-tech firms.

At the firm-level, our results suggest that firms can improve the returns to their R&D investments by locating some of their R&D activities abroad. However, if the objective is to improve the productivity of R&D investments, the target countries need be chosen based on the knowledge sourcing opportunities. Moreover, our results show that there are significant costs associated with international R&D that smaller or less R&D-intensive firms may not be able to cover. Thus, while large European firms can significantly benefit from international knowledge sourcing, the results may not apply to smaller firms. Our analysis is also limited to the manufacturing industry in four European countries. Further research is needed to explore whether the results also apply to other types of firms, industries and countries. Moreover, while our results suggest that the higher R&D returns stem from access to more advanced knowledge, we do not observe firms' motives for international R&D or the exact nature of their international R&D activities. More detailed data would allow an analysis that would identify the exact channels of higher R&D returns.

From a policy perspective, our results suggest that the increasing relocation of R&D activities abroad does not necessarily weaken the home country's competitiveness and welfare as improved firm productivity can also benefit the home country. Instead, international R&D collaboration and knowledge sourcing by firms should be favored to improve the innovativeness and competitiveness of firms.

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Knowledge spillovers through inventor mobility: the effect on firm-level patenting

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Abstract Labor mobility is heralded as a key channel of knowledge spillovers between firms. However, the empirical evidence on labor mobility's effects on firm performance leaves many unanswered questions. In this paper, we analyze the effect of inventor mobility on firm-level patenting activity by studying a sample of European R&D investing firms. Especially, the characteristics of mobile inventors and their previous employers are analyzed to discover the prerequisites of successful knowledge transfer. The empirical results suggest that mobile patent inventors transfer knowledge and affect the hiring firm's future innovation performance. Inventor mobility in general does not significantly increase patenting; however, hiring inventors with several prior patents and different kinds of technological expertise contributes to firms' future patenting. Furthermore, hiring inventors from actively patenting firms contributes to future patenting. We also find that outbound mobility of inventors weakens the source firm's patenting performance, especially when the firm loses inventors who have been highly productive, have worked in the firm's core field of technology or move to technologically similar firms.

Keywords Patenting · Inventor · Knowledge spillovers · Labor mobility

JEL Classification O33 · O34

1 Introduction

Knowledge spillovers between firms and countries are an important driver of knowledge diffusion and economic growth. The mechanisms of knowledge spillovers are understood to include market transactions, labor mobility, research collaboration, communication at technical conferences, pure externalities, etc. The link between labor mobility and

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knowledge spillovers has been noted at least since Arrow (1962) and an increasing interest in the determinants and consequences of labor mobility has been evidenced in recent years. Interfirm labor mobility is now recognized as a key channel of knowledge spillovers. The extant research attributes the growth and innovativeness of regions to labor mobility (Saxenian 1994; Samila and Sorenson 2011; Miguélez and Moreno 2013) and shows that the hiring of knowledge carriers, i.e., employees with specific qualifications or expertise, improves firm productivity (Balsvik 2011; Stoyanov and Zubanov 2012; Maliranta et al. 2009; Parrotta and Pozzoli 2012). However, some prior studies also find a negative association between firm performance and worker turnover (Ilmakunnas et al. 2005; Michie and Sheehan 2003; Hancock et al. 2013). Thus, our understanding of the firm performance effects of labor mobility remains incomplete. Especially, the empirical evidence is inconclusive on the effects of labor mobility on firm-level innovation performance.

Knowledge spillovers not only reflect imitation and learning from industry leaders but they may also lead to new uses and combinations of knowledge and, thus, to the creation of new innovations. This paper focuses on the effect of inventor mobility on firms' innovation output by analyzing a sample of R&D investing European firms and their patenting activity. The study most closely relates to a study conducted by Kaiser et al. (2015), who, using Danish linked employer-employee data, show that R&D worker mobility is positively related to number of patent applications. In contrast to Kaiser et al. (2015) study, the present paper analyses inventor mobility and especially considers the prior patenting expertise of mobile inventors and the characteristics of their previous employers to discover the prerequisites of successful knowledge transfer. This paper follows many prior studies and utilizes patent data to track inventor mobility. These prior studies have often used patent citation data as an indicator of knowledge spillovers through inventor mobility (Almeida and Kogut 1999; Singh and Agrawal 2011; Agarwal et al. 2009; Corredoira and Rosenkopf 2010). However, patent citations do not reveal the firm-level effect on innovation output, which is the main interest of the present paper.

Prior literature has emphasized learning by hiring; however, outbound mobility is equally important because workers who leave a firm represent a knowledge leak and a loss of skills but at the same time may act as a channel of reverse knowledge spillovers to the firm (Agrawal et al. 2006; Corredoira and Rosenkopf 2010). Therefore, we also analyze the outbound mobility of inventors and whether its effects depend on the characteristics of inventors and their new employers.

In the empirical part of this paper, a patent production function is estimated using negative binomial estimation with pre-sample means to account for unobservable time-invariant firm effects. The empirical results reveal that inbound inventor mobility per se does not have a statistically significant effect on firms' patent output. However, the results indicate that firms' patent output is improved through hiring of inventors with many prior patents and who possess technological knowledge that differs from the firms' main field of technology. Similarly, a firm's patent output increases after it recruits inventors from firms that are patenting intensively, whereas hires from low-patenting firms have no significant effect on a firm's patenting. Thus, the first group of recruits appears to be able to transfer more valuable technological knowledge than the latter group.

In addition, we find that leaving inventors have a negative overall effect on a firm's future patent output, indicating that their skills and expertise cannot be easily replaced. However, the leaving inventors' field of technological expertise and patenting experience are important. The loss of inventors with many patents or experience in a firm's core field of technology is especially detrimental for the firm's future patenting. Moreover, when leaving inventors obtain employment at a high-patenting hiring firm, the effect is strongly negative, whereas leavers who become employed at low-patenting firms do not have a significant effect on future patenting. This finding is contrary to the reverse knowledge spillover hypothesis put forward in some recent studies and may indicate that firms systematically engaging in R&D and patenting are able to hire better inventors than firms with less intensive patenting activities. Our results show that employee mobility can be beneficial for firm-level innovativeness, although the negative effects of outbound mobility may also cause the firms to invest less in R&D.

The remainder of the paper is organized as follows. The second section summarizes the theoretical background and the related literature. The third section describes the data and variable formation. The fourth section discusses the estimation approach. The fifth section presents and discusses the empirical results. Finally, the sixth section concludes the paper.

2 Literature background

2.1 Implications of labor mobility

This chapter discusses the implications of labor mobility for firm performance. First, labor mobility may enable interfirm learning through knowledge spillovers. A significant part of a firm's R&D-related knowledge and organizational capabilities are tacit, and workers acquire this knowledge through job tenure (Almeida and Kogut 1999; Cooper 2001; Parrotta and Pozzoli 2012). This part of knowledge cannot be easily codified or protected by patents. Thus, when employees move, they can carry the acquired knowledge to the new employer. The knowledge spillovers through labor mobility are not pure externalities because the new employer pays for the knowledge in the form of wages; however, the work contracts do not always fully compensate for the technology transfer, which allows the hiring firms to benefit from knowledge externalities (Stoyanov and Zubanov 2014). Moreover, mobility does not necessarily directly degrade the source firm's knowledge stock; however, if employees join a rival firm, the source firm's relative position and competitiveness suffer (Somaya et al. 2008).

Second, the hiring firms benefit from the private skills and expertise of their new employees. These skills are rival in nature, and as an employee moves to another firm, these skills benefit the hiring firm and the old employer, i.e., the source firm, loses access to them. The size of the gain or loss then depends on the skills of the employee and how central they are for the firm (Wezel et al. 2006; Siebert and Zubanov 2009).

Third, the source firm may also enjoy access to new technological knowledge because mobile employees may retain their existing social contacts at their previous employer, resulting in continued knowledge transfer (Agrawal et al. 2006). These contacts may be especially useful if an employee moves to a customer or a partner firm (Somaya et al. 2008). Another explanation for reverse knowledge spillovers is that employee mobility may enhance the previous employer's awareness of the new employer and its innovations (Corredoira and Rosenkopf 2010). Thus, the old employer may enjoy reverse knowledge spillovers, and the overall effect of outbound mobility remains unclear. Moreover, outbound mobility may also have positive effects when it is associated with rational downsizing of unproductive R&D activities, which allows more efficient use of scarce resources.

Fourth, labor mobility may also increase the employer-employee match quality (Jovanovic 1979). Better match quality will lead to higher labor productivity, which can explain a significant share of differences in labor productivity (Jackson 2013). In support of this argument, Hoisl (2007, 2009) and Latham et al. (2011) present evidence that mobility can increase the productivity of inventors.

Fifth, labor mobility may create significant transaction costs, which is often emphasized in the labor turnover literature (Hancock et al. 2013). When employees leave a firm, they lose their firm-specific human and social capital. Moreover, the hiring and training of new employees is costly and takes time, which may erode the firm's knowledge stock and skill base. Furthermore, the informal communication structures within the firm are disrupted.

Finally, the implications of labor mobility are likely to depend on the type of knowledge and skills that are transferred through labor mobility. Heterogeneous and technologically distant knowledge may allow firms to reposition them technologically and improve their performance (Lazear 1999; Rosenkopf and Nerkar 2001; Tzabbar 2009). However, firms also need cognitive and technological proximity to maintain absorptive capacity that allows them to understand and use new knowledge (Cohen and Levinthal 1990; Nooteboom et al. 2007). If the recruited employees contribute knowledge and expertise that are too different from the firm's existing knowledge base, the firms may struggle to utilize the knowledge.

2.2 Empirical evidence on labor mobility and firm performance

We now review prior empirical studies that have analyzed the effect of labor mobility on firm-level performance. The management literature has typically found that employee turnover has negative effects on several aspects of firm performance [for a review of the literature, see, e.g., Hancock et al. (2013) and Mawdsley and Somaya (2016)]. Additionally, e.g., Ilmakunnas et al. (2005) find that overall employee turnover has a negative effect on firm productivity growth; however, employee churning, i.e., when separations are always replaced by hiring, has a positive effect. Moreover, some recent studies using linked employer-employee data have analyzed knowledge spillovers through mobility, i.e., they analyze the performance effects of the hiring of knowledge carriers. These studies show that hiring employees with tertiary education or experience in R&D work improves firm productivity at least under certain circumstances (Parrotta and Pozzoli 2012; Maliranta et al. 2009). Other firm characteristics matter as well, and hiring workers from multinational firms (Balsvik 2011; Poole 2013) or firms that are more productive (Stoyanov and Zubanov 2012) acts as a channel of knowledge spillovers. Interfirm spillovers from IT investments are also shown to be transmitted through IT employee mobility (Tambe and Hitt 2013). Learning by hiring is also shown to enable the development of new products (Rao and Drazin 2002).

To our knowledge, the studies by Kaiser et al. (2015) and Müller and Peters (2010) are among the few to analyze the firm-level innovation performance effects of R&D labor mobility. Related themes have also been analyzed: the mobility of star employees (Agrawal et al. 2014; Tzabbar and Kehoe 2014) and university scientists (Ejsing et al. 2013). The paper most closely related to the present study is that by Kaiser et al. (2015), who use Danish linked employer-employee data and show that the patenting activity of Danish firms increases when they hire R&D workers from a patenting firm. R&D worker mobility from or to a non-patenting firm has no effect on a firm's patent output. Thus, not only mobility but also the availability of technological knowledge determines the benefits of R&D worker mobility. Furthermore, Müller and Peters (2010) find that the churning of R&D employees has an inverted U-shaped relationship with firm innovation performance. Mobility increases the probability of innovations but only up to a specific point. In addition, Koski and Pajarinen (2015) find evidence that mobile inventor-specific knowledge contributes to firm's patenting, although their results vary across industries.

Several prior studies have analyzed the innovation performance effects of labor market flexibility. In contrast to the above-mentioned studies, these studies typically find that temporary work contracts and high overall labor turnover have a negative association with new-to-market innovations at the firm-level (Michie and Sheehan 2003; Zhou et al. 2011; Giannetti and Madia 2013; Martínez-Sánchez et al. 2011).[1]

Since Jaffe et al. (1993), the prior empirical literature has often interpreted patent citations as a paper trail of knowledge that reveals how knowledge spills over from one inventor and firm to another. Analyzing patent citation patterns, Almeida and Kogut (1999) argue that labor mobility is a driver of growth and innovativeness in Silicon Valley.[2] The studies also provide evidence on the importance of labor mobility for firms' learning using patent citation data (Breschi and Lissoni 2009; Singh and Agrawal 2011; Lenzi 2010). Citation patterns can help to describe firms' technological search processes; however, they do not represent firms' innovation performance. Moreover, patent citations may contain systematic measurement error as a measure of knowledge flows, e.g., because a great share of citations are added by patent examiners rather than inventors or patent applicants (Roach and Cohen 2013; Alcacer and Gittelman 2006; Nelson 2009). The share of examiner citations is especially large in Europe because the European Patent Office (EPO) does not require inventors to declare all references (Criscuolo and Verspagen 2008; Breschi and Lissoni 2005).

Related empirical studies indicate that the occurrence of knowledge spillovers and the effects of labor mobility depend on the firms' technological characteristics. Song et al. (2003) and Rosenkopf and Almeida (2003) find that inventor mobility is more likely and leads to greater knowledge transfer (as measured by patent citations) when the hired inventors possess different kinds of technological expertise than the hiring firm possesses. Similarly, Boschma et al. (2009) find that plant-level productivity increases when employees with related, but not too similar, skills are hired. Hiring of technologically distant scientists can also allow firms to reposition them technologically (Tzabbar 2009). Parrotta and Pozzoli (2012), however, find that technological proximity is beneficial for learning by hiring. These results indicate that firms benefit from different technological knowledge but may need some degree of technological overlap to maintain absorptive capacity. However, Müller and Peters (2010) and Kaiser et al. (2015) do not analyze whether these aspects affect firm-level innovation performance.

The effects of outbound employee mobility have received somewhat less attention in prior studies. However, Corredoira and Rosenkopf (2010) find evidence of reverse spillovers through outbound mobility. Specifically, they find that semiconductor firms that lose employees more often cite the patents of firms hiring these employees. At the same time, outbound mobility may also cause knowledge leaks. Kim and Marschke (2005) and Agarwal et al. (2009) show that firms use pre-emptive patenting and patent litigation to protect themselves against potential knowledge leaks through mobility. Nevertheless, Somaya et al. (2008) find that outbound mobility can have a positive effect on firm performance when employees are hired by cooperators and a negative effect when employees are hired by competitors. Moreover, Kaiser et al. (2015) find evidence that outbound R&D worker mobility to patenting firms increases a firm's patenting, while

[1] The studies also find that functional flexibility within the firm is positively associated with innovation performance.

[2] Also, e.g., Miguélez and Moreno (2013) show that inventor mobility affects the innovativeness of regions.

leavers to non-patenting firms have a statistically insignificant effect on patenting. Thus, the effects of outbound mobility appear to depend on the characteristics of the hiring firm. Leaving workers' characteristics may also play a role in the association between worker mobility and performance. Leaving key employees are likely to have a more negative effect on firm performance (Siebert and Zubanov 2009; Campbell et al. 2012). Thus, the overall effect of outbound mobility on firm innovation performance remains unclear.

In sum, prior empirical evidence indicates that labor mobility has positive performance effects at the regional and individual inventor level. However, the firm-level effects of employee mobility remain rather mixed. The hiring of highly skilled employees contributes to firm productivity but the overall effect of employee turnover is not clear.

3 Data description

The main dataset used in this study is drawn from the EPO PATSTAT patent database.[3] Additionally, financial and firm ownership data from Bureau van Dijk's Orbis database are used. From Orbis, we include European manufacturing firms that have consolidated balance sheet data available and report R&D expenditures at least once during the time period 2005–2011. Only firms that apply for patents are included in the estimation of the patent production function. We use patent applications filed at the EPO after the year 1995. In comparison with national patent applications, the EPO patent applications have fewer gaps in the inventor and technological field information, which are the key pieces of information used in our empirical approach. However, the EPO patents are often second filings; thus, the time lag between the invention and the patent filing may be longer.

Patents are matched to firms based on applicant names. The OECD HAN database and manual matching are used for name matching. The patent data are aggregated at the corporate group level under the assumption that the parent firm (ownership over 50 %) is the ultimate owner of its subsidiaries' patents. This aggregation is performed using firm ownership information obtained from the Orbis database and checking the merger or acquisition date when a subsidiary is observed to file patents.

3.1 Measuring inventor mobility

Patent applications contain information on the inventors and applicants of patents, thus allowing us to trace the employment histories of inventors given that the patent applicant is nearly always the employer of the inventor (Hoisl 2007). Several prior studies, e.g., Song et al. (2003) and Singh and Agrawal (2011), have used patent data to track inventor mobility.

We count the number of inventors listed on the firm's patent applications in each year. We differentiate between the different types of inventors as follows: inventors who appear in the patent data for the first time (new), inventors who have been listed in an earlier patent application by another firm (hires) and inventors who have been listed in an earlier patent application by the same firm (stayers). We also count the number of leaving inventors (leavers), i.e., inventors who are no longer among the current inventors of the firm but were in the firm in the previous year and moved to another firm.

Because we do not directly observe an inventor's employment contracts, we assume that the hiring occurs in the year of the inventor's first patent application at the new firm. Patent

[3] EPO Worldwide Patent Statistical Database (PATSTAT), October 2013.

applications that list the inventor as the applicant are ignored and not considered as a move because they do not include a change in employment. An inventor is considered to leave the firm in the year after the inventor's last patent at the firm if the inventor subsequently appears in a patent application by another firm. If an inventor appears only on a single patent application, we cannot observe mobility.

While the patent applicant is typically the inventor's employer, in some occasions, e.g., due to strategic alliances or mergers, the applicant may change even though the inventor has not changed employment. Unfortunately, these instances cannot be separated in the present study and, thus, may result in an overestimation of the number of moves. Co-inventions, i.e., patents that are co-applied by several firms, are ignored when counting mobility to partially address this issue.

This methodology allows us to measure mobility if the inventor applies for a patent after his/her change in employment. Thus, our estimate underestimates the true inventor mobility and covers only job switches that are followed by new patents. Outbound mobility may also be further underestimated because patent data are truncated because new patents are published with a time lag and future patenting is unknown. These issues are further discussed in chapter 5.3.

3.2 Identifying individual inventors

The spelling of an inventor's name may differ across patent applications, which must be considered to track inventor mobility. Identical inventor names may refer to different inventors, and different spellings may refer to one inventor. First, we remove inventors' titles and common variations in the address information. Then, we match two records as representing one inventor if the following criteria are met:

1. The records have identical names and the same NUTS3 region or patent assignee
2. The records have similar names (spelling variation in middle names is ignored) and the same street address or patent assignee
3. The records have similar names, the same technological field and the same NUTS3 region

The regional location of inventors is based on the OECD Regpat database (February 2015 version).

3.3 Patent output

Our dependent variable is the number of patent applications filed by a firm in a given year. As a robustness test, we also use citation-weighted patents, which are counted by weighting each patent application by one plus the number of citations it receives within 3 years.[4] Patent counts, even when weighted with citations, are an imperfect proxy for innovation. Not all inventions are patentable, and some firms may prefer to rely on trade secrecy and lead time and do not patent their inventions. These conditions also vary considerably across industries. Therefore, the analysis focuses on the manufacturing sector where, in general, patents are more prevalent. We analyze only firms that have applied for at least one patent and control for firm-specific permanent heterogeneity in patenting.

[4] Citation information is taken from OECD Citations database (February 2015) and contains all citations that firm's patents receive within 3 years either as EPO or Patent Cooperation Treaty (PCT) patent publication.

3.4 Source firms' and inventors' past patenting activity

The occurrence of knowledge spillovers likely depends on the level of R&D knowledge in the source firm. Ideally, we would like to track the R&D investments of source firms; however, we observe the R&D investments for only a small subset of all possible source firms. Therefore, we need to rely on the patent data and measure the extent of source firms' patenting activity. We define high-patenting firms as source firms that have filed more than five patent applications in the year before the inventor moves to the new firm. Source firms with fewer patents are classified as low-patenting firm. Similarly, we also measure the extent of patenting in the firms that hire leaving inventors. The threshold is set based on the median among the source firms of hired inventors.[5]

We also wish to measure the inventors' R&D knowledge and skills. Because our variable of interest is firms' patent output, the inventor's past patent output seems the most relevant inventor specific measure. Thus, we track the patenting of mobile inventors prior to the move. We classify inventors with more than three prior patents as high-patenting inventors and those inventors with fewer patents as low-patenting inventors. The threshold is again set based on the median number among the mobile inventors. The leaving inventors are similarly classified.

3.5 Technological similarity

The technological similarity between a mobile inventor's prior patenting activity and her new employer's expertise is also considered. Similarly, we measure the technological similarity between the new employer and the source firm and how the similarity affects knowledge spillovers.

The International Patent Classification (IPC) at the 2-digit level is used to form 52 technology classes applying the categorization developed by Cincera (2005); see "Appendix Table 7". Technological similarity is measured by comparing the most common technology classes in firms and inventors' patents. Some patents have several technology codes, and we consider and weight all of them to determine the most common technology class. Following the literature, we count the technological specialization of firms considering all patent applications filed by the firms, while for inventors, only patents filed before the move are considered. Inventors are assumed to possess technological expertise in the hiring firm's core field of technology when the main technology classes of the inventor and the firm match. Inventors are assumed to have technologically related expertise when their main technology class is different from that of the hiring firm but they have made some inventions in the hiring firm's main technology field. When inventors have no patenting experience in the hiring firm's core technology field, they are categorized as having non-core technological expertise.

The technological similarity of the source firms is measured similarly: the firms are categorized as technologically similar, technologically related and technologically different depending whether their main fields of technology match. The technological similarity of firms recruiting leaving inventors is also measured.

[5] Alternative thresholds and considering the regularity of patenting over several years yield similar results.

3.6 R&D investments and the number of employees

Data on firms' employees and R&D expenditures are obtained from the Orbis database. The R&D stock measure is constructed using R&D expenditures and the perpetual inventory method with a depreciation rate of 15 %, as is typical in the literature (Hall et al. 2010). The initial value of the R&D stock is formed using the R&D expenditure in the first year and scaling it up using the depreciation rate and assumed steady-state growth rate (5 %). The R&D investments are deflated to year 2010 prices using the country-level GDP deflator obtained from OECD Statistics.

3.7 Descriptive statistics

Our final sample includes 935 firms and 4763 firm-year observations in time period 2005–2011. The availability of R&D expenditure data is the main delimiting variable leading to unbalanced panel. These firms come from 19 European countries.[6] We match these firms to 382,315 patent applications in the time period 1995–2011. In the time period considered in our empirical estimation (2005–2011)[7], the data includes 168,979 patents and 263,840 inventor observations.

Figure 1 presents summary statistics for inventor mobility. New inventors, who are observed in the patent data for the first time, constitute 39 % of inventor observations. 54 % of inventors are observed to stay at the same firm and approximately 7 % of inventors have been recently hired from other firms. These shares are quite similar across countries even though labor market conditions vary across countries.

Table 1 provides summary statistics for the estimation sample. Many smaller firms do not report R&D expenditures; thus, most of our sample firms are large firms with a median workforce of over 1800 employees. Therefore, our results may not readily apply to smaller firms. The median R&D stock is approx. 56 million euros. The median number of patent applications per year is 2, and we observe no patent applications (in a given year) for approximately one-third of the observations. Table 1 also presents summary statistics for inbound and outbound inventor mobility and the characteristics of mobile inventors. The numbers differ from Fig. 1, because Table 1 presents the figures at the firm-level. Correlations for these variables are presented in "Appendix Table 8". The average share of hired inventors of total number of inventors is 6.7 %, and approximately 4.8 % of inventors is observed to leave the firm in each year. These figures contain zeros for the observations with no patents in a given year, and thus also no inventors.

We divide the inventors and source firms to high- and low-patenting groups based on the median values of prior patenting; hence, these groups are roughly equal in size. However, the average share of hired inventors with low past patenting or from low-patenting firms is slightly larger, whereas the leaving inventors and their hiring firms more often belong to the high-patenting groups. Moreover, hires from firms with the same or related technological specialization appear more common than hires from technologically different firms. When we examine hired inventors' previous patenting, we observe that a large share of them have no experience in the firm's core technological field. However,

[6] The countries are Austria, Belgium, Denmark, Finland, France, Germany, Hungary, Ireland, Italy, Latvia, Luxemburg, the Netherlands, Norway, Spain, Slovenia, Sweden, Switzerland and the United Kingdom. Approximately two-thirds of the sample firms come from the United Kingdom, Germany, France or Switzerland.

[7] Patent data from years 1995–2004 is used to measure the background characteristics of inventors.

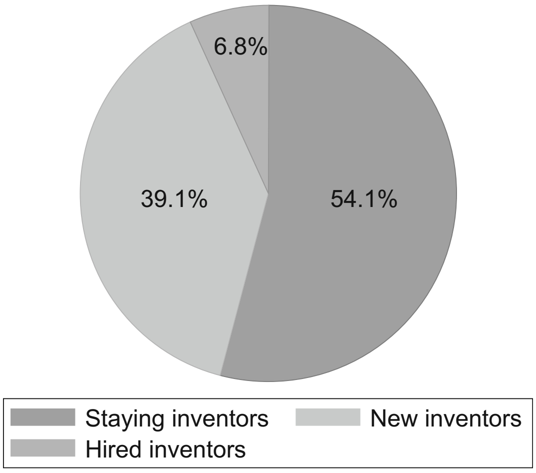

Fig. 1 Inventor churn. *Note* 263,840 inventor observations

hires with prior experience in the firm's main field of technology are the most common group. The figures are similar for outbound inventor mobility. Leaving inventors with prior patenting experience in the firm's core technological field and leavers to technologically similar firms form the largest groups.

4 Empirical approach

This section describes the patent production function and the adopted estimation approach. Following Kaiser et al. (2015), we estimate a patent production function, where the dependent variable is the number of patent applications filed by a firm in a given year. This is a count variable; thus, we use a count data model in the estimations. The number of patents is modeled to depend on the firm's R&D investment stock, employment, which is also a control for firm size, and the lagged number of patent inventors:

$$E(P_{it}) = \exp\left(\ln A_{it} + \alpha \ln L_{it} + \beta \ln R\&D_{it} + \gamma \ln QL^{I}_{i,t-1} + \eta_i\right) \tag{1}$$

where P_{it} refers to the number of patent applications in firm i in year t, L_{it} to the number of employees, $R\&D_{it}$ to the firm's R&D stock, $QL^{I}_{i,t-1}$ to the quality-adjusted number of inventors in the previous year and η_i to a firm-specific effect. A_{it} captures other factors affecting the production of patentable inventions such as time, sectoral and country effects.[8] The inventors employed in the firm (L^{I}) consist of staying inventors (L^{S}), hires from other firms (L^{H}), and first-time inventors (L^{N}). These groups may differ in their patent productivity which allows us to count the quality-adjusted number of inventors (Hellerstein et al. 1999). Normalizing the effect of staying inventors to unity gives us:

$$QL^{I} = L^{S} + \alpha^{H} L^{H} + \alpha^{N} L^{N} = L^{I}\left(1 + \left(\alpha^{H} - 1\right)\frac{L^{H}}{L^{I}} + \left(\alpha^{N} - 1\right)\frac{L^{N}}{L^{I}}\right) \tag{2}$$

In our empirical approach, the inventors who left the firm, L^{L}, are also included and considered as a distinctive group. However, these inventors no longer belong to the current

8 Estimated model includes dummies for years, industries and countries (based on the location of the firm's headquarters).

Table 1 Descriptive statistics

Variable	Mean	Median	SD
Patents	33.745	2	137.375
No patent dummy	0.341	0	0.474
Citation weighted patents	53.744	3	226.076
Employees	13462.360	1857	37323.290
R&D stock	831.712	55.742	3361.587
Number of inventors	55.394	4	209.836
Share of hires	0.067	0.000	0.146
Hires, high past patenting	0.027	0	0.087
Hires, low past patenting	0.040	0	0.111
Hires from high-patenting firms	0.031	0	0.091
Hires from low-patenting firms	0.036	0	0.113
Hires with similar tech. expertise	0.031	0	0.103
Hires with related tech. expertise	0.013	0	0.057
Hires with non-core tech. expertise	0.022	0	0.079
Hires from tech. similar firms	0.029	0	0.102
Hires from tech. related firms	0.027	0	0.090
Hires from tech. different firms	0.010	0	0.055
Share of new	0.300	0.300	0.303
Share of leavers	0.048	0	0.122
Leavers, high past patenting	0.029	0	0.094
Leavers, low past patenting	0.019	0	0.069
Leavers to high-patenting firms	0.022	0	0.069
Leavers to low-patenting firms	0.027	0	0.098
Leavers with similar tech. expertise	0.025	0	0.089
Leavers with related tech. expertise	0.012	0	0.059
Leavers with non-core tech. expertise	0.011	0	0.048
Leavers to tech. similar firms	0.021	0	0.084
Leavers to tech. related firms	0.019	0	0.068
Leavers to tech. different firms	0.009	0	0.050

4763 observations, 935 firms

inventors and thus their number divided by the number of inventors in the previous year (L^L/L_{-1}). Taking logs of Eq. 2 and using the approximation ln $(1 + x) \approx x$, we can plug the inventor types into the patent production function. This leads to the following equation:

$$E(P_{it}) = \exp\left(\ln A_{it} + \alpha \ln L_{it} + \beta \ln R\&D_{it} + \gamma_0 \ln L^I_{i,t-1} + \gamma_H \frac{L^H_{i,t-1}}{L^I_{i,t-1}} + \gamma_N \frac{L^N_{i,t-1}}{L^I_{i,t-1}} + \gamma_L \frac{L^L_{i,t-1}}{L^I_{i,t-2}} + \eta_i\right) \tag{3}$$

In addition to the above mentioned factors, we also take into account the state dependency in the firm's patenting activity. We control for the firm's previous patenting activity because past inventions present a stock of knowledge that can be used for future inventions and can thus have a substantial effect on current patenting (Blundell et al. 2002). We control for the log number of patents lagged by one and two periods and include dummy variables for zero patents.

Next in the empirical approach, we consider the differences in the characteristics of previous employers and mobile inventors by separating the mobile inventors into groups according to their characteristics. We analyze the effect of mobile inventors' past patents, the source firm's patenting, the mobile inventors' technological fit with the hiring firm and the source firm's technological similarity. The characteristics of outbound mobility are similarly analyzed.

Our dependent variable in the estimations is a count variable; thus, we need to use Poisson or negative binomial regression. The empirical methodology also needs to control for firm-specific permanent heterogeneity in patenting (different patent propensity due to different technological environment, different R&D practices, different R&D investment appropriability conditions etc.). A fixed effects or random effects model is commonly employed. However, because lagged patenting is used as an explanatory variable, the strict exogeneity assumption does not hold and a fixed or random effects model cannot be used. Therefore, we use pre-sample mean estimation developed by Blundell et al. (1995) and applied, for example, by Czarnitzki et al. (2009) and Kaiser et al. (2015). The model uses pre-sample patent information to approximate the firm fixed effects in a pooled cross-sectional count model. In our model, we use the log of mean patents per year in the pre-sample period of 1995–2004 and a dummy variable that indicates firms that had no patents in the pre-sample period.

We use a negative binomial model to allow over-dispersion in the data. The test for the equality of mean and variance shows that the negative binomial model is preferred to the Poisson model.

5 Results

5.1 Main results

This section presents and discusses the empirical results. Table 2 presents the results of the baseline model and analyzes the effect of inventors' and source firms' prior patenting. In Table 3, the role of technological similarity is analyzed. The tables display the coefficients, and the cluster robust standard errors are presented in parentheses. Statistically significant coefficients are presented with asterisks. The coefficients do not directly translate into marginal effects; however, the signs and significance levels of coefficient estimates are applicable. The marginal effects are reported in Table 4.

The first column in Table 2 presents the baseline estimation. Further columns show how the effect of mobility depends on mobile inventors' prior patenting and the source firm's patenting. Our main control variables in the estimations are the firm's previous patenting and R&D stock, which have coefficients that are highly significant and have expected signs. The state dependency in the firm's patenting is considerable, as all variables controlling for the firm's past patenting are highly significant. In addition, pre-sample patenting, which controls for the time-invariant firm-specific heterogeneity, is highly significant. Neither the number of employees nor the log number of inventors has a significant effect on future patenting. With respect to the number of inventors, the finding is due to the high correlation between the number of patent applications and inventors.[9]

[9] Not controlling for the firms' past patenting in the estimation would lead us to observe positive coefficient for the number of inventors which is almost identical to the coefficient for number of patents reported in Table 2.

Table 2 Effect of inventor mobility on number of patents at the firm-level

	1	2	3
L.ln(Total inventors)	−0.006	0.002	−0.003
	(0.041)	(0.040)	(0.040)
L.Share of hires	0.143		
	(0.126)		
L.Hires, high past patenting		0.417*	
		(0.218)	
L.Hires, low past patenting		−0.056	
		(0.163)	
L.Hires from high-patenting firms			0.535***
			(0.183)
L.Hires from low-patenting firms			−0.169
			(0.166)
L.Share of new	0.234**	0.238***	0.238***
	(0.091)	(0.090)	(0.090)
L.Share of leavers	−0.469***		
	(0.148)		
L.Leavers, high past patenting		−0.600***	
		(0.210)	
L.Leavers, low past patenting		−0.292	
		(0.209)	
L.Leavers to high-patenting firms			−0.985***
			(0.236)
L.Leavers to low-patenting firms			−0.149
			(0.170)
L.ln(Patents)	0.535***	0.523***	0.521***
	(0.047)	(0.045)	(0.044)
L2.ln(Patents)	0.260***	0.264***	0.272***
	(0.024)	(0.024)	(0.024)
L.No patent dummy	−0.282***	−0.277***	−0.304***
	(0.086)	(0.088)	(0.087)
L2.No patent dummy	−0.463***	−0.465***	−0.450***
	(0.082)	(0.080)	(0.081)
Pre-sample patenting	0.104***	0.105***	0.105***
	(0.023)	(0.022)	(0.023)
No pre-sample patenting dummy	−0.249**	−0.249**	−0.245**
	(0.114)	(0.114)	(0.113)
ln(R&D stock)	0.068***	0.069***	0.068***
	(0.017)	(0.017)	(0.017)
ln(Employees)	−0.001	−0.001	0.001
	(0.014)	(0.014)	(0.014)

Table 2 continued

	1	2	3
Pseudo R-squared	0.282	0.282	0.283
Pseudo Log likelihood	−11633.308	−11629.666	−11620.650

4763 observations. 935 firms. Negative binomial PSM estimation. Dependent variable is the number of patents per year. Standard errors are clustered on firm and are shown in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All estimations include year, industry and country controls and a constant term

Regarding inventor mobility, the coefficient of the share of hires is positive but not significant, as shown in column 1. This result implies that recently hired inventors are not significantly more productive for a firm's patenting than staying inventors. The coefficient of the share of new inventors is always positive and significant, implying that first-time inventors are associated with higher future patenting. Because these inventors appear in the patent data for the first time, we do not observe any background characteristics of them. Therefore, the background of their positive effect remains unclear. However, the share of leaving inventors has a strongly negative and statistically significant coefficient. Thus, inventors who leave the firm to join another firm imply a considerable negative development in the source firm's future patenting.

In column 2, we separate the mobile inventors with a number of patents above the median value and those with a number below the median value. The results show that hiring inventors with a high number of prior patents is associated with significantly higher future patenting, whereas hiring inventors with few patents does not have a significant effect. Similarly, the number of previous patents by leaving inventors is an important determinant of losses through outbound mobility. Losing productive inventors has a stronger negative effect on future patenting, whereas leaving inventors with few past patents do not have a significant effect.

Next, we more closely examine the characteristics of source and hiring firms. In column 3, we see that inventors who are hired from a high-patenting firm improve the hiring firm's patent output, whereas inventors from a low-patenting firm have no effect on patenting. This finding implies that inventors from high-patenting firms transfer more valuable knowledge. We also note that leaving inventors have a more negative effect on future patenting when they leave to a high-patenting firm. Leavers who obtain employment in low-patenting firms do not significantly affect patenting. Leavers who become employed in high-patenting firms should imply a greater potential for reverse knowledge spillovers. However, their effect is strongly negative, which does not support the reverse knowledge spillovers argument. An alternative explanation is that losing these inventors to high-patenting firm entails greater loss in competitiveness or that these inventors are more productive and, thus, their loss leads to a greater loss in skills. This result might imply that firms that intensively invest in patenting are better able to hire the best inventors from their competitors. However, when we divided mobile inventors both by inventors' and firms' prior patenting and re-estimate the model,[10] the estimation results confirmed that both the investor's and the hiring firm's prior patenting influence the effects of inbound and outbound mobility. The correlations in "Appendix Table 8" show that inventors who move to high-patenting firms are also somewhat more likely to have many prior patents. Therefore,

[10] Results are available upon request.

Table 3 Effect of inventor mobility and technological similarity on number of patents

	4	5
L.ln(Total inventors)	−0.010	−0.007
	(0.042)	(0.040)
L.Hires with core tech. expertise	−0.021	
	(0.197)	
L.Hires with related tech. expertise	0.205	
	(0.261)	
L.Hires with non-core tech. expertise	0.342*	
	(0.191)	
L.Hires from tech. similar		0.003
		(0.197)
L.Hires from tech. related		0.359**
		(0.182)
L.Hires from tech. different		0.028
		(0.255)
L.Share of new	0.228**	0.239***
	(0.091)	(0.091)
L.Leavers with core tech. expertise	−0.484**	
	(0.218)	
L.Leavers with related tech. expertise	−0.654**	
	(0.260)	
L.Leavers with non-core tech. expertise	−0.209	
	(0.268)	
L.Leavers to tech. similar		−0.424**
		(0.199)
L.Leavers to tech. related		−0.720**
		(0.290)
L.Leavers to tech. different		−0.083
		(0.252)
L.ln(Patents)	0.538***	0.534***
	(0.048)	(0.045)
L2.ln(Patents)	0.261***	0.264***
	(0.024)	(0.024)
L.No patent dummy	−0.289***	−0.282***
	(0.087)	(0.087)
L2.No patent dummy	−0.458***	−0.463***
	(0.082)	(0.081)
Pre-sample patenting	0.104***	0.105***
	(0.023)	(0.023)
No pre-sample patenting dummy	−0.247**	−0.244**
	(0.116)	(0.113)
ln(R&D stock)	0.069***	0.067***
	(0.017)	(0.017)

Table 3 continued

	4	5
ln(Employees)	−0.002	−0.001
	(0.014)	(0.014)
Pseudo R-squared	0.282	0.282
Pseudo Log likelihood	−11630.741	−11629.533

4763 observations. 935 firms. Negative binomial PSM estimation. Dependent variable is the number of patents per year. Standard errors are clustered on firm and are shown in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All estimations include year, industry and country controls and a constant term

at least based on observable inventor productivity, the poaching of best employees may partially explain why losing inventors to high-patenting firms decreases patenting; however, it does not explain it completely.

Table 3 shows the hiring firm's technological similarity with the source firms and the hired inventors' prior expertise. The technological fit with the mobile inventors appears to impact the results of mobility. The results of model 4 show that hiring inventors who contribute different technological expertise is helpful for future patenting, whereas those who provide additional core expertise do not have a statistically significant effect on patenting. The technological field of the source firm also has a significant effect (model 5). Inventors who move to the firm from an employer with a related main field of technology significantly help to increase future patenting. Thus, firms seem to benefit from technologically different but not too distant knowledge. Inventors from firms in the same technological field or a completely different field have no significant effect on patenting, i.e., they are equally productive as inventors staying at the firm. Based on these results, it also appears that the source firm characteristics are more significant than individual inventor characteristics in explaining gains from mobility.

With respect to outbound mobility, the results presented in Table 3 show that leaving inventors that have worked in the firm's core field of technology have a strongly negative effect on the firm's patenting, whereas leaving inventors with non-core technological experience do not have a significant effect.[11] The results are in line with the view that losing inventors with core competences is more likely to degrade a firm's knowledge base and innovativeness. Leaving inventors with non-core technological experience appear less harmful and also have a more positive effect on the future performance of the hiring firm. Thus, non-core technological knowledge appears less firm-specific and more general in nature, implying wider applicability and easier replacement. However, leavers with non-core technological experience may also reflect the downsizing of non-essential R&D activities.

Moreover, when inventors leave to a firm that operates in the same or a related technological field, the effect on patenting is strongly negative in the source firm. When inventors leave to a firm working in a different technological field, there is no effect. Firms working in the same technological field may be direct competitors of the firm, and the knowledge leaks through outbound mobility are a direct risk to competitiveness. Instead, mobility to technologically different firms does not appear a similar risk and may also

[11] Simultaneously controlling for the mobile inventors' prior productivity does not alter the finding.

Table 4 Marginal effects at means

	1	2	3	4	5
L.Share of hires	0.488				
	(0.435)				
L.Hires, high past patenting		1.426*			
		(0.757)			
L.Hires, low past patenting		−0.192			
		(0.556)			
L.Hires from high-patenting firms			1.826***		
			(0.639)		
L.Hires from low-patenting firms			−0.578		
			(0.568)		
L.Hires with core tech. expertise				−0.072	
				(0.675)	
L.Hires with related tech. expertise				0.703	
				(0.896)	
L.Hires with non-core tech. expertise				1.169*	
				(0.651)	
L.Hires from tech. similar firms					0.009
					(0.672)
L.Hires from tech. related firms					1.228*
					(0.635)
L.Hires from tech. different firms					0.095
					(0.872)
L.Share of new	0.800***	0.814***	0.812***	0.781**	0.815***
	(0.311)	(0.308)	(0.307)	(0.309)	(0.309)
L.Share of leavers	−1.604***				
	(0.519)				
L.Leavers, high past patenting		−2.050***			
		(0.731)			
L.Leavers, low past patenting		−0.998			
		(0.716)			
L.Leavers to high-patenting firms			−3.360***		
			(0.842)		
L.Leavers to low-patenting firms			−0.507		
			(0.581)		
L.Leavers with core tech. expertise				−1.655**	
				(0.755)	
L.Leavers with related tech. expertise				−2.237***	
				(0.903)	
L.Leavers with non-core tech. expertise				−0.716	
				(0.917)	
L.Leavers to tech. similar firms					−1.451**
					(0.683)

Table 4 continued

	1	2	3	4	5
L.Leavers to tech. related firms					−2.461**
					(1.009)
L.Leavers to tech. different firms					−0.284
					(0.861)

4763 observations, 935 firms. Standard errors are shown in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

enable reverse knowledge spillovers and bring complementing technological expertise and connections for the firm.

The coefficients of a negative binomial model do not directly reveal the marginal effects of the explanatory variables. Thus, Table 4 presents the marginal effects of the key explanatory variables, as estimated at the means of covariates. They show how the expected number of patent applications per year changes as the values of the explanatory variables increase. Table 4 shows an increase of up to 1.8 patent applications due to inbound mobility and decrease up to 3.4 patents due to outbound mobility. The average share of hires of all inventors is 0.067, which would imply approximately 0.12 more patent applications per year if inventors are hired from a high-patenting firm when compared with no mobility. Compared to the median number of patents (2 patents per year), the gain from average hiring rate can reach up to a 6 % increase in patenting. Counted similarly, average outbound mobility may decrease patenting up to 0.16 patents per year. Thus, the knowledge spillovers through mobility appear somewhat limited in size, and the drawbacks of outbound mobility may exceed the benefits.

5.2 Robustness

We account for the heterogeneity in the value of patents. Research has well documented that the value of patents is heavily skewed (Lanjouw et al. 1998; Harhoff et al. 1999), and a common solution has been to use patent citations to approximate the patent value. The estimations with quality weighted patent output confirm our main results. The exception is that the role of technological characteristics is less significant in explaining gains from inbound mobility, although the coefficients have similar magnitudes. The results of these estimations are presented in Tables 5 and 6.

We also re-estimated the model using granted patents instead of patent applications as the dependent variable accounting for the concern that firms may use patent filing as a strategic tool and employee mobility may change firms' patenting strategies rather than their inventive output. Granted patents have undergone the patent office's examination process, and firms' strategic choices are likely to confound them less than patent application numbers. However, the granting process may take several years; thus, only the first half of the sample period could be used to re-estimate the model. Overall, using granted patents instead of applications did not change the main results.[12] However, in comparison with our baseline model, the model showed that the effect of inbound mobility was more positive and statistically significant.

[12] Results of additional robustness tests are available upon request.

Table 5 Effect of inventor mobility on citation-weighted patents

	1	2	3
L.ln(Total inventors)	0.051	0.057	0.055
	(0.043)	(0.044)	(0.044)
L.Share of hires	0.116		
	(0.147)		
L.Hires, high past patenting		0.381*	
		(0.225)	
L.Hires, low past patenting		−0.065	
		(0.202)	
L.Hires from high-patenting firms			0.532***
			(0.194)
L.Hires from low-patenting firms			−0.182
			(0.204)
L.Share of new	0.250**	0.254**	0.250**
	(0.106)	(0.106)	(0.106)
L.Share of leavers	−0.528***		
	(0.161)		
L.Leavers, high past patenting		−0.672***	
		(0.223)	
L.Leavers, low past patenting		−0.332	
		(0.236)	
L.Leavers to high-patenting firms			−1.126***
			(0.259)
L.Leavers to low-patenting firms			−0.230
			(0.190)
L.ln(Citation-weighted patents)	0.456***	0.446***	0.440***
	(0.039)	(0.038)	(0.038)
L2.ln(Citation-weighted patents)	0.273***	0.276***	0.284***
	(0.029)	(0.030)	(0.030)
No patent dummy	−0.083	−0.080	−0.108
	(0.102)	(0.103)	(0.102)
L2.No patent dummy	−0.334***	−0.335***	−0.319***
	(0.094)	(0.094)	(0.095)
Pre-sample citation-weighted patenting	0.105***	0.106***	0.105***
	(0.032)	(0.032)	(0.032)
No pre-sample patenting dummy	−0.219	−0.220	−0.218
	(0.148)	(0.148)	(0.147)
ln(R&D stock)	0.096***	0.097***	0.097***
	(0.021)	(0.021)	(0.021)
ln(Employees)	−0.029	−0.030*	−0.028
	(0.018)	(0.018)	(0.018)
Pseudo R-squared	0.233	0.234	0.234

Table 5 continued

	1	2	3
Pseudo Log likelihood	−13363.046	−13360.232	−13352.872

4763 observations. 935 firms. Negative binomial PSM estimation. Dependent variable is the number of citation weighted patents per year. Standard errors are clustered on firm and are shown in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All estimations include year, industry and country controls and a constant term

We also tested the robustness of our results by excluding firms with few patents or a very high number of patents, smallest and largest firms in terms of employees[13] and industries with the highest and lowest patent intensity. The main results and implications remained unchanged. Patent production function was also estimated using longer lags of mobility variables and firms' past patenting. The main findings did not change.

Finally, country-specific estimations of model 1 were conducted. Unfortunately, the number of observations is low for many countries and thus the estimates were often imprecise. However, the point estimates showed that the main findings are replicated in several country-specific estimations, whereas for approximately half of the countries, the results indicate an inverse U-shaped relationship between inbound mobility and patent output (and U-shaped for outbound mobility).[14] Thus, it appears that despite the country-specific differences in labor markets, inventor mobility is quite similarly associated with innovative output in many European countries.

5.3 Identification issues

Despite the abovementioned robustness tests, our results are subject to some endogeneity concerns that do not allow us to make strong causal claims about our results. First, positive assortative matching of firms and inventors is a potential concern (Becker 1973). The most inventive firms may be able to attract the most productive inventors, which could lead us to observe a positive correlation between hiring and patenting. In addition, a negative effect of overall outbound mobility could be partially biased by the fact that less innovative firms may not be able to retain their inventors or may lose their greatest talents. Thus, assortative matching could lead us to overestimate the gains from inbound mobility and the losses from outbound mobility. However, we directly measure the firms' and inventors' past patent productivity to take this issue into account. Despite this approach, unobserved differences could bias our results with respect to overall mobility. However, it is doubtful whether the unobserved differences should be similarly correlated with the technological characteristics and thus bias the effect of inflow and outflow of different and similar technological skills.

Second, the effects of hiring may reflect either research productivity gains or changes in a firm's propensity to patent. For example, firms may use patenting to protect themselves against leaving inventors and adopt a more aggressive patenting strategy (Kim and Marschke 2005). However, the protective patenting hypothesis does not explain, e.g., why

[13] 10th and 90th percentiles are used as cut-off points.

[14] In the whole sample, the point estimates also give some indication of a U-shaped relationship; however, the estimates are statistically insignificant, in contrast to those in Table 2.

Table 6 Effect of inventor mobility and technological similarity on citation-weighted patents

	4	5
L.ln(Total inventors)	0.044	0.049
	(0.043)	(0.043)
L.Hires with core tech. expertise	−0.032	
	(0.237)	
L.Hires with related tech. expertise	0.099	
	(0.344)	
L.Hires with non-core tech. expertise	0.343	
	(0.217)	
L.Hires from tech. similar		−0.011
		(0.230)
L.Hires from tech. related		0.320*
		(0.194)
L.Hires from tech. different		0.028
		(0.297)
L.Share of new	0.245**	0.253**
	(0.106)	(0.106)
L.Leavers with core tech. expertise	−0.595**	
	(0.238)	
L.Leavers with related tech. expertise	−0.769***	
	(0.280)	
L.Leavers with non-core tech. expertise	−0.084	
	(0.334)	
L.Leavers to tech. similar		−0.632***
		(0.221)
L.Leavers to tech. related		−0.687**
		(0.331)
L.Leavers to tech. different		0.067
		(0.334)
L.ln(Citation-weighted patents)	0.461***	0.454***
	(0.040)	(0.039)
L2.ln(Citation-weighted patents)	0.274***	0.279***
	(0.029)	(0.029)
No patent dummy	−0.089	−0.085
	(0.103)	(0.103)
L2.No patent dummy	−0.330***	−0.330***
	(0.094)	(0.094)
Pre-sample citation-weighted patenting	0.105***	0.105***
	(0.033)	(0.032)
No pre-sample patenting dummy	−0.219	−0.213
	(0.149)	(0.148)
ln(R&D stock)	0.097***	0.095***
	(0.021)	(0.021)
ln(Employees)	−0.031*	−0.029*

Table 6 continued

	4	5
	(0.018)	(0.018)
Pseudo R-squared	0.234	0.234
Pseudo Log likelihood	−13359.936	−13359.098

4763 observations. 935 firms. Negative binomial PSM estimation. Dependent variable is the number of citation weighted patents per year. Standard errors are clustered on firm and are shown in parentheses

* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$. All estimations include year, industry and country controls and a constant term

hiring only from technologically different firms increases patenting. In fact, protective patenting could better explain why mobility to and from technologically similar firms, i.e., possible competitors, would increase patenting, but our findings point to the contrary conclusion. Moreover, Kim and Marschke (2005) suggest that a high degree of outbound mobility should have a positive effect on patenting because of higher patenting propensity; however, our results point to a negative overall effect. Thus, while we cannot separate whether mobility affects patent productivity or propensity to patent, the protective patenting hypothesis does not seem to explain our main findings.

Third, there is a potential selection bias because we observe only inventors who patent in their new employer's service. Firms with lower patenting propensity may thus appear to have lower inventor mobility and lower patenting. However, we control for firm effects and, thus, take time-invariant patenting propensity into account. The selection also leads us to observe only more successful mobility, whereas less successful mobility, i.e., mobility that does not lead to patents, remains unobserved. This could lead us to overestimate the gains from mobility. However, the overall effect of inbound mobility is not statistically significant, and it is not clear whether the partial observation of mobility should affect the dependency of results on technological fields or level of prior patenting.

6 Conclusions

Although labor mobility is heralded as a driver of knowledge diffusion, innovation and economic growth, detailed evidence on its effects on firm-level innovation performance remains incomplete and fragmented. This paper provides new empirical evidence on the importance of labor mobility for the innovation output of firms by analyzing the mobility of patent inventors. The study also contributes by shedding light on the role of mobile inventors' and source firms' characteristics in enabling knowledge spillovers. Prior literature using patent citations has identified inventor mobility as a source of knowledge spillovers. Our results confirm these findings and show that inventor mobility not only affects citation patterns but also has a significant effect on firm-level patenting outcomes.

The empirical results show that, overall, recently hired patent inventors are not significantly more productive than staying inventors in terms of firms' future patent output. Instead, the gains depend on the characteristics of hired inventors and their source firms, and the latter characteristics appear relatively more important. Hiring inventors with many prior patents and hiring inventors from high-patenting firms results in a significant improvement in firms' future patenting. These results imply that these mobile inventors possess more valuable skills and expertise and are able to transfer valuable technological knowledge from their previous employers. The estimated marginal effects imply up to a 0.12 increase in patent applications per year at an average rate of hiring compared with no mobility. Among the sample firms, the median number of patents per year is 2, thus implying a relatively modest 6 % increase in patenting.

Moreover, we find that inventors with different technological expertise and inventors from technologically related but not too similar firms bring complementary skills and knowledge that benefit firms' future innovation performance. This finding is in line with earlier studies on labor mobility and firm productivity (Timmermans and Boschma 2014; Boschma et al. 2009). Non-compete and non-disclosure agreements may be one explanation why it is more beneficial to hire inventors with different technological expertise, because these agreements may hinder inventors from transferring valuable knowledge to technologically similar firms. These agreements are common for key employees in many European countries, although the national laws differ, e.g., with respect to requirements for employee compensation and limitations in duration and geographic scope of non-compete agreements.

In addition, we analyze inventors who leave the firm and the characteristics of firms that hire them. Outbound mobility is found to negatively contribute to firms' future patent output which can cancel the gains of inbound mobility. While outbound mobility can be advantageous in terms of reverse spillovers and rational downsizing of unproductive R&D, on average, these benefits cannot compensate for the outflow of skills and expertise. The negative relationship is stronger when the leaving inventors have been more productive in the past, have worked in the firm's core field of technology or move to a technologically similar firm. These inventors appear to possess skills central to the firm's innovation activities. Therefore, when they leave, the firm experiences deteriorating innovation performance. Inventors possessing non-core technological expertise and inventors leaving to technologically different firms do not have a significant negative effect on future patenting. The lack of a negative effect may be explained by the less firm-specific, and thus more easily replaced knowledge that these inventors possess. These inventors may also continue to act as a source of complementing technological knowledge through reverse knowledge spillovers. Unfortunately, the present study cannot separate these effects; however, this issue and related questions provide interesting avenues for future research to extend the present study.

Moreover, the results of the present study show that inventors who leave the firm to join a low-patenting firm have no effect on future patenting, while leavers who obtain employment in high-patenting firms have a strongly negative effect. This finding does not point to significant reverse knowledge spillovers highlighted in prior studies; rather, it indicates knowledge leaks and loss in competitiveness. Our analysis indicates that this finding may be partially, but not entirely, due to better firms poaching most productive inventors. Overall, our results do not support the view that the reverse knowledge spillovers could compensate the loss of skills and inventor expertise associated with outbound mobility. In this respect, our results differ from those of previous studies, most notably from the results of Kaiser et al. (2015). However, they analyze on average smaller firms, which also apply for fewer patents. Smaller firms may be able to gain more from mobility (Rao and Drazin 2002). Moreover, outbound knowledge spillovers may pose a more serious risk of knowledge leaks for the larger firms analyzed in the present study. These differences may partially explain the differing results.

Caution is required when interpreting the causality of our results. Firms can choose who they hire, and even though we can observe and measure inventors' and firms' past patent productivity, it is possible that positive assortative matching on unobservable characteristics could bias our results. The protective patenting hypothesis (Kim and Marschke 2005) cannot, however, explain our main findings. Moreover, further research is needed to confirm whether our results also apply to mobility of other knowledge workers besides patent inventors.

Finally, our results have practical implications for firms and the entire economy. We show that employee mobility can help to provide different kind of technological knowledge for the firms. Thus, mobility can be beneficial for firm-level innovativeness and may improve firm productivity and growth in the economy, as also argued in the prior literature. Nevertheless, the negative effect of outbound mobility may also cause the firms to invest less in R&D and in their employees because these investments are lost if employees leave. However, this study analyzes firm-level performance effects and ignores the benefits of creative destruction at the macroeconomic level. More innovative firms are likely to win market shares and grow in size, implying that labor market flexibility should be considered a tool to facilitate knowledge transfer between firms. Beneficial effects of policies also depend on future market restructuring through creative destruction because the immediate effects on continuing firms are not unambiguous.

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Appendix

See Tables 7–9.

Table 7 Technological classification using 2-digit IPC codes

Class	2-digit IPC	Share of patents
1	A01	0.015
2	A21, A22, A23, A24	0.008
3	A41, A42, A42, A44, A45, A46	0.003
4	A47, A63	0.009
5	A61, A62	0.109
6	B01	0.018
7	B02, B03, B04, B05, B06, B07, B08, B090	0.008
8	B21, B22	0.006
9	B23	0.008
10	B24, B24, B26, B27, B28	0.008
11	B29	0.010
12	B30, B31, B32	0.004
13	B41, B42, B43, B44	0.010
14	B60	0.045
15	B61, B62, B63, B64	0.017
16	B65, B66, B67, B68	0.020

Table 7 continued

Class	2-digit IPC	Share of patents
17	B81, B82	0.004
18	C01, C06	0.001
19	C02	0.006
20	C03, C04	0.062
21	C05, C07	0.034
22	C08	0.017
23	C09	0.003
24	C10	0.006
25	C11	0.022
26	C12, C13	0.004
27	C21, C22	0.006
28	C23	0.002
29	C25, C30	0.010
30	C40	0.009
31	D01, D02, D03, D04, D05, D06, D07, C14	0.006
32	D21	0.006
33	E01, E02, E03, E04	0.003
34	E05, E06	0.046
35	E21	0.034
36	F01, F02, F03, F04	0.021
37	F15, F16, F17	0.003
38	F21, F22, F23, F24, F25, F26, F27, F28	0.053
39	F41, F42	0.012
40	G01	0.008
41	G02	0.011
42	G03	0.045
43	G04, G05	0.019
44	G06	0.014
45	G07, G08, G09, G10, G12	0.001
46	G11	0.066
47	G21	0.024
48	H01	0.017
49	H02	0.111
50	H03	0.014
51	H04	0.001
52	H05	0.000

Table 8 Correlation matrix for variables measuring inbound inventor mobility

	Variable	1	2	3	4	5	6	7	8	9	10	11	12	13	14
1	Patents	1													
2	Number of inventors	0.976	1												
3	Share of hires	0.003	0.002	1											
4	Hires, high past patenting	0.016	0.015	0.653	1										
5	Hires, low past patenting	−0.009	−0.010	0.806	0.077	1									
6	Hires from high-patenting firms	0.041	0.040	0.637	0.498	0.449	1								
7	Hires from low-patenting firms	−0.029	−0.030	0.785	0.446	0.684	0.022	1							
8	Hires with core tech. expertise	−0.021	−0.026	0.708	0.484	0.552	0.310	0.668	1						
9	Hires with related tech. expertise	0.026	0.029	0.513	0.447	0.326	0.430	0.319	0.078	1					
10	Hires with non-core tech. expertise	0.013	0.014	0.563	0.255	0.542	0.461	0.359	−0.029	0.104	1				
11	Hires from tech. similar firms	−0.005	−0.011	0.687	0.471	0.536	0.276	0.669	0.840	0.193	0.053	1			
12	Hires from tech. related firms	0.012	0.017	0.619	0.441	0.470	0.680	0.256	0.200	0.557	0.473	−0.004	1		
13	Hires from tech. different firms	−0.003	−0.003	0.366	0.136	0.375	0.063	0.424	−0.009	0.090	0.620	−0.024	0.010	1	
14	Share of new	0.075	0.081	0.057	0.026	0.054	0.048	0.035	0.012	0.043	0.058	0.016	0.045	0.046	1

Table 9 Correlation matrix for variables measuring outbound inventor mobility

	Variable	1	2	3	4	5	6	7	8	9	10	11	12
1	Patents	1											
2	Share of leavers	0.021	1										
3	Leavers, high past patenting	0.022	0.829	1									
4	Leavers, low past patenting	0.007	0.641	0.102	1								
5	Leavers to high-patenting firms	0.069	0.598	0.539	0.324	1							
6	Leavers to low-patenting firms	−0.023	0.824	0.652	0.570	0.039	1						
7	Leavers with core tech. expertise	−0.012	0.747	0.633	0.460	0.377	0.665	1					
8	Leavers with related tech. expertise	0.025	0.586	0.556	0.279	0.417	0.436	0.067	1				
9	Leavers with non-core tech. expertise	0.045	0.449	0.259	0.442	0.314	0.338	−0.010	0.127	1			
10	Leavers to tech. similar firms	0.010	0.706	0.559	0.487	0.394	0.601	0.748	0.217	0.159	1		
11	Leavers to tech. related firms	0.027	0.607	0.541	0.337	0.540	0.375	0.348	0.485	0.303	0.039	1	
12	Leavers to tech. different firms	−0.001	0.438	0.354	0.292	0.069	0.497	0.099	0.411	0.420	−0.006	0.060	1

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