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DISCUSSION PAPER

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Intended and Unintended Knowledge Spillovers in Innovation

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Intended and Unintended Knowledge Spillovers in Innovation

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Abstract

Firms can use different sources of external knowledge for developing and implementing innovations. Some knowledge is provided deliberately by the source and constitutes intended knowledge spillovers, e.g., knowledge disclosed in publications or patent files. Other sources represent unintended knowledge spillovers, such as reverse engineering of technologies or hiring workers from other firms. Based on data from the Community Innovation Survey, this paper analyses the role of different types of intended and unintended knowledge spillovers for innovation output at the firm level. Among intended knowledge spillovers, using knowledge from patents shows the strongest link to innovation output, particularly in case of product innovations with a high degree of novelty (world-first innovations). Knowledge from publications is not associated with a significantly higher innovation output. Among unintended spillovers, both reverse engineering and hiring of workers positively contribute to innovation output of firms, with stronger effects for reverse engineering. Interestingly, there is a strong link between reverse engineering and process innovation output (unit cost reduction), which reflects the fact that firms using this knowledge source operate in a market environment characterized by high price competition, which incentivizes an innovation strategy based on cost efficiency.

JEL-Classification: O31, O33, D83

Keywords: Knowledge sources, innovation output, intended knowledge spillovers, unintended knowledge spillovers, reverse engineering

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1 Introduction

Knowledge spillovers have been intensively studied in the economics of innovation for many years. The foundations were laid by Marshall (1920) and Arrow (1962), among others, and the findings have been applied in several areas. Significant examples are endogenous growth theory (e.g. Romer 1986, Aghion and Howitt 2009, Grossman and Helpman 1994, Aghion and Jaravel 2015), microeconomic analysis of incentives for R&D (de Bondt 1997) or welfare aspects of R&D (cooperative versus non-cooperative) with spillovers (d'Aspremont and Jacquemin 1998). In international economics, knowledge spillovers of foreign direct investment on the productivity of domestic firms are considered.[1] Many of the contributions are empirical studies on the determinants of knowledge spillovers like regional location and technological linkages as well as their effects on firms. However, there are few studies that examine how ideas actually find their way to other firms.

We analyze empirically which sources firms choose when they intend to benefit from knowledge spillovers for their own innovation activities. We differentiate between spillovers that are intended by the generators of knowledge on the one hand, and not intended spillovers on the other (Arvanitis et al. 2020). We examine the role of these different sources of spillovers for innovation results in the firms receiving the knowledge spillovers.

There are many empirical studies on knowledge spillovers. Prominent examples include Jaffe (1986), Cohen and Levinthal (1989), Grilliches (1992), Cassiman and Veugelers (2002), Audretsch and Feldman (2006), Bloom et al. (2013), Arvanitis et al. (2020), Audretsch and Belitzki (2022), Banal-Estanol et al. (2022). These studies often use a weighted sum of knowledge capital relevant to individual firms. Knowledge capital is frequently measured by accumulated R&D expenditures or the patent stock of other firms in sectors, regions or fields of technology related to those of the focus firm. One way to derive weights is through a technological linkage matrix. The approach of Jaffe (1986) is to link firms by overlaps of the technology classes to which their patents are assigned (technological "distance"). An alternative weighting is to link firms by their geographical proximity. Geographical proximity provides an opportunity to better exchange knowledge (e.g. Audretsch and Feldman 2006, Feldman 1999). In this literature, intra-industry and inter-industry spillovers are examined.

[1] The results are mixed. See among others Aitken and Harrison (1998), Javorcik (2004), Haskel et al. (2007), Blalock and Gertler (2008), Liu (2008), Gorodnichenko et al. (2014), Lu et al. (2017), Khachoo et al. (2018), Stojcic and Orlic (2020).

Some studies show that spillovers have a positive impact on profitability of the receiving firms (Czarnitzki und Kraft 2012, Tseng 2022).

There are some studies which explicitly consider spillover sources (Czarnitzki and Kraft 2012, Capelli et al. 2014, Terjesen and Patel 2017, Demircioglu et al. 2019, Audretsch and Belitzki 2022). Information on spillovers usually comes from surveys in which firms were asked whether they have used information from various external sources and how important this information was (e.g. to complete a certain innovation activity). The possible spillover sources are often differentiated by the position along value chains (e.g. competitors, suppliers, customers) or by the institutional sector of knowledge providers (e.g. consultants, commercial labs, private R&D service providers, universities or government research labs, see e.g. Frenz and Ietto-Gillies 2009, Czarnitzki and Kraft 2012, Capelli et al. 2014, Terjesen and Patel 2017, Demircioglu et al. 2019, Audretsch and Belitzki 2022).

The approach used in this paper is to separate external knowledge sources used by a firm by intended and unintended sources of spillovers and to empirically test the significance of the two knowledge sources for firms' innovation results. Levin et al. (1987) and Harabi (1997) come closest to our approach. Levin et al. (1987) surveyed 650 high-level R&D executives on various topics including channels of knowledge spillover. They ask about the importance of the following sources of knowledge: licensing technology, patent disclosures, publications or technical meetings, conversations with employees of innovating firms, hiring R&D employees from innovating firms, reverse engineering of product and independent R&D. The importance of these sources of knowledge is assessed by means of a seven point Likert scale. The most important sources are independent R&D, licensing technology and reverse engineering.

The study by Harabi (1997) has a similar structure. 358 experts in Switzerland were asked about the importance of various sources of knowledge. The knowledge sources are taken from Levin et al. (1987). The ranking of the most important sources of knowledge are independent R&D, reverse engineering of product and publications or technical meetings. Several studies investigate in particular the role of labor mobility and innovation.[2]

Similar to Levin et al. (1987) and Harabi (1997), we consider several spillovers sources, but in contrast to their approach we combine the use of these sources with firm data on innovation

[2] See e.g. Görg and Strobl (2005), Moen (2005), Maliranta et al. (2008), Stoyanev and Zubanov (2012), Kaiser et al. (2015), Braunherjelm et al. (2018), Serafinelli (2019), Castillo et al. (2020) and Ali-Yrkkö et al. (2022).

results. We distinguish three types of intended knowledge spillovers (trade fairs, trade journals and other publications, and patent files), and two types of unintended spillovers (reverse engineering, hiring of employees who bring along relevant know-how from other firms). Specifically, we examine the influence of the different knowledge sources on the introduction of an innovation and, in the next step, the role they play for the success of the innovations. Success is measured by the share of firms' sales obtained from new products, and by the extent to which unit costs of production have been reduced through process innovations. For product innovation, we separate incremental innovations (imitations) from innovations that are new for the market the firm serves, and further distinguish regional market novelties from world-first innovations (radical innovations).

A focus of our research is on reverse engineering since little research has been done on this spillover source. Neither the characteristics of the firms that use this form of knowledge acquisition, nor the effects of this source on innovation have been analyzed extensively yet. This study aims to add some empirical evidence on the role of reverse engineering for innovation. For this purpose, we investigate which corporate strategies and which types of market environment are linked to the use of the different spillover sources. This is a relevant information for all spillover sources, but it is of particular interest for reverse engineering firms to explain their innovation behavior.

2 Motivation and Theoretical Background

The significance of spillovers is well documented in the literature. Our focus is on the different ways of accessing external knowledge and how important these external sources are for a firm's innovation performance. A key contribution of this study is to separate between into intended and unintended knowledge transfer. Some knowledge sources are made freely accessible (e.g. publications), implying that the dissemination of knowledge is intended by the knowledge provider. Other knowledge sources are not intended by the creators of the knowledge to be used by other firms (in particular not by competitors). However, such kind of spillovers clearly exist. We use five variables, of which three represent intended knowledge sharing and two unintended knowledge sharing.

2.1 Sources of intended spillovers

We consider three main types of knowledge sources that provide intended spillovers to other firms: trade fairs, trade journals and other publications, and patent files. Trade fairs represent an intended spillover sources since exhibitors deliberately go to trade fairs to inform about their products and technologies, aiming to increase their sales. By doing so, knowledge may be revealed that might be of use for other firms. Although the knowledge that can be obtained at trade fairs is likely to be limited since it is difficult to identify critical technical details about products from just viewing them, there is evidence of the importance of trade fairs for both increasing the sales performance of exhibitors and the diffusion of innovations shown at trade fairs (Seringhaus and Rosson 2001, Kerin and Cron 1987, Bathelt 2017). Firms presenting innovations or new technologies at trade fairs will therefore have to balance between the disclosing of information to spur sales, and to restrict the detail of information that is presented at trade fairs.

A second source for intended knowledge spillovers are trade journals and other publications about new products, new technologies or new research findings. While firms are usually not expected to publish results of their R&D activities in publicly available journals, recent research has shown that there is a significant publication activity by authors working at firms (Blind et al. 2022). The motivation for. Nevertheless, this can still provide a stimulus for innovation efforts by other firms.

Another potential source of knowledge are patent files. Patent files contain detailed information about the technical characteristics of inventions. Patent files are disclosed to the public (usually 18 months after filing) by patent authorities in order to prevent unnecessary parallel research and to avoid possible patent infringements.

The patent has the purpose to protect against imitations by granting a monopoly right for using the technology described in the patent for a limited period of time. The use of patents for inventions varies (partly depending on the particular industry) and some firms rely more on secrecy, market leadership or advance on the learning curve. The review of patent files is certainly useful before starting own innovation efforts in a specific area. It is also possible to obtain ideas for further developments or alternative paths for solving a technical problem.

2.2 Sources of unintended spillovers

Firms can also try to gain access to knowledge that is not planned to be disclosed to others. Using such knowledge constitutes unintended spillovers from the knowledge producers' point of view. Such sources of knowledge may be particularly interesting for the knowledge user as by using this knowledge, they may challenge the innovations of the firms that produced the knowledge, e.g. by copying an innovative idea, or by improving an existing technical solution.

One type of an unintended knowledge source is reverse engineering. Reverse engineering refers to the reconstruction of products (including process technology). By disassembling the products, the technical properties can be identified. With this knowledge, in many cases the product can be imitated, but also improvements and further developments can be induced (Zhang and Zhou 2016). Reverse engineering seems to be a convenient way to reduce R&D costs in product development.

Reverse engineering must not necessarily be limited to product innovation, although the starting point is a particular product. The innovator usually has a first-mover reputation advantage over the second-mover imitator. Therefore the reverse engineering firm must somehow offset this disadvantage at the market and this is frequently realized by a lower price. This lower price might be the result of cost savings because reverse engineering in all likelihood will be cheaper than the R&D expenditures that the innovator had to bear. In addition, the imitator might optimize the production technology to lower costs and therefore reverse engineering may well imply an up-to date technology and process innovation. Nathan and Sarkar (2014) point out that reverse engineering involves process innovation to make the product cheaper. Similarly Zhang and Zhou (2016) report that Chinese firms invest much in advanced overseas technologies, as this is necessary for successful reverse engineering activity.

A second source for unintended knowledge spillovers is hiring of employees who bring along relevant know-how from other firms. The poaching of employees with specific knowledge on innovations can help to accelerate the success of a company's own research activities. Not all attempts to poach employees are permitted. For example, they are not permitted if they are intended to deliberately weaken direct competitors. Firms can prevent their employees from switching to competing companies by including non-competition clauses and confidentiality agreements in their employment contracts.

3 Data and Methodology

3.1 Data

Our data basis is the German part of the Community Innovation Survey (CIS). The German CIS is a panel survey conducted annually by the Center for European Economic Research

(ZEW, Mannheim, Germany) on behalf of the German Federal Government and is also known as Mannheim Innovation Panel (MIP; see Peters and Rammer 2013 for more details on the survey).

The panel survey includes both regular questions (asked in every survey wave) and one-off questions that are included only in a specific survey year. The survey for the reference year 2018 included such a one-off question on various external sources of knowledge that a firm used for its business activities. The question contained eight items of knowledge sources, including the five items that constitute our key explanatory variables: trade fairs, scientific/trade publications, patents, reverse engineering, and employing new staff that bring in know-how from other firms.[3] Our sample consists out of more than 5,000 firms from manufacturing and business-oriented services.

The analysis is conducted in two steps. In the first step, the significance of the five sources of spillovers is analyzed in terms of their contribution to the introduction of a new or improved products on the market (product innovation - *Pd*) or the implementation of a new or improved processes in the firm (process innovation - *Pc*). In the second step, the commercial success of innovations is measured by the share of sales generated by product innovations (*Pd_s*), and the share of unit cost reduction resulting from process innovations (*Pc_s*). In the case of the introduction of innovations, there could be a bias towards large firms. Large firms are very likely to introduce several innovations in each period, but these may be insignificant with respect to the firm's total sales volume or total cost savings. Smaller firms, on the other hand, are less likely to innovate, but in case they do introduce innovations, these may be very significant for the firm's commercial success (see Rammer et al. 2009). The opposite problem occurs when the share of sales generated by new products is used (Audretsch and Belinski 2022). Larger firms tend to have lower shares of sales based on new products, while the share of sales generated by new products can be very high for start-ups and small firms. For this reason, both the incidence of innovation and the magnitude of the economic results obtained from innovation need to be considered. In addition, it is essential to control for firm size and firm age to take into account the different nature of the innovation indicators for small and large as well as young and old firms.

[3] The three other items are: standardization documents, social networks, open source software. Note that the item on employing new staff that bring in know-how was included in the German CIS only, while the other seven items were part of the standard CIS questionnaire.

Product innovations can represent different degrees of novelty, for which different types of knowledge may be relevant. Following Rammer et al. (2022), we distinguish incremental innovations (products new to the firm, but not new to the market - *Incr*) from market novelties (*Mnov*), the latter describing product innovations that were new for the market which is served by the firm. Since some firms may operate on a regionally delineated market only, while others serve the world market, it is useful to take the regional reach of a firm's market into account. We therefore separate world-first innovations (new for the world market - *Wnov*) from market novelties that are only new to a regional market (*Rnov*). For each type of product innovation, we are able to measure their share in total sales (*Incr_s, Mnov_s, Wnov_s, Rnov*_s). For process innovation, no information on the novelty is available. Instead, we distinguish between cost-reducing (*Cost*) and other process innovation (*Othp*), e.g. new processes that improve the quality of the process outcome (see Rammer 2023). As a quantitative output measure, we use the share of unit cost reduction obtained from process innovation (*Cost_s*) (see Piening and Salge 2015).

The share of sales generated by the different types of product innovation is measured for the year 2018 and relates to product innovations introduced during 2016 and 2018. For process innovation, the share of unit cost reduced in 2018 by process innovations introduced during 2016 and 2018 is used as indicator of the commercial success of these innovations.

Our spillover variables are coded as dummy variables with unit value if a firm uses the particular source of knowledge spillover and zero otherwise. The spillover sources are coded as *Fair* for trade fairs, *Publ* for trade journals and other scientific and technical publications, *Patent* for patent specifications, *Reverse* for reverse engineering and *Hiring* for hiring of employees from other firms for the purpose of know-how transfers.

We include several control variables. Total innovation expenditures consist of R&D expenditures as well as various types of non-R&D expenditure related to the development and implementation of product or process innovation such as investment in capital goods and software, acquisition of external knowledge (e.g., patents, and licenses), employee training, expenses for marketing and design, and preparing the production of innovations. Since R&D and non-R&D expenditure are different in nature with respect to the novelty of knowledge associated with the respective activity, and with respect to the uncertainty that the activity will actually contribute to successful innovations, we separate R&D from non-R&D expenditure and measure both in relation to the number of full-time employees (*R&Dint, nR&Dint*).

Other control variables are the log of firm age (*Age*) and the log of the number of full-time employees (*Size*). While it is generally useful to control for age and size heterogeneity, our specific research context requires the inclusion of both variables in order to control for systematic size and age effects on our dependent variables as discussed above. Another important control variable is human capital, since the generation, development and implementation of innovations strongly rests on the skills and creativity of employees. We include human capital intensity (*HC*) as additional control variable, which is defined as the share of employees with a university degree. Finally we consider whether firms are part of an enterprise group (*Group*) as then support from other partners within the group in need or (group-internal) knowledge spillovers are possible.

3.2 Methodology

We use a two-step estimation model. In the first step, we investigate whether the use of the five knowledge sources described above have a significant impact on the introduction of innovations. We distinguish between the different types of product and process innovation described above, using dummy variables that get the value 1 in case a firm has introduced the respective type of innovation during a three-year reference period (2016 to 2018). All estimations are performed by Probit.

In the second step, we analyze the direct economic returns from innovations. Compared to earlier studies on the relation between knowledge sources and innovation outcome by Levin et al. (1987) and Harabi (1997), our study relies on quantitative outcome variables for innovation (sales share, share of cost reduction) instead of expert assessment. As many firms are not innovating and therefore the dependent variable is frequently zero, estimations are based on Tobit.

Firms that use certain knowledge sources are likely to differ systematically from firms not using these sources with respect to certain structural features (e.g., size, human capital). At the same time, these differences may have an impact on the link between external knowledge sourcing and innovation output. In order to control for this likely selection bias, we use a matching model that takes into account observed heterogeneity.[4] We employ a propensity score matching with kernel matching based on a normal (Gaussian) kernel. We match on the

[4] We also tested instrument variable approaches to tackle likely endogeneity issues. Despite using a large number of potential candidates, we were not able to find a strong and theoretically compelling instrument that would have significantly affected the use of unintended knowledge sources, but was unrelated to innovation outcome.

probability to using sources of unintended knowledge spillovers (*UnintKS*) since these two sources are more distinct ways of acquiring external knowledge compared to sources of intended knowledge spillovers, which are used by most firms. 6.3% of the firms in our sample use reverse engineering and 21.5% hiring of employees, while trade fairs are used by 63.7% and publications by 67.1%. Patents are the only source of intended knowledge spillover that is used from a small fraction of firms (10.3%). The matching variables include *Age, Size, HC, Group* and industry dummies as well as several variables that are important determinants of the use of unintended knowledge spillovers. Three variables represent the focus of the firm's competitive strategy on continuous improvement of offering (*CS_impr*), price leadership (*CS_price*) and quality leadership (*CS_qual*). Firms following such competitive strategies are likely to look for external knowledge from competitors that they do not want to disclose. Another set of variables captures the competitive environment with respect to characteristics of the firm's main product market, based on the firm managers' assessment of the relevance of different product market characteristics. We consider the role of product aging (*PM_aging*, i.e., short product life cycles), threat by market entrants (*PM_entry*), the ease to which product can be substituted by competitors (*PM_subst*), and price elasticity of demand (PM*_prelas*). Finally, we consider the role of financial constraints since firms with a limited access to external financing may have to rely more on knowledge from external sources. We use a dummy variable that indicates whether a firm has tried to obtain credit financing but was refused by the bank, or whether a firm did refrain from applying for credits because the attempt was considered to be unpromising (*FC_cred*). All variables are taken from respective questions in the German CIS. The results of the matching model are reported in Table 6 in the Appendix. Definitions and descriptive statistics for all model variables are shown in Table 1.

Table 1: Definition and descriptive statistics of model variables

Variable	Definition	Mean	Std.Dev.	Min	Max
Pd	1 if product innovation during 2016 and 2018, 0 otherwise	0.402	0.490	0	1
Incr	1 if product innovation only new to the firm during 2016 and 2018, 0 otherwise	0.314	0.464	0	1
Mnov	1 if product innovation new to the market during 2016 and 2018, 0 otherwise	0.137	0.344	0	1
Rnov	1 if product innovation new to a regional market during 2016 and 2018, 0 otherwise	0.088	0.283	0	1
Wnov	1 if product innovation new to the world market during 2016 and 2018, 0 otherwise	0.055	0.229	0	1
Pc	1 if process innovation during 2016 and 2018, 0 otherwise	0.543	0.498	0	1
Cost	1 if product innovation during 2016 and 2018 that led to unit cost reduction, 0 otherwise	0.164	0.370	0	1
Othpc	1 if product innovation during 2016 and 208 that did not lead to unit cost reduction, 0 otherwise	0.368	0.482	0	1

Pd_s	Sales share of product innovation in 2018	9.749	19.720	0	100
Incr_s	Sales share of product innovation only new to the firm in 2018	9.027	19.159	0	100

Table 1: continued

Variable	Definition	Mean	Std.Dev.	Min	Max
Mnov_s	Sales share of product innovation in 2018 new to the market	2.159	9.749	0	100
Rnov_s	Sales share of product innovation in 2018 new to a regional market	0.944	5.865	0	100
Wnov_s	Sales share of product innovation in 2018 new to the world market	0.872	6.604	0	100
Cost_s	Share of unit cost reduction from process innovation in 2018	1.530	5.085	0	80
Fair	1 if firm acquired external knowledge through trade fairs or exhibitions during 2016 and 2018, 0 otherwise	0.637	0.481	0	1
Publ	1 if firm acquired external knowledge through publications in scientific or trade journals during 2016 and 2018, 0 otherwise	0.671	0.470	0	1
Patent	1 if firm acquired external knowledge from patent files during 2016 and 2018, 0 otherwise	0.109	0.312	0	1
Reverse	1 if firm acquired external knowledge through reverse engineering during 2016 and 2018, 0 otherwise	0.063	0.243	0	1
Hiring	1 if firm acquired external knowledge through employing staff from other firms during 2016 and 2018, 0 otherwise	0.215	0.411	0	1
UnintKS		0.247	0.431	0	1
R&Dint	R&D expenditure per full time employee in 2018 (1,000 €)	2.889	8.332	0	51.82
nR&Dint	Innovation expenditure other than R&D per full time employee in 2018 (1,000 €)	1.293	4.915	0	51.82
Age	Age of the firm in years (log)	3.112	0.852	-0.693	6.039
Size	No. of full time employees (log)	3.105	1.579	-0.693	11.98
HC	Share of graduated employees	0.249	0.291	0	1
Group	1 if a firm belongs to an enterprise group, 0 otherwise	0.283	0.451	0	1
CS_impr	1 if competitive strategy "improving existing offers" is of high or medium importance, 0 otherwise	0.749	0.434	0	1
CS_price	1 if competitive strategy "price leadership" is of high or medium importance, 0 otherwise	0.404	0.491	0	1
CS_qual	1 if competitive strategy "quality leadership" is of high or medium importance, 0 otherwise	0.878	0.327	0	1
PM_aging	1 if competitive environment characteristic "rapid aging of products" applies fully or mainly, 0 otherwise	0.214	0.41	0	1
PM_entry	1 if competitive environment characteristic "high threat of competitive position of incumbents by market entrants" applies fully or mainly, 0 otherwise	0.565	0.496	0	1
PM_subst	1 if competitive environment characteristic "products are easy to be substituted by competitor products" applies fully or mainly, 0 otherwise	0.463	0.499	0	1
PM_prelas	1 if competitive environment characteristic "price increase immediately leads to loss of customers" applies fully or mainly, 0 otherwise	0.457	0.498	0	1
FC_cred	1 if firm unsuccessfully tried to obtain credit financing or if firm refrained from obtaining credit financing because it was unpromising, 0 otherwise	0.071	0.257	0	1

4 Results

4.1 Introduction of innovations

The results of the first stage estimations are presented in Table 2. The spillover variables significantly contribute to explaining the probability to introduce product or process innovation. While these variables are hence important determinants of innovation behavior, interesting differences are found between spillover sources and types of innovations. For product innovations, all knowledge sources except publications are highly significant. The higher the degree of product innovation novelty, the more concentrated is the contribution of external knowledge source. For world-first innovations, patents are the only source that shows a significant effect. For regional market novelties, trade fairs and, to a lesser extent, reverse engineering are further relevant sources. For process innovation, all five knowledge sources are highly significant. This also applies to process innovation that lead to unit cost reduction, whereas other types of process innovation (e.g., those that improve quality characteristics of the process) neither patents nor reverse engineering show a positive effect. For reverse engineering, we even find a negative association, suggesting that firms that apply this way of external knowledge sourcing are less likely to implement this type of process innovation.

When looking at the effects of each of the three sources that provide intended knowledge spillovers, attending trade fairs plays a significant role for incremental product innovation, but is also helpful for market novelties on regional markets. In this case, firms observe new solutions brought on the market by firms from other regions and use this information to introduce similar innovation at the regional market that is served by the firm. Trade fairs are also important sources for process innovation, including both cost-reducing and other process innovation. Trade journals and other scientific and technical publications have a strong effect on process innovation, but almost none on product innovations. Information from patent files is relevant for both product and process innovation, and the only source that drives world-first innovations. Information contained in patents can be used as a stimulus for own further research, which subsequently leads to new technological solutions.

In the case of unintended spillovers, both reverse engineering and hiring of employees are positively linked to product and process innovations. It is striking that both types of knowledge spillovers are more relevant for incremental product innovation. This is plausible, since the non-intentional spillovers transfer already existing knowledge to other firms, and the products developed on this basis are not new to the market, but rather imitations. It is not excluded that further developments also emerge, but according to our results this is not often the case. This is in line with the conclusions of Jirjahn and Kraft (2011).

Table 2: Knowledge sources and introduction of innovations: results of Probit estimations (marginal effects) using PSM-based weights

	Product innovation					Process innovation		
	Total (*Pd*)	Incre-mental (*Incr*)	Market novelty			Total (*Pc*)	Cost reduction (*Cost*)	Other (*Othpc*)
			Total (*Mnov*)	Regional (*Rnov*)	World-first (*Wnov*)			
Fair	0.087*** (0.023)	0.097*** (0.022)	0.035** (0.014)	0.038*** (0.013)	0.006 (0.008)	0.124*** (0.022)	0.043** (0.018)	0.104*** (0.022)
Publ	0.042* (0.025)	0.032 (0.024)	0.010 (0.016)	0.016 (0.014)	-0.007 (0.009)	0.077*** (0.022)	0.042** (0.018)	0.046** (0.022)
Patent	0.171*** (0.035)	0.132*** (0.033)	0.154*** (0.027)	0.080*** (0.023)	0.081*** (0.018)	0.138*** (0.030)	0.063** (0.027)	0.030 (0.032)
Reverse	0.122*** (0.039)	0.143*** (0.037)	0.066** (0.027)	0.045* (0.023)	0.022 (0.014)	0.086*** (0.032)	0.120*** (0.032)	-0.072** (0.034)
Hiring	0.127*** (0.023)	0.119*** (0.022)	0.021 (0.014)	0.020 (0.013)	0.001 (0.007)	0.137*** (0.020)	0.061*** (0.018)	0.057*** (0.021)
R&Dint	0.011*** (0.002)	0.005*** (0.001)	0.004*** (0.001)	0.002*** (0.001)	0.001*** (0.000)	0.003* (0.002)	0.000 (0.001)	0.002* (0.001)
nR&Dint	0.014*** (0.004)	0.007*** (0.002)	0.004*** (0.002)	0.004*** (0.001)	0.001* (0.001)	0.013*** (0.004)	0.007*** (0.002)	0.001 (0.002)
Age	-0.007 (0.011)	0.004 (0.011)	-0.019*** (0.007)	-0.011* (0.006)	-0.008** (0.004)	-0.017 (0.010)	-0.014 (0.009)	-0.004 (0.011)
Size	0.004 (0.008)	0.007 (0.007)	0.003 (0.005)	0.002 (0.004)	0.005** (0.002)	0.027*** (0.007)	0.020*** (0.006)	0.003 (0.008)
HC	0.113*** (0.042)	0.106*** (0.040)	0.018 (0.027)	0.005 (0.023)	0.024* (0.014)	0.020 (0.038)	-0.026 (0.034)	0.054 (0.038)
Group	0.045** (0.021)	0.026 (0.020)	0.030** (0.013)	0.014 (0.012)	0.010 (0.007)	0.020 (0.019)	0.013 (0.016)	0.010 (0.020)
# obs.	5,093	5,093	5,093	5,093	5,093	5,093	5,093	5,093

Marginal effects of Probit models with robust standard errors (standard errors in parentheses). Observations weighted by 1/(1-pscore), pscore being the propensity score derived from a propensity score matching for the probability to use sources for unintended knowledge spillovers (*UnintKS*), using kernel matching based on a normal (Gaussian) kernel and a bandwidth parameter of 0.06. All models include industry fixed-effects.
***, **, *: significant at p<0.01, p<0.05, and p<0.1, respectively.

It is also striking that both unintended sources also have an impact on process innovations. This is not surprising for hiring of employees, but less obvious for reverse engineering. However, as noted above, there is evidence in the literature that firms with this strategy innovate in the production process. We will discuss this point in more detail later in section 4.5.

4.2 Commercial success of innovations

The results of the second stage estimations for quantitative measures of innovation success are reported in Table 3. In general, the effects of knowledge sources on different types of quantitative measures of innovation output are very similar to the results for the probability to produce a certain type of innovation output. Again, we find a strong link between four knowledge sources (trade fairs, patents, reverse engineering, hiring of staff) and product innovation. For publications, we find no link to product innovation output, but only a weak one for unit cost reduction from process innovation. The other four knowledge source are also positively linked to obtaining cost savings owing to process innovation.

Table 3: Knowledge sources and commercial success of innovations: results of Tobit estimations using PSM-based weights

	Sales share of product innovations					Share of unit cost reduction from process innovation (*Cost_s*)
	Total (*Pd_s*)	Incremental (*Incr_s*)	Market novelties			
			Total (*Mnov*_s)	Regional (*Rnov_s*)	World-first (*Wnov_s*)	
Fair	7.097***	7.016***	5.145**	6.748***	1.191	3.280***
	(1.868)	(1.869)	(2.611)	(2.618)	(3.731)	(1.033)
Publ	3.042	3.029	1.292	5.016*	-3.300	1.850*
	(1.879)	(1.878)	(2.542)	(2.561)	(3.682)	(1.026)
Patent	8.509***	8.228***	15.089***	7.719***	20.302***	2.813**
	(2.054)	(2.063)	(2.559)	(2.652)	(3.462)	(1.212)
Reverse	8.704***	8.559***	6.506**	5.162*	7.837*	5.856***
	(2.374)	(2.380)	(3.118)	(2.889)	(4.171)	(1.389)
Hiring	7.435***	7.404***	2.823	2.617	0.679	3.069***
	(1.537)	(1.542)	(2.005)	(1.881)	(2.871)	(0.890)
R&Dint	0.705***	0.688***	0.643***	0.388***	0.650***	0.049
	(0.096)	(0.095)	(0.110)	(0.108)	(0.125)	(0.057)
nR&Dint	0.865***	0.867***	0.856***	0.548***	0.653**	0.438***
	(0.203)	(0.202)	(0.239)	(0.174)	(0.299)	(0.104)
Age	-2.818***	-2.898***	-3.328***	-1.751	-2.574*	-1.215***
	(0.866)	(0.867)	(1.060)	(1.106)	(1.422)	(0.450)
Size	-1.082**	-1.080**	-0.286	-0.612	0.533	0.456
	(0.503)	(0.505)	(0.607)	(0.612)	(0.803)	(0.287)
HC	13.295***	13.572***	9.253**	2.178	16.609**	0.242
	(3.177)	(3.177)	(4.411)	(3.581)	(7.221)	(1.826)
Group	1.480	1.265	3.467*	0.835	5.558*	0.144
	(1.510)	(1.514)	(2.000)	(1.882)	(2.922)	(0.847)
# obs.	4,998	4,998	4,998	4,998	4,998	4,998

Estimated coefficients of weighted Tobit models with robust standard errors (standard errors in parentheses). Observations weighted by 1/(1-pscore), pscore being the propensity score derived from a propensity score matching for the probability to use sources for unintended knowledge spillovers (*UnintKS*), using kernel matching based on a normal (Gaussian) kernel and a bandwidth parameter of 0.06. All models include industry fixed-effects.
***, **, *: significant at p<0.01, p<0.05, and p<0.1, respectively.

For product innovation with a higher degree of novelty, patents are again the most important source of external knowledge. This is particularly true for sales generated by world-first innovation. For regional market novelties, knowledge gained at trade fairs is a similarly important source. The sales share from incremental product innovation is positively affected by four of the five knowledge sources at a similar magnitude. Scientific and trade publications represent the only knowledge source that is not significantly linked to product innovation output. This result may be linked to the fact that the majority of firms (67.1%) are using this source. Knowledge contained in any form of scientific or trade publication seems to be a too general source to make a difference in terms of innovation output. One would probably need information on different types of publications in order to identify a likely effect of publications on the innovation results of firms.

4.3 Firm characteristics and knowledge sourcing

A noticeable result of the analysis above is the positive effect of unintended knowledge spillovers on process innovation output. Both reverse engineering and hiring of employees show a positive effect on the probability to introduce process innovation and to obtain a reduction in unit cost from these innovations. At first glance, this is a surprising result as reverse engineering is usually targeted at competitor products, since these can easily be purchased on the market and examined to understand their construction elements. For process innovation, firms usually do not have access to the technology which is used by competitors in their production process. For hiring employees who worked in other firms before, it is argued that the new knowledge they bring to the hiring firm is more relevant for developing and marketing product innovation (see Stojcic et al. 2018, Hamilton and Davison 2018). For process innovation, a single new worker will have rather little impact on the organization and performance of processes and procedures, which are usually team efforts and require the interaction of several workers and the integration of various tasks, although hiring employees with specific process-related capabilities such as data analytics may also spur process innovation (Wu et al. 2020).

As already mentioned in the theoretical part, it is quite plausible that firms pursue different strategies of innovation, which will have consequences for their demand for external knowledge. Innovation leaders are more likely to pursue a high-price strategy, since they are the first firms with new products on the market and thus have a first-mover advantage. They will hence face a lower pressure to unit cost reduction. However, for imitating firms, it is probably necessary to adopt a low-price strategy in order to achieve a relevant market share. The lower R&D costs are a contribution to this. Furthermore, price reductions can be achieved through more efficient production. This requires advanced production facilities, i.e., the implementation of new or improved process technology.

We test these hypotheses by the help of further information from the survey on the importance of competitive strategies pursued by the firms. Two variables are particularly relevant for this purpose. On the one hand, the survey includes information on pricing strategies. To identify the importance of low prices, it asks whether the firm focuses on a low-price strategy (price leadership), using a four-point Likert scale to identify the importance of this strategy. We use a dummy variable (price-strategy), with unit value if a firm reports of a high importance. On the other hand, we examine whether the firms strive for high quality (quality leadership). Here, too, we form a dummy variable with a value of one in the case firms report a high importance of this strategy.[5] Note that firms can pursue both strategies at the same time, either because they have a broader product portfolio that includes some products focusing on low price and other on high quality, or because markets are characterized by both a high cost pressure and strong demand preferences for high quality (which is typical for many high-tech markets such as semiconductors).

Table 4 present the results of Probit estimations explaining the two described dependent dummy variables. We use *Age, Size, HC, Group* and industry dummies as control variables. We find that pursuing a low-price strategy is linked with a higher probability to use reverse engineering. This result supports the notion that the use of reverse engineering is associated with a strategy to undercut incumbent firms on price. For all other knowledge sources, a focus on price leadership is either unrelated or exerts a negative effect on the probability to use the respective source. For all knowledge source, a focus on quality leadership is a relevant driver. This indicates that maintaining a high product quality requires firms to search broadly for relevant external knowledge by observing markets and competitors through all available sources.

As a further indicator for price pressure, we use information on credit constraints that a firm faces from a question on the use of bank credit. Firms were asked whether they applied for a credit and whether they received credit or not. For those not applying for credit, firms were asked whether they did not so because there was no demand for credit, or because they found an application as unpromising, i.e., that they expected not to get the credit anyway. We combine the positive answers on not having received a credit and refraining from application because of being unpromising to a dummy variable (*FC_cred*). The estimations results show that firms with credit constraints are more likely to use trade fairs, patents and reverse

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[5] Descriptive statistics of these and other explanatory variables used in this sub-section are shown in Table 11 in the Appendix.

engineering as knowledge sources. While the result for trade fairs and reverse engineering may indicate the attempt to use 'cheap' sources, the result for patents may be linked to a reluctance of banks to finance firms that search for more novel knowledge and incorporate this knowledge into their own innovative attempt, which is likely to show a more risky business strategy.

Table 4: Knowledge sources and market characteristics: results of Probit estimations

	Fair	*Publ*	*Patent*	*Reverse*	*Hiring*
CS_price	-0.027	-0.050**	0.011	0.023**	0.018
	(0.023)	(0.022)	(0.009)	(0.011)	(0.018)
CS_qual	0.119***	0.102***	0.010*	0.013**	0.056***
	(0.015)	(0.015)	(0.005)	(0.006)	(0.012)
FC_cred	0.073***	0.003	0.050***	0.025*	0.031
	(0.026)	(0.026)	(0.015)	(0.014)	(0.024)
Age	-0.018**	0.012	-0.004	-0.003	-0.035***
	(0.009)	(0.008)	(0.003)	(0.004)	(0.007)
Size	0.094***	0.072***	0.024***	0.013***	0.080***
	(0.006)	(0.005)	(0.002)	(0.002)	(0.004)
HC	0.255***	0.244***	0.112***	0.048***	0.158***
	(0.031)	(0.030)	(0.012)	(0.013)	(0.024)
Group	-0.027	-0.050**	0.011	0.023**	0.018
	(0.023)	(0.022)	(0.009)	(0.011)	(0.018)
# obs.	5,019	5,019	5,019	5,019	5,019

Marginal effects of Probit models with robust standard errors (standard errors in parentheses). All models include industry fixed-effects.
***, **, *: significant at p<0.01, p<0.05, and p<0.1, respectively.

In addition, we also examine whether firms that rely on unintended spillovers use particularly advanced technologies. To this end, we use a question from the survey that inquires on whether the firms purchased machines, devices or equipment in the years 2016 to 2018 that a) had an unchanged technical level, b) were technologically improved, or c) were based on completely new technologies (allowing multiple answers). We form three dummy variables that take unit value if the firms select one of the three alternatives (multiple answers possible). The three dummies form the dependent variables in Probit estimations which include the spillover and control variables on the right hand side. The results are reported in Table 5.

The most important result are the significant coefficients of the two unintended spillover variables. Firms using reverse engineering are significantly more likely to have acquired new capital goods (in all three categories), some of which were also based on technologies not used in the firm before. The employee hiring firms were significantly more likely to acquire new capital goods that represent improved or completely new technologies. These results indicate that firms, which accumulate knowledge about unintended sources show a strong tendency to acquire new and advanced production technologies. This in turn supports our previously presented findings regarding the effects of the unintended spillover variables on the introduction of process innovations as well as the associated cost reductions.

Table 5: Knowledge sources and technology adoption: results of Probit estimations

	Technology adoption (purchase of external technology)		
	Same technology as used before (*TA_same*)	Improved technology (*TA_impr*)	Entirely new technology (*TA_new*)
Fair	0.008	0.123***	0.062***
	(0.016)	(0.018)	(0.012)
Publ	0.092***	0.180***	0.022*
	(0.015)	(0.018)	(0.012)
Patent	0.020	0.044	0.051***
	(0.022)	(0.027)	(0.018)
Reverse	0.061**	0.096***	0.082***
	(0.027)	(0.030)	(0.023)
Hiring	0.005	0.099***	0.087***
	(0.015)	(0.018)	(0.014)
R&Dcont	-0.008	0.015*	-0.014**
	(0.007)	(0.009)	(0.006)
R&Docc	0.060***	0.071***	0.024***
	(0.005)	(0.006)	(0.004)
Age	-0.036	-0.076**	-0.050**
	(0.028)	(0.031)	(0.022)
Size	-0.009	-0.030*	-0.013
	(0.014)	(0.017)	(0.011)
HC	0.008	0.123***	0.062***
	(0.016)	(0.018)	(0.012)
Group	0.092***	0.180***	0.022*
	(0.015)	(0.018)	(0.012)
# obs.	5,625	5,625	5,625

Marginal effects of Probit models with robust standard errors (standard errors in parentheses). All models include industry fixed-effects.
***, **, *: significant at p<0.01, p<0.05, and p<0.1, respectively.

5 Robustness tests

We carry out a number of robustness tests in order to demonstrate the reliability of our results. First, we use OLS models instead of Tobit models to analyze the determinants of innovation success. Secondly, we perform propensity score matching based on Epanechnikov kernels instead of Gaussian kernels. Thirdly, we estimate the model separately for manufacturing and services, since one may expect different links of knowledge sources to innovation outcomes if products are mainly of immaterial nature, and product and process innovation is closely interlinked (which both is more often the case in services).

5.1 OLS

With respect to robustness tests, we use OLS as an alternative to Tobit in explaining the success of the innovations introduced. This simple and robust specification with OLS is now often used for estimations with limited dependent variables. The results can be found in Table 7 in the Appendix.

The results do not change much compared to Tobit. For trade fairs, we find an effect on the share of sales generated by innovations for the European market. Reverse engineering and hiring of employees continue to have an effect on sales generated with new products, but the coefficients are now only significant at the 10% level. The effect of reverse engineering on process innovation remains significant at a higher level.

5.2 Matching with Epanechnikov kernel

As an alternative to propensity matching with Gaussian kernels, we apply Epanechnikov kernels for the models on quantitative innovation output. Otherwise the specification remains the same. The results are presented in Table 8 in the Appendix.

The results change only very marginally compared to the results obtained from matching with Gaussian kernels (see Table 3). Again, using knowledge form patents shows the strongest effects for product innovation output and are still the only knowledge source which significantly contributes to radical innovation (sales from world-first innovations). Both unintended spillovers sources significantly affect the sales share of any type of product innovations, and in particular sales from incremental innovations. In addition, both unintended spillovers sources show a positive impact on cost reductions from process innovation.

5.3 Separate estimations for manufacturing and services

So far, we have performed all estimations on the entire sample of firms, which represent both manufacturing and services industries. However, there may significant differences between the two sectors, owing to the different nature of products offered. In manufacturing, firms usually offer physical products (goods) which require both a certain type of production technology (machinery) and technologies to process and combine certain materials in order to achieve certain product functionalities. In services, in contrast, products are often produced in direct interaction with the users of the service and rely to a much lower extent of physical goods or physical technology, while digital technologies (e.g., software applications) are a particularly important technology for services. In general, goods of competitors are easier to observe (e.g., at trade fairs) and easier to analyze (e.g., through reverse engineering) than services. In addition, knowledge contained in patents usually refers to physical technologies whereas services or digital technologies are more difficult to patent.

In order to investigate likely sector differences in the role of different types of knowledge spillovers for innovation, we estimate both steps of our empirical approach separately for firms from manufacturing and from services. The results of the sample split models can be found in Table 9 (for step 1 on the probability to innovate) and Table 10 (for step 2 on the commercial success of innovations) in the Appendix.

The results of both steps reveal different knowledge sources tend to show different links to the different types of innovation output in manufacturing and services. As expected, the link between knowledge contained in patents and innovation is closer in manufacturing. This is particularly true for incremental product innovation and cost-reducing process innovation. Interestingly, we find a positive effect of patents in case of world-first innovations by service firms. This may be linked to the fact that world-first innovation in services are often associated with the use of novel digital technology, which at least partially relies on patented knowledge (e.g., new technical ways of storing, transmitting or analyzing information).

For trade fairs, we find a significant positive effect for incremental product innovation in case of services and for more radical product innovation (regional market novelties) in case of manufacturing. Publications are a relevant knowledge source for cost-reducing process innovation in the services sector, while in manufacturing it is other types of process innovation (e.g., quality improvements) that are stimulated by knowledge from scientific or trade publications.

For the two types of unintended knowledge spillover, reverse engineering is relevant in both sectors for product innovation. In the service industries, the positive link is only found for incremental innovations, while in manufacturing, reverse engineering is also relevant to produce regional market novelties. With respect to process innovation, the positive link to cost reduction is found in both sectors. Hiring of employees is positively associated with incremental product innovation in both sectors, while the positive link to regional market novelties is limited to services. Cost reductions from process innovation are stimulated in both sectors by the inflow of workers from other firms.

6 Conclusion

Our study aimed to quantify the role of intended and unintended knowledge spillover using firm-level data. We look at the introduction of product and process innovations and their commercial success in terms of revenue generated by new products, and unit cost reductions resulting from process innovation.

We find that the use of external knowledge sources is positively associated with both the probability to introduce innovations, and the associated commercial success. The role of knowledge sources for innovation differs by intended and unintended spillovers. Among the sources of intended knowledge spillovers, trade fairs are of relevance for the introduction of new-of-market product innovations as far as novelties for the German or European market is concerned. Firms using trade fairs as knowledge source are also more likely to introduce process innovations. Publications in trade journals or scientific journals are linked to the introduction of process innovations, but not to product innovation. For both sources, we do not find a positive association with the success of innovations, neither in terms of revenues from product innovation nor for cost reductions.

The third type of intended knowledge spillovers distinguished in the paper are patents. Firms using this source are more likely to introduce any type of innovation, including world-first product innovation, for which patents are the only knowledge source that leads to higher sales with this type of innovation. The positive link is also present when looking at the commercial success of product and process innovations.

Unintended knowledge spillovers via reverse engineering are significantly positively linked to both incremental innovations (imitations) and cost reductions. Similarly, employee poaching is useful for introducing and commercializing incremental product innovations and process innovations. The link to innovation output is stronger for reverse engineering compared to hiring of employees. While the imitating firms benefit from positive externalities of spillovers, the firms that originally developed the innovations cannot realize the full benefits from the newly created knowledge. Consequently, private returns from developing innovations are lower than the social returns. Our study therefore implies, as do other studies (see among others Becker 2015, Hud and Hussinger 2015, Howell 2017), that subsidizing R&D increases social welfare.

An innovative aspect of our study is to analyze reverse engineering in more detail. Reverse engineering is relatively under-researched in the context of spillovers and little is known about this form of spillovers. Existing empirical studies often focus on emerging or lagging economies (Adomako et al. 2022, Zhang and Zhou 2016, Liu and White 2001, Nathan and Sarkar 2014). Our paper shows based on novel data for a representative sample of German firms, that reverse engineering is also a relevant and successful approach to obtain innovation-related knowledge from other firms in the context of highly innovative economies. Companies relying on this source follow a low-price as well as a high-quality strategy. Furthermore, they are credit constrained and invest in established, but also in improved and totally new technology. These factors indicate that reverse engineering firms are not only product innovators, as often assumed in the literature (see Levin et al. 1987, Samuelson and Scotchmer 2002), but also process innovators. Process innovation from reverse engineering may either result from the need to retool manufacturing facilities in order to manufacture the reverse-engineered product (Samuelson and Scotchmer 2002: 1588) or as a distinct goal of the reverse engineering activity. The latter can be illustrated by a practice case[6] that shows that reverse engineering may focus "*on making a product easy and fast to manufacture without compromising on its performance and quality. Identifying the most efficient way to manufacture components is essential for lean manufacturing, and proves beneficial to the organization in terms of cost savings and quality control*."

The focus on process innovation by firms using reverse engineering is consistent with their goal of a low-cost production connected with the adoption of a low-price strategy, as well as with our empirical findings. As Nathan and Sarkar (2014) demonstrate, reverse engineering is not just about copying others products, but may also be linked to others' process innovations with the aim to reduce production costs. Innovations based on reverse engineering often involve a change in the operating systems to be able to offer the imitated product cheaper than the original innovator. In order to proceed with a reverse engineering strategy, the firms also need a certain amount of accumulated knowledge and in-house development capacity to effectively understand the technological solution employed by the original innovator, and to to proactively imitate and modify the original product (Lee and Yoon 2015).

Our study also has limitations. The question we use on spillover sources has been included in the innovation survey in one survey year only. As a result of this cross-sectional nature of the data, we are not able to test the impact of changes e.g. in a difference-in-differences setting. Furthermore, we were not able to perform instrumental variable techniques since no strong

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[6] See the blog by Steve park (April 21th, 2021), https://reverse-engineering-service.de/en/reverse-engineering-in-manufacturing

instrument is available in our data that would explain the use of individual spillover sources but is not correlated to innovation output. We leave it to future research to address these issues.

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8 Appendix

Table 6: Determinants of the use of sources of unintended knowledge spillovers: results of Probit estimations

	UnintKS
Age	-0.035***
	(0.007)
Size	0.084***
	(0.004)
HC	0.165***
	(0.025)
Group	0.059***
	(0.014)
CS_impr	0.072***
	(0.014)
CS_price	0.003
	(0.012)
CS_qual	0.033
	(0.022)
PM_aging	0.058***
	(0.015)
PM_entry	-0.029**
	(0.013)
PM_subst	0.013
	(0.012)
PM_prelas	0.035***
	(0.013)
FC_cred	0.035
	(0.023)
# obs.	6,003

Marginal effects of Probit models with robust standard errors (standard errors in parentheses). All models include industry fixed-effects.
***, **, *: significant at p<0.01, p<0.05, and p<0.1, respectively.

Table 7: Knowledge sources and commercial success of innovations: results of OLS estimations using PSM-based weights

	Sales share of product innovations					Share of unit cost reduction from process innovation (*Cost_s*)
	Total (*Pd_s*)	Incremental (*Incr_s*)	Market novelties			
			Total (*Mnov_s*)	Regional (*Rnov_s*)	World-first (*Wnov_s*)	
Fair	1.555*	1.535*	0.194	0.354	-0.160	0.640***
	(0.802)	(0.798)	(0.397)	(0.219)	(0.336)	(0.180)
Publ	0.709	0.709	-0.272	0.215	-0.487	0.100
	(0.813)	(0.808)	(0.414)	(0.218)	(0.364)	(0.198)
Patent	2.728**	2.537*	1.598**	0.157	1.441**	0.587
	(1.314)	(1.304)	(0.783)	(0.451)	(0.655)	(0.384)
Reverse	3.905**	3.818**	0.721	0.488	0.233	1.811***
	(1.545)	(1.533)	(0.904)	(0.466)	(0.782)	(0.595)
Hiring	2.637***	2.612***	0.086	-0.059	0.145	0.485**
	(0.810)	(0.804)	(0.415)	(0.229)	(0.351)	(0.241)
R&Dint	0.510***	0.504***	0.255***	0.100***	0.155***	0.027
	(0.073)	(0.072)	(0.055)	(0.035)	(0.044)	(0.022)
nR&Dint	0.494***	0.488***	0.309***	0.102**	0.207*	0.148***
	(0.138)	(0.136)	(0.117)	(0.047)	(0.110)	(0.055)
Age	-1.961***	-1.946***	-0.770***	-0.351**	-0.419**	-0.427***
	(0.453)	(0.450)	(0.231)	(0.172)	(0.172)	(0.113)
Size	-0.884***	-0.888***	-0.317***	-0.156***	-0.161**	-0.056
	(0.249)	(0.248)	(0.092)	(0.054)	(0.072)	(0.071)
HC	6.953***	6.928***	2.433**	0.496	1.937**	0.561
	(1.781)	(1.772)	(1.067)	(0.473)	(0.980)	(0.463)
Group	-0.392	-0.421	-0.198	-0.322	0.124	-0.162
	(0.746)	(0.743)	(0.373)	(0.221)	(0.305)	(0.199)
# obs.	4,998	4,998	4,998	4,998	4,998	4,998
R^2 adjusted	0.220	0.218	0.147	0.060	0.111	0.069

Estimated coefficients of weighted OLS models with robust standard errors (standard errors in parentheses). Observations weighted by 1/(1-pscore), pscore being the propensity score derived from a propensity score matching for probability to use sources for unintended knowledge spillovers (*UnintKS*), using kernel matching based on a normal (Gaussian) kernel and a bandwidth parameter of 0.06. All models include industry fixed-effects.
***, **, *: significant at p<0.01, p<0.05, and p<0.1, respectively.

Table 8: Knowledge sources and commercial success of innovations: results of Tobit estimations using PSM-based weights using Epanechnikov kernel

	Sales share of product innovations					Share of unit cost reduction from process innovation (*Cost_s*)
	Total (*Pd_s*)	Incremental (*Incr_s*)	Market novelties			
			Total (*Mnov_s*)	Regional (*Rnov_s*)	World-first (*Wnov_s*)	
Fair	7.124***	7.044***	5.148**	6.768***	1.185	3.246***
	(1.869)	(1.871)	(2.606)	(2.617)	(3.725)	(1.031)
Publ	2.967	2.959	1.304	5.046**	-3.259	1.824*
	(1.879)	(1.878)	(2.538)	(2.560)	(3.675)	(1.025)
Patent	8.593***	8.303***	15.132***	7.770***	20.234***	2.849**
	(2.057)	(2.065)	(2.563)	(2.664)	(3.453)	(1.215)
Reverse	8.694***	8.549***	6.623**	5.317*	7.701*	5.849***
	(2.369)	(2.375)	(3.122)	(2.889)	(4.171)	(1.390)
Hiring	7.407***	7.380***	2.763	2.520	0.755	3.067***
	(1.539)	(1.544)	(2.001)	(1.879)	(2.866)	(0.890)
R&Dint	0.705***	0.689***	0.640***	0.388***	0.646***	0.048
	(0.096)	(0.095)	(0.110)	(0.108)	(0.125)	(0.056)
nR&Dint	0.860***	0.863***	0.850***	0.543***	0.653**	0.433***
	(0.203)	(0.202)	(0.239)	(0.174)	(0.299)	(0.104)
Age	-2.911***	-2.981***	-3.480***	-1.909*	-2.589*	-1.321***
	(0.871)	(0.871)	(1.065)	(1.118)	(1.419)	(0.454)
Size	-1.080**	-1.079**	-0.238	-0.572	0.561	0.474
	(0.504)	(0.506)	(0.606)	(0.613)	(0.802)	(0.288)
HC	13.041***	13.321***	9.447**	2.310	16.646**	0.185
	(3.185)	(3.186)	(4.441)	(3.601)	(7.223)	(1.845)
Group	1.365	1.157	3.255	0.678	5.447*	0.049
	(1.514)	(1.519)	(2.003)	(1.887)	(2.918)	(0.848)
# obs.	4,998	4,998	4,998	4,998	4,998	4,998

Estimated coefficients of weighted Tobit models with robust standard errors (standard errors in parentheses). Observations weighted by 1/(1-pscore), pscore being the propensity score derived from a propensity score matching for the probability to use sources for unintended knowledge spillovers (*UnintKS*), using kernel matching based on a Epanechnikov kernel and a bandwidth parameter of 0.06. All models include industry fixed-effects.
***, **, *: significant at p<0.01, p<0.05, and p<0.1, respectively.

Table 9: Knowledge sources and probability to innovate: results of Probit estimations using PSM-based weights: split models by sector

	Product innovation										Process innovation					
	Total (*Pd*)		Incremental (*Incr*)		Market novelty						Total (*Pc*)		Unit cost reduction (*Cost*)		Other process innovation (*Othpc*)	
					Total (*Mnov*)		Regional (*Rnov*)		World-first (*Wnov*)							
	manufac-turing	services	manufac-turing	services	manufac-turing	services	manufac-turing	services	manufac-turing	services	manufac-turing	services	manufac-turing	services	manufac-turing	services
Fair	0.022	0.139***	0.033	0.151***	0.052**	0.013	0.047**	0.023	0.029**	-0.009	0.121***	0.127***	0.045	0.034	0.108***	0.107***
	(0.035)	(0.032)	(0.034)	(0.029)	(0.022)	(0.018)	(0.019)	(0.017)	(0.014)	(0.008)	(0.031)	(0.031)	(0.028)	(0.023)	(0.031)	(0.030)
Publ	0.052	0.026	0.046	0.017	0.007	0.010	0.010	0.018	-0.018	-0.002	0.081***	0.067**	0.006	0.080***	0.083***	0.001
	(0.034)	(0.036)	(0.033)	(0.033)	(0.025)	(0.018)	(0.022)	(0.016)	(0.018)	(0.007)	(0.030)	(0.031)	(0.028)	(0.021)	(0.031)	(0.032)
Patent	0.194***	0.107	0.134***	0.126*	0.183***	0.081*	0.110***	0.004	0.099***	0.064**	0.159***	0.022	0.086**	0.060	0.031	-0.038
	(0.039)	(0.084)	(0.039)	(0.073)	(0.033)	(0.044)	(0.030)	(0.028)	(0.024)	(0.030)	(0.033)	(0.074)	(0.034)	(0.050)	(0.037)	(0.065)
Reverse	0.114**	0.153**	0.142***	0.148**	0.086**	0.043	0.056*	0.036	0.031	0.022	0.058	0.139***	0.103**	0.150***	-0.072*	-0.068
	(0.050)	(0.062)	(0.047)	(0.059)	(0.039)	(0.036)	(0.031)	(0.034)	(0.024)	(0.017)	(0.039)	(0.052)	(0.041)	(0.051)	(0.041)	(0.058)
Hiring	0.106***	0.147***	0.113***	0.127***	0.006	0.040**	0.011	0.033**	0.005	-0.001	0.134***	0.132***	0.061**	0.055**	0.055*	0.057*
	(0.031)	(0.033)	(0.031)	(0.031)	(0.022)	(0.019)	(0.018)	(0.017)	(0.013)	(0.008)	(0.026)	(0.030)	(0.026)	(0.023)	(0.029)	(0.032)
R&Dint	0.008***	0.013***	0.004*	0.006***	0.003***	0.004***	0.001	0.003***	0.002***	0.001***	0.002	0.005**	-0.001	0.001	0.002	0.003
	(0.003)	(0.003)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.001)	(0.000)	(0.002)	(0.002)	(0.002)	(0.001)	(0.002)	(0.002)
nR&Dint	0.007*	0.059***	0.005*	0.012**	0.003	0.006***	0.003**	0.006***	0.002	0.001**	0.009**	0.032***	0.008***	0.006***	-0.002	0.006*
	(0.003)	(0.010)	(0.003)	(0.005)	(0.002)	(0.002)	(0.001)	(0.001)	(0.001)	(0.001)	(0.004)	(0.009)	(0.002)	(0.002)	(0.002)	(0.004)
Age	-0.011	-0.008	0.003	0.004	-0.025**	-0.011	-0.012	-0.010	-0.013*	-0.002	-0.005	-0.037**	-0.012	-0.017	0.004	-0.015
	(0.015)	(0.016)	(0.015)	(0.016)	(0.010)	(0.009)	(0.009)	(0.008)	(0.007)	(0.004)	(0.014)	(0.015)	(0.013)	(0.011)	(0.015)	(0.015)
Size	0.011	-0.001	0.014	0.002	0.006	0.002	0.001	0.003	0.013***	-0.001	0.030***	0.025**	0.022**	0.017**	0.005	0.001
	(0.011)	(0.010)	(0.011)	(0.010)	(0.008)	(0.006)	(0.007)	(0.005)	(0.005)	(0.002)	(0.011)	(0.010)	(0.009)	(0.007)	(0.011)	(0.010)
HC	0.136*	0.113**	0.145*	0.101**	0.016	0.019	-0.016	0.014	0.052*	0.014	-0.008	0.042	-0.084	0.012	0.095	0.030
	(0.081)	(0.050)	(0.077)	(0.048)	(0.050)	(0.027)	(0.043)	(0.025)	(0.030)	(0.012)	(0.069)	(0.045)	(0.067)	(0.036)	(0.071)	(0.046)
Group	0.047	0.036	0.042	0.004	0.039*	0.016	0.023	0.002	0.012	0.008	0.005	0.037	-0.006	0.036*	0.011	0.005
	(0.029)	(0.031)	(0.028)	(0.029)	(0.020)	(0.016)	(0.017)	(0.015)	(0.013)	(0.008)	(0.024)	(0.029)	(0.024)	(0.022)	(0.027)	(0.030)
# obs.	2,611	2,482	2,611	2,482	2,611	2,482	2,611	2,482	2,611	2,094	2,611	2,482	2,611	2,482	2,611	2,482

Marginal effects of weighted Probit models with robust standard errors (standard errors in parentheses). Observations weighted by 1/(1-pscore), pscore being the propensity score derived from a propensity score matching for the probability to use sources for unintended knowledge spillovers (*UnintKS*), using kernel matching based on a normal (Gaussian) kernel and a bandwidth parameter of 0.06. All models include industry fixed-effects.

***, **, *: significant at p<0.01, p<0.05, and p<0.1, respectively.

Table 10: Knowledge sources and commercial success of innovations: results of Tobit estimations using PSM-based weights: split models by sector

	Sales share of product innovations										Share of unit cost reduction from process innovation (*Cost_s*)	
	Total (*Pd_s*)		Incremental (*Incr_s*)		Market novelties							
					Total (*Mnov_s*)		Regional (*Rnov_s*)		World-first (*Wnov_s*)			
	manufac-turing	services	manufac-turing	services	manufac-turing	services	manufac-turing	services	manufac-turing	services	manufac-turing	services
Fair	2.088	11.564***	1.946	11.623***	6.633**	1.432	6.505**	4.449	3.353	-5.940	1.998*	4.709**
	(2.555)	(2.658)	(2.552)	(2.665)	(3.071)	(4.719)	(2.643)	(4.686)	(4.122)	(8.362)	(1.171)	(1.863)
Publ	3.977	1.880	4.005*	1.824	-0.373	3.414	3.865	5.833	-3.425	-5.913	0.159	5.832***
	(2.421)	(2.920)	(2.415)	(2.927)	(2.874)	(4.676)	(2.609)	(4.482)	(3.965)	(8.287)	(1.128)	(2.077)
Patent	9.201***	5.024	8.875***	4.865	13.737***	12.068*	7.071***	3.819	16.495***	27.837***	2.757**	4.879
	(2.252)	(4.561)	(2.250)	(4.593)	(2.587)	(6.552)	(2.330)	(7.111)	(3.503)	(8.761)	(1.165)	(3.183)
Reverse	5.355**	15.569***	5.020*	15.836***	5.036*	9.164	4.681*	4.027	4.769	22.436*	3.653**	10.499***
	(2.583)	(4.306)	(2.588)	(4.303)	(2.984)	(7.628)	(2.709)	(6.382)	(3.724)	(13.343)	(1.491)	(2.742)
Hiring	5.402***	9.512***	5.449***	9.347***	1.033	7.027*	0.220	7.616**	0.732	0.116	2.747***	3.502**
	(1.900)	(2.446)	(1.901)	(2.458)	(2.140)	(4.049)	(1.815)	(3.570)	(2.817)	(8.036)	(1.004)	(1.734)
R&Dint	0.427***	1.002***	0.417***	0.981***	0.391***	1.134***	0.074	0.888***	0.470***	1.240***	-0.038	0.181*
	(0.127)	(0.135)	(0.126)	(0.135)	(0.129)	(0.198)	(0.097)	(0.199)	(0.150)	(0.283)	(0.071)	(0.093)
nR&Dint	0.490**	1.700***	0.496**	1.696***	0.465**	1.866***	0.254*	1.301***	0.395	1.675**	0.424***	0.457***
	(0.221)	(0.227)	(0.220)	(0.226)	(0.223)	(0.344)	(0.139)	(0.351)	(0.255)	(0.699)	(0.125)	(0.157)
Age	-1.469	-4.515***	-1.539	-4.603***	-2.438**	-4.835**	-0.919	-2.978	-1.951	-3.063	-0.861*	-1.788**
	(1.011)	(1.474)	(1.011)	(1.481)	(1.115)	(2.249)	(1.019)	(2.247)	(1.431)	(4.286)	(0.503)	(0.872)
Size	-1.293**	-0.677	-1.286**	-0.684	-0.484	0.556	-0.749	0.157	0.578	1.561	0.450	0.583
	(0.641)	(0.746)	(0.640)	(0.751)	(0.638)	(1.248)	(0.657)	(1.140)	(0.758)	(2.443)	(0.367)	(0.476)
HC	18.148***	12.289***	18.364***	12.598***	12.453**	8.642	1.052	3.259	19.675***	19.843	0.330	0.874
	(5.408)	(4.066)	(5.393)	(4.080)	(5.919)	(7.121)	(4.710)	(5.708)	(7.569)	(16.030)	(2.901)	(2.756)
Group	3.403*	-1.159	3.190*	-1.369	2.980	3.770	1.169	-0.277	4.009	8.356	-0.601	2.036
	(1.878)	(2.354)	(1.877)	(2.370)	(2.094)	(4.050)	(1.797)	(3.672)	(2.740)	(8.278)	(0.925)	(1.599)
# obs.	2,562	2,436	2,562	2,436	2,562	2,436	2,562	2,436	2,562	2,436	2,562	2,436

Estimated coefficients of weighted Tobit models with robust standard errors (standard errors in parentheses). Observations weighted by 1/(1-pscore), pscore being the propensity score derived from a propensity score matching for the probability to use sources for unintended knowledge spillovers (*UnintKS*), using kernel matching based on a normal (Gaussian) kernel and a bandwidth parameter of 0.06. All models include industry fixed-effects.
***, **, *: significant at p<0.01, p<0.05, and p<0.1, respectively.

Table 11: Definition and descriptive statistics of variables for the models on firm characteristics and knowledge sourcing

Variable	Definition	Mean	Std.Dev.	Min	Max
CS_price	1 if competitive strategy "price leadership" is of high importance, 0 otherwise	0.111	0.314	0	1
CS_qual	1 if competitive strategy "quality leadership" is of high importance, 0 otherwise	0.656	0.475	0	1
FC_nocred	1 if firm unsuccessfully tried to obtain credit financing or if firm refrained from obtaining credit financing because it was unpromising, 0 otherwise	0.070	0.255	0	1
TA_same	1 if technology acquired during 2016 and 2018 is based on the same state as the technology used before, 0 otherwise	0.270	0.444	0	1
TA_impr	1 if technology acquired during 2016 and 2018 is based on improved technology, 0 otherwise	0.564	0.496	0	1
TA_new	1 if technology acquired during 2016 and 2018 based on entirely new technology, 0 otherwise	0.159	0.366	0	1

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