// NO.23-031 | 08/2023

DISCUSSION PAPER

// PAOLO CARIOLI AND DIRK CZARNITZKI

Skills Shortage and Innovation Openness

Skills Shortage and Innovation Openness*

Paolo Carioli† Dirk Czarnitzki‡

May 2023

Abstract

Skills shortage has become a key policy issue in highly developed and innovation-oriented economies, with non-negligible consequences on firms' innovation activities. We investigate the effect of skills shortage on firms' innovation openness, which is considered to be one of the key drivers of innovation performance. We hypothesize that scarcity of personnel causes firms to cooperate more broadly with external partners. Using cross-sectional data from the German contribution to the Community Innovation Survey (CIS), and exploiting detailed information on the extent to which firms could fill their job vacancies, we find that, on average, a one standard deviation increase in skills shortage more than doubles a firm's cooperation breadth. We contribute to the literature on human capital in relation to open innovation by characterizing the necessity of openness as a way to mitigate the scarcity of skills.

Keywords: open innovation, R&D collaboration, skills shortage
JEL codes: O36, J63

*We thank Bettina Peters for providing valuable comments on this study during the 9th InnoPat conference (ZEW, Mannheim, November 2022). We are also thankful for the comments by other participants of the 9th InnoPat conference (Fabian Gaessler, Christoph Grimpe, Neus Palomeras). In addition, we thank Maikel Pellens, Steven Vanhaverbeke and Jesse Wursten for helpful comments on earlier versions. We gratefully acknowledge financial support by the Research Foundation Flanders (grant number G0C6921N; FWO Fundamental Research Ph.D. fellowship, grant number 11D2623N).

†Faculty of Economics and Business, KU Leuven; Center for R&D Monitoring at KU Leuven. Contact: paolo.carioli@kuleuven.be

‡Faculty of Economics and Business, KU Leuven; Center for R&D Monitoring at KU Leuven, and Centre for European Economic Research (ZEW). Contact: dirk.czarnitzki@kuleuven.be

1 Introduction

Scarcity in skilled labour has raised serious concerns in highly developed and innovation-oriented economies (Horbach and Rammer, 2022). First, this issue is due to demographic changes in ageing societies: the decreasing proportion of young workers newly entering the labour market cannot supply the growing demand for skills in knowledge-intensive economies. Second, education systems may not effectively anticipate the direction and the pace of technological changes, thus exacerbating the phenomenon of skills shortage (Toner, 2011). Skilled labour is a critical input to the innovation process (Freel, 2005; Leiponen, 2005) and previous studies mainly find negative effects of skills shortage on productivity (Coad et al., 2016) and on the development of new technologies (Toivanen and Väänänen, 2016). Skills shortage is more likely to arise in innovative firms and it may cause innovation failures, like abandonment of projects (Horbach and Rammer, 2022).

If we consider the German business sector as an example, skills shortage is one of the most threatening obstacles to innovation. In the 2019 wave of the German Community Innovation Survey (Rammer, 2020), firms reported hampering factors. Not finding qualified personnel ranks first among all obstacles with respect to preventing further innovation activities: almost every fifth firm (18%) mentioned skills shortage as a reason for not innovating. In addition, almost 15% of firms reported that the lack of qualified personnel caused delays in ongoing innovation projects.

In this paper we investigate the impact of skills shortage on innovation openness, which is often seen as one of the key drivers of innovation performance (Laursen and Salter, 2006; Leiponen and Helfat, 2010). Given the positive association between Open Innovation strategies and innovation performance, we consider studying the consequences of skills shortage on openness important.

There is dearth of research on how skills shortage and innovation openness are intertwined. Human capital has been progressively recognized as a crucial factor for the effective integration of both external and internal sources of knowledge (Bogers et al., 2018; Leiponen, 2005). This is in line with the notion of absorptive capacity, which provides firms with the ability to evaluate and assimilate outside knowledge, as a key condition for innovation openness (Cohen and Levinthal, 1990). On the one hand, skills shortage is expected to be associated with a reduced level of absorptive capacity (Cohen and Levinthal, 1990; Lewandowska, 2015), which is needed to learn from external sources, and hence should hamper innovation openness. On the other hand, the lack of critical skills for innovation activities can also promote firms' innovation search and collaboration efforts, given that external sources of knowledge could compensate for the insufficiency of internal resources (Miotti and Sachwald, 2003; Cassiman and Veugelers, 2006).

We hypothesize that a firm's skills shortage leads to an increase in innovation openness. Due to skills shortage, firms cannot optimally invest in R&D for knowledge creation without further adjustments, and hence an increased level of innovation openness enables to compensate for the lack of internal know-how. We test this hypothesis using cross-sectional data from the German contribution to the Community Innovation Survey (CIS) and estimate the impact of skills shortage - measured as the number of job vacancies that could not be filled as planned - on cooperation breadth.

Our results show that a one standard deviation increase in skills shortage more than doubles a firms' cooperation breadth. This implies that innovation openness is a mechanism adopted by firms to compensate for the lack of internal know-how that is needed to innovate. We contribute to the literature by shedding light on the impact of skills shortage on innovation openness and by characterizing the *necessity* of innovation openness.

Our findings suggest that policy instruments aimed at supporting open innovation may help firms to mitigate the problem of skills shortage. From a managerial perspective, our results indicate that the design of cooperation strategies with external partners should be adapted in relation to the level of skill demand and the outcome of the hiring process of new employees.

The following sections present the theoretical background of this study (2), the data and methods (3), the econometric results (4) and the conclusions (5).

2 Theoretical background

The Open Innovation model, a key contribution to the field of innovation management, is a widespread model of distributive and collaborative way of innovation (Chesbrough, 2003; Bogers et al., 2017). This model states that firms should not just draw on their own resources for developing innovations. Rather, firms should collaborate with others, build on external ideas, and spin out technologies when they cannot commercialize them profitably themselves (Chesbrough, 2003). On the one hand, this model is embedded in the notion that the generation and recombination of technological ideas require the exploration of unfamiliar information and novel practices (Fleming, 2001); on the other hand, it relies on the possibility of developing technologies for which complementary assets are lacking (Teece, 2010). Scholars have shown the manifold advantages of innovation openness, including cost and risk sharing, pooling of resources and competences, and enhancing learning and creativity (Chesbrough and Bogers, 2014).

There is a strong connection between the skills of a firm's human capital and open innovation strategies. The level of innovation openness reflects a strategic decision that results from a firm's balancing of managing costs and benefits of openness (Felin and Zenger, 2014). Firms organize their production processes internally if the transaction costs of coordinating production using market mechanisms is greater than doing so within the firm (Williamson, 1981). The open innovation model is thus linked to transaction costs theory with respect to the extent to which firms orchestrate knowledge flows through their permeable organizational boundaries. Innovation openness involves transaction costs of searching, evaluating and monitoring external sources of knowledge (Faems et al., 2010). In particular, inbound open strategies are not only associated with costs deriving from control and monitoring processes, but also with costs deriving from the need to develop or acquire specific skills and competencies (Greco et al., 2019). Therefore, the skills and the background of the firm's workforce are fundamental for the effectiveness of open innovation strategies, as they are critical to their inherent hidden costs caused by the complex interaction with external sources.

Cohen and Levinthal (1990) coined the notion of absorptive capacity to describe the ability to evaluate outside knowledge and integrate it with internal ideas and routines. In the context of openness, this capacity is as an essential condition for firms' ability to appropriate the value generated through inflows and outflows of knowledge across open boundaries. R&D employees, who represent the key drivers of the innovation engine, play a pivotal role in absorbing external information, while also elaborating knowledge recipes and recombination routines that mirror firms' accumulation of knowledge in the discovery process (Dosi and

Nelson, 2010; Ter Wal et al., 2017). These knowledge recipes are inextricably linked to the technical and scientific know-how embedded in human capital (Bogers et al., 2018).

The extant literature on skills and innovation mainly highlights the pivotal role played by skills and training activities for innovation performance, e.g. Freel (2005), and the importance of both technical-academic skills and relational-social skills in the innovation process (Sousa and Rocha, 2019). In a complementary way, previous studies document a negative impact of a shortage of skills on productivity and on the development of new technologies. For instance, skills shortage is an important innovation barrier for high productivity firms (Coad et al., 2016) and leads to innovation failures (Horbach and Rammer, 2022). Similarly, low distances to technical universities (which are assumed to lower skills shortage) are found to be associated with a higher number of patents by inventors (Toivanen and Väänänen, 2016).

Yet, the effect of a firm's shortage of skills on innovation openness has received less academic attention, despite openness is an important driver of innovation perfomance (Laursen and Salter, 2006; Leiponen and Helfat, 2010). On the one hand, the adoption of open strategies for innovation can often be a response to the lack of adequate internal resources to implement a close innovation strategy, and may even represent a solution to the difficulty to recruit knowledgeable employees associated with firms' small size, financial limitations or low business attractiveness (Chesbrough, 2003). Thus, a shortage of skills at the firm-level may stimulate a higher propensity to draw from external sources of information and/or to collaborate with external actors, which possess the resources that the firm is seeking (Cassiman and Veugelers, 2006; Miotti and Sachwald, 2003). On the other hand, given that internal knowledge, problem solving means and prior learning experience are determinants of absorptive capacity (Lewandowska, 2015), and given that innovation openness is associated with coordination and monitoring costs, skills scarcity at the firm level may have a detrimental impact on openness, to the extent that it reduces the capability to integrate the knowledge sourced from external partners and incorporate it with internal ideas and routines. A recent study by Bello-Pintado and Bianchi (2020) confirms the fundamental link between internal skills and openness. The authors find that the adoption of open search strategies demands the recruitment of new employees with higher technical and social skills.

Given the expected surge of skill shortage in industrialized economies due to ageing of populations, we are interested in investigating whether firms increase the openness of their innovation processes to mitigate detrimental effects of lacking human capital in-house. We thus hypothesise that firms experiencing a shortage of skills rely more on cooperation with external partners to integrate the missing elements of knowledge and to compensate for the lack of internal know-how.

We argue that this mechanism reflects a firm's strategic decision in relation to the necessary inputs for the knowledge creation process. Due to skills shortage, firms cannot invest the optimal level of R&D that is required for the creation of knowledge without further adjustments. Such adjustments involve compensating for that sub-optimal investment in R&D with an increased level of inbound innovation openness, conditional on the (existing) level of absorptive capacity that is needed to manage more openness and to orchestrate knowledge flows. Consequently openness, besides being a solution adopted to enhance innovation performance (Laursen and Salter, 2006; Leiponen and Helfat, 2010), may represent a coping mechanism to the inability or difficulty to find appropriate skills or know-how that are required for the innovation process. Hence, in this study the following hypothesis will be tested.

Hypothesis: Firms' skills shortage leads to higher levels of inbound innovation openness.

We account for potential reverse causality due to the above mentioned theoretical ambiguities by implementing instrumental variable regressions.

3 Data and methods

3.1 Data

The empirical analysis is based on unique firm-level data from the Mannheim Innovation Panel (MIP) provided by the Leibniz Centre for European Economic Research (ZEW). The MIP represents the German contribution to the Community Innovation Survey (CIS), which is supervised by the Statistical Office of the European Commission (Eurostat). While the CIS is a biannual survey, the German CIS is conducted annually and adopts a panel approach, hence allowing to track firms' innovation behaviour over time. Each survey wave collects data of around 8,000 firms every year. The survey is voluntary (25%-30% response rate) and is usually completed by CEOs or innovation managers. It is based on a stratified random sample (Behrens et al., 2017). Data from the 2017, 2018 and 2019 MIP are used, since the corresponding survey waves include relevant questions on skills shortage and innovation openness. In addition, we exploit information on financial performance measures from the Creditreform database (the largest German credit rating agency) and locational information to implement an instrumental variables strategy which addresses endogeneity concerns of skills shortage in the analysis.

After combining consecutive survey waves, we take into account only firms with full information on all model variables, thus reducing the final sample size to 3775.[1] When compared to the original sample, the reduced sample shows a similar distribution in terms of size classes and industries (see Table 10 in the Appendix) as in the raw data; in addition, our final sample shows a similar share of firms reporting that they could not fill (some of) their job openings as planned (i.e., approx. 37% of firms in our sample).

3.2 Measures

3.2.1 Dependent variable

Our goal is to estimate the impact of skills shortage on innovation openness. Following Laursen and Salter (2014), we measure innovation openness, our dependent variable, as co-operation breadth, which indicates the number of different types of cooperation involved in a firm's innovation strategy. We use data from the 2019 wave of the MIP on firms' R&D/innovation cooperation, by taking into account the location of the partner (i.e., Germany at the national level (i), Europe (ii), USA (iii), Asia (iv), other countries (v))[2] and the partner type (i.e., suppliers (i), customers from the private sector (ii), customers from the public sector (iii), competitors (iv), consultants (v), universities (vi), government or public research institutes (vii), non-profit organizations (viii), others (ix)). The variable denoting cooperation breadth is thus equal to 45 if the firm engages in all possible types of cooperation

[1]For some robustness checks, the inclusion of a variable denoting past cooperation breadth and a variable denoting past payroll cost per employee leads to a reduction of the sample size to 3033; similarly, the use of alternative outcome variables for licensing-in/purchasing IPRs from third parties reduces the sample size to 3178 observations.

[2]The survey question also includes German at the regional level as a possible location for the cooperation partner. We do not consider this location for methodological reasons explained in section 3.3.

(9 cooperation partner types, each at 5 possible locations), and is equal to 0 if no cooperation types are used. Differently from Laursen and Salter (2014), we consider the geographical location of the partner as a distinct dimension in the construction of this variable (e.g., cooperating with a competitor at the national level counts as a different type of cooperation than cooperating with a competitor located in the U.S.). The distinction between these locations captures a difference in their underlying spatial challenges, in terms of access and separation of co-creators, which may require managerial efforts to find suitable partners, to coordinate joint activities, or to enable an effective communication (Bogers et al., 2017). Anyhow, we add a robustness check in which we operationalize cooperation breadth and employ the same methodology as in Laursen and Salter (2014).

Furthermore, we conduct robustness checks in which we test our hypothesis with other measures of innovation openness. Following Köhler et al. (2012) in their characterization of the heterogeneity of various knowledge sources in the context of open innovation, we explore whether skills shortage differently impacts the cooperation breadth involving market partners (suppliers, customers from the private sector, customers from the public sector, competitors, consultants) and non-market partners (universities, government or public research institutes, non-profit organizations) (section 4.2.2 - Table 6). The decision of a firm to compensate for the shortage of internal skills with innovation openness may be linked to the type of partner and the kind of knowledge it can provide. More specifically, firms experiencing skills shortage may be more inclined to increase the breadth of cooperation with market partners than with non-market partners. Although scientific institutions produce new knowledge and technology that provide important business opportunities (Cohen et al., 2002), university knowledge is frequently further removed from commercial application and requires substantial investments in development to commercialize it. Firms need specialized absorptive capacities to transfer this type of knowledge. The often tacit and ambiguous nature of university knowledge requires firms and universities to develop a mutual understanding and language in practice over time (Laursen and Salter, 2004, 2006). Therefore, we check whether there is a differential impact of skills shortage on cooperation with market partners and non-market partners.

In other robustness checks we use alternative outcome variables capturing inbound openness besides cooperation (section 4.2.3 - Table 8). Open innovation involves managing knowledge flows purposefully, hence we explore if skills shortage is positively associated to contracted-out R&D and to purchasing or licensing-in IPRs from third parties.

First, we consider a binary indicator for contracted-out R&D in 2018, to measure the degree to which firms reacted to a scarcity of skills by relying on R&D activities conducted by third parties[3].

Second, we use as dependent variable the proportion of extramural R&D in 2018, as the ratio of the firm's investment in extramural R&D activities and the total amount invested by the firm in both internal and external R&D activities (intramural plus extramural R&D activities). Wadhwa et al. (2017) who use this variable to operationalize openness argue that "extramural R&D involves creative work related to product development performed by another entity for a fee and excludes expenditure on the acquisition of non-R&D-related external knowledge or equipment" and that "examining the amount spent on extramural R&D allows [...] to be precise about how much of a firm's technology mix comes from external knowledge/technology compared to the firm's internal R&D efforts" (p. 880).

Third, we use a binary indicator for licensing-in and/or purchasing IPRs, and two additional binary variables denoting whether firms licence-in or purchase IPRs from enterprises/private individuals ("Licening-in PRV") or from universities/public research organisations ("Licening-in PUB"). Specifically, we focus on licensing-in since our goal is to investigate whether there is a compensation mechanism implemented by firms relying on external knowledge/technology due to a lack of internal skills; therefore, outbound open innovation in the form of licensing-out own IPRs to third parties is not taken into consideration in this context.

3.2.2 Explanatory variables

The 2018 wave of the MIP contains a section on skill demand for the reference year 2017, which includes a question on the extent to which firms could fill job openings and on the level of qualification required for the job openings. Skills shortage, our explanatory variable, is operationalized as the number of vacancies that could not be filled at all, or that could

[3]As explained in the 2019 MIP questionnaire, cooperation on R&D or on other innovation activities requires active collaboration of the focal firm. Conversely, pure contracted-out R&D of work does not necessarily indicate active collaboration of the focal firm.

be filled only with delay, or that could not be filled with the required personnel in 2017 (Horbach and Rammer, 2022). This variable captures the scarcity of skills at the firm level caused by the impossibility to fill a job vacancy, or to a delay in the hiring process of the required employees, or to the misalignment between the required skills for the vacancy and the skills of the new hire(s).

We additionally use a narrower definition of skills shortage that considers only vacancies that were not filled at all (Horbach and Rammer, 2022) and investigate if they had a stronger impact on openness (section 4.2.5 - Table 12).

In our estimation, we include a set of control variables.[4] To control for firms' absorptive capacity, we use firm-level R&D intensity, defined as R&D expenditures divided by total sales in 2017 (Cohen and Levinthal, 1990). In addition, we control for the proportion of employees with a university degree, which measures the importance of the academic knowledge embedded in human capital at the firm level (Lewandowska, 2015).

We also control for firm size, in terms of number of employees[5] and number of employees squared, and age of the firm (in logarithm). Firm size and age may influence the cooperation breadth of a firm, while also having an effect on the likelihood to experience a shortage of skills at the firm level. Being part of an enterprise group is also controlled for, as this can impact the necessity to engage in collaboration with external partners.

Furthermore, we control for the number of academic qualifications required for the job vacancies in 2017 divided by the total number of vacancies. We consider it important to control for this variable as the demand for academic skills may be a determinant of the breadth of cooperation openness. In particular, in the 2018 wave of the MIP firms reported whether an academic qualification was required for their job vacancies (i.e., (i) computer sciences, maths, statistics; (ii) other science and engineering; (iii) others, like business or law). We operationalize the variable indicating academic qualifications per vacancy by dividing the count of distinct academic qualifications by the total number of vacancies.

We also include 16 industry dummies and 16 regional dummies to control for different propensities for collaboration openness across industries and geographic space.

[4]All controls are lagged either from the 2017 MIP or 2018 MIP, with reference years 2016 or 2017 (Table 1).

[5]In order to avoid double counting, we subtract the number of vacancies that were filled as planned from the total number of employees (and divide by 1000).

In an extended set of regressions we include other relevant control variables. We add as control variable payroll costs (including employee benefits and social security contributions) divided by the total number of employees in 2016. This variable measures firms' capability to attract the best talents from the market by offering them a competitive compensation. Our objective is to check if a potential effect of skills shortage on innovation openness changes on the basis of firms' capability to be a competitive employer in the labour market. Moreover, we control for past cooperation breadth in 2016. The 2017 MIP wave includes a similar question on the cooperation strategy adopted by firms for their innovations: firms could report the location and the type of their cooperation partners. Cooperating for innovation may reflect a long-lasting and persistent managerial orientation, and cooperation breadth is likely to be influenced by previous experience in engaging in a variety of cooperative agreements. Furthermore, R&D collaborations augment the human capital of participating knowledge workers, thus increasing their outside employment options, resulting in higher levels of their outgoing mobility (Simeth and Mohammadi, 2022). This mechanism may increase firms' demand for new employees, and hence it is important to control for past cooperation breadth.

3.2.3 Descriptive statistics

Table 1 and Table 2 show the descriptive statistics of these variables (see also Table 9 in the Appendix for cross-correlations). Our indicator for cooperation breadth has an average value of around 0.39, with 20 being the maximum number of distinct channels of cooperation in which the firms in our sample engaged.

On average, around 2 job vacancies were not filled as planned (i.e., they were not filled at all, or filled only with delay or filled without the required personnel). Considering that 17 is the median number of employees in our sample, the skills shortage produced by the vacancies that were not filled as planned seems to represent a non-negligible problem, i.e. it corresponds to approximately 10% of the median firm's workforce. Moreover, the number of job vacancies that were not filled as planned accounts for around 31% of the total number of job vacancies.

As far as size and age classes are concerned, skills shortage is a more severe problem for larger and for younger firms, which can be explained by the fact that larger firms may

Table 1: Descriptive statistics

Variables	Mean	St. Dev.	Min	Max	Source
Dependent variable					
Cooperation breadth $_{i,2018}$	0.386	1.474	0	20	MIP 2019
Alternative dependent variables					
Cooperation breadth with non-market partners $_{i,2018}$	0.175	0.708	0	15	MIP 2019
Cooperation breadth with market partners $_{i,2018}$	0.200	0.882	0	14	MIP 2019
Contracted-out R&D (0/1) $_{i,2018}$	0.114	0.318	0	1	MIP 2019
Extramural R&D (%) $_{i,2018}$	0.030	0.130	0	1	MIP 2019
Licensing-in/Purchasing IPRs from third parties (0/1) $_{i,2018}$ [a]	0.038	0.192	0	1	MIP 2019
Licensing-in/Purchasing IPRs from enterprises (0/1) $_{i,2018}$ [a]	0.034	0.180	0	1	MIP 2019
Licensing-in/Purchasing IPRs from universities/PROs (0/1) $_{i,2018}$ [a]	0.005	0.071	0	1	MIP 2019
Explanatory variables					
Skills shortage $_{i,2017}$	1.722	5.699	0	100	MIP 2018
Unfilled vacancies $_{i,2017}$	0.524	2.608	0	100	MIP 2018
Control variables					
N. employees (- filled positions) (/1000) $_{i,2017}$	0.222	3.579	0	158.739	MIP 2018
R&D intensity $_{i,2017}$	0.018	0.080	0	1	MIP 2018
Age $_{i,2017}$	30.143	27.849	0	367	MIP 2018
Employees with an academic degree (%) $_{i,2017}$	0.234	0.284	0	1	MIP 2018
Part of an enterprise group (0/1) $_{i,2017}$	0.211	0.408	0	1	MIP 2018
Academic qualifications per vacancy $_{i,2017}$	0.110	0.246	0	1	MIP 2018
Payroll cost per employee (Million Euros) $_{i,2016}$ [b]	0.040	0.020	0.002	0.105	MIP 2017
Past cooperation breadth $_{i,2016}$ [b]	0.325	1.295	0	27	MIP 2017
Instrumental variables					
Empl. with an academic degree (avg.) per district and sector $_{i,2017}$	2270.228	7564.500	0	86127.980	Creditreform
Bankruptcies (avg.) per district and sector $_{i,2017}$	21.362	57.996	0	437	Creditreform
N	3775				

[a] Only for 3178 observations.

[b] Only for 3033 observations.

Table 2: Descriptive statistics on skills shortage

	Mean	St. Dev.	
Skills shortage by size class (n. of employees)			
1 to 49	0.763	2.199	MIP 2018
50 to 249	2.896	6.034	MIP 2018
250 to 499	5.196	8.876	MIP 2018
500 and more	10.794	19.723	MIP 2018
Skills shortage by age class (n. of years)			
less than 3	2.811	11.566	MIP 2018
3 to 5	2.010	3.311	MIP 2018
5 to 15	1.728	4.929	MIP 2018
15 and more	1.695	5.789	MIP 2018
Skills shortage by aggregate economic sectors			
Research-intensive Industry	2.228	6.737	MIP 2018
Other Industry	1.333	3.635	MIP 2018
Knowledge-intensive Services	1.250	3.976	MIP 2018
Other Services	2.779	9.094	MIP 2018
N	3775		

Table 3: Descriptive statistics - Firms with/without skills shortage

	Skills shortage = 0		Skills shortage > 0		T-tests on mean
	Mean	St. Dev.	Mean	St. Dev.	differences
Cooperation breadth $_{i,2018}$	0.333	1.373	0.478	1.630	***
Coop. breadth with non-market partners $_{i,2018}$	0.156	0.655	0.207	0.790	**
Coop. breadth with market partners $_{i,2018}$	0.167	0.805	0.258	0.999	***
Contracted-out R&D (0/1) $_{i,2018}$	0.099	0.298	0.141	0.348	***
Extramural R&D (%) $_{i,2018}$	0.025	0.119	0.039	0.147	***
Licensing-in/Purchasing IPRs from third parties (0/1) $_{i,2018}$ ^{a}	0.035	0.185	0.044	0.204	
Licensing-in/Purchasing IPRs from enterprises (0/1) $_{i,2018}$ ^{a}	0.030	0.170	0.040	0.196	
Licensing-in/Purchasing IPRs from universities/PROs (0/1) $_{i,2018}$ ^{a}	0.005	0.070	0.005	0.071	
N. employees (- filled positions) (/1000) $_{i,2017}$	0.204	3.753	0.254	3.256	
R&D intensity $_{i,2017}$	0.019	0.083	0.017	0.074	
Age $_{i,2017}$	30.744	28.507	29.099	26.648	*
Employees with an academic degree (%) $_{i,2017}$	0.247	0.294	0.210	0.262	***
Part of an enterprise group (0/1) $_{i,2017}$	0.185	0.388	0.256	0.436	***
Academic qualifications per vacancy $_{i,2017}$	0.075	0.217	0.170	0.280	***
Payroll cost per employee (Million Euros) $_{i,2016}$ ^{b}	0.039	0.021	0.040	0.020	
Past cooperation breadth $_{i,2016}$ ^{b}	0.285	1.117	0.396	1.549	**
Empl. with an academic degree (avg.) per district and sector $_{i,2017}$	2177.076	7117.326	2431.894	8283.695	
Bankruptcies (avg.) per district and sector $_{i,2017}$	22.549	61.078	19.303	52.175	*
N	2395		1380		

Note: *** (**, *) indicate a significance level of 1% (5%, 10%).

[a] Only for 3178 observations (2007 obs. for sub-sample with no skills shortage, 1171 obs. for sub-sample with skills shortage).

[b] Only for 3033 observations (1922 obs. for sub-sample with no skills shortage, 1111 obs. for sub-sample with skills shortage).

demand more labour and that younger firms may be less attractive than well-established firms for candidates looking for a job. Firms operating in research-intensive industries and in non research-intensive service sectors show a higher number of vacancies that were not filled as planned.

The subsample of firms with skills shortage (at least some of their job openings were not filled as planned) shows on average a higher level of cooperation breadth (approx. 30% higher), a higher propensity to contract R&D to third parties and a higher proportion of extramural R&D in relation to total R&D expenditures (Table 3).

These descriptive figures illustrate a pattern in which firms experiencing a difficulty to properly fill their job openings tend to rely more on innovation openness or exchanges of knowledge with external partners/sources of knowledge. Firms experiencing a shortage of skilled labour have on average a higher intensity of academic qualifications per vacancy and a higher level of past cooperation breadth.

3.3 Methods and instrumental variables

In our econometric study, we specify two different functional forms in order to test the robustness of the results. First, we specify a linear relationship between innovation openness and skills shortage which we estimate with OLS regressions. Second, we also test an exponential functional form which we estimate with a Poisson count data model.[6] The choice of a Poisson regression model can be explained by the fact that our dependent variable (cooperation breadth) takes on non-negative integer values (Wooldridge, 2010).

The empirical strategy takes into account the interdependence of skills shortage and firms' openness to collaborations with external entities (cooperation breadth). Endogeneity issues are involved in the analysis of the level of openness, because the decision to collaborate with external partners due to a lack of skilled labour might also alleviate skills shortage. Moreover, firms might decide to increase open innovation and demand more skilled people, resulting in a higher propensity to experience a shortage of skills. We address these issues with an instrumental variables approach, thus comparing the results obtained with OLS and Poisson regressions to the estimates obtained with IV and IV Poisson regressions.[7]

Shortage in skills is instrumented by the number of bankrupt firms in 2017 per German district and sector (at NACE 2-digit level) (in logarithm). We exploit information on firms' bankruptcies from the database of Creditreform and use spatial data (the location of firms in distinct German districts, i.e., local markets) to construct this instrument. The higher the number of firms in financial distress at the local level and in the same sector, the higher the supply of employees potentially looking for a new job in the same district and in the same sector, and hence the more likely the firms fill their job vacancies. In other words, we expect this instrument to have a negative effect on skills shortage.

We argue that the instrument is valid, as there seems to be no direct link between a firm's cooperation breadth and the number of other firms going bankrupt in the same district and sector. It could possibly be argued that firms in the same sector and location of the focal firm are in the set of potential cooperation partners, thus a higher number of bankruptcies in the

[6]The Poisson model relies on the assumption of equality of the conditional mean and variance, $E(y|x) = Var(y|x)$. If this is rejected, the Poisson model is still consistent if the conditional mean is correctly specified. We show quasi maximum likelihood estimations, as we correct the standard errors to account for overdispersion (Wooldridge, 2010).

[7]The IV Poisson regression model is estimated using the efficient two-step GMM.

same sector and district lowers the potential set of partners, directly impacting (lowering) the likelihood of cooperation. To address this concern, when we consider the distinct locations of the cooperation partners to construct our dependent variable (cooperation breadth), we exclude the cooperation channels at the regional level (which includes the district level). Hence, we assume that the number of bankruptcies in the same district and sector is not directly linked to a firm's decision to increase the breadth of cooperation channels outside the region of the focal firm. We argue that this assumption is credible because our outcome variable does not denote the number of partners with which a firm is cooperating, but the number of distinct types of cooperation channels; therefore, a higher number of bankruptcies in the same sector and district does not have a direct impact on the decision regarding the breadth of cooperation channels outside the region. Moreover, cooperation breadth takes into account three different types of non-market partners outside the region of the focal firm (i.e., universities, government or public research institutes, non-profit organizations), which are unaffected by the number of bankrupt firms at the district and sector level. In addition, this instrument is constructed based on bankrupt firms in the same NACE 2-digit level of the focal firm, thus it mainly captures the number of its bankrupt competitors. Competitors are among the least frequent partners in cooperation: cooperating with rivals is risky due to the threat of theft or unplanned outgoing spillovers (Miotti and Sachwald, 2003; Laursen and Salter, 2014). Based on data from 2019 MIP, among all partner types from the corporate sector, only cooperating with customers was less common than cooperating with competitors or other enterprises in the same sector (Rammer, 2020). This is another reason why there should not be a direct impact of the number of bankrupt firms operating in the same district and sector on our indicator for cooperation breadth.

A second instrument is given by the average number of employees with an academic degree per district and NACE 2-digit sectoral level in 2017 (in logarithm). To construct this instrument we exploit spatial data and compute the total number of employees working per district and sector, and we multiply it by the average proportion of employees with an academic degree working per district and sector. We expect a positive effect of this instrument on skills shortage due to the clustering of firms with a high demand for academic skills in certain geographic areas. In other words, certain districts are characterized by the presence of firms with a high concentration of employees with a university degree, resulting in a higher demand for academic skills (e.g., highly industrialized areas). The supply of personnel with academic qualifications is insufficient for the demand in these local markets, resulting in firms experiencing a shortage of skilled labour. This mechanism is described by Horbach and Rammer (2022) in relation to innovative firms: "[...] more innovative firms and firms with higher innovation ambition are likely to demand more skills, or more diversified skills, than non-innovative firms or firms with less ambitious innovation strategies. With a higher skill demand, they are more likely to experience a shortage in specific skills they need" (p. 6). This instrument also captures the level of competition in the local labour market and in the same sector: the higher the level of competition in the local market for skilled labour, the more difficult it is for firms to fill their job vacancies. Conversely, the number of employees in the same district and in the same NACE 2-digit sector is not directly linked to cooperation breadth, since the definition of cooperation breadth in this context excludes all cooperation channels within the same region of the focal firm.

4 Results

4.1 Baseline Regressions

Table 4 shows both the baseline OLS and Poisson model as well as their IV versions. For the linear specification, we log-transform the variable denoting cooperation breadth (Cameron and Trivedi, 2005)[8]. The first column of Table 4 shows the coefficients estimated with OLS; skills shortage has a positive and significant coefficient. A regression-based test on endogeneity rejects the hypothesis that skills shortage is an exogenous variable (t-value = -2.59; p-value = 0.01). We therefore switch to the IV-regression. Before discussing the 2nd stage results, we briefly comment on the IV-regressions' first stage result. The results are presented in Table 5.

Most importantly, the two instrumental variables, the log-number of employees with aca-

[8]Transformation of a count variable may be considered to implement least-squares methods, even if this approach is inferior to Poisson regressions. In particular, Cameron and Trivedi (2005) describe as standard transformation the logarithmic one; to deal with zeros, a solution is to add a constant term, such as 0.5, and to model $ln(y + 0.5)$ by OLS. We adopt this transformation in our analysis. In addition, conversion to a linear model has the advantage of convenience if there is an endogenous right-hand variable that needs to be instrumented, which is the case in our estimation.

demic degrees per district and sector and the log-number of bankrupt firms per district and sector, are both statistically significant at the 1% and 5% level, respectively. The joint F-statistic for these excluded instruments amounts to 9.41. We thus do not expect substantial bias in our IV regression due to weak instruments (Stock et al., 2002).

The signs of the instrumental variables are also in line with our expectations. The number of employees with academic degree captures the demand for high-skilled labor in a firm's district and sector, and therefore has a positive sign in the regression of skill shortage. The higher the demand, the more likely is the focal firm to not fill its vacancies. The reverse applies to firm bankruptcies. These capture of positive supply shock in the focal firm's district and sector and therefore vacancies are less likely to remain unfilled.

Turning to the second stage of the IV regression presented in Table 4 (2nd col.), we find that the estimated coefficient of the skills shortage variable is positive and statistically significant at the 5% significance level. We also pass the Hansen J test on overidentifying restrictions, i.e. we do not have to reject the Null hypothesis that our instrumental variables are valid.

The 3rd and 4th columns of Table 4 show the Poisson and IV Poisson model estimates, which confirm our main hypothesis. Skills scarcity has a positive influence on cooperation breadth. Based on the coefficient obtained with the IV Poisson estimation, a one standard deviation increase in skills shortage leads on average to an increase in cooperation breadth by around 111%[9]. In other words, the scarcity of skills produced by a one standard deviation increase in vacancies that are not filled as planned more than doubles a firm's cooperation breadth.

The coefficients of the control variables are in line with our previous expectations. R&D intensity and the proportion of employees with an academic degree both increase firms' cooperation breadth, which confirms the key role of absorptive capacity for openness. Firm size, measured by the number of employees, positively influences cooperation breadth, in line with the assumption that larger firms are better able to invest in open innovation actions with a broader variety of cooperation partners[10]. Being part of an enterprise group increases cooper-

[9] $\exp(0.114 \times (1.722 + 5.699)) - \exp(0.114 \times 1.722) = 1.11$

[10] Except for in the IV and IV Poisson specification, where the coefficient is insignificant (Table 4, column 2 and column 4).

Table 4: Skills shortage and cooperation breadth - Baseline regressions

	Cooperation breadth (log) $_{i,2018}$		Cooperation breadth $_{i,2018}$	
	OLS	IV	Poisson	IV Poisson
Skills shortage $_{i,2017}$	0.005**	0.054**	0.016**	0.114***
	(0.003)	(0.021)	(0.008)	(0.028)
Number of employees $_{i,2017}$	0.080***	0.033	0.073**	-0.060
	(0.011)	(0.032)	(0.035)	(0.073)
Number of employees sq. $_{i,2017}$	-0.000***	-0.000	-0.000	0.001
	(0.000)	(0.000)	(0.000)	(0.000)
R&D intensity $_{i,2017}$	2.041***	2.068***	2.511***	3.225***
	(0.252)	(0.253)	(0.299)	(0.481)
Age (log) $_{i,2017}$	-0.000	0.005	0.019	0.247
	(0.013)	(0.015)	(0.095)	(0.171)
Part of an enterprise group (0/1) $_{i,2017}$	0.151***	0.052	0.897***	0.082
	(0.029)	(0.052)	(0.127)	(0.393)
Empl. with an academic degree (%) $_{i,2017}$	0.216***	0.243***	0.985***	1.449***
	(0.046)	(0.050)	(0.229)	(0.393)
Academic qual. per vacancy $_{i,2017}$	0.191***	0.201***	0.527***	1.250***
	(0.050)	(0.050)	(0.168)	(0.313)
Constant	-0.053	-0.091	-3.400***	-4.027***
	(0.065)	(0.072)	(0.620)	(0.844)
16 sector dummies	Yes	Yes	Yes	Yes
16 regional dummies	Yes	Yes	Yes	Yes
N	3775	3775	3775	3775
R^2	0.23	0.05		
Pseudo-R^2			0.26	
Test of overidentifying restrictions		χ^2=0.14 (p=0.71)		χ^2=0.19 (p=0.66)

Robust standard errors in parentheses

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

In the IV and IV Poisson specifications, *Skills shortage* is instrumented by *Empl. with an academic degree (avg.) per district and sector* (log) and *Bankruptcies (avg.) per district and sector* (log).

Table 5: First stage IV 2SLS regression

	Skills shortage $_{i,2017}$
Empl. with an academic degree (avg.) per district and sector (log) $_{i,2017}$	0.251***
	(0.059)
Bankruptcies (avg.) per district and sector (log) $_{i,2017}$	-0.320**
	(0.131)
Number of employees $_{i,2017}$	0.920*
	(0.486)
Number of employees sq. $_{i,2017}$	-0.007**
	(0.003)
R&D intensity $_{i,2017}$	-0.872
	(0.540)
Age (log) $_{i,2017}$	-0.148
	(0.128)
Part of an enterprise group (0/1) $_{i,2017}$	1.893***
	(0.329)
Empl. with an academic degree (%) $_{i,2017}$	-1.320***
	(0.338)
Academic qual. per vacancy $_{i,2017}$	-0.271
	(0.191)
Constant	0.606
	(0.555)
16 sector dummies	Yes
16 regional dummies	Yes
N	3775
R^2	0.10
Robust F(2,3735)	9.41 (p=0.00)

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

ation breadth[11]. Firms that can leverage the collaborative network of enterprises within their group may be more likely to incorporate a managerial orientation towards cooperation, which results in the tendency to establish alliances outside the group. As expected, the intensity of academic skills per job vacancy positively influences cooperation breadth, since this variable measures a higher demand for employees with a higher education degree.[12]

4.2 Extensions and robustness checks

4.2.1 Additional control variables

As explained in Section 3.2.2, we run a second set of regressions in which we control for past payroll costs per employee (in 2016), which measure a firm's competitiveness on the labour market, and past cooperation breadth (in 2016), which captures previous experience with open innovation processes[13]. For reasons of brevity, we show in Table 6 only the Poisson and IV Poisson models with the additional controls, since these estimation methods are the most appropriate with our count dependent variable. The baseline results remain unchanged when we add these controls: the coefficient for skills shortage remains positive and significant and increases in magnitude if compared to the estimations presented in Table 4. In the IV Poisson regression (Table 6, 2nd col.) we test the relevance of our instruments with the first-stage F-statistic, and there is no concern regarding weak instruments. Furthermore, the validity of the instruments is not rejected either.

4.2.2 Market vs non-market partners

We have also investigated whether we find differential results between market partners and non-market partners for collaboration. Table 7 shows the results of of the IV and IV Poisson

[11]Except for in the IV and IV Poisson specifications, where the coefficient is positive but insignificant (Table 4, column 2 and column 4).

[12]However, the variables indicating academic qualifications per vacancy may be endogenous in our regression. The choice of the breadth of cooperation due to the intensity of academic/non-academic qualifications of a firm's skill demand may influence the intensity of qualifications itself. For the purpose of our analysis, we discard this potential endogeneity issue.

[13]To control for past cooperation breadth, we follow a procedure that mirrors the entry stock estimator proposed by Blundell et al. (1995). This method consists of controlling for unobserved heterogeneity by using the pre-sample average of the dependent variable. In this case, the pre-sample average of cooperation breadth corresponds to past cooperation breadth in 2016. We added this variable as log(past cooperation breadth$_{i,2016}$) in our specification. If the firm did not cooperate for innovation in 2016, a dummy is used to capture the "quasi-missing" value in log of cooperation breadth in 2016 (see also Czarnitzki and Toole (2011)).

Table 6: Skills shortage and cooperation breadth - Additional controls

	Cooperation breadth $_{i,2018}$	
	Poisson	IV Poisson
Skills shortage $_{i,2017}$	0.023***	0.133***
	(0.008)	(0.035)
Number of employees $_{i,2017}$	0.027*	0.044
	(0.015)	(0.031)
Number of employees sq. $_{i,2017}$	-0.000	-0.000
	(0.000)	(0.000)
R&D intensity $_{i,2017}$	1.221***	1.872***
	(0.348)	(0.599)
Age (log) $_{i,2017}$	-0.029	-0.251
	(0.101)	(0.154)
Part of an enterprise group $_{i,2017}$	0.621***	-0.188
	(0.132)	(0.448)
Empl. with an academic degree (%) $_{i,2017}$	0.387*	0.557
	(0.221)	(0.389)
Academic qual. per vacancy $_{i,2017}$	0.473***	1.172***
	(0.182)	(0.321)
Payroll cost per employee $_{i,2016}$	-1.077	-10.777
	(3.601)	(6.863)
Past cooperation breadth (log) $_{i,2016}$	0.343***	-0.010
	(0.101)	(0.203)
No past cooperation (0/1) $_{i,2016}$	-1.791***	-2.126***
	(0.177)	(0.325)
Constant	-1.381*	0.200
	(0.784)	(1.059)
16 sector dummies	Yes	Yes
16 regional dummies	Yes	Yes
N	3033	3033
Pseudo R^2	0.41	
Test of overidentifying restrictions (χ^2)		0.28 (p=0.60)
Robust F stat. on joint sig.		9.27 (p=0.00)

Robust standard errors in parentheses

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

Skills shortage is instrumented by *Empl. with an academic degree (avg.) per district and sector* (log) and *Bankruptcies (avg.) per district and sector* (log).

models in which we estimate the impact of skills shortage on cooperation breadth with non-market (first and second columns) and market partners (third and fourth columns). The effect of skills shortage is positive and significant in both the IV and IV Poisson specifications when the dependent variable is cooperation breadth with market partners, and is positive and significant only in the IV Poisson model when the outcome variable is cooperation breadth with non-market partners. A test for cross-equation equality of coefficients[14] does not indicate a differential impact of skills shortage on cooperation breadth with market partners and with non-market partners.

Table 7: Cooperation breadth with market/non-market partners

	Cooperation breadth $_{i,2018}$			
	non-market partners		market partners	
	IV	IV Poisson	IV	IV Poisson
Skills shortage $_{i,2017}$	0.032	0.109***	0.064**	0.104***
	(0.021)	(0.025)	(0.029)	(0.022)
Number of employees $_{i,2017}$	0.117***	-0.020	0.129*	-0.055
	(0.045)	(0.090)	(0.070)	(0.097)
Number of employees sq. $_{i,2017}$	-0.000	0.000	-0.001	0.000
	(0.000)	(0.001)	(0.000)	(0.001)
R&D intensity $_{i,2017}$	2.271***	3.409***	1.576***	2.673***
	(0.376)	(0.519)	(0.311)	(0.491)
Age (log) $_{i,2017}$	0.006	0.433	0.016	0.252
	(0.014)	(0.315)	(0.025)	(0.253)
Part of an enterprise group $_{i,2017}$	0.043	-0.526	0.088	0.282
	(0.051)	(0.618)	(0.067)	(0.365)
Empl. with an academic degree (%) $_{i,2017}$	0.182***	1.901***	0.209***	1.493***
	(0.048)	(0.465)	(0.064)	(0.457)
Academic qual. per vacancy $_{i,2017}$	0.111**	1.099***	0.174***	1.322***
	(0.050)	(0.295)	(0.066)	(0.328)
Constant	-0.062	-5.144***	-0.099	-3.873***
	(0.060)	(1.215)	(0.099)	(0.953)
16 sector dummies	Yes	Yes	Yes	Yes
N	3775	3775	3775	3775
R^2	0.24		0.02	
Test of overidentifying restrictions (χ^2)	1.89 (p=0.17)	0.05 (p=0.82)	0.01 (p=0.94)	0.52 (p=0.47)
Robust F Statistic	10.71 (p=0.00)		10.71 (p=0.00)	

Robust standard errors in parentheses

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

Skills shortage is instrumented by *Empl. with an academic degree (avg.) per district and sector* (log) and *Bankruptcies (avg.) per district and sector* (log).

[14]This test was implemented by estimating the linear IV regressions as system of equations using 3SLS.

4.2.3 Alternative measures of openness

We also test if the hypothesized effect is robust to using other variables capturing inbound innovation openness besides cooperation breadth. Table 8 illustrates the results obtained by using these alternative indicators of openness. Skills shortage exhibits a positive and significant coefficient in the regressions with contracted-out R&D (OLS and IV), extramural R&D (%) (fractional logit) and licensing-in or purchasing of IPRs from third parties (IV). When we account for the type of partner from which firms license-in IPRs, we find that skills shortage is significantly and positively associated to licensing-in from enterprises/private individuals, whereas a positive and insignificant effect if found when it comes to universities/public research organizations (Table 8, fifth and sixth columns). Overall, the use of alternative variables for inbound openness and flows of knowledge/technology provides support to our main hypothesis and corroborates the previous findings related to cooperation breadth.

Table 8: Contracted-out R&D - Extramural R&D (%) - Licensing-in/Purchasing of IPRs

	Contracted-out R&D $_{i,2018}$		Extramural R&D (%) $_{i,2018}$	Licensing-in $_{i,2018}$	Licening-in PRV	Licening-in PUB
	OLS	IV	Fractional logit	IV	IV	IV
Skills shortage $_{i,2017}$	0.002**	0.064***	0.015**	0.020**	0.017**	0.004
	(0.001)	(0.017)	(0.007)	(0.008)	(0.008)	(0.003)
Number of employees $_{i,2017}$	0.028***	-0.031	0.065**	-0.011	-0.016	0.001
	(0.005)	(0.033)	(0.028)	(0.009)	(0.010)	(0.005)
Number of employees sq. $_{i,2017}$	-0.000***	0.000	-0.000**	0.000*	0.000**	0.000
	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)	(0.000)
R&D intensity $_{i,2017}$	0.665***	0.700***	1.594***	0.163**	0.050	0.038
	(0.112)	(0.117)	(0.392)	(0.066)	(0.038)	(0.036)
Age (log) $_{i,2017}$	0.004	0.011	0.016	0.004	0.007	-0.001
	(0.007)	(0.011)	(0.090)	(0.006)	(0.006)	(0.002)
Part of an enterprise group $_{i,2017}$	0.074***	-0.053	0.460***	-0.009	-0.000	-0.010
	(0.015)	(0.041)	(0.170)	(0.022)	(0.020)	(0.007)
Empl. with an academic degree (%) $_{i,2017}$	0.054**	0.088**	0.297	0.056***	0.039**	0.018**
	(0.024)	(0.035)	(0.330)	(0.020)	(0.018)	(0.008)
Academic qual. per vacancy $_{i,2017}$	0.102***	0.114***	0.636***	0.015	0.011	-0.007
	(0.026)	(0.028)	(0.221)	(0.016)	(0.014)	(0.005)
Constant	-0.002	-0.050	-4.601***	-0.037	-0.046*	-0.004
	(0.041)	(0.055)	(0.835)	(0.025)	(0.025)	(0.007)
16 sector dummies	Yes	Yes	Yes	Yes	Yes	Yes
16 regional dummies	Yes	Yes	Yes	Yes	Yes	Yes
N	3775	3775	3775	3178	3178	3178
R^2	0.14					
Pseudo-R^2			0.06			
Test of overidentifying restrictions (χ^2)		0.04 (p=0.84)		0.05 (p = 0.82)	0.36 (p = 0.55)	0.90 (p = 0.34)
Robust F Statistic		9.41 (p=0.00)		8.45 (p=0.00)	8.45 (p=0.00)	8.45 (p=0.00)

Robust standard errors in parentheses
* $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$
In the IV specifications, *Skills shortage* is instrumented by *Empl. with an academic degree (avg.) per district and sector* (log) and *Bankruptcies (avg.) per district and sector* (log).

4.2.4 Alternative operationalizations of cooperation breadth

We also implement an alternative operationalization of the dependent variable as in Laursen and Salter (2014). Instead of modeling the cooperation breadth as count variable, we divide it by its upper bound of 45 cooperation types and obtain a variable that ranges between 0 and 1, i.e. we use a percentage transformation of our openness measure. We therefore estimate fractional response models, in which $E(y|x)$ is modeled as a logistic function. The model can be estimated by quasi-maximum likelihood (Papke and Wooldridge, 1996). We replicate the specifications described above with fractional logit regressions (cf. Table 11, Appendix). Our findings are confirmed: skills shortage positively impacts cooperation breadth.

Similar results are obtained if we construct cooperation breadth without taking into account the distinct locations of the partners. This way, the indicator for innovation openness ranges from 0 to 6, since 6 is the maximum number of types of cooperation partner in the operationalization of Laursen and Salter (2014), i.e., suppliers, clients or customers, competitors, consultants and private R&D institutes, universities, and public research institutes (cf. Table 11, Appendix).

4.2.5 Alternative specification of skills shortage

As far as the operationalization of skills shortage is concerned, we previously took into account the sum of job vacancies that were not filled as planned, including those that could be filled only with delay or without the desired personnel. However, one could argue that the vacancies that were filled with a delay or without the desired candidates may have a different impact on cooperation breadth if compared to the vacancies that were not filled at all. For instance, vacancies that are filled with a delay lead to a temporary inability to acquire specific skills, but not to a long-term insufficiency of skills, and may not have an impact on the cooperation strategy of a firm, since increasing cooperation breadth requires time and managerial efforts. We conduct a robustness test in which we exclude the delayed filled vacancies and the vacancies that were filled without the desired personnel from our measure for skills shortage, thus obtaining a variable denoting the number of unfilled vacancies. When we regress cooperation breadth on this alternative measure of skills shortage, we observe that its coefficient becomes larger, in line with the expectation that vacancies that remain unfilled have a stronger positive effect on cooperation breadth (cf. Table 12, Appendix).[15]

Furthermore, we tested potential non-linear effects of skills shortage on cooperation breadth by adding the squared of skills shortage as independent variable in the Poisson specification. Following the theoretical arguments of Müller and Peters (2010) on the effect of churning of R&D personnel on innovation performance, we explored if the effect of skills scarcity on cooperation breadth becomes negative if skills scarcity exceeds a certain threshold (inverse u-shaped relationship). We did not find evidence for a potential inverse U-shaped relationship between skills shortage and cooperation breadth.

5 Conclusions

This article contributes to a recent and growing academic interest in evaluating Open Innovation in relation to human capital (Bogers et al., 2018). In particular, we investigate the impact of skills shortage, measured as the number of a firm's job vacancies that were not filled as planned, on innovation openness. We find that skills shortage at the firm level is associated with a notable increase in cooperation breadth. This result sheds light on the *necessity* of innovation openness, as a way to compensate for the lack of internal skills and know-how. This effect confirms that open innovation strategies occur in a dynamic way, which requires firms to be able to absorb critical knowledge for both outside-in and inside-out flows (Bello-Pintado and Bianchi, 2020). The design of an open innovation strategy thus seems to be intertwined with a firm's skill demand, given a certain level of absorptive capacity. We contribute to the existing literature on skills shortage by documenting its impact on openness, which has an important role for innovation performance.

Furthermore, the results of this study have policy and managerial implications. First, from a policy perspective, this paper suggests that promoting open innovation activities can be a useful instrument to alleviate the problem of skills shortage, which has severe consequences on innovation and on productivity (Coad et al., 2016; Toivanen and Väänänen, 2016; Horbach and Rammer, 2022). Firms might find it useful to rely on external sources of knowledge when skills shortage prevents them from acquiring from the labour market the set

[15] In this robustness test, we should note that the first-stage F-statistic of excluded instruments only amounts to 5.01 and we are thus somewhat concerned about potential bias induced by weak instruments.

of skills that is needed for their innovation activities. On the other hand, policymakers should also introduce measures to improve firms' human capital as a way to enable and strengthen the open innovation processes. For instance, recruitment policies (e.g., public support for recruiting and training qualified employees) could be adopted as a complementary instrument to reinforce the effects of open innovation actions (Bello-Pintado and Bianchi, 2020).

Second, from a managerial viewpoint, this analysis demonstrates that innovation openness involves significant challenges for firms, as it requires to adapt the breadth of cooperation strategies in response to the outcome of the hiring process of new employees. Firms seem to respond to skills shortage with an increase in the breadth of types of cooperation, suggesting that exchanges of knowledge and know-how with external partners can mitigate the internal scarcity of competences and skills. This effect does not suggest, however, that firms can perfectly substitute internal knowledge for innovation by increasing cooperation breadth. The possibility to mitigate skills shortage with an increased level of innovation openness depends on the existence of a certain level of internal capacity to implement successfully new types of cooperations. As a consequence, another implication for practitioners is to intensify the adoption of human resource practices, such as team rewards or extensive selection, that are useful to attract and retain high-skilled employees (Laursen and Foss, 2014; Vanhaverbeke et al., 2014).

While this paper adds new insights into the interdependence between skills shortage and innovation openness, much more research is certainly needed. First, this study is a cross-sectional analysis that considers the dynamics between skills shortage and innovation openness only partially, mainly by controlling for path dependence in terms of previous cooperation breadth. A more rigorous assessment between the dynamics between scarcity of skills and openness can be implemented using a panel study design in future research endeavours. Second, we chose to measure innovation openness in terms of cooperation breadth, following a common operationalization adopted in the literature (Laursen and Salter, 2006, 2014). While we conduct additional tests with alternative variables denoting inbound open innovation processes, further research could examine the influence of skills shortage on another well-established measure of openness, namely external search breadth (Laursen and Salter, 2014), or could use indicators based on co-patenting. Such alternative measures may help to capture distinct managerial practices and reflect other peculiarities of the compensation mechanism existing between skills shortage and innovation openness. Third, our sample is confined to Germany, where skills scarcity is a key policy concern (Horbach and Rammer, 2022), and hence future empirical studies are called for to test our hypothesis in other countries.

References

Behrens, V., Berger, M., Hud, M., Hünermund, P., Iferd, Y., Peters, B., Rammer, C., and Schubert, T. (2017). Innovation activities of firms in germany-results of the german cis 2012 and 2014: Background report on the surveys of the mannheim innovation panel conducted in the years 2013 to 2016. Technical report, ZEW-Dokumentation.

Bello-Pintado, A. and Bianchi, C. (2020). Consequences of open innovation: effects on skill-driven recruitment. *Journal of Knowledge Management*, 24(2):258–278.

Blundell, R., Griffith, R., and Reenen, J. V. (1995). Dynamic count data models of technological innovation. *The Economic Journal*, 105(429):333–344.

Bogers, M., Foss, N. J., and Lyngsie, J. (2018). The "human side" of open innovation: The role of employee diversity in firm-level openness. *Research Policy*, 47(1):218–231.

Bogers, M., Zobel, A.-K., Afuah, A., Almirall, E., Brunswicker, S., Dahlander, L., Frederiksen, L., Gawer, A., Gruber, M., Haefliger, S., et al. (2017). The open innovation research landscape: Established perspectives and emerging themes across different levels of analysis. *Industry and Innovation*, 24(1):8–40.

Cameron, A. C. and Trivedi, P. K. (2005). *Microeconometrics: methods and applications*. Cambridge University Press.

Cassiman, B. and Veugelers, R. (2006). In search of complementarity in innovation strategy: Internal R&D and external knowledge acquisition. *Management Science*, 52(1):68–82.

Chesbrough, H. and Bogers, M. (2014). Explicating open innovation: Clarifying an emerging paradigm for understanding innovation. *New Frontiers in Open Innovation. Oxford: Oxford University Press, Forthcoming*, pages 3–28.

Chesbrough, H. W. (2003). *Open innovation: The new imperative for creating and profiting from technology*. Harvard Business Press.

Coad, A., Pellegrino, G., and Savona, M. (2016). Barriers to innovation and firm productivity. *Economics of Innovation and New Technology*, 25(3):321–334.

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

Cohen, W. M., Nelson, R. R., and Walsh, J. P. (2002). Links and impacts: the influence of public research on industrial R&D. *Management Science*, 48(1):1–23.

Czarnitzki, D. and Toole, A. A. (2011). Patent protection, market uncertainty, and rd investment. *The Review of Economics and Statistics*, 93(1):147–159.

Dosi, G. and Nelson, R. R. (2010). Technical change and industrial dynamics as evolutionary processes. *Handbook of the Economics of Innovation*, 1:51–127.

Faems, D., De Visser, M., Andries, P., and Van Looy, B. (2010). Technology alliance portfolios and financial performance: value-enhancing and cost-increasing effects of open innovation. *Journal of Product Innovation Management*, 27(6):785–796.

Felin, T. and Zenger, T. R. (2014). Closed or open innovation? problem solving and the governance choice. *Research Policy*, 43(5):914–925.

Fleming, L. (2001). Recombinant uncertainty in technological search. *Management Science*, 47(1):117–132.

Freel, M. S. (2005). Patterns of innovation and skills in small firms. *Technovation*, 25(2):123–134.

Greco, M., Grimaldi, M., and Cricelli, L. (2019). Benefits and costs of open innovation: the beco framework. *Technology Analysis & Strategic Management*, 31(1):53–66.

Horbach, J. and Rammer, C. (2022). Skills shortage and innovation. *Industry and Innovation*, 29(6):734–759.

Köhler, C., Sofka, W., and Grimpe, C. (2012). Selective search, sectoral patterns, and the impact on product innovation performance. *Research Policy*, 41(8):1344–1356.

Laursen, K. and Foss, N. (2014). *Human Resource Management Practices and Innovation*, pages 506–529. Oxford Handbooks in Business and Management. Oxford University Press, United Kingdom.

Laursen, K. and Salter, A. (2004). Searching high and low: what types of firms use universities as a source of innovation? *Research Policy*, 33(8):1201–1215.

Laursen, K. and Salter, A. (2006). Open for innovation: the role of openness in explaining innovation performance among uk manufacturing firms. *Strategic Management Journal*, 27(2):131–150.

Laursen, K. and Salter, A. J. (2014). The paradox of openness: Appropriability, external search and collaboration. *Research Policy*, 43(5):867–878.

Leiponen, A. (2005). Skills and innovation. *International Journal of Industrial Organization*, 23(5-6):303–323.

Leiponen, A. and Helfat, C. E. (2010). Innovation objectives, knowledge sources, and the benefits of breadth. *Strategic Management Journal*, 31(2):224–236.

Lewandowska, M. S. (2015). Capturing absorptive capacity: concepts, determinants, measurement modes and role in open innovation. *International Journal of Management and Economics*, 45(1):32–56.

Miotti, L. and Sachwald, F. (2003). Co-operative R&D: why and with whom?: An integrated framework of analysis. *Research Policy*, 32(8):1481–1499.

Müller, K. and Peters, B. (2010). Churning of R&D personnel and innovation. *ZEW-Centre for European Economic Research Discussion Paper*, (10-032).

Papke, L. E. and Wooldridge, J. M. (1996). Econometric methods for fractional response variables with an application to 401 (k) plan participation rates. *Journal of Applied Econometrics*, 11(6):619–632.

Rammer, C. (2020). Dokumentation zur Innovationserhebung 2019. ZEW Dokumentationen 20-01, ZEW - Leibniz Centre for European Economic Research.

Simeth, M. and Mohammadi, A. (2022). Losing talent by partnering up? the impact of R&D collaboration on employee mobility. *Research Policy*, 51(7):104551.

Sousa, M. J. and Rocha, Á. (2019). Skills for disruptive digital business. *Journal of Business Research*, 94:257–263.

Stock, J. H., Wright, J. H., and Yogo, M. (2002). A survey of weak instruments and weak identification in generalized method of moments. *Journal of Business & Economic Statistics*, 20(4):518–529.

Teece, D. J. (2010). Technological innovation and the theory of the firm: the role of enterprise-level knowledge, complementarities, and (dynamic) capabilities. In *Handbook of the Economics of Innovation*, volume 1, pages 679–730. Elsevier.

Ter Wal, A. L., Criscuolo, P., and Salter, A. (2017). Making a marriage of materials: The role of gatekeepers and shepherds in the absorption of external knowledge and innovation performance. *Research Policy*, 46(5):1039–1054.

Toivanen, O. and Väänänen, L. (2016). Education and invention. *Review of Economics and Statistics*, 98(2):382–396.

Toner, P. (2011). Workforce skills and innovation: An overview of major themes in the literature. OECD Science, Technology and Industry Working Papers 2011/1, OECD Publishing.

Vanhaverbeke, W., Chesbrough, H., and West, J. (2014). Surfing the new wave of open innovation research. *New frontiers in open innovation*, 281:287–288.

Wadhwa, A., Bodas Freitas, I. M., and Sarkar, M. (2017). The paradox of openness and value protection strategies: Effect of extramural R&D on innovative performance. *Organization Science*, 28(5):873–893.

Williamson, O. E. (1981). The economics of organization: The transaction cost approach. *American Journal of Sociology*, 87(3):548–577.

Wooldridge, J. M. (2010). *Econometric analysis of cross section and panel data.* MIT press.

Appendix

Table 9: Cross-correlation table

Variables	1	2	3	4	5	6	7	8	9	10
1. Cooperation breadth $_{i,2018}$	1.000									
2. Skills shortage $_{i,2017}$	0.105	1.000								
3. N. employees $_{i,2017}$	0.311	0.078	1.000							
4. R&D intensity $_{i,2017}$	0.254	-0.017	0.010	1.000						
5. Employees with an academic degree (%) $_{i,2017}$	0.151	-0.042	-0.004	0.277	1.000					
5. Age $_{i,2017}$	0.011	0.004	0.063	-0.074	-0.163	1.000				
7. Part of an enterprise group $_{i,2017}$	0.153	0.172	0.095	-0.028	0.001	0.051	1.000			
8. Academic qualifications per vacancy $_{i,2017}$	0.099	-0.029	-0.019	0.123	0.351	-0.067	0.016	1.000		
9. Empl. with academic degree (avg.) (district/sector) $_{i,2017}$	0.058	0.012	0.008	0.081	0.378	-0.096	-0.006	0.158	1.000	
10. Bankruptcies (avg.) (district/sector) $_{i,2017}$	-0.003	-0.009	-0.013	0.017	0.333	-0.101	-0.049	0.087	0.643	1.000
N = 3775										

Table 10: Industry composition

Industry	%
Consumer goods	10.07
Other materials	10.12
Chemicals and pharmaceuticals	2.57
Metals and metal products	7.47
Electronics and electrical equipment	5.96
Machinery and equipment	6.99
Vehicles	1.48
Utilities, waste management, mining	9.51
Wholesale trade	4.19
Transport and logistics services	7.76
Media services	2.33
Software, IT services	4.58
Financial services	2.99
Legal, accounting, consulting, advertising serv.	8.90
Engineering and R&D services	9.11
Other producer services	5.96
$N = 3775$	100

Table 11: Robustness checks - Fractional logit model

	(Cooperation breadth)/45 $_{i,2018}$		[Cooperation breadth (0-6)]/6 $_{i,2018}$	
	Frac. logit	IV Frac. logit	Frac. logit	IV Frac. logit
Skills shortage $_{i,2017}$	0.018**	0.638**	0.025**	0.492**
	(0.008)	(0.244)	(0.010)	(0.208)
Number of employees $_{i,2017}$	0.089***	-0.493	0.144**	-0.301
	(0.023)	(0.929)	(0.060)	(0.737)
Number of employees sq. $_{i,2017}$	-0.000***	0.004	-0.001**	0.002
	(0.000)	(0.015)	(0.000)	(0.011)
R&D intensity $_{i,2017}$	2.654***	3.017***	3.169***	3.433***
	(0.322)	(0.553)	(0.395)	(0.551)
Age (log) $_{i,2017}$	0.030	0.102	0.026	0.083
	(0.096)	(0.161)	(0.092)	(0.118)
Part of an enterprise group $_{i,2017}$	0.901***	-0.351	0.830***	-0.110
	(0.130)	(0.440)	(0.132)	(0.424)
Empl. with an academic degree (%) $_{i,2017}$	1.010***	1.501***	1.108***	1.484***
	(0.234)	(0.380)	(0.235)	(0.319)
Academic qual. per vacancy $_{i,2017}$	0.545***	0.690***	0.727***	0.834***
	(0.172)	(0.216)	(0.171)	(0.209)
Constant	-7.255***	-7.807***	-5.271***	-5.693***
	(0.629)	(1.499)	(0.617)	(0.755)
First-stage residuals		-0.623**		-0.470**
		(0.246)		(0.209)
16 sector dummies	Yes	Yes	Yes	Yes
16 regional dummies	Yes	Yes	Yes	Yes
N	3775	3775	3775	3775
Psuedo-R^2	0.14		0.18	

Robust standard errors in parentheses

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

In the IV Fractional logit specifications, *Skills shortage* is instrumented by *Empl. with an academic degree (avg.) per district and sector* (log) and *Bankruptcies (avg.) per district and sector* (log); in addition, standard errors are boostrapped with 200 replications.

Table 12: Job vacancies that were not filled at all - IV 2SLS

	Cooperation breadth (log) $_{i,2018}$
Unfilled vacancies $_{i,2017}$	0.154**
	(0.069)
Number of employees $_{i,2017}$	0.059***
	(0.020)
Number of employees sq. $_{i,2017}$	-0.000**
	(0.000)
R&D intensity $_{i,2017}$	2.119***
	(0.257)
Age (log) $_{i,2017}$	0.006
	(0.015)
Part of an enterprise group $_{i,2017}$	0.083*
	(0.050)
Empl. with an academic degree (%) $_{i,2017}$	0.212***
	(0.055)
Academic qual. per vacancy $_{i,2017}$	0.203***
	(0.051)
Constant	-0.056
	(0.070)
16 sector dummies	Yes
16 regional dummies	Yes
N	3775
Test of overidentifying restrictions (χ^2)	0.01 (p=0.91)
Robust F Statistic	5.01 (p=0.00)

Robust standard errors in parentheses

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

Skills shortage is instrumented by *Empl. with an academic degree (avg.) per district and sector* (log) and *Bankruptcies (avg.) per district and sector* (log).

//
IMPRINT

ZEW – Leibniz-Zentrum für Europäische Wirtschaftsforschung GmbH Mannheim

ZEW – Leibniz Centre for European Economic Research

L 7,1 · 68161 Mannheim · Germany
Phone +49 621 1235-01
info@zew.de · zew.de