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03.22

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Impressum:

Working Papers on Innovation and Space
Philipps-Universität Marburg

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Published in: 2022

Skill shortages and industry clusters – Empirical evidence from German establishment data

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Abstract:

Regional and sector-specific skill shortages are either foreseeable or a reality in Germany. It is unclear whether shortages of skilled workers are more apparent in industry-specific agglomerations due to competitive labor poaching or less apparent benefitting labor pooling. This paper analyses the association of skill shortages and the level of industrial clustering in Germany. The results show, that firms located in an industrial cluster have a significantly lower chance of experiencing skill shortages in terms of vacancies for qualified jobs. At the same time, if firms located in industrial clusters face skill shortage, they struggle more to fill such vacancies.

Keywords: Skill shortage, cluster, location quotient, Establishment panel data

JEL Classifications: J23, J63, R10

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1 Introduction

Analyses of the skilled labor supply have been gaining relevance for about two decades, even though there has not yet been a widespread skill shortage in Germany. Such shortages in the supply of skilled workers are not a temporary phenomenon. Demographic trends, structural change and increasing total employment are leading to skill shortages in various labor market sectors (Arnold et al., 2017; Bellmann et al., 2015; Bellmann & Leber, 2017; Burstedde et al., 2020; Kettner, 2012). Small and medium-sized firms in general and specifically those with a demand for skilled workers in technical and healthcare occupations are specifically affected (Czepek et al., 2015; Dummert et al., 2014). Even currently, the general labor demand - despite the Corona pandemic - is greater than in 2010 after the 2008 economic and financial crisis (Burstedde et al., 2020). The supply of skilled labor is a key aspect to maintain an innovative and competitive economy and therefore further insights into the development of skill shortages are needed (Burstedde et al., 2020). The economic costs of skill shortages affect individuals, firms and the overall economy. Individual costs for employees and for firms cover a wide range of consequences and can partly turn from temporary to permanent (Brunello & Wruuck, 2019).

Besides industry- and occupation-based influences on skilled labor supply, the scientific literature shows that firm characteristics and firm location matter as well for skill shortages (e.g. Bellmann & Hübler, 2014). Based on these results, one could assume, that firm location in terms of a surrounding industrial agglomeration matters, too. Positive cluster effects, such as labor pooling, knowledge spillovers and the emergence of innovations in the area of economic agglomerations and industrial clusters are widely discussed. However, agglomerations and clusters also have negative effects on firms (e.g. Wrobel, 2015), such as labor poaching. Regional and sector-specific bottleneck scenarios in terms of skilled labor recruitment are already either foreseeable or already a reality in Germany (Czepek et al., 2015). As a consequence, competition for skilled workers has already intensified, with sometimes drastic consequences for disadvantaged firms. However, so far it is unclear whether such shortages of skilled workers are more apparent in industry-specific agglomerations, caused by labor poaching and intense competition, or less apparent due to the attractiveness of the shared labor market.

This gap is approached by investigating the availability of skilled workers under the specific conditions of industry-specific agglomerations and clusters. The following research question is examined: Are skill shortages associated with the level of agglomeration of industrial clustered firms in Germany? To this end, we use firm-level data on skill shortages and combine it with spatial data on industry clustering.

Our result imply that firms in industry clusters have a lower chance of suffering from a skill shortage and yet at the same time firms in industry clusters have, if they face skill shortage, a higher ratio of unfilled qualified labor positions to current skilled labor positions in the firm.

The paper is structured as follows. After a general introduction to relevant aspects, the theoretical and empirical evidence on aspects of skill shortage and the link to industrial clusters are presented. The following methods and data section explains structural characteristics of the used data sets as well as the identification of industrial clusters and the economic approach on which the regression analysis is based. The results section presents the outcomes of different regression models and discusses them. Finally, the concluding remarks will summarize the main aspects of the article and some policy recommendations.

2 Theoretical Background

2.1 Skill shortages

A Shortage of skills needed (and skill mismatches[1]) can be costly to employees, firms and society in general since they can negatively affect earnings, productivity and innovation processes (Brunello & Wruuck, 2019). Such skill shortages in general arise whenever employers are unable to recruit workers with the needed set of skills within the accessible labor market and at the common rate of pay (Quintini, 2011). Different macroeconomic developments can be held responsible for skill shortages. The literature identifies especially demographic, technological or organizational changes as relevant (Bellmann & Hübler, 2014). The relevant demographic changes are based on a decline in population, later labor market entries and a growing participation of females in the labor market (Bellmann & Hübler, 2014). Technological changes generally increase the demand for skilled workers due to the skill-biased technological change (Bellmann & Hübler, 2014; Haskel & Martin, 2001). The relevant organizational changes are related to schooling deficiencies and political challenges to maintain a sufficient quality of human capital (Bellmann & Hübler, 2014).

Negative impact on firms due to skill shortages range from unfilled positions to recruitment of workers with lower skills than required and even to production losses as a consequence. Furthermore, skill shortages can limit investment and the adoption of new technologies, with negative impact on productivity (Bennett & McGuinness, 2009; Brunello & Wruuck, 2019; Morris et al., 2020; Tang & Wang, 2005). In general, the costs of shortages to firms depend on the duration of the shortage

[1] A skill mismatch approach is more employee focussed and describes the insufficient fit between acquired skills of workers and the required skills of hiring firms Brunello und Wruuck (2019, S. 4). Since the Analysis is focused on the firm level, the related terminology of skill mismatches is not used in this paper

(Brunello & Wruuck, 2019). Analyzing panel data, Bellmann and Hübler (2014) find that skill shortages in firms are usually short-term phenomena.

Appearing skill shortages can be identified with different approaches, depending on the respective data base, since there is no all-encompassing indicator (Bellmann & Leber, 2017). In Germany, research institutes, trade unions, employer associations and ministries provide most empirical evidence on current skill shortages – e.g. Federal Institute for Vocational Training, German Trades Union Confederation, Federation of German Industry, Federal Ministry of Labor and Social Affairs (including the Federal Employment Agency) and Federal Ministry of Economics and Technology (Bellmann & Hübler, 2014).

One usual approach is based on official data using the average duration of vacancies and the ratio of applicants or employed individuals to vacancies. Both indicators are used to derive indications of shortages for regions and occupations. Yet the use of official data has shortcomings, since only vacant positions reported by firms are taken into account – these are approximately half of all vacant positions within the very same firms (Bellmann & Leber, 2017; Czepek et al., 2015). Furthermore information on the reporting firms are missing.

A different approach to analyze skill shortages within the labor market draws on firm data based on standardized surveys, such as the IAB Establishment Panel (Bellmann & Hübler, 2014; Bellmann & Leber, 2017; Brunow & Grünwald, 2015; Hinz, 2019; Horbach, 2014). Firm level data focuses on aspects such as vacancy times for open positions, open positions in relation to employees (total employees or a specific group of employees) or items which directly refer to labor shortage in general or specifically skill shortage. In contrast to the data from the Federal Employment Agency described above, firm level data contains relevant information on the firms surveyed, which are relevant for the econometric analysis since firm characteristics partly explain differences in shortages of skilled workers (e.g. Bellmann & Hübler, 2014).

2.2 Industry clusters between labor pooling and labor poaching

Following Marshall's (1920) specialization approach, there are three main aspects of agglomeration of firms: the availability of intermediate and final goods, labor pooling and technological spill-overs (Combes & Duranton, 2006; van der Panne, 2004). Due to our interest in skill shortage, we will focus on the second aspect: labor pooling.

Labor pooling is perceived as a strong motive and advantage for firms to locate within an existing cluster since access to needed workers is presumably easier. It is argued that firms who are able to recruit from a larger pool are more likely to find workers with the needed characteristics. Vice versa, employees are more likely to find a job suited to their skill set within clusters (Combes & Duranton, 2006). Helsley and Strange (1990) describe this improved matching ability of a large labor pool as an often cited source of agglomeration economies.

However, sector specific agglomeration of firms has not exclusively positive outcomes (Grashof, 2020; Wrobel, 2015). Regionally clustered firms sharing a beneficial local labor market, face a tradeoff between positive labor pooling effects and the costs of negative effects of competitive labor poaching. Labor poaching results in loss of key workers to neighboring firms, higher wage bills in order retain your current workers, and increasing costs to hire new employees. Furthermore by poaching, competitors obtain with new employees also knowledge about the former employer (Combes & Duranton, 2006).

Based on the previous aspects of skill shortages, the positive cluster effect of labor pooling and the negative cluster effect of labor poaching could presumably enhance or reduce the appearance of skill shortages within industry clusters. Based on the theoretical background and empirical evidence of previous studies, it is a priori not clear which effects on skill shortages dominates. Therefore, we formulate two competing hypothesis. On the one hand, the local labor market pool could allow cluster related firms to fill vacancies faster compared to firms of the same industry outside of a cluster. Thus, the following hypothesis is proposed:

Hypothesis 1: Assuming that the positive labor pooling effects are predominate and the negative labor poaching are negligible,

a) firms in industry clusters have a lower chance of suffering from a skill shortage and

b) firms in industry clusters have a lower ratio of unfilled qualified labor positions to current skilled labor positions in the firm.

On the other hand, the negative cluster effect of labor poaching would cause firms located in clusters to suffer more from competitive pressure. More vacant positions for qualified jobs and therefore skill shortages would be a result. Thus, the following hypothesis is proposed:

Hypothesis 2: Assuming that the negative labor poaching are predominate and the positive labor pooling effects are negligible,

a) firms in industry clusters have a higher chance of suffering from a skill shortage and

b) firms in industry clusters have a higher ratio of unfilled qualified labor positions to current skilled labor positions in the firm.

3 Methods and data

For the empirical investigation of the connection between skill shortages and the level of agglomeration of industrial clustered firms in Germany, multiple data sources and variables are necessary. First, industrial clusters are identified with the help of a location quotient. Second, the IAB Establishment Panel is used to identify skill shortages within firms. Finally, generalized linear mixed regression models are applied for the time period 2009 to 2019.

3.1 Data set and structural characteristics

In regard to the accuracy of reported skill shortages, employers and managers are likely to have more accurate information than employees themselves (Brunello & Wruuck, 2019, S. 25). Therefore, a well-established firm survey is used as data set. The IAB Establishment panel is an employer survey conducted annually since 1993 – since 1996 in eastern Germany – with currently about 16,000 interviewed firms throughout Germany. It is conducted by the Institute for Employment Research (IAB) of the Federal Employment Agency (BA) in cooperation with Kantar Public.

The representative survey focuses on the determinants of employment within firms, which are recorded across all sectors and firm sizes. The total population includes all establishments with at least one employee subject to social insurance contributions as of June 30 of the previous year (used cut-off date). The sample drawn is disproportionately stratified according to firm size, sector and federal state and allows representative statements to be made by using extrapolation factors such as a firm weight or an employee weight (Bechmann et al., 2021).

The IAB Establishment panel is designed as a longitudinal panel survey, which observes the selected establishments repeatedly on 30 June of each year. Questions on employment development, business policy, firm investments, personnel structure and movement as well as payment, among other things, form the recurring core of the survey (Bechmann et al., 2021). The descriptive statistics and descriptions of all used variables are provided within the appendix (see table A3 and A4).

3.2 Skill shortage indicators

In the here provided econometric analysis, skill shortages are measured by different variables (see table 1): Firstly, a dummy variable D_UQJ is used, where D_UQJ = 1 if the firm reported that it was unable to fill vacancies for qualified jobs and D_UQJ = 0 otherwise. Skilled workers include employees with a university degree, employees who completed vocational training and those who have comparable professional experience. Secondly, we calculate the ratio of the number of unfilled qualified jobs (UQJ) to the total number of qualified employees (QE), receiving the indicator UQJ/QE.

Table 1 lists three further indicators that are used in other scientific article (e.g. Bellmann & Hübler, 2014): the number of unfilled qualified jobs (UQJ), the ratio (UQJ/TE) of number of unfilled qualified jobs (UQJ) to the total number of employees (TE), and the ratio (UQJ/TD) of number of unfilled qualified jobs (UQJ) to the total demand of employees (TD).

The first line (D_UQJ) in table 1 reveals increasing skill shortages between 2009 and 2019: around 4 % of firms experience problems in filling vacant positions for qualified jobs in 2009 while nearly 23 % of firms confirm these problems in 2019. Looking at the total number of unfilled qualified jobs (UQJ) (line 2), in 2019 firms on average have slightly more unfilled positions for qualified jobs then 2009. More important, the number of qualified vacancies is small, yet the dispersion is large. That means the majority of firms have a small number of qualified job vacancies, while simultaneously a small number of firms have a large number of unfilled qualified job positions. [2]

Table 1 Descriptive statistics of skill shortage indicators

	2009		2012		2015		2019	
	mean	(std. dev.)	mean	(std. dev.)	mean	(std. dev.)	mean	(std. dev.)
D_UQJ	0.041	(0.200)	0.096	(0.295)	0.127	(0.334)	0.229	(0.420)
UQJ	2.423	(3.882)	2.263	(5.066)	2.495	(6.737)	3.082	(6.131)
UQJ/TE	0.283	(0.466)	0.215	(0.244)	0.263	(0.284)	0.211	(0.239)
UQJ/QE	0.471	(0.713)	0.377	(0.722)	0.397	(0.432)	0.360	(0.489)
UQJ/TD	1.269	(0.979)	1.044	(0.706)	1.113	(0.794)	1.135	(0.766)

Notes: D_UQJ is based on a question of the questionnaire, and therefore not on UQJ; for UQJ, UQJ/TE, UQJ/QE and UQJ/TD only firms that have unfilled qualified job vacancies are considered, causing the number of observations for the different indicators to vary greatly; the number of observations between the displayed years also varies due to the sampling strategy (see section 3.3).

3.3 Identification of clusters using a location quotient

Since our analysis aims to examine the effects of industrial clusters on skill shortage in firms, identifying regional industrial clusters adequately is essential. The location quotient (LQ) or specialization quotient, as applied by Brenner (2017), is a measure of regional specialization and is frequently used to identify agglomerations and measure their strength of clustering (e.g. Brenner, 2006; Crawley et al., 2013; Held, 1996; Isaksen, 1996; Sternberg & Litzenberger, 2004) . It is defined as,

$$LQ_{ind,reg} = \frac{\frac{v_{ind,reg}}{v_{ind,sp}}}{\frac{v_{ec,reg}}{v_{ec,sp}}} \tag{1}$$

[2] In addition to descriptive statistics in table 1, kernel density estimations and histograms show the same results and are therefore not displayed.

where *v* is the variable for which clustering is to be studied (usually employment) and *ind* stands for a specific industry (sector) of the entire economy (*ec*), while *reg* stands for a specific region within the studied space (*sp*) (Brenner, 2017).

In order to use location quotients for cluster identification, mostly a threshold is defined. The existing scientific literature applies various thresholds, which means that no general threshold has been established. The thresholds range from 1 (e.g. Held, 1996), to a value of 2 (European Cluster Observatory) and up to a value of 3 (e.g. Isaksen, 1996), while the US Cluster Mapping declares the top 25 % regions based on the location quotient in each sector as clusters (Brenner, 2017). Furthermore, thresholds can be deduced from the data itself (Brenner, 2006). In this paper, the location quotient is used as continues variable without grouping data by different thresholds in order to prevent a loss of information.

The identification of clusters using the location quotient has it's shortcomings. In general, the location quotient requires comparably little activity in an industry to reach high values in small regions (Carroll et al., 2008), using absolute employment numbers instead of the LQ favors large regions. Finally, the definition of industries is crucial to identify clusters based on the location quotient (Brenner, 2017).

3.4 Econometric approach

Based on different regression models, this papers analysis the relation between skill shortages in firms and their location in an industrial cluster between 2009 and 2019. All models include variables to capture the firm characteristics, industry specificities, and a wide range of regional differences.

The different regression models are all based on a sample, covering all years from 2009 to 2019 (see table 2). In order to make sure that firms are not considered multiple times due to the panel structure of the data set, we generate a sample that includes each firm only once. The year 2012 is used as *anchor year* meaning all observations of 2012 are included and used as starting point. This choice is based on the availability of the location quotient, which is given for the year 2012. Based on 2012, observations from the other years are only included, if the observed firm is not already included in the dataset of the year 2012 and the closest observation in time is selected first.[3] For the years 2009/2015, 2010/2014 and 2011/2013 a randomized shuffled process is used, since the inverted time differences

[3] For example, if a firm is not observed in the year 2012, but during the years 2016 and 2017, the observation of the year 2016 is selected since the difference between 2012 and 2016 (+4) is smaller than between 2012 and 2017 (+5).

to the year 2012 are identical (3, 2 and 1).[4] As displayed in table 2, the means deviate only to a minor extent.[5]

Table 2 Descriptive statistics of the used sample

	Full sample			Single observation sample		
Year		D_UQJ			D_UQJ	
	obs.	mean	(std. dev.)	obs.	mean	(std. dev.)
2009	15,523	0.047	0.212	2,646	0.041	0.200
2010	15,615	0.065	0.247	2,610	0.062	0.242
2011	15,283	0.080	0.272	2,832	0.072	0.259
2012	15,556	0.096	0.295	15,556	0.096	0.295
2013	15,725	0.090	0.286	3,026	0.115	0.320
2014	15,577	0.099	0.299	2,768	0.112	0.316
2015	15,500	0.112	0.315	2,731	0.127	0.334
2016	15,341	0.148	0.355	2,335	0.170	0.376
2017	15,421	0.168	0.374	2,581	0.196	0.397
2018	15,263	0.214	0.410	2,714	0.245	0.430
2019	15,439	0.225	0.417	3,863	0.229	0.420

Notes: The dummy variable D_UQJ is used to illustrate the different observation count in each sample for each year.

The used location quotient (Log LQ3_ con) is based on the year 2012 due to availability restrictions and is calculated on the 3-digit-level.[6] Due to strong deviation of the contained values, the location quotient is transformed to (lq-1) / (lq+1), resulting in a variable that ranges between -1 and 1. With the help of a district and a sector identifier, the location quotient is matched to the main dataset. Using the IAB Establishment panel, the cluster identification via location quotient is necessary, because the currently about 16,000 observed firms each year are not sufficient to perform this step solely on the basis of the main data set. The descriptive statistics of the location quotient used in the different regression models is provided within the appendix (see table A2).

To control for firm-specific influences, logarithmized firm size, exports, investments, positive sales expectation, fulfilled training requirements, hiring and further training of employees as well as firms structures like the existence of a works council or the foundation before 1990 are added. Furthermore, the share of mini jobs, share of female employees and the share of share of skilled employees are included. Moreover, it is controlled for each containing year and 18 sectors. In order to control for regional differences, age of population, commuters balance, gross domestic product (GDP), population

[4] *Set seed* and *shuffle* were used in stata 16 to receive a reproducible yet randomized result. Five shuffles were conducted and the result with the best fit was chosen.
[5] To ensure robust results, regression results based on the full sample, using clustered standard errors have been compared to regression results based on the single observation sample, using robust stand errors.
[6] The process of model testing included the location quotient on the NACE rev 2, 2-digit as well as 3-digit level to ensure robust results. The German equivalent is used: *Klassifikation der Wirtschaftszweige 2008, Ebene der 2- und 3-Steller.*

density, share of students, and unemployment rate are included. Since the establishment data does not contain such information, the variables have been matched to the existing data set.

The used firm-level database, combining the IAB Establishment panel, the location quotient and the data set to control for regional differences, consists of 43,662 firms in Germany. All models were constructed in a stepwise procedure, where control variables were added or removed to improve the model fit. Before the main analysis started, kernel density estimations and histograms were used to check the value distribution of the main variables.

The first part of the analysis is based on the skill shortage indicator D_UQJ, which is used as depended variable. Since D_UQJ is a dummy variable, a binary logistic regression model is an appropriate choice; coefficients and marginal effects are reported (see table 3). Additionally, a binary probit regression model is reported to ensure robust results. The second part of the analysis is applied to all firms that report skill shortage and is based on the skill shortage indicator UQJ/QE, which is used as depended variable.

$$UQJ/QE = \frac{\text{number of unfilled qualified jobs (UQJ)}}{\text{total number of qualified employees (QE)}} \quad (2)$$

Since UQJ/QE is a continuous variable with strong concentration of values just above zero, a negative binomial regression model and a poisson regression model as robustness check, are used. All models are using robust standard errors.

4 Results and discussion

Descriptions and descriptive statistics of all used variables, including firm characteristics, sectors, regional differences and years, are presented in the appendix (see table A3 and A4). We estimate four models (1 to 4) that differ in the dependent variables and the regression estimators in use (see table 3). First, the general results for both dependent variables (D_UQJ and UQJ/QE) are presented. Second, the outcomes for the variable of interest are presented. Third, the results are discussed.

Looking at variable D_UQJ for all firms (model 1 and 2), we generally find that the likelihood of a lack of qualified workers is larger in firms with a higher number of employees, especially in the social sector as well as in the business-related services sector. As described above, the dependent is a dummy variable showing whether the firm has a reported lack of employees for qualified jobs (and therefore is suffering from a skill shortage). Firms which take investments, have a positive sales expectation, train employees and offer further training are surprisingly more likely to suffer from skill shortage. Compared to firm size, the marginal effects are significantly smaller for these variables. If a firm has a works council or is founded before 1990 the chance of suffering from a skill shortage is lower.

Table 3 Regression models of skill shortages, 2009-2019

	(1)	(2)	(3)	(4)
	D_UQJ		**UQJ/QE**	
	Logit	**Probit**	**Negbin**	**Poisson**
Log firm size	0.267***	0.269***	-0.424***	-0.420***
	(0.001)	(0.001)	(0.026)	(0.026)
Exports	0.000	0.000	-0.439***	-0.443***
	(0.005)	(0.005)	(0.058)	(0.060)
Investments	0.023***	0.024***	-0.044	-0.039
	(0.004)	(0.004)	(0.061)	(0.066)
Positive sales expectation	0.019***	0.019***	-0.052	-0.054
	(0.004)	(0.004)	(0.053)	(0.055)
Training requirements fulfilled	0.031***	0.030***	-0.090	-0.088
	(0.004)	(0.004)	(0.060)	(0.063)
Hiring	0.083***	0.080***	0.190***	0.191***
	(0.004)	(0.004)	(0.058)	(0.060)
Further training	0.042***	0.040***	-0.273***	-0.274***
	(0.005)	(0.004)	(0.093)	(0.097)
Works council	-0.052***	-0.052***	-0.740***	-0.758***
	(0.005)	(0.005)	(0.084)	(0.090)
Foundation before 1990	-0.021***	-0.021***	-0.394***	-0.398***
	(0.004)	(0.004)	(0.066)	(0.069)
Share of mini jobs	-0.040***	-0.039***	-0.124	-0.147
	(0.012)	(0.011)	(0.163)	(0.171)
Share of female employees	-0.047***	-0.045***	-0.469***	-0.475***
	(0.008)	(0.007)	(0.081)	(0.083)
Share of skilled employees	0.079***	0.076***		
	(0.007)	(0.007)		
Production sector	-0.032*	-0.031*	-0.471***	-0.469***
	(0.018)	(0.017)	(0.140)	(0.141)
Social sector	0.081***	0.079***	-0.295**	-0.290**
	(0.017)	(0.016)	(0.137)	(0.139)
Business-related services sector	0.070***	0.066***	0.696***	0.682***
	(0.016)	(0.015)	(0.143)	(0.139)
West Germany	-0.036***	-0.036***	0.241***	0.247***
	(0.006)	(0.006)	(0.085)	(0.092)
Age of population	-0.001	-0.001	-0.073***	-0.071***
	(0.001)	(0.001)	(0.022)	(0.022)
Commuters balance	0.000	0.000	0.002*	0.002*
	(0.000)	(0.000)	(0.001)	(0.001)
Gross domestic product (GDP)	0.000	0.000	-0.003	-0.003
	(0.000)	(0.000)	(0.003)	(0.003)
Population density	-0.000**	-0.000**	-0.000***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Log LQ3_ con	-0.015***	-0.015***	0.136*	0.145*
	(0.005)	(0.005)	(0.080)	(0.086)
Cons	-3.623***	-2.039***	3.864***	3.826***
	(0.603)	(0.338)	(1.014)	(1.038)
N	37,877	37,877	6,398	6,398
Pseudo-R^2	0.160	0.161	0.206	0.213

*Notes: For effects deriving from estimation of model (1) and (2), marginal effects (dy/dx) are reported; for effects deriving from estimation of model (3) and (4), coefficients are reported, which are in the form of the logarithm of counts (UQJ/QE), rather than actual counts, to interpret the results in a count metric, the coefficient must be exponentiated for ln(UQJ/QE); robust standard errors in parentheses; significance level: * p < 0.10, ** p < 0.05, *** p < 0.01*

Furthermore, the higher the share of mini jobs and female employees, the lower the chance of having vacancies for qualified jobs. Less surprising is the significant result that the higher the share of qualified workers, the more likely a lack of qualified employees is. Looking at the differences between eastern and western Germany, firms located within the western states of Germany have a significantly lower chance of experiencing a skill shortage. Besides this, the additional regional differences are mostly not significantly correlated with skill shortage. Population density represents an exception: a vanishingly small negative yet significant relationship is observed.

Focusing on firms with a reported skill shortage (model 3 and 4), we find that the lack of qualified workers is reduced, on average, in exporting firms since the job vacancy rate UQJ/QE is reduced. Furthermore, contrary to Sheldoni and Li (2013), who focused on labor poaching among foreign-invested enterprises in China, we find that longer-standing and larger firms are not suffering most. In Model 3 and 4, a larger firm size and later foundation date reduces the job vacancy rate. In line with models 1 and 2, job vacancy rates are lower for firms having a works council or being founded before 1990. Further training offers for employees and higher shares of female employees come together with lower job vacancy rates for qualified jobs. Regional differences are mostly not significantly correlated with skill shortage. Age of population and population density are exceptions: small negative yet significant relationships are observed.

Analyzing the variable of interest within the different models (Log LQ3_ con), we find that firms located in an industrial cluster have a significantly lower chance of experiencing a skill shortage in model 1 and 2. The higher the level of industry-specific agglomeration, the lower the chance of having vacancies for qualified jobs. Hence, hypothesis 1a can be confirmed and hypothesis 2a rejected. Overall, comparing the results of model 1 and 2, the logit and probit estimates show matching results with some variations in the effect sizes. Looking only at firms with a reported skill shortage (model 3 and 4), the agglomeration effect changes: the higher the level of industry-specific agglomeration, the higher the ratio of unfilled qualified labor positions to skilled labor positions in the firm. Therefore, if firms are experiencing a skill shortage, an increasing level of agglomeration appears to increase the job vacancy rate and therefore the skill shortage. Again, comparing model 3 and 4, both estimations show matching results. Therefore, hypothesis 1b is rejected while hypothesis 2b is confirmed.

Comparing the effect sizes between the variables, we find that firm size and other firm characteristics (e.g. share of female employees) have a rather large effect compared to the regional factors and compared to the location quotient. This is robust across all models and in line with the literature since Bellmann and Hübler (2014) achieve similar results in terms of firm characteristics and Czepek at al. (2015) with regard to the sector related outcomes. Looking at the main result from model 1 and 2 including all firms, a higher level of industry-specific agglomeration reducing the chance of having vacancies for qualified jobs is in line with the majority of the literature on labor market pooling. Firms located in a cluster benefit from a labor market pool, as discussed in the literature (Grashof, 2020; Marshall, 1920). Therefore, our finding confirms the aspects of labor market pooling discussed in the theoretical literature, even though the magnitude of the effects is small (Andini et al., 2013). In contrast, model 3 and 4 provide coefficients that suggest the opposite: Firms which reported a skill shortage experience, on average, a higher job vacancy rate if they are located in stronger industry-specific agglomerations. We interpret this as follows: Within agglomerations labor pooling decreases the likelihood of skill shortage. But, if despite this effect a firm in an agglomeration is experiencing skill shortage, this skill shortage is more severe due to labor poaching by nearby competitors. Within agglomerations there are often quite different firms with various potentials to attract employees, e.g. due to size, reputation, scope and salaries. As a consequence, the more attractive firms might benefit from the agglomeration while the less attractive firms experience more the negative effects of labor poaching.

5 Conclusion

Regional and sectoral shortages in terms of skilled labor recruitment are already either foreseeable or already a reality in Germany. As a consequence, competition for skilled workers has already intensified, resulting in disadvantages for firms. However, it is unclear whether such shortages of skilled workers are more or less apparent in industrial-specific agglomerations. This gap is addressed in this paper by investigating the occurrence of skill shortage in dependence of regional specialization. To this end, firm-level data on skill shortages and spatial data on industry clustering are analyzed.

Our result show that firms located in an industrial cluster have a significantly lower chance of experiencing skill shortage: The higher the level of industry-specific agglomeration, the lower the chance of having vacancies for qualified jobs. At the same time, focusing only on firms with a reported skill shortage, the agglomeration effect changes: the higher the level of industry-specific agglomeration, the higher the ratio of unfilled qualified labor positions (UQJ) to skilled labor positions (QE) in firm experiencing skill shortage. By this, our results confirm the contradicting agglomeration effects of labor pooling and labor poaching, which is stated in the literature. Beyond that, our results also provide further details on these effects. On the one hand, looking at all firms, they seem to benefit from agglomerations by facing a lower probability to experience skill shortage. On the other hand, those firms that experience such problems, probably to a lower attractiveness for skilled worker, have, on average, stronger problems than they would have outside of the agglomeration.

This can be used to formulate some tentative policy recommendations. Since the results show that firms located in an industrial cluster have a significantly lower chance of experiencing skill shortages, the funding of cluster concepts by policymakers and regional economic development entities appears successful. Industrial clusters can be part of regional development concepts which address upcoming skill shortages to ensure regional economic resilience. At the same time, our results show that some firms in industry clusters experience stronger problems due to the clustering. Therefore, the actors within an industrial cluster might consider measures that make labor pooling more balanced between more and less attractive firms.

References

Andini, M., Blasio, G. de, Duranton, G. & Strange, W. C. (2013). Marshallian labour market pooling: Evidence from Italy. *Regional Science and Urban Economics*, *43*(6), 1008–1022. https://doi.org/10.1016/j.regsciurbeco.2013.04.003

Arnold, D., Hillerich-Sigg, A. & Nolte, A. (2017). *Fachkräftemangel: Reaktionen der Betriebe sowie Auswirkungen auf Investitionsentscheidungen und Wachstum: Studie im Auftrag des Bundesministeriums für Wirtschaft und Energie*. Abschlussbericht. Mannheim. Zentrum für Europäische Wirtschaftsforschung (ZEW).

Bechmann, S., Tschersich, N., Ellguth, P. & Kohaut, S. (2021). *Methoden- und Feldbericht zum IAB-Betriebspanel: - Welle 28 (2020)* (FDZ-Methodenreport Nr. 07).

Bellmann, L., Dummert, S., Ebbinghaus, M., Krekel, E. M. & Leber, U. (2015). Qualifizierung von Beschäftigten in einfachen Tätigkeiten und Fachkräftebedarf. *Zeitschrift für Weiterbildungsforschung*, *38*(2), 287–301. https://doi.org/10.1007/s40955-015-0022-0

Bellmann, L. & Hübler, O. (2014). The Skill Shortage in German Establishments Before, During and After the Great Recession. *Jahrbücher für Nationalökonomie und Statistik*, *234*(6), 125. https://doi.org/10.1515/jbnst-2014-0608

Bellmann, L. & Leber, U. (2017). Fachkräftebedarf der Wirtschaft. In L. Bellmann & U. Leber (Hrsg.), *Bildungsökonomik* (S. 109–130). De Gruyter. https://doi.org/10.1515/9783110446227-007

Bennett, J. & McGuinness, S. (2009). Assessing the impact of skill shortages on the productivity performance of high-tech firms in Northern Ireland. *Applied Economics*, *41*(6), 727–737.

Brenner, T. (2006). Identification of Local Industrial Clusters in Germany. *Regional Studies*, *40*(9), 991–1004. https://doi.org/10.1080/00343400601047408

Brenner, T. (2017). *Identification of Clusters: An Actor-based Approach* (Working Papers on Innovation and Space). Marburg.

Brunello, G. & Wruuck, P. (2019). *Skill Shortages and Skill Mismatch in Europe:: A Review of the Literature* (Discussion Paper Series Nr. 12346). Bonn. Institute of Labor Economics (IZA).

Brunow, S. & Grünwald, L. (2015). *Exports, agglomeration and workforce diversity:: An empirical assessment for German establishments* (IAB-Discussion Paper Nr. 3). IAB - Institut für Arbeitsmarkt- und Berufsforschung.

Burstedde, A., Flake, Regina, Jansen, Anika, Malin, L., Risius, P., Seyda, S. & Schirner, Sebastian, Werner, Dirk. (2020). *Die Messung des Fachkräftemangels:: Methodik und Ergebnisse aus der IW-Fachkräftedatenbank zur Bestimmung von Engpassberufen und zur Berechnung von Fachkräftelücken und anderen Indikatoren* (IW-Report Nr. 59). Köln. Institut der deutschen Wirtschaft (IW).

Carroll, M. C., Reid, N. & Smith, B. W. (2008). Location quotients versus spatial autocorrelation in identifying potential cluster regions. *The Annals of Regional Science*, *42*(2), 449–463. https://doi.org/10.1007/s00168-007-0163-1

Combes, P.-P. & Duranton, G. (2006). Labour pooling, labour poaching, and spatial clustering. *Regional Science and Urban Economics*, *36*(1), 1–28. https://doi.org/10.1016/j.regsciurbeco.2005.06.003

Crawley, A., Beynon, M. & Munday, M. (2013). Making Location Quotients More Relevant as a Policy Aid in Regional Spatial Analysis. *Urban Studies*, *50*(9), 1854–1869. https://doi.org/10.1177/0042098012466601

Czepek, J., Kubis, A., Leber, U., Müller, A., Dummert, S. & Stegmaier, J. (2015). *Betriebe im Wettbewerb um Arbeitskräfte: Bedarf, Engpässe und Rekrutierungsprozesse in Deutschland* (IAB-Bibliothek Nr. 352). Bielefeld. Institut für Arbeitsmarkt- und Berufsforschung der Bundesagentur für Arbeit (IAB). https://elibrary.utb.de/doi/book/10.3278/9783763940929

Dummert, S., Kubis, A., Leber, U. & Müller, A. (2014). *Betrieblicher Arbeitskräftebedarf: 2006 - 2012*. Aktuelle Ergebnisse aus der Projektarbeit des Instituts für Arbeitsmarkt- und Berufsforschung (IAB-Forschungsbericht 3/2014).

Grashof, N. (2020). Sinking or swimming in the cluster labor pool? A firm-specific analysis of the effect of specialized labour. *Jena Economic Rersearch papers*(6).

Haskel, J. & Martin, C. (2001). Technology, wages and skill shortages: evidence from UK micro data. *Oxford Economic Papers*, *53*, 642–658.

Held, J. R. (1996). Clusters as an Economic Development Tool:: Beyond the Pitfalls. *Economic Development Quarterly*, *10*(3), 249–261.

Helsley, R. & Strange, W. (1990). Matching and Agglomeration Eoonomies in a System of Cities. *Regional Science and Urban Economics*, *20*, 189–212.

Hinz, T. (2019). Personnel policy adjustments when apprentice positions are unfilled: Evidence from German establishment data. *International Journal of Manpower*, *40*(5), 958–978. https://doi.org/10.1108/IJM-03-2018-0105

Horbach, J. (2014). *Determinants of Labor Shortage - with particular Focus on the German Environmental Sector* (IAB-Discussion Paper Nr. 22). IAB - Institut für Arbeitsmarkt- und Berufsforschung.

Isaksen, A. (1996). Towards increased regional specialization? The quantitative importance of new industrial spaces in Norway, 1970– 1990. *Norsk Geografisk Tidsskrift - Norwegian Journal of Geography*, *50*(2), 113–123. https://doi.org/10.1080/00291959608542834

Kettner, A. (2012). *Fachkräftemangel und Fachkräfteengpässe in Deutschland:: Befunde, Ursachen und Handlungsbedarf* [Dissertation]. Technischen Universität Berlin, Berlin.

Marshall, A. (1920). *Principles of economics* (8. Aufl.). *Palgrave classics in economics*. Palgrave Macmillan. http://www.palgraveconnect.com/pc/doifinder/10.1057/9781137375261 https://doi.org/10.1057/9781137375261

Morris, D., Vanino, E. & Corradini, C. (2020). Effect of regional skill gaps and skill shortages on firm productivity. *Environment and Planning A: Economy and Space*, *52*(5), 933–952. https://doi.org/10.1177/0308518X19889634

Quintini, G. (2011). *Over-Qualified or Under-Skilled: A review of existing literature* (OECD Social, Employment and Migration Working Papers Nr. 121). https://doi.org/10.1787/5kg58j9d7b6d-en

Sheldon, P. & Li, Y. (2013). Localized poaching and skills shortages of manufacturing employees among MNEs in China. *Journal of World Business*, *48*(2), 186–195. https://doi.org/10.1016/j.jwb.2012.07.003

Sternberg, R. & Litzenberger, T. (2004). Regional clusters in Germany--their geography and their relevance for entrepreneurial activities. *European Planning Studies*, *12*(6), 767–791. https://doi.org/10.1080/0965431042000251855

Tang, J. & Wang, W. (2005). Product Market Competition, Skill Shortages and Productivity: Evidence from Canadian Manufacturing Firms. *Journal of Productivity Analysis*, *23*(3), 317–339. https://doi.org/10.1007/s11123-005-2213-y

van der Panne, G. (2004). Agglomeration externalities: Marshall versus Jacobs. *Journal of Evolutionary Economics*, *14*(5), 593–604. https://doi.org/10.1007/s00191-004-0232-x

Wrobel, M. (2015). 'One for all and all for one': Cluster, employment, and the global economic crisis. Evidence from the German mechanical engineering industry. *Papers in Regional Science*, *94*(2), 273–295. https://doi.org/10.1111/pirs.12065

Appendix – Additional Tables

Table A1 Full regression models of skill shortages, 2009-2019

	(1)	(2)	(3)	(4)
	D_UQJ		UQJ/QE	
	Logit	**Probit**	**Negbin**	**Poisson**
Log firm size	0.267***	0.269***	-0.424***	-0.420***
	(0.001)	(0.001)	(0.026)	(0.026)
Exports	0.000	0.000	-0.439***	-0.443***
	(0.005)	(0.005)	(0.058)	(0.060)
Investments	0.023***	0.024***	-0.044	-0.039
	(0.004)	(0.004)	(0.061)	(0.066)
Competitive pressure	0.025***	0.023***	0.036	0.033
	(0.006)	(0.006)	(0.063)	(0.064)
Positive sales expectation	0.019***	0.019***	-0.052	-0.054
	(0.004)	(0.004)	(0.053)	(0.055)
Employment dvlpmt. expectation	0.115***	0.121***	-0.023	-0.024
	(0.004)	(0.004)	(0.055)	(0.057)
Training requirements fulfilled	0.031***	0.030***	-0.090	-0.088
	(0.004)	(0.004)	(0.060)	(0.063)
Hiring	0.083***	0.080***	0.190***	0.191***
	(0.004)	(0.004)	(0.058)	(0.060)
Further training	0.042***	0.040***	-0.273***	-0.274***
	(0.005)	(0.004)	(0.093)	(0.097)
Works council	-0.052***	-0.052***	-0.740***	-0.758***
	(0.005)	(0.005)	(0.084)	(0.090)
Foundation before 1990	-0.021***	-0.021***	-0.394***	-0.398***
	(0.004)	(0.004)	(0.066)	(0.069)
Non-owner Management	-0.017***	-0.018***	0.227**	0.237**
	(0.004)	(0.004)	(0.098)	(0.101)
Share of mini jobs	-0.040***	-0.039***	-0.124	-0.147
	(0.012)	(0.011)	(0.163)	(0.171)
Share of female employees	-0.047***	-0.045***	-0.469***	-0.475***
	(0.008)	(0.007)	(0.081)	(0.083)
Share of skilled employees	0.079***	0.076***		
	(0.007)	(0.007)		
Mining sector	-0.038*	-0.038*	-0.535***	-0.537***
	(0.022)	(0.021)	(0.187)	(0.188)
Food sector	0.008	0.006	-0.349**	-0.346**
	(0.020)	(0.019)	(0.154)	(0.156)
Textiles sector	-0.005	-0.005	-0.144	-0.139
	(0.020)	(0.019)	(0.170)	(0.171)
Production sector	-0.032*	-0.031*	-0.471***	-0.469***
	(0.018)	(0.017)	(0.140)	(0.141)
Investments sector	0.025	0.025	-0.459***	-0.456***
	(0.017)	(0.016)	(0.128)	(0.128)
Construction sector	0.085***	0.083***	-0.207	-0.202
	(0.017)	(0.016)	(0.123)	(0.123)
Retail sector	-0.016	-0.017	-0.272**	-0.266**
	(0.017)	(0.015)	(0.127)	(0.127)

	(1)	(2)	(3)	(4)
	D_UQJ		UQJ/QE	
	Logit	**Probit**	**Negbin**	**Poisson**
Traffic sector	0.002	0.002	-0.192	-0.194
	(0.018)	(0.017)	(0.154)	(0.155)
Communication sector	0.048**	0.045**	-0.151	-0.148
	(0.019)	(0.019)	(0.170)	(0.170)
Finance and insurance sector	0.010	0.011	0.375*	0.409*
	(0.020)	(0.019)	(0.221)	(0.243)
Hospitality sector	0.045**	0.041**	-0.051	-0.046
	(0.018)	(0.017)	(0.133)	(0.132)
Education and teaching sector	0.004	0.004	-0.028	-0.003
	(0.019)	(0.018)	(0.281)	(0.298)
Social sector	0.081***	0.079***	-0.295**	-0.290**
	(0.017)	(0.016)	(0.137)	(0.139)
Business-related services sector	0.070***	0.066***	0.696***	0.682***
	(0.016)	(0.015)	(0.143)	(0.139)
Service sector	0.043**	0.040**	0.113	0.118
	(0.019)	(0.018)	(0.144)	(0.145)
NGO sector	-0.034	-0.033	0.216	0.224
	(0.025)	(0.023)	(0.176)	(0.177)
Public administration sector	-0.079***	-0.079***	-0.523**	-0.517**
	(0.020)	(0.019)	(0.238)	(0.242)
West Germany	-0.036***	-0.036***	0.241***	0.247***
	(0.006)	(0.006)	(0.085)	(0.092)
Age of population	-0.001	-0.001	-0.073***	-0.071***
	(0.001)	(0.001)	(0.022)	(0.022)
Commuters balance	0.000	0.000	0.002*	0.002*
	(0.000)	(0.000)	(0.001)	(0.001)
Gross domestic product (GDP)	0.000	0.000	-0.003	-0.003
	(0.000)	(0.000)	(0.003)	(0.003)
Population density	-0.000**	-0.000**	-0.000***	-0.000*
	(0.000)	(0.000)	(0.000)	(0.000)
Share of students	-0.000	-0.000	0.000	0.000
	(0.000)	(0.000)	(0.000)	(0.000)
Unemployment rate	-0.004***	-0.004***	0.004	0.004
	(0.000)	(0.000)	(0.011)	(0.011)
Year 2010	0.033**	0.036***	-0.179	-0.207
	(0.013)	(0.013)	(0.230)	(0.250)
Year 2011	0.065***	0.064***	0.243	0.223
	(0.012)	(0.012)	(0.246)	(0.262)
Year 2012	0.065***	0.063***	-0.117	-0.140
	(0.010)	(0.010)	(0.236)	(0.251)
Year 2013	0.074***	0.073***	-0.065	-0.094
	(0.012)	(0.011)	(0.239)	(0.257)
Year 2014	0.077***	0.075***	0.001	-0.023
	(0.012)	(0.012)	(0.246)	(0.264)
Year 2015	0.095***	0.094***	-0.159	-0.188
	(0.012)	(0.012)	(0.226)	(0.242)
Year 2016	0.120***	0.120***	-0.050	-0.078
	(0.012)	(0.012)	(0.230)	(0.248)

	(1)	(2)	(3)	(4)
	D_UQJ		**UQJ/QE**	
	Logit	**Probit**	**Negbin**	**Poisson**
Year 2017	0.142***	0.140***	0.080	0.051
	(0.012)	(0.012)	(0.255)	(0.272)
Year 2018	0.166***	0.166***	0.145	0.119
	(0.012)	(0.012)	(0.239)	(0.256)
Year 2019	0.148***	0.148***	0.073	0.042
	(0.012)	(0.011)	(0.236)	(0.251)
Log LQ3_ con	-0.015***	-0.015***	0.136*	0.145*
	(0.005)	(0.005)	(0.080)	(0.086)
Cons	-3.623***	-2.039***	3.864***	3.826***
	(0.603)	(0.338)	(1.014)	(1.038)
N	37,877	37,877	6,398	6,398
R^2	0.160	0.161	0.206	0.213

*Notes: Robust standard errors in parentheses, significance level: * p < 0.10, ** p < 0.05, *** p < 0.01.*

Table A2 Descriptive statistics of the localization quotient

	2009		**2012**		**2015**		**2019**	
	mean	(std. dev.)	mean	(std. dev.)	mean	(std. dev.)	mean	(std. dev.)
LQ3_con	1.868	(4.680)	2.157	(6.466)	1.680	(3.894)	1.794	(5.082)
Log LQ3_ con	0.026	(0.361)	0.073	(0.349)	0.020	(0.340)	0.021	(0.352)

Table A3 Descriptive statistics of firm characteristics, sectors, regional differences and years

	2009		2012		2019	
	mean	(std. dev.)	mean	(std. dev.)	mean	(std. dev.)
Log firm size	1.534	(1.198)	1.888	(1.100)	2.078	(1.260)
Exports	0.129	(0.336)	0.107	(0.309)	0.146	(0.353)
Investments	0.432	(0.495)	0.560	(0.496)	0.589	(0.492)
Competitive pressure	0.900	(0.298)	0.867	(0.339)	0.839	(0.366)
Positive sales expectation	0.161	(0.368)	0.201	(0.400)	0.368	(0.482)
Pos. employment dvlpmt. expect.	0.103	(0.304)	0.128	(0.334)	0.248	(0.432)
Training requirements fulfilled	0.484	(0.499)	0.578	(0.493)	0.542	(0.498)
Hiring	0.232	(0.422)	0.306	(0.461)	0.398	(0.489)
Further training	0.330	(0.470)	0.530	(0.499)	0.545	(0.497)
Works council	0.062	(0.241)	0.079	(0.271)	0.093	(0.291)
Foundation before 1990	0.399	(0.489)	0.372	(0.483)	0.292	(0.454)
Non-owner Management	0.094	(0.292)	0.093	(0.291)	0.112	(0.315)
Share of mini jobs	0.173	(0.239)	0.172	(0.214)	0.162	(0.215)
Share of female employees	0.447	(0.359)	0.477	(0.328)	0.476	(0.329)
Share of skilled employees	0.483	(0.344)	0.572	(0.301)	0.588	(0.320)
Agriculture sector	0.014	(0.118)	0.020	(0.142)	0.018	(0.135)
Mining sector	0.019	(0.138)	0.020	(0.143)	0.010	(0.101)
Food sector	0.024	(0.155)	0.023	(0.152)	0.018	(0.134)
Textiles sector	0.024	(0.153)	0.030	(0.172)	0.014	(0.119)
Production sector	0.046	(0.209)	0.055	(0.229)	0.048	(0.214)
Investments sector	0.116	(0.320)	0.112	(0.327)	0.128	(0.335)
Construction sector	0.072	(0.260)	0.077	(0.267)	0.066	(0.249)
Retail sector	0.161	(0.367)	0.143	(0.350)	0.128	(0.334)
Traffic sector	0.052	(0.224)	0.040	(0.196)	0.039	(0.194)
Communication sector	0.019	(0.137)	0.020	(0.141)	0.023	(0.152)
Finance and insurance sector	0.028	(0.167)	0.027	(0.162)	0.022	(0.146)
Hospitality sector	0.055	(0.229)	0.045	(0.208)	0.067	(0.251)
Education and teaching sector	0.022	(0.147)	0.037	(0.190)	0.030	(0.172)
Social sector	0.094	(0.292)	0.105	(0.306)	0.124	(0.330)
Business-related services	0.136	(0.343)	0.116	(0.321)	0.167	(0.373)
Service sector	0.041	(0.200)	0.034	(0.182)	0.040	(0.198)
NGO sector	0.018	(0.133)	0.020	(0.141)	0.013	(0.115)
Public administration sector	0.049	(0.216)	0.057	(0.232)	0.036	(0.186)
West Germany	0.696	(0.459)	0.614	(0.486)	0.649	(0.477)
Age of population	43.382	(1.602)	44.461	(1.953)	45.039	(2.248)
Commuters balance	-4.446	(30.481)	-7.257	(27.524)	-5.383	(25.627)
Gross domestic product (GDP)	30,298	(13,223)	31,508	(13,588)	38,183	(15,022)
Population density	708.30	(807.70)	591.15	(739.35)	614.09	(765.13)
Share of students	27.067	(42.753)	27.727	(43.237)	31.359	(45.253)
Unemployment rate	8.357	(3.173)	7.849	(3.289)	5.467	(2.126)
Year 2009	1.000	(0.000)	0.000	(0.000)	0.000	(0.000)
Year 2012	0.000	(0.000)	1.000	(0.000)	0.000	(0.000)
Year 2019	0.000	(0.000)	0.000	(0.000)	1.000	(0.000)

Table A4 Variable description of firm characteristics, sectors, regional differences and years

Variable	Description
Log firm size	Total number of employees. logarithmized
Exports	= 1 if firm is exporting products/goods outside of Germany (dummy)
Investments	= 1 if firm is investing in one or more of the following areas: buildings; IT; production equipment, factory and office equipment; or means of transport, transport systems (dummy)
Competitive pressure	= 1 if firm assess the competitive pressure as low, medium or high; = 0 if the firm assess no competitive pressure (dummy)
Positive sales expectation	= 1 if firm expects a rather increasing development of the business volume; = 0 if development of the business volume is stagnating or declining (dummy)
Positive Employment dvlpmt. expectation	= 1 if firm expects a rather increasing development of the total employment (dummy)
Training requirements fulfilled	= 1 if firm meets statutory training requirements (dummy)
Hiring	= 1 if firm did hire workers (dummy)
Further training	= 1 if firm promotes further training by releasing employees from activities and covering costs (dummy)
Works council	= 1 if firm has a works council elected in accordance with the Works Constitution Act (dummy)
Foundation before 1990	= 1 if firm was established before 1990 (dummy)
Non-owner Management	= 1 if firms management or board of leadership is exclusively formed by managers; owners/members of the owner families are not included (dummy)
Share of mini jobs	Share of marginally employed persons in all employees; a person is considered to be marginally employed if he or she either has a monthly salary of no more than € 450 or is only employed for a short period of time (max. for 3 months or for 70 days per year)
Share of female employees	Share of female employees in all employees
Share of skilled employees	Share of skilled employees in all employees; a person is considered to be skilled if he or she either is a trained trades person or holds a university degree
Sectors	= 1 if firm is assigned to the respective sector according to the time-consistent WZ03/08 industry classification of the IAB (dummy); 18 sectors are included
West Germany	= 1 if firm is located in one of the 10 west German states (Baden-Wuerttemberg, Bavaria, Bremen, Hamburg, Hesse, Lower Saxony, North Rhine-Westphalia, Rhineland-Palatinate, Saarland, Schleswig-Holstein) (dummy)
Age of population	Average age of the population in years
Commuters balance	Net commuting per 100 employees (subject to social security contributions) at place of work
Gross domestic product (GDP)	Gross domestic product in € 1,000 per inhabitant
Population density	Inhabitants per km²
Share of students	Share of students at colleges and universities per 1,000 inhabitants
Unemployment rate	Share of unemployed in the civilian labor force in %
Years	= 1 if firm is assigned to the respective year (dummy); the included years are 2009 to 2019

Appendix – Data Availability Statement

The data that support the findings of this study are available for scientific use and must be applied for via data application. The privacy restrictions of the IAB Establishment panel apply. Further information on the used dataset are provided by the Institute for Employment Research (IAB) of the Federal Employment Agency (BA) (https://iab.de/das-iab/befragungen/iab-betriebspanel/; https://staging-fdz.iab.de/unsere-datenprodukte/betriebsdaten/iab-betriebspanel/).