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Skill shortages and industrial clusters—empirical evidence from German establishment data

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Abstract

Regional and sectoral skill shortages have attracted considerable attention in recent research on regional economics and economic geography. These shortages are a reality for many firms and organizations, with adverse consequences for individuals, firms, and the economy as a whole. Yet, it remains unclear whether skill shortages are more severe in industrial clusters due to intensified competition and labor poaching, or whether they are less severe because of labor pooling. This study examines the relationship between skill shortages and industrial clustering in Germany. Using generalized linear mixed regression models, the analysis draws on the IAB Establishment Panel dataset to assess the extent of shortages among clustered firms. The findings indicate that firms located in industrial clusters face a significantly lower probability of skill shortages, measured in terms of unfilled vacancies for skilled jobs. At the same time, however, clustered firms experiencing shortages encounter greater difficulties in filling these vacancies.

JEL Classification J23 · J63 · R10

1 Introduction

The analysis of skilled labor supply has gained increasing relevance over the past two decades. In Germany, the shortage of skilled labor has intensified in recent years. This trend is reflected in a marked rise in the number of particularly affected occupations (BA, 2023). Regional as well as sector-specific bottlenecks in skilled labor recruitment are already foreseeable or have in some cases become a reality

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(Czepek et al. 2015). In addition, the number of vacancies for skilled workers has increased almost continuously over the past decade, reaching an all-time high of more than 1.3 million vacancies in 2022 (Tiedemann & Malin 2023). The number of vacancies for unskilled workers also rose, totaling 244,211 in 2022 (Tiedemann & Malin 2023). Even during the corona pandemic, overall labor demand remained higher than in 2010 following the 2008 economic and financial crisis (Burstedde et al. 2020).

Besides sectoral and occupational influences on the supply of skilled labor, one could assume that the location of the firm in relation to other firms, organizations, networks, and institutions in the surrounding area. While positive cluster effects such as labor pooling, knowledge spillovers, and the emergence of innovations within industrial clusters are widely discussed, negative cluster effects on firms (e.g., Wrobel 2015), such as labor poaching, are also considered. However, it remains unclear whether skill shortages are more intense in industrial clusters because of labor poaching and strong competition between firms, or less intense due to the attractiveness of a shared labor market and other benefits. We define industrial clusters as geographic concentrations of interconnected firms and institutions, including actors across the entire value chain (Porter 1998, 2000). Further characteristics attributed to clusters are the division of labor and cooperation among entities; specialization of firms and/or the labor force (Sellitto & Luchese 2018); and a shared institutional setting based on social factors and trust (Frankowska 2020; Götz & Jankowska 2017; Sarturi et al. 2016).

We address this research gap by examining the availability of skilled workers under the specific conditions of industrial clusters. To understand whether skill shortages are associated with industrial clusters in Germany, we test two competing hypotheses. On the one hand, the local labor market pool could allow clustered firms to fill vacancies more quickly than firms in the same industry outside a cluster. On the other hand, the negative cluster effect of labor poaching could cause clustered firms to face stronger competitive pressure. The result would be more vacancies for skilled jobs and thus skill shortages. Generalized linear mixed regression models are used to analyze firm-level data on skill shortages in combination with spatial data on industrial clustering. Industrial clusters are identified using a location quotient, and the IAB Establishment Panel is employed to analyze skill shortages within firms.

Results suggest that firms located in industrial clusters are significantly less likely to experience skill shortages. However, this effect appears to reverse for firms reporting a skill shortage. Such firms have a higher ratio of unfilled skilled labor positions to current skilled labor positions. Thus, our results point to the contradictory effects of labor pooling and labor poaching found in the literature.

The study is structured as follows. After this general introduction, Sect. 2 presents the theoretical and empirical evidence on aspects of skill shortages and the link to industrial clusters. Section 3 describes the structural characteristics of the dataset used, the skill shortage indicators, the identification of industrial clusters, and the econometric approach. Section 4 presents the results of the different regression models and discusses them. Finally, Sect. 5 summarizes the main findings and limitations, outlines potential aspects for further research, and presents related policy recommendations.

2 Theoretical background

2.1 Skill shortages in general

In general, skill shortages arise whenever employers are unable to recruit workers with the required set of skills within the accessible labor market and at the common wage rate (Quintini 2011). Yet, evidence on skill shortages remains contentious due to contradictory results across surveys (Cappelli 2015). This is partly because there are different ways of measuring skill shortages (see Sect. 3.2).

The reasons for skill shortages are manifold. Different macroeconomic developments can be held responsible for skill shortages across various labor market segments. The literature mainly identifies demographic, technological, and organizational changes as relevant (Arnold et al. 2017; Bellmann et al. 2015; Bellmann & Hübler, 2014; Bellmann & Leber 2017; Burstedde et al. 2020; Kettner 2012; OECD 2019). Demographic changes include population decline, fewer school leavers, later labor market entry, a rising number of retirees, and increased female participation in the labor market (Bellmann & Hübler 2014). The technological changes generally increase the demand for skilled workers due to skill-biased technological change (Bellmann & Hübler 2014; Haskel & Martin 2001). Organizational changes are linked to schooling deficiencies and political challenges in maintaining adequate human capital quality (Bellmann & Hübler 2014).

The negative effects of skill shortages are diverse. The related economic costs affect individuals, firms, and the economy as a whole. The negative impact on firms ranges from unfilled positions, to hiring workers with lower skills than required, and even to production losses. Furthermore, skill shortages can limit investments and the adoption of new technologies, with negative impacts on performance and productivity (Bennett & McGuinness 2009; Brunello & Wruuck 2019; Morris et al. 2020; Tang & Wang 2005). Small and medium-sized firms in general, and especially those with a demand for skilled workers in technical and health professions, are affected (Czepek et al. 2015; Dummert et al. 2014). As a result, competition for skilled workers can become more intense, sometimes with drastic consequences for disadvantaged firms. In general, the costs of shortages to firms depend on the duration of the shortage (Brunello & Wruuck 2019).

2.2 Skill shortages and industrial clusters: labor pooling vs. labor poaching

Following Marshall's (1920) specialization approach, there are three main channels of agglomerated localized economies: the availability of intermediate and final goods due to shared specialized suppliers, labor pooling and matching, and knowledge externalities due to spillover effects (Combes & Duranton 2006; Delgado et al. 2014; Du & Vanino 2021; Van der Panne 2004). Given our interest in skill shortages, we focus specifically on labor pooling.

Labor pooling is perceived as a strong motive and advantage for firms to locate within an existing cluster, as access to the required labor force is presumed to be

easier. It is argued that co-located firms within the same industry benefit from thick labor markets based on access to a large pool of skilled workers (Combes & Duranton 2006; Du & Vanino 2021; Glaeser & Resseger 2010). Clustered firms that are able to recruit from a larger labor pool are more likely to find workers with suitable characteristics, reduce uncertainty about future labor demand and lower labor management costs (Du & Vanino 2021). Conversely, workers are more likely to find jobs matching their skills within clusters (Combes & Duranton 2006). Helsley and Strange (1990) describe the improved matching ability of a large labor pool as a frequently cited source of agglomeration economies, which results in them being reinforced.

However, industrial clusters of firms do not have exclusively positive effects (Grashof 2020; Wrobel 2015). Regionally clustered firms sharing a local labor market face a tradeoff between positive labor pooling effects and negative spillover effects related to competitive labor poaching. Labor poaching results in a limited number of skilled workers being available, the loss of key employees to more successful co-located firms, higher wage bills to retain current workers, and increased costs to hire new employees (Du & Vanino 2021). Moreover, new hires give competitors knowledge about former employers (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 incidence of skill shortages within industrial clusters. Based on the theoretical background, it is a priori not clear which effect on skill shortages dominates. We therefore formulate two competing hypotheses. On the one hand, the local labor market pool could allow cluster-related firms to fill vacancies faster compared to firms in the same industry outside a cluster. Thus, the following hypotheses are proposed:

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

- a) firms in industrial clusters have a lower probability of suffering from skill shortages and
- b) firms in industrial clusters that already face skill shortages 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 predominates and the positive labor pooling effects are negligible,*

- a) firms in industrial clusters have a higher probability of suffering from skill shortages and
- b) firms in industrial clusters that already face skill shortages 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 datasets and variables are necessary. Firstly, we identify industrial clusters using a location quotient. Secondly, we use the IAB Establishment Panel data to identify skill shortages within firms. Finally, we apply generalized linear mixed regression models.

3.1 Main dataset

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). Therefore, we use a well-established firm survey as dataset. 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 Verian (formerly 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 enterprises with at least one employee liable for social security contributions on 30 June of the previous year (cut-off date used). 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 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 of all variables used are provided within the appendix (see Table A2 and A3).

3.2 Skill shortage indicators

Emerging skill shortages can be identified using different approaches depending on the database, as there is no all-encompassing indicator (Bellmann & Leber 2017). In Germany, research institutes, trade unions, employer associations, and ministries provide the majority of empirical evidence on current skill shortages (e.g., Federal Institute for Vocational Training, German Trade Union Confederation, Federation of

Table 1 Descriptive statistics of skill shortage indicators. *Source:* Authors' own illustration

	2009		2012		2015		2019	
	mean	(std. dev.)						
<i>unfilled_qualified_jobs_dum</i>	0.041	(0.200)	0.096	(0.295)	0.127	(0.334)	0.229	(0.420)
<i>unfilled_qualified_jobs/qualified_emp</i>	0.471	(0.713)	0.377	(0.722)	0.397	(0.432)	0.360	(0.489)

The dummy variable *unfilled_qualified_jobs_dum* is based on a question from the questionnaire; for *unfilled_qualified_jobs/qualified_emp*, 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 Sect. 3.4)

German Industry, Federal Ministry of Labor and Social Affairs (including the Federal Employment Agency), and Federal Ministry of Economics and Technology).

One 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. However, the use of official data has shortcomings, as only vacancies reported by firms are considered; these account for only about half of all vacancies within the same firms (Bellmann & Leber 2017; Czepek et al. 2015). Furthermore, information on the reporting firms is 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 focus 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 to skill shortage. In contrast to the data from the Federal Employment Agency described above, firm-level data contains information on the surveyed firms, which is relevant for the econometric analysis because firm characteristics partly explain differences in shortages of skilled workers (e.g., Bellmann & Hübler 2014).

Within the econometric analysis, we measure skill shortages by different variables, both based on (the number of) unfilled qualified job positions (see Table 1), which are also part of the main dataset as separate variables.¹ Firstly, we use the dummy variable *unfilled_qualified_jobs_dum*, where *unfilled_qualified_jobs_dum* = 1 if the firm reported that it was unable to fill vacancies for qualified jobs, and *unfilled_qualified_jobs_dum* = 0 otherwise. Skilled workers include employees with

¹ All three relevant variables are part of the main dataset (see Employer Survey 2019, questions 30, 42, and 46, <https://fdz.iab.de/en/betriebsdaten/iab-establishment-panel-iab-bp-version-9321-v1/> (accessed 30 March 2025)). The numbering of variables in the questionnaire may vary from year to year.

a university degree, employees who completed vocational training, and those who have comparable professional experience.² Secondly, we calculate the ratio of the number of unfilled qualified job positions to the total number of qualified employees, receiving the variable *unfilled_qualified_jobs/qualified_emp*. Both indicators have already been used as skill shortage indicators in other studies (e.g., Bellmann & Hübler 2014).

$$\text{unfilled_qualified_jobs/qualified_emp} = \frac{\text{number of unfilled qualified jobs}}{\text{total number of qualified employees}} \quad (1)$$

The descriptive statistics reveal an increasing number of firms that reported skill shortages between 2009 and 2019. Looking at all the firms of the sample, in 2009, around 4% of firms experienced problems in filling vacant positions for qualified jobs while nearly 23% of firms confirm these problems in 2019 (*unfilled_qualified_jobs_dum*, see Table 1). At the same time, the degree of shortages appears to be stable. Looking at the ratio of unfilled qualified jobs to qualified employees (*unfilled_qualified_jobs/qualified_emp*), from 2012 onward, firstly, firms on average have a slightly lower ratio of unfilled qualified positions compared to 2009, and secondly, the value of the ratio is relatively constant. Skill shortages therefore appear to be a problem that is reportedly affecting an increasing number of firms, but at the same time does not appear to be increasing in intensity for the affected firms. Furthermore, for both variables, the displayed means are smaller than the standard deviations. This indicates that firms are affected by skill shortages to very different degrees. Additional kernel density estimations and histograms show the same results and are therefore not additionally shown.

3.3 Industrial cluster indicator – location quotient

As our analysis aims to examine the effect of industrial clusters on skill shortages in firms, it is essential that regional industrial clusters are properly identified. The location quotient (LQ) is a measure of regional specialization and is frequently used to identify clusters and to measure their strength of clustering (e.g., Brenner 2017, 2006; Crawley et al. 2013; Held 1996; Isaksen 1996; Sternberg & Litzenger 2004). It is defined as,

$$LQ_{ind,reg} = \frac{\frac{V_{ind,reg}}{V_{ind,sp}}}{\frac{V_{ec,reg}}{V_{ec,sp}}} \quad (2)$$

² Even though these three distinct labor market groups represent different segments, they are included in one definition, as the variable is defined this way by the survey questionnaire of the main dataset (see questionnaire of the Employer Survey 2019, question 42, <https://fdz.iab.de/en/betriebsdaten/iab-estab-shipment-panel-iab-bp-version-9321-v1/> (accessed 30 March 2025)).

Table 2 Descriptive statistics of the localization quotient. *Source:* Authors' own illustration

	2009		2012		2015		2019	
	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)

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).³

Generally, there are different approaches to use such quotients to identify industrial clusters. Firstly, based on predefined thresholds. As the existing literature uses different thresholds, they range from the value of one (e.g., Held 1996) up to a value of three (e.g., Isaksen 1996), while the US Cluster Mapping declares the top 25% of regions in each sector as clusters (Brenner 2017). Secondly, thresholds can be deduced from the data itself (Brenner 2006) by grouping based on quantiles. Thirdly, the location quotient data are treated as a continuous variable without grouping the data by different thresholds to avoid loss of information. While the first two approaches aim to identify clusters as such and to categorize them into groups based on the intensity of the clustering, we use the third approach, which assigns quotas to assess the strength of the clustering. Therefore, we retain all the information.

Due to availability constraints, the location quotient used (Log LQ3_con) is based on the year 2012 and is calculated at the three-digit level.⁴ Furthermore, we transform the location quotient to $(lq-1) / (lq+1)$, resulting in a variable that ranges between -1 and 1, to account for the strongly varying distribution of the values.⁵ The descriptive statistics of the location quotient are provided below (see Table 2).

3.4 Econometric approach

According to different regression models, we analyze the relation between skill shortages of firms and their location in an industrial cluster. To capture firm characteristics, industry specifics, changes over time, and a wide range of regional differences, all models include the same set of control variables.

The different regression models are all based on a pooled sample, as the analysis focuses on the general relationship between the variables and is less interested in

³ This quotient focuses on employment and does not include information on institutional settings or network structures, based on social factors and trust.

⁴ 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 (WZ) 2008, 2-digit as well as three-digit level*. Unfortunately, the underlying dataset does not include data more recent than 2012. This dataset is based on the Federal Employment Agency's firm file, covering about two million firms. This file is derived from the employment statistics, to which employers report all employees subject to social security contributions under the number of their firm.

⁵ Similarly distributed wage data are typically log-transformed to correct for right-skewness.

Table 3 Descriptive statistics of the used sample. *Source:* Authors' own illustration

Year	Full sample			Single-observation sample		
	unfilled_qualified_jobs_dum			unfilled_qualified_jobs_dum		
	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)

The dummy variable *unfilled_qualified_jobs_dum* is used to illustrate the different observation count in each sample for each year

their change over time. In addition, the limited availability of the location quotient prevents a reliable panel analysis. The pooled sample includes the years from 2009 to 2019 (see Table 2) and allows for a large number of observations and greater precision in the model estimates. To ensure that firms are not considered multiple times, we generate a single-observation sample that includes each firm once. We use the year 2012 as baseline, including all observations of this year. This choice is based on the availability of the location quotient, which is only available for the year 2012 or earlier. We include further observations from other years, considering the closest observation to the baseline year 2012 first.⁶ For the years 2009/2015, 2010/2014, and 2011/2013, we use a randomized shuffled procedure because the inverse time differences with respect to 2012 are identical (3, 2, and 1).⁷ As a result, the means and standard deviations of the two samples differ only slightly, as shown in Table 3.⁸

Using the IAB Establishment Panel, cluster identification via the location quotient is necessary because the approximately 16,000 firms observed each year are insufficient to perform this step solely on the basis of the main dataset. Using a district and a sector identifier, we match the location quotient to the main dataset.

⁶ If a firm is not observed in 2012 but appears in subsequent years, the nearest available year to 2012 is selected (e.g., 2016 instead of 2017).

⁷ A randomization procedure was implemented in stata 16 by setting a *seed* and applying a *shuffle* to ensure reproducible yet randomized results. Five shuffled samples were generated, and the sample with the best fit was selected.

⁸ To ensure robust results, regression results based on the full sample, using clustered standard errors, have been compared with regression results based on the single-observation sample, using robust standard errors.

To control for firm-specific influences, we add log-transformed firm size, exports, investments, positive sales expectations, training requirements met, hiring and training of employees, and firm structures such as the existence of a works council or a foundation before 1990. Furthermore, we include the shares of mini-jobs, female employees, and skilled employees. Moreover, we control for each year and for 18 sectors. To control for regional differences, we added the age of the population, the commuter balance, gross domestic product (GDP), population density, the share of students, and the unemployment rate. As the establishment data do not contain this information, we match the variables to the existing dataset. Overall, the analyzed dataset includes 43,662 firms located in Germany and is based on the three datasets described above (IAB Establishment Panel data, the location quotient, and regional controls).

We construct the models with a partially stepwise procedure to improve the model fit.⁹ The basic model and its covariates are largely based on the variables used by Bellmann and Hübler (2014), who also analyzed skill shortages in firms using the IAB Establishment Panel data.¹⁰ In a second step, we add regional and temporal control variables. We base the first part of the analysis on the skill shortage indicator and dependent variable *unfilled_qualified_jobs_dum*. As *unfilled_qualified_jobs_dum* is a dummy variable, a binary logistic regression model is an appropriate choice; coefficients and marginal effects are reported (see Table 3). The sample size is slightly reduced and includes observations on 37,877 firms.¹¹ In addition, we use a binary probit regression model to ensure robust results. The second part of the analysis applies to all firms reporting skill shortages and is based on the skill shortage indicator and dependent variable *unfilled_qualified_jobs/qualified_emp*. By focusing only on firms that reported a skill shortage, the size of the underlying sample is significantly reduced to 6,398 firms.¹² As *unfilled_qualified_jobs/qualified_emp* is a continuous variable with a high concentration of values just above zero, we use a negative binomial regression model (Negbin) and a Poisson regression model as robustness checks. We use robust standard errors in all models.

⁹ We use the stepwise modeling approach to keep the model simple at first and reduce the risk of overfitting. The most relevant predictors are theoretically derived based on Bellmann and Hübler (2014), rather than selected in a forward and backward elimination process, in order to avoid omitting theoretically important variables.

¹⁰ Their selection of statistically relevant firm characteristics is based on a least angle regression (LARS), as the existing literature provides only limited explanations for the variation in skill shortages across firms (Bellmann & Hübler 2014).

¹¹ This deviation is due to the fact that information must be available for each variable included in the regression. If this is not the case for individual firms, they are excluded from the sample. The time structure of this sample is similar to the full single-observation sample (see Table 3) because the total number of observations is only 8.6% smaller.

¹² The time structure of this sample differs slightly from the full single-observation sample because of the focus on firms facing skill shortages (see Table 3). Since this sample only contains firms that suffer from skill shortages, more firms from later years are included, as the number of firms reporting skill shortages increases over the years (see Table 1, *unfilled_qualified_jobs_dum*).

4 Results and discussion

Descriptions and descriptive statistics of all variables used, including firm characteristics, sectors, regional differences, and years, are presented in the Appendix (see Tables A2 and A3). We estimate four models (1 to 4), which differ in the dependent variables and the regression estimators used (see Table 4). Firstly, we present the general results for both dependent variables (*unfilled_qualified_jobs_dum* and *unfilled_qualified_jobs/qualified_emp*). Secondly, we present the outcomes for the variable of interest. Thirdly, we discuss the results.

Looking at the variable *unfilled_qualified_jobs_dum* for all firms (Models 1 and 2), we generally find that the probability of experiencing a shortage of skilled labor is greater for firms with a higher number of employees, especially in the social sector and in business services. As described above, the dependent variable is a dummy variable that indicates whether the firm has a reported shortage of employees for skilled jobs (and therefore faces skill shortages). Surprisingly, firms that make investments, have positive sales expectations, train employees, and provide training are more likely to suffer from skill shortages. Compared to firm size, the marginal effects of these variables are significantly smaller. If a firm has a works council or was founded before 1990, it is less likely to suffer from skill shortages.

Furthermore, the higher the share of mini-jobs and female employees, the lower the probability of having vacancies for qualified jobs. Less surprising is the significant result that the higher the share of qualified workers, the more likely a shortage of qualified employees becomes. Looking at the differences in spatial dependency between eastern and western Germany, firms in the western states are significantly less likely to experience a shortage of skilled workers. Other regional differences are mostly not significantly correlated with skill shortages. Population density is an exception: we observe a vanishingly weak, negative, but significant relationship.

Focusing on firms with reported skill shortages (Models 3 and 4), we find that, on average, skill shortages are reduced in exporting firms as the job vacancy rate *unfilled_qualified_jobs/qualified_emp* decreases. Moreover, in contrast to Sheldon and Li (2013), who focused on labor poaching in foreign-invested firms in China, we find that larger and longer-established firms are not the most affected. In Models 3 and 4, a larger firm size and later foundation date reduce the job vacancy rate. Consistent with Models 1 and 2, firms that have a works council or were founded before 1990 have lower vacancy rates. Additional training offers for employees and a higher share of female employees are associated with lower job vacancy rates for qualified jobs. Regional differences are mostly not significantly correlated with skill shortages. The age of the population and population density are exceptions: we observe weak, negative, but significant relationships.

The analysis of the variable of interest (Log LQ3_con) within the different models shows that the results with regard to the hypotheses are ambiguous. Focusing on hypothesis 1, we find that firms located in an industrial cluster have a significantly lower probability of experiencing skill shortages in Models 1 and

Table 4 Regression models of skill shortages, 2009–2019. *Source:* Authors' own illustration

	(1)	(2)	(3)	(4)
	unfilled_qualified_jobs_dum	unfilled_qualified_jobs_dum	unfilled_qualified_jobs/qualified_emp	unfilled_qualified_jobs/qualified_emp
	Logit	Probit	Negbin	Poisson
Log firm size	0.267*** (0.001)	0.269*** (0.001)	-0.424*** (0.026)	-0.420*** (0.026)
Exports	0.000 (0.005)	0.000 (0.005)	-0.439*** (0.058)	-0.443*** (0.060)
Investments	0.023*** (0.004)	0.024*** (0.004)	-0.044 (0.061)	-0.039 (0.066)
Positive sales expectation	0.019*** (0.004)	0.019*** (0.004)	-0.052 (0.053)	-0.054 (0.055)
Training requirements fulfilled	0.031*** (0.004)	0.030*** (0.004)	-0.090 (0.060)	-0.088 (0.063)
Hiring	0.083*** (0.004)	0.080*** (0.004)	0.190*** (0.058)	0.191*** (0.060)
Further training	0.042*** (0.005)	0.040*** (0.004)	-0.273*** (0.093)	-0.274*** (0.097)
Works council	-0.052*** (0.005)	-0.052*** (0.005)	-0.740*** (0.084)	-0.758*** (0.090)
Foundation before 1990	-0.021*** (0.004)	-0.021*** (0.004)	-0.394*** (0.066)	-0.398*** (0.069)
Share of mini-jobs	-0.040*** (0.012)	-0.039*** (0.011)	-0.124 (0.163)	-0.147 (0.171)
Share of female employees	-0.047*** (0.008)	-0.045*** (0.007)	-0.469*** (0.081)	-0.475*** (0.083)
Share of skilled employees	0.079*** (0.007)	0.076*** (0.007)		
Production sector	-0.032* (0.018)	-0.031* (0.017)	-0.471*** (0.140)	-0.469*** (0.141)
Social sector	0.081*** (0.017)	0.079*** (0.016)	-0.295** (0.137)	-0.290** (0.139)
Business-related services sector	0.070*** (0.016)	0.066*** (0.015)	0.696*** (0.143)	0.682*** (0.139)
West Germany	-0.036*** (0.006)	-0.036*** (0.006)	0.241*** (0.085)	0.247*** (0.092)
Age of population	-0.001 (0.001)	-0.001 (0.001)	-0.073*** (0.022)	-0.071*** (0.022)
Commuter balance	0.000 (0.000)	0.000 (0.000)	0.002* (0.001)	0.002* (0.001)
GDP	0.000 (0.000)	0.000 (0.000)	-0.003 (0.003)	-0.003 (0.003)
Population density	-0.000** (0.000)	-0.000** (0.000)	-0.000*** (0.000)	-0.000** (0.000)

Table 4 (continued)

	(1)	(2)	(3)	(4)
Log LQ3_con	-0.015*** (0.005)	-0.015*** (0.005)	0.136* (0.080)	0.145* (0.086)
Cons	-3.623*** (0.603)	-2.039*** (0.338)	3.864*** (1.014)	3.826*** (1.038)
N	37,877	37,877	6,398	6,398
Pseudo-R ²	0.160	0.161	0.206	0.213

For effects deriving from the estimation of Models 1 and 2, marginal effects (dy/dx) are reported; for effects deriving from the estimation of Models 3 and 4, coefficients are reported, which are in the form of the logarithm of counts (unfilled_qualified_jobs/qualified_emp), rather than actual counts. To interpret the results in a count metric, the coefficient must be exponentiated for $\ln(\text{unfilled_qualified_jobs}/\text{qualified_emp})$; robust standard errors are in parentheses; significance level: * $p < 0.10$, ** $p < 0.05$, *** $p < 0.01$

2, as the coefficient is negative. The higher the level of agglomeration, the lower the probability of having vacancies for qualified jobs. Therefore, hypothesis 1a is confirmed. As we compare the results of Models 1 and 2, the logit and probit estimates show consistent results with minor variations regarding the effect sizes. Focusing only on clustered firms that report skill shortages (Models 3 and 4), the cluster effect changes in three ways: the effect size increases, the coefficient turns positive; yet, the level of significance decreases. In terms of interpretation, this implies that the higher the level of agglomeration, the higher the ratio of unfilled qualified labor positions to skilled labor positions in the firm. Thus, if firms are experiencing skill shortages, increasing agglomeration appears to increase both the job vacancy rate and the skill shortage. Again, comparing Models 3 and 4, both estimations show consistent results. Therefore, hypothesis 1b is rejected. If we now look at hypothesis 2 on the basis of these results, 2a) must be rejected, while 2b) is confirmed. Overall, the results are ambiguous in the sense that firms located in an industrial cluster have a lower probability of experiencing skill shortages, but at the same time have problems filling qualified vacancies if they already suffer from skill shortages.

Comparing the effect sizes across 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. These results are robust across all models and in line with the literature, as Bellmann and Hübler (2014) gain similar results for firm characteristics and Czepek et al. (2015) for sectoral outcomes. Looking at the main result from Models 1 and 2 including all firms, a higher level of agglomeration reduces the probability of having vacancies for qualified jobs, which is in line with most of the literature on labor market pooling. Firms located in an industrial cluster benefit from a labor market pool as discussed in the literature (Grashof 2020; Marshall 1920). Therefore, our results confirm the aspects of labor market pooling discussed in the literature, although the magnitude of the effects is small (Andini et al. 2013). In contrast, Models 3 and 4 provide coefficients that suggest the opposite: firms reporting skill shortages have higher vacancy rates

if they are located in stronger industrial clusters. We interpret this as follows: within clusters, labor pooling reduces the likelihood of skill shortages. However, despite this effect, if a firm in an industrial cluster is experiencing skill shortages, these shortages are more severe due to labor poaching by co-located competitors. Within a cluster, there are often heterogeneous firms with different potential to attract workers, e.g., due to firm size, reputation, scope, and salaries. As a result, the more attractive firms may benefit from the surrounding specialized labor market, while the less attractive firms are more likely to experience the negative effects of labor poaching.

5 Conclusion

This study discusses the phenomenon of regional and sectoral shortages in the recruitment of skilled labor that are foreseeable or already a reality in Germany. However, it is not clear whether such skill shortages are more or less pronounced in industrial clusters. The analysis addresses this gap by investigating the occurrence of skill shortages in clustered firms based on firm-level data.

Overall, skill shortages appear to be a relevant problem that is affecting an increasing number of firms. In 2009 around 4% of firms experienced problems in filling vacant positions for qualified jobs while nearly 23% of firms confirm these problems in 2019. At the same time, the degree of shortages appears to be stable. This affects firms in industrial clusters in two ways. With respect to the first hypothesis, firms in an industrial cluster have a significantly lower probability of experiencing skill shortages. The higher the level of agglomeration, the lower the probability of having vacancies for skilled jobs. Regarding the second hypothesis, the cluster effect changes for firms with reported skill shortage: higher agglomeration corresponds to a higher ratio of unfilled qualified labor positions to skilled labor positions. Thus, our results confirm the contradictory effects of labor pooling and labor poaching reported in the literature and provide further detail on them. Overall, firms in industrial clusters benefit from a lower probability of skill shortages. However, if they already face skill shortages, they are less attractive to skilled workers and encounter more problems than they would outside the industrial cluster.

This study has several limitations. Firstly, the analysis cannot identify causal effects based on the estimated regressions. Secondly, the results are based on a German establishment dataset. Although it is a representative employer survey, the findings can only be applied to labor markets outside Germany to a limited extent. Germany has a distinct labor market with a strong industrial focus and a unique education system that emphasizes practical, on-the-job training alongside vocational schools, in addition to universities. Thirdly, the results are based on a pooled sample which does not allow the analyses of temporal changes. Fourthly, survey data at the firm-level may be subject to a reporting bias, as firm representatives might emphasize negative aspects to defend their firm's or sector's interests. Fifthly, cluster identification based on a location quotient has shortcomings: it can yield high values in small regions with relatively little activity (Carroll et al. 2008), using absolute employee numbers instead of the quotient favors large regions, and information on institutional settings or network

structures are not included. Furthermore, the industry definition is crucial for the identification of clusters with the location quotient (Brenner 2017). Sixthly, due to the expiry of research data access we were unable to rerun regression models or adopt alternative clustering measures throughout the final submission process.

The relationship between skill shortages and industrial clusters should be the subject of further research. Firstly, researchers could analyze additional datasets, including other firm surveys, to confirm the results. Secondly, the relationship should be examined in other labor markets, ideally with a similar basic structure but without Germany's specific features, such as a strong industrial focus and unique education system. Thirdly, future datasets should include additional characteristics of surveyed firms beyond the control variables used in this study.

Overall, the rising number of firms affected by skill shortages indicates the need for action. While firms must act on their own, economic policy measures that shape local preconditions are also required (König & Brenner 2025). Therefore, we propose the following policy recommendations. Industrial clusters could be part of regional development policy approaches that address their growth or renewal, as our results indicate that firms in industrial clusters experience fewer skill shortages. At the same time, firms may face problems due to negative cluster effects. To address this, firms already suffering from skill shortages could receive specialized support from local economic development agencies to prevent relocation, decline, or failure. Such support could include joint training initiatives or the creation of specialist classes in cooperation with vocational schools (König 2023). As a first step, developing a regional strategy for skilled labor that involves firms, chambers and associations, network organizations, social partners, and regional policy actors could initiate these processes and serve as a starting point. In principle, such measures should be designed in a way that reflects the growing number of affected firms. Instead of narrowly targeting a small number of specific firms, measures should address multiple factors and be accessible to a wider set of firms.

Appendix

See Tables 5, 6, 7

Table 5 Full regression models of skill shortages, 2009–2019. *Source:* Authors' own illustration

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

Table 5 (continued)

	(1)	(2)	(3)	(4)
	(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)
	unfilled_qualified_jobs_dum		unfilled_qualified_jobs/qualified_emp	
	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)
Commuter balance	0.000	0.000	0.002*	0.002*
	(0.000)	(0.000)	(0.001)	(0.001)
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

Table 5 (continued)

	(1)	(2)	(3)	(4)
	(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)
	(1)	(2)	(3)	(4)
	unfilled_qualified_jobs_dum	unfilled_qualified_jobs/qualified_emp		
	Logit	Probit	Negbin	Poisson
Year 2016	0.120***	0.120***	-0.050	-0.078
	(0.012)	(0.012)	(0.230)	(0.248)
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

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

Table 6 Descriptive statistics of firm characteristics, sectors, regional differences and years. *Source:* Authors' own illustration

	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)
Positive employment development. expectation	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)
Textile 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)
Investment 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)
Commuter balance	-4.446	(30.481)	-7.257	(27.524)	-5.383	(25.627)
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 7 Variable description of firm characteristics, sectors, regional differences and years. *Source:* Authors' own illustration

Variable	Description
Log firm size	Total number of employees, log-transformed
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 development 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 (for a maximum of three months or 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 WZ 03/08 industry classification of the IAB (dummy); 18 sectors are included
West Germany	= 1 if firm is located in one of the ten 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
Commuter balance	Net commuting per 100 employees (subject to social security contributions) at place of work
GDP	Gross domestic product in € 1,000 per inhabitant
Population density	Inhabitants per km ²
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 percent
Years	= 1 if firm is assigned to the respective year (dummy); the included years are 2009 to 2019

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Data availability The data that support the findings of this article 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/>).

Declarations

Conflict of interest The authors declare no competing interests.

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