Swiss Leading House

Economics of Education • Firm Behaviour • Training Policies

Working Paper No. 217

Beggars cannot be choosers: The effect of labor market tightness on hiring standards, wages, and hiring costs

Carolin Linckh, Samuel Muehlemann and Harald Pfeifer

Universität Zürich
IBW – Institut für Betriebswirtschaftslehre

b
UNIVERSITÄT
BERN

Working Paper No. 217

Beggars cannot be choosers: The effect of labor market tightness on hiring standards, wages, and hiring costs

Carolin Linckh, Samuel Muehlemann and Harald Pfeifer

April 2024

The Swiss Leading House on Economics of Education, Firm Behavior and Training Policies is a Research Program of the Swiss State Secretariat for Education, Research, and Innovation (SERI).

www.economics-of-education.ch

Beggars cannot be choosers: The effect of labor market tightness on hiring standards, wages, and hiring costs

Carolin Linckh
BIBB Bonn & ROA Maastricht

Samuel Muehlemann
LMU Munich, IZA Bonn & ROA Maastricht

Harald Pfeifer
BIBB Bonn, IZA Bonn & ROA Maastricht

April 2024

Abstract

This paper analyzes the relationship between labor market tightness and firms' hiring behavior. We use unique linked employer-employee data to show that firms lower their hiring standards in tight labor markets, but we find no evidence that firms increase the starting wages of new hires. Exploiting detailed data on pre- and post-match hiring costs, we find that both cost components increase with the degree of tightness in the labor market. However, as pre-match search costs make up only a small share of the total hiring costs, our results highlight the importance of the post-match hiring costs for firms' adjustment to tightness.*

Keywords: Recruiting, Labor market tightness, Wages, Hiring standard, Hiring cost, On the Job Training
JEL Classification: J23, J24, J31, J63

*We thank the participants of the 15th IAB Ph.D. Workshop in Nuremberg and the 26th Colloquium of Personnel Economics in Zurich, and Felix Wenzelmann for excellent comments and discussions. We are grateful to Hans Dietrich from IAB as well as Holger Alda, Beatrice van Berg, and Felix Lukowski from BIBB for their valuable support with data linkage.

1 Introduction

Firms aiming to hire workers from the external labor market must constantly adjust to changing supply conditions, such as demographic changes. Conversely, technological changes or macroeconomic fluctuations may affect a firm's labor demand. In recent years, firms in many Western countries face increasingly tight labor markets, as indicated by decreasing unemployment and an increasing number of unfilled vacancies (Kiss et al., 2022; Domash and Summers, 2022). Although wages simply adjust upward in competitive labor markets, this is not always the case when markets experience frictions. Consequently, firms may face a trade-off between reducing vacancy duration and offering higher wages (Reder, 1955). Indeed, several empirical studies using US and UK data report that entry wages are positively related to labor market tightness and that firms that offer higher wages find it easier to fill their vacancies (Azar et al. 2022; Bassier et al. 2023; Marinescu and Wolthoff 2020; Webber, 2022). By contrast, evidence from continental Europe, where labor markets tend to be more regulated, suggests that the association between tightness and entry wages is much weaker (Mueller et al., 2023; Carrillo-Tudela et al., 2023). This raises the question of whether firms adjust to other aspects of their recruitment process. Manning (2006) shows that firms can increase employment not only by raising entry wages, but also by increasing their recruitment effort.[1] Finally, as Reder (1955) notes, firms may reduce their hiring standards when qualified job applicants are scarce, but the consequence is that a firm must provide additional training to ensure that the new hire eventually reaches the desired skill level to adequately carry out his or her job. However, no empirical research examines the relationship between labor market tightness and hiring standards. A notable exception is the study by Le Barbanchon et al. (2023), which demonstrates that French companies lower their hiring standards in terms of necessary work experience but not in terms of educational requirements.

Our main contribution to the literature is that we provide evidence of the consequences of a firm's hiring behavior in tight labor markets. These potential consequences not only comprise increasing search and recruitment costs but also a longer onboarding period and higher disruption costs during the onboarding period. Disruption costs are a type of informal training by coworkers that are also important in other contexts (Bartel et al., 2014; Papay et al., 2020).

To empirically assess the consequences of a firm's hiring behavior in times of higher tightness, we link unique firm-level data that provide information on the hiring costs of a specific vacancy with administrative information on the worker who filled that vacancy.

[1] Other studies confirm this association, although some show that recruitment effort plays a relatively modest role (e.g., Carrillo-Tudela et al. 2023).

These administrative data contain rich information on the individual characteristics of the hired workers and their corresponding starting wages. To our knowledge, our data is the first to link information at the worker level with detailed information on hiring costs at the firm level. More precisely, the survey dataset contains information about the entire hiring process, including search and recruitment costs, as well as costs related to formal and informal training, associated productivity losses, and information about the duration of the onboarding period. Moreover, our data allow us to use worker and firm AKM effects (named after Abowd, Kramaz, and Margolis, who introduced them in Abowd et al., 1999), which are measures of unobserved ability at the individual level and account for unobserved factors associated with a wage premium at the firm level. Furthermore, we use official statistics on labor market tightness (i.e., the relationship between unfilled vacancies and the number of unemployed workers in a given occupation, regional labor market, and time of firm entrance). Finally, to measure a firm's hiring standards, we follow Carrillo-Tudela et al. (2023) and define a relative selectivity measure as the difference between the AKM worker effect of a new hire and the average AKM worker effect in the firm.

Our data show that the costs of hiring skilled workers from the external labor market are substantial, amount to 10,000 EUR on average, which corresponds to 22 weeks of pay for a newly hired skilled worker. Exploiting the level of detail in our survey data shows that 84% of the total hiring costs accrue after the work contract is signed, as new hires need to acquire new skills to adequately carry out their tasks. This happens via external training, independent learning on the job, other forms of self-directed learning, or by acquiring the necessary knowledge and skills from coworkers. The costs arising from training coworkers are substantial, amounting to approximately 50% of the total hiring costs. Our results provide evidence of several relationships between labor market tightness and the hiring process. First, we find no evidence that tightness is associated with a new hire's starting wage. Second, tightness is positively associated with job-posting costs. Third, tightness is negatively associated with hiring standards. To support this argument, we examine two facets of hiring standards: occupational experience and innate, general worker ability, as measured by the worker AKM effect. Our results show that when tightness increases, firms have lower hiring standards in terms of workers' general abilities. However, we find no association between tightness and occupational experience of new hires. Finally, tightness is positively associated with the duration of the adaptation period, costs of external training, and time spent informally training new hires. More nuanced estimations show (weak) evidence that new hires do not reach the productivity level of an average skilled worker at the end of the adaptation period under a high level of tightness, which is consistent with firms lowering their hiring standards. This finding implies that firms' investments during the adaptation period do not seem to completely compensate for lower matching quality when tightness is high.

The remainder of this paper is organized as follows. Section 2 discusses the related empirical literature. We describe the data and characteristics of our sample in Section 3. Section 4 and Section 5 present the components of hiring costs and our estimation approach, respectively. We report the regression results and the robustness checks in Section 6. Section 7 discusses our results in the context of the literature and their implications. Finally, Section 8 concludes the paper.

2 Empirical Literature

2.1 Labor market tightness and hiring costs

Empirical evidence on the association between labor market tightness and directly observable hiring costs is scarce despite its importance to the theoretical literature (e.g., Pissarides, 2000; Shimer, 2005; Pissarides, 2009).[2]

For Germany, Muehlemann and Pfeifer (2016) provide the first cross-sectional evidence that local unemployment is negatively associated with average hiring costs, albeit only marginally statistically significant, and is driven by higher adaptation costs when unemployment decreases. However, their data lack a measure for the number of local vacancies. Carbonero and Gartner (2022) exploit data from the German Job Vacancy Survey and find that a tightness-induced increase in the search duration for a new hire is significantly associated with the costs to fill a vacancy. Kiarsi and Muehlemann (2021) also use data from the German Job Vacancy Survey and find that an increase in tightness, as measured at the occupational level across regions, is significantly associated with non-labor search costs, but not with the time that firms spend to interview job candidates. While not directly observing the search costs to fill a vacancy, Carrillo-Tudela et al. (2023) analyze the extent to which firms can use search effort (the number of search channels that firms utilize to fill their vacancies) to increase matching efficiency. Their findings suggest that search efforts play only a minor role.

In Switzerland, Blatter et al. (2012) report that a decrease in regional unemployment is positively associated with search and adaptation costs. On average, a decrease in regional unemployment by one percentage point is associated with an increase in average hiring costs in the magnitude of 0.63 weekly wage payments for skilled workers.

[2]Data on directly observable hiring costs exist for France, Germany, Switzerland, and the US. In this section, we review only the literature focusing on the association of labor market tightness and hiring costs. For a more detailed overview of survey methodologies and general findings, we refer to the literature review in Muehlemann and Strupler Leiser (2018) or Manning (2011).

Muehlemann and Strupler Leiser (2018) subsequently introduce that concept of disruption costs, measured as the time a new hire prevents their coworkers to carry out their tasks during the onboarding period. They report the association of various subcomponents of hiring costs with labor market tightness, as measured by the industry-level vacancy-unemployment ratio. In particular, they report that a two-standard deviation increase in tightness is associated with a 25% increase in average (not marginal) search costs but find no association with adaptation costs in a panel regression. The authors note that the effect of tightness on search costs is considerably larger in a fixed-effects panel regression than in a cross-sectional correlation, highlighting the importance of unobserved heterogeneity at the firm level. Aepli et al. (2024) analyze overall hiring costs in Germany and Switzerland, using indicator variables of labor market tightness at the firm level and find evidence that labor market tightness significantly increases hiring costs in both countries. In line with the empirical findings thus far, we expect firms to increase their recruitment efforts when skilled workers are scarce. Additionally, we expect to observe lower match quality with increasing labor market tightness, which, in turn, entails higher onboarding investments for firms.

2.2 Labor market tightness and hiring standards

One reason some firms succeed in hiring (faster) despite a high labor market tightness is that they adjust their hiring standards, as some search and matching models propose (e.g., Sedláček, 2014; Carrillo-Tudela et al., 2023).

There is a paucity of empirical studies that analyze the association between labor market tightness and hiring standards. Carrillo-Tudela et al. (2023) show an important role of employers' hiring standards for matching efficiency. They use two binary measures for hiring standards related to the qualification and experience of the new hire: one variable indicating whether a new hire's qualification is below the expected qualification and a second variable indicating whether the new hire's experience is below the expected experience. They do not explicitly test the association between tightness and hiring standards, but find that hiring standards in terms of qualification and experience are negatively related to hiring rates. In addition, they construct a selectivity measure based on AKM worker effects, which they interpret as the extent to which a new hire's unobserved ability differs from that of the incumbent workforce. Their results show that hiring rates are negatively related to this selectivity measure. Thus, their findings suggest that firms that hire more new workers per period have lower hiring standards.

Mueller et al. (2023) combine vacancy information with matched employer-employee data for Austria. They use work experience, previous unemployment, hiring from employment, and the AKM worker effect of new hires as indicators of a firm's hiring standards. They argue that hiring standards ”explain about 20% of the patterns of vacancy filling within and across establishments” (Mueller et al. 2023, p.37). However, the authors acknowledge that their data do not include information on the new hire’s education level or the learned (or previous) occupation, which may lead to an underestimation of the importance of adjusting hiring standards in Austria. Additionally, similar to Carrillo-Tudela et al. (2023), they do not directly test the association between tightness and hiring standards.

Le Barbanchon et al. (2023) link an administrative dataset on job vacancies in France with matched employer-employee data to study the effect of hiring frictions on hiring outcomes. They measure hiring frictions in terms of a firm’s ability to successfully fill a vacancy and vacancy duration in a local labor market. Furthermore, the authors employ multiple indicators to assess hiring standards at the job level, including experience and educational background, as well as the type of contract offered for the position (open-ended, temporary, or full-time/part-time). They report that firms lower their hiring standards in terms of the required experience when they face difficulties in filling their vacancies, but not in terms of the required education or contract type. Moreover, in line with Carrillo-Tudela et al. (2023), they find that firms that hire at a faster rate are more likely to reduce their hiring standards. Given these, albeit rare, findings in the literature, we expect firms in tighter labor markets to lower their hiring standards to fill their vacancies.

2.3 Labor market tightness and entry wages

Mueller et al. (2023) explore the relationship between the duration of a vacancy and the starting wage. They find that vacancy duration is negatively correlated with starting wages. However, their reported elasticities are small, implying that variations in entry wages are not the most important factor in successfully filling vacancies. Similarly, Carrillo-Tudela et al. (2023) demonstrate that wage generosity plays only a quantitatively minor role. Bertheau et al. (2023) link a Danish firm-level survey to administrative data and analyze the determinants of hiring decisions. They do not find that paying higher wages is associated with firms being less discouraged by skill shortages, thus complementing the findings of Mueller et al. (2023).

However, the association between entry wages and a firm’s difficulty in filling a vacancy is stronger in less-regulated labor markets. Using US data on job postings, Azar et al. (2022) find that labor market tightness is positively associated with posted wages. Moreover, using the same data, Marinescu and Wolthoff (2020) find that a 10% increase in posted wages is associated with a 7.7% increase in applications. However, in their study, the reason some firms offer higher wages than others is not strictly because of an increase in labor market tightness. Webber (2022) examines how labor market frictions evolve over the business cycle. He reports a substantial decrease in labor supply elasticity between 1998 and 2012, with an apparent pro-cyclical pattern leading to at least a 4 percent drop in earnings for average workers. Although Webber (2022) points out that it is not purely business cycle factors that drive the decline in labor market competition, he provides indirect evidence of the link between wages and tightness in the US labor market. In the UK, Bassier et al. (2023) exploit within-firm variations in wages and vacancy duration using data from online job advertisements, and find that firms that pay higher wages find it easier to fill vacancies. Based on the previous literature, we expect that firms in a regulated labor market (such as the German labor market) do not extensively increase their starting wages when facing skill shortages.

3 Data

3.1 Data Sources

To study the relationship between labor market tightness and recruitment costs, we link firm-level survey information from the BIBB Cost-Benefit Survey (BIBB-CBS) 2017/18 to administrative labor market records from the Institute for Employment Research (IAB) and official statistics from the Federal Employment Agency (FEA).

The BIBB-CBS 2017/18 is a representative survey of apprenticeship training and the recruitment of skilled workers in Germany and comprises 4,045 computer-assisted personal interviews with firm representatives. *infas* The Institut für angewandte Sozialforschung GmbH conducted the survey between September 2018 and July 2019 (Schoenfeld et al., 2020; Wenzelmann and Schoenfeld, 2022). The interviewers posed questions on the training and external recruitment of skilled workers with reference to a specific occupation of the firm for which they were either trained or recruited. A key advantage of BIBB-CBS is its exceptionally rich information on nearly all aspects of firms' hiring practices. The survey quantified the costs of the application procedure, continuing training during adaptation periods, initial productivity differences of new skilled workers, and costs arising from coworkers providing informal learning for the last-hired skilled worker. Thus, the data provide specific cost information for all the phases of the hiring process, including post-match hiring costs, which are usually not observed in firm-level surveys.

We link the firm-level survey data to two administrative data sources. The first source of administrative data was the Integrated Employment Biographies (IEB). The IEB covers all individuals in Germany with at least one entry in their social security records during the observation period (Antoni et al., 2019).[3] While the IEB combines several sources of administrative records, we mainly use employment notifications derived from Employee History (BeH). The BeH provides day-to-day information on working-time status (i.e., full-time, part-time, or marginal employment), daily gross wage, worker's occupation (a 5-digit code according to the German Classification of Occupations 2010 (KldB 2010)), and socio-demographic characteristics. The second administrative data source is the Establishment History Panel (BHP, *Betriebshistorikpanel*), which aggregates the BeH to the firm level at 30$^{\text{th}}$ June each year (Ganzer et al., 2022). Among other characteristics, the BHP contains information on the firm's economic sector, location, structure of employees by qualifications and wages, and the first appearance of the firm in the register data. Our data also include the AKM effects stemming from the Mincerian wage equation estimated by Bellmann et al. (2020). Worker AKM effects capture the proportion of workers' individual skills and other factors that are rewarded equally across employers in their wage earnings. Firms' AKM effects reflect firm-specific pay premiums or discounts.

Finally, we use official statistics on posted vacancies and job-seekers from the FEA[4] to capture labor market tightness. We determine the number of job-seekers and registered vacancies monthly on a set day. The concept of job-seekers is broader than that of unemployed persons, as it includes individuals who search for employment subject to social security for at least 15 hours per week, are registered at the FEA or Job Center and are legally allowed to perform such a job (Federal Employment Agency, 2023). The stock of vacancies includes non-subsidized vacancies with a duration of more than seven days registered with the FEA or Job Center for mediation (Federal Employment Agency, 2018). Firms are not obligated to register vacancies with the FEA. Both the stock of job-seekers and registered vacancies are available at the 2-digit (target) occupation level according to KldB 2010 and at the regional level of the Federal States.

3.2 Linking the BIBB-CBS survey to the IEBs and identifying the most recently hired skilled worker

The first step of our data preparation is to link the IEB micro data to the CBS information at the firm level (Step 1 in Figure 1).[5] We link administrative data to 2,434 of the 4,045 survey firms that explicitly allowed the data to merge. We exclude those

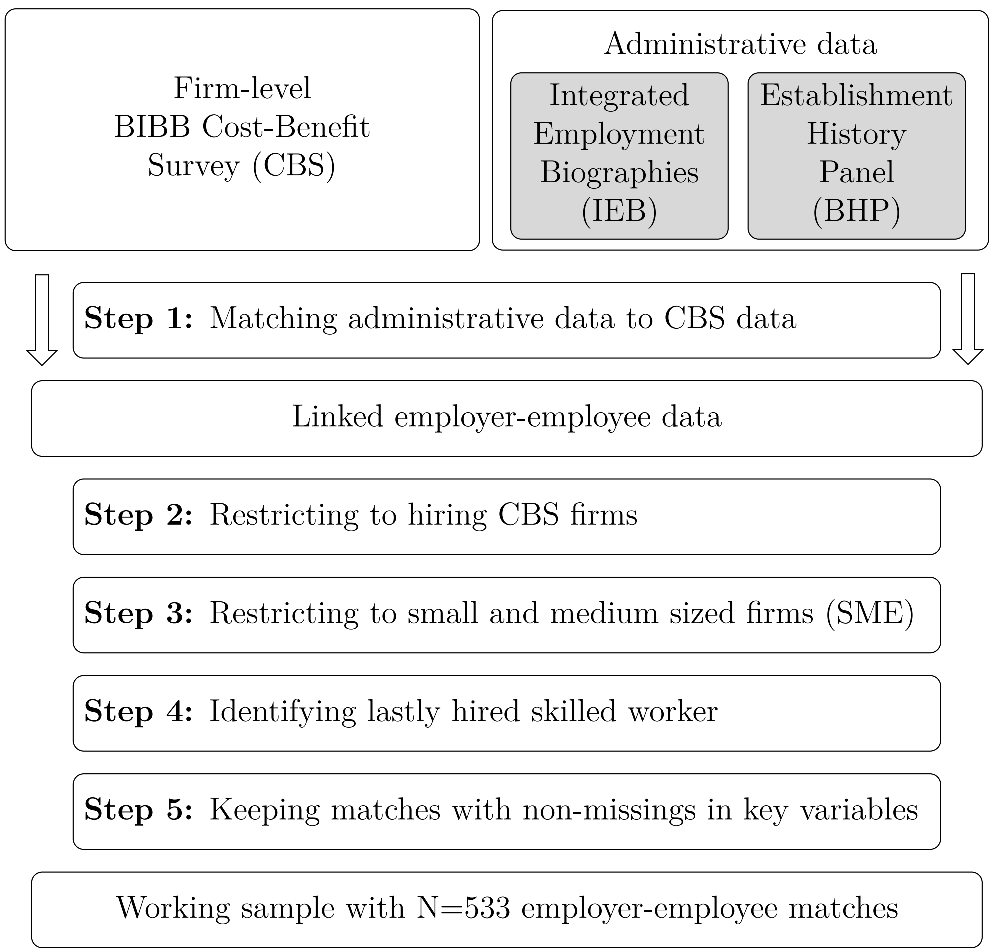
[3]The observation period in our study is 2014-2019. Note that the IEB does not include civil servants, self-employed persons, and regular students.

[4]`https://statistik.arbeitsagentur.de/SiteGlobals/Forms/Suche/Einzelheftsuche_Formular.html?gtp=15084_list%253D7&submit=Suchen&topic_f=berufe-heft-kldb2010`

[5]Section A in the Appendix provides a detailed description of how we linked and prepared the data.

surveyed firms that exhibit no identifier in the administrative data and firms with more than 1,000 employees because the record data for those firms contain only 20% of the sample. To ensure a sufficiently high linkage quality, we compare the number of reported and registered employees in both data sources. Following Dietrich et al. (2014), we define linkage quality as sufficiently high if the absolute difference between the number of employees reported in the survey and the number of registered employees in the IEB is less than half of the respective firm size category width. This plausibility restriction indicates that 90.02% of the CBS firms (2,128 of 2,364) can be linked with justifiable deviations, which is comparable to the linkage of the BIBB-CBS 2007 described in Dietrich et al. (2014) and the Linked Employer-Employee-Data of the IAB (Ruf et al., 2023).

Figure 1: From record linkage to working sample



Source: Own illustration.

Before identifying the newly hired skilled workers to which the hiring information in the survey refers, we must restrict to the firms that hired a skilled worker between 2015 and 2019 in Step 2. This timeframe results from the fact that the hiring information in the survey refers to the last worker hired since 2015, and the last interviews were conducted in 2019. A total of 1,610 CBS firms recruited skilled workers. In step 3, we restrict our data to employees that enter small and medium-sized firms (SME) with at most 249 employees. Because SMEs rarely hire several employees with similar characteristics simultaneously, there is a high chance of finding the most recent hire. Restricting our analysis to SMEs is justifiable in our view because they make up the vast majority of firms in Germany[6] and play a crucial role in the annual turnover (Soellner, 2014). This yields a sample of 1,527 CBS firms. No worker ID would allow us to directly identify the last-hired skilled worker to whom the hiring information in the CBS refers. However, the CBS provides information on the skill level, occupation, occupational experience, and entrance date of the last-hired worker that we exploit for this purpose in step 4. Maintaining the last-hired skilled worker yields a sample of 899 employer-employee matches. To obtain the working sample for our main analysis, we restrict the sample to hires that work full-time when they enter the CBS firm, and delete observations with missing values in our main explanatory variables in Step 5.[7] This yields a working sample of 533 employer-employee matches. The distribution of the hiring dates over the sample period shows that most matches occurred in 2017 and 2018, the years closest to the interview date (see Figure C1).

To check the quality of the linking procedure and the dataset that results from identifying the most recently hired skilled workers, we test for systematic differences in the firms' consent to data merge and for systematic differences of firms in the working sample. Table A2 shows that firms that agreed to the data merge are somewhat more often very small (<= 9 employees), have more often 50-249 employees, are less often located in West Germany (5 ppt less in the working sample) and firms in the manufacturing and construction sector are over-represented. Higher linkage consent rates for firms located in East Germany have also been observed in other record linkages (Warnke, 2017). The regression on the variable indicating whether the firm is in the working sample (or not) shows that firms in the working sample are larger and that public administration, education, human health services, residential care, and social work activities are somewhat under-represented (Table A3). Overall, we argue that our data merge is of high quality and that we tackle potential concerns about the lack of representativeness of our sample by including specific controls for firm size, sector, region, and other firm and worker characteristics in our regressions.

For our final data preparation, we follow the guidelines of Dauth and Eppelsheimer

[6]According to the Federal Statistical Office, 99.3% of all firms in Germany in 2021 have less than 250 employees.

[7]Note that some information on the mean wages of skilled workers are missing in the BHP. We transfer values from the following year up to the following three years in case of missing data. This is plausible because we use this information to control for the overall wage level among skilled workers within the firm.

(2020). If an individual holds more than one job simultaneously, we keep his/her main job, which is defined as the job with the highest daily wage. Furthermore, we calculate real wages (daily wages in EUR, deflated by the CPI to 2015 values) and impute top-coded wages at the upper limits for compulsory social insurance. We add information on the average wage by qualification group and economic sector from the BHP. Finally, we match official statistics on the stock of posted vacancies and job-seekers to the linked data for the exact month of firm entry, as well as at the level of occupation (KldB 2010, 2-digit) and federal state.

3.3 Descriptive statistics

Table 1 provides the descriptive statistics of our working sample of 533 employer-employee matches between January 2015 and May 2019. Of the vacancies, 31.7% are filled with female skilled workers and 45.6% were filled with workers aged 20-34 years. For most, those with upper secondary vocational training had the highest education level (81.2%), followed by a university degree (12.8%). Of the sample firms, 22.5 % are very small with a most 9 employees. The average degree of labor market tightness is 0.28. A closer look at our tightness variable (v/u) shows that there is substantial variation between and within occupations over time (Table C2). In 2018 and 2019, labor market tightness was particularly high in the occupations of mechatronics, production and processing of raw materials, in occupations concerning construction, and healthcare. Occupations in these groups are also reported as the main country-wide bottlenecks in 2018 and 2019 (Federal Employment Agency, 2019). The filled vacancies in metal-making, mechatronics, building construction, traffic, and logistics show the largest increases in tightness over the sample period, which also corresponds to reported Germany-wide statistics (Federal Employment Agency, 2019). Thus, the tightness conditions we analyze are in line with the overall picture in Germany.[8]

4 Components of Hiring Costs

The overall hiring cost of a skilled worker i in firm j consists of three components: search costs SC_j, adaptation costs AC_j, and disruption costs DC_j.[9] Search costs are also referred to as pre-match hiring costs, whereas adaptation and disruption costs incur after the contract is signed are referred to as post-match hiring costs.

[8] Furthermore, we compare the tightness (over time) in the sample matches with the overall reported tightness in those occupations for January 2015 and January 2019 using the official statistics of the FEA (compare Section 3.1) and cannot find conspicuous differences.

[9] In describing the composition of hiring costs, we partly lean on Muehlemann and Pfeifer (2016) and Muehlemann and Strupler Leiser (2018).

Table 1: Summary Statistics

	Mean
Worker Characteristic	
Female (%)	31.71
Age group	
20-34	45.59
35-49	34.15
50-65	20.26
Highest Education (%)	
Vocational training	81.24
University (of applied sciences) degree	12.76
Regular employment s.t. social security previous to firm entrance (%)	59.47
Real daily entry wage (in EUR)	89.48 (33.51)
Occupation	
Production of raw materials and goods, and manufacturing (%)	31.89
Construction, architecture, surveying and technical building services (%)	15.95
Business organization, accounting, law and administration (%)	15.95
Commercial services, trading, sales and hotel business and tourism (%)	15.01
Firm Characteristics	
Firm located in East Germany (%)	13.88
Very small firms (%)	22.51
Industry	
Service (%)	64.73
Construction (%)	18.01
Manufacturing (%)	15.20
Labor market tightness (v/u)	0.28 (0.22)
Number of observations	533

Notes: The shares by occupation are the most frequent occupational groups (1-digit, Kldb2010). Daily wages in EUR are deflated by the CPI to 2015 levels.
Source: BIBB Cost-Benefit Survey 2017/18, Integrated Employment Biographies, Official Statistics of the German Federal Employment Agency. Standard deviations are in parentheses.

Search costs $SC_j = k_j + l_j + e_j$ are the sum of job-posting costs k_j (such as the costs for vacancy posts or inquiries at the employment office), the costs of preparing, conducting, and evaluating interviews with job candidates l_j, and the costs for external advisors or placement agencies e_j. Adaptation costs arise due to the lower (initial) productivity of the newly hired skilled worker and firm-financed training courses during the adaptation period, and are given by $AC_j = m_j^i(1 - \overline{p}_j^i)w_j^i + (C_j^i + IC_j^i)$. $\overline{p}_j^i$ is the relative productivity of the new hire during the adaptation period compared with an

Table 2: Main components of hiring costs

	Working Sample			Overall Sample		
	Mean	SD	Share	Mean	SD	Share
Search Costs (SC)	1,726.87	2,964.76	16.29%	1,568.30	2,603.96	13.85%
Cost of job posting	672.53	1,125.53		626.00	1,043.20	
Use of external advisors/headhunters	0.54	-		0.57	-	
Time spent for job interviews (in hours)	17.57	21.50		18.52	23.70	
Average hourly skilled worker wage	23.27	6.64		23.02	6.80	
Adaptation costs (AC)	3,737.82	5,893.66	35.25%	4,051.85	6,089.44	35.77%
Duration of adaptation period (in months)	3.37	3.03		3.64	3.56	
Costs for external training courses	256.72	745.75		287.80	885.07	
Disruption costs (DC)	5,139.08	8,870.42	48.46%	5,707.27	9,642.16	50.35%
Disruption time (in hours)	181.90	296.54		200.37	309.07	
Total hiring costs (HC)	10,603.77	14,366.83	100.00%	11,327.42	15,066.17	100.00%
Observations	533			2,874		

Note: All costs are given in EUR unless otherwise stated.
Source: BIBB Cost-Benefit Survey 2017/18.

average skilled worker with a comparable job in the firm. m_j^i represents the number of months for which a new hire is less productive than an average skilled worker with a comparable job. w_j^i is the average new hire's wage during the adaptation period. The costs of training courses and the second term entail the direct and indirect cost components. Direct costs C_j include course fees and other direct expenses. The indirect costs IC_j are opportunity costs, because a new hire is absent from the workplace during the training course. Disruption costs arise as new hires disrupt the production process within the firm and are defined as $DC_j = h_j^m w_j^m + h_j^{sw} w_j^{sw}$, where h_j^m (h_j^{sw}) denotes the average number of hours that incumbent managers (skilled workers) provide informal training to the new hire and h_j^m (h_j^{sw}) is their hourly wage level. Thus, the overall firm-level hiring costs for the last filled skilled worker vacancy are $HC_j = SC_j + AC_j + DC_j$.

Table 2 summarizes the hiring cost components for the last hires in the working sample and the overall BIBB-CBS. The average hiring cost was approximately 10,000 EUR. Only 16% of these costs are due to the direct search costs of finding and interviewing suitable candidates. Disruption costs comprise nearly 50% of these costs, whereas adaptation costs comprised 35.3%. Thus, a major portion of hiring costs accrue after the contract is signed, as new hires need to acquire new skills to adequately carry out their tasks. This shows that new hires acquire much of their new skills either by independently learning on the job and other forms of self-directed learning, or by acquiring the necessary knowledge and skills from coworkers. The different shares of the cost components compare well with those in the overall sample. However, firms in the working sample show a slightly higher share of search costs, whereas their disruption costs are lower than those in the overall sample.

Table 3: Summary statistics at different values of tightness

	Quartiles of (v/u)			
	x≤P25	P25<x≤P50	P50<x≤P75	x>P75
Search Costs				
Cost of job posting (in EUR)	469.22 (923.30)	478.19 (875.07)	849.40 (1229.01)	894.82 (1345.05)
Use of external advisors/ headhunters	0.52 (-)	0.46 (-)	0.60 (-)	0.57 (-)
Time spent for job interviews (in hours)	19.63 (24.30)	14.85 (16.19)	17.38 (22.71)	18.41 (21.84)
Adaptation Costs				
Duration of adaptation period (in months)	3.11 (2.59)	2.88 (2.52)	3.64 (2.91)	3.87 (3.86)
Costs for external training courses (in EUR)	154.60 (423.69)	160.53 (480.65)	308.52 (748.33)	403.99 (1106.84)
Productivity deduction at end of adaptation period (in %)	7.91 (12.19)	8.41 (11.14)	9.60 (13.22)	11.32 (14.69)
Disruption Costs				
Disruption time (in hours)	160.03 (208.31)	136.98 (199.68)	198.74 (281.53)	232.03 (431.53)
Firm AKM effects	0.22 (0.18)	0.26 (0.17)	0.17 (0.17)	0.17 (0.18)
Selectivity Measure for hiring standard	-0.05 (0.29)	0.01 (0.30)	-0.02 (0.29)	-0.08 (0.28)
Occupational experience in years	8.73 (8.37)	10.11 (9.37)	8.83 (8.26)	10.68 (9.59)
Ln (entry wage)	4.38 (0.32)	4.43 (0.35)	4.44 (0.36)	4.49 (0.33)
Number of observations	134	133	133	133

Note: Standard errors in parentheses. The selectivity measure for the firm's hiring standard is defined as difference between the worker-AKM effect of the new hire and the average AKM-effects of the rest of the firm's workforce (compare Equation 2). The entry wage is the daily wage in EUR deflated by the CPI to 2015 levels.
Source: BIBB Cost-Benefit Survey 2017/18, Integrated Employment Biographies, Official Statistics of German Federal Employment Agency.

To gain the first intuition, Table 3 presents the averages of the hiring cost components, as well as the firm and worker characteristics for each tightness quartile. The table shows that the costs of job posting and external training courses increase with higher tightness quartiles. Furthermore, the average adaptation period and disruption time increased almost consistently with tightness distribution. Similarly, we observe a positive correlation between productivity deductions at the end of the onboarding period and tightness. This suggests that new hires are comparatively less productive at the end of the adaptation period when they are hired in situations of skill shortage. The selectivity measure for the firm's hiring standard reflects the innate ability of the new hire compared to the average workforce, and is defined as the difference between the worker AKM effect of the new hire and the average AKM effects of the rest of the firm's workforce. The selectivity measure, occupational experience, and entrance wages do not show a clear relationship with tightness.

5 Estimation Approach

We link the survey information on the recruitment costs of the respective filled vacancies to labor market tightness as well as worker and firm characteristics.

The hiring cost components are positively skewed, with some meaningful zero-valued observations. Therefore, we apply a Poisson pseudo-maximum likelihood (Poisson PML) estimator (Wooldridge, 2010; Santos Silva and Tenreyro, 2011), which was recently applied, for example, in Flueckiger et al. (2022). The job-posting costs for firm j that hired a skilled worker at time t in occupation o are given by

$$k_{jto} = \exp\left(\alpha + \beta_1(\frac{v}{u})_{tor} + \beta_2 X_{jt} + \beta_3\tau_t + \beta_4\gamma_s\right) + \epsilon_j, \tag{1}$$

where $(\frac{v}{u})_{tor}$ is the vacancy-unemployment ratio of a filled vacancy at time t in occupation o and federal state r. We control for year and sector fixed effects (represented by τ_t and γ_s, respectively). X_{jt} is a vector with firm-specific characteristics, including location in East or West Germany, firm size, hiring rate, average wage for skilled workers in the hiring year, and the firm AKM effect. The hiring rate is defined as the number of newly hired skilled workers divided by the average employment stock of skilled workers in the hiring year and the occupation of the filled vacancy (cf. Lochner et al., 2021; Muehlemann and Strupler Leiser, 2018).

In the regressions on the adaptation period (m_j^i) and disruption time ($h_j^m + h_j^{sw}$), we additionally control for characteristics specific to skilled worker i filling the vacancy; namely, their gender, occupation-related experience, and person AKM effects. Thus, the vector with the control variables becomes X_{ijt} for these estimations.

6 Empirical Results

This section presents our results on the relationship between labor market tightness and a firm's search efforts, hiring standards, and entry wages.

Table 4: Summary of regression results

	Parsimonious Model	Model with Full Controls
Job-posting costs (in EUR)	0.156***	0.138**
	(0.054)	(0.055)
Time spent for job interviews (in h)	-0.009	0.007
	(0.051)	(0.052)
Headhunters/external placement agency	0.029	0.034
	(0.023)	(0.022)
Hiring standard (std)	-0.099**	-0.115***
	(0.043)	(0.043)
Occupational experience (in years)	0.040	0.029
	(0.040)	(0.040)
Ln Entry wage	0.014	0.008
	(0.014)	(0.014)
Duration adaptation period (in months)	0.103**	0.115***
	(0.042)	(0.041)
Productivity deduction end of adaptation period (in %)	0.110	0.131*
	(0.070)	(0.071)
Costs for external training courses (in EUR)	0.309**	0.272***
	(0.124)	(0.100)
Disruption time (in h)	0.143**	0.187***
	(0.057)	(0.053)
Observations	533	533

Notes: Coefficients and robust standard errors in parentheses refer to the Poisson PML regressions of the dependent variables (rows) on the standardized (v/u) ratio (Table B1–B10). In the parsimonious model (Model 1 in the Tables B1–B10), we control for year- and sector fixed effects and the firm's location in East or West Germany. In the model with full controls (last specification in the Tables B1–B10), we additionally include controls for the firm size, hiring rate and firm AKM effects for search costs and add the age, gender, occupational experience, and worker AKM effects in the estimations on post-match hiring costs. The full model on the hiring standard (entry wage) additionally controls for the employment s.t. social security before the firm entrance (the firm's coverage of a collective agreement). The entry wage is the daily wage in EUR deflated by the CPI to 2015 levels. Significance levels are * p<0.1, ** p<0.05, *** p<0.01.
Source: BIBB Cost-Benefit Survey 2017/18, Integrated Employment Biographies, Official Statistics of German Federal Employment Agency.

We subsequently show the results of the association between tightness and post-match hiring costs (i.e., adaptation and disruption costs). For a clear overview, we summarize the main results in Table 4.

6.1 Tightness and search costs

Filling a vacancy successfully depends on a firm's recruitment efforts, which can be reflected in increased spending on advertising a vacancy, more time spent screening applicants and inviting candidates for job interviews, or contracting headhunters and external placement agencies. We find that labor market tightness is positively and significantly associated with the cost of job posting, which is consistent with Muehlemann and Strupler Leiser (2018). In the baseline specification, a one-standard deviation increase in the v/u ratio is associated with a 15.6% increase in job-posting costs (Table B1, Model 1). The magnitude of the coefficient remains largely unaffected when we include control variables such as firm size, hiring rate, skilled workers' wages, and AKM effects. Although the job-posting costs are strongly associated with the wage levels of skilled workers (Table B1, Model 4), the coefficient of tightness decreases only slightly.[10] In our preferred specification, in which we control for firm fixed effects (Table B1, Model 5), an increase in the v/u ratio by one standard deviation is associated with an approximately 13.8% increase in the cost of job posting, corresponding to 93 EUR on average. We find no association between the time firms spend on job interviews and the probability to make use of using external placement agencies.

6.2 Tightness and hiring standards

Although German firms spend more financial resources posting vacancies, we cannot assess whether this increased recruitment effort is sufficient to hire workers who fully meet the firm's requirements. To empirically test whether firms lower their hiring standards in tight labor markets, we use a measure of the new hire's ability relative to the average worker's ability in the firm. We follow Carrillo-Tudela et al. (2023) and define the selectivity measure s_{jt} as the difference between the AKM effect of a newly hired skilled worker (α_i^{new}) and the average AKM effects of the rest of the workforce (N_{jt}), except from the new hire.

$$s_{jt} = \alpha_i^{new} - \frac{1}{N_{jt}} \sum_{i \in N_{jt}} \alpha_i. \tag{2}$$

[10] Firms that pay higher wages might be more specialized, which may require a more specific and expensive job posting. However, we find no statistically significant evidence that a higher wage rate for skilled workers also increases the likelihood of firms using external advisors or headhunters (Model 4 in Table B3).

Regressing (v/u) on our selectivity measure suggests that firms lower their hiring standards in terms of general innate ability when facing tighter labor markets. An increase in tightness by one standard deviation is associated with a decrease in the relative hiring standard of 0.12 standard deviations (Table B4, Model 4). The effect size remains similar if we control for the new hire's occupational experience and their labor market participation subject to social security immediately before firm entry (Table B4, Models 5 and 6). This indicates that relaxing the requirements with respect to hires' occupational experience does not seem to be an adjustment channel for firms to reduce hire friction. To provide direct evidence for this, we regress occupational experience in years at the time of firm entry on tightness (Table B5).[11] This result indicates an economically small and statistically insignificant coefficient. Thus, we find no evidence that firms make concessions on occupational experience when labor markets are tight.

6.3 Tightness and entry wages

A third channel to increase the speed and likelihood of filling vacancies is to raise the entry wages for new hires. However, we do not find a statistically significant relationship between the tightness and entry wages of new hires (Table B6), even when controlling for the coverage of collective agreements that lower the firm's wage-setting power. The lack of wage adjustments may be due to the institutional peculiarities of the German labor market. Our finding is largely in line with Mueller et al. (2023) but contrary to the findings in less-regulated labor markets (Azar et al. 2022; Bassier et al. 2023; Marinescu and Wolthoff 2020).

6.4 Tightness and adaptation costs

Lowering hiring standards can potentially result in a decline in the productivity of newly hired individuals relative to those hired based on higher standards. Lower productivity may induce a higher initial training investment. Therefore, we analyze whether filling a vacancy in tight labor markets is associated with a longer adaptation period, lower productivity of new hires after completing the onboarding period, or increased costs for external training courses and informal training provided by coworkers.

Table B7 presents the estimation results for the association between the tightness of the labor market and adaptation period duration. We find that a one standard deviation increase in tightness is associated with a 11.5% increase in the duration of the adaptation period (Model 6), which corresponds to 0.4 months or roughly 12 days

[11] As occupational experience is correlated with age, we also run a quantile regression that allows the partial effect of tightness on occupational experience to differ across the distribution of experience. This does not yield different results.

given an average adaptation period of 3.4 months in our sample.

Furthermore, labor market tightness is positively and statistically significantly associated with the costs of external training courses during the adaptation period (C_j). Our preferred specification shows that an increase in labor market tightness by one standard deviation is associated with a 27.2 % increase in firms' costs for external training courses (Table B8). However, although the relative effect size is strong, the absolute costs are comparably small, as firms spend an average of 257 EUR (Table 2) on external training for a new hire.

Finally, our results indicate that the lower general ability of new hires in tight labor markets is related to workers' productivity in the middle term. The point estimate of the Poisson PML regression implies that an increase in tightness by one standard deviation is associated with a 13.1% lower productivity of new hires by the end of the onboarding period relative to the average skilled worker in the firm (Table B9). However, we cannot confirm this finding in any of our robustness checks (see Section 6.6).

6.5 Tightness and disruption costs

The results in Table B10 show that labor market tightness is consistently and positively related to disruption time. According to the full model (6), a one standard deviation increase in the (v/u) ratio is associated with an 18.7% increase in disruption time. A firm facing an average disruption time of 182 hours (Table 2) would experience an increase of 34 hours spent by coworkers and managers providing informal learning when tightness increases by one standard deviation. Controlling for firm and worker AKM effects does not significantly change the point estimate to a remarkable extend (Models 4-6 in comparison to Models 2-3 in Table B10). Furthermore, controlling for a new hire's occupational experience before entering the firm has no effect on the coefficient of tightness, implying that our estimates are not driven by the lower occupational experience of the new worker in times of tight labor markets.

6.6 Robustness

To verify our results, we conduct several robustness checks (Table B11). First, we run separate regressions using additional and varying controls. Our treatment of labor market tightness is merged at the occupational level. Nevertheless, we challenge our findings by controlling for the occupational fields defined in Tiemann et al. (2008) (e.g., Bachmann et al., 2022 or Lechmann and Schnabel, 2014 for applications). Apart from the coefficient of the costs for external training courses, which becomes statistically insignificant, our results remain stable. In our main specifications, we rely on self-reported economic sector data from the CBS survey, as we perceive this information as highly reliable and expect it to capture recent changes more accurately than administrative data. Nevertheless, we alternatively use sector information from administrative data and show that this does not change our findings meaningfully. Third, we test the sensitivity of our results to log-like specifications frequently used in settings with intensive and extensive margins (Chen and Roth, 2023). Instead of Poisson PML regressions, we use ln(Y+1) and inverse hyperbolic sine (ihs) transformations. [12] In both log-like transformations, the coefficient of productivity deduction at the end of the adaptation period remains economically the same but becomes statistically insignificant. We argue that firms lower their hiring standards when labor markets are tight, but investments in the informal learning provided by coworkers can (partially) compensate for the productivity differential, such that we do not find a robust productivity deduction at the end of the adaptation period. The point estimate for job-posting costs is higher in the ihs-transformation. However, one needs to be careful in interpreting this coefficient as semi-elastic (Bellemare and Wichman, 2020), and we thus regard the coefficient as confirmation of a statistically significant relationship. Overall, the log-like transformations confirm the highly statistically significant relationship between tightness and job-posting costs, adaptation period duration, and disruption time.

7 Discussion

Here, we discuss our findings. We begin by embedding our results on the association between hiring costs and tightness in the empirical findings. The observed significance and economic relevance of the relationship between tightness and search costs correspond fairly well to the studies so far. We find that an increase in the tightness of one standard deviation is associated with an estimated increase in the cost of job posting of 13.8%, which is in line with Muehlemann and Strupler Leiser (2018), who report a corresponding increase in advertising costs of 31% for Switzerland using panel data, and Kiarsi and Muehlemann (2021), who use the German Job Vacancy Survey and document that a 10% increase in tightness is associated with an 8.7% increase in non-labor expenses to fill a vacancy (mainly costs for job advertising). Similarly, the statistically insignificant relationship between tightness and the overall time spent on job interviews is consistent with the findings of Kiarsi and Muehlemann (2021).

However, the situation is different for post-match hiring costs, which make up more than 80% of overall hiring costs. We find that a one standard deviation increase in tightness is associated with an 11.5% (on average, 12 days) increase in the duration of the

[12] The inverse hyperbolic sine transformation is $arcsinh(Y) = ln(Y + \sqrt{Y^2 + 1})$; see Bellemare and Wichman (2020).

adaptation period, which is in contrast to Muehlemann and Strupler Leiser (2018), who report no statistically significant relationship in the cross-section and even a negative effect of -11.6% in a panel data regression. Furthermore, we find a positive association between training course costs and tightness, whereas Muehlemann and Strupler Leiser (2018) do not report a statistically significant relationship. A possible explanation for these diverging results is that a stronger increase in search costs in Swiss firms in response to tighter labor markets may be sufficient for firms to find suitable new hires without having to reduce hiring standards or increase post-match training. However, the Swiss data do not include information on hiring standards or starting wages for new hires; thus, an explicit empirical comparison of the differences in the hiring behavior of German and Swiss firms is not possible.

Our most striking finding is that tightness leads to an increase in the informal training of coworkers; a one standard deviation increase in tightness is associated with an additional 34 hours of informal training, which is an economically meaningful effect size.

The strong association between post-match hiring costs and tightness raises the question about the underlying mechanism. As we find a lower hiring standard for firms in tighter labor markets, the most obvious link is that higher post-match training investments are driven by a lower ability of new hires or lower match quality. To test this hypothesis, we conduct a mediation analysis.[13] In contrast, we find no evidence that the lower ability of workers leads to higher post-match costs.[14] These results suggest that tightness drives the post-match costs on a larger scale. Only the association between tightness and the costs of training courses has a statistically significant indirect effect via hiring standards; however, size is negligible. We argue that firm production operates at a high capacity when the labor market is tight. The resulting high work volume of coworkers extends the onboarding period and the amount of informal training that coworkers provide to the new hire.

Our study is the first to report a strong relationship between labor market tightness and firm-level investments in informal training, using employer-employee data. Therefore, we also align with the literature on the importance of informal coworker learning (compare Bishop, 1997 and Asplund, 2004 for overviews). One strand of the research in this field focuses on the effects of coworker learning on individual human capital accumulation. Loewenstein and Spletzer (1999), one of the first empirical studies in this area, use US data on youth, including information on informal on-the-job training. They show that most workers receive informal training at the beginning of their jobs

[13]We use generalized structural equation analysis to adequately model the regressions.

[14]We also test whether the innate ability of coworkers, measured by their worker AKM-effects, extends the time for informal learning but do not find evidence for that.

and that the combination of formal and informal training contributes to within-job wage growth to a sizable amount. Although the authors mention the importance of distinguishing between formal training, informal training, and learning-by-doing, their data were largely affected by measurement errors. Newer studies analyzing the effects of informal learning from coworkers on individual returns to human capital show that having more highly paid or educated coworkers is strongly associated with future wage growth (Jarosch et al., 2021 for Germany; Nix, 2020 for Sweden) but cannot quantify the amount of informal training provided.

Another strand of research directly measures the production effects of coworker learning at the institutional level. Bartel et al. (2014), for example, report positive production effects of human capital that are specific to shared knowledge, experiences, and relationships among team members using disruptions in the composition within nursing teams. Papay et al. (2020) study the effects an intervention that encourages coworker learning among school teachers and find improvements in their job performance. In addition, the positive effect of coworker training on the productivity of untrained workers, either due to knowledge spillover or peer pressure, has been documented (De Grip and Sauermann, 2012). We contribute to the literature on the informal training provided by coworkers from a different angle, as we have direct measures of the amount of training and its relationship to labor market tightness.

Although we draw on highly detailed merged survey-register data to estimate how firms adjust their hiring behavior when labor markets are tight, our study has some limitations. To measure a firm's hiring standard, we rely on the AKM worker effects, which are common in the literature (Carrillo-Tudela et al., 2023; Mueller et al., 2023; Butschek and Sauermann, 2022; Butschek, 2022). As Butschek (2022) pointed out, measuring the hiring standard via AKM effects has the advantage of being a continuous measure that is more nuanced than the level of schooling. This especially holds true in our case, as the highest level of education for the vast majority of new hires is vocational training. However, wages reflect productivity to a limited extent in professions such as education, collective bargaining restricts the link between productivity and wages, and worker AKM effects often also capture a worker-firm match quality element (see Butschek, 2022 for an extensive discussion). Further, our regressions are restricted to the reported hiring costs for successful job matches. Job-posting costs, interview costs, and costs for external advisors that were incurred but did not lead to a job start were not reported in our data. Thus, we may slightly underestimate the relationship between tightness and job-posting costs. One might consider the lack of exogenous variation as a limitation of our study. However, we do not argue this. Our specifications show that including an extensive set of worker- and firm-specific control variables in our regressions has little influence on the association between labor market tightness and our outcome variables. This suggests that the tightness variable is unrelated to the control variables, and we can interpret it as an exogenous shock.

8 Conclusion

This study analyzes the relationship between the tightness of the labor market and firms' hiring behavior. First, we find no evidence that firms adjust their starting wages in response to changes in labor market tightness. Second, our results show that firms lower their hiring standards when labor markets are tight, as they fill their vacancies with skilled workers who have lower levels of innate ability, despite spending more financial resources on job postings. However, the economic magnitude of these effects is relatively low. More importantly, we find a substantial and direct effect of labor market tightness on post-match hiring costs, which make up 84% of total hiring costs. In particular, we find that hiring skilled workers when labor markets are tight results in a longer adaptation period, more external training courses, lower productivity, and increased informal training by coworkers. Thus, while firms facing tight labor markets invest more in the search for suitable candidates and lower hiring standards, they also spend significantly more resources to ensure that a new hire reaches full productivity within the first months of the new job. While previous research emphasize that search costs increase with tightness, our results contribute to a more comprehensive understanding of a firm's entire hiring process, including the onboarding period of a new hire.

References

Abowd, J. M., Kramarz, F., and Margolis, D. N. (1999). High wage workers and high wage firms. *Econometrica*, 67(2):251–333.

Aepli, M., Muehlemann, S., Pfeifer, H., Schweri, J., Wenzelmann, F., and Wolter, S. C. (2024). The Impact of Hiring Costs for Skilled Workers on Apprenticeship Training: A Comparative Study. IZA Discussion Paper No. 16919, Institute of Labor Economics.

Antoni, M., Schmucker, A., S. S., and Vom Berge, P. (2019). Sample of Integrated Labour Market Biographies (SIAB) 1975-2017. FDZ-Datenreport, Institute for Employment Research (IAB).

Asplund, R. (2004). The provision and effects of company training: A brief review of the literature. ETLA Discussion Papers, The Research Institute of the Finnish Economy (ETLA).

Azar, J., Marinescu, I., and Steinbaum, M. (2022). Labor market concentration. *Journal of Human Resources*, 57(S):167–199.

Bachmann, R., Gokay, D., and Frings, H. (2022). Labor market polarization, job tasks, and monopsony power. *Journal of Human Resources*, 57(S):11–49.

Bartel, A. P., Beaulieu, N. D., Phibbs, C. S., and Stone, P. W. (2014). Human capital and productivity in a team environment: Evidence from the healthcare sector. *American Economic Journal: Applied Economics*, 6(2):231–259.

Bassier, I., Manning, A., and Petrongolo, B. (2023). Vacancy Duration and Wages. IZA Discussion Paper No. 16371, Institute of Labor Economics.

Bellemare, M. F. and Wichman, C. J. (2020). Elasticities and the Inverse Hyperbolic Sine Transformation. *Oxford Bulletin of Economics and Statistics*, 82(1):50–61.

Bellmann, L., Lochner, B., Seth, S., and Wolter, S. (2020). AKM effects for German labour market data. FDZ-Methodenreport, IAB.

Bertheau, A., Larsen, B., and Zhao, Z. (2023). What makes hiring difficult? Evidence from linked survey-administrative data. IZA Discussion Paper No. 16268, Institute of Labor Economics.

Bishop, J. (1997). *What we know about employer-provided training: A review of the literature*, volume 16 of *Research in Labor Economics*, pages 19–87. Greenwich, Conn.

Blatter, M., Muehlemann, S., and Schenker, S. (2012). The costs of hiring skilled workers. *European Economic Review*, 56(1):20–35.

Butschek, S. (2022). Raising the bar: Minimum wages and employers' hiring standards. *American Economic Journal: Economic Policy*, 14(2):91–124.

Butschek, S. and Sauermann, J. (2022). The effect of employment protection on firms' worker selection. *Journal of Human Resources*, 0919-10433R1.

Carbonero, F. and Gartner, H. (2022). A note on the relation between search costs and search duration for new hires. *Macroeconomic Dynamics*, 26(1):263–276.

Carrillo-Tudela, C., Gartner, H., and Kaas, L. (2023). Recruitment policies, job-filling rates and matching efficiency. *Journal of the European Economic Association*, 21(6):2413–2459.

Chen, J. and Roth, J. (2023). Logs with zeros? some problems and solutions. *The Quarterly Journal of Economics*, qjad054.

Dauth, W. and Eppelsheimer, J. (2020). Preparing the sample of integrated labour market biographies (SIAB) for scientific analysis: a guide. *Journal for Labour Market Research*, 54(10).

De Grip, A. and Sauermann, J. (2012). The effects of training on own and co-worker productivity: Evidence from a field experiment. *The Economic Journal*, 122(560):376–399.

Dietrich, H., Alda, H., Pfeifer, H., Wenzelmann, F., Schönfeld, G., Schiel, S., and Seth, S. (2014). Linked Employer-Employee Data on Firms' Training Costs: Enriching Register based LEE Data with Firm Level Data on Apprenticeship Training. *Schmollers Jahrbuch*, 134:237–248.

Domash, A. and Summers, L. H. (2022). How tight are US labor markets? Working paper No. 29739, National Bureau of Economic Research.

Federal Employment Agency (2018). Statistik der gemeldeten Stellen. Data Quality Report.

Federal Employment Agency (2019). Fachkräfteengpassanalyse. Blickpunkt Arbeitsmarkt.

Federal Employment Agency (2023). Statistik der Arbeitslosen, Arbeitsuchenden und gemeldeten erwerbsfähigen Personen. Data Quality Report.

Flueckiger, M., Hornung, E., Larch, M., Ludwig, M., and Mees, A. (2022). Roman transport network connectivity and economic integration. *Review of Economic Studies*, 89:774–810.

Ganzer, A., Schmucker, A., Stegmaier, J., and Stüber, H. (2022). Establishment history panel 1975-2020. Fdz data report, Institute for Employment Research (IAB).

Jarosch, G., Oberfield, E., and Rossi-Hansberg, E. (2021). Learning from coworkers. *Econometrica*, 89(2):647–676.

Kiarsi, M. and Muehlemann, S. (2021). The importance of proportional and fixed hiring costs in search and matching models. Leading House Working Paper No. 174.

Kiss, A., Morandini, M., Turrini, A., and Vandeplas, A. (2022). Slack and tightness: Making sense of post Covid-19 labour market developments in the EU. European Economy Discussion Papers No. 178, European Commission.

Le Barbanchon, T., Ronchi, M., and Sauvagnat, J. (2023). Hiring frictions and firm growth. Discussion Paper No. 7891, Centre for Economic Policy Research.

Lechmann, D. S. and Schnabel, C. (2014). Are the self-employed really jacks-of-all-trades? testing the assumptions and implications of Lazear's theory of entrepreneurship with German data. *Small Business Economics*, 42(1):59–76.

Lochner, B., Merkl, C., Stüber, H., and Gürtzgen, N. (2021). Recruiting intensity and hiring practices: Cross-sectional and time-series evidence. *Labour Economics*, 68:101939.

Loewenstein, M. and Spletzer, J. (1999). General and specific training: Evidence and implications. *Journal of Human Resources*, 34(4):710–733.

Manning, A. (2006). A generalised model of monopsony. *The Economic Journal*, 116(508):84–100.

Manning, A. (2011). *Imperfect Competition in the Labor Market*, volume 4 of *Handbook of Labor Economics*, chapter 11, pages 973–1041. Elsevier.

Marinescu, I. and Wolthoff, R. (2020). Opening the black box of the matching function: The power of words. *Journal of Labor Economics*, 38(2):535–568.

Muehlemann, S. and Pfeifer, H. (2016). The structure of hiring costs in Germany: Evidence from firm-level data. *Industrial Relations*, 55:193–218.

Muehlemann, S. and Strupler Leiser, M. (2018). Hiring costs and labor market tightness. *Labour Economics*, 52:122–131.

Mueller, A. I., Osterwalder, D., Zweimüller, J., and Kettemann, A. (2023). Vacancy durations and entry wages: Evidence from linked vacancy–employer–employee data. *The Review of Economic Studies*, rdad051.

Nix, E. (2020). Learning spillovers in the firm. Working paper, Institute for Evaluation of Labour Market and Education Policy (IFAU).

Papay, J. P., Taylor, E. S., Tyler, J. H., and Laski, M. E. (2020). Learning job skills from colleagues at work: Evidence from a field experiment using teacher performance data. *American Economic Journal: Economic Policy*, 12(1):359–388.

Pissarides, C. A. (2000). *Equilibrium unemployment theory*. MIT press.

Pissarides, C. A. (2009). The unemployment volatility puzzle: Is wage stickness the answer? *Econometrica*, 77(5):1339–1369.

Reder, M. W. (1955). The theory of occupational wage differentials. *The American Economic Review*, 45(5):833–852.

Ruf, K., Schmucker, A., Seth, S., and Umkehrer, M. (2023). Linked-Employer-Employee-Data of the IAB: LIAB Cross-Sectional Model 2 (LIAB QM2) 1993-2021. FDZ Data Report, Institute for Employment Research (IAB).

Santos Silva, J. and Tenreyro, S. (2011). Further simulation evidence on the performance of the poisson pseudo-maximum likelihood estimator. *Economics Letters*, 112:220–222.

Schoenfeld, G., Wenzelmann, F., Pfeifer, H., Risius, P., and Wehner, C. (2020). Training in Germany – an investment to counter the skilled worker shortage. Results of the 2017/18 BIBB Cost-Benefit Survey. BIBB Report, Federal Institute for Vocational Education and Training (BIBB).

Sedláček, P. (2014). Match efficiency and firms' hiring standards. *Journal of Monetary Economics*, 62:123–133.

Shimer, R. (2005). The cyclical behavior of equilibrium unemployment and vacancies. *American Economic Review*, 95(1):25–49.

Soellner, R. (2014). The economic importance of small and medium-sized enterprises in Germany. Wirtschaft und Statistik, Federal Statistical Office.

Tiemann, M., Schade, H.-J., Helmrich, R., Hall, A., B. U., and Bott, P. (2008). Berufsfeld-Definitionen des BIBB auf Basis der Klassifikation der Berufe 1992. Wissenschaftliche Diskussionspapiere des BIBB, Federal Institute for Vocational Education and Training (BIBB).

Warnke, A. J. (2017). An investigation of record linkage refusal and its implications for empirical research. ZEW Discussion Paper No. 17-031, ZEW – Leibniz Centre for European Economic Research.

Webber, D. A. (2022). Labor market competition and employment adjustment over the business cycle. *Journal of Human Resources*, 57(S):S87–S110.

Wenzelmann, F. and Schoenfeld, G. (2022). Kosten und Nutzen der dualen Ausbildung aus Sicht der Betriebe. Berichte zur Beruflichen Bildung, Federal Institute for Vocational Education and Training (BIBB).

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

A Data

We use linked data to study the relationship between labor market tightness and hiring standards, wages, and hiring costs. This section explains the process by which we link the records and identify the most recently hired skilled worker in detail.

A.1 Record linkage

We only link administrative data to those survey firms that explicitly allowed the data merge. For this purpose, the CBS contains a question regarding consent to link survey data to IAB administrative data. This question entails information on IAB's data protection policy. Of the 4,045 survey firms, 2,434 agreed to the data merge. Each firm address has a unique ID used to link the survey data to individual- and firm-level administrative data. However, 37 survey firms have no equivalent identifiers in their administrative data, so we dropped these firms. For firms with more than 1,000 employees, a 20%-sample of all employees was recorded.[15] Because we focus on the most recently hired skilled workers, we exclude these large-sample firms. This yielded 2,364 merged firms with a maximum of 1,000 employees.

To ensure a sufficiently high linkage quality, we compare the number of employees that the survey firms report for the reference day (30$^{\text{th}}$ September 2017) to the aggregated employment records encompassing this date in the IEB (cf. Dietrich et al., 2014). We must consider two aspects here. First, the survey restricts the number of employees to the firm's permanent staff[16] and we have to pick the respective records in the IEB. Second, for some employees, the IEB showed duplicate job spells, including the reference day. We excluded duplicates from the IEB data to assess the number of employees. Following Dietrich et al. (2014), we define linkage quality as sufficiently high if the absolute difference between the number of employees reported in the survey and the number of employees in the IEB is less than half of the respective firm size category width. This comparison shows that 90.02% of CBS firms (2,128 of 2,364 CBS firms) can be linked with justifiable differences in firm size, which is comparable to the linkage quality of BIBB-CBS 2007 described in Dietrich et al. (2014). Note that 198 of the firms that cannot be linked show significant differences in firm size, whereas four firms cannot be merged because of missing firm size data, and 34 firms show no registered employees on the reference day.

[15] Note that the size of the firms is determined at the reference day of the survey, the 30$^{\text{th}}$ September 2017.

[16] The survey asks for the number of employees subject to social security at the reference date, including family helpers and working proprietors and excludes are temporary agency workers, freelance employees, contractors, free-based employees, interns, and apprentices.

We largely follow the guide in Dauth and Eppelsheimer (2020) to calculate real wages (daily wages in EUR, deflated by the CPI to 2015 levels) and imputing top-coded wages at the upper limits for compulsory social insurance. If an individual holds more than one job simultaneously, we retain their main job, which is defined as the job with the highest daily wage. We added information on the average wage by qualification group and economic sector from the BHP. The BHP can be linked through the firm ID. Furthermore, we merge AKM worker and firm effects with our data made available by the IAB (Bellmann et al., 2020). Using the longitudinal information on each worker allows us to mark employer changes, re-employment, and times of unemployment. As the spells were cut prior to 30$^{\text{th}}$ September 2014, we mark the employees' entry and exits from firms for the subsequent changes. We excluded individuals with more than 100 status changes within the observation period, as this indicates exceptional short-term employment relationships.

A.2 Identifying the most recently hired skilled worker in the administrative data

Our record linkage yields 241,331 employees in 2,128 CBS firms. These form the initial sample used to identify newly hired skilled workers (see Table A1). No worker ID would allow us to directly identify the last-hired skilled worker to whom the hiring information in the CBS refers. However, the CBS provides information on the occupation, occupational experience, entrance year, and skill level of the last-hired worker that we exploited for this purpose. We reduced the pool of potential employees step-by-step instead of dropping all firms because a few employees entered two different CBS firms during the observation period.

Table A1 lists the steps undertaken to identify the last-hired skilled workers in the IEB. In our first step, we restrict the survey to persons entering a CBS firm that recorded a newly hired skilled worker since 2015, which applies to 1,610 CBS firms. In the second step, we restrict employees to small and medium-sized firms (SMEs) with at most 249 employees; as those firms rarely hire several employees with similar characteristics simultaneously, we have a high chance of finding the correct reported hire. In the third step, we restrict the IEB to individuals that entered one of the CBS-SME between 2015 and 2019 and show the non-missing survey information on the entrance year. This timeframe results from the fact that the hiring information from the survey refers to the last worker hired since 2015, and the last interviews were conducted in 2019. In the fourth step, we restricted the sample to skilled workers employed regularly in the CBS firm. We assessed skilled workers as workers whose skill requirement is professional or specialist, as measured by the 5$^{\text{th}}$ digit of the occupational code (KldB 2010) at the entry stage. To retain regularly employed workers, we exclude workers labeled as apprentices, interns, or working students, as well as workers who are marginally employed or part of publicly subsidized employment at the hiring stage. In the fifth step, we aligned BIBB-CBS survey and IEB information to ensure occupational correspondence by keeping new hires whose occupations are equal in the survey and IEB data at the 2-digit level of the KldB 2010. Second, we ensured plausibility with respect to occupational experience by restricting the sample to employees whose age is plausible, given the reported years of occupational experience in the CBS.[17] Third, we ensured that the entrance date in the IEB corresponded to the survey information. More precisely, we assumed that the employee's entrance year observed in the IEB deviates by a maximum of one year from the specified entrance year in the survey. Furthermore, we kept hired skilled workers whose entry to the BIBB-CBS firm was before the interview date, such that the reported duration of the adaptation period had already passed until the interview took place.[18] Moreover, we dropped hired employees who stayed within the CBS firm for a shorter than the reported adaptation period. The employees in the resulting sample of 958 CBS firms met the criteria for hired skilled workers as reported in the survey. In our sixth and final step, we adopted the firm's perspective and retain the employees hired closest to the interview date.[19] The resulting sample comprised 899 employer-employee matches from the most recent hires.

[17]More precisely, we dropped individuals whose ages at the hiring stage were less than the years of occupational experience plus 15 years. In case the information on occupational experience is missing, we did not sort out the individuals.

[18]Note that we allowed for a maximal deviation of half a month in the difference between (entrance and interview date in months) and the duration of the adaptation period in months.

[19]We dropped 59 CBS firms that simultaneously hired more than one skilled worker meeting all of the criteria at their last hiring date.

Table A1: Steps to identify the newly hired skilled worker in the IEB

	No. of individuals	No. of CBS-firms
Initial Sample	241,331	2,128
Step 1: Restricting to workers entering a CBS-firm that recorded a newly hired skilled worker since 2015 in the survey	98,557	1,610
Step 2: Restricting to workers entering a small and medium-sized CBS-firm (SME-CBS)	73,045	1,527
Step 3: Restricting to workers that enter a SME-CBS between 2015 and 2019 with non-missing survey information on the entrance year	69,982	1,455
Step 4: Restricting to skilled workers that are employed at a regular basis (not registered as apprentices, interns, working students, marginally employed or publicly subsidized at the hiring stage)	31,468	1,370
Step 5: Restricting to employees whose attributes w.r.t their occupation, occupational experience as well as entrance- and tenure information are consistent in survey- and IEB data		
- **Occupation**: Correspondence in occupational code (KldB 2010, 2-digit)	13,749	1,236
- **Occupational experience**: Employee's age at the hiring stage is at least the years of occupational experience plus 15 years	12,187	1,190
- **Entrance date/tenure**:	3,820	958
- Entrance year in IEB corresponds to the survey information (+/- 1 year)		
- Entrance date in IEB is before the interview date and such that the reported duration of the adaptation period in the survey at the interview date		
- Observed tenure in CBS firm is at least as long as the reported adaptation period		
Step 6: Keeping the lastly hired skilled worker that entered the firm closest to the interview date	899	899

Source: BIBB Cost-Benefit Survey 2017/18, Integrated Employment Biographies.

Table A2: Probit Regression on the firm's consent to the data merge

	Firm's consent to data merge			
	(1)		(2)	
	Coeff	SE	Coeff	SE
Firmsize				
10-49 employees	-0.094	(-0.061)	-0.107*	(-0.063)
50-249 employees	-0.167**	(0.067)	-0.156**	(0.070)
Region				
West Germany	-0.313***	(0.079)	-0.303***	(0.079)
Sector				
Manufacturing (C)			0.376**	(0.167)
Construction (F)			0.430***	(0.167)
Wholesale and retail trades (G)			0.226	(0.158)
Transportation and storage (H)			0.069	(0.203)
Accomodation and food service activities (I)			0.221	(0.175)
Information and communication; Real estate activities; Business service (J,L,M,N)			0.024	(0.156)
Financial and insurance activities (K)			0.061	(0.247)
Public administration and defence (O)			0.006	(0.221)
Education (P)			-0.060	(0.238)
Human health services; Residential care and social work activities (Q)			0.190	(0.166)
Other services (R,S,T,U)			0.019	(0.172)
Constant	0.675***	(0.085)	0.499***	(0.167)
Pseudo R^2	0.007		0.017	
Observations	2,548		2,548	

Notes: Probit regression on the firm's consent to data merge. The sample comprises N=2,548 recruiting SMEs in the sample from which N=1,587 agreed to the data merge and N=961 did not agree. Robust standard errors in parentheses. Significance levels are * p<0.1, ** p<0.05, *** p<0.01.
Source: BIBB Cost-Benefit Survey 2017/18.

Table A3: Probit Regression on firm being in the Working Sample or not

	Firm is in the Working Sample			
	(1)		(2)	
	Coeff	SE	Coeff	SE
Firmsize				
10-49 employees	0.395***	(0.079)	0.381***	(0.082)
50-249 employees	0.393***	(0.088)	0.418***	(0.092)
Region				
West Germany	0.105	(0.092)	0.132	(0.094)
Sector				
Manufacturing (C)			0.068	(0.218)
Construction (F)			0.186	(0.215)
Wholesale and retail trades (G)			-0.139	(0.209)
Transportation and storage (H)			-0.080	(0.274)
Accomodation and food service activities (I)			0.034	(0.229)
Information and communication; Real estate activities; Business service (J,L,M,N)			-0.168	(0.209)
Financial and insurance activities (K)			-0.185	(0.332)
Public administration and defence (O)			-0.756**	(0.324)
Education (P)			-0.947**	(0.382)
Human health services; Residential care and social work activities (Q)			-0.512**	(0.225)
Other services (R,S,T,U)			-0.319	(0.235)
Constant	-0.795***	(0.102)	-0.690***	(0.219)
Pseudo R^2	0.015		0.039	
Observations	1,587		1,587	

Notes: Probit regression on dummy variable indicating whether firm is in Working Sample. The sample comprises N=1,587 recruiting CBS-SMEs that agreed to to the data merge from which N=533 firms are in the Working Sample and N=1,054 are not. Robust standard errors in parentheses. Significance levels are * p<0.1, ** p<0.05, *** p<0.01.
Source: BIBB Cost-Benefit-Survey 2017/18, Integrated Employment Biographies.

B Regression tables

Table B1: Poisson PML regression with job-posting costs as dependent variable

	Job-posting costs (in EUR)				
	(1)	(2)	(3)	(4)	(5)
(v/u) (std)	0.156***	0.146***	0.150***	0.122**	0.138**
	(0.054)	(0.056)	(0.056)	(0.054)	(0.055)
10-49 employees		0.973***	1.061***	0.862***	0.850***
		(0.236)	(0.236)	(0.237)	(0.244)
50-249 employees		1.386***	0.992***	1.192***	1.196***
		(0.253)	(0.343)	(0.260)	(0.266)
Ln (hiring rate)		0.083	0.212*	0.074	0.068
		(0.092)	(0.122)	(0.091)	(0.091)
Ln (hiring rate) x (50-249 employees)			-0.264		
			(0.165)		
Ln (skilled worker wage)				0.877***	
				(0.314)	
Constant	5.755***	5.282***	5.429***	1.597	5.106***
	(0.832)	(0.797)	(0.766)	(1.522)	(0.798)
Year Controls	yes	yes	yes	yes	yes
Sector Controls	yes	yes	yes	yes	yes
East Germany	yes	yes	yes	yes	yes
Firm AKM Effects	no	no	no	no	yes
R^2	0.112	0.175	0.184	0.189	0.182
Observations	533	533	533	533	533

Notes: The job-posting costs are measured in EUR and comprise the costs for vacancy posts, inquiries at the employment office and the like. The labor market tightness (v/u) is the relation between vacancies and unemployment and is standardized. The wage for skilled workers represents the mean and stems from the BHP. The hiring rate is defined as the number of newly hired skilled workers divided by the average employment stock of skilled workers in the hiring year and occupation of the filled vacancy within the IEB. Robust standard errors in parentheses. Significance levels are * p<0.1, ** p<0.05, *** p<0.01.

Source: BIBB Cost-Benefit Survey 2017/18, Integrated Employment Biographies, Official Statistics of German Federal Employment Agency.

Table B2: Poisson PML regression with time for job interviews as dependent variable

	Time for job interviews (in hours)				
	(1)	(2)	(3)	(4)	(5)
(v/u) (std)	-0.009	0.010	0.013	-0.004	0.007
	(0.051)	(0.051)	(0.051)	(0.054)	(0.052)
10-49 employees		0.528***	0.582***	0.481***	0.488***
		(0.151)	(0.160)	(0.153)	(0.160)
50-249 employees		0.840***	0.556***	0.760***	0.781***
		(0.148)	(0.183)	(0.152)	(0.159)
Ln (hiring rate)		0.209***	0.290***	0.206***	0.204***
		(0.057)	(0.081)	(0.055)	(0.056)
Ln (hiring rate) x (50-249 employees)			-0.195*		
			(0.109)		
Ln (skilled worker wage)				0.411*	
				(0.235)	
Constant	2.850***	2.834***	2.922***	1.085	2.778***
	(0.734)	(0.705)	(0.692)	(1.252)	(0.710)
Year Controls	yes	yes	yes	yes	yes
Sector Controls	yes	yes	yes	yes	yes
East Germany	yes	yes	yes	yes	yes
Firm AKM Effects	no	no	no	no	yes
R^2	0.069	0.116	0.126	0.126	0.119
Observations	533	533	533	533	533

Notes: The time for job interviews comprise the time in hours that skilled workers and managers spend to prepare, conduct, and evaluate interviews with job candidates. The labour market tightness (v/u) is the relation between vacancies and unemployment and is standardized. The wage for skilled workers represents the mean and stems from the BHP. The hiring rate is defined as the number of newly hired skilled workers divided by the average employment stock of skilled workers in the hiring year and occupation of the filled vacancy within the IEB. Robust standard errors in parentheses. Significance levels are * p<0.1, ** p<0.05, *** p<0.01.
Source: See footnote in Table B1.

Table B3: OLS regression with use of external advisors/headhunters as dependent variable

	Use of external advisors/headhunters (1=yes)				
	(1)	(2)	(3)	(4)	(5)
(v/u) (std)	0.029	0.034	0.034	0.029	0.034
	(0.023)	(0.022)	(0.023)	(0.022)	(0.022)
10-49 employees		0.220***	0.221***	0.199***	0.201***
		(0.058)	(0.059)	(0.059)	(0.060)
50-249 employees		0.332***	0.321***	0.298***	0.302***
		(0.068)	(0.108)	(0.071)	(0.071)
Ln (hiring rate)		0.047*	0.049	0.046*	0.045*
		(0.027)	(0.033)	(0.027)	(0.027)
Ln(hiring rate) x			-0.007		
(50-249 employees)			(0.054)		
Ln (skilled worker wage)				0.158	
				(0.096)	
Constant	0.473**	0.419**	0.422**	-0.250	0.394*
	(0.201)	(0.203)	(0.204)	(0.460)	(0.208)
Year Controls	yes	yes	yes	yes	yes
Sector Controls	yes	yes	yes	yes	yes
East Germany	yes	yes	yes	yes	yes
Firm AKM Effects	no	no	no	no	yes
R^2	0.076	0.117	0.117	0.122	0.120
Observations	533	533	533	533	533

Notes: The dependent variable indicates the use of external advisors or headhunters during the recruitment process (yes=1, no=0). The labor market tightness (v/u) is the relation between vacancies and unemployment and is standardized. The wage for skilled workers represents the mean and stems from the BHP. The hiring rate is defined as the number of newly hired skilled workers divided by the average employment stock of skilled workers in the hiring year and occupation of the filled vacancy within the IEB. Robust standard errors in parentheses. Significance levels are * p<0.1, ** p<0.05, *** p<0.01.
Source: See footnote in Table B1.

Table B4: OLS regression with a selectivity measure for the hiring standard as dependent variable

	Hiring Standard (std)				
	(1)	(2)	(3)	(4)	(5)
(v/u) (std)	-0.099**	-0.098**	-0.109**	-0.119***	-0.115***
	(0.043)	(0.044)	(0.044)	(0.043)	(0.043)
Ln (hiring rate)		0.055	0.061	0.056	0.059
		(0.059)	(0.059)	(0.058)	(0.059)
10-49 employees		-0.263**	-0.263**	-0.211*	-0.236**
		(0.114)	(0.112)	(0.117)	(0.119)
50-249 employees		-0.226	-0.231*	-0.163	-0.196
		(0.139)	(0.138)	(0.143)	(0.144)
Age			0.012***	0.005	0.006
			(0.004)	(0.005)	(0.005)
Female			-0.167	-0.168	-0.148
			(0.114)	(0.112)	(0.113)
Occ. experience (in years)				-0.014	-0.016
				(0.017)	(0.017)
Squared occ. experience (in years)				0.001*	0.001*
				(0.001)	(0.001)
Employment s.t. social security before CBS entrance					0.175*
					(0.090)
Year Controls	Yes	Yes	Yes	Yes	Yes
Sector Controls	Yes	Yes	Yes	Yes	Yes
East Germany	Yes	Yes	Yes	Yes	Yes
R^2	0.049	0.065	0.087	0.106	0.112
Observations	532	532	532	532	532

Notes: The selectivity measure for the firm's hiring standard is defined as standardized difference between the worker-AKM effect of the new hire and the average AKM-effects of the rest of the firm's workforce (compare Equation 2). The labor market tightness (v/u) is the relation between vacancies and unemployment and is standardized. The hiring rate is defined as the number of newly hired skilled workers divided by the average employment stock of skilled workers in the hiring year and occupation of the filled vacancy within the IEB. Robust standard errors in parentheses. Significance levels are * p<0.1, ** p<0.05, *** p<0.01.
Source: See footnote in Table B1.

Table B5: Poisson PML regression with the occupational experience of the new hire as dependent variable

	Occupational experience (in years)				
	(1)	(2)	(3)	(4)	(5)
(v/u) (std)	0.040	0.026	0.025	0.026	0.029
	(0.040)	(0.041)	(0.031)	(0.041)	(0.040)
10-49 employees		-0.215*	-0.238***	-0.212*	-0.217*
		(0.111)	(0.076)	(0.114)	(0.111)
50-249 employees		-0.251**	-0.285***	-0.246*	-0.263**
		(0.125)	(0.095)	(0.132)	(0.127)
Ln (hiring rate)		-0.035	0.017	-0.035	-0.039
		(0.048)	(0.040)	(0.048)	(0.047)
Female		-0.161*	-0.000	-0.161*	-0.127
		(0.091)	(0.080)	(0.091)	(0.090)
Age			0.048***		
			(0.003)		
Ln (entry wage)			0.066		
			(0.095)		
Constant	1.767***	1.902***	0.174	1.906***	0.223
	(0.358)	(0.364)	(0.500)	(0.368)	(0.589)
Year Controls	yes	yes	yes	yes	yes
Sector Controls	yes	yes	yes	yes	yes
East Germany	yes	yes	yes	yes	yes
Firm AKM Effects	no	no	no	yes	yes
Worker AKM Effects	no	no	no	no	yes
R^2	0.091	0.108	0.478	0.108	0.135
Observations	533	533	533	533	533

Notes: The occupational experience in years stems from the BIBB-CBS. The labor market tightness (v/u) is the relation between vacancies and unemployment and is standardized. The hiring rate is defined as the number of newly hired skilled workers divided by the average employment stock of skilled workers in the hiring year and occupation of the filled vacancy within the IEB. The individual entry wage stems from the IEB and is the daily wage in EUR deflated by the CPI to 2015 levels. Robust standard errors in parentheses. Significance levels are * p<0.1, ** p<0.05, *** p<0.01.
Source: See footnote in Table B1.

Table B6: OLS regression with the entry wage of newly hired skilled workers as dependent variable

	Ln Entry Wage					
	(1)	(2)	(3)	(4)	(5)	(6)
(v/u) (std)	0.014	0.008	0.008	0.008	0.008	0.008
	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)	(0.014)
10-49 employees		0.079**	0.075**	0.078**	0.075**	0.077**
		(0.037)	(0.035)	(0.035)	(0.035)	(0.035)
50-249 employees		0.188***	0.182***	0.185***	0.183***	0.185***
		(0.047)	(0.047)	(0.047)	(0.047)	(0.047)
Ln (hiring rate)		0.020	0.027	0.027	0.028	0.028
		(0.020)	(0.020)	(0.020)	(0.020)	(0.020)
Female		-0.130***	-0.111***	-0.111***	-0.111***	-0.110***
		(0.037)	(0.035)	(0.035)	(0.035)	(0.035)
Age			0.007***	0.007***	0.007***	0.007***
			(0.001)	(0.002)	(0.001)	(0.002)
Occ. experience				0.001		0.002
				(0.002)		(0.005)
Occ. experience squared						-0.000
						(0.000)
Collective agreement					0.016	0.015
					(0.029)	(0.030)
Year Controls	Yes	Yes	Yes	Yes	Yes	Yes
Sector Controls	Yes	Yes	Yes	Yes	Yes	Yes
East Germany	Yes	Yes	Yes	Yes	Yes	Yes
R^2	0.182	0.237	0.289	0.289	0.289	0.290
Observations	532	532	532	532	532	532

Notes: The individual entry wage stems from the Integrated Employment Biographies and is the daily wage in EUR deflated by the CPI to 2015 levels. The labor market tightness (v/u) is the relation between vacancies and unemployment and is standardized. The hiring rate is defined as the number of newly hired skilled workers divided by the average employment stock of skilled workers in the hiring year and occupation of the filled vacancy within the IEB. Robust standard errors in parentheses. Significance levels are * p<0.1, ** p<0.05, *** p<0.01.
Source: See footnote in Table B1.

Table B7: Poisson PML estimation with the duration of adaptation period as dependent variable

	Duration of adaptation period (in months)					
	(1)	(2)	(3)	(4)	(5)	(6)
(v/u) (std)	0.103**	0.117***	0.116***	0.113***	0.114***	0.115***
	(0.042)	(0.041)	(0.039)	(0.040)	(0.041)	(0.041)
10-49 employees		0.327***	0.289***	0.263**	0.261**	0.254**
		(0.107)	(0.106)	(0.106)	(0.106)	(0.107)
50-249 employees		0.450***	0.364***	0.349***	0.341***	0.337***
		(0.116)	(0.119)	(0.119)	(0.120)	(0.121)
Ln (hiring rate)		0.129***	0.118***	0.122***	0.121***	0.117***
		(0.042)	(0.042)	(0.042)	(0.041)	(0.041)
Female		0.102	0.155*	0.107	0.113	0.106
		(0.087)	(0.088)	(0.086)	(0.086)	(0.087)
Age			-0.000			
			(0.003)			
Ln (entry wage)			0.366***			
			(0.127)			
Occ. experience						-0.016
						(0.013)
Occ. experience squared						0.000
						(0.000)
Constant	1.317***	1.274***	-0.239	1.175***	0.771	0.735
	(0.275)	(0.284)	(0.576)	(0.270)	(0.572)	(0.574)
Year Controls	yes	yes	yes	yes	yes	yes
Sector Controls	yes	yes	yes	yes	yes	yes
East Germany	yes	yes	yes	yes	yes	yes
Firm AKM Effects	no	no	no	yes	yes	yes
Worker AKM Effects	no	no	no	no	yes	yes
R^2	0.159	0.188	0.202	0.204	0.203	0.203
Observations	533	533	533	533	533	533

Notes: The adaptation period is the number of months that the new hire is less productive than an average skilled worker within the firm. The labor market tightness (v/u) is the relation between vacancies and unemployment and is standardized. The hiring rate is defined as the number of newly hired skilled workers divided by the average employment stock of skilled workers in the hiring year and occupation of the filled vacancy within the IEB. The individual entry wage stems from the IEB and is the daily wage in EUR deflated by the CPI to 2015 levels. Robust standard errors in parentheses. Significance levels are * p<0.1, ** p<0.05, *** p<0.01.
Source: See footnote in Table B1.

Table B8: Poisson PML regression with the costs for external training courses during the adaptation period as dependent variable

	Costs for external training courses (in EUR)					
	(1)	(2)	(3)	(4)	(5)	(6)
(v/u) (std)	0.309**	0.289***	0.292***	0.278**	0.272**	0.272***
	(0.124)	(0.109)	(0.108)	(0.108)	(0.106)	(0.100)
10-49 employees		0.907***	0.821**	0.755**	0.760**	0.750**
		(0.348)	(0.349)	(0.356)	(0.361)	(0.360)
50-249 employees		1.541***	1.368***	1.311***	1.337***	1.320***
		(0.386)	(0.421)	(0.418)	(0.423)	(0.421)
Ln (hiring rate)		0.149	0.117	0.135	0.141	0.143
		(0.156)	(0.155)	(0.158)	(0.158)	(0.159)
Female		0.160	0.248	0.190	0.175	0.169
		(0.262)	(0.276)	(0.265)	(0.273)	(0.269)
Age			-0.005			
			(0.011)			
Ln (entry wage)			0.621*			
			(0.355)			
Occ. experience						0.028
						(0.044)
Occ. experience squared						-0.001
						(0.001)
Constant	4.529***	3.967***	1.552	3.833***	4.945***	4.985***
	(1.071)	(1.017)	(1.686)	(1.025)	(1.808)	(1.813)
Year Controls	yes	yes	yes	yes	yes	yes
Sector Controls	yes	yes	yes	yes	yes	yes
East Germany	yes	yes	yes	yes	yes	yes
Firm AKM Effects	no	no	no	yes	yes	yes
Worker AKM Effects	no	no	no	no	yes	yes
R^2	0.115	0.199	0.208	0.203	0.204	0.222
Observations	533	533	533	533	533	533

Notes: The labor market tightness (v/u) is the relation between vacancies and unemployment and is standardized. The hiring rate is defined as the number of newly hired skilled workers divided by the average employment stock of skilled workers in the hiring year and occupation of the filled vacancy within the IEB. The individual entry wage stems from the IEB and is the daily wage in EUR deflated by the CPI to 2015 levels. Robust standard errors in parentheses. Significance levels are * p<0.1, ** p<0.05, *** p<0.01.
Source: See footnote in Table B1.

Table B9: Poisson PML regression with the productivity deduction at end of adaptation period as dependent variable

	Productivity deduction at end of adaptation period (in %)					
	(1)	(2)	(3)	(4)	(5)	(6)
(v/u) (std)	0.110	0.130*	0.128*	0.131*	0.131*	0.131*
	(0.070)	(0.069)	(0.068)	(0.070)	(0.070)	(0.071)
10-49 employees		0.065	0.053	0.075	0.075	0.053
		(0.169)	(0.166)	(0.171)	(0.171)	(0.168)
50-249 employees		0.139	0.110	0.156	0.155	0.153
		(0.174)	(0.174)	(0.186)	(0.186)	(0.185)
Ln (hiring rate)		0.147*	0.131	0.149*	0.149*	0.136
		(0.087)	(0.085)	(0.088)	(0.088)	(0.084)
Female		0.157	0.149	0.156	0.157	0.140
		(0.157)	(0.156)	(0.156)	(0.156)	(0.153)
Age			-0.011*			
			(0.006)			
Ln (entry wage)			0.156			
			(0.205)			
Occ. experience						-0.065***
						(0.021)
Occ. experience squared						0.002**
						(0.001)
Constant	1.900***	2.035***	1.671	2.050***	1.992**	1.922**
	(0.610)	(0.610)	(1.074)	(0.617)	(0.950)	(0.927)
Year Controls	yes	yes	yes	yes	yes	yes
Sector Controls	yes	yes	yes	yes	yes	yes
East Germany	yes	yes	yes	yes	yes	yes
Firm AKM Effects	no	no	no	yes	yes	yes
Worker AKM Effects	no	no	no	no	yes	yes
R^2	0.080	0.093	0.097	0.094	0.093	0.120
Observations	533	533	533	533	533	533

Notes: The dependent variable represents the productivity deduction of the new hire at the end of the adaptation period in % compared to an average skilled worker within the firm. The labor market tightness (v/u) is the relation between vacancies and unemployment and is standardized. The hiring rate is defined as the number of newly hired skilled workers divided by the average employment stock of skilled workers in the hiring year and occupation of the filled vacancy within the IEB. The individual entry wage stems from the IEB and is the daily wage in EUR deflated by the CPI to 2015 levels. Robust standard errors in parentheses. Significance levels are * $p<0.1$, ** $p<0.05$, *** $p<0.01$.
Source: See footnote in Table B1.

Table B10: Poisson PML regression with the disruption time of skilled workers and managers as dependent variable

	Disruption time (in hours)					
	(1)	(2)	(3)	(4)	(5)	(6)
(v/u) (std)	0.143**	0.186***	0.184***	0.179***	0.187***	0.187***
	(0.057)	(0.051)	(0.051)	(0.051)	(0.053)	(0.053)
10-49 employees		0.529***	0.488***	0.457***	0.451***	0.457***
		(0.169)	(0.169)	(0.170)	(0.171)	(0.174)
50-249 employees		0.683***	0.586***	0.571***	0.535***	0.555***
		(0.199)	(0.198)	(0.189)	(0.194)	(0.197)
Ln (hiring rate)		0.282***	0.280***	0.275***	0.271***	0.267***
		(0.065)	(0.066)	(0.065)	(0.064)	(0.065)
Female		0.264	0.329**	0.266	0.281*	0.280*
		(0.167)	(0.165)	(0.166)	(0.167)	(0.165)
Age			0.005			
			(0.005)			
Ln (entry wage)			0.387**			
			(0.185)			
Occ. experience						-0.030
						(0.021)
Occ. experience squared						0.001
						(0.001)
Constant	4.112***	4.174***	2.454***	4.052***	2.651***	2.687***
	(0.543)	(0.534)	(0.905)	(0.540)	(1.003)	(1.026)
Year Controls	yes	yes	yes	yes	yes	yes
Sector Controls	yes	yes	yes	yes	yes	yes
East Germany	yes	yes	yes	yes	yes	yes
Firm AKM Effects	no	no	no	yes	yes	yes
Worker AKM Effects	no	no	no	no	yes	yes
R^2	0.132	0.169	0.170	0.179	0.172	0.175
Observations	533	533	533	533	533	533

Notes: The disruption time is the average number of hours that managers and skilled workers provide informal training to the new hire. The labor market tightness (v/u) is the relation between vacancies and unemployment and is standardized. The hiring rate is defined as the number of newly hired skilled workers divided by the average employment stock of skilled workers in the hiring year and occupation of the filled vacancy within the IEB. The individual entry wage stems from the IEB and is the daily wage in EUR deflated by the CPI to 2015 levels. Robust standard errors in parentheses. Significance levels are * p<0.1, ** p<0.05, *** p<0.01.
Source: See footnote in Table B1.

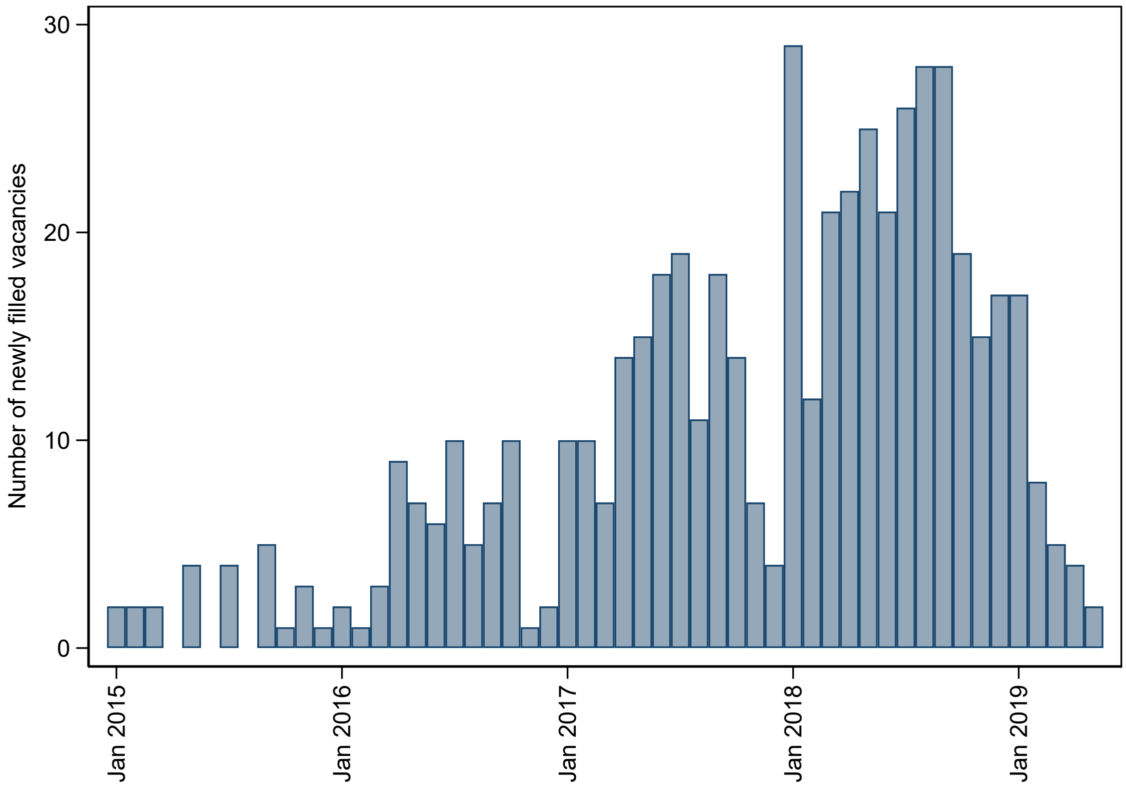
Table B11: Robustness

	Main model	Different variable choices		Using log-linear transformation	
		Additionally controlling for occupational fields	Using economic sector control from IAB-data	ln(Y+1)	ihs-transformed
Job-posting costs (in EUR)	0.138**	0.113*	0.165***	0.150**	1.607**
	(0.055)	(0.062)	(0.061)	(0.717)	(0.787)
Time spent for job interviews (in h)	0.007	-0.014	-0.016	-0.126	-0.157
	(0.052)	(0.054)	(0.054)	(0.230)	(0.258)
Headhunters/external placement agency	0.034	0.008	0.032		
	(0.022)	(0.025)	(0.023)		
Hiring standard (std)	-0.115***	-0.094*	-0.107**		
	(0.043)	(0.051)	(0.043)		
Occupational experience (in years)	0.029	0.064	0.014	0.013	0.013
	(0.040)	(0.043)	(0.041)	(0.043)	(0.043)
Ln Entry wage	0.008	0.019	0.005		
	(0.014)	(0.016)	(0.014)		
Duration adaptation period (in months)	0.115***	0.130***	0.125***	0.074***	0.089**
	(0.041)	(0.047)	(0.039)	(0.028)	(0.036)
Productivity deduction end of adaptation period (in %)	0.131*	0.166**	0.137**	0.103	0.119
	(0.071)	(0.081)	(0.066)	(0.069)	(0.084)
Costs for external training courses (in EUR)	0.272***	0.131	0.361***	0.162	0.163
	(0.100)	(0.129)	(0.096)	(0.129)	(0.151)
Disruption time (in h)	0.187***	0.200***	0.206***	0.196**	0.210**
	(0.053)	(0.058)	(0.059)	(0.090)	(0.101)
Observations	533	533	533	533	533

Notes: Coefficients and robust standard errors in parentheses refer to the regressions of the dependent variables (rows) on the standardized v/u ratio. The individual entry wage stems from the IEB and is the daily wage in EUR deflated by the CPI to 2015 levels. We use slightly broader categories for economic sectors (compare Table A2-A3) when additionally including occupational fields. Significance levels are * p<0.1, ** p<0.05, *** p<0.01. Source: BIBB Cost-Benefit Survey 2017/18, Integrated Employment Biographies, Official Statistics of German Federal Employment Agency.

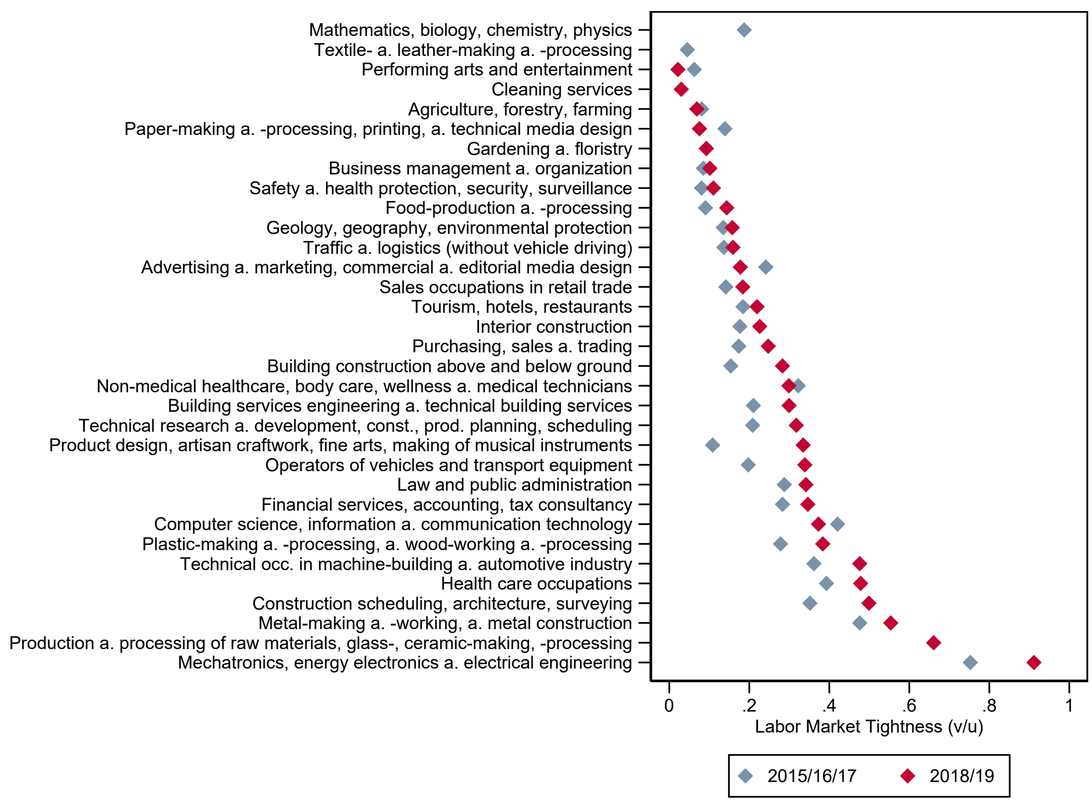
C Figures

Figure C1: Filled vacancies in the working sample by date of firm entrance



Note: The working sample comprises N=533 employer-employee matches.
Source: BIBB Cost-Benefit Survey 2017/18, Integrated Employment Biographies.

Figure C2: Labor Market Tightness over Time in the Sample Occupations



Notes: The figure presents the averages of the labor market tightness in the sample occupations in the first years (2015,2016,2017) and last years (2018,2019) of the observation period.
Source: BIBB Cost-Benefit Survey 2017/18, Integrated Employment Biographies, Official Statistics of German Federal Employment Agency.