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Article

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Journal for Labour Market Research

Provided in Cooperation with:

Institute for Employment Research (IAB)

Suggested Citation: Bauer, Anja (2024) : Accounting for qualification in mismatch unemployment, Journal for Labour Market Research, ISSN 2510-5027, Springer, Heidelberg, Vol. 58, Iss. 1, pp. 1-23, <https://doi.org/10.1186/s12651-024-00386-7>

This Version is available at:

<https://hdl.handle.net/10419/308509>

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ORIGINAL ARTICLE

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Accounting for qualification in mismatch unemployment

Anja Bauer^{1*}

Abstract

The paper shows how important it is to consider the requirement level when measuring mismatch unemployment. While the mismatch between occupations decreases over time, the imbalances in the distribution of unemployed workers and vacant jobs across requirement levels increased, which, in sum, led to a stagnation of mismatch on the combined occupation-requirement level. Furthermore the paper shows that mismatch unemployment emerges especially at the level of un- and semi-skilled activities, as there is excess supply regardless of the occupations. And, more importantly, the excess supply is rising recently.

Keywords Allocation, Job finding rate, Mismatch, Occupation, Qualification

JEL Classification J6, E24

1 Introduction

Labor market tightness has risen sharply in Germany in the last decade, and many occupations are affected by shortages of skilled workers due to demographic shrinkage (Bossler et al. 2022). In addition, employment growth has slowed since the COVID-crisis and the job-finding rate has not risen to pre-crisis levels. Moreover, long-term unemployment is on the rise. Against this background, the question arises to what extent the current observations can be attributed to mismatch unemployment, i.e. a misallocation of unemployed persons and job vacancies. Principally, mismatch occurs whenever the “qualifications or skills of workers, individually or in the aggregate, are different from the qualifications or skills

required for the jobs” (Sattinger 2012, p. 3). The literature distinguishes between two types of mismatch: (1) mismatch within a match, where workers do not fit well to the job they are operating and (2) mismatch before the match, often labeled as “mismatch unemployment”, where unemployed workers and open job vacancies would not form a match even if search frictions or imperfect information did not exist. This paper looks at the latter type, which stems from structural shifts in labor demand and/or supply. Research on mismatch unemployment dates back to the 1980s (see Jackman and Roper 1987; Jackman et al. 1991; Schioppa 1991) but new advances were made in the seminal paper by Şahin et al. (2014). In the aftermath of the Global Financial Crises (GFC), the authors

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showed that mismatch unemployment explains up to one third of the rise in unemployment after the Great Recession (Şahin et al. 2014). After the COVID-crisis (CC) the topic gained interest again, but mismatch appeared to play a minor role in the aftermath of the COVID-19 shock in the US (Forsythe et al. 2022). Recent studies confirm this result for different countries, like the UK (Pizzinelli and Shibata 2023; Turrell et al. 2021; Patterson et al. 2016) or Japan (Shibata 2020).¹

The contribution of my paper to this literature is two-fold. First, not much is known about mismatch unemployment thus far for Germany (see for example, Bauer 2013; Hutter and Weber 2017). However, Germany is an interesting case to study because as a European country with typically quite significant structural unemployment, mismatch unemployment might behave differently than in countries such as in the US or in the UK. So I contribute to the question of how the German experience is different. Second, I highlight the importance of considering the requirement level in analysing mismatch unemployment for Germany. Şahin et al. (2014)'s approach, and the resulting mismatch indicator quickly emerged as a benchmark, as it is easily implementable, often used in the literature and, under certain conditions, also comparable across countries. However, it is not clear which dimensions (e.g., occupations, skills, sectors, regions, or even interactions among these dimensions) adequately measure mismatch unemployment. For example, Pizzinelli and Shibata (2023) look at sectors and occupations, but conclude that there might exist "more subtle dimensions over which mismatch may play a role". However, it is of relevance to know in which dimension mismatch unemployment exists, as it has an influence on which policy measure could be effective in reducing mismatch unemployment. In this respect, the paper contributes to the discussion on mismatch unemployment by looking at another dimension, namely the requirement level which serves as a proxy for qualification. If mismatch unemployment occurs at the occupational level, the unemployed would have to be motivated to change the occupation in order to reduce mismatch unemployment. However, if mismatch unemployment occurs at the qualification level, it would be more expedient to provide the unemployed workers with further qualifications within an occupation (or to encourage firms to make concessions regarding the entry skill set). The German

Occupational Classification 2010 (Kldb2010) is designed such that it combines occupational expertise with the requirement level within the job (similar as in ISCO). In that respect it allows to analyse mismatch unemployment across occupations and the requirement level.

I find that between 5 and 18% of hires are lost due to a misallocation looking at the time horizon from 2007 to 2022. Across this period, mismatch unemployment came down from over 40% to 12 to 22% on the occupation-level and to 22 to 32% when taking the requirement level into account. Most of this evolution happened until 2012, afterwards there is only little movement over time except in the CC. During the CC, mismatch unemployment spiked temporarily. Comparing the occupation to the occupation-requirement level, the results show that mismatch unemployment is rising stronger on the occupation-requirement level since 2021. More important, I can show that a substantial part of mismatch unemployment results from a misallocation on the qualification level rather than on the occupational level. First, across the requirement level, the share of hires lost due to imbalances in demand and supply almost doubled across the period. Second, in the market for unskilled and semi-skilled workers, an over-supply exists in almost all occupations. Reversely, on higher requirement levels, more occupations exhibit shortages. Looking at the cyclical patterns during the GFC and CC reveals, that the CC hit occupations differently across the requirement levels than the GFC. During the GFC, a decrease in under-supply at the (complex) specialist activities level is visible, while the CC rather increased the over-supply in occupations at the unskilled and semi-skilled requirement level.

2 The German labor market

First, I briefly discuss the Beveridge Curve. While movements along the curve are associated with ups and downs in the business cycle, movements of the curve are rather associated with structural changes that affect the overall functioning of the labor market. In Germany, the Beveridge curve shifted inward in the mid 2000s after a set of labor market reforms (the so-called Hartz reforms) were introduced (see Fig. 1). There is a vast literature on the underlying sources of this shift ranging from intensified job search due to lower unemployment benefits, a better placement through the restructuring of the Employment Agency, and wage moderation (Launov and Wälde 2013; Krebs and Scheffel 2013; Launov and Wälde 2016; Bradley and Kügler 2019; Hochmuth et al. 2021). During the GFC and the CC the German labor market hovered around a stable Beveridge curve. While the period of the GFC was located in the lower right end of the curve, an upward movement is visible in the 2010s. The period of the CC is located at the upper left end of the curve.

¹ What these papers have in common, is that they extend the approach of Şahin et al. (2014) by exploring different data sources, different groupings of labor markets, or data of different countries. Other papers, like Herz and Van Rens (2020) or Barnichon and Figura (2015) instead rely on different approaches to measure mismatch unemployment. Nonetheless, also these other approaches rely on some kind of segmentation of the labour market and thus the same issue arises as the choice of the level of disaggregation is crucial.

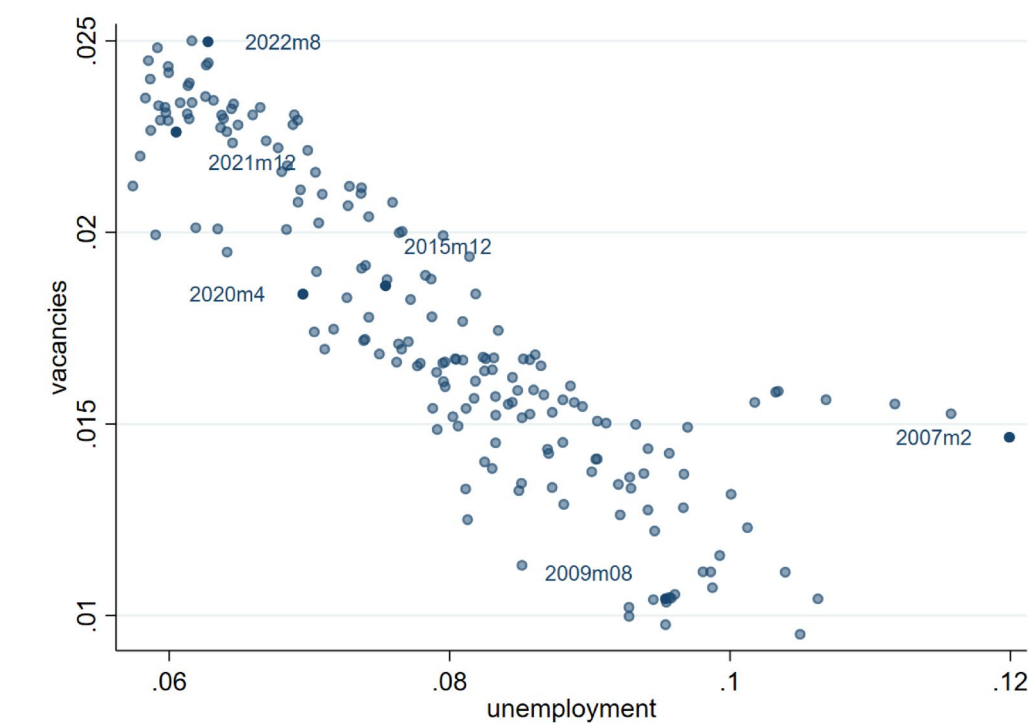


Fig. 1 Beveridge Curve 2007–2022. Vacancies and Unemployment are normalised as rates by employment. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

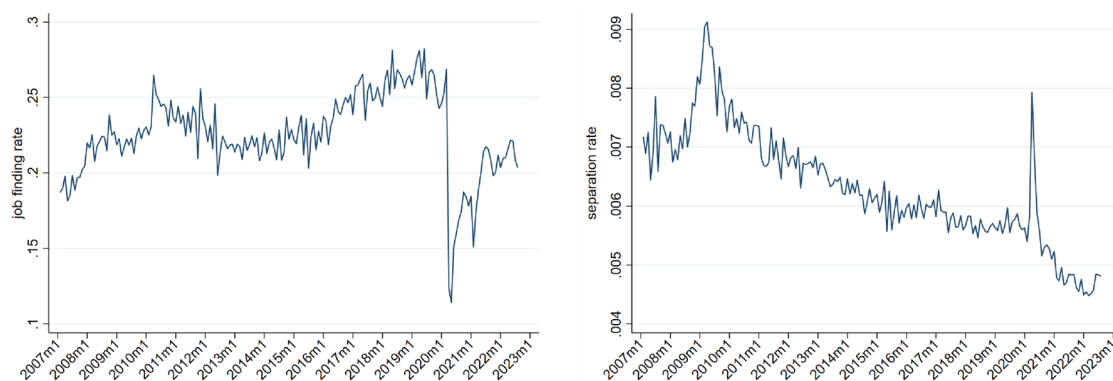


Fig. 2 Flow rates, 2007–2022. The job-finding rate is calculated as the movement from unemployment to employment over the stock of last periods unemployment. The separation rate is calculated as movement from employment to unemployment over last periods stock of employment. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

Regarding that picture, one would expect that in Germany mismatch unemployment also did not play a major role during the CC.

However, looking at job-finding and separation rates over time, there seems to be a persistent shock to the job-finding rate (see left panel of Fig. 2). The job-finding rate was increasing in the mid 2010's. The increase stopped around 2018 and then the COVID-19 shock hit, which led to a drop of the job-finding rate, from which it recovered

to some extent, but did not reach the pre-pandemic level until the end of 2022. While the separation rate spiked during the first phase of the CC, it quickly recovered and followed again its downward trend (Bauer and Weber 2021b). If at all, the separation rate dropped even more in the aftermath of the CC. At the same time, the number of vacant jobs was rising strongly since the second quarter 2020 (see [IAB Job Vacancy Survey](#)) and labour shortages are also rising (see [Labour Shortage Index](#)). A questions

that naturally arises, is why the unemployed persons do not match with these vacant positions. It might be due to frictions, or structural imbalances such as a bad fit between the unemployed and the vacant positions, which would be considered as mismatch unemployment.

3 Method

I am applying a method proposed by Şahin et al. (2014) which derives an indicator that is widely used as benchmark indicator. The main idea is that the labor market comprises several submarkets. While frictional unemployment is created by frictions within each submarket that prevent unemployed workers to match with unfilled vacancies, mismatch unemployment arises because of an suboptimal allocation of vacancies and unemployed workers across submarkets. In my analysis I define submarkets to be different occupations and occupation-requirement level combinations as outlined above. This suboptimal allocation (compared to a planner's solution) can be captured by an index.

3.1 Theory

The index M measures hires that are lost due to a mismatch by comparing the actual (observable) number hires h to an ideal number of hires h^* . The number of hires (actual and ideal) depends on the distribution of unemployed workers and job vacancies over a defined range of submarkets (e.g., occupations). In each distinct market, hires are governed by a Cobb-Douglas type matching function with constant returns to scale ($h_{it} = \phi_i v_{it}^\alpha u_{it}^{1-\alpha}$). Hence search frictions exist in every market and are captured by matching efficiency.² The ideal number of hires comes out of the model's social planner solution, in which the planner can move unemployed persons costlessly across markets. This leads to an equalization of market-specific labor market tightness (vacancy to unemployment ratio) across markets (weighted by matching efficiency). This ensures "that the planner allocates more job seekers to those labor markets with more vacancies and higher matching efficiency" (Şahin et al. 2014, p. 3534).

$$M_t = 1 - \frac{h_t}{h_t^*} = 1 - \sum_{i=1}^I \left(\frac{\phi_i}{\bar{\phi}_t} \right) \left(\frac{v_{it}}{v_t} \right)^\alpha \left(\frac{u_{it}}{u_t} \right)^{1-\alpha} \quad (1)$$

where i refers to a submarket, t denotes time-variant variables at monthly intervals, v is the vacancy stock, u is the unemployment stock.

The first term of the expression relates to matching efficiency, i.e., $\bar{\phi}_t = \left[\sum_{i=1}^I \phi_i^\alpha \left(\frac{v_{it}}{v_t} \right) \right]^\alpha$, where ϕ denotes matching efficiency.

3.2 Estimations

The matching elasticity α is extracted by a simple OLS regression of a reduced form matching function. The regression equations read as follows:

$$\ln(jfr_t) = \beta_0 + \alpha \ln(\theta_t) + e_t \quad (2)$$

The job-finding-rate jfr_t is defined as changes from unemployment to employment over last period's stock of unemployment ($jfr_t = EU_t/U_{t-1}$) and θ_t denotes labour market tightness as the ratio of vacancies to unemployment $\theta_t = V_t/U_t$. For the matching elasticity I receive a coefficient of $\alpha \approx 0.5$. I verified this result in several different specifications in which the coefficient ranges between 0.41 and 0.54, depending on the time period covered, and whether and which time trends are used.

The submarket-specific matching efficiency ϕ_i is deducted by panel estimations. I regress the submarket-specific labor market tightness θ_{it} on the submarket's job-finding rate jfr_{it} , where, again, θ_{it} is defined as the ratio of unfilled vacancies to unemployed workers and the job-finding rate is measured as transitions between unemployment and employment over last period's stock of unemployment. β_i is capturing the fixed effect of every submarket and e_{it} is the error term.

$$\ln(jfr_{it}) = \beta_i + \beta_1 \ln(\theta_{it}) + e_{it} \quad (3)$$

where

$$\phi_i = \exp(\beta_i) \quad (4)$$

I use the submarket-specific constant out of this fixed effects regression and exponentiate it to receive the submarket-specific matching efficiency. This gives me a matching efficiency that ranges between 0.7 and 2.2 across occupations at the 3-digit level.

4 Data

The data that the method is applied to is administrative data of the Federal Employment Agency, which covers the universe of unemployed workers and vacancies that are registered at the Federal Employment Agency. I rely on very detailed occupation information, which is collected at the 5-digit level in the German Classification of Occupations (Kldb2010). I can distinguish unemployed workers by the occupation of origin (occupation of last employment or apprenticeship) and destination of search. The vacancy data relates to jobs, which are registered at the Federal Employment Agency, which is not

² Though matching efficiency could be arguably time-varying, I assume it to be time-constant. Robustness checks show that the differences between a time-constant and time-varying variant are small.

mandatory. In a robustness check, I combine this administrative data with survey data, which projects vacancies at a national level (i.e., [IAB Vacancy Survey](#), see Appendix Fig. 12). The job-findings relate to movements from the status “unemployed and searching for work” to “employment subject to social security (without any subsidised employment)” and the separations are calculated vice versa. Furthermore I exclude the military occupations as there is no vacancy information available for them.

The panel includes stocks of unemployed by occupations and stocks of vacancies by occupations, and occupation-specific job-findings and separations, at a monthly interval running from January 2007 to December 2022. Based on this information, I aggregate unemployment, vacancies, job-findings and separations to the national level by summing over the occupations.³

A remarkable feature of the German Occupation Classification is its horizontal and vertical dimension. That means, it allows to distinguish occupations by the occupational expertise (assessed by required skills, abilities and knowledge) and requirement levels (complexity within an occupation; Paulus and Matthes 2013). At a 5-digit level the classification comprises 1300 different occupations. The 5th digit, which holds the requirement level, has four categories: (1) Unskilled or semi-skilled activities, (2) Specialist activities, (3) Complex specialist activities, (4) Highly complex activities. Those categories reflect the formal vocational qualifications typically demanded for a certain occupational activity. It is independent of a person's formal qualification as not just formal qualifications required to perform the occupation are used for classification but also informal education and/or professional experience are important.⁴ At the 4-digit level, the classification has around 700 occupations, which implies that not all requirement levels are present in all 4-digit occupations.⁵

For the main analysis, I use an aggregation which maps the 5-digit classification into 14 occupation segments (Matthes et al. 2015). These occupational segments divide

the labour market such that the switching between different occupations is minimised. This is important as the approach of Şahin et al. (2014) is most reliable in such a set-up, as it minimizes potential bias. Basically, it ensures that unemployed workers in an occupation search for vacancies in that particular occupation, or simply speaking the chosen classification represents the relevant market.⁶ For the exploration of the qualification dimension, I rely on the 5th digit of the scale and also interact it with the occupation segments.

5 Results

Figure 3 shows the indices over time conducted as in Eq. 1. They have very similar patterns over time, but different levels ranging from 0.05 (occupation segments, left panel) to almost 0.2 (3-digit occupation \times requirement level, right panel), which means that, less than 20% of hires are lost due to mismatch. Between 2008 and 2010 mismatch decreased, then it increased again until 2012. Afterwards there is a distinct movement between the left and right panel of Fig. 3. While there is slow downward movement in the occupation mismatch measure (left panel), there is rather a stagnation for the occupation-requirement level (right panel). In the second half of 2016 the indices start to increase slightly, which might be an effect of the refugee inflow in 2015 and 2016. As Brücker et al. (2020) and Bundesagentur für Arbeit (2020) point out, unemployment of asylum seekers increased steadily from 2016 to 2020, although on average, 35% of the refugees who entered Germany between 2013 and 2016 found a job after the second half of 2018. This might explain the decrease in the mismatch index until the COVID-19-crisis unfolded. The interruptions in the beginning of 2020 due to the CC are visible in both series.

To explore the differences between the left and the right panel of Fig. 3, I plot the mismatch index exclusively for the requirement level (see Fig. 4). Though the requirement level cannot be evaluated stand-alone because the interpretation differs slightly within occupations,⁷ it is

³ This procedure has the advantage that it excludes movements beyond the occupation dimension as, e.g., not all unemployed workers have a valid occupation information. I use the stocks of unemployment for the occupation of destination, hence these missing data is negligible. The series of unemployment reported by the Federal Employment Agency and the series I generate by aggregating the occupation panel data is fairly similar, the gap is small. For the other series, the same holds.

⁴ See <https://statistik.arbeitsagentur.de/DE/Statischer-Content/Grundlagen/Methodik-Qualitaet/Methodische-Hinweise/uebergreifend-MethHinweise/Anforderungsniveau-Berufe.html> and for a deeper understanding: https://www.arbeitsagentur.de/datei/Klassifikation-der-Berufe_ba017989.pdf, p.27 et seqq..

⁵ The data limitations are the following: The German Occupation Classification was renewed in 2010, and a conversion to the old classification is possible but leads to coding errors. Hence, the movements over time before 2011 are fraught with higher insecurities. On top, quality issues in unskilled and low skilled occupations between September 2009 and June 2010 are present and not resolvable.

⁶ The index used to measure mismatch proposed by Şahin et al. (2014) has the property that it is rising in the number of submarkets: The more markets are observed, the higher the misallocation between the markets, which increases the share of mismatch unemployment. Hence there is a certain bias: If the markets are similar, workers would not just search in their stated target occupation but also in very similar occupations.

⁷ The Federal Employment Agency gives the following interpretation of the requirement level: “The requirement level describes the complexity of an occupational activity. It is always typical for a specific occupation and is also independent of a person's formal qualifications. Although the formal qualifications required to perform the occupation are used for classification, informal education and/or professional experience are also important. See <https://statistik.arbeitsagentur.de/DE/Statischer-Content/Grundlagen/Methodik-Qualitaet/Methodische-Hinweise/uebergreifend-MethHinweise/Anforderungsniveau-Berufe.html>.



Fig. 3 Mismatch indices, 2007–2022, occupations (left) and occupationsxrequirement level (right). All series are seasonal adjusted using X-12-ARIMA. Data before 2011 is converged from KldB88 to KldB2010 and might be fraught with coding errors. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

informative on whether the qualification imbalances rose. And indeed, the index is rising across time, and shows an upward trend that is especially pronounced after 2018. Concluding, while mismatch across occupations decreased over time, the imbalances with respect to the qualification mix in the economy rose, such that mismatch across occupation segments in combination with the requirement level increased. Furthermore, a counterfactual simulation in which I hold the distribution of the requirement level constant across time, shows, that this would lead to a parallel in the mismatch index for occupation segments (see Fig. 14 in the Appendix.)

5.1 Implications for unemployment

A feature of Şahin et al. (2014)'s approach is, that it allows to construct a counterfactual unemployment rate (which is a reference for how unemployment would behave without mismatch). For this purpose, a counterfactual job finding rate which measures job findings relative to unemployment in the absence of mismatch, is conducted. By the assumption of a standard law of motion for the unemployment rate, a counterfactual unemployment rate can be backed out. The counterfactual unemployment rate is as follows:

$$u_{t+1}^* = s_t + (1 - s_t - f_t^*)u_t^* \quad (5)$$

Given an initial value for u_t^* , a sequence of counterfactual unemployment rates with the standard law of motion (s_t denotes the separation rate) can be calculated. Necessary to calculate the sequence of counterfactual unemployment rates is the counterfactual job finding rate f_t^* , which is defined as follows:

$$f_t^* = \bar{\phi}_t \Phi_t \left(\frac{v_t}{u_t^*} \right)^\alpha = f_t \cdot \frac{1}{1 - M_t} \left(\frac{u_t}{u_t^*} \right)^\alpha \quad (6)$$

As starting value, I choose $u_t^* = u_t$. As the unemployment rate in my data is downward biased,⁸ it is not helpful to depict the counterfactual and actual unemployment rate in levels. Therefore I proceed with a calculation where I use the difference between actual and counterfactual unemployment (i.e., mismatch unemployment) over the actual unemployment rate. This measure can be interpreted as the percentage share of mismatch unemployment on actual unemployment.

⁸ Note that I generate the series for unemployment by summing across occupations for every point in time. That implies, that the unemployment rate is somewhat lower than the official unemployment rate given that there are missing occupation information. Furthermore, the military sector is excluded.

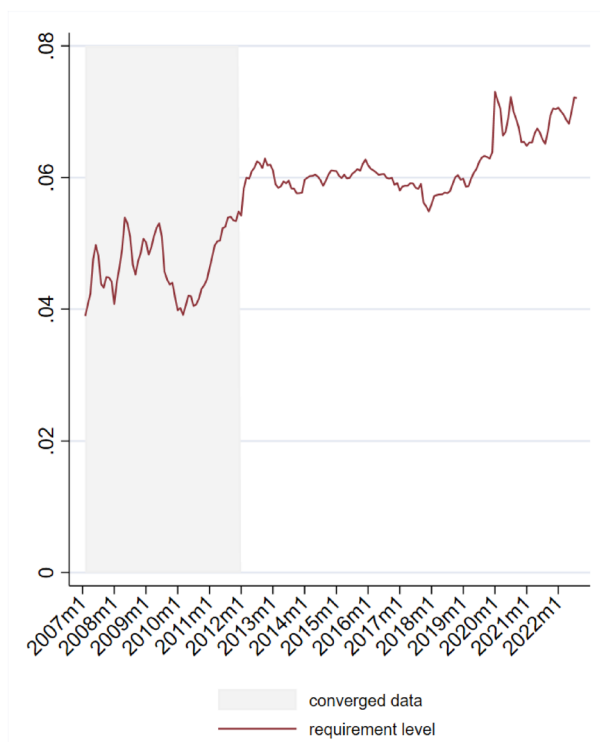


Fig. 4 Mismatch index for requirement level. All series are seasonal adjusted using X-12-ARIMA. Data before 2011 is converged from KldB88 to KldB2010 and might be fraught with coding errors. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

Figure 5 plots this share over time. Mismatch unemployment ranges, on average, between 13 and 22% of total unemployment on the occupation level in the end of 2022, and between 23 and 33% on the occupation \times requirement level. The share decreased from high values in the beginning of about 40 to 50% to these lower levels. During the CC, the mismatch share rose quickly but only temporarily. Compared to other countries, the shown patterns overall behave similarly. Forsythe et al. (2022) shows that during the CC mismatch only occurred temporarily in the US. Pizzinelli and Shibata (2023) confirms this pattern for the US and the UK. In their data, as in mine, the COVID-19-shock induces a spike, which is not the case in Forsythe et al. (2022). After the CC, there is an upward movement. This upward movement brings the occupation series back to the pre-crisis level, but for the interaction of occupations and requirement level, mismatch unemployment rises above its pre-crisis level. In absolute numbers, the share of mismatch unemployment in total unemployment rose about 2 percentage points from 20.5% (mean between January 2019 and January 2020) to 22.4% (in August 2022) for the occupation segments \times requirement level. Hence, the rise

in the imbalances in the qualification mix spills over to unemployment.

When I plot the share of mismatch unemployment for occupation segments and for occupation segments \times requirement level overlapping across time (see Fig. 6), this becomes even clearer. While there is a similar movement before the COVID-crises in the series, a strong increase after that can be seen, which is particularly pronounced for the interaction of occupations and the requirement level.⁹ When COVID-19 hit the German economy, the government enforced two strict lockdowns, one in spring 2020 and one in winter 2020/2021 (Bauer and Weber 2021a). In the first lockdown, the unemployment rate increased from 5.1 to 6.3% (i.e., by more than 600,000 persons), the pool of registered vacant positions dropped by 20% (see [Key Figures for the Labour Market - Germany \(Monthly Report\)](#)).¹⁰ However, compared to other countries, the German “short-time-work-scheme” served as a stabilizer and saved jobs (Gehrke and Weber 2020; Christl et al. 2022). This implies that the effect of COVID-19 on unemployment in Germany is rather moderate compared to the US. Nonetheless, this is suggestive evidence that the tight labor market in Germany may be explained partially by a misallocation on the qualification level.

6 Occupations and the requirement level in detail

To strengthen my results, I exploit the qualification dimension in more depth. First, Fig. 7 depicts the vacancy and unemployment shares across the requirement level over time. Apparently, the distribution of the requirement level for the vacancy shares is different than for the unemployment shares. Furthermore the development over time is different: the relative demand for high complex jobs is fairly stable, while the relative demand for complex jobs, but also for jobs at the unskilled and semi-skilled level increased over time. Contrary, the relative demand for specialists sank. Having a look at the unemployment shares, shows: the relative supply at the unskilled and semi-skilled level is also increasing, but much stronger than the demand. The relative supply at the specialist level is decreasing much stronger than on the demand side. Overall, the figure indicates that the increase in mismatch unemployment is closely related to shortages of skilled labour.

Tightly connected to this result is the question whether the differences across the requirement level emerge from

⁹ In June 2022 both series increased again when the refugees from the Ukraine entered the unemployment pool in Germany.

¹⁰ According to the IAB-Job Vacancy survey, the pool of all vacant positions dropped by even 40% from 4th quarter 2019 to second quarter 2020.



Fig. 5 Mismatch Unemployment, 2008–2022. All series are seasonal adjusted using X-12-ARIMA. The series starts in 2008 to account for the effect of the starting value on the series in the beginning. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

certain occupations.¹¹ Especially, because shortages of skilled labour are not observed in all occupations. Therefore, I decompose the contribution every occupation has had in terms of unemployment by looking at deviations between actual unemployment and optimal unemployment for each occupation across requirement levels. The decomposition is calculated under the condition that the social planner is not able to distribute more unemployed workers than actual unemployed workers exist. Per construction, values below zero imply that the social planner would like to distribute more unemployed to the sector than actually are present, i.e., $(u - u^* < 0)$. Conversely, values above zero would indicate that the occupation exhibits more unemployed than the social planner would choose. This exercise is similar to the decomposition exercise of Pizzinelli and Shibata (2023) and takes the demand side, hence the vacancy evolution, as given. Put differently, the exercise shows for each requirement level, in which occupation segment the social planner would love to distribute unemployed workers in comparison to the actual distribution to minimize mismatch. Per construction, values below zero imply that the social planner would choose to distribute more unemployed workers than there actually are present (labour shortages) while values above zero would indicate that there are more

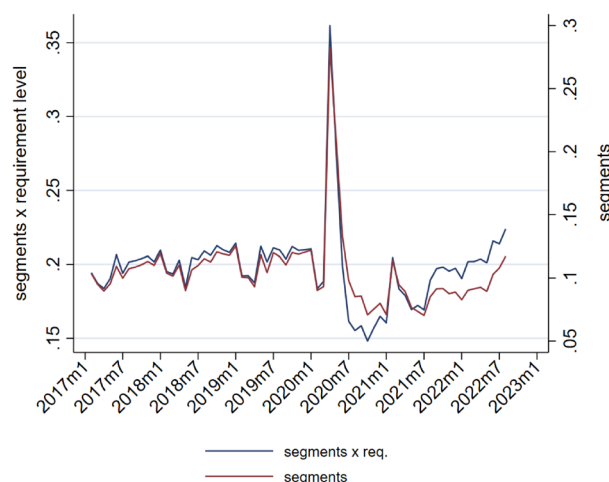


Fig. 6 Mismatch Unemployment, 2017–2022. All series are seasonal adjusted using X-12-ARIMA. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

unemployed workers than optimal (excess supply). Figure 16 shows the results for occupations independently of the requirement level. Overall, 6 out of 14 occupations show excess unemployment, 5 out of 14 occupations show shortages and 3 occupation segments switch over time.

¹¹ Figure 15 in the appendix shows the occupation shares within Fig. 7.

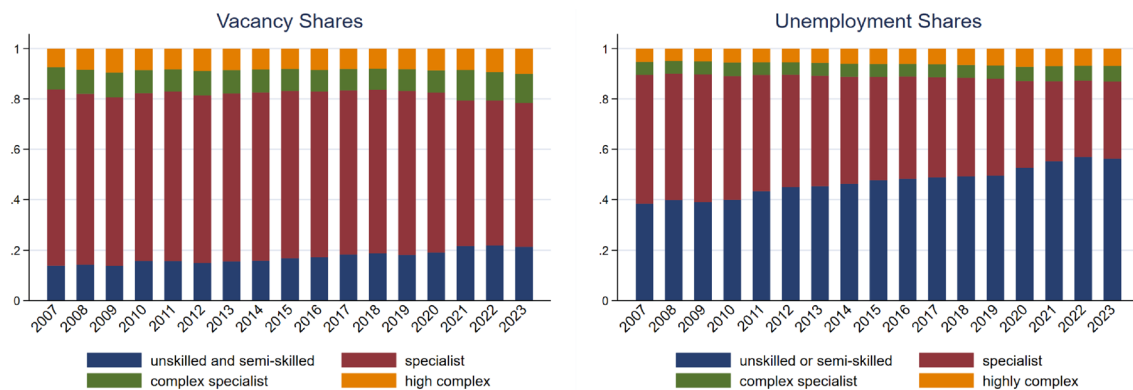


Fig. 7 Distribution of vacancies and unemployment across the requirement level, 2007–2022. All series are seasonal adjusted using X-12-ARIMA. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

When I illustrate this decomposition by requirement level (see Fig. 8), three things stand out: First, in the market for unskilled and semi-skilled workers, an over-supply exists in almost all occupations. Reversely, on higher requirement levels, more occupations exhibit shortages. These results are well in line with findings from Böheim and Christl (2022) who explore the skill dimension of mismatch in terms of tasks and find that mismatch unemployment increased especially in manual-routine jobs. The qualitatively strongest shortages prevail among specialist activities. Second, over time, excesses and shortages appear to be persistent. Third, the GFC and CC hit different occupations and hence show different effects across the requirement levels. During the GFC, there is a strong impact in manufacturing and related occupations. These occupations have a large share of specialists activities, and hence a reduction of shortages at the (complex) specialist level is visible, but also an increase in over-supply at the un- and semi-skilled level. The CC hit occupations in “cleaning” and in “the food industry, in gastronomy and in tourism” or “in commerce and trade”, which typically have a higher share of un- and semi-skilled activities. Therefore, an increase of over-supply of these occupations is visible almost exclusively at the unskilled and semi-skilled requirement level. The medical and non-medical health care occupations appear to behave differently. Shortages in health care increase during recessions, but almost all of this increase happens at the special and complex specialist requirement levels. Comparing my results to the results in Pizzinelli and Shibata (2023) show the following: First, while for the US and the UK the effects of the GFC are pronounced and long-lasting, the effects are not as persistent in Germany. During the CC Pizzinelli and Shibata (2023) (Fig. 5) show that the effects are short-lived and driven by the leisure and hospitality sector which is in line with my results. For

the UK, the health sector also showed shortages, which were stronger in the CC than in the GFC. In Germany, we also see an under-supply, however, it was stronger during the GFC than in the CC, in absolute terms.

To outline that more detailed, Fig. 9 shows the overall behaviour of excess demand and supply across selected occupation segments and how the effects differ for the requirement levels within. The figure reveals, that manufacturing occupations were hit hard during the GFC and went from excess demand to excess supply and that this reaction mainly came from decreased shortages for specialists. During the CC, there is only little reaction. For occupations in the food industry, in gastronomy and in tourism it is the opposite: During the GFC they went from a balanced path to excess supply. However, they were hit hard during the CC and faced a strong increase in excess supply, which stems to a large part from the unskilled and semi-skilled level. Furthermore, occupations in building and interior construction over time went from excess supply to excess demand, whereby the GFC but also the CC intensified the reactions, especially at the specialists’ level. Occupations in commerce and trade overall show a decrease in excess supply, however, the level of excess supply at the unskilled and semi-skilled level increases over time, while it decreases strongly and is also reverting to excess demand at the specialists’ level.

Concerning the question how these results translate back into the evolution of the mismatch indices of Fig. 5 it becomes clear, that the latest increase in mismatch evolves in the market for unskilled and semi-skilled occupations. In particular, occupations which were hit hard by the CC (especially occupations in cleaning services, occupations in commerce and trade, occupations in the food industry, in gastronomy and in tourism and occupations in traffic and logistics) did not fully revert back to the pre-CC level of over-supply. But it also shows, that

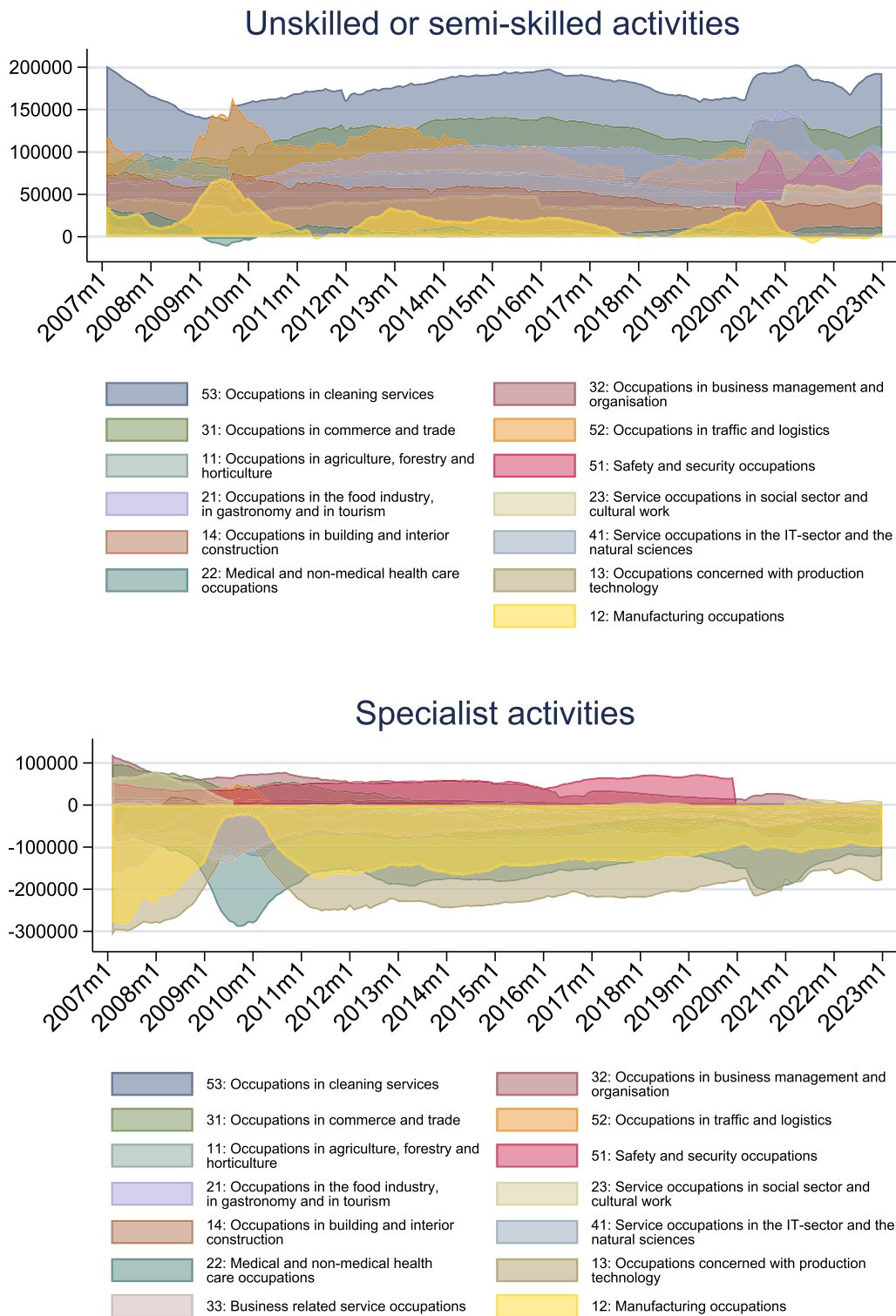


Fig. 8 Distance between actual and optimal unemployment within requirement level across occupation segments. Statistic is calculated by assuming that $\sum_i u^* = \sum_i u$. Note that there are changes in the assignments of occupations with respect to the requirement level in the segments of safety and security occupations and the service occupations in social sector and cultural work which I adjusted to be consistent over time. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

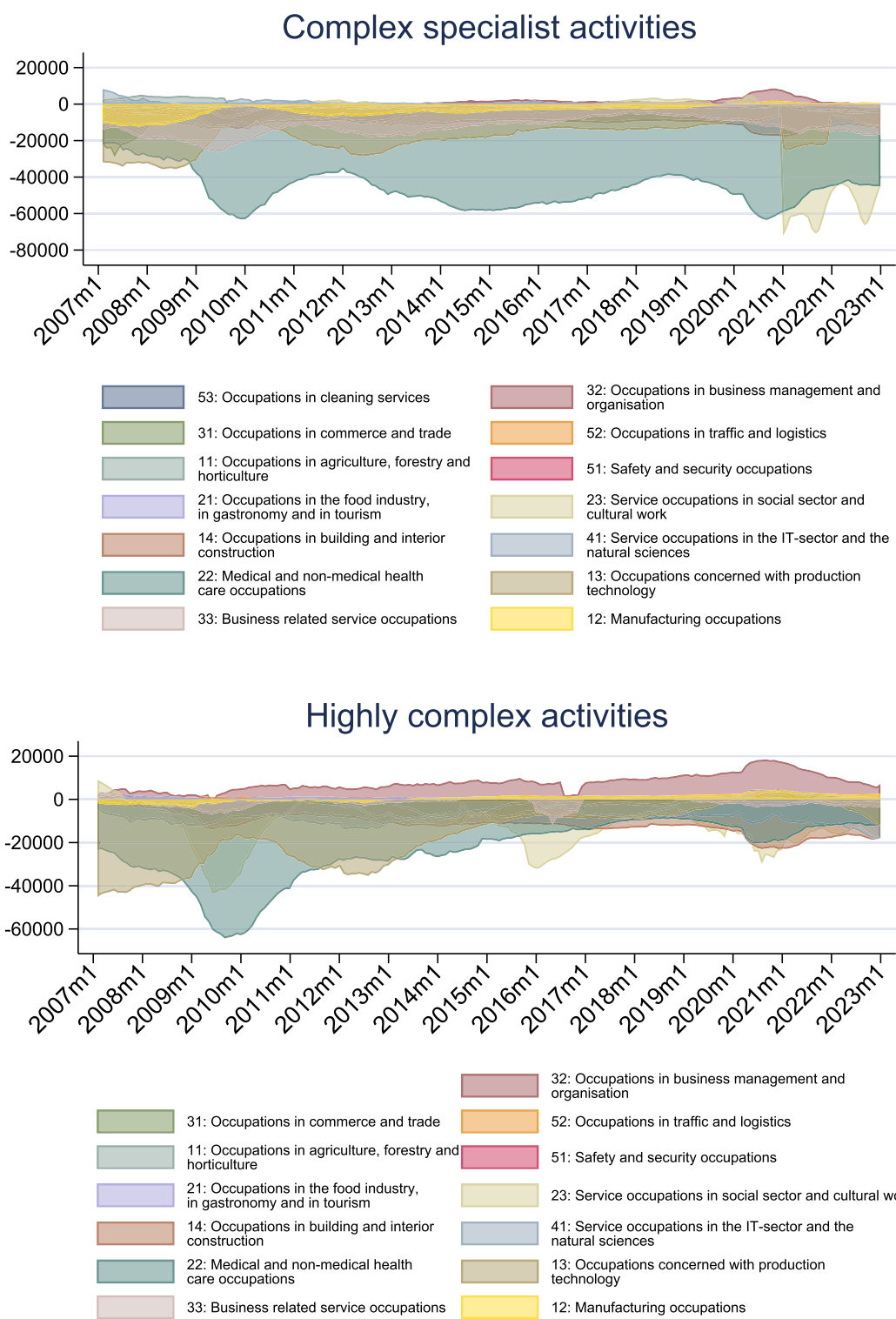


Fig. 8 continued

the shifts in demand and supply at different requirement levels are not just a temporary effect of the CC, as the imbalances already rose before the CC. Put differently, the CC reinforced the already existing pattern.

7 Discussion

The advantage of the used approach is that it is easy implementable with a large amount of data, and that it is widely used as benchmark indicator, hence comparable across countries under certain assumptions. Compared to other countries like the UK or the US, in Germany mismatch is of a similar magnitude on a comparable basis. For the 2-digit occupations in Germany (comprising 36 occupations), the mismatch index is at a level of 7% in 2022. At the 2-digit occupation level for the UK (24 occupations) and the US (25 occupations), Pizzinelli and Shibata (2023) calculated a level of 4 percent, and 7% respectively. Forsythe et al. (2022) finds a similar magnitude of 7% in the US as well. As in the UK and in the US, in Germany the mismatch index for occupations tends to decline over time. Concluding, there are other factors than an occupational mismatch that drive labour market tightness and low job-finding rates especially after the CC. For Germany, I highlight the impact of the requirement level, for which I can show that it is on the rise especially since 2018.

In order to decrease this type of mismatch, it would be necessary that unemployed workers upskill, for example, from an unskilled and semi-skilled level to be a specialist, or that firms make concessions in the type of workers they are recruiting. Both options come with a cost. Though in theory, the social planner moves unemployed workers costlessly across the submarkets, in reality, there are both direct and indirect costs that need to be taken into account. With regard to the direct costs, the Federal Employment Agency acts as a social planner and bears the costs for various measures aimed at a change of occupation or an upgrade of qualification, which implies that the assumption in the model is not irrational in that respect. What remains are indirect costs that reduce mobility between the requirement levels. Nonetheless, there is movement between the requirement levels, see Table 2. For un- and semi-skilled workers, the most frequent move is to the level of specialists, while for specialists, it is vice versa. Between 2017 and 2022, however, the upward mobility for the un- and semi-skilled decreased. For specialists, the upward mobility (i.e., to upskill to complex or highly complex activities) increased.¹² Nonetheless, there are certain other barriers: For example, changes from unskilled to high complex activities are very rare, particularly because of individual cognitive skills and desires. This cannot be taken into account with the approach under consideration. In that respect my results show the upper limit of what is possible.

On the other side, given the tight labour market, one could argue that firms could make concessions in the type of workers they are going to hire. However, that might lead to mismatch “on the job”, where workers might be under-qualified for the position. Empirically, there is no incidence, that firms made concessions in the recent past to mitigate skilled labour shortages: As Bossler and Popp (2024, p. 39) point out, though firms could make “concessions, for instance, by raising wages or by recruiting workers with lower skills [...] the estimates suggest that the extent of firms’ wage and skill concessions was fairly small in practice.” In the future that might be a mechanism for firms which could then possibly influence the rate of underqualification. A recent study for Germany shows that overqualified workers tend to have higher wage growth, are more likely to move upward the career ladder, and engage more often in on-the-job training, such that overqualification is only temporary. For under-qualified workers the effects point in different directions but are overall rather insignificant (Roller et al. 2020). An exemption is the effect that underqualified workers at the requirement level “specialists” appear to receive less on-the-job training than their adequately qualified colleagues.

Summarized, to help workers improve their qualification level, before or after hiring, would mitigate the increase of mismatch at the requirement level while limiting the negative side effects.

8 Conclusion

This paper stresses that an overlooked but relevant dimension of mismatch in Germany appears to be the requirement level. Crucially, mismatch between unemployed workers and vacant jobs in the labour market for unskilled and semi-skilled activities is persistent and tends to increase since the CC. This increase is to some extent driven by occupations which were hit hard during the CC, such as occupations in cleaning services, in commerce and trade, in the food industry, in gastronomy and in tourism but there also appears to be a structural component. Hence activation policies in form of further training that aims to improve the qualification of unemployed workers within a certain occupation is key to align demand and supply across requirement levels. While it would help to decrease excess supply at the un- and semi-skilled level, it could also help to alleviate shortages in the labour market for skilled workers in the longer run.

¹² Table 3 in Appendix shows the mobility rate between occupations. The overall mobility rate increased only slightly between occupations.

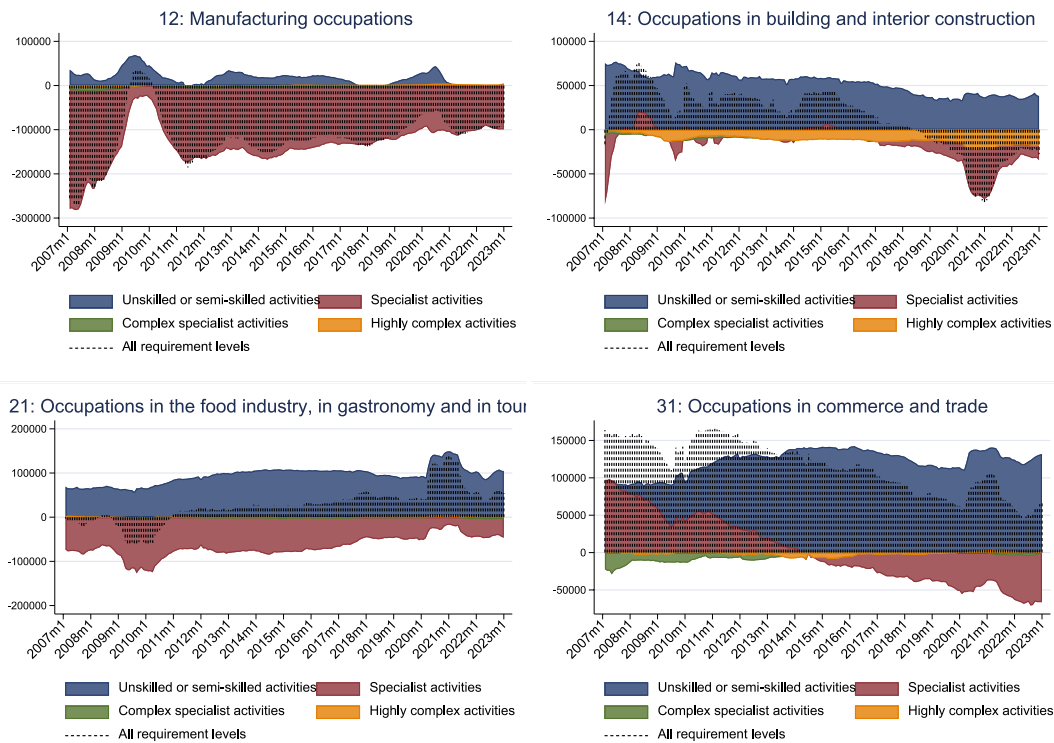


Fig. 9 Distance between actual and optimal unemployment across occupation segments

Appendix

Further results

If I zoom in, and plot the mismatch index for occupation segments against the mismatch index of the occupation segments-requirement level for a time period beginning in 2017, the movement before the Covid-Crisis is similar, but after that the index for occupation segments reverts to its downward trend, while the index for occupation-segments in combination with the requirement level tends to move horizontally, thereby increasing the gap between the two (Fig. 10).

Figure 11 shows the mismatch index, using the vacancy and unemployment shares across the occupation segments for subsamples reflecting the four requirement levels.¹³ To be more precise, I calculate the requirement-specific job-finding rate, separation rate and unemployment rate. I plot the mismatch index over time within every requirement level (blue solid line), the implied share of mismatch unemployment on the requirement-specific unemployment rate (green dotted line). Furthermore, I calculate the share of mismatch unemployment in a certain requirement level on total unemployment (red dotted line) in the economy for two reasons. First, the unemployment rate is not equally distributed across

the requirement level, i.e. unemployment is much higher in unskilled and semi-skilled activities than in (highly) complex specialist activities. Second, the evolution over time might also be different. Looking at Fig. 11, two points are important: First, the index for unskilled and semi-skilled activities is relatively high compared to the other indices and does not show a strong decrease after the CC, while for the other requirement levels the indices decrease. Second, looking at the evolution of mismatch unemployment for unskilled and semi-skilled activities on total unemployment, there is an upward trend, indicating that the result of Fig. 5 stems from this group.

Robustness

The occupation information of the unemployment pool is available in various specifications. I have information on the number of unemployed in the occupation of origin, the occupation of search, and in case there is a flow between unemployment and employment also the occupation which was taken up. The occupation of searched

¹³ For the matching elasticity and matching efficiency I use the same numbers as in the main part of the analysis to avoid to misinterpret changes in these variables.

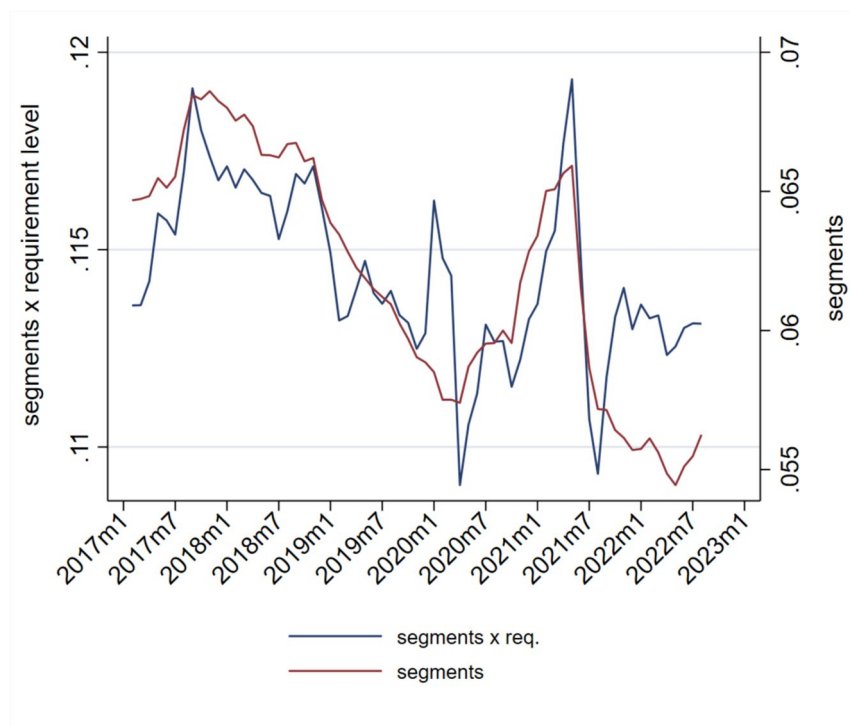


Fig. 10 Mismatch indices, 2015–2022. All series are seasonal adjusted using X-12-ARIMA. The series starts in 2008 to account for the effect of the starting value on the series in the beginning. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

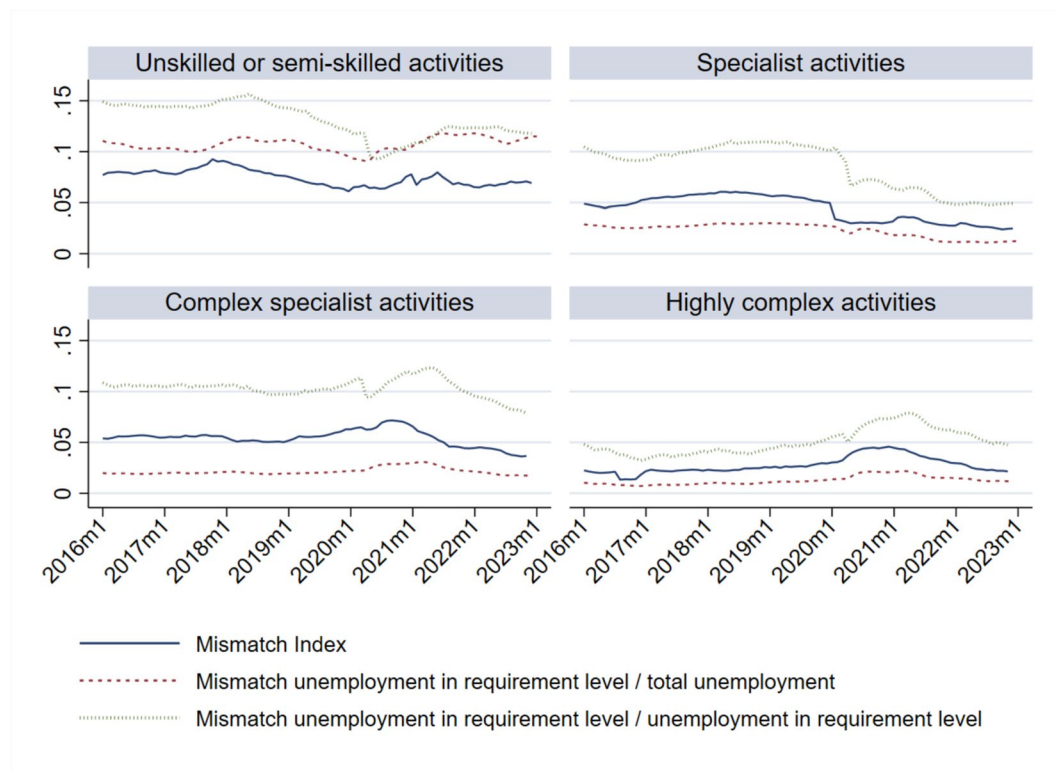


Fig. 11 Mismatch index within different requirement levels Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

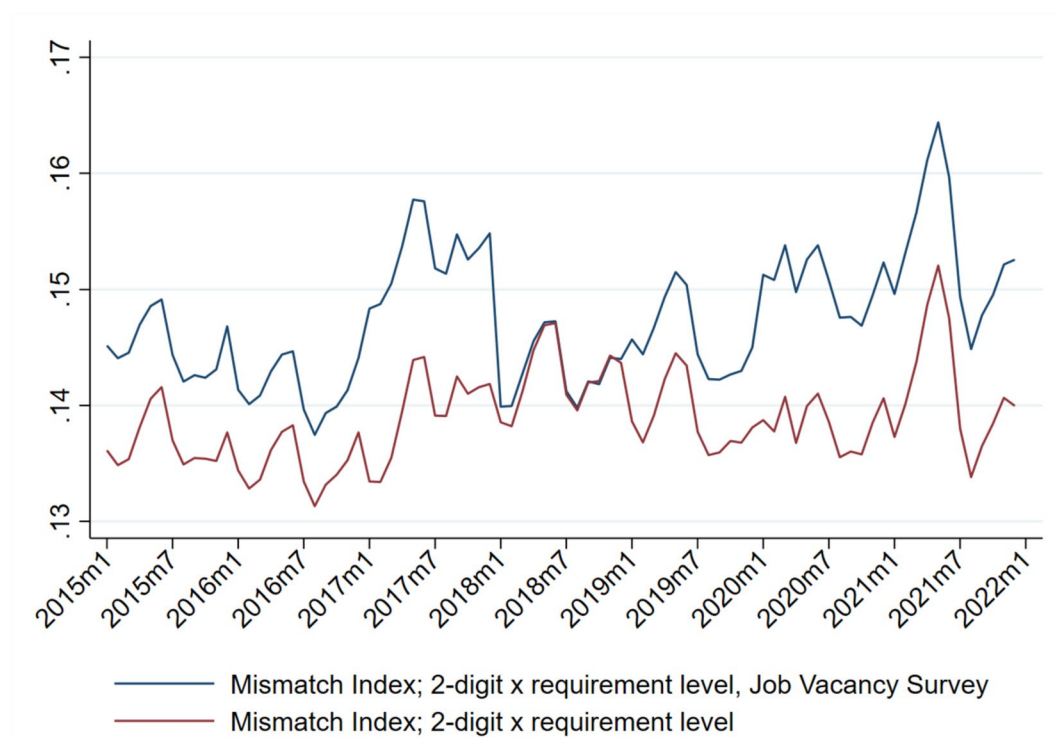


Fig. 12 Mismatch Index registered vs. IAB Job Vacancy Survey, 2008–2022. All series are seasonal adjusted using X-12-ARIMA. The series starts in 2008 to account for the effect of the starting value on the series in the beginning. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

is used in the main analyses. In a comparison of the baseline and the occupation of origin, the latter has a lower level but a similar movement over time. When I alternate the job findings to be the one of actual take-up, there is almost no difference in the indices.

Second, I explored the influence of matching efficiency on the index. I calculated two alternative versions of the index, (1) an index with time-varying matching efficiency, and (2) an index without the term related to matching efficiency in Eq. (1). While the first version appears to be more volatile than the baseline, the latter has a very similar movement over time, however at a different level.

In the main analysis, I used registered vacancies of the Federal Employment Agency. In Germany for firms it is not mandatory to register the vacancies, hence this series is prone to underreporting and also bias with regards to the requirement levels. To circumvent this issue, I use the relation of registered vacancies to all vacancies by requirement level of the IAB Job Vacancy Survey. The IAB Job Vacancy Survey is a representative survey, that allows for projections of the overall stock of the vacancies in the economy. However, there are some shortcomings. First, the data is available only in a quarterly frequency. Second, the data is not representative across

the occupation dimension. Luckily, information on the requirement level of a vacant position is available, which is especially valuable for my findings. I project the vacancies separately at every requirement level and aggregate them up afterwards. This gives me a new measure for the vacancy shares. Overall, the relation of registered to all vacancies varies between 33 and 49% during the observation period. With respect to the requirement level, the higher the expertise required the less likely it is that the vacancy is registered at the Federal Employment Agency. Figure 12 shows that the index behaves similar over time, however the index constructed with IAB Job Vacancy data is higher in the beginning and the end of the observation period. However there is no systematic bias in the time series.

Counterfactuals

In Fig. 13 I compare the baseline index to an index where I either hold the vacancy share fixed at the beginning of the period or the unemployment share. This is a similar exercise as in Hutter and Weber (2017). This allows to receive a hint to which extent the

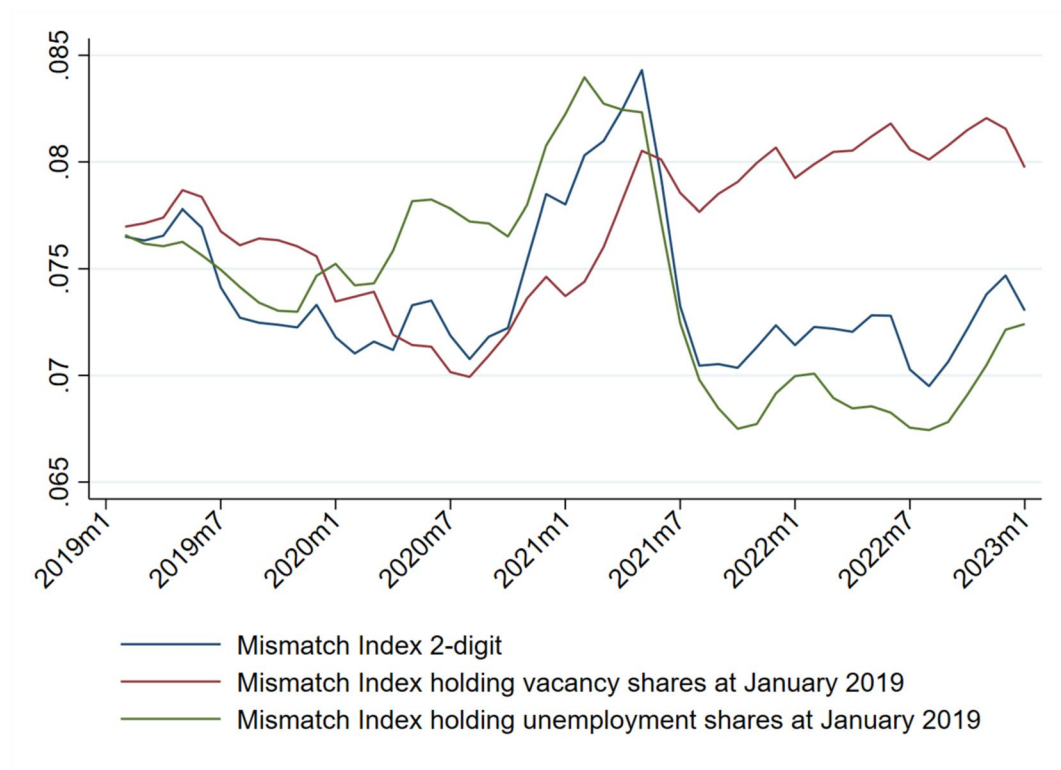


Fig. 13 Mismatch indices holding either the unemployment shares or the vacancy shares constant. All series are seasonal adjusted using X-12-ARIMA. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

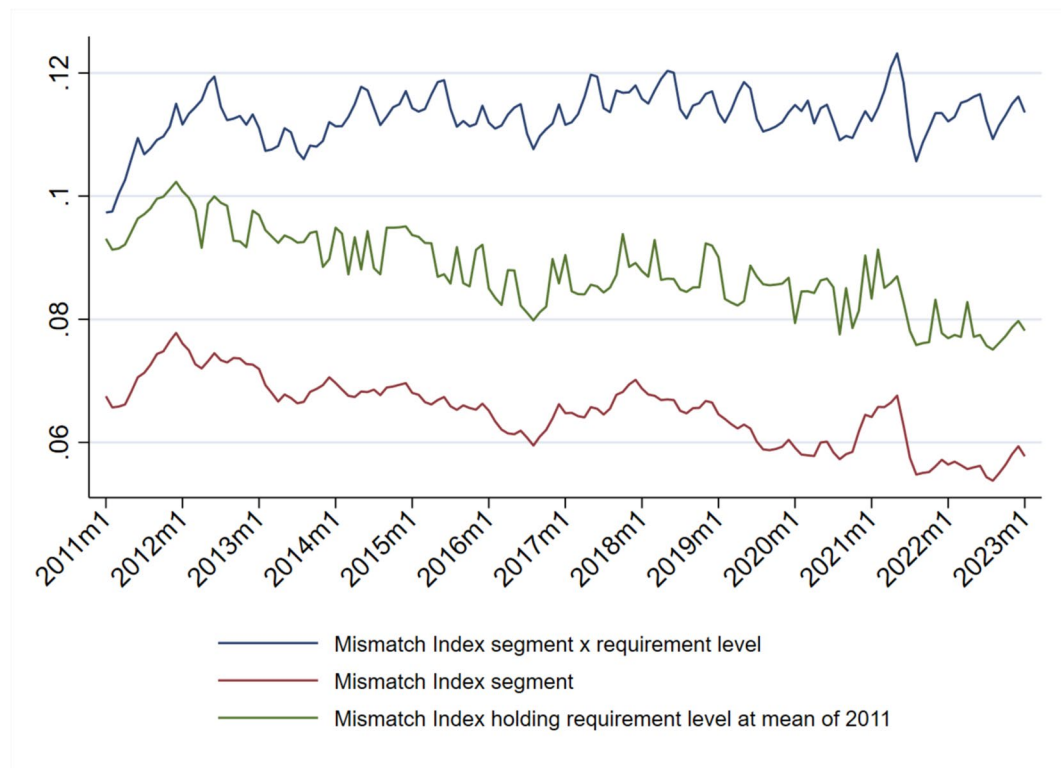


Fig. 14 Mismatch indices holding the requirement level distribution constant (at the mean level of 2011) across time. All series are seasonal adjusted using X-12-ARIMA. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

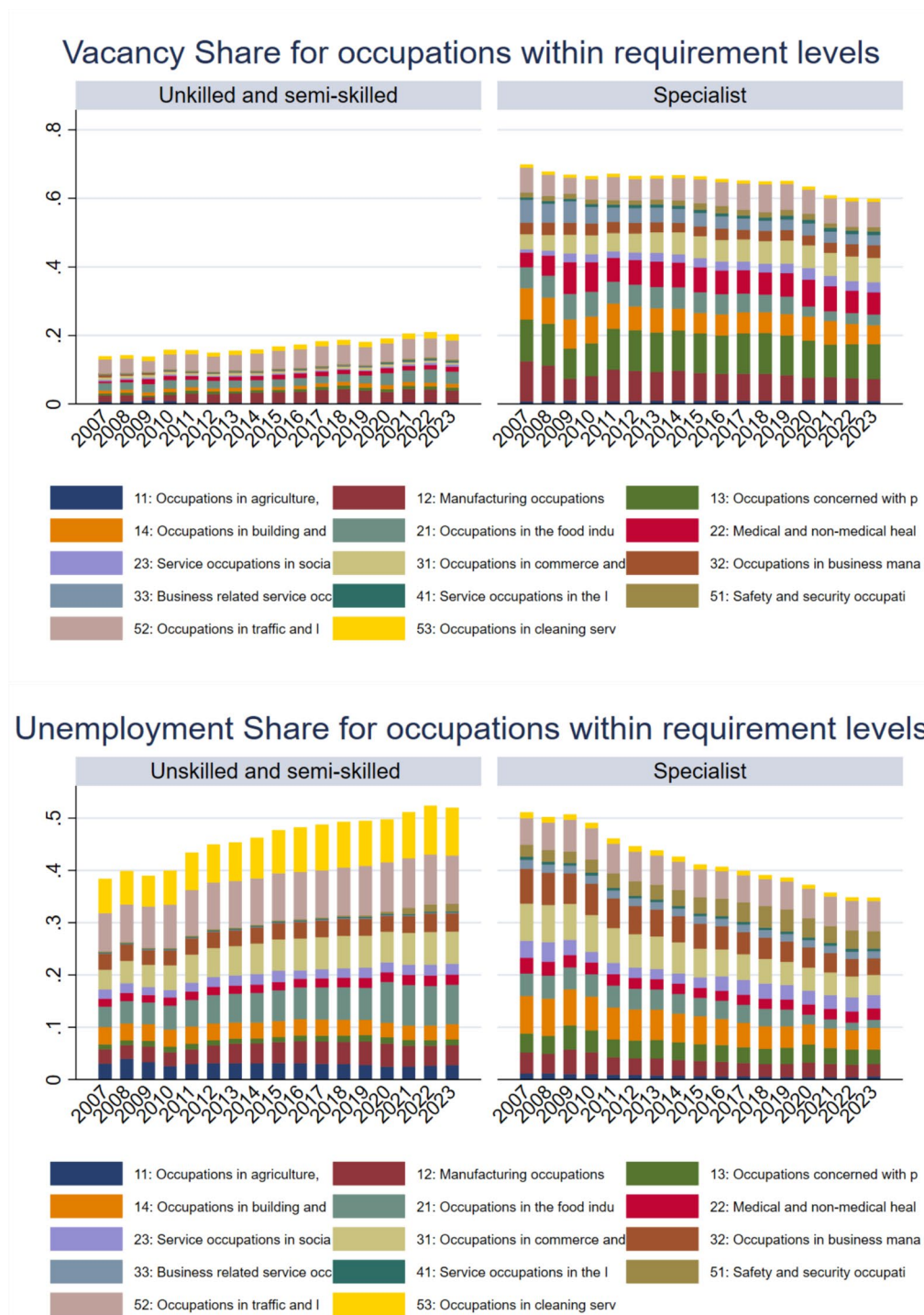


Fig. 15 Distribution of vacancies and unemployment across the requirement level, 2007–2022. All series are seasonal adjusted using X-12-ARIMA. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

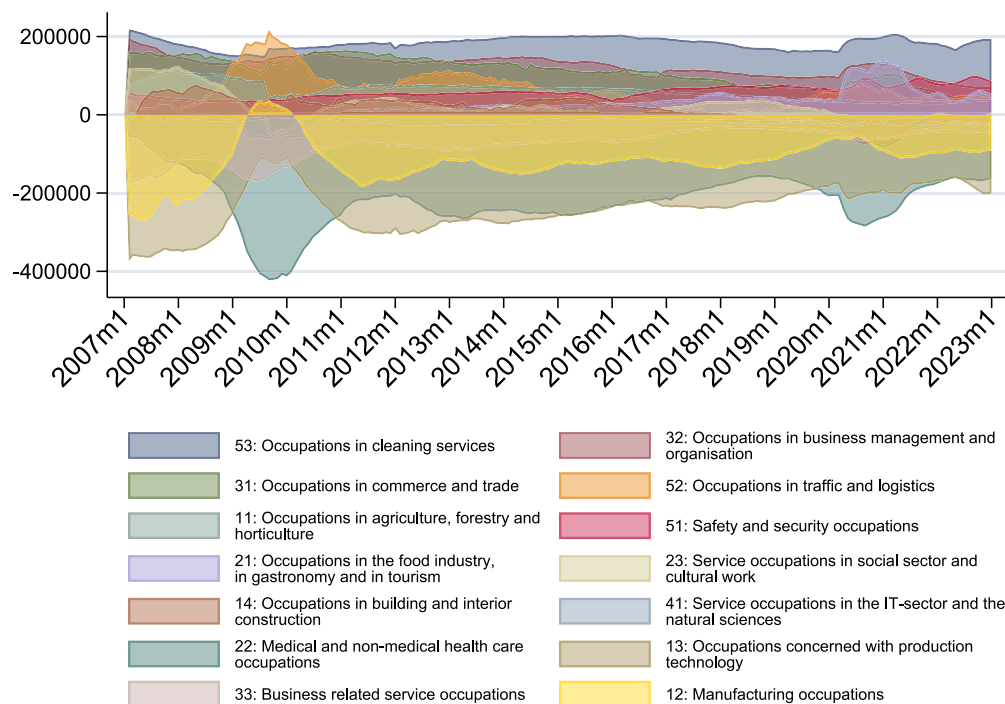


Fig. 16 Distance between actual and optimal unemployment across occupation segments. Statistic is calculated by assuming that $\sum_i u^* = \sum_i u$. Values below zero indicate shortages, above zero excesses in terms of unemployed persons. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

Table 1 Percentage change between business cycle dates in the distance between actual and optimal unemployment across occupation segments

Occupation segment	GFC	CC
21: Occupations in the food industry, in gastronomy and in tourism	-3.70	1.07
22: Medical and non-medical health care occupations	-1.80	-0.16
23: Service occupations in social sector and cultural work	-0.83	-0.63
41: Service occupations in the IT-sector and the natural sciences	-0.66	-0.49
14: Occupations in building and interior construction	-0.43	-0.27
33: Business related service occupations	-0.33	-0.20
11: Occupations in agriculture, forestry and horticulture	-0.22	-0.01
31: Occupations in commerce and trade	-0.20	0.23
53: Occupations in cleaning services	-0.14	0.10

Peak and trough dates are given by the German Economic Council. The GFC period refers to data from January 2008 (peak) to April 2009 (trough) and for the CC to data between February 2020 (peak) and April 2020 (trough)

movement over time is induced by movements in the distribution of vacancies or unemployed. The figure shows the movements from January 2019 to the end of 2022. While the patterns are similar until mid 2021, after the second half of 2021 there appears some divergence. The index holding the vacancy shares constant, tends sideways. Hence, if it were just the distribution of unemployment that would have moved mismatch unemployment stayed elevated (compare red line with

blue line). The forces that pulled mismatch unemployment down after the COVID19-shock is likely to be the rebound of vacancies (see green line in comparison to blue line). However, the slight upward movement in mid 2022 appears to be a less favorable evolution of vacancies.

In Fig. 14 I compare the index for occupation segments to an index at the occupation segments \times

requirement level, for which calculation I used the distribution of the vacancy and unemployment shares in 2011 and hold it constant until 2022. The figure shows, that this counterfactual leads to a parallel shift of the mismatch index in comparison to the index for occupation segments. The index increases due to the increase in the number of submarket. More important, the counterfactual index shows that the deviation between occupation segments and occupation segments \times requirement in the trend must stems from the evolution of the distribution of the requirement level across the vacancy and unemployment shares.

Requirement levels and occupations

For the sake of readability, I focus on the level of un- and semi-skilled and specialist activities and plot the evolution of the vacancy and unemployment shares across the different occupation segments. In both requirement levels, the occupational shares are differently distributed, but there is no particular occupation, which drives the increases and decreases. The figure shows, that the unemployment shares for un-skilled and semi-skilled workers increased stronger than the vacancy shares, and for the level of specialists there is a stronger decrease in the unemployment shares than in the vacancy shares (Fig. 15).

Occupation segments

It stands out that especially occupations with a high share of unskilled and semi-skilled unemployed workers tend to show excesses like occupations in cleaning services, occupations in business management and organisation, occupations in commerce and trade. Occupations which

exhibit shortages like manufacturing occupations, occupations concerned with production technology, medical and non-medical health care occupations or service occupations in the IT-sector and the natural sciences tend to have a higher share of unemployed that search for (highly) complex specialist activities. Two occupation segments, namely occupations in building and interior construction and occupations in social sector and cultural work, switch from excesses to shortages over time. Occupations in the food industry, in gastronomy and in tourism change from shortages to excesses. Given the different nature of the GFC and the CC, Fig. 16 shows that different occupations played a role during the crises. While during the GFC shortages in the occupations concerned with production technology and manufacturing occupations were reduced, excess in occupations in traffic and logistics increased. During the CC, it has been occupations in the food industry, in gastronomy and in tourism and somewhat occupations in cleaning services where excesses increased. A special case are medical and non-medical health care occupations, where in both crises shortages increased (Fig. 16).

To analyse the cyclical pattern, tied to different occupations as highlighted above, Table 1 shows the changes in the deviation between actual and optimal unemployment across occupation segments among peak and trough of the GFC and the CC. It shows that these do not follow a clear pattern. While in some occupations distances decreased in both crises, in other occupations they almost did not react, and for some occupations the differences evolved differently in the two crises.

Within-segment evolution

See Fig. 17.

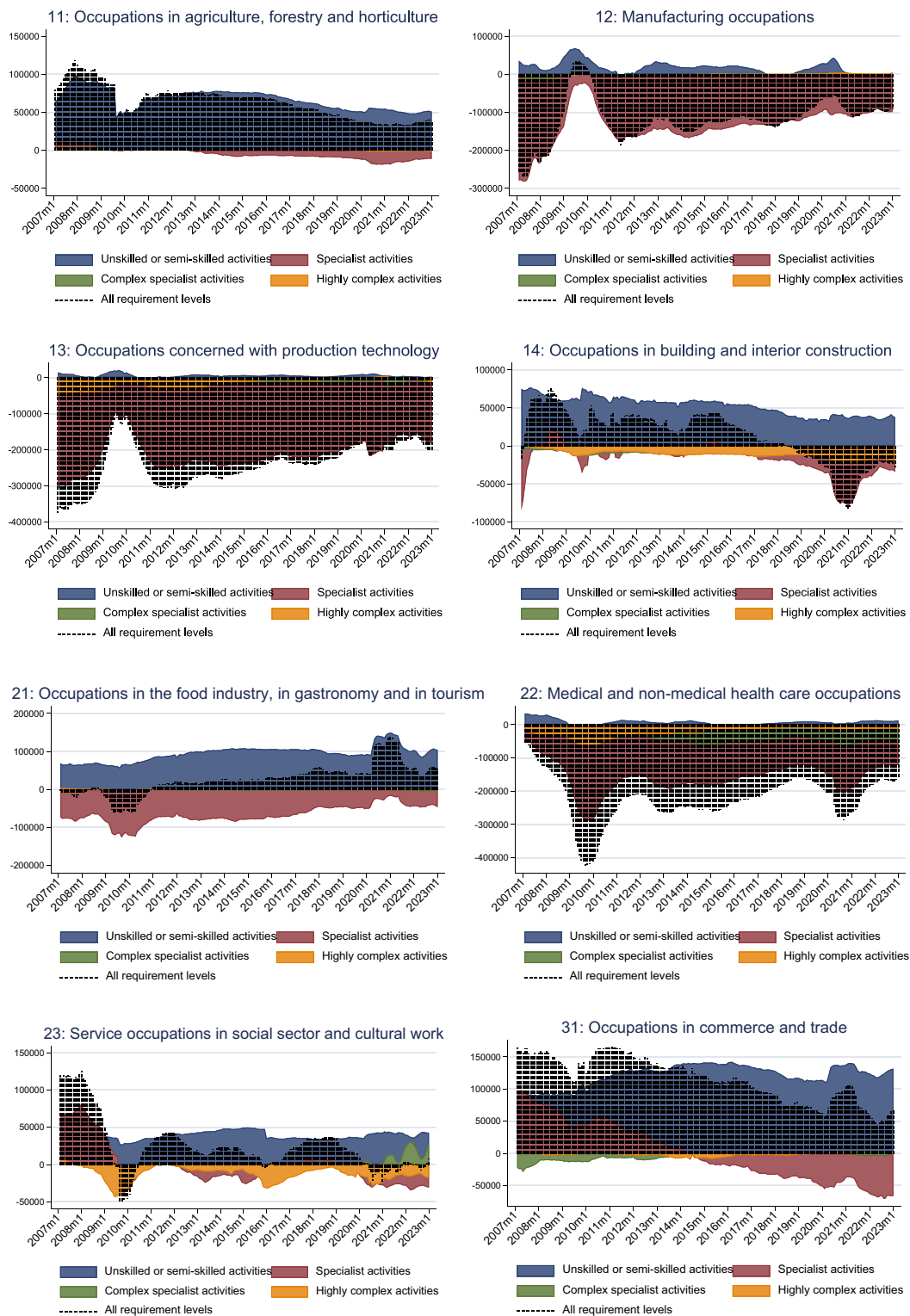


Fig. 17 Distance between actual and optimal unemployment across occupation segments. Statistic is calculated by assuming that $\sum_i u^* = \sum_i u$. Note that there are changes in the assignments of occupations with respect to the requirement level in the segments of safety and security occupations and the service occupations in social sector and cultural work. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

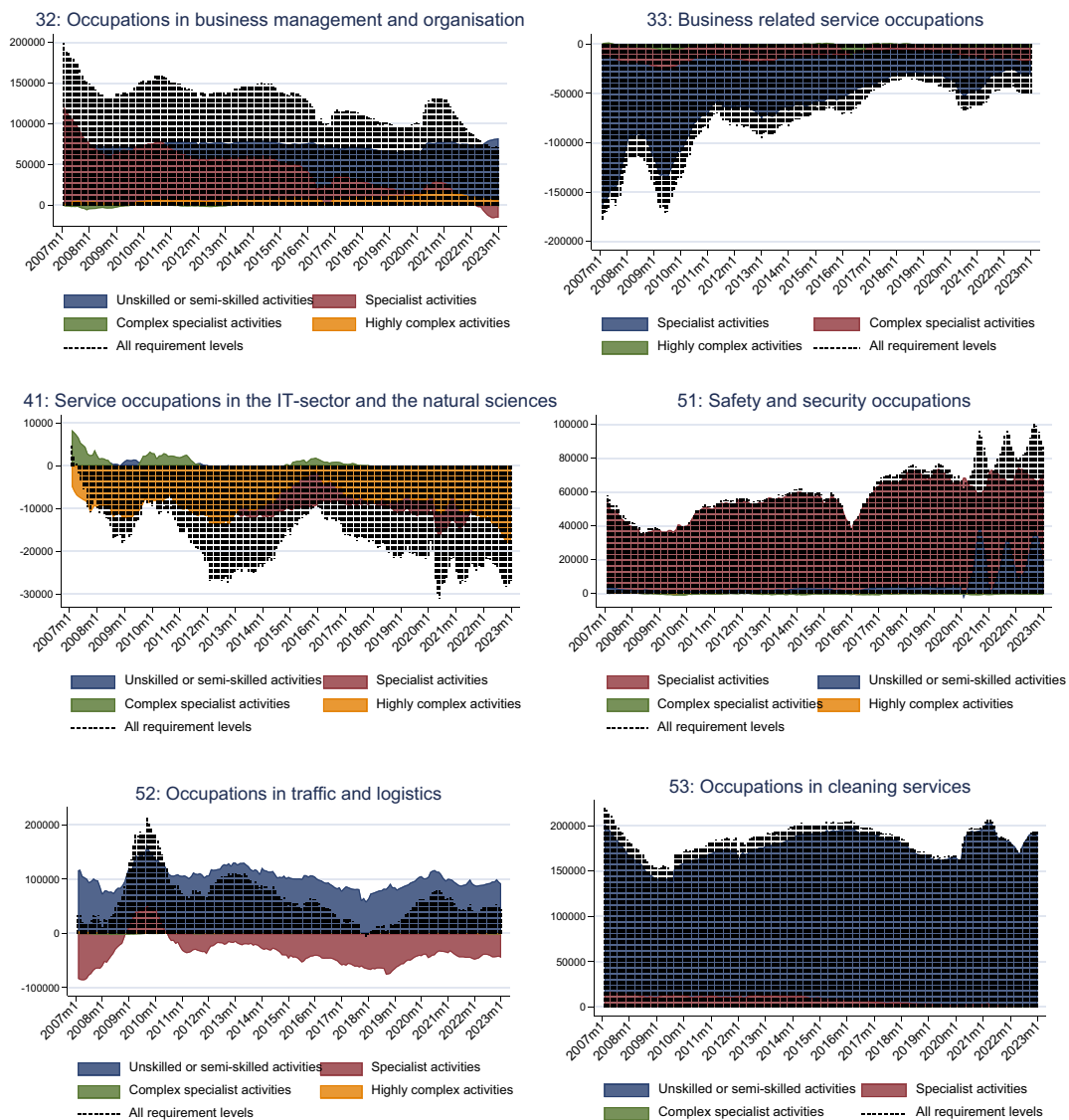


Fig. 17 continued

Mobility

This section shows the mobility upon hiring across requirement levels (see Table 2) and occupation segments (see Table 3) in 2017 and 2022. The chances of moving to a higher requirement level as searched for upon hiring between 2017 and 2022 overall decreased. Especially for the un- and semi-skilled workers the effect is large.

The chances of switching occupation segments increased overall slightly. In occupations such as Safety and security occupations, Medical and non-medical health care occupations or Manufacturing occupations the chances of moving to another segments increased clearly, while the chances decreased for service occupations in social sector and cultural work.

Table 2 Mobility across requirement levels in 2017 and 2022. Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

2017	Hired at				Mobility
	Unskilled	Specialist	Complex	Highly complex	
Searched for					
Unskilled	0.60	0.37	0.02	0.01	0.40
Specialist	0.19	0.70	0.06	0.04	0.11
Complex specialist	0.06	0.33	0.40	0.21	0.21
Highly complex	0.03	0.13	0.13	0.71	0.00
2022	Hired at				Mobility (up)
	Unskilled	Specialist	Complex	Highly complex	
Job searched for					
Unskilled	0.67	0.29	0.02	0.02	0.33
Specialist	0.29	0.59	0.08	0.05	0.13
Complex specialist	0.09	0.29	0.42	0.21	0.21
Highly complex	0.05	0.11	0.15	0.69	0.00

Mobility (up) describes the share of moves between unemployment and employment which are above the requirement level searched for

Table 3 Mobility rates across occupation segments in 2017 and 2022 for UE transitions. Source: Statistical Office of the Federal Employment Agency, own calculations. Available at: https://statistik.arbeitsagentur.de/SiteGlobals/Forms/Suche/Einzelheftsuche_Formular.html?topic_f=beschaeftigung-sozbe-bst-berufl-mobi ©IAB

Target occupation	2017 Rate of mobility*	2022 Rate of mobility
Occupations in agriculture, forestry and horticulture	51.46	54.05
Manufacturing occupations	63.05	68.45
Occupations concerned with production technology	71.11	69.46
Occupations in building and interior construction	49.19	49.29
Occupations in the food industry, in gastronomy and in tourism	52.86	55.65
Medical and non-medical health care occupations	35.43	41.45
Service occupations in social sector and cultural work	57.48	45.88
Occupations in commerce and trade	62.35	58.82
Occupations in business management and organisation	76.37	75.70
Business related service occupations	x	x
Service occupations in the IT-sector and the natural sciences	84.17	82.44
Safety and security occupations	52.73	59.01
Occupations in traffic and logistics	47.38	47.44
Occupations in cleaning services	49.53	52.02
Across all occupation segments	53.87	54.63

*Mobility describes the share of moves between unemployment and employment to a different occupation segment than searched for

Acknowledgements

I thank Enzo Weber, Ben Lochner and Alex Parker for their valuable comments and suggestions. Furthermore I want to thank participants of the ASSLE Taiwan 2023, 19th IWH/IAB Workshop on labour market policy, and of the 16th Workshop on Labour Economics of the Institute for Labour Law and Industrial Relations in the European Union (IAAEU) and Trier University for their valuable input.

Funding

I received no financial support for the research, authorship, and/or publication of this article. The author confirms sole responsibility for the following: study conception, data collection, econometric analysis and discussion of results.

Data availability

The datasets analysed in the current study are partially publicly available at the Federal Employment Agency (<https://statistik.arbeitsagentur.de/>). The job-finding and separation rates at the occupational level are not publicly available due to data protection reasons but are available from the corresponding author on reasonable request.

Declarations

Competing interests

I declare that I have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Received: 9 February 2024 Accepted: 30 October 2024

Published online: 26 December 2024

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