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Accounting for Qualification in Mismatch Unemployment

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Contents

Abstract

This paper shows the evolution of mismatch unemployment over the period from 2007 to 2022 in Germany. A substantial part of mismatch unemployment results from a misallocation on the qualification level rather than on the occupational level. Taking the qualification level into account, an upward trend in mismatch unemployment in the aftermath of the COVID-Crisis emerges that raises the share of mismatch unemployment in total unemployment about 3 percentage points in comparison the pre-COVID level. Furthermore, I can show that the COVID-Crisis had a different impact on the occupation-qualification level than the Global Financial Crisis. In a nutshell, the COVID-crisis hit especially the labor market for unskilled and semi-skilled workers.

Zusammenfassung

Dieses Papier zeigt die Entwicklung der Mismatch-Arbeitslosigkeit in Deutschland im Zeitraum von 2007 bis 2022. Ein wesentlicher Teil der Mismatch-Arbeitslosigkeit resultiert aus einer Fehlallokation auf der Qualifikationsebene und nicht auf der beruflichen Ebene. Unter Berücksichtigung des Qualifikationsniveaus zeigt sich ein Aufwärtstrend der Mismatch-Arbeitslosigkeit nach der Covid-Krise, der den Anteil der Mismatch-Arbeitslosigkeit an der Gesamtarbeitslosigkeit um etwa 3 Prozentpunkte über dem Vor-Krisen-Niveau liegt. Zudem hatte die Covid-Krise einen anderen Einfluss auf das Berufsqualifikationsniveau als die globale Finanzkrise. Zusammenfassend lässt sich sagen, dass die Covid-Krise vor allem den Arbeitsmarkt für un- und angelernte Arbeitskräfte getroffen hat.

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Keywords

allocation, job finding rate, mismatch, occupation

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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/Popp, 2022). In addition, employment growth has slowed since the COVID-crisis and the job-finding rate has not risen to pre-crisis levels. Long-term unemployment is also 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.

Research on mismatch unemployment dates back to the 1980's (see Jackman/Roper et al. (1987),Jackman/Layard/Savouri (1991) and Schioppa et al. (1991)) and is often discussed after recessions. New advances were made in the seminal paper by Şahin et al. (2014). In the aftermath of the Global Financial Crises (GFC), the authors showed that mismatch unemployment explains up to one third in 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/Shibata, 2023; Turrell et al., 2021; Patterson et al., 2016) or Japan (Shibata, 2020). [1]

While Şahin et al. (2014)'s approach is easily implementable, 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/Shibata (2023) look at sectors and occupations, but conclude that there might exist "more subtle dimensions over which mismatch may play a role". This paper contributes to the discussion on mismatch unemployment by looking at another dimension, namely the requirement level which serves as a proxy for qualification. 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 levels, which are based on qualification. Furthermore, not much is known about mismatch unemployment thus far for Germany (see for example,Bauer (2013) Hutter/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 different than in countries like the US or the UK. So I

[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/Van Rens (2020) or Barnichon/Figura (2015) instead rely on different approaches to measure mismatch unemployment.

contribute to the question how the German experience is different compared to existing studies that analyse different countries, and between the GFC and the CC.

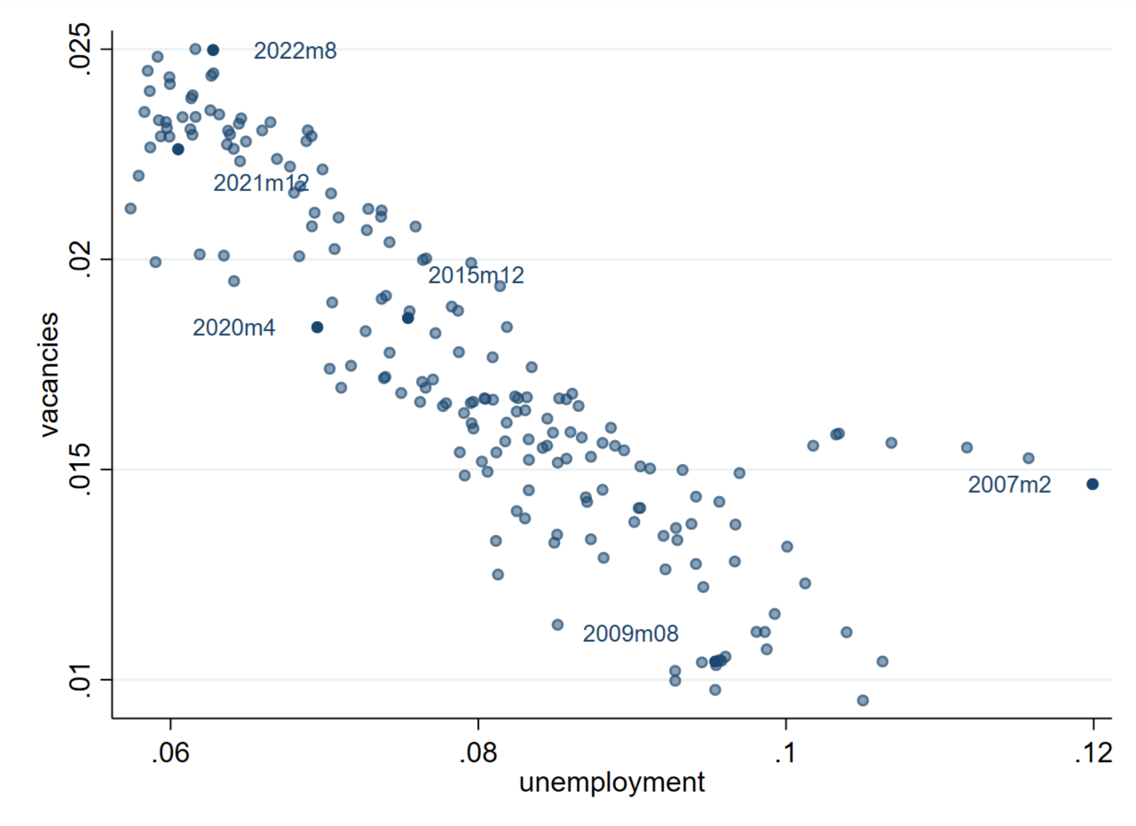
I find that between 5 and 20 percent of hires are lost due to a misallocation looking at the time horizon from 2007 to 2022. Across this period, mismatch unemployment came down from about 40 percent to 20 percent on a 3-digit occupation level, and from 40 to 30 percent on the 3-digit occupation-requirement level. Most of this evolution happened until 2012, afterwards there is only little movement 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 on the occupation-requirement level since 2021.

2 The German labor market

A good starting point for a discussion on mismatch unemployment is 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 2000's after a set of labor market reforms (the so-called Hartz reforms) were introduced (see Figure 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 restructuring the Employment Agency, and wage moderation (Launov/Wälde, 2013; Krebs/Scheffel, 2013; Launov/Wälde, 2016; Bradley/Kügler, 2019; Hochmuth et al., 2021). During the GFC and the CC the German labor market circled 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 2010's. The period of the CC is located at the upper left end of the curve. 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 Figure 2).The job-finding rate was increasing in the mid 2010's. The increase stopped around 2018 and the job-finding rate was moving sideways or even down. 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, it quickly recovered and followed again its downward trend (Bauer/Weber, 2021b). If at all, the separation rate dropped even more in the aftermath of the CC. At the same time,

Figure 1: Beveridge Curve 2007-2022



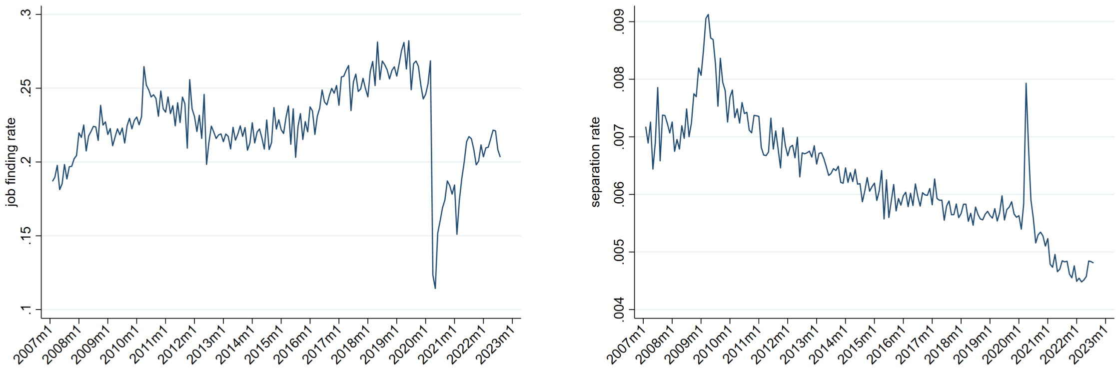
Notes: Vacancies and Unemployment are normalised as rates by employment.
Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

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 due to structural imbalances such as a bad fit between the unemployed and the vacant positions.

3 Data

I use 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

Figure 2: Flow rates, 2007-2022



Notes: The job-finding rate is calculated as the movements between unemployment and employment over the stock of last periods unemployment. The separation rate is calculated as movements between employment and unemployment over last periods stock of employment.
Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

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 mandatory. Because of that, in a robustness check, I combine this administrative data with survey data, which projects vacancies at a national level (i.e., IAB Vacancy Survey). The job-findings relate to movements between 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.

I end up with a panel that 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 up unemployment, vacancies, job-findings and separations to the national level by summing over the occupations. [2]

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.

[2] 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.

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/Matthes et al., 2013). At a 5-digit level the classification comprises 1300 different occupations. The 5th digit, however, relates to the requirement level, which 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. 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.

For the main analysis I choose the baseline to be the 2-digit occupation code of this classification (i.e., 37 occupations). This level is granular enough to account for changes in certain occupations but not too granular such that it contains a lot of missing values or zeros. Furthermore, I use an aggregation which maps the 5-digit classification into 14 occupation segments (Matthes/Meinken/Neuhauser, 2015). For the exploration of the qualification dimension, I rely on the 5th digit of the scale and also interact it with different occupation scales and occupation segments.

4 Method

The method proposed by Şahin et al. (2014) 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 as outlined above. This suboptimal allocation (compared to a planner's solution) can be captured by an index.

4.1 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. Hence search frictions exist in every market and are captured by matching efficiency [3]. 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).

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

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., $\bar{\phi}_t = \left[\sum_{i=1}^{I} \phi_i^{\frac{1}{\alpha}} \left(\frac{v_{it}}{v_t}\right)\right]^{\alpha}$, where ϕ denotes matching efficiency.

4.2 Estimations

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

$$ln(\mathit{jfr}_t) = \beta_0 + \alpha ln(\theta_t) + e_t \tag{2}$$

The job-finding-rate jfr_t is defined as changes from unemployment to employment over last period's stock of unemployment ($\mathit{jfr}_t = EU_t/U_{t-1}$) 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 to 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

[3] 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.

last period's stock of unemployment. β_i is capturing the fixed effect of every submarket and e_{it} is the error term.

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

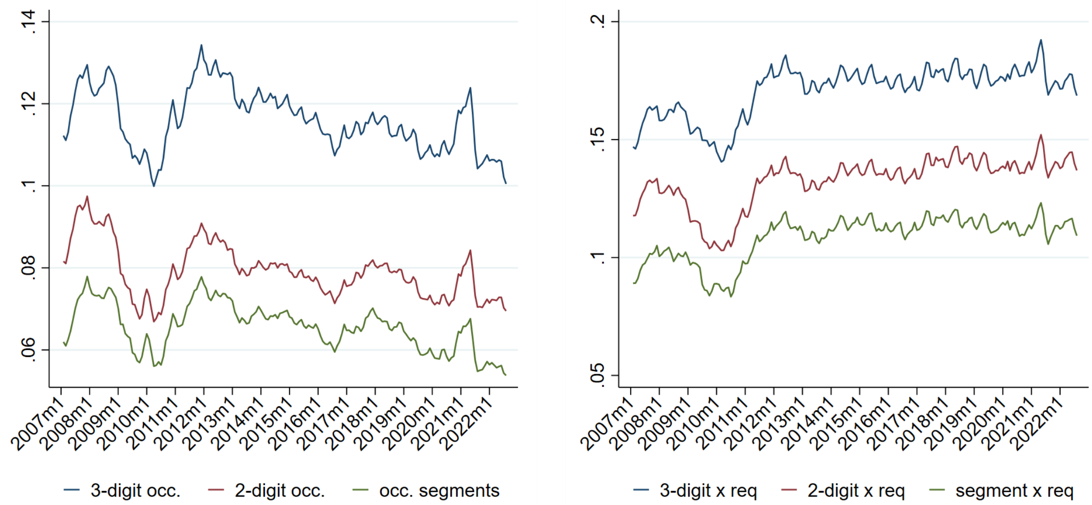
where

$$\phi_i = exp(\beta_i) \tag{4}$$

I use the submarket-specific constant out of this fixed effects regression and exponate 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.

5 Results

Figure 3: Mismatch indices, 2007-2022, occupations (left) and occupations x requirement level (right)



Notes: All series are seasonal adjusted using X-12-ARIMA.
Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

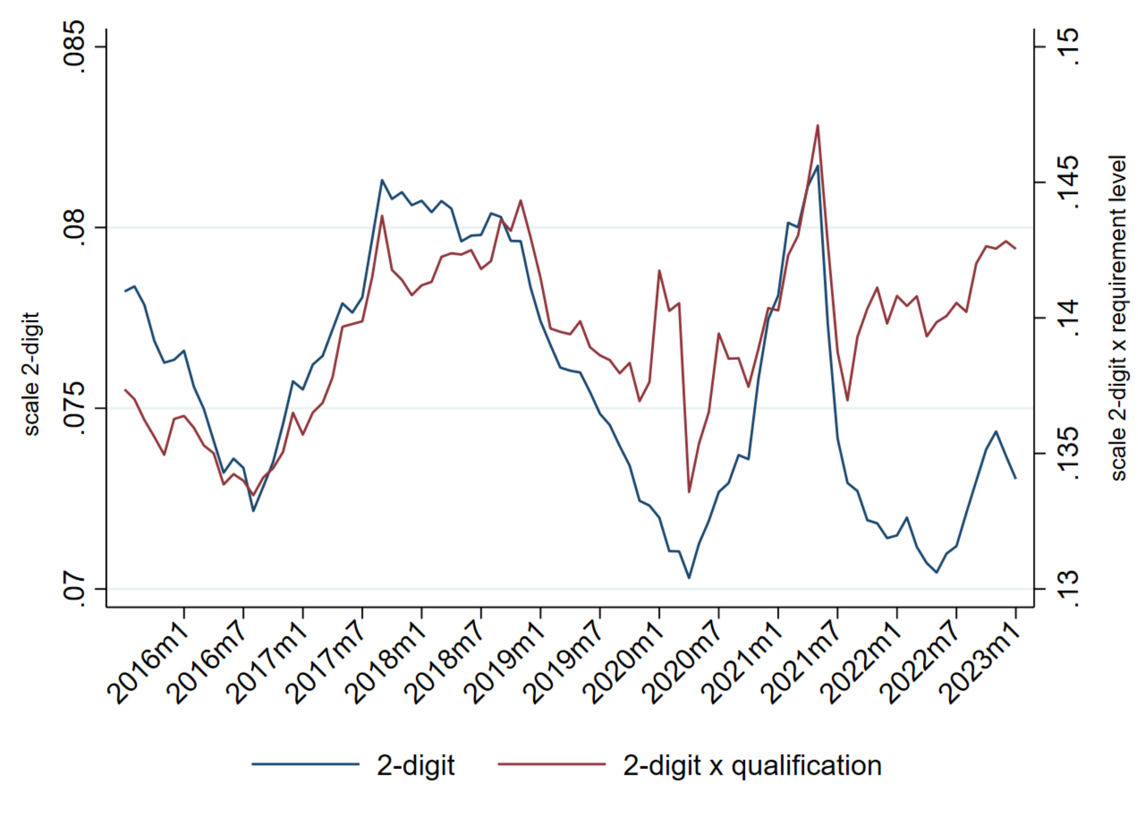
Figure 3 shows the indices over time constructed as in equation 1. They have very similar patterns over time, but different levels ranging from 0.05 (occupation segments, left panel) to almost 0.2 (3-digit occupation x requirement level, right panel), which means that, at most, 20 percent of hires are 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 figure 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). The interruptions in the beginning of 2020 due to the COVID-19-crisis are visible in both series. Concluding, while occupational mismatch seemed to decline in Germany over time, there are imbalances in the qualification mix in the economy that keep mismatch up. To get a sense whether this movement contributed to the tight labor market in the aftermath of the CC, I plot the mismatch index of the 2-digit occupation level against the mismatch index on the 2-digit occupation-requirement level for a time period beginning in 2016 (see figure 4).

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/Kosyakova/Schuss (2020) and Bundesagentur für Arbeit (2020) point out, unemployment of asylum seekers increased steadily from 2016 to 2020, but on average, 35 percent of the refugees who entered Germany between 2013 and 2016 found a job after the second half of 2018. That appears to be in line with my results as there is this increase in the mismatch measure until the beginning of 2018, and then the decrease afterwards. It is well known that the skill set of refugees is very different from the skill set of the German population. The number of asylum seekers that have no or only a primary education is rather high. Overall, after 2018 refugees took up employment more rapidly, which might explain the decrease in mismatch unemployment until the CC unfolded.

When COVID-19 hit the German economy, the government enforced two strict lockdowns, one in spring 2020 and one in winter 2020/2021 (Bauer/Weber, 2021a). In the first lockdown, the unemployment rate increased from 5.1 to 6.3 percent (i.e., by more than 600 thousand persons), the pool of registered vacant positions dropped by 20 percent (see Key Figures for the Labour Market - Germany (Monthly Report)).[4] However, compared to other countries, the German ”short-time-work”-scheme served as a stabilizer and saved jobs (Gehrke/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. Regarding mismatch unemployment, the CC increased it temporarily. It came down during the opening up after the second lockdown in 2021, and as Figure 4 shows, returned to pre-crisis level only at the 2-digit level. In comparison, the series on the interaction of 2-digit occupations with the requirement level stayed elevated and follows a different trend now. In absolute numbers, the series of the mismatch index on the 2-digit occupation level rose from 7.0 percent in April 2020 to 8.2 percent in May 2021 an then reverted back to 7.1 percent in May 2022. For the interaction of the 2-digit classification and the requirement level, the values increased from 13.4 to 14.7 and back to 14.0 percent. In June 2022 both series increased again when the refugees of the Ukraine entered the unemployment pool in Germany. This is suggestive

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

Figure 4: Mismatch indices, 2015-2022



Notes: All series are seasonal adjusted using X-12-ARIMA.
Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

evidence that the tight labor market in Germany may be explained by a misallocation on the qualification level.

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:

$$u^*_{t+1} = s_t + (1 - s_t - f^*_t)\, u^*_t \tag{1}$$

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:

$$f_t^* = \bar{\phi}_t \Phi_t \left(\frac{v_t}{u_t^*} \right)^{\alpha} = f_t \cdot \frac{1}{1 - M_t} \left(\frac{u_t}{u_t^*} \right)^{\alpha} \tag{2}$$

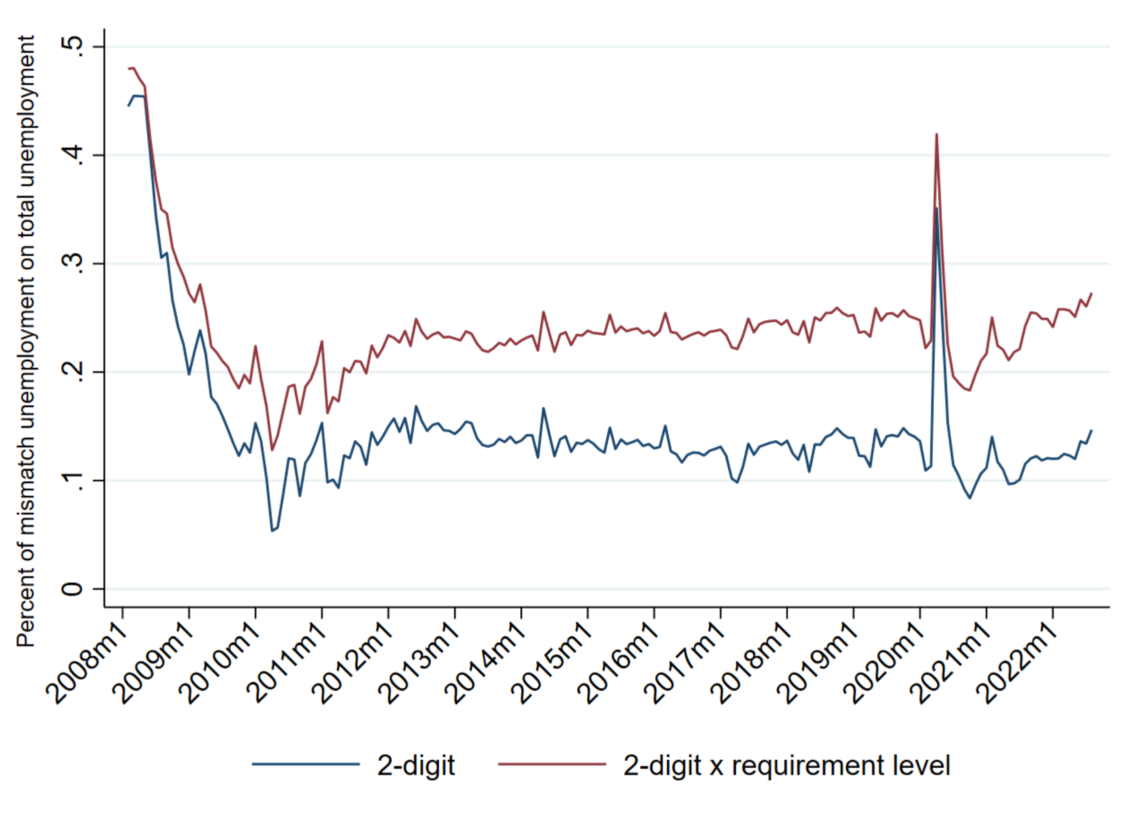
As starting value, I choose $u_t^* = u_t$. As the unemployment rate in my data is downward biased [5], it is not helpful to depict the counterfactual and actual unemployment rate in levels. Therefore I proceed with a calculation where I use the difference between actual and counterfactual unemployment (i.e., mismatch unemployment) over the actual unemployment rate. This measure can be interpreted as the percentage share of mismatch unemployment on actual unemployment.

Figure 5 plots this measure over time. Mismatch unemployment ranges, on average, between 13 (2-digit-occupations) and 24 percent (2-digit occupations x requirement level) of total unemployment in mid 2010. The share decreased from high values in the beginning of about 40 percent to this lower levels. During the CC, the mismatch share rose quickly but only temporarily. However afterwards, there is an upward movement. This upward movement brings the 2-digit occupation series back to the pre-crisis level, but for the interaction of 2-digit occupations and qualification, mismatch unemployment rises above its pre-crisis level. In absolute numbers, it means that the share of mismatch unemployment in total unemployment rose about 3 percentage points from 24.6 percent (mean between April 2019 and March 2020) to 27.3 percent (in August 2022). So here, again there is an rise in mismatch due to the qualification component.

To get an intuition, which occupations were driving mismatch unemployment over time, I decompose the mismatch unemployment measure by occupation. The decomposition is calculated under the condition that the social planner is not able to distribute more unemployed than actual unemployed 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. Figure 6 shows the results. Overall, 6 out of 14 occupations show excess unemployment, 5 out of 14 occupations show shortages and 3 occupation segments switch over time. 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

[5] 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.

Figure 5: Mismatch Unemployment, 2008-2022

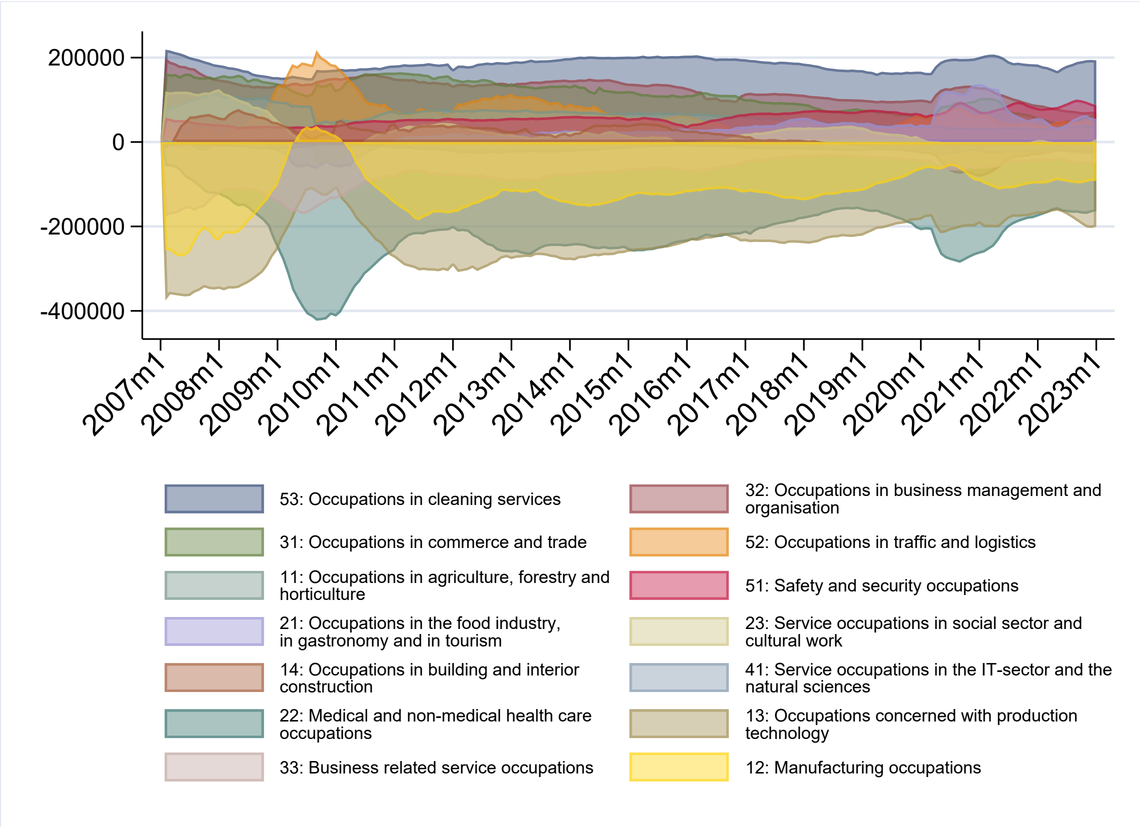


Notes: All series are seasonal adjusted using X-12-ARIMA. The series starts in 2008 to account for the effect of the starting value on the series in the beginning.
Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

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, Figure 6 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.

This exercise is similar to the decomposition exercise of Pizzinelli/Shibata (2023), however the results differ. 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/Shibata (2023) (Figure 5) show that the effects 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.

Figure 6: Distance between actual and optimal unemployment across occupation segments



Notes: 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

5.2 The requirement level in detail

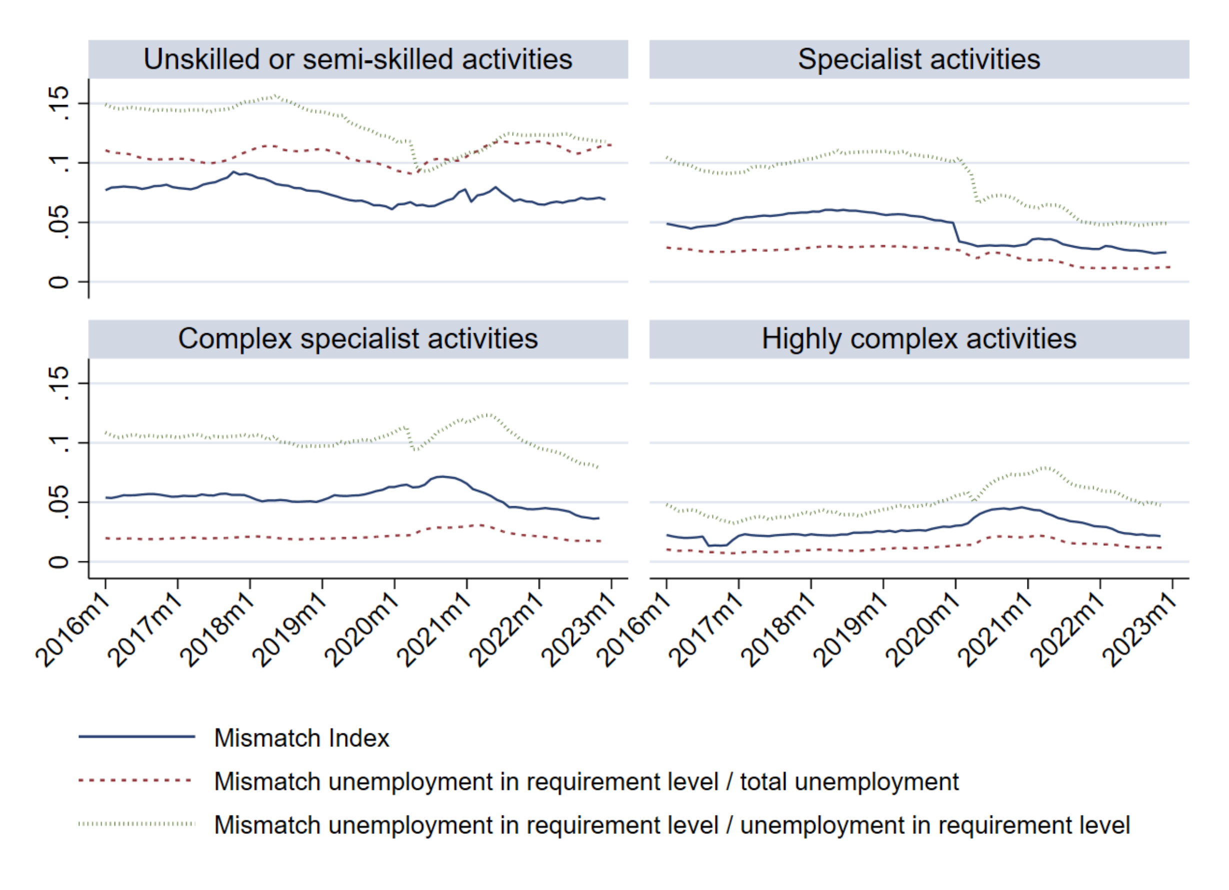
To strengthen my results, I exploit the skill dimension in more depth by dividing my data into subsamples reflecting the four requirement levels. This allows me to recalculate the indices on different levels, and gives some indication which requirement level drives the overall movement.

Figure 7 shows the mismatch index, using the vacancy and unemployment shares across the occupation segments within a certain requirement level.[6] 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 Figure 7, 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 Figure 5 stems from this group.

Tightly connected to this result is the question whether the differences across the requirement levels emerge from different occupations, especially by hard-hit occupations during the COVID-crisis. Again, 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. As figure 8 shows, 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/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 occupations differently across the requirement levels. During the GFC, the decrease in under-supply happened at the (complex) specialist activities level, while the increase of over-supply during the CC of the occupations in the food industry, in gastronomy and in tourism acted almost exclusively at the unskilled and semi-skilled requirement level. Again the medical and non-medical health care occupations appear to be different. Shortages in health care increase during recessions, but almost all of this increase happens at the special and complex specialist requirement levels.

[6] 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.

Figure 7: Mismatch index within different requirement levels



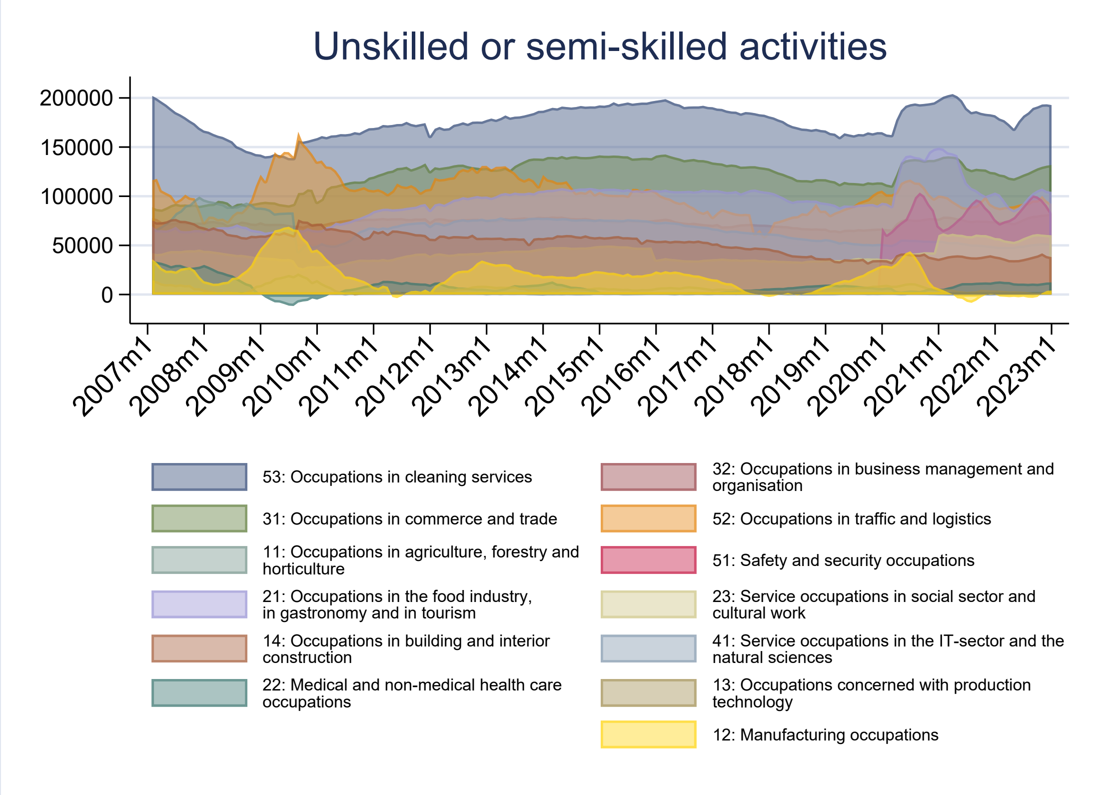
Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

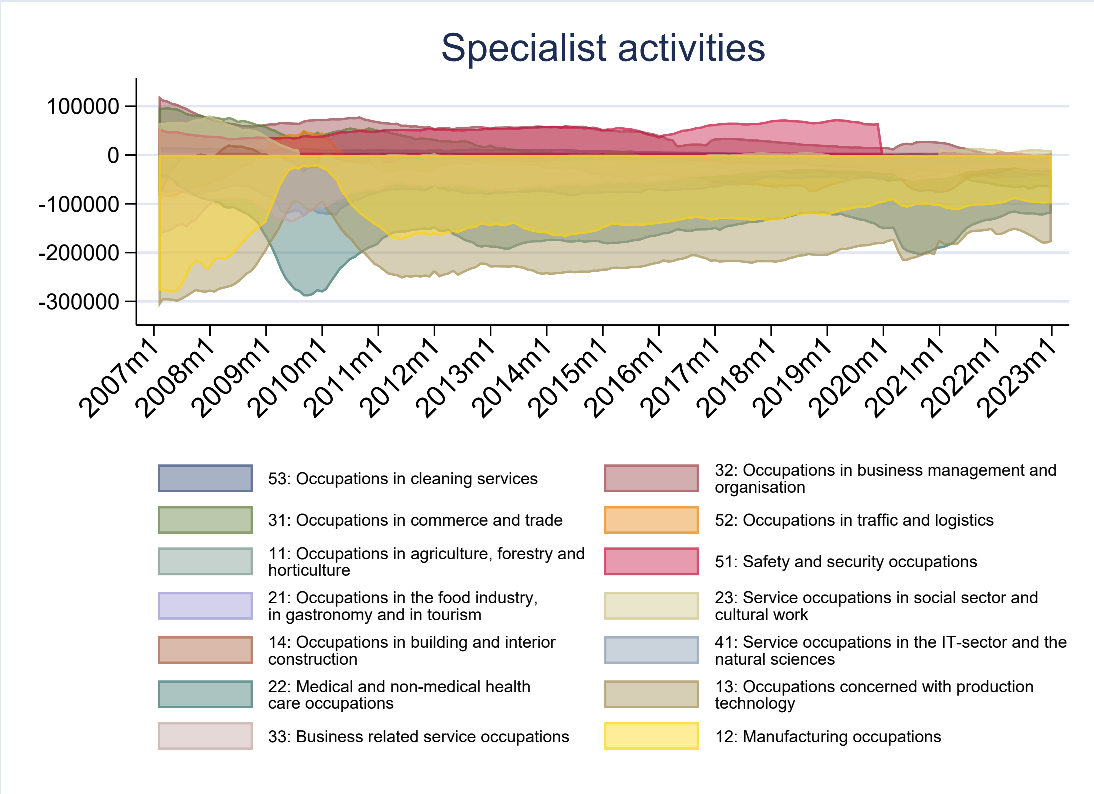
Concerning the question how these results translate back into the evolution of the mismatch indices of Figure 7 it becomes clear, that mismatch evolves in the market for unskilled and semi-skilled occupations, and here in particular, because occupations which were hit hard by the CC (especially occupations 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 revert back to the pre-CC level of over-supply.

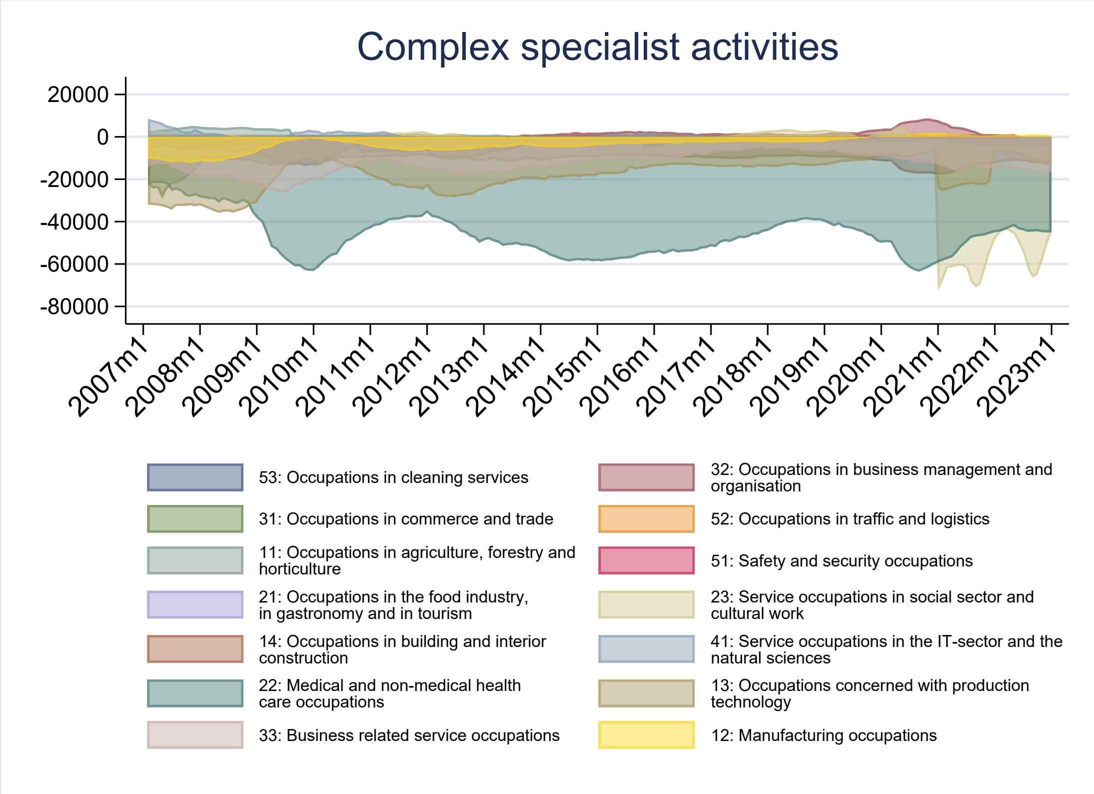
6 Conclusion

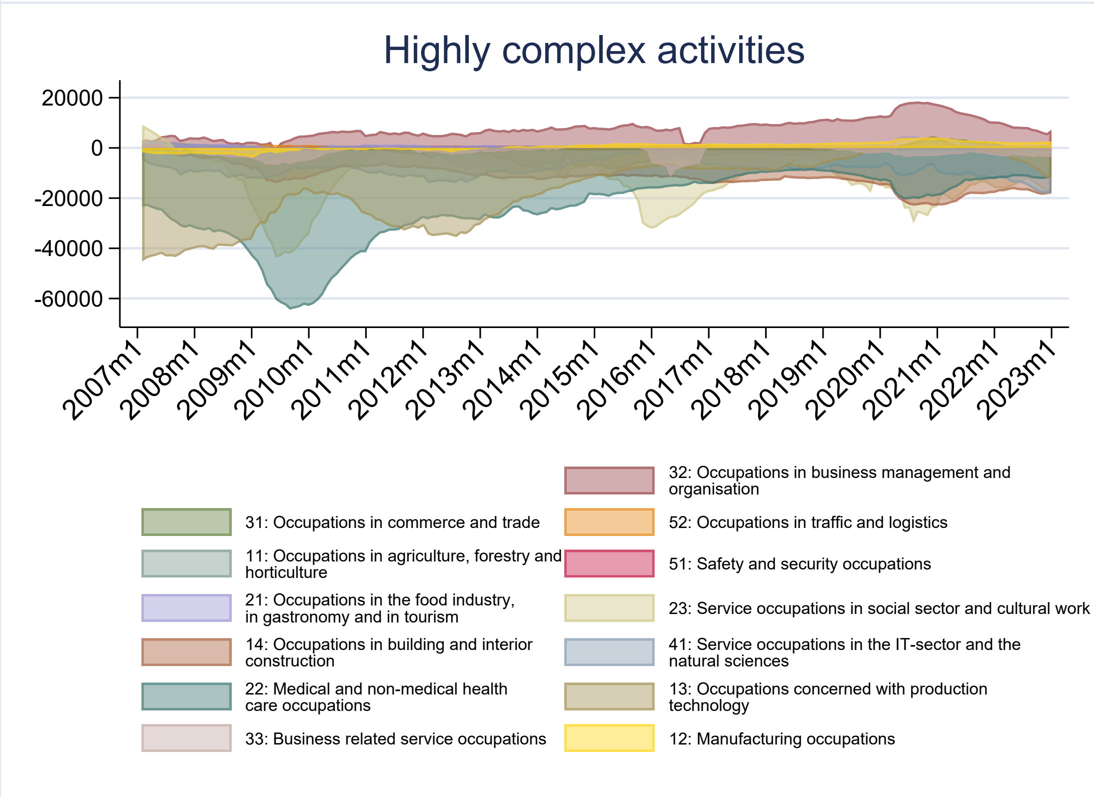
This paper shows, using the approach of Şahin et al. (2014), that over the last 15 years the number of matches that are not realized due to mismatch, or more specifically, misallocation, lies below 20 percent in the occupation and occupation-requirement dimension. This number translates into a share of at most 20 to 30 percent of mismatch

Figure 8: Distance between actual and optimal unemployment within requirement level across occupation segments









Note: 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

unemployment on total unemployment on a 2-digit occupation level (and requirement level combination respectively). Compared to other countries, the shown patterns overall behave similar. Forsythe et al. (2022) shows that during the CC mismatch only occurred temporarily in the US. Pizzinelli/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).

Furthermore, I show that mismatch measured in terms of hires lost at the occupational level appears to decline, but at the occupation-requirement level appears to be stagnate after 2012. I explore the importance of the requirement level which serves as a proxy for qualification. While mismatch unemployment on the low- and semi-skilled activity level is high and rising, mismatch unemployment decreased between 2013 and 2022, and especially after the CC at higher requirement levels. In a decomposition exercise, I shed light on the driving patterns of this result. I can show that on the level of low- and semi-skilled activities an excess supply of workers (measured in relation to a planners solution) in most occupations exist, while shortages are present in higher requirement levels.

The decomposition also allows for a comparison of the GFC and the CC. The GFC and CC hit differently in terms of mismatch across occupations. In the GFC, occupations in traffic and logistics, manufacturing occupation, and occupations concerning the production process were driving the results, during the CC it has been occupations in cleaning services,occupations in commerce and trade, occupations in the food industry, in gastronomy and in tourism. However, while the GFC hit certain occupations at almost all requirement levels, the CC hit mainly the labor market for unskilled to semi-skilled workers. Put differently, the CC intensified supply excess in occupations, that faced a large share of unskilled-to semi-skilled workers even before the onset of the pandemic.

In a nutshell, an overlooked but relevant dimension of mismatch in Germany appears to be the requirement level. More precisely, 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 of mismatch on the market for unskilled and semi-skilled workers is driven by persistence in hard hit occupations such as occupations in cleaning services,occupations in commerce and trade, occupations in the food industry, in gastronomy and in tourism. Hence activation policies in form of further training that aims to improve the requirement level of the unemployed is key to align demand and supply across requirement levels. While it would help to decrease excess supply in the semi-skilled level, it could also help to alleviate shortages in the labour market for skilled workers.

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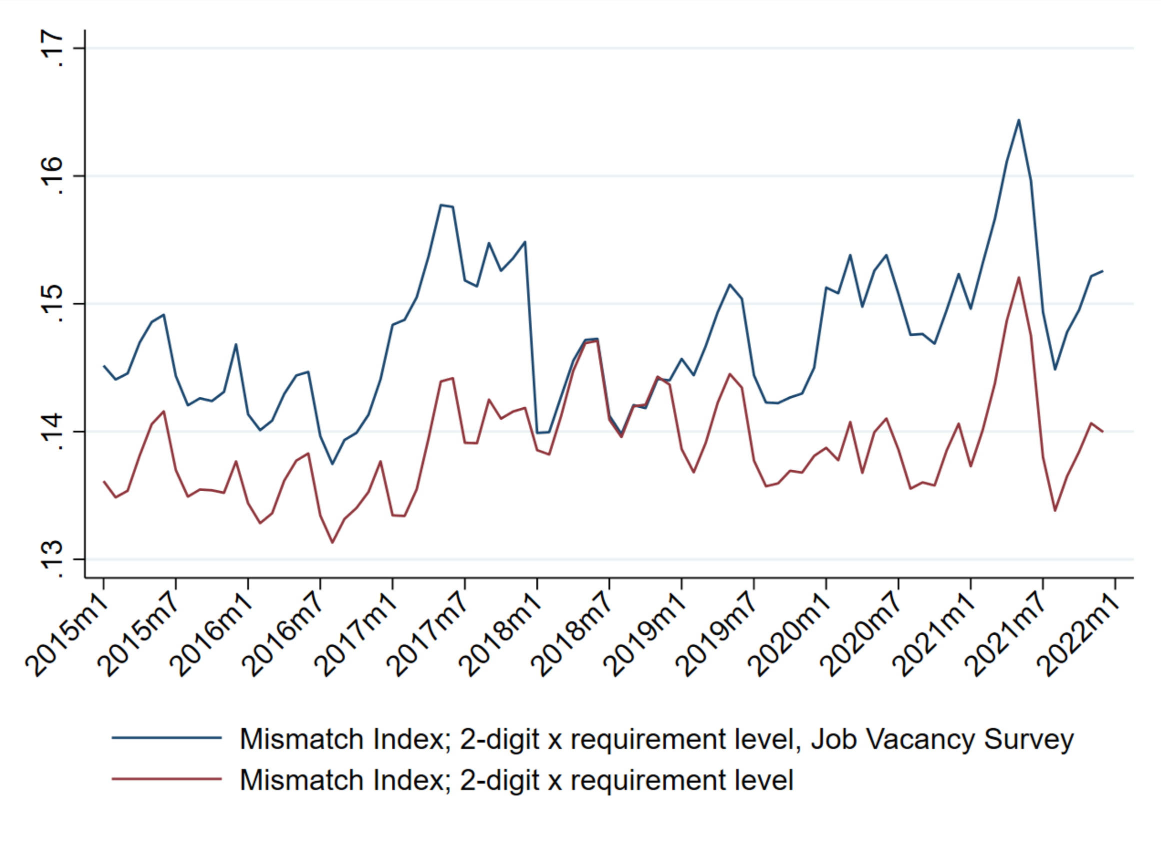
Appendix

7 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 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) and index without the term related to matching efficiency in equation 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 percent during the observation period. With respect tot the requirement level, the higher the expertise required the less likely it is that the vacancy is registered at the Federal Employment Agency. Figure A9 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.

Figure A9: Mismatch Index registered vs. IAB Job Vacancy Survey, 2008-2022

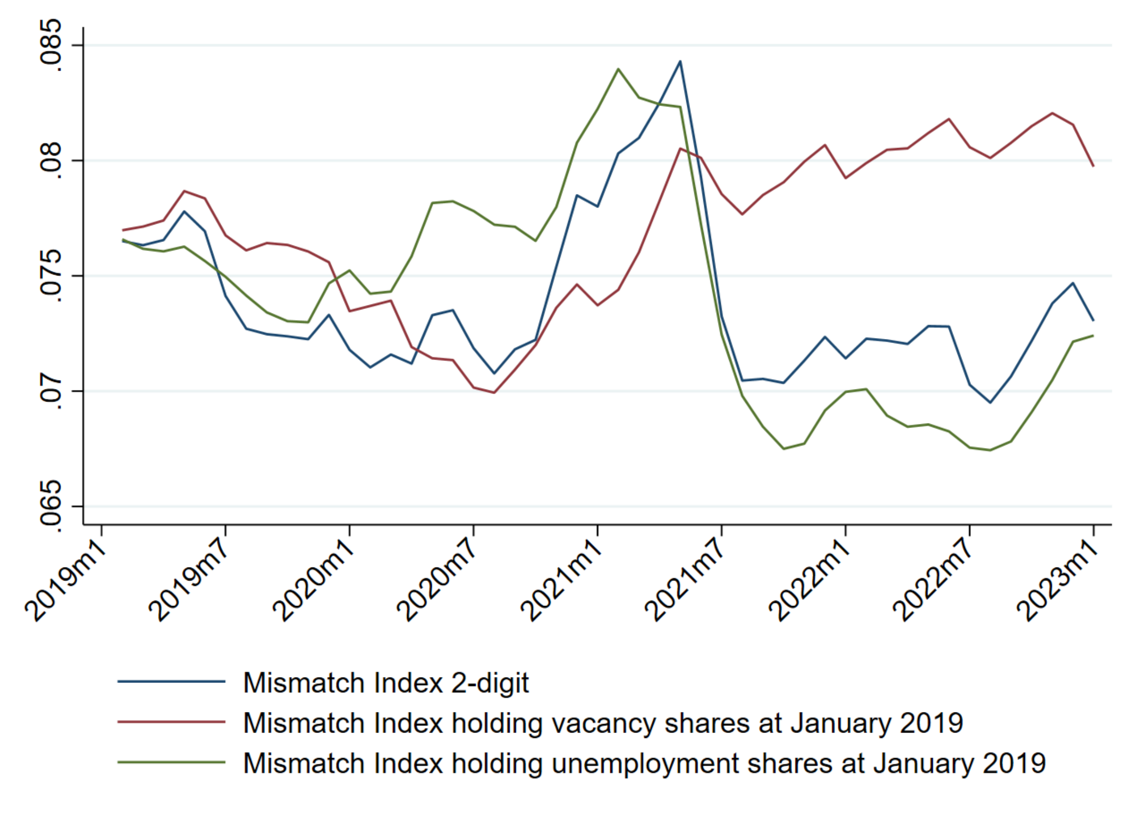


Notes: All series are seasonal adjusted using X-12-ARIMA. The series starts in 2008 to account for the effect of the starting value on the series in the beginning.
Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

8 Vacancies and Unemployment

In Figure A10 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/Weber (2017). This allows to receive a hint to which extent the 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.

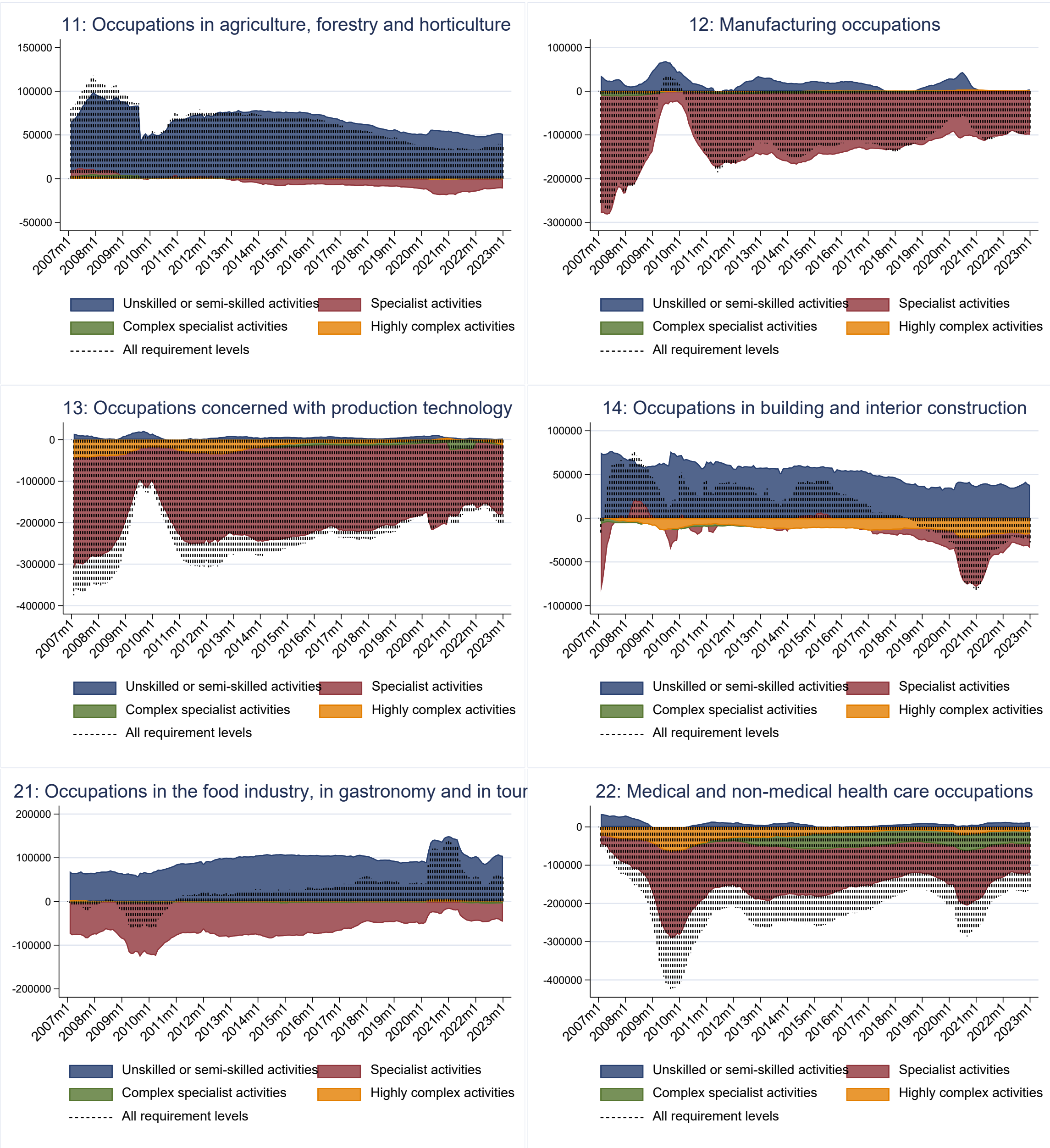
Figure A10: Mismatch indices holding either the unemployment shares or the vacancy shares constant

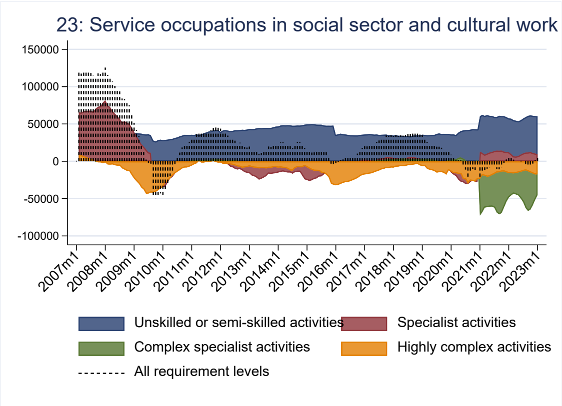


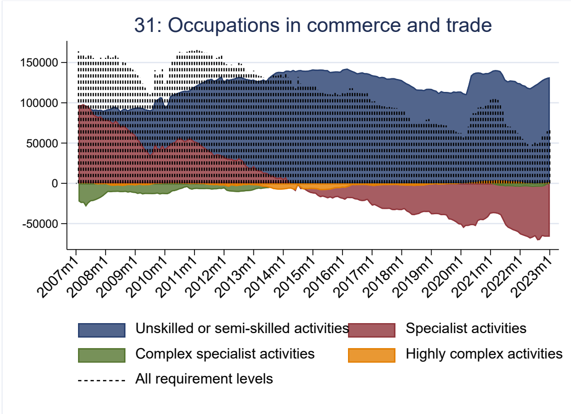
Notes: All series are seasonal adjusted using X-12-ARIMA.
Source: Statistical Office of the Federal Employment Agency, own calculations. ©IAB

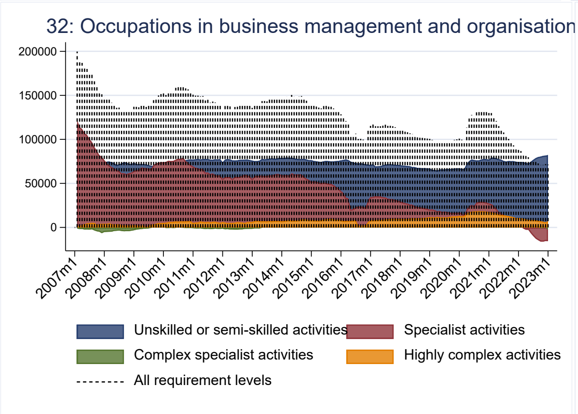
9 Within-segment evolution

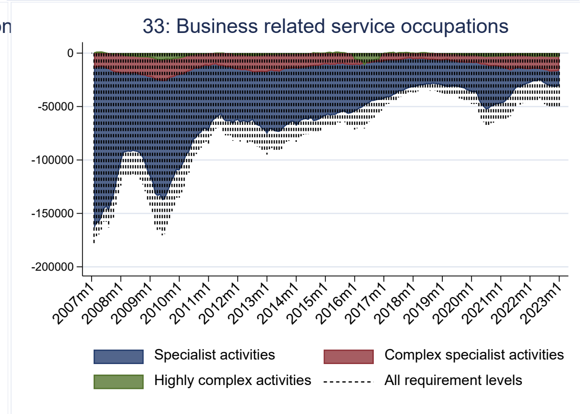
Figure A11: Distance between actual and optimal unemployment across occupation segments

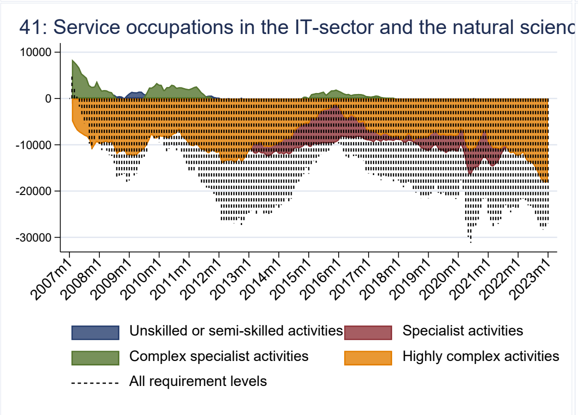


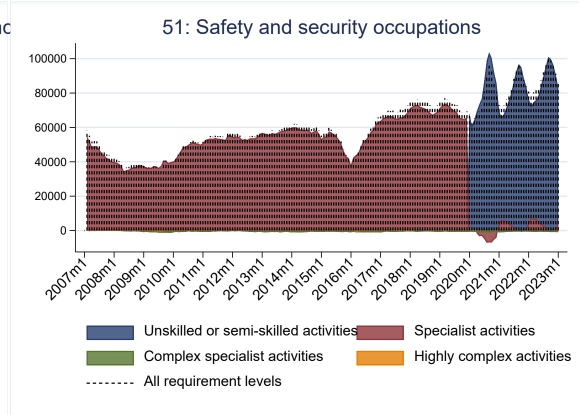

23: Service occupations in social sector and cultural work
150000
100000
50000
0
-50000
-100000
2007m1 2008m1 2009m1 2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1 2019m1 2020m1 2021m1 2022m1 2023m1
Unskilled or semi-skilled activities
Specialist activities
Complex specialist activities
Highly complex activities
All requirement levels

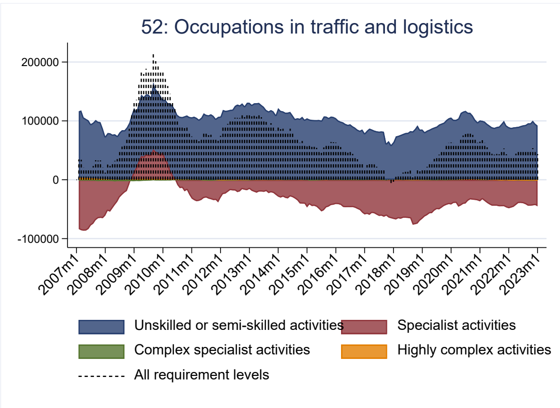

31: Occupations in commerce and trade
150000
100000
50000
0
-50000
2007m1 2008m1 2009m1 2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1 2019m1 2020m1 2021m1 2022m1 2023m1
Unskilled or semi-skilled activities
Specialist activities
Complex specialist activities
Highly complex activities
All requirement levels

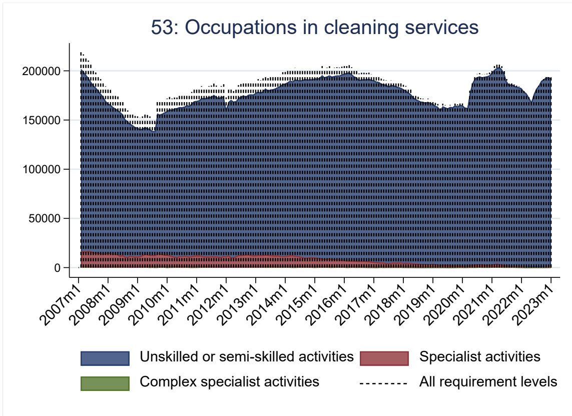

32: Occupations in business management and organisation
200000
150000
100000
50000
0
2007m1 2008m1 2009m1 2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1 2019m1 2020m1 2021m1 2022m1 2023m1
Unskilled or semi-skilled activities
Specialist activities
Complex specialist activities
Highly complex activities
All requirement levels


33: Business related service occupations
0
-50000
-100000
-150000
-200000
2007m1 2008m1 2009m1 2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1 2019m1 2020m1 2021m1 2022m1 2023m1
Specialist activities
Complex specialist activities
Highly complex activities
All requirement levels


41: Service occupations in the IT-sector and the natural scienc
10000
0
-10000
-20000
-30000
2007m1 2008m1 2009m1 2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1 2019m1 2020m1 2021m1 2022m1 2023m1
Unskilled or semi-skilled activities
Specialist activities
Complex specialist activities
Highly complex activities
All requirement levels


51: Safety and security occupations
100000
80000
60000
40000
20000
0
2007m1 2008m1 2009m1 2010m1 2011m1 2012m1 2013m1 2014m1 2015m1 2016m1 2017m1 2018m1 2019m1 2020m1 2021m1 2022m1 2023m1
Unskilled or semi-skilled activities
Specialist activities
Complex specialist activities
Highly complex activities
All requirement levels





Note: 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

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