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OCCUPATIONAL MISMATCH IN THE LABOUR MARKET OF SELECTED EU COUNTRIES

Abstract

Purpose: This paper aims to examine the occupational structures of selected EU member countries and assess their compatibility with the labour market demands, aiming to identify potential structural mismatches. The search evaluates the alignment between existing knowledge and skills in specific qualifications and those required by employers, utilizing disaggregated data from registered employment offices in Austria, Croatia, Slovenia, and Spain, spanning from 2010 to 2022.

Methodology: Methodologically, the study uses Beveridge curves, labour market tightness, and matching efficiency estimates to measure the matching needs of employers and unemployed job seekers within various occupation groups. The analysis focuses on the impact of economic downturns and fluctuations in unemployment rates on different occupation groups, with a particular emphasis on more complex and better-paid occupations.

Results: Results indicate that workers in higher-skilled occupations may experience a more resilient position within the aggregate labour market trends. However, the study reveals that deviations from these trends among occupation groups are relatively minor, underscoring the substantial influence of overall labour market conditions on all segments.

Conclusion: The research finds that differences in occupation groups have a limited impact on the broader labour market trends. Regardless of occupation complexity, improvements and deteriorations in labour market conditions affect all groups uniformly. These findings suggest a nuanced interplay between occupational structures and aggregate labour market dynamics, emphasising the need for comprehensive policy considerations to address potential mismatches and promote overall labour market efficiency.

Keywords: Mismatch, occupational groups, Beveridge curve, matching efficiency, labour market tightness

1. *Introduction*

The current divide between the prevailing educational and occupational framework, the skills acquired in schools and universities, and the skills demanded in the professional sphere poses a significant challenge. This discrepancy becomes increasingly challenging to navigate in the face of rapid technological advancements, presenting a substantial threat to economic growth and development. Over the long term, such a misalignment has the potential to markedly contribute to structural unemployment in the economy. It is crucial to acknowledge that the efficacy of the matching process also depends on business cycles.

This research primarily focuses on the fundamental aspect of the matching process, specifically addressing the alignment of employers' needs with those of unemployed job seekers to fill available positions. The overall efficiency of this matching dynamics fluctuates throughout the economic cycle due to variations in the average characteristics of the labour market. Regardless of the examined dimension (i.e., education mismatch or skill mismatch), occupational mismatch always highlights some inefficiency of a country's educational system and labour market (Flisi et al., 2017). In this part of the research, the main theoretical assumptions and existing empirical findings regarding the compatibility of the existing occupational group structure and labour market needs within the European Union will be elaborated. Most labour markets are tighter than they were before COVID-19. According to IMF research (Duval et al., 2022), the main reason why employment remains restrained, particularly compared to the pre-crisis trend, is that disadvantaged groups – including low-skilled workers, older workers, or women with young children – have yet to fully return to the labour market. To investigate the labour market more deeply, we apply the labour market matching model to various occupation groups, focusing on the link between unemployment and vacancies (new job posts). As the dynamics of job matching evolve with shifting business cycles, it becomes crucial to assess the real-time correlation. The most effective visual representation of the matching process in the labour market is the Beveridge curve, which illustrates the empirical trade-off between job vacancies and unemployment.

The Beveridge curve serves as an instrument for assessing the efficiency of labour market operations. Its negative slope signifies a tendency for vacancy and unemployment rates to exhibit inverse movements throughout the business cycle. Movements in the vacancy-unemployment space are usually related to labour market tightness and labour market efficiency (Consolo & da Silva, 2019). We examine the process of demand and supply matching by estimating labour market tightness and matching efficiency, by using the traditional aggregate matching function (Cobb-Douglas form), which relates the flow of new hires to the stock of vacancies and unemployment. To study trends in different occupation groups in the labour market instead, we focus on disaggregated data. For instance, economic downturns, causing spikes in unemployment, may disproportionately impact workers in occupations demanding lower levels of knowledge and skills.

This research adds to the current prevailing literature by utilising registered data from national employment offices in four chosen EU countries (Austria, Croatia, Slovenia, and Spain). The available data is disaggregated based on different occupations, providing a valuable perspective in this regard. Previous research mainly used Labour Force Survey data that are not disaggregated into ten ISCO-88 classification of occupations[1].

Based on the conceptual framework of the existing available literature, we develop the main research question: Do workers in different occupation groups experience similar movements in labour market tightness and matching efficiency?

Our methodological approach is divided into two parts. Firstly, we construct the Beveridge curves for different occupation groups of the four countries in our sample – Austria, Croatia, Slovenia, and Spain, and secondly, we estimate labour market tightness and matching efficiency for different occupation groups for each country. The paper is divided into six parts. After introduction, the second part provides a theoretical and conceptual background regarding different aspects of the labour market outcomes for different occupation groups, as well as focus on both historical and recent empirical evidence of labour market developments in different countries. The third part explains data and variables used, provides summary statistics, and describes the implemented model. The fourth part presents the results of disaggregated Beveridge curves and the estimates of labour market tightness and matching efficiency. In the fifth part, we discuss the results and explain the main limitations of our findings, while the sixth and final chapter concludes the paper.

1 ISCO-88 (International Standard Classification of Occupations – ISCO) outlines a broad structure of ten major occupational groups. 2, 3 and 4 digits and levels at the aggregate level are: 1. Legislators, senior officials and managers, 2. Professionals, 3. Technicians and associate professionals, 4. Clerks, 5. Service workers and shop and market sales workers, 6. Skill agricultural and fishery workers, 7. Craft and related workers, 8. Plant and machine operators and assemblers, 9. Elementary occupations, 10. Armed forces (Europa.eu, 2022).

2. Literature review

Meeting the demands of the labour market involves establishing a successful match that emphasises the interplay between unemployment and job creation. Enhanced productivity amplifies the rewards associated with job creation, leading to an elevated rate of job formation. Consequently, a higher job creation rate facilitates the process for unemployed individuals to secure employment, ultimately decreasing unemployment. This accounts for the observed counter-cyclical (pro-cyclical) nature of unemployment (job creation), (Hornstein et al., 2005). The balance between unemployment and job vacancies fluctuates based on the robustness of the labour market requirements. In a strong labour market characterised by low unemployment and high job vacancies, increases in job openings are less likely to significantly impact unemployment. This characteristic is reflected in the steep slope of the Beveridge curve[2]. Intuitively, when lots of employers are looking to hire workers but few active job seekers are available, the process of filling job openings is slowed down by the relative scarcity of available workers (Bok et al., 2022) and the efficiency of the functioning of the labour market decreases.

Beyond its slope, the shifts of the Beveridge curve (when vacancies rise and unemployment does not fall or falls too slowly) may signal the existence of structural characteristics in the labour market (Obadić, 2016) that determine how quickly job matches occur and how long they last. The ease with which job matches are established reflects the efficiency of the matching process. A decrease in matching, indicating reduced efficiency in connecting the unemployed with available positions, corresponds to a simultaneous rise in both unemployment and job vacancies. This results in an outward shift of the Beveridge curve. Conversely, an inward shift of the Beveridge curve signals an improvement in matching efficiency. Movements along the curve itself when unemployment and vacancies move in opposite directions indicate cyclical fluctuations in economic activity (Obadić, 2005).

The Beveridge curve tends to undergo shifts over time. For instance, outward shifts in the Beveridge curve were observed across various regions in Europe during the early 1970s. One of the reasons for this is an increase in the number of unemployed individuals with an unchanged number of vacancies due to the beginning of the recession (reduced aggregate demand), and the other resulted in reduced efficiency of the adjustment process due to structural factors, such as the existence of a more rigid labour market (Obadić, 2016). During the transition period in many new EU member states, the Beveridge curve exhibited an outward shift. This indicates an increase in the number of unemployed individuals relative to vacancies, even though there were instances of a rise in job openings. Such shifts of the Beveridge curve outwards with a simultaneous increase in supply and demand indicate reduced matching efficiency, i.e. an increase in the share of structural unemployment, or may be an indication of problems of structural mismatch.

In their analysis of the United States between January 2001 and December 2017, Lange & Papageorgiou (2020) found that the Beveridge curve shifted during the Great Recession and this shift was accompanied by a decline in matching efficiency (Lange & Papageorgiou, 2020). Barrero et al. (2021) investigated the onset of the COVID-19 pandemic. They asserted that the COVID-19 recession and subsequent recovery induced a significant reallocation shock, leading to unusually large shifts of jobs and workers across various industries. These changes were pushed by stable shifts in demand, such as a move from in-person services to delivered goods and an increase in industries and occupations favourable to remote work. The pandemic consistently displaced low-skilled and older workers from employment, but the transformation of labour markets was less extensive than initially anticipated after the initial wave (Duval et al., 2022). The labour markets have tightened, as evident in the outstanding flow in unfilled job vacancies (Duval et al., 2002). Similar findings were proposed by Pizzinelli and Shibata (2023). They measured the US and the UK misallocation between job seekers and vacancies across sectors until the fourth quarter of 2021, and found that total loss in employment caused by the rise in mismatch was smaller during the COVID-19 crisis than in the aftermath of the global financial crisis. During the COVID-19 recession, both countries experienced a sharp but short-lived rise in mismatch in the second and third quarters of 2020, because employment recovery started in the second half of 2020 for the US and in early

2 The negative relationship between unemployment and job vacancies was first identified by William Beveridge in the 1940s, and therefore the current curve bears his name. With this curve, he wanted to determine the extent to which the economy deviates from a state of full employment (Bleakly & Fuhrer, 1997).

2021 for the UK, after the abolishment of the lockdown measures (Pizzinelli & Shibata, 2023). This poses challenges for both employers and workers, hindering the job-matching process and leading to an outward shift of the Beveridge curve.

The findings from *LinkedIn's Economic graph* data suggest that the current outward shift in the U.S. Beveridge curve has to do primarily with cyclic factors driven by an overheated economy rather than structural problems in the labour market stemming from a decrease in matching efficiency. These cyclic factors will likely diminish soon as the economy slows, suggesting that the outward shift in the Beveridge curve should largely move backward as aggregate demand relaxes (Ghayad & Dickens, 2012; Ghayad, 2022). More precisely, the COVID-19 pandemic resulted in a strong outward shift of the Beveridge curve, marked first with a substantial increase in unemployment and followed by increasing job vacancies even as the unemployment rate returned to pre-pandemic levels. As shown by Forsythe et al. (2022), by spring 2022, the U.S. labour market had largely recovered and was characterised by extremely tight markets and a slightly depressed employment-to-population ratio driven largely by retirements. The COVID-19 pandemic has dramatically and permanently changed the way we live and work. We do see that employment has reallocated somewhat away from low-skilled service jobs, and, considering the job vacancy patterns, conclude that worker preferences or changes in job amenities are driving this shift.

The data for the Netherlands analysed in the Cabus and Somers' (2018) paper show that mismatch rates, which measure employers' view on the match between employees' skills and the job requirements, are lower in those sectors in which the average years spent in formal education by workers is lower. For example, sectors such as "Construction", and "Trade, catering, repair" reported relatively low mismatch rates both in 1991 and 2011, around 12-13%. The average number of years spent in formal education was relatively low in these two sectors as well, around 12.6 in 2011. On the other hand, the "Education" sector reported a mismatch rate of 35.5% in 2011, with an average of 16.5 years spent in formal education for workers in this sector. This clearly indicates that mismatch rates increase as job complexity increases, and sectors with relatively simpler (which, of course, does not mean easier since many of the low-skill jobs are physically very demanding) jobs have fewer problems finding workers who fit the position. However, putting these differences in sectors aside, the authors find that increases in the average schooling level of the workforce result in lower mismatch rates (Cabus & Somers, 2018).

In line with this theoretical background and the analysis of previous empirical studies, we evaluate the labour market developments in different occupation groups, as well as the relationship between newly created hires and current labour market conditions, i.e. unemployment and vacancies. The construction of the Beveridge curves allows us to compare the movements in the labour market among different occupation groups. The computation of labour market tightness enables us to examine variations in tightness dynamics across occupation groups and estimate matching functions. Through the estimation of various matching functions, we estimate the effectiveness of the matching process (matching efficiency) within different occupation groups in the four EU countries.

Therefore, we expect that the differences in occupation groups do not have a significant influence on labour market movements. We anticipate that economic downturns, which lead to increased unemployment and lower vacancies, will be felt in a similar way regardless of the differences in occupation groups, and the same outcome is expected during expansions. Moreover, we expect that labour market segments in different occupations experience similar movements in labour market tightness and matching efficiency over time.

3. Methodology

3.1 Data source and key variables

Our analysis includes four EU countries - Austria, Croatia, Slovenia, and Spain, for which disaggregated data according to occupation were available to us. The data are monthly, from January 2010 to October 2022, and were collected by national employment offices. The dataset includes three variables – Employed, Unemployed and Vacancies. Employed represents new hires, flows from the stock of the unemployed people into employment based on a new employment relationship or the start of other business activities by the previously unemployed person. Unemployed is a stock variable which represents the number of unemployed persons according to the situation on the last day of the month.

The variable Vacancies represents the stock of demanded workers that employers reported to the Employment Service during the reporting period.

We use the data disaggregated by 10 International Standard Classification of Occupations (ISCO-88) groups - managers, professionals, technicians and associate professionals, clerical support workers, service and sales workers, skilled agricultural, forestry and fishery workers, craft and related trades workers, plant and machine operators and assemblers, elementary occupations and armed forces. The occupation groups differ somewhat for Austria and are not in line with the ISCO classification, as outlined in the results section.

In constructing the Beveridge curve, the standard approach involves defining the unemployment rate as the proportion of unemployed workers to the total of employed and unemployed workers. Usually, the textbook measure of the job vacancy rate relates the number of vacancies to the size of the labour force (Obadić, 2005), while statistical databases (for example, Eurostat) often provide slightly different measures and define it as the ratio of job openings to the sum of employed workers plus job openings (Shimer, 2005). Both metrics are widely utilised, but maintaining consistency is crucial when comparing job vacancy rates across different occupation groups and time periods. Our approach to constructing the Beveridge curves differs slightly. Since we obtained the data on vacancies, unemployment and newly employed workers from different national employment offices, we were unable to obtain the data on the stock of currently employed workers needed to calculate both the unemployment and vacancy rates. To the best of our knowledge, these data disaggregated by occupation categories do not exist, i.e. they are not collected.

However, this does not present an issue for constructing Beveridge curves. According to earlier definitions, both the unemployment and vacancy rates share the same denominator - either the sum of employed and unemployed workers or the sum of employed workers and job openings. Dividing the numerator by the same number, therefore, does not change the shape of the Beveridge curves, but only expresses (in the case of Beveridge curves) values as percentages. Such practice can be found in different papers (Gomez-Salvador & Soudan, 2022; Lange & Papageorgiou, 2020, etc.), and we also follow this approach.

3.2 Descriptive statistics

In this part of the paper, descriptive statistics for four examined countries included in our analysis are presented. We use three variables in our analysis – new flows into employment, the stock of unemployed workers and vacant positions. With these variables, we can construct the Beveridge curves, as well as estimate the matching functions. Summary descriptive statistics are presented for different occupation groups. Each time series contains a total of 154 observations, from January 2010 to October 2022. The tables (see Tables 1-4) present the mean, standard deviation, minimum value and maximum value for the aforementioned variables and countries we use in the empirical estimations.

Table 1 Summary statistics for different occupation groups, Austria

	Agricultural	Industry and small trade - 1st subgroup	Industry and small trade - 2nd subgroup	Industry and small trade - 3rd subgroup	Goods and services, sales personnel, transport	Services	Trained technicians	Administrative and clerical	Health service, teaching and cultural occupations	Total
Employed mean	1056	7948	3479	5708	6097	11237	1489	4685	3325	45213
Employed standard deviation	1098	7318	1411	1666	1259	6210	324	849	1336	12784
Employed minimum value	314	855	961	2176	3481	4509	669	2660	1899	17925
Employed maximum value	4426	32010	8162	10388	9413	28551	2269	7126	8676	82280
Unemployed mean	6052	34039	20950	49379	50034	72498	11359	41063	23086	310674

	Agricultural	Industry and small trade - 1st subgroup	Industry and small trade - 2nd subgroup	Industry and small trade - 3rd subgroup	Goods and services, sales personnel, transport	Services	Trained technicians	Administrative and clerical	Health service, teaching and cultural occupations	Total
Unemployed standard deviation	2903	18885	5014	8986	9106	20216	1748	5895	4780	62465
Unemployed minimum value	2594	15655	13183	33831	35535	40722	8284	31704	13932	207944
Unemployed maximum value	12286	76675	33067	74021	81909	167936	15601	60713	37246	522253
Vacancies mean	609	5933	8109	5973	8116	10219	5138	5280	4022	53400
Vacancies standard deviation	354	3264	3909	4093	4715	5346	3342	3676	2731	30439
Vacancies minimum value	134	1378	2907	1771	3316	4661	1353	1834	1540	21763
Vacancies maximum value	1572	13231	17079	18736	21730	30397	13555	15545	11324	141139

Source: Authors' calculations based on the Public Employment Service Austria (2022) data

Table 2 Summary statistics for different occupation groups, Croatia

	ISCO 0	ISCO 1	ISCO 2	ISCO 3	ISCO 4	ISCO 5	ISCO 6	ISCO 7	ISCO 8	ISCO 9	Total
Employed mean	1	2	1518	2491	1709	3188	109	1903	769	2258	13949
Employed standard deviation	3	2	609	855	678	1863	52	914	355	1131	5523
Employed minimum value	0	0	414	765	535	919	22	550	249	788	4760
Employed maximum value	23	10	4121	5088	3438	8215	249	4420	1753	5803	28764
Unemployed mean	15	47	16700	32817	31202	42626	2308	33033	12568	61948	233265
Unemployed standard deviation	9	22	3956	11770	10742	18356	651	19008	6592	16942	86291
Unemployed minimum value	0	15	9542	15214	14636	14068	1322	9260	4041	36489	105796
Unemployed maximum value	41	201	24406	54891	49105	76755	3481	63198	22849	92013	384376
Vacancies mean	9	17	2352	2453	1161	3417	68	2384	823	3183	15869
Vacancies standard deviation	57	7	989	942	486	1770	41	1019	441	1676	5825
Vacancies minimum value	0	4	371	547	237	665	5	515	177	508	5035
Vacancies maximum value	550	46	5430	4903	2229	7722	227	4976	2525	9120	30241

Source: Authors' calculations based on the Croatian Employment Services (2022) data

Table 3 Summary statistics for different occupation groups, Slovenia

	ISCO 0	ISCO 1	ISCO 2	ISCO 3	ISCO 4	ISCO 5	ISCO 6	ISCO 7	ISCO 8	ISCO 9	Total
Employed mean	5	92	524	475	364	810	33	930	386	879	4497
Employed standard deviation	3	24	229	109	94	232	24	478	121	333	1285
Employed minimum value	0	45	148	179	148	275	5	285	145	356	1986
Employed maximum value	23	152	1393	744	667	1767	136	2737	683	2263	8730
Unemployed mean	57	1807	6658	8386	7748	13477	603	13327	7174	18303	77539
Unemployed standard deviation	13	342	1366	1918	1090	2225	116	3928	2159	3240	15532
Unemployed minimum value	32	1140	3990	4528	4967	8319	300	5760	3520	9854	42412
Unemployed maximum value	94	2435	9129	11392	9404	17375	874	20790	10802	23619	103987
Vacancies mean	7	176	2059	1088	599	1662	46	2825	1050	2040	11553
Vacancies standard deviation	23	84	843	365	242	530	24	884	348	877	3404
Vacancies minimum value	0	60	632	313	115	560	10	1057	305	584	4336
Vacancies maximum value	160	444	4950	2139	1183	2880	133	5622	1917	4476	19527

Source: Authors' calculations based on the Employment Service of Slovenia (2022) data

Table 4 Summary statistics for different occupation groups, Spain

	ISCO 0	ISCO 1	ISCO 2	ISCO 3	ISCO 4	ISCO 5	ISCO 6	ISCO 7	ISCO 8	ISCO 9
Employed mean	174	2392	38782	35096	37325	107208	27801	67612	25906	115304
Employed standard deviation	37	640	15587	9639	8338	30827	4641	11034	4008	23681
Employed minimum value	95	1045	13689	19029	19103	53236	17901	40766	16945	73780
Employed maximum value	330	4593	128981	74718	65984	219764	40432	90578	35419	214191
Unemployed mean	1663	33900	295335	284524	410547	931465	81305	559203	220217	1097998
Unemployed standard deviation	474	5650	46485	44795	58458	97415	10275	186134	63350	131373
Unemployed minimum value	990	24199	213785	211542	314003	747077	60160	289992	125768	860665
Unemployed maximum value	2383	43698	411043	371974	521021	1127461	99669	866547	328344	1326683
Vacancies mean	7	107	3355	3072	2137	5672	7372	5874	1424	14156
Vacancies standard deviation	23	50	1234	1345	779	2247	2787	2039	1541	4725

	ISCO 0	ISCO 1	ISCO 2	ISCO 3	ISCO 4	ISCO 5	ISCO 6	ISCO 7	ISCO 8	ISCO 9
Vacancies minimum value	0	10	859	384	275	2100	1280	2078	235	5319
Vacancies maximum value	156	293	7103	10891	5512	20813	19529	15797	18167	38464

Source: Authors' calculations based on the Spanish Public Employment Service (2022) data

As pointed out earlier, the data is disaggregated according to different ISCO occupation groups for Croatia, Slovenia and Spain. Austria is an exception and uses a different classification methodology, as analysed further in the results section. It should also be emphasised that different national legal regulations exist regarding the obligation to report labour market needs by employers. That, for example, explains the relatively low number of vacancies compared to the number of unemployed workers for Spain.

To better explain possible compatibility between the existing offers and needs on the labour market, we estimate different matching functions for each observed country according to occupational groups.

3.3 Model

In the majority of macroeconomic models incorporating search and matching friction, the dynamics of new hires moving into the pool of job openings and the level of unemployment are typically represented through the aggregate matching function (Petrongolo & Pissarides, 2001; Pissarides, 2000; Bernstein et al., 2022). In the analysis of the labour market, the matching function is employed to grasp the interconnection between the number of job vacancies and unemployed workers, as well as to separate how alterations in one variable impact the other. One of the most common aggregate matching function models used in the labour market is the Cobb-Douglas matching function[3]. The function is typically represented as (Blanchard & Diamond, 1992; Kohlbrecher et al., 2014; Barnichon & Figura, 2015, Lange & Papageorgiou, 2020):

$$M_t = ßU_t^{\alpha}V_t^{1-\alpha}, \tag{1}$$

where *M* is the number of matches or the number of outflows from the unemployed to the employed or hires, *U* is the number of unemployed workers, *V* is the number of vacancies, *ß* indicates the efficiency of the labour market, exponents α and *1-α* are parameters that reflect the responsiveness of matches to changes in vacancies and unemployment, respectively, and t stands for linear time trend. The matching function is strictly increasing, strictly concave, twice differentiable in both arguments, and exhibits constant returns to scale (Petrongolo & Pissarides, 2001). The Cobb-Douglas matching function is universal in search and matching models, even though it imposes a constant[4] elasticity of matches with respect to vacancies that is unlikely to hold empirically (Kohlbrecher et al., 2014; Bernstein et al., 2022).

Following Barnichon and Figura (2015) and Consolo and da Silva (2019), we first define the job finding rate f_t as the ratio of new hires to the stock of the unemployed, $f_t = \frac{M_t}{U_t}$, so that

$$f_t = \beta\theta_t^{1-\alpha} \,. \tag{2}$$

$\theta = \frac{V}{U}$ defines labour market tightness, and then we estimate the matching function in the log-linear form

$$lnf_{i,t} = \beta_0 + (1-\alpha) * ln\theta_{i,t} + \varepsilon_{i,t} \tag{3}$$

The variable M *(Employed)* represents new hires, outflows from the stock of unemployment into employment. The *U (Unemployed)* variable represents the number of unemployed persons in the records according to the situation on the last day of the month and *V* (*Vacancies*) represents the stock of demanded workers that employers reported to the

3 It is named after economists Paul H. Douglas and Charles W. Cobb, who first proposed it in the 1950s.

4 The specification in log form imposes constant returns to scale so the coefficients sum to one (Lange & Papageorgiou, 2020).

national employment offices during the reporting period. As already mentioned, f_t is the job finding rate, θ_t is labour market tightness, and ε_t denotes regression residuals. The subscript *i* refers to different countries for which we estimate separate regression equations, *i* = Austria, Croatia, Slovenia, and Spain. Subscript *t* refers to monthly data from February 2010 to October 2022. The equation is estimated by using OLS.

The job finding rate f_t is related to a quantitative margin and a qualitative margin. The quantitative margin is the level of market tightness (vacancy-unemployment ratio), while the qualitative margin is related to the efficiency of the matching process (Consolo & da Silva, 2019). The regression residuals ε_t from Equation 3 capture the efficiency of the matching process or movements in matching efficiency for a particular occupation group in a specific country. The theoretical correlation between the job finding rate and labour market tightness is positive, indicating that increased tightness is expected to lead to a higher job finding rate. The question arises as to why we assess matching efficiency by utilising regression residuals. Let us assume that regression residuals are negative for a specific period. This means that the difference between the real (observed, empirical) job finding rate and the job finding rate predicted by the estimated matching function is negative. In other words, the observed job finding rate is lower than what one would expect based on the corresponding labour market tightness (the explanatory variable in regression) level and the estimated matching function. This means that, for some reason independent of the current labour market tightness level, the job finding rate decreased, and this is interpreted as a decrease in matching efficiency. Positive residuals derived from the matching function estimates are construed in a similar manner, signifying an enhancement in matching efficiency. This implies a higher observed job finding rate than what would be anticipated based on the corresponding level of labour market tightness during that specific period.

Prior to computing labour market tightness and deriving estimates for the matching functions and matching efficiency, we create Beveridge curves using data on vacancies and unemployed individuals. As detailed in the Data section, we form the Beveridge curves by employing the overall counts of vacancies and unemployed workers, rather than presenting them as vacancy and unemployment rates. This approach does not alter the shapes of the Beveridge curves, enabling us to analyse both the shifts along the Beveridge curve and the inward and outward movements of the curve.

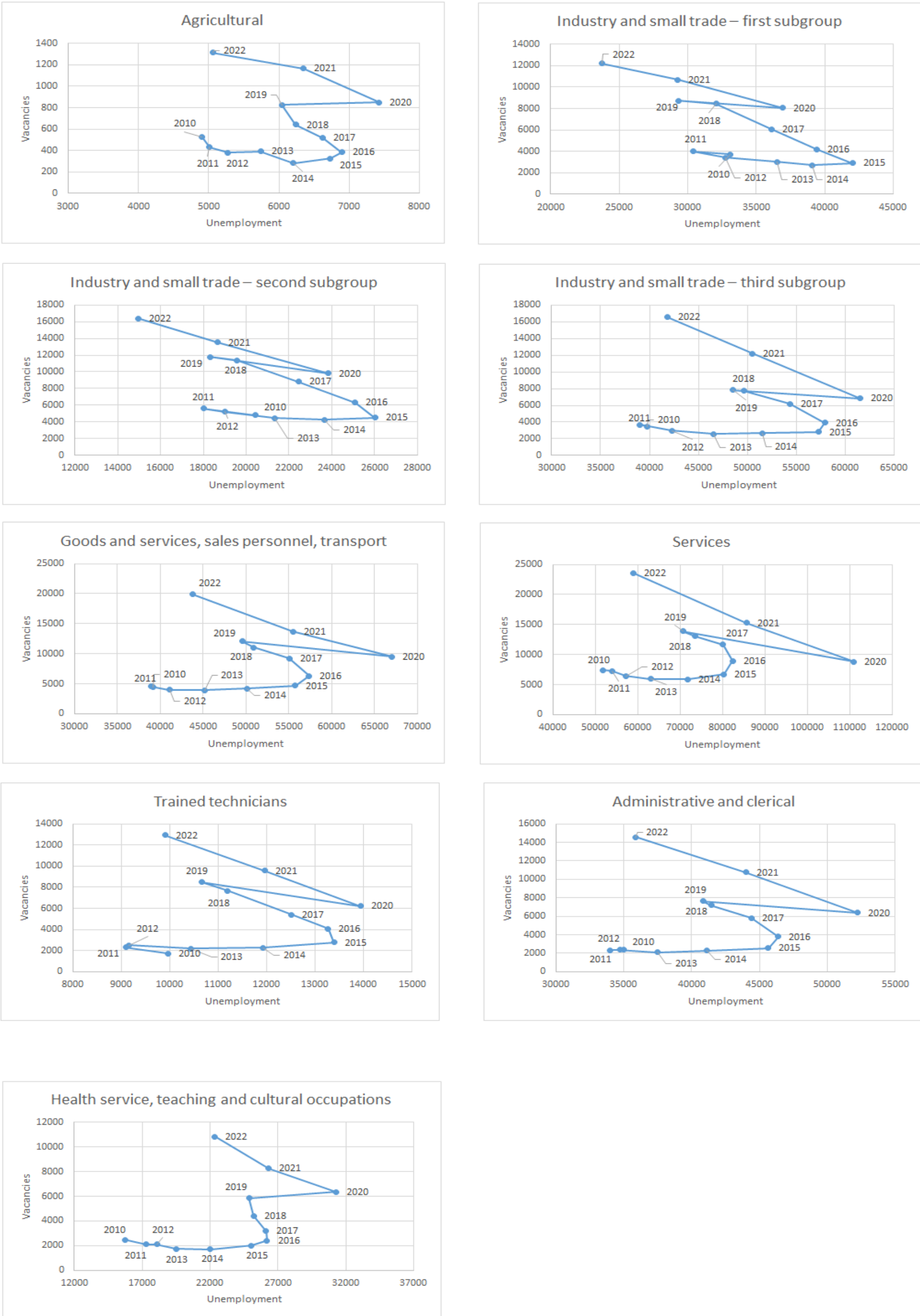
4. Results

Our research results section is divided into two parts. We present first the Beveridge curves disaggregated by occupation and then the estimates of labour market tightness and matching efficiency for different occupation groups for each country.

4.1 Beveridge curves disaggregated by occupation

In our further analysis, the disaggregated Beveridge curves are derived according to different ISCO-88 occupations for each country. Figure 1 shows disaggregated Beveridge curves for Austria.

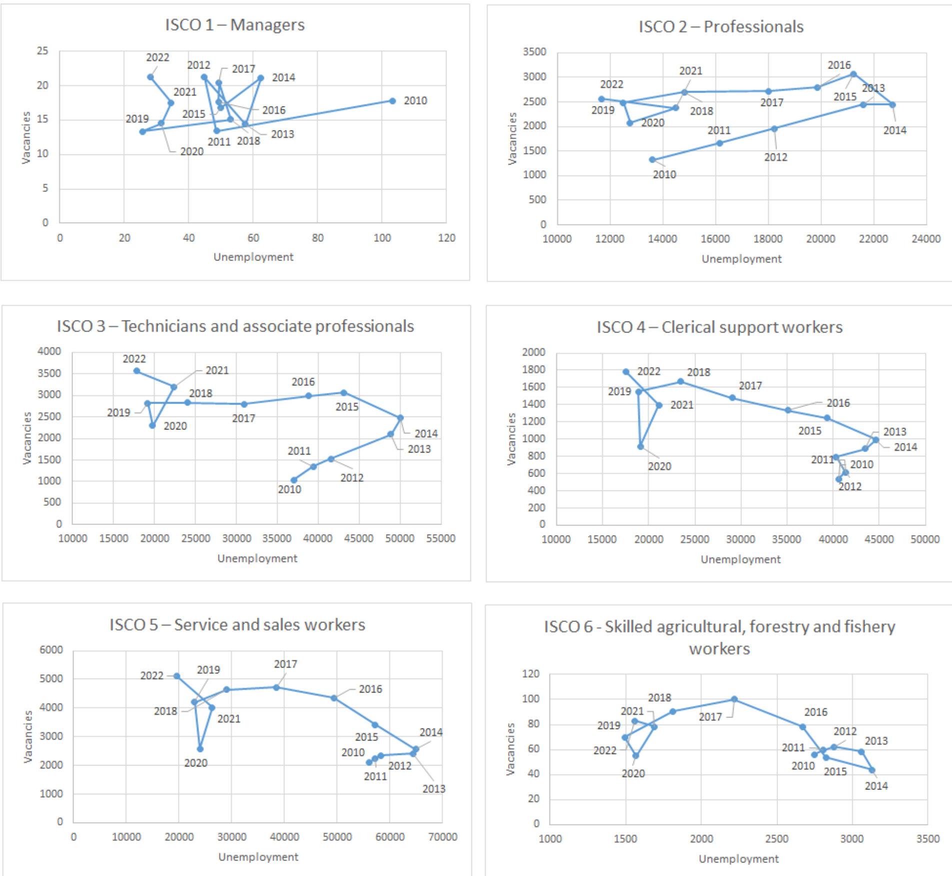
Figure 1 Disaggregated Beveridge curves for different occupation groups, Austria

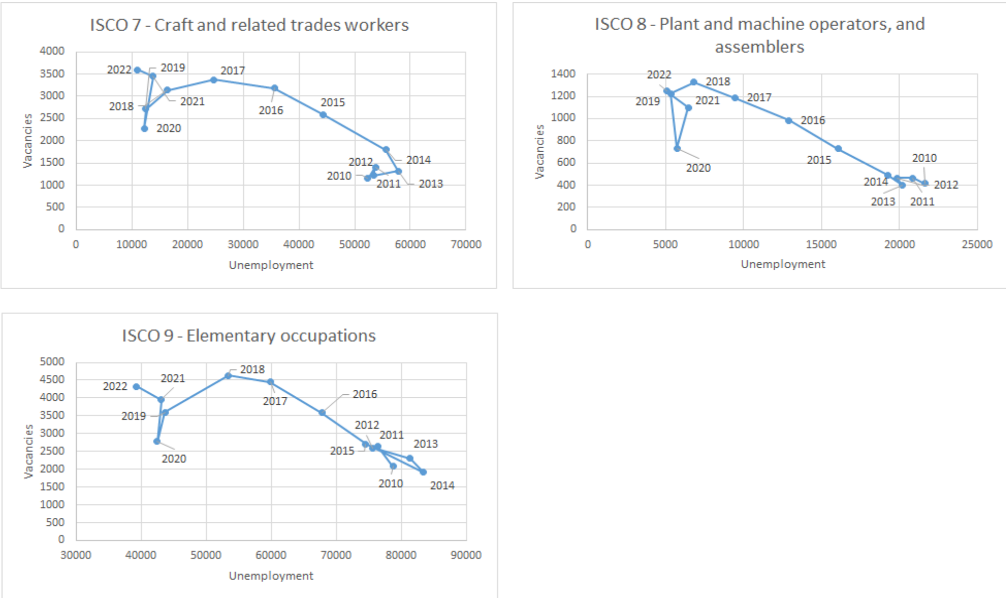


Source: Authors' calculations based on the Public Employment Service Austria (2022) data

All Beveridge curves for different occupation groups in Austria show relatively similar behaviour – the early years of the period, from 2010 to around 2016, are marked by an outward shift of the Beveridge curve, i.e. an increase in unemployment for roughly the same level of vacancies. The period from 2016 to 2019 is then marked by improving labour market conditions for workers, with unemployment decreasing and vacancies increasing for all occupation groups, with the exception of "Health service, teaching and cultural occupations". In this group, there is only a slight decrease in unemployment with an identical increase in vacancies as in other groups, which cannot indicate an improvement in matching in that group of classifications. As already mentioned, according to the aggregate Beveridge curve for Austria, the 2020 pandemic resulted in a completely different trend in Austria, which was not present in any of the other countries in our group. Austria faced a significant increase in recorded unemployment – a strong increase in the number of unemployed workers and roughly similar levels of vacancies as in 2019. The worsening of labour market conditions was short-term, and 2021 and 2022 saw the continuation of the labour market tightening, with unemployment decreasing and vacancies increasing. The Beveridge curves disaggregated by occupation have similar shapes to the aggregate Beveridge curve, indicating rather similar developments in all areas of the Austrian labour market.

Figure 2 Disaggregated Beveridge curves for different occupation groups, Croatia





Source: Authors' calculations based on the Croatian Employment Services (2022) data

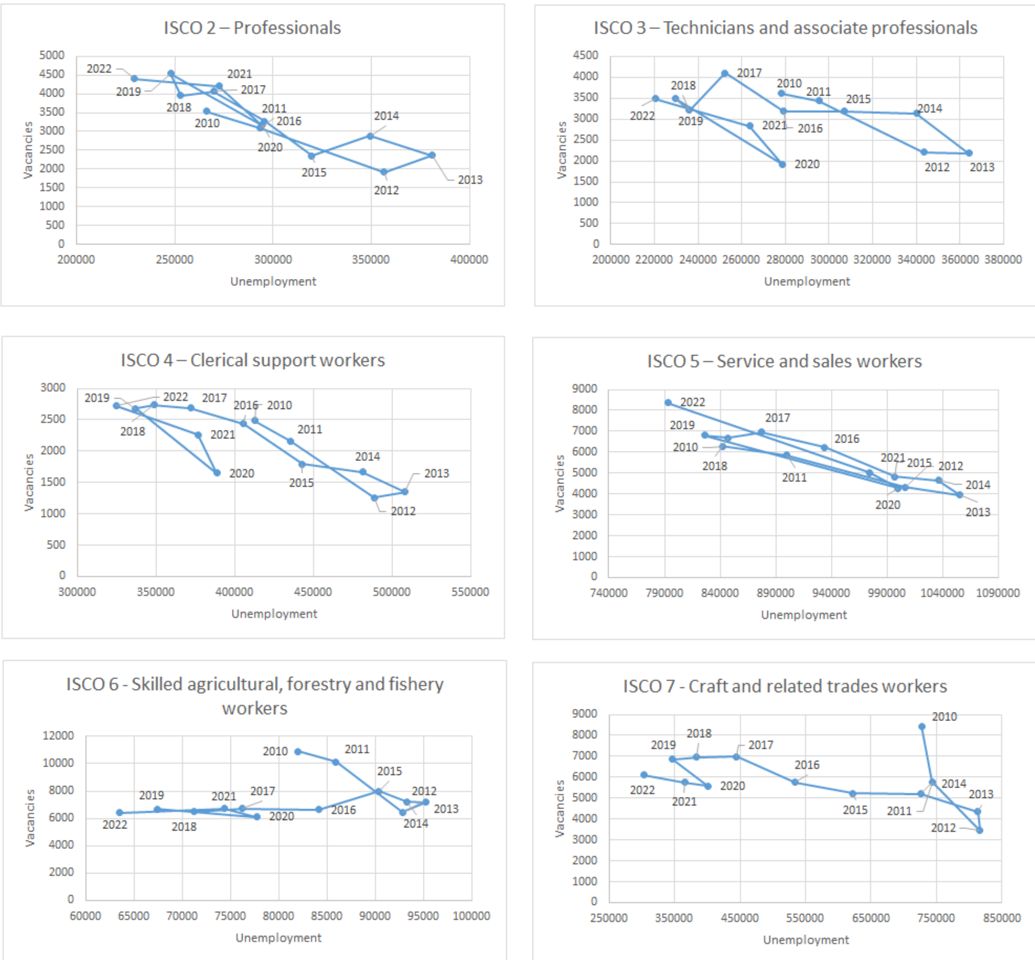
ISCO 2, 3, 4, 5 and 7 occupation groups show relatively similar behaviour. Firstly, the period from 2010 to 2014 was marked by increased unemployment, but also somewhat higher vacancies. The increases in unemployment vary from mild (ISCO 7, Craft and related trades workers) to severe (ISCO 2, Professionals), moving the Beveridge curve outwards. The period from 2014 to 2022 shows comparable movements for all but the ISCO 1 group. As the labour market conditions improved, unemployment decreased and vacancies increased, while as expected, 2020 was characterised by a drop in vacancy numbers. Unemployment did not rise noticeably in 2020 due to government measures to preserve jobs (wage subsidy measures for the private sector) in order to avoid increases in unemployment. Due to the significant recovery of aggregate demand, the year 2022 was marked by a shortage of workers in all occupation groups, which indicates increasing tightness in the Croatian labour market.

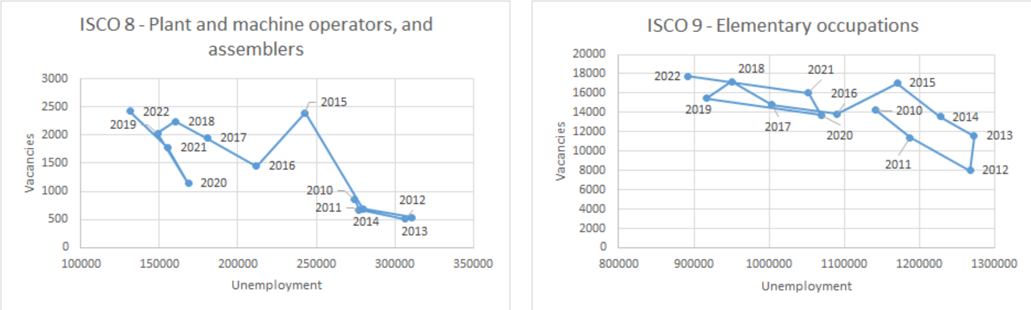
Figure 3 Disaggregated Beveridge curves for different occupation groups, Slovenia

Source: Authors' calculations based on the Employment Service of Slovenia (2022) data

With the exception of ISCO 8, all occupation groups for Slovenia recorded increased unemployment and decreasing vacancies from 2010 to 2014, a worsening of labour market conditions. However, the subsequent period showed major improvements in labour market conditions – decreasing unemployment and increasing vacancies. As was the case in Spain and Austria, 2020 deviated from these positive developments, but the labour market continued to strengthen in 2021 and 2022. ISCO 1 (Managers) and ISCO 7 (Craft and related trades workers) groups show major improvements from 2014 to 2022, with unemployment decreasing for a roughly constant level of vacancies. The largest post-pandemic increase in labour demand is present in the ISCO 2 (Professionals) and ISCO 9 (Elementary occupations) groups. This is in line with Obadić's (2020) findings that changes in employment shares of different occupation groups in EU-28 indicate present "job polarisation" - high-paid professionals, but also low-paid service and sales workers raise their shares in overall employment considerably. Medium-paid occupations, such as clerical support workers or craft and related trades workers and machine operators, suffered the largest losses in terms of employment share (Obadić, 2020).

Figure 4 Disaggregated Beveridge curves for different occupation groups, Spain





Source: Authors' calculations based on the Spanish Public Employment Service (2022) data

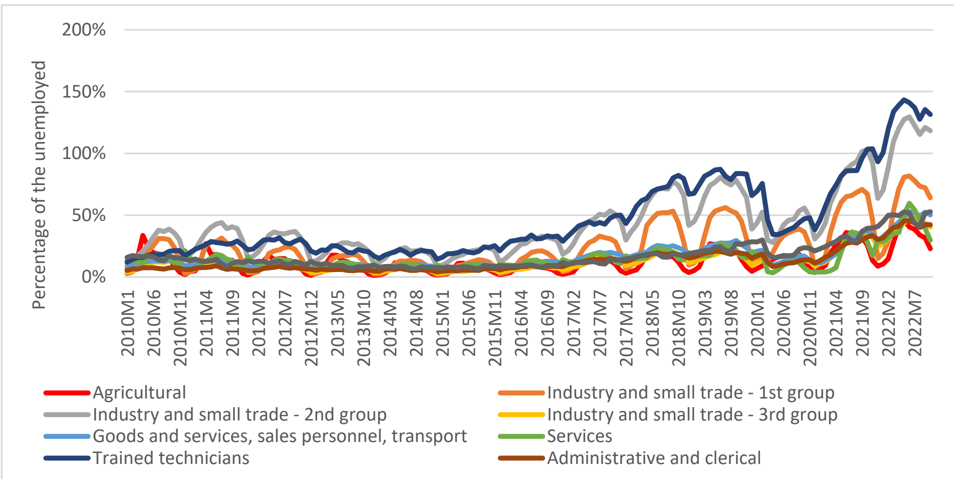
Disaggregated Beveridge curves for different occupation groups for Spain vary for different occupation groups but also show similar general patterns. The 2010-2013 period was marked by the worsening of the labour market conditions – unemployment increased, and the number of vacant positions decreased. The later period shows improvements in the labour market conditions – an inward move along the negatively sloped Beveridge curve (higher vacancies and lower unemployment) for ISCO 2, 3, 4, 5, 8 and 9 levels, as well as an inward straightforward shift (lower unemployment for roughly similar levels of vacancies) for ISCO 6 and 7 groups. All groups show short-term negative developments in 2020 – lower vacancies and increased unemployment, but also a subsequent recovery in 2021 and 2022. A similar conclusion as in the case of Austria applies to Spain – all occupation groups exhibit trends similar to the Beveridge curve for aggregate unemployment and vacancies.

In the next section, we present labour market tightness and our estimates of matching efficiency for different occupation groups for each country.

4.2 *Empirical matching process – labour market tightness and matching efficiency by occupation groups*

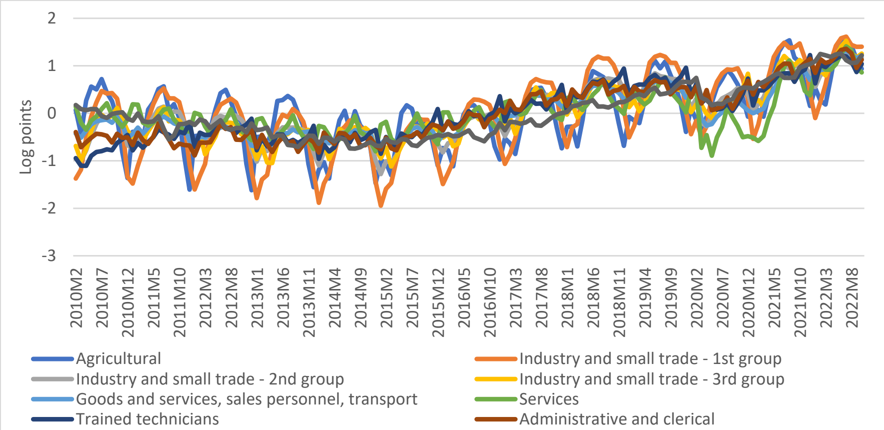
In this part of our analysis, we present labour market tightness and matching efficiency for different occupation groups in Austria, Croatia, Slovenia, and Spain. The corresponding estimates of the matching function (Equation 3) are shown in the Appendix.

Figure 5 Tightness by occupation groups, Austria, January 2010 – October 2022



Source: Authors' calculations based on the Public Employment Service Austria (2022) data

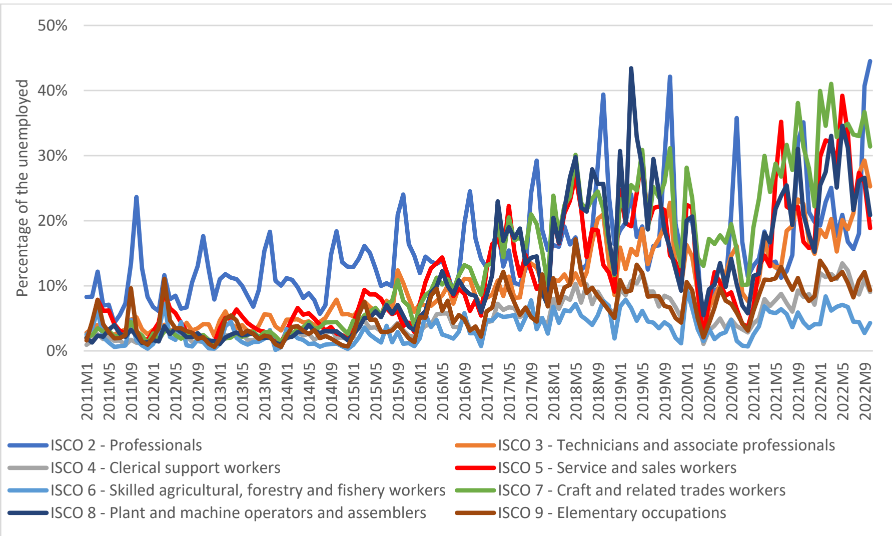
Figure 6 Matching efficiency by occupation groups, Austria, February 2010 – October 2022



Source: Authors' calculations based on the Public Employment Service Austria (2022) data

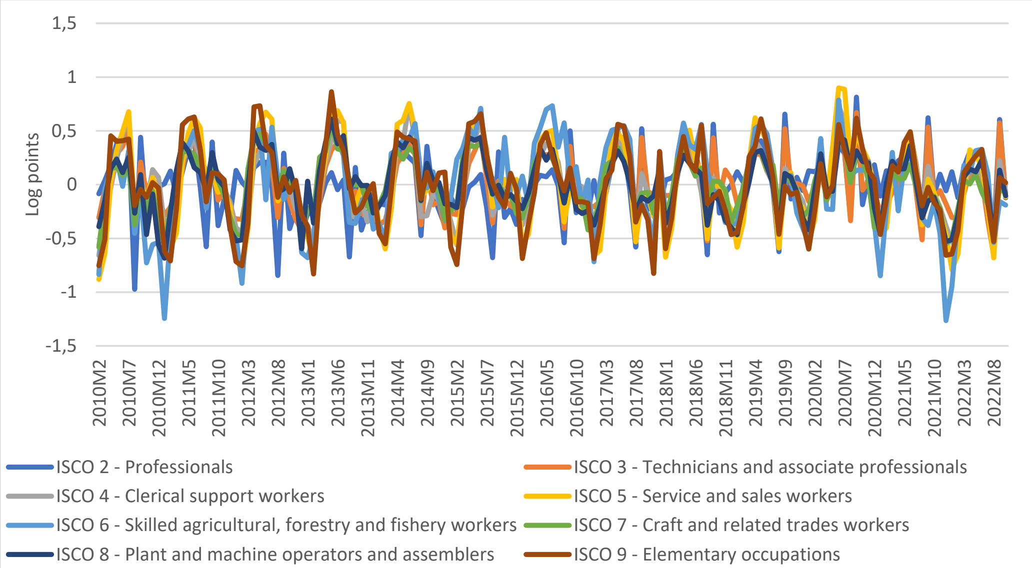
Disaggregated by occupation, different groups of workers in Austria recorded an increase in labour market tightness during the ending years of the period. This increase was the strongest for Trained technicians and workers in the 2nd group of industry and small trade (woodworking occupations, leather producers and textile occupations). Regardless of the strength of the increase, a tight labour market is evident in 2022 for all occupation groups. Along with labour market tightening, matching efficiency recorded a steady increase from the beginning to the last years of the period, indicating that the education and skills of all occupation groups are in line with the needs of the labour market in Austria. Matching efficiency was highest in 2021 and 2022, the years also marked by the highest tightness, indicating highly aligned skills and education of the unemployed with the labour market needs in all occupation groups.

Figure 7 Tightness by occupation groups, Croatia, January 2010 – October 2022



Source: Authors' calculations based on the Croatian Employment Services (2022) data

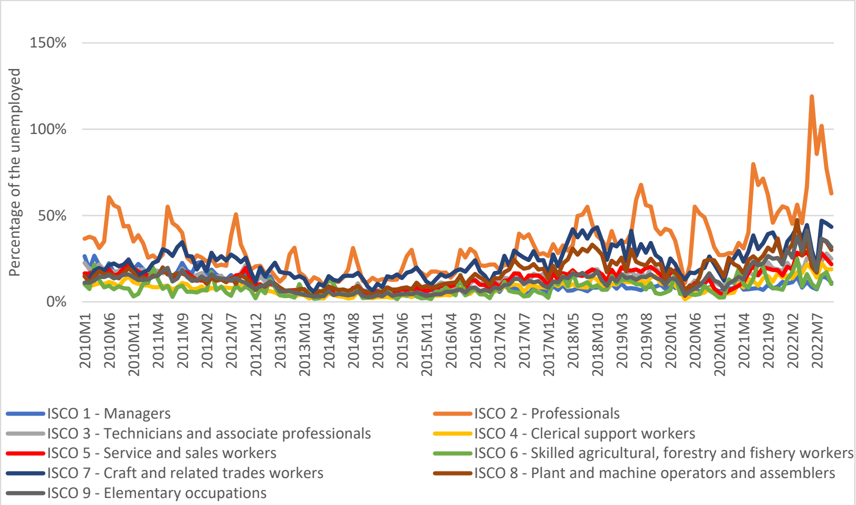
Figure 8 Matching efficiency by occupation groups, Croatia, February 2010 – October 2022



Source: Authors' calculations based on the Croatian Employment Services (2022) data

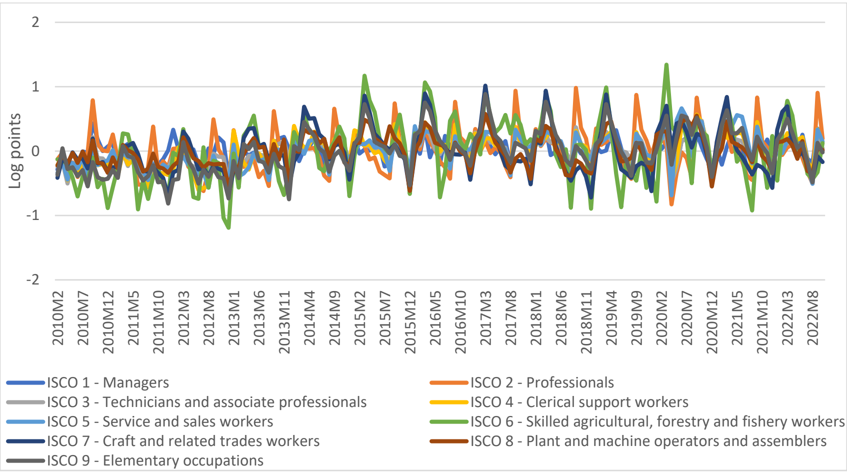
An increase in labour market tightness at the end of the period (2021 and 2022) is noticeable in all occupation groups but with considerable differences in magnitude. The increase was strongest for occupation groups such as service and sales workers, craft and related workers and professionals, and weakest for skilled agricultural, forestry and fishery workers. Labour market efficiency remained relatively similar during the entire period for all groups of workers, though the 2010-2012 period recorded somewhat lower levels of matching efficiency compared with the remaining part of the period. Since matching efficiency did not decrease along with increased tightness at the end of the period, this points to the conclusion that the skills of workers in different occupation groups are in line with the needs of the labour market. This conclusion holds more strongly for groups that experienced larger increases in tightness in 2021 and 2022 (craft and related trades, service and sales, professionals, plant and machine operations and assemblers, and technicians and associate professionals), which means that increases in demand for these workers did not result in fewer matches, or less successful job finding, compared to what one would expect based on the estimate of the matching function.

Figure 9 Tightness by occupation groups, Slovenia, January 2010 – October 2022



Source: Authors' calculations based on the Employment Service of Slovenia (2022) data

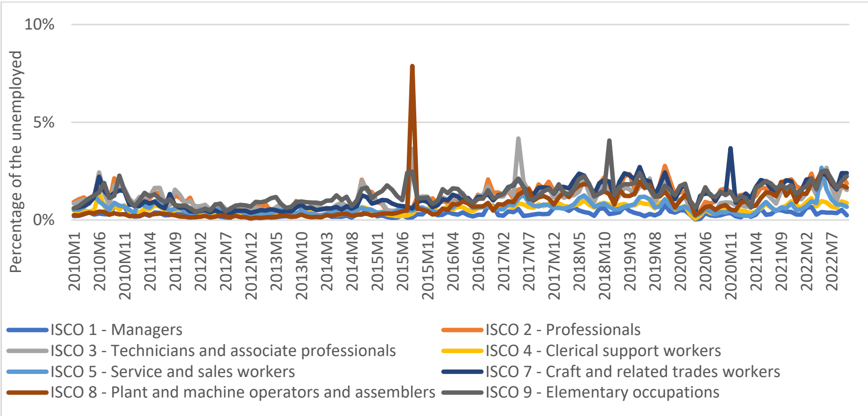
Figure 10 Matching efficiency by occupation groups, Slovenia, February 2010 – October 2022



Source: Authors' calculations based on the Employment Service of Slovenia (2022) data

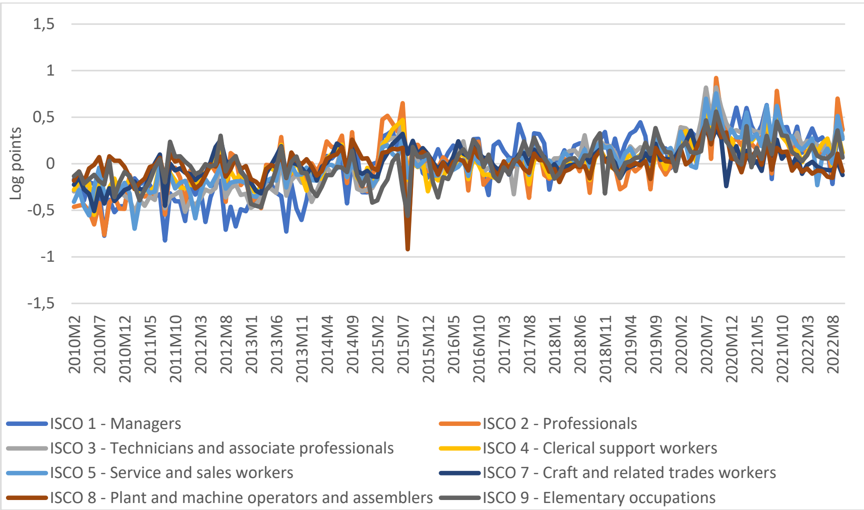
Matching efficiency in Slovenia was lowest during the early years of the period (2010-2013), increasing afterward. Matching efficiency remained relatively stable during the later years of the period, reaching relatively high levels during the period from 2015 to 2017. Interestingly enough, matching efficiency actually increased during 2020, the year which also recorded a drop in labour market tightness. Tightness increased in 2021 and 2022 compared to 2020, especially for ISCO 2 - Professionals, and matching efficiency dropped only slightly compared to 2020 and the 2015-2017 period. This indicates that higher demand for workers (tightness) in Slovenia translated into more matches between the unemployed and employers without considerable losses in matching efficiency in 2021 and 2022. Therefore, the needs of the labour market are well adjusted with the education and skills of workers among different ISCO occupation groups. The only exception to this general trend is the ISCO 6 (skilled agricultural, forestry and fishery workers) group, which did not record considerable increases in tightness in 2021 and 2022, but did record a minor drop in matching efficiency.

Figure 11 Tightness by occupation groups, Spain, January 2010 – October 2022



Source: Authors' calculations based on the Spanish Public Employment Service (2022) data

Figure 12 Matching efficiency by occupation groups, Spain, February 2010 – October 2022



Source: Authors' calculations based on the Spanish Public Employment Service (2022) data

Matching efficiency in different occupation groups in Spain gradually increased over the 2010-2022 period, with lower efficiency in the first and higher efficiency in the second half of the period. Labour market tightness was relatively high during 2021 and 2022 in most occupation groups but with several exceptions such as ISCO 1 (managers), ISCO 4 (clerical supports workers) and ISCO 5 (service and sales workers). Overall, the results indicate that different occupation groups in Spain follow very similar trends when it comes to matching efficiency movements over time.

5. Discussion

Worker groups in different occupations in the selected group of countries experience similar trends in the labour market. However, there are exceptions to this general pattern in some countries and some occupation groups.

The Austrian labour market, disaggregated by occupation, shows very similar movements in the Beveridge curves. The Croatian labour market groups also follow similar trends, though with exceptions such as the ISCO 1 group, and slightly different shapes of the Beveridge curves for workers with higher levels of education. ISCO groups in Slovenia follow similar general patterns as well, but certain groups show their own peculiarities. For example, we found a huge increase in labour demand for ISCO 2 and ISCO 9 groups. The Beveridge curves for different labour market groups in Spain resemble the aggregate Beveridge curve but with their own peculiarities in groups like ISCO 6 and ISCO 7. Despite these exceptions, we believe it can justifiably be concluded that during the analysed period in the selected group of countries, different occupation groups in the labour market followed broadly similar trends in movements of vacancies and unemployment. In some countries, this co-movement is very strong (Austria), and in others, it is weaker (Spain, though the results for Spain need to be interpreted with caution due to the relatively low number of reported vacancies, i.e. missing data).

When it comes to our research question regarding the similarities in movements in labour market tightness and matching efficiency among the different occupation groups, similar conclusions hold – different occupation groups experienced relatively similar trends in Austria, Croatia, Slovenia, and Spain. However, this does not hold for every occupation group or during every time frame. Notable exceptions are, for example, ISCO 6 and ISCO 9 groups in Croatia regarding tightness – other occupation groups experienced an increase in tightness at the end of the period compared to the period before the pandemic, while tightness in these two groups remained like at the pre-pandemic levels.

Despite the differences in the levels of tightness and their volatility at different points in time, the general trends in tightness are similar in almost all occupation groups in the countries we have analysed. For instance, all occupation groups in Austria first show a decrease, and then an increase in matching efficiency. The trend of increasing matching efficiency is noticeable in all occupation groups in Slovenia and Spain. All occupation groups in Croatia recorded relatively unchanging matching efficiency in the 2010-2022 period.

The prediction of future labour market trends and needs is often ungrateful and difficult. However, the COVID-19 pandemic and the ongoing technological progress in the labour market and the production processes (more frequent use of advanced robots, AI, etc.) continues to drive labour market changes. This, though, is not the only driver of the changes in the labour markets of the European Union member states. Other drivers include demand and supply factors such as population ageing and the consequent labour market shortages, and the developments in labour market institutions and policies. Well-designed active labour market policies could speed up job matching, for example through short-term training programmes that help detached (and employed) lower-skilled workers build the skills required for new fast-growing occupations or more traditional jobs that have experienced acute shortages. To accommodate shifting worker preferences, labour laws and regulations also need to facilitate telework. Immigration, whose sharp reduction slightly amplified labour shortages in some cases, could also help "grease the wheels" of the labour market (Duval, et al., 2022). As demonstrated by recent research exploring spatial variations in overall worker movements (Kuhn et al., 2021), the growing inclination towards remote work might have resulted in a geographical mismatch, as job seekers relocated away from densely populated areas where job opportunities are still concentrated. The COVID-19 pandemic has profoundly and eternally altered our lifestyle and work habits. We observe a notable shift in employment, particularly away from low-skilled service jobs. Considering the patterns in job vacancies, we can suppose that this change is driven by worker preferences or adjustments in job-related benefits.

6. Conclusion

In this paper, we have analysed the alignment of education and skills in different occupation groups with the labour market needs in Austria, Croatia, Slovenia, and Spain. Our research has two main findings. First, worker groups in different occupations in the selected group of countries experience similar trends in the labour market. This means that, for instance, during periods of decreasing unemployment and increasing vacancies in the aggregate labour market, workers in different occupation groups also record the same positive developments in a relatively homogeneous fashion in terms of the direction of these movements, though with different magnitudes. On the other hand, economic downturns, marked with increasing unemployment and decreases in vacancies are also felt relatively homogeneously among workers in different occupation groups.

The second main finding is that workers in different occupation groups experience similar movements in labour market tightness and matching efficiency. For example, during periods of increases in the aggregate labour market tightness, defined as the ratio of vacant job positions to the stock of unemployed workers, labour market tightness also increases in different occupation groups and vice versa. A similar conclusion holds for matching efficiency, i.e. the market's ability to match unemployed workers to vacant job positions. It should also be emphasised that, though these two conclusions hold in general, exceptions to both conclusions exist in some occupation groups and in some periods of time. Future policy decisions should focus on tackling the issue of occupational mismatch and skill gaps to eliminate gaps between human capital in different occupation groups and increase their capacity regardless of the state of the business cycle. Further studies should take a step further and examine more nuanced dimensions through which mismatch may play a role in some countries. For example, examining the difference in occupational mismatch among the regions of individual member countries is important, as job seekers are increasingly encouraged to work from home and are moving away from high-density areas where vacancies are still primarily located.

References

1. Barnichon, R. & Figura, A. (2015). Labor Market Heterogeneity and the Aggregate Matching Function. *American Economic Journal: Macroeconomics*, *7*(4), 222-249. http://dx.doi.org/10.1257/mac.20140116
2. Barrero, J. M., Bloom, N., Davis, S. J. & Meyer, B. H. (2021). COVID-19 is a persistent reallocation shock. *AEA Papers and Proceedings*, *111*, 287-291. https://doi.org/10.1257/pandp.20211110
3. Bernstein, J., Richter, A. W. & Throckmorton, N. A. (2022). *The Matching Function and Nonlinear Business Cycles* (Working Paper No. 2201). Dallas, TX: Federal Reserve Bank of Dallas. https://doi.org/10.24149/wp2201
4. Bleakly, H. & Fuhrer, J. C. (1997). Shifts in the Beveridge curve, job matching and labor dynamics. *New England Economic Review*, *28*(Sept), 3-19.
5. Blanchard, O. J. & Diamond, P. (1992). The Flow Approach to Labor Markets. *The American Economic Review*, *82*(2), 354-359. https://doi.org/10.3386/w4000
6. Bok, B., Petrosky-Nadeau, N., Valetta, R. G. & Yilma, M. (2022). *Finding a Soft Landing along the Beveridge Curve* (FRBSF Economic Letter No. 2022-24). San Francisco, CA: Federal Reserve Bank of San Francisco.
7. Cabus, S. J. & Somers, M. A. (2018). Mismatch between education and the labour market in the Netherlands: is it a reality or a myth? The employers' perspective. *Studies in Higher Education*, *43*(11), 1854-1867. https://doi.org/10.1080/03075079.2017.1284195
8. Consolo, A. & da Silva, A. D. (2019), *The euro area labour market through the lens of the Beveridge curve* (ECB Economics Bulletin No. 4/2019). Frankfurt am Main: European Central Bank.
9. Croatian Employment Services (2022). *Statistics*. https://www.hzz.hr/en/statistics
10. Duval, R., Longji Li, Y. L., Oikonomou, M., Pizzinelli, C., Shibata, I., Sozzi, A. & Tavares, M. M. (2022). *Labor Market Tightness in Advanced Economies* (IMF Staff Discussion Notes No. 2022/001). Washington, DC: International Monetary Fund. https://doi.org/10.5089/9798400204340.006

11. Employment Service of Slovenia (2022). *About ESS*. https:// www.ess.gov.si/en/about-ess
12. Europa.eu (2022). *International Standard classification of occupations 2, 3 and 4 digits (ISCO-88 (com))*. https://ec.europa.eu/eurostat/documents/1978984/6037342/ISCO-88-COM.pdf
13. Flisi, S., Goglio, V., Meroni, E. C., Rodrigues, M. & Vera-Toscano, E. (2017). Measuring Occupational Mismatch: Overeducation and Overskill in Europe—Evidence from PIAAC. *Social Indicators Research*, *131*,1211-1249. https://doi.org/10.1007/s11205-016-1292-7
14. Forsythe, E., Kahn, L. B., Lange, F. & Wiczer, D. (2022). Where have all the workers gone? Recalls, retirements, and reallocation in the COVID recovery. *Labour Economics*, *78*, 102251. https://doi.org/10.1016/j.labeco.2022.102251
15. Ghayad, G. & Dickens, W. (2012). *What Can We Learn by Disaggregating the Unemployment-Vacancy Relationship?* (Research Department Public Policy Brief No. 12-3). Boston, MA: Federal Reserve Bank of Boston.
16. Ghayad, R. (2022). *The Labor Market through the Lens of the Beveridge Curve*. Linkedin Economic Graph. https://economicgraph.linkedin.com/content/dam/me/economicgraph/en-us/PDF/eg-analytics-report-aug2022.pdf
17. Gomez-Salvador, R. & Soudan, M. (2022). *The US labour market after the COVID-19 recession* (ECB Occasional Paper Series No. 298). Frankfurt am Main: European Central Bank. https://doi.org/10.2866/964976
18. Hornstein, A., Krusell, P. & Violante, G. L. (2005). Unemployment and Vacancy Fluctuations in the Matching Model: Inspecting the Mechanism. *Federal Reserve Bank of Richmond Economic Quarterly*, *91*(3), 19-51.
19. Kohlbrecher, B., Merkl, C. & Nordmeier, D. (2014). *Revisiting the Matching Function* (Kiel Working Paper No. 1909). Kiel: Kiel Institute for the World Economy. https://doi.org/10.2139/ssrn.2505377
20. Kuhn, M., Manovskii, I. & Qiu, X. (2021). *The Geography of Job Creation and Job Destruction* (NBER Working Paper No. 29399). Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w29399
21. Lange, F. & Papageorgiou, T. (2020). *Beyond Cobb-Douglas: Flexibility Estimating Matching Functions with Unobserved Matching Efficiency* (NBER Working Paper No. 26972). Cambridge, MA: National Bureau of Economic Research. https://doi.org/10.3386/w26972
22. Obadić, A. (2005). *Makroekonomika tranzicijskog tržišta rada – S posebnim osvrtom na Hrvatsku*. Politička kultura.
23. Obadić, A. (2016). Tržište rada. In Obadić, A. & Tica, J. (Eds.), *Gospodarstvo Hrvatske* (pp. 203-246). Faculty of Economics and Business, University of Zagreb.
24. Obadić, A. (2020). Influence of technological change and digital technology on job polarization and occupational change. In Družić, G. & Gelo, T. (Eds.). *Conference Proceedings of the International Conference on Economics of Decoupling (ICED)* (pp. 433-450). Zagreb: Croatian Academy of Sciences and Arts (Economic Research Division) and Faculty of Economics and Business, University of Zagreb.
25. Petrongolo, B. & Pissarides, C. A. (2001). Looking into the Black Box: A Survey of the Matching Function. *Journal of Economic Literature*, *39*(2), 390-431, https://doi.org/10.1257/jel.39.2.390
26. Pizzinelli, C. & Shibata, I. (2023). Has COVID-19 induced labor market mismatch? Evidence from the US and the UK. *Labor Economics*, *81*, 102329. https://doi.org/10.1016/j.labeco.2023.102329
27. Pissarides, C. A. (2000). *Equilibrium Unemployment Theory*. MIT Press.
28. Public Employment Service Austria (2022). *Public Employment Service Austria (AMS)*. https://www.ams.at/organisation/public-employment-service-austria
29. Shimer, R. (2005). A Theory of the Matching Function. In *2005 Meeting Papers* (Vol. 673). Society for Economic Dynamics.
30. Spanish Public Employment Service (2022). Statistical bulletins. https://www.sepe.es/HomeSepe/en/que-es-el-sepe/estadisticas/publicaciones-estadisticas.html

Appendix

Table 1 - Matching function estimated coefficients and p-values (shown in brackets), Austria and Croatia

Austria			Croatia		
Occupation	Constant	lnTightness	ISCED occupation	Constant	lnTightness
Agricultural	-0.81 (0.00)	0.77 (0.00)	2 – Professionals	-1.32 (0.00)	0.55 (0.00)
Industry and small trade – first subgroup	-0.81 (0.24)	0.56 (0.00)	3 – Technicians and associate professionals	-1.28 (0.00)	0.49 (0.00)
Industry and small trade – second subgroup	-0.18 (0.53)	0.45 (0.00)	4 – Clerical support workers	-1.27 (0.00)	0.49 (0.00)
Industry and small trade – third subgroup	-0.34 (0.37)	0.89 (0.00)	5 – Service and sales workers	-1.47 (0.00)	0.45 (0.00)
Goods and services, sales personnel, transport	-1.19 (0.00)	0.36 (0.05)	6 - Skilled agricultural, forestry and fishery workers	-2.06 (0.00)	0.29 (0.00)
Services	-0.92 (0.00)	0.57 (0.00)	7 - Craft and related trades workers	-1.97 (0.00)	0.32 (0.00)
Trained technicians	0.73 (0.09)	0.84 (0.00)	8 - Plant and machine operators, and assemblers	-1.82 (0.00)	0.34 (0.00)
Administrative and clerical	-0.40 (0.46)	0.85 (0.00)	9 – Elementary occupations	-1.99 (0.00)	0.45 (0.00)
Health service, teaching and cultural occupations	-1.47 (0.00)	0.23 (0.15)			

Source: Authors' calculations

Table 2 - Matching function estimated coefficients and p-values (shown in brackets), Slovenia and Spain

Slovenia			Spain		
ISCED occupation	Constant	lnTightness	ISCED occupation	Constant	lnTightness
1 – Managers	-2.95 (0.00)	0.02 (0.60)	1 – Managers	-0.75 (0.02)	0.33 (0.00)
2 – Professionals	-2.44 (0.00)	0.12 (0.02)	2 – Professionals	0.39 (0.06)	0.54 (0.00)
3 – Technicians and associate professionals	-2.45 (0.00)	0.21 (0.00)	3 – Technicians and associate professionals	-0.23 (0.33)	0.41 (0.00)
4 – Clerical support workers	-2.51 (0.00)	0.22 (0.00)	4 – Clerical support workers	-0.13 (0.49)	0.43 (0.00)
5 – Service and sales workers	-2.30 (0.00)	0.25 (0.00)	5 – Service and sales workers	0.08 (0.75)	0.44 (0.00)
6 - Skilled agricultural, forestry and fishery workers	-1.83 (0.00)	0.47 (0.00)	6 - Skilled agricultural, forestry and fishery workers	-0.65 (0.00)	0.17 (0.00)
7 - Craft and related trades workers	-2.47 (0.00)	0.17 (0.02)	7 - Craft and related trades workers	-0.01 (0.94)	0.45 (0.00)
8 - Plant and machine operators, and assemblers	-2.50 (0.00)	0.23 (0.00)	8 - Plant and machine operators, and assemblers	-0.65 (0.00)	0.28 (0.00)
9 – Elementary occupations	-2.62 (0.00)	0.20 (0.00)	9 – Elementary occupations	-0.20 (0.27)	0.47 (0.00)

Source: Authors' calculations