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Labour market tightness and matching efficiency in different labour market segments – do differences in education and occupation matter?

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Abstract

This paper analyses the existing educational and occupational structures of several EU member countries and their alignment with the needs of the labour market. Such a situation may indicate a structural mismatch in labour market in which the mismatch between the skills taught in schools and universities and the skills needed in the workplace appears. To evaluate this mismatch, the paper investigates the matching needs of employers and unemployed job seekers by disaggregating the registered employment office data by education and occupation groups in selected EU countries separately. More educated workers, as well as workers in more complex and better-paid occupations, might fare better when it comes to the aggregate labour market trends. For example, economic downturns and increases in unemployment might be felt more heavily by workers with lower education and those who work in professions requiring fewer skills. In this paper, we analyse the data for a selected group of countries (Austria, Croatia, Estonia, Slovenia, and Spain) from 2010 till 2022, using the Beveridge curves and estimate the labour market tightness and matching efficiency for different education and occupation groups. Our results show that differences in education levels and occupation result in relatively small deviations from aggregate trends in the labour market. Aggregate labour market trends therefore strongly impact all groups in the labour market, whether the market is segmented by education levels or by occupation. In other words, both the improvements in the labour market conditions and the worsening of labour market conditions have similar effects across different labour market segments.

Key words

educational structure, structural unemployment, Beveridge curve, matching efficiency, labour market tightness, EU

JEL classification

J21, J22, J23, J63

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1. Introduction

The existing educational structure in EU member states may not always align with the needs of the labour market. A mismatch between the existing educational structure, skills that are taught in schools and universities, and the skills needed in the workplace is a serious problem. Such incompatibility is increasingly difficult to keep pace within the context of rapid technological progress and it is a key threat to economic growth and development considering that in the long term, such a situation can strongly influence the increase of structural unemployment in the economy. It should not be forgotten that the effectiveness of the matching process also depends on the business cycles. The main approach in this research concentrates on the key base of the matching process which relates to matching the needs of employers and unemployed job seekers to fill vacancies. The aggregate matching efficiency moves over the cycle because of variations in the average characteristics of the labour market. An important feature of the labour market is its matching efficiency, i.e., the market's ability to match unemployed workers to jobs (Barnichon, Figura, 2015, p. 222).

In this part of the research, the main theoretical assumptions and existing empirical findings regarding the compatibility of the existing educational structure and labour market needs within the European Union would be elaborated. The correlation between education and better employability is indisputable and has been proven countless times in numerous social and economic research. The relationship between educational attainment and labour market compatibility has become particularly important during the COVID-19 pandemic. Namely, individuals with high education could keep their jobs much easier in the significant unexpected situations in the labour market as social distancing and "lock-down" measures in spring 2020 certainly were. Most labour markets are tighter than they were prior to COVID-19. According to IMF research (2022), the main reason why employment remains restrained, particularly compared to the pre-crisis trend, is that disadvantaged groups – including, the low-skilled, older workers, or women with young children – have yet to fully return to the labour market. The decline in immigration also seems to have amplified labour shortages among low-skilled jobs (Duval, et al., 2022, p. 5). The abovementioned needs to be specially investigated and therefore in this paper, we concentrate our research on the labour market matching model according to educational attainment, focusing on the interaction between unemployment and new job posts (vacancies).

As the job matching process changes over time in relation to business cycles, it is important to consider the relationship in real-time. The best way to graphically show the matching process in the labour market is by the Beveridge curve which shows the empirical relationship of the trade-off between job vacancies and unemployment. The Beveridge curve is thought to be an indicator of the efficiency of the labour market functioning. The negative slope of the Beveridge curve indicates that vacancy and unemployment rates tend to move in opposite directions over the business cycle. Movements in the vacancy-unemployment space are usually related to labour market tightness and labour market efficiency (Consolo, da Silva, 2019). In order to best empirically evaluate the process of demand and supply matching, we estimate the labour market tightness and matching efficiency. Therefore, we also use the traditional aggregate matching function. The matching function relates the flow of new hires to the stock of vacancies and unemployment which are typically modelled with a Cobb-Douglas matching function, i. e. the job-finding rate.

The majority of the existing research focuses on general labour market trends or the aggregate data for a specific country. Instead of focusing on general trends in the labour market, this research is a step forward because we analyse disaggregated data. Our focus is on how different levels of education and occupation of workers' groups respond to general trends in the labour market. For example, economic downturns, which lead to increases in unemployment, might be felt more severely by those groups of workers with lower education levels and those who work in occupations which require less knowledge and skills. Therefore, we have developed the following research questions:
(1) Do different levels of education of worker groups experience the impact of aggregate labour market trends in different ways?
(2) Do different classifications of occupations of worker groups experience the impact of aggregate labour market trends in different ways?

In this respect, this research contributes to the existing literature by using national employment office service registered data for five selected EU countries (Austria, Croatia, Estonia, Slovenia, and Spain) for which data were available, disaggregated according to the level of education and classification of occupations. Due to the differences in the data collection process, the educational levels are not unified among the countries since different employment offices use different methodologies. Previous research mainly used Labour Force Survey data which are not disaggregated to all nine ISCED levels of education[1] or ten ISCO-88 classification of occupations[2].

Our methodological approach consists of two steps. First, we construct the Beveridge curves for the aggregate labour markets of the five countries in our sample – Austria, Croatia, Estonia, Slovenia, and Spain – and then for disaggregated one. The Beveridge curves are constructed for the aggregate labour market (Figure 1) and for different education (Figure 2-6) and occupation groups (Figure 7-10) for each country. Then we present the estimates of the labour market tightness and matching efficiency for different education and occupation groups for each country. While the method based on the matching function directly captures the matching process, the Beveridge curve efficiency measure also captures the dynamics of job separations as well as potential labour force movements from inactivity to the labour market (Consolo, da Silva, 2019). The paper is structured in the following way. In the second chapter, we provide a theoretical background regarding the different aspects of the labour market and the relationship between education and labour market outcomes, as well as focus on both historical and recent empirical evidence of labour market developments in different countries. The third chapter focuses on the data and methodology we use, provides summary statistics for these data and describes the methodology used in this paper. The fourth chapter presents the results, including aggregate and disaggregated Beveridge curves and the estimates of the labour market tightness and matching efficiency. In the fifth chapter, we discuss the results and explain the main limitations of our findings, while the sixth and final chapter concludes the paper. The conclusions are drawn based on our empirical findings.

2. Theoretical and Empirical Literature Review

2.1. Theoretical Background

Education has to form young people's human capital by providing them with the necessary skills and knowledge to prepare them for entering the labour market. To be able to help students achieve a favourable skills match, education programmes need to both know and meet the requirements of the labour market (Bolli, *et al.*, 2012, p. 324). The requirements of the labour market are achieved by establishing a successful matching that focuses on the interaction between unemployment and job creation. Higher productivity increases the return to job creation and thereby increases the rate of job creation. In turn, a higher rate of job creation makes it easier for unemployed workers to find jobs and thereby reduces unemployment. This explains the observed counter-cyclical (pro-cyclical) behaviour of unemployment (job creation) (Hornstein, Krusell, Violante, 2005, p. 19).

The trade-off between unemployment and vacancy can vary depending on the strength of the labour market needs: when the labour market is strong, with low unemployment and high vacancies, unemployment is likely to be relatively unaffected by increases in job openings. This will be reflected

[1] International Standard Classification of Education (ISCED) based on the ISCED 2022 classification includes 9 levels: ISCED 0 = Early childhood education, ISCED 1 = Primary Education, ISCED 2 = Lower Secondary Education, ISCED 3 = Upper Secondary Education, ISCED 4 = Post-secondary non-Tertiary Education, ISCED 5 = Short-cycle tertiary education, ISCED 6 = Bachelors degree or equivalent tertiary education level, ISCED 7 = Masters degree or equivalent tertiary education level, ISCED 8 = Doctoral degree or equivalent tertiary education level, (World Bank, 2022).

[2] ISCO-88 major groups constitute the broad structure of ten classification of occupations 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).

in the Beveridge curve[3] being quite steep. 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, p. 2) 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, p. 235) that determine how quickly job matches occur and how long they last. The simplicity of forming job matches represents the efficiency of matching. Reduced matching between the unemployed and vacant positions i.e., reduced efficiency of the mentioned process, where there is a simultaneous increase in the number of unemployed and vacant jobs, leads to an outward movement of the Beveridge curve. On the contrary, an inward shift of the Beveridge curve indicates improved matching efficiency. Movements along the curve itself when unemployment and vacancies move in opposite directions indicate cyclical fluctuations in economic activity (Obadić, 2005, p. 91).

It should be noted that heterogeneities across workers and labour markets are key aspects of unemployment fluctuations and therefore it is important to segment the labour market into distinct submarkets (Barnichon, Figura, 2015). As such, educational and skill mismatches are distinct empirical phenomena with different labour market outcomes. It is not necessarily the case that all forms of mismatch are involuntary in nature and, therefore, represent a productivity constraint. Some mismatch cases may also arise out of choice as workers trade off lower wages for other intrinsic aspects of the job that increase satisfaction, such as enhanced work-life balance or increased social responsibility. This is one reason why it is important to apply estimation techniques that are robust to the influence of unobserved individual heterogeneity bias (Mavromaras *et al.,* 2013, p. 383).

Scholarship policy is particularly important in establishing the era of alignment between the existing educational structure and the needs of the labour market. Namely, the scholarship allows for a process-oriented questioning of work transitions (McBride *et al.,* 2015). For example, in welfare states with historically strong welfare institutions, access to welfare professions has been channelled through established training/educational institutions and regulated by the state through the recognition of qualifications and/or professional licensing fixing the conditions for entry and instituting procedures for recruitment (Samaluk, 2021). Some researchers have already shown that today’s youth-work transitions are characterised by the rising school-leaving age, extended early career insecurity and intersectoral differences, but little attention has been given to the education-to-work transitions of becoming welfare professionals (Samaluk, 2021).

When it comes to the assessment of the responsiveness of the education system to labour market needs, OECD (2019) proposes three indicators. The employability of graduates can be measured by the employment rates of recent vocational education and training (VET) and tertiary graduates. The high employability of recent graduates (those who have graduated within the last three years) is an indicator of an education system which is responsive to the needs of the labour market. OECD's Skills for Jobs database records shortages and surpluses of certain skills, a great indicator of how well the education system is equipping graduates with skills demanded in the labour market. Thirdly, a similar indicator comes from the Survey of Adult Skills, which measures the recent graduates' performance in literacy, numeracy and problem-solving. For example, the biggest ability shortages in OECD countries in 2017 were reported for verbal and reasoning abilities. The biggest surpluses were recorded for endurance and physical strength abilities (OECD, 2019). According to a report by the OECD and ILO (2014) promoting vocational education and training (VET) can improve the youth labour market by better satisfying its needs. Indeed, studies on the outcome of education theorise that VET programmes, which teach vocational skills and prepare for specific occupations or types of occupations, should meet the requirements of the labour market better than purely general education programmes, i.e. programmes teaching general skills (Bolli, *et al.,* 2021). They argue that through these VET programmes, students learn occupation-specific skills that are directly applicable in the workplace when entering the labour market. Critics argue that VET might be an advantage only in the short run, while in the long run,

[3] 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 it, he wanted to determine how far the economy is from the state of full employment (Bleakly, Fuhrer, 1997, p. 1).

occupation-specific skills might restrict employees' mobility and become obsolete before adapting to new technologies (Hampfl, Woessmann, 2017).

There are several forms of educational mismatch of supply and demand in the labour market. There are situations when a person has a lower/higher education level than demanded on the market to the situation where there is a correlation in terms of the level but not in terms of the type of qualifications for a particular position. The probability of being overeducated increases with education level, which is a common result in many international findings (Ramos, *et al.,* 2012). Many studies using cross-sectional data have found that labour market mismatch in the form of over-education or over-skilling is associated with negative labour market outcomes in the form of lower wages, reduced job satisfaction and higher labour turnover (Mavromaras *et al.*, 2013, p. 382, Jovović *et al.*, 2017). Majority of these studies have been based on cross-sectional data and therefore may be biased due to the problem of unobserved individual heterogeneity (Mavromaras *et al.*, 2013, p. 383; Verhaest *et al.*, 2012).

2.2. Empirical Evidence

The Beveridge curve tends to shift over time. For example, outward shifts of the Beveridge curve appeared almost everywhere in Europe in the early 1970s. One of the reasons for this is the increase in the number of unemployed with the 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, p. 235). In most of the new EU member states, during the transition period, the Beveridge curve shifted outwards, which means that the number of unemployed persons increased in relation to the number of vacancies, although in some cases there was an increase in vacancies. For example, in Croatia, this trend has existed continuously since 1997, with the curve being moved the farthest from the origin in 2001 and 2002 when Croatia faced the historically highest number of unemployed persons (Obadić, 2016, p. 236). Shifts of the Beveridge curve outwards with a simultaneous increase in supply and demand indicate a reduced matching efficiency, i.e. an increase in the share of structural unemployment or may be an indication of problems of structural mismatch in the Croatian labour market. In their analysis of the United States between January 2001 to December 2017, Lange *et al.* (2020) find that the Beveridge curve shifted during the Great Recession and this shift is also quantified by the estimated decline in matching efficiency (Lange, *et al.*, 2020, p. 19).

Barrero *et al.* (2021) have investigated the outbreak of the COVID-19 pandemic. They have argued that the COVID-19 recession and recovery created a reallocation shock that has necessitated unusually large movements of jobs and workers across industries. These movements are driven by persistent changes in demand patterns, such as shifts away from in-person services toward delivered goods and shifts towards industries and occupations that support remote work. The pandemic has persistently pushed low-skilled and older workers out of employment but has transformed labour markets less than was generally envisaged after the first wave (Duval *et al.,* 2022, p. 3). Labour markets have become tight, as indicated by a sharp rise in unfilled job vacancies (Duval *et al.,* 2002, p. 3) which create challenges for employers and workers that impede the job-matching process and cause an outward shift of the Beveridge curve. There was one time in the past when the relationship shifted outward in a similar manner. During the 1970s, vacancies rose without a normal drop in unemployment, and the Beveridge curve shifted outward for much of the 1980s. Through that period, it was thought that the labour market was doing a worse job than usual of matching workers and jobs, resulting in a higher NAIRU (non-accelerating inflation rate of unemployment) (Ghayad, Dickens, 2012).

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 in the near future as the economy slows, suggesting that the outward shift in the Beveridge curve should largely move backwards as aggregate demand relaxes (Ghayad, 2022). More precisely, the COVID-19 pandemic dramatically shifted the Beveridge curve outward, first with the rapid increase in unemployment, followed by increasing job vacancies even as the unemployment rate returned to pre-pandemic levels.

Shifting from general labour market trends to the labour market developments in specific education groups, many studies using cross-sectional data have found that labour market mismatch in the form of over-education or over-skilling is associated with negative labour market outcomes in the form of lower wages, reduced job satisfaction and higher labour turnover (Mavromaras, *et al.,* 2013, p. 382). The analysed incidence of different types of educational mismatches (vertical and horizontal) among native and immigrant workers using microdata provided by Eurostat from the Adult Education Survey (AES) show that immigrants are more likely to be overeducated than natives (Nieto *et al.,* 2015). In their analysis, Nieto and others (2015) conclude that this effect is higher for immigrants from non-EU countries than for those from other EU countries, although the probability of being overeducated decreases more quickly with years of residence for non-EU immigrants. The pace of assimilation is notably slow for all immigrants. Nieto and others consider that there is a certain risk that immigrants from outside the EU will remain permanently trapped in bad jobs, regardless of their levels of education (Nieto *et al.,* 2015, p. 554). Sanromá *et al.* (2008) point out that immigrants living in Spain accumulate knowledge and experience that are perfectly adapted to the local labour market, thus making for an easier assimilation process that reduces the intensity of overeducation. However, the pace of assimilation is notably slow-around 15 years of living in Spain would be necessary to eliminate the educational mismatch and differs depending on the origin country.

Levels and others (2014) used micro-data on 30,805 school leavers in 20 European countries from the 2009 European Labour Force Survey and show that the level of stratification of secondary education is associated with better vertical job matches. They also find that the positive relationship between being vocationally trained, and education-to-job matches is stronger in systems with stronger institutional linkages. The positive relation between being vocationally trained and vertical job matches is less strong in more vocational-oriented systems (Levels, *et al.,* 2014). The detailed analysis of Hoidn and Šťastnŷ (2021) shows that there are large differences in how education type and level influence job market success both among young people and throughout careers. Their findings indicate that vocational education helps young graduates succeed in the labour market compared with lower levels of education (Hoid and Šťastnŷ, 2021, p. 22; Wolbers, 2007). The *changing nature and role of vocational education and training (VET) in Europe* shows that vocational education still seems to “divert” young people from formal (tertiary) education even though more and more opportunities for progression have been developing for some time. In countries with school-based vocational education (BE, BG, CZ, FI, IT, HR, LU, PL, RO, SK, SL), vocational education graduates have a higher risk of unemployment, unskilled employment and lower matching than general education graduates (Cedefop, 2017).

Increases in the average schooling level of workers also make it easier for workers to find employment (Obadić, 2017). The report published by the Montenegrin Employers Federation in 2016 shows that more educated workers in Montenegro record higher activity and employment rates, as well as lower unemployment rates. Serbia and Ukraine recorded similar patterns, with the time to first significant job being lower for workers with University and College degrees compared to workers with lower levels of education. More educated workers also had a higher chance of finding registered work as opposed to many unregistered jobs taken by workers with less education (European Training Foundation, 2008).
The research by Ellison (2017) concludes that the loss of EU co-funding of programmes designed to support vulnerable young people as they make the transition between education and employment will be considerable unless the UK government fully replaces this funding (Elisson, 2017, p. 693). The analysis shows that co-ordinated use of EU funding instruments aimed at rebalancing economic and social inequalities between wealthier and poorer regions and groups within the EU is evidenced as improving labour market outcomes for young people living in the most disadvantaged regions of the UK (Elisson, 2017, p. 675).

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 per cent. The average number of years spent in formal education was relatively low in these two sectors as well, around 13% 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 very demanding physically) jobs have fewer problems with finding workers who fit the position well. However, putting these differences in sectors aside, the authors find that increases in the average schooling level of the workforce results in lower mismatch rates, and their estimates show that a one-month increase in companies' workforce average schooling level decreases the probability that companies report mismatch by 3 percentage points (Cabus and Somers, 2018).

Gavriluţă *et al.* (2022) analyse the correlation between education levels and employability rates in the EU-28 during the COVID-19 economic crisis, estimating the impact of social restrictions of the pandemic in the field of employability. They estimated a middle positive statistical correlation between tertiary education (university, post-university studies, or PhD) and high levels of employability in the EU-28 during 2019-2021 and observed the fact that employability rates are related to high levels of education. The results show that high levels of association between education level (tertiary) and employment rates are visible in Sweden, Germany, the Netherlands, and the Baltic states. In contrast, for Greece, Spain and Italy they estimated a strong association between low levels of tertiary education and low levels of employment (Gavriluţă *et al.*, 2022, p. 15). Such results by Gavriluţă *et al.* (2022), bring to the conclusion that tertiary education could be seen as an important factor in increasing the quality of employability as individuals with higher education are able to adapt to the new changes and challenges within the labour market (new types of services, digitalization, teleworkable services, etc.). Another way to measure how responsive the education system is to labour market needs, or rather does the education system do a good job in providing the graduates with skills needed in the labour market, is to look at the mismatch between the qualification of workers and the demands of the job they currently work on. A study done by Allen, Pavlin and van der Velden (2011) showed that in some European countries a considerable proportion of graduates work in jobs that do not require a diploma. This figure was the highest for Spain, in which 63% of graduates worked on jobs not requiring a diploma, and stood at or above 30 per cent in Turkey, Italy, Hungary and the United Kingdom. On the other hand, Austria recorded only 6% of workers in this position.

Acceptable parameterizations of the model developed by Şahin, *et al.* (2014) imply that mismatch across industries and occupations during the Great Recession (2007-2009) can explain at most 1/3 of the total recent rise in the U.S. unemployment rate. They identified many potential causes of mismatch, by disaggregating data on unemployment and vacancies according to occupation, industry, education, and geography. Geographical mismatch plays no apparent role, but mismatch by occupation level increased markedly during the recession but declined throughout 2010 which is an indication of a cyclical pattern in the mismatch. When they compute occupational mismatch separately for different education groups, they find its contribution to the observed increase in the unemployment rate is almost twice as large for college graduates than for high-school dropouts (Şahin, *et al.* 2014).

Considering the existing theoretical background and the analysis of previous empirical studies, we evaluate the labour market developments in different education and 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 education and occupation groups, as well as compare these movements with the aggregate labour market Beveridge curves constructed for a specific country.

The calculation of labour market tightness allows us to analyse the differences in movements in tightness amongst different education and occupation groups, as well as the estimation of matching functions. By the estimation of different matching functions, we estimate the success of the matching process (matching efficiency) in selected EU countries by education and occupation.

Based on the initial research questions and the analysis of the existing available literature, four basic research hypotheses are formed:

H1: Worker groups of different levels of education experience trends similar to aggregate movements in unemployment and vacant positions.
H2: Workers in different occupation groups experience trends similar to aggregate movements in unemployment and vacant positions.
H3: Worker groups of different levels of education experience similar movements in labour market tightness and matching efficiency.
H4: Workers in different occupation groups experience similar movements in labour market tightness and matching efficiency.

Therefore, we expect that the differences in education levels and 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 education levels and occupation and expect the same outcome during the expansion. Moreover, we expect that labour market segments with different education levels and in different occupations experience similar movements in labour market tightness and matching efficiency over time.

3. Data and Methodology

3.1. Data

Our analysis includes selected five EU countries - Austria, Croatia, Estonia, Slovenia, and Spain for which registered disaggregated data according to education and occupation groups 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 an 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 in the records 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 Croatian Employment Service during the reporting period.

For each of these countries, the three labour market variables are disaggregated by education level according to the national employment office data collection practices. The data for Spain is disaggregated by 9 different ISCED education levels. The data for Slovenia is disaggregated in a similar way, only without the data for level 0 – Early childhood education. Austrian data is split into five categories: Compulsory education, Vocational education, High school, Higher education and Academic education. The data for Estonia is split into only three groups – Lower education, Middle level and Higher education. Croatian data includes those without completed Elementary education, those with completed Elementary education, those with completed High school, and the two groups with the highest education levels – those with the first level of Higher education and those with completed College.
Unfortunately, it was impossible to unify the levels of education among the countries since different national employment offices collect education data in different ways, which are often not fully comparable. However, the data does allow for the analysis of the general differences in the matching process according to the level of education – though the education groups are not unified, it is always clear which groups have higher educational attainment levels compared to others.

Data limitation is related to different availability of data at the individual disaggregated level for the selected group of countries. The disaggregated data for individual countries are not unique due to the different ways of defining individual education levels, especially with regard to the collection of data on job vacancies. Namely, employers do not express their needs about vacancies in detail disaggregated by all nine ISCED levels or ten ISCO classification groups.

We also 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 data disaggregated by occupation was not available for Estonia but was available for the other 4 countries. The occupation groups differ somewhat for Austria and are not in line with the ISCO classification, as outlined in the results section.

To construct the Beveridge curve, typically the unemployment rate is defined as the ratio of unemployed workers to the sum 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 measures are commonly used, but it is of course important to be consistent when comparing job vacancy rates across regions and time.

Our approach to creating the Beveridge curves is slightly different. 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 our knowledge, this data disaggregated by education and occupation levels do not exist in line with the method of collecting data on vacancies that employers report to individual national employment offices.

This, however, does not pose a problem for the construction of the Beveridge curves. According to the previous definitions both the unemployment and the vacancy rate have 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 scientific research (Gomez-Salvador and Soudan, 2022; Lange and Papageorgiou, 2020, etc.).

3.2. Descriptive statistics

In this part of the paper, descriptive statistics for five 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 are able to construct the Beveridge curves, as well as estimate the matching functions. Summary descriptive statistics are presented for the different education, as well as occupation groups. Each time series contains a total of 154 observations, from January 2010 to October 2022. The tables (see Tables 1-9) 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 education groups, Austria

	Compulsory education	Vocational education	High school education	Higher education	Academic education	Total
Employed mean	16489	18755	2522	4368	2793	44927
Employed standard deviation	5150	6968	531	980	1029	12688
Employed minimum value	5562	6505	1229	2519	1361	17759
Employed maximum value	30558	38443	4031	7564	6393	78601
Unemployed mean	140114	100039	16408	31735	20708	309005
Unemployed standard deviation	27820	23122	2628	7711	6163	61877
Unemployed minimum value	90496	64342	12328	20528	10718	206786
Unemployed maximum value	228738	166211	27623	59345	35778	514981
Vacancies mean	19692	25050	1794	4492	2358	53386
Vacancies standard deviation	13759	11347	1221	2702	1701	30433
Vacancies minimum value	6631	11902	641	1688	650	21760
Vacancies maximum value	63157	54779	4952	11677	6885	141076

Source: Authors’ calculations based on Public Employment Service Austria (2022) data.

Table 2 - 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
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 Public Employment Service Austria (2022) data.

Table 3 - Summary statistics for different education groups, Croatia

	Without elementary education	Elementary education	High school education	First level higher education	College education	Total
Employed mean	257	1893	9190	1033	1576	13949
Employed standard deviation	139	1011	4001	355	720	5523
Employed minimum value	66	572	3008	323	426	4760
Employed maximum value	818	4998	20094	2229	4807	28764
Unemployed mean	13212	48505	142034	12738	16776	233265
Unemployed standard deviation	4625	20019	55643	3299	4047	86291
Unemployed minimum value	5928	20449	61653	7138	9388	105796
Unemployed maximum value	19848	78808	241506	19639	24575	384376
Vacancies mean	1063	3742	7643	1075	2342	15864
Vacancies standard deviation	833	1657	3193	513	1101	5828
Vacancies minimum value	52	811	2265	145	326	5035
Vacancies maximum value	4043	9130	15950	2345	6143	30241

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

Table 4 - 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 Croatian Employment Services (2022) data.

Table 5 - Summary statistics for different education groups, Estonia

	Low education	Middle education	High education	Total
Employed mean	802	2114	1229	4145
Employed standard deviation	247	592	326	1102
Employed minimum value	305	983	568	1905
Employed maximum value	1696	4604	2448	7940
Unemployed mean	8042	20527	11826	40395
Unemployed standard deviation	3087	8396	3300	14591
Unemployed minimum value	4195	12045	8071	24605
Unemployed maximum value	19552	51762	20932	92246
Vacancies mean	2134	1809	426	4369
Vacancies standard deviation	678	402	175	1078
Vacancies minimum value	380	951	197	1798
Vacancies maximum value	4210	2907	1078	7700

Source: Authors' calculations based on Estonian Unemployment Insurance Fund (2022) data.

Table 6 - Summary statistics for different education groups, Slovenia

	ISCED 1 and 2	ISCED 3	ISCED 4	ISCED 5	ISCED 6	ISCED 7	ISCED 8	Total
Employed mean	1140	232	1201	1513	616	541	33	5277
Employed standard deviation	484	232	1202	1513	617	541	33	5279
Employed minimum value	461	232	1203	1514	618	542	33	5287
Employed maximum value	3236	497	2337	2489	1104	1516	77	10002
Unemployed mean	28679	5010	21671	25218	8437	6022	469	95506
Unemployed standard deviation	5133	4999	21652	25215	8454	6034	470	95480
Unemployed minimum value	16492	4988	21630	25213	8472	6048	471	95451
Unemployed maximum value	36888	7241	30659	35492	11161	8370	727	129843
Vacancies mean	3200	878	3318	1947	922	1194	95	11555
Vacancies standard deviation	1205	880	3313	1943	922	1195	95	11548
Vacancies minimum value	922	883	3309	1940	922	1196	94	11546
Vacancies maximum value	6732	1631	7140	3850	1508	3380	443	19527

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

Table 7 - 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 Employment Service of Slovenia (2022) data.

Table 8 - Summary statistics for different education groups, Spain

	ISCED 0	ISCED 1	ISCED 2	ISCED 3	ISCED 4	ISCED 5	ISCED 6	ISCED 7	ISCED 8	Total
Employed mean	7356	75651	40113	221929	65523	16146	12592	18167	124	457600
Employed standard deviation	2052	18765	9329	33638	17380	4361	11768	4931	37	90806
Employed minimum value	4459	47474	21509	148205	35284	7255	131	7552	66	297883
Employed maximum value	16925	145657	70213	344654	128291	39492	59307	44783	303	846782
Unemployed mean	50270	497145	290120	2126002	578818	136182	55927	180188	1174	3915826
Unemployed standard deviation	6080	48080	41633	389001	82501	38561	37127	42726	174	598914
Unemployed minimum value	35350	413622	219568	1461611	437751	78476	1708	110039	874	2879783
Unemployed maximum value	59387	603562	376951	2808568	739900	209670	132914	269352	1480	5040125
Vacancies mean	688	985	1026	2423	1225	814	81	409	14	7664
Vacancies standard deviation	626	542	404	1064	463	310	68	191	13	2523
Vacancies minimum value	3	188	353	639	171	215	1	35	1	1990
Vacancies maximum value	3167	3095	2211	8085	3192	1979	454	1689	86	15778

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

Table 9 - 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	Total
Employed mean	174	2392	38782	35096	37325	107208	27801	67612	25906	115304	457601
Employed standard deviation	37	640	15587	9639	8338	30827	4641	11034	4008	23681	90807
Employed minimum value	95	1045	13689	19029	19103	53236	17901	40766	16945	73780	297883
Employed maximum value	330	4593	128981	74718	65984	219764	40432	90578	35419	214191	846782
Unemployed mean	1663	33900	295335	284524	410547	931465	81305	559203	220217	1097998	3916159
Unemployed standard deviation	474	5650	46485	44795	58458	97415	10275	186134	63350	131373	598799
Unemployed minimum value	990	24199	213785	211542	314003	747077	60160	289992	125768	860665	2880582
Unemployed maximum value	2383	43698	411043	371974	521021	1127461	99669	866547	328344	1326683	5040218
Vacancies mean	7	107	3355	3072	2137	5672	7372	5874	1424	14156	43176
Vacancies standard deviation	23	50	1234	1345	779	2247	2787	2039	1541	4725	11785
Vacancies minimum value	0	10	859	384	275	2100	1280	2078	235	5319	14470
Vacancies maximum value	156	293	7103	10891	5512	20813	19529	15797	18167	38464	87588

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

As explained in Data section 3.1., the data are not unique across different countries. However, this does not pose a problem since we do not compare the labour market movements between different countries but focus on the developments and changes through time within the same country across different groups instead. Moreover, when it comes to both the education and occupation groups, there are major similarities between these groups, making them comparable to a certain degree. It is also necessary to consider the fact that there are different national legal regulations regarding the obligation to report labour market needs by employers. For example, that also 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 national educational and occupational groups.

3.3. Methodology

In almost all macroeconomic models with search and matching friction, the flow of new hires to the stock of vacancies and unemployment are modelled by the aggregate matching function (Petrongolo, Pissarides, 2001; Pissarides, 2000; Bernstein, *et al.*, 2022). The matching function is used in labour market analysis to understand how the number of job vacancies and unemployed workers relate to one another and how changes in one variable affect the other. It is also used to estimate the number of matches in a labour market and to study the effects of different labour market policies on the matching process. One of the most common aggregate matching function models used in the labour market is the Cobb-Douglas matching function[4]. The function is typically represented as (Blanchard, Diamond, 1992; Kohlbrecher *et al.*, 2014; Barnichon *et al.*, 2015, Lange *et al.*, 2020):

$$M_t = ßU_t^{\alpha}V_t^{1-\alpha} \qquad (1)$$

where M is the number of matches or the number of outflows from unemployed to employed or hires, U is the number of unemployed workers, V is the number of vacancies, β indicates the efficiency of the labour market and exponents α and $1\text{-}\alpha$ 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, and twice differentiable in both arguments, and exhibits constant returns to scale (Petrongolo and Pissarides, 2001). The Cobb-Douglas matching function is ubiquitous in search and matching models, even though it imposes a constant[5] elasticity of matches with respect to vacancies that is unlikely to hold empirically (Kohlbrecher, *et al.*, 2014; Bernstein, *et al.*, 2022, p. 18).

Following Barnichon and Figura (2015, p. 225) and Consolo and Dias da Silva (2019, p. 6), we first define the job finding rate f_t as the ratio of new hires to the stock of unemployed, $f_t = \frac{M_t}{U_t}$, so that

$$f_t = \beta\theta_t^{1-\alpha} \qquad (2)$$

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

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

The variable M *(Employed)* represents new hires, outflows from the stock of unemployment into employment. *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 national employment offices during the reporting period. As already mentioned, f_t is the job finding rate, θ_t labour market tightness and $\mathcal{E}_t$ denotes regression residuals. Subscript *i* refers to different countries for which we estimate separate regression equations, *i* = Austria, Croatia, Estonia, 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 $\mathcal{E}_t$ from equation 3 capture the efficiency of the matching process or movements in the matching efficiency for a particular education/occupation group in a specific country. The theoretical relationship between the job finding rate and labour market tightness is positive – higher tightness should result in a higher job finding rate. Why do we measure the matching efficiency using regression residuals? Let's assume

[4] It is named after economists Paul H. Douglas and Charles W. Cobb, who first proposed it in the 1950s.
[5] The specification in log form imposes constant returns to scale so the coefficients sum to one (Lange, *et al.*, 2020, p. 27).

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 (explanatory variable in a regression) level and the estimated matching function. This means that, for some reason independent of the current labour market tightness level, job finding rate decreased, and this is interpreted as a decrease in the matching efficiency. Such a trend occurred in the EU after the 2008 crisis period when labour market efficiency and tightness started to move in opposite directions (Consolo, da Silva, 2019). Positive residuals from the estimates of the matching function are interpreted in a similar fashion, as an increase in the matching efficiency, or higher observed job finding rate compared to what one would expect based on the corresponding labour market tightness level in that period.

Before calculating labour market tightness and estimating the matching functions and matching efficiency, we construct the Beveridge curves using the data for the vacancies and unemployed. As explained in the Data section, we construct the Beveridge curves by using the total number of vacancies and unemployed workers, instead of expressing them as vacancy and unemployment rates. This does not change the shapes of the Beveridge curves, therefore allowing us to analyse the movements along the Beveridge curve, as well as the inward and outward shifts in the Beveridge curve.

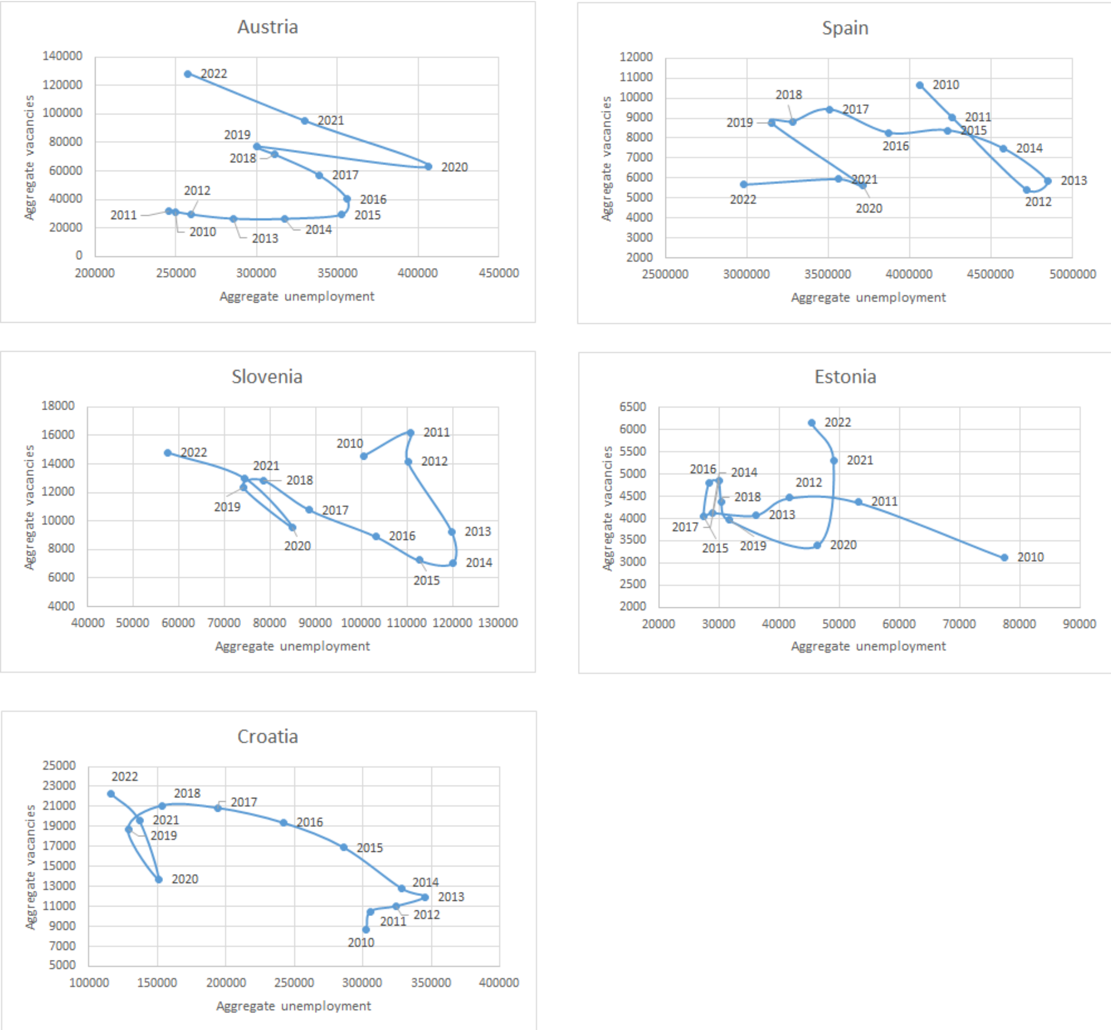
4. Results

Our research results section is divided in two parts. First, we present the Beveridge curves for the aggregate labour markets of each observed country, as well as disaggregated Beveridge curves by education and occupation groups. Then we present the estimates of the labour market tightness and matching efficiency for different education and occupation groups for each country.

4.1. Beveridge curves for the aggregate labour markets

The shape and the position of the Beveridge curves provide important information about the functioning of the labour market. The aggregated Beveridge curve is a combination of different country-specific dynamics (Consolo, Dias da Silva, 2019). Therefore, the Beveridge curves (Figure 1) can shed light on the nature of the aggregate matching process, and are presented for the selected five countries over the January 2010 – October 2022 period

Figure 1 - The aggregate level Beveridge curves for selected countries, 2010-2022, annual averages



Source: Authors' calculation based on Public Employment Service Austria, Croatian Employment Services, Estonian Unemployment Insurance Fund, Employment Service of Slovenia and Spanish Public Employment Service data.

The aggregate Beveridge curves for Slovenia shows an inward shift over time. For the same level of aggregate vacant positions available in the country, the level of aggregate unemployment almost halved when comparing the starting and the ending years of the 2010-2022 period. This inward shift of the Beveridge curves certainly indicates steady improvements in labour market conditions in Croatia, Slovenia and Spain because all three experienced a significant reduction in total unemployment, but only Slovenia managed it with approximately the same number of vacancies. Spain, on the other hand, shows both a decrease in unemployment and vacancies over time. After the period of worsening labour market conditions from 2010 to 2013, unemployment decreased significantly until 2019, along with an increase in vacancies. In 2020 there was a movement along the Beveridge curve, with unemployment increasing and vacancies decreasing. The labour market recovered in 2021 and 2022, with an inward shift of the Beveridge curve, i.e. with a simultaneous decrease in unemployment and vacancies.

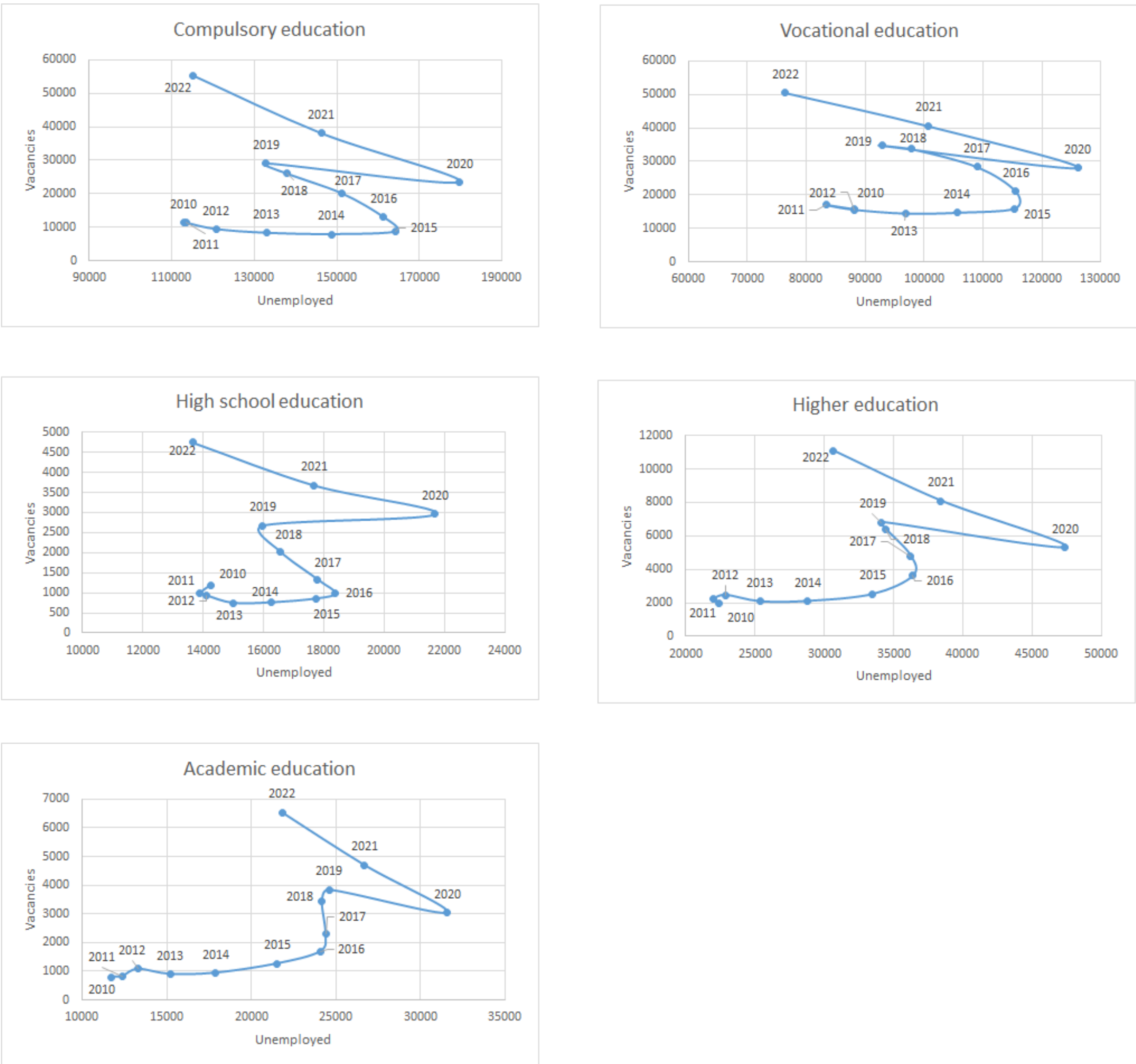
The Beveridge curve for Croatia shows a typical anticlockwise movement characterised by an increase in vacancies that is faster than the decrease in unemployment during the recovery phase. This, however, does not necessarily mean that improvements in the matching process between the unemployed workers and the vacant positions are the only factor responsible for this inward shift. For example, Croatia experienced strong emigration during this period, which explains some part of the decline in aggregate unemployment. The Austrian Beveridge curve, on the other hand, shows outward movements over time, implying a less efficient matching process. An outward shift is especially visible in 2020, after the start of the COVID-19 pandemic. The Austrian economy quickly recovered afterwards, and 2021 and 2022 saw an increase in vacancies along with a decrease in unemployment, a shift along the Beveridge curve. The Beveridge curve for Estonia first shows an inward shift and then a strong vertical shift to the right following the COVID-19 pandemic. Interestingly enough, Croatia, Spain and Slovenia did not record such shifts during and after the pandemic period. A relatively strong increase in the number of vacancies in Austria, Croatia and Estonia in the last two post-pandemic years is a potential indicator of strong cyclical shifts which are probably caused by labour shortages and overheating of the economy.

Further analysis displays disaggregated Beveridge curves according to different levels of education for each country.

4.2. Beveridge curves disaggregated by education levels

In this section, we present and analyse the Beveridge curves constructed for each analysed country considering different education levels given the diverse level of disaggregation according to national employment offices data.

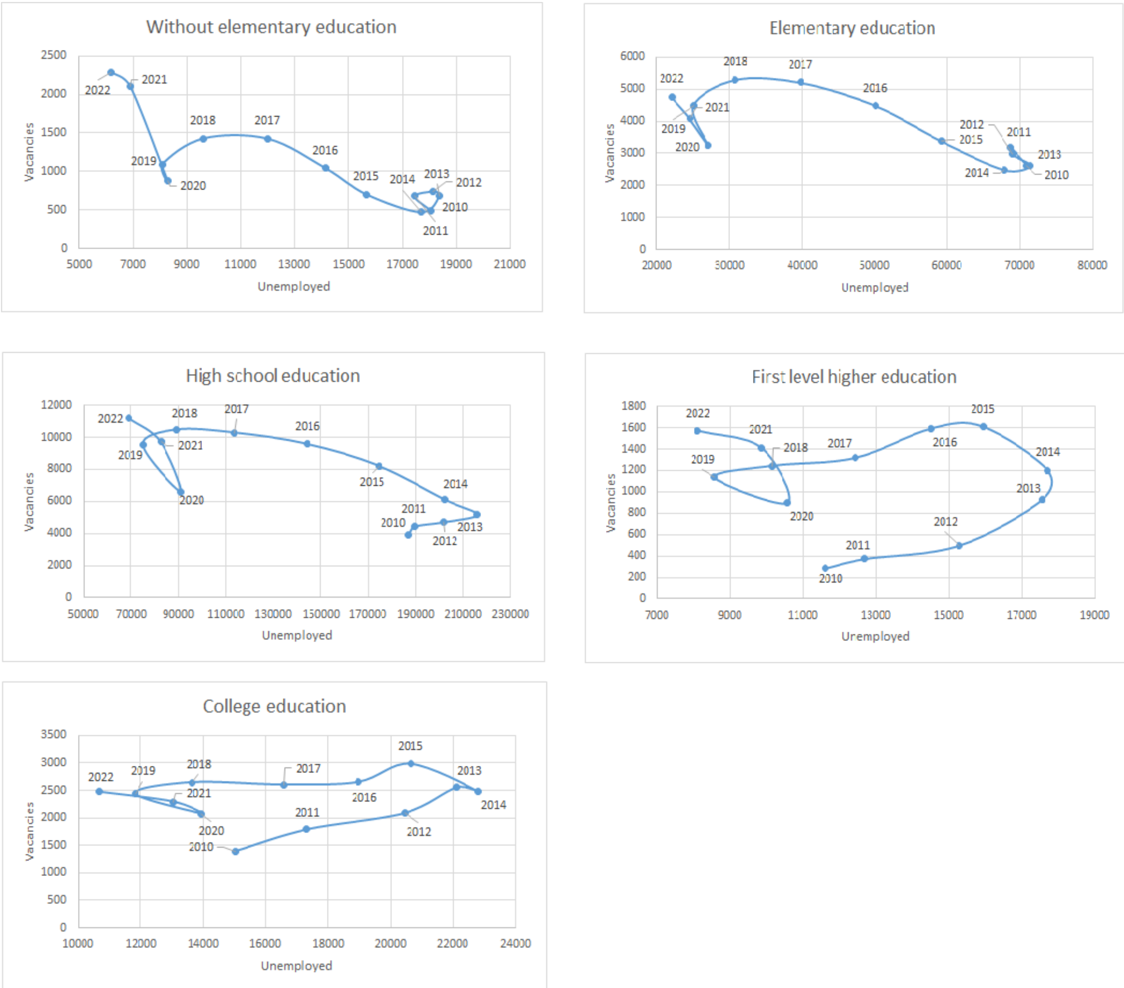
Figure 2 - Disaggregated Beveridge curves for different levels of education, Austria



Source: Authors’ calculations based on Public Employment Service Austria (2022) data.

Beveridge curves disaggregated by education levels for Austria show similar and highly comparable behaviour to the aggregate Beveridge curve for Austria displayed in Figure 1. Beveridge curves for different education level groups show similar patterns, with the slight exception of the Academic education group in the initial observed period, leading to the conclusion that differences in education levels do not influence the shape of the Beveridge curves for Austria, with all education groups recording similar movement as the aggregate labour market.

Figure 3 - Disaggregated Beveridge curves for different levels of education, Croatia



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

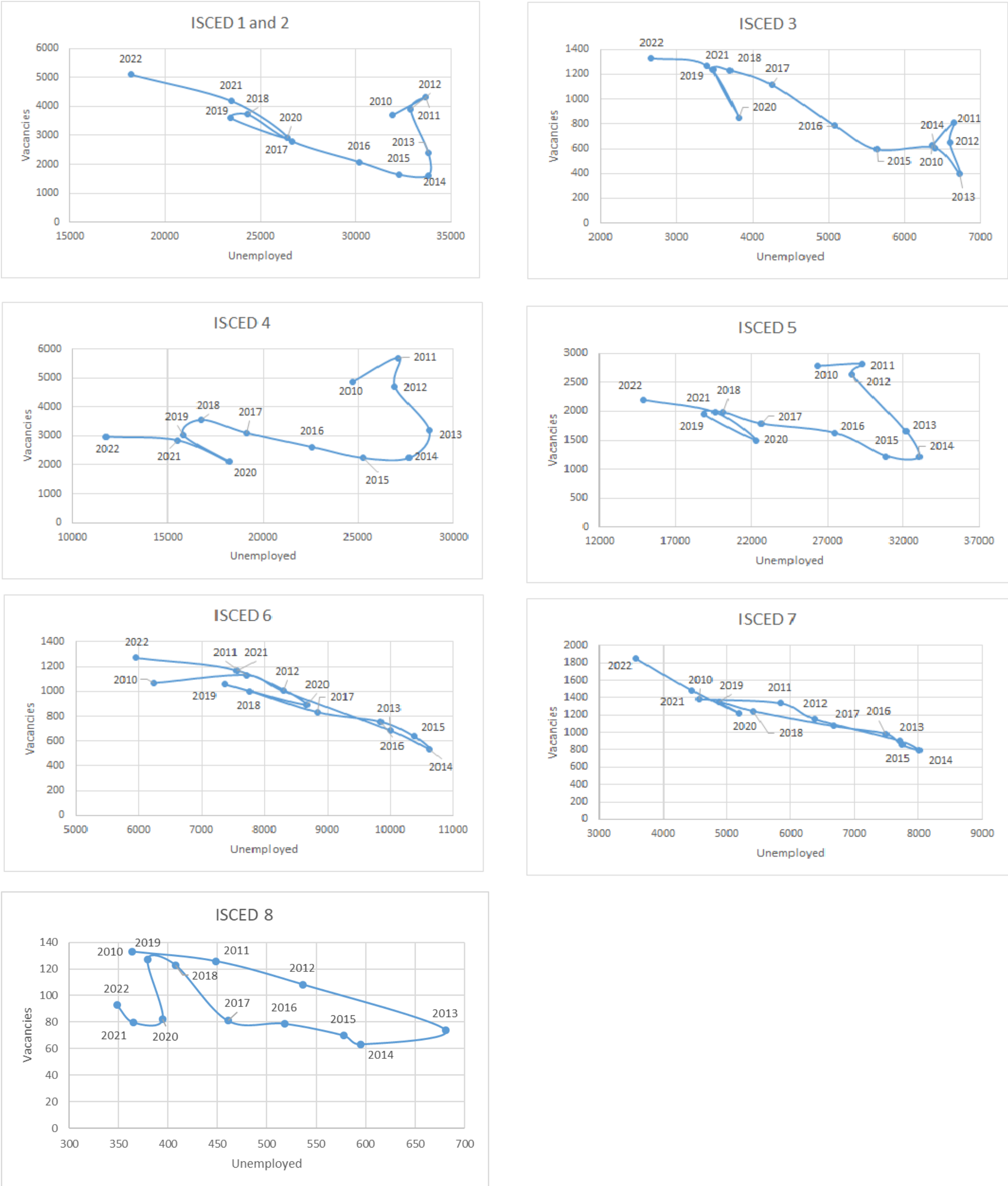
Disaggregated Beveridge curves for categories "Without elementary education", "Elementary education" and "High school education" are relatively similar, showing the negative relationship between unemployment and vacancies, as well as the improvement in labour market conditions for the unemployed workers in 2022 compared to 2010. "First level higher education" and "College education" groups follow similar movements, but also show that the relative decrease in the number of unemployed workers was less pronounced from 2010 to 2022 compared to the other three education groups. The mentioned decrease is especially present in the last two post-pandemic years. In these last two years, the increase in the number of vacancies is particularly pronounced at the level "First level higher education", pointing to labour shortages in the economy.

Figure 4 - Disaggregated Beveridge curves for different levels of education, Estonia

Source: Authors' calculations based on Estonian Unemployment Insurance Fund (2022) data.

The Beveridge curves for all three education groups for Estonia show somewhat similar movements. An inward shift from 2010 is visible for all three education groups, and then a strong almost vertical shift caused by a significant increase in vacancies in 2022. Such a shift is especially noticeable at the highest levels of education indicating a significantly increased demand and a strong shortage of highly educated workers.

Figure 5 - Disaggregated Beveridge curves for different levels of education, Slovenia



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

Beveridge curves disaggregated by education level for Slovenia show different behaviour over time. ISCED 6 and 7 levels clearly show the negative relationship between vacancies and unemployment. ISCED 1 and 2, ISCED 4 and ISCED 5 education levels mostly resemble the aggregate Beveridge curve shape for Slovenia. The aggregate Beveridge curve shows a similar shape to the curves for these education levels since most unemployed workers and vacant positions belong to these education groups.

Figure 6 - Disaggregated Beveridge curves for different levels of education, Spain

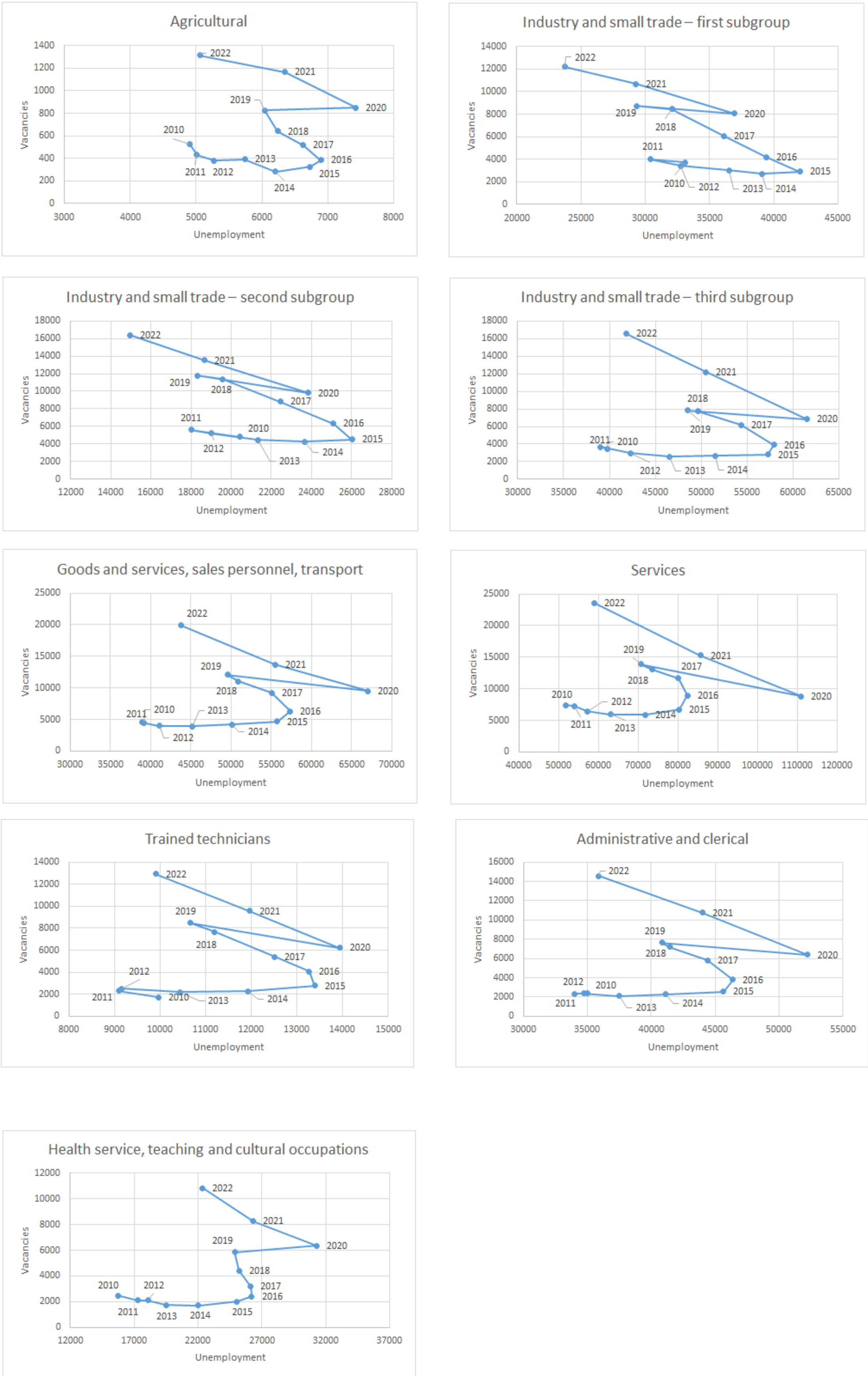
Source: Authors' calculations based on Spanish Public Employment Service (2022) data

Disaggregated Beveridge curves for Spain demonstrate considerable differences in shapes. While some of the curves, for example, those for ISCED 3, 5 and 7 educational levels have rather similar patterns as the aggregate one, the curves for ISCED 0 and 1 educational levels differ from the movement of the other education groups. In line with the aggregate Beveridge curve for Spain, most education groups recorded an inward shift of the Beveridge curve over time as Spain witnessed a strong decrease in unemployment. A smaller inward shift is noticeable for groups with lower education levels (ISCED 0, 1 and 2) compared to ISCED 5 and ISCED 7 groups. The Beveridge curve for the ISCED 6 level is not shown due to a relatively low number of observations.

4.3. Beveridge curves disaggregated by occupation

In our further analysis, the disaggregated Beveridge curves according to different ISCO-88 occupations for each country are derived. The results are presented for all countries except Estonia since disaggregated data by occupation groups were not available at the Estonian employment office (Estonian Unemployment Insurance Fund). Figure 7 shows disaggregated Beveridge curves for Austria.

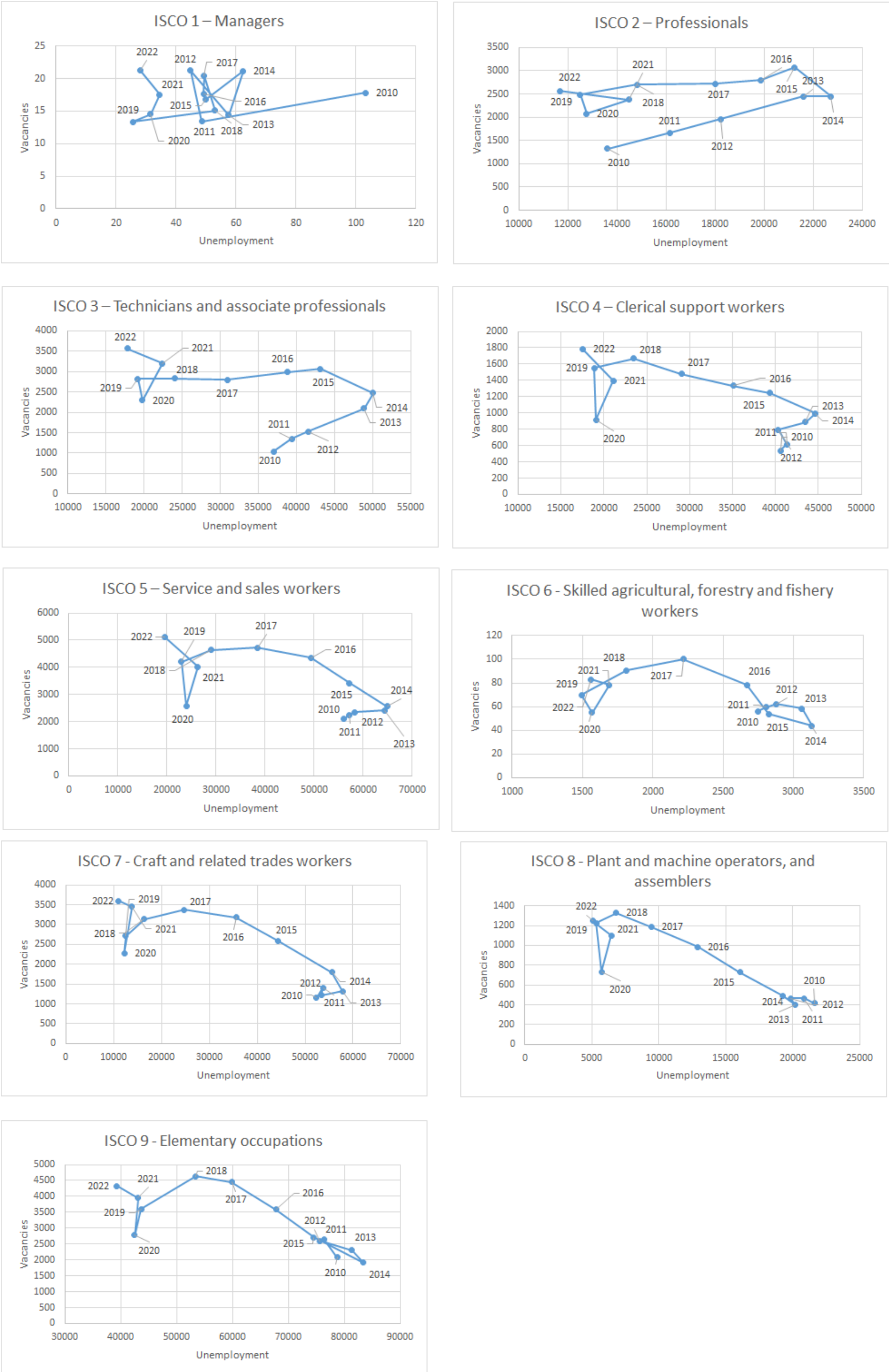
Figure 7 - Disaggregated Beveridge curves for different occupation groups, Austria



Source: Authors' calculations based on 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 except “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 were 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 both the aggregate Beveridge curve and the Beveridge curves disaggregated by education, indicating rather similar developments in all areas of the Austrian labour market.

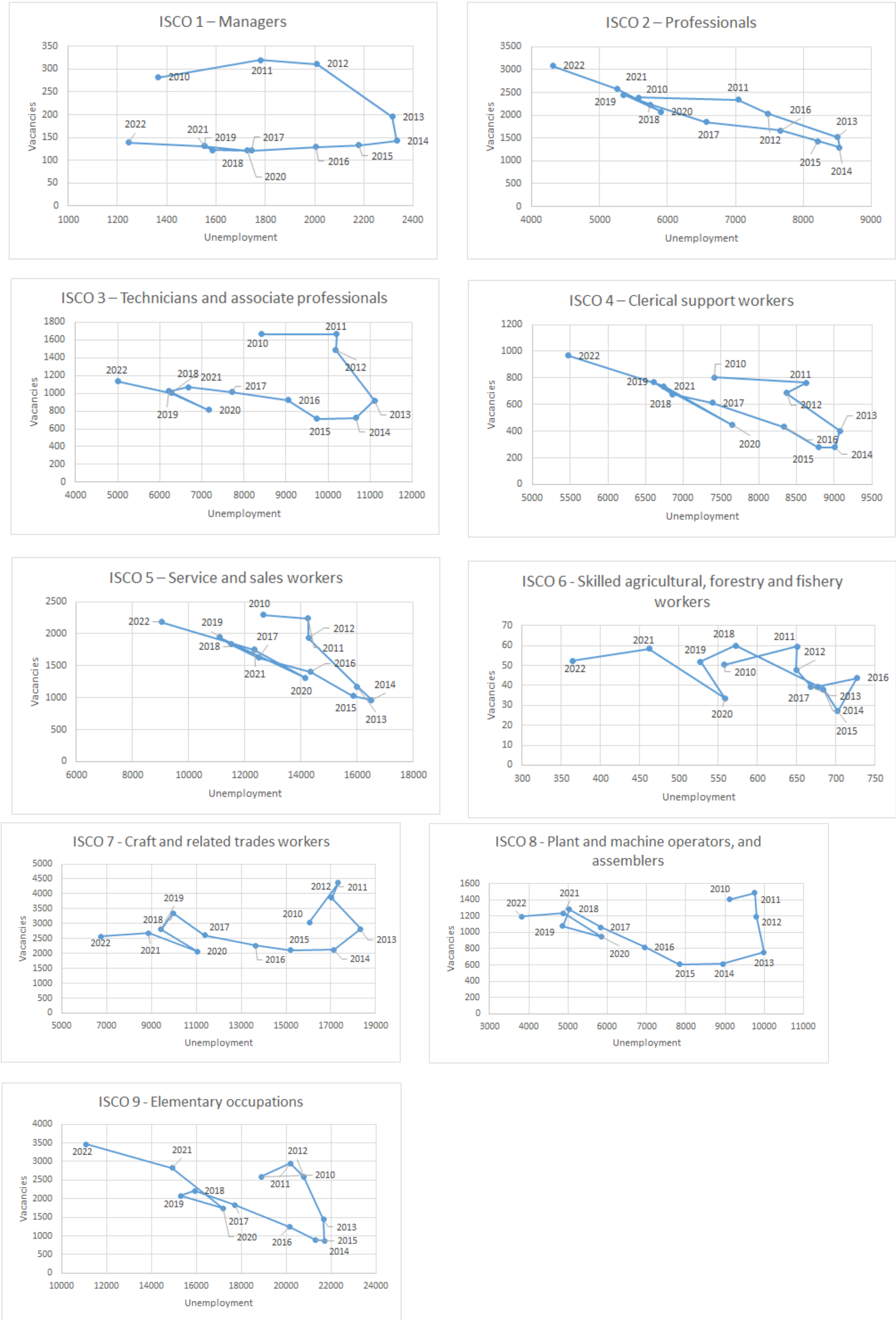
Figure 8 - Disaggregated Beveridge curves for different occupation groups, Croatia



Source: Authors' calculations based on 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 among all occupation groups, which indicates an increasing tightness in the Croatian labour market.

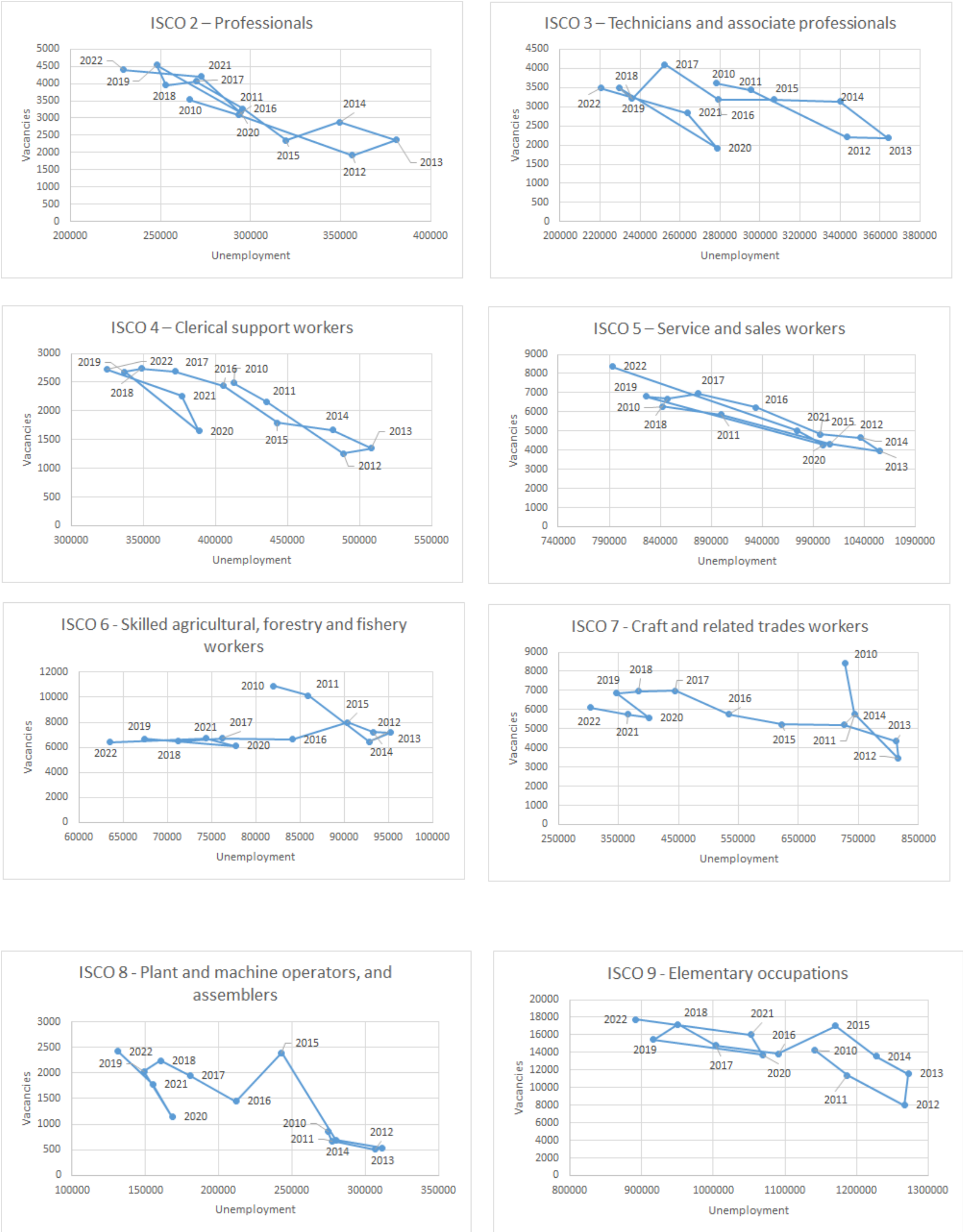
Figure 9 - Disaggregated Beveridge curves for different occupation groups, Slovenia



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

Except for 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 polarization" - 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 10 - Disaggregated Beveridge curves for different occupation groups, Spain



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

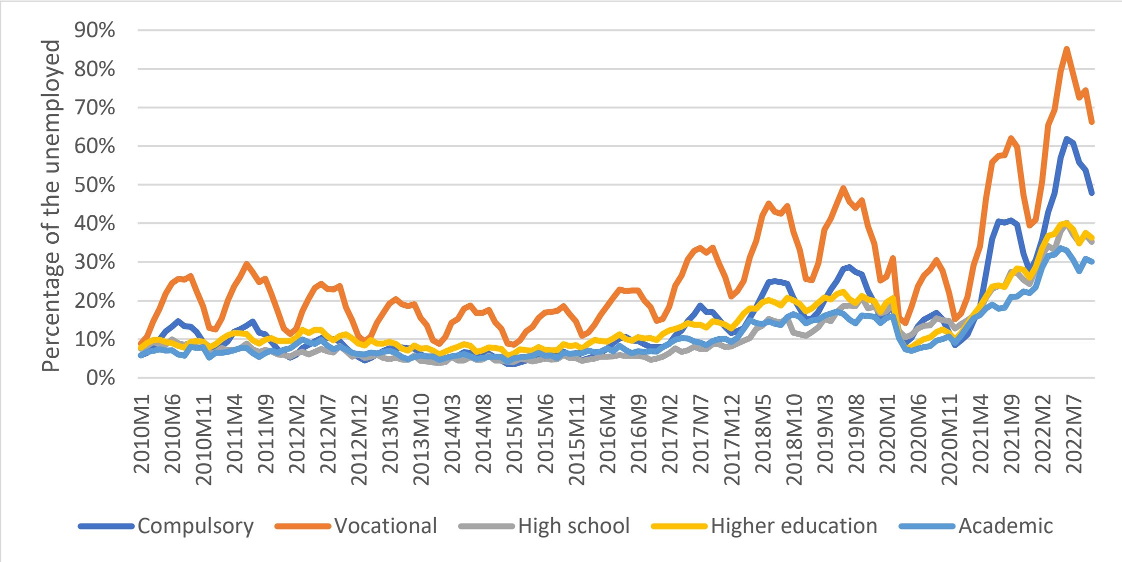
Disaggregated Beveridge curves for different occupation groups for Spain vary for different occupation groups, but also show similar general patterns. The 2010-2013 period is marked by the worsening of the labour market conditions – unemployment increased, and the number of vacant positions decreased. 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 show similar trends to the Beveridge curve for aggregate unemployment and vacancies.

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

4.4. Empirical matching process – labour market tightness and matching efficiency by education levels

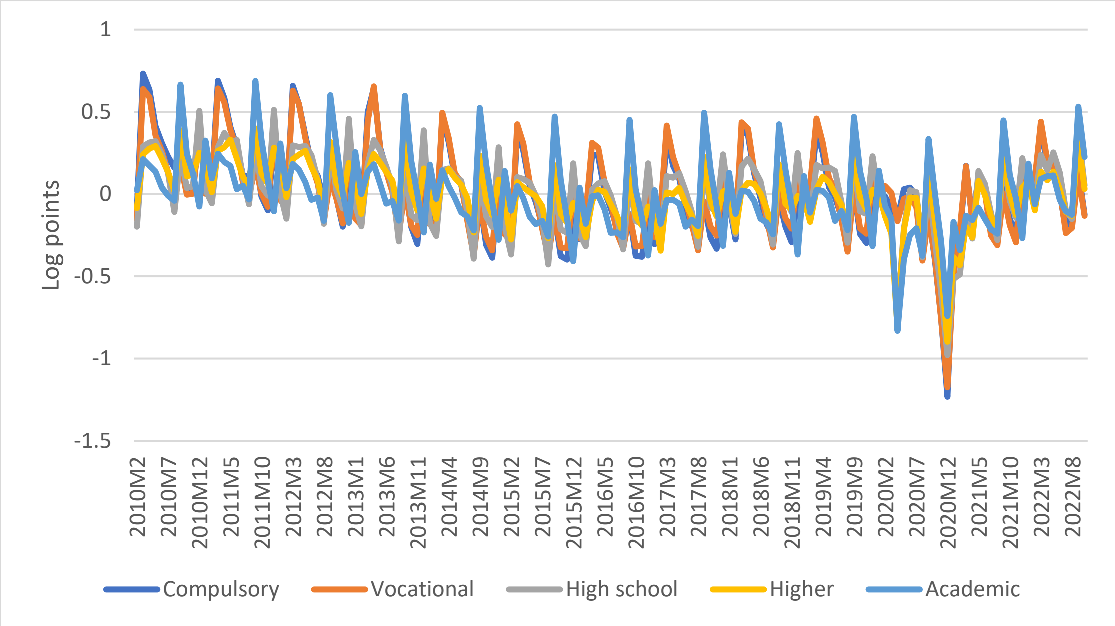
According to our methodological approach in this section, we continue with the second step of our analysis to explain the level of labour market tightness and efficiency of the matching process. Therefore, we calculate and show the movements in labour market tightness and present the results of the estimation of matching efficiency by education levels in the selected group of countries, in line with Equation 3. The results for different countries are presented in alphabetical order.

Figure 11 - Tightness by education levels, Austria, January 2010 – October 2022



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

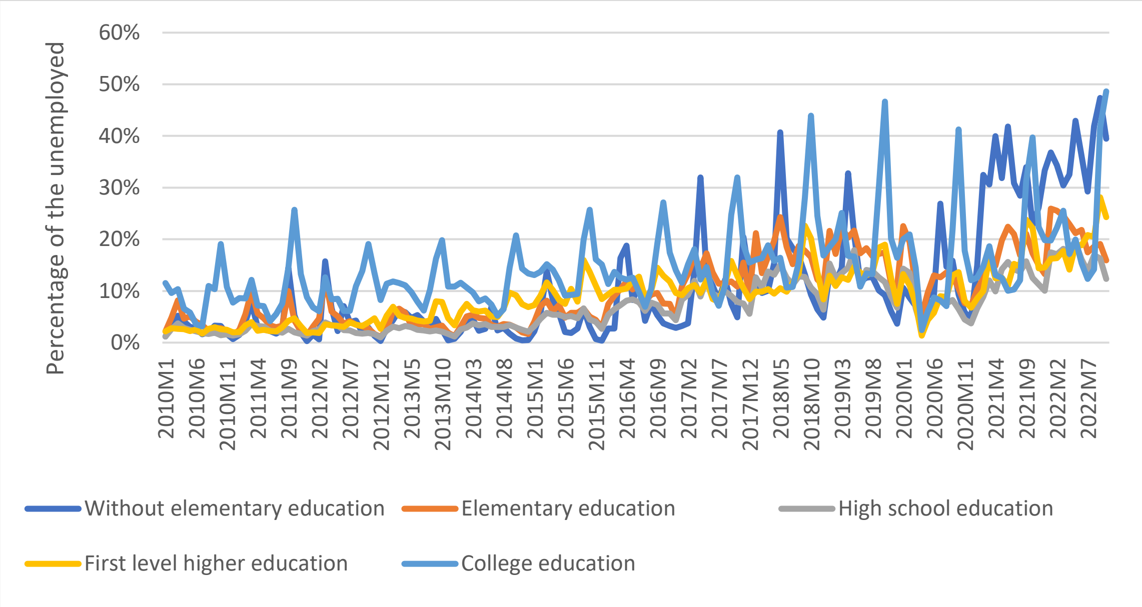
Figure 12 - Matching efficiency by education levels, Austria, February 2010 – October 2022



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

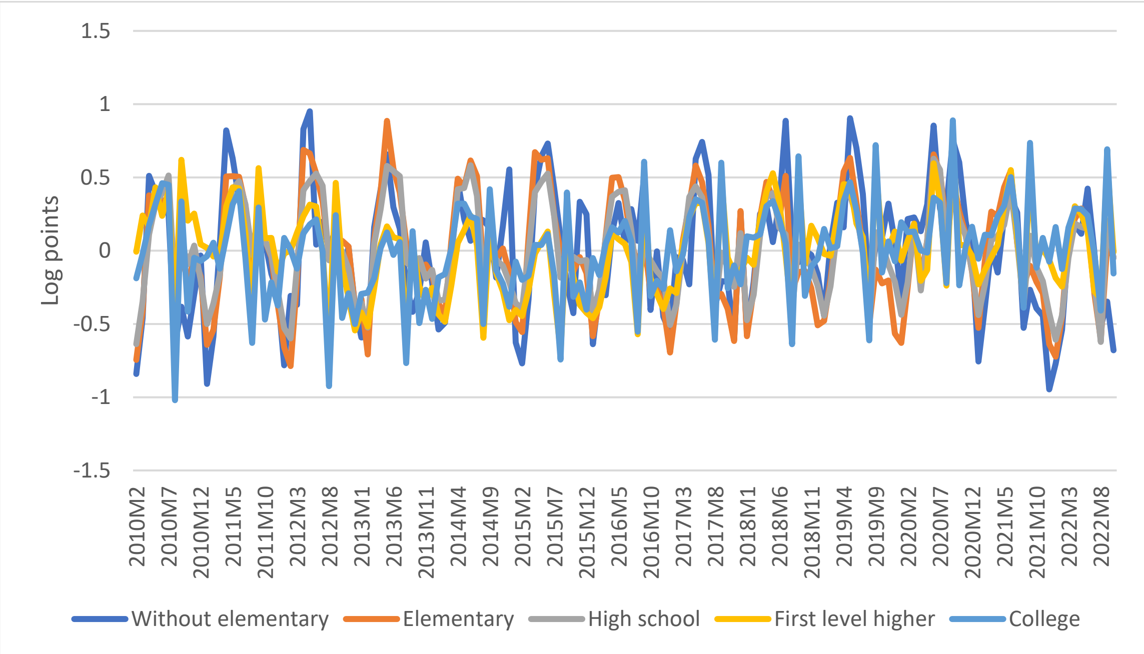
The results for Austria show that labour market tightness is continuously increasing throughout the period with significant growth after 2020 in all five education groups. However, this increase is the greatest for groups of workers with lower education levels, Compulsory and Vocational education. Matching efficiency shows similar general trends in all five education groups as well, though some groups (for example, Academic) have higher amplitudes. Matching efficiency was, on average, higher during the early years of the period for all groups. Matching efficiency experienced a slump in 2020 due to disruptions caused by the pandemic and lockdowns but rebounded afterwards. In general, post-pandemic increases in tightness for all education groups led to improvement in the matching efficiency, pointing to the conclusion that the education and skills of Austrian workers, regardless of the education level, are in line and matched with the labour market needs. This is most evident for workers with Compulsory and Vocational education, who experienced the strongest increases in labour market tightness without a decrease in matching efficiency. Regarding the matching efficiency, a similar conclusion holds as for the Beveridge curves – all groups of workers, regardless, of education levels, follow similar trends.

Figure 13 - Tightness by education levels, Croatia, January 2010 – October 2022



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

Figure 14 - Matching efficiency by education levels, Croatia, February 2010 – October 2022

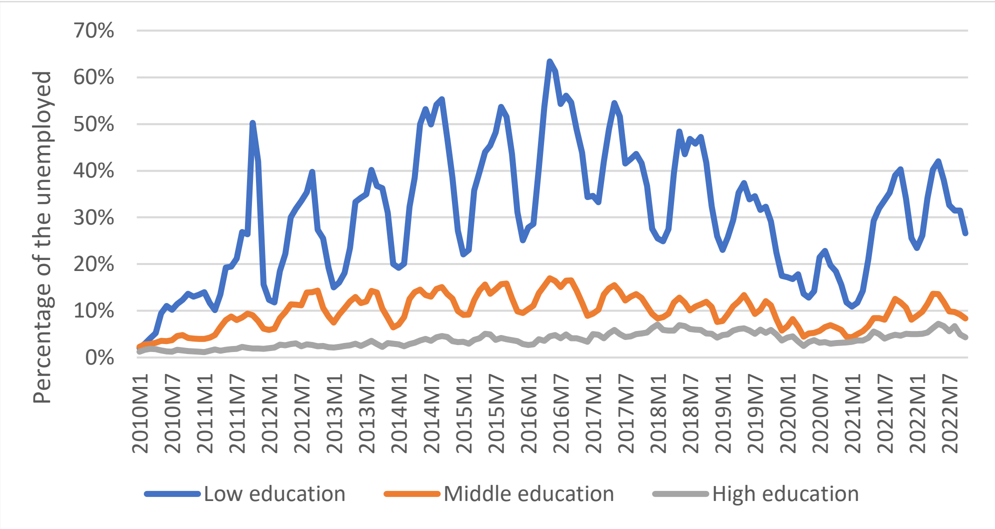


Source: Authors' calculations based on Croatian Employment Services (2022) data.

When it comes to labour market tightness in Croatia, all education groups experienced an increase in tightness towards the end of the period. The tightness was relatively high in 2018 and 2019, especially for those with college education and experienced a temporary slump in 2020. The rebound was strong, resulting in higher average tightness in 2022 compared to 2018 and 2019. Two groups of workers, those without elementary education and those with college education show the highest tightness at the end of the period. The tightness at the end of the observed period was highest for workers without elementary education and college education, outperforming all other education groups on average in 2021 and 2022. Turning our attention to the matching efficiency, matching efficiency for all education groups in Croatia remained relatively stable and equal over time, without periods of noticeable increases or decreases in the matching efficiency. There is, however, a noticeable drop in the matching efficiency for workers without elementary education towards the end of the period, precisely when the tightness increased. This means that, although the demand for workers without elementary education increased strongly, this increase in demand did not result in increases in the job finding in line with what one would expect based on the estimate of the matching function. The Croatian labour market for relatively uneducated workers was very tight in 2021 and 2022, resulting in a strong inflow of foreign workers with the same characteristics. The drop in matching efficiency can therefore be attributed to employers hiring foreign workers because they were not able to meet their needs among the pool of domestic ones. That means that some of the employed workers were foreign workers who were not previously registered with the Croatian Employment Services.

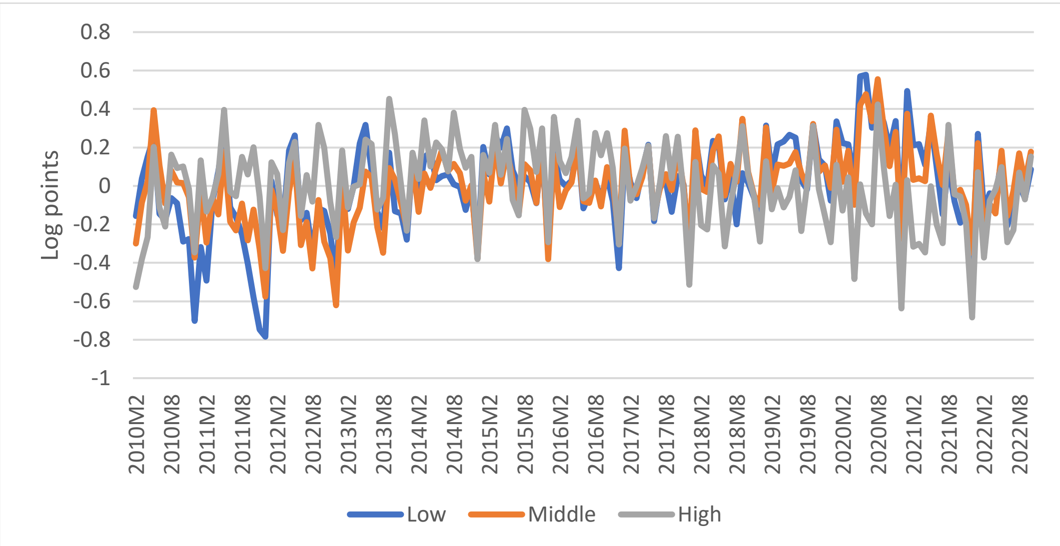
Workers with college education, on the other hand, show stable levels of matching efficiency at the end of the observed period, pointing towards the conclusion that higher tightness didn't lead to reduced matching efficiency. Therefore, their skills and knowledge are in line with the demands of the labour market. Workers with elementary and high school education recorded a slight drop in matching efficiency along with increased tightness in 2021 and 2022.

Figure 15 - Tightness by education levels, Estonia, January 2010 – October 2022



Source: Authors' calculations based on Estonian Unemployment Insurance Fund (2022) data.

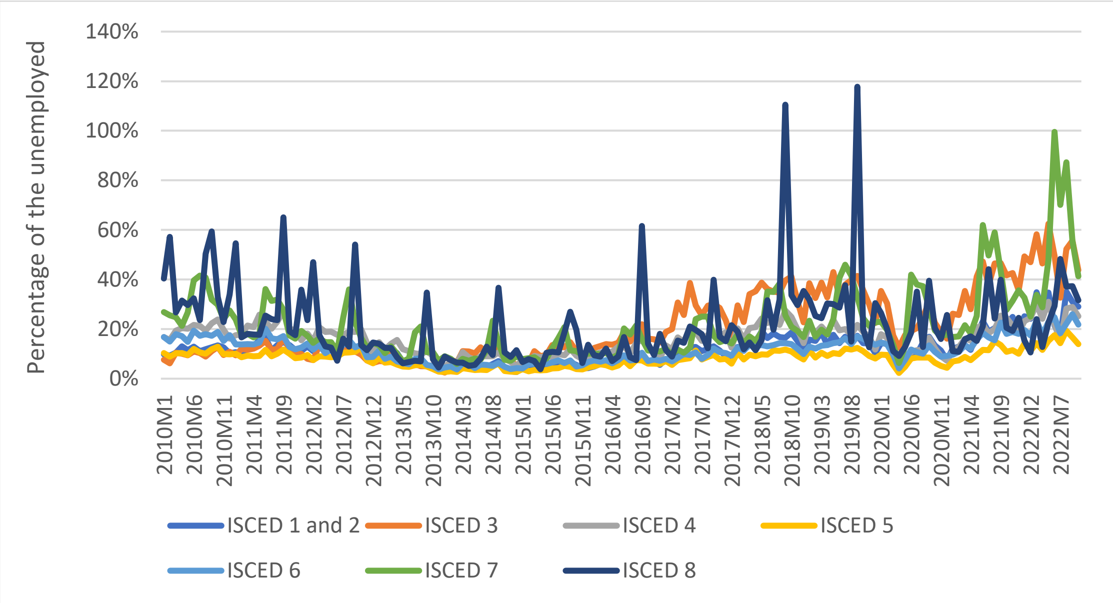
Figure 16 - Matching efficiency by education levels, Estonia, February 2010 – October 2022



Source: Authors' calculations based on Estonian Unemployment Insurance Fund (2022) data.

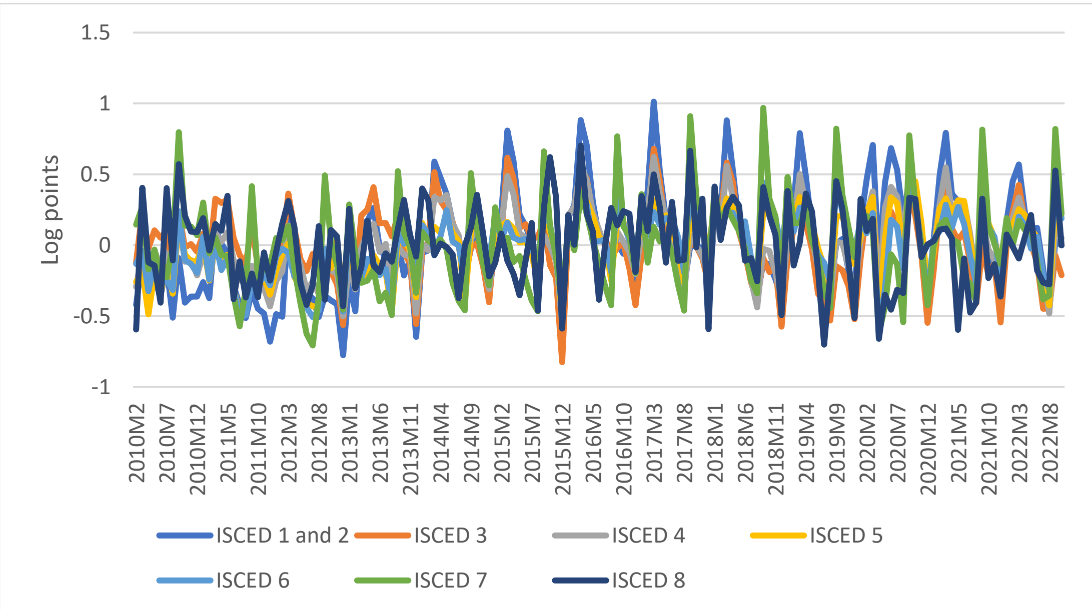
The analysed results for Estonia show that matching efficiency for workers with low and middle education increased over time, being at the lowest point during the 2010-2013 period, and surprisingly reaching a peak during 2020 except the "lockdown" period. On the contrary, workers in the „High" education group experienced a drop in matching efficiency from 2019 to 2021, with matching efficiency rebounding in 2022 and converging to the efficiency of the other two groups. All three education groups experienced a drop in labour market tightness in 2020, and a rebound to approximately the previous levels of tightness afterwards. A significant difference in the levels of tightness, with the average tightness in the „Low" education group considerably higher compared to the average tightness for workers with „High" education, perhaps can be explained by the searching behaviour of employers as employers search for highly educated workers and professionals more and more through other channels aside from the national employment office.

Figure 17 - Tightness by education levels, Slovenia, January 2010 – October 2022



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

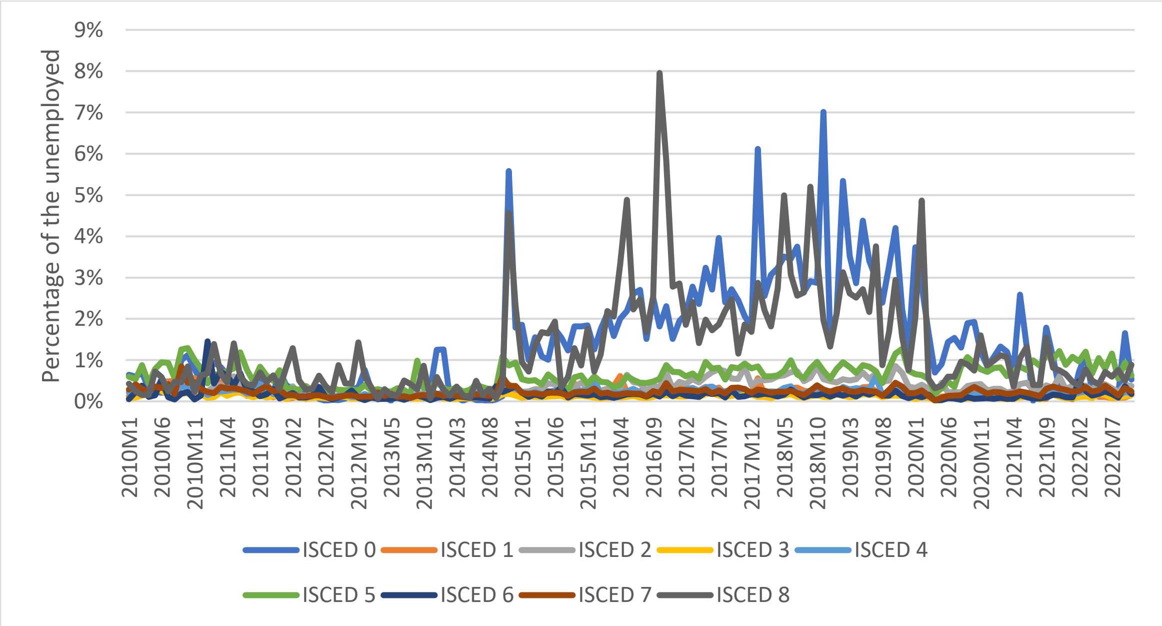
Figure 18 - Matching efficiency by education levels, Slovenia, February 2010 – October 2022



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

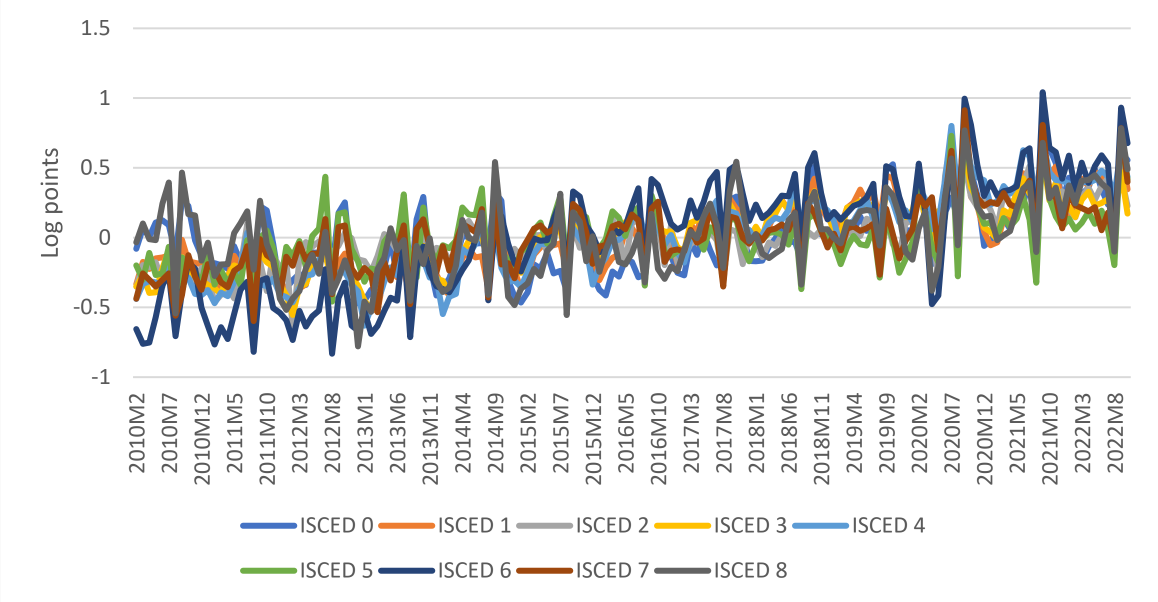
In line with the trends in other countries, labour market tightness in Slovenia slumped in 2020 in all ISCED education groups and rebounded afterwards. The labour market was relatively tight in 2022, with the highest tightness in ISCED 7 (Master's or equivalent level) and ISCED 3 (Upper secondary education) groups. Matching efficiency for different education groups' movements are highly correlated, being lower than the average of the entire analysed period from 2010 to 2013, reaching relatively high levels during the 2015-2019 period, followed by a decrease in 2020. The average matching efficiency for all education groups in 2021 and 2022 remained only slightly lower compared to the 2015-2019 period peak. This, however, still points towards the conclusion that the educational structure of the labour market in Slovenia is adequately aligned with the needs of employers. Tightness increased during 2021 and 2022, especially for ISCED 7 and 8, but this did not result in decreased matching efficiency, which means that higher demand for workers (higher tightness) translated directly into more matches between the unemployed workers and vacant positions without losses in efficiency due to higher demand for workers.

Figure 19 - Tightness by education levels, Spain, January 2010 – October 2022



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

Figure 20 - Matching efficiency by education levels, Spain, February 2010 – October 2022



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

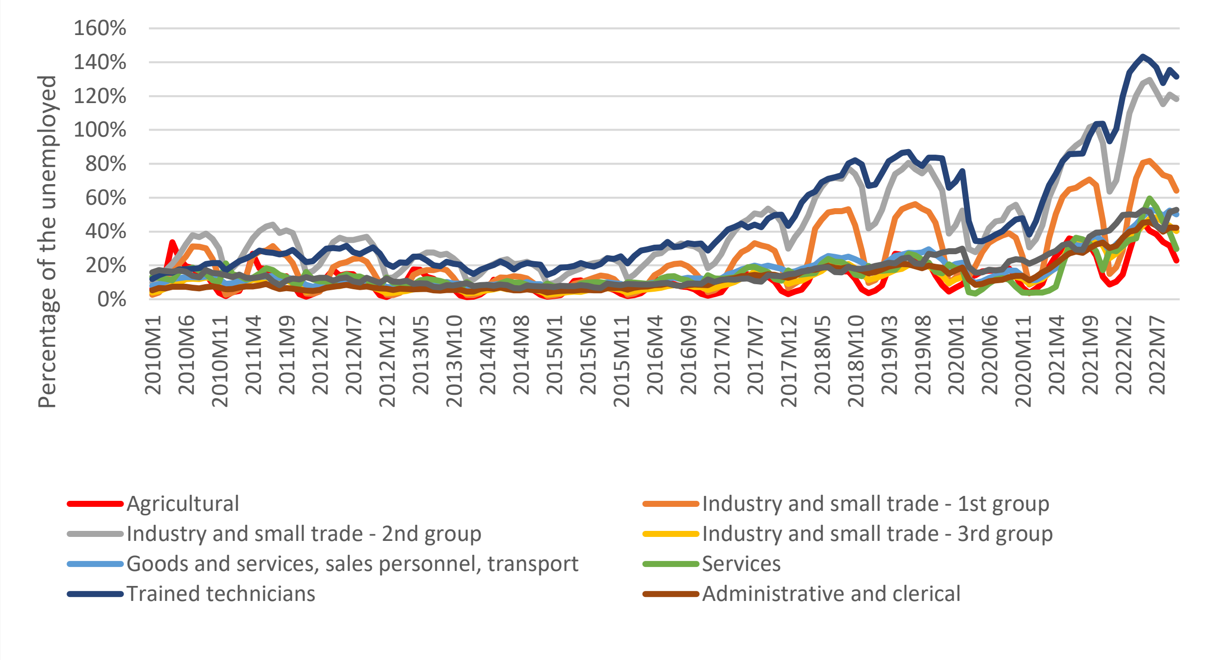
Regarding the labour market tightness trends for Spain, it is important to emphasize that the number of vacancies for all education and occupation groups is relatively low expressed as a percentage of unemployed workers compared to other countries, resulting in lower tightness figures. This indicates that only a minority of new workers in Spain are found through the national employment office, and probably most of the new matches are made through alternative channels (other private employment agencies and head-hunting agencies). Therefore, these are not visible in the official national employment office statistics for vacancies.

All ISCED education groups for Spain show roughly similar behaviour – the matching efficiency recorded a continuous increase over time, from relatively low levels in the first half of the period to relatively high levels at the end of the observed period. Aside from ISCED 0 and ISCED 8 groups, which experienced increases in tightness from 2015 to 2020, tightness remained roughly similar throughout the entire period in all other education groups. Along with increased matching efficiency, this implies that the mismatch between education and skills of the unemployed in different education groups and the labour market needs decreased in the 2010-2022 period.

4.5. Empirical matching process – labour market tightness and matching efficiency by occupation groups

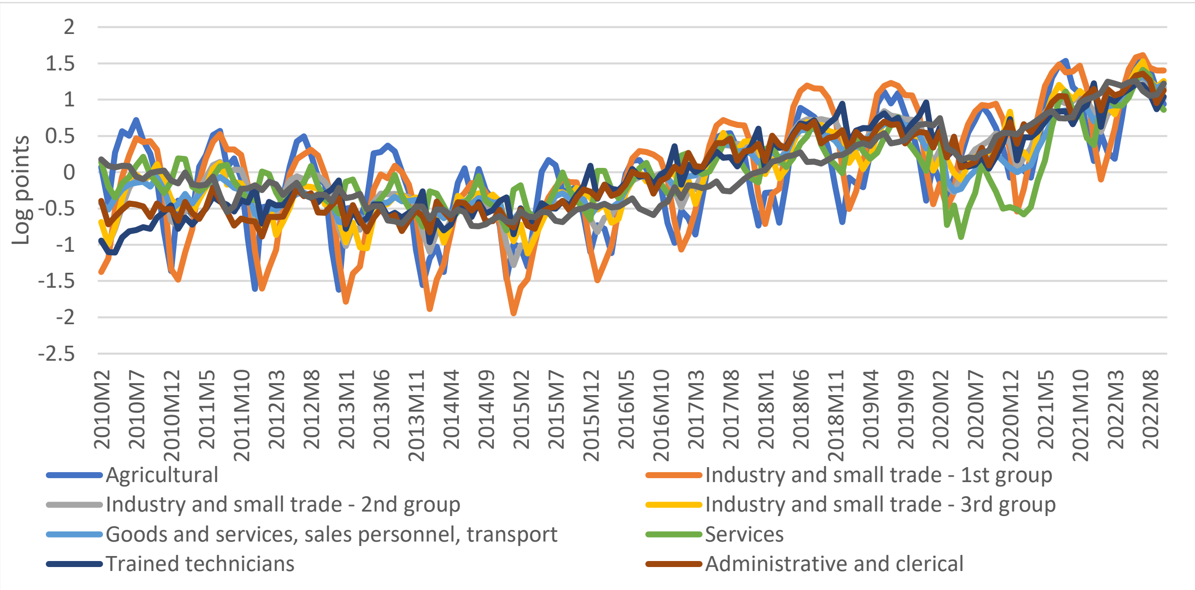
In this part of our analysis, we present the labour market tightness and matching efficiency for different occupation groups in all selected countries (Austria, Croatia, Slovenia and Spain) except Estonia since disaggregated data by occupation groups are not available at the Estonian employment office.

Figure 21 - Tightness by occupation groups, Austria, January 2010 – October 2022



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

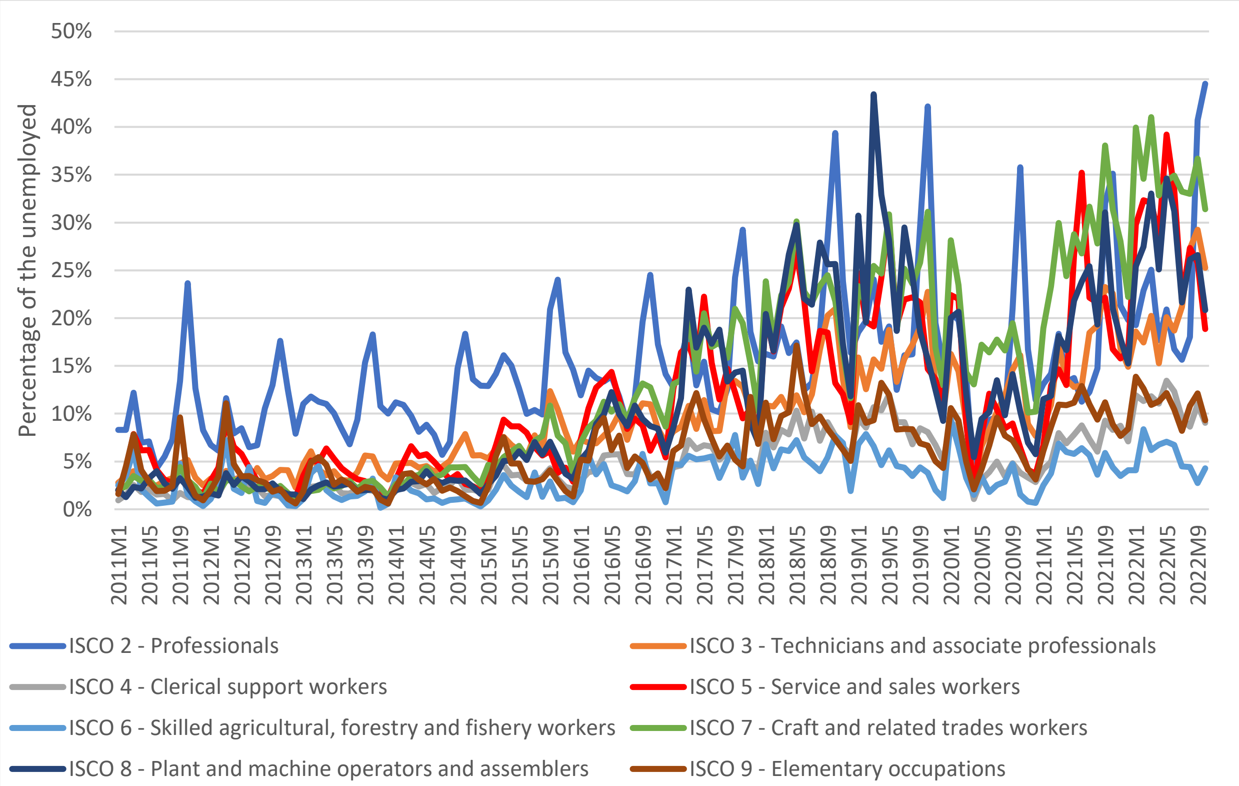
Figure 22 - Matching efficiency by occupation groups, Austria, February 2010 – October 2022



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

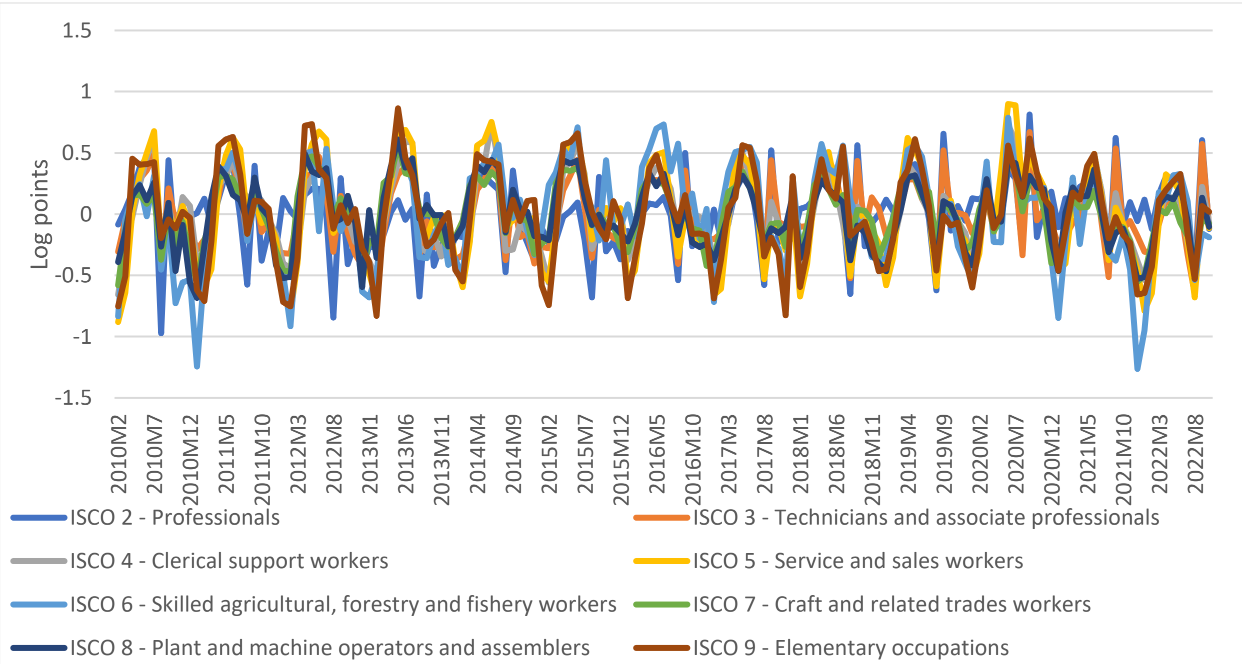
Disaggregated by occupation, different groups of workers in Austria recorded an increase in labour market tightness during the ending years of the period. This increase was the strongest for Trained technicians and workers in the 2nd group of industry and small trade (woodworking occupations, leather 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. The 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 23 - Tightness by occupation groups, Croatia, January 2010 – October 2022



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

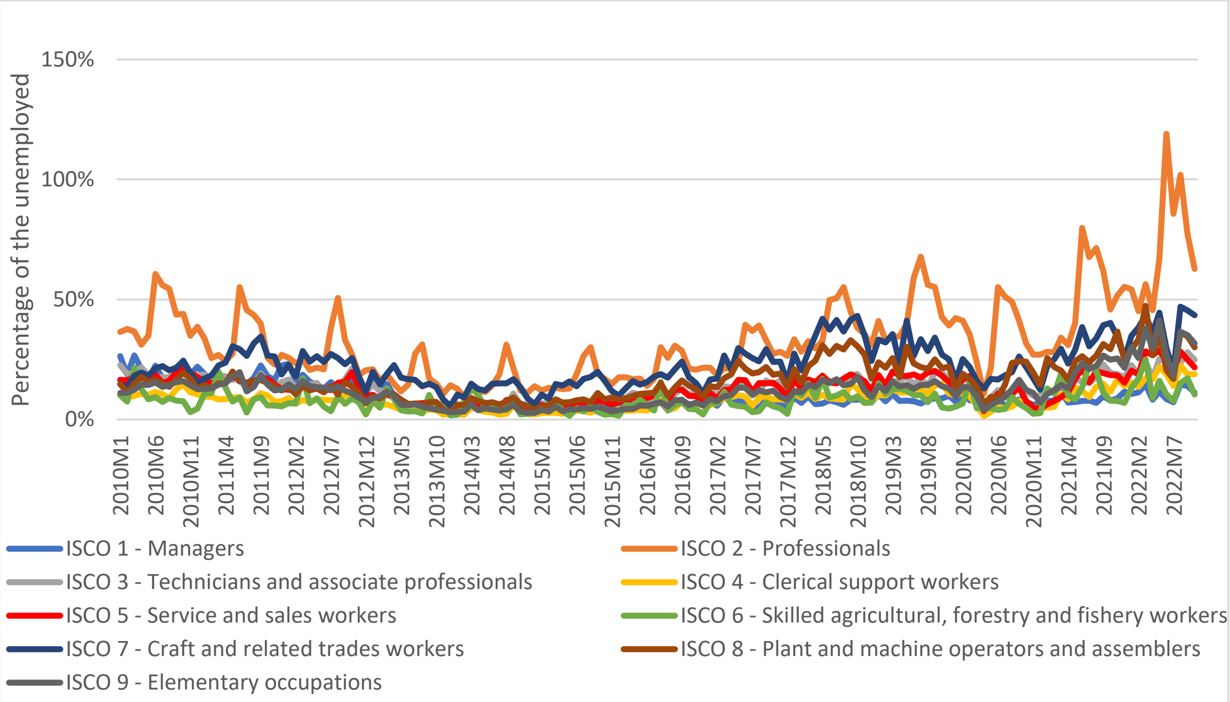
Figure 24 - Matching efficiency by occupation groups, Croatia, February 2010 – October 2022



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

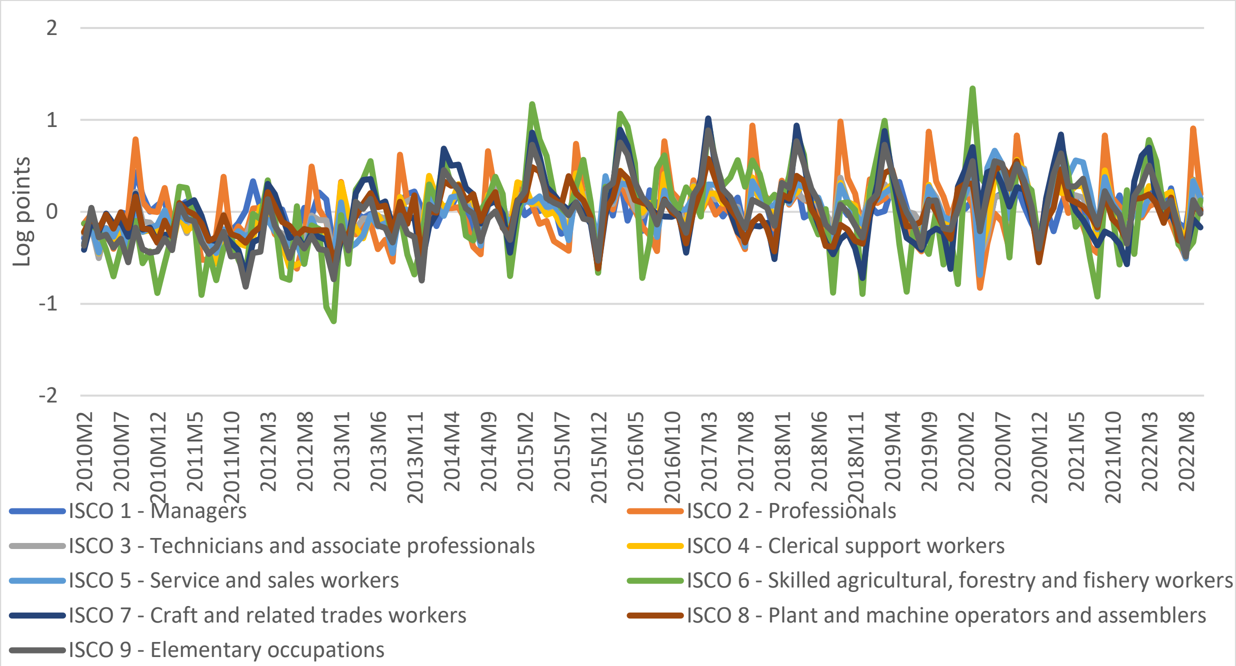
An increase in labour market tightness at the end of the period (2021 and 2022) is noticeable in all occupation groups, but with considerable differences in magnitude. The increase was strongest for occupation groups such as service and sales workers, craft and related workers and professionals, and 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 remained of the period. Since the matching efficiency did not decrease along with the increased tightness at the end of the period, this points towards 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 which 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 25 - Tightness by occupation groups, Slovenia, January 2010 – October 2022



Source: Authors’ calculations based on Employment Service of Slovenia (2022) data.

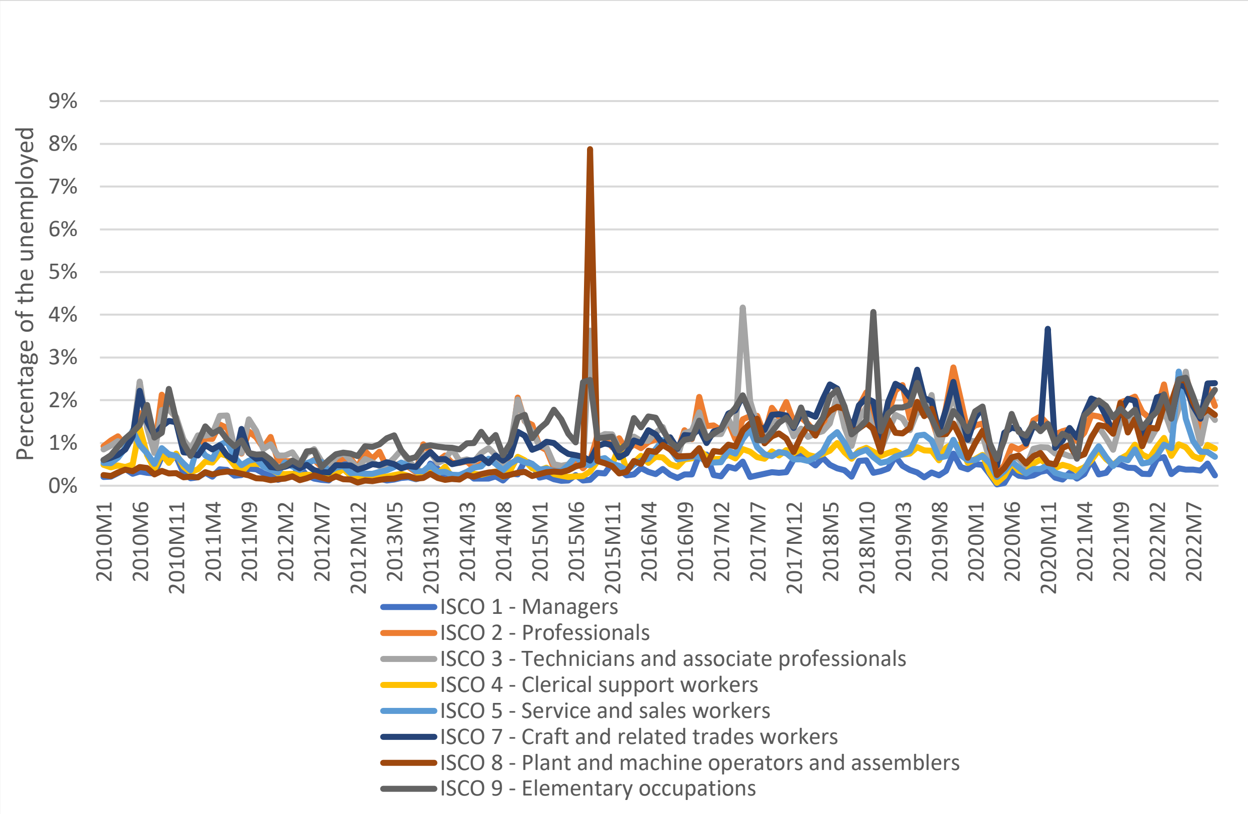
Figure 26 - Matching efficiency by occupation groups, Slovenia, February 2010 – October 2022



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

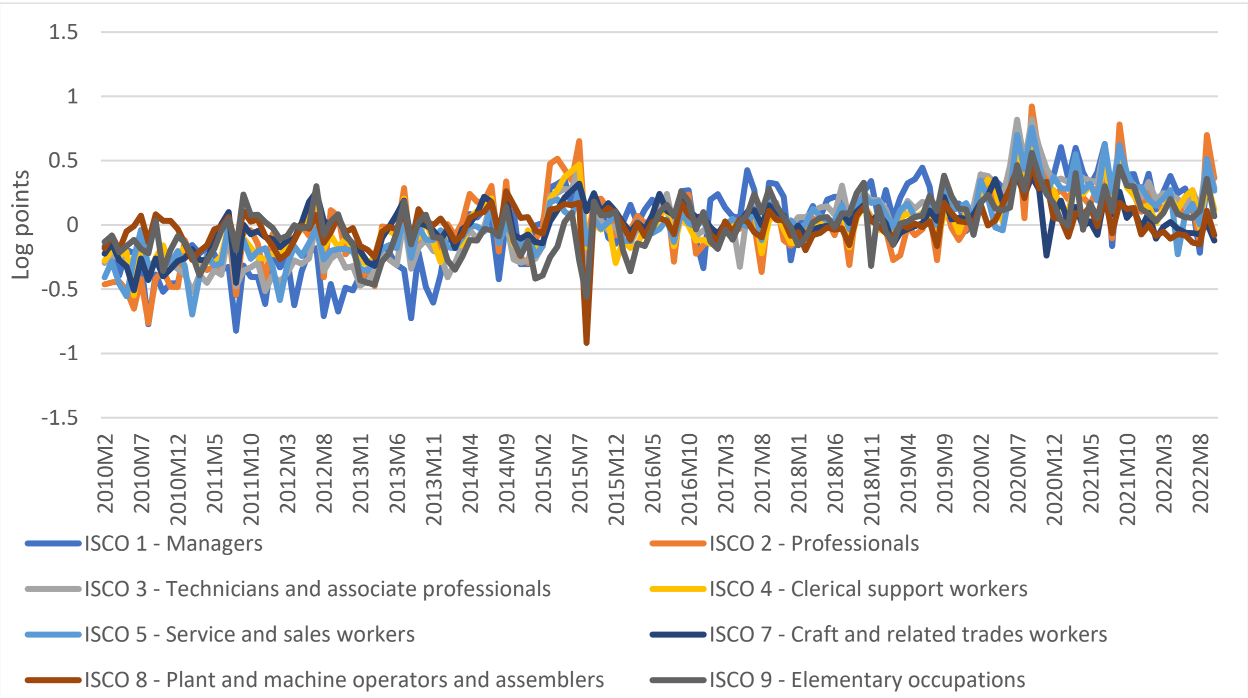
Matching efficiency in Slovenia for different occupation groups follows similar trends as the efficiency for different education levels. The efficiency was lowest during the early years of the period (2010-2013), increasing afterwards. Matching efficiency remained relatively stable during the later years 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 workers 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 the matching efficiency.

Figure 27 - Tightness by occupation groups, Spain, January 2010 – October 2022



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

Figure 28 - Matching efficiency by occupation groups, Spain, February 2010 – October 2022



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

Matching efficiency disaggregated by occupation groups in Spain results in identical results as disaggregation by education levels – matching efficiency 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 and Limitations

In accordance with the four fundamental research hypotheses set out in the second section, the Beveridge curves constructed for different education and occupation groups in Austria, Croatia, Estonia, Slovenia, and Spain provide strong evidence in favour of the first two hypotheses. Worker groups with different levels of education and worker groups in different occupations do indeed experience similar trends to the aggregate trends in the labour market, which is confirmed by the similar shapes of the Beveridge curves among the different education and occupation groups.

However, there are exceptions to this general pattern in some education and occupation groups. The Austrian labour market, whether disaggregated by education or occupation, shows very similar movements in the Beveridge curves. 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. ISCED and 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. In the Estonian labour market disaggregated by education, we found an almost vertical shift of the Beveridge curve for the highest levels of education, showing a strong shortage and demand for highly educated workers. The Beveridge curves for different labour market groups in Spain resemble the aggregate Beveridge curve, but with their own peculiarities in groups such as ISCED 0, 1, 2 and ISCO 6, and ISCO 7.

Despite these exceptions, we believe it is reliable to conclude that in the analysed period in the selected group of countries, different education and occupation groups in the labour market follow 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 hypotheses 3 and 4 regarding the similarities in movements in labour market tightness and matching efficiency among the different education and occupation groups, similar conclusions hold – different education and occupation groups experience relatively similar trends in Austria, Croatia, Estonia, Slovenia, and Spain (the data disaggregated by occupation was not available for Estonia). This, though, is not valid for all groups and in all periods. 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 relatively like the pre-pandemic levels. In Estonia, matching efficiency for those with high education remained relatively stable in 2020, while the other two education groups experienced an increase. These exceptions, however, are not very frequent and we, therefore, believe that the results are in favour of hypotheses 3 and 4.

Though the levels of tightness, as well as their volatility at different points in time, differ, similar general trends in tightness are observable in almost all education and occupation groups in the countries we have analysed. This co-movement is even stronger when it comes to matching efficiency. For example, the trend of increasing matching efficiency over time is shared by almost all occupation groups in Austria. The same trend of increasing matching efficiency over time is visible in all education and occupation groups in Slovenia and Spain. In Croatia, with relatively unchanged matching efficiency over time, the efficiency remained relatively similar over the 2010-2022 period in all education and occupation groups except for workers without elementary and college education who outperformed all other groups in the post-pandemic increase in tightness. Therefore, we conclude that the data and the results provide relatively strong support for all four hypotheses in our paper.

Considering the analysis carried out and the increasingly uncertain economic circumstances that surround us, it is even difficult to predict the future trends and needs of the labour market. It is becoming increasingly obvious that technological changes (introduction of more sophisticated robots, artificial intelligence, etc.) in the labour market continue to be a significant driver of future changes, but are no longer a key factor in determining the basic required skills. In addition to all of the above, the labour markets in the EU member states already depended on other supply and demand factors, such as the ageing of the population, the level of economic transformation in each member state, and different and specific development of labour market institutions and policies.

Well-designed active labour market policies could speed up job matching, including through short-term training programs 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).

Finally, we are aware of some limitations of our findings, so they should be interpreted with caution. The first is related to the different availability of data at the individual disaggregated level for the selected group of countries, because many employment service offices in EU countries do not collect the data disaggregated by all nine ISCED levels or ten ISCO classification groups that we have used in the analysis. Second, the data itself have some limitations considering different labour market legislation and different rules regarding the obligation of employers to report vacant positions to employment offices. Third, the last two analysed years (2020 and 2021) should be conditionally considered due to the period of lockdown and subsequent partial closures due to the COVID-19 pandemic.

6. Conclusion

The analysis in this research included the labour market data for Austria, Croatia, Estonia, Slovenia and Spain during the period from January 2010 to October 2022. Our results performed by the construction of Beveridge curves, the estimation of labour market tightness and matching efficiency point toward the conclusion that different occupation and education groups in the same country experience relatively similar labour market trends in the movements of vacancies, unemployment, labour market tightness and matching efficiency. Several exceptions to this rule exist, but these general trends hold relatively strongly. The results indicate that differences according to the levels of education and occupation did not result in significant deviations from the aggregate labour market trends during the 2010-2022 period. Economic upswings and downswings during the business cycle have a strong impact on the labour market, and this impact was also transmitted to the disaggregated level in relatively similar ways.

Future research should make clear whether the results presented for the selected observed cases can be further generalized by extending the analysis to a larger set of countries. Considering the data on labour market vacancies, future research should aim to include both the official data from the national employment offices, as we did and the data from different private agencies. The data on vacancies from different private agencies would give a more comprehensive picture of the labour market needs, especially in countries such as Spain in which the national employment office vacancy figures are relatively low. Labour market changes in some specific groups, such as IT workers and professionals, are not recorded in the national employment office unemployment figures because in many countries these groups of workers often do not seek their jobs through national employment offices.

Therefore, future studies should need to draw attention to the quality of national data sets and put greater focus on legislative country-specific aspects. Namely, the structure of the economy, the degree of labour market flexibility, employment protection legislation rules, and some specific regional and sectoral circumstances should be also taken into consideration. But it is certainly necessary to consider how the

COVID-19 pandemic has significantly changed the general situation in the labour markets around the world in the last three years, contributing to labour market tightness at almost all levels of education and occupation groups. In some cases, the pandemic has led to improvements in labour market efficiency as businesses have adapted to changing market conditions. In other cases, it showed weaknesses in labour market institutions and policies that will need to be addressed to improve labour market efficiency over the long term. Survey data is likely the most suitable approach for studying the labour market developments in these cases.

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