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MISMATCH DECOMPOSITION IN THE ESTONIAN LABOUR MARKET

Master's thesis

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ABSTRACT

The thesis aims to estimate the mismatch at regional, occupational and industrial levels in the Estonian labour market. Previous studies, to the knowledge of the author, have been done in assessing skills mismatch in Estonia, but not in analysing and quantifying mismatch at different levels. In the current thesis, search and matching theory and mismatch index framework were used to estimate mismatch between unemployed and vacancies at different levels. Findings show that 4-5 percent of hirings have been lost within the Estonian labour market in the period from January 2011 to January 2021 due to regional, occupational or industrial mismatch. From the analysis of matching efficiencies, it followed that certain disaggregated labour markets are subject to frictions resulting from possible mismatch. As the estimation of mismatch unemployment indicated a contribution to unemployment in Estonia, further research is needed to understand the cause of lower matching efficiencies and, thereby, potentially higher mismatch in some disaggregated labour markets in Estonia.

Keywords: mismatch, search and matching theory, regional mismatch, occupational mismatch, industrial mismatch, unemployment, vacancies, mismatch index, Estonian labour market

INTRODUCTION

Decreasing unemployment and increasing employment rates are set as aims in Estonian as well as in European and international organisations' development plans. Unemployment may occur due to different frictions in the labour market, whereas previous research in the field (Bauer 2013; Erken et al. 2015; Marthin 2012; Patterson et al. 2016; Sahin et al. 2014; Shibata 2013) has shown that mismatch between labour supply and demand explains some of the unemployment in the labour markets. Mismatch could occur, for example, because of differences in skills required in the labour market and skills possessed by the labour supply or due to differences in the geographical locations. It is important to understand the underlying reasons of unemployment to design and implement appropriate labour market policies.

Unemployment and vacancies in Estonia vary across different counties, occupations and industries, which raises the question to what extent mismatch between labour supply and demand exists at these levels. To the knowledge of the author, there have been some research in assessing skills mismatch in Estonia (Kutsekoda 2020), but not in quantifying the mismatch at different levels and in estimating their effect on unemployment. Analysing mismatch in such detail would allow to gain further understanding of the unemployment dynamics in the Estonian labour market. The author's bachelor thesis studied, mathematically, the processes regarding matching job vacancies and the unemployed based on the labour market search and matching theory developed by Pissarides (2000). The contribution of this thesis would be the understanding to what extent mismatch between unemployed and vacancies at regional, occupational and industrial levels is existing in the Estonian labour market and, thereby, possibly hindering the efficient matching process.

The aim of this thesis is hence to estimate and map mismatch at regional, occupational and industrial levels. The thesis, therefore, intends to analyse mismatch at these different levels to have an insight into the underlying reasons, which might be causing unemployment and, thereby, hindering the efficient functioning of the labour market.

The main research questions assessed in this thesis are:

1) How is mismatch in the labour market addressed in the search and matching theory framework?
2) To what extent does regional, occupational and industrial mismatch exist in the Estonian labour market?

In order to answer the research questions, the thesis is structured in the following way. The first chapter provides the theoretical background for the analysis and is based on the labour market search and matching theory, developed mainly by Pissarides (2000). One of the main advantages of the theory is that it allows to analyse empirically frictions like mismatch in the labour market without adding too much complexity into the model. The main component in the search and matching theory is the labour market matching function, which describes hiring in the labour market by creating matchings between the unemployed and vacancies. It will be analysed how mismatch is treated in the matching function and, how it affects the creation of job matchings as well as the equilibrium unemployment and vacancy rates. The chapter concludes with a discussion about the findings from previous empirical research regarding mismatch and its impact on unemployment.

To have a deeper understanding of the labour market in Estonia, unemployed and vacancies at regional, occupational and industrial levels will be analysed in the second part of the thesis. Additionally, labour market policies alongside with the corresponding legislation are introduced in the second part of the thesis. Based on the theoretical background and characteristics of the Estonian labour market, it will be analysed whether there are signs of possible mismatch between labour supply and demand. The empirical analysis of estimating mismatch, in the Estonian labour market, is conducted in the subsequent chapters.

The third chapter of the thesis presents the data and explains the methodology used in the empirical analysis for estimating regional, occupational and industrial mismatch. The data are derived from the Estonian Unemployment Insurance Fund (Eesti Töötukassa, EUIF 2021a, 2021b, 2021c, 2021d)[1] and used to estimate aggregate and region, occupation and industry level specific matching functions for the period 2011-2021. This enables to use the analytical framework

[1] As data on occupational and industrial levels is not publicly available in such detail then this data was received from EUIF upon request.

developed by Sahin et al. (2014) to calculate mismatch indices at these different levels. Application of this methodology allows to understand which elements might contribute to the mismatch and, thereby, to the unemployment in the Estonian labour market.

The results of the empirical analysis are presented in the fourth chapter. Firstly, the estimated matching functions are introduced alongside with the corresponding robustness analysis. Thereafter, the mismatch indices at regional, occupational and industry levels in the Estonian labour market are analysed. Finally, the chapter concludes with the discussion to analyse the results based on the theoretical background, Estonian labour market framework and previous empirical research.

The author of the thesis would like to express her gratitude towards the supervisor Simona Ferraro for her support and advice during the process of writing the thesis.

1. THEORETICAL BACKGROUND

This chapter provides an overview of the labour market matching model and its properties based on the search and matching theory. First, there is an explanation of the fundamentals of the theory, how the search and matching theory has evolved and why mismatch exists in the labour market. Thereafter, the cornerstone of the theory so called aggregate matching function will be introduced and analysed to explain how mismatch is treated in the matching function and how it influences the creation of job matchings. The third part of the theoretical background connects the concept of mismatch with the Beveridge curve, in order to analyse how mismatch affects the equilibrium unemployment and vacancy rates. The chapter concludes with a discussion about the findings from empirical research regarding the mismatch and its impact on unemployment.

1.1. Search and matching theory

The search and matching theory regarding labour market develops a framework that enables to analyse the job search, the creation and destruction as well as the effects they have on the dynamics of unemployment (Diamond 1982; Mortensen, Pissarides 1994; Pissarides 1979; 1985; 2000; 2011). One of the main reasons for the development of the theory was the weakness from the neoclassical Walrasian theory of general equilibrium and Keynesian theory to answer the question on why there is unemployment and excess of vacancies in the labour market (Pissarides 2011; Yashiv 2007). The Walrasian theory assumes that there exists perfect information between the participants in the labour market and a perfect allocation of workers for employers is achieved with the wage equal to the marginal product of labour. This perfect allocation is then defined as full employment. (Kandel, Simhon 2002) The Walrasian theory, thereby, implies that there is no long-term unemployment in the labour market.

The Keynesian theory assumes that there exists involuntary unemployment as consequence of negative demand shocks, which has an adverse effect on investment. Consequently, it creates an involuntary unemployment as there is less labour demand. (Bulow, Summers 1986; Smith, Zoega 2009) Both existing fundamental theoretical approaches, Walrasian and Keynesian take the unemployed individuals as passive economic subjects not looking for a job, which however do not coincide with the empirics (Pissarides 2011). Moreover, both theories did not provide sufficient explanations on the existence of unemployment, especially of the long-term unemployment. This has opened the ground for the development of the search and matching theory.

Search and matching theory was developed mainly by Diamond (1982), Mortensen (1985; 1994) and Pissarides (1979; 2000) whereas the comprehensive framework was formed by Pissarides (2000). It relies on the assumption that there exists a continuous trade between the participants in the labour market, which is subject to different frictions (Diamond 1982; Pissarides 2000). The frictions can be identified as information asymmetry between job seekers and employers as well as differences in the characteristics of the labour force and vacancies (Pissarides 2000). The acknowledgment of heterogeneity and frictions in the labour market, in the context of search and matching theory, gives reasoning for the unemployment and unfilled vacancies existing empirically in the labour markets also for longer term. Hence, search and matching theory abandons the assumption of long-term full employment of the neoclassical theory and offers a new framework to analyse why there is long-term unemployment.

Search and matching theory states that unemployment exists because the flows from and into employment take place consistently, meaning that during each matching process between a job seeker and a vacancy, a matched job is also being destructed (Pissarides 2000). This assumption relies on an empirically existing phenomenon where in every period, some unemployed individuals find a job and vacancies are filled but some employed labour force will become unemployed, creating new vacancies. The theory also enables to find the equilibrium unemployment rate where the flows from unemployment to employment and *vice versa* (v.v.) are equal (Pissarides 2000). The aim of search and matching theory is, therefore, to explain the existence of unemployment through a process of matching, which is constantly taking place between the job seekers and the employers who are looking for employees.

In the process of job matching, characteristics and preferences of both the unemployed and of the employers have an impact on the outcome of job matchings influencing the level of the equilibrium unemployment and vacancy rates. As described by Petrongolo and Pissarides (2001), the matching function is a black box that contains different frictions. Those frictions influence the process of job matchings. Frictions identified as information asymmetry, differences of the characteristics of job seekers and vacant positions, including mismatch are a fundamental part of a labour market as they explain why job matchings are not formed right away when unemployed and vacancies meet (Pissarides 2000; 2011). One of the main advantages of the search and matching theory is that it allows to analyse these frictions without adding too much complexity into the model (Petrongolo, Pissarides 2001). It considers the possibility of different frictions present in the labour market and enables to assess the impact of these empirically.

Although the inclusion of frictions in the model without adding too much complexity is seen as a strength of the search and matching theory by Petrongolo and Pissarides (2001), the implicit existence of heterogeneities, incl. frictions in the environment of the model is also criticised. From implicit existence of frictions follows that they are exogenous in the search and matching model. Therefore, frictions are existing in the labour market but are not determined by the matching process between labour supply and demand. (Lagos 2000, Shimer 2007) Therefore, frictions, e.g. mismatch between the unemployed and vacancies is existing in the search and matching framework but is not determined by the matching process.

Mismatch is often addressed in the context of structural unemployment, considered as the natural rate of unemployment that would exist if there were no cyclical unemployment resulting from business cycle fluctuations (Daly et al. 2012; Pissarides 2000). It is a structural occurrence as it would also exist in the absence of some other typical frictions in the labour market: search frictions and information asymmetry (Bauer 2013). Mismatch in the search and matching theory is connected with the structural unemployment because it incorporates and describes the heterogeneities among the characteristics of unemployed and vacancies in the labour market, which can occur, for example, due to differences in skills of the unemployed and the skill requirements of the vacant positions (Petrongolo, Pissarides 2001; Pissarides 2011). The search and matching model incorporates hence, the mismatch in the matching process and analyses the different reasons for the existence of the long-term unemployment in a labour market.

The following subchapter introduces the cornerstone of search and matching theory, the aggregate matching function in order to further analyse the formation of job matchings. It will also be analysed how mismatch, a possible friction in the labour market, is treated in the framework of the search and matching theory and, which components of the matching function might indicate mismatch in the labour market. Henceforth, the dynamics of mismatch in connection with the Beveridge curve will be explained.

1.2. Aggregate matching function and mismatch

The framework of search and matching theory is based on the matching function. It describes and models the creation of job matchings, by forming the number of new hirings from unemployed and vacancies in the labour market, at any point in time. The matching function is meant to capture the process of matching in the labour market. The aggregate matching function in the search and matching theory has the following form:

$$m_t L_t = m_t(u_t L_t, v_t L_t), \qquad (0.1)$$

where L_t is the number of workers in the labour force, u_t is the unemployment rate, v_t is the vacancy rate, m_t is the job matching rate, $u_t L_t \equiv U_t$ defines the number of unemployed, $v_t L_t \equiv V_t$ is the number of vacancies and, $m_t L_t \equiv M_t$ defines the number of job matchings. The subscript t indicates a fixed time period. (Pissarides 2000)

The Equation (1.1) is based on the assumption that new matchings are taking place only between unemployed and vacancies, as it is argued that only unemployed individuals search actively for new jobs and, that on-the-job search does not significantly change the fundamentals of the matching function nor the development of equilibrium unemployment rate (Pissarides 2000). Search and matching theory, therefore, provides a tool in the form of matching function to assess the dynamics of matching unemployed and vacancies.

Moreover, the Eq. (1.1) is assumed to be increasing in both u and v and to have the property of constant returns to scale (CRS) and, hence, homogeneity of degree one (Pissarides 2000). These characteristics explain that if the unemployment rate and vacancy rate increase x-times, job matchings also increase x-times or, in other words, the more unemployed and vacancies, the more job matchings are made in absolute terms. Additionally, they indicate that there exists a maximum point where the highest number of job matchings is reached, based on the unemployed and vacancies within the labour market. Therefore, the aggregate matching function (1.1) implies that there exists a possibility to match the unemployed and vacancies to reach the maximum number of job matchings. Frictions like mismatch, present in the labour market, may hinder the formation of maximum hirings.

The aggregate matching function (1.1) has been also empirically tested and it has been concluded that a log-linear form of a Cobb-Douglas function suites the data well (Blanchard, Diamond 1990;

Kohlbrecher et al. 2014; Kommer 2018; Petrongolo, Pissarides 2001; Pissarides 2000). The aggregate matching function as Cobb-Douglas function has the following form:

$$M_t(U_t, V_t) = \Phi U_t^{\beta} V_t^{\alpha}, \qquad (1.2)$$

where M_t is the number of job matchings, U_t the number of unemployed, V_t the number of vacancies at time t and Φ the matching efficiency, whereas $0 < \alpha, \beta < 1$. The parameters α and β show the sensitivity of job matchings to changes in the number of unemployed and vacancies and therefore, determine the impact unemployed and vacancies have in forming job matchings. If the assumption of CRS holds, then $\alpha + \beta = 1$. (Barlevy 2011)

Some previous empirical studies have found that the function (1.2) with CRS, as assumed in the theory, describes well the data on job matchings between unemployed and vacancies (Blanchard, Diamond 1990; Kohlbrecher et al. 2014; Kommer 2018; Petrongolo, Pissarides 2001). Some studies have also found evidence of increasing returns to scale (Kommer 2018; Petrongolo, Pissarides 2001). For data on Estonian labour market, the returns to scale of the function (1.2) depends on the period included in the analysis. There is evidence for both increasing as well as CRS for the matching function in the form of (1.2) applied on Estonian labour market data. (Kommer 2018) Although previous research (Kommer 2018; Petrongolo, Pissarides 2001) has not in every case confirmed the assumption of CRS of the aggregate matching function, it still has affirmed the empirical applicability of the search and matching theory. The aggregate matching function has shown usefulness in describing the job matching process and its efficiency for different labour market settings.

The matching function as Cobb-Douglas function (1.2) includes an additional variable, which is not present in the aggregate matching function (1.1). That variable captures important information about the functioning of a labour market. The variable Φ known as matching efficiency contains information about how efficiently the matchings between unemployed and vacant positions are formed. It akin to the Solow residual in the Cobb-Douglas production function, meaning that it captures the variability of the outcome which is not explained by the inputs of the function (Barnichon, Figura 2015). Regarding the matching function framework, the matching efficiency Φ contains the factors that are influencing the formation of job matchings, but not described by the observed values of the vacancy and unemployment rates. As mismatch is a situation in which the unemployed and vacancies in the labour market do not fit together, e.g. due to differences in skills of the job seekers and skill requirements of the vacant positions, then it has an influence on the efficiency of the creation of job matchings in a labour market.

The Solow residual in the aggregate production function is, however, not directly empirically observable. The same applies to the matching efficiency, which is difficult to measure empirically as well. By estimating the log-linear aggregate matching function in the form of the Cobb-Douglas function (1.2), the matching efficiency Φ is a constant in the model and, therefore, mostly found as a residual in the estimation. The matching efficiency can be decomposed into composition and dispersion effects. The composition effect occurs because of the different types of reasons and durations for unemployment, which determine how actively the unemployed search for jobs. The distribution effect results from differences across labour market segments as mismatch can be more dominant in some sectors of the economy than others. (Barnichon, Figura 2015) Therefore, the matching efficiency can capture different frictions in the labour market, including mismatch.

As mismatch hinders the formation of job matchings between unemployed and vacant position in a labour market, then, in case there occurs mismatch, it should have a diminishing effect on the matching efficiency Φ. Given the stocks of unemployed and vacancies in a labour market, there would be less formation of job matchings in case the characteristics among unemployed and vacancies do not match as would result from a labour market without mismatch. Research based on the data on Estonian labour market has shown that the level of matching efficiency is rather low (Kommer 2018). This indicates that possibly frictions exist in the Estonian labour market including mismatch between unemployed and vacancies.

In conclusion, the aggregate matching function as fundamental part of the search and matching theory, depicts the formation of job matchings between unemployed and vacancies. As previous empirical research has concluded, matching function in the form of a Cobb-Douglas function is the most preferable function to adopt in conducting an empirical analysis. This indicates that the number of job matchings is influenced by the matching efficiency that captures different frictions in the labour market, including mismatch. The more there is mismatch in a labour market, the higher will also be the unemployment and vacancy rates. To arrive at the equilibrium unemployment rate and analyse how it is affected by frictions in the labour market, another important component of the aggregate matching function framework, the so-called Beveridge curve is often used. The Beveridge curve and its connection to mismatch will be analysed in the next subchapter.

1.3. Mismatch and the Beveridge curve

The Beveridge curve, named after William Beveridge, depicts the negative correlation between the vacancy rate and the unemployment rate (Beveridge 1944). It is used to analyse the efficiency of job matchings in the labour market taking into account various shocks that affect the labour market. It also enables to analyse frictions in the labour market and their influence on the job matching efficiency. (Elsby et al. 2015) This chapter analyses how the Beveridge curve is included in the search and matching theory and how mismatch impacts the Beveridge curve.

The Beveridge curve in the search and matching theory is characterised by the steady-state condition for the unemployment rate. In his study, Pissarides (2000) indicates the labour market steady-state equilibrium as determined by the following three equations:

$$u = \frac{\lambda}{\lambda + \theta q(\theta)}, \tag{1.3}$$

$$p - w - \frac{(r+\lambda)pc}{q(\theta)} = 0, \tag{1.4}$$

$$w = (1-\beta)z + \beta p(1 + c\theta), \tag{1.5}$$

where equation (1.3) is the equilibrium condition for the unemployment rate, i.e. the Beveridge curve, equation (1.4) the equilibrium condition for job creation and, equation (1.5) the equilibrium condition for wages. The variables in the equations (1.3) – (1.5) are defined as u being the unemployment rate, $\theta = \frac{v}{u}$ the labour market tightness as ratio between vacancies and unemployment or, in other words it indicates how many vacancies exist in the labour market per one unemployed person. If labour market tightness θ is greater than one, then unemployed have an advantage in the labour market compared to the employers regarding bargaining conditions, and v.v. in the case θ is less than one. Additionally, λ is defined as the separation rate from employment to unemployment meaning the intensity of employed workers becoming unemployed, $q(\theta)$ is the arrival rate of unemployed to vacancies, $p > 0$ is a constant that takes value of output of the job for the employer, pc are the costs of employing a new worker, r the rate of return, w wage, z the unemployment benefit and β is the bargaining power of job seekers.

As explained previously, according to the search and matching theory, flows to and from unemployment take place constantly. To determine the equilibrium unemployment rate, the Beveridge curve sets the flows into and out of unemployment equal in order to be interpreted as the matching possibility frontier (Daly et al. 2012; Petrongolo, Pissarides 2001). For the derivation of the Beveridge curve, it is more convenient to rewrite the aggregate matching function in Eq. (1.2) as:

$$m_t(u_t, v_t) = \Phi u_t^{\beta} v_t^{\alpha}, \tag{1.6}$$

where $u_t L_t \equiv U_t$, $v_t L_t \equiv V_t$ and $m_t L_t \equiv M_t$. In case the aggregate matching function (1.1) takes the form of a Cobb-Douglas function (1.6) with CRS, then the Beveridge curve would imply that:

$$(1-u)\lambda = \Phi u^{1-\alpha} v^{\alpha}, \tag{1.7}$$

meaning that the flow into unemployment $(1-u)\lambda$, is equal to the flow out of unemployment $\Phi u^{1-\alpha} v^{\alpha}$, i.e. the new matchings. By dividing (1.7) through $u^{1-\alpha}$ and, Φ the new following form follows:

$$v^{\alpha} = \frac{\lambda}{\Phi}(u^{\alpha-1} - u^{-\alpha}), \tag{1.8}$$

and, by taking the power of $\frac{1}{\alpha}$, the Beveridge curve is derived:

$$v = \left[\frac{\lambda}{\Phi}(u^{\alpha-1} - u^{-\alpha})\right]^{\frac{1}{\alpha}}. \tag{1.9}$$

As discussed in Barlevy (2011), the equation (1.9) is the Beveridge curve in case of aggregate matching function as in Eq. 1.1 in the form of a CRS Cobb-Douglas function (1.6).

This means that the Beveridge curve enables to find the different possible combinations of vacancy and unemployment rates where the flows into and out of unemployment are equal. The equilibrium in the labour market at a specific point in time, however, is achieved by adding the job creation curve to the model. The equilibrium rates for vacancies and unemployment are derived by the intersection of the Beveridge curve, i.e. the equation (1.3), with the modified job creation curve i.e. the equation (1.4) where wages are determined by the equation (1.5) (Pissarides 2000). The job creation curve indicates the willingness of employers to create new vacancies given the current labour market conditions and, thereby, designates the labour demand curve (Daly et al. 2012; Pissarides 2011).

The equilibrium vacancy and unemployment rates, therefore, are influenced not only by the separation rate from employment to unemployment λ but, also by different characteristics of the labour market such as the unemployment benefits z, the bargaining power of job seekers β and the costs of a vacancy for the employer. The graphical illustration for the determination of equilibrium rates for vacancies and unemployment is depicted in figure 1.

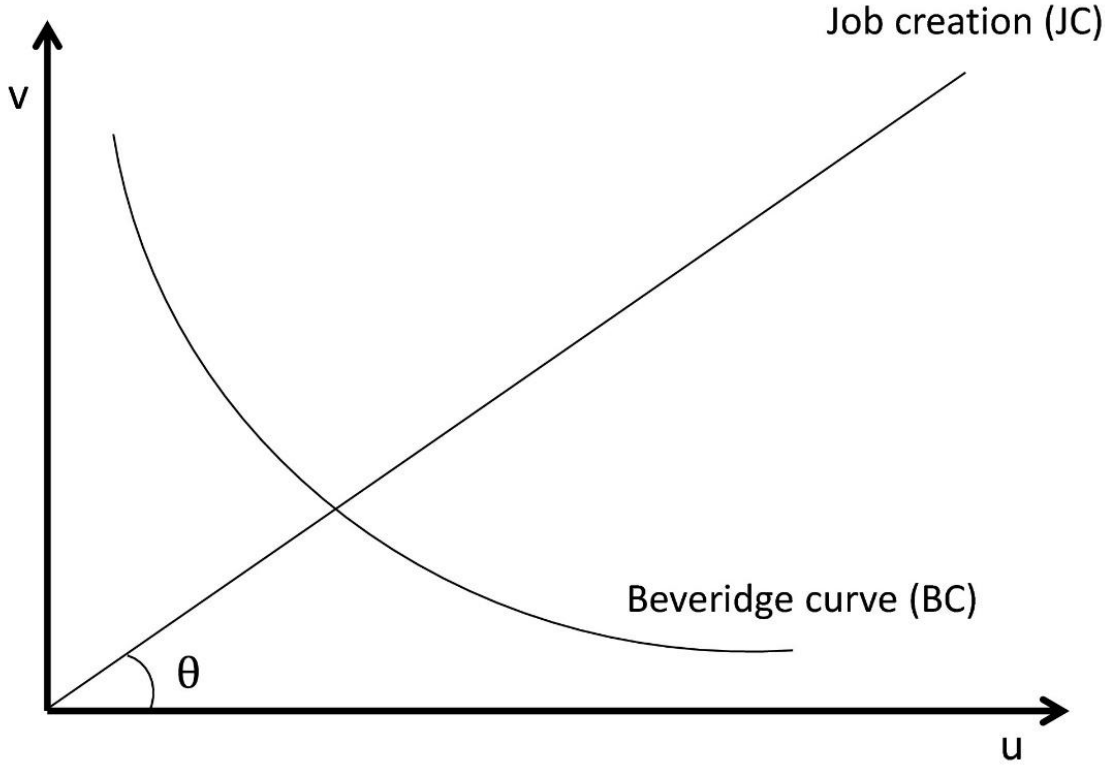

Figure 1. Beveridge curve and job creation curve in u-v space.
Source: Pissarides (2000, 20)

Beveridge curve is assumed to be convex to the origin due to the property of CRS of the matching function. Convexity and long-term inverse relationship between the vacancy and unemployment rates have also found confirmation in the empirical research. (Petrongolo, Pissarides 2001) The modified job creation curve has a slope of the labour market tightness $\theta = \frac{v}{u}$, and goes through the origin (Pissarides 2000). The modified job creation curve is a constant line in the vacancy and unemployment rates space, since besides the market tightness θ, it consists of constants that can change the slope of the curve but cannot determine the shape of it. As it depicts labour market demand curve, its constants influence how many vacancies the employers are willing to create. This impacts the market tightness θ and therefore, the angle of the curve.

Shifts in the Beveridge curve occur when there are changes in the matching efficiency Φ that is influenced by labour market shocks and, by frictions like mismatch (Daly et al. 2012). A lower matching efficiency results in less job matchings, which reduces the arrival rate of unemployed to vacancies, $q(\theta)$. Frictions resulting in lower matching efficiency shift the Beveridge curve away from the origin, which *ceteris paribus* results in higher unemployment and vacancy rates (Pissarides 2011). Higher unemployment rate in case of lower arrival rate of unemployed to vacancies is visible in the equation (1.3) whereas higher vacancy rate is visible in the equation (1.9).

At a given market tightness, lower arrival rate rotates the job creation curve down and will result in higher unemployment rate but in a small, if any, change in the vacancy rate (Pissarides 2000). Therefore, a lower matching efficiency in a labour market, which may occur due to mismatch between unemployed and vacant positions, results in higher equilibrium rate of unemployment. This may also be interpreted as a rise in structural unemployment rate (Daly et al. 2012).

The Beveridge curve along with the job creation curve enables to find the equilibrium rates for unemployment and vacancies. As the Beveridge curve is empirically observable in the case of a CRS Cobb-Douglas matching function, then it is often used to estimate changes in the labour market matching efficiency. Shifts in Beveridge curve indicate changes in the frictions including mismatch, in a labour market. The following chapter will examine how the mismatch, also regarding the Beveridge curve, has been empirically studied in the previous research.

1.4. Mismatch assessment in previous empirical research

Although search and matching theory stems from 1980s, most of the studies about mismatch in labour markets are published in the recent decade. One of the reasons for a more intensified research in this field could be the increase in relevance of unemployment related issues, due to the rise and persistence of unemployment in Europe and the United States of America (USA) after the last economic recession in 2008-2010 (see appendix 1). This increased the importance of understanding the underlying reasons for unemployment.

Mismatch has been researched by estimating the Beveridge curve and its dynamics. Barlevy (2011) estimates the mismatch and its effect on unemployment using the data for USA by analysing shifts of the Beveridge curve. By finding the matching efficiency based on the estimation of a Cobb-Douglas matching function (1.6), it is possible to use the equation for the Beveridge curve (1.9) to conclude how the efficiency has changed, after the economic recession in 2008-2010 from the base level[2] before the recession. The results yield that there was a decrease in matching efficiency and, given that the matching efficiency has been used as a proxy for mismatch, then it is possible to conclude that there was a rise in mismatch in the labour market in USA, after the economic recession. (Barlevy 2011) Ochsen (2009) uses estimations of Beveridge curves on the data for Organisation for Economic Co-operation and Development (OECD) countries and concludes that in many of those, there was an increase in mismatch in 1970s and a decrease in 1990s. Neither of these studies estimated the effect of mismatch on unemployment but do conclude that there has been a simultaneous rise in mismatch and unemployment (Barlevy 2011; Ochsen 2009).

The effect of mismatch on unemployment using Beveridge curves on data on the labour market of USA is studied by Daly et al. (2012). They analyse whether the natural rate of unemployment has increased after the economic recession in the years 2008-2010 and if mismatch could be an underlying reason. Their analysis shows that mismatch has not experienced a significant increase after the economic recession and the authors do not draw a conclusion that it has contributed to a rise in natural rate of unemployment. (Daly et al. 2012) However, as it is visible from previous research, it is possible to apply the framework of search and matching theory to estimate mismatch empirically based on dynamics of matching efficiency and Beveridge curve.

Estimating mismatch and its effect on unemployment based on shifts in Beveridge curve enables to observe the aggregate effects but does not allow to analyse different types of mismatch existing in the labour market and, how much they contribute to changes in unemployment rates. Sahin et al. (2014) have developed an analytical framework based on the search and matching theory to provide a tool in the form of mismatch indices and calculate mismatch in different industry sectors, occupations, regions etc. In this way, the index might help to estimate the direct effect as well as the feedback effect that different types of mismatch have on changes of unemployment rates, for which they use the changes in aggregate job-finding rates. The direct effect of mismatch is assumed to arise from less job matchings, compared to a labour market with no mismatch, whereas the feedback effect derives from the effect that mismatch has on unemployment and vacancy rates. (Sahin et al. 2014)

[2] As base level, Barlevy (2011, 89) uses the matching efficiency in the period December 2000 – August 2008.

Sahin et al. (2014) use the framework to analyse to what extent different kinds of mismatches contribute to changes in the unemployment rate, in the labour market of USA. Their results show that industry- and occupation-based mismatch both increased during the global financial recession in 2008 and have experienced a recent decline, whereas the change in regional mismatch is not that evident. Additionally, industrial and occupational mismatches explain up to one third of the recent increase in unemployment, whereas the region-based mismatch is not significant. (Sahin et al. 2014) Bauer (2013) using the same framework developed by Sahin et al. (2014), analyses the mismatch in the German labour market. The results do not show a significant increase in industrial, occupational nor in regional mismatch for the time span 2000-2010 (Bauer 2013). Compared to the results of Sahin et al. (2014), Bauer's (2013) analysis shows even higher contribution of mismatch to unemployment changes. This indicates that mismatch may be a more significant reason for unemployment in German labour market than in the labour market of USA. Similar approach of mismatch indices has been used to estimate mismatch at the labour market of Netherlands, Sweden, Japan and Malaysia (Erken et al. 2015; Marthin 2012; Said et al. 2021; Shibata 2013).

Furthermore, Hutter and Weber (2016) use the framework by Sahin et al. (2014) to estimate qualification-, occupation- and region-based mismatches in German labour market. They conclude that qualification- and occupation-based mismatches have increased after the recent economic recession, whereas regional mismatch has decreased. Additionally, they combine a model based on CRS Cobb-Douglas matching function to forecast hirings and conclude that models with mismatch indicators outperform the base models without a measure for mismatch. (Hutter, Weber 2016) Hence, mismatch indices can be used to estimate their effects on unemployment rate changes as well as to forecast job matchings.

Herz and van Rens (2020) take the research about mismatch one step further and build a theoretical framework based on search and matching theory and, the aggregate matching function in the form of Cobb-Douglas function (1.3) to analyse why mismatch occurs in the labour market in the USA. As possible underlying frictions resulting in mismatch, they consider worker mobility, job mobility and wage determination. The first two depict barriers of unemployed and vacancies to enter specific segments of the labour market that can be caused, for example, by skill or knowledge requirements in specific fields. Wage determination illustrates the efficiency of reaching a Nash equilibrium in dividing the surplus that job matching creates, between the job seeker and the employer. (Herz, van Rens 2020) The mismatch due to wage determination can, therefore, result from a disagreement of appropriate wages in labour market segments. The analysis by Herz and van Rens (2020) shows that mismatch has played an important role in explaining the unemployment in the USA, whereas the most significant underlying reason seems to be barriers to job mobility.

Besides the analytical framework of Beveridge curve and job creation curve, search and matching theory has provided a basis for the development of indices as well as other concepts to study mismatch and the frictions causing it. By using disaggregated data on unemployed and vacancies, it is possible to analyse which types of mismatch e.g. sectoral, occupational or regional exist in the labour market and how they contribute to unemployment. The mismatch index framework developed by Sahin et al. (2014) and the accounting method for analysing underlying frictions of mismatch by Herz and van Rens (2020), however, require disaggregated data on vacancies and unemployed. Lack of disaggregated data might not always make it possible to apply these frameworks empirically.

Due to data availability issues concerning disaggregated data on unemployed and vacancies, often other, more aggregated proxies for mismatch indicators have been used to study the dynamics of mismatch and its contribution to unemployment. European Commission (2013) and Dimian et al. (2017) use more aggregated data to build mismatch indices, whereas results of both studies show that the dynamics of mismatch indices differ across countries and types of mismatch. Those studies estimate educational mismatch as proxy for skill mismatch for which Estonia has experienced a decline from the beginning of 2000s to 2013 (Dimian et al. 2017; European Commission 2013). The sectoral mismatch estimated by European Commission (2013, 77) had increased in Estonia sharply during economic recession in 2008-2010 and declined back to its previous level after it. Dimian et al. (2017) have also concluded that occupational mismatch affects changes in unemployment rate significantly in the long-term. Therefore, based on the aggregate and approximate mismatch indices, there might be differences in mismatch dynamics across different labour markets, which indicates that national educational and labour market policies could play a role in mismatch unemployment.

As data on education, wages and skill requirements at workplaces is, to some extent, available in different surveys, overqualification and overeducation have been widely analysed also regarding educational and labour market policies. Sevilla and Farias (2020) study overeducation and overskilling in Chilean labour market using survey data. Their analysis indicates that both overeducation and overskilling are present and increasing in the labour market, especially among younger generations (Sevilla, Farias 2020). Similarly, research on overeducation and overskilling in United Kingdom (UK) by McGuinness and Sloane (2011) uses data from a survey that contains data on employees' perception of possible mismatch regarding their skills and knowledge. They conclude that policies should tackle overskilling as it seems to be a cause for lower welfare at the individual level as well as regarding the whole economy. Additionally, wage penalties arise both in the case of overskilling as well as overeducation. (McGuinness, Sloane 2011) Therefore, previous studies have indicated that mismatch could have an impact on the welfare level of an economy.

The effect that mismatch may have on the welfare level of a country has been studied by Patterson et al. (2016). They use the approach by Sahin et al. (2014) to measure the sectoral mismatch in the labour market in UK and to estimate to what extent it has an impact on the unemployment and output levels. Their analysis yields the result that sectoral mismatch explains up to two third of the deviation of labour productivity from its growth-trend in UK after the economic recession (Patterson et al. 2016). Therefore, it can be concluded that mismatch in a labour market may explain a large part of labour productivity deviations in an economy and, thereby, influence the welfare level of a country.

In conclusion, previous empirical research has shown that aggregate matching function framework in search and matching theory has been a useful tool to study mismatch in a labour market and the effects of it on unemployment. Existing literature has used different methods, e.g. shifts in Beveridge curves, mismatch indices and developed accounting frameworks to measure mismatch in a labour market and, to estimate its effect on unemployment as well as on welfare of an individual and of an economy. The research on mismatch has concluded that there exists mismatch in labour markets, although the extent and significance of the types of mismatch varies across countries and across different studies. Additionally, previous research has shown that mismatch does explain changes in unemployment rates and has even occurred to be a significant variable in forecasting job matchings. The following chapters will provide an overview of the Estonian labour market, followed by the description of data and explanation of methodology used in this thesis to study mismatch and its effect on unemployment in Estonian labour market.

2. LABOUR MARKET IN ESTONIA

This chapter provides a short overview of the characteristics of the Estonian labour market by analysing the unemployment and vacancies at regional, occupational an industrial levels. It also discusses to what extent mismatch might have entail in the reasons for existing unemployment. Additionally, the Estonian labour market legislation and policies will be introduced to understand the dynamics of the Estonian labour market and to recognize how the possible factors contributing to unemployment are assessed. In the second subchapter, the current measures in assessing possible mismatch in the Estonian labour market will be introduced.

2.1. Unemployment and vacancies

To have a better understanding of the dynamics and phenomena in the Estonian labour market, the unemployment and vacancies are analysed in this section. In the previous years, Estonian labour market has been characterised by low unemployment rates. The unemployment rate has been the highest in 2010 by reaching a rate of 16.6% due to the economic recession following from the global financial crisis in the years 2008-2010 (see appendix 1). The unemployment rate fell quite sharply after the recession and reached the lowest level of 4.5 percent in 2019. During the COVID-19 pandemic the unemployment rate has increased again, reaching 6.8 percent in 2020. The unemployment increased especially in the first half of 2020 mostly due to a decrease in job hirings, resulting probably from restrictions on economic activity due to the pandemic. Additionally, some people were exiting unemployment and labour force in general as the possibilities of finding a job decreased. The unemployment rate remained stable in the second half of the year. (Matsulevitš et al. 2021) As the COVID-19 pandemic is still ongoing, it is however difficult to foresee the dynamics of unemployment rate in the following periods.

Although the Estonian labour market recovered rather well from the economic recession in 2008-2010, whereas the unemployment rate after the recession has been lower than the EU-average (see appendix 1), the labour market in Estonia is faced with the ageing population and shrinking labour force (OECD 2021a). Now, it is also confronted with the challenges opposed by the COVID-19 pandemic. This raises the importance of understanding frictions, incl. mismatch, which could hinder the efficient functionality of the labour market.

At the regional level there is some diversity in the number of unemployed and vacancies across counties (see figures 2 and 3). The increase in the number of unemployed in the first half of 2020 is mostly visible in Harju county where it is higher in the entire time series, starting from 2011. It is higher due to the inclusion of the capital of Estonia, where the economic activity is higher than in other counties. In the first half of 2020, a decrease in the number of vacancies is also visible, particularly and again in Harju county, as there the number of vacancies is also higher. In other counties, a decrease in vacancies in the beginning of 2020 is not clearly visible. Increase in the number of unemployed accompanied by a decrease in the number of vacancies may indicate mismatch in the labour market at the regional level, as it becomes more difficult for the unemployed to find a suitable match in the vacancies.

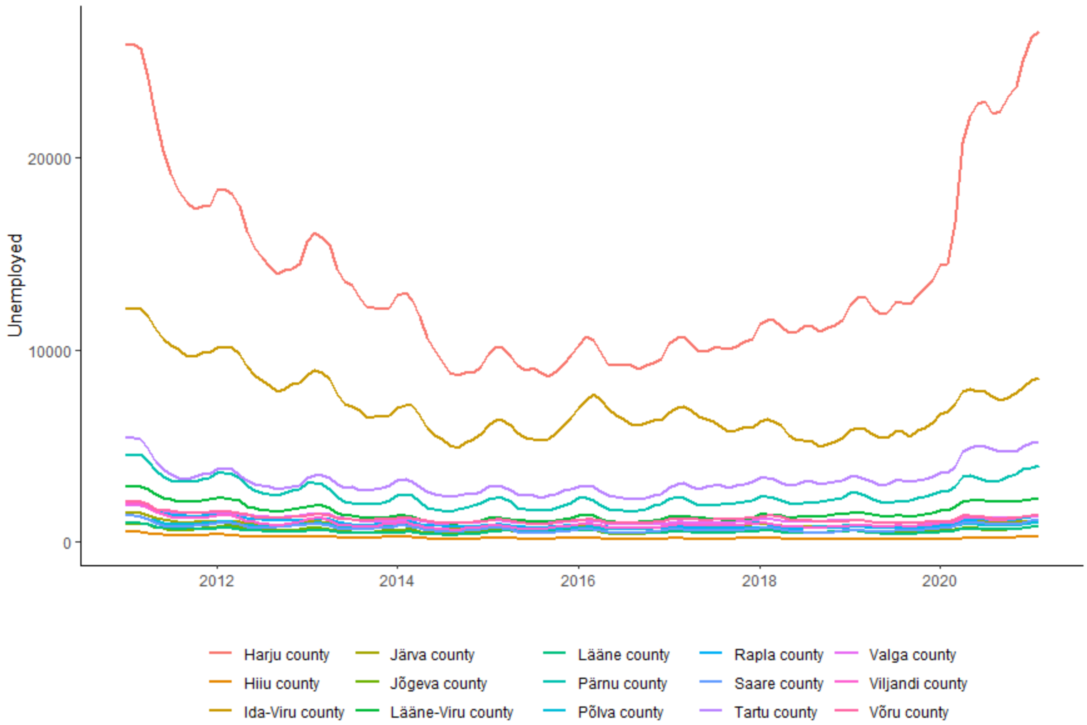

Figure 2. Unemployed in Estonia across counties, January 2011 – January 2021.
Source: EUIF, composed by author

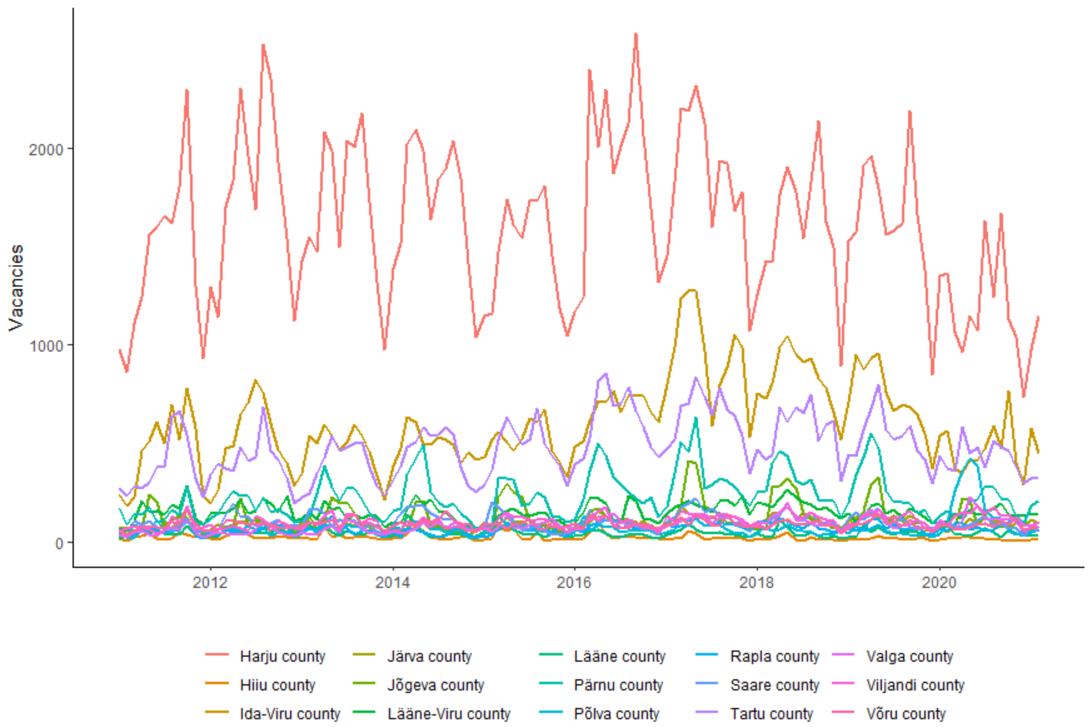

Figure 3. Vacancies in Estonia across counties, January 2011 – January 2021.
Source: EUIF, composed by author

Although other counties beside Harju have similar number of unemployed, Ida-Viru county stands out with somewhat higher number of unemployed. Ida-Viru county is in Northeastern Estonia where the unemployment rate has been on an average 6.8 percentage points higher than the unemployment rate in Estonia in general (see appendix 2). However, there are also higher number of vacancies in Ida-Viru than in other counties beside Harju, which may mean that the unemployed and vacancies do not coincide in characteristics. The economic structure in Northeastern Estonia is characterised by mining industry and oil shale production that are the main employers in the region. Higher unemployment rate and lower labour force participation rates are most likely resulting from the decrease of activities of these industries to meet the climate goals set by the Estonian government and the European Union. (Michelson et al. 2020) Hence, due to higher unemployment, but also somewhat higher vacancies than in other counties beside Harju county, there is an indication of regional mismatch regarding Ida-Viru county.

At occupational level, in the first half of 2020 the number of unemployed increased most in the category of services and sales workers (International Standard Classification of Occupations (ISCO) 5) (see figure 4 and appendix 3). In this category, the number of unemployed has been one of the highest in the entire time series starting from 2011 along with categories of craft and related trades workers (ISCO 7) and elementary occupations (ISCO 9). Although in all these categories also the number of vacancies has been the highest, it has decreased in the category of services and sales workers in the first half of 2020, whereas the number of vacancies has remained high in the category of elementary occupations (see figure 5). Generally, in these categories where the number of unemployed is the highest there are also more vacancies, but the category of plant and machine operators and assemblers (ISCO 8) stands out with high number of vacancies and lower number of unemployed. Hence, the divergence in the trends of unemployed and vacancies as well as the co-existence of high number of unemployed and vacancies may indicate some mismatch at the occupational level.

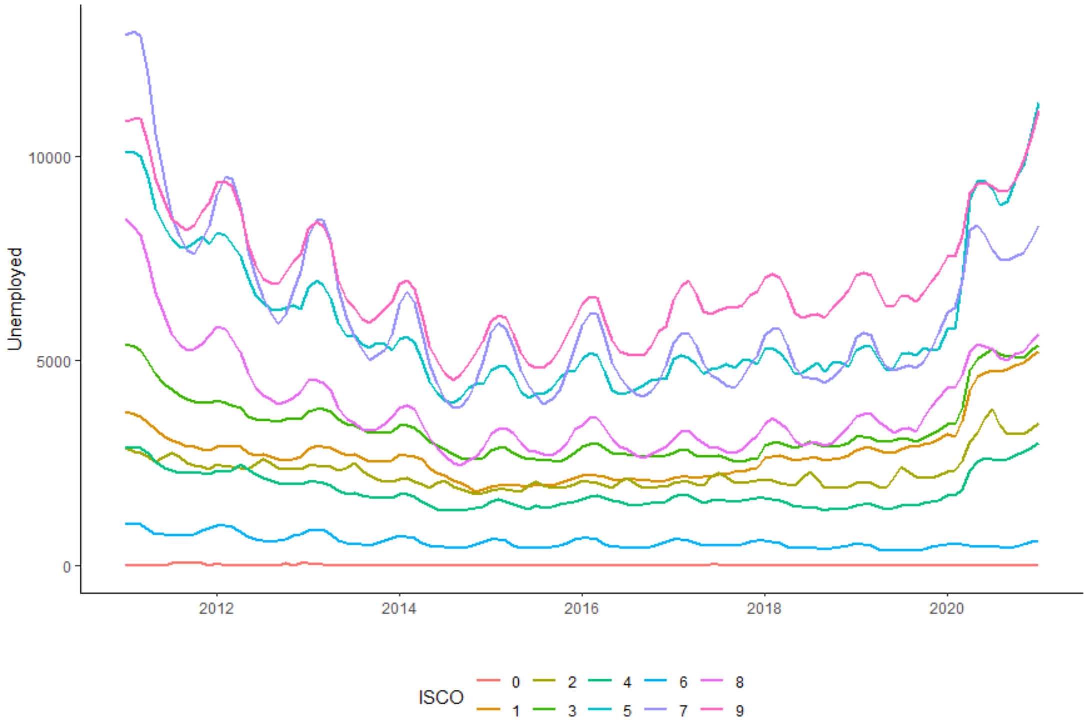

Figure 4. Unemployed in Estonia based on their previous occupation across occupational levels of the ISCO classification, January 2011 – January 2021.

Source: EUIF, composed by author

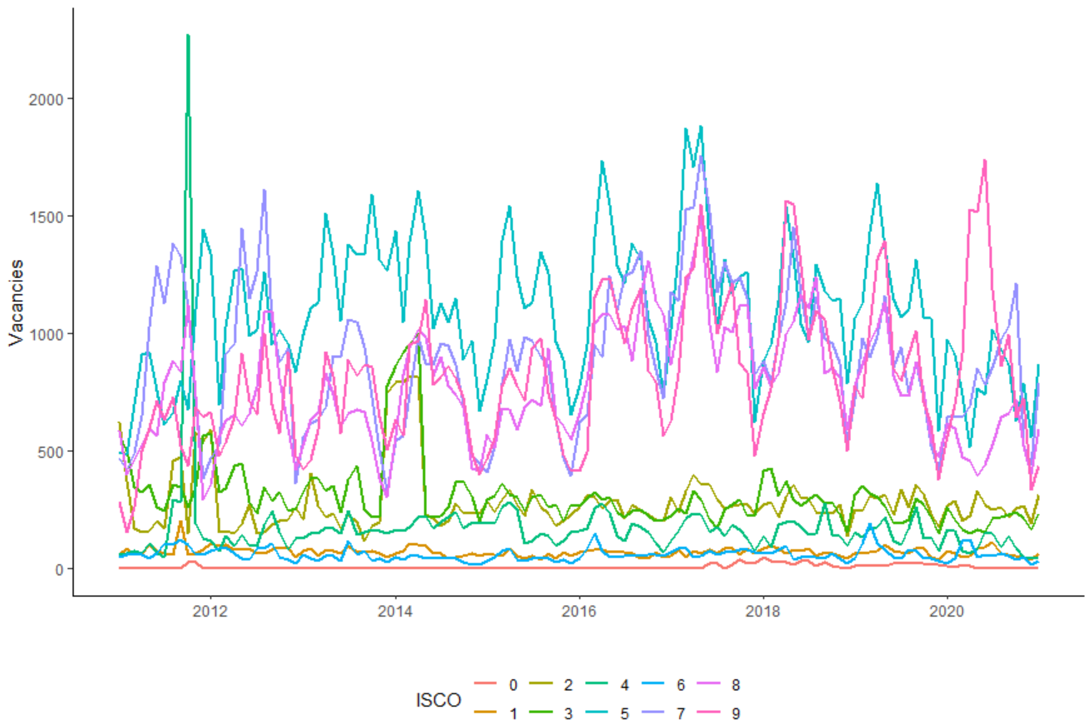

Figure 5. Vacancies in Estonia across occupational levels of the ISCO classification, January 2011 – January 2021. [3]

Source: EUIF, composed by author

At industrial level, the number of unemployed has been the highest in categories of wholesale and retail trade; repair of motor vehicles and motorcycles (Statistical Classification of Economic Activities in the European Community (NACE) G) and manufacturing (NACE C) where the number of unemployed increased the most in the beginning of 2020 (see figure 6 and appendix 4). It increased also sharply in accommodation and food service activities (NACE I) due to the restrictions imposed by the governments on travel and tourism sectors as well as on retail with the aim of tackling the COVID-19 pandemic. The number of unemployed is also somewhat higher from the beginning of 2020 in administrative and support service activities (NACE N) and construction (NACE F) whereas the increase in unemployed in these activities may also be impacted by the travel restrictions as NACE N includes activities related to traveling and some Estonians who work in the field of construction are employed in Finland, which might have changed due to the uncertainty regarding traveling to Finland.

[3] The spike in the number of vacancies in the category of clerical support workers (ISCO 4) is most likely due to the population census survey 2011.

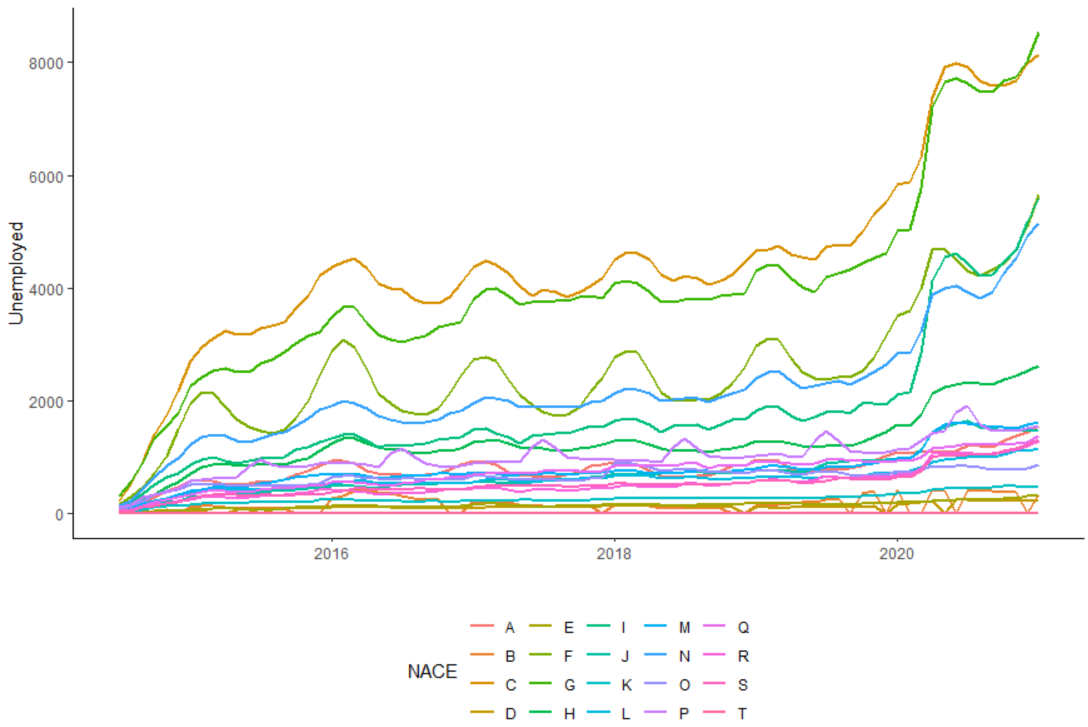

Figure 6. Unemployed in Estonia based on their previous employer's field of activity of the NACE classification, July 2014 – January 2021.[4]
Source: EUIF, composed by author

By analysing the number of vacancies across industries, the higher number of vacancies up to the beginning of 2020 stands out in the manufacturing industry (see figure 7). However, the number of vacancies decreased in 2020. As the number of unemployed in this category has, on the other hand, increased then this might indicate a possible mismatch at the industrial level. In all other categories, the number of vacancies seems also to be higher where the number of unemployed is higher. An exception stands out in the beginning of 2020, where there is a sharp increase in the number of vacancies in agriculture, forestry and fishing (NACE A) which might also be resulting from the travel restrictions as this industry is dependent on seasonal migrant workers. Therefore, these changes in the trends of unemployed and vacancies across industries in the beginning of 2020 might entail mismatch at the industrial level.

[4] As explained by EUIF, starting from July 2014 the number of unemployed where the unemployed person's previous employer's NACE was known increased rapidly due to a change in regulation that all employers had to register their employees in the employment register (Töötamise register (TÖR)). Therefore, for time series comparison purposes the figure excludes data before July 2014.

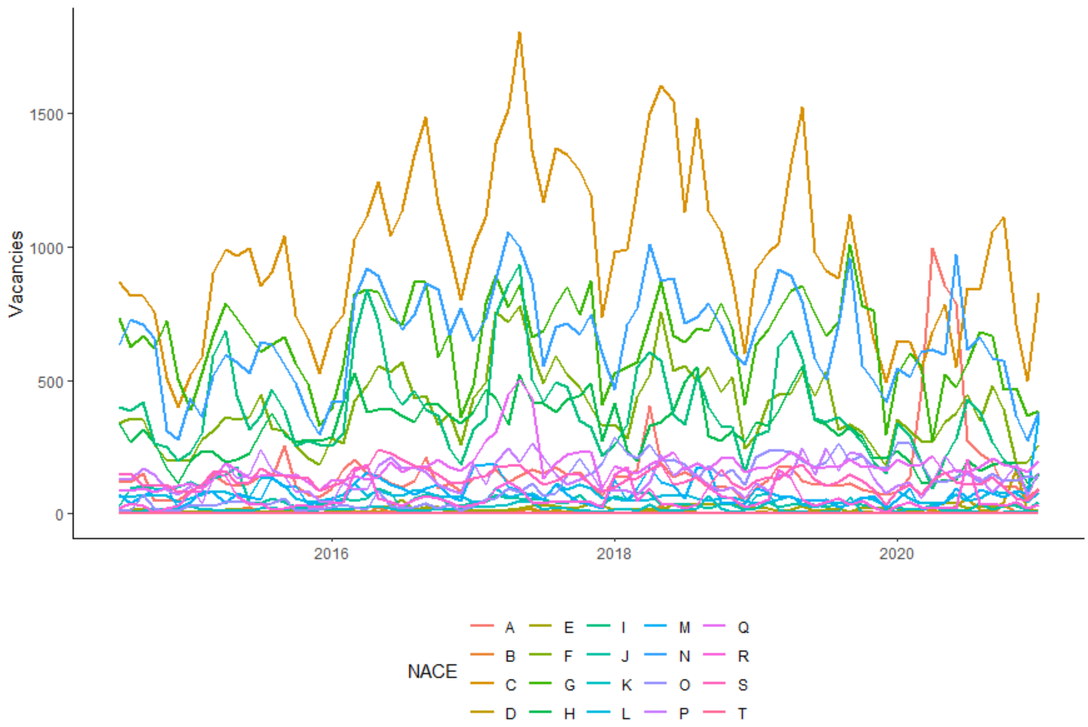

Figure 7. Vacancies in Estonia across field of activities of the NACE classification, July 2014 – January 2021.
Source: EUIF, composed by author

Hence, based on the analysis of data on unemployed and vacancies there are some categories in which both the number of unemployed and vacancies is higher than in others, which may indicate the possibility of mismatch at regional, occupational and industrial levels. The following subchapter will discuss the Estonian labour market legislation and policies to understand how the labour market is designed and unemployment assessed. It will also be discussed what have been the current measures in evaluating possible mismatch in the Estonian labour market.

2.2. Labour market policies

Regarding labour market policies, one of the most important legislation impacting all employers is the employment protection legislation (EPL). EPL aims to protect employees from arbitrary job dismissals, as it sets conditions on which an employer may be dismissed from its work. On the other hand, a strict EPL policy may hinder the efficient allocation of workers to jobs where the matching is most successful. (OECD 2020) Therefore, strict EPL may cause higher inflexibility and, thereby, lower matching efficiency between the unemployed and vacancies and generating more mismatch in the labour market.

Estonian labour market is characterised with flexible EPL that regulates on which conditions employers and employees can exit a work relationship. Based on the strictness of employment protection index about individual and collective dismissals, calculated by OECD (2021c), Estonia has an index lower than OECD average, hence, indicating that the EPL is less strict. EPL in Estonia is regulated by the Employment Contracts Act (ECA) which came into force during the economic crisis in 2009 to improve the flexibility of the labour market (Malk 2013). Therefore, the labour market legislation sets a good ground for an efficient unemployed and vacancy allocation to avoid mismatch which may otherwise be caused by inflexible EPL.

Another key measure for increasing labour market participation and employment rates and for reducing unemployment rate are active labour market policies (ALMPs), e.g. training offers, programmes to promote employment etc., implemented by the government sector. ALMPs aim, thereby, to improve the matching between unemployed and vacancies to achieve a better functioning of the labour market. According to the report published by OECD (2021a), the framework of ALMPs in Estonia suites well for the labour market needs and has a positive effect on the labour market outcomes. However, the complexity of the regulatory framework for the ALMP provision should be reduced to further enhance the functionality of ALMPs (OECD 2021a).

Labour market policies are mainly covered in Estonia by the Labour Market Services and Benefits Act (LMSBA), Unemployment Insurance Act (UIA) and by the Employment Programme 2021-2023 (THP). Obligations arising from the acts and from THP are set to be performed by the Estonian Unemployment Insurance Fund (EUIF) which belongs in the government sector. UIA sets the rights and conditions for the procedure of receiving unemployment benefits, hence, for the passive labour market policy (PLMP), whereas the LMSBA sets the conditions for registered unemployment and for the system of ALMPs. Labour market services delineated in LMSBA are, for example, job mediation, training, career counselling, coaching, wage subsidy etc., and the unemployed are assisted by the individual action plan (LMSBA § 9, § 10). The ALMPs are further discussed in THP which is a government decree to regulate the provision of labour market services set in the context of THP. THP is compiled and updated regularly by EUIF and sets more precise plans regarding services provided for unemployed.

The range of ALMPs offered by the EUIF has increased in the recent decade which possibly has had a positive impact in decreasing unemployment and increasing labour force participation rate. However, previous analysis, based on data of the year 2016, has indicated that the participation rate of unemployed in ALMPs is lower than in EU, although the evaluation of specific ALMPs has shown that the measures are in general successful and increased the likelihood of unemployed entering employment. (Piirits et al. 2018) Public expenditure on ALMPs, measured in % of gross domestic product (GDP), has increased in Estonia from 2015 onwards, whereas the expenditure on PLMPs has remained at relatively same level in the post-recession period, i.e., from the year 2011 onwards (see appendix 5). Although ALMPs and PLMPs help to tackle unemployment, they are not designed to specifically assess the possible mismatch in the labour market.

Regional mismatch in the Estonian labour market has been addressed in the years 2016-2018 with a pilot programme of mobility support measure aimed to subsidise commuting costs for working 30 km away from the place of residence (Melesk et al. 2019). One of the most comprehensive measures used in Estonia to estimate possible mismatch in the labour market and to improve labour market functioning is the compilation of OSKA report, which analyses the skills required in the Estonian labour market in the long term and skills possessed and attained by the labour force. The report, therefore, focuses on the possible extent of skills mismatch and delineates the sectors and occupations which are in labour shortage, such as the information and communications technology (ICT) sector, mechanical engineers' and machine operators' occupations (Kutsekoda 2020). OSKA report also analyses the current educational and training programme system and provides guidelines on how to improve it in order to meet the labour demand.

To the knowledge of the author, upon now evaluation of mismatch in the Estonian labour market has been focusing mainly on skills mismatch (Kutsekoda 2020). However, the analysis of unemployment and labour force participation rates has indicated that there could be possible regional, occupational and industrial mismatch existing in the Estonian labour market. In the next chapters of this thesis, an empirical analysis will be conducted to estimate mismatch in the Estonian labour market based on different levels: regional, occupational and industrial. The next chapter explains data and methodology used in the analysis.

3. DATA AND METHODOLOGY

In this chapter, data and methodology used in this thesis to estimate labour market matching functions and mismatch at regional, occupational and industrial level in Estonian labour market will be explained. The first subchapter introduces the data used in the empirical analysis, its descriptive statistics and limitations. In the following subchapter, the methodology is explained.

3.1. Data

Data used in the empirical analysis in this thesis was derived from EUIF which gathers data on the registered unemployment as well as vacancies in Estonia and publishes the relevant datasets on its homepage, every month. Monthly data on unemployment, vacancies and hirings is available starting from January 2003 or January 2004, depending on the dataset. However, as was explained by the EUIF, in the earlier years there were less data sources available to compile statistics on unemployed and hirings, hence the data prior to 2011 is less accurate. In the empirical analysis it seemed to cause issues with model assumptions, mainly with stationarity. Therefore, the empirical analysis in this thesis was conducted on the monthly time series from January 2011 to January 2021.

For the estimation of mismatch at occupational and industrial levels, monthly data on unemployed based on the unemployed person’s previous occupation and employer’s field of activity was received from EUIF, upon request in the detail of ISCO and NACE. Similarly, monthly data on vacancies in the detail of ISCO and NACE levels were received from EUIF upon request. The different ISCO and NACE levels used in the analysis are presented in appendices 3 and 4 accordingly. In case the unemployed person’s previous occupation or employer’s field of activity was unknown, then these data were left out from the empirical analysis. Data on ISCO levels were used for the estimation of occupational mismatch whereas data on NACE levels were used for the estimation of industrial mismatch. For the estimation of mismatch at regional level, the time series on unemployed and vacancies across Estonian counties was derived from the homepage of EUIF

(2021a; 2021d). In case the unemployed person's or vacancy's county was unknown or it was registered abroad, then these data were left out from the empirical analysis. The time series for unemployed and vacancies used in the analysis are illustrated in appendices 6 and 7 correspondingly.

To estimate labour market aggregate matching functions and mismatch at regional, occupational and industrial levels, data on hirings at those levels are also needed. The time series on hirings is illustrated in appendix 8. For the regional level, the data on hirings is available at the homepage of EUIF (2021c) where data on the transitions out of unemployment into employment across counties is published. Based on the information received from EUIF, however, data on hirings is not collected on ISCO or NACE levels. Therefore, hirings at those levels were estimated based on vacancy outflow method used in previous empirical research (Patterson et al. 2016). Hirings at ISCO and NACE levels were calculated, therefore, as vacancy outflows, i.e. the difference between vacancies which were available during a month and which were available at the end of a month at each specific ISCO and NACE level. The data for these calculations were derived from the homepage of the EUIF (2021d; 2021e).

Although using administrative data from EUIF has advantages of being representative, disaggregated and published on a regular basis, there are also some limitations to be considered in the interpretation of the results. Firstly, the datasets only include unemployed who have registered their unemployment at the EUIF, which likely results in a lower number of unemployed than is existing in the labour market. Additionally, there could be some underreporting of vacancies as it is not compulsory to register vacancies at the EUIF. Another disadvantage is the possible underreporting of data on hirings and lack of it at ISCO and NACE levels. However, these are limitations existing in the previous empirical research and could only be improved if there were additional data sources available (Bauer 2013; Erken et al. 2015; Marthin 2012; Patterson et al. 2016; Sahin et al. 2014). In case of Estonia, an additional data source for the number of unemployed could be statistics collected by SE, but as data on unemployment is not collected by SE on such a disaggregated level and does not contain data on hirings and vacancies, it was not used in this thesis.

3.2. Methodology

This chapter will explain the methodology used in the empirical analysis to estimate labour market matching functions and mismatch at the regional, occupational and industrial levels. The methodology of the empirical analysis is based on previous research in the field and mainly, on the framework developed by Sahin et al. (2014) who have provided an empirical tool in the form of mismatch index, to estimate mismatch between unemployed and vacancies at different levels, e.g. industrial, occupational, regional at the labour market. The mismatch index has the following form:

$$MM_t = 1 - \sum_{i=1}^{I} \frac{\phi_i}{\bar{\phi}_t} \left(\frac{V_{it}}{V_t}\right)^{\alpha} \left(\frac{U_{it}}{U_t}\right)^{1-\alpha}, \quad (3.1)$$

where $\bar{\phi}_t = \left[\sum_{i=1}^{I} \phi_i^{\frac{1}{\alpha}} \left(\frac{V_{it}}{V_t}\right)\right]^{\alpha}$, ϕ_i are the market-specific matching efficiencies, V_{it} and U_{it} are correspondingly the market-specific vacancies and unemployed and, α the vacancy share, which is also called the matching elasticity. The subscript t indicates a time period and subscript i indicates a disaggregated labour market, e.g. a county, an occupation or an industry. MM_{t} shows the mismatch at regional, occupational or industrial level, depending on which level the mismatch is estimated. The definition of the mismatch index MM_t is derived from the article by Sahin et al. (2014) whereas the modified estimation for $\bar{\phi}_t$ is derived from Bauer (2013) and Erken et al. (2015).

The mismatch index (3.1) is derived by Sahin et al. (2014) from the aggregate matching function (1.2) with an assumption of CRS. In order to calculate mismatch indices (3.1), it was hence necessary to estimate the aggregate matching function (1.2) to find α. Additionally, matching functions at regional, occupational and industrial levels needed to be estimated to find the market-specific matching efficiencies ϕ_i. The number of vacancies V_{it} and unemployed U_{it} at any disaggregated labour market i.e. for every i, were derived from the datasets of EUIF described in the previous subchapter.

For the estimation of an aggregate matching function, a similar methodology as in previous empirical research (Bauer 2013; Erken et al. 2015; Marthin 2012; Patterson et al. 2016; Sahin et al. 2014) was applied. Therefore, to find the vacancy share α, the following time series model based on the aggregate matching function was estimated:

$$ln\left(\frac{M_t}{U_t}\right) = ln(\Phi) + \alpha ln\left(\frac{V_t}{U_t}\right) + \gamma_{1,1}Month_t + \gamma_{1,2}D\_2020\_04_t + \gamma_{1,3}D\_Q2_t + \gamma_{1,4}D\_Q4_t + \varepsilon_t, \quad (3.2)$$

where M_t is the number of hirings in period t derived from the dataset of EUIF (2021c), $Month_t$ a variable for time trend, $D\_2020\_04_t$ a dummy for the period April 2020, i.e. it is equal to one in the period April 2020 and zero in all other periods. A dummy was added for the period April 2020 due to an unusual decrease in hirings and a rapid increase in unemployment, as Estonia was in state emergency due to the COVID-19 pandemic. D_Q2_t and D_Q4_t are the seasonal quarterly dummies, ε_t the error term and $\gamma_{1,1}$ to $\gamma_{1,4}$ the estimated coefficients. All other notations and variables are the same as described in previous equations.

The outcome of the Augmented Dickey-Fuller test resulted in an adoption of the alternative hypothesis that the time series for hirings was stationary, hence an important assumption of time series models was satisfied. A variable for time trend was included in the model (3.2) to consider possible spurious regression problem. There could be a situation in which hirings are increasing due to increase in unemployed or vacancies, or in both variables. An inclusion of time trend will account for this situation. Seasonal quarterly dummies were included in the model (3.2) to account for the seasonality, which was visible in all of the time series, i.e. for unemployed, vacancies and hirings. The model was also estimated using a seasonal dummy for the third quarter, D_Q3_t, but as this was insignificant then it was disregarded in the final model, to have more accurate results regarding the vacancy share α. Model (3.2) was also estimated using monthly dummies, but the results of these model estimations indicated a quarterly seasonality.

To estimate mismatch indices (3.1) at regional, occupational and industrial levels, the Eq. 3.1 requires also market-specific matching efficiencies ϕ_i. Hence, by using panel regression methods, the following model was estimated for regional and industrial levels:

$$ln\left(\frac{M_{it}}{U_{it}}\right) = ln(\phi_i) + \delta ln\left(\frac{V_{it}}{U_{it}}\right) + \gamma_{2,1}D\_2020\_04_{it} + \gamma_{2,2}D\_Q2_{it} + \gamma_{2,3}D\_Q3_{it} + \gamma_{2,4}D\_Q4_{it} + \varepsilon_{it}, \quad (3.3)$$

where the subscript i denotes a specific market, e.g. a county or an industry based on a NACE 1-digit level, ε_{it} is the error term and δ as well as $\gamma_{2,1}$ to $\gamma_{2,4}$ the estimated coefficients. All other notations and variables are the same as described in previous equations.

As the coefficient for the dummy for April 2020, $D\_2020\_04_{it}$, was insignificant at level 0.05 in the panel regression models for occupational levels, then the following model was estimated for occupational levels:

$$ln\left(\frac{M_{it}}{U_{it}}\right) = ln(\phi_i) + \mu ln\left(\frac{V_{it}}{U_{it}}\right) + \gamma_{3,1}D\_Q2_{it} + \gamma_{3,2}D\_Q3_{it} + \gamma_{3,3}D\_Q4_{it} + \varepsilon_{it}, \qquad (3.4)$$

where the subscript i denotes a specific market, i.e. an occupation based on an ISCO 1-digit level, ε_{it} is the error term and μ as well as $\gamma_{3,1}$ to $\gamma_{3,3}$ the estimated coefficients. All other notations and variables are the same as described in previous equations.

In conclusion, to find county-specific matching efficiencies ϕ_i to estimate mismatch at regional level, the model (3.3) was used. Similarly, to find industry-specific matching efficiencies ϕ_i based on NACE 1-digit levels to estimate mismatch at industrial level, the model (3.3) was used as well. However, to find occupation-specific matching efficiencies ϕ_i based on ISCO 1-digit levels to estimate mismatch at occupational level, the model (3.4) was used.

Before model estimations based on Eq. (3.3) and (3.4), first the Augmented Dickey-Fuller test was performed which was significant for all, regional, occupational and industrial hirings, hence, the time series were stationary. Thereafter, the models (3.3) and (3.4) were estimated by using both fixed and random effects with accordingly county-, occupation- and industry-specific effects in order to estimate market-specific matching efficiencies ϕ_i. As at the industrial level there were few vacancies in the categories mining and quarrying (NACE B) and activities of households as employers; undifferentiated goods - and services - producing activities of households for own use (NACE T), then these categories were left out from the model estimation and, henceforth, from the mismatch index calculation to provide more accurate results.

The application of a Hausman test resulted in an adoption of the null hypothesis for all levels which indicated that the random effects model should be preferred over the fixed effects model. This is also in accordance with the search and matching theory as changes in matching efficiencies ϕ_i, which in case of random effects models are assumed to be uncorrelated with the independent variable $\frac{V_{it}}{U_{it}}$, shift the Beveridge curve, and do not represent movements along the curve (Bauer 2013). Hence, for the calculation of mismatch indices with Eq. 3.1 the model estimates of the random effects model were used in all, regional, occupational and industrial levels. The following chapter analyses the results of the model estimations and mismatch indices at all levels.

4. RESULTS AND DISCUSSION

This section gives an overview of the main results and discusses them. First, the results of the aggregate matching function estimations are introduced followed by the robustness check of the results. In the second part, the results for county-, industry- and occupation-level mismatch indices will be analysed. Robustness checks to the main results for mismatch indices are also provided. The chapter concludes with a discussion of the results with reference to the search and matching theory and previous empirical literature.

4.1. Matching function estimations

In the following chapters, the results for the matching function estimations will be presented. The first subchapter analyses the main results of the estimated model, whereas the second subchapter provides some robustness checks for the main results. The results of matching function estimations are important regarding the vacancy share, i.e. the coefficient α in Eq. 3.2 used to calculate mismatch indices (3.1) in the second part of the analysis.

4.1.1. Main results

Results of the aggregate matching function model estimated using the Eq. 3.2 are presented in table 1 below. All coefficients, except the seasonal dummy for the second quarter (D_Q2) are significant at level 0.001, whereas the coefficient for D_Q2 is significant at level 0.05. Additional analysis of the properties of the model showed that based on the analysis of residual plots, the residuals of the model are normally distributed and the Augmented Dickey-Fuller test yielded a p-value of 0.01, hence the alternative hypothesis may be adopted, so the fitted values of the model are stationary. The adjusted R-squared is 0.667, and it can be concluded that the aggregate matching function in the form of Cobb-Douglas function (1.2) suits the data well.

Table 1. Results of aggregate matching function estimations

Variables	Coefficient
Intercept	-1.383 ***
Month	0.002 ***
V/U	0.440 ***
D_2020_04	-0.722 ***
D_Q2	0.125 **
D_Q4	-0.140 ***

Notes: Results are based on Eq. 3.2. Significance level * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$
Source: EUIF, author's calculations

The result yielded that the matching efficiency derived by taking the exponential of the intercept, is rather low, i.e. approximately 0.251. This can be interpreted as, in case the number of unemployed and vacancies are equal and the time dummies are zero then, every fourth unemployed will find an efficient match in the vacancies in time t. Although this seems to indicate that the matching efficiency in the Estonian labour market in the period of 01.2011 – 01.2021 is rather low, it should be interpreted with caution, because it also depends on the model specifications, as underlined in the analysis by Bauer (2013, 29). This was also evident in the analysis of this thesis, as by estimating the model (3.2) with the lag of $\frac{V}{U}$ then the coefficient was -1,478 whereas it was -1.210 when estimating model (3.2) without the linear trend. A more comprehensive indication of matching efficiencies may be obtained through matching functions on the different levels, i.e. county, occupation and industry. These results will be presented in the chapter 4.2.

Additionally, the results of the model estimation based on Eq. 3.2 show that the coefficient for $\frac{V}{U}$, i.e. the vacancy share or matching elasticity α is 0.44, in line with previous empirical literature. Sahin et al. (2014) and Patterson et al. (2016) analyses resulted in α being approximately 0.5 depending on the data and model used. As the vacancy share is slightly below 0.5 then, it can be concluded that change in the number of vacancies has a smaller effect on the change in hirings than a change in the number of unemployed. In order to see if the estimation for the vacancy share, which will be used in the mismatch indices calculations afterwards, is robust and will therefore yield reliable estimations of mismatch, some robustness checks will be introduced in the following subchapter.

4.1.2. Robustness check

For robustness check, model in the form of Eq. 3.2 without an assumption of CRS but in the form of an aggregate matching function (1.2) was estimated. Therefore, the vacancy and unemployment shares are estimated separately to see whether the vacancy share is similar to the one presented in table 1, and to see if the CRS holds. The results of these estimations are presented in table 2 below and are rather similar to the ones of the main results in table 1. All variables, except the intercept, are significant at the level of 0.001. Similarly to the main results, the seasonal dummy for the third quarter was disregarded as it was insignificant. As before, additional analysis of the properties of the model showed that based on the analysis of residual plots, the residuals of the model are normally distributed and according to the Augmented Dickey-Fuller test, the fitted values of the model are stationary. The adjusted R-squared is a bit lower than in the base model, 0.531, but based on the results, it still can be concluded that the aggregate matching function in the form of Cobb-Douglas function (1.2) suits the data well.

Table 2. Results of aggregate matching function estimations

Variable	Coefficient
Intercept	0.308
Month	0.002 ***
U	0.475 ***
V	0.344 ***
D_2020_04	-0.716 ***
D_Q2	0.136 ***
D_Q4	-0.160 ***

Note: Significance level * $p < 0.05$, ** $p < 0.01$, *** $p < 0.001$

Source: EUIF, author's calculations

As the sum of the coefficients for U (0.475) and V (0.344), i.e. the unemployed and vacancies, is approximately one, this indicates that the assumption of CRS seems to hold in the Estonian labour market in the period of 01.2011 – 01.2021. The vacancy share is 0.344, hence, smaller by 0.1 compared to the main results in table 1. Additionally, the matching efficiency is a bit higher with 1.361 but it is insignificant and hence, an accurate interpretation is not possible. However, as the coefficients for the dummy variables are significant and similar to the ones in table 1 and the vacancy share is not very different from the main model estimation, whereas the CRS seems to hold as well, then the results of the main model seem to be robust. The following chapter will present the results of the mismatch indices for both vacancy shares α, in order to see if the small divergence in the coefficients leads to similar results, which would furthermore confirm the robustness of the aggregate matching function estimations in table 1.

4.2. Mismatch indices

In the following, results of the mismatch indices calculated by estimating panel regression models in the form of Eq. 3.3 and 3.4 and, by applying Eq. 3.1, with α values received from the analysis presented in the previous chapter will be explained. The first subchapter presents the main results of the mismatch indices at regional, occupational and industrial levels, whereas the second subchapter provides robustness checks for the main results.

4.2.1. Main results

Mismatch indices calculated using Eq. 3.1 for Estonia at the regional, occupational and industrial levels for the period from January 2011 to January 2021 are illustrated in figures 8, 9 and 10 correspondingly. They represent mismatch indices for both vacancy shares, i.e. α values resulting from aggregate matching function estimations explained in the previous chapter. The mismatch results for these two different vacancy shares are quite similar at all the levels: mismatch at the county level is on the average 0.045 and 0.039 at regional, 0.042 and 0.046 at occupational and 0.050 and 0.052 at industrial level for $\alpha = 0.34$ and $\alpha = 0.44$ respectively (see appendix 9). Thus, approximately 4-5 percent of hirings that would be possible in a labour market with optimal allocation are lost due to either regional mismatch at the county level, occupational mismatch at ISCO 1-digit level or industrial mismatch at NACE 1-digit level.

Mismatch indices at the regional level are similar to the ones reached in the empirical analysis by Sahin et al. (2014) on the labour market data of USA and, by Marthin (2012) on the Swedish labour market data where the mismatch index at the county level was also below 0.1. The results regarding mismatch indices at the occupational and industrial levels, however, are a bit lower than in the results of previous studies (Bauer 2013; Erken et al. 2015; Marthin 2012; Said 2021; Shibata 2013). Hence, the mismatch estimation methodology seems to have suited mismatch estimation based on the Estonian labour market data.

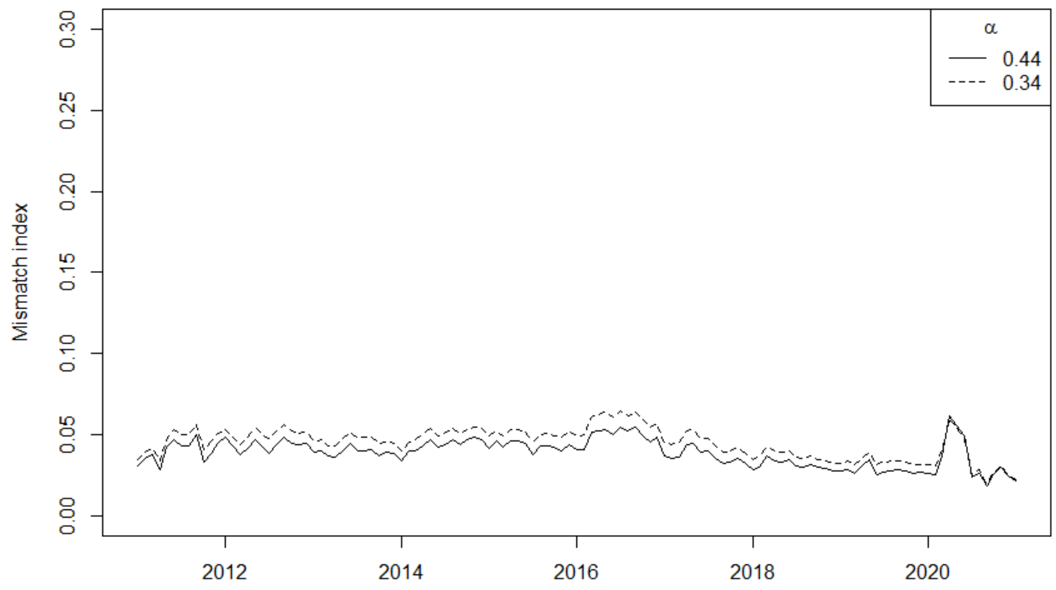

Figure 8. Mismatch indices for Estonia at regional level for different vacancy share α values, period 01.2011 – 01.2021.
Source: EUIF, author’s calculations

The mismatch indices at regional, i.e. county level for the lower vacancy share $\alpha = 0.34$, are generally higher than when $\alpha = 0.44$ (see figure 8). In the year 2020, however, the mismatch indices for the two different matching elasticities seem to overlap. Some overlapping is also visible in the year 2011. The mismatch index is the highest in the year 2016 as well as in the first half of 2020. By using the vacancy share 0.34, mismatch index at the county level reaches the maximum value of 0.065 in the period of July 2016 whereas for the vacancy share 0.44 the maximum value of 0.061 is reached in the period April 2020. Although there seems to be a small downward trend from the year 2016 onwards, the mismatch index increased again sharply in April 2020. The growth is most likely due to the rapid increase in unemployed resulting from the COVID-19 pandemic as Estonia along many other countries imposed strict restrictions, incl. travel restrictions contributing to people, mainly in the tourism sector and customer service becoming unemployed.

Mismatch indices at the occupational level for different α values, in figure 9, are overlapping more compared to mismatch indices at regional level in figure 4. The mismatch index at occupational level is highest in October 2011[5] and the lowest in September 2017. Although there is some volatility in the time series of the mismatch index, most likely due to the seasonality of the unemployment, vacancies and hirings, there is not a clear down- or upward trend visible in figure 9. Similarly as for mismatch at regional level there is a spike visible in the beginning of 2020 resulting from the increase in unemployment in all of the categories, except in the category of skilled agricultural, forestry and fishery workers (ISCO 6) (see figure 4), and a decline in vacancies in some categories, e.g. in the category of services and sales workers (ISCO 5) (see figure 5).

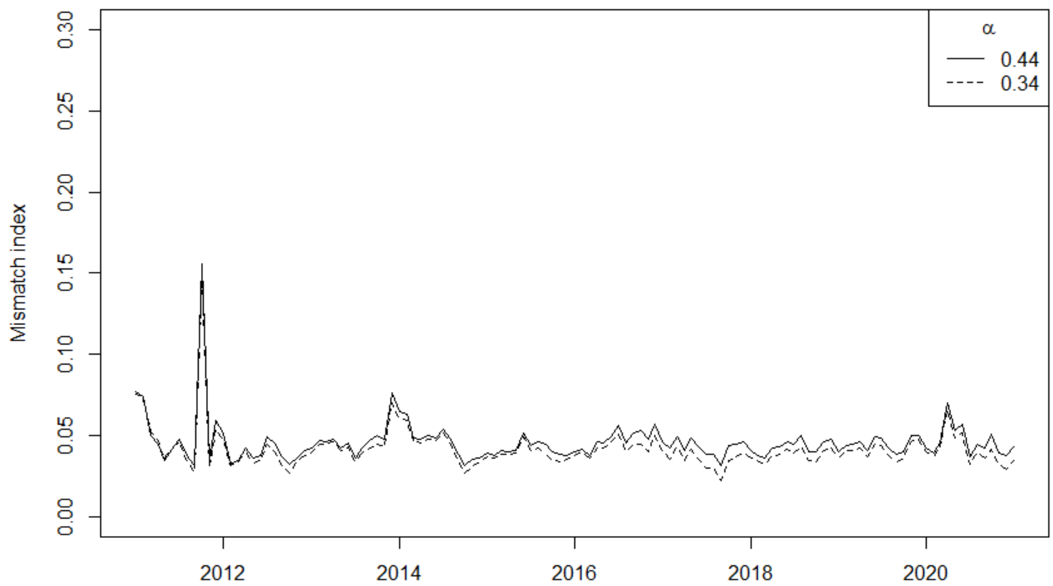

Figure 9. Mismatch indices for Estonia at occupational level for different vacancy share α values, period 01.2011 – 01.2021.
Source: EUIF, author's calculations

The time series of mismatch index at the industrial level, depicted in figure 10, is a bit more volatile than mismatch indices at regional or occupational levels, especially before the second half of 2014[6]. Similarly as in the time series of mismatch index at the occupational level, the mismatch indices for different vacancy share α values overlap for most of the time series. The maximum

[5] The spike in the mismatch index in October 2011 is caused by one time extraordinary high number of vacancies in the category of clerical support workers (ISCO 4), most likely due to the population census survey 2011.
[6] As explained by EUIF, starting from July 2014 the number of unemployed where the unemployed person's previous employer's NACE was known increased rapidly due to a change in regulation that all employers had to register their employees in the employment register (Töötamise register (TÖR)).

value of about 0.16 for mismatch at industrial level is reached in April 2020, whereas the minimum value of about 0.02 is achieved in July 2015. There is a spike in October 2011[7], akin the mismatch index at the occupational level.

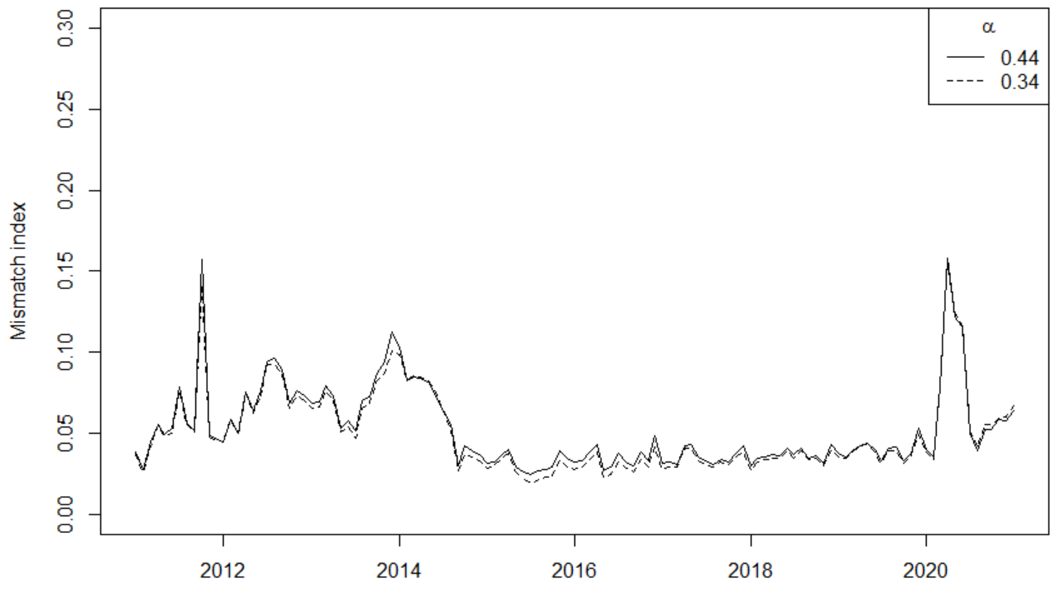

Figure 10. Mismatch indices for Estonia at industry level for different vacancy share α values, period 01.2011 – 01.2021.
Source: EUIF, author's calculations

The results of matching efficiencies ϕ_i give an indication in which markets, e.g. counties in case of regional level, the matching process between unemployed and vacancies is taking place more efficiently and in which markets there seems to be more mismatch. The matching efficiencies across counties are ranging from 0.820 to 1.173, whereas matching efficiencies are the highest in Viljandi (1.173) and Lääne (1.087) counties and lowest in Valga (0.852) and Ida-Viru (0.820) counties (see appendix 10). The range of the efficiencies at regional level is, therefore, similar in results to the studies by Marthin (2012) and Bauer (2013). The matching efficiencies across occupations are ranging from 0.845 in craft and related trades workers (ISCO 7) to 1.433 in armed forces occupations (ISCO 0), whereas the matching efficiencies across industries vary between

[7] The spike in the mismatch index in October 2011 is caused by one time extraordinary high number of vacancies in the category of public administration and defence; compulsory social security (NACE O), most likely due to the population census survey 2011.

0.817 for construction (NACE F) and 1.298 for public administration and defence; compulsory social security (NACE O) (see appendices 11 and 12). The range of the efficiencies is not as diverse as in previous research (Bauer 2013; Erken et al. 2015; Marthin 2012; Said 2021; Shibata 2013). The discussion of these results will follow in chapter 4.3.

There was a spike visible in the first half of 2020 in the time series of mismatch indices across all levels: regional, occupational and industrial. As this might have an impact on the matching efficiencies and, thereby, on the mismatch indices then the following subchapter will provide a robustness analysis by excluding the time series after 2019 from the analysis.

4.2.2. Robustness check

To test whether the results represented in previous subchapter are robust, then this subchapter provides one possible robustness check by estimating the Eq. 3.3 and 3.4 for the period January 2011 to December 2019, and thereafter calculating the mismatch indices based on Eq. 3.1. The results of the mismatch indices are illustrated in figures 11-13 and the changes compared to the main results are depicted in appendix 13.

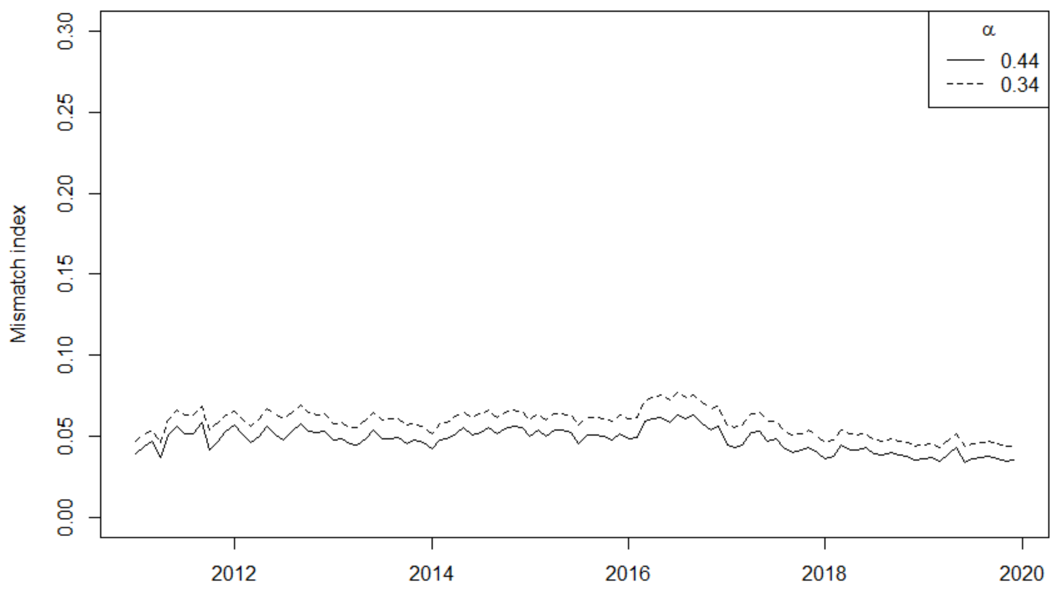

Figure 11. Mismatch indices for Estonia at regional level for different vacancy share α values, period 01.2011 – 12.2019.
Source: EUIF, author’s calculations

Mismatch indices at the regional level of the robustness analysis, depicted in figure 11, are very similar to the ones in the main result, presented in figure 8. The miniscule difference between the results is also visible in appendix 13. The average difference between the main and robust mismatch indices are -0.012 and -0.008 for $\alpha = 0.34$ and $\alpha = 0.44$ respectively, meaning that the mismatch indices of the main results are on average by 0.012 or 0.008 smaller than the mismatch indices of the robustness analysis. As the standard deviations of the differences for both α values are approximately zero (see appendix 13).

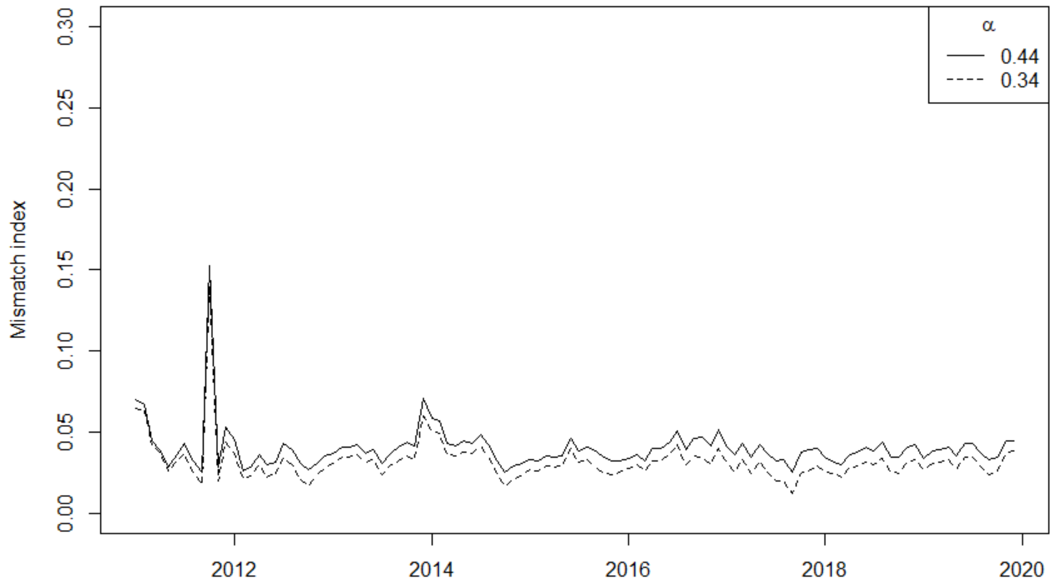

Figure 12. Mismatch indices for Estonia at occupational level for different vacancy share α values, period 01.2011 – 12.2019.
Source: EUIF, author's calculations

Additionally, mismatch indices at occupational level resulting from the robustness analysis, illustrated in figure 12, are very similar to the indices in the main results in figure 9, as is also visible in the appendix 13. In contrast to the differences at the regional and industrial level, at the occupational level the differences between the mismatch indices of the main results and of the robustness analysis are positive. On average the differences between the mismatch indices at occupational level are 0.010 and 0.006 for $\alpha = 0.34$ and $\alpha = 0.44$ respectively, hence, the mismatch indices of the main result are a bit higher than of the robustness analysis, but the standard deviation of the differences is about zero, indicating miniscule volatility (see appendix 13).

Similarly to the results of the robustness analysis for mismatch indices at regional and occupational levels, the indices at the industrial level are alike in the main results, illustrated in figure 10, and in the robustness analysis, depicted in figure 13. The difference between the results is on average -0.008 and -0.006 for $\alpha = 0.34$ and $\alpha = 0.44$ accordingly, and similarly as for mismatch at regional and occupational levels, the standard deviation of the difference is about zero. Thus, the mismatch indices at the industrial level are a bit smaller in the main results compared to the results of the robustness analysis, however, the differences are very small for the entire time series (see appendix 13).

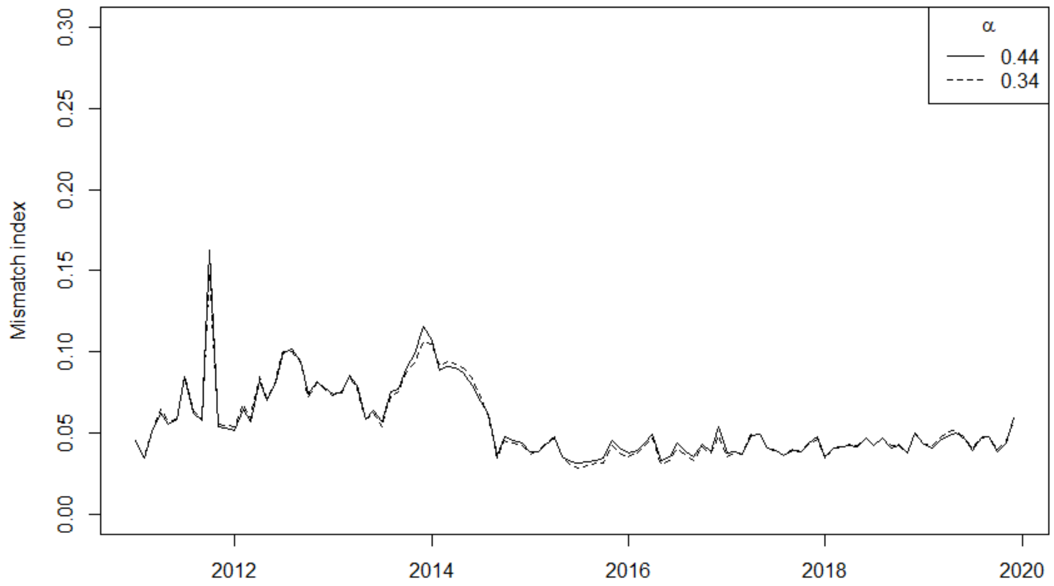

Figure 13. Mismatch indices for Estonia at industrial level for different vacancy share α values, period 01.2011 – 12.2019.
Source: EUIF, author's calculations

Although the matching efficiencies yielded in the robustness analysis on the data for the period January 2011 to December 2019 vary from the matching efficiencies represented in the main results for the period January 2011 to January 2021, the differences between them are small and the overall magnitude and dynamics between different counties, occupations and industries is similar (see appendices 10 to 12). Therefore, in conclusion, based on the robustness analysis the main results of the mismatch estimations seem to be robust at all, i.e. regional, occupational and industrial levels. The following subchapter will discuss the main results and will provide explanations based on the search and matching theory and Estonian labour market characteristics.

4.3. Discussion

Based on the results of the analysis in chapter 4.2., there exists mismatch in the Estonian labour market at all levels: regional, occupational and industrial. The magnitude of mismatch at those levels was also rather similar and low being on average about 4-5 percent (see appendix 9). Thus, about 5 percent of hirings, which would be possible in an optimal allocation of unemployed and vacancies, are lost due to unemployed and vacancies being inefficiently allocated across counties, occupations or industries. Regarding mismatch, it is important to note that e.g. regional mismatch takes only regional allocation of unemployed and vacancies into account and does not look at the occupational or industrial level, hence, does not consider possible differences in skills. The same applies for mismatch at occupational or industrial level.

As stressed by Sahin et al. (2014), the conclusion that there exists low mismatch at some aggregate level, does not imply that there is low mismatch at a disaggregated level. Higher mismatch at more detailed levels is visible in the results of some previous research (Bauer 2013; Marthin 2012; Sahin et al. 2014). Hence, there could be higher mismatch than presented in the results in chapter 4.2. at the level of disaggregated labour markets, i.e. smaller municipalities or at more detailed ISCO or NACE levels. There could be some occupations or industries with similar characteristics implying that the skills of a person being unemployed in a specific occupation or industry might suit to other occupations or industries as well. In the mismatch index methodology, however, these cases are not considered. Additionally, the mismatch in the Estonian labour market might be higher, as the analysis in this thesis used data on unemployed based on their previous employment position, but these might already incorporate mismatch as well. Moreover, assessing this would require more detailed data and additional analysis, which would exceed the scope of the thesis.

Based on the analysis in chapter 2.2., the EPL in Estonia shows a rather flexible labour market that may contribute to the efficient formation of new hirings between unemployed and vacancies and, thereby, to a lower mismatch in the labour market. Additionally, lower mismatch might also be resulting from the appropriate framework of ALMPs which generally suits the labour market needs, as was discussed in chapter 2.2. To understand which specific counties, occupations and industries might contribute to the mismatch at those levels, the matching efficiencies will be analysed.

An indication of regional mismatch followed from the analysis in chapter 2.1., especially for Ida-Viru county and from the analysis of mismatch at regional level, it can be concluded that matching efficiency was the lowest for Ida-Viru county (see appendix 10). Based on search and matching theory, matching efficiencies give an insight about where matchings between unemployed and vacancies are performed more quickly. Hence, in labour markets where the matching efficiency is lower there are more frictions in the labour market, e.g. mismatch between the unemployed and vacancies which hinders the creation of new hirings. As expected in chapter 2.1., the labour market in Ida-Viru county is the least efficient compared to other counties and might be resulting from higher number of unemployed due to a decrease of activities of the mining industry in the region.

Furthermore, at regional level matching efficiencies seemed to be lower in counties that do not have larger cities and are further away from the capital Tallinn, located in Harju county, such as Valga, Võru and Hiiu counties (see appendix 10). Higher level of vacancies in counties with larger cities makes it easier to find a job and might motivate residents of neighbouring counties to commute to Tallinn, resulting in lower levels of unemployment in those counties and, hence, in lower levels of mismatch. It can be analysed further on, if the mobility support measure provided in the years 2016-2018 might have contributed to the downward trend of the mismatch index, at regional level from 2016-2019 as it seems that the possibility of commuting might lead to higher matching efficiencies and, thereby, to lower mismatch at regional level.

The matching efficiencies were highest in Viljandi and Lääne counties indicating that characteristics of unemployed and vacancies match in these counties. Based on the results or on the analysis in chapter 2.1., however, it is not evident what might generate a higher matching efficiency in those counties. Further analysis of mismatch, e.g. by calculating mismatch by combining different levels as occupational and regional or industrial and regional, might give more insight to what are the driving factors of higher matching efficiencies in Viljandi and Lääne counties, and of less efficient functioning of the labour markets of Ida-Viru, Valga, Võru and Hiiu counties.

At occupational and industrial levels, the matching efficiencies seemed to be higher in categories that require some specialised skills, such as armed forces occupations (ISCO 0), education (NACE

P) or human health and social work activities (NACE Q) (see appendices 11 and 12). Hence, it seems that in these categories the labour markets function well compared to others, which is also indicated by low number of unemployed and vacancies (see figures 4-7). Matching efficiency was also higher for clerical support workers (ISCO 4) and public administration and defence; compulsory social security (NACE O) which possibly result from the population census survey conducted in 2011 that lead to a spike in vacancies in this occupation and industry which were filled mostly already within a month.

Based on the analysis in chapter 2.1., it was expected that there is some mismatch in the category of craft and related trades workers (ISCO 7) and plant and machine operators and assemblers (ISCO 8) which also followed from the matching efficiencies from the mismatch analysis (see appendix 11). Therefore, the labour shortage in the occupations of machine operators, based on OSKA report (Kutsekoda 2020), classified under ISCO 7 and 8 might lower the matching efficiencies and increase mismatch at occupational level. There may also be other occupations beside machine operators classified in this group, which might increase the number of unemployed but do not have coinciding vacancies. Labour shortage, based on OSKA report (Kutsekoda 2020), in construction (NACE F) might also explain the low matching efficiency in this industry (see appendix 12). Although there was an increase in the number of unemployed in the beginning of 2020, it seems to not be the cause of the low efficiency as the robustness analysis by excluding the years after 2019 resulted in an even lower efficiency.

As low matching efficiency indicates frictions in the labour market and results in higher mismatch and higher unemployment, then it would be necessary to compile additional analysis by using, e.g. the methodology developed by Herz and van Rens (2020) which could explain if mismatch, e.g. in categories of ISCO 7 and 8 as well as NACE F occur because of some job or worker mobility issues or due to inefficiency in wage determination. Furthermore, estimation of mismatch indices at a more disaggregated level, e.g. at ISCO and NACE 2-digit levels, might give more insight to these dynamics, but these were not conducted as it would have exceeded the scope of the thesis. This analysis might also provide more understanding why there exists low matching efficiency in the categories of professionals (ISCO 2) and financial and insurance activities (NACE K), as the low efficiencies were not expected based on the analysis in the second chapter.

By estimating mismatch unemployment, i.e. unemployment resulting from mismatch in the labour market, it resulted in mismatch contributing to the unemployment on average up to 7 percent (see appendix 14). Therefore, as mismatch at regional, occupational and industrial levels results in higher unemployment in Estonia, then it is important to address the issue and to conduct further analysis. Analysis using more disaggregated levels would help to understand which detailed labour markets are not functioning as efficiently, whereas the analysis of studying possible job and worker mobility and wage determination issues might give more insight to why there exists mismatch in those categories. The results of the analysis would help to improve labour market policies to achieve lower unemployment.

CONCLUSION

The aim of this thesis was to estimate and map the mismatch at regional, occupational and industrial levels in the Estonian labour market. Gaining more knowledge about the scope of mismatch is important as it enables to understand possible reasons of unemployment and, to design and implement appropriate labour market policies. Therefore, the thesis assessed two main research questions: firstly, how mismatch in the labour market is addressed in the search and matching theory framework, and secondly, to what extent does regional, occupational and industrial mismatch exist in the Estonian labour market.

To answer the first research question, the fundamentals of the search and matching theory were studied in the first chapter of the thesis. The main component in the theory is the aggregate matching function, considered in the form of a Cobb-Douglas function, which describes the formation of new matchings between unemployed and vacancies. The number of job matchings is influenced by the matching efficiency that captures different frictions in the labour market, including mismatch. Hence, lower matching efficiency indicates inefficiency and possible mismatch in the labour market. Lower matching efficiency shifts the Beveridge curve further away from the origin, thus, increasing the equilibrium unemployment rate.

In order to answer the second research question by estimating mismatch at regional, occupational and industrial levels in the Estonian labour market, the mismatch index framework was used. The analysis used monthly data from EUIF for the time series of January 2011 to January 2021. The analysis at the regional level was conducted in the detail of counties, at occupational level in the detail of ISCO 1-digit level and at industrial level in the detail of NACE 1-digit level. First, the aggregate matching function and the matching functions at regional, occupational and industrial levels were estimated to find the vacancy share and matching efficiencies, needed to calculate mismatch indices at regional, occupational and industrial levels.

The estimation of mismatch resulted in being on average about 4 percent at regional and occupational levels and about 5 percent at industrial level. Thus, approximately 4-5 percent of hirings that would be possible in a labour market with optimal allocation are lost due to either regional mismatch at the county level, occupational mismatch at ISCO 1-digit level or industrial mismatch at NACE 1-digit level. The results were robust to the analysis conducted for the time series of January 2011 to December 2019 to exclude the spike in unemployment and mismatch resulting from the emergency state due to COVID-19 pandemic.

The analysis of the matching efficiencies at the regional level revealed that the labour markets in Ida-Viru, Valga, Võru and Hiiu counties seem to function less efficiently compared to others. For Ida-Viru county, it likely results from higher number of unemployed due to a decrease of activities of the mining industry, whereas for the other counties the distance from larger cities may play a role. However, further research by e.g. including variables related to commuting into the model estimations is needed to understand if the possibility of commuting might lead to higher matching efficiencies and less mismatch. Additionally, calculating mismatch with the combinations of different levels as occupational and regional or industrial and regional, would provide more insight to what the driving factors of higher matching efficiencies in Viljandi and Lääne counties might be.

At the occupational and industrial levels, the inefficiency reflecting in low matching efficiencies in the categories of craft and related trades workers, plant and machine operators and assemblers and construction, resulting from possible labour shortage, seemed to increase mismatch at occupational and industrial levels. Further research, by e.g. studying possible job and worker mobility and wage determination issues might help to understand what is causing the inefficiency in these labour markets. Furthermore, calculating mismatch indices at a more disaggregated level would possibly provide more knowledge to why there exists low matching efficiency in the categories of professionals and financial and insurance activities.

The estimation of mismatch at the regional, occupational and industrial levels in the Estonian labour market provided understanding of which labour markets are functioning less efficiently than others. It is important to gain further knowledge in the causes of these inefficiencies as the estimation of mismatch unemployment resulted in mismatch contributing to the unemployment on average up to 7% in the Estonian labour market. Therefore, gaining more knowledge regarding these issues would help to design appropriate labour market policies, e.g. in the form of training or mobility support to lower unemployment in Estonia.

KOKKUVÕTE

MITTESOBITUVUSE UURIMINE EESTI TÖÖTURU ANDMETEL

Pauline Kommer

Käesoleva magistritöö eesmärgiks oli hinnata ja kaardistada mittesobituvust Eesti tööturul regionaalsel, ametialade ja tegevusalade tasemel. Mittesobituvuse ulatuse uurimine võimaldab paremini mõista töötuse võimalikke põhjuseid ning kujundada sobivaid tööturumeetmeid töötuse vähendamiseks. Antud lõputöös uuriti, kuidas käsitletakse mittesobituvust tööturu sobitamisteooria kontekstis ning missugusel määral eksisteerib mittesobituvus Eesti tööturul regionaalsel, ametialade ja tegevusalade tasemel.

Esimesele uurimisküsimusele vastamiseks käsitleti töö esimeses osas tööturu sobitamisteooria aluspõhimõtteid. Teooria põhineb tööturu sobitamisfunktsioonil, mis kirjeldab uute töösuhete loomist töötute ja vabade töökohtade vahel, ning mille puhul on empiiriliselt kinnitust leidnud Cobbi-Douglase funktsiooni kuju. Töösuhete loomise arvu mõjutab sobitamise efektiivsus, võttes arvesse erinevaid tööturul esinevaid ebaefektiivsuse liike, k.a mittesobituvust. Mida madalam on sobitamise efektiivsus, seda ebaefektiivsem on tööturg, viidates võimalikule mittesobituvusele töötute ja vakantside vahel. Madalam sobitamise efektiivsus nihutab tööturu sobitamisteooriast lähtuvalt Beveridge kõvera keskpunktist kaugemale, mille tulemusel suureneb töötuse tasakaalumäär. Seega suurendab mittesobituvus töötute ja vabade töökohtade vahel töötuse tasakaalumäära.

Lõputöö teisele uurimisküsimusele vastamiseks hinnati mittesobituvust Eesti tööturul nii regionaalsel, ametialade kui tegevusalade tasemel, kasutades hindamiseks mittesobituvuse indeksite metoodikat. Empiirilise analüüsi läbiviimisel võeti aluseks Eesti Töötukassa igakuised andmed, vaadeldavaks perioodiks oli 2011. aasta jaanuar kuni 2021. aasta jaanuar. Regionaalsel tasemel käsitleti maakondade detailsust, ametialade tasemel ISCO klassifikaatori ning tegevusalade tasemel NACE klassifikaatori esimese astme detailsust. Kõigepealt hinnati tööturu

agregeeritud sobitamisfunktsiooni ning seejärel sobitamisfunktsioone piirkondlikul, ametialade ja tegevusalade tasemetel, mis võimaldas leida mittesobituvuse indeksite arvutamiseks vajalikud sobitamise efektiivsused ja vakantside osakaalu.

Mittesobituvuse hindamisel saadi tulemuseks, et regionaalsel ning ametialade tasemel on mittesobituvus keskmiselt 4% ning tegevusalade tasemel keskmiselt 5%. Seega võib väita, et ligikaudu 4-5% uutest töösuhetest, mis oleksid potentsiaalselt võimalikud tööturul, kus töötud ja vakantsid on optimaalselt jaotatud, jääb mittesobituvuse tõttu tööturul regionaalsel, ametialade või tegevusalade tasemel moodustamata. Saadud tulemused olid sarnased töös täiendavalt läbi viidud robustsusanalüüsi tulemustega, kus hinnati mittesobituvust perioodil 2011. aasta jaanuarist kuni 2019. aasta detsembrini, jättes analüüsist välja järsud kasvud töötuses ning mittesobituvuses, mis tulenesid COVID-19 pandeemiast tingitud eriolukorrast.

Sobitamise efektiivsuste analüüsi tulemusel saab öelda, et regionaalsel tasemel toimivad Ida-Viru, Valga, Võru ja Hiiu maakondade tööturud ebaefektiivsemalt, võrreldes teiste maakondadega. Ida-Viru maakonna puhul tuleneb suurem ebaefektiivsus tõenäoliselt kaevanduse tegevusala mahu vähenemisest tingitud kõrgest töötusest, teiste maakondade puhul võib madalam efektiivsuse põhjuseks olla kaugus suurematest linnadest. Edaspidi oleks huvitav uurida riigisisese pendelrände võimalikku seost sobitamise efektiivsuse ja mittesobituvuse vahel, kaasates mudelisse täiendavaid muutujaid pendelrände kohta. Töö edasiarendusena on samuti võimalik analüüsida kõrgema sobitamise efektiivsuse olemasolu Viljandi ja Lääne maakondades, hinnates mittesobituvuse indekseid regionaalse ja ametialade või regionaalse ja tegevusalade taseme kombinatsioonidel.

Ametialade ja tegevusalade tasemel eristusid madalama sobitamise efektiivsusega oskus- ja käsitööliste ning seadme- ja masinaoperaatorite ja koostajate ametialad ning ehituse tegevusala, mille madalam efektiivsus ja võimalik mittesobituvus võib olla põhjustatud tööjõupuudusest antud valdkondades. Mõistmaks, mis põhjustab ebaefektiivsust nimetatud kategooriates, saab töö edasiarendusena uurida võimalikke töökoha ja töötaja mobiilsusest ning palga läbirääkimistest tingitud ebaefektiivsusi. Lisaks võib mittesobituvuse indeksite arvutamine detailsemal tasemel anda ülevaadet, miks tippspetsialistide ametialas ning finants- ja kindlustustegevuse tegevusalas eksisteerib madal sobitamise efektiivsus.

Mittesobituvuse hindamine, kasutades Eesti tööturu andmeid erinevatel tasemetel, võimaldas tuvastada, missuguste maakondade, ametialade või tegevusalade tööturud toimivad vähem efektiivsemalt võrreldes teistega. Kokkuvõtvalt saab välja tuua, et mittesobituvus töötute ja vakantside vahel panustab töötusesse Eestis keskmiselt kuni 7%. Oluline on mõista, mis põhjustab ebaefektiivsust Eesti tööturul, et kujundada sobivaid tööturumeetmeid, nt täiendõppe või mobiilsustoetuse vormis, ja vähendada mittesobituvusest tulenevat töötust.

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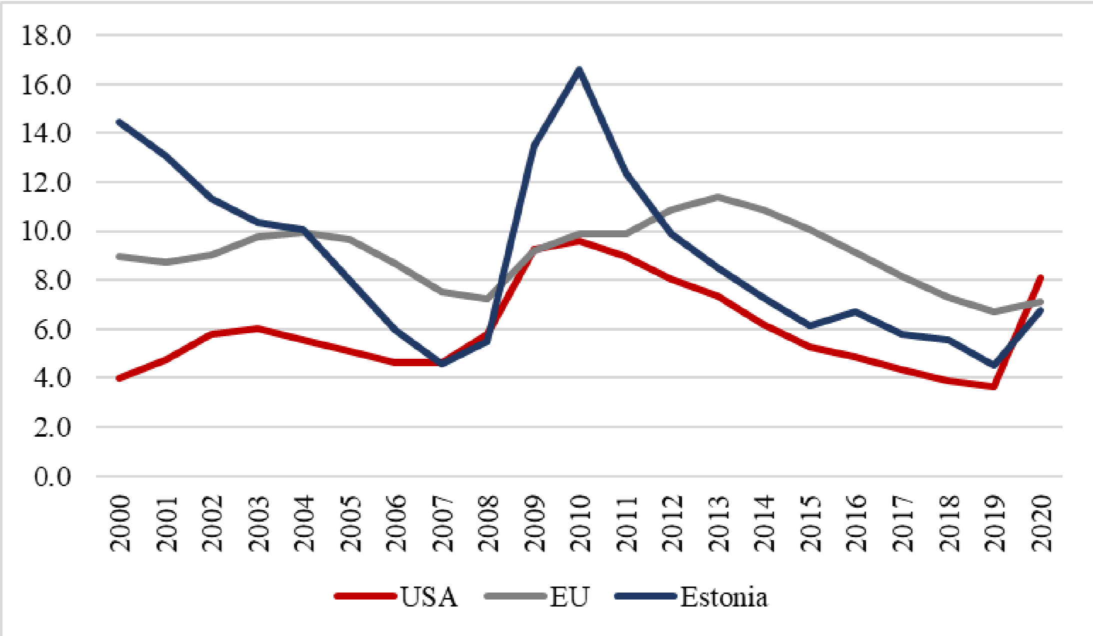
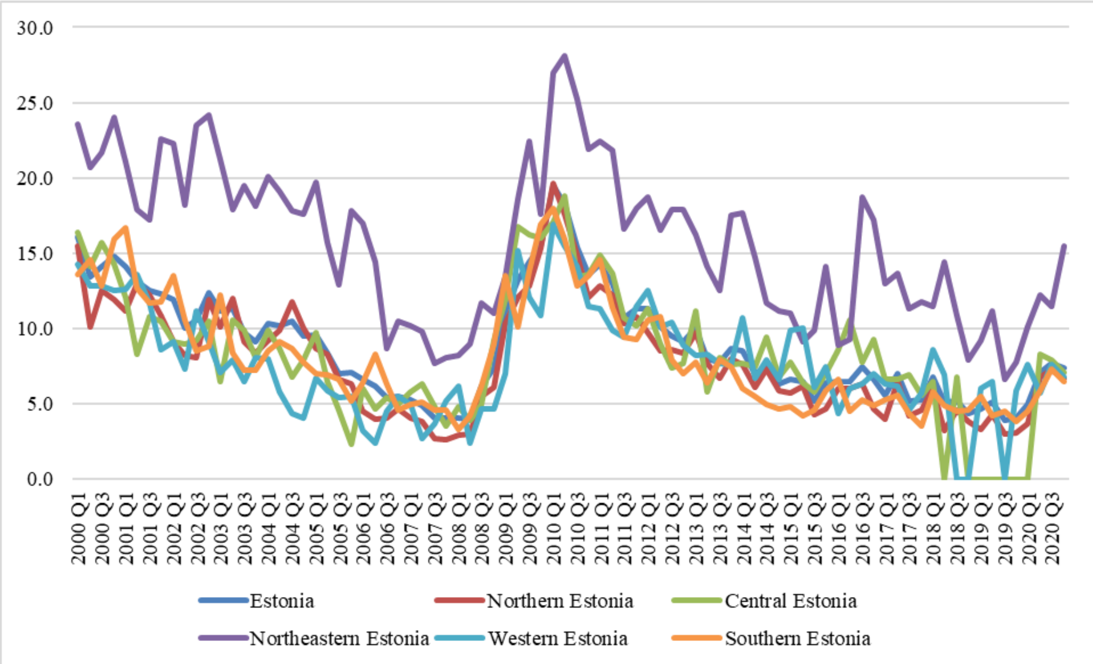
APPENDICES

Appendix 1. Unemployment rates in the EU, USA and Estonia, 2000 – 2020, %



Source: OECD (2021d). EU – European Union (27 countries), composed by author

Appendix 2. Quarterly regional unemployment rates, 2000 Q1 – 2020 Q4, %



Source: Statistics Estonia (table TT467), composed by author. Due to confidentiality, data for Central Estonia is not published for the periods 2018 Q2 and 2018 Q4 – 2020 Q1 and data for Western Estonia is not published for the periods 2018 Q3 – 2018 Q4 and 2019 Q3.

Appendix 3. ISCO 1-digit level codes and names

ISCO 1-digit level code	ISCO 1-digit level name
0	Armed forces occupations
1	Managers
2	Professionals
3	Technicians and associate professionals
4	Clerical support workers
5	Services and sales workers
6	Skilled agricultural, forestry and fishery workers
7	Craft and related trades workers
8	Plant and machine operators and assemblers
9	Elementary occupations

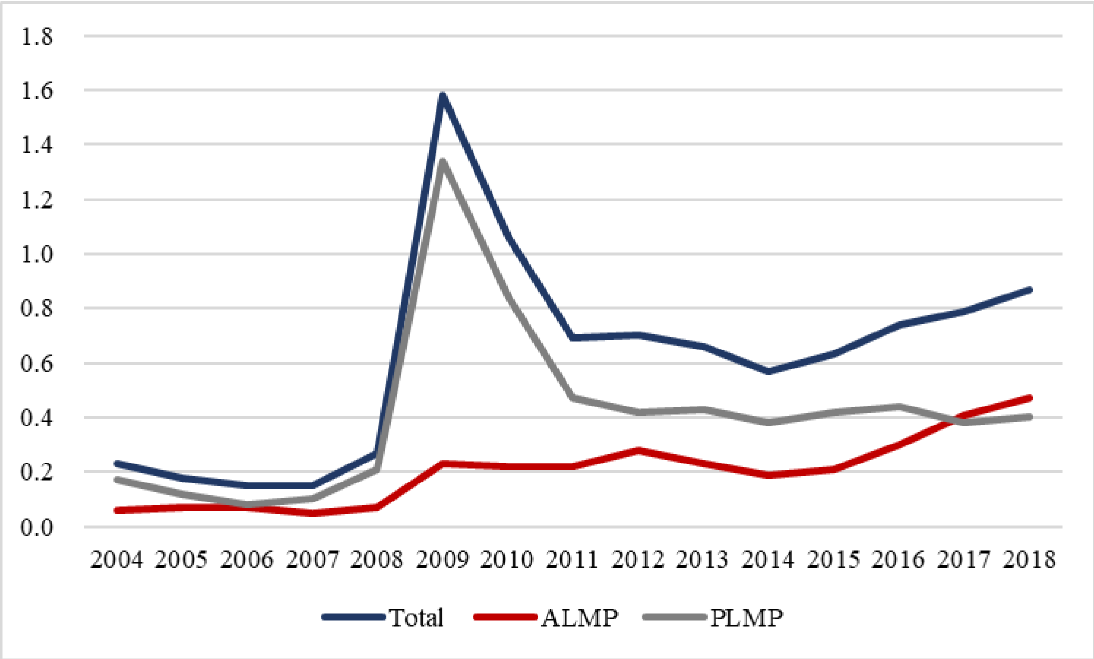
Source: International Standard Classification of Occupations (ISCO), composed by author

Appendix 4. NACE 1-digit level codes and names

NACE 1-digit level code	NACE 1-digit level name
A	Agriculture, forestry and fishing
B	Mining and quarrying
C	Manufacturing
D	Electricity, gas, steam and air conditioning supply
E	Water supply; sewerage; waste management and remediation activities
F	Construction
G	Wholesale and retail trade; repair of motor vehicles and motorcycles
H	Transporting and storage
I	Accommodation and food service activities
J	Information and communication
K	Financial and insurance activities
L	Real estate activities
M	Professional, scientific and technical activities
N	Administrative and support service activities
O	Public administration and defence; compulsory social security
P	Education
Q	Human health and social work activities
R	Arts, entertainment and recreation
S	Other services activities
T	Activities of households as employers; undifferentiated goods - and services - producing activities of households for own use

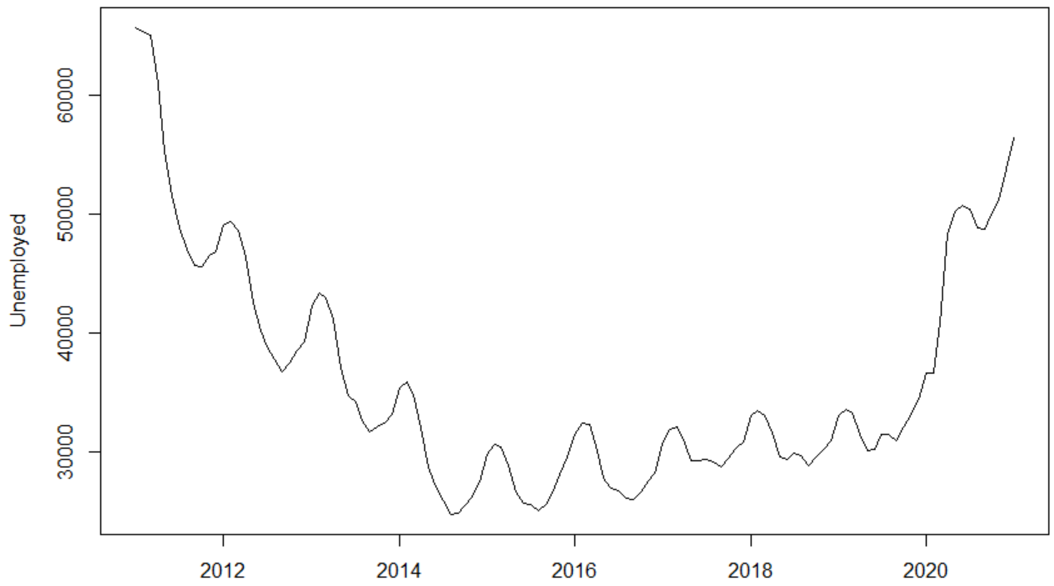
Source: Statistical Classification of Economic Activities in the European Community (NACE), composed by author

Appendix 5. Public expenditure on ALMPs and PLMPs in Estonia, 2004 – 2018, % of GDP



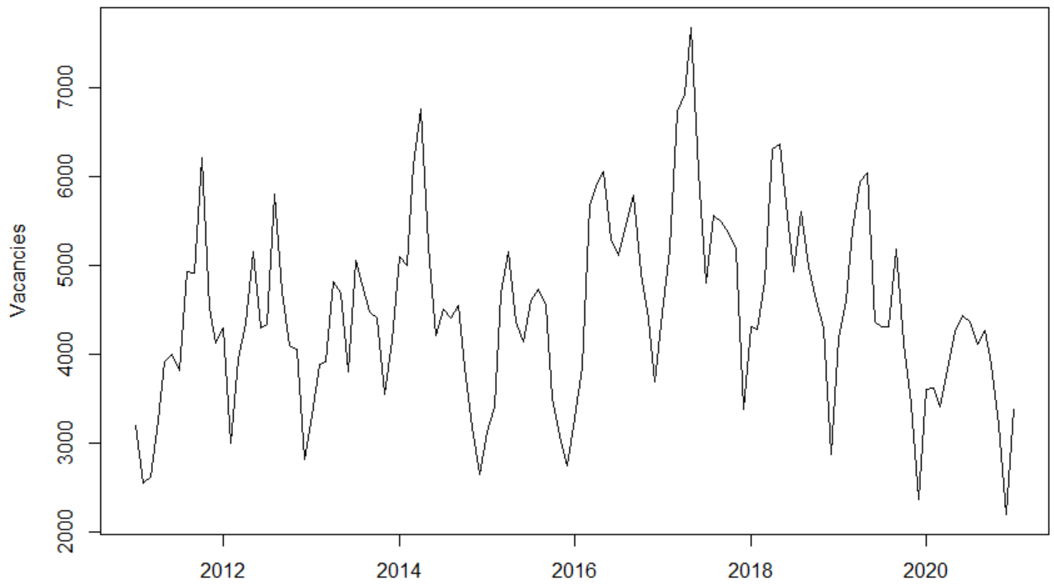
Source: OECD (2021b), composed by author

Appendix 6. Unemployed in Estonia, 01.2011 – 01.2021



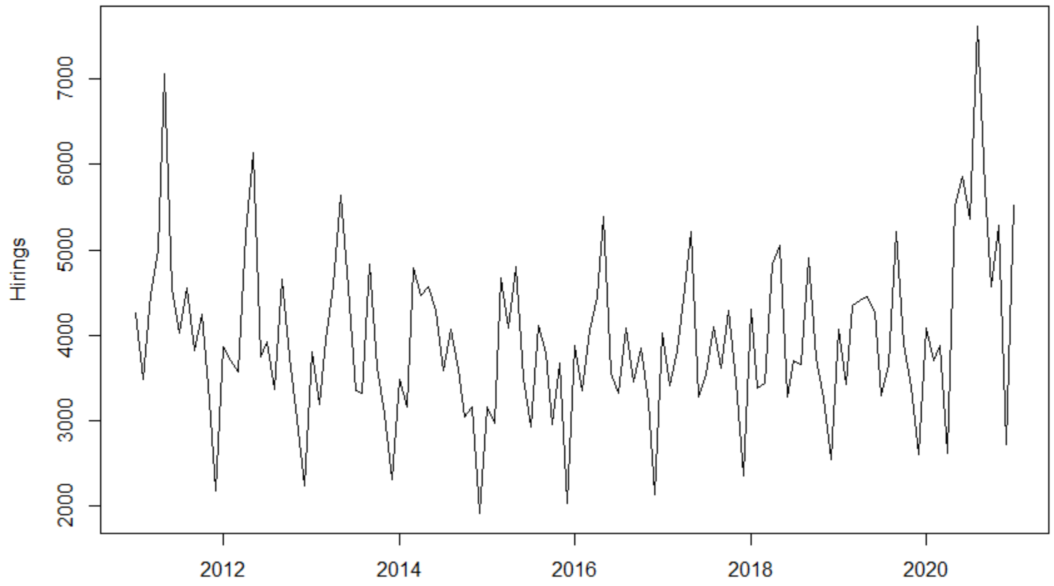
Source: EUIF, composed by author

Appendix 7. Vacancies in Estonia, 01.2011 – 01.2021



Source: EUIF, composed by author

Appendix 8. Transitions out of unemployment into employment in Estonia, 01.2011 – 01.2021



Source: EUIF, composed by author

Appendix 9. Summary statistics of mismatch indices at regional, occupational and industrial levels in Estonia, 01.2011 – 01.2021

	Region	Region	Occupation	Occupation	Industry	Industry
	$\alpha = 0.34$	$\alpha = 0.44$	$\alpha = 0.34$	$\alpha = 0.44$	$\alpha = 0.34$	$\alpha = 0.44$
Minimum	0.020	0.018	0.022	0.031	0.019	0.025
Maximum	0.065	0.061	0.146	0.155	0.156	0.158
Median	0.047	0.040	0.040	0.044	0.039	0.042
Mean	0.045	0.039	0.042	0.046	0.050	0.052
Standard deviation	0.010	0.008	0.013	0.013	0.025	0.025

Source: EUIF, author's calculations

Appendix 10. Matching efficiencies across counties in Estonia

	Matching efficiency	
	Main result	Robustness check
County/Period	01.2011-01.2021	01.2011-12.2019
Viljandi county	1.173	1.188
Lääne county	1.087	1.097
Rapla county	1.052	1.057
Pärnu county	1.041	1.038
Põlva county	1.033	1.066
Saare county	1.033	1.027
Lääne-Viru county	1.018	1.018
Jõgeva county	1.016	1.003
Harju county	1.015	1.002
Tartu county	1.004	0.997
Järva county	0.990	0.987
Hiiu county	0.962	0.955
Võru county	0.958	0.955
Valga county	0.852	0.865
Ida-Viru county	0.820	0.805

Source: EUIF, author’s calculations

Appendix 11. Matching efficiencies across occupations in Estonia

		Matching efficiency	
		Main result	Robustness check
ISCO	Occupation	01.2011-01.2021	01.2011-12.2019
0	Armed forces occupations	1.433	1.401
1	Managers	0.957	0.977
2	Professionals	0.857	0.842
3	Technicians and associate professionals	0.941	0.933
4	Clerical support workers	1.218	1.249
5	Services and sales workers	1.070	1.076
6	Skilled agricultural, forestry and fishery workers	0.858	0.849
7	Craft and related trades workers	0.845	0.852
8	Plant and machine operators and assemblers	0.870	0.867
9	Elementary occupations	1.099	1.103

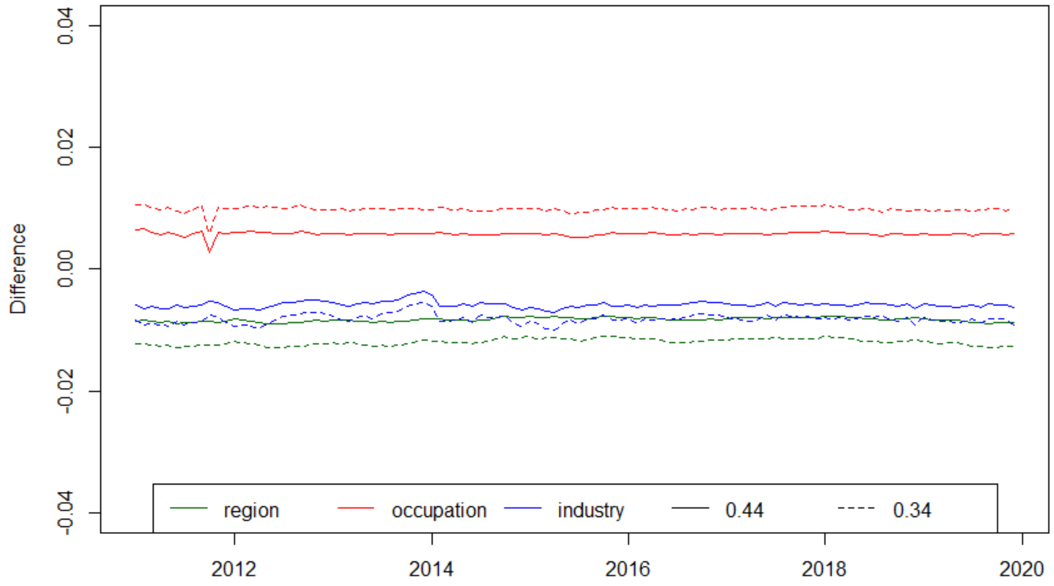
Source: EUIF, author’s calculations

Appendix 12. Matching efficiencies across industries in Estonia

		Matching efficiency	
		Main result	Robustness check
NACE	Industry	01.2011-01.2021	01.2011-12.2019
A	Agriculture, forestry and fishing	1.006	1.004
C	Manufacturing	0.919	0.904
D	Electricity, gas, steam and air conditioning supply	1.052	1.160
E	Water supply; sewerage; waste management and remediation activities	1.143	1.153
F	Construction	0.817	0.804
G	Wholesale and retail trade; repair of motor vehicles and motorcycles	1.050	1.044
H	Transporting and storage	0.916	0.912
I	Accommodation and food service activities	1.007	0.991
J	Information and communication	0.977	0.960
K	Financial and insurance activities	0.880	0.859
L	Real estate activities	1.026	1.034
M	Professional, scientific and technical activities	0.976	0.983
N	Administrative and support service activities	0.915	0.916
O	Public administration and defence; compulsory social security	1.298	1.312
P	Education	1.086	1.081
Q	Human health and social work activities	1.074	1.066
R	Arts, entertainment and recreation	1.007	0.992
S	Other services activities	0.947	0.944

Source: EUIF, author’s calculations

Appendix 13. Differences between mismatch indices of the main results and of the robustness check at different levels for different vacancy share α values, 01.2011-12.2019



Source: EUIF, author’s calculations

Appendix 14. Mismatch unemployment

To estimate the contribution of mismatch between unemployed and vacancies at regional, occupational and industrial level to the unemployment, the methodology of counterfactual unemployment was used. The contribution of mismatch to unemployment, i.e. mismatch unemployment is measured as the difference between unemployment and counterfactual unemployment. Counterfactual unemployment reflects the amount of unemployed in absence of mismatch. The methodology for the calculation of counterfactual unemployment was derived from the framework developed by Sahin et al. (2014), whereas the modifications as in Erken et al. (2015) were also used to calculate counterfactual unemployment using number of unemployed instead of rate as in Sahin et al. (2014). The counterfactual number of unemployed was calculated as

$$U_{t+1}^{*} = U_t^{*} + s_t\big(E_t + (U_t - U_t^{*})\big) - f_t^{*}U_t^{*}, \tag{A14.1}$$

where $f_t^{*} = f_t \frac{1}{1-MM_t}\left(\frac{U_t}{U_t^{*}}\right)^{\alpha}$ and $f_t = \frac{H_t}{U_t}$, $s_t = \frac{S_t}{E_t}$, where S_t are separations, E_t is the number of employed, MM_t is the mismatch index from the main results in chapter 4.2.1., $\alpha = 0.44$ the vacancy share from the main results in chapter 4.1.1., H_t are the hirings, U_t is the number of unemployed, U_t^{*} is the counterfactual number of unemployed, whereas $U_1^{*} = U_1$.

For the calculation of counterfactual number of unemployed (A14.1) monthly data on separations S_t is derived from the dataset published at the homepage of EUIF (2021b) as transitions from employment to unemployment. The number of employed E_t is derived from the database of Statistics Estonia (2021), but as the data is available on a quarterly not monthly basis then an approximation of setting the monthly number of employed equal to the corresponding quarterly number of employed is used. The number of hirings H_t are derived from EUIF (2021c) and the number of unemployed U_t from the dataset of EUIF received upon request. The number of hirings H_t is multiplied by 1.15 as based on previous research of comparing the data on number of hirings published by EUIF with the data sources available to Tax and Customs Board (Maksu- ja Tolliamet) have shown that the number of hirings is about 10-15% higher than the EUIF reports (Kommer 2018). The results of the analysis are presented in the following figures 14-16.

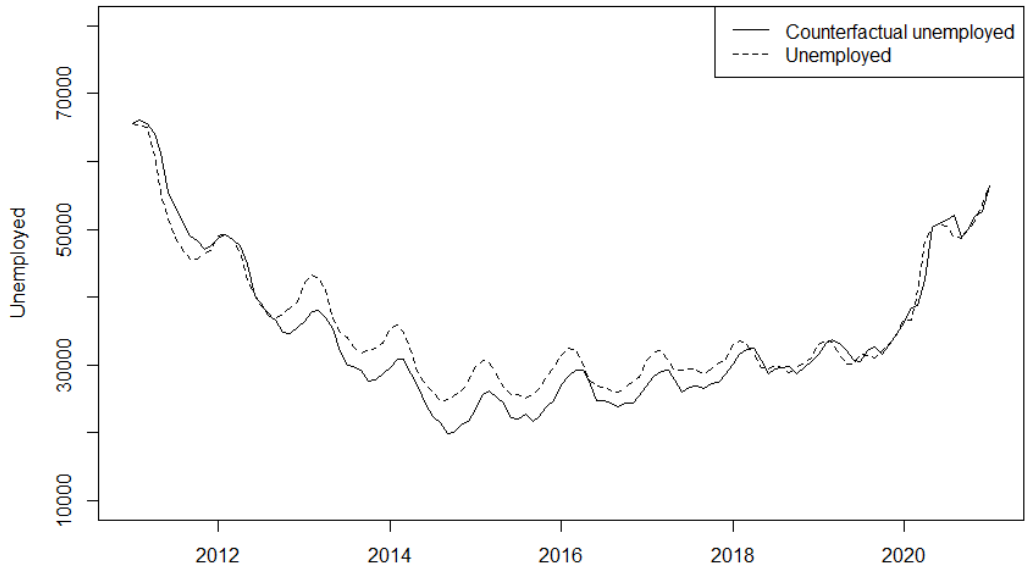


Figure 14. Unemployed and counterfactual number of unemployed in Estonia at the regional level, period 01.2011 – 01.2021.
Source: EUIF, Statistics Estonia, author's calculations

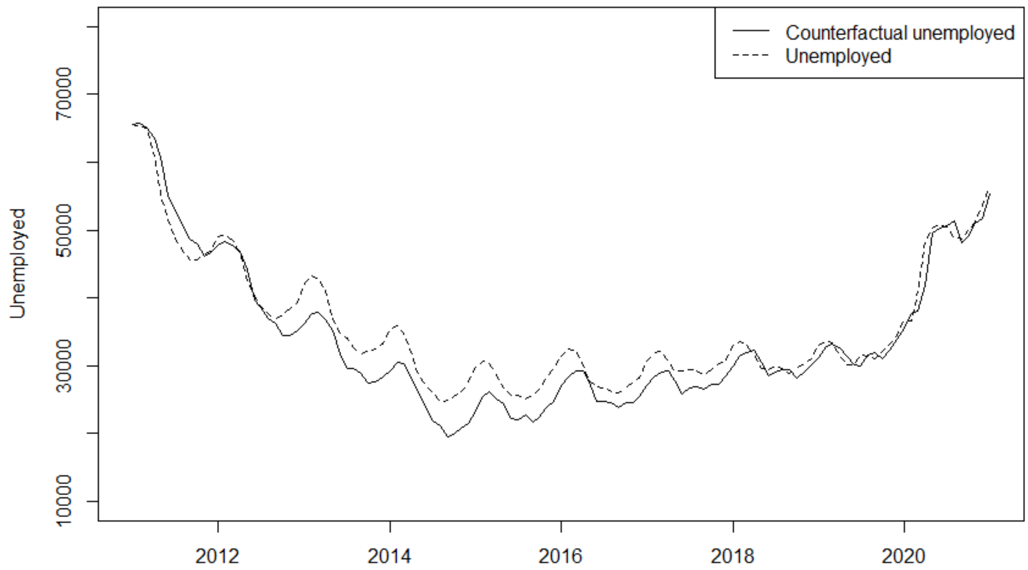


Figure 15. Unemployed and counterfactual number of unemployed in Estonia at the occupational level, period 01.2011 – 01.2021.
Source: EUIF, Statistics Estonia, author's calculations

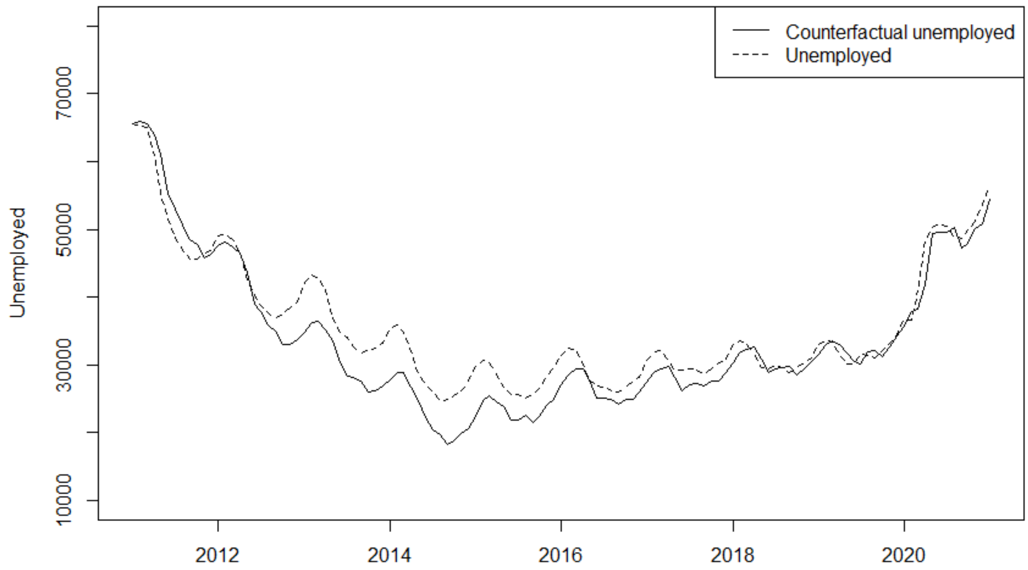


Figure 16. Unemployed and counterfactual number of unemployed in Estonia at the industrial level, period 01.2011 – 01.2021.
Source: EUIF, Statistics Estonia, author's calculations

In most of the periods the counterfactual number of unemployed relies below the number of unemployed which is also to be expected as unemployment should be lower in the absence of mismatch. At the beginning of the time series the number of unemployed is lower than the counterfactual number of unemployed which may result from data quality issues or from the selection of the starting point U_1^* for the iteration process. At the end of the time series there is some overlapping of the data series visible which may be resulting from the rapid increase of the number of unemployed in the beginning of 2020.

At regional, occupational and industrial levels the number of unemployed are on an average accordingly 1558, 1894 and 2206 higher than the counterfactual number of unemployed. Hence, the mismatch unemployment at the regional, occupational and industrial levels is on an average 1558, 1894 and 2206 respectively. The contribution of mismatch unemployment to the number of unemployed is on an average about 5.4%, 6.3% and 7.1% at regional, occupational and industrial levels accordingly.

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