Mismatch Unemployment in the Finnish Labour Market

Abstract

In this paper, I study mismatch between job-seekers and vacancies across sectors in the Finnish labour market between 2006 and the beginning of 2015. The amount of lost hires caused by the imbalance between job-seekers and vacancies is measured by a mismatch index, which allows us to construct an efficient allocation of job-seekers across sectors. Further, this efficient allocation is used to define a counterfactual unemployment rate to measure the magnitude of mismatch.

Studying the causes of unemployment is increasingly important especially in Finland, where the share of long-term unemployed job-seekers has shown a steady increase after the financial crisis. This paper presents mismatch theory as one possible explanation for the prolonged unemployment in the Finnish labour market.

This study utilizes the labour market data from Local Labour Offices made available by the Ministry of Employment and the Economy. The rich panel data set consists of monthly information on job seekers, vacancies and hires between 2006 and April 2015. The data is compiled both in geographical and occupational dimensions to allow the estimation of a mismatch index across both sectors.

Mismatch measurements indicate possible gains to be made in hires by allocating job-seekers efficiently. Spatially lost hires vary monthly between 5 and 7 percent when sector-specific efficiencies are considered. Occupational mismatch indices show wider variation ranging monthly from 2 to 14 percent depending on the level of disaggregation. Mismatch peaked especially sharply across occupations as the financial crisis burst in 2008. According to the approximation of counterfactual unemployment rates, mismatch explains around one fifth of the aggregate unemployment rate. Most notably, the results indicate that mismatch is currently increasing on all dimensions. In line with previous studies from the US and Sweden, mismatch is more severe across occupations than regions.

TABLE OF CONTENTS

TABLES

FIGURES

1 Introduction

The modelling of labour market dynamics is central to understand the foundation of unemployment, which dilutes welfare, income, equality and worker skills. Typically the labour market is described as flows of jobs and workers constantly reorganising themselves; jobs are being created and others destroyed and some workers being hired and others losing their jobs. These constant reallocations create frictions that lead to the simultaneous existence of unemployed job-seekers and vacancies (Cahuc et al. 2014). Recently, the research has taken matching function as the main approach to incorporate these frictions into the labour market models.

The matching model provides a framework to study labour market mismatch as well. Mismatch refers to "a theory of former steel workers remaining near a closed plant in the hope that it reopens" (Shimer, 2007). Hence, mismatch concept attempts to answer, whether unemployment is affected by job-seekers looking for work in the wrong sectors. In other words, it aims to encompass the degree of heterogeneity in job-seekers across various dimensions, which can relate to worker skill, location or occupation (Petrongolo and Pissarides, 2001). As weak economic development in Finland since 2008 has initiated prolonged unemployment, it raises interest, whether labour mismatch has hindered the recovery of the labour market. Looking more closely the labour flows in the Finnish labour market reveal a continuous decrease in the job-finding rate simultaneously with a lower unemployment inflow now than pre-crisis. Sahin et al. (2014) argue that mismatch could explain these type of dynamics.

In this paper, I utilize a panel data set to study mismatch unemployment in the Finnish labour market between 2006 and April 2015. The data set includes monthly information of job-seekers, vacancies and hires across geographical and occupational dimensions. The empirical analysis has three phases. First, the matching functions are estimated to obtain sector-specific matching efficiencies and vacancy shares. Then, taking the observed vacancies as given, I measure the amount of lost hires produced by mismatch in the Finnish labour market across regions and occupations. Third, counterfactual unemployment rates in the absence of mismatch are calculated and compared with actual rates to demonstrate the magnitude of mismatch.

Using the constructed mismatch index this thesis aims to answer how imbalanced is the distribution of unemployed job-seekers given the observed productive efficiencies, matching efficiencies and vacancies across the labour market. Especially the changes in the matching process before and after the latest financial crisis will be discussed. In addition, the prevailing characteristics of the Finnish labour market are described thoroughly.

This paper complements other Finnish studies that focus on labour matching with disaggregated data and provides a fresh angle with the mismatch index which, to my knowledge, has not been measured before with Finnish data. Additionally, the mismatch index approach allows convenient international comparison with studies from the US and Sweden. Mismatch measurements might have relevance also from the policymaker perspective. Aggregate labour market policies may have an inefficient effect on employment if severe labour mismatch weakens the labour market matching process. Moreover, policies supporting labour mobility could dilute geographical mismatch or means that improve labour re-education could suppress possible occupational mismatch.

The rest of the paper is structured as follows. Section 2 describes the development of the matching model and presents the Beveridge curve as an early tool for illustrating labour market matching. Section 3 discusses the features of the baseline matching model. After the introduction of this widely studied model, the framework is utilized in Section 4 as a basis to construct the theory behind mismatch index. Section 5 goes through the panel data set that is used in the empirical measurements. Section 6 presents the results across geographical and occupational sectors and final section concludes.

2 Background

This section covers how the matching model has made inroads into become the prevailing approach to explaining labour market dynamics. The second part presents the Beveridge curve as an important antecedent in modelling labour market matching.

Matching function is based on the assumption that the hiring process in the labour market is time-consuming and affected by transaction costs and frictions (Pissarides, 2000). The importance of frictions in explaining unemployment has been understood already in the early generations of labour market studies, but the modelling proved to be difficult for a long time (Petrongolo and Pissarides, 2001). The discussion about frictions in macroeconomic theories of labour markets dates back to the aftermath of Great Depression in the 1930's. Hicks (1932) was one of the earliest academics to distinguish the effect of frictions on unemployment, but Keynes (1936) was perhaps the first one to use the term "frictional" unemployment, even though he defined this kind of unemployment only to be compatible with full employment (Petrongolo and Pissarides, 2001). Keynes presented high persistent unemployment as one kind of steady state equilibrium. Until then the predominant classical view established by economists including Alfred Marshall and David Ricardo understood economy as a self-regulating mechanism with a unique steady-state equilibrium, which could not easily rationalize the existence of involuntary unemployment.

An antecedent for the matching model was the proposition of the "natural rate" of unemployment by Friedman (1968) and Phelps (1967) as an attempt to distinguish the structural factor of unemployment (Yashiv, 2007). Lilien (1982) argues that the natural rate can be thought of as a relatively constant level of frictional unemployment necessary to carry out the continuous process of labour allocation. Nevertheless, the introduction of the concept of natural rate by Friedman and Phelps was an attempt to explain the breakdown of the relationship between unemployment and inflation constructed by Phillips (1958), which was a prevailing approach until the 1970's.

What led to the current search and matching model was the goal of developing a theory where unemployment would be an equilibrium outcome. Phelps (1968) and Mortensen (1970) summarized frictions in a labour flow model, which depended on the firm's relative

wage offer. The biggest contribution of their model was the realization of large flows of workers and jobs in the labour market (Petrongolo and Pissarides, 2001).

2.1 Beveridge curve

The negative relationship between job vacancies and unemployment was empirically observed already before the development of the matching model. Presenting Beveridge curve is therefore apparent when studying labour mismatch, since it has been partly used to study structural unemployment shocks in the past (see e.g. Blanchard and Diamond, 1989). The downward sloping curve in unemployment-vacancy-locus was named as the Beveridge curve after William Beveridge, who was the first to observe such relationship in 1930's. Yet, the graphical and mathematical illustration remained to the later generations of macroeconomic studies (see e.g. Dow and Dicks-Mireaux, 1958).

Figure 1 below demonstrates the simple downward sloping Beveridge curve in unemployment-vacancy locus. In a textbook case, an exogenous rise in mismatch (or some other reallocation shock) decreases the rate of job matching at a given labour market tightness and consequently the curve shifts outwards of the origin (shift from BC to BC'). Now, with the same amount of vacancies (v*) there are more unemployed job-seekers (u* shifts to u'), while higher mismatch decreases the amount of hires. In contrast, when mismatch declines the BC curve moves towards the origin and unemployment decreases from u' to u*.

Figure 1 Beveridge curve
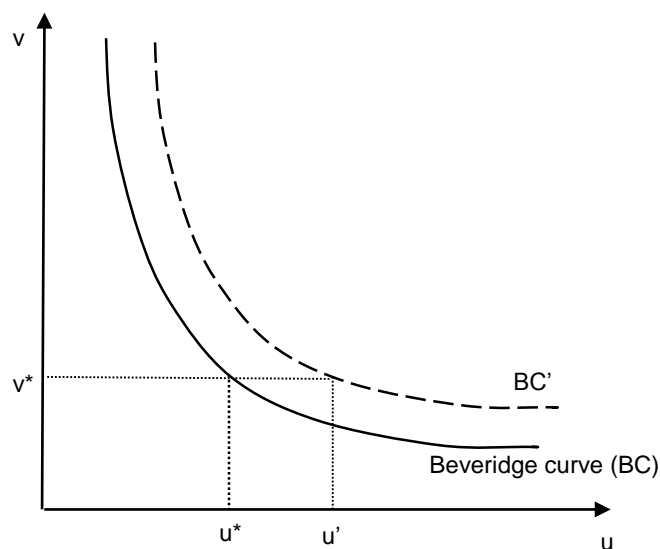
Consequently, movements along the curve are associated with the state of the business cycle (Arpaia et al., 2014). In an economic downturn labour demand is often relatively weak, suggesting that firms are reluctant to hire, leading to a low level of unfilled vacancies simultaneously with high unemployment. The equilibrium unemployment moves down the curve. Vice versa, positive labour demand shocks raise the labour demand and move the steady-state unemployment upwards along the curve.

Petrongolo and Pissarides (2001) form the UV-curve as an equilibrium relation that equates flows into unemployment with flows out of unemployment. They suggest that if the outflow from unemployment is given by the matching function, the Beveridge curve slopes downward as empirically witnessed. Hence, the matching model does not contradict with the evidence of the Beveridge curve, even though it is consistent with other mechanisms as well. Moreover, they list the estimations of equilibrium relation and Beveridge curve as a first strand of studies, where empirical evidence on matching function stems from.

Especially in the early literature estimating the empirical Beveridge curve has been popular, since it exploits data only on stock variables, which were better available than flow variables at the time (Lahtonen, 2006). Even today there is a vast amount of studies from US and from Europe using cross-country panel data to study BC curve (see e.g. Arpaia et al., 2014; Orlandi, 2012 and Bonthuis et al., 2013). These studies are popular as they provide a clear and explicit view on labour matching.

However, this measurement of static difference in stocks is prone to changes in unemployment duration that hamper test of changes in UV analysis (Rodenburg, 2011). Further, the approach suffers some major shortcomings, including sensitivity to sample size and the impossibility to distinguish the stability of the shift (Arpaia et al. 2014). As any other labour market study, also Beveridge curve measurements are challenged by the unreliability of vacancy data and before the introduction of the search model, the Beveridge curve dynamics abstracted from labour force entry and exit and omits job-to-job flows (Elsby et al., 2015). Hence, later studies have enriched the model to account for these as well and have focused more on estimating the shifts indirectly through job finding and separation rates (e.g. Daly et al., 2012; Barnichon and Figura, 2010).

Still, Beveridge curve has a relevant meaning, when studying labour mismatch. According to Blanchard and Diamond (1989), studying the UV-relationship can provide a lot of information on the effectiveness of the matching process. This is usually linked to the shifts of the Beveridge curve in the unemployment-vacancy space (Arpaia et al., 2014). Albaek and Hansen (2004) suggest that an outward shift in the Beveridge curve implies a rise in unemployment for reasons other than lack of labour demand. They propose two main channels for this shift: An increase in the reallocation of workers, which implies a rise in both vacancies and unemployment or an increase in mismatch between vacancies and job seekers, suggesting a decreased amount of hires with the current level of vacancies and unemployment.

3 Matching model

This section introduces the standard matching model as a theoretical framework, which the empirical part of the paper is structured on. Further, this will be extended as a multi-sector version of the standard model as an underlying form for the empirical measurements.

The matching model presented in this section follows the model suggested by Petrongolo and Pissarides (2001). The standard model describes how the stock of vacancies matches with the stock of job-seekers. In its simplest form, the aggregate matching function can be written as

$$M = m(U,V), \tag{1}$$

where M is the number of jobs formed at a given time interval, U is the number of job-seekers and V is the number of vacant jobs. Commonly, U consists of unemployed job seekers, but also employed workers or individuals outside labour force looking for a job may be included. The function is assumed to be nonnegative ($M_V > 0$, $M_U > 0$) and increasing in both arguments $M(0, U) = M(V, 0) = 0$. Also, a general assumption is that the function is concave. This implies that if either the number of job seekers or vacancies increase, then the number of matches increase but at decreasing rate. Further, in discrete-time models if M is the flow of matches and U and V are the stocks at the beginning of the period, then $M(U,V) \leq min(U,V)$. If no frictions arise in the matching process, i.e. job-seekers and vacancies would be instantaneously matched, the number of matches would be $M = min$ (U,V).

3.1 Empirical specification

Empirical analysis usually prefers log-linear form as a functional form of the matching model implying a Cobb-Douglas function

$$M_t = \delta U_t^{\alpha} V_t^{\beta} \tag{2}$$

where t denotes time, δ is a scale parameter and α and β are elasticity parameters with respect to U and V. Further, most studies compiled by Petrongolo and Pissarides (2001) imply that matching function imposes constant returns to scale. Then $\alpha + \beta = 1$, otherwise not.

$$\frac{M(V,U)}{V} = M\left(1, \frac{U}{V}\right) = m(\theta) \tag{3}$$

The returns to scale of the matching function raise plenty of interest, since it reveals if a larger labour market in terms of vacancies and job-seekers have a better matching efficiency. Also, returns to scale above one would imply the possibility of several steady state equilibria. According to Pissarides (2000), constant returns ensure constant unemployment rate along the balanced growth-path.

However, the common log-linear specification has received critique due to the lack of theoretical and micro foundations. Moreover, the constant elasticity imposed by Cobb Douglas form is not always empirically supported. Hence, some other forms have proven to be more suitable for addressing non-linearity in the empirical matching process. For instance, Yashiv (2000) uses a translog function to address the non-linearity. Other popular alternatives in addition to log-linear and trans-log specification are non-linear and CES functions.

Coles and Smith (1998) note that aggregation of data, when job-seekers and vacancies across sectors do not interact, may bias the returns-to-scale downwards. This has been discussed in the Finnish context as well. Kangasharju et al. (2005) argue that the empirical evidence on constant returns to scale becomes less evident, when the basic Cobb-Douglas model is extended or when disaggregated data is used. Moreover, they note that translog specification seems to provide constantly higher returns to scale. Interestingly, when they include the flow of new vacancies and unemployment spells in explanatory variables, they find clear constant returns with Cobb-Douglas specification.

3.2 Stock-flow matching

A general assumption in matching function studies is random search, where job seekers pick a vacant job randomly and then apply for it. Sampling vacancies is assumed to be time consuming in random matching unlike in the stock-flow model. Random search is a convenient assumption to simplify the estimation and is sometimes also realistic if by presumption there is some luck or coincidence in hearing about vacant jobs (Petrongolo and Pissarides, 2001). In fact, many empirical studies approach matching from this assumption.

In real life, search contains arguably a systematic element, which is noted in the so called stock-flow matching. In this approach, agents are seen as heterogeneous and disaggregated

into old and new traders. Gregg and Petrongolo (2005) note that thanks to different information channels, workers have information about the available vacancies. They describe stock-flow matching as follows. When a worker loses her job, she screens the available stock of vacancies to see if her skills match with any of them and applies simultaneously as many jobs as she likes. Then upon contact the worker and the firm decide together whether they form a match or continue to search. Further, the unmatched keep searching because there are no other available trading partners, since they scanned all of them in the beginning of the period. Following, the job seekers and vacant jobs will attempt to match with the flow of new workers and vacancies. Symmetrically flow of new vacancies search for a match on the current stock of unemployed. Gregg and Petrongolo (2005) remark that under stock-flow matching traders have a high probability to match in the first period, when they enter the market. After this initial sampling matching rates fall, because agents have to wait for new entries to trade with.

Hence, in the stock-flow model frictions are caused by the heterogeneity of agents and mismatch between them and not by coordination failure (Lahtonen, 2006). A similar view is presented by Coles and Smith (1998), who demonstrate s simple model of what they call marketplace matching that describes how the stock of traders on one side of the market matches with the flow on the other side. Using British job market data they find support for the view, since the matching behaviour of workers change with the duration of unemployment.

Stock-flow approach emphasizes the relevance of job-seeker and vacancy inflows during the observation period into the beginning-of-the period pools, because the use of stock data on a continuous matching process may raises some issues, when analysing aggregate matching functions (Gregg and Petrongolo, 2005). Gregg and Petrongolo address this issue as a temporal aggregation problem, which occurs when a continuous-time matching process is estimated with discrete-time (stock) data. Because dependent variable (the number of hires or matches) is a flow variable and explanatory variables are stock variables, this issue arises because the explanatory variables are depleted by the response variable (Lahtonen, 2006). Gregg and Petrongolo focus on this problem by proposing a combination of beginning-of-the-period stocks with new inflow during the time interval. I use this approach of combining stock and inflow also in calculating the mismatch indices.

Choosing between random search and stock-flow matching is not unambiguous. Finnish studies have found evidence supporting both approaches as the outcomes are not fully consistent. Lahtonen (2006) finds that unemployed job-seekers are more likely to match with the flow of new vacancies than with the stock of existing vacancies. However, in exceptional market conditions as in the depression in the 1990's Lahtonen finds some evidence on random search with time-consuming search due to the vast amount of job-seekers per vacant job. Moreover, using disaggregated data Soininen (2006) finds support for stock-flow matching in the Finnish context as well, but on the other hand on the aggregate level the traditional matching function with random search gets more support. Thus, probably the actual behaviour of job-seekers lies somewhere between these assumptions.

Still, the attributes assumed concerning the matching function are important when choosing the type of data. Gregg and Petrongolo (2005) note that labour market flows play a crucial role on the right-hand side of estimated matching equations. Nevertheless, in my case the choice of data is not self-evident. The problem is that the data set does not specify, whether a hired job-seeker previously belonged to stock or inflow. The information of the duration of unemployment is not enough itself. Hence, to encompass stock-flow matching in the best possible way, vacancies and unemployed job-seekers are calculated in the spirit of Gregg and Petrongolo (2005) by adding the inflow of new vacancies and job-seekers to the stock at the beginning of time period. This choice follows the empirical choice of Marthin (2012), who have similar issues in modelling stock-flow search with Swedish data. Yet, it is worth remembering that adding complete flows may bias estimates upwards compared to using stocks only (Ilmakunnas and Pesola, 2003).

3.3 Matching efficiency

Matching efficiency plays a vital part when assessing the labour market mismatch. Variation in matching efficiency is one of the main driver of fluctuations in unemployment rate (Lubik, 2013. The rate at which matches are formed from the factors of production, the job-seekers and vacancies, has a significant effect on the duration and rate of unemployment (Bunders, 2003). Moreover, Hynninen et al. (2009) discover that inefficiencies have a significantly increasing effect on unemployment. Regionally, the differences in efficiencies cause variation in how many matches regions are able to produce with given inputs. Commonly, differ-

ences across regions reflect the slow operation of equilibrium mechanisms, such as the insufficient response of migration to employment or the slow response of wages to changes in labour demand or supply (Hynninen et al. 2009). The regional disparities may be caused by skill mismatch, job search intensity or the functioning of local labour offices (LLO's). Usually, they are found to be persistent over time.

Hynninen (2007) points out that total matching efficiency is divided in two parts: technical efficiency and cost efficiency. In the context of the labour market, the discussion of efficiency mostly relates with the technical component, which is derived from production theory. It explains how efficiently matches are produced by given levels of job seekers and vacancies by capturing the factors that are independent of the amounts of inputs (Hynninen, 2007). Cost efficiency, on the other hand, is not actually relevant in labour matching process, because the prices of inputs cannot be determined as in other production functions and thus cost function cannot be derived in this case.

In terms of aggregate matching efficiency, Barnichon and Figura (2013) highlight two effects that cause variation in efficiency. First, the composition of unemployment pool may change over time. The amount of long-term unemployed may for instance become more represented in the labour market. This composition effect causes variation in the average search efficiency and therefore affects matching efficiency as well. The second effect is the dispersion effect, in which the aggregate job finding probability is driven down by the fact that other submarkets have higher labour market tightness than others.

Problematically, Barnichon and Figura (2013) argue that standard matching function does not take the composition and dispersion effects into account, since it assumes constant matching efficiency. This assumption of time-invariant matching efficiency is still widely used in empirics since it seems to provide a relatively good approximate description of the labour market. Barnichon and Figura remark that this assumption requires a relatively stable degree of heterogeneity in the labour market to be valid. They note that aggregate efficiency has pro-cyclical behaviour because these composition and dispersion effects are procyclical. This view is supported by Ilmakunnas and Pesola (2003), who find pro-cyclical variation in matching efficiencies according to frontier estimation suggesting that regional matching efficiencies are highly dependent on business cycles. Moreover, their measurements reveal a negative trend in efficiency.

3.4 On-the-job search

In reality, unemployed workers form only one part of the whole pool of job seekers. Instead, job-to-job transitions or flows directly out of the labour force to employment form a large number of matches as well (Petrongolo and Pissarides, 2001). While the importance of adjusting the matching model studies to include also currently employed job-seekers has been emphasized by previous studies, the majority of empirical measurements ignore this due to data scarcity (Lahtonen, 2006).

Exceptionally Broersma and Van Ours (1999) include employed workers in their empirical study and find that accounting for non-unemployed job searchers affects the returns to scale of the matching function. Also Pissarides (1994) argues that adding employed job-seekers to the model showed that on-the-job search creates congestion for unemployed workers. Further he notes that firms actually direct more vacancies to employed workers, which leads to ranking between employed and unemployed job seekers.

By default the dependent variable of job-seekers in my data set includes only unemployed job seekers. Adjusting the measurements to allow on-the-job search is somewhat problematic, since if employed workers looking for a new job do not report to the Local Labour Offices as job-seekers, they are impossible to recognize in data analysis in this case. Nonetheless, the effect of on-the-job search can be controlled as far as the registered employed job-seekers are concerned. In Section 6.3 the effect of allowing on-the-job search is studied more carefully by adding the registered and employed job seekers in the data. Overall, it seems that employed job-seeker do not affect the shares of job-seekers across sectors and does not therefore affect mismatch measurement significantly.

3.5 Mismatch

Defining the type of mismatch discussed in this paper is crucial. Essentially, mismatch reflects the poor compatibility of job seekers and open vacancies. As Petrongolo and Pissarides (2001) note, mismatch is an "empirical concept that measures the degree of heterogeneity in the labour market across a number of dimensions, usually restricted to skills, industrial sector, and location".

Mismatch is a part of empirical work focusing on the modelling of individual behaviour attempting to establish microfoundations for the matching model. These studies reflect the

strand of studies, which use data on individual transitions to estimate hazard functions for unemployed workers (Petrongolo and Pissarides, 2001).

Variables affecting the aggregate matching rate besides the matching function are classified in two groups. First group is the search contribution of the individuals and the second group includes shifts unrelated to individual search decisions such as aggregation issues and technological advances in job matching. Mismatch can be studied from the second point of view as a microfoundation for the aggregate matching function.

Petrongolo and Pissarides suggest that mismatch can originate from various sources:

1) Skill mismatch: Differences in the skills possessed by labour and demanded by firms for a given position.
2) Geographical mismatch: Imperfect labour mobility, while job seekers and vacancies are located in various regions. In earlier literature, these differences in location are also referred to as imbalance in numbers in the local market.
3) Industry mismatch: The need for industry-specific skills that may not easily be learned by generally available measures.

The measurement of mismatch has important implications. If mismatch would be non-existent in all three dimensions noted above, vacancies and job-seekers would match instantaneously. Yet, because of the existence of mismatch, labour market matching is characterized by the search and application process (Petrongolo and Pissarides, 2001). Hence, an increase in mismatch indicates that at a given level of job-seekers and vacancies, the amount of hires must fall implying a shift in aggregate matching function.

Many of the earliest formal models of mismatch classified as a source for unemployment ground on urn-ball structure, which was first studied by probability theorists (see e.g. Hall, 1977). In this framework, firms play the role of urns and workers the role of balls, which are randomly placed in urns. Job seekers and vacancies are assumed to be homogeneous and without knowledge about each other's actions (Lahtonen, 2006). Even with exactly the same number of balls and urns, the random assignment causes some jobs to remain unfilled as some jobs receive many workers, of whom only one can be hired. Petrongolo and Pissarides (2001) suggest that in this setting the lack of information about other workers' actions gen-

erates coordination failures, which leads to unemployment. Nonetheless, the approach suggested by Hall (2000) has more resemblance on mismatch. He links the importance of the number of workers per location and the unemployment rate. The random assignment of workers causes congestion in some locations, which decreases the matching rate.

Mismatch studies trace also back to the theories of "sectoral shift hypothesis" and structural unemployment, which was thought to arise from fast structural change in the economy (Petrongolo and Pissarides, 2001). That is, supply shocks such as advances in technology or rapid changes in oil markets speed up the need of workers to adapt their skills to match with the requirements of firms. This skill mismatch then leads to longer unemployment duration with the given number of vacancies. Structural shifts have been studied for instance by Lilien (1982), who suggests that the distribution of jobs and workers changes over a business cycle possibly explaining fluctuations in aggregate employment. Nonetheless, the positive correlation between unemployment growth and the dispersion of employment growth reported by Lilien has been criticized as unable to make a distinction between aggregate demand fluctuations and sectoral shifts (Petrongolo and Pissarides, 2001).

The theory of deriving the matching function over distinct markets is an interesting perspective for mismatch, since it resembles the geographical mismatch in the way that regional labour supply and demand do not match in either case. This derivation relies on the existence of disequilibrium across several micro markets and assumes limited labour mobility (Petrongolo and Pissarides, 2001). Assumingly, these micro markets do not suffer from frictions but from a disequilibrium of job seekers and vacancies, which means that the demand and supply of labour in each market are unequal. The conditions for this matching function to exist are the frictions created by the non-existent mobility of labour and capital across markets, which give rise to the aggregate matching function (Petrongolo and Pissarides, 2001). This immobility implies that markets with unemployment can coexist with markets with vacancies, but distinctively to the idea of mismatch, no market has both since no frictions arise within the market. In other words, the short side of each distinct market clears.[1]

Aggregation over all markets gives an aggregate matching function that contains both vacancies and job seekers. In the case of perfect mobility, this aggregate matching function would not exist, since labour would move until the short side would clear (Petrongolo and

---

[1] The matching function in each market is $M_i = min(U_i, V_i)$

Pissarides, 2001). Similar to the geographical mismatch discussed earlier, the disequilibrium in this approach refers to imbalance in labour demand and supply in each market. Nonetheless, distinctively to mismatch, in the aggregation problem markets with unemployment can coexist with markets with job vacancies, but no market has both (Petrongolo and Pissarides, 2001).

Mismatch hypothesis has provided mixed results in empirical studies. Petrongolo and Pissarides (2001) note that mismatch has neither been successful in explaining large fluctuations nor secular rises in the unemployment rate in different countries. Hence, they argue that mismatch may explain some shifts in the aggregate matching function but are not credible as the main shift variable. However, according to Petrongolo and Pissarides mismatch functions at the time suffered from many problems and thus mismatch may explain more of the variance in matching than found in the literature. Hence, in the later research mismatch has been further developed to encompass these variations (see e.g. Albaek and Hansen, 2004; Shimer, 2007).

In this paper, the theoretical framework that is used to conceptualize mismatch in unemployment follows the idea of a mismatch index by Sahin et al. (2014). This method grounds on the presumption that an economy consists of several distinct sectors, which are segmented by industry, occupation, geography, or a combination of these attributes. Each separate labour market is assumed to be frictional, enabling the use of matching function. The method constructed by Sahin is still relatively new and has been used in only few international papers. Marthin (2012) studies unemployment mismatch in Sweden with the index and Shibata (2013) utilizes the method to the Japanese labour market. Most recently, Erken et al. (2015) use a simple mismatch index without heterogeneity between the sectors to study mismatch in Netherlands. They find that from international perspective mismatch explains only a small share of the rise in unemployment during the latest financial crisis.

Other recent studies have estimated the extent of mismatch in the labour market by various methods. Barnichon and Figura (2013) propose an approach to study the cyclicality of labour mismatch over a long time sample. They focus on the simultaneous roles of the dispersion and composition effects. They claim that the standard matching function, implied that job finding rate depends only on labour market tightness, was stable in the US over 1967-2007 but after that the observed job finding rate was significantly lower than the one estimated by the matching function. Hence, the authors argue that the matching function does not fully

18

capture the heterogeneities across individuals, which are key to understand the fluctuations in the job finding rate.

Shimer (2007) proposes a dynamic stochastic model of mismatch. The environment modelled by Shimer resembles the proposition by Sahin et al. Nonetheless, the crucial difference is that Shimer handles a vacancy as a manifestation of a firm's failure to hire and not as firm's effort to hire. Also, the quantitative behaviour of the model has close resemblance with a stock-flow matching model. Shimer's approach emphasizes that unemployed workers are attached to an occupation and geographic location, where jobs are currently scarce.

3.6 Findings on Finnish labour market matching

The labour market has many peculiar features in different countries, which is why implications from an international research using local data are hard to draw across borders. Fortunately, several empirical papers have also studied the characteristics of labour market matching in Finland. The data ranges from regionally aggregated panel data to aggregate time series and these studies give a thorough review of the labour market matching in the Finnish labour market. In this section, I will present some of the most comprehensive papers.

In her dissertation, Hynninen (2007) concentrates on the technical efficiency of the matching function by using regionally aggregated panel data from the local labour offices in Finland. Her thesis consists of four sections, which first study the spatial spill-overs in local matching function from the neighbouring areas. Second, a model with heterogeneous job seekers is introduced to provide estimates for employability from the job seeker's point of view. These results imply a negative effect on matches in LLO's as the share of long-term unemployed job seekers increase. Third essay relates labour market heterogeneity with population density, which shows that in high-density areas the heterogeneity of job seekers is emphasized in matching. Fourth, using stochastic frontier approach Hynninen supports the view of Ilmakunnas and Pesola (2003) that technical efficiency in matching shows a negative trend in the Finnish labour market.

Ilmakunnas and Pesola (2003), focus on the technical efficiency in the regional matching using annual observations for the period 1988-1997. By utilizing stochastic frontier approach as an estimation method for matching efficiency, they find evidence for constant returns to

scale with the unemployment outflow as dependent variable. Moreover, Ilmakunnas and Pesola find a negative trend as well as pro-cyclical variation in the matching efficiency. Following closely similar stochastic frontier approach, Hynninen et al. (2009) estimate the regional differences with Finnish data. They find that average unemployment rate would decrease by 2.4 percentage points if all LLO's worked with full efficiency.

Lahtonen (2006) studies the effect of heterogeneous job seekers on matching function and focuses especially on the characteristics of job seekers. By disaggregating the pool of job seekers into three education groups, Lahtonen finds a positive effect on matches for primary educated job seekers, whereas seekers with secondary education display negative effect on matches. Also, long-term unemployed job seekers and seekers under 25 or over 50 are found to have negative effect on the number of monthly matches. Moreover, along with the results by Hynninen (2007), Lahtonen suggests that high-density areas are more productive in matching than low-density areas.

Soininen (2006) studies the matching efficiency in Finland by using cointegrated VAR-method to analyse aggregate matching process, stock-flow matching and matching between occupational groups. Using aggregate time-series data from 1982 to 2005 Soininen finds that aggregate matching process changed severely between the 80s and the mid-90s in Finland. In addition Soininen finds that unemployment duration has a negative effect on the probability of re-employment. Yet, stock-flow matching does not find support on the aggregate level but significant variation is found between occupational groups.

Bunders (2003) measures the efficiency of the matching process with Finnish panel data in the period 1988-2002. The average duration of vacancies is used as proxy for matching efficiency. The study suggests that the matching efficiency varied between the time periods and was least efficient at the end during 2001-2002. Moreover, he finds significant differences between regional and occupation groups and in especially Southern Finland the mismatch is higher than in the north and east of the country. Also, Bunders finds increasing economies of scale in the matching function.

4 Mismatch measurement

The idea of the mismatch index is to compare the observed allocation of unemployed workers across sectors with an ideal allocation. The constructed index presented here follows the theoretical environment proposed by Sahin et al. (2014). In the model, unemployed workers are allocated according to a social planner, who has no limitations in moving idle labour across sectors, but frictions are assumed to have an effect on the matching within markets. By constructing the planner's solution, we are able to determine the optimal number of hires that can be obtained by the planner's allocation of job seekers across sectors. The difference between the optimal and observed hires equals the fraction of lost hires that is represented by the mismatch index. Through generating the counterfactual unemployment rate, this method allows us to estimate the share of unemployment caused by mismatch across sectors.

This model is distinctive in a sense that no equilibrium allocations need to be solved. The empirical joint distribution of unemployed job-seekers and vacancies across sectors is the equilibrium outcome of the model. Further, the counterfactual distribution is constructed from a simple planner's problem that can be solved analytically (Sahin et al. 2014). Beneficially, this setup is robust and easy to implement with a distinct labour market and with multiple sources of heterogeneity. Yet, a downside of this methodology is that it does not separately quantify sources of misallocation and results are presented only on a general level.

Let's next go through the theoretical logic behind the mismatch index. First, I will start by describing the economic environment, where different sectors have various vacancy rates and matching efficiencies. Then, this environment is generalized by heterogeneity in productivity and job destruction rates across the labour market. Further, to derive the ideal unemployment rate in various sectors, the planner's optimal allocation rule is derived. This chapter demonstrates a recapitulation of the formal solution.

4.1 Benchmark environment

To start with, in the benchmark environment the economy is composed of a large number I sectors indexed by i. Time is discrete and indexed by t. Vacancies (v_{it}) are assumed to arise exogenously across sectors. The labour force consists of risk-neutral individuals who can

either be employed in sector i (e_{it}) or unemployed in sector i (u_{it}).[2] In the baseline model only unemployed individuals are searching for work and on-the-job search is ruled out, but later this restriction is relaxed to obtain a more realistic composition of job seekers. Also, people outside labour force are not seen as job-seekers. Labour productivity in sector i at time t is denoted as z_{it}, which is strictly positive across sectors.

Further, the labour market is assumed to be frictional and new hires (h_{it}) between unemployed (u_{it}) and vacancies (v_{it}) are determined by the matching function $\Phi_t \phi_{it} m(u_{it}, v_{it})$, where m is strictly increasing and concave in both arguments (u_{it}, v_{it}) and homogenous of degree one. The term $\Phi_t \phi_{it}$ measures matching efficiency in sector i with Φ_t denoting the aggregate component and ϕ_{it} the idiosyncratic sector-level component.

4.2 Planner's solution

The planner's solution is a socially optimal rule to allocate unemployed workers across sectors. The condition demonstrated in Equation 4 below states that the planner allocates more job-seekers to the labour market with more vacancies and higher matching efficiencies to equalize their marginal contributions to the hiring process across markets.

$$\phi_{it} m_{u1}\left(\frac{v_{1t}}{u_{1t}^*}\right) = \cdots = \phi_{it} m_{u1}\left(\frac{v_{it}}{u_{it}^*}\right) = \cdots = \phi_{it} m_{uI}\left(\frac{v_{It}}{u_{It}^*}\right), \tag{4}$$

where m_{ui} is the derivative of the m function with respect to u_i. Planner's allocation is denoted by "*".

Now, this planner's allocation rule is used to derive the mismatch index, which measures the fraction of hires lost in a specific sector i.e. ($1-h_t/h_t^*$), where h_t denotes the observed hires and h_t^* the optimal number of hires in the planner's solution. Suppose there are i sectors in the economy (regions or occupations) with a given number of vacancies and sector-specific as well as aggregate matching efficiencies. Then, the number of hires in each sector can be determined by the following matching function in Cobb-Douglas form:

$$h_{it} = \Phi_t \phi_{it} v_{it}^\alpha u_{it}^{1-\alpha}, \tag{5}$$

---

[2] Hence, $\sum_{i=1}^{I}(e_{it} + u_{it}) = 1$

where h_{it} are hires in sector i at date t, Φ_t is the aggregate matching efficiency, ϕ_{it} is the sector-specific matching efficiency, v_{it} is the vacancies and u_{it} the unemployment in sector i at time t and $\alpha \in (0,1)$.

4.3 Mismatch index

To get an intuition of the mismatch index let's consider a simplified environment where sectors are homogeneous i.e. sector-specific productivities and matching efficiencies are omitted. Now, the optimal solution simply equalizes the ratio of vacancies and unemployment across sectors.

Summing across all sectors the aggregate amount of hires at time t is

$$h_t = \Phi_t v_t^\alpha u_t^{1-\alpha} \left[\sum_{i=1}^{I} \left(\frac{v_{it}}{v_t} \right)^\alpha \left(\frac{u_{it}}{u_t} \right)^{1-\alpha} \right] \tag{6}$$

and the optimal amount of hires is

$$h_t^* = \Phi_t v_t^\alpha u_t^{1-\alpha} \tag{7}$$

Hence $1 - \sum_{i=1}^{I} \left(\frac{v_{it}}{v_t} \right)^\alpha \left(\frac{u_{it}}{u_t} \right)^{1-\alpha}$ is the fraction of hires lost due to asymmetric distribution of vacancies and unemployment. Further, the mismatch index can be described as

$$M_t^h = 1 - \frac{h_t}{h_t^*} = 1 - \frac{\Phi_t v_t^\alpha u_t^{1-\alpha} \left[\sum_{i=1}^{I} \left(\frac{v_{it}}{v_t} \right)^\alpha \left(\frac{u_{it}}{u_t} \right)^{1-\alpha} \right]}{\Phi_t v_t^\alpha u_t^{1-\alpha}} \tag{8}$$

$$M_t^h = 1 - \sum_{i=1}^{I} \left(\frac{v_{it}}{v_t} \right)^\alpha \left(\frac{u_{it}}{u_t} \right)^{1-\alpha} \tag{9}$$

This simplified form has close resemblance with a simple correlation measurement of vacancies and job-seekers between sectors. The empirical evidence using this index absent any heterogeneity among sectors is also demonstrated in the empirical part.

Now, let's assume heterogeneity across sectors and account it in our index. Let's first consider an economy, where the labour market differs in matching efficiencies but not in productivities. Thus, summing up hires across sectors the aggregate number of hires, h_t, are given by

$$h_t = \Phi_t v_t^\alpha u_t^{1-\alpha} \left[\sum_{i=1}^I \emptyset_{it} \left(\frac{v_{it}}{v_t} \right)^\propto \left(\frac{u_{it}}{u_t} \right)^{1-\propto} \right] \tag{10}$$

Further, when planner allocates the unemployed workers across sectors the optimal amount of hires, h_t^*, becomes

$$h_t^* = \Phi_t v_t^\alpha u_t^{1-\alpha} \left[\sum_{i=1}^I \emptyset_{it} \left(\frac{v_{it}}{v_t} \right)^\propto \left(\frac{u_{it^*}}{u_t} \right)^{1-\propto} \right] \tag{11}$$

and the mismatch index becomes

$$M_{\emptyset t}^h = 1 - \frac{h_t}{h_t^*} = 1 - \frac{\Phi_t v_t^\alpha u_t^{1-\alpha} \left[\sum_{i=1}^I \emptyset_i \left(\frac{v_{it}}{v_t} \right)^\propto \left(\frac{u_{it}}{u_t} \right)^{1-\propto} \right]}{\Phi_t v_t^\alpha u_t^{1-\alpha} \overline{\emptyset}_t} \tag{12}$$

$$M_{\emptyset t}^h = 1 - \sum_{i=1}^I \left(\frac{\emptyset_i}{\overline{\emptyset}_t} \right) \left(\frac{v_{it}}{v_t} \right)^\propto \left(\frac{u_{it}}{u_t} \right)^{1-\propto} \tag{13}$$

where $\overline{\emptyset}_t = \left[\sum_{i=1}^I \emptyset_{it}^{\frac{1}{\alpha}} \left(\frac{v_{it}}{v_t} \right) \right]^\alpha$ is an aggregator of the sector-level matching efficiencies.

Next, let's consider a similar economy, where labour market differs also in the level of productive efficiency, z_i in addition to matching efficiency $\emptyset_{it}$. To simplify notation, let's define the sector overall efficiency as $x_{it} = z_{it}\emptyset_{it}$.

The mismatch index can now be written as

$$M_{xt}^h = 1 - \frac{h_t}{h_t^*} = 1 - \frac{\Phi_t v_t^\alpha u_t^{1-\alpha} \left[\sum_{i=1}^I \emptyset_i \left(\frac{v_{it}}{v_t} \right)^\propto \left(\frac{u_{it}}{u_t} \right)^{1-\propto} \right]}{\Phi_t v_t^\alpha u_t^{1-\alpha} \overline{\emptyset}_{xt}} \tag{14}$$

24

$$M_{xt}^h = 1 - \frac{h_t}{h_t^*} = 1 - \sum_{i=1}^{I} \left(\frac{\emptyset_{it}}{\overline{\emptyset}_{xt}}\right) \left(\frac{v_{it}}{v_t}\right)^{\propto} \left(\frac{u_{it}}{u_t}\right)^{1-\propto} \qquad (15)$$

where $\overline{\emptyset}_{xt}$ is an aggregate of market-level overall efficiencies weighted by their vacancy share.

$$\overline{\emptyset}_{xt} = \sum_{i=1}^{I} \emptyset_{it} \left(\frac{x_{it}}{\overline{x}_t}\right)^{\frac{1-\propto}{\propto}} \left(\frac{v_{it}}{v_t}\right) \qquad (16)$$

and

$$\overline{x}_t = \left(\sum_{i=1}^{I} x_{it}^{\frac{1}{\alpha}} \frac{v_{it}}{v_t}\right)^{\alpha} \qquad (17)$$

The mismatch index has three useful properties, which are also relevant in empirical measurements. Most importantly, *Mt* is increasing in the level of disaggregation of sectors. Therefore, mismatch should always be considered with respect to the degree of the level of disaggregation (Sahin et al. 2014). Also, the number of sectors should be as equal as possible when different dimensions are compared (Marthin 2012). Second, the index is between zero and one ($0 < M_t < 1$). Under maximum mismatch vacancies and job-seekers do not coexist in any market and the mismatch index equals one. If there is no mismatch in any sector, the index equals zero. Finally the third property states that an aggregate shock, which changes the total number of vacancies or job-seekers but leave the shares across sectors unaffected, does not shift the mismatch index.

4.4 Counterfactual unemployment

Despite the intuitive results of the mismatch index, it doesn't give an answer to the magnitude of the effect mismatch has on the unemployment rate. To do this, a counterfactual unemployment rate absent mismatch is constructed, which is then compared with the actual observed unemployment rate.

Nonetheless, approximating the counterfactual unemployment is problematic since it requires to take a stand of the equilibrium of an unobserved counterfactual economy (Elsby et al. 2015). This counterfactual economy is unknown and therefore direct reflections of lost

hires on unemployment are impossible to draw. The optimal unemployment rate is still useful to outline to get an idea of the approximate magnitude of mismatch. Nevertheless, these estimations should be approached cautiously as the counterfactual unemployment is a result of an iteration problem, where previous levels of unemployment affect current state directly.

First, the job-finding rate is the observed probability of unemployment outflow. As calculating f_t as per Sahin proved to be problematic[3], I decided to follow Shimer (2005) in defining the job-finding rate as follows:

$$f_t = 1 - \frac{u_{t+1} - u_{t+1}^S}{u_t} \tag{18}$$

where u_t^S is the amount of short-term unemployed.[4] Then, the index modelled above can be used to derive a more efficient job-finding rate

$$\text{Optimal job finding rate: } f_t^* = \frac{h_t^*}{u_t^*} = \Phi_t \left(\frac{v_t}{u_t^*}\right)^\propto = f_t \frac{1}{(1-M_{xt}^h)} \left(\frac{u_t}{u_t^*}\right)^\propto \tag{19}$$

This counterfactual job-finding rate f_t^* is always higher than the observed job-finding rate f_t as the mismatch index M_{xt}^h is between 0 and 1 and the ratio of actual and counterfactual unemployment rate $\frac{u_t}{u_t^*}$ is always greater than one. Hence, this leads to lower counterfactual unemployment rates.

Shimer (2005) defines separation rate from employment as

$$s_t = \frac{u_{t+1}^S}{e_t}, \tag{20}$$

which estimates the inflow to unemployment as proxy for separations. Unfortunately, the data does not verify, whether the flow is from out of the labour force or from employment, so in this sense it is imperfect. Moreover, Shimer (2005) argues that calculating separation rate as the ratio of short-term unemployed workers to employed workers leads to a significant time-aggregation bias. Therefore, Shimer adjusts this by adding the job-finding rate to the equation to take into account the possibility of finding another job within a month. None-

---

[3] Sahin defines job-finding rate as $f_t = (1 - M_{xt}^h)\Phi_t\overline{\emptyset}_{xt}\left(\frac{u_t}{u_t}\right)^\propto$. My results showed job-finding rate over 1 consecutively, which would mean that hirings would exceed the number of job-seekers in several months.
[4] In my data set, I am able to specify those unemployed less than a month as short-term

theless, Marthin (2012) argues that this is unnecessary if the unemployment duration is estimated down to one week as in my case it is, because becoming unemployed and directly getting re-employed in one week is unlikely. Since the Finnish data provides similarly high weekly frequency, I decide to leave the job-finding rate out as well.

Given an initial value of $u_0{}^*$, which is chosen to satisfy the planner's solution in Equation 4, the counterfactual unemployment rate can be obtained by iterating forward on the equation

$$u_{t+1}^* = s_t + (1 - s_t - f_t^*)u_t^* \tag{21}$$

4.5 Derivation of sector-specific optimal allocation of job-seekers

This notation of optimal allocation is derived following the example by Marthin et al. (2012). First, let's start the derivation of optimal job-seeker allocation by rewriting the Planner's solution with sector-specific productivities and efficiencies (Equation 4):

$$z_{it} m_{u1} \left(\frac{v_{1t}}{u_{1t}^*} \right) = \cdots = z_{it} m_{u1} \left(\frac{v_{it}}{u_{it}^*} \right) = \cdots = z_{it} m_{uI} \left(\frac{v_{It}}{u_{It}^*} \right) \tag{22}$$

Now, according to this solution job-seekers should be allocated to equal the marginal utility of an additional job-seeker in each sector. Hence, more job-seekers are allocated to sectors with higher efficiency and productivity.

Matching function was defined as

$$m(v_i, u_i) = v_{it}^\alpha u_{it}^{1-\alpha} \tag{23}$$

Now, plugging this matching function (23) to planner's solution (22) gives

$$z_1 \phi_1 \left(\frac{v_1}{u_1^*} \right)^\alpha = z_i \phi_i \left(\frac{v_{it}}{u_{it}^*} \right)^\alpha = \cdots = z_I m_I \left(\frac{v_{It}}{u_{It}^*} \right)^\alpha \tag{24}$$

Let's assume the labour market to consist only from two sectors. Then, the solution above contract to

$$z_i \phi_i \left(\frac{v_{it}}{u_{it}^*} \right)^\alpha = z_j \phi_j \left(\frac{v_{jt}}{u_{jt}^*} \right)^\alpha, \tag{25}$$

which can be rearranged to obtain expression for $u_{it}{}^*$

$$u_{it}^* = \frac{v_{it}}{v_{jt}} u_{jt}^* \frac{(z_i\phi_i)^{\frac{1}{\alpha}}}{(z_j\phi_j)^{\frac{1}{\alpha}}} \tag{26}$$

Summing this across j sectors

$$\sum_{j=1}^{J} u_{jt}^* = u_t = \sum_{j=1}^{J} \frac{v_{it}}{v_{jt}} u_{it}^* \frac{(z_j\phi_j)^{\frac{1}{\alpha}}}{(z_i\phi_i)^{\frac{1}{\alpha}}} = \sum_{j=1}^{J} (z_j\phi_j)^{\frac{1}{\alpha}} v_{jt} \frac{u_{it}^*}{v_{it}(z_i\phi_i)^{\frac{1}{\alpha}}} \tag{27}$$

Finally, by rearranging the above and noting that

$\sum_{i=1}^{I}\left(v_{it}(z_{it}\phi_i)^{\frac{1}{\alpha}}\right) = \sum_{j=1}^{J}\left(v_{jt}(z_{jt}\phi_j)^{\frac{1}{\alpha}}\right)$ we can express the optimal unemployment in

sector *i* at time *t* shown in Equation 28. This allows us to estimate the optimal allocation of job-seekers across sectors.

$$u_{it}^* = (z_i\phi_i)^{\frac{1}{\alpha}} \frac{v_{it}}{\sum_{i=1}^{I}\left(v_{it}(z_{it}\phi_i)^{\frac{1}{\alpha}}\right)} u_t \tag{28}$$

5 Data

The data is retrieved from the Ministry of Labour employment register[5] covering 112 months from 2006 to April 2015. This panel data set includes information on job seekers, vacancies and hirings reported in the local labour offices (LLO's) on occupational and regional dimensions. The time span is restricted by what is made publically available by the Ministry. Nevertheless, the time frame is arguably adequate for this study, since it covers several years before and after the burst of the financial crisis in 2008.

The data at hand is convenient for matching function studies for several reasons. First, the frequency is high; monthly data is required for empirical measurement, since the majority of vacancies are usually filled within a month or two and majority of unemployment spells end within the same time frame. High frequency also reduces temporal aggregation problems discussed earlier. Second, the data set contains information both from the characteristics of job seekers as well as vacancies, which enables an accurate disaggregation of the data to obtain information on the effect of certain characteristics of job seekers in matching (Lahtonen, 2006). Third, the data set includes also job seekers, who are employed or currently out of labour force but have registered in their local labour office. This attribute enables the examination of on-the-job search. Also, a favourable attribute of the data is monthly frequency and the reporting of inflows in addition to the beginning of the period stocks.

Information on hirings is usually complicated to obtain, which is why empirical studies use other ways to measure them. Typical proxies include the total employment inflow, unemployment outflow and the flow of filled vacancies (Hynninen et al., 2009). In this study, I chose the unemployment outflow as a measurement for hirings (the output of the matching function) due to good data availability. Specifically, with regional data I am able to separate the unemployment outflow to employment, which prevents the bias that job-seeker outflow to out-of-the-labour-force could cause. Unfortunately, the data set does not enable this for occupational data, for where only the total unemployment outflow is available. This causes the job finding rate to be overestimated in the occupational dimension. Here I also tested the use of ended job searches, which amount to significantly less on monthly basis compared to

---

[5] see www.toimialaonline.fi

flow out of unemployment. Also, here it is not specified, whether the search for a job-seeker ended to employment or out of the labour force.

Job-seekers, who are classified as having been employed through employment services, have been filtered from the unemployment outflow to get an unbiased variable. [6] Nonetheless, workers, who have shifted from working reduced week or have temporarily been laid off, but have again continued regular working time, are included in the outflow. Finally, entrepreneurs, who receive a start-up grant belong to the outflow as well. The independent variables, job-seekers and vacancies are the sum of the end-stock of previous month added with the inflow during the current month. [7]

In the context of empirical matching function studies, it is relevant to distinguish the sectors, where matches can be realistically made (Klinger and Rothe, 2012). Spatially, several international studies have focused on distinguishing relevant local travel-to-work-areas to form relevant sectors (see e.g. prefectures in Japan used by Kano and Ohta (2005) or Burda and Profit (1996) with local labour offices in Czech Republic). Hence, travel-to-work areas as regional aggregation would arguably make the most realistic setting and is also preferred by most studies. However, only part of the Finnish data is provided based on the 70 travel-to-work areas in Finland. Because of the data, I use Centres for Economic Development, Transport and the Environment (ELY Centres) as regions in the model, which also broadly represent travel-to-work areas. There are a total of 17 ELY-centres in Finland, but Åland Islands is excluded due to its isolation of the other labour market regions which are all large enough to be considered as a separate labour market.[8]

I prefer occupational disaggregation instead of industrial partly due to better data availability, but also because occupations provide a more realistic market, within which workers might find jobs. Fahr and Sunde (2001) argue that basically all job-seekers are more attached to their profession than to the industry they work in. Moreover, separating labour markets

---

[6] "A job-seeker is classified as having been "employed through employment services" if his/her employer is granted pay subsidy or if a government departments or agencies have been allocated funds for covering the employment costs resulting from hiring the job-seeker (those employed by the State)." (Ministry of Employment and the Economy, retrieved 29.9.2015 https://www.tem.fi/en/work/employment_service_statistics/definitions_tables_and_figures/registered_jobseekers)

[7] These variable are chosen to encompass the stock-flow nature of matching in the best possible way as explained in chapter 3.6.

[8] The ELY-centres in the data include also a "Foreign countries" classification, which presumably contains vacancies and job-seekers abroad that are reported in LLO's. However, this group is also excluded from the data as I focus only on the local labour market.

by occupation also takes better into account the skill requirements, education and matching qualities for certain jobs than industry classification, which usually employ all sorts of occupations. It would be even more meaningful to study the educational unemployment rates than occupational, as education is even more stable characteristic of a worker than occupation (Layard et al. 2005).

Occupations are disaggregated according to the layers represented by ISCO[9] definition. In this study, I use only the first and second level from the four possible ones. The first level, ISCO10, is divided into ten different occupations as for instance *managers* or *professionals.* The second level, ISCO50, is a more precise classification and has 50 occupations, such as *chief executives, senior officials and legislators* or *subsistence farmers, fishers, hunters and gatherers.*[10] The study is restricted to these two ISCO levels, since the number of hires on two more specific levels would have small group sizes and several missing data points, which would weaken the statistical analysis. Fortunately, the Ministry of Employment and the Economy uses the ISCO standard so the occupational data is easily at hand.

5.1 Data Coverage

As with most similar studies, the data on vacancies has issues of incompleteness. First, jobs are underreported in LLO's, since private firms do not have any lawful need to report vacancies (Rodenburg, 2011). Although in the Finnish context public employers have a statutory duty to inform vacancies in LLO's[11]. Nonetheless, private firms don't have a clear financial incentive to report vacancies in LLO's, since they might find it more efficient to directly use other recruiting channels. Quite the contrary, unemployed workers are more willing to report to LLO's as job-seekers, since this is insisted in receiving any unemployment benefits in Finland.

Based on an employer survey, Räisänen (2014) estimates that slightly below 50 percent of employers use LLO's as a recruiting channel. During the sample period of 2006-2013 the

---

[9] ISCO= International Standard Classification of Occupations, maintained by International Labour Organization

[10] Army officials and army workers were combined in the ISCO50 level, since their labour market status can be assumed to be similar. Also, I removed the occupation *street vendors and shoeblacks* due to lack of data points. Moreover, category X was not included in either panel data sets. This group contains students, entrepreneurs and those with no defined occupation. The effect of excluding this group remains minimal, since the data points are few and far between with unsubstantial shares in total job-seekers and vacancies.

[11] See act 1348/2002 on vacancy reporting http://www.finlex.fi/fi/laki/alkup/2002/20021348 retrieved 30.11.12015

use of LLO's in recruiting has shown a slightly increasing trend with a varying share between 37 to 46 percent. Nevertheless, the importance of state-run employment offices in recruiting in the Finnish labour market should not be understated. The establishments still find local labour offices having the most significant effect on filling the vacancy from all recruiting channels (Räisänen, 2014). Nonetheless, Soininen (2006) argues that a general view is that vacancies in workforce offices are low-skill biased since high-skill jobs are matched elsewhere. This possible bias is good to keep in mind when assessing the results but unfortunately the data set does not enable the control of this possible skill bias.

The statistics from LLO's can be considered as a reliable indicator for the behaviour of vacancies as long as the market share of LLO's remain rather constant. Table 1 shows the most recent data on market share of LLO's in firm recruiting according to the survey by Räisänen (2014).

Table 1 The usage of LLO in recruiting (%)

Year	2006	2007	2008	2009	2010	2011	2012	2013
Market share	44 %	43 %	41 %	39 %	37 %	42 %	46 %	46 %

However, Hynninen (2007), argues that job seeker/vacancy ratio is countercyclical. In an economic downturn finding a job is hard, since many job-seekers compete of a few open vacancies available. From the employer point of view, filling a vacancy is more expensive in an economic upturn, since fewer workers are searching. The data supports these arguments, as the amount of vacancies show a significant drop at the start of the crisis, while simultaneously the amount of job-seekers peaked[12]. Also, Michaillat (2012) states that during recessions the acute job shortage diminishes the effect of matching frictions and each job is filled quickly. Even though the share of reported vacancies shows this procyclical trend, it seems to be stable enough to provide a reliable measurement of vacancies.

Moreover, to assess the data coverage thoroughly, let's compare it with a quarterly survey conducted by Statistics Finland. This survey gathers data of an annual sample size of around 10 000 workplaces[13]. Figure 2 below demonstrates that the yearly averages of vacancies reported by the Ministry of Employment (TEM) are constantly below the average measured

---

[12] The average monthly number of job-seekers amounted around 242 000 during years 2007 and 2008 and over 300 000 during years 2009 and 2010.
[13] The sample population is around 150 000 active establishments that are listed in the register maintained by Statistics Finland. See http://tilastokeskus.fi/til/atp/index.html for further information.

by Statistics Finland. The share of vacancies reported by TEM is 20-30 percent lower in comparison with the survey. Nevertheless, the ratio between the reported vacancies remains arguably constant enough to allow robust estimations from the vacancies reported by TEM.

The amount of unemployed job-seekers varies also between TEM and Statistics Finland due to different unemployment definitions[14]. Nonetheless, these differences do not affect the data coverage specifically, since the definition causes only constant variation in the unemployment measurements, which does not affect the reliability of my estimates.

Figure 2 Yearly average of vacancies
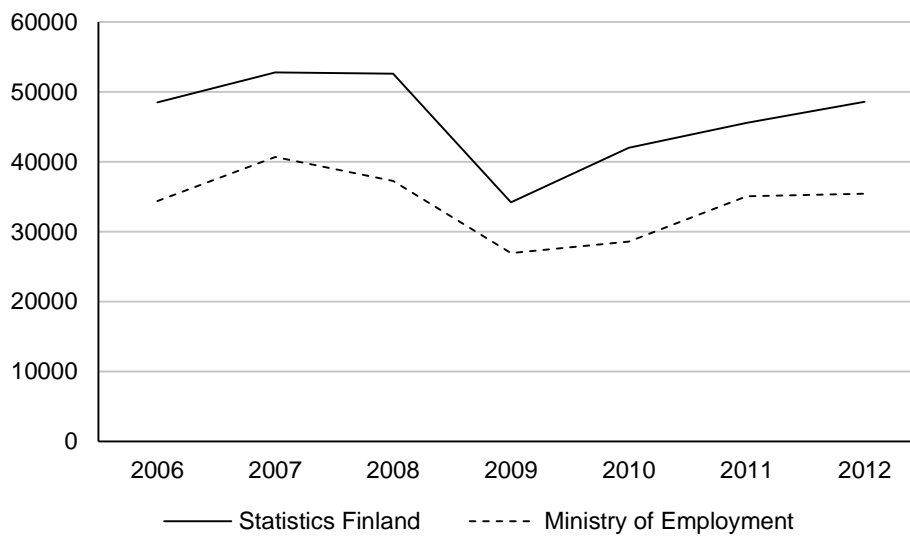
Niemeläinen (2014) notes that the vacancy data from TEM is also positively correlated with vacancies reported in an online recruiting agency (Oikotie). Moreover, she notes that the two sources convey similar information of the amount of vacancies, but the data provided by TEM covers the whole country more comprehensively than the online agency.

5.2 Productive Efficiency

On the regional level labour productivity is calculated by simply comparing the regional differences in output values. The annual values of production in each ELY-centre are retrieved from a database maintained by Statistics Finland[15]. First, I index all the production value levels (2006=1) and thereafter I normalize the values for annual productivity around

---

[14] According to Statistics Finland the main explanation is that the Labour Force survey by Statistics Finland also accounts for disguised unemployment i.e. "persons outside the labour force who would want gainful work and would be available for work within a fortnight, but who have not actively looked for work in the past four weeks". http://www.stat.fi/til/tyti/kas_en.html retrieved 10.12.2015.

[15] The data was retrieved from toimialaonline.fi, where the regional accounts are stored. The latest available data was December 2014, which I decided to use for the data points in the beginning of 2015 as well.

the average for all regions in the specific year. Finally, these relative differences in productivity are used as proxy to measure the differences in labour productivity. Since regional production value is provided only on an annual basis, I use the yearly value for each month of that specific year assuming that monthly changes in productivity remain sufficiently low.

At the occupational level, I use annual data on salaries from the Statistics Finland as a measure of productivity. Sahin et al. (2014) argue that wages are an imperfect proxy, since besides productivity they are affected by unionization rates, compensation rates and monopoly rents. To address this they normalize the wages around average for each occupation. I conduct this in my calculations similarly as for the regional productivities. Again, yearly values for productivity are used for each month in that specific year. The differences in both regional and occupational productivities turn out to be very small and thus have only a minimal effect on the mismatch indices.

5.3 Matching function estimation

The matching efficiencies are estimated by performing fixed effects panel regressions with hirings per unemployed job-seekers as dependent variable and vacancies per unemployed job-seekers as explanatory variable. The matching function is assumed to have constant returns to scale. The Cobb-Douglas form used as a baseline specification is then transformed into log-linear form by taking logarithms on both sides. This way we get clear implications for the elasticity parameters.

$$ln\left(\frac{h_{it}}{u_{it}}\right) = ln\Phi_t + ln\,\phi_i + \alpha ln\left(\frac{v_{it}}{u_{it}}\right) \qquad (29)$$

Now, $ln\Phi_t$ is the time fixed effects and will be interpreted as the time variation in matching efficiency. Basically the time variation is captured with yearly time dummies. Additionally, each time series are Hodrick-Prescott filtered (with parameter 100) to eliminate high frequency changes and cyclical patterns and better visualise the changes.

The sector fixed effects is denoted as $ln\,\phi_i$ and finally, α is the vacancy share interpreted as the elasticity of matching function. The sectoral matching efficiency parameters, ϕ_i, will capture all the sector-specific shifts divergent from the aggregate matching efficiency. The exponents of $ln\,\phi_i$ are treated as deviations from the geometric mean to derive relative differences between the sectors.

Fixed effects regression is convenient to evaluate the time-invariant characteristics of the sectors. However, fixed effects tend to catch the returns to scale effects especially when regions differ widely in scales, which implicates an estimation bias (Ibourk et al. 2004). Table 2 presents the whole set of the vacancy share parameter. The standard errors are corrected to take into account the correlation of error term over time within the sector.

Table 2 Elasticities

	α	Robust standard errors	t
Aggregated	0.41***	0.09	4.5
With time fixed effects	0.32***	0.08	4.3
Sector fixed effects			
Geographic	0.28***	0.02	12.79
Occupation	0.09***	0.02	3.57

Note: Year-dummy is added to capture for time fixed effects in the aggregated data. The occupation-specific elasticity is based on the more disaggregated ISCO 50 occupational data.

In the aggregate regressions elasticity seems to drop from 0.41 to 0.32 when yearly dummy variables are used to capture time fixed effects. In the panel regressions, elasticity is lower varying between 0.28 and as low as 0.09. I decided to use an average vacancy share of 0.3. This value provides an upper bound nature of results and is in the range of previous research as well. Using a higher elasticity will put more weight on the distribution of vacancies and a lower efficiency will weigh more the sector-specific efficiencies (Marthin, 2012). The most realistic setting would probably be to use different vacancy shares for all sectors, but I chose to use a homogeneous alpha to simplify comparability.

These elasticity estimates are consistently lower than those obtained by Sahin et al., who decide to use 0.5 as an estimation of the vacancy share.[16] Yet, my estimates follow the elasticities obtained by Marthin (2012) with Swedish data. He argues that the results obtained by Sahin et al. in the US may partly reflect the traditional view of the US labour market as having a high job-finding rate and hence large elasticities. Further, Marthin argues that the lack of appropriate data for stock-flow matching could be one reason for lower elasticities than measured in US. With the geographic case, I have slightly higher elasticities than Marthin, but in the aggregate and occupational cases the elasticities are almost equal. As per Kangasharju et al. (2005), including variables measuring the flow of new vacancies and job

---

[16] In the aggregate regressions they report vacancy share parameters between 0.32 and 0.67 without specifying the values more carefully. In the panel regression their estimates vary between 0.24 and 0.53 showing significantly higher elasticity parameter than my estimations.

seekers increases the magnitude of elasticities, which might explain part of the increase in my results as well.

It is worth noting that the number of vacancies posted by firms may be affected by shocks to unobserved matching function. Simple OLS regression of the job finding rate on labour market tightness is exposed to simultaneity bias (Borowczyk et al. 2013). Hence, when estimating the matching functions one should consider the possible endogeneity problem of vacancies. Sahin et al. approach this problem by modelling the matching efficiency through time-varying polynomials as suggested by Borowczyk et al. In my estimations, I replace the time trend used by Sahin et al. with yearly dummies to obtain yearly observations for the variation of matching efficiency in time.

5.4 Descriptive statistics

The job finding rate and hirings per unemployed behave similarly over time as presented in Figure 3. Basically, both variables measure how many hirings occur in relation with job-seekers, although the difference in magnitude is significant. Before the financial crisis hirings seemed to be on a stable track, but from 2008 onwards both rates show a steep decline. The job finding rate has fallen from 0.30 to as low as 0.15 and hirings per unemployed have decreased from around 0.16 to below 0.06.

Figure 3 Job finding rate and hirings per unemployed
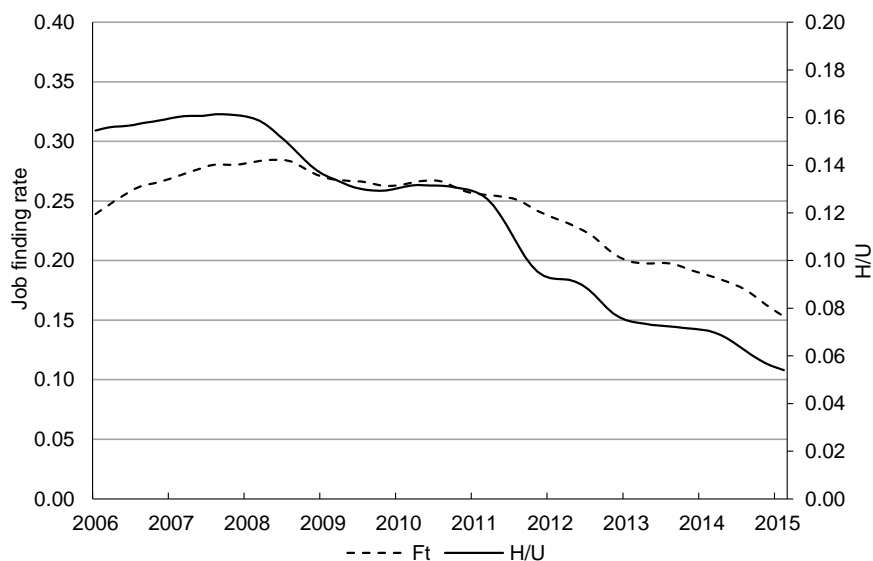
Note: Job-finding rate is calculated according to Equation 17 and hiring ratio (H/U) is simply hirings per unemployed job-seekers.

One reason for the low hiring ratio is that it only includes the outflow from unemployment to employment registered in LLO's, whereas job-finding rate describes the overall likelihood of finding work. Barnichon and Figura (2011) explain that the job finding rate is suggested to decline with unemployment duration. They show to cited reasons. First, long-term unemployment reduces worker skills and networks in job-finding, making it more difficult to find employment. Further, prolonged unemployment may signal some unwanted characteristics of the job-seeker. This view is supported by the Finnish employment data, which shows a steep incline in long-term unemployment from 2009 onwards.[17] The share of long-term unemployed has exceeded 30 percent of the whole pool of unemployed job-seekers.

Table 3 Descriptive labour market statistics across regions

	Unemployment rate (%)	Vacancy rate (%)	Tightness	Hiring rate
Uusimaa	7.5	1.3	0.16	0.07
Varsinais-Suomi	9.4	1.1	0.11	0.15
Satakunta	10.9	1.3	0.11	0.12
Häme	11.0	1.2	0.10	0.11
Pirkanmaa	11.2	1.1	0.09	0.10
Kaakkois-Suomi	12.3	1.2	0.09	0.11
Etelä-Savo	11.5	1.3	0.10	0.13
Pohjois-Savo	11.5	1.3	0.10	0.13
Pohjois-Karjala	14.7	1.0	0.06	0.13
Keski-Suomi	13.1	0.9	0.06	0.13
Etelä-Pohjanmaa	8.5	1.4	0.14	0.20
Pohjanmaa	7.0	1.4	0.18	0.14
Pohjois-Pohjanmaa	12.0	1.1	0.08	0.15
Kainuu	14.3	1.0	0.06	0.14
Lappi	14.1	1.6	0.10	0.17
mean	11.3	1.2	0.10	0.13
median	11.5	1.2	0.10	0.13

Note: Vacancy rate is the ratio of vacancies and the labour force in the specific region. Tightness describes the ratio between vacancies and unemployed job seekers and hiring rate measures the ratio of unemployment period endings and the number of unemployed workers. All figures are averages over 2006 – April 2015.

Table 3 above demonstrates the regional descriptive statistics for the various ELY-centres. All figures are averages from 2006 to April 2015. The table reveals wide disparities across regions. On average, Pohjanmaa has had the lowest unemployment rate at 7.0 percent, whereas Pohjois-Karjala has had over twice as high unemployment at 14.7 percent. Also

---

[17] Long-term unemployment is defined as unemployment duration over one year.

other variables show high variation but in divergent order relative to unemployment. Hence, labour market tightness seems to have an inverse relationship with the unemployment rate. Pohjanmaa has for instance the highest ratio between vacancies and unemployed job-seekers and the lowest unemployment rate of all regions. Hiring rate, on the other hand, seems to deviate from this link. Nevertheless, for this study the hiring rate offers interesting insights in regions ability to create matches. In fact, the hiring rate largely corresponds with the region-specific matching efficiencies presented earlier in matching function estimations.

5.5 Overview of unemployment in Finnish labour market

The employment shock in 2008 was far from the substantial increase in unemployment after the banking crisis in the beginning of 1990's. At the time, the downtrend in the Finnish economy initiated a steep increase in the unemployment rate, which peaked at around 20 percent in 1994. Contrary, for most of the 1980's the unemployment rates were far below the European average at around five percent.

Figure 4 Finnish unemployment rate between 1989 and April 2015
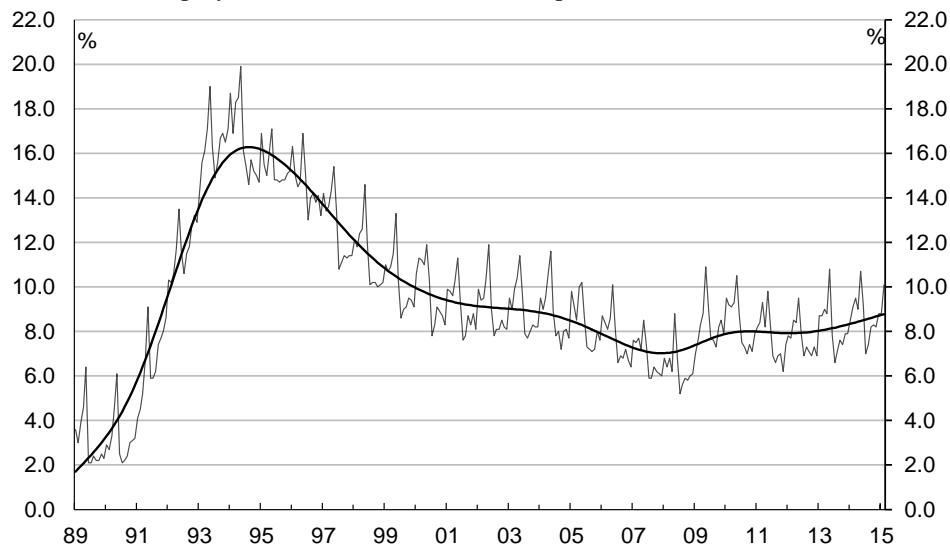
Note: The figure shows the actual observed unemployment rate added with HP-filtered trend. The data is exceptionally retrieved from Statistics Finland to obtain sufficiently long time period.

Nonetheless, Finland went through a relatively quick recovery in terms of GDP growth after the 1990's crisis. Still, the unemployment rate remained high on average through most of the 90's despite the continuous minor improvement in employment. Koskela and Uusitalo (2004) claim that one reason for the rather sluggish recovery was that jobs created and destroyed during and after the crisis were in different fields. This supports the view that structural changes occurring during deep economic depressions are one of the main reasons for

the prolonged long-term employment effects of financial crises (Reinhart and Rogoff, 2009). This leads to an asymmetric impact of financial crisis on the labour market: the initial negative effect is deep in the beginning of the downturn following with a slow recovery. The high unemployment levels after the crisis in 1990's demonstrate this well. In contrast, a similar affect has not been witnessed after the latest crisis.

Initially, the negative shock due to the latest financial crisis was surprisingly well absorbed in the Finnish labour market. The average unemployment rate peaked at 8.7 percent in Finland at the beginning of 2010, which was around one percentage point lower than the EU average.[18] Schauman and Vanhala (2011) argue that thanks to temporary lay-offs, the actual redundancies and labour market search frictions remained lower than expected. Moreover, a drop in the labour force participation might be one explanation for the surprisingly modest incline at unemployment rate. Since 2008 the participation rate for the working age cohort (15-74 year old) has shown a steady decline from levels above 67 percent to below 65 percent, which translates into an increase of 110 thousand individuals outside the labour force.

Despite the quick adaptation of the labour market, unemployment in Finland has again started to rise contrary to the EU average. Schauman and Vanhala (2011) claim that regardless of the relatively small increase in unemployment compared with the steep drop of GDP at the beginning of 2010, the long-term unemployment still follows a peculiar trend to financial crisis. First, the share of long-term unemployed decreases due to the overall increase in unemployment. Thereafter, the share rises, since the inflow to unemployment starts to decrease. However, also the absolute number of long-term unemployed has shown a steady increase from around 40 thousand to over 110 thousand during 2009-2015[19]. This large share of long-term unemployed might also reflect as a lagging increase in mismatch. Overall, during the time span from 2006 to the beginning of 2015 unemployment has been rather steady in retrospect. Consequently, it is unlikely that labour matching has suffered as large negative changes after the latest financial crisis as in the 90's.

---

[18] EU average as per Eurostat harmonized monthly unemployment rate.
[19] Based on the October 2015 employment survey published by TEM.
See https://www.tem.fi/files/44368/TKAT_Loka_2015.pdf Retrieved 3rd December 2015.

6 Results

The results imply that mismatch unemployment exists in the Finnish labour market due to the imbalance of job seekers and vacancies. The construction of the mismatch indices and counterfactual unemployment rates reveal that the mismatch effect is somewhat larger in occupational than in regional dimension. I walk through the actual estimation results by first discussing the geographical and then the occupational mismatch indices. It should be kept in mind that the planner's benchmark allocation is derived under costless reallocation, which leads to a tendency to an upper bound in results (Sahin et al. 2014).

6.1 Geographical mismatch

The 15 distinctive regions show wide variation in matching efficiencies. Table 4 presents each ELY-centre with its estimated matching efficiency. These efficiencies are averages over the whole time period.

Table 4 Matching efficiencies across regions

ELY center	Matching efficiency
Uusimaa	0.47
Varsinais-Suomi	1.16
Satakunta	0.92
Häme	0.84
Pirkanmaa	0.77
Kaakkois-Suomi	0.89
Etelä-Savo	1.02
Pohjois-Savo	1.04
Pohjois-Karjala	1.14
Keski-Suomi	1.09
Etelä-Pohjanmaa	1.47
Pohjanmaa	0.94
Pohjois-Pohjanmaa	1.16
Kainuu	1.20
Lappi	1.35

Notes: These matching efficiencies are obtained with an OLS regression with region-specific fixed effects, which is described more thoroughly in Section 5.3. ELY-centres are treated as group variables and yearly dummies are used to capture the variation in time. These matching efficiencies are the group fixed effects for each ELY-centre and they can be interpreted as the deviation from geometric mean. In other words, given that the vacancy per job seeker ratio would be equal in each region, for instance Lappi would hire 1.35 times more than the average across the whole country.

Of all regions Uusimaa has clearly the lowest matching efficiency, which means that with an equal ratio of job seekers per vacancies with other regions, Uusimaa would hire over 50 percent less workers than on average in the whole country. In contrast, the most efficient region, Etelä-Pohjanmaa, would hire on average almost 50 percent more job-seekers than the geometric mean.

The matching efficiencies demonstrate a vague negative relationship with unemployment rates shown in Table 3. It seems that regions with high unemployment have relatively high matching efficiency. Similar pattern is found by Bunders (2003) in the Finnish labour market. He comes to a conclusion that regions with high unemployment rates such as Lappi and Pohjois-Karjala suffer from low labour demand instead of low efficiency or mismatch. However, high matching efficiency and high unemployment in these regions may also reflect the higher usage of employment services in search for work leading in more registrations in LLO's (Ilmakunnas and Pesola, 2003).

Moreover, a low vacancy rate may push the efficiency up for instance in Kainuu, where unemployment and matching efficiency are high simultaneously with one of the lowest vacancy rates. The weakest efficiency is found in central areas with rapid growth such as Uusimaa, where mismatch might have better ability to explain unemployment. Also, the low efficiency is in line with the results found by Hynninen (2007) that high population density has negative effect on matching efficiency. Despite the low efficiency in Uusimaa, the high tightness ratio indicates sufficient labour demand, which probably limits the rise in the unemployment rate.

Figure 5 below plots all three mismatch indices on regional level between 2006 and April 2015. $M_{\emptyset t}$ and M_{xt} follow a similar path while M_t is significantly lower implying high simple correlation between vacancies and job-seekers across ELY-centres. Nevertheless, as the indices $M_{\emptyset t}$ and M_{xt} include the large variations in the region-specific matching efficiencies shown in Table 4, they illustrate clearly higher mismatch. Hence, matching efficiency seem to have a higher effect on mismatch than the joint distribution of vacancies and job-seekers.

Depending on the index used, the fraction of hires lost due to the imbalanced allocation of vacancies and job seekers ranges from 0.7 percent to 9.7 percent during the whole time period. The index peaks on the last data point, April 2015, to 9.7 percent, which translates into more than 2377 lost hires. The rise in mismatch remained subtle during the financial crisis

and in 2012 the indices returned again roughly on the pre-crisis level. Hence, the aggregate shock seemed to hit the regions rather equally. However, the indices including efficiencies show a steady rise from 2013 onwards implying a rise in mismatch again.

**Figure 5** Geographical mismatch indices
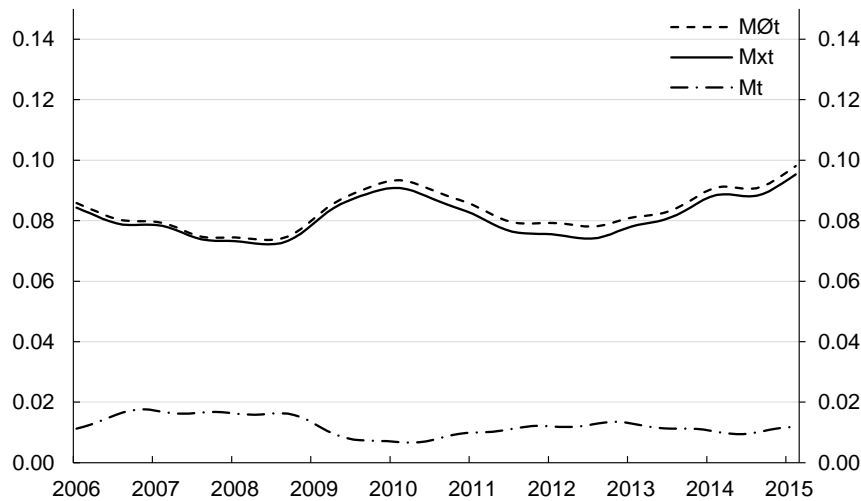
Note: The figure contains three different indices: *Mt* represents mismatch without taking into account region-specific productivities and matching efficiencies. $M_{\varnothing t}$ includes sector-specific efficiencies and M_{xt} includes also sector specific productivities.

Figure 6 draws the counterfactual unemployment rate and the actual unemployment rate. As discussed in Section 4.4, the function is mostly illustrative since the calculations are based on an iteration with simplifying assumptions. I use the index $M_{\varnothing t}$ to estimate the counterfactual rate, as this provides an upper bound of mismatch. The grey bars in the graph present the difference between the actual and counterfactual rate.

The main finding here is that during the time period mismatch explains 1.5 to 3.0 percentage points of the whole unemployment rate. The difference shows a steady decline until the mid-2008 but then the crisis seemed to initiate the widening of the gap between counterfactual and actual unemployment. From 2012 when the unemployment started to rise again, the gap started to show a steady incline. At the beginning of 2015, mismatch accounted for 3.0 percentage points of the actual unemployment rate. The unemployment effect estimated proves to be significantly larger than what is estimated in previous empirical work by Sahin et al. and Marthin, even though the estimated mismatch indices don't have as large distinction.

Figure 6 Counterfactual unemployment rate, regional level
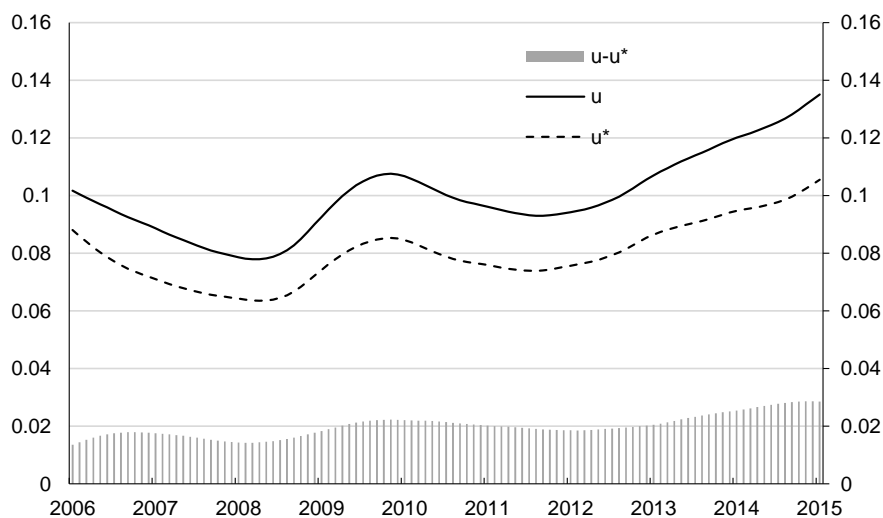
Note: This graph compares the actual unemployment rate *u* with counterfactual unemployment rate *u**. The grey bars denote the difference between the actual and efficient rate.

Figure 7 presents the efficient and actual allocation of job-seekers derived from the planner's solution. On April 2015, slightly over 30 percent of job-seekers should be reallocated to form the optimal allocation. Most notably the share of job-seekers in Uusimaa should drop from 26 percent to 6 percent because of the poorest matching efficiency in the area. Etelä-Pohjanmaa should have 11 percentage points higher share amounting to 13 percent of the whole pool of unemployed job seekers. Matching efficiency has a significantly higher impact on the efficient allocations compared to vacancy share due to the estimated low elasticity.

Figure 7 Actual and efficient allocation of job-seekers across regions
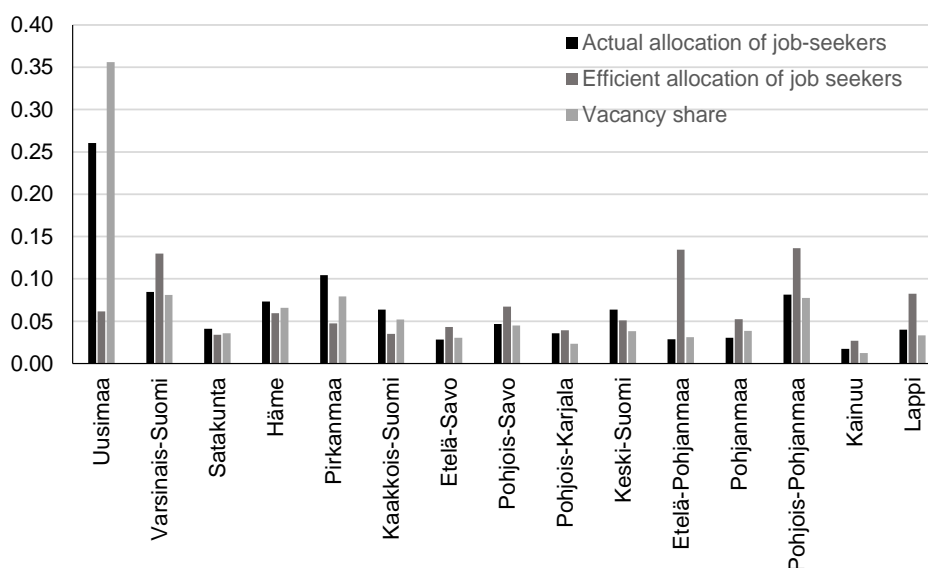
Note: The optimal allocation in this figure is derived in Section 4.5. This is an example of the efficient allocation at the latest point in time. Shares are used to make various sizes of regions comparable.

43

6.2 Occupational mismatch

Table 5 presents the matching efficiencies across ten occupation groups. The efficiencies show modest differences with *Managers* having the lowest efficiency (0.72) and *Service and sales workers* the highest efficiency (1.33). The low efficiencies for managers and armed forces occupations might result from underreporting of vacancies as these two groups show significantly less vacancies than other occupations.

Table 5 Occupation-specific matching efficiencies (ISCO10)

ISCO10 Occupational group	Matching efficiency
Service and sales workers	1.33
Craft and related trades workers	1.14
Skilled agricultural, forestry and fishery workers	1.05
Professionals	1.02
Elementary occupations	1.01
Clerical support workers	0.99
Technicians and associate professionals	0.98
Plant and machine operators, and assemblers	0.98
Armed forces occupations	0.84
Managers	0.72

Notes: These matching efficiencies on Table 5 and Table 6 are obtained with an OLS regression with occupation-specific fixed effects, which is described more thoroughly in Section 5.3.

Figure 8 draws the mismatch indices across the ISCO10 occupation groups. Overall, all three indices behave similarly, but M_t index is lower than $M_{\varnothing t}$ and M_{xt}. Before the recession in mid-2007 the hires lost due to mismatch across occupations ranged from 2 to 4 percent. Thereafter, mismatch shows a steep increase in the early stages of financial crisis in 2008 and in mid-2009 the share of lost hires vary between 6 and 10 percent.

Figure 8 Occupational mismatch indices (ISCO10)
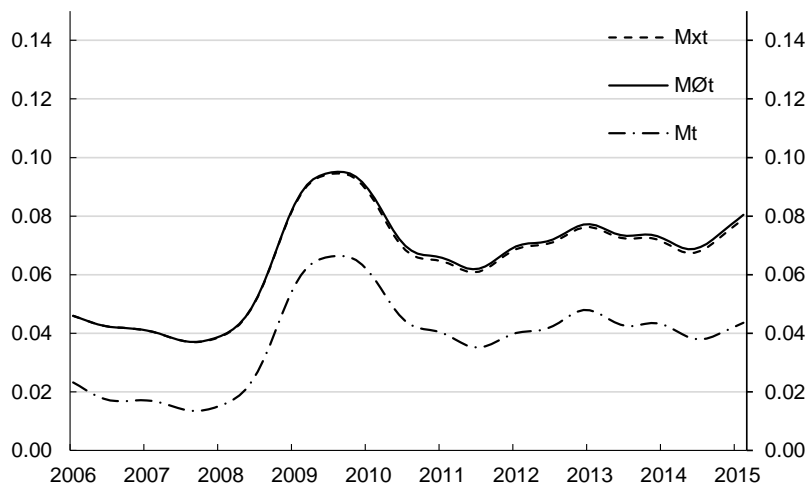
Note: This figure demonstrates the share of lost matches due to mismatch by occupation in each point in time. $M_{\varnothing t}$ includes sectoral matching efficiencies. M_{xt} summarizes also the differences in productivity across occupations. Mt simply demonstrates the correlation of job-seekers and vacancies across sectors.

The indices stabilize relatively fast after the first shock and start to show a decline already in late-2009. Still, mismatch remains clearly above the pre-crisis level and show an increasing trend since mid-2014. Sahin et al. (2014) note that their occupational indices start to increase one year ahead of the financial crisis. This pattern is not as clear in my results, even though mismatch starts to increase already in mid-2008, right in the earliest stage of the financial crisis.

Table 6 Occupation specific matching efficiencies (ISCO50)

ISCO50 Occupational group	Matching efficiency
Personal care workers	1.59
Health associate professionals	1.43
Personal service workers	1.33
Food preparation assistants	1.31
Legal, social, cultural and related associate professionals	1.29
Food processing, wood working, garment and other craft workers	1.24
Teaching professionals	1.18
Information and communications technicians	1.16
Electrical and electronic trades workers	1.15
Cleaners and helpers	1.15
Hospitality, retail and other services managers	1.14
Legal, social and cultural professionals	1.11
Protective services workers	1.11
Metal, machinery and related trades workers	1.10
Building and related trades workers, excluding electricians	1.08
Market-oriented skilled agricultural workers	1.08
Armed forces occupations	1.07
Drivers and mobile plant operators	1.03
Handicraft and printing workers	1.03
Sales workers	1.03
General and keyboard clerks	1.01
Customer services clerks	0.99
Production and specialised services managers	0.99
Other clerical support workers	0.96
Science and engineering professionals	0.95
Health professionals	0.95
Assemblers	0.95
Science and engineering associate professionals	0.92
Stationary plant and machine operators	0.91
Market-oriented skilled forestry, fishery and hunting workers	0.89
Business and administration professionals	0.84
Information and communications technology professionals	0.84
Labourers in mining, construction, manufacturing and transport	0.82
Numerical and material recording clerks	0.79
Business and administration associate professionals	0.78
Agricultural, forestry and fishery labourers	0.73
Administrative and commercial managers	0.71
Refuse workers and other elementary workers	0.66
Chief executives, senior officials and legislators	0.63

The disparities in efficiencies widen with 50 occupational groups. From Table 6 we notice that the group *Personal care workers* and *Health associate professionals* have the highest efficiencies. In contrast, within the manager group, *Chief executives, senior officials and legislators* have the lowest efficiency. This might be due to the low usage of LLO's in their recruiting, as these are usually high-skilled jobs that might be matched elsewhere as noted by Soininen (2006).

Figure 9 draws the lost hires across the 50 occupation groups. These mismatch indices follow similar pattern as on ISCO10-level but on a higher rate. Hence, it reflects the property of the mismatch index that the index increases in the level of disaggregation. The indices rise up to 8 percentage points in the beginning of 2008 and the highest index $M_{\emptyset t}$ peaks at 0.14. The timing of the increase in occupational mismatch seems to lead slightly the effect observed on geographical dimension. M_t implies on average 2.5 percentage point lower amount of lost hires than $M_{\emptyset t}$ and $M_{xt.}$ Contrary to regional indices, the occupational mismatch has been larger mismatch during the crisis than at the latest data point in early-2015.

**Figure 9** Occupational mismatch indices (ISCO50)
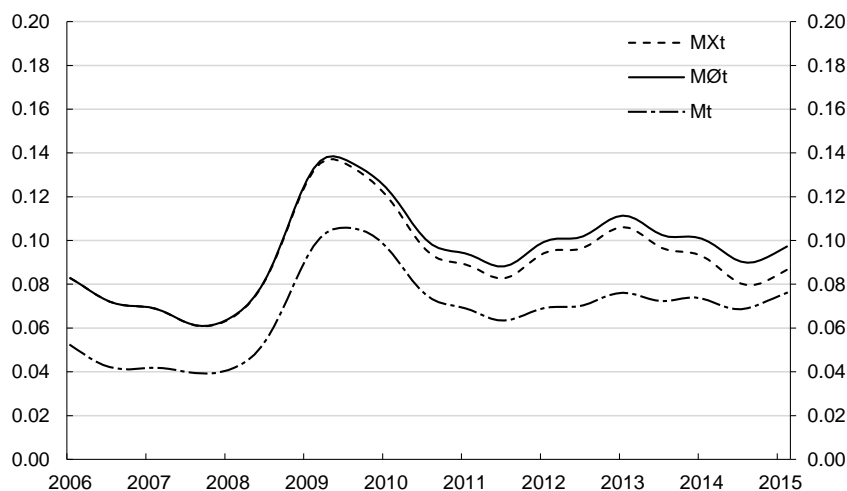
Note: This figure demonstrates the share of lost matches due to mismatch by occupation in each point in time. $M_{\emptyset t}$ includes sectoral matching efficiencies. M_{xt} summarizes also the differences in productivity across occupations. M_t simply demonstrates the correlation of job-seekers and vacancies across sectors.

The estimated counterfactual unemployment rates on occupational dimension are presented in Figure 10. Again, I use $M_{\emptyset t}$ to measure the efficient allocation. The counterfactual rates with both occupational groups follow a similar behaviour, but seem to converge towards the latest data point. The counterfactual rates approached the actual rate in 2008 but the crisis again initiated a widening of the gap.

46

Also, occupational mismatch seems to explain overall a higher share of the actual unemployment rate than regional mismatch. As discussed before, one reason might be that on occupational dimension the data does not specify outflow from unemployment to employment specifically but only the total outflow from unemployment.

Occupational mismatch explains here on average 2.5 percentage points of the aggregate unemployment rate during the whole time period. The gap shows recently a rising trend towards the peak in late-2009 at around 3 percentage points. Hence, mismatch unemployment across occupations explains at most around one fifth of the actual unemployment rate.

Figure 10 Counterfactual unemployment rate, occupational level
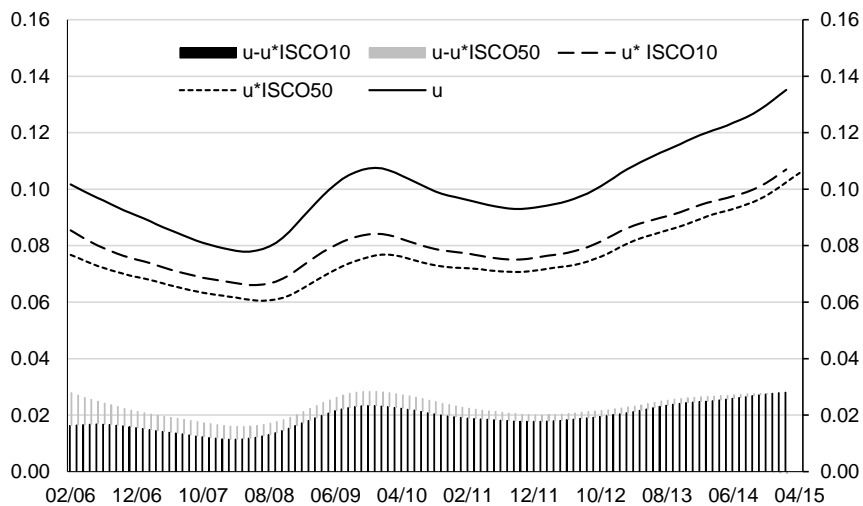

Note: The solid line presents the actual unemployment rate and the dashed line show the counterfactual unemployment rates based on two occupational divisions: ISCO10 and ISCO50. The black bars on the bottom show the difference between actual and ISCO10 level unemployment and the black and grey bars combined are the difference between the actual and the counterfactual unemployment rate on ISCO50 level.

Figure 11 demonstrates the efficient allocation across ISCO10 specified occupation groups. As the matching efficiencies and vacancy shares already suggest, service and sales workers should have more than twice as large allocation of job-seekers as observed in April 2015. In contrast, the job-seeker allocation in the group *craft workers* should decrease from 25 percent to around 10 percent.

However, especially the occupational mismatch should be interpreted cautiously. The various inefficiencies and reallocation issues are even harder to account for than in geographical dimension, as educational inflexibilities and differences in hiring processes are all included in the mismatch indices (Marthin, 2012).

Figure 11 Actual and efficient allocation (ISCO10)
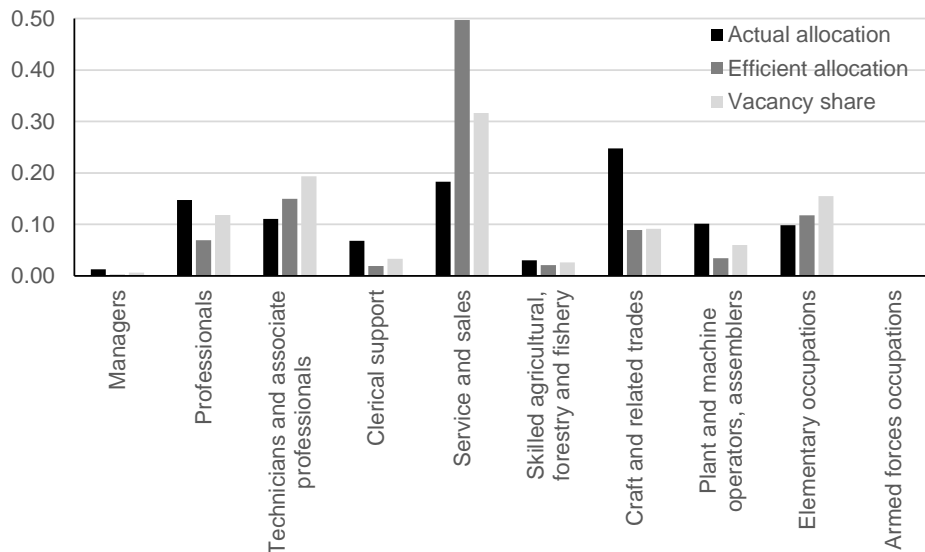
Note: The optimal allocation in this figure is derived in Section 4.5. This is an example of the efficient allocation at the latest point in time. Shares are used to make various sizes of regions comparable.

I also assessed, whether job polarization - the falling demand for middle-skill routine work and labour concentration to high and low skilled work - is a useful concept to describe the labour market in Finland. According to Author et al. (2003), technological change is skill-biased because exposure to computerization varies in different occupations. Hence, they categorize occupations to abstract or manual tasks and routine or non-routine tasks. Later, Goos and Manning (2007) illustrated that the routine tasks easily substituted by computers are most often middle-skill tasks and therefore technological change might lead to job polarization leading to concentration in high and low-skilled jobs. To study, whether the dynamics of mismatch is captured by this, I categorize ISCO10 occupations into four categories; cognitive/non-routine, cognitive/routine, manual/non-routine, manual/routine as per Author et al. 2003. This categorisation is shown in Table 7 below.

I find that this classification explains occupational mismatch well as it accounts for around 80 percent of the ISCO10 level occupational mismatch. The vacancy share dropped especially for the manual occupations during the crisis, which caused naturally the increase in the vacancy shares of non-routine and cognitive occupations. Also the sector-specific efficiencies are higher for the cognitive occupations. Interestingly job polarization does not explain the most recent rise of mismatch, since mismatch across these four categories shows a negative trend from 2013 onwards opposite to the occupational mismatch indices.

Table 7 Occupation classifications to study job polarization

ISCO10 Occupational group	Classification
Managers	Cognitive/Non-Routine
Professionals	Cognitive/Non-Routine
Technicians and associate professionals	Cognitive/Non-Routine
Elementary occupations	Cognitive/Non-Routine
Clerical support workers	Cognitive/Routine
Service and sales workers	Cognitive/Routine
Skilled agricultural, forestry and fishery workers	Manual/Non-Routine
Craft and related trades workers	Manual/Non-Routine
Armed forces occupations	Manual/Non-Routine
Plant and machine operators, and assemblers	Manual/Routine

6.3 Allowing on-the-job search

I adjusted the model to allow on-the-job search by including all registered employed job seekers to the estimations. Naturally, this does not cover all employed job seekers but gives an idea of the effect of on-the-job search. This approach does neither account for ordinary job-to-job switches, where LLO receives no data of the new hiring. Still, this aspect is considered in order to study the robustness of chosen variables and to check, whether employed job-seekers cause any bias in the coefficients.

Employed job-seekers form a large share of aggregate job-seekers in the data. For instance, in January 2015 there were slightly over 137 thousand employed job-seekers while unemployed job-seekers amounted to 359 thousand. This share seems high, especially because these are actually registered job-seekers, who should be prepared to accept job offers from Local Labour Office. Nonetheless, both full time and part time workers and those who are employed by means of wage subsidies from the government are included.

Adjusting the data with employed job seekers results only in minor changes in the mismatch index. For instance, the geographical mismatch with sector-specific efficiencies shows 0.986 correlation between the adjusted and original one. Similarly, Sahin et al. find very small effects on mismatch indices when employed job seekers are added in the model.[20] This suggests that employed job-seekers are actually distributed similarly than unemployed workers and the mismatch index and vacancy per job-seekers shares remain unaffected.[21]

---

[20] The correlation with the modified and original version is over 0.987, which imply a minimal effect. (Sahin et al. 2014)

[21] One of the attributes of the mismatch index is that an aggregate increase in vacancies or job-seekers does not affect the mismatch index if the shares between sectors remain intact.

6.4 Limitations of the study

I made some robustness checks with the job-seeker variable. When constructing the combination of stock and new inflow during the month of job-seekers, I added new job searches as the new inflow. I tested to switch this flow to new beginning unemployment periods, which on average sums up to roughly double the amount compared with the job searches. Yet, the effect when using this flow variable turned out to be minimal, as the correlation with the original mismatch index amounted to 0.99.

Using a proper stock-flow specification was not possible with this data set, since the vacancies and job-seekers belonging to the stock or flow are not identified specifically. Yet, this setup would have perhaps been more realistic than the approach I used in this study. As Lahtonen (2006) notes, on the aggregate level in the Finnish labour market only a small part are stock-stock matches. Instead most job-seekers match with the flow of new vacancies. At first, I used only the beginning of period stocks, but decided to add flow variables for job seekers and vacancies as well. Obtaining accurate information on the worker flows would provide an interesting comparison.

Moreover, I decided to use a fixed elasticity parameter for the matching function of 0.3, as this is broadly the average of estimated elasticities and most of all provides an upper bound for mismatch. In reality, elasticity would show some variation in time and between sectors. Hence, static elasticity parameter is somewhat simplistic but on the other hand it offers good comparability. Sahin et al. find that overall using heterogeneous α leads to higher mismatch but only by 0.2 percentage points. Nonetheless, I made some sensitivity analysis by varying the vacancy share. Increasing vacancy share to 0.4 from the benchmark rate of 0.3 reduces mismatch rates and puts more weight on the joint distribution of vacancies and job seekers.

The model used in this paper ignores the fact that workers might search for work on different occupation that they previously worked in. Yet, this direction of search is ignored because it has most relevance in the industry sector, where workers are least tied to their last sector. As discussed earlier in Section 5, Fahre and Sunde (2001) argue that workers are more attached to their profession than industry. Also the data does not specify if an individual job-seekers is hired in different occupation than documented by the job-seekers announcement in the beginning of unemployment.

Yet again, a major shortcoming of the model is that the formation of the mismatch indices don't specify the causes of mismatch or explain the witnessed dynamics more carefully. In this study I attempted to provide outlines for potential interpretations of the mismatch dynamics, but a more thorough analysis would require further studies.

7 Conclusion

In this study, I measure labour market mismatch in Finland between 2006 and April 2015 by calculating a mismatch index on geographical and occupational dimensions. This index compares an efficient allocation between job-seekers and vacancies with the actual observed allocation to estimate labour mismatch. Overall, it seems that inefficient allocation of job-seekers across sectors causes losses in hires and increases the aggregate unemployment rate.

Spatially lost hires vary monthly between five and seven percent when sector-specific efficiencies are considered. According to the estimated counterfactual unemployment, this could explain around one fifth of the aggregate unemployment rate. On the occupational level mismatch increased sharply in 2008 as the financial crisis burst and the indices peaked between 0.09 and 0.14 depending on the level of disaggregation. This explains up to three percentage points of the aggregate unemployment rate. Moreover, job polarization seems to account for a large part of occupational mismatch and therefore warrants further attention.

Nonetheless, the most notable finding causing some concern is the recent trend in mismatch as the actual size of mismatch is open to interpretation. The results indicate that mismatch is currently increasing on all dimensions. Geographically mismatch already exceeds the level witnessed in the middle of the latest financial crisis and occupational mismatch has shown a growing trend since mid-2014. Also this probably translates into the current increase in the share of long-term unemployment hampering the labour market recovery in Finland.

There are only a few previous studies using this method to measure mismatch. Nonetheless, at least studies with Swedish and American labour market data similarly indicate that occupational mismatch affects unemployment more than geographical. In the US, regional mismatch is almost non-existent reflecting flexible labour mobility. Mismatch is approximately on equal levels in Sweden, but the effect on the aggregate unemployment rate is reported being moderate in comparison with my estimations.

The mismatch index proves as a convenient framework to further study the dynamics of matching on different labour market layers especially with the rich data provided in Finland. However, it should be kept in mind that the framework does not provide details of the causes behind inefficient allocation. Hence, further studies could concentrate on the sources behind the misallocations and sectoral disparities.

References

Author, D. H., Levy, F. and Murnane, R. J. (2003): The Skill Content of Recent Technological Change: An Empirical Exploration. *The Quarterly Journal of Economics,* 11, 1279-1333.

Albaek, K. and Hansen, H. (2004): The Rise in Danish Unemployment: Reallocation or Mismatch? *Oxford Bulletin of Economics and Statistics,* 4(66).

Arpaia, A., Kiss, A. and Turrini, A. (2014): Is Unemployment Structural or Cyclical? Main Features of Job Matching in the EU after the Crisis. *IZA Policy Paper,* 91.

Barnichon, R. and Figura, A. (2011): What drives matching efficiency? A Tale of Composition and Dispersion. *Federal Reserve Board staff working paper,* 2011-10.

Barnichon, R. and Figura, A. (2013): Labour Market Heterogeneity and the Aggregate Matching Function. *Barcelona GSE Working Paper Series,* 727.

Blanchard, O. and Diamond, P. (1989): The Beveridge Curve. *Brookings Papers on Economic Activity*, 20, 325-332.

Bonthuis, B., Jarvis, V. and Vanhala, J. (2013): What's Going on Behind the Euro Area Beveridge Curve(s)? *European Central Bank Working Paper Series,* 1586.

Borowczyk-Martins, D., Jolivet, G. and Postel-Vinay, F. (2012): Accounting for endogeneity in matching function estimation. *Review of Economic Dynamics,* 16(3), 440-451.

Bunders, M. (2003): The matching function in the Finnish labour market 1988-2002 – regional and occupational differences in the efficiency of the matching process. *Bank of Finland Discussion Papers,* 32/2003.

Broersma, L, and Van Ours, J. (1999): Job searchers, job matches and the elasticity of matching. *Labour Economics (6)*, 77-93.

Burda, M. C. and Profit, S. (1996): Matching across space: Evidence on mobility in the Czech Republic. *Labour Economics,* 3, 255-278.

Coles, M. G, and Smith, E. (1998): Marketplaces and Matching. *International Economic Review.* 39, 239-254.

Daly, M. C., Hobjin, B., Sahin, A., and Valletta, R. G. (2012): A Search and Matching Approach to Labour Markets: Did the Natural Rate of Unemployment Rise? *The Journal of Economic Perspectives*, 26(3), 3-26.

Dow, J. C. R. and Dicks-Mireaux, L. A. (1958): The Excess Demand for Labour. A Study of Conditions in Great Britain, 1946-1956. *Oxford Economics Papers, New Series,* 10(1), 1-33.

Elsby, M. W. L., Michaels, R. and Ratner, D. (2015): The Beveridge Curve: A Survey. *Journal of Economic Literature,* 53(3) 571-630.

Erken, H., van Loon, E. and Verbeek, W. (2015): Mismatch on the Dutch Labour Market in the Great Recession. *De Economist,* 163, 435-459.

Fahr, R. and Sunde, U. (2001): Disaggregate Matching Functions. *IZA Discussion Paper,* 335.

Friedman, M. (1986): The Role of Monetary Policy. *The American Economic Review,* 57(1).

Goos, M. and Manning, A. (2007): Lousy and Lovely Jobs: The Rising Polarization of Work in Britain. *The Review of Economics and Statistics,* 89(1), 118-133.

Gregg, P. and Petrongolo, B. (2005): Stock-flow matching and the performance of the labour market. *European Economic Review,* 49, 1987-2011.

Hall, R. E. (1977): An Aspect of the Economic Role of Unemployment. *National Bureau of Economic Research,* Working Paper 226.

Hall, R. E. (2000): Reorganization. *Carnegie-Rochester Conference Series on Public Policy.* 52, 1-22.

Hicks, J. R. (1932): *The Theory of Wages.* London: Macmillan, 2nd ed., 1963.

Hynninen, S. (2007): Matching in Local Labour Markets Empirical Studies from Finland. *Jyväskylä Studies in Business and Economics,* 56.

Hynninen, S., Kangasharju, A., Pehkonen, J. (2009): Matching inefficiencies, regional disparities and unemployment. *Government Institute for Economic Research,* VATT Working Papers 4/2009.

Ibourk, A., Maillard, B., Perelman, S. and Sneessens, H. (2004): Aggregate Matching Efficiency: A Stochastic Production Frontier Approach, France 1990-1994. *Empirica,* 31, 1-25.

Ilmakunnas, P. and Pesola, H. (2003): Regional Labour Market Matching Functions and Efficiency Analysis. *Labour*, 17(3), 413-437.

Kangasharju, A., Pehkonen, J. and Pekkala, S. (2005): Returns to scale in a matching model: evidence from disaggregated panel data. *Applied Economics,* 37, 115-118.

Kano, S. and Ohta, M. (2005): Estimating a matching function and regional matching efficiencies: Japanese panel data for 1973-1999. *Japan and the World Economy,* 17, 25-41.

Keynes, J. M. (1936): The General Theory of Employment, Interest and Money. *Macmillan and Co.*

Klinger, S. and Rothe, T. (2012): The impact of labour market reforms and economic performance on the matching of the short-term and the long-term unemployed. *Scottish Journal of Political Economy.* 59, 1.

Koskela, E. and Uusitalo, R. (2004): Unintended convergence – how Finnish unemployment reached the European level. *Bank of Finland discussion papers,* 2004(6).

Layard, R., Nickell, S. and Jackman, R. (2005): Macroeconomic Performance and the Labour Market. *Oxford University Press 2005.*

Lahtonen, J., (2006): Matching Heterogeneous Job Seekers and Vacancies. Empirical Studies Using Finnish Data. *Jyväskylä Studies in Business and Economics,* 50.

Lilien, D. M. (1982): Sectoral Shifts and Cyclical Unemployment. *Journal of Political Economy,* 90(4), 777-793.

Lubik, T. A. (2013): The Shifting and Twisting Beveridge Curve: An Aggregate Perspective. Working Paper. *The Federal Reserve Bank of Richmond,* 13-16.

Marthin, G. (2012): Measuring Mismatch in the Swedish Labour Market. *Rapport till Finanspolitiska rådet,* 2012/3.

Michaillat, P. (2012): Do Matching Frictions Explain Unemployment? Not in Bad Times. *American Economic Review,* 102(4), 1721-1750.

Mortensen, D. T. (1970): Job Search, the Duration of Unemployment, and the Phillips Curve. *The American Economic Review,* 60(5), 847-862.

Niemeläinen, J. (2014): Työmarkkinat muuttuvat – ovatko tilastot ajan tasalla? *BoF Online 12/2014.* Bank of Finland.

Orlandi, F. (2012): Structural unemployment and its determinants in the EU countries. *European Commission Economic Papers,* 455/2012.

Phillips, A. W. (1958): The Relation between Unemployment and the Rate of Change of Money Wage Rates in the United Kingdom, 1861-1957. *Economica, Vol.* 25, No. 100, 283-299.

Petrongolo, B. and Pissarides, C. A. (2001): Looking into the Black Box: A Survey of the Matching Function. *Journal of Economic Literature,* 39:390-431.

Pissarides, C. A. (1994): Search Unemployment with On-the-job Search. *The Review of Economic Studies,* 61(3), 457-475.

Pissarides, C. A. (2000): Equilibrium Unemployment Theory. Second edition. *Cambridge, MA: MIT Press.*

Reinhart, C. M. and Rogoff, K. S. (2009): The Aftermath of Financial Crises. *American Economic Review*, 99, 466–472.

Rodenburg, P. (2011): The remarkable transformation of the UV curve in economic theory. *The European Journal of the History of Economic Thought,* 18:1, 125-153.

Räisänen, H. (2014): Työvoiman hankinta toimipaikoissa 2013. *TEM-analyyseja,* 59/2014.

Sahin, A., Song, J., Topa, G. and Violante, G. L. (2014): Mismatch Unemployment. *American Economic Review.* 104(11), 3529–3564.

Schauman, H., and Vanhala, J. (2011): Beveridge-käyrä, kriisit ja työmarkkinoiden rakenteelliset muutokset Suomessa. *BoF Online,* 2/2011. Bank of Finland.

Shibata, I. (2013): Is Labor Market Mismatch a Big Deal in Japan? *IMF Working Paper*, 13/196.

Shimer, R. (2005): The Cyclical Behaviour of Equilibrium Unemployment and Vacancies. *American Economic Review,* 95, 25-49.

Shimer, R. (2007): Mismatch. *American Economic Review.* 97 (4), 1074-1103.

Soininen, H. (2006): Empirical Studies on Labour Market Matching. *Publications of the Swedish School of Economics and Business Administration*, 159.

Yashiv, E. (2000): The Determinants of Equilibrium Unemployment. *The American Economic Review.* 90, 1297-1322.

Yashiv, E. (2007): Labour search and matching in macroeconomics. *European Economic Review.* 51, 1859-1895.