The role of the short-term employed in the matching process before and after the crisis. Empirical evidence from the Netherlands.

Pablo de Pedraza, Kea Tijdens, Stefano Visintin
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© Pablo de Pedraza, Kea Tijdens, Stefano Visintin, Amsterdam
Contact: Pablo de Pedraza, pablodepedraza@usal.es
General contact: aias@uva.nl

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The role of the short-term employed in the matching process before and after the crisis:

Empirical evidence from the Netherlands

Pablo de Pedraza
Kea Tijdens

University of Amsterdam
Amsterdam Institute for Advanced labour Studies (AIAS)

Stefano Visintin

Universidad Camilo José Cela

WP 165
# Table of contents

Abstract ........................................................................................................... 5

1. Introduction ............................................................................................... 6

2. Theoretical framework and empirical bias ................................................. 9

3. Data ............................................................................................................ 14

4. The Dutch labour market .......................................................................... 17

5. Augmented matching functions: the role of employed people ............... 19

6. Matching functions using alternative measures of labour supply and demand pools ............................................................ 24

Conclusions .................................................................................................... 26

Figures and tables ......................................................................................... 28

References ..................................................................................................... 38
The role of the short-term employed in the matching process before and after the crisis

Abstract

This study uses data from 2001 to 2014 to explore the role of employed jobseekers in the Dutch labour market matching process, accounting for employed workers’ heterogeneities using employment spells. The elasticity of hires with respect to the short-term employed was significant, positive and countercyclical, while elasticities relating to new entrants were procyclical. The findings are at odds with the idea of mismatch and a shortage of skills. Search frictions for employers were lower after the crisis and vacancies were filled faster. In a loose labour market context with increasing short-term employment, employers increase their hiring of employed workers. The matching function displays constant returns to scale (CRTS) when using an alternative labour supply measure that includes the short-term employed as jobseekers. The theoretical implications concern the traditional CRTS assumption when using unemployment as a labour supply measure. In relation to policy implications, this points to the need for fiscal policies to fight unemployment.

JEL classification: J20-22-23, J60-63-64, E24

Keywords: matching function, Beveridge curve, matching efficiency, Great Recession
1. Introduction

The matching function (MF) distils the complex process by which jobseekers and vacancies generate new matches into a simple functional relationship. In its simplest form, it is a production function, where the unemployed and vacancies are inputs and worker-job matches are the output. However, concerns regarding whether the stock of unemployed people is an accurate labour supply measure have recently increased significantly (Barnichon and Figura 2014, Hall and Schulhofer-Wohl 2015, Sedlacek 2016, Van Ours 2015). The literature has shown that the traditional specification of the MF lost its ability to capture the number of hires during the crisis and the post-crisis slump. Using the stock of unemployed people as a proxy for the total pool of jobseekers and/or treating each labour market state (e.g. unemployed, employed and inactive) as homogenous may mask important differences and fluctuations, inaccurately measure the number of agents participating in the market and bias the estimated elasticities and conclusions regarding returns to scale and matching efficiency.

In this paper, we explore the role of employed jobseekers (Gerritsen and Hoj 2013, Kahn 2012) in the matching process before and after the Great Recession in the Netherlands. We deal with employment heterogeneity in terms of the length of time employed and find significant and countercyclical elasticities in hiring with respect to short-tenure employees. Our results are relevant from theoretical, empirical and policymaking points of view. They have implications for the meaning of returns to scale in the matching process, in the empirical definition of the pool of jobseekers, and for the support required to reduce unemployment, which is specifically related to appropriate fiscal policies (Diamond 2011).

The MF and the Beveridge curve (BC) are centrepieces in the theory of search and matching in the labour market. They are also complementary tools that have been extensively used in the empirical literature to study labour market dynamics and their relationship with the economic cycle. Studies of labour markets after the Great Recession have used both the MF and BC, focusing mainly on the US. Pissarides (2013), for example, used the BC to compare how micro and macro rigidities were related to policy changes in the UK, the US and Germany. In general, microeconomic rigidities were associated with higher trade union power, lower search efforts, lower labour mobility and the extension of unemployment benefits. Macroeconomic rigidities related to lower public expenditure and more depressed economies that are unable to generate new jobs. Efforts to improve the matching efficiency (e.g. the German employment matching services\(^1\)) shift the BC inwards, as they reduce search frictions. Outward shifts of the BC are often cited in support of mismatch but there may be other plausible explanations (Abraham 2015).

The literature exploring the MF in the US during the recent crisis developed around a debate about the causes of the decline in participation in the US labour market and the fact that an increase in vacancies since mid-2009 had not been accompanied by a substantial decrease in unemployment, which was considered in some of the literature to provide evidence of a mismatch. Barnichon and Figura (2014) showed how the US MF – specified as a function that relates new hires to the stocks of vacancies and unemployed people – overestimated the number of worker-job matches. In the US context of a decrease in matching efficiency and an increase in unemployment, when the quality

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\(^1\) See Dustman at al. (2014) for further explanations of the German experience, and Van Ours (2015) for a cross-country comparison of Great Recession labour market implications in 20 OECD countries, which shows that the best remedy for unemployment seems to be employment growth.
of the pool of unemployed people worsens (as indicated by the increase in long-term unemployment), the pool of unemployed jobseekers becomes less successful in their search, generating a lower outflow than expected. Barnichon and Figura concluded that the main reason behind MF failure is an increase in long-term unemployment.

Concerns about the post-crisis US MF are not only related to the changing characteristics of the unemployed. Veracierto (2011) evaluated the consequences of including non-participants and found that the results were quite sensitive to different specifications. Sedlacek (2016) showed that unless the numbers of unemployed and non-unemployed jobseekers (namely inactive and employed) are perfectly correlated over the business cycle, the omission of jobseekers from outside unemployment produces omitted variable bias when estimating the matching efficiency. One reason for ignoring non-unemployed jobseekers is the lack of high-quality data. While unemployed people, by definition, are searching for a job, only an unknown proportion of employed and inactive people are actively searching. Search intensities differ across and within each labour market state. Sedlacek (2016) used information on relative employment inflows from different labour market states in combination with data on total hires to determine the latent variables. Hall and Schulhofer-Wohl (2015) built upon Veracierto (2011) and categorized individuals into nine labour market states. They measured matching efficiency in the US and found that the outward shift in the BC in the post-crisis period was the result of pre-crisis trends and not due to a downward shift in matching efficiency. Abraham (2015) reviewed the empirical evidence available on skill mismatch and considered that the mismatch idea was at odds with it. It has also been emphasized that employability may depend on the state of the labour market, rather than skills (Diamond 2011, Abraham 2015).

The aim of this paper is to test whether the empirical evidence for the countries mentioned above also applies elsewhere. We study the particular case of the Dutch labour market from 2001 to 2014 using the total number of hires as the dependent variable throughout the paper. During the crisis, the Dutch labour market was characterized by a BC outward shift, stable participation rates, low vacancy levels and increasing unemployment, especially youth unemployment, accompanied by increasing matching efficiency.

We estimated a standard MF from 2001 to 2014 and observed that from 2001 to 2008, the stocks of vacancies and unemployed were effective in explaining the total number of hires. However, such a specification of the MF starts failing after 2008. For a short period between 2008 and 2010, it reproduces the US experience reported by Barnichon and Figura (2014), namely a decline in matching efficiency. After 2010, it shows a sharp increase in matching efficiency that is not accompanied by unemployment reductions. This contradicts the theoretical interpretation of BC outward shifts (Pissarides 2013, Dolado and Sanchez 1997) as due to lower matching efficiency and micro rigidity. We explore this contradiction, arguing that it arises from an MF misspecification: the BC only captures the unemployment-vacancy (UV) space, while the MF uses the total number of hires. The number of matches observed is higher than predicted by the MF but this does not reduce unemployment levels. Contrary to what occurred in the US, the quality of the pool of jobseekers may be ‘improved’ due, for example, to an increase in active employed jobseekers. This might explain why the matching process is more efficient in reducing unemployment.

As a result, we consider the problem to be related to an omitted variable (Sedlacek, 2016) and focus on the role of employed jobseekers. We built upon two stylized facts that have been shown
in the literature: the existence of transitions from employment to employment (Hall and Schulhofer-Wohl 2015) and different search intensities among employed people according to tenure (Gerritsen and Hoj 2013, Kahn 2012). In principle, short-term employed workers are more likely to be active jobseekers than long-term ones. We use the length of time employed to account for heterogeneity in employed people and used the short-term employed to proxy the proportion of employed workers actively searching.

We found that the elasticities in hiring with respect to short-tenure employment (less than 11 months) were clearly countercyclical and increased during bad times. We checked the robustness of our results by controlling for other labour market states and heterogeneities on both sides of the market. Rather than mismatch or shortage of skills (Rabobank 2015, Kahn 2015), we found that vacancies were filled faster after the crisis. This is in line with the idea that employability and qualification for a job may depend on the state of the labour market rather than skills (Diamond 2011, Abraham 2015). In our case study, employed workers, after the crisis, seem to be considered by the employers to be more attractive than the unemployed, and especially more attractive than new entrants into the labour market. Therefore, we tested alternative measures of labour supply and demand and re-estimated the MF, which became more stable over the business cycle and displayed constant returns to scale when short-term employees were included in the labour supply measure.

The remainder of the paper is structured as follows. In Section 2 we describe the BC and MF theoretical framework and the relevance of the specification of the MF to the estimation of elasticities and matching efficiency. In Section 3 we describe the data. In Section 4 we introduce the general characteristics of the Dutch labour market and of the shocks that affected it from 2001 to 2014 using the observable UV relationship and the standard specification of the MF. In Section 5 we estimate elasticities from the augmented MF and their values before and after the crisis. Based on the results, in Section 6 we estimate the MF using alternative definitions of labour supply and demand. We conclude with a discussion of the role of employed jobseekers, the existence of returns to scale and the policy implications.
2. Theoretical framework and empirical bias

In the theory of search and matching, unemployment is obtained from an equation that describes steady state unemployment; namely, a situation in which the unemployment level remains stable because the inflow into unemployment equals the outflow from unemployment. The Beveridge curve (BC) can be derived from it and represented as downward sloping and convex to the origin in the vacancy (v) unemployment (u) rates space (Figure 1). A negative change in the level of aggregate activity, such as the Great Recession, drives unemployment and vacancies in opposite directions, leading to a reduction in the number of vacancies posted and an increase in unemployment levels. This is reflected in counter-clockwise movements around the BC – from point A to point B in Figure 1 – following a bow-shaped trajectory below the BC. When the effects of the transitory negative shock cease and the economy experiences a positive aggregate activity shock, the number of vacancies posted increases and the unemployment level decreases, and the economy moves back from B to A. A change in the intensity of reallocation leads job creation and job destruction rates to move in the same direction and shift the BC away from the origin: both unemployment and vacancy rates increase and the economy moves from A to a point such as C.

BC shifts away from the origin may reflect larger degrees of separation, labour force growth rates or a decline in matching efficiency (Blanchard and Diamond 1989, 1990) between the unemployed and vacancies. Transitory aggregate activity shocks, especially if followed by stagnation or weak recovery and no job creation for a long period, may be a source of mismatch because they generate a pool of long-term unemployed workers. In addition, when the economy is still recovering, employers tend to search less intensively, hold out for better workers (Abraham 2015) and very often prefer those already employed rather than the unemployed. As a result, the economy does not return from B to A but moves, at best, to points such as D or D’, implying weaker matching efficiency, higher u for a given v and low job creation. The move from point B back to A does not take place because the economy does not experience a strong recovery and because the negative aggregate activity shock leaves behind a less efficient matching process. Although the flow into unemployment may recover (i.e. drop) and perhaps also the number of hires (i.e. increase), the outflow from unemployment will remain low for longer.

The modelling device used to capture the matching process is the matching function (MF). It is analogous to a production function with two inputs – the number of vacancies (V) and the number of unemployed people (U) – that produce an output – the total number of hires (H). The theoretical literature generally assumes a constant-returns-to-scale Cobb-Douglas functional form such as:

\[ H_t = \lambda U_{t-1}^\alpha V_{t-1}^\beta \]

where \( H \) refers to new hires in period \( t \); \( U \) to the stock of unemployed at the end of period \( t-1 \); \( V \) to the stock of vacancies at the end of period \( t-1 \); \( \lambda \) to the efficiency of the matching process that captures heterogeneities and frictions without making them explicit; \( \alpha_U \) to the elasticity of \( H \) with respect to \( U \) that measures the positive externality of \( U \) on \( V \); \( \alpha_U - 1 \) to the negative externality of \( U \) on \( U \) that captures the congestion in the labour market; \( \beta \) to the elasticity of \( H \) with respect to \( V \) that measures the positive externality of \( V \) on \( U \); and \( \beta - 1 \) to the nega-
tive externalities of $V$ on $V$. The constant-returns-to-scales assumption implies that $\alpha^U + \beta = 1$. Only constant returns to scale lead to a stable unemployment rate (Pissarides 1990).

Equation (1) very often indistinctly uses outflow from unemployment and total number of hires to measure job matches. Throughout this paper we examine this specification using total number of hires, which assumes that only the unemployed look for jobs, or at least that the stock of unemployed is a good measure of the total number of jobseekers. It is assumed to capture the complex process of producing new hires without the need to take into account non-unemployed jobseekers (i.e. employed and inactive individuals) or to make other labour market heterogeneities explicit. For many years, such a specification has led to good estimates in many countries (Petrongolo and Pissarides 2001) and provided a useful framework to analyse labour markets.

However, $\alpha^U$ as a measure of the elasticity of $H$ with respect to the total number of jobseekers is biased unless the numbers of unemployed and non-unemployed jobseekers are perfectly correlated over the business cycle (Sedlacek 2016). Elasticities may change over the business cycle, as do flows to employment from unemployment, inactivity or employment (Van Ours 2015). In other words, the omission of jobseekers from outside unemployment and the heterogeneities within each labour market state may produce omitted variable bias (Sedlacek 2016) and make conclusions regarding elasticities, returns to scale and matching efficiency unreliable.

We can augment (1) by including the stock of non-unemployed jobseekers ($X$) and by using $\alpha$ to denote elasticity with respect to the total number of jobseekers:

$$H_t = \lambda (U + X)^{\alpha_U} V^{\beta}$$

Van Ours (1999) identified the direction of the bias of $\alpha^U$ as a measure of $\alpha$ in the following way: $X$ is probably not independent of $U$ and we can assume that if unemployment rises, the growth in the number of non-unemployed jobseekers will probably be less than proportional. This assumption is based on two premises: employed workers are risk averse and will reduce their search activities in a growing unemployment context, and those outside the labour force will also reduce their search activities in a growing unemployment context because of the discouraged worker effect. Thus, relationship between $\alpha^U$ and $\alpha$ is:

$$\alpha^U = \left( \frac{\partial H}{\partial U} \right) \left( \frac{U}{H} \right) = \alpha \left( \frac{U}{U + X} \right) \left( 1 + \frac{\partial X}{\partial U} \right)$$

Moreover, the elasticity of the stock of non-unemployed (employed and inactive) jobseekers with respect to unemployment is:

$$\varepsilon^X_U = \left( \frac{\partial X}{\partial U} \right) \left( \frac{U}{X} \right)$$

2 Detailed explanations of the theory of search and matching can be found in Pissarides 2000, 2011 and 2012.
Thus:

\[ \alpha^U = \alpha \left( \frac{U + \varepsilon^U X}{U + X} \right) \]

If the increase in the stock of non-unemployed jobseekers is less than proportional to unemployment, \( \varepsilon^U < 1 \) and \( \alpha^U < \alpha \). When using total job matches (H), if the stock of non-unemployed jobseekers is ignored, \( \alpha^U \) underestimates \( \alpha \) as a measure of the elasticity of hires with respect to the total number of jobseekers.

Nevertheless, (2) relaxes the assumption that only unemployed people look for jobs, while still assuming that jobseekers are homogeneous. We may reconsider the two premises, taking into account the heterogeneities within X in the context of the Great Recession, where there was an increase in temporary jobs. The first premise – namely, that employed workers will reduce their search activities in a growing unemployment context – may be true among stable workers with long tenures and/or permanent contracts, but not among those with short tenures and/or temporary contracts. If the latter are risk averse, they will increase their search efforts as unemployment grows, looking for an alternative, more stable situation. This will hold in a situation where the layoff of temporary workers increases, since they experience a greater risk of losing their jobs, and when many short-term employees switch to permanent positions, because they are encouraged by this possibility. In addition, in a context of increasing numbers of temporary jobs, there may be a point when the increase in the stock of non-unemployed jobseekers is more than proportional to unemployment.

The second premise – that those outside the labour force will reduce their search activities in a growing unemployment context – may hold among new young entrants, who are discouraged by increasing levels of unemployment among the young, but may not hold for inactive women (out of the labour force) in families where the first earner is facing increasing job insecurity or job loss, or among new entrants who realize that those already employed, even for a short period of time, are more attractive to firms. In other words, the stock of non-unemployed jobseekers may be less than proportional to unemployment or not, but the fact that they are risk averse does not mean that they will reduce their search activities in a growing unemployment context. In fact, the elasticity of the stock of non-unemployed jobseekers with respect to unemployment, \( \varepsilon^X_U \), may vary among the three labour state groups – unemployed, employed and inactive – as well as within each of them and across time, as economic and labour market circumstances change. We can assume that \( \varepsilon^X_U \) differs among employed people depending on, for example, their type of contract, tenure, job insecurity and so on, and among inactive people depending on, for example, their age or family situation. Thus, we can think of X as a stock of non-unemployed jobseekers comprising stocks of types of employed and inactive workers \( (x_1, x_2, \ldots x_n) \), and rewrite (2) as:

\[ H_t = \lambda(U + (X = f(U, x_1) + f(U, x_2) + \ldots f(U, x_n)) t^{-1} V_{t-1}^\beta \]
Allowing the stocks of non-unemployed jobseekers to react differently to the stock of unemployed jobseekers and to other labour market circumstances (U) implies a vector of elasticities \( (\varepsilon_{U}^{x_1}, \varepsilon_{U}^{x_2}, \ldots, \varepsilon_{U}^{x_n}) \) that determines non-unemployed jobseekers’ search behaviour. The types of employed and inactive workers \( (x_1, x_2, \ldots, x_n) \) also differ in their attractiveness to firms and their chances of finding jobs; for example, employed workers are more attractive to firms than inactive and unemployed people. When the labour market is tight, firms have more incentive to hire workers who are not perfect matches than they would in periods of a loose labour market (Diamond 2011, Kahn 2015). As a result, the elasticities of H with respect to \( (x_1, x_2, \ldots, x_n) \) differ across stocks and change over the business cycle, and we can reformulate (2) as an augmented MF:

\[
H_t = \lambda U_{t-1}^{\alpha} \prod_{i=1}^{n} X_{i,t-1}^{\alpha_i} V_{t-1}^{\beta}
\]

Equation (4) may still suffer from misspecification problems because of heterogeneities within unemployment stocks and vacancies. These heterogeneities can be captured by assuming that agents on both sides operate differently depending on how long they have been in the market. In contrast to the standard ‘random matching function’, the ‘stock-flow’ matching approach (Coles and Petrongolo 2008, Coles and Smith 1998, 1994, Coles, Jones and Smith 2004) assumes that when a worker becomes unemployed, they observe the stock of vacancies and if they find a suitable match, they exit unemployment. If a suitable vacancy does not exist, in the subsequent periods, the worker does not look for a match in the stock of vacancies but in the inflow of new vacancies. This assumption is symmetrical for vacancies.

The stock of unmatched agents on one side of the market matches the inflow of new agents on the other side. This is relevant in the context of very low stock and flow of vacancies and growing stocks of jobseekers. In such a situation of a loose labour market and low economic activity, it is assumed that employers would reduce their search intensity and hold out for the better workers, while a growing stock of jobseekers, composed, for example, of short-term employed and unemployed, would be waiting for the flow of new vacancies. Employers would prefer to fill their positions with experienced and employed workers who are actively looking for another job, rather than with the unemployed. Among the unemployed, the long-term and the inexperienced would find it harder to find a job. Among vacancies, new ones would be filled quickly, given the low number of vacancies per jobseeker. Combined with \( (x_1, x_2, \ldots, x_n) \), we can consider different types of unemployed people \( (u_1, u_2, \ldots, u_n) \) and assume that the elasticities of H with respect to each type are different. The same would apply to vacancies \( (v_1, v_2, \ldots, v_n) \). The resulting augmented equation (4) is as follows:

\[
H_t = \lambda \prod_{i=1}^{n} U_{i,t-1}^{\alpha_i} \prod_{i=1}^{n} X_{i,t-1}^{\alpha_i} \prod_{i=1}^{n} V_{i,t-1}^{\beta_i}
\]

If (5) captures the matching process, the empirical estimates of (1) would suffer omitted variable bias. Bias direction would depend on how each labour market state reacts to unemployment levels and other economic and labour market circumstances and how heterogeneous they are. Some premises may hold during good times, some may hold during bad times (of increasing unemployment and employment instability). To summarize, in the context of the post-crisis slump, there are increasing concerns regarding biased outcomes when using specifications where the measure of job matches does not correspond to the measure of job searches (Van Ours 1999, Burgess 1993). A
specification using the total number of hires needs to take into account other labour market states, as well as heterogeneities on both sides of the market.

From (5) we obtain different elasticities of hires with respect to different types of unemployed people \((\alpha_{U1}, \alpha_{U2}, ..., \alpha_{Un})\), different types of non-unemployed jobseekers \((\alpha_{X1}, \alpha_{X2}, ..., \alpha_{Xn})\) and different types of vacancies \((\beta^1, \beta^2, ..., \beta^n)\). The constant-returns-to-scale assumption in (5) implies that:

\[
\sum_{i=1}^{n} \alpha^{U_i} + \sum_{i=1}^{n} \alpha^{I_i} + \sum_{i=1}^{n} \beta^{i} = 1
\]

This is a relevant economic policy issue (Cahuc 2014), as (6) may not lead to a stable unemployment rate (Pissarides 1990) because it accounts for non-unemployed jobseekers. Equation (6) does not reflect how an increase in unemployment generates outflow from it, but how the increase in the total pool of jobseekers generates hires. It is possible that in a loose labour market context, with low economic activity and increasing temporary jobs and employed jobseekers, employers mainly hire workers who are already employed. This would generate negative externalities for the unemployed.

The need to use a measure of matches that corresponds to the measure of jobseekers was reported in the literature (Burgess 1993) well before the crisis, but has not been taken into account very often to obtain more accurate measures of labour supply and demand: Jolivet (2009) being a notable exception. In the empirical estimations below, we will use estimations from (5) to remove misspecification errors, identify the role of the employed and take into account heterogeneities. In a second stage, we will build upon empirical versions of (5) to calculate alternative measures of labour supply (LS) and labour demand (LD), and estimate:

\[
H_i = \lambda LS^{\alpha}_{i-1} LD^{\beta}_{i-1}
\]

Where LS = \((x_1, x_2, ..., x_n) + (u_1, u_2, ..., u_n)\) and LD = \((v_1, v_2, ..., v_n)\) and from which, returning to the homogeneity assumption, we can obtain elasticities for the entire stock of jobseekers and empirical estimates of the matching efficiency in the labour market.
3. Data

In order to estimate the MF in its basic (1) and augmented specifications (5 and 7), we built a panel dataset matching quarterly data on the number of hires, vacancies, unemployed, inactive and employed people using the NACE classification of economic activities at letter codes level (N = 56*14 = 784). We followed an approach similar to that of Broersma and Van Ours (1999), who used data on six economic sectors covering the period 1989-1994. We combined data from three sources: the European Labour Force Survey (LFS), Statistics Netherlands (CBS) and the Dutch public Employee Insurance Agency (UWV).

We obtained our dependent variable, namely number of hires (H), from the LFS, where job hires are defined as employees who were employed in a reference week and had started working for their employer no more than three months earlier. The resulting data do not allow the identification of transition rates between labour market states. Therefore, we cannot identify whether those hired were unemployed, inactive or in other employment. There are no alternative data sources that would allow us to overcome this problem.

We also used European LFS data on unemployment. We assigned a sector to unemployed individuals according to the sector of their previous job, and assumed that an unemployed worker previously working in a specific sector would produce outflow in that sector. While the sectoral approach has been used in other literature (Broersma and Van Ours 1999, Sahin et al. 2015), it has been criticized because individuals frequently change industries and occupations (Abraham 2015). Nevertheless, it is also common in the literature to assume that each sector of activity is a labour market segment and that unemployed workers will search in a labour market segment in which they are more likely to find a job. Researchers have often used data at regional or district levels to overcome the lack of a long time series and to analyse specific conjunctures (Munich et al. 1997, Pedraza 2007). This assumes that an unemployed worker looking for a job is an additional input unit in the matching process of that region, which neglects mobility across regions. At the moment of writing, quarterly data on vacancies for the Netherlands are not available at the regional level. Only taking unemployed people with previous sector data into account means that unemployed people without previous jobs are omitted from the analysis (Broersma and Van Ours 1999). We will come back to this later. Finally, we used vacancy data from the CBS, which obtains data on the stock of vacancies for each period from employer surveys.

We used data from the LFS to measure the number of employed and to take into account their heterogeneities. The data allowed us to differentiate among employed people based on tenure spells. We differentiated between being employed for 3-5 months (E35m), 6-12 months (E612m), 1-2 years (E612m) and more than 2 years (E2y).

Although the employed was our target variable, we also went further in avoiding misspecification problems as much as possible, taking into account heterogeneities of unemployed people and those who were inactive, as well as vacancies. To take into account heterogeneities among the unemployed we used two strategies. First, we focused on unemployed people

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3 http://ec.europa.eu/eurostat/
4 http://www.cbs.nl/
5 http://www.uwv.nl/
6 That was the case, for example, in the literature focusing on the Czech Republic’s transition (Pedraza 2007).
without previous jobs and, therefore, without a sector. These are mainly new young entrants and women attempting to re-enter the labor force. In order to assign them to a sector, we assumed that each sector of activity is a labor market segment; that unemployed workers will search in a labor market segment in which they are more likely to find a job; and that the aggregated probabilities of unemployed workers without a previous sector finding a job in each specific sector equals employment in that sector as a proportion of total employment.7 We thus generated a category of unemployed people that we assumed to be a proxy for potential new entrants or re-entrants in each sector (Unewentrants).

\[ U_{\text{newentrants},t} = U_{u,t} \frac{E_{i,t}}{\sum_{j=1}^{n} E_{j,t}} \]

\( U_{u,t} \) being the total number of unemployed people in quarter \( t \) whose sector was unknown,8 and the number of employed people in sector \( i \) in quarter \( t \).

Second, we wanted to use the length of time people were unemployed to calculate additional stocks of the unemployed. However, at the quarterly and sectoral levels, the LFS sample size does not allow for reliable disaggregation of the unemployed into the flow of recently unemployed, the stock of unemployed, or into long- and short-term unemployed. We attempted to overcome this using data from the UWV. The UWV data make it possible to identify the flow of recently unemployed people with unemployment benefits. Literature on unemployment spells shows that jobseeking increases as the end of unemployment benefits approaches (Uusitalo and Verho 2010), and we can attempt to capture this. We have differentiated three different flows of unemployed people entering unemployment and receiving unemployment benefits within one quarter: those entering unemployment during the first month (\( UB\text{month1} \)), the second month (\( UB\text{month2} \)) or the third month (\( UB\text{month3} \)). We assume that, on average, those who entered unemployment during the first month will be closer to the benefit’s end.

Similarly, to the unemployed, we assigned a sector to inactive individuals using data on their previous sector. Thus, we only took into account inactive workers who had a previous job in a specific sector (I). This made it possible to include a measure of inactivity in our panel.

Finally, according to the stock-flow literature, the stock of vacancies and the flow of new jobs interact differently with the stock of jobseekers. CBS data differentiates between the stock (V) and flow of new vacancies (newV). In addition, in a changing and uncertain economic context, firms may post vacancies but then cancel them, which causes negative externalities for other vacancies and jobseekers. The CBS data also allowed us to identify vacancies that had been cancelled (cancelV) during a specific period.

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7 To the best of the authors’ knowledge, no attempt has been made to tackle this using sectoral data.
8 We include only the Eurostat category ‘not applicable’, which excludes the non-respondents to the question about sector of activity.
In summary, we defined a vector of unemployed jobseekers:

\[ (u_1, u_2, \ldots, u_n) = (U, \text{Newentrants}, UBmonth1, UBmonth2, UBmonth3) \]

a vector of non-unemployed:

\[ (x_1, x_2, \ldots, x_n) = (E35m, E612m, E12y, E12y, I) \]

and a vector of three different types of vacancies:

\[ (v_1, v_2, \ldots, v_n) = (V, \text{newV}, \text{cancelV}) \]

The dataset we built has advantages and disadvantages. Aggregating at the sectoral level has two advantages. First, it increases the number of observations, allowing the estimation of pre- and post-crisis MFs using similar sample sizes. It also allows us to: explore the role of the employed; include the three labour market states; and account for some heterogeneities on both sides of the labour market. Second, similar datasets using aggregated data that is directly available from Eurostat can be elaborated for other European countries, although variables defined using data from the CBS and the UWV would need specific national alternatives that, in some cases, may not be available. Nevertheless, the approach is not new. In the literature Sahin et al. (2013) and Broersma and Van Ours (1999) also use industry level data as an indication of the market an individual is operating in.

Our data, however, also have some limitations. As mentioned above, a sectoral approach has been criticized because individuals commonly change industries (Abraham 2015), yet we are assuming that an unemployed worker previously working in a specific sector will produce outflow in that sector. In order to include unemployed people without a sector in the analyses, we proceeded as explained above, but this may be a strong assumption. In addition to sectoral issues, our data do not allow us to distinguish between hires from unemployment and hires from employment. This implies that this paper does not directly contribute to the literature that distinguishes between job-finding and job-to-job transitions (Shimer 2005a, 2005b). While it was not possible to account for long-term unemployment, we were able to find alternatives to account for heterogeneities on both sides of the market and calculate parameters before and after the crisis.
4. The Dutch labour market

During the Great Recession, the Netherlands’ labour market was relatively stable compared to that of other EU countries (Gerritsen and Hoj 2013, ECB 2014). Nevertheless, unemployment grew from 2.8% at the end of 2008 to 7.5% at the beginning of 2014 (Figure 2); the youth unemployment rate was 12% in 2014, double its 2001 historical minimum; separation rates, measured as the ratio of recently unemployed people to total employment in the previous quarter, increased during the onset of the crisis (2008-2010) recovering slightly during the second part (2012-2013), but had not returned to pre-crisis levels in 2014 (ECB 2014). At the same time, employment rates remained stable and even increased during the onset of the crisis (Figure 3), unlike the US and southern Europe. During the initial stage of the crisis, employment with tenure shorter than one year decreased, but sharply increased afterwards; the proportion of tenures longer than two years increased throughout the crisis; and tenures of between one and two years remained stable (Figure 4). In our analyses of the MF, we focus on the Dutch case rather than generalize conclusions or make a comparison to the EU or US.

The BC is called the UV relationship when referring to the observable levels of unemployment and vacancies, which are often represented by a scatter plot. Quarterly unemployment and vacancy rates from 2001 to 2014 (56 observations) are reported in Figure 5. Based on the theoretical explanations above (Figure 1), we can observe a negative aggregate activity shock taking place between 2001 and 2003, followed by a reallocation shock between 2003 and 2005. The effect of these shocks resulted in an increase in unemployment from 2.1% (2001Q3) to 5.3% (2005Q1). The period between 2005 and 2008 is characterized by a positive shock that moved unemployment and vacancies in opposite directions, increasing vacancy rates and decreasing unemployment levels to 2.6% (2008Q3). For the period between 2008 and 2013, during the Great Recession, the Dutch economy exhibited macroeconomic rigidity – namely a lack of new jobs and very low vacancy rates – as well as microeconomic rigidity, that is, jobs were not being taken up by the unemployed, as in the past, implying a more than doubled unemployment rate with respect to the 2002 rate (with a similar vacancy rate). At the microeconomic level, there was a recovery during the second half of 2014, as unemployment decreased, while vacancies remained at low levels.

In principle, the microeconomic rigidity observed should be caused by mismatch/hysteresis that increases with long-term unemployment (Figure 6). Such a situation is supposed to be accompanied by a reduction in matching efficiency on the labour market, which could be tackled by labour market policies such as incentives to work and a reduction in unemployment benefits, or with active labour market policies aimed at increasing employment probabilities for the long-term unemployed. An alternative explanation is that employers are less active in filling their job openings with the unemployed while experienced candidates are available. In this case, fiscal policy may be an alternative, as the aggregate demand may increase labour market tightness, which would, in principle, be an incentive for firms to hire the unemployed, even if they are not the perfect match (Diamond 2011, Abraham 2015).
The first column of Table 1 shows the results of estimating (1), assuming that the number of hires in period \( t \) is a function of the number of vacancies at the end of period \( t-1 \) and the stock of unemployed in \( t-1 \). We refer to the linearized version of (1) as the benchmark matching function MF0:

\[
\ln H_{t,t} = \ln \lambda + \alpha \ln U_{t,t-1} + \beta \ln V_{t,t-1} + v_{t,t}
\]

The estimated parameters (first column of Table 1) are significant and reflect decreasing returns to scale (\( \alpha + \beta < 1 \)). Using estimates from MF0, we calculated matching efficiency: \( \lambda \) (in logs) reported in Figure 7. According to these results, matching efficiency decreased appreciably in 2008 and 2009, and increased after 2010. This result apparently contradicts the BC movements observed in Figure 5 that would lead to the conclusion of decreasing matching efficiency during the same period.

Barnichon and Figura (2014) demonstrated how the US MF failed, with the number of observed hires being lower than predicted by the MF. In the US context, with decreasing matching efficiency and increasing unemployment, they hypothesized that as the average quality of the pool of unemployed worsens, the observed outflow should be lower than expected. In the Dutch context, which is characterized by increasing long-term unemployment and increasing matching efficiency, the causes of the latter are very unlikely to be found in the composition of the unemployed pool. Rather than changes in the unemployment pool, MF0 estimates might reflect the failure of the assumption that unemployed workers are a good proxy for the whole pool of jobseekers, especially during the post-crisis slump. Another factor related to other labour market states, such as an increase in employees actively looking for another job, may be playing a role here. This is the reason why this paper focuses on the role of the employed.

Figure 8 reports MF0 errors calculated as the observed number of hires minus the number of hires predicted by MF0 estimates. It shows how the explanatory power of the conventional matching function fails after the recession. From 2001 to 2009, MF0 is remarkably stable and performs well in explaining the observed total hires. However, during a short period of time at the end of 2009, MF0 overestimates the number of hires, while from 2010 on, the number of observed hires turns out to be much higher than predicted: the MF systematically underestimates the number of new hires in the Netherlands from 2010 on. From an econometric point of view, omitted variables bias might have occurred, suggesting that there may be a pool of jobseekers, not included in MF0, whose ability to generate hires improves the matching process, and whose elasticities to hires changes over the cycle. In the following section, we will explore this possibility by augmenting the specification of the matching function and estimating different versions of (5). We will explore to what extent employed jobseekers, more specifically, short-tenure employees, play a role.
5. Augmented matching functions: the role of employed people

In the previous section, we showed that for two quarters after the onset of the crisis, the Dutch MF overestimated matches: the number of hires observed was slightly lower than predicted by the matching function. From 2010 to 2014, however, the MF systematically underestimated hires: the number of hires observed was greater than predicted. Similarly, to the US context, the standard MF is not a good approximation of the labour market matching process; however, the reasons for overestimation and underestimation are different. The reasons for overestimation of outflow are mainly to be found in changes that worsen the unemployed pool (indicated by an increase in long-term unemployment) (Barnichon and Figura 2014), while underestimation in the context of increasing long-term unemployment cannot be the consequence of changes that worsen the quality of the jobseekers’ pool. Therefore, we explore whether the sharp increase in employed people with short tenures, which ‘improves’ the jobseeker pool, is behind these results.

For that purpose, we estimated three different versions of MF (5). M.F5.1 includes the number of employed and inactive people as explanatory variables without controlling for their heterogeneities. M.F5.2 accounts for heterogeneities within employed people, while M.F5.3 and M.F5.4 control for other heterogeneities in the unemployment pool and the labour demand side. Each specification was based on the literature and existing evidence. We estimated each version for the entire period as well as before and after 2008. Table 1 reports the results for the entire period, and Table 2 differentiates between the periods before and after the crisis in 2008.

The literature has shown that both employed (Hall and Schulhofer-Wohl 2015) and inactive (Veracierto 2011) individuals play a role in the matching process. MF5.1 augments MF0 by including employed workers and inactive people who have had a previous job in a specific sector.

\[ \ln H_{i,t} = \ln \lambda + \alpha \ln U_{i,t-1} + \beta \ln V_{i,t-1} + \alpha_i \ln I_{i,t} + \alpha_k \ln E_{i,t} + \nu_{i,t} \]  

(MF5.1)

Both variables are significant and have a positive impact on the number of hires when we estimate MF5.1 for the entire period (Table 1). After the crisis (Table 2), the elasticity with respect to employment is three times higher than before, while with respect to the stock of inactive people it is zero. Thus, we can conclude that the role of the employed in the matching process changed after the crisis, becoming more relevant. Search efforts and reemployment probabilities are not homogenous across employed workers, therefore, treating each labour market state as homogenous may mask important differences and fluctuations. However, the proportion of employed people actively searching is unknown. Thus, we cannot identify search intensity and eligibility for another job, but we can assume that the length of time employed affects search behaviour. Workers with longer tenures and permanent contracts are better protected, have higher severance rights, and are less likely to be fired or leave their jobs and, therefore, be active jobseekers. In the case of the Netherlands, different search attitudes, mainly due to job tenure spells (Gerritsen and Hoj 2013), have been identified among employed workers (Kahn 2012): the longer workers have been employed, the lower their search intensity. Our data is able to capture this heterogeneity and
MF5.2 controls for it, distinguishing between employed people who have been employed for 3-5 months (E35m), 6-11 months (E611m), 1-2 years (E12y) and more than 2 years (E2y).

\[
\begin{align*}
\ln H_{i,t} &= \ln \lambda + \alpha \ln U_{i,t-1} + \beta \ln V_{i,t-1} \\
&+ \alpha_{E35m} \ln E35m_{i,t} + \alpha_{E611m} \ln E611m_{i,t} \\
&+ \alpha_{E12y} \ln E12y_{i,t} + \alpha_{E2y} \ln E2y_{i,t} + \nu_{i,t}
\end{align*}
\]

(MF5.2)

Each pool of employed people has a different impact on hires: the longer the employment tenure, the lower the elasticity to hires (Table 1). The elasticity with respect to the pool of employed people with tenures shorter than 11 months is significant and positive. As shown in Table 2, the estimated elasticities of hires with respect to the stock of workers employed for less than 5 months are countercyclical: the estimated value after 2008 (\(\alpha_{E35m} = 0.469\)) is almost twice the estimated value for the pre-crisis period (\(\alpha_{E35m} = 0.240\)). Similarly, elasticity with respect to the stock of employed workers with tenure of 6-11 months is zero before the crisis but has positive and significant values after 2008 (\(\alpha_{E611m} = 0.166\)). Elasticities with respect to hires of these two types of employed people are higher during times of growing unemployment. Thus, short-term employed people are active jobseekers, especially after a crisis. Of the premises described in Section 2 above, those supporting an increase in the elasticities of employment are confirmed for short-term employed people. There are also some results pointing to negative externalities for employed workers with long tenures.

Specifications MF5.3 and 5.4 augment 5.2 by accounting for other heterogeneities on both sides of the labour market. In this way, we attempted to minimize misspecification problems and test whether the 5.2 results are consistent across specifications. First, according to stock-flow matching, new flows of vacancies interact with the market differently from the stocks (Coles and Petrongolo 2008). In particular, flows and stocks in the labour market are affected differently by shocks (Dixon, Lim and van Ours 2015). In addition, some vacancies may be posted but later cancelled, which may display negative externalities in the matching process. MF5.3 controls for flow of new vacancies in period t, its lagged value (t-1) and for vacancies that are cancelled during t.

Second, thus far, we have been using vacancy, employed, inactive and unemployed individuals by quarter and sector of activity, and for unemployed and inactive individuals, we have also been using the previous job’s sector. This approach (Broersma and Van Ours 1999, Sahin et al. 2015) excludes unemployed people without previous jobs from the analyses – mainly new young entrants and women attempting to re-join the labour force. To include them as an input in the matching function, we assigned them a sector (as explained in the data section). We consider these numbers to be a proxy of new entrants to the labour market.
The role of the short-term employed in the matching process before and after the crisis

MF5.3

\[ \ln H_{i,j} = \ln \lambda + \alpha \ln U_{i,j-1} + \beta \ln V_{i,j-1} \]
\[ + \alpha_1 \ln I_{i,t} \]
\[ + \alpha_{Unew} \ln Unewents_{i,t} \]
\[ + \alpha_{E35m} \ln E35m_{t,j} + \alpha_{E611m} \ln E611m_{t,j} + \alpha_{E12} \ln E12y_{i,t,j} + \alpha_{E2} \ln E2y_{i,t,j} \]
\[ + \beta_{new} \ln newV_{i,t,j} + \beta_{new-1} \ln newV_{i,t-1} \]
\[ - \beta_{cancel} \ln cancelV_{i,t,j} + v_{i,t} \]

Previous conclusions regarding the role of the employed are consistent with our 5.3 specification. There are some additional results that are worthy of note. Current and lagged numbers of new vacancies have a significant and positive impact on hires. Once the effects of new and cancelled vacancies are taken into account, the stock of vacancies is no longer significant. Before the crisis, only the lagged numbers of new vacancies were significant. After the crisis, new vacancies display positive elasticities in the same quarter they are posted (see Table 2). Vacancies are filled at a faster pace during the crisis. This result is at odds with the mismatch hypothesis and the idea of firms having difficulties in filling their job openings. The inclusion of cancelled vacancies captures the negative impact generated in the market by vacancies that are posted and then cancelled. Many jobseekers may waste search resources in applying for cancelled vacancies. This impact was much more significant and stronger after the crisis.

The elasticity of hires with respect to our measure of new entrants was positive, significant and procyclical: it was much higher before the crisis \( \alpha_{Unew} = 0.934 \) than after \( \alpha_{Unew} = 0.419 \). In principle, it should be harder to enter the market during the crisis. Our results may reflect the source of increasing youth unemployment. However, given the strong assumptions that we relied on to generate the new entrants’ variable, we should treat this with caution.

It is also worth mentioning that MF0 \( R^2 \) is 0.92 when estimating the pre-crisis period and only 0.87 for the post-crisis period. In MF5.3, the \( R^2 \) values are closer, at 0.94 and 0.96, respectively. Thus, accounting for heterogeneities in the labour market makes the MF more stable over the business cycle.

MF5.4 attempts to control for more heterogeneities in the pool of unemployed people. In principle, search intensity should increase as the end of unemployment benefits approaches (Uusitalo and Verho 2010). As is the case with vacancies, recently unemployed people behave differently from the stock of unemployed people. Thus, MF5.4 includes the number of recently unemployed people in period \( t \) with unemployment benefits. It differentiates between three pools of unemployed people in quarter \( t \) according to whether they became unemployed in the first month (UBmonth1), the second month (UBmonth2) or the third month (UBmonth3) of the quarter. In general, those who became unemployed in the first month would be closer to the end of the period of unemployment benefits and thus should be more actively searching, and therefore displaying higher elasticities.
Pablo de Pedraza, Kea Tijdens, Stefano Visintin (2016)

\[
\ln H_{i,t} = \ln \lambda + \alpha \ln U_{i,t-1} + \beta \ln V_{i,t-1} \\
+ \alpha_I \ln I_{i,t} \\
+ \alpha_{\text{Unnew}} \ln \text{Unnewentrants}_{i,t} \\
+ \alpha_{U\text{month}1} \ln UBmonth1_{i,t} + \alpha_{U\text{month}2} \ln UBmonth2_{i,t} + \alpha_{U\text{month}3} \ln UBmonth3_{i,t} \\
+ \alpha_{E35m} \ln E35m_{i,t} + \alpha_{E611m} \ln E611m_{i,t} + \alpha_{E12y} \ln E12y_{i,t} + \alpha_{E2y} \ln E2y_{i,t} \\
+ \beta_{\text{new}} \ln \text{newV}_{i,t} + \beta_{\text{newt-1}} \ln \text{newV}_{i,t-1} \\
- \beta_{\text{cancel}} \ln \text{cancelV}_{i,t} + v_{i,t}
\]

(MF5.4)

The conclusions regarding the role of the employed are consistent with the 5.4 specification.\(^9\) The elasticity of \(H\) with respect to recently unemployed workers (receiving unemployment benefits) in the first month of the quarter is positive and significant, while it is negative in the second month and zero in the third. This pattern changes when we distinguish between the pre- and post-crisis periods. It is difficult to draw further conclusions from 5.4 regarding the search efforts of the three groups. This would need further exploration but is beyond the scope of this paper.

It is important to note that the estimated parameters for the stocks of vacancies did not capture any effect once new vacancies were taken into account, and the estimated elasticity of unemployment, although significant in every specification, decreased as we introduced more variables: the estimated value moved from \(\alpha_U = 0.2\) in MF0 to \(\alpha_U = 0.076\) in MF5.4. The elasticity of \(H\) with respect to \(U\) was overestimated in MF0.

Although MF5.3 and MF5.4 allowed us to explore the composition of the unemployment pool, our data limitation implies that our estimations are better at identifying the sources of errors arising from the role of the employed population in the matching process.\(^{10}\) Our estimations should improve MF performance when the matching efficiency of the labour market increases after 2009. Figures 9-11 compare MF0 errors (Figure 8) with errors from MF5.1 to MF5.3 The inclusion of the new explanatory variables improved MF performance, especially when employment tenure was taken into consideration.

We can summarize our conclusions as follows. Elasticities of hires with respect to short-tenure employment (less than 11 months and especially less than 5 months) are clearly countercyclical and increase during bad times in all specifications. In the context of increasing job instability and temporary employment, the short-term employed increase their search intensity, aiming for a more stable situation. In the Dutch post-crisis labour market, elasticity with respect to our measure of new entrants was half what it was before the crisis, and elasticity with respect to the short-term employed was almost double. The stocks of people employed between one and two years were completely acyclical. Elasticities with respect to inactive people and new entrants were clearly procyclical: they were much lower after the onset of the crisis. This explains the mechanisms

\(^9\) The sectoral classification used by the UWV differs from that used by the Labour Force Survey. Therefore, MF5.4 was calculated after recoding both classifications, which implied a reduction in the number of observations. Estimations of 5.1 to 5.3 using this sample do not differ greatly with respect to what is reported.

\(^{10}\) LFS do not make it possible to infer the number of LTU per quarter and sector. According to Eurostat, at such aggregation levels it would not be reliable to infer population numbers from the LFS sample. This would have allowed the impact of the quality of the unemployment pool to be thoroughly explored, and probably improve estimates for the period when the matching efficiency dropped.
behind the combination of increasing matching efficiency with outward movement of the BC and increasing unemployment. An increase in the number of employed jobseekers ‘improves’ the pool of jobseekers and matching efficiency but does not reduce unemployment.

From the labour demand point of view, matching frictions are lower after the crisis. New vacancies and the lagged value of new vacancies play different roles before and after the crisis; after the crisis, new vacancies display positive externalities in the matching process more rapidly than before the crisis. Vacancies are quickly filled by workers who have been waiting for something suitable in the market or have changed jobs. The employability of those already employed is higher and employers prefer employed candidates. The traditional MF could not capture the complex process of producing new hires: the stocks of unemployed and vacancies were not good proxies for labour supply and demand during and after the Great Recession. Heterogeneities on both sides of the market must be considered. In the following section, we take into account these results to re-estimate MF0 using alternative measures of labour supply (LS) and labour demand (LD) to calculate (7) and efficiently estimate \( \lambda \), the efficiency parameter of the matching process in the labour market.
6. Matching functions using alternative measures of labour supply and demand pools

MF0 is the typical form assumed for the MF; however, as shown in the previous section, unemployed workers are not the only jobseekers, and the stock of vacancies is not an accurate measure of labour demand. In this section, we explore alternative measures of labour supply and demand taking into account the above results. An alternative approach to the typical MF was followed by Jolivet (2009), who used US data to build different indicators of labour supply to include the employed and individuals outside the labour market as jobseekers, weighted by transition parameters aimed at capturing the search effort. We used the results reported in the previous section to include types of employed people, unemployed people and vacancies, and estimated (7) using a linearized version:

\[
\ln H_{i,j} = \ln \lambda + \alpha_{LS} \ln LS_{i,j} + \beta_{LD} \ln LD_{i,j} + v_{i,j}
\]

For labour supply (LS) we considered the following function, which maps a vector of binary variables \((u, e < 11, ue, i)\).

\[
LS(u, e < 11, ue, i, newub) = \\
u \cdot U_{i,j-1} + \\
e < 11 \cdot (E35m_{i,j} + E611m_{i,j}) + \\
ue \cdot Unewentrants_{i,j} + \\
i \cdot I_{i,j} + \\
newub \cdot UBmonth_{i,j}
\]

Depending on whether the binary variables have a value of 1 or 0, we have alternative definitions of labour supply. We also considered this vector for labour demand \((v, vc, vnew, lvnew)\).

\[
LD(v, vc, vnew, lvnew) = \\
v \cdot V_{i,j-1} - \\
v \cdot cancelV_{i,j} + \\
vnew \cdot V_{i,j} + \\
lvnew \cdot newV_{i,j-1}
\]

The traditional benchmark matching function, MF0, is a special case, where \(LS(u, e < 11, ue, i, newub) = (1, 0, 0, 0)\) and \(LD(v, vc, vnew, lvnew) = (1, 0, 0, 0)\) and only the stocks of unemployed workers and vacancies are considered as LS and LD measures, respectively. Table 3 reports the results for the entire period of study, while Table 4 differentiates between the period before and the period after the onset of the crisis. The columns in both tables are organized by first adding components to LS and then adding components to LD.
The inclusion of employed people with less than 11 month's tenure (Column 2) increases $R^2$ (from 0.862 to 0.903) but reduces the estimated parameter and significance of the stock of vacancies. Adding new entrants and inactive people (Columns 3 and 4) does not increase elasticities with respect to LS, but does increase the significance of LD, although it reflects a much lower elasticity than in MF0 ($\beta_{LD} = .614$ vs $\beta_{LD} = .138$). Removing cancelled vacancies does not change the picture significantly, but including the flow of new vacancies and its lagged value increases the coefficient $\beta_{LD}$. All of the estimates in Columns 4-7 display constant returns to scale.

Figures 12-17 show the estimated matching efficiency for each of the above calculations. They all have the same shape as MF0, but the inclusion of employed people with short tenures captures the lesser reduction of the estimated matching efficiency at the beginning of the crisis. Efficiency returns to MF0 values when inactive people and new entrants are included in the measure of LS. All of the specifications lead to a sharp increase in matching efficiency after 2010:1, but in all of them it remains lower than in MF0.

Table 4 shows the same estimate when differentiating between before and after the onset of the crisis. With respect to Columns 1-4, similar conclusions are obtained for both periods, namely that, in general, the elasticity with respect to LS was higher during the post-crisis slump. The inclusion of additional measures of LD increases the coefficient $\beta_{LD}$ especially after the crisis (i.e. from $\beta_{LD} = .176$ to $\beta_{LD} = .296$ during the pre-crisis period, and from $\beta_{LD} = .089$ to $\beta_{LD} = .353$ during the post-crisis period). $R^2$ values are always slightly higher before the crisis. Estimated elasticities using definitions $LS(u, e < 11, ue, i, newub) = (1, 1, 1, 1)$ and $LD(v, vc, vnew, lvnew) = (1, 1, 1, 0)$ are acyclical and the estimated elasticities for both periods are very similar. This demonstrates that this definition of LS and LD is more stable over the business cycle than the traditional definition based only on the unemployed and vacancy rates.
Conclusions

Using the Beveridge curve (BC) and the traditional specification of the Matching Function (MF) to study the Dutch post-crisis labour market matching process leads to an apparent contradiction: an outward shift of the BC is accompanied by increasing matching efficiency. However, the failure of the standard MF in predicting worker-job matches in the US and in the Netherlands are different in nature: due to declining matching efficiency throughout the crisis in the former, and an initial decline followed by a sharp increase in the latter. In the Dutch case, the traditional specification (MF0) performs well when explaining the total number of hires from 2001 to 2007; however, it fails afterwards. The initial decline in matching efficiency, which can be expected in the context of increasing unemployment and long-term unemployment, was followed by a sharp increase which was not accompanied by decreasing unemployment. We have explored this issue as a misspecification of the MF – as an omitted variable problem related to the role of employed workers and their heterogeneities. Our dataset, a sectoral panel that covers the period 2001-2014, allowed us to account for the role of employed jobseekers and their heterogeneities using tenure time. We also accounted for other heterogeneities in the unemployed pool of jobseekers and labour market vacancies and used these results to re-estimate the MF using alternative labour supply and demand measures. Below, we present our conclusions and their implications.

First, short-term employed people were active jobseekers, which is especially apparent in the post-crisis period. In a distressed labour market, short-term temporary workers increase their search intensity and employers find them more attractive than unemployed candidates. As a result, the elasticity of hires with respect to short-term employed people was significant, positive and countercyclical. However, employed workers with tenures of one year or more are, in general, not active jobseekers. Indeed, elasticities for people employed for more than one year were acyclical.

Second, the elasticities with respect to the stock of unemployed people were not constant across stocks of unemployed people: while elasticity for the stock of unemployed people with previous work experience was slightly countercyclical, the role of new entrants (measured using unemployed without previous sector) into the labour force was procyclical, and elasticity after the crisis was half of what was before the crisis. This helps to explain the growth of the youth unemployment rate during the period observed, as it seems more difficult to enter the market during the crisis and compete with employed jobseekers.

Third, before the crisis, the elasticity of hires with respect to vacancies was dominated by the lagged flow of new vacancies. After the crisis, elasticity was dominated by the current flow of new vacancies. Thus, additional vacancies generate hires at a faster rate after the crisis. Growing unemployment and active employed jobseekers generate a stock of workers waiting for suitable vacancies to appear on the market, reducing search frictions for employers. Employers react as expected during loose labour market periods: hiring employed rather than unemployed workers (Diamond 2011).

Fourth, the combination of countercyclical elasticities with respect to short-term employees and procyclical elasticities with respect to the stock of unemployed people explains the combination of growing unemployment and increasing matching efficiency in MF0 using the total number of hires and suffering from the omitted variables bias. This is an important result, as it implies the need to obtain more accurate measures of labour supply and demand. We explored this possibility
using our results and re-estimated the matching function. While constant returns to scale in (1) are generally assumed in the theoretical literature, we only accepted this after taking non-unemployed jobseekers into account. If the numbers of jobseekers and vacancies increase, the number of matches will increase proportionally. However, this result does not imply that if the numbers of vacancies and unemployed people increase, the outflow from unemployment will increase proportionally. The existence of constant returns to scale in the matching process for the total number of hires does not reflect how unemployment growth generates exits from it. In fact, a matching process where employed jobseekers increase their search intensity, may increase matching efficiency but generate negative externalities for unemployed people, especially for potential new entrants to the labour market. In our case, constant returns to scale, implying stable unemployment, could not be calculated under the assumption that the total number of hires captures the outflow from unemployment.

Putting the pieces together we can discern an important policy implication: if the hiring attitudes of employers change over the cycle as labour market tightness changes, monetary and fiscal policies may reduce unemployment. In the context of tighter labour markets, where macro rigidities are reduced and labour market tightness increases, employers may consider unemployed youth more employable. This is in line with Diamond (2011), Abraham (2015) and Kahn (2015), and does not reflect mismatch as a source of structural unemployment. Thus, it appears that monetary and fiscal policies may alleviate youth unemployment.
Figures and tables

Figure 2: Unemployment rate in the Netherlands (%)

Source: Eurostat Labour Force Survey

Figure 3: Employment rate in the Netherlands (%)

Source: Eurostat Labour Force Survey
The role of the short-term employed in the matching process before and after the crisis

**Figure 4**: Relevant variables as proportion of total labour force + inactive (employed + unemployed with sector + unemployed without sector + inactive)

Source: Eurostat Labour Force Survey

**Figure 5**: Observable levels of unemployment and vacancy rates

Source: Eurostat Labour Force Survey
Figure 6: Long-term unemployment as proportion of active population

Source: Eurostat Labour Force Survey

Figure 7: Matching Efficiency, Log residual

Source: Authors’ calculations from Eurostat and Statistics Netherlands (CBS)
Figure 8: Observed-predicted number of hires MF0

Source: Authors’ calculations from Eurostat and Statistics Netherlands (CBS)

Figure 9: MF0 errors vs MF5.1

Source: Authors’ calculations from Eurostat and Statistics Netherlands (CBS)
Figure 10: MF0 errors vs MF5.2

Source: Authors’ calculations from Eurostat and Statistics Netherlands (CBS)

Figure 11: MF0 errors vs MF5.3

Source: Authors’ calculations from Eurostat and Statistics Netherlands (CBS)
Figures 12 to 17: Matching efficiency estimates using alternative LS & LD definitions

Source: Authors’ calculations from Eurostat and Statistics Netherlands (CBS)
Table 1. Traditional (MFO) and augmented (MF5.1 to MF5.4) matching functions 2001-2014

<table>
<thead>
<tr>
<th></th>
<th>MFO</th>
<th>MF5.1</th>
<th>MF5.2</th>
<th>MF5.3</th>
<th>MF5.4</th>
</tr>
</thead>
<tbody>
<tr>
<td>lnV_{i,t}</td>
<td>0.614***</td>
<td>0.313***</td>
<td>0.029</td>
<td>-0.014</td>
<td>-0.011</td>
</tr>
<tr>
<td></td>
<td>(0.038)</td>
<td>(0.040)</td>
<td>(0.031)</td>
<td>(0.041)</td>
<td>(0.05)</td>
</tr>
<tr>
<td>ln newV_{i,t}</td>
<td>0.060</td>
<td>0.186***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.051)</td>
<td>(0.058)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln newV_{i,t-1}</td>
<td>0.205***</td>
<td>0.064</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.057)</td>
<td>(0.066)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln U_{i,t}</td>
<td>0.200***</td>
<td>0.101***</td>
<td>0.098***</td>
<td>0.069***</td>
<td>0.046*</td>
</tr>
<tr>
<td></td>
<td>(0.030)</td>
<td>(0.031)</td>
<td>(0.025)</td>
<td>(0.024)</td>
<td>(0.027)</td>
</tr>
<tr>
<td>ln E_{i,t}</td>
<td>0.465***</td>
<td></td>
<td></td>
<td></td>
<td></td>
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<tr>
<td></td>
<td>(0.068)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln E35m_{i,t}</td>
<td>0.377***</td>
<td>0.315***</td>
<td>0.333***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.035)</td>
<td>(0.034)</td>
<td>(0.042)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln E61 lm_{i,t}</td>
<td>0.195***</td>
<td>0.142***</td>
<td>0.218***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.055)</td>
<td>(0.054)</td>
<td>(0.064)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln E12y_{i,t}</td>
<td>0.154**</td>
<td>0.075</td>
<td>-0.001</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.064)</td>
<td>(0.062)</td>
<td>(0.071)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln E2y_{i,t}</td>
<td>-0.123***</td>
<td>-0.405***</td>
<td>-0.294***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.033)</td>
<td>(0.076)</td>
<td>(0.081)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln I_{i,t}</td>
<td>0.156***</td>
<td>0.227***</td>
<td>0.077*</td>
<td>0.059</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.050)</td>
<td>(0.036)</td>
<td>(0.039)</td>
<td>(0.046)</td>
<td></td>
</tr>
<tr>
<td>ln cancelV_{i,t}</td>
<td>-0.098***</td>
<td>-0.065**</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.023)</td>
<td>(0.025)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln Unewentrants_{i,t}</td>
<td>0.547***</td>
<td>0.396***</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.110)</td>
<td>(0.117)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln UBmonth1_{i,t}</td>
<td>0.071*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.037)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln UBmonth2_{i,t}</td>
<td>-0.100*</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.053)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln UBmonth3_{i,t}</td>
<td>0.029</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.042)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>3.294***</td>
<td>-0.740</td>
<td>1.474***</td>
<td>2.141***</td>
<td>2.248***</td>
</tr>
<tr>
<td></td>
<td>(0.320)</td>
<td>(0.455)</td>
<td>(0.211)</td>
<td>(0.295)</td>
<td>(0.349)</td>
</tr>
<tr>
<td>Observations</td>
<td>714</td>
<td>714</td>
<td>712</td>
<td>712</td>
<td>579*</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.862</td>
<td>0.882</td>
<td>0.928</td>
<td>0.936</td>
<td>0.938</td>
</tr>
<tr>
<td>ll</td>
<td>140.8003</td>
<td>-98.3226</td>
<td>-24.7771</td>
<td>18.2738</td>
<td>54.0726</td>
</tr>
</tbody>
</table>

Source: elaborated with data from LFS, CBS and UWV. Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Estimations include quarterly and yearly dummies.

The sectoral classification used by the UWV differs from that used by the Labour Force Survey, therefore MF5.4 figures were calculated after recoding both classifications, which implied a reduction in the number of observations. For economy of space we do not report estimations of 5.1 to 5.4 using this sample. Conclusions do not greatly differ with respect to what is reported.
Table 2. Traditional (MF0) and augmented (MF5.1 to MF5.4) matching functions before and after 2008

<table>
<thead>
<tr>
<th></th>
<th>MF0</th>
<th>MF5.1</th>
<th>MF5.2</th>
<th>MF5.3</th>
<th>MF5.4</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>ln $H_{ij}$</td>
<td>ln $H_{ij}$</td>
<td>ln $H_{ij}$</td>
<td>ln $H_{ij}$</td>
<td>ln $H_{ij}$</td>
</tr>
<tr>
<td>ln $E_{i,j}$</td>
<td>0.271*** (0.074)</td>
<td>0.804*** (0.125)</td>
<td>0.271*** (0.051)</td>
<td>0.536*** (0.049)</td>
<td>0.240*** (0.049)</td>
</tr>
<tr>
<td>ln $E35m_{i,j}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln $E611m_{i,j}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln $E12y_{i,j}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln $E2y_{i,j}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln $I_{i,j}$</td>
<td>0.327*** (0.068)</td>
<td>-0.099</td>
<td>0.350*** (0.060)</td>
<td>0.140*** (0.043)</td>
<td>0.068</td>
</tr>
<tr>
<td>ln $cancelmV_{i,j}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln $U_{i,j}$</td>
<td>0.934*** (0.199)</td>
<td>0.419*** (0.141)</td>
<td>0.684*** (0.229)</td>
<td>0.284*** (0.142)</td>
<td></td>
</tr>
<tr>
<td>ln $UBmonth1_{i,j}$</td>
<td>0.029</td>
<td>0.075</td>
<td>(0.057)</td>
<td>(0.054)</td>
<td></td>
</tr>
<tr>
<td>ln $UBmonth2_{i,j}$</td>
<td>0.022</td>
<td>-0.185** (0.082)</td>
<td>(0.070)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>ln $UBmonth3_{i,j}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>3.656*** (0.351)</td>
<td>2.307*** (0.485)</td>
<td>0.200</td>
<td>-3.088*** (0.464)</td>
<td>-0.902</td>
</tr>
<tr>
<td>Observations</td>
<td>350</td>
<td>364</td>
<td>350</td>
<td>364</td>
<td>350</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.918</td>
<td>0.869</td>
<td>0.922</td>
<td>0.885</td>
<td>0.928</td>
</tr>
</tbody>
</table>

Source: elaborated with data from LFS, CBS and UWW. Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Estimations include quarterly and yearly dummies.

The sector classification used by the UWW differs from that used by the Labour Force Survey; therefore MF5.4 does not include residual matches that are coded to industries in the classification of the Labour Force Survey. This implies that the number of observations in the sample. For economy of space we do not report estimates of 5.1 to 5.4 using this sample. Conclusions do not greatly differ with respect to what is reported.
Table 3. Matching function using alternative measures of labour supply and demand. Results for period 2001 to 2014

<table>
<thead>
<tr>
<th>$\ln V_{i,j-1}$</th>
<th>MF0</th>
<th>MFA</th>
<th>MFB</th>
<th>MFC</th>
<th>MFD</th>
<th>MFE</th>
<th>MFF</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\ln H_{i,j}$</td>
<td>0.614*** (0.038)</td>
<td>0.045 (0.032)</td>
<td>0.105*** (0.034)</td>
<td>0.138*** (0.031)</td>
<td>0.200*** (0.030)</td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

$LS = (1, 1, 0, 0)$

$LS = (1, 1, 1, 0)$

$LS = (1, 1, 1, 1)$

$LD = (1, 1, 0, 0)$

$LD = (1, 1, 1, 0)$

$LD = (1, 1, 1, 1)$

Constant 3.294*** (0.320)

Observations 714

R-squared 0.862

LL 140,8003

$Source: elaborated with data from LFS, CBS and UWV. Standard errors in parentheses. *** p < 0.01, ** p < 0.05, * p < 0.1. Estimations include quarterly and yearly dummies. LS ($u < 11, ue, i$) and LD ($v, vc, vnew, lvnew$) are vectors of binary variables (1, 0)

$LS(u, e < 11, ue, i, newub) = u \cdot U_{i,j-1} + e < 11 \cdot (E35_{m,j} + E61_{m,j}) + ue \cdot Unewentrants_{i,j} + i \cdot I_{i,j} - newub \cdot UBmonth_{i,j}$

$LD(v, vc, vnew, lvnew) = v \cdot V_{i,j-1} - vc \cdot cancelV_{i,j} + vnew \cdot V_{i,j} + lvnew \cdot newV_{i,j-1}$

$MF A, MF B, MF C, MF D, MF E, and MF F refer to (7) \ln H_{i,j} = \ln \lambda + \alpha_{LS} \ln LS_{i,j} + \beta_{LD} \ln LD_{i,j} + v_{i,j}$ and LS and LD measures indicated by the binary variables.
### Table 4. Matching function using alternative measures of labour supply and demand. Pre- and post-crisis results (before and after 2008)

<table>
<thead>
<tr>
<th></th>
<th>MF0 ln $H_{i,t}$</th>
<th>MFA ln $H_{i,j}$</th>
<th>MFB ln $H_{i,j}$</th>
<th>MFC ln $H_{i,t}$</th>
<th>MFD ln $H_{i,j}$</th>
<th>MFE ln $H_{i,j}$</th>
<th>MFF ln $H_{i,j}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>ln $V_{i,j-1}$</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>0.582*** (0.045)</td>
<td>0.616*** (0.060)</td>
<td>0.098*** (0.049)</td>
<td>-0.020 (0.040)</td>
<td>0.149*** (0.048)</td>
<td>0.033 (0.048)</td>
<td>0.176*** (0.042)</td>
</tr>
<tr>
<td>ln $U_{i,j-1}$</td>
<td>0.194*** (0.040)</td>
<td>0.246*** (0.046)</td>
<td></td>
<td></td>
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<td></td>
<td></td>
</tr>
<tr>
<td>LS = (1,1,0,0)</td>
<td></td>
<td></td>
<td>0.803*** (0.047)</td>
<td>0.964*** (0.047)</td>
<td>0.789*** (0.049)</td>
<td>0.967*** (0.050)</td>
<td>0.815*** (0.045)</td>
</tr>
<tr>
<td>LS = (1,1,1,0)</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td>0.815*** (0.045)</td>
<td>0.930*** (0.048)</td>
<td>0.820*** (0.045)</td>
</tr>
<tr>
<td>LS = (1,1,1,1)</td>
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<td></td>
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<td></td>
<td></td>
<td>0.744*** (0.052)</td>
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<td></td>
<td></td>
<td>0.702*** (0.052)</td>
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<tr>
<td>LD=(1,0,0,0)</td>
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<tr>
<td>LD=(1,1,1,0)</td>
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<tr>
<td>LD=(1,1,1,1)</td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
<td>0.169*** (0.040)</td>
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<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Constant</td>
<td>3.656*** (0.351)</td>
<td>2.307*** (0.485)</td>
<td>0.893*** (0.234)</td>
<td>-0.440** (0.200)</td>
<td>0.398 (0.261)</td>
<td>-1.334*** (0.278)</td>
<td>-0.325 (0.264)</td>
</tr>
<tr>
<td></td>
<td>(0.351)</td>
<td>(0.485)</td>
<td>(0.234)</td>
<td>(0.200)</td>
<td>(0.261)</td>
<td>(0.278)</td>
<td>(0.264)</td>
</tr>
<tr>
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<td></td>
<td></td>
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<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Observations</td>
<td>350</td>
<td>364</td>
<td>362</td>
<td>371</td>
<td>362</td>
<td>371</td>
<td>362</td>
</tr>
<tr>
<td>R-squared</td>
<td>0.918</td>
<td>0.869</td>
<td>0.914</td>
<td>0.905</td>
<td>0.915</td>
<td>0.883</td>
<td>0.918</td>
</tr>
</tbody>
</table>

Source: elaborated with data from LFS, CBS and UWW. Standard errors in parentheses *** p < 0.01, ** p < 0.05, * p < 0.1. Estimations include quarterly and yearly dummies LS (u, e < 11, ue, v) and LD(v, vc, vnew, knew) are vectors of binary variables (1,0)

$LS(u,e<11,ue,v,vnew)=u\cdot U_{ij-1}+e \cdot (E35m_{ij-1}+E61m_{ij})+ue\cdot Unemployed_{ij-1}+i\cdot I_{ij}-newub\cdot UBmonth_{ij}$

$LD(v,vc,vnew,knew)=v\cdot V_{ij-1}-vc\cdot cancelV_{ij}+vnew\cdot V_{ij}+knew\cdot newV_{ij}$

$MFA, MFB, MF C, MF D, MF E, and MF F refer to (7) ln H_{ij} = \ln \lambda + \alpha_{LS} \ln LS_{ij} + \beta_{LD} \ln LD_{ij} + v_{ij} and LS and LD measures indicated by the binary variables.$
References


The role of the short-term employed in the matching process before and after the crisis


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University of Amsterdam
Amsterdam Institute for Advanced labour Studies
Postal address
PO Box 94025
1090 GA Amsterdam
The Netherlands

Visiting address
Roetersstraat 31
1018 WB Amsterdam
The Netherlands

📞 +31 20 525 4199
🔍 +31 20 525 4301
✉️ aias@uva.nl
🌐 www.uva-aias.net