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SISÄLLYSLUETTELO

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VII Matching models of unemployed job searchers – Does churning help to lower unemployment?

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1 INTRODUCTION

Improving the dynamics of the labour market is generally seen as a means to raise its efficiency. A more efficient labour market eventually leads more job searchers to obtain their most suitable job. Many reforms in European countries were initiated in order to make labour markets more efficient, so that, in the end, all labour market participants would benefit (Nickell and Layard, 1999; Schömann et al., 2013). Many of the associated reforms tie in with other institutional modernisations, concerning for example dismissal legislation, labour contracting policies and the like. One reason for making these reforms was that firms could adapt faster to changing economic circumstances so jobs are created and destroyed more easily in a Schumpeterian way. Firms would hence be optimizing their production process by e.g., implementing innovations, which will raise turnover and profit that, in the end, will give more jobs. A second reason is that easier hiring and separation of employees will improve job matching to eventually get the 'right worker on the right job', which is beneficial for both the firm in terms of efficiency and in the end profits, but also for the employee in providing him or her better career perspectives. Faster adaptation of firms and better job matching will consequently lead to lower unemployment and hence lesser use of unemployment benefits and other unemployment provisions. In this paper we investigate the proposition that a more efficient, i.e., a more dynamic, labour market, measured by job- or worker flows at the firm level, does indeed has a dampening effect on the use of unemployment benefits and social security arrangements as direct measurements of unemployment.

Job or worker flows are often studied in the context of a matching function. Job flows in a matching function relate the flow of jobs being filled to the initial stocks of job searchers and available free jobs. Worker flows in a matching function relate the flow of persons finding a job to both initial stocks of job searchers and available free jobs. Apart from these two so-called matching stocks, a matching function also reflects the efficiency of the matching process. A matching function itself is not a fully-fledged multiple equation econometric model, as it merely states that the flow of filled jobs or job finders relates to the matching stock of job searchers, the stock of free jobs and the efficiency of the matching process. Each one of these three types may be represented by different sets of explanatory variables. The matching function itself was introduced by Pissarides (1979) and Mortensen (1982). With the proliferation of data on labour market flows, it has since then been applied in many studies for a great number of countries. See Petrogolo and Pissarides (2001) for a review. Recent matching function studies are e.g. Barnichon and Figura (2013) and Hall and Schulhofer-Wohl (2015).

Data on flows of filled jobs or job finders that were used to estimate matching functions also triggered an entirely new line of (empirical) research in the early 1990's under the heading of labour market dynamics. It started with seminal papers of Blanchard *et al*. (1990) on US worker flows, and Davis and Haltiwanger (1992) on US job flows. These two studies also led to a host of similar studies for various countries. Since then a whole new branch of literature has arisen that uses job or worker flows, or both, as corner stones of research in firm and industry level responses to economic business cycles (Burgess et al. 1999, 2001), economic shocks (Bresnahan et al. 1999), institutional circumstances (Haltiwanger, Scarpetta and Schweiger, 2014; Bassanini and Carnero, 2013; Bassanini, 2010) and in various country-specific settings (most recently, Blasco and Pertold-Gebicka, 2013; Bulté and Struyven, 2014).

The combination of both job and worker flow data gave rise to a new labour market phenomenon entitled churning (Burgess et al. 1999). Churning is defined as the difference between worker reallocation, i.e., the sum of worker inflow and outflow, and job reallocation, i.e., the sum of job creation and job destruction. It tells us something about the extent to which worker flexibility is connected to job flexibility or the extent to which workers who move into and out of different jobs is related to the dynamics of jobs being newly created or existing jobs being destroyed. Churning is high when firms move or 'churn' workers over existing jobs, i.e., without jobs being created or destroyed. On the other hand, when workers only move between jobs because of jobs being newly created or existing jobs being destroyed, churning is low.

Understanding the pace and magnitude of reallocation of jobs or workers is highly relevant. For one thing because it tells us something about the way labour markets react to economic shocks and how this is influenced by industry and firm-level characteristics and by institutional, i.e. regulatory, circumstances. Haltiwanger et al., (2014) found in their cross-country comparison that firm size is dominant in accounting for variation in the pace of job reallocation across countries, but that stringent hiring and firing regulations tend to reduce the pace of job reallocation. Bassanini et al. (2013) find similar results for OECD countries and conclude that the more restrictive regulations, the smaller the rate of within-industry job-to-job transitions will be, in particular towards permanent jobs. Institutional arrangements and dismissal regulation are also important in explaining cross-country differences (Bassanini, 2013; OECD, 2014). Bachman and Burda (2010) study interaction between structural change and labour market dynamics in Germany. Combes et al. (2004) study labour dynamics from the perspective of regional inequalities in France. For the Netherlands, job flows were studied by Broersma and Gautier (1997) and worker flows by Broersma et al. (2000).

This paper estimates standard matching functions, linking flows of job finders from two types of unemployment provisions in the Netherlands to the initial stocks of each one of these two groups of unemployed job searchers, to the initial stock of job vacancies and to the efficiency of the matching process. Efficiency is represented here by a number of different flow and stock variables. The most important flow variable will be churning, i.e., worker reallocation minus job reallocation. Besides this more or less standard matching story, we will also estimate a kind of 'matching' model of the flows of job losers, linking the flow of job losers to the initial stock of filled jobs and the initial stock of one of our two unemployment provisions. This job outflow model not only depends on these two alternative 'matching' variables, but also to efficiency of 'matching', in this case: the efficiency of job loss. Again this efficiency process will be represented by different flow and stock variables.

Apart from these matching and efficiency variables, the size of the local or regional labour market area in which job searchers look for a job, is also important as explanatory characteristic of worker and job flows. It is well-known that the lower the education of a job searcher is, the smaller the search area for a vacant job will be (Basker, 2002). For low educated job searchers, this area is usually in close vicinity of his or her place of living.

Section 2 specifies these two processes of matching. Section 3 describes the data that were used to estimate both types of matching models. Section 4 presents the estimation results we found with these models and makes clear whether unemployment in- and outflow are determined by worker flows or job flows or both, i.e. churning. Finally, section 5 concludes our findings.

2 MATCHING AND EFFICIENCY

2.1 Theoretical model specification

This study is about modelling flows of persons moving into or out of a job in a certain area and within a certain period of time. Persons moving towards a job are studied here in the framework of a matching function. A matching function relates flow data during a certain period to its 'building' stock variables at the start of that period. Essentially, a matching function is based on the flow of job finders, comprising two categories.[1] First, job switchers, i.e., persons moving from one job to another, and second, 'genuine' job finders, i.e., persons moving from non-employment to employment.

The flow of job switchers concerns persons moving from one job to another between points in time *t-1* and *t* and relates it to its 'building' stock variables (a) the stock of workers searching for another job and (b) the stock of unoccupied jobs that need filling, both at the start of period *t*, i.e., at the end

1 Matching functions can also be based on the number of filled vacancies during a certain period, but in this study we abstain from that possibility due to lack of adequate data.

of $t\text{-}1$[2]. On the other hand, we also have the flow of job finders, persons moving from non-employment towards a job between $t\text{-}1$ and t.[3] Focusing on persons in unemployment, who are compelled to search for a job, the flow of persons moving from unemployment towards a job between $t\text{-}1$ and t is related to (a) the stock of unemployed persons, and (b) the stock of unoccupied jobs that need filling, both at the start of t , i.e. at the end of $t\text{-}1$.

In addition, there is the opposite flow of job losers, i.e., workers who leave their job and move to unemployment between $t\text{-}1$ and t. In a similar kind of matching function setting, this flow is then determined by (a) the stock of employed persons and (b) the 'available space' there is in an unemployment arrangement, again both at the end of period $t\text{-}1$. Do note that the available 'space' in these unemployment arrangements is in fact limitless, as these are all so-called 'open-end' arrangements, where the number of new entrants does not depend on the number of persons already present within these arrangements.

The general form of a matching function relates the flow of job finders, between two points in time, who live in a certain area, to the initial stocks of job searchers and vacant jobs in that (or surrounding) area(s) and to the matching efficiency. This depends on the size of the search area of job searchers and vacant jobs. The general, multiplicative, form of a matching function is

$$F_{X,Y,t} = \gamma_t \, X_{t-1}^{\alpha} Y_{t-1}^{\beta}, \qquad (1)$$

where $F_{X,Y,t}$ is the flow of persons finding a job in a certain area between $t\text{-}1$ and t. This depends on the initial stock of job searchers, X_{t-1}, in that area, the initial stock of available vacant jobs, Y_{t-1}, in that area and on the (regional) matching efficiency γ_t of this area. The larger the area of this region is, the smaller the effect of neighbouring regions will be in the regional matching process.

It is next important to distinguish the type of job searcher that is at stake. Different types of job searchers not only depend on the state they are in, like having a job, being unemployed or graduated from school, but also on their personal characteristics, like their age or level of education they have obtained. Particularly this latter aspect determines the extent to which job searchers search for employment outside their living region. Different types of job searchers in a matching context are discussed in Mumford and Smith (1999) and in Broersma and van Ours (1999). The effect of different regions in a matching context are discussed in Gorter and van Ours (1994) and Fahr and Sunde (2006). Instead of different job searchers it is also possible in a matching function to distinguish different types of free jobs. Mostly it concerns vacancies, but it may also refer to other types of available free jobs, without a vacancy being posted. Or it may refer to different types of vacancies like referring to certain levels of education or experience.

As far as the matching efficiency, γ_t , is concerned, this refers to the ability of a (regional) labour market to match job searchers to vacant jobs. This matching efficiency depends on characteristics of both stocks

2 The latter refers to ultimo stocks. In case of annual data, these are stocks at December 31 in a year.

3 Persons in non-employment comprise two broad categories. They are either unemployed or non-participant job searchers. The first group is those who have income from unemployment insurance (*UI*, in Dutch: WW) or those depending on income support or social assistance (*SA*, in Dutch: WWB). The non-participant job searchers have no financial support and comprise e.g. school-leavers. Unemployed job searchers have an obligation to search for work, while non-participant job searchers do not have this obligation. Because only the flows and stocks of *UI* and *SA* are available at the municipality level, our analysis will be restricted to these two categories of unemployed job searchers.

and flows of job searchers and vacant jobs and on the dispersion of labour market conditions within the search area under consideration. The conditions determining γ_t depend on a number of different explanatory variables.

Instead of the outflow of unemployed towards a job, a matching function can also be used to model the *total* outflow of unemployed. This means that not only the flow towards a job, but also towards non-participation, like retirement, disability, being discouraged, are included in the unemployment outflow. In such a case the dependent variable is no longer $F_{X,Y}$, the flow of persons moving from X to Y, as in (1), but it can best be expressed as $F_{X,...}$ i.e., the flow of persons moving from X to all possible destinations.

2.2 Empirical model specification

The data we have are quite unique as they are firm level data on the entry of new workers to a firm and on the workers exiting a firm. The way this data set is constructed has two consequences. First, we have no information on individual persons, but only on individual firms, who hire new workers or layoff existing ones. Second, we have no similar firm-level information on hires from any other source but unemployment. Hence, we do not have information on hires of employed job searchers from other firms, hires of school leavers, or of non-participants. These may be quite substantial, as most hires are employed switching between jobs and school leavers. Hires from unemployment come at best third in line.[4] Matching model (1) is a general specification, as it may refer to any job finder, any stock of job searchers and any type of free job. The latter are also observed at the firm-level.

Taking account of all these aspects, our empirical specification for matching function (1) can be written in two forms, related to the two unemployment definitions we have information on. First, it can be modelled as the total flow of persons out of unemployment insurance (*UI*). Second, it can be modelled as the total flow of persons out of social assistance (*SA*). Hence, instead of the outflow of unemployed persons towards a job, our matching function refers to *total* outflow of unemployed, i.e., not only those moving towards a job (Y_1), but also towards all other available options (Y_2, …), referred to as non-participation. Examples are the flows from *UI* towards *SA*[5], towards old-age pensions, or towards any other form of non-participation

$$\log(F_{UI\to})_t = \log\gamma_t + \alpha\log UI_{t-1} + \beta_1\log Y_{1,t-1} + \beta_2\log Y_{2,t-1} + \cdots. \quad (2)$$

In fact, a similar specification holds for the outflow out of social assistance (*SA*), where *UI* should be replaced by *SA*.

Again, this total outflow out of unemployment, be it from *UI* or *SA*, may take place towards a job, but also towards non-participation. A person in *UI* or *SA* is uncertain as to whether he or she will fill the vacancy that is applied to, due to competition with other job searchers. However, persons moving out of *UI* or *SA* to other destinations than a job do not have to apply, as they would have to do in case of a job vacancy. Once the requirements are met, usually age and partner income, they will always be accepted.

4 http://statline.cbs.nl/Statweb/publication/?DM=SLNL&PA=80597NED&D1=0-7&D2=0&D3=0&D4=2,l&HDR=G3&STB=G1,G2,T&VW=T

5 This only holds for the outflow of persons from unemployment insurance *(UI)*

This means that in a matching function setting the total outflow out of *UI* is only determined by the number of persons in *UI* and the number of vacant jobs *V*. This *total* outflow out of *UI*, available per municipality between 2007–2011, can however still be used in a matching function setting because (a) the outflow due to filling a vacancy is still the largest and uncertain component of this destination, as on average 60% of the total outflow out of *UI* is due to filling a vacancy *V* and (b) neither of the other outflow destinations depend on specific eligibility criteria, apart from age and partner income, so the ´applicants´ will always be accepted in that case. Starting from equation (2), this means that Y_2 does not determine so the outflow depends only on *UI* and Y_1. Therefore, this very much looks like (1), but the difference is the size of matching efficiency, γ_t, in (1) and (2).

In the empirical model (2), all variables appear as shares of the lagged municipality population between 15 and 64. This scaling is done because municipalities may differ strongly in their number of inhabitants and hence the outflow of unemployed will also differ. In order to neutralize this effect of municipality size, we scale all variables by the lagged total population of a working age, 15–64, that live in the municipality.

$$\log\left(\frac{F_{UI\rightarrow}}{P_{15-64,t-1}}\right) = \mu + \log\left(\frac{\gamma_t}{P_{15-64,t-1}}\right) + \alpha\log\left(\frac{UI_{t-1}}{P_{15-64,t-1}}\right) + \beta\log\left(\frac{V_{t-1}}{P_{15-64,t-1}}\right)$$

$$= \mu_0 + \textstyle\sum_r \mu_r(D_r) + \gamma_1\log\left(\frac{CH_t}{P_{15-64,t-1}}\right) + \gamma_2\log\left(\frac{Inc_{low,t-1}}{P_{15-64,t-1}}\right) + \qquad (3)$$

$$+\gamma_3\log\left(\frac{Minor_{t-1}}{P_{15-64,t-1}}\right) + \alpha\log\left(\frac{UI_{t-1}}{P_{15-64,t-1}}\right) +$$

$$\beta\log\left(\frac{V_{t-1}}{P_{15-64,t-1}}\right) + \varepsilon$$

The efficiency of matching is represented by different indicators. In equation (3) μ_0 is a constant and the D_r's represent regional dummies, so that regional differences in job finding among *UI*-recipients can be identified. Furthermore, efficiency also depends on churning, represented by *CH*, which equals worker inflow plus worker outflow minus job inflow (job creation) and job outflow (job destruction). This means that churning equals worker reallocation minus job reallocation, again as share of the lagged population aged between 15 and 64. Matching efficiency also depends on low income recipients, *i.e.* households with an income below 120% of the social minimum, also as share of the population 15–64. Low income recipients are not necessarily unemployed, but increasingly comprise workers on 'minor´ jobs, which are often temporary, part-time jobs via an employment agency. In the Netherlands this share of temporary, part-time jobs has risen strongly the past two decades.[6] Finally, efficiency may also comprise the share of persons of a non-Western ethnic minority group.[7] That group particularly has difficulties in finding a job; only when employment growth eventually settles in and gets stronger, this group will usually benefit, but often at a later stage. In the appendix, Table A1 describes all variables.

This *CH* is a flow variable and thus enters the model contemporaneously, i.e., it has the same timing as the dependent flow variable of the total outflow from unemployment insurance (*UI*). The other efficiency variables, low-income recipients (Inc_{low}) and non-Western job searchers (*Minor*) are stocks and therefore enter the model with a lag. Finally, the remaining explanatory variables in (3) comprise our two matching variables, the lagged number of persons with an *UI*-benefit and the lagged number of vacancies V. The stocks of the other destinations a person out of *UI* may move to, like pensions or non-participation, will, as argued before, always be accepted once requirements, like age or partner income, are met and they will hence be included in γ_t.

The total outflow of unemployed on social assistance (*SA*) in a matching context, can in fact be written in a very similar way

$$\log\left(\frac{F_{SA\rightarrow}}{P_{15-64,t-1}}\right) = \mu + \log\left(\frac{\gamma_t}{P_{15-64,t-1}}\right) + \alpha\log\left(\frac{SA_{t-1}}{P_{15-64,t-1}}\right) + \beta\log\left(\frac{V_{t-1}}{P_{15-64,t-1}}\right)$$

$$= \mu_0 + \textstyle\sum_r \mu_r(D_r) + \gamma_1\log\left(\frac{CH_t}{P_{15-64,t-1}}\right) + \gamma_2\log\left(\frac{Inc_{low,t-1}}{P_{15-64,t-1}}\right) + \tag{4}$$

$$+\gamma_3\log\left(\frac{Minor_{t-1}}{P_{15-64,t-1}}\right) + \alpha\log\left(\frac{SA_{t-1}}{P_{15-64,t-1}}\right) +$$

$$\beta\log\left(\frac{V_{t-1}}{P_{15-64,t-1}}\right) + \varepsilon.$$

The same efficiency variables are used as in (3). However, the matching variables are now the stocks of the lagged number of persons with an *SA*-benefit and again the lagged number of vacancies V, both as shares of the lagged population 15-64 that live in the municipality. Notice that also here the total outflow out of *SA* is (a) towards a job by filling a vacancy or (b) towards non-participation, i.e. disability, pension or non-participation. The latter are again all captured by matching efficiency.

The reverse flow of workers that lose their job in a certain area between two points in time, can in fact also be based on a similar theoretical model specification as the (matching) flow of job searchers finding a job. The flow of workers losing their job because they are fired has two known destinations in the Netherlands. When they

6 Note that also the share of self-employed workers is part of the flow from *UI* (or *SA*) to a job.

7 These primarily comprise persons from Morocco, Turkey, Surinam and the Dutch Antilles.

held their job during a certain required period, they will get an unemployment insurance (*UI*) benefit once they become unemployed. In fact, in the period under investigation job losers in the Netherlands were entitled to an *UI*-benefit only when they were employed for at least 26 weeks during 36 weeks prior to being laid-off. The level of the *UI*-benefit depends on the wage that was received in the job that was held, with a certain maximum wage. The duration of the *UI*-benefit depends on the total length of being employed, also with a minimum and maximum duration of the job being held between 3 and 38 months. When this entitlement duration exceeds its maximum term and the *UI*-recipient still has not found a job, he or she will have to exit *UI* and move towards social assistance, *SA*, when there is no partner income. This *SA* has a lower benefit level than *UI* at the social minimum. If job losers have held a job for a shorter period of time than 26 weeks or several of such short-lived jobs, they are only entitled to a *SA*-benefit. Still, the initial number of beneficiaries that are in either of these two social security arrangements, be it *UI* or *SA*, will have no effect on the inflow of new beneficiaries. Besides these two destinations after job loss, workers can also lose their job due to reaching a maximum age and move to pensioning or due to other reasons, like having and raising a child, or becoming discouraged when confidence in finding work is lost or becoming disabled.

Like matching function (1) this reverse flow of job loss can be modelled in a similar way. The flow of job losers during period t, the dependent variable, is then determined by the ´losing´ variables (as opposed to the ´matching´ variables) at the start of period t comprising of, first, the initial number of filled jobs, J, and, second, on the initial number of persons already present in the possible destinations, X, to which they move, i.e.,

$$F_{J,X,t} = \rho_t \, J^{\delta}_{t-1} X^{\eta}_{t-1}. \tag{5}$$

Flow model (5) will finally also depend on efficiency characteristics of the different groups of jobs and benefit recipients. Like γ_t in (1), the efficiency ρ_t in (5) comprises flow and stock variables that help explain $F_{J,X,t}$. Notice that now the destination X of ´job losers´, be it either to *UI* or *SA* or other forms of non-participation, is always accepted once certain requirements, like job duration or age, are fulfilled and the uncertainty that was found when applying for a vacancy is now not the case. So, no matter the size of the number of persons already receiving *UI*, the new inflow will always be accepted and the ´job loss´ function, to distinguish it from matching function (1), can be specified as

$$\log\left(F_{J\to UI}\right)_t = \log\rho_t + \delta\log J_{t-1} + \eta\log UI_{t-1} = \log\rho_t + \delta\log J_{t-1}. \tag{6}$$

The number of persons initially present in *UI* does not determine the size of the flow of job losers towards *UI*, $F_{J\to UI}$. So the flow of job losers towards *UI* depends only on the (initial) number of filled jobs, J, from which they originate and on their job duration. This latter aspect will automatically be satisfied as we consider the flow into *UI* where this inclusion criterion will always be tested.

Just like we found several destinations Y for persons leaving unemployment in matching function (2), our 'job loss' function (5) may have several origins X of persons that end up in unemployment. In case of leaving jobs (J) towards unemployment insurance (UI) in equation (6) we only have one origin. Workers with job duration of at least 26 weeks will enter UI. In case of the flow of workers from jobs towards social assistance (SA) we have two origins, namely (1) from leaving jobs that are occupied less than 26 weeks or (2) after reaching the maximum term of an UI-benefit. The loss function towards SA is

$$\log(F_{\rightarrow SA})_t = \log\gamma_t + \alpha_1 \log J_{t-1} + \alpha_2 \log UI_{1,t-1} + \beta \log SA_{t-1} + \cdots. \tag{7}$$

$$= \quad \log\gamma_t + \alpha_1 \log J_{t-1} + \alpha_2 \log UI_{1,t-1}.$$

Again the initial number of persons receiving SA does not determine the size of the flow towards SA. Equation (6) can be rewritten as

$$\log\left(\frac{F_{J\rightarrow UI,t}}{P_{15-64,t-1}}\right) = \rho_0 + \sum_r \rho_r(D_r) + \ \rho_1 \log\left(\frac{CH_t}{P_{15-64,t-1}}\right) + \rho_2 \log\left(\frac{Inc_{low,t-1}}{P_{15-64,t-1}}\right) + \tag{8}$$

$$+\rho_3 \log\left(\frac{Minor_{t-1}}{P_{15-64,t-1}}\right) + \delta \log\left(\frac{J_{t-1}}{P_{15-64,t-1}}\right).$$

The flow towards social assistance, $F_{\rightarrow SA}$, which may stem from either job losers with a low job duration or from UI-recipients reaching their maximum duration without finding a job. It can hence be rewritten as,

$$\log\left(\frac{F_{\rightarrow SA,t}}{P_{15-64,t-1}}\right) = \rho_0 + \sum_r \rho_r(D_r) + \ \rho_1 \log\left(\frac{CH_t}{P_{15-64,t-1}}\right) + \rho_2 \log\left(\frac{Inc_{low,t-1}}{P_{15-64,t-1}}\right) + \tag{9}$$

$$+\rho_3 \log\left(\frac{Minor_{t-1}}{P_{15-64,t-1}}\right) + \delta_1 \log\left(\frac{J_{t-1}}{P_{15-64,t-1}}\right) +$$

$$\delta_2 \log\left(\frac{UI_{t-1}}{P_{15-64,t-1}}\right).$$

where $F_{\rightarrow SA,t}$ is the flow of persons moving from whatever source towards social assistance in period t. The eligibility requirement of no alternative source of income will always be checked. It is clear that the signs and sizes of the parameters of the various models, i.e., equations (3), (4), (8) and (9), determine the differences between the inflow and outflow models and different effects of both unemployment definitions.

3 DATA

We have constructed a dataset from several sources at the municipality (LAU 2) level in the Netherlands for the years 2007 to 2011. We used information on each of the 407 municipalities for our empirical analysis.[8] These are data on the total outflow of persons from either unemployment insurance (*UI*) or social assistance (*SA*) and *vice versa*, the total inflow of persons towards either unemployment insurance (*UI*) or social assistance (*SA*). There are no comparable micro level data available for the large flows of job switchers and school-leavers. As a consequence we are confined to *UI* and *SA*.

These flow data are available from Statistics Netherlands. We have aggregated these micro flows to the municipality where the persons live in order the get the same regional classification as our matching stock variables, *i.e.*, unemployed (either in *UI* or *SA*) and vacancies. We use the actual count data of the vacancies registered to employment offices of the employee insurance agency (UWV in Dutch). These vacancies are primarily suited for those job searchers that are registered at these employment offices and those are exactly the persons on *UI* and *SA* in our stocks. So job searchers and vacancies do go together.

The arrangement of *UI* in the Netherlands is for all employees being insured against unemployment and the entitlement depends on the number of working years that has been fulfilled. *SA* is an arrangement for all Dutch inhabitants in order to maintain a minimum subsistence level. Persons on both *UI* and *SA* are compelled to actively search for a job. The total outflow from these two arrangements is, however, not necessarily always towards jobs, but can also be towards old age pension once they become 65, towards non-participation when they no longer have belief in finding work, or once their maximum *UI*-term is reached. Aggregate data from Statistics Netherlands show that between 2002 and 2012 on average 60% of the total outflow out of *UI* was towards a job, while this was a mere 40% of the total *SA*-outflow. The inflow into *UI* does however always originate from a job when it was occupied during a minimum amount of time; the inflow into *SA* can originate from a job, with a short job duration, but also from other states, like *UI*-recipient who exceeded their maximum term.

We also have to realise that not all available free jobs, Y in equation (1), need to be registered as vacancies, V. There are also free jobs available for which no official vacancy has been posted. Moreover, there are no vacancies for self-employed. In fact, the main reason to start as self-employed is the opportunity one sees in starting one's own business at a certain location. However, specifically for unemployed job searchers from *UI* or *SA*, which we use in our analysis, combined with the vacancies registered at the employment agencies, V, do provide a good measure for available job opportunities to them in a certain area. Additional variables that capture

8 Due to mergers of municipalities their number has changed over time. To solve this problem, municipalities were regrouped into the division of 2013. Due to data-restrictions two municipalities (Venray and Horst aan de Maas) were also merged.

the efficiency level γ_t in (1) and ρ_t in (5) comprise both flows and stocks and were discussed earlier at the various model specifications.

One of these explanatory variables in our matching functions is churning (Burgess et al. 1999, 2001). As these matching functions are all in logarithmic form, we should hence also consider the logarithm of churning. This equals the difference between the logarithm of the flows of worker reallocation, $\log F_{WR,t}$, and job reallocation, $\log F_{JR,t}$, in period t. Given the definition of these flows, this can be rewritten as the logarithm of worker inflow, $\log F_{Win,t}$, plus the logarithm of worker outflow, $\log F_{Wout,t}$, minus the logarithm of job creation, $\log F_{JC,t}$, and minus the logarithm of job destruction, $\log F_{JD,t}$. Considering churning relative to the population between 15 and 64, as before, yields

$$\log\left(\frac{CH_t}{P_{15-64,t-1}}\right) = \log\left(\frac{F_{WR,t}}{P_{15-64,t-1}}\right) - \log\left(\frac{F_{JR,t}}{P_{15-64,t-1}}\right) = \log\left(\frac{F_{Win,t} \cdot F_{Wout,t}}{P_{15-64,t-1}}\right) - \log\left(\frac{F_{JC,t} \cdot F_{JD,t}}{P_{15-64,t-1}}\right)$$

$$= \log\left(\frac{F_{Win,t}}{P_{15-64,t-1}}\right) + \log\left(\frac{F_{Wout,t}}{P_{15-64,t-1}}\right) - \log\left(\frac{F_{JC,t}}{P_{15-64,t-1}}\right) - \log\left(\frac{F_{JD,t}}{P_{15-64,t-1}}\right) \tag{10}$$

These worker and job flows that lie at the heart of churning, all stem from the same source as our flows of job finders and job losers. Statistics Netherlands provides these flow data at the individual level that we have aggregated to municipality levels in order to be able to link them to stocks of job searchers from either *UI* or *SA* and the stock of vacancies, V. As mentioned earlier, the latter are identified as the stock of vacancies reported to the local employment agencies of the UWV and these are also shown at the municipality level. For more on churning and how it is calculated from worker inflow, worker outflow, job creation and job destruction, see Ilmakunnas and Maliranta (2005).

By definition, worker reallocation is larger than job reallocation, because a worker needs to be separated when a job is destroyed, but the other way around need not be the case: when a worker leaves the firm, the job he leaves behind does not need to be destroyed, as it can also be filled by another, new candidate. If both worker reallocation and job reallocation have the same value, i.e., workers only move because of jobs being newly created and existing ones being destroyed, churning is at its minimum of 0. Churning is at its maximum when there is only worker reallocation, but no job reallocation.

4 EMPIRICAL RESULTS

This empirical section presents the estimation results of equation (3), (4), (8) and (9) with maximum likelihood (ML) estimation on about 2000 observations. Table 1 gives the estimation results for (3) in all 407 municipalities of The Netherlands between 2007 and 2011. As discussed in section 2, the matching variables are the initial stocks of *UI*-recipients and vacancies *V* in the municipality under consideration and the initial specification includes a constant and time trend, but no efficiency or regional density dummies yet. The model in Table 1 column 2 is a standard matching function where the *UI*-outflow rate is related to the stocks of UI_{-1} and V_{-1}, an intercept and a time trend. The estimated coefficients for both lagged matching stocks have significant values of about 0.35 and 0.03, respectively. Note that they do not sum to unity, so there are no constant returns to scale. This is entirely due to the fact that our matching variables enter with a lag in our model specification.[9] Note that our specification with lagged matching variables is the only sensible specification, as the flow in period *t* is related to the stocks available at the start of period *t*, i.e., the end-stocks in period *t-1*. In all specifications we include a time trend. This coefficient is about 0.1 and highly significant in all specifications, implying that there is variation over time, but this effect is robust and not sensitive to alternative specifications.

Next, we add efficiency flow and stock variables to the model in column 3 of Table 1. In essence more churning will lower the *UI*-outflow rate, but its effect is not significant. In column 4 of Table 1 churning is hence deleted from the model and we end up with only those variables that do have significant effects. The effect of the efficiency stocks have opposite signs. A 1%-point rise in the share of low-income recipients raises the *UI*-outflow rate by 0.4%-points, while a 1%-point rise in the share of minorities will lower the *UI*-outflow rate by 0.04%-point. The share of low-income households in a population easier finds or holds a job than an equally high share of minorities.

Next we look at the effect of adding regional dummy variables to our model.[10] Adding dummies for each of the 40 NUTS-3 regions makes the effect of vacancies disappear. When instead 12 NUTS-2 dummies were added, we find that vacancies are only significant at 10%. In other words, these dummies, without any economic interpretation, take away the effect of truly economic viable variables. We therefore add regional dummies that do have a kind of interpretation that can be used in a matching function. In the final two columns of Table 1, we present the estimation results of our matching model where dummies of regional density for each municipality involved are added.[11]

9 Even when a matching function for the UI-outflow rate was estimated with contemporaneous stocks of *UI* and *V*, the sum of the matching coefficients would be equal to 0.96, which is still less than unity.

10 In a fixed-effect model specification, i.e. adding a dummy for each of the 407 municipalities, their effect completely absorbs the effect of our two matching variables, which is why we do not proceed with that specification.

11 These dummies are based on a division by urban density of the municipality the job searcher lives in. Urban density is divided in five categories, based on the so-called address density of the municipality, i.e. the number of addresses per km2, ranging from ‘very highly urban’ to ‘non-urban’. We have a dummy variable giving a 1 (‘very highly urban’) when there are 2500 or more addresses per km2 and giving a 0 elsewhere. It is ‘highly urban’ (giving a 1) when the address density is between 1500-2500 addresses per km2 (and 0 elsewhere). It is ‘moderately urban’ when address density is between 1000–1500 addresses per km2, ‘weakly urban’ when density is between 500-1000 addresses per km2 and finally the numeraire is ‘non-urban’ when density is under 500 addresses per km2. Source: Statistics Netherlands.

Table 1. *Estimation results, total outflow from unemployment insurance (UI) in the Netherlands, 2007-2011 (ML estimation)*

	$\log\left(\frac{F_{UI\to J}}{P_{15-64,-1}}\right)_t$						
Constant	-198.1 (-12.63)	-193.7 (12.38)	-192.1 (-12.36)	-200.5 (-13.96)	-202.4 (-13.97)	-192.5 (-12.78)	-192.5 (-12.76)
Matching variables							
$\log\left(\frac{UI}{P_{15-64}}\right)_{t-1}$	0.346 (9.23)	0.335 (9.46)	0.336 (9.48)	0.211 (10.03)	0.238 (11.39)	0.331 (16.05)	0.335 (16.35)
$\log\left(\frac{V}{P_{15-64}}\right)_{t-1}$	0.033 (2.69)	0.042 (3.02)	0.036 (2.98)	0.008 (0.62)	0.020 (1.67)	0.036 (2.91)	0.037 (3.04)
Efficiency variables							
*churning flo**w:***							
$\log\left(\frac{CH}{P_{15-64,-1}}\right)_t$		-0.025 (-0.84)					
specific stocks:							
$\log\left(\frac{Inc_{low}}{P_{15-64}}\right)_{t-1}$		0.361 (9.43)	0.365 (9.59)	0.144 (3.32)	0.139 (3.43)	0.388 (10.31)	0.371 (10.15)
$\log\left(\frac{Minor}{P_{15-64}}\right)_{t-1}$		-0.038 (-2.95)	-0.044 (-3.93)	0.070 (5.12)	0.049 (3.78)	-0.057 (-3.69)	-0.051 (-4.45)
time trend	0.098 (12.63)	0.097 (12.45)	0.096 (12.42)	0.099 (13.87)	0.100 (13.90)	0.096 (12.84)	0.096 (12.82)
Regional dummies*							
None	×	×	×				
40 NUTS-3 dummies				×			
12 NUTS-2 dummies					×		
*5 Urban density dummies:***							
very highly urban						-0.083 (-1.23)	
highly urban						0.059 (1.37)	
moderately urban						0.076 (2.05)	0.058 (2.28)
weakly urban						0.015 (0.52)	
Number of observations	2004	2004	2004	2004	2004	2004	2004
Log likelihood	-1235.6	-1187.7	-1188.0	-1062.0	1093.6	1182.0	-1185.4
R^2	0.25	0.29	0.29	0.37	0.35	0.29	0.29

* The parameter values for each of the regional dummies are also reported. An: × means no dummy. Variables with insignificant coefficients are deleted from the final model specifications.
** The fifth category of urban density and numeraire is non-urban density, i.e. less than 500 addresses per km2 (footnote 11).

In densely populated cities, matching may be higher because there are more vacancies and more job searchers, so eventually jobs may be filled easier. Note that this depends entirely on the efficiency with which these job searchers are matched to these vacancies. It may just as well be the case that job searchers and vacancies are harder to match in high density cities than in low density ones, e.g. because the quality of job searchers and requirements for vacancies in these large cities do not match. In columns 7 and 8 of Table 1, we however find that both our matching elasticities and our efficiency stocks are very much in line with the ones of the model without regional dummies. Only municipalities of moderate size have a slightly higher job matching rate of 0.06%-point, implying that an average population density is more efficient for outflow towards employment than a highly urbanized or very rural area. Hence, there may be some effect of averagely sized municipality on job matching from *UI*, but its impact is small and weakly significant. In other words, the *UI* matching model is basically the one in column 7 of Table 1. More labour market dynamics due to churning does not affect the outflow of *UI*.

Table 2 shows the estimation results for equation (4). Here, *SA*-outflow, as share of the population of 15-64, is the dependent variable for all 407 municipalities in the Netherlands between 2007 and 2011. Since the elasticity of the lagged stock of job searchers on social assistance (SA_{-1}) is significant and close to 1, it dominates the effect of vacancies and other variables.[12]

When efficiency flow and stock variables are added to this model specification, we find no significant effect of churning but we do find significant, but practically opposite values for our two efficiency stock variables. This means that a rise in *SA*-recipients implies about an equally large rise in *SA*-outflow, but the effects of flow and stocks of efficiency variables vanishes as their effect is either insignificant or they cancel out. In contrast to Table 1 the time trend has in this case no significant effect implying that business cycle effects are important for the outflow from *UI* but not for the outflow from *SA*.

Adding either 40 regional NUTS-3 or 12 regional NUTS-2 dummies to our *SA*-outflow model does not change this picture. In fact now neither efficiency flow nor stocks are significant, implying that indeed only the matching variable SA_{-1} remains significant for explaining *SA*-outflow. Again, also in this case this significant coefficient of SA_{-1} is close to unity implying a largely constant stock of *SA*-recipients, as every additional share of *SA*-recipients yields an equally large share of *SA*-outflow.

12 Do note that when a model was estimated with only lagged vacancies as explanatory variable its effect on SA-outflow is still significantly positive, but small. Its effect is clearly dominated by the lagged SA-stock, when that variable is included in the model.

Table 2. *Estimation results, total outflow from social assistance (SA) in the Netherlands, 2007-2011 (ML estimation)*

	$\log\left(\frac{F_{SA\rightarrow J}}{P_{15-64,-1}}\right)_t$							
Constant	-2.320	-4.991	-6.111	-9.536	-9.251	-10.37	-3.781	-4.154
	(-0.37)	(-0.80)	(-1.10)	(-1.52)	(-1.48)	(-1.67)	(-0.68)	(-0.75)
Matching variables								
$\log\left(\frac{SA}{P_{15-64}}\right)_{t-1}$	0.975	1.008	1.006	0.931	0.914	0.912	1.023	1.031
	(68.32)	(63.81)	(64.58)	(51.37)	(69.57)	(69.09)	(62.79)	(67.38)
$\log\left(\frac{V}{P_{15-64}}\right)_{t-1}$	-0.011	-0.001		0.001	-0.001			
	(-1.52)	(-0.14)		(0.05)	(-0.21)			
Efficiency variables								
churning flow:								
$\log\left(\frac{CH}{P_{15-64,-1}}\right)_t$		-0.020		-0.004				
		(-1.03)		(-0.23)				
specific stocks:								
$\log\left(\frac{Inc_{low}}{P_{15-64}}\right)_{t-1}$		0.062	0.064	0.001			0.036	
		(2.47)	(2.60)	(0.005)			(1.43)	
$\log\left(\frac{Minor}{P_{15-64}}\right)_{t-1}$		-0.063	-0.069	-0.013			-0.025	-0.020
		(-6.31)	(-7.75)	(-1.13)			(-2.17)	(-1.83)
time trend	0.001	0.002	0.003	0.004	0.004	0.004	0.002	0.002
	(0.18)	(0.69)	(0.99)	(1.31)	(1.26)	(1.44)	(0.58)	(0.60)
*Regional dummies**								
None	×	×	×					
40 NUTS-3 dummies				×	×			
12 NUTS-2 dummies						×		
*5 Urban density dummies:***								
very highly urban							-0.261	-0.273
							(-4.71)	(-4.96)
highly urban							-0.146	-0.159
							(-4.19)	(-4.71)
moderately urban							-0.171	-0.179
							(-5.82)	(-6.23)
weakly urban							-0.098	-0.103
							(-4.50)	(-4.77)
Number of observations	1996	1996	1996	1996	1996	1996	1996	1996
Log likelihood	361.6	390.7	390.0	458.0	457.1	427.8	409.1	408.1
R^2	0.86	0.87	0.87	0.89	0.89	0.88	0.87	0.87

* The parameter values for each of the regional dummies are also reported. An: × means no dummy. Variables with insignificant coefficients are deleted from the final model specifications.
** The fifth category of urban density and numeraire is non-urban density, i.e. less than 500 addresses per km2 (footnote 11).

However, adding regional density dummies to our *SA*-model does give a change implying that differences between rural and urban areas do matter for SA-outflow. First, these density dummies all have a significant negative effect on *SA*-outflow. So in more densely populated municipalities the *SA*-outflow rate is lower than in sparsely populated municipalities. Second, when urban-rural differences are taken into account, the stocks of low income households no longer have a significant effect on *SA*-outflow, but the effect for minorities does remain significant, although its magnitude halves when area dummies are included. It is a fact that minorities often live in the more densely populated municipalities. Low-income recipients, on the other hand, live less concentrated. In other words, these density dummies do pick up the effects of the efficiency stocks, with a possible exception for minorities. Inclusion of these dummies does yield a better model fit in terms of a higher likelihood, but its effect on the R^2 is not really observable.

What does become clear from Table 2 is that the effect of lagged *SA* job searchers dominates all other effects. So each additional *SA*-recipient yields an equally large outflow out of *SA*. This means that the actual stock of *SA*-recipients has a more or less fixed size. In other words, once you are in *SA* it is difficult to get out regardless of labour market dynamics.

Table 3 presents the estimation results for model (8) of the inflow rate into unemployment insurance (*UI*) from a job. As argued before, in this case the sole 'matching' variable comprises the (lagged) stock of occupied jobs, from which this flow originates. The (lagged) level of the stock of the existing *UI* recipients, which would have been the second matching variable, does in fact not limit this inflow, because once the entitlement criteria are fulfilled, all persons losing their job are entitled to an *UI*-benefit. The efficiency variables are once again the same as were used for the unemployment outflow models of Tables 1 and 2.

The basic *UI*-inflow model, based only on the 'matching' stock of occupied jobs, yields no significant effects, apart from constant and trend effects (column 2 of Table3). Even in a model without a time trend the 'matching' variable remains insignificant (not shown in Table 3). When, however, efficiency variables are added to the model the picture does change. When adding the churning flow to the *UI*-inflow model, both the lagged stock of jobs and the churning flow yield a significant (but opposite) effect. A 1%-point rise in the number of lagged occupied jobs, as share of the population 15-64, raises the inflow rate towards *UI* with 0.3%-points, while a 1%-point rise in the churning flow, as share of the population 15-64, will lower the *UI* inflow rate with about 0.3%-points. This makes sense because the more persons holding a job, the larger the possibility that some may lose it, while at the same time more churning leads to more persons eventually arriving at the right job, thereby lowering the chances of becoming unemployed, hence a negative sign. This implies that more job mobility does prevent inflow into *UI*. This result remains robust throughout the various model specifications presented in Table 3.

Table 3. Estimation results, total inflow (from a job) towards unemployment insurance (UI) in the Netherlands, 2007–2011 (ML estimation)

	$\log\left(\frac{F_{J\rightarrow UI}}{P_{15-64,-1}}\right)_t$							
Constant	-323.3	-312.3	-310.9	-314.3	-314.6	-311.9	-313.9	-316.2
	(-21.89)	(-21.33)	(-21.30)	(-21.51)	(21.53)	(-21.31)	(-21.34)	(-21.55)
Matching variables								
$\log\left(\frac{J}{P_{15-64}}\right)_{t-1}$	0.025	0.349	0.352	0.280	0.268	0.348	0.389	0.377
	(0.64)	(4.25)	(4.30)	(3.84)	(3.62)	(4.29)	(4.56)	(4.45)
Efficiency variables								
churning flow:								
$\log\left(\frac{CH}{P_{15-64,-1}}\right)_t$		-0.309	-0.346	-0.269	-0.262	-0.333		
		(-4.32)	(-5.10)	(-4.24)	(-4.05)	(-4.61)		
worker and job reallocation:								
$\log\left(\frac{WR}{P_{15-64,-1}}\right)_t$							-0.478	-0.372
							(-4.39)	(-4.76)
$\log\left(\frac{JR}{P_{15-64,-1}}\right)_t$							0.097	
							(1.41)	
specific stocks:								
$\log\left(\frac{Inc_{low}}{P_{15-64}}\right)_{t-1}$		0.482	0.454	0.166	0.168	0.516	0.514	0.503
		(9.76)	(9.76)	(3.39)	(3.47)	(10.35)	(10.31)	(10.22)
$\log\left(\frac{Minor}{P_{15-64}}\right)_{t-1}$		-0.030		0.109	0.090	-0.054	-0.052	-0.058
		(-1.61)		(6.27)	(5.12)	(-2.35)	(-2.27)	(-2.86)
time trend	0.159	0.156	0.155	0.155	0.156	0.155	0.156	0.158
	(21.89)	(21.39)	(21.35)	(21.40)	(21.44)	(21.37)	(21.43)	(21.61)
Regional dummies*								
None	×	×	×					
40 NUTS-3 dummies				×				
12 NUTS-2 dummies					×			
*5 Urban density dummies:***								
very highly urban						-0.080	-0.084	
						(-0.78)	(-0.81)	
highly urban						0.135	0.132	0.105
						(2.05)	(2.00)	(2.18)
moderately urban						0.158	0.157	0.130
						(2.74)	(2.72)	(3.14)
weakly urban						0.057	0.055	
						(1.35)	(1.30)	
Number of observations	2015	2015	2015	2015	2015	2015	2015	2015
Log likelihood	-1491.8	-1433.4	-1434.6	1298.7	1334.9	-1425.7	-1424.2	-1427.3
R^2	0.15	0.22	0.22	0.35	0.32	0.23	0.23	0.23

* The parameter values for each of the regional dummies are also reported. An: × means no dummy. Variables with insignificant coefficients are deleted from the final model specifications.

** The fifth category of urban density and numeraire is non-urban density, i.e. less than 500 addresses per km2 (see footnote 11).

When we include the efficiency stocks in the model, the share of low-income recipients is highly significant, but the stock of minorities remains just below the 10% significance level in the model without regional dummies. Enlarging this model with regional NUTS-3 or NUTS-2 dummies yields largely similar explanatory effects for the lagged matching variable (jobs) and efficiency flow (churning) as before. Do note that the effect of the efficiency stocks is now no longer opposite but positive in both cases.

However, adding rural-urban dummies based on population density to this model the two efficiency stocks do have opposite and significant effects. Furthermore, these dummies do show (weakly) significant positive effects of both the moderate and strongly populated municipalities on *UI*-inflow. In fact, we found a very similar result for the model of the *UI*-outflow in Table 1[13].

In the final specification we split-up churning into its two building blocks and the results show that only worker reallocation remains significant to explain the inflow into *UI*. A 1%-point rise in worker reallocation will lower the inflow towards *UI* with almost 0.4%-points. In other words, more flexibility in the in- and outflow of workers into or out of a job, will lower the *UI*-inflow substantially, certainly when it is compared to the effect it had on the *UI*-outflow from Table 1. The process of economic restructuring resulting in job creation and job destruction is not significant.

Finally, Table 4 shows the estimation results for the *SA*-inflow rate of model (9). In this case even without efficiency variables, the two lagged matching variables, jobs and *UI*-recipients, are included. Note that the effect of *UI*-recipients has no significant effect on the *SA*-inflow rate, but jobs do. A 1%-point rise in this job share raises the *SA*-inflow rate with 0.2%-points. The parameter value of this variable remains around this value even when efficiency flows and stocks and regional dummies are added to the model.

A 1%-point rise in churning leads to a fall in *SA*-inflow of about 0.1%-point, i.e., more churning prevents even workers on a short-term contract from becoming unemployed. This holds for *UI*-inflow but also for *SA*-inflow. Do note that an equally sized rise in churning to the *UI*-inflow gives a three times stronger effect than one on the *SA*-inflow. So churning not only has a much larger effect on unemployment inflow than on outflow, its effect on *UI*-inflow is also much larger than on *SA*-inflow. This can be seen when the effect of churning is compared between Table 1 (*UI*-outflow) and Table 3 (*UI*-inflow) and between Table 2 (*SA*-outflow) and Table 4 (*SA*-inflow). More churning causes less unemployment inflow, particularly in *UI*, and hence leads to a lower level of unemployment.

13 Do note that the dummy for strong urban densities could, despite its near-significance, validly be omitted from the model of Table 1. For the *UI*-inflow model of Table 3 this was however not the case.

Table 4. Estimation results, total inflow towards social assistance (SA) in the Netherlands, 2007–2011 (ML estimation)

	$\log\left(\frac{F_{J\rightarrow SA}}{P_{15-64,-1}}\right)_t$							
Constant	-280.1	-263.6	-263.3	-263.0	-261.9	-266.6	-267.5	-266.8
	(-45.14)	(-39.66)	(-40.85)	(-40.26)	(-40.04)	(-40.05)	(-41.35)	(-41.34)
Matching variables								
$\log\left(\frac{J}{P_{15-64}}\right)_{t-1}$	0.199	0.191	0.191	0.237	0.202	0.155	0.167	0.172
	(4.38)	(3.57)	(3.57)	(4.86)	(4.05)	(2.93)	(3.12)	(3.24)
$\log\left(\frac{UI}{P_{15-64}}\right)_{t-1}$	-0.003	-0.002		-0.008	-0.007	0.000		
	(-0.26)	(-0.20)		(-0.76)	(-0.64)	(0.00)		
Efficiency variables								
churning flow:								
$\log\left(\frac{CH}{P_{15-64,-1}}\right)_t$		-0.107	-0.107	-0.070	-0.075	-0.120		
		(-2.81)	(-2.82)	(-1.91)	(-2.02)	(-3.15)		
worker and job reallocation:								
$\log\left(\frac{WR}{P_{15-64,-1}}\right)_t$							-0.161	-0.156
							(-2.84)	(-2.77)
$\log\left(\frac{JR}{P_{15-64,-1}}\right)_t$							0.018	
							(0.54)	
specific stocks:								
$\log\left(\frac{Inc_{low}}{P_{15-64}}\right)_{t-1}$		0.222	0.222	0.123	0.113	0.239	0.239	0.237
		(5.97)	(5.97)	(3.47)	(3.16)	(6.42)	(6.43)	(6.39)
$\log\left(\frac{Minor}{P_{15-64}}\right)_{t-1}$		0.155	0.156	0.297	0.291	0.051	0.052	0.072
		(6.36)	(6.38)	(15.11)	(14.02)	(1.69)	(1.75)	(2.77)
time trend	0.137	0.130	0.130	0.129	0.129	0.131	0.132	0.131
	(42.99)	(39.53)	(40.69)	(40.01)	(39.82)	(41.18)	(41.23)	(41.19)
Regional dummies*								
None	×	×	×					
40 NUTS-3 dummies				×				
12 NUTS-2 dummies					×			
*5 Urban density dummies:***								
very highly urban						0.736	0.737	0.694
						(4.82)	(4.82)	(5.22)
highly urban						0.465	0.467	0.440
						(4.92)	(4.93)	(6.32)
moderately urban						0.100	0.102	
						(1.20)	(1.23)	
weakly urban						-0.060	-0.059	
						(-0.95)	(-0.94)	
Number of observations	2004	2004	2004	2004	2004	2004	2004	2004
Log likelihood	-265.8	-221.8	-221.8	-35.78	-86.65	-192.9	-191.8	-194.8
R^2	0.13	0.29	0.29	0.67	0.60	0.37	0.37	0.36

* The parameter values for each of the regional dummies are also reported. × means no dummy. Variables with insignificant coefficients are deleted from the final model specifications.
** The fifth category of urban density and numeraire is non-urban density, i.e. less than 500 addresses per km2 (see footnote 11).

The efficiency stocks of low-income recipients and minorities both have a significant positive effect on *SA*-inflow. Note that for the *UI*-inflow of Table 3 we found opposite effects: the effect of low incomes was positive, while the effect of minorities was negative. From the results of Table 4 we find that a 1%-point rise in the share of low- income recipients raises *SA*-inflow with 0.2%-points. A 1%-point rise in the share of minorities raises the SA-inflow with some 0.15%-points.

Adding NUTS-3 or NUTS-2 regional dummy variables to our *SA*-inflow model has virtually no effect on the matching variables, while as far as efficiency is concerned, effects of churning and low income recipients get smaller, while that of minorities get larger.

However, adding density dummies will now lower the effect of minorities to a mere 0.05%-point. So this time adding these dummies does affect the role of minorities on *SA*-inflow. This minorities-effect is clearly taken over by these urban density dummies, which comes as no surprise as minorities are known to live in the larger municipalities and exactly the dummies for these large municipalities have a significant positive effect.

Also note that the sheer size of the density dummies does point towards the fact that, apart from minorities, the larger municipalities also contain other groups of inhabitants with specific problems that make them as it were 'locked in' in social assistance, like single mothers, low educated, drug addicts and so on.

In the final two columns of Table 4 churning is replaced by its two 'building' flows, worker reallocation and job reallocation and the insignificant *UI*-recipients are omitted. Just like we found in Table 3 for the *UI*-inflow, now also worker reallocation appears to be the only significant source of churning. The effect of worker reallocation on *SA*-inflow in Table 4 is however two to three times smaller than the one on *UI*-inflow in Table 3. A 1%-point rise in worker reallocation will lower the SA-inflow rate with 0.15%-points, while a similar rise lowers *UI*-inflow with 0.4%-points.

The urban density effect particularly holds for the *SA*-unemployed and much less for the *UI*-unemployed. For both *UI*-inflow (Table 3) and *UI*-outflow (Table 1), urban density only has a small effect for moderately sized municipalities. The *SA*-inflow and outflow, on the other hand, do have particularly strong effects for municipalities in both the high and very high urban density classes (all relative to non-urban density classes). *SA*-inflow and SA-outflow are therefore much more concentrated in the larger cities, which makes sense as many *SA*-recipients are concentrated in these large cities.

5 CONCLUSION

We started this paper with the question whether more labour market dynamics influences unemployment. It is an undisputed trend in the Dutch economy that labour markets have become more flexible and volatile, because of a tendency towards more flexible labour contracts and a rising number of self-employed workers with no personnel. This leaves labour market participants with more uncertainty regarding prospects about their labour market careers and increases the risk of labour market segmentation (OECD, 2014). This is justified by higher (economic) efficiency in terms of higher output and higher labour productivity because organizations can adapt faster to changing economic circumstances. They can in a Schumpeterian way create and destroy jobs more easily and hire personnel in a more flexible way. Hence, they optimize their production process e.g., by implementing innovations, causing higher turnover, more profit and, in the end, job growth. It also optimizes the matching function that will speed up worker reallocation (hiring and firing of personnel). This rise in labour market efficiency will eventually also increase output and labour productivity and also increase employment, diminish unemployment and also facilitates an optimal career from the perspective of the employee.

We study the effect of more dynamics on the efficiency of the labour market by means of adding the churning rate to a standard matching function approach, which relates the flow of jobs being filled to the initial stocks of available vacancies and job searchers. This churning ratio is defined as the difference between worker reallocation (the sum of worker in- and outflow) and job reallocation (the sum of job creation and job destruction). Churning tells us something about the extent to which worker flexibility is connected to job flexibility or the extent to which workers that move into and out of different jobs is related to the dynamics of jobs being newly created or existing jobs being destroyed. We use data for the Netherlands at the municipal level (LAU-2) for the period of 2007-2011.

Our conclusion is that more labour market dynamics measured via the churning ratio has no significant effect on the outflow from *UI* and *SA* towards jobs, but in contrast and surprisingly it does have a significant - negative - effect on the inflow of workers towards unemployment, be it *UI* or *SA*. When we split the churning effect into a worker and a job reallocation variable, it turns out that only the worker reallocation process is significant and not the job reallocation.

This effect holds even when we control for specific efficiency stocks on the labour market, like the share of minorities or the share of low-income recipients and for the inclusion of various types of regional dummies. For the matching variables we find that high shares of stocks of either *UI*- and *SA*-recipients leads to a higher outflow towards jobs and, at least for *UI*-outflow, also for the stock of vacancies. For the inflow from jobs towards *UI* and *SA* we find that more jobs will lead to more inflow, which is expected since the risk of becoming unemployed in thick labour markets is higher. In case of the inflow towards *SA*, we have in fact two origins.

We advise against a kind of standard inclusion of regional dummies to our model, where these dummies have no economic interpretation. This typically goes for a standard inclusion of dummies based on regional subdivisions according to the NUTS classification. We have argued the inclusion of regional dummies should at least enlighten the model estimation by providing some kind of economic interpretation. A regional classification based on urban density that we have suggested offers a more promising route that the standard dummies.

Urban density appears to have mixed effects, depending on the type of unemployment arrangement (*UI* or *SA*) and whether we consider the in- or outflow of unemployment. In dense urban areas the inflow in *SA* is higher, while the outflow is lower, illustrating the low prospects of long-term unemployed and the excluded bottom end of the labour market, particularly in larger cities.

Our results indicate that a more efficient labour market in terms of a higher churning rate, which is primarily caused by strong worker reallocation, does not positively alter the prospects for everyone, but instead protects only those that are already at work at the cost of those that are in an income arrangement (*SA*). Once you are in a job, it is easier to stay in, even if this means that one must hop from job to job or from contract to contract. But once you are out, it is hard to step in on the job carousel again. This is an important policy implication. Indeed, more flexibility diminishes unemployment, i.e., prevents people becoming unemployed, but this comes at a cost: a rise in exclusion of those that are already outside the labour market.

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APPENDIX – Descriptive statistics of the municipalities in the Netherlands in 2007-2011

Variable	Description	Mean (×1000)	Max (× 1000)	Min (× 1)	St. dev (× 1000)
P15-64	Population of working age	27.2	570.8	580	43.7
UI inflow	Unemployment insurance inflow	0.86	25.2	13	1.7
UI outflow	Unemployment insurance outflow	0.85	289.1	13	1.6
SA inflow	Social assistance inflow	0.24	11.2	0	0.7
SA outflow	Social assistance outflow	0.24	10.9	0	0.7
Vacancies	Open job vacancies at employee insurance agency (UWV)	0.1	3.8	0	0.3
Churning	Worker reallocation minus job reallocation (existing firm only)	6.6	208.5	34	14.1
Worker reallocation	Worker inflow plus worker outflow (existing firms only)	9.4	287.8	46	20.9
Job reallocation	Job creation plus job destruction (existing firms only)	2.8	79.6	12	5.9
Low income recipients	Households with an income of at most 120% of the social minimum	5.4	146.6	0	11.1
Minorities	Non-western minorities	3.0	197.4	0	14.3

The in- and outflows of UI are very close together, just as those of SA. This is a familiar phenomenon of labour market flows. Do note that also here the in- and outflow, in numbers of (1000) persons, of UI are about three times larger than those of SA. All model variables are taken as share of the population 15-64.

Aluetalouksia tutkimassa

Kehitys, työmarkkinat ja muuttoliike

Hannu Tervon juhlakirja

Aluetaloustiede on ollut merkittävässä asemassa taloustieteen tutkimuksessa ja opetuksessa Jyväskylän yliopiston kauppakorkeakoulussa. Tämä kirja tarjoaa läpileikkauksen aluetaloustieteelliseen tutkimukseen painottaen erityisesti työmarkkinoiden kysymyksiä. Kirjassa tarkastellaan alueiden kasvua ja kehitystä, alueellisia työmarkkinoita ja muuttoliikettä alueiden välillä.

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