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MEDIATION SERVICES AND THE OUTFLOW FROM SHORT-TERM UNEMPLOYMENT: AVERAGE AND RELATIVE EFFECTIVENESS OF PUBLIC EMPLOYMENT OFFICES

LINDA VAN DONK

JAAP DE KONING

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Contact Jaap de Koning

Address SEOR, Erasmus University Rotterdam
Postbus 1738
3000 DR ROTTERDAM

Telephone +31-10-4082598

Fax +31-10-4089650

E-mail seor-secr@few.eur.nl

Website www.seor.nl

CONTENTS

1 INTRODUCTION

This paper has two aims. The first aim is to determine the average effect of the service provision by public employment offices in the Netherlands. To what extent do their activities lead to higher outflow rates from unemployment? The second aim is to measure the variation in performance among employment offices. Such variation gives an indication of the possibilities to improve effectiveness.

To what extent employment offices are able to increase the outflow from unemployment to jobs is highly relevant from the perspective of transitional labour markets, which are expected to be the labour markets of the future. In such labour markets expected job duration is shorter and more workers will become unemployed compared to the labour markets of the past. Re-entering employment within a few months is crucial as job entry chances tend to become lower the longer unemployed a person is. Institutions assisting those workers to get a new job quickly are badly needed under such conditions. In the Dutch situation public employment offices (or CWI[1] as they are called nowadays) are supposed to perform this task. The question we want to answer in this paper is whether they succeed in this task.

In the Dutch situation public employment offices play a rather restricted role in active labour market policy. Their main task is to provide jobseekers and employers with information on jobs and jobseekers respectively. Furthermore, employment offices advise jobseekers in their search for jobs by selecting suitable vacancies, help them writing application letters and provide them with job search training. Active mediation between a jobseeker and an employer also happens. However, the emphasis is on self-service and facilitating self-service in job search.

Dutch employment offices are not involved in the implementation of vocational training and subsidized labour and more time-consuming forms of job counseling for the unemployed. These measures come under the responsibility of the bodies dealing with unemployed benefits[2]. Usually,

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[1] Their official name is Centres for Work and Income (CWI). In spite of what their name suggests, they do not provide unemployment benefits. They only refer clients to the appropriate benefit agency. For a description of the tasks performed by the CWI, see appendix 1.

[2] A more detailed account of the Dutch system is given in De Koning (2005).

unemployed jobseekers are not entitled to these measures during the first six months of their unemployment period. During this period most of them have to rely completely on the services provided by the public employment offices. Therefore, in our analyses we concentrate on the outflow from short-term unemployment. This does not mean that employment offices do not provide any services to other jobseekers. In fact, jobseekers unemployed longer than six months can also make use of the self-service facilities offered by the employment offices. However, they will only rarely get the type of personal assistance offered to short-term unemployed jobseekers. Those in unemployment longer than six months usually engage in specific schemes offered by the relevant benefit agency. Therefore, outflow rates for this client group is likely to depend also or particularly on the latter schemes. And given the fact that we lack data on schemes offered by the benefit-paying agencies, an analysis of outflow rates for those out of unemployment does not seem to be useful[3].

The central question we want to answer is: do the activities of the public employment offices increase the outflow rate for those in unemployment less than six months? The method used is aggregate impact analyses. For almost all (127) employment offices we have monthly data for 10 months during the year 2004, which allows us to apply panel data methods. The staff-client ratio is taken as the input variable.

Several studies evaluating the impact of job counseling on job entry chances can be found in the literature. Most of these studies use microdata to measure the impact. In the literature review by De Koning (forthcoming)[4], 22 of these studies on job counseling are mentioned. Two-third of these studies report significantly positive effects and ten percent mixed results, while only one quarter point to insignificant or negative results. Aggregate impact studies in this field are rare (see De Koning (2001) for a review of aggregate impact studies of active labour market policy). An advantage of aggregate impact studies is that in principle they lead to inferences about the impact of active policies on aggregate entities such as total unemployment. Displacement effects are incorporated in them, while they are not in the effects measured on the basis of micro data.

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[3] We have actually estimated similar models for the outflow probability from long-term unemployment. The results also point to a positive effect of the CWI, but the size of the effect is smaller. However, these models do not pass basic specification tests, which points to omitted variables.

[4] Which is based on a Dutch study by De Koning, Gelderblom, Zandvliet and Van den Boom (2005).

An earlier aggregate impact study by Arents and De Koning (2001) comes nearest to what we do in this paper. It uses differences in intensity of active labour market policy between regions and changes in intensity over time to examine its impact. Their paper applies panel data methods to pooled time series data on the regional branches of the Dutch Public Employment Service in the old structure when the PES was also engaged in measures such as occupational training and subsidy schemes. The number of unemployed hired was taken as the dependent variable. Expenditure on active measures per client was used as policy indicator. In fact two indicators were used: expenditure on subsidy schemes and training, and remaining expenditure. The latter was assumed to reflect job counseling and mediation. Only for the latter indicator some evidence of a positive effect on hiring rates was found.

For recent years data on the number of people hired from the pool of unemployed is not available. We have to use the outflow from unemployment as an approximation. As our analysis is confined to short-term unemployment, this approximation might be reasonable.

In his review of the international evaluation literature De Koning concludes that although for some types of active policies, including job counseling, the evidence is pointing to positive effects on job entry rates, the impacts found tend to be relatively small. On average, the more successful active policies may increase job entry rates by perhaps 5 to 10 percent points. This is somewhat disappointing and it may not be enough to compensate for the costs of the measures involved. Therefore, improvement seems to be highly needed. But is it also possible? Variation in performance among different implementation sites would indicate that there is room for improvement. And this brings us to the second part of our analysis, in which we attempt to measure the differences in performance between the individual employment offices.

We use the framework used in production function analysis to measure the relative efficiency of the individual employment offices in terms of outflow rates from unemployment. Analysing the relative performance of public sector offices is often referred to as benchmarking. In fact our analysis is similar in spirit as benchmark analysis by Mosley and Müller (forthcoming), although their performance measure relates to training and subsidy schemes in stead of job counseling and mediation.

The structure of this paper is as follows. Section 2 describes the model underlying the empirical analyses. Subsequently, section 3 presents the data, followed by the results of the empirical analyses in section 4. Then,

section 5 discusses how the results can be used to benchmark the various CWI centres. The final section, section 6, contains the conclusions.

2 MODEL

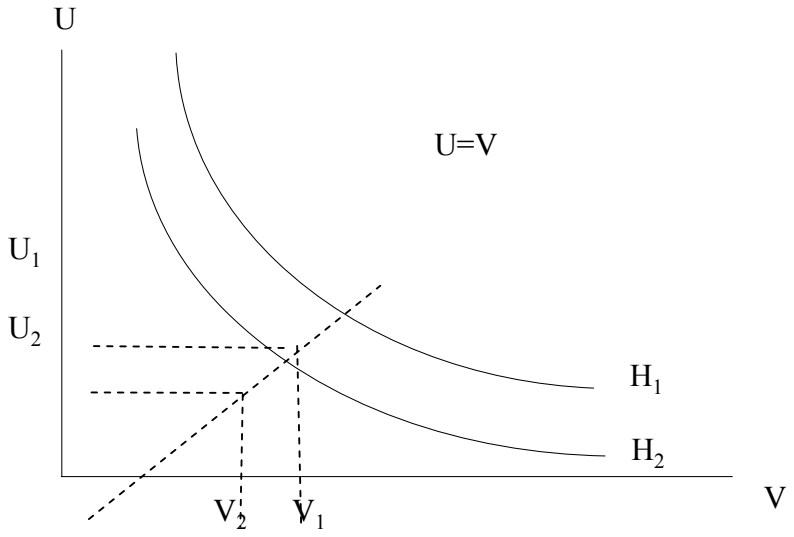
The theoretical basis of our research is the so-called matching function, which goes back at least to Holt and David (1966) and Phelps (1970). In the matching function in its most simple form, the number of unemployed that find a job (H) depends on the number of unemployed (U) and the number of vacancies (V), or in mathematical form:

$$H = f(U,V) \quad with \quad \frac{\partial f}{\partial U}, \frac{\partial f}{\partial V} > 0 \quad and \quad \frac{\partial^2 f}{\partial U^2}, \frac{\partial^2 f}{\partial V^2} < 0 \tag{1}$$

Equation (1) assumes that the number of unemployed persons that find a job is positively related to the numbers of unemployed and vacancies available. As long as there are vacancies (unemployed) left, an increase in the number of unemployed (vacancies) will lead to more vacancy fillings (unemployed finding a job). However, if the number of vacancies (unemployed) gets relatively small, a further increase in the number of unemployed (vacancies) will only have a small effect on the number of hirings. There is clearly a limit to the number unemployed that can be hired and the number of vacancies that can be filled.[5] This means that the second-order derivatives are negative. All combinations (U,V) that result in the same number of unemployed persons finding a job, are graphically represented in Figure 1. This figure is the analogy of an isoquant in production functions.

[5] If the difference between the number of vacancies and the number of unemployed becomes very high, one would expect the number of hirings to approach the minimum of the two.

Figure 1 Isoquants of the matching function



Assuming that the size of the labour market is of no influence on the quality of matching (that is f is homogeneous of degree 1), it holds that:

$$P = H/U = f(1, V/U) = f^*(x), \quad \frac{\partial f^*}{\partial x} > 0 \tag{2}$$

where *x* equals V/U and P denotes the probability for the unemployed to find a job.

In what respect can the role of the matching function be related with the activities of public employment offices? It could be assumed that due to these activities the unemployed and employers with vacancies will match with each other more easily. This can also be interpreted as follows: given the number of unemployed and vacancies, more unemployed will find a job and more vacancies will be filled with than without the activities of the employment offices. In figure 1 this could be expressed by a shift from isoquant H_2 to H_1. Clearly, the curve further away from the origin leads to yields a higher number of hires at given numbers of unemployed and vacancies.

What does this mean for the functioning of the labour market? We can show this by extending the model with an equation for employment. Suppose that per period λ per cent of the employed flows out of employment without finding another job. Then, it holds that:

$$\Delta L = H - Q = f(U,V) - \lambda L(-1) \tag{3}$$

Where L represents employment and Q the number of quits.

In a stationary situation with a constant labour supply, the equilibrium value for L will also be constant, implying:

$$f(U,V)/L = f(U/L, V/L) = \lambda \tag{4}$$

In this case, the matching function is closely related to so-called U/V-relation which is a measure for the functioning of the labour market. To illustrate this, suppose that a Cobb-Douglas type of function (which is in fact the functional form mostly used in the empirical literature on matching functions; see for example Blanchard and Diamond, 1989, and Petrongolo & Pissarides) is a good approximation of the matching function:

$$H = \eta U^{\gamma} V^{1-\gamma} \qquad \eta > 0; 0 < \gamma < 1 \tag{5}$$

Then the resulting U/V-relation is:

$$(U/L)^{\gamma} (V/L)^{1-\gamma} = \lambda / \eta \tag{6}$$

An upward shift in the matching function as a result of activities of employment offices implies an increase in ή. It thus implies a shift of the U/V-curve *towards* the origin. And a U/V-curve located more closely to the origin means that at a given number of vacancies, unemployment will be lower, and vice versa.

Additionally, equation (6) demonstrates that the location of the U/V-curve is also influenced by the rate of employees leaving employment without (immediately) finding a job. In principle, this rate can also be influenced by active labour market policy. Especially training of the unemployed might not only improve the probability of finding a job when unemployed, but additionally reduce the probability of becoming unemployed again after having found a job. For the type of services that is offered by the CWI however, such long-term effects seem to be less relevant[6].

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[6] However, few studies on training and subsidised labour show significant long-term effects (De Koning et al., 2005).

There is empirical evidence for the proposition that for an unemployed person the probability of finding a job is smaller the longer he is already unemployed (see OECD (2002) for a review of the literature). There might be a number of factors underlying this duration dependence. Firstly, employers will regard long-term unemployment as an indication for lack of motivation and/or competencies. This may turn out to be a self fulfilling prophecy: a jobseeker who does not find a job, in spite of applying for one many times, possibly gets discouraged. Additionally, long-term unemployment will lead to a loss of work rhythm and as a result hired long-term unemployed need a longer training period than other new employees. This distinction can be expressed by defining separate matching functions for different duration classes, for example[7]:

$$H^d = f^d(U^d, V) \tag{7}$$

where d represents a specific duration class and thus H^d en U^d hirings from duration class d and the number of unemployed in duration class d, respectively..

The we have for the job entry probability for the unemployed in duration class d, P^d:

$$P^d = H^d / U^d = f^d(1, V/U^d) \tag{8}$$

For the model to be used in our empirical analysis, the Cobb-Douglas form given by (5) is the starting point. From now on the index s will be used to refer to the short-term unemployed as the model will only applied to the latter. However, in addition to the V/U variable a number of other explanatory variables are included. The first one is a variable indicating the mismatch between labour demand and labour supply.

Essentially, friction between demand and supply in the labour market is caused by the heterogeneity of labour. The supply as well as the demand side shows variation in competences and location. In the aforementioned model these factors are not explicitly included. An alternative approach treats the labour market as consisting of many submarkets that correspond with professional and regional submarkets. Some submarkets will have shortages, others surpluses. By assuming that demand and supply are divided over the submarkets according to a continuous distribution, a macro disequilibrium function can be derived that is completely analogous to

[7] Den Butter and Van Ours (1990) distinguish matching functions that make a distinction in duration classes for the unemployed as well as vacancies.

equation (6) (see for example Kooiman and Kloek (1979). Later on, effort is made to combine the aggregation approach with the abovementioned flow approach (Muysken, Bierings, & De Regt, 1993).

In our case geographical mismatch is less relevant as fairly small regions form the entities in our empirical analysis. However, skills mismatch might be important. Therefore, the following discrepancy variable is added to the equation:

$$dis_r = \sqrt{\sum_{j=1}^{6}\left(\frac{U_{jr}^s}{U_r^s} - \frac{V_{jr}}{V_r}\right)^2} \qquad (9)$$

In this expression U_{jr}^s and V_{jr} denote the numbers of short-term unemployed (s refers to short-term unemployment) and vacancies, respectively, for skills category j in region r. The corresponding variables without index j are total short-term unemployment and total vacancies in region r, respectively. There are five types of education: the level not higher than the first step in secondary education, the second step in general education, the second step in vocational education, higher vocational education and university education; the sixth category is education unknown. A higher value of dis is expected to be associated with a lower hiring rate.

We also expect the demographic structure of the unemployment to be relevant. Employers tend to favour young male jobseekers of Dutch origin when it comes to hiring personnel. The reasons behind their reluctance to hire people from other categories have partly to do with considerations of costs and productivity. Older people, for example, tend to earn higher wages than younger workers owing to seniority rules in pay systems, but may not be more productive[8]. However, prejudice may also partly explain why older unemployed have more difficulties in finding jobs. Prejudice may even be more important in relation to women and ethnic minorities. In any case, our hypothesis is that with a given vacancy-unemployment ratio the number of hirings from unemployment is lower the higher the shares of women, older people and ethnic minorities in unemployment are. Unemployment duration is also relevant in principle, but not in our case as our analysis deals with short-term unemployment only.

Finally, we have two variables representing the efforts of the employment offices. The first of these variables is ratio between the number of staff

[8] For a review of the literature on productivity and pay in relation to age, we refer to Gelderblom and De Koning (2002).

members in an employment office dealing with mediation services and the number of clients. The staff variable is measured in full-time equivalents. Roughly 60 per cent of the staff of an employment office deals with mediation services. Our hypothesis is that the higher the staff-client ratio is, the higher the number of hirings from unemployment is.[9]

However, with the same resources one office may reach better results than another office. That might be due, for example, to the quality of the staff or a better organisation of the work processes. We assume that quality varies among offices, but is for each office constant over time.

Using a Cobb-Douglas specification, assuming linear homogeneity and adding an error term, we then end up with the following model:

$$\log(P_{rt}^{s}) = \underline{a}' \underline{x_{rt}^{s}} + \beta dis_{rt} + \gamma (V/U)_{rt} + \delta SCR_{rt} + q_r + \varepsilon_{rt} \qquad (10)$$

In this equation x denote a vector with the shares of the various categories in unemployment, SCR is the staff-client ratio, q is the employment office's quality and ε an error term. The other variables have already been defined earlier.

3 DATA

The data for the 127 centers were obtained from two information systems of the CWI; the Management Information Portal (MIP) and the Online Analytical Processing-module (OLAP). The number of full-time equivalents was obtained through an additional information file. We have monthly data. The length of the data period varies among the different variables.

The main limitation of the data is that we have no information on the number of hires from unemployment, but only on the total outflow from unemployment. It is quite possible that some of the persons flowing out of unemployment become inactive rather than employed. However, one should keep in mind that our empirical analysis completely focuses on short-term unemployment. Therefore, we think that in our case outflows may still be a good indicator for outflow to work.

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[9] One could argue that the service level of a public employment office is not only determined by the number of staff members but als by the available physical infrastructure, but we do not have data on the latter.

The administrative data from the CWI give a reasonable approximation of unemployment. Unemployed jobseekers are obliged to register at the CWI in order to become eligible to a benefit. However, CWI unemployment data may not fully reflect the unemployed jobseekers without benefit. This group will only be motivated to register at the CWI when they expect CWI service provision to increase their job entry chances.

Vacancy data are also taken from the CWI. Here the coverage of total vacancies is less good than for unemployment. Probably, only one quarter of all vacancies are registered at the CWI. Still, the CWI vacancy data may give a reasonable indication of the development of total vacancies. At least they do on the national level if we compare them with data from the national statistical bureau that are supposed to cover the whole vacancy market. Unfortunately, the national statistical bureau hardly publishes vacancy data on the level of CWI establishments. Only once a year such data is published, but only stock data are given and the quality of the data seems to be poor.

In the previous section the variables of the model were already discussed. Box 1 indicates how we have measured them exactly. Table 1 gives a number of statistics for the various variables.

Box 1 Definitions of the variables used

Outflow probability = $$\frac{(Outflow\ from\ \ short-term\ unemployment\ during\ month)}{(Stock\ of\ \ short-term\ unemployed\ at\ the\ beginning\ of\ \ month)+(Inflow\ during\ month)}$$

Vacancy-unemployment ratio = $$\frac{(Stock\ of\ \ vacancies\ at\ beginning\ of\ \ month)+(Inflow\ during\ month)}{(Stock\ of\ \ short-term\ unemployed\ at\ beginning\ of\ \ month)+(Inflow\ during\ month)}$$

Share of demographic category j in unemployment = $$\frac{(Stock\ of\ \ short-term\ unemployed\ in\ category\ \ j\ at\ beginning\ of\ \ month)}{(Total\ \ stock\ of\ \ short-term\ unemployed\ at\ beginning\ of\ \ month))}$$

Where j refers to two age categories (the old and the young), skills level, gender and ethnic origin (Dutch vs. Non-Dutch)

Staff-client ratio = $$\frac{(Number\ of\ \ staff)}{(Total\ \ stock\ of\ \ unemployed\ at\ beginning\ of\ \ month)+(Inflow\ during\ month)}$$

Skills discrepancy = $$=\sqrt{\sum_{j=1}^{6}\left(\frac{U_j}{U}-\frac{V_j}{V}\right)^2}$$

Where U refers to the stock of short-term unemployed and V to the stock of vacancies; j refers to skills categories

All variables are measured on the regional level and refer to individual CWI offices (employment offices)

The total group of unemployed jobseekers consists of roughly 30 per cent of persons with a short duration of unemployment. This relatively small group is good for 63 per cent of the total outflow. Thus, the concern outflow probability of unemployed jobseekers with a short duration of unemployment is 15 per cent, against 5 per cent for unemployed jobseekers with a long duration of unemployment and 8 per cent for the total group. As expected the outflow probability of those with a short duration of unemployment is larger than for the total group, but this is not necessarily related to the efforts that are made by the CWI. The pattern of the outflow probability of these persons over time is heterogeneous among the centers. This is also the case for the absolute outflow. On the contrary, the stock value of unemployed jobseekers with a short duration of unemployment does reveal a slight pattern that is confirmed by most centers, and may be related to cyclical movement.

The mean tightness in the labour market for the total group is 0.10; only one vacancy per 10 unemployed jobseekers. Taking into account only the group with a short duration of unemployment, 3 vacancies are available per 10 persons. In the beginning of 2004 the situation was worse, but in the course of the year, the tightness improved slightly for most centers. This overall improvement is caused by the increase of registered vacancies during the year. Given the fact that the supply of vacancies is more dynamic and more sensitive to the business cycle than the number of unemployed jobseekers, it is likely that the increase is due to the recovery of the economy.

Generally, one full-time staff member has to serve about 200 unemployed jobseekers. Assuming that a full time equivalent consists of 40 hours per week, this means that a co-worker or (senior) advisor Work and Income can spend 12 minutes on each unemployed jobseeker. This amount varies between a minimum of 6 minutes and a maximum of almost 37 minutes, but based on the standard deviation, most centers are covered within the range of 5.5 to 19 minutes. When unemployed jobseekers with a long duration of unemployment are not taken into account, it shows that in nearly all centers an employee can spend an average of between 22 and 58 minutes per unemployed jobseeker. This seems to be a fair amount of time, certainly when keeping in mind the emphasis on one's own responsibility and self-service.

A point for potential concern for the SCR variable is that the staff number is divided by total unemployment in the region. Therefore, a correlation between the SCR variable and the dependent variable could reflect the unemployment situation (high unemployment coinciding with low outflow rates) rather than the efforts of the CWI. Furthermore, the SCR variable could be correlated with the size of the CWI and then reflect differences in

effectiveness between CWI of different size. However, the correlation of the SCR variable with both unemployment and size is low.

The mismatch term *discrepancy* does differ among centres, but does not show a lot of variation over time.

Half of the unemployed jobseekers with a short duration of unemployment is female. Most of them are of Dutch origin, namely over 80 per cent. More than a third has a low educational background. The group is composed for 18 per cent of persons younger than 24 and 16 per cent of elderly; 50+.

Table 1 Descriptive statistics of unemployed jobseekers with a short duration of unemployment

	Mean	Median	Maximum	Minimum	Standard deviation	Number of observations
Stock of short-term unemployed (< 6 months)	1605	1348	5267	82	952	1778
Short-term unemployment as a share of total unemployment	0.31	0.31	0.64	0.15	0.06	1778
Outflow probability from short-term unemployment	0.15	0.15	0.31	0.06	0.03	1368
Outflow number from short-term unemployment	268	243	903	2	148	1524
Outflow from short-term unemployment as a share of total outflow	0.63	0.64	0.96	0.2	0.11	1522
Number of vacancies	469	394	2232	40	319	1523
Ratio between vacancies.(stock + inflow) and short-term unemployment (stock plus inflow)	0.30	0.25	2.65	0.02	0.21	1240
Staff-client ratio (*100)	0.51	0.49	1.52	0.25	0.14	1777
Staff input in minutes per registered unemployed jobseeker	12.2	11.8	36.4	6	3.4	1777
Discrepancy between skills structures of unemployment and vacancies	0.45	0.43	0.87	0.29	0.09	1651
The share of women in short-term unemployment	0.47	0.48	0.58	0.25	0.04	1778
The share of people of Dutch origin in short-term unemployment	0.83	0.87	1.07	0.31	0.13	1778
The share of the low-skilled in short-term unemployment	0.38	0.38	0.65	0.18	0.07	1778
The share of the young in short-term unemployment	0.18	0.18	0.31	0.05	0.04	1778
The share of the old in short-term unemployment	0.16	0.16	0.27	0.08	0.03	1778

4 ESTIMATION RESULTS

We will estimate two types of model. In the first type of model the variables are taken in levels, while the second model is in first differences. In the level model the quality of individual employment offices (the variable q in equation (10)) is treated as fixed effects; in the first differences model this variable of course drops out of the model (since we assume that q varies among offices, but is constant over time).

Table 2 Regression results for the outflow rate from short-term (ST) unemployment in a level model [10]

	M (1)	M (2)	M (3)	M (4)
Log(vacancies /ST unemployment)	0.048	0.089	-0.046	0.047
	(5.192)**	(5.755)**	(5.284)**	(3.089)**
Share of the young	-0.152	1.419	-0.242	0.736
	(-1.155)	(5.125)**	(-2.029)*	(3.217)**
Share of the old	0.487	-1.160	0.571	-0.258
	(2.823)**	(-2.994)**	(3.848)**	(-0.812)
Share of the low educated	-0.015	0.398	-0.105	-0.158
	(-0.191)	(2.031)*	(-1.563)	(-0.982)
Share of clients of	0.195	0.525	0.148	0.138
Dutch origin	(4.068)**	(2.159)*	(3.523)**	(0.778)
Share of women	0.092	-0.741	0.497	-0.419
	(0.733)	(-4.214)**	(4.172)**	(-2.558)*
Skills discrepancy	0.192	0.137	0.200	0.136
	(3.893)**	(1.867)	(4.714)**	(2.398)*
Staff-client ratio	0.342	0.718	0.326	0.566
	(8.508)**	(4.764)**	(9.299)**	(4.779)**
Constant	-2.341	-2.431	-2.545	-2.256
	(-26.823)**	(-10.893)**	(-31.400)**	(-12.556)**
Centre fixed effects (p-value Wald test)	No	Yes (0.000)	No	Yes (0.000)
Monthly fixed effects (p-value Wald test)	No	No	Yes (0.000)	Yes (0.000)
p-value homoskedasticity (Bartlett-test)	0.475	1.000	1.000	1.000

[10] In total 127 centres and 1240 observations are included. The sample period includes 10 months; from January up to and including October 2004. The t-statistics are given in parentheses.

Table 2 gives the results for the model in levels. Initially OLS was applied to the model, but the Bartlett test convincingly rejected the existence of homoskedasticity. Given the considerable variation in size between the regions this may come as no surprise. In table 2 only results with weighted least squares are shown.

In addition to fixed effects for offices, one might also include monthly time dummies for the months. These time dummies might account for unobserved factors that vary over time and are more or less the same for all offices (regions). This leads to four models:

- model 1: no fixed effects for the offices(that is taking quality differences between offices not into account) and no time dummies for the months;
- model 2: only fixed effects for the offices;
- model 3: time dummies for the months, but no fixed effects for the offices;
- model 4: both fixed effects for the offices and time dummies.

As table 2 shows the model with neither centre fixed effects nor time dummies does not pass the specification test. The other models do. However, in the remaining three models only few explanatory variables consistently have the expected sign. The staff-client ratio variable is one of them. It is always significant as has the right sign: a higher ratio leading to more outflow from short-term unemployment. Also the share of clients of Dutch origin has always the right sign, but it is not always significant. The model with centre fixed effects and time dummies (model 4), is the severest test for the model. In this model all variables have the expected sign except for the skills discrepancy variable.

The coefficient of the vacancy-unemployment ratio is relatively small in size. In the literature, usually higher values are obtained. However, Broersma and Van Ours (1998) state, based on an overview of an international comparison of almost 30 studies on matching elasticity, that different measures for stock and flow values of jobseekers, imply quite different values for the elasticity of the vacancy-unemployment variable. It is also important to note that we used vacancies that are registered at the CWI. What might play a role too is that during a recession a higher percentage of vacancies is registered and filled by the public employment service (De Koning, Donker van Heel, Gelderblom, Van Nes, & Zandvliet, 1995).Therefore, registered vacancies may fluctuate less than total vacancies, which may also affect the estimates.

Characteristics that have a significant effect in model 4 are young age and gender. The larger the share of young people is, the higher the outflow rate

from unemployment is. The share of women has a negative effect. Both signs are as expected. The other characteristics are not significant although they have the expected sign. Clearly, one would expect that larger shares of older unemployed and of unemployed from non-Dutch origin affect the outflow rate negatively. In the case of the low-skilled it is less clear what should be expected. Although, the low-skilled experience an unemployment rate that is well above the average, this does not necessarily imply that their expected unemployment duration is also longer. It may well be that the higher unemployment among the low-skilled is caused by more frequent unemployment spells. In any, case the sign and significance level of the estimator concerned varies among the models: in model the estimator is negative and not significant.

The significantly positive influence of the discrepancy variable is unexpected, while a larger extent of mismatch was expected to have a negative influence on the outflow probability. Perhaps areas with high shares of low-skilled in unemployment also tend to have a weak employment structure resulting in a smaller number of hirings. And despite the weak employment structure the low-skilled may still be over-represented in unemployment. Then, we would find that the share of the low-skilled in unemployment tends to be higher than the share of vacancies requiring only low skills in total vacancies, while at the same time the outflow from unemployment is relatively low.

The variable representing the efforts made by the employment offices in increasing the outflow rate from unemployment has a significantly positive sign in all models. This seems to be a robust result indicating that what the CWI does indeed raises the outflow from short-term unemployment. We come back to the policy implications of this finding later.

Table 3 Regression results for the outflow probability from short-term unemployment in a first differenced model[11]

Variables:	M(5)	M(6)	M(7)
log(vacancies/ST unemployment)	0.083	0.081	-0.016
	(4.051)**	(3.903)**	(-1.127)
Share of the young	2.12	2.108	0.770
	(5.642)**	(5.591)**	(2.726)**
Share of the old	-2.488	-2.491	-1.124
	(-4.666)**	(-4.669)**	(-2.632)**
Share of the low educated	0.606	0.619	-0.229
	(2.079)*	(2.111)*	(-0.961)
Share of clients of	1.027	0.992	0.696
Dutch origin	(2.562)*	(2.428)*	(2.487)*
Share of women	-1.419	-1.461	-1.253
	(-4.826)**	(-4.732)**	(-5.198)**
Skills discrepancy	-0.008	-0.011	0.100
	(-0.080)	(-0.107)	(1.547)
Staff-client ratio	1.207	1.183	0.819
	(4.385)**	(4.213)**	(3.455)**
Constant		0.002	0.030
		(0.438)	(3.219)**
Monthly fixed effects (p-value Wald test)	No	No	Yes (0.000)
p-value homoskedasticity (Bartlett-test)	1.000	1.000	1.000

An alternative way to correct for centre specific effects that are constant over time and to correct for trends in the variables is to estimate the model in first differences (Wooldridge, 2003). In a first-differenced model, the unobserved constant centre specific effects are simply differenced away. Table 3 gives the results for three models in first differences:

- model 5: no constant term and no time dummies;
- model 6: constant term included, but no time dummies;

[11] In total 127 centres and 1089 observations are included. The sample period includes February 2004 up to and including October 2004. The t-statistics are given in parentheses.

– model 7: a constant term and time dummies both included.

In a model in first differences a constant term represents a trend in the level of the dependent variable. Again weighted least squares has been applied.

All three models pass the test for homoskedasticity. If we do not include time dummies, the constant term is not significant. The result of including time dummies is that these time dummies plus the constant term completely take over the role of the vacancy-unemployment variable. From that point of view, one might prefer models 5 and 6 to model 7, even although the time dummies are significant.

In all three models most variables are significant and have the expected sign. Only the share of the low-skilled changes sign and is not significant anymore in model 7. This coincides with a change of sign of the discrepancy variable, which seems to support the idea expressed earlier that the two are related. In none of the models in first differences the discrepancy variable is significant. The staff-client ratio has a significantly positive impact on the outflow probability in all three models. Therefore, in all regressions the coefficient of main interest, the policy variable of the employment offices, is positively significant.

5 AVERAGE AND RELATIVE EFFECTIVENESS OF THE EMPLOYMENT OFFICES

On the basis of the model estimates, we can compute the average effect of the efforts by the employment offices on the outflow rate from short-term unemployment. The coefficient of the variable is a semi-elasticity, and the elasticity is thus given by multiplying it with the variable itself. This elasticity is only applicable within the range of the data given and notice, that for each observation of every centre the elasticity differs. A reliable measure for the elasticity is based on a reliable estimation of the coefficent multiplied with the median of the variable and is called elasticity around the average point (Anxo, Carcillo, & Erhel, 2001). In level model 4 for example, the elasticity is 0.28. Thus, an increase of 10 per cent in the staff-client ratio leads to an increase of 2.8 per cent of the outflow probability. Earlier it was stated that on average, 12 minutes were spent on each unemployed jobseeker. Thus, an increase of 10 per cent suggest that spending a little more than 13 minutes, would increase the outflow probability with 2.8 per cent which seems a fair result. Another way of looking at the outcomes is that a 50 per cent increase in the number of full-time equivalents per client would raise the average outflow probability from short-term unemployment from 0,15 to 0,17.

Models 2, 5, 6 and 7 can be seen as acceptable alternatives to model 4. The size of the staff-client ratio variable varies considerably between these models. In model 5 it is even 1,2, which would lead to an elasticity of 0,60, which doubles the effect on the outflow rate. So, we may conclude that on the basis of the estimation outcomes, a 50 per cent increase in staff size is most likely to increase the average outflow rates of employment offices from 0,15 to a figure between 0, 17 and 0,19.

So far, we discussed the average effectiveness of employment offices in terms of raising outflow rates from short-term unemployment. However, it is unlikely that each centre is equally efficient. It is the purpose of benchmarking to indicate which centers perform well and which ones perform badly. Then measures can be taken to improve the performance of the bad performance, which would increase average performance.

The estimation results can also be used to get indications of the relative performance of the different employment offices. In order to show this, we rewrite our estimation equation (10) as:

$$\log(P_{rt}^{s}) = \log(\overline{P_{rt}^{s}}) + q_r + \varepsilon_{it} \tag{11}$$

Where q_r represents the quality of region's r employment office and $\overline{P_{rt}^{s}}$ is the efficient outflow rate:

$$\log(\overline{P_{rt}^{s}}) = \underline{a}' \underline{x_{rt}^{s}} + \beta dis_{rt} + \gamma (V/U)_{rt} + \delta SCR_{rt} \tag{12}$$

Equations (11) and (12) can be seen in analogy to a production function. Equation (12) then represents the efficient matching technology. In production function analysis one usually only observes the actual production level and not production capacity. In our case we could say that we only observe the actual outflow rate and not the rate that would result from a fully efficient employment office. Then, q_r indicates the efficiency of centre r. If we rank the centers from the most efficient one to the least efficient one, and assume that the most efficient office is fully efficient, then for this office q would equal zero, while it is negative for the other offices.

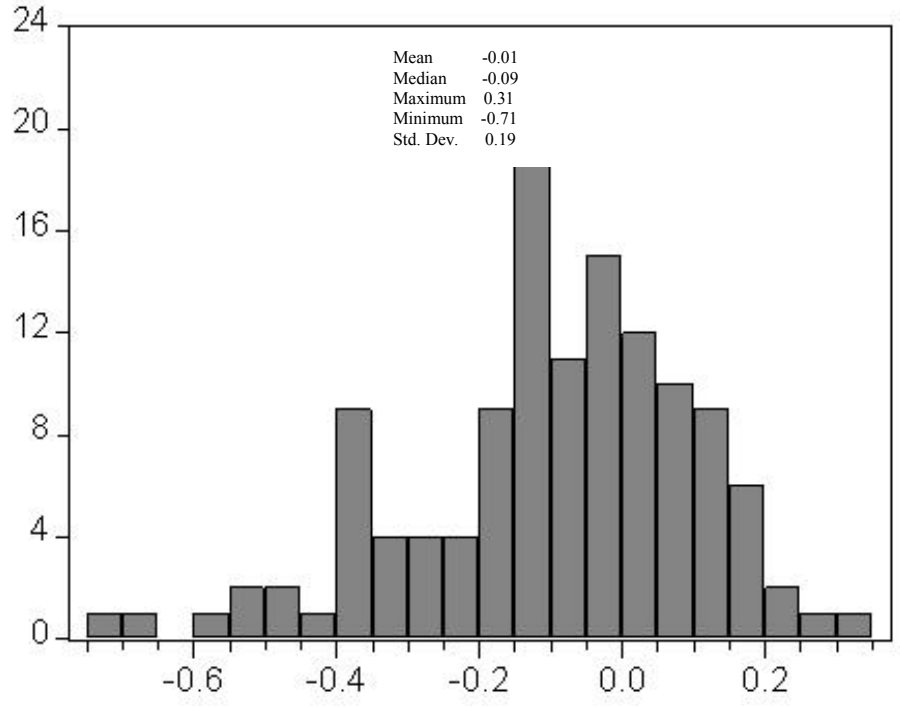
This would mean that the fixed effects can be interpreted as indicating the quality of the different offices[12]. As one centre is taken as the reference centre in the estimations they should be interpreted as indicating relative efficiency. Given the fact that the period under consideration is short, the assumption of constant efficiency per centre may not be unrealistic. Under the assumption that the fixed effects give a reasonable representation of relative efficiency, they can be considered to be indicators for the corrected relative placement results of the centers. By using the earlier regression models, we correct first of all for differences in the composition of unemployment. Regions with a high share of young unemployed, for example, will have higher placement results with all other factors taken as constant. The models also correct for differences in the labour market situation and in the number of staff per unemployed jobseeker. Therefore, comparing centers on the basis of the fixed effects is better than comparing gross placement rates. However, we acknowledge that the fixed effects may also capture the influence of unobserved exogenous factors that have nothing to do with efficiency.

Basically, only 10 observations are available to estimate each fixed effects term. It is difficult to say what this means for the accuracy of the estimates. More time points would be preferable, of course.

The distribution of the estimated fixed effects terms is given in figure 2. Note that in the estimation one centre (*not* the worst performer) acts as the reference centre, implying that the figures cannot directly interpreted as efficiency levels. However, the figure does indicate the variation in performance among the centers. Approximately 83 per cent of the centers appear within a (-0.3; 0.3) interval around the mean. This means that most centers are between 30 per cent more and 30 per cent less efficient than the average performer. The ranking on the basis of the fixed effects is quite different from the ranking of the gross placement rates. On the basis of fixed effects, only one of the top ten centers in the ranking according to the gross placement rates still appears in the top ten. The worse 10 performing centers however, are more stable positioned within the ranking, 8 of them are in both cases part of the worse 10.

[12] An alternative would be to treat the q-variables as random terms. Then the stochastic frontier approach could be applied to the model. A disadvantage of this approach is that we would have to assume that the quality term is independent from the other explanatory variables which may not be realistic.

Figure 2 Distribution of the fixed effects terms for the individual centers



6 CONCLUSIONS

In this paper we found evidence for a significant positive effect of the activities of employment offices in the Netherlands on the outflow rate from short-term unemployment. Using short time-series for 127 regional employment offices we found consistent evidence for a positive effect of the staff-client ratio on the regional outflow rate. The results imply that a 50 per cent increase in staff size would increase the average regional outflow rate from 15 to a figure between17 to 19 per cent, depending on the model. This is the expected increase, which is of course subject to a certain amount of uncertainty as indicated by the standard errors of the estimators.

Under the assumption that the systematic centre-specific component in the residuals represents efficiency, the centre fixed effects can be interpreted to indicate the relative efficiency of the different centers. It appears that most centres are within a range of 30 per cent above and 30 per cent below the average performer. If this is true, considerable efficiency gains are still possible. However, one should keep in mind that the fixed effects may only partly reflect relative efficiency and also capture the influence of unobserved exogenous variables. Still, the models used take several factors

into account that are outside the control of individual employment offices. These factors are the shares of different groups (the young, the old, the low-skilled, people from Dutch origin and women), the vacancy-unemployment ratio, the staff-client ration and the skills discrepancy (the latter variable proved to be significant with the wrong sign in the models in levels and insignificant in the models in first differences). Therefore, judging the centers on the basis of the estimated fixed effects is at least better than using the gross outflow rates.

Our approach can be improved in several ways and these improvements seem to be warranted before the results are to be used to actually benchmark the regional offices. Most importantly, it would be better to use data on the outflow to employment in stead of total outflow, which we used. In principle, such data exist. The organisation responsible for implementing social security laws (UWV) disposes of individual data that makes it possible to infer when exactly a person has a job. This data can be matched with the data from the CWI. For each client leaving CWI registration one could then find out whether and when he found a job.

It would also be important to know more about the reintegration activities that take place under the responsibility of the municipalities and the earlier mentioned UWV. In the Dutch situation these organisations get funding for activating measures such as training and subsidised labour. If we had information of the participation of unemployed clients in these activating measures, it would improve the analysis in two ways. First of all, it would improve our analysis of the outflow from short-term unemployment. Although, municipalities and UWV mostly target their reintegration activities to clients that are already unemployed for some time, interventions early during the unemployment period are not totally excluded. Such interventions may affect outflow rates. Therefore, accounting for such early interventions may improve the estimation. More importantly, information on reintegration activities by the municipalities and the UWV would allow us to also estimate reliable models for the outflow from long-term unemployment. A more comprehensive evaluation of active labour market policy would then be possible.

Finally, we mention the possibility of using data on individual unemployed from the various regions. With such data it might be better possible to get reliable estimates of the impact of the CWI on the job entry probabilities. This may particularly be the case when also data would be available about the services provided to individual clients. However, a disadvantage of using individual data is that the effects found do not represent possible displacement effects. In that sense we think that aggregate and micro

impact analyses should be done both, and should not be regarded as substitutes.

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APPENDIX 1 RANGE OF TASKS OF THE CWI

The CWI have the following tasks:

- Registering jobseekers and vacant jobs of employers.
- Proposing suitable vacancies to jobseekers and suitable jobseekers to employers seeking for personnel.
- Recommending the UWV and the municipal social services about the possibilities to integrate jobseekers who are difficult to place in the labour market.
- Collecting and analysing information on behalf of the promotion of the functioning of and insight in the labour market.
- Collecting applications for benefit, allowances and assistance, as well as declarations of unemployment.
- Providing information concerning the choice of a profession as well as the required education.
- Ensuring (un-)demanded provision of reliable information on and advice about the labour market as well as about the implementation of its tasks to interested parties.
- Providing permission for resignation and employment.
- (Re-)indication in accordance with the Sheltered Work Provision Act (*WSW*).

The CWI translates the range of tasks to objectives that in summary pursue a more transparent labour market and strive for a better functioning labour market

APPENDIX 2 DATA

Except for CWI 'Nieuwkomers Zuidwest Nederland' (Newcomers Southwest Netherlands), CWI 'Jongeren' (Youth), Vacancy Service Amsterdam and CWI Culture, all the other centers are included in the analyses, in total 127. The centres Eindhoven Mercado and Eindhoven Stadhuisplein are combined. Until 2004 these two centers were one. The opposite holds for Tilburg. Until 2004 Tilburg had two centers, which merged in 2004. Finally, the Zaltbommel and Tiel are separate centers, but in reality the number of full-time equivalents of Zaltbommel are included in the human resource system of CWI Tiel. Therefore, the two centers are aggregated to one, named CWI Tiel.

Not all data were available for the total range of 2003 and 2004. The availability of stock values of unemployed jobseekers and vacancies was no problem. Flow data of vacancies are available up to and including October 2004. The CWI was implementing a new system when the data were gathered; therefore the database was not up-to-date. Outflow specified to duration of unemployment was only available for 2004, therefore, the analyses only concern the first ten months of 2004. The inflow of short-term unemployed jobseekers (nww^{sd}) was not obtained and therefore approximated by $nww^{sd}{}_t - nww^{sd}{}_{t-1} + outflow_t{}^{sd}$ However, outflow is corrected for unemployed jobseekers who register again within 30 days, and the discrepancy of registering flows and stocks led some times to negative inflow numbers. These (29) observations were deleted and not included in the analyses.

Data about the policy variable, the mean number of full-time equivalents, were delivered in a separate file, containing data on all occupations per centre on quarterly basis. Occupations were filtered for the ones not associated with job-broking activities, and after that interpolated to monthly data.