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Macro Matching and Micro Search Durations looking inside the black box of job formation

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In recent labour market research the concept of the matching function is introduced to study relationships between stocks of job seekers and vacancies and the process of job formation. Matching functions are used to study changes in the performance of labour markets. In the analysis these studies mainly use macro time series data. In this paper we study the process of job formation in the labour market by using micro data. Our data cover a short time period. Therefore, we cannot analyze changes in the matching technology over time. We do find differences in matching technology between disaggregate labour markets. This suggests that one should be careful in drawing firm conclusions based on analyses of aggregate labour markets. Changes at the aggregate level may reflect changes in composition of the labour market in stead of changes in matching technology.

1. INTRODUCTION

Recent research in labour economics and macroeconomics stresses the importance of flows in understanding developments in the labour market. The basic idea is that inflows and outflows, determining developments in stocks, provide more information than the developments in stocks as such. An important concept in this system of stocks and flows is the matching function.
The general idea is that in the labour market job seekers and employers with vacancies are searching for each other, contact and match. This is formalised into a matching function relating the stock of job seekers (N) and vacancies (V) to the flow of matches (F) (see for example Blanchard and Diamond (1989), Jackman, Layard and Pissarides (1989)). In its general form this function may be written as:

$$F = m(N,V) \qquad m_n>0 \qquad m_v>0 \tag{1}$$

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The function m(.,.) describes the speed at which this matching process takes place, and gives an indication of the functioning of the labour market. m(.,.) is determined by factors like information imperfections, geographical and skill distribution, and by individual labour market behaviour of job seekers and employers. This individual behaviour concerns the choice of search and recruitment channels, the number of search methods used and job acceptance and job offer decisions of the worker and employer. The matching function gives a summary description of the performance of the labour market. So, if there are differences between the matching processes at a disaggregate level, the aggregate matching function represents 'average' labour market performance.

The matching function is not necessarily stable over time. In theory, there are two determinants of change. First, there may be differences in the matching process at a disaggregate level. Labour market efficiency in some parts of the labour market may be higher than in other parts. Over time the composition of the labour market may change. If the share of sub-labour markets with a less than average performance increases, aggregate performance decreases even if at the level of the sub-labour markets there is no change in performance at all. Second, if the matching technology of the sub-labour markets deteriorates, there is an increasing malfunctioning of the aggregate labour market as well. This deterioration may be due to changes in the behaviour of job seekers, employers or both.

There have been several empirical studies on the matching function which we discuss in more detail in section 2. Most of these studies use macro time series data to estimate the parameters of (1). In a few cases, for some countries, an increased malfunctioning of the labour market is found. The determinants of this increased malfunctioning are still unclear, because it is difficult to distinguish between compositional effects and structural changes in the matching technology. In understanding the (mal)functioning of the labour market the various micro aspects of the matching process and the relative importance of each of these aspects in the speed of the job formation process need to be determined. That is the primary goal of the present paper. In understanding these micro economic decisions aggregate data will not be of much use. We therefore specify matching functions at the disaggregate level, and use micro economic data to estimate these functions. The micro matching approach enables us to analyze search behaviour of employers and workers in an integrated framework and to distinguish the intensity in which contacts between job seekers and vacancies take place from the (conditional on a contact) matching probability.

Our data which cover a short time period in 1986-1988, do not permit us to analyze changes in the matching technology. We do find differences in matching technology between disaggregate labour markets. This suggests that one should be careful in drawing firm conclusions based on analyses of aggregate labour markets. Changes at the aggregate level may reflect changes in composition of the labour market in stead of changes in matching technology.

The remainder of the paper is organised as follows. Section 2 gives a brief survey of empirical studies of matching functions, mainly using aggregate data. Section 3 presents our theoretical model in which we show the relationship between the macro matching function and micro duration and contact rate data. In section 4 we briefly discuss the likelihood function and the data used. Section 5 presents the results and section 6 concludes.

2. MACRO MATCHING

Most studies find or assume that the matching function has constant return to scale. We specify a constant returns to scale Cobb-Douglas matching function:

$$F = \lambda \, . \, N^{\alpha} \, V^{1-\alpha} \tag{2}$$

in which λ is an efficiency parameter

Since available data do not allow for a direct estimate of (2), mostly two kinds of assumptions are made. First, a steady-state labour market may be assumed, in which the average duration of search of unemployed workers (T_u) equals the average duration of search of employed workers (T_s). As a results the stocks of job seekers and vacancies are equal to the product of the flows and the average durations of search:

$$\begin{aligned} N &= S + U = F_s.T_s + F_u.T_u = (F_s+F_u).T_u = F.T_u \\ V &= F.T_v \end{aligned} \tag{3}$$

in which S (U) stands for the number of employed (unemployed) job seekers, F_s (F_u) for the flow of matches of employed (unemployed) job seekers, and T_v is the average vacancy duration. Rewriting equation (2) we get:

$$1 = \lambda \, . \, T_u^{\alpha}.T_v^{1-\alpha} \tag{4}$$

So under the assumption of steady-state, the matching function (2) may be transformed into a stable relationship between the average unemployment duration and the average vacancy duration. As a result, using data on unemployment and vacancy duration, the parameters of the matching function (2) can be estimated. This approach is followed by Schager (1985), Jackman et. al (1989) and Van Ours (1991).

In a second approach to estimate the parameters of (2) the number of employed job seekers is ignored. Then (2) becomes:

$$F = \lambda \,.\, U^{\alpha}\, V^{1-\alpha} \tag{5}$$

The relationship (5) plays a central role in the traditional Beveridge curve, the latter being the relationship between unemployment rates and vacancy rates derived under the assumption that the flow into unemployment equals the flow out of unemployment. Pissarides (1986), Belderbos & Teulings (1988), Blanchard & Diamond (1989) and Van Ours (1991) estimate relationships like (5).

The parameter λ in (4) or (5) tells us something about the functioning of labour market. If λ is constant over time, there are movements along the Beveridge curve: changes in unemployment (unemployment duration) will be accompanied by changes in opposite direction of vacancies (vacancy duration). If λ changes over time, the relationship shifts, indicating an improvement or a deterioration of the labour market performance.

In the past decades, there have been numerous studies investigating the Beveridge curve. Explicit analysis of the matching function has occurred less frequently, starting in the second half of the 1980's. It is not our intention to give a complete survey of matching function studies, instead we list some of the empirical studies using the concept of the matching function in Table 1.

Most studies use annual macro time series data, but the information used to construct the dependent or independent variables differs substantially. Blanchard and Diamond (1989) use new hires as their dependent variable and help-wanted information as a proxy for the number of vacancies. Pissarides (1986) and Jackman, Layard and Pissarides (1989) use outflow from unemployment as the dependent variable. Schager (1985) uses information on unemployment durations and vacancy durations. Van Ours (1991) uses information on flows and stocks of notified vacancies. Belderbos and Teulings (1988) use regional information from three subsequent Dutch labour force surveys (1981-1983-1985) to estimate their matching function.

Table 1
Results of empirical analysis of the matching functions

	Country	Period	Results[a]
Blanchard /Diamond (1989)	USA	1968-81	α=0.41 (f) shift
Pissarides (1986)	UK	1967-83	α=. (f)[b] shift
Jackman et. al. (1989)	UK	1968-87	α=0.38 (a) shift
Schager (1985)	Sweden	1963-84	α=0.51 (a) shift 1967-69
Belderbos/ Teulings (1988)	Netherlands	1979-85	α=0.60 (f) no shift
Van Ours (1991)	Netherlands	1961-87	α=0.44 (f) shift 1968/69

a) (a) = assumes constant returns to scale
(f) = finds constant returns to scale
b) no direct estimate because of the use of a linear instead of a loglinear matching function (quarterly data)

The empirical estimates of the parameters of (4) or (5) also differ substantially. The first three studies find a deterioration of the US and UK labour market. The last three find no deterioration for the Swedish and the Dutch labour market in the 1970's and 1980's. It is difficult to establish the exact nature of the deterioration of the UK labour market. In theory the efficiency parameter λ is the result of three underlying processes: contact rate, job offer probability and job acceptance probability. The contact rate is determined by the search intensity of both job seekers and employers. Jackman et. al. (1989) have a line of reasoning to attribute the structural shift of the matching function to a decrease in the effectiveness of search, with workers becoming more choosy about taking jobs or firms becoming more choosy about hiring workers.

It is also difficult to understand why the Dutch labour market at the end of the eighties matches job seekers and vacancies as efficient as it did in the seventies. By the end of the eighties the share of long term unemployed workers was much higher than in the seventies[1].

In order to get a better understanding of the matching process, and hence of the (mal)functioning of the labour market, the various micro aspects of the matching process and the relative importance of each of these aspects in the matching process need to be determined. This paper makes an empirical attempt in this direction. By disentangling the efficiency parameter into separate components, and assessing the relative importance of each of these components we hope to increase our understanding of the matching process of the Dutch labour market. We also analyze differences in matching functions of disaggregate labour markets. Thus, we investigate whether or not compositional changes may be important in the explanation of changes in the aggregate performance. Our data do not allow us to analyze developments in the Dutch labour market, so we cannot distinguish between compositional effects and the effects of a change in matching technology over time.

3. MICRO MATCHING

3.1 The model

In our model the labour market is divided into separate sub-markets distinguished by job-type. We assume that the number of matches at each sub-market is generated by the individual search behaviour of both workers and employers. At the supply side individual workers make decisions regarding search method use and wage requirements that optimize their expected lifetime utility. As in Lindeboom, Van Ours and Renes (1993a), we distinguish three different search methods: advertisements (**adv**), public employment office (**peo**) and informal search methods (**inf**)[2]. At the demand side of the labour market the optimization problem of the individual employer is similar. For each sub market the decisions at the micro level can be aggregated to give the pool of searchers N_{ij} and V_{ij}. Job-type is indexed by i, and refers to occupation education and region (for definitions see Appendix 1). The index j refers to the use of search channels, j=adv, peo, inf. So, the total labour market consists of segments stratified according job type and search channel use. In each segment workers (N_{ij}) and vacancies (V_{ij}) may contact and eventually match. In what follows, we will basically specify functions for the number of matches that are generated in each segment of the labour market. In section 3.2 we will briefly describe how the parameters of these matching functions can be estimated.

1. Similar results for the Dutch labour market using traditional UV-analysis were found by Budd, Levine and Smith (1987) and Jackman, Pissarides and Savouri (1990).

2. For workers (employers) informal search include checking with friends or relatives (friends, relatives or own personnel) or inquiring for work by an employer (recruiting those who inquired).

For the number of contact that are generated in each segment we specify the following Cobb-Douglas function:

$$C_{ij}=\lambda_{1ij}N_{ij}^{\alpha j}V_{ij}^{\beta j} \tag{6}$$

The parameters α_j and β_j can be interpreted as geometric weights indicating the relative importance of supply (N) and demand (V) in the market. Much of the previously discussed macro studies are about the (empirical) estimates of these weights. We allow these parameters to differ for each search or recruitment channel. The parameter λ_1 is the contact probability which translates the set of potential contacts to actual contacts. This parameter reflects the effectiveness of search in generating contacts, independent of the number of searchers and vacancies that operate in the market.

Next, conditional on the number of contacts, the flow of matches that are generated at the market is determined by the probability that a contact turns into a match (λ_{2ij}).

$$F_{ij}=\lambda_{2ij}.C_{ij}=\lambda_{2ij}.\lambda_{1ij}N_{ij}^{\alpha j}V_{ij}^{\beta j} \tag{7}$$

The parameter λ_{2ij} is governed by employer's job offers decisions and worker's acceptance decisions. The product of λ_{2ij} and λ_{1ij}, denoted by λ_{ij}, is the efficiency parameter of the market, to which we also refer as the 'total match probability'. This parameter indicates the speed at which potential contacts are translated into actual matches. So λ_{2ij}, λ_{1ij}, α_j and β_j are the parameters of interest

Estimation of equations (6) and/or (7) to obtain estimates of λ_{2ij}, λ_{1ij}, α_j and β_j, $\forall$ i,j requires disaggregate data on C, F, N and V. In general these data are not available. Therefore, we proceed along the lines of Lindeboom, Van Ours and Renes (1993a,1993b).

3.2 Empirical specification

From a manpower survey we obtained data on the number of workers (N_i) and the number of vacancies (V_i) per job type. These (aggregate) numbers need to be stratified according to search channel use, so we have to determine what fraction of N_i and V_i is assigned to each of the distinguished search channels. For that purpose we define q_{ij} and p_{ij}. q_{ij} is defined as the probability that for a randomly selected vacancy of type i search channel j is used. In case q_{ij} is known, it follows that $V_{ij}=q_{ij}.V_i$. Analogously, with p_{ij} as the probability that a randomly selected worker of type i uses search method j, we write: $N_{ij}=p_{ij}.N_i$. Note that in each market employers (workers) may use multiple recruitment channels (search methods), hence the sum over j of V_{ij} (N_{ij}) may very well exceed V_i (N_i).

Still we lack data on the flow of matches (F_{ij}). The flow of matches in a small interval, let's say <t,t+dt>, may be derived from the pool (stock) of vacancies at time t and the instantaneous rate of leaving that pool (the hazard rate). Hence, the hazard rate for vacancies of job type i and search channel j (θ^v_{ij}) may be written as the ratio of F_{ij} to V_{ij}. Analogously the hazard rate for a searcher of job type i and search channel j (θ^n_{ij}) is defined as F_{ij}/N_{ij}. Given the specification of the matching function (7) we have the following relations:

$$\theta^n_{ij}=F_{ij}/N_{ij}=\lambda_{1ij}\lambda_{2ij}N_{ij}^{\alpha j-1}V_{ij}^{\beta j} \tag{8a}$$

$$\theta^v_{ij}=F_{ij}/V_{ij}=\lambda_{1ij}\lambda_{2ij}N_{ij}^{\alpha j}V_{ij}^{\beta j-1} \tag{8b}$$

The estimation procedure consist of roughly two steps. First, in a separate analysis of micro data on the use of search and recruitment channels we estimate the probabilities q_{ij} and p_{ij}. With the manpower survey data on N_i and V_i we generate data on N_{ij} and V_{ij}.[3] In the second stage, using search duration data and vacancy duration data, we estimate the hazard rates for search and vacancy durations in a joint likelihood to obtain estimates of the parameters of interest. For more details of the datasets used in the analysis we refer to section 4. For more details on the estimation procedure we refer to Lindeboom, Van Ours and Renes (1993a).

It may be clear that from duration data alone λ_{2ij} and λ_{1ij} can not be identified. For that purpose we need additional information. Our datasets (a workers survey and an employers survey) contain such information. We augment our (empirical) model, and assume that the number of contacts is generated by a time homogenous Poisson process with contact rate μ. For a vacancy of type i for which channel j is used, the contact rate μ^v_{ij} is defined as C_{ij}/V_{ij}. Analogously, for workers we have $\mu^n_{ij}=C_{ij}/V_{ij}$. Then using equation (6) it follows that:

$$\mu^n_{ij}=C_{ij}/N_{ij}=\lambda_{1ij}N_{ij}^{\alpha j-1}V_{ij}^{\beta j} \tag{8c}$$

$$\mu^v_{ij}=C_{ij}/V_{ij}=\lambda_{1ij}N_{ij}^{\alpha j}V_{ij}^{\beta j-1} \tag{8d}$$

The equations (8a) to (8d) form the basis of the likelihood function, of which the specification is given in section 4.2.

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3. Data on N_i are not directly obtained from the manpower survey. This survey consists only information on the number of unemployed searching workers and the total number of employed workers. To obtain the number of searching employed workers, we had to determine what fraction of the employed workers was looking for a job. This fraction (probability) was also estimated using micro data on search behaviour. Furthermore, for employed workers, the decision to search may be correlated with the choice of search method. We therefore also estimated bivariate probit models. The two processes appeared to be uncorrelated.

For the contact probability, λ_{1ij}, and the conditional match probability, λ_{2ij}, we take the familiar logit specification,

$$\lambda_{kij}=\exp(X'\gamma_{kj})/(1+\exp(X'\gamma_{kj})), \qquad k=1,2,\ j=adv,peo,inf. \tag{9}$$

The vector X contains the characteristics of the disaggregated labour market (occupation, education, region and work experience). These characteristics apply to both workers and vacancies. In our empirical analysis, discussed in section 5, we restrict the parameter vector γ_1 and γ_2 to be the same for each search channel. The structure of the empirical model is that of a competing risk model. Conditional on the choice of search methods, each vacancy duration (or search duration) may be terminated by one of the recruitment channels (search methods) used.

So far, the total labour market is divided into segments of job type and search channel use. Implicitly it is assumed that within each submarket homogenous groups of workers and employers exist. Personal characteristics are assumed to be of no importance in the matching process. However, search behaviour, generating the contact probabilities, and job acceptance decisions, may differ for males and females or for unemployed searchers and employed searchers. For example, unemployed workers may use different search methods or may search more intensively than employed workers. Perhaps more importantly, for a specific job employers may prefer to hire for example an employed male worker over an unemployed female worker. Employers are legally not permitted to recruit just for male or female workers or just for unemployed or employed workers. Still, differences in the conditional match probabilities may be observed. Therefore, we augment the model to allow for differences according to labour market status and gender. We distinguish employed males (em), employed females (ef), unemployed males (um) and unemployed females (uf).

From the employers point of view we have additional risks within the existing competing risk framework. From the workers point of view we have a model of competition between the different groups that operate on the market. So within each segment i,j of the labour market, we can distinguish the flows of matches for the different subgroups that operate on that segment of the market. For each of these flows we write:

$$F^k_{ij}=\lambda^k_{2ij}.\lambda^k_{1ij}N_{ij}^{\alpha j}V_{ij}^{\beta j}.(N^k/N), \quad k=em,ef,um,uf \tag{10}$$

The corresponding hazards for each subgroup can be defined as the ratio of F^k/N^k for job seekers and F^k/V for vacancies. In the empirical specification we extend the logit specification (9) by allowing for separate dummy variables d_{kj}, k=em,ef,um,uf, j=adv,peo,inf. The parameters associated with the dummy variables are δ_{1kj} for the contact rate and δ_{2kj} for the conditional match probability, k=em,ef,um,uf, j=adv,peo,inf.

N^k_{ij}/N_{ij}

4. DATA AND LIKELIHOOD FUNCTION

4.1 Data

In our analysis we use three data sources. First a manpower survey to obtain (aggregated) data on the number of workers (N_i) and the number of vacancies (V_i). Next, we use a workers survey and an employers (vacancy) survey. We use information on the employer's recruitment behaviour and the worker's search behaviour to estimate the probabilities p_{ij} and q_{ij}. These probabilities are used to generate data on N_{ij} and V_{ij}. Information concerning search duration, recruitment duration, the number of applicants arrived and the number of applications made are used to estimate the parameters γ_1, γ_2, δ_{1kj} and δ_{2kj}, k=em,ef,um,uf, j=adv,peo,inf.

The vacancy data we use in our analysis are from a Dutch vacancy survey, collected by the Organization for Labour Market Research (OSA). This survey consists of two waves. In the first wave, conducted in November-January 1986-1987, firms that had vacancies provided information on these vacancies. Furthermore information was obtained on choice of search method, incomplete duration of the vacancy (elapsed duration) and the number of applicants that had arrived up to the moment of the survey. In the second wave, conducted approximately four months after the first interview, information was collected on for example residual vacancy duration. Furthermore, it was established which search method generated the successful applicant.

The data on employed and unemployed job seekers are from 2 waves of the OSA labour force panel consisting of about 2000 households. We use the waves of September 1986 and September 1988. From these waves we obtain information on search behaviour, the number of applications made, elapsed and residual search duration and if a (new) job was found, which search method generated the job offer.

4.2 Likelihood function

Denote T as a random variable associated with a job search duration, θ^n is the corresponding hazard. Analogously S, with hazard rate θ^v is defined as a random variable associated with employers search (vacancy) duration. Since we sample from the stock of employers and job search durations, we must base our likelihood on the distribution of the relevant variables in the stock. Let T_1 and S_1 denote the elapsed job search and vacancy duration at the date of selection. Similarly, let T_2 and S_2 denote the (residual) search durations beyond the date of selection. We assume a constant inflow rate and absence of duration dependence in the hazards. As a consequence elapsed and residual durations are independently and identically exponential distributed (Ridder (1984)).

Information on the number of contacts is obtained conditional on elapsed search duration. Hence it seems natural to write the joint probability for the event $C=x$, $S_1=s_1$, $S_2=s_2$ as $Pr(C=c \mid S_1=s_1,S_2=s_2).Pr(S_1=s_1,S_2=s_2)$. Of course, the event $C=x$, $T_1=t_1$, $T_2=t_2$ is defined analogously. For both employers and workers we assume a sequential search strategy. Given a contact it is immediately decided whether or not a match is 'rejected' (either by employer or worker). Recent evidence, van Ours and Ridder (1992, 1993b), indicates that this assumption may be violated. The number of rejected matches is assumed to be generated by a Poisson process with parameter ν (omitting the index s and v),

$$\nu = \mu.(1-\lambda_2) \tag{11}$$

Since S_1 and S_2 are exponentially distributed, we may write $Pr(C=x \mid S_1=s_1-,S_2=s_2) = Pr(C=x \mid S_1=s_1)$ simply as:

$$- \exp(-\nu^v s_1)(\nu^v s_1)^x/x! \tag{12}$$

The likelihood contribution for a vacancy is based on the product of (12) and the joint density of S_1 and S_2. The latter being simply the product of two identical marginal probabilities.

For job seekers, the derivation of the appropriate likelihood function is somewhat more complicated. For employed workers we do not observe elapsed search duration T_1, and only the number of contacts in the previous 26 weeks are given. Consequently, a modified likelihood function based on $Pr(C=x,T_2)$ must be derived. Since T_1 and T_2 are exponentially distributed, the latter probability may be written as the product of two marginal probabilities. For $Pr(C=x)$ we write:

$$\int_0^\infty Pr(C=x\ T_1=t_1).Pr(T_1=t_1)dt_1 = \int_0^\infty [\ \{\ \exp(-\nu^n t_1).(\nu^n t_1)^x/x!\ \}I_{[0,26]}(t_1)$$

$$+ \{\ \exp(-\nu 26).(\nu 26)^x/x!\ \}I_{<26,\infty}(t_1)].\theta^n.\exp(-\theta^n.t_1)dt_1 \tag{13}$$

It appears that the data on the number of applicants and the number of applications made by workers may be imprecise. Therefore in using (12) and (13), we will only use information on whether or not applicants have arrived, respectively a worker has made an application.

The total likelihood function is derived using both workers' search and employers' search data. Since the hazard rates and the contact rates for vacancies and job seekers are a function of the same set of parameters λ_1, λ_2, γ_{1kj}, γ_{2kj}, α_j and β_j, consistent estimates of these parameters can be obtained with either employers' search or workers' search data. Combining both sources of information, as we do in our likelihood, is however more efficient.

5. ESTIMATION RESULTS

The estimation results are reported in Table 2 below. First, we discuss the results on γ_1 and γ_2 (the results on the characteristics of the disaggregate labour market) reported in the first part of Table 2. The contact probability λ_1, reflecting the efficiency of search, appears to be lower than average for production and construction, and higher than average for administrative workers. This means that conditional on supply (the number of workers/job seekers, N_{ij}) and demand (the number of vacancies,V_{ij}) in the sub-market, the probability of a contact for these groups of workers is smaller respectively larger than average. For production and construction workers the low contact probabilities are associated with high conditional match probabilities (λ_2). Furthermore, we find on average high contact probabilities for extended primary and low vocational workers, and on average low contact probabilities for secondary vocational, higher and academically educated workers. Again for some of these workers the high (low) contact rates are associated with on average low (high) conditional match probabilities. This complementary relationship between contact probabilities and conditional match probabilities may be explained by using the job search model as the conceptual framework. The parties engaged in search (worker and employer) will be more (less) choosy if the arrival rate of possible matches is very high (low). Furthermore, on average high contact probabilities are found for the northern and the southern part of The Netherlands, and for the more experienced worker. Again, most of the low contact probabilities are associated with on average high conditional match probabilities.

Let's turn to the results on the parameters δ_{1kj} and δ_{2kj}, reported in the second part of Table 2. Labour market status and gender of the worker also influence the contact probability and the conditional match probability. This influence differs between search channels. When interpreting the estimation results of for example contact rates, it is important to realize that search channels have very different characteristics. The use of advertisements is open to every worker. For the employment office, where contacts between workers and employers are regulated by the staff of these offices, the situation is quite different. The use of informal channels is restricted to workers with social networks.

The employed male is taken as a reference group. For advertisements unemployed workers (male and female) have a lower contact probability than employed workers. Employed workers appear to search more effectively than unemployed workers. There does not seem to be much of a difference in the conditional match probability. Consequently, the total match probability, which is simply the product of the contact probability and the conditional match probability, is smaller for unemployed workers. For the employment office the results seem to be somewhat confusing. Especially the extreme small contact probability and the extreme large conditional match probability for employed females seems to be odd. Inspection of the data reveals that the number of employed females using the employment office is very small, resulting in apparently exaggerated effects on the contact and the conditional match probability. For the other subgroups we see not much of a difference between the contact probabilities, whereas on average higher conditional match probabilities are found for unemployed workers. Still, the total match probability λ is very small for the employment office (this will become clear in the sequel when we discuss the results of Table 3).

For the informal search channel we see that, compared to the employed male worker, unemployed male workers and especially female workers have very low contact probabilities. Their social networks are probably not focused on the labour market. This low contact probability is partly compensated by a much higher conditional match probability. Once they are in contact, the probability of a match is very high.

So, we may conclude that job-type and search method use play an important role in the total match probability (or efficiency parameter λ), defined as the product of the contact probability and the conditional match probability. To give an idea of the total effects of employment status and gender on this matching probability, we calculated contact probabilities, conditional match probabilities and total match probability probabilities. We use the employed male worker as a reference group and calculated the probabilities by using average values of the other explanatory variables. The calculated probabilities are thus conditional on the observed job characteristics (X).

$$\frac{\Theta^k}{\Theta^{em}} = \frac{\lambda_1{}^k\lambda_2{}^k N^\alpha V^\beta}{\lambda_1{}^{em}\lambda_2{}^{em} N^\alpha V\beta} = \frac{\lambda_1{}^k\lambda_2{}^k}{\lambda_1{}^{em}\lambda_2{}^{em}}$$

The results are reported in Table 3. The table shows substantial differences in match probabilities over the different groups of workers and for different search channels. For advertisements low contact probabilities are found for unemployed workers while there does not seem to be much of a difference with respect to gender. No large differences are found in the conditional match probabilities. As a result the match probability is relatively small for unemployed workers. As indicated before, for the employment office the results are somewhat confusing for employed females. Not taking the separate components of the matching probability into account, we see relatively favourable odds for the unemployed (male) worker. In absolute terms, the unemployed using the employment office experience higher matching probabilities than those using advertisements. Finally, for the informal search channel, employed males have much higher contact probabilities than (un)employed females and unemployed males. However, conditional on a contact, large match probabilities are found for (un)employed females and unemployed males.

To summarize the main results from Table 3: matching probabilities are relatively large for employed workers, as compared to unemployed workers, and informal search channels are most effective in matching employed workers and vacancies, whereas the employment office is most effective in matching unemployed workers and vacancies.

Table 2
Estimation results

	contact probability λ_1	conditional match probability λ_2
i) Results on γ_1 and γ_2		
Occupation		
Services	-0.09 (0.8)	-0.61 (4.9)
Administrative	0.20 (2.6)	0.14 (1.5)
Production	-0.49 (6.9)	0.34 (3.1)
Construction	-1.75 (12.2)	2.08 (9.7)
Education		
Ext. primary	0.90 (5.2)	-0.23 (1.1)
Secondary	0.28 (1.7)	0.63 (3.1)
Low vocat.	0.32 (2.5)	0.31 (1.9)
Sec. vocat.	-0.39 (2.5)	0.78 (4.7)
Higher/acad	-0.70 (4.7)	1.15 (6.0)
Region		
North	1.06 (7.4)	-1.39 (8.0)
East	-0.52 (8.3)	0.12 (1.3)
South	0.46 (6.6)	-0.26 (3.0)
Experience	0.36 (6.6)	-0.36 (4.9)
ii) Group specific constants δ_{kj}, k=em,ef,um,uf, j=adv,peo,inf. (employed male as reference)		
Advertisements		
Constant (employed male)	-1.75 (5.3)	-2.22 (10.0)
Employed,female	0.02 (1.0)	-0.04 (0.2)
Unempl, male	-1.22 (6.6)	0.18 (0.8)
Unempl, female	-1.15 (7.2)	-0.04 (0.2)
Employment office		
Constant (employed male)	-1.57 (6.5)	-3.13 (8.7)
Employed,female	-3.25 (9.5)	12.1 (11.6)
Unempl, male	-0.17 (0.3)	1.30 (2.3)
Unempl, female	-0.69 (1.2)	1.42 (2.0)

Table 2 Estimation results (continued)

Informal		
Constant (employed male)	-1.34 (4.4)	-1.91 (8.4)
Employed,female	-1.91 (8.8)	4.00 (4.7)
Unempl, male	-0.89 (3.8)	0.59 (2.1)
Unempl, female	-2.11 (6.4)	0.50 (1.0)
iii) Geometric weights α_j *and* β_j, *j=adv,peo,inf.*		
Advertisements		
α	0.46 (8.5)	
β	0.56 (17.6)	
Employment office		
α	0.0 l.b.	
β	1.0 u.b.	
Informal		
α	0.16 (2.6)	
β	0.81 (21.0)	
-logL	11440.6	

a) absolute t-values in parentheses

So far, the results presented are conditional on the number of job seekers and the number of vacancies. However, low values of for example λ_1 (λ_2) do not necessary imply that the number of matches (or the contact rate and the conditional match rate) is low, since for each submarket the supply (N_{ij}) and demand (V_{ij}) ratio should also be taken into account. We therefore briefly discuss the results on the scale parameters α_j and β_j. We therefore return to the third part of Table 2. Note that in the context of an aggregate (macro) model the weights α and β can be interpreted as elasticities of the (aggregate) flow of matches F ($F = \sum F^k$). For the flows F^k also the ratio of N^k to N is of importance. An increase in the share of workers of type k, holding other factors constant, will increase the observed flow of matches for subgroup k (F^k).

For advertisements and informal search channels α exceeds 0 which implies that changes in the number of workers result in changes in the (aggregate) flow of matches. For these channels the number of matches is determined by both supply and demand. The value of α for advertisements of 0.46 is quite in line with previous results from macro studies (see Table 1). In contrast to the large α for advertisements, we find small values for the public employment office and the informal search channels. The results may indicate that in macro studies the value of α is mainly determined by the results on the advertisements. Our results show that in a disaggregate market large differences may exist in the parameter values of α and/or β.

For the employment office the results indicate that only the number of vacancies is important. This is in concordance with the organisational structure of most of these public employment offices. The staff of these offices determines the way in which registered vacancies are offered to searchers. Given the total flow, the proportion of searchers of type k hired, the disaggregate flow F^k, is determined by the ratio N^k/N. An increase in the number of vacancies is of no influence for the hazard θ^{vk} and the contact rate c^{vk}, the hazard θ^{nk} increases proportionally. An increase in the number of searchers is only of influence for the hazard θ^{vk}, if the ratio of N^k/N is altered.

Finally, we tested for constant returns to scale ($\alpha_j + \beta_j=1$). For each of the distinguished search channels we cannot reject the hypothesis of constant returns to scale.

The results regarding the values of α_j and β_j indicate that the effect of supply and demand differ for the search methods that we considered. Changes in the share of workers of a specific type result into changes in the flow of matches of a specific type. In that case the aggregate flow of matches remains unchanged. Taking the results on γ_1, γ_2 and δ_{kj} into account we conclude that large differences exist between the matching processes at the disaggregate level.

6. CONCLUSIONS

In recent labour market research the concept of the matching function is introduced to study relationships between stocks of job seekers and vacancies and the process of job formation. Matching functions are used to study changes in the performance of labour markets. In the analysis these studies mainly use macro time series data. Therefore, if a change in the performance of the labour market is established, it is difficult to indicate the origin of this change. If there are differences in the performance of disaggregate labour markets a change at the aggregate level may be due to a change in the composition of the labour market, or due to an overall deterioration of the matching technology.

In this paper we study the process of job formation in the labour market by using micro data. In our analysis we show that macro matching functions and micro contact rates and hazard rates are closely related. By estimating the parameters of these rates we also find the parameters of the matching function. Moreover, we are able to take a closer look into the process of job formation itself, by distinguishing between contact and conditional matching probabilities.

Table 3
Calculated contact probabilities and conditional match probabilities

	contact probability λ_1	cond match probability λ_2	match probability $\lambda=\lambda_1\lambda_2$
reference group = employed male worker			
Advertisements			
employed male	1 (0.125)	1 (0.125)	1 (0.016)
employed female	1.14	0.73	0.81
unempl male	0.32	1.17	0.38
unempl female	0.34	0.97	0.31
Employment office			
employed male	1 (0.146)	1 (0.054)	1 (0.008)
employed female	0.048	18.5	0.88
unempl male	0.86	3.20	2.75
unempl female	0.54	3.60	1.88
Informal			
employed male	1 (0.177)	1 (0.163)	1 (0.029)
employed female	0.18	5.61	0.97
unempl male	0.46	1.60	0.72
unempl female	0.11	1.49	0.17

From our analysis it appears, that the matching process in labour markets disaggregated with respect to occupation, education, region, working experience and search channel, is quite different. Furthermore, there appear to be differences according to labour market status and gender.

Since our analysis is restricted to a short period in time, we can not study changes in labour market performance. Our analysis suggests that over time changes in the composition of the stock of job seekers with respect to employment status and gender may have influenced the efficiency of the matching process as described with one aggregate matching function. Furthermore, the changes in the use of search channels may have been important. Informal search channels have the highest matching probability for employed workers. If, due to changes in the industrial structure many workers loose their job, their informal networks become obsolete, which reduces the overall efficiency of the matching process.

Our main conclusion is that it is possible to use the macro concept of the matching function to analyze search at the micro level. The matching function provides an integrated framework of mutual search of job seekers and employers. Our analysis can be extended by introducing more structure, consistent with the underlying optimization behaviour of workers and employers. By using micro-data from different time periods one could also investigate to what extent a possible aggregate decline in labour market performance is due to a change in composition or due to an overall deterioration of the labour market. We leave all of this to future research.

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APPENDIX Definitions of the variables used in the analysis

Occupation
- Services (including nurses)
- Administrative
- Production
- Construction

Reference group: other occupation

Education (Classification according to Dutch Central Bureau of Statistics)
- Ext. primary: 30
- Secondary: 40
- Low vocational: 32-38
- Sec. vocational:42-49
- Higher/academic: 50-59, 61-67

Reference group: lower education (20)

Region
- North: Groningen, Friesland, Drenthe
- East: Overijssel, Gelderland, Flevoland
- South: Zeeland, Noord-Brabant, Limburg

Reference group: West (Utrecht, Noord-Holland, Zuid-Holland)

Experience more than 3 years (required when vacancy)
Reference group: less than 3 years

b. Sample averages

Occupation		
	Services	0.24
	Administrative	0.22
	Production	0.32
	Construction	0.03
	other (ref. group)	0.19
Education		
	Lower education	0.08
	Ext. primary	0.08
	Secondary	0.08
	Low vocational	0.26
	Sec. vocational	0.27
	Higher/academic	0.22
Region		
	North	0.06
	East	0.26
	South	0.22
	West	0.46
Experience	> 3 years	0.39
	≤ 3 years	0.61