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MATCHING JOB SEEKERS AND VACANCIES

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ABSTRACT

Searching for a job takes time. Employers also need time to fill a vacancy. Therefore, at any time we will find that employers and workers are searching for each other. We analyze the matching process for employers and workers who use personnel advertisement as a search channel. The matching model is estimated using micro economic data from an employers survey and a workers survey. We find that there are differences in matching probabilities for workers distinguished by job type, labour market status and gender. An additional analysis in which we use information on workers (reservation) wages indicates that, conditional on the observed job characteristics, employers prefer employed workers over unemployed workers.

1. INTRODUCTION

Workers find a (new) job and employers find a new employee as a result of a process in which both sides of the labour market interact. Workers at the supply side of the labour market are confronted with employers from the demand side of the labour market. The number of matches is determined by the total number of job seekers and vacancies operating through that market and the probability that a potential contact is actually translated into a match. Consistent with this notion we start our analysis with matching functions defined for specific labour markets, distinguished by education, occupation, region and search channel use. We estimate the parameters of the matching function for workers and employers who use personnel advertisement as a search channel.

The parameters of a matching function are the matching probability and scale parameters (geometric weights) indicating the relative importance of supply and demand. The matching probability can be written as a contact probability and the probability that, conditional on a contact, worker and employer agree on the terms of the contract. The contact probability reflects the effectiveness of the labour market in generating contacts. The conditional match probability, depending on a job offer and a job acceptance probability, reflects the characteristics of the wage formation.

As a first step we estimate the model using 'macro' data on the total numbers of job seekers and vacancies combined with micro data on the duration of job search and the vacancy duration. Extra information on the number of contacts between employers and workers enables us to identify the contact probability from the conditional match probability. Additionally, we try to disentangle job offer probabilities from job acceptance probabilities. We find that job characteristics, employment status and gender are important characteristics of the matching process. We also find that, conditional on the observed job characteristics, employers prefer employed workers over unemployed workers. We find no differences in employers' preferences with respect to gender.

This paper has two distinguishing characteristics. First, search information from both sides of the labour market are combined into an integrated analysis. Secondly, the probability of finding a job and/or filling a job vacancy are decomposed into a contact probability, a job offer probability and a job acceptance probability. The plan of the paper is as follows. The theoretical model is presented in section 2. Section 3 gives the empirical implementation. Section 4 describes the data and presents the likelihood. Section 5 contains the estimation results. Section 6 concludes.

2. THE MODEL

In the labour market the pool of employers searching for a new employee and the number of workers searching for a (new) job is generated by the search process at the individual level. The number of matches depends on the relative number of workers and employers searching in the market as well as on the speed at which a potential contact between job seeker and employer is translated into a match. In the literature the speed is seen as a measure of the efficiency of the labour market.

Workers and employers may meet if they operate on the same market, i.e. they have to match on job type and search channel use. Therefore, the total labour market is divided into different submarkets, each distinguished according to job type and search channel use. An employer searching for an academic worker may prefer to use advertisements over, for example, the employment office. Furthermore different type of job seekers may also prefer to use different search channels. In our model, job type is characterised by education, occupation and region. In a previous analysis on the effectiveness of different search methods we consider informal search channels, the employment office and advertisements. For reasons of simplicity and homogeneity of the considered sample, in this paper we restrict ourselves to advertisements.

In each submarket (indexed by i) the number of contacts (C) between job seekers and vacancies in a period of time [t,t+dt> depends on the number of job seekers (N) and the number of vacancies (V) at time t, and the contact probability. The contact probability (λ_1) reflects the intensity of search, and differs for each type of job. More formally, we specify, for each job type the familiar Cobb-Douglas specification:

$$C_i = \lambda_{1i}.N_i^{\alpha}V_i^{\beta} \tag{1}$$

The parameters α and ß reflect the weights assigned to the number of jobseekers and the number of vacancies, indicating the relative importance of supply and demand. Relatively small values of α are associated with a labour market in which the number of job seekers hardly play a role in the matching process. We assume α and ß to be the same for all type of jobs.

Conditional on the number of contacts between job seekers and employers (vacancies) , the flow of filled vacancies (F), or equivalently the flow of job seekers finding a (new) job, is determined by the conditional probability that a contact results in a match (λ_2). This 'conditional match probability' depends on the job offer and job acceptance probability, both reflecting the characteristics of wage formation.

$$F_i = \lambda_{2i}.C_i = \lambda_{2i}.\lambda_{1i}.N_i^{\alpha}V_i^{\beta} \tag{2}$$

The efficiency parameter of the market (λ) is defined as the product of the contact probability and the probability that, conditional on a contact, a contact results in a match ($\lambda = \lambda_1.\lambda_2$). This parameter may also be interpreted as the efficiency parameter indicating the speed at which, conditional on the number of job seekers and the number of vacancies, potential contacts result in a match.

Examples of previous empirical studies using aggregate time series to estimate matching functions are Blanchard and Diamond (1989), Jackman, Layard and pissarides (1989) and Van Ours (1991). This paper differs markedly from the previous contributions. As in Lindeboom, van Ours and Renes (1991) the model is estimated on two micro economic datasets. Furthermore, we put special effort in identifying the contact probability (λ_1) from the conditional match probability (λ_2). Finally, using a very rough procedure, we will disentangle the conditional match probability into a job offer probability component and a job acceptance component. We will be more precise about this in the next section, where we discuss the empirical implementation of the model.

3. EMPIRICAL IMPLEMENTATION

To estimate the matching function as specified in (2), for each submarket we need data on the flow of matches, the number of job seekers and the number of vacancies. In general information on F, N and V stratified to the use of advertisement and job type are not available. We will follow the same approach as in Lindeboom, van Ours and Renes (1991). The matching function (2) will be reformulated, and micro data on vacancy and search durations combined with aggregate data on the total number of job seekers and vacancies will be used to estimate the model. Below we briefly sketch this procedure.

Data on the number of vacancies per job type (V_i^*) are available in The Netherlands. To construct the data on N^*_i we use the following approach. There are data available on the number of unemployed job seekers categorized by job type. We also have data on the total number of employed workers per job type. To determine what fraction from the employed workers is looking for a job, we use micro data on the search behaviour of employed individuals. From this micro data we estimate the probability that someone working in job type i will be searching for a new job. Combining this probability with the total number of employed workers per job type gives us the total number of employed job seekers. Note that we implicitly assume that workers are looking for a job of the same type.

Given the stratified data on the number of jobseekers and vacancies per job type (V_i^* and N_i^*), we have to determine which fraction is assigned to the use of advertisements. For that purpose we define q_i as the probability that for a randomly selected vacancy, of job type i, advertisements are used as a search/recruitment method. Using this probability in combination with V_i^* we obtain the number of vacancies of job type i and advertisement use as: $V_i=q_i.V_i^*$. Analogously, with p_i defined as the probability that a randomly selected worker of type i uses advertisements, we obtain $N_i=p_i.N_i^*$.

Furthermore, data on the flow of matches (F_i) are not available in the Netherlands. However, from the pool of vacancies (V_i) at time t, the flow of filled vacancies in a small interval dt can be obtained using the instantaneous rate of leaving this pool (the hazard rate). Hence we may write the hazard rate for vacancy durations, θ^v_i, as a simple ratio of F_i to V_i. Analogously, the hazard rate for the search duration, θ^s_i, follows from the ratio of F_i to N_i. So we have

$$\theta^v_i = F_i/V_i \tag{3a}$$

$$\theta^s_i = F_i/N_i \tag{3b}$$

And using equations (2), (3a) and (3b) we may rewrite equation (2) as:

$$\theta^v_i = \lambda_{1i}.\lambda_{2i}.N_i^{\alpha}V_i^{\beta-1} \tag{4a}$$

$$\theta^s_i = \lambda_{1i}.\lambda_{2i}.N_i^{\alpha-1}V_i^{\beta} \tag{4b}$$

So, the matching function may be rewritten in terms of hazard rates of workers and vacancies, with λ_{1i}, λ_{2i}, α and ß as parameters of interest. To estimate this micro model we need data from a worker's survey and/or an employer's survey combined with data on N_i and V_i. The model will be estimated in (roughly) two steps. First from micro data on the use of search/recruitment methods we estimate the probabilities p_i and q_i using simple probit analyses[1]. In combination with data on the number of vacancies and job seekers per job type we obtain N_i and V_i. In the second stage, using data on search and vacancy durations we can estimate the parameters α, β and λ_i $(=\lambda_{1i}.\lambda_{2i})$.

Sofar we have been unclear about the parameterisation λ_1 and λ_2, and without additional information, these two parameters can not be identified. Furthermore it would be very interesting to see if, given the identification of λ_1 and λ_2, λ_2 could be disentangled into a job offer component, reflecting the employers hiring decision, and a job acceptance decision, reflecting the workers acceptance decision. Below we will discuss these issues.

Parameterisation of λ_1 and λ_2

In the empirical implementation of the model the crucial components of the efficiency parameter λ (λ_{1i} and λ_{2i}) are specified as a function of the characteristics of a job X. The vector X contains education occupation, work experience and region. For both parameters we assume the logit specification.

$$\lambda_1 = \exp(X'\gamma_1)/(1+\exp(X'\gamma_1) \tag{5}$$

$$\lambda_2 = \exp(X'\gamma_2)/(1+\exp(X'\gamma_2) \tag{6}$$

Clearly there may also be differences in contact rates and conditional matching probabilities for different subgroups on the labour market. Search behaviour, generating the contact probability may differ, for example, for employed male workers and unemployed female workers. And conditional on a contact employers may for example prefer employed male workers over unemployed female workers. Although, employers are legally not permitted to use employment status or gender as selection criteria, differences in conditional match probabilities may be observed. From the employer's point of view (the demand side) matching can be seen as a competing risk problem in which failure (termination of the vacancy duration) may be caused by either of the four sub groups: employed males, employed females, unemployed males and unemployed females. From the supply side of the market the different subgroups are in competition for the same type of job. We therefore specify different matching functions for unemployed male workers (um), unemployed female workers (uf), employed male workers (em) and employed female workers (ef). For employed male workers we write:

$$F^{em}=\lambda_1^{em}.\lambda_2^{em}.N^{\alpha}V^{\beta}.(N^{em}/N) \tag{7a}$$

[1] For this part we rely on Lindeboom, van Ours and Renes (1991) where we are more precise about this part of the analysis.

And analogously for the other subgroups we write:

$$F^{ef}=\lambda_1^{ef}.\lambda_2^{ef}.N^{\alpha}V^{\beta}.(N^{ef}/N) \tag{7b}$$

$$F^{um}=\lambda_1^{um}.\lambda_2^{um}.N^{\alpha}\ V^{\beta}.(N^{um}/N) \tag{7c}$$

$$F^{uf}=\lambda_1^{uf}.\lambda_2^{uf}.N^{\alpha}V^{\beta}.(N^{uf}/N) \tag{7d}$$

For each subgroup (em, ef, um, uf), the corresponding hazards can be defined as the ratio of F^k/V for vacancies and F^k/N^k for workers, $k\epsilon\{em,ef,um,uf\}$. The matching functions, and hence the different hazards, are allowed to differ in λ_1 and λ_2. In the specification of these parameters we only allow for a constant shift (this corresponds with the incorporation of a dummy).

Identification of λ_1 and λ_2, and disentangling λ_2

To identify λ_1 from λ_2 we need additional information on the number of contacts between workers and employers. Our data sets have such information. We assume that the number of contacts has a Poisson distribution with a contact rate μ. For a vacancies we define the contact rate (per week) μ_i^v as the ratio of the number of applicants to V_i ($\mu_i^v=C_i/V_i$). Analogously we define the contact rate for a worker as μ_i^s as the ratio of the number of applications to N_i ($\mu_i^s=C_i/N_i$). Of course, since the contact rate is a function of λ_1, separate dummies for each of the subgroups are incorporated.

Note that contact probability λ_1 tells us something about the search behaviour of employers and workers of each specific job type, independent from the relative number of jobseekers and workers that operate on the market. The conditional match λ_2 tells us something about the employer's hiring decision, and the worker's job acceptance decision. In search theoretic models that do not allow for variable search intensity, the joboffer arrival rate reflects both elements of λ_1 and λ_2. In such a model small values of the offer arrival rate may be due to employers and workers decision. The job offer component in the conditional matching probability purely reflects the employers hiring decision.

Identification of the offer and the acceptance components may be quite cumbersome. Accepted wages, reservation wages from workers and (probably) reservation productivities from employers are required. Then the structure of the matching process in terms of reservation productivities, reservation wages and wages, as the outcome of the bargaining process, should be explicitly modelled. Of course also simplifying restrictions could be imposed to ease estimation. However, although we have reservation wages for employed and unemployed workers, we lack information of wages for the vacancy data, and we never observe the reservation productivities. For that reason we employ a very pragmatic method. On the workers sample we estimate simple, ad hoc reduced form wage equations and reservation wage equations. From these estimation results for each type of worker (or for an average worker) workers acceptance probabilities are calculated. Imposing a sequential structure, these calculated probabilities are confronted with the estimated conditional match probability λ_2 to obtain the employer's job offer component as a simple ratio

$$\text{Pr(job offer)} = \lambda_2 \ / \ \text{Pr(accept a job} \mid \text{job offer)} \tag{8}$$

4. DATA AND LIKELIHOOD

4.1 Data

The vacancy data we use in our analysis are from a Dutch vacancy survey[2]. The data were collected by the Organization for Labour Market Research (OSA). This survey was held in two steps. In the first step firms that had vacancies provided information on these vacancies. From this first step, conducted in November-January 1986-1987, we know for example the incomplete duration of the vacancy and the number of applicants that had arrived up to the moment of the survey. In the second step, conducted approximately four months after the first interview, information was collected on for example the date at which vacancies were filled (if they were filled) and the characteristics of the employee who was hired. The dataset contains no information on wage offers or accepted wages. Different search channels are used to find new employees. In this study we only consider the effectiveness of the advertisements as a search channel. From a previous analysis (Lindeboom, Van Ours and Renes (1991)) we know that informal search channels and the public employment office are more effective for unemployed workers. To get a homogenous set of vacancies we analyze a subsample of 970 vacancies for which advertisements were used as a search channel.

The data on employed and unemployed job seekers are from 2 waves of the OSA labour force panel. This panel consists of about 2000 households, the first survey was held in April 1985. Subsequent waves where held in September 1986 and September 1988. To analyze search behaviour of unemployed and employed workers we use the 1986 survey, containing information on 4115 respondents. After discarding observations for which essential variables are missing the sample contained 2442 employed and 212 unemployed workers[3]. In the analysis we only use those jobseekers who used advertisements as a search channel. We have 187 employed job seekers and 105 unemployed job seekers. In this survey information on reservation wages of job seekers and actual wages of workers is available.

Table 1 gives information on the data we used in the analysis. The table shows the use and the effectiveness of personnel advertisements for both job seekers and employers.

Table 1 Use and effectiveness of personnel advertisements; sample information

	Total	Found by ads (%)	Found otherwise (%)	Total found[a)] (%)
Vacancies	970	42	24	66
Employed job seekers	187	20	24	44
Unemployed job seekers	105	6	24	30

[a)] The percentages are calculated using a period of 4 months for vacancies and 2 years for workers.

[2] For an extended description of this survey we refer to Van Ours (1989) and Van Ours and Ridder (1992).

[3] A person was considered to be unemployed if he or she was not working and actively seeking for a job, irrespective of the registration at the public employment office.

Table 1 shows that of the 970 vacancies for which personnel advertisements were used 42% was filled by advertisements and 24% by the use of another search channel. In total 34% of the vacancies was left unfilled in the course of 4 months. For employed job seekers the average effectiveness of advertisements is much higher than for unemployed job seekers: 20% of the employed workers has found a new job by using advertisement, while for unemployed workers this is only 6%. Other search channels are on average equally efficient for employed and unemployed workers.

Table 2 also shows that advertisements are on average more effective as a recruitment channel for employed workers, and more effective for female than for male workers. In our analysis we will study to what extent these differences in effectiveness are actually due to employment status and gender and to what extent these differences are due to for example skill differences between employed, unemployed, male and female workers.

Table 2 Effectiveness of advertisements by employment status and gender

	Searchers finding a job by ads (%) Employed	Unemployed	Vacancies filled by ads (%) Employed	Unemployed
Male	20	2	42	31
Female	22	10	52	45

4.2 Likelihood

From the matching function (2) we derived a micro model in which the hazard rates for workers and vacancies of a specific job type i are a function of λ_i, N_i and V_i. To identify λ_1 from λ_2 we combine data on job search and vacancy durations with information on the number of contacts between employers and workers.

Denote T as a random variable associated with a job search duration, θ^s 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 $\Pr(C=c|S_1=s_1,S_2=s_2).\Pr(S_1=s_1,S_2=s_2)$. 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), 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),

$$\nu = \mu.(1-\lambda_2) \tag{9}$$

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

$$- \exp(-\nu^v s_1)(\nu^v s_1)^x/x! \tag{10}$$

The likelihood contribution for a vacancy is based on the product of (10) and the joint density of S_1 and S_2. The latter being simply the product of two identical marginal probabilities.

For jobseekers 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:

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

$$+ \{ \exp(-\nu 26).(\nu 26)^x/x! \,\} I_{<26,\infty}(t_1)].\theta^s.\exp(-\theta^s.t_1)dt_1 \tag{11}$$

The total likelihood is derived using both information on vacancy and job search duration. It appears that the data on the number of applicants and the number of applications made by workers may be imprecise. Hence, in using (10) and (11), we will only use information on whether or not applicants have arrived, respectively a worker has made an application (i.e. $C=0$ versus $C>0$).

Next, given the estimation results on λ_1 and λ_2, we use reduced form wage and reservation wage equations to estimate acceptance probabilities for different type of workers. For information on wages and reservation wages we had to rely on the workers survey. The acceptance probabilities are used to calculate job offer probabilities according to (8).

5. ESTIMATION RESULTS

We estimate the parameters λ_1, λ_2, α and β by using information on search durations of both employers and employees combined with data on the total number of jobseekers and vacancies in the market. In order to identify the contact probability (λ_1) and the conditional match probability (λ_2) we also use information on the total number of applications by jobseekers and the number of applicants arriving at a vacancy.

From the Labour Force Survey we estimate acceptance probabilities using information on actual and reservation wages. Combining these probabilities with the estimation results on the conditional matching probability (λ_2) enables us to identify the job offer probability.

Results on the parameters of the matching function

The contact probability and the conditional match probability depend on occupational variables (with 'other occupations' as the reference group), educational variables (reference group: primary education), experience (measured as a dummy variable which equals 1 if (required) work experience exceeds 3 years) and regional variables (the western part of the Netherlands as the reference group). The estimation results are shown in table 3.

Occupation, education, region and experience are characteristics of disaggregated labour markets. These characteristics apply to both job seekers and vacancies. Differences in contact probabilities and conditional match probabilities over the different disaggregated labour markets can be attributed to either sides of the labour market. For instance, a low contact probability may be due to inefficient search behaviour of (a group of) workers, inefficient search behaviour of employers or both. Labour market status and gender are personal characteristics. Employers are legally not permitted to recruit just for male or female workers or just for unemployed of employed workers. However after termination of the vacancy duration we observe from which subgroup (distinguished by employment status and gender) the jobseeker is recruited.

Table 3 Estimation results for λ_1 and λ_2 [a)]

	contact probability λ_1	conditional match probability λ_2
Constant	-2.93 (6.6)	-1.95 (7.2)
Occupation		
Services	-0.08 (0.4)	-0.86 (5.0)
Administrative	-0.13 (1.2)	0.28 (2.0)
Production	-0.65 (4.8)	0.42 (2.3)
Construction	-2.01 (8.9)	2.42 (6.8)
Education		
Ext. primary	1.31 (5.3)	-0.52 (1.9)
Secondary	0.75 (3.7)	0.12 (0.5)
Low vocational	0.39 (2.0)	0.60 (2.8)
Sec. vocational	0.63 (2.8)	0.34 (1.4)
Higher/academic	-0.26 (1.3)	1.04 (4.4)
Region		
North	0.95 (4.3)	-1.41 (6.0)
East	-0.66 (7.8)	0.29 (2.7)
South	-0.07 (0.9)	0.01 (0.1)
Experience	0.76 (11.2)	-0.65 (6.5)
Employed, female	-0.67 (3.3)	-0.16 (0.6)
Unemployed, male	-0.55 (3.1)	-0.80 (3.3)
Unemployed, female	-0.74 (3.6)	-0.91 (3.2)
α	0.41 (5.4)	
β	0.65 (12.4)	
-logL	6920.9	
-logL ($\alpha+\beta=1$)	6921.7	

a) absolute t-values between parentheses

The contact intensity probability λ_1 appears is to be smaller than average for production and construction workers. This means that after correcting for possible differences in the numbers of job seekers and vacancies, the probability of a contact for these groups of workers is smaller than average. Advertisements are not often used for by production and construction workers, nor will employers use advertisements to look for this type of labour. The search intensity is not very high. Hence, a low contact probability is a logical result. For the conditional match probability parameter λ_2 the opposite holds. This probability is higher for production and construction workers.

Distinguished by educational level it appears that the labour markets for the least and the most educated workers have the smallest contact probability. For higher vocational educated and academic workers this low contact probability is compensated by the highest conditional match probability. For the workers with the lowest education, there is no such compensation.

There are also differences by region. In the northern part of the Netherlands the contact intensity is higher, in the eastern part it is lower than on average. Again both differences in contact intensity are compensated by opposite differences in conditional acceptance probabilities. Finally, on markets for experienced workers the contact intensity is higher than for inexperienced workers, while the conditional acceptance probability is lower.

Labour market status and gender of the worker also influence contact intensity and conditional match probability. Employed female workers and unemployed workers have a lower contact probability than employed male workers. Employed male workers appear to search more effectively than the other groups of workers. The conditional match probability is larger for employed workers as for unemployed workers. There is no significant difference in the conditional match probability of male and female workers.

A final estimation result presented in table 3 concerns the scale parameters α and β. From a likelihood-ratio test it appears that the constant returns to scale restriction $\alpha+\beta=1$ cannot be rejected. The matching function obviously has constant returns to scale.

To give an idea of the total effects of employment status and gender on the match probability, we present calculated contact probabilities and match probabilities in table 4. 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.

Table 4 shows substantial differences in match probabilities over the different groups of workers: female workers have a lower match probability than males. Unemployed workers have the lowest match probability. Comparing the two components of the match probability it is obvious that both differences in contact probability and conditional match probability contribute to the differences in match probability. The contact probability of employed male workers is about twice as high as for the other groups. For the conditional match probability the main difference is between employed and unemployed workers. The conditional match probability for the unemployed workers is less than half of that of employed workers.

Table 4 Calculated contact probabilities and conditional match probabilities

	contact probability (weekly basis) λ_1	conditional match probability λ_2	match probability $\lambda=\lambda_1\lambda_2$
employed male	0.063	0.154	0.010
reference group = employed male worker			
employed male	1	1	1
employed female	0.52	0.87	0.45
unemployed male	0.59	0.49	0.29
unemployed female	0.49	0.44	0.22

Matching probabilities: job offer and job acceptance

An interesting question is to what extent the differences in conditional match probability are due to employers' behaviour (job offer probability) or workers' behaviour (job acceptance probability). To estimate the acceptance probabilities for the different groups of workers we used information on reservation wages of job seekers and actual wages of workers (see appendix 2). Using this information we calculated job offer probabilities for the different groups of workers. The results of these calculations are given in table 5.

Table 5 Calculated job offer and acceptance probabilities

	job offer probability P_o	acceptance probability P_a	conditional match probability $\lambda_2=P_oP_a$
employed male	0.30	0.50	0.15
reference group = employed male worker			
employed male	1	1	1
employed female	1.07	0.81	0.87
unemployed male	0.36	1.35	0.49
unemployed female	0.47	0.94	0.44

From this table it appears that there are differences in acceptance probabilities, but these differences attribute only a little to the differences in conditional match probability. The main difference is that the job offer probability for employed workers is more than twice as high than the job offer probability for unemployed workers. We therefore conclude that the differences in match probability between groups of workers distinguished by employment status are to a large extent due to differences in job offer probability. Given that a contact occurs between a worker and an employer with a job vacancy, employers prefer to offer the job to an employed worker. There does not seem to be a gender difference in job offer probabilities and conditional match probabilities.

Some caveats have to be made. The probabilities are calculated for an average person in the sample. However, men and women, employed and unemployed workers differ in their characteristics. For example, women have lower educational levels and less experience than men. The average woman thus has a lower contact intensity and a lower conditional match probability compared to the average man. As shown in appendix 3 the job offer probability for the average employed female worker is also much smaller than for the average employed worker. There is also a substantial difference between the average unemployed male and the average unemployed female worker. Given that a contact occurred between a job seeker and a vacancy the job offer probability is smaller for females, not because they are females, but because on average they have less favourable characteristics.

Furthermore, it should be noted that very little is known about the quality of the actual job offers that are made. Whether men and women, employed and unemployed workers receive the same job offers, remains unrevealed in this study.

6. CONCLUSIONS

In this paper we analyze the matching of job seekers and vacancies. We decompose the probability of finding a job and filling a job vacancy into a contact probability and a conditional matching probability. The latter is further decomposed in a job offer probability and a job acceptance probability.

In the analysis we use information from both sides of the labour market. We use information on job search durations, vacancy durations, numbers of applications of job seekers and numbers of applicants arriving on vacancies. Furthermore we use information on reservation wages of job seekers and actual wages of workers.

We show in this paper that there are differences in contact and matching probabilities between labour markets distinguished by occupation, education, region and working experience. Both sides of the labour market can generate these differences. There are also differences in match probability for workers distinguished by labour market status and gender: the match probability for unemployed workers is lower than for employed workers. Part of these differences are due to differences in contact probability: unemployed workers search less efficient than employed workers. Part of the differences may be attributed to differences in acceptance probability. The most important however are the differences in job offer probability: once a contact is made unemployed workers have a substantial lower probability than employed workers to get a job offer from the employer. Conditional on the observed characteristics employers prefer an employed worker to an unemployed worker. We find no differences in job offer probability for men and women.

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Appendix 1 Definition and sample averages the variables used in the analysis

a. Definitions

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
$\leq$ 3 years	0.61

Appendix 2 Wages and reservation wages

Reduced form reservation wage equations are estimated for both employed job seekers (w^r_e) and unemployed jobseekers (w^r_u). From the workers sample we also estimated a reduced form wage equation. The Mill's ratio is included to correct for sample selectivity. The results of the Probit analysis, used to calculate the Mill's ratio, are reported in table A2.

Table A1 Estimation results on wages and reservation wages

	log(w)	log(w^r_e)	log(w^r_u)
Constant	2.60 (12.7)	2.66 (14.0)	2.25 (10.5)
Occupation			
Services	-0.20 (2.0)	-0.32 (3.6)	-0.26 (1.6)
Administrative	-0.17 (1.5)	-0.11 (1.1)	-0.26 (1.3)
Production	-0.20 (1.9)	-0.35 (3.8)	-0.22 (1.3)
Construction	-0.40 (1.7)	-0.24 (1.4)	-0.08 (0.3)
Education			
Ext. primary	-0.11 (0.8)	0.12 (0.9)	-0.13 (1.0)
Secondary	0.09 (0.4)	-0.01 (0.1)	0.22 (1.2)
Low vocational	-0.18 (1.5)	-0.04 (0.3)	-0.14 (1.1)
Sec. vocational	-0.07 (0.6)	0.18 (1.7)	-0.17 (1.3)
Higher/academic	0.16 (1.2)	0.34 (3.0)	-0.02 (0.1)
Region			
North	-0.14 (0.0)	0.03 (0.3)	-0.05 (0.4)
East	-0.00 (1.4)	0.01 (1.5)	-0.06 (0.6)
South	-0.06 (0.7)	0.11 (2.4)	-0.01 (0.1)
Log(experience)	0.16 (3.1)	0.07 (1.4)	0.14 (3.0)
Gender	-0.35 (4.6)	-0.17 (2.4)	0.12 (1.3)
Mill's ratio	0.12 (0.7)		
$\bar{R}^2$	0.27	0.31	0.18

Table A2 Probit estimation results employed-unemployed (unemployed=1)

Constant	-2.96 (4.2)
Occupation	
Services	1.19 (2.5)
Administrative	0.41 (0.8)
Production	0.85 (1.7)
Construction	1.39 (1.8)
Education	
Ext. primary	0.07 (0.2)
Secondary	-0.36 (0.6)
Low vocational	-0.12 (0.4)
Sec. vocational	-0.43 (1.3)
Higher/academic	-0.44 (1.3)
Region	
North	-0.04 (0.1)
East	-0.17 (0.7)
South	0.14 (0.6)
Age	0.02 (2.1)
Gender	0.52 (0.3)
Nation (1=non-Dutch)	0.54 (1.3)
Unempl spells '80-'86	1.37 (8.7)

Appendix 3 Differences between the average employed and unemployed male and female worker

Table A3 presents calculated probabilities for four groups of workers: employed male, employed female, unemployed male and unemployed female workers. The differences between the groups not only reflect differences due to labour market status and gender, but also differences due to differences in average characteristics like occupation, education and working experience between the groups.

Table A3 Calculated contact, job offer, acceptance and match probabilities

	Contact λ_1	Job offer P_o	Acceptance P_a	match λ
Employed male	0.119	0.252	0.506	0.015
Reference group = employed male worker				
Employed male	1	1	1	1
Employed female	0.70	0.57	0.81	0.32
Unemployed male	0.64	0.39	1.35	0.34
Unemployed female	0.77	0.22	0.94	0.16

The table shows that there are substantial differences in match probability between the different groups of workers: female and unemployed workers have a lower match probability. Unemployed female workers have the lowest match probability. Comparing the three parts of the match probability it is obvious that all parts contribute to the differences in match probability, but the differences in job offer probability are by far the most important. The average job offer probability for the unemployed female worker is only 22% of that of the employed male workers.

We therefore conclude that the differences in match probability between groups of workers distinguished by employment status and gender are to a large extent due to differences in job offer probability. Given that a contact occurs between a worker and an employer with a job vacancy, most employers prefer to offer the job to an employed male worker. Employed female workers are less popular, while unemployed female workers are on average the least popular.

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