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# Job Search, Search Intensity, and Labor Market Transitions

## An Empirical Analysis

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**Hans G. Bloemen**

### ABSTRACT

*In this paper we present an empirical structural job search model with endogenously determined search intensity. The model describes both the behaviour of unemployed job seekers and on-the-job search. We use data on various indicators for the intensity of search to study the influence of the intensity of search on labour market transitions. The estimation results give us insight in the effectiveness of search. The impact of the benefit level on the search intensity of unemployed job seekers is quantified. Moreover, the estimation results are used to gain insight in the 'discouraged worker' effect.*

### I. Introduction

Job search models usually model the behaviour of job seekers as a sequential process in which wage offers arrive randomly with a certain rate of arrival.<sup>1</sup> The emphasis is on the job acceptance decision, characterized by a reservation wage rate, and the model generates implications for the distribution of unemployment duration and accepted wages. The model has been extended in various directions. Equilibrium search models (see Burdett and Mortensen 1998; Ridder and Van den Berg 1998) endogenize the wage distribution, by incorporating equilibrium implications. In the present paper we focus on another extension of the basic framework by endogenizing the job offer arrival rate. Individuals may influence the job offer arrival

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1. See, for instance, McKenna (1985) for an overview of the basic job search model, and Devine and Kiefer (1991) for a discussion of the empirical literature.

rate by varying the intensity of search. The optimal intensity of search will be chosen at the level at which the marginal returns to search are equal to the marginal cost of search.

Burdett and Mortensen (1978) present a search model with endogenous search effort. In their model, an increase in the time spent on search increases the average number of job offers arriving within a given time interval, but also causes a utility loss due to a decrease in leisure time, which gives the cost of search. In Mortensen (1986) a simpler version of the same model is presented. An explicit cost of search function<sup>2</sup> is formulated and an increase in search effort raises the job offer arrival rate. Benhabib and Bull (1983) model search intensity somewhat differently. They deviate from the sequential search framework by allowing the individual to choose at the end of the period the job with the maximum wage from the jobs s/he applied for. Thus, expected returns to search arise from the expected increase of the largest wage offer as intensity increases, rather than from an increase in the job offer arrival rate. Mortensen and Vishwanath (1994) address the impact of different search channels in the context of an equilibrium search model. The unemployed can get wage offers from the wage offer distribution and wage offers from the distribution of wages earned. The first type of offers is interpreted as job offers obtained through a direct application and the second type is interpreted as job offers obtained through an informal contact by a friend or relative.

In this paper we estimate an empirical model of job search with endogenous search intensity, based on the model by Mortensen (1986). This empirical model provides insight into the impact of the benefit level on the decision to search and on the search effort, the effectiveness of search and the “discouraged worker” effect. The results of the analysis of the model are important for predicting the possible effects of economic policy. In the political debate it is often argued that lowering unemployment benefits raises the search effort of the unemployed, and therefore increases the probability of a transition into work. Lowering benefits, though, may be a less effective policy tool for the discouraged.

To our knowledge, there are only a few empirical studies in which the relation between search effort and unemployment duration is analyzed. Yoon (1981) and Lindeboom and Theeuwes (1993) provide empirical work on the effect of search. Fougère, Bladel and Roger (1997) estimate a structural model with endogenous search intensity. Koning, Van den Berg and Ridder (1997) estimate a structural model, which includes the choice and impact of two different search methods (formal, by means of applications, and informal by means of referral).

The model in this paper considers the search behaviour of the unemployed as well as the behaviour of those who are searching on-the-job. To make the model suitable for empirical application, some of Mortensen’s simplifying assumptions have to be relaxed. We allow for differences in the cost of search for workers and nonworkers. Moreover, differences in the job offer arrival rate between different labour market states may occur. Search intensity in the original model is a one-dimensional concept, but several indicators of search appear in the data, some of which are related to

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2. This cost of search function need not necessarily be interpreted in terms of financial cost, but may rather be interpreted in terms of utility.

different search channels. Thus, in the empirical specification we allow for the choice of different channels of search. The data used are from the Dutch Socio Economic Panel.

In Section II the economic model is presented. In Section III the data are described. Section IV contains the empirical specification, while the results are presented in Section V. In the final section, we present the conclusions.

## II. The Economic Model

The model by Mortensen (1986) serves as a basis for the empirical specification. The original model by Mortensen (1986) describes both the search behaviour of the unemployed and on-the-job search. Wage offers arrive randomly from a wage offer distribution  $F(\cdot)$  and individuals maximize the expected present value of net income. In the model the level of search intensity affects the speed at which job offers arrive: a higher intensity of search increases the job offer arrival rate. More specifically, Mortensen (1986) assumes “search effort”  $s$  to be proportional to a “market-determined” search efficiency parameter  $\lambda$ . Thus, the arrival rate is  $s\lambda$ . The cost of search<sup>3</sup> is an increasing convex function of search intensity  $c(s)$ , with properties  $c(0) = 0$ ,  $c'(s) > 0$  and  $c''(s) > 0$ . The cost of search function and the search efficiency parameter are the same for unemployed job seekers and employed who are searching on-the-job. As a consequence, the unemployed who maximizes his/her expected discounted net future income value is willing to accept any job with a wage higher than the benefit income  $b$ , since once employed, s/he can continue searching under the same conditions. In other words, for the unemployed the reservation wage  $\xi$  is equal to the benefit level  $b$ . Employed job seekers will accept any job offer with a wage higher than the current wage. The optimal level of search effort is the value of search effort at which the expected returns to search are equal to the marginal cost of search, provided that this value of search effort is nonnegative. A corner solution arises if the marginal cost of search exceeds the marginal returns of search at positive levels of search effort. In the latter case it is optimal not to search.

To use the Mortensen (1986) model for the purpose of specifying an empirical model of job search with endogenous search intensity, we need to allow for some facts that are observed in the data: (i) unemployed job seekers and on-the-job seekers have different transition rates into a (new) job; (ii) unemployed job seekers and on-the-job seekers are observed to search with a different intensity; (iii) for a number of individuals who report not to be searching we observe a transition into a job; (iv) there are differences in the characteristics of individuals; (v) we need to provide a link between the theoretical, one-dimensional concept of search intensity and the available observable indicators of search; (vi) for a number of employed respondents a transition into unemployment is observed. In this section, the emphasis is on the incorporation of these items in the economic model. The stochastic specification is discussed in Section IV.

3. In Burdett and Mortensen (1978) the cost of search is the value of leisure forgone due to spending time on search.

With regards to points (i) and (ii): we allow parameters of the job offer arrival rate and the cost of search function to be different for individuals in a different labour market state. Throughout the paper, we will denote the market efficiency parameter by  $\lambda_l$  and the cost of search function by  $c_l(s)$ ,  $l = e, u$ , where the subscript  $e$  denotes the state of employment and  $u$  the state of unemployment. Differences in the search conditions between labour market states causes the reservation wage  $\xi$  to be different from  $b$ . For the employed the reservation wage is still equal to the current wage.<sup>4</sup>

Note that a difference in the efficiency parameter  $\lambda_l$  between labour market states is sufficient to generate different transition rates for different labour market states, even if cost of search were the same. However, differences in the cost of search may arise if the value of unemployment were to include a leisure or an investment component that is heterogenous in the population. With regards to points (iii) and (iv): in the data (see Section III) information on search is self-reported: survey respondents can state to be searching for a job or not. For a fraction of the individuals who report not to be searching, a transition into employment (or into another job) is observed. Measurement or reporting error in the search indicators may be one reason for these observations. The stochastics of the empirical specification that incorporates reporting error are discussed in Section IV. A second reason for observing transitions for nonsearchers may be that individuals are invited to take up a particular job. Personal contacts may play an important role here. Irrespective of the reason, we need to adapt the specification of the job offer arrival rate, since in the original model a search effort of zero implies a zero job offer arrival rate and consequently a zero transition rate. For an individual labelled  $i$  who is in the labour market state  $l$ ,  $l = e, u$ , we specify the job offer arrival rate as  $(\alpha_{l0} + \alpha_{lS}) \lambda_{il}$ . The factor  $\lambda_{il}$  is the market-determined part of the arrival rate that depends on the characteristics of individual  $i$ . More specifically:  $\lambda_{il} = \exp(\kappa_l' z_i)$ , in which  $\kappa_l$  is a parameter vector and  $z_i$  is a vector of individual specific variables, related to demand side conditions, which, for reasons of identification, does not contain an intercept.  $\alpha_l$  measures the impact of search intensity on the arrival rate. The parameters  $\alpha_{l0}$  and  $\alpha_l$  may be interpreted as 'baseline' parameters related to search intensity, whereas  $\lambda_{il}$  is a factor describing individual specific deviations from this baseline. The parameter  $\alpha_{l0}$  is identified by the observed transitions of nonsearchers. The parameter vector  $\alpha_l$  is identified by observations on individuals who are searching, and  $\kappa_l$  is identified by variation in individual characteristics.<sup>5</sup>

With regard to point (v): Mortensen's (1986) model is formulated in terms of a one-dimensional variable "search intensity," while the paper does not deal with observability issues related to this variable. The data, described in Section III, contain several indicators of search intensity. A possible way to link the various indicators to the theoretical concept of "search intensity" is to construct a one-dimensional variable for instance by defining a linear combination of the observed indicators. However, the different indicators of search intensity are related to different channels or methods of search, which are potentially different with

4. In this version of the paper we abstain from nonzero cost of turnover.

5. In the remainder of the paper we will drop the subscript  $i$  from  $\lambda_{il}$ .

respect to their effectiveness and search cost. A typical individual observed to be searching for a job does not necessarily use all of the search channels. Mapping the observed indicators into a one-dimensional variable would result in a loss of information on the use of various search channels. To exploit such information we will model the use of each particular search channel in the same way as Mortensen (1986) models the search decision: it is optimal to use a search channel if the marginal returns to search of the particular channel equals the marginal cost of using it. As a result, in the empirical model search intensity  $s$  is a vector of search indicators. Accordingly, in the sequel the search effectiveness parameter  $\alpha_l$  and the marginal cost of search  $c_l'(s)$ ,  $l = e, u$ , represent vectors of equal dimension as  $s$ .<sup>6</sup> In the empirical specification, the cost of search function is chosen to be additively separable in search channels for reasons of convenience:

$$c_l(s) = \sum_{j=1}^S c_{l_j}(s_j), \quad l = e, u,$$

and  $S$  indicates the number of search channels. In general this would preclude complementarity of search channels.<sup>7</sup> In the empirical specification common indicators of observed and unobserved heterogeneity will be included in the different terms of the cost of search function so that a close link between the different terms in the cost of search a function is established. Finally, with regard to point (vi), we allow for an exogenous layoff rate  $\sigma$ . The considerations above lead to the following model assumptions.

**Assumption 1**

The job offer arrival rate for labour market state  $l$ ,  $l = e, u$  is  $(\alpha_{l0} + \alpha_{lS}) \lambda_l$ , with  $\alpha_{l0} > 0$ ,  $\alpha_{lS} > 0$ ,  $\lambda_l > 0$ . Search effort is indicated by  $s$ ,  $s \geq 0$ , and  $s$  is allowed to be a vector of which each component represents a search channel.

**Assumption 2**

The cost of search in the labour market state  $l$  is defined by the cost of search function  $c_l(s)$ , which is convex, has the property  $c_l'(s) > 0$ , and is additively separable in search channels.

**Assumption 3**

A job is characterized by the wage. A wage offer arrives from the wage offer distribution  $F(\cdot)$ .

**Assumption 4**

There is an exogenous layoff rate  $\sigma$ .

**Assumption 5**

The benefit income level for someone unemployed is denoted by  $b$ .

**Assumption 6**

Individuals maximize the expected present value<sup>8</sup> of income net of search costs. The solution of the maximization problem is characterized by the optimal intensity

6. In Section IV, we will specify the cost of search function showing that it is easy to map the underlying optimal search levels of the various search indicators into a one-dimensional variable, which may be interpreted as the latent "search intensity."

7. Van den Berg and Van der Klaauw (2001) present a specification that allows for complementarity between search intensities associated with different search channels.

8. The rate of time preference will be denoted by  $\rho$ .

of search  $s_l^*$ ,  $l = e, u$ , a reservation wage  $\xi$  for the unemployed and a reservation wage  $w$  for the employed, which is equal to the current wage.

Let  $W(w)$  denote the value function for someone employed at wage  $w$  and  $V$  the value function of someone unemployed. The reservation wage  $\xi$  is implicitly defined by  $W(\xi) = V$  which leads to the following equation.<sup>9</sup>

$$(1) \quad \xi = b + \left\{ (\alpha_{u0} + \alpha_u s_u^*) \lambda_u - (\alpha_{e0} + \alpha_e s_e^*) \lambda_e \right\} \\ \int_{\xi}^{\infty} [W(x) - W(\xi)] dF(x) + c_e(s_e^*) - c_u(s_u^*)$$

In (1)  $s_l^*$  denotes the optimal search intensity in state  $l$ . Note that if the parameters of the job offer arrival rate and the cost of search functions are the same for the different labour market states, the reservation wage  $\xi$  is equal to the benefit level  $b$ , as in the original model by Mortensen (1986). Let  $\bar{s}_l$  denote the level of search for which the marginal cost of search channel  $j$  is equal to the marginal returns of search:

$$(2) \quad c'_{ij}(\bar{s}_{ij}) = \alpha_{ij} \lambda_l \int_{x_l}^{\infty} [W(x) - W(x_l)] dF(x), l = e, u$$

in which  $\alpha_{ij}$  denotes the search effectivity parameter of search channel  $j$  in the labour market state  $l$ ,  $l = e, u$ , and  $x_u = \xi$ ,  $x_e = w$  for someone employed at wage  $w$ . Then the optimal level of search intensity  $s_{lj}^*$  equals  $\max\{0, \bar{s}_{lj}\}$ . Thus, optimal search intensity satisfies the marginal cost equals marginal returns to search condition if the outcome is positive. Condition (2) reveals some important properties of the optimal search intensity.<sup>10</sup> First, note that by the convexity of the cost of search function (Assumption 2) the marginal cost of search is increasing in search intensity. This implies that if the effectiveness of search, represented by the factor  $\alpha_{ij} \lambda_l$ , rises, the optimal intensity of search by channel  $j$  rises as well. Note that this also applies to the decision to search: a low value of the effectiveness of search may induce workers not to search. Second, Conditions 1 and 2 describe the simultaneous movement of the optimal search intensity and the reservation wage. Since condition 1 implies a positive relation between the benefit level and the reservation wage for the unemployed, a higher benefit level reduces the intensity of search according to condition 2. For the employed, the reservation wage is equal to the current wage. Thus, search intensity is lower the higher is the wage. Once someone employed has found a job with a sufficiently high wage, s/he will stop searching.

For reasons of future reference, we denote the marginal returns to search by channel  $j$  for labour market  $l$  state by  $R_{lj}$ :

$$(3) \quad R_{lj} \equiv \alpha_{ij} \lambda_l \int_{x_l}^{\infty} [W(x) - W(x_l)] dF(x), l = e, u, x_u = \xi, x_e = w$$

9. Since the general shape of the reservation wage equation is well known in the literature, we do not present an analytical derivation. We restrict ourselves to showing the form of the reservation wage equation in our particular model.

10. These properties are the same as in Mortensen (1986), but for reasons of exposition we repeat them here.

### III. The Data

We use data from the Dutch Socio-Economic Panel (SEP), a household panel survey collected by Statistics Netherlands (CBS). From 1984 on households were interviewed twice a year, in April and October.

Information on income was collected only in October. In the survey waves of October 1987, April 1988, and October 1988, detailed information on search was collected. Survey respondents were asked to report their labour market state. They could do so by indicating one out of the following seven states:

1. In education
2. In the military forces
3. Full or part time employed
4. Unemployed
5. Disabled
6. Retired
7. Other

Thus, we emphasize that the (un)employment state is self-reported, and that the selection of the (un)employed is made on basis of this self-reported state. We selected male individuals, younger than 65, who report to be employed or unemployed in the wave of October 1987. In addition, in April 1988 and October 1988, employed and unemployed individuals, that had not yet been selected in the previous wave(s), are added. Survey respondents report one of the labour market state out of the states listed above on a month by month basis, for the past six months, and this information is used to construct the duration of spells of employment and unemployment. Note that, depending on the wave of sampling, the observation period for an individual is up to eighteen months. In addition the backward recurrence times of employment and unemployment spells can be determined from the survey information.<sup>11</sup> This is based on the question “How long have you been unemployed?” and “At which month/year did your present job start?” The sample thus obtained is a stock sample, which will be accounted for in the estimation of the model. We only consider single spell employment durations. Given the average job duration (see Table 3) there are very few observations for which multiple employment spells may be observed. Right hand censoring is accounted for in the construction of the likelihood function.

Information on search behaviour of the survey respondents is obtained from various questions:

*“Are you searching for a paid job at the moment, or if you already have a paid job, are you searching for a different one?”*

11. This is based on the question ‘How long have you been unemployed?’ and ‘At which month/year did your present job start?’

Possible answers are: “*Yes, I am searching seriously*”, “*Yes, I am thinking about it*”, and “*No*”.

If the respondent has answered positively to this first question, some additional questions are asked:

“*Have you been looking for work in the past two months (yes/no)?*” The respondents are told that “looking for work” in this context means responding to an advertisement, placing an advertisement, gaining information from employers, relatives or the employment office, screening the advertisements, etc.

“*How many times have you applied for a job in the past two months?*”<sup>12</sup>

“*Are you registered at the employment office?*”

Note that the information on search is self-reported: someone is defined to be a searcher if he answered positively to the first question. Also note that the questionnaire imposes no restrictions between the additional questions for searchers, neither on the routing nor on the outcomes. For example, a respondent who reports to have been applying for a job, does not necessarily report to have been “looking,” and a respondent who reports to be searching does not necessarily report a positive number of applications. These features of the phrasing of the questionnaire need to be incorporated in the model specification.

Furthermore, we would like to address the question whether there is a relation between the reported information on search and the eligibility to unemployment benefits. According to the Dutch Unemployment Law (WW) an individual is eligible to unemployment benefits if (i) he is unemployed or his working week schedule has been reduced by five or more hours, (ii) he has been employed for at least 26 weeks of the 39 weeks previous to employment (no matter the length of the working week), (iii) he is available for a “suitable”<sup>13</sup> job only. An individual who is not eligible for unemployment benefits may be eligible for social welfare benefits. Note that in the law “availability” for a job is the criterium for unemployment benefits.

At the time of the survey, though, there was not an active government policy in terms of sanctions to someone entitled to benefits who was unwilling to accept a “suitable” job. In 1996, the Law on Penalties and Measures<sup>14</sup> was introduced in which explicit sanctions against the unwilling unemployed are formulated. This suggests that positive response of a survey respondent to the use of search channels is not just a reflexion of benefit entitlement. Also note that the data we use are based on survey information rather than on administrative data from the unemployment registry. Therefore, there is no direct link between “unemployment” according to our definition and benefit entitlement.

In practice, anyone who wants to claim an unemployment or social welfare benefit has to register at the employment office. As shown later on, none of the employed who are looking for a job reports to be registered at the employment

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12. “Applying for a job” means writing a letter of application, making a phone call, etc.

13. A “suitable” job usually means a job that matches the education level of the unemployed.

14. Wet Boeten en Maatregelen.



office. Although registration at the employment office may have a positive impact on finding a job, it is directly related to entitlement to benefits, and the choice to register at the employment office is likely to be different from the decision to equate marginal returns and marginal cost of search. Moreover, for individuals who do not report to be searching, we do not observe directly whether or not they are registered at the employment office. Therefore, we decided not to use information on registration at the employment office as an indicator of search. Using the survey information we can construct three search indicator variables  $\hat{s}_1$ ,  $\hat{s}_2$ , and  $\hat{s}_3$  for an individual who reports to be searching:

$$\begin{aligned} \hat{s}_1 &= 1 && \text{if searching seriously} \\ &= 0 && \text{if not} \\ (4) \quad \hat{s}_2 &= 1 && \text{if looking for work in the past two months} \\ &= 0 && \text{if not} \\ \hat{s}_3 &= && \text{number of applications in the past two months}^{15} \end{aligned}$$

The indicator  $\hat{s}_1$  will be referred to as the “search attitude” indicator: it is one for respondents who report to be “searching seriously.” The relation between indicators  $\hat{s}_2$  and  $\hat{s}_3$  and the survey question is straightforward. In Section IV we provide a link between the observed indicators in Equation 4 and the optimal search intensity introduced in Section II. Note that the indicators  $\hat{s}_j$ ,  $j = 1, 2$  do provide information on the intensity of search, even though they are binary indicators: the decision to search and search intensity are closely related. Individuals who report to be searching seriously have a higher underlying latent search intensity than individuals who report not to.<sup>16</sup>

Information on labour market state and search can be used to distinguish four groups in the sample: employed searching for a job, employed not searching for a job, unemployed searching for a job, and unemployed not searching for a job. Note that the group of unemployed who are not searching follows from the above definitions of labour market state and self-reported search: someone is registered in the sample as an unemployed who is not searching if he reports to be unemployed, by selecting the state of unemployment out of the seven labour market states listed earlier, and if he answers “no” to the question whether he is searching for a job.

Table 1 displays information about the number of observations and transitions in the sample. The percentage of job-to-job transitions is higher among the employed searching for a job than among the employed who are not searching. A similar observation can be made for the unemployed. Figures 1 and 2 present Kaplan-Meier estimates of the survivor functions for the raw data, without correction for any source of heterogeneity. Neglected heterogeneity will bias downward

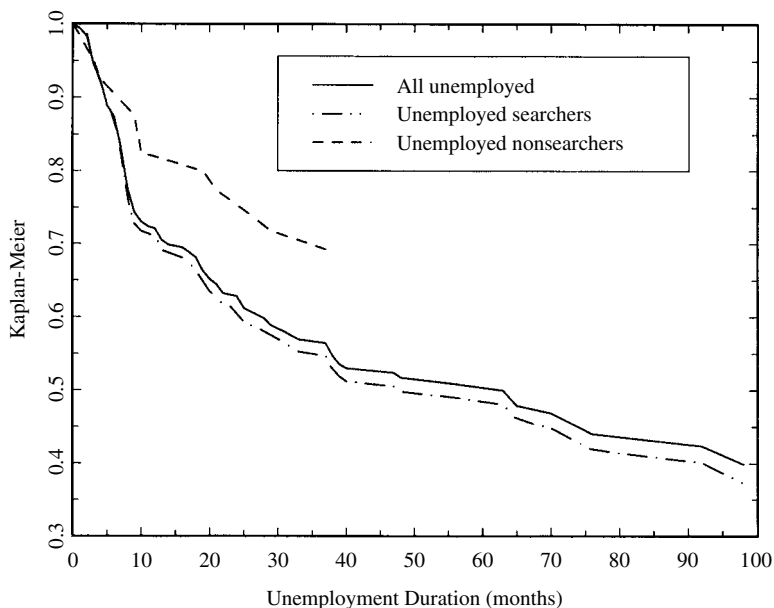
15. Thus we obtain the number of applications per time unit. In measuring the number of applications over two months, the fact that individuals with a backward recurrence time of one month report applications per month, rather than over two months, has to be accounted for. We do this by rescaling the number of applications. Note that the procedure of rescaling can be justified if the number of applications in a given time interval are assumed to follow the Poisson distribution.

16. A comparison with labour supply can be made: indicators for participation and the number of working hours both provide information on labour supply.

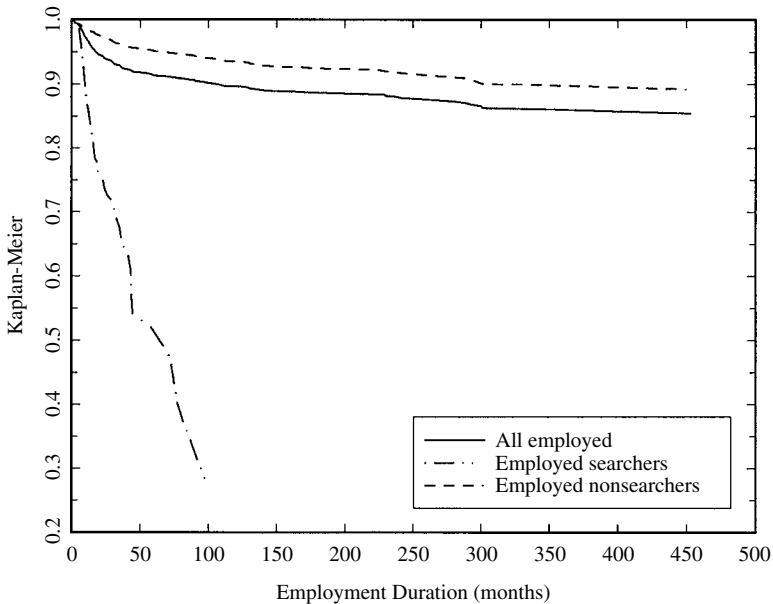
any estimate of duration dependence. These figures also show the survivor function for the duration data separately for those who are searching and those who are not. The survivor function of unemployment duration in Figure 1 decreases rapidly in the first ten months of unemployment. After ten months, its slope decreases, indicating negative duration dependence, which may be partly attrib-

**Table 1**  
*Observed transitions*

	Employed 3,266 observations		Unemployed 352 observations	
	Searchers	Nonsearchers	Searchers	Nonsearchers
Observations (percentages)	500 (15)	2,766 (85)	312 (89)	40 (11)
Transitions (transition rates in percentages)				
into employment	107 (21)	142 (5)	139 (45)	13 (33)
into unemployment	20 (4)	165 (6)		



**Figure 1**  
*Kaplan-Meier of Unemployment Duration*



**Figure 2**  
*Kaplan-Meier of Job Duration*

uted to neglected heterogeneity. Most transitions occur within three years. Since most of the unemployed are searching for a job, there is not much difference between the survivor function of unemployment duration of the entire sample of unemployed and the survivor function of the unemployed who are searching. The survivor function of unemployment duration of the unemployed who are not searching is based on few observations and we see in Figure 1 that its estimate is above that of the searching group, suggesting lower transition rates for those who are not searching.

Figure 2 shows the Kaplan-Meier survivor function for employment duration. There is a large difference between the survivor function of the employed who are searching on the job and those who are not. The scale of employment duration is different between the two groups. For the employed who are not searching there is evidence of strong negative duration dependency. Apart from “true” negative duration dependence, this may be explained by the prediction of the search model that once individuals have found a job with a satisfactory wage level, they stop searching for another job and stay employed.

Table 2 contains information about the indicators of search. As the indicators of search are only applicable to those individuals who report to be searching for a job, the information in Table 2 relates to this subsample. From the 500 employed who are searching on-the-job, 47.8 percent report to be “searching seriously.” The percentage of these who is “looking for work,” in the way defined before, is 74.6. Among the

**Table 2***Sample statistics search indicators (subsample frequency in percentages)*

Indicator	Employed 500 observations sample frequency	Unemployed 312 observations sample frequency
Searching seriously	47.8	81.8
Looking for work	74.6	78.2
Number of applications past 2 months > 0	56.5	64.1
Number of applications past 2 months = 1	25.6	16.3
Number of applications past 2 months = 2	13.4	11.5
Number of applications past 2 months = 3	6.4	9.3
Number of applications past 2 months = 4	3.8	7.1
Number of applications past 2 months ≥ 5	7.5	19.9

group of employed people who are searching 56.5 percent have actually been applying for a job in the past two months. A large part of them (25.6 percent) has been applying for a job only once, whereas 13.4 percent applied twice. Among the subsample of 312 unemployed who are searching for a job, 81.8 percent report to be “searching seriously.” This is obviously a higher percentage than we found for those employed. The remaining search indicators also show that the unemployed search more intensely than the employed: 78.2 percent are “looking for work,” whereas 64.1 percent have applied for a job in the past two months.

Table 3 provides sample statistics of duration, weekly income, and background characteristics of the employed and the unemployed who are searching and those who are not. The mean of duration is based on both completed and right hand censored spells. The mean of duration for the unemployed who do not search is eight months higher than the mean for the unemployed who are searching for a job. The mean weekly benefit income of the unemployed who are not searching for a job is higher than that of the other unemployed.

There is a considerable difference between the mean wage of the employed who are searching and the mean wage of the employed who do not search. The mean wage of those who are searching is lower than the mean wage of those who do not search. This is in accordance with the theoretical model spelled out in the previous section, which predicts a negative relation between the current wage and the decision to search.

The available background characteristics are age, four education dummies for the level of education, *educ1*, *educ2*, *educ3* and *educ4*, with *educ1* the lowest level of education (the highest level, *educ5*, serves as reference group),<sup>17</sup> three sectoral dummies, *sec1*, *sec2*, and *sec3*, the regional dummies *region1*, *region2*, and *region3*, and a

17. When estimating the model, for the specification of the job offer arrival rates we will merge the education levels 4 and 5 together to one level, which serves as the reference level.

**Table 3**  
*Sample statistics income and background variables*

Employed (n=3,266)	Searchers (n = 500)		Nonsearchers (n = 2,766)	
Variable	Mean	Standard Deviation	Mean	Standard Deviation
Age	32	7.8	38	10.7
Family size (persons)	3.2	1.3	3.3	1.3
Wage before transition (guilders/week)	517.6	233.2	602.9	432.3
Duration (months)	19.0	13.1	135.3	117.8
Education level	Mode 3		Mode 3	
Binary variables: sample percentages				
Dutch nationality	96.6		96.4	
Regions				
1. Industrialized west	44.4		43.0	
2. East	24.8		23.8	
3. South	20.8		23.1	
4. Agricultural	10.0		10.1	
Married	65.6		76.6	
Sector of education				
1. Technical	28.6		34.4	
2. Economic/administrative	17.4		17.8	
3. No specialization	27.6		27.7	
4. Services	23.4		19.3	
Unemployed (n = 352)	Searchers (n = 312)		Nonsearchers (n = 40)	
Variable	Mean	Standard Deviation	Mean	Standard Deviation
Age	31	11.7	47	15.4
Family size (persons)	3.0	1.6	2.4	1.2
Benefit income (guilders/week)	150.5	164.2	193.4	155.7
Positive benefit income (guilders/week)	284.7	112.8	286.44	93.2
Wage after transition into employment	378.2 (n = 77)	179.4	504.3 (n = 7)	253.1
Duration (months)	27.1	27.2	35.0	29.5

**Table 3** (continued)

Education level	Mode 1	Mode 1
Binary variables: sample percentages		
Dutch nationality	92.3	95.0
Regions		
1. Industrialized west	37.2	42.5
2. East	27.9	35.0
3. South	23.4	5.0
4. Agricultural	11.5	17.5
Married	35.5	57.5
Sector of education:		
1. Technical	24.4	17.5
2. Economic/administrative	10.6	10.0
3. No specialization	52.6	50.0
4. Services	11.2	20.0

dummy for marital status which is one if married and zero if not. *Sec1* is a dummy for education in the technical sector which includes chemistry, physics, mathematics and biology, *sec2* refers to economic and administrative education, *sec3* is general education and the fourth sector, which serves as a reference sector and is not included as a dummy, is the service sector. *Region1* is a dummy for the strongly industrialized western part of the Netherlands, *Region2* is the east where we find a mixture of industrial and agricultural activities, *Region3* is the south of the Netherlands characterized both by the presence of some large companies and agricultural industry and the fourth region, which is the region of reference for which no dummy variable is included, is the remaining part of the country with a sizeable agricultural sector. Note that the mean age for those who are searching is lower than for those who are not, in either labor market state.

The estimation of the model will also include the estimation of the parameters of the wage offer distribution. For this purpose we will use information on accepted wages for the unemployed who experienced a transition into employment (see Table 3), the wages of employed individuals before a transition (Table 3) and the accepted wages of the employed individuals after a transition (Table 4). In Section IV we construct the likelihood contribution for these different types of observations on wages. Table 3 shows that for 84 of the unemployed individuals with a transition we observed the accepted wage.<sup>18</sup> On the average, accepted wages are higher than benefit levels. Table 4 shows information on the accepted wages of the employed for which both the wage before a transition and the wage after a transition is observed. The quar-

18. In the SEP, the number of observations on accepted wages is typically lower than the number of observations for which a transition is observed. This can be partly attributed to item nonresponse that is typical for information on income and partly to item and wave nonresponse related to the fact that information on income is collected in the October survey only.

**Table 4**  
*Wages before and after a job to job transition*

Subsample	Wage Income Before Transition	Wage Income After Transition
Employed nonsearchers (both wages observed, n = 100)		
Mean	526	559
25 percent quantile	372	427
Median	475	508
75 percent quantile	600	658
Employed searchers (both wages observed, n = 95)		
Mean	425	524
25 percent quantile	294	390
Median	404	459
75 percent quantile	531	600

tiles of the distribution of wages before a transition are lower than their equivalents for accepted wages observed after a transition. Note that the quartiles of the observed wages of the employed who have been searching and experienced a transition into a new job look quite similar to the quartiles of the observed wages before a transition of the employed who have not been searching. This may indicate that the employed who have been searching, after having made a transition, have become similar to those who have not been searching. Finally, we note that although table 3 suggests an overall increase in the distribution of wages, there are also individuals reporting a lower wage after the transition than before. This is obviously inconsistent with the reservation wage property of the employed, and hence we will include measurement error in observed wages in the next section in order to account for such observations.

#### IV. Empirical Specification

The behaviour of individuals searching for a job is described by the reservation wage Equation 1 and the optimal search Condition 2. To implement the model empirically we provide a link between the optimal search intensity derived in Section II and the available search indicators in the data. For this purpose we specify in Section IVA a cost of search function and we introduce stochastics into the model. The model will be estimated by (simulated) maximum likelihood and the likelihood contributions are presented in Section IVB.

##### A. Specification

In order to obtain explicit expressions for the optimal intensity of search along various channels we specify the following cost of search function:

$$\begin{aligned}
 c_l(s) &= \sum_{j=1}^3 c_{l_j}(s_j), l = e, u \\
 (5) \quad c_{l_j}(s_j) &= \gamma_{0l,j} C_{l_j} \left[ \exp\left(\frac{s_j}{\gamma_{0l,j}}\right) - 1 \right]
 \end{aligned}$$

in which  $\gamma_{0l,j}, l = e, u$  are parameters. Note that Equation 5 is concave if  $\gamma_{0l,j} > 0$  and  $C_{l_j} > 0$ . We allow for observed heterogeneity  $q$  and unobserved heterogeneity  $\tilde{q}$  in (5) by specifying

$$(6) \quad C_{l_j} = \exp\left(-\frac{\gamma'_{l_j} q + \tau_{l_j} \tilde{q}}{\gamma_{0l,j}}\right)$$

Solving the first order Condition 2 using Equation 5 leads to the following equation:

$$(7) \quad \bar{s}_{l_j} = \gamma'_{l_j} q + \gamma_{0l,j} \ln R_{l_j}(\tilde{q}) + \tau_{l_j} \tilde{q}, l = e, u$$

with  $R_{l_j}(\tilde{q})$  as defined in Equation 3. We added the argument  $\tilde{q}$  to express the dependence of  $R_{l_j}$  on the unobserved  $\tilde{q}$ , as  $\tilde{q}$  enters the computation of the reservation wage. This will identify the effect of  $\tilde{q}$  separately from the effect of the reporting errors introduced later on.<sup>19</sup> We assume that  $\tilde{q}$  is normally distributed with mean zero and variance 1. In the sequel we will suppress the argument  $\tilde{q}$  to simplify notation.

Note that it is straightforward to make solution in Equation 7 for different search channels  $j$  compatible with a single dimensional latent search intensity: a linear combination of Equation 7 over different channels of search leads again to a “search intensity” that is linear in  $q$  and in marginal returns to search. If, in addition, we specify

$$(8) \quad \gamma_{l_j} = \vartheta_{l_j} \gamma_l, \vartheta_{l1} = 1, j = 2, 3, l = e, u$$

with  $\vartheta_{l_j}$  a scalar, then  $\gamma'_l q$  has the interpretation of a common single index for the marginal cost of search that may affect the cost of search for different search channels to a different extent according to the value of  $\gamma_{0l,j}$ .

To compute  $\bar{s}_{l_j}$  in Equation 7 we need to calculate the marginal returns to search  $R_{l_j}$  which by Equation 3 involves the computation of the expected income gain due to search, represented by the integral in Equation 3. There is no closed form solution for this integral.<sup>20</sup> There are several solutions to this problem and we discuss two of them, both having their own specific advantages and disadvantages. The first is the introduction of a fixed stopping rule. As an example, we may assume that once someone has become employed he can change jobs only once, so the second job only can be ended by a layoff.<sup>21</sup> This rule enables the computation of the expected income gain due to search. However, it will also change the reservation wage: The reservation wage will not be equal to the current wage. Since on-the-job search with a reserva-

19. Note that this approach is equivalent to the common practice in the estimation of the wage distribution in search models, in which the variance of the offer distribution is identified separately from the variance of the distribution of measurement error. As we will show later on, for employed individuals the computation of  $R_{l_j}$  is based on the latent accepted wage, instead of the observed wage, which also will depend on  $\tilde{q}$ .

20. This can be regarded as a curse of dimensionality problem.

21. Alternatively, we may assume a larger, but still finite, number of job moves that may occur, to further improve the approximation. Depending on the values of the parameters, the approximation of the reservation wage may converge to the ‘true’ reservation wage at a finite number of moves.



tion wage equal to the current wage nowadays is commonly applied in equilibrium search models (Burdett and Mortensen 1998; Ridder and Van den Berg 1998), this would imply a deviation from the common practice in the literature.

A second option is to maintain the reservation wage property of the original model (which says that the reservation wage for an employed is the current wage), but to approximate the expected gains in search with a value that we can evaluate. We may compute the expected gains of search that would hold if the individual would keep the new job forever. This value can easily be computed.<sup>22</sup> The consequences for the computation of the reservation wage  $\xi$  by Equation 1 for the unemployed may be limited, because it is the difference between gains of search in different labor market states that determines this reservation wage: in the extreme case in which search conditions are equal in different labour market states, the level of the gains of search does not even affect  $\xi$ . In the empirical implementation, we choose the second option, which implies that we approximate the integrand in Equation 3 by

$$(9) \quad (\rho + \sigma)[W(x) - W(x_l)] \approx x - x_l$$

The advantage of this approximation is that some important implications of the model are preserved: the reservation wage of the employed is their current wage, and the reservation wage of the unemployed still depends, as in Equation 1, on the difference between the gains and the cost of search in the different labour market states.

Next, we provide a link between the observed search indicators  $\hat{s}_j$  in Equation 4 and the values  $\tilde{s}_j$  from Equation 7 that equate marginal cost of search and marginal returns to search. In the data there are two types of indicators: (i) dichotomous indicators, and (ii) a count variable (the number of applications). Let  $\varepsilon_{lj}$ ,  $l = e, u$  denote random errors, and let  $\hat{s}_{lj}$ ,  $l = e, u, j = 1, 2$  denote a dichotomous search indicator. We define the following relations:<sup>23</sup>

$$(10) \quad \begin{aligned} \hat{s}_{lj} &= 1 \text{ if } \tilde{s}_{lj} \equiv \tilde{s}_{lj} + \varepsilon_{lj} > 0 \\ &= 0 \text{ if } \tilde{s}_{lj} \equiv \tilde{s}_{lj} + \varepsilon_{lj} \leq 0 \end{aligned}$$

and

$$(11) \quad \tilde{s}_{lj}^* = \max \{0, \tilde{s}_{lj}\}, l = e, u, j = 1, 2$$

In Equation 10  $\tilde{s}_{lj}$  represents the stochastic equivalent of the outcome of the marginal cost equals marginal returns condition: it deviates from the “true” solution by the error

22. As a motivation for this choice we may assume that the behaviour of the individual is myopic or subject to bounded rationality: The individual does have a notion of the expected job that comes next to the current state, but he is unable to form expectations of jobs that come after the next job.

23. The additive specification of the errors  $\varepsilon_{lj}$  in Equation 10 enables us to express the probability of searching in terms of the distribution function of  $\varepsilon_{lj}$  (see Section IVB). The specification allows for (zero mean) deviations between the ‘true’ search indicator  $\hat{s}_{lj}$  and the latent indicator  $\tilde{s}_{lj}$ . The disadvantage of specifying the distribution of the binary search indicators in this way is that the errors  $\varepsilon_{lj}$  do not stem from the structural model: the identification and the econometric treatment of the corner solutions are based on the introduction of these errors. This can only be circumvented if a more refined stochastic structure in the structural model itself were introduced, for instance by the inclusion of unobserved heterogeneity in the search efficiency parameters and the specification of stochastics in the marginal cost of search of each indicator of search intensity. Due to the nonlinearity of the reservation wage equation and the optimal search equation the stochastics will enter the optimal search intensity highly nonlinearly and the probability of search cannot explicitly be expressed in terms of the distribution function of the random errors.

term  $\epsilon_{ij}$ , which may represent reporting error. Equivalently, in Equation 11  $\tilde{s}_l^*$  represents the latent optimal search intensity including a stochastic error. Equation 10 implicitly defines the probability that someone in the labour market state  $l$  reports the use of search channel  $j$  ( $\hat{s}_{lj} = 1$ ).

The stochastic specification for the number of applications is more complicated. The number of applications,  $\hat{s}_{l3}$ ,  $l = e, u$ , is a variable that can only take discrete values (like 0, 1, 2, and so on). How can we, both conceptually and technically, fit a discrete random variable into a continuous time search framework? Conceptually, we may assume that individuals who search more intensively meet potential job opportunities at a higher rate and when an opportunity is met an application is submitted.

Technically, it seems most natural to model the number of applications as a count variable. The Poisson distribution is commonly used to model count variables (see Winkelmann (2000)). The mean of this Poisson distribution should be the optimal number of applications, generated by the model. Accordingly, for individuals who are searching for a job we specify

$$(12) \quad P(\hat{s}_{l3} | \tilde{s}_{l3} > 0) = \frac{[m_l]^{\hat{s}_{l3}} \exp\{-m_l\}}{\hat{s}_{l3}!}, l = e, u$$

with  $m_l$  implicitly defined by

$$(13) \quad \begin{aligned} \tilde{s}_{l3}^* &\equiv \ln(1 + m_l) \text{ with} \\ \tilde{s}_{l3} &= \tilde{s}_{l3} + \epsilon_{l3} \text{ and } \tilde{s}_{l3}^* = \max\{0, \tilde{s}_{l3}\}, l = e, u \end{aligned}$$

Consequently, the mean number of applications  $m_l$  follows from the (latent) optimal search intensity  $\tilde{s}_{l3}$  defined by the model in Equation 7.

A few notes apply. First, note that the logarithmic relation between the latent search indicator  $\tilde{s}_{l3}^*$  in Equation 13 and the number of applications  $\hat{s}_{l3}$  is simply a matter of definition: up till Equation 13 we had not provided any formal link between data on search intensity  $\hat{s}_{l3}$  and the latent search intensity  $\tilde{s}_{l3}$ ; Equations 12 and 13 provide this link. The logarithmic transformation in Equation 13 is nothing more than a monotonic reparametrization. Second, note that Equation 13 implies that the job offer arrival rate is logarithmic in the number of applications. Third, note that the complication in the modelling of the number of applications stems from the fact that we are modelling a time-aggregated variable within a continuous time framework: if an individual reports three applications we know that he has rejected two job offers, since search is assumed to take place at a constant rate. Fourth, conditioning on  $\tilde{s}_{l3} > 0$  indicates that Equation 12 applies to searchers only. For individuals who are not searching, we assume that the Poisson distribution (Equation 12) does not apply. For them the condition  $\tilde{s}_{l3} \leq 0$  holds. Summarizing, we write

$$(14) \quad \begin{array}{ll} \text{Searchers: } & \hat{s}_{l3} \sim \text{Poisson}(m_l), \hat{s}_{l3} = 0, 1, 2, \dots \quad \text{and } \tilde{s}_{l3} > 0 \\ \text{Nonsearchers:} & \hat{s}_{l3} = 0 \quad \text{by } \tilde{s}_{l3} \leq 0 \end{array}$$

Note that Equation 14 provides a natural distinction between observing zero applications for someone who reports to be searching and the absence of applications for someone who reports not to search.

To complete the stochastic specification for the observed search indicators, we assume that  $\epsilon_l = (\epsilon_{l1}, \epsilon_{l2}, \epsilon_{l3})'$ ,  $l = e, u$  follows a normal distribution:

$$(15) \quad \varepsilon_l \sim N(0, \Sigma_l), l = e, u$$

with

$$(16) \quad \Sigma_l = \begin{pmatrix} 1 & \sigma_{l,12} & \sigma_{l,13} \\ \sigma_{l,12} & 1 & \sigma_{l,23} \\ \sigma_{l,13} & \sigma_{l,23} & \sigma_{l,3}^2 \end{pmatrix}, l = e, u$$

Note that the covariance matrix is not restricted to be diagonal: thus we allow for correlation in reporting error of the different search indicators. By the relation  $\tilde{s}_l = \hat{s}_l + \varepsilon_l$ , Equation 15 implicitly defines the density function of  $\tilde{s}_l$  which we will denote by  $g(\tilde{s}_l; \Sigma_l), l = e, u$  for future reference. Wage offers arrive from the lognormal density with log-variance  $\tau^2$ . Furthermore we assume that accepted wages are observed with a log-normally distributed measurement error with log-variance  $\sigma_m^2$ . Finally, the layoff rate  $\sigma$  is made dependent on individual characteristics  $a$  by specifying  $\sigma = \exp(\zeta' a)$ .

### B. Likelihood Contributions

The parameters of the job offer arrival rate, the cost of search function, the wage offer distribution, the layoff rate, and the parameters of the distribution of reporting error in search indicators and measurement error in wages are estimated simultaneously by the method of simulated maximum likelihood. In this section we will show how the likelihood contributions for the model outlined in the previous two sections can be formulated.

To construct the likelihood contribution for an observation  $(t_i, \hat{s}, w_1^o, w_2^o)$  consisting of duration  $t_i$ , search indicator  $\hat{s} = (\hat{s}_1, \hat{s}_2, \hat{s}_3)'$ , the *observed* wage before a transition  $w_1^o$  (employed only) and the *observed* wage after a transition  $w_2^o$ , we first will address the separate parts that are involved: (i) the density function of duration ( $t_i$ ), conditional on the value of the (latent) search intensity  $\tilde{s}_l^*, l = e, u$  (defined in Equations 10 and 13); (ii) the density function of the latent search intensity  $\tilde{s}_l^*, l = e, u$ ; (iii) the distribution of wages; (iv) the Poisson distribution for the observed number of applications (defined in Equation 14). As we will see, combining the various parts of the likelihood contribution involves (after multiplication) the integration over the latent search intensity as well as integration over the latent (accepted) wages and unobserved heterogeneity.

(i) Denoting transition intensities for transitions from unemployment into employment by  $\theta_{ue}(\tilde{s}_u^*)$  and job to job transitions by  $\theta_{ee}(\tilde{s}_e^*)$  we have:<sup>24</sup>

$$(17) \quad \theta_{le}(\tilde{s}_l^*) = (\alpha_{10} + \alpha'_l \tilde{s}_l^*) \lambda_l \bar{F}(x_l), l = e, u, x_u = \xi, x_e = w_1$$

Since transition rates in models of search both depend on the arrival rate and the wage offer probability, separate identification of wage offer parameters from the job offer arrival rates usually is extremely difficult: in datasets the covariates that are likely to affect the wage offer distribution are often the same as the covariates that affect the arrival rate. Information on search indicators as we use here typically provides

24. Here the same remark applies as in Equation 10: measurement error enters the expression even though it does not follow from the structural model.

an additional source of information to distinguish the effect of the arrival rate from the effect of the wage offer distribution. However, introducing search indicators does not solve the problem of nonparametric identification in search models: by the structure of the model the respective distributions of duration, search indicators and *observed* wages depend on all the covariates included in the model, and it is the structure of the model that allows for identification. Nevertheless there is a link between the different data series and specific subsets of model parameters: The wage data enable the identification of the parameters of the wage offer distribution (given the structure of the model), the presence of search indicators allow for the identification of the cost of search function and the data on duration allow for the identification of the arrival rates (again conditional on the structure of the model in Equation 17).

The density functions of unemployment duration and job duration, conditional on search intensity, wages and unobserved heterogeneity,<sup>25</sup> are

$$\begin{aligned}
 f_u(t_u | \tilde{s}_u^*) &= \theta_{ue}(\tilde{s}_u^*) \exp\{-\theta_{ue}(\tilde{s}_u^*)t_u\}, 0 < t_u < \infty \\
 f_e(t_e | \tilde{s}_e^*) &= \theta_{ee}(\tilde{s}_e^*) \exp\{-(\theta_{ee}(\tilde{s}_e^*) + \sigma)t_e\}, 0 < t_e < \infty \\
 (18) \quad &\text{job to job transitions} \\
 f_e(t_e | \tilde{s}_e^*) &= \sigma \exp - (\theta_{ee}(\tilde{s}_e^*) + \sigma)t_e, 0 < t_e < \infty \\
 &\text{employment to unemployment transitions}
 \end{aligned}$$

(ii) By Equations 10 and 13 the latent search intensity  $\tilde{s}_l^*$ ,  $l = e, u$  is a function of  $\tilde{s}_l$  for which we denoted the density function (conditional on unobserved heterogeneity and wages) by  $g(\tilde{s}_l, \Sigma_l)$  in the previous subsection. The relation between  $\tilde{s}_l$  and  $\tilde{s}_l^*$  will be used in completing the likelihood contribution later on.

(iii) For the likelihood contribution of wages we need to distinguish between *observed* wages and (latent) *accepted* wages. The *accepted* wages are assumed to be drawn from the wage offer distribution  $f(w)$  (assumed to be log-normal), while the *observed* wages are the accepted wages measured augmented with a log-normal measurement error. In the sequel, we denote observed wages with a superscript  $o$ . Moreover, for employed individuals we observe a wage during the current spell of employment and we may observe a new wage after a transition into a new job. We will denote current wages by subscript 1 and wages after a transition (irrespective of the initial state) by subscript 2. For unemployed individuals, the model implies that the distribution of the (latent) accepted wage is the offer distribution truncated to wages higher than the reservation wage  $\xi$ :  $f(w_2)/\bar{F}(\xi)$  defined for  $w_2 > \xi$ , zero elsewhere. For the current (latent) wage  $w_1$  of employed respondents the model implies that this wage must be higher than the reservation wage for the unemployed. Consequently, the density is  $f(w_1)/\bar{F}(\xi)$ ,  $w_1 > \xi$ , zero elsewhere.<sup>26</sup> At this point it is important to realize that for the employed the latent search intensity  $\tilde{s}_e^*$  also depends on the current wage  $w_1$ . If someone employed transits into a new job, the model implies that the new wage  $w_2$  must be higher than the old wage  $w_1$ .

25. Note that the conditioning on wages and unobserved heterogeneity runs through  $\tilde{s}_l^*$ . To keep notation simple, we do not express wages and unobserved heterogeneity explicitly in the notation.

26. Again, note that the distribution of accepted wages  $w_2$  of the unemployed and current wages  $w_1$  of the employed depend on unobserved heterogeneity  $\tilde{q}$ , which we suppress in the notation.

Thus, we have the density  $f(w_2)/\bar{F}(w_1)$ ,  $w_2 > w_1$ , zero elsewhere. Without measurement error in wages, the support of current wages  $w_1$  for the employed and accepted wages  $w_2$  for the unemployed would depend on the model parameters through  $\xi$  and standard conditions for applying maximum likelihood would not be satisfied. Moreover, for the employed, without measurement error a zero likelihood contribution arises if a wage  $w_2$  observed after a transition is lower than the wage  $w_1$  before. If measurement error is included, the appearance of such an observation can be attributed to measurement or reporting error. We define the relation between observed and accepted wages by

$$(19) \quad \ln w_j^o = \ln w_j + \psi_j, \psi_j \sim N(0, \sigma_m^2), j = 1, 2$$

Equation 19 implicitly defines the density function of observed wages  $w_j^o$  conditional on the (latent) accepted wage  $w_j$ ,  $j = 1, 2$ , which we will denote by  $g^o(w_j^o | w_j)$  in the sequel.

(iv) The Poisson distribution of the observed number of job offers has already been discussed in Equations 12 and 14. We will denote this distribution by  $P(\hat{s}_{l3} | \bar{s}_{l3})$  below.

Completing the likelihood contributions now involves the multiplication of the various parts and the integration over the latent variables. For an unemployed searching for a job with a completed duration  $t_u$ , a vector of search indicators  $\hat{s}_u$ , and an observed wage  $w_u^o$ , we have the following likelihood contribution:

$$(20) \quad \int_{A(\hat{s}_u)} f_u(t_u | \bar{s}_u^*) g(\tilde{s}_u; \Sigma_u) P(\hat{s}_{u3} | \bar{s}_{u3}) \int_{\xi}^{\infty} g^o(w_2^o | w_2) \frac{f(w_2)}{\bar{F}(\xi)} dw_2 d\bar{s}_l, l = e, u$$

In Equation 20, the region of integration  $A(\hat{s}_u)$  is defined by the observed search indicators through Equations 10 and 14. Moreover, Equation 10 defines the dependence of  $\bar{s}_u^*$  on the variable of integration  $\tilde{s}_u$ .<sup>27</sup> The likelihood contributions for individuals who do not search, right hand censored unemployment spells, and for completed unemployment spells without an observation on the accepted wage, are straightforward simplifications of Equation 20.

For an employed searching for a job, with completed job duration  $t_e$ , who is observed to have an initial wage  $w_1^o$ , a new wage  $w_2^o$ , and search indicators  $\hat{s}_e$ , the likelihood contribution is

$$(21) \quad \int_{\xi}^{\infty} \int_{A(\hat{s}_e)} f_e(t_e | \bar{s}_e^*) g(\tilde{s}_e; \Sigma_e) P(\hat{s}_{e3} | \bar{s}_{e3}) \int_{w_1}^{\infty} g^o(w_1^o | w_1) g^o(w_2^o | w_2) \frac{f(w_1)}{\bar{F}(\xi)} \frac{f(w_2)}{\bar{F}(w_1)} dw_2 d\bar{s}_l dw_1$$

Again, Equation 10 defines the dependence of  $\bar{s}_e^*$  on the variable of integration  $\tilde{s}_e$ . Moreover, the optimal search intensity depends on the initial wage  $w_1$ , by Equations 3 and 7. For this reason, integration over the latent wage  $w_1$  is done in the outer integral. Finally, note that in Equations 20 and 21 we implicitly condition on unobserved heterogeneity  $\tilde{q}$ , defined in Equation 6. The likelihood contributions can be completed by weighting the contributions with the standard normal density function of  $\tilde{q}$  and integrating over  $\tilde{q}$ , which enters Equations 20 and 21 by  $\bar{s}_l, \bar{s}_l^*$  and  $\xi$ .

27. We could have explicitly denoted this in the notation by writing  $\bar{s}_e^* = \bar{s}_e^*(\tilde{s}_u)$ .

To evaluate the likelihood contribution, we need to calculate four and five dimensional integrals of normally distributed random variables. This problem can be handled by using the smooth recursive conditioning algorithm (SRC) for simulating multidimensional integrals over normally distributed random variables and applying simulated maximum likelihood (SML) as described in Börsch-Supan and Hajivassiliou (1993). The Monte Carlo integration involves the generating of random numbers for unobserved heterogeneity, latent current wages for the employed (generated such that they are higher than the reservation wage), and values for the latent vector of search indicators  $\bar{s}_t$ .<sup>28</sup>

To allow for the fact that the available data on duration is a stock sample, we condition on backward recurrence times (conform Lancaster 1979; Ridder 1984). The derivation of the joint density of duration and search intensity, conditional on backward recurrence times is given in appendix 2.

## V. Estimation Results

In this section we present the estimation results.

### A. Parameter Estimates

The estimation results of the structural model are reported in the Tables 5 through 8. The rate of time preference  $\rho$  has been fixed, such that on a yearly basis the discount rate is 5 percent. In the simulated maximum likelihood procedure we use 60 replications from the error distribution of the search indicators, wages, and unobserved heterogeneity to simulate the integrals in Equations 20 and 21.

Table 5 contains the parameter estimates of the job offer arrival rates and the lay-off rate. For the unemployed, the exogenous part of the job offer arrival rate,  $\lambda_u$ , is decreasing with age for the unemployed who are older than 25. Recall from Table 3 that the mean age for the subsample of the unemployed who are not searching is higher than the mean age of the subsample of unemployed who are searching. A lower value of  $\lambda_u$  for unemployed individuals with a higher age implies lower returns to search (everything else being equal) for older unemployed, and therefore decreases the incentives to search. Unemployed individuals that only followed a general type of education (*sec 3*) have the lowest arrival rate. For the employed individuals  $\lambda_e$  is decreasing in age. As for the unemployed, employed individuals without skill-specific education (*sec 3*) have the lowest value of the arrival rate  $\lambda_e$ . Moreover, in the West, more industrialized region of the Netherlands, employed individuals have higher arrival rates. The lay-off rate decreases with age until the age of 30, after which it increases. Individuals in the service sector have the highest lay-off rate, and individuals with the lower levels of education tend to have the higher layoff rates.

The lower part of Table 5 contains the coefficient estimates of the various search indicators of the job offer arrival rate. For both the unemployed and the employed the

28. In Equations 20 and 21 the integration over accepted wages  $w_2$  can be handled without simulation.

**Table 5**

*Estimates of the structural model  
Arrival rates and the lay-off rate*

Variable	Arrival rate $\lambda_u$ , the unemployed		Arrival rate $\lambda_e$ , the employed		Layoff-rate	
	Estimate	Standard Error	Estimate	Standard Error	Estimate	Standard Error
Const	—	—	—	—	-4.2**	0.3
Log(age/17)	6.7**	1.3	0.32	1.0	-2.7**	0.7
Square of log(age/17)	-8.5**	1.0	-2.2**	0.8	2.3**	0.5
<i>sec1</i> (technical)	0.04	0.80	0.80	0.77	-0.68**	0.17
<i>sec2</i> (econ/adm)	-0.55	0.62	0.15	0.58	-0.51**	0.20
<i>sec3</i> (not specialized)	-2.30**	0.6	-1.4**	0.6	-0.65**	0.20
<i>region1</i> (west)	0.40**	0.19	0.95**	0.20	—	—
<i>region2</i> (east)	-0.23	0.18	0.17	0.20	—	—
<i>region3</i> (south)	0.11	0.20	0.41*	0.22	—	—
<i>educ1</i> (lowest)	0.68	0.52	0.17	0.49	0.53**	0.24
<i>educ2</i>	0.49	0.56	0.34	0.54	0.42**	0.19
<i>educ3</i>	0.48	0.59	0.06	0.57	0.18	0.18
Marital status	0.22	0.18	0.99**	0.16	-0.58**	0.17
Nationality	-1.7**	0.3	1.1**	0.3	—	—
Effectiveness of search						

Variable	Unemployed ( $\alpha_u$ )		Employed ( $\alpha_e$ )	
	Estimate	Standard Error	Estimate	Standard Error
Intercept $\alpha_{i0}$	14.7**	4.7	0.27**	0.09
Attitude	2.2**	1.1	0.86	0.55
Screening	1.8	1.2	0.93**	0.44
Applications	29.6**	7.9	4.0**	1.4

\* significant at the 10 percent level

\*\* significant at the 5 percent level

number of applications has the largest impact on the arrival rate, compared to the other search indicators. Moreover, the effect of the number of applications is significant for both labour market states. For the unemployed, the search attitude (“searching seriously”) is also significant. The “screening” indicator does not have a significant coefficient estimate. This indicates that, for instance, “screening” *alone*, without taking any further action, does not significantly affect the job offer probability. For the employed, we do find a significant effect of “screening” on the arrival rate.

Table 6 shows the parameters of the cost of search function. Recall that a parameter  $\gamma_{ij}$  has a negative impact on the marginal cost of search and consequently a positive

**Table 6***Estimates of the parameters of the cost of search function*

	Unemployed		Employed	
	Estimate	Standard Error	Estimate	Standard Error
Search indicator $\gamma_i' q$				
$\gamma_{i1}$ (constant)	-1.5**	0.7	-2.1**	0.4
$\gamma_{i2}$ (log(family size))	0.13*	0.08	0.07	0.04
$\gamma_{i3}$ (marital status)	-0.013	0.08	-0.31**	0.08
$\gamma_{i4}$ (log(age/17))	-0.95*	0.53	2.4**	0.5
$\gamma_{i5}$ (square of log(age/17))	0.94**	0.48	-2.3**	0.4
Effect of returns of search on search intensity				
$\gamma_{0i,1}$ (attitude)	0.90**	0.15	0.11*	0.06
$\gamma_{0i,2}$ (screening)	0.86**	0.19	0.59**	0.09
$\gamma_{0i,3}$ (applications)	0.98**	0.10	0.30**	0.05
Parameter $\vartheta_j$				
$\vartheta_{j2}$ (screening)	0.81	0.58	2.0**	0.4
$\vartheta_{j3}$ (applications)	2.6**	1.2	1.2**	0.2
Parameter $\tau_j$		(Unobserved heterogeneity)		
$\tau_{j1}$ (attitude)	0.63**	0.19	0.61**	0.16
$\tau_{j2}$ (screening)	0.89**	0.27	0.90**	0.20
$\tau_{j3}$ (applications)	0.79**	0.11	0.53**	0.06

\*significant at the 10 percent level

\*\*significant at the 5 percent level

impact on the optimal search intensity. We find that the unemployed with a larger family search harder, which is plausible. The parameter estimate of  $\gamma_{0u,j}$ ,  $j = 1, \dots, 3$ , is significant for all of the three search indicators. This parameter measures the impact of returns to search on the optimal search intensity. Apparently the returns to search are important in determining the optimal search intensity. For the employed marital status has a significant positive impact on the cost of search. The cost of search decreases with age until the age of 29 after which the cost of search increase. For the employed, we see that returns to search significantly affect the optimal search intensity for the various search channels (parameter  $\gamma_{0e,j}$ ).

Table 7 contains the estimates of the covariance matrix of reporting errors of the search indicators. The estimates of the covariances between the various search channels are all positive and significant. Note that the estimated covariance matrices are positive definite. Finally, Table 8 shows the parameter estimates of the wage offer distribution. The mean wage offer rises with age until the age of 53, after which it falls. Wage offers are higher the higher is the level of education. Individuals without skill-specific training obtain higher wage offers, all things equal. Note that the standard



**Table 7**

*Estimates of the structural model*  
*Parameters of error distribution,  $\Sigma$ ,  $l = e, u$*

	Unemployed		Employed	
	Estimate	Standard Error	Estimate	Standard Error
$\sigma_{l,12}$ (attitude-screening)	0.59**	0.09	0.58**	0.08
$\sigma_{l,13}$ (attitude-applications)	0.37**	0.07	0.65**	0.07
$\sigma_{l,23}$ (screening-applications)	0.38**	0.08	0.73**	0.07
$\sigma_{l,3}$ (applications)	0.67**	0.06	1.04**	0.06

\*\*significant at the 5 percent level

**Table 8**

*Estimates of the structural model*  
*Parameters of wage offer distribution*

	Estimate	Standard Error
Constant	-11.1**	1.6
Log age	8.4**	1.0
Log age squared	-1.1**	0.1
<i>educ1</i>	-0.40**	0.08
<i>educ2</i>	-0.35**	0.07
<i>educ3</i>	-0.32**	0.08
<i>educ4</i>	-0.11**	0.03
<i>sec1</i>	-0.04	0.10
<i>sec2</i>	0.11	0.08
<i>sec3</i>	0.25**	0.08
$\tau$	0.39**	0.03
$\sigma_m$	0.38**	0.002

$\tau$  standard deviation wage offer distribution

$\sigma_m$  standard deviation measurement error

\*\* significant at the 5 percent level

deviation of the wage offer distribution is slightly larger than the standard deviation of the distribution of measurement error in wages. The numbers suggest that about half of the variation in observed wages is due to variation in wage offers while the other half is due to measurement error.

### B. Elasticities

Up till now we have only looked at the separate coefficient estimates. In order to gain more insight into the implications of the model we computed several elasticities. Analytic expressions for the elasticities are presented in Appendix 2. The elasticities have been evaluated at the mean values of the observed characteristics of the unemployed and the employed (see Table 3).<sup>29</sup> The computed values of various elasticities are shown in Table 9.<sup>30</sup> For the unemployed we computed the impact of the benefit level on the reservation wage. This quantifies the impact of the benefit level on the

**Table 9**  
*Elasticities (standard errors in parentheses)*

$\partial \ln y / \partial \ln x$		In Mean Characteristics
y	x	Lab. Market State
The unemployed		
Reservation wage	Benefit level	0.028** (0.003)
Number of applications	Benefit level	-0.0021** (0.0003)
Probability of search	Benefit level	-0.00010** (0.00003)
Hazard (arrival rate)	Number of applications	0.34** (0.02)
Hazard	Benefit level	-0.22** (0.02)
Number of applications	Arrival rate	0.12** (0.01)
The employed		
Number of applications	Wage	-1.4 (3.0)
Hazard (arrival rate)	Number of applications	0.025* (0.015)

\* significant at the 10 percent level

\*\* significant at the 5 percent level

29. For the dummy variables we chose the service sector, education Level 3, and Region 1. To compute the elasticities we simulated the (latent) levels of a search indicator by generating 60 replications from the joint distribution of the (latent) search indicators. If a generated search indicator is negative, it represents a corner solution of the marginal cost equals marginal returns of search condition. In this case, the simulated optimal level of search is zero. For each replication the elasticity is computed. The elasticities reported here are the average over replications.

30. Standard errors have been computed to account for variation in the elasticities that is due to variation around the estimated parameter values.

decision to accept or to reject a job. The elasticity of the reservation wage with respect to the benefit level is 0.028 and it is significantly different from zero.

For the unemployed it is interesting to consider the effect of an increase in the benefit level on search. We present the elasticity for the number of applications, since this is the search indicator that can be directly observed, and therefore it is the easiest to interpret. The computation of the elasticity is based on Equation 30 in Appendix 2. We evaluate the elasticity at the (simulated) mean level of the Poisson distribution. The elasticity of the (mean) number of applications with respect to the benefit level is  $-0.0021$ . It is significantly different from zero, although the size of the elasticity is small.

We can also compute the elasticity of the probability that it is optimal to apply for a job ( $P(\tilde{s}_{u3} > 0)$ ) with respect to the benefit level. This elasticity takes the value of  $-0.00010$  for someone with the mean characteristics of the unemployed. Again, the estimate of the elasticity is significant, but its size is small. Together with the results for the previous two elasticities we may conclude that the impact of the benefit level on the acceptance decision is higher than on the decision to search.

To quantify the effectiveness of the number of applications on the hazard, we compute the elasticity of the hazard with respect to the (mean) number of applications, leaving the job acceptance probability constant. Note that this shows a partial effect only. The intensity of search and the reservation wage are simultaneously determined, and therefore a change in the mean number of applications and the acceptance probability will always go together. The value of the elasticity, however, provides insight into the effectiveness of search. We find that a 10 percent increase in the number of applications leads to an increase of 3.4 percent in the hazard. Note that this is a *ceteris paribus* effect, for a given value of  $\lambda_u$ : for a low value of  $\lambda_u$  the eventual (absolute) effect of an increase in the number of applications will be much lower than for someone with a higher value of  $\lambda_u$ . The total elasticity of the hazard with respect to the benefit level is  $-0.22$ , which indicates that the impact of the benefit level on the hazard is not negligible.

To further quantify the discouraged worker effect we also computed the elasticity of the optimal number of applications with respect to the exogenous part of the arrival rate  $\lambda_u$ . This elasticity takes the value 0.12 at the mean characteristics of the unemployed. This shows that the more effective way to stimulate individuals to search is to improve their labour market opportunities,<sup>31</sup> rather than to decrease the level of benefits. For employed individuals we computed the elasticity of the number of applications with respect to the wage. We find a value of  $-1.5$  which suggests quite a sizeable impact of the wage on the number of applications. However, the value of the elasticity is not significantly different from zero. A possible explanation may be found in Table 4 which contains information on the wages of the employed, both before and after a job-to-job transition.

For the group of employed people that report to be searching, the distribution of wage income *after* a transition looks quite similar to the wage distribution *before* a transition of the employed who do not search. Thus, a transition of the employed who

31. This may, for instance, be achieved by schooling: Table 5 showed that individuals with only general (nonspecialized) type of education have a significantly lower arrival rate, given everything else.

are searching is enough to make them similar to those who do not search and therefore the wage may show a sizeable negative impact on search. Since the majority of the employed does not search, variation in wages *within* the subsample of the employed who do not search does not add to the explanation of the number of applications, which may explain the imprecision of the estimate of the elasticity.

To quantify the effectiveness of the number of applications, we computed the elasticity of the job-to-job transition intensity, leaving the reservation wage constant. The elasticity takes the value 0.025 and this estimate is significantly different from zero. Thus, the number of applications of the employed has a smaller impact on a transition than for the unemployed.

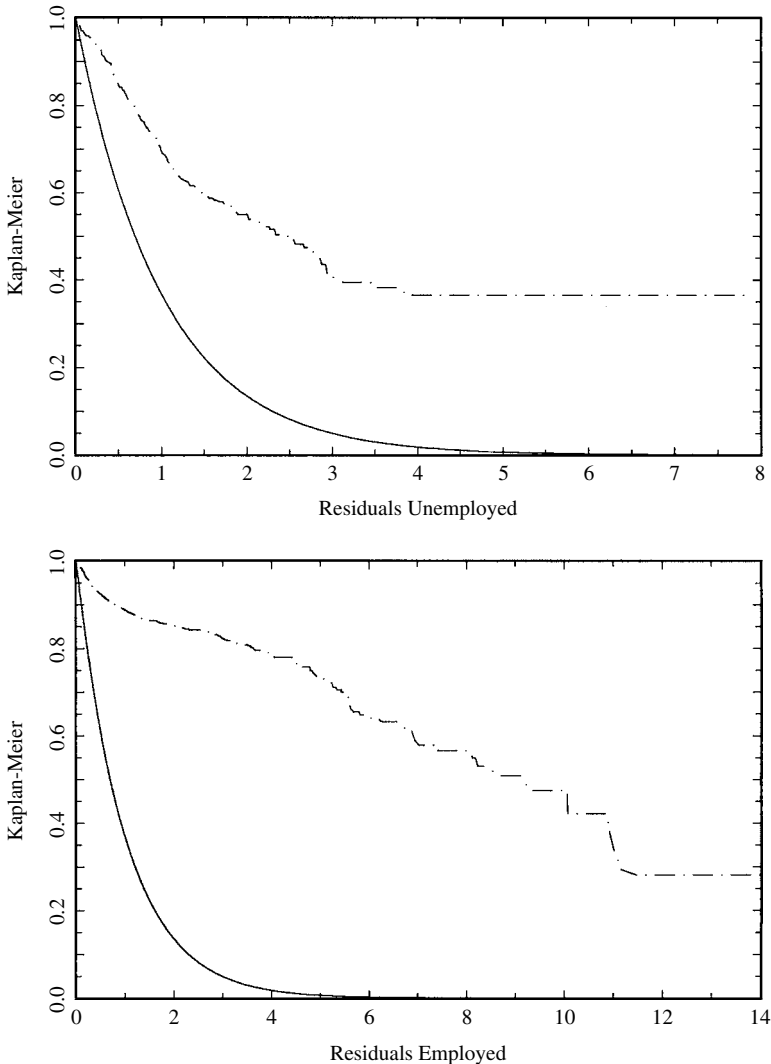
### C. Residual Analysis

In the structural modeling of duration data, usually a lot of structure is imposed on the data, both by the application of economic theory and by the choice of functional forms. The strength of a structural model is that it enables us to disentangle items like the cost of search, the returns to search, the arrival rate, the discouraged worker effect and the acceptance decision. All this makes a structural model a good point of departure for evaluating policy measures. However, because of the structure imposed, the fit of the duration data in structural models usually leaves much to be desired. For this reason studies in which structural search models are used usually do not provide any analysis for the goodness-of-fit of the duration data.<sup>32</sup> We will present the Kaplan-Meier estimates of the generalized residuals of the model. One of the stronger assumptions that is imposed is the stationarity<sup>33</sup> of the search model, which implies the absence of duration dependence of the various transition intensities. Plotting the Kaplan-Meier estimates of the distribution of the generalized residuals can provide us insight into the direction and the degree of the possible duration dependence. This may give us further insight into the search process, may enable us to predict the direction of possible biases in the estimates and may provide suggestions for future extensions of the model. Appendix 3 comments on the computation of the generalized residuals. The generalized residuals follow an exponential distribution with Parameter 1, if the model is correctly specified: Neglected sources of heterogeneity or neglected duration dependence will show deviations from this exponential distribution. It should be noted that neglected heterogeneity cannot be distinguished from neglected negative duration dependence.

The dashed-dotted line in the upper panel of Figure 3 shows the Kaplan-Meier estimate of the distribution function of the residuals for the unemployed individuals. The straight line shows the exponential distribution function with Parameter 1. The distribution of the residual is clearly above the exponential distribution, indicating possible evidence of neglected negative duration dependence or neglected heterogeneity. The lower panel of Figure 3 shows the Kaplan-Meier estimate of the distribution of the generalized residuals of the employed. The difference with the exponential distribution is very large. From Table 3 it was clear that the job duration of the employed indi-

32. A notable exception is Bloemen (1997).

33. Introducing nonstationarity in the model is technically complicated and numerically burdensome, see, for instance, Van den Berg (1990). Moreover, the question is whether it is desirable in the context of a structural model to make, say the arrival rate, a function of time, whereas we may prefer to *explain* duration dependence in a structural model.



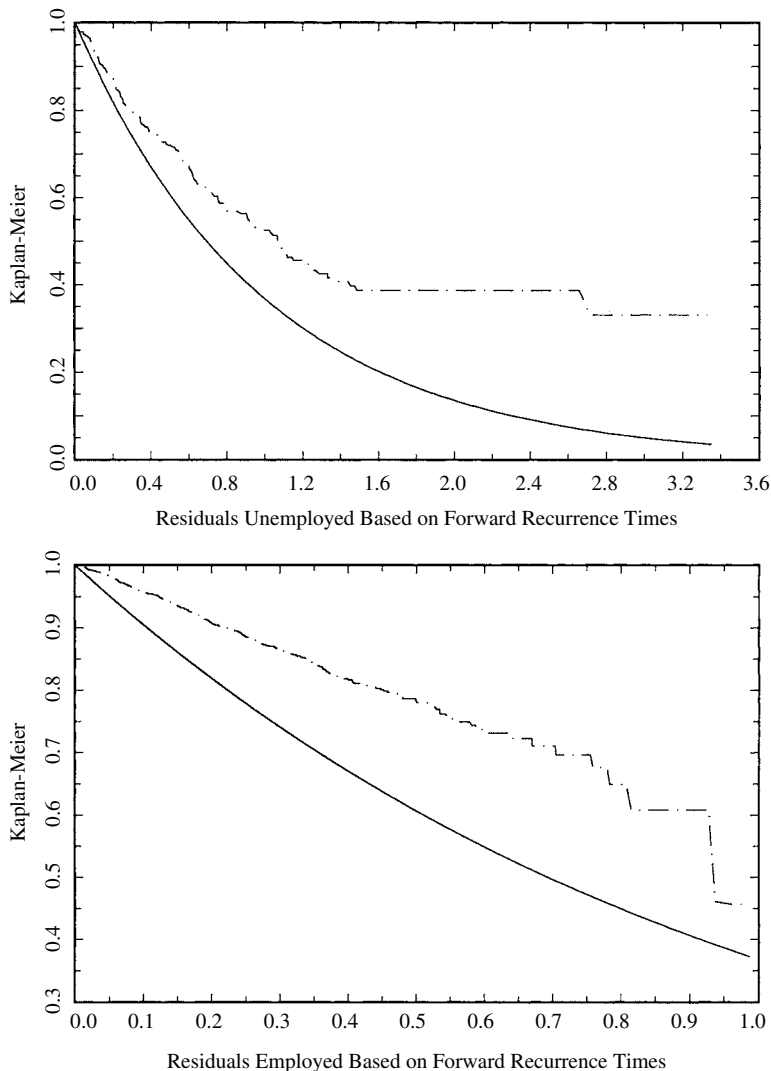
**Figure 3**  
*Distribution of Residuals*

iduals that do not search can be quite long: a stationary exponential distribution, like we use in the modeling, apparently cannot fit these low turnover rates and high survivor probabilities at higher levels of duration.

Note that the sample we use is largely a stock sample. In the estimation we allowed for that by conditioning on backward recurrence times. Another way to look at residuals is to split up duration in forward recurrence times and backward recurrence time.

Since we conditioned on backward recurrence times, we actually have explained the forward recurrence times, given survival up to a period which is as long as the backward recurrence time. Under the null hypothesis that the model is specified correctly, the residuals based on forward recurrence times and on backward recurrence times each follow an exponential distribution with Parameter 1.

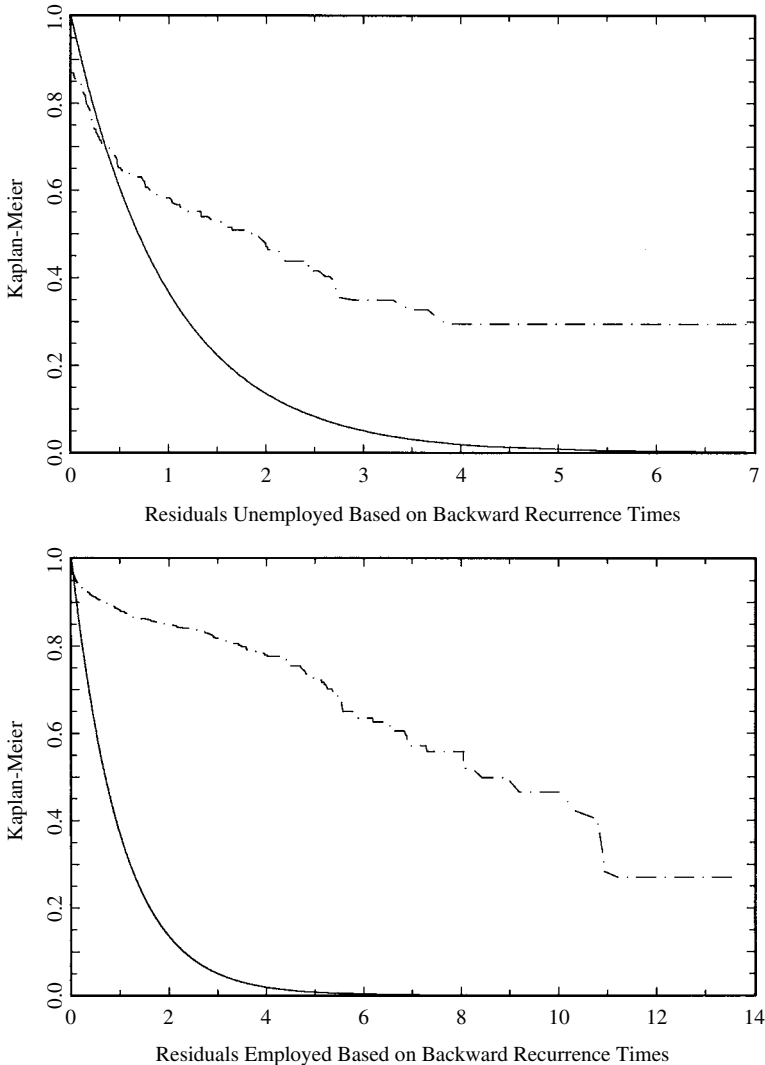
Figure 4 shows the Kaplan-Meier estimates based on the forward recurrence times for the unemployed and the employed. The distribution of the residuals based on for-



**Figure 4**  
*Distribution of Forward Residuals*

ward recurrence times of the unemployed follows the exponential distribution reasonably close, except for a few outliers. For the employed, a comparison of the distribution of residuals based on forward recurrence times with the exponential distribution gives a much better result than the picture based on total duration, but the difference between the two distributions is still large.

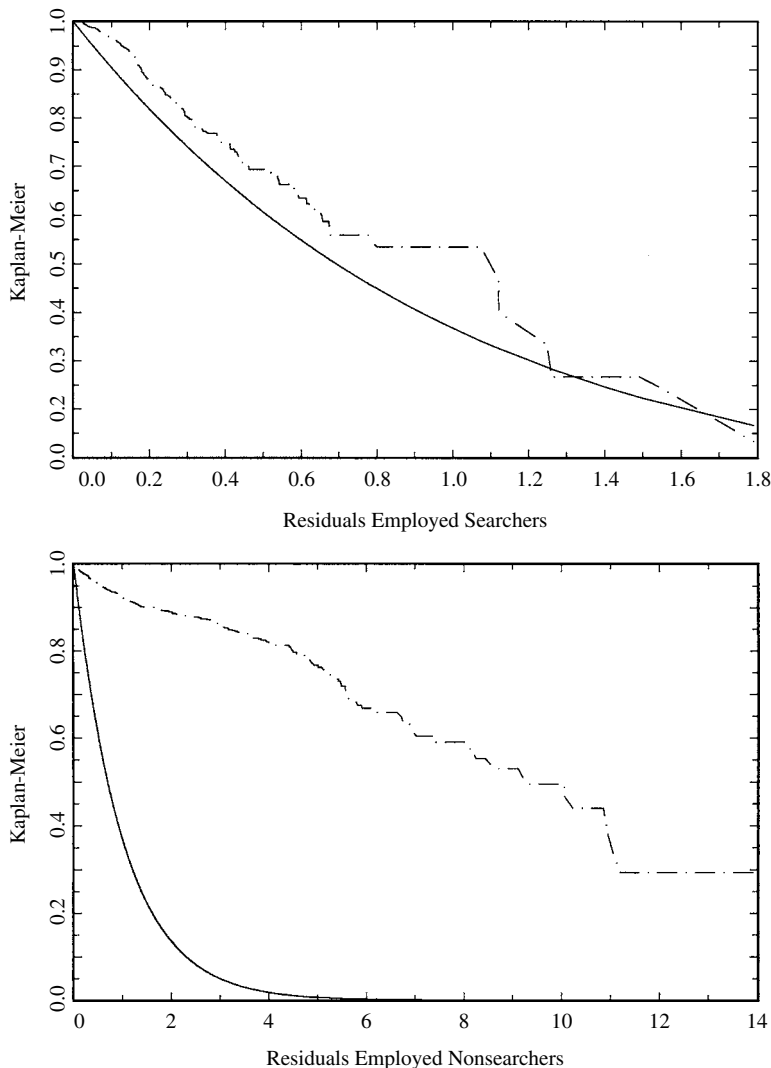
Figure 5 shows the Kaplan-Meier estimates of the distribution of the residuals



**Figure 5**  
*Distribution of Backward Residuals*

based on backward recurrence times for the unemployed and employed. The plots are very similar to those shown in figure 3. This suggests that the model reasonably manages to fit transitions (or, fit the forward recurrence times), especially for the unemployed, *given* that one belongs to the stock of a given labour market state, but that the probability of being part of that stock is not fitted well, due to negative duration dependence, which is in particular strong for the employed.

Finally, Figure 6 shows the Kaplan-Meier estimates of the residuals of the



**Figure 6**  
*Distribution of Residuals by Search Status*



employed (based on total duration) for the employed who are searching for a job and for the employed who are not searching separately. For those who are searching we do better than for the entire sample (Figure 3): the distribution function of the residuals is closer to the exponential distribution. For those who do not search the estimate of the distribution function is comparable to the estimate shown in Figure 3. Given that the group of employed people who do not search forms the vast majority of the sample of the employed, the difference between Figures 6 and 3 shows that introducing the distinction between individuals who search and individuals who do not search clearly adds to the explanation of the duration of employment. However, introducing search alone is not sufficient to explain the low turnover rates at higher durations.

## VI. Conclusions

We have specified an empirical version of the search model of Mortensen (1986), in which the intensity of search is a choice variable for the individual. A higher level of search intensity increases the job offer arrival rate, but at the same time the cost of search rises. The individual chooses the intensity of search on the basis of a comparison of marginal returns of search with marginal cost of search. If the marginal returns to search are too high compared to the marginal cost of search, the individual will decide not to search. We extended the Mortensen (1986) framework to allow for differences in arrival rates and differences in the cost of search between the state of employment and the state of unemployment.

We use data on male individuals from the Dutch Socio Economic Panel (Statistics Netherlands). The dataset contains two dichotomous indicators for the intensity of search (search attitude, “screening” or not) as well as information on the number of applications. In the empirical specification the observed indicators of search are linked to the optimal search intensity derived from the economic model. In the empirical model we impose the structure of the economic model: The reservation wage for the unemployed is computed from the reservation wage equation, the equations for the various search indicators are based on the marginal cost equals marginal returns of search condition and transition intensities for transitions from unemployment to employment and for job to job transitions are specified as the product of the job offer arrival rate and the job acceptance probability.

The stochastic specification allows for unobserved heterogeneity in the cost of search, reporting errors in the search indicators and measurement error in wages. To deal with the integration over the latent variables and to allow for correlation in the stochastic structure of the different search indicators we employ the method of simulated maximum likelihood to estimate the model parameters. We use information on unemployment duration, employment duration, search indicators and wages to simultaneously estimate the job offer arrival rates, the layoff rate, the parameters of the cost of search function and the wage offer distribution.

For the unemployed we find that the job offer arrival rate decreases with age. This turns out to be an important result for the interpretation of the difference between unemployed individuals who report to be searching for a job and unemployed individuals who do not search: The mean age of those who do not search is considerably

higher than the mean age of the unemployed who are searching. The unemployed with general (no specialized) education also have lower job offer arrival rates. The number of applications of the unemployed affects the arrival rate significantly, as does the search attitude. "Screening" is not found to have a significant effect on the arrival rate. For the unemployed we find that the cost of search decreases with family size and age (for age over 28). Furthermore, the returns of search are important in the determination of optimal search intensity.

Also for the employed we find that arrival rates decrease with age (for a given level of search intensity), and individuals without skill-specific training have lower arrival rates. The arrival rate also shows a regional effect: individuals living in the industrialized western part of the Netherlands have higher arrival rates. The layoff rate first decreases with age, but rises with age for individuals who are older than 30. Individuals with the lower levels of education have the highest layoff rates. The number of applications is the most effective search indicator for the employed, and screening also shows a significant effect on the arrival rate. Marital status has a positive effect on the cost of search for the employed. The cost of search decreases with age until the age of 29, after which it increases. We computed various elasticities to quantify the implications of the model. We evaluated elasticities at the mean characteristics of the employed and the unemployed. We also computed standard errors which show that most estimates of the elasticities are significantly different from zero. For the unemployed, the estimates of the elasticity of the reservation wage with respect to the benefit level and the elasticity of the hazard with respect to the benefit level are 0.028 and  $-0.22$  respectively, which suggests a measureable effect of the benefit level on the job acceptance decision and on mean unemployment duration. The estimates of the elasticities of the number of applications and the probability of search with respect to the benefit level are  $-0.0012$  and  $-0.00010$  respectively. The estimates are significantly different from zero at the 5 percent level, but they also show that the impact of benefits on search is small. The elasticity of the number of applications with respect to the exogenous part of the arrival rate (that represents job opportunities, or effectiveness of search) is much higher, namely 0.12. These findings together with the estimated decrease of the arrival rate for the older unemployed and the much higher average age for the subsample of the unemployed who do not search, suggest that a "discouraged worker effect" may be behind the decision not to search. The elasticity of the hazard rate with respect to the number of applications is 0.34 for the unemployed and 0.025 for the employed which suggests that, given everything else, it is more effective to search while being unemployed. For the employed we find an elasticity of the number of applications with respect to the current wage of  $-1.5$ . This suggests a sizeable impact of the wage, but this value is not significantly different from zero, as shown by its standard error.

We also studied the generalized residuals of the model in order to gain insight into the fit of the model and, in particular, to test for neglected duration dependence. For the unemployed the residual analysis shows that there is probably neglected duration dependence. A plot of the residuals based on forward recurrence times looks reasonably good, which suggests that the model manages to track transitions. For the employed, the misspecification of the model is clear. The exponential model without duration dependence cannot explain the low turnover rates at high durations observed in the data. However, it emerges that the inclusion of search intensity in the model improves on the model specification: not distinguishing individuals who are search-

ing from those who do not search would have led to an inferior fit. In spite of this, the inclusion of search intensity *alone* is not enough to explain the high survivor rates of the individuals who do not search.

## Appendix 1

### The Stock Sample Density

The stock sample density of duration and search intensity, conditional on the backward recurrence time is derived. The analysis is based on Ridder (1984). The subindices  $e$  and  $u$ , indicating the labour force state, will be suppressed. Let  $f(t|s, w)$  denote the flow conditional density of duration, conditional on search intensity and the wage. To reduce the necessary notation, search intensity is treated as an observed continuous non-negative random variable here. The extension to multidimensional variables of the type in Section III is straightforward. Let  $f(s|w)$  denote the density of search intensity conditional on the wage, and let  $g(w)$  denote the marginal density of observed wages. Then the joint flow density of duration, search intensity and observed wages is

$$(22) \quad f(t|s, w)f(s|w)g(w), 0 < t < \infty, 0 < s < \infty, 0 < w < \infty$$

Now assume that the inflow rate into the given labour force state is  $i(-p, l)$ , in which  $-p$  denotes the time of inflow into the state, if the point of sampling is taken as reference, and  $l$  is calendar time.<sup>34</sup> The stock density is the flow density, conditional on entrance at  $p$  time units ago, and conditional on duration  $t$  exceeding the backward recurrence time  $p$ . Then the joint stock density of duration, backward recurrence time, search intensity and observed wages is.<sup>35</sup>

$$(23) \quad h(p, t, s, w) = \frac{i(-p, l)f(t|s, w)f(s|w)g(w)}{\int_0^\infty \int_0^\infty \int_0^\infty i(-\tilde{p}, l)\bar{F}(\tilde{p}|\tilde{s}, \tilde{w})f(\tilde{s}|\tilde{w})g(\tilde{w})d\tilde{w}d\tilde{s}d\tilde{p}}$$

$$0 < p < \infty, p < t < \infty, 0 < s < \infty, 0 < w < \infty$$

We are interested in the stock density of duration, search intensity and wages conditional on the backward recurrence time:

$$(24) \quad h(t, s, w|p) = \frac{h(p, t, s, w)}{h(p)}$$

in which

$$(25) \quad h(p) = \int_0^\infty \int_0^\infty \int_p^\infty h(p, \tilde{t}, \tilde{s}, \tilde{w})d\tilde{t}d\tilde{s}d\tilde{w}$$

Combining Equations 24 and 25 with Equation 23 yields the required density:

$$(26) \quad h(t, s, w|p) = \frac{f(t|s, w)f(s|w)g(w)}{\int_0^\infty \int_0^\infty \bar{F}(p|\tilde{s}, w)f(\tilde{s}|\tilde{w})g(\tilde{w})d\tilde{s}d\tilde{w}}$$

$$0 < s < \infty, p < t < \infty, 0 < w < \infty$$

34. We assume that the inflow rate does not depend on unobserved heterogeneity in the cost of search.

35. Note that we treat the subsample of employment spells and the subsample of unemployment spells as two separate samples here. Treating them as one sample changes the selectivity correction in  $h(p, t, s, w)$ , but leaves the final result, the density conditional on backward recurrence times, unaffected.

## Appendix 2

### Elasticities

In this section we present the expressions for the elasticities that serve as a basis for the computation of the elasticities presented in Section V. For the evaluation of the elasticities, we first give the value function for someone employed:

$$(27) \quad (\rho + \sigma) W(w) = w - c_e(s) + \lambda_e (\alpha_{e0} + \alpha_e S) \int_w^\infty [W(x) - W(w)] dF(x) + \sigma V$$

For the expression for the elasticities of the reservation wage of the unemployed,  $\xi$  with respect to the benefit level  $b$ , we have

$$(28) \quad \frac{b}{\xi} \frac{d\xi}{db} = \frac{\rho + \sigma + \theta_{ee}(\xi)}{\rho + \sigma + \theta_{ue}} \frac{b}{\xi}$$

in which  $\theta_{ee}(\xi)$  represents the transition intensity of a job-to-job transition, evaluated at the reservation wage  $\xi$ :  $\theta_{ee}(\xi) = (\alpha_{e0} + \alpha_e s_e^*(\xi)) \lambda_e \bar{F}(\xi)$ . In the derivation of (28), we have used the derivative of the value function for someone employed with respect to the wage,  $W'(w)$ :

$$(29) \quad W'(w) = \frac{1}{\rho + \sigma + \theta_{ee}(w)}$$

Note that the sign of the elasticity in Equation 28 is positive: A higher benefit level leads to a higher reservation wage, and consequently to a decrease in the job acceptance probability.

The elasticity of the underlying (latent) level of search intensity of search indicator  $j$  with respect to the benefit level  $b$  has been determined on basis of the first order condition for the optimal intensity of search for someone unemployed, in Equation 2. In determining the derivative, use has been made of the derivative of  $\xi$  with respect to  $b$  (see Equation 28), and the derivative of the value function  $W'(w)$  in (29). This leads to the following expression for the elasticity:

$$(30) \quad \frac{b}{s_{uj}} \frac{ds_{uj}}{db} = - \frac{\alpha_{uj} \lambda_u \bar{F}(\xi)}{c_{uj}''(s_{uj})} \frac{\rho + \sigma}{\rho + \sigma + \theta_{ue}} \frac{b}{s_{uj}}$$

Note that by the convexity of the cost of search function (Assumption 2 in Section II) the sign of the second order derivative of the cost of search function is positive, so the sign of the elasticity Equation 30 is negative: a higher benefit level leads to a lower intensity of search.

The elasticity of the underlying (latent) level of search intensity of search indicator  $j$  with respect to the factor  $\lambda_u$ , the exogenously determined part of the job offer arrival rate, has been determined by differentiation of the first order condition for optimal search intensity (Equation 2), the derivative of the value function (Equation 29), the specification of the cost of search function (Equation 5), and the derivative of the reservation wage  $\xi$  with respect to  $\lambda_u$  that was obtained by differentiating Equation 1. This results in the following expression for the elasticity:

$$(31) \quad \frac{\lambda_u}{s_{uj}} \frac{ds_{uj}}{d\lambda_u} = \gamma_{0u,j} \frac{\rho + \sigma}{\rho + \sigma + \theta_{ue}} \frac{1}{s_{uj}}$$

The sign of the elasticity in Equation 31 is positive: a higher value of  $\lambda_u$  leads to a higher search intensity. However, an increase in  $\lambda_u$  has two opposing effects on the level of search intensity. The (direct) positive effect is immediately clear from

Equation 2: A higher value of  $\lambda_u$  leads to higher returns of search and therefore increases the incentive to search. The negative (indirect) effect runs through the reservation wage: a higher value of  $\lambda_u$  increases the value of search, and therefore increases the reservation wage (the individual tends to wait for a better offer). By Equation 2, a higher reservation wage goes together with a lower level of search intensity. From Equation 31 it follows that the positive effect dominates.<sup>36</sup>

For employed individuals, we determined the effect of the current wage on the intensity to search. Use has been made of Equation 29. This results in the following elasticity:

$$(32) \quad \frac{w}{s_{ej}} \frac{ds_{ej}}{dw} = - \frac{\alpha_{ej} \lambda_e \bar{F}(w)}{c_{ej}''(s_{ej}(w))(\rho + \sigma + \theta_{ee}(w))} \frac{w}{s_{ej}}$$

The sign of the elasticity Equation 32 is positive: a higher current wage reduces the incentive to search.

Finally, we determined the elasticities of the transition intensities with respect to the intensity of search. For the transition from unemployment into employment we have the following elasticity for search intensity indicator  $j$ :

$$(33) \quad \frac{s_{uj}}{\theta_{ue}} \frac{d\theta_{ue}}{ds_{uj}} = \left[ \alpha_{uj} \lambda_u \bar{F}(\xi) + \frac{(\alpha_{u0} + \alpha_u s_u) f(\xi) c_{uj}''(s_{uj})(\rho + \sigma + \theta_{ee}(\xi))}{\alpha_{uj} \bar{F}(\xi)} \right] \frac{s_{uj}}{\theta_{ue}}$$

In the derivation of Equation 33 use has been made of (29) and, for the determination of the relation between the reservation wage and the level of search intensity, of Equation 2.

For job-to-job transitions, the elasticity is

$$(34) \quad \frac{s_{ej}}{\theta_{ee}} \frac{d\theta_{ee}}{ds_{ej}} = \left[ \alpha_{ej} \lambda_e \bar{F}(w) + \frac{(\alpha_{e0} + \alpha_e s_e) f(w) c_{ej}''(s_{ej})(\rho + \sigma + \theta_{ee}(w))}{\alpha_{ej} \bar{F}(w)} \right] \frac{s_{ej}}{\theta_{ee}}$$

### Appendix 3

#### Generalized Residuals

It is a well-known result in duration analysis (see Cox and Oakes 1984) that if we define a random variable that is equal to the integrated hazard of a hazard rate model, this random variable follows the exponential distribution with Parameter 1, provided that the model is correctly specified. In duration analysis, this result forms the basis for the analysis of the goodness-of-fit of the model. In the context of duration models, the random variable, constructed this way, is the generalized residual. By constructing the nonparametric Kaplan-Meier estimator of the survivor function of the residuals and comparing this to the exponential distribution with Parameter 1, the model specification can be tested.

36. In the expression for Equation 31 we made use of the specification of the cost function in Equations 5. It should be noted, however, that the specific functional form chosen in Equation 5 is not the result of the positive sign of Equation 31. Any other specification of cost of search that satisfies the regularity conditions (see Assumption 2) will lead to a positive sign.

An additional complication in the computation of the generalized residuals in the present paper is that the density of duration contains a latent endogenous variable. We computed the hazard rate of the model by dividing the marginal density of duration by the marginal survivor function of duration. The marginal density function of duration is obtained by integrating Equation 20 for the unemployed and Equation 21 for the employed over wages and search intensity.

The generalized residuals are computed by determining the integrated hazard (evaluated in the observed duration, or in the forward or backward recurrence time, see Section V) on the basis of this hazard.

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