JOB SEARCH, SEARCH INTENSITY AND LABOUR MARKET TRANSITIONS:
AN EMPIRICAL ANALYSIS

by

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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 searchers and on-the-job search. We use data on various indicators (or search channels) for the intensity of search, like the monthly number of applications, 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 searchers is quantified. Moreover, the estimation results are used to gain insight in the “discouraged worker” effect. The generalized residuals are studied to discuss the fit of the model.

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1 Introduction

Job search models usually model the behaviour of a job searcher as a sequential process in which wage offers arrive randomly with a certain rate of arrival. 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 e.g. 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. Searchers may influence the job offer arrival rate by varying the intensity of search. The optimal intensity of search will be chosen by the level at which the marginal returns to search equal 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 in a given time interval, but also causes a utility loss due to a decrease in leisure time, which establishes the cost of search. In Mortensen (1986) a simpler version of the same model is presented. An explicit cost of search function 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 searcher at the end of the period to choose 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. Searchers 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

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

4 This cost of search function need not necessarily be interpretated in terms of financial cost, but may rather be interpreted in terms of utility.
offers obtained from 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). An empirical model may be used to gain insight in 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 are important for predicting the possible effects of policy analysis. 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 both on-the-job searchers and searchers without a job. To make the model suitable for empirical application, some of Mortensen’s simplifying assumptions have to be relaxed. We allow for differences in cost of search for workers and non-workers. 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 in the data several indicators of search, some of which are related to different search channels, appear. 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. The panel contains several indicators for search intensity, related to different search instruments.

In section 2 the economic model is presented. In Section 3 the data are described. Section 4 contains the empirical specification, while the results are presented in section 5. The final section concludes.
2 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 \( F(.) \) 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 specific, Mortensen (1986) assumes ‘search effort’ \( s \) to be proportional to a ‘market determined’ search efficiency parameter \( \lambda \). Thus, the arrival rate is \( s \lambda \). Cost of search\(^5\) is an increasing convex function of search intensity \( c(s) \), with properties \( c(0) = 0, c'(s) > 0 \) and \( c''(s) > 0 \). Cost of search and search efficiency are the same for unemployed searchers and on-the-job searchers. As a consequence, the unemployed searcher 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 searchers 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 marginal cost of search exceeds 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 searchers and on-the-job searchers have different transition rates into a (new) job; (ii) unemployed job searchers and on-the-job searchers are observed to search with a different intensity; (iii) for a number of individuals who report to be nonsearching we observe a transition into a job; (iv) there are differences in characteristics of individuals; (v) we need to provide a link between the theoretical,\(^5\) In Burdett and Mortensen (1978) the cost of search is the value of leisure forgone due to spending time on search.
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 4.

Ad (i) and (ii): we allow parameters of the job offer arrival rate and cost of search functions 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 still is equal to the current wage.\footnote{In this version of the paper we abstain from nonzero cost of turnover.}

Ad (iii) and (iv): In the data (see section 3) 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 4. A second reason for observing transitions for nonsearchers may be that individuals are invited for a particular job. Personal contacts may play an important role in that. 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 labour market state $l, l = e, u$, we specify the job offer arrival rate as $(\alpha_{l0} + \alpha_l s)\lambda_{il}$. The factor $\lambda_{il}$ is the market determined part of the arrival rate that depends on the characteristics of individual $i$. More specific: $\lambda_{il} = \exp(\kappa_l' z_i)$, 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
\( \alpha_{t0} \) is identified by the observed transitions of nonsearchers. The parameter vector \( \alpha_t \) is identified by observations on searchers, and \( \kappa_t \) is identified by variation in individual characteristics.\(^7\)

Ad (v): the Mortensen (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 3, 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 e.g. 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 in effectiveness and search cost. A typical searcher observed in the data does not necessarily use all of the search channels. Mapping the observed indicators into a one-dimensional variable results in a loss of information on the use of various search channels. To exploit the information on the various search channels we will model the use of a 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 \( \alpha_t \) and the marginal cost of search \( c'_l(s) \), \( l = e, u \), represent vectors of equal dimension as \( s \).\(^8\) In the empirical specification, the cost of search function is chosen to be additively separable in search channels for reasons of convenience: \( c_l(s) = \sum_{j=1}^{S} c_{lj}(s_j) \), \( l = e, u \), and \( S \) indicates the number of search channels. In general this would preclude complementarity of search channels.\(^9\) However, in the empirical specification common indicators of observed and unobserved heterogeneity will be included in the different terms of the cost of search function close link between the different terms in the cost of search a function is established.

\(^7\) In the remainder of the paper we will drop the subscript \( i \) from \( \lambda_{it} \).

\(^8\) In section 4, we will specify the cost of search function and we show that according to the chosen specification it is easy to map the underlying optimal search levels of the various search indicators into a one-dimensional variable that may be interpreted as the latent ‘search intensity’.

\(^9\) Van den Berg and Van der Klaauw (2001) present a specification that allows for complementarity between search intensities associated with different search channels.
Ad (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 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 $F(.)$.

**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\footnote{The rate of time preference will be denoted by $\rho$.} of income net of search costs.

The solution of the maximization problem is characterized by the optimal intensity 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 $W(\xi) =$
\[ V \text{ which leads to the following equation:}^{11} \]
\[ \xi = b + \{ (\alpha_{u0} + \alpha_us^*_u)\lambda_u - (\alpha_{e0} + \alpha_es^*_e)\lambda_e \} \int_{\xi}^{\infty} [W(x) - W(\xi)]dF(x) + c_e(s^*_e) - c_u(s^*_u) \]  
\[ (2.1) \]

In (2.1) \( s^*_j \) 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 \( \bar{s}_j \) denote the level of search for which marginal cost of search channel \( j \) is equal to the marginal returns of search:
\[ c^j_{ij}(\bar{s}_j) = \alpha_{ij}\lambda_l \int_{x_1}^{\infty} [W(x) - W(x_l)]dF(x), l = e, u \]  
\[ (2.2) \]
in which \( \alpha_{ij} \) denotes the search effectivity parameter of search channel \( j \) in 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 \( s^*_ij \) equals \( \max\{0, \bar{s}_j\} \). Thus, optimal search intensity satisfies the marginal cost equals marginal returns to search condition if the outcome is positive.

Condition (2.2) reveals some important properties of the optimal search intensity.\(^{12} \)

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, condition (2.2) implies that the optimal search intensity (and the decision to search) is inversely related to the reservation wage. Since for the unemployed there is a positive relation between the benefit level and the reservation wage, a higher benefit level reduces the intensity of search. 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.

\(^{11}\) 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.

\(^{12}\) These properties are the same as in Mortensen (1986), but for reasons of exposition we repeat them here.
For reasons of future reference, we denote the marginal returns to search by channel $j$ for labour market $l$ state by $R_{lj}$:

$$R_{lj} := \alpha_l \lambda_l \int_{x_l}^{\infty} [W(x) - W(x_l)]dF(x), l = e, u, x_u = \xi, x_e = w \quad (2.3)$$

3 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 choosing one of various possibilities: (i) in education; (ii) in the forces; (iii) full or part time employed; (iv) unemployed; (v) disabled; (vi) retired; (vii) other. Thus, we emphasize that employment state is self-reported, and that the selection of the unemployed 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 are added that have not yet been selected in the previous wave(s). Survey respondents report their labour market state according to the list above on a month by month basis, and this information is used to construct the duration of spells of employment and unemployment. In addition the backward recurrence times of employment and unemployment spells can be determined from the survey information. The sample thus obtained is a stock sample, which will be accounted for in the estimation of the model.

Information on search behaviour of the survey respondents is obtained by 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?"

Possible answers are: "Yes, I am searching seriously", "Yes, I am thinking

\textsuperscript{13} This is based on the question 'How long have you been unemployed?' and 'At which month/year did your present job start?"
about it”, and “No”.

If the respondent has answered positively to this first question, some additional questions have to be answered:

“Have you been looking for work in the past two months (yes/no)?”

“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?”

“Are you registered at the employment office?”

Note that the information on search is self-reported. Also note that the questionnaire imposes no restrictions on the routing between the search questions. For example, if respondents report to have been applying for a job, this does not necessarily mean that they reported to have been ‘looking’. 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) someone is eligible to unemployment benefits if (i) someone is unemployed or someone’s working week has been decreased by 5 hours or more, (ii) someone has been employed for at least 26 weeks of the 39 weeks previous to employment (no matter what is the length of the working week), (iii) someone is available for a ‘suitable’ job only. Someone 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 policy of government 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\(^\text{16}\) 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.

In practice, someone who wants to claim an unemployment or social welfare benefit

\(^{14}\) “Applying for a job” means writing a letter of application, making a phone call, etc.

\(^{15}\) A ‘suitable’ job usually means a job that matches the education level of the unemployed.

\(^{16}\) Wet Boeten en Maatregelen.
has to register at the employment office. As shown later on, none of the employed searchers reports to be registered at the employment office. Although registration at the employment office may have a positive impact on finding a job, it is directly related to the 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:

\[
\begin{align*}
\hat{s}_1 &= 1 \text{ if searching seriously} \\
&= 0 \text{ if not} \\
\hat{s}_2 &= 1 \text{ if looking for work in the past two months} \\
&= 0 \text{ if not} \\
\hat{s}_3 &= \text{number of applications in the past two months}^{17}
\end{align*}
\]

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 4 we provide a link between the observed indicators in (3.1) and the optimal search intensity introduced in section 2.

The information on labour market state and search can be used to distinguish four groups in the sample: Employed searchers, employed non-searchers, unemployed searchers, and unemployed non-searchers. Note that the group of unemployed non-searchers arises due to the above definition of labour market state and self-reported search: someone is registered in the sample as an unemployed non-searcher if he reports to be unemployed out of the seven possible labour market states listed above and if he answers ‘no’ to the question whether he is searching for a job.

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17Thus we obtain the number of applications per time unit. In measuring the number of applications per two months, it has to be accounted for the fact that individuals with a backward recurrence time of one month report applications per month, rather than per two months. 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.
Table 1 displays information about the numbers of observations and transitions in the sample. The percentage job-to-job transitions is higher among the employed searchers than among the employed nonsearchers. A similar observation is made for the unemployed.

The figures 1 and 2 present Kaplan-Meier estimates of the survivor functions of the raw data, without correction for any source of heterogeneity. Neglected heterogeneity will bias downward any estimate of duration dependence. The figures also show the survivor function of the duration data for searchers and nonsearchers separately.

The survivor function of unemployment duration in figure 1 decreases fastest in the first 10 months of unemployment. After 10 months, its slope decreases, indicating negative duration dependence, which may be partly attributed to neglected heterogeneity. Most transitions occur within three years. Since most of the unemployed are searchers, there is not much difference between the survivor functions of unemployment duration of the entire sample of unemployed and the survivor function of unemployed searchers. The survivor function of unemployment duration of nonsearchers is based on few observation and we see in figure 1 that its estimate is above that of searchers, suggesting lower transition rates for nonsearchers.

Figure 2 shows the Kaplan-Meier survivor function for employment duration. There is a large difference between the survivor function of searchers and nonsearchers. The scale of employment duration is different between the two groups. For nonsearchers we see a 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 the searchers, the information in table 2 relates to the subsample of searchers. From the 500 employed searchers, 47.8% reports to be “searching seriously”. The percentage of them who is “looking for work”, in the way defined before, is 74.6. Among the group of employed searchers 56.5% has actually been applying for a job in the past two months. A large part of them (25.6%) has been applying for a job only
once, whereas 13.4% applied twice. Among the subsample of 312 unemployed searchers, 81.8% reports to be “searching seriously”. This is obviously a higher percentage than we found for the employed searchers. The remaining search indicators also show that the unemployed search more intensely than the employed: 78.2% is “looking for work”, whereas 64.1% has been applying for a job in the past two months.

Table 3 provides sample statistics of duration, weekly income, and background characteristics of employed and unemployed searchers and nonsearchers. The mean of duration is based on both completed and right hand censored spells. The mean of duration of unemployed nonsearchers is 8 months higher than the mean of unemployed searchers. The mean weekly benefit income of unemployed nonsearchers is higher than for unemployed searchers.

There is a considerable difference between the mean wage of employed searchers and the mean wage of employed nonsearchers. The mean wage of searchers is lower than the mean wage of nonsearchers. This is in accordance with the theoretical model in the previous section, which predicts a negative relation between the current wage and the decision to search.

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), three sectoral dummies, sec1, sec2 and sec3, the regional dummies region1, region2 and region3, and a 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 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 in which there is a mixture of industry and agriculture, Region3 is the south of the Netherlands with some larger 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 with a sizeable agricultural sector. Note that the mean age for searchers is lower than for non-searchers in both labour market states.
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 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 4 we construct the likelihood contribution for these different type of observations on wages. Table 3 shows that for 84 of the unemployed individuals with a transition we observed the accepted wage.\(^{18}\) On average, accepted wages are higher than benefit levels. Table 4 shows information on the accepted wages of employed for which both the wage before a transition and the wage after a transition is observed. The quartiles 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 searchers after a transition look quite similar to the quartiles of the observed wages of nonsearchers before a transition. This may indicate that searchers, after having made a transition become similar to nonsearchers and hence will stop searching. This is not inconsistent with the apparent difference in transition rates between searchers and nonsearchers that follows from figure 2. 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 wage in the next section in order to account for such observations.

4 Empirical specification

The behaviour of the individual searcher is described by the reservation wage equation (2.1) and the optimal search condition (2.2). To implement the model empirically we provide a link between the optimal search intensity derived in section 2 and the available search indicators in the data. For this purpose we specify in section 4.1 a cost of search

\(^{18}\) In the SEP, numbers of observations on accepted wages are typically lower than the number of observations for which a transition is observed. This may 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.
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 4.2.

4.1 Specification

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

\[ c_l(s) = \sum_{j=1}^{3} c_{lj}(s_j), l = e, u \]

\[ c_{lj}(s_j) = \gamma_{0lj} C_{lj} \left[ \exp\left( \frac{s_j}{\gamma_{0lj}} \right) - 1 \right] \]  

(4.1)

in which \( \gamma_{0lj}, l = e, u \) are parameters. Note that (4.1) is concave if \( \gamma_{0lj} > 0 \) and \( C_{lj} > 0 \). We allow for observed heterogeneity \( q \) and unobserved heterogeneity \( \tilde{q} \) in (4.1) by specifying

\[ C_{lj} = \exp\left( -\frac{\gamma_{lj} q + \tau_{lj} \tilde{q}}{\gamma_{0lj}} \right) \]  

(4.2)

Solving the first order conditions (2.2) using (4.1) leads to the following equations:

\[ \tilde{s}_{lj} = \gamma_{lj} q + \gamma_{0lj} \ln R_{lj}(\tilde{q}) + \tau_{lj} \tilde{q}, l = e, u \]  

(4.3)

with \( R_{lj}(\tilde{q}) \) as defined in (2.3). We added the argument \( \tilde{q} \) to express the dependence of \( R_{lj} \) 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 effect of the reporting errors introduced later on.\textsuperscript{19} 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, but in the construction of the likelihood contributions we should keep in mind its inclusion.

Note that it is straightforward to make solution (4.3) for different search channels \( j \) compatible with a single dimensional latent search intensity: a linear combination of (4.3) over different channels of search leads again to a ‘search intensity’ that is linear in

\textsuperscript{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 \( \tilde{q} \).
\( q \) and in marginal returns to search. If, in addition, we specify
\[
\gamma_{ilj} = \theta_{ilj}\gamma_l, \theta_{il1} = 1, j = 2, 3, l = e, u
\]
with \( \theta_{ilj} \) a scalar, then \( \gamma_{ij}^*q \) 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 in a different extent according to the value of \( \gamma_{0ilj} \).

To compute \( s_{ij} \) in (4.3) we need to calculate the marginal returns to search \( R_{ij} \) which by (2.3) involves the computation of the expected income gain due to search, represented by the integral in (2.3). Since the model allows for search on the job (i.e. there is no stopping rule), there is no closed form solution for this integral. 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 job only once, so the second job only can be ended by layoff. 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 reservation wage equal to the current wage nowadays is a commonly applied in equilibrium search models (see 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 (i.e. the reservation wage for an employed searcher 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. 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 is unable to form expectations of jobs that come after the next job. The expected gains of search though will be overestimated if they are computed this way. The consequences for the computation of the reservation wage \( \xi \) by (2.1) for the unemployed
may be limited, because it is the difference between gains of search in different labour market states that determine 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 ξ. In the empirical implementation, we choose for the second option, which implies that we approximate the integrand in (2.3) by

\[(\rho + \sigma) [W(x) - W(x_l)] \approx x - x_l \]  (4.5)

The advantage of this approximation is that some characteristic 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 (2.1), on the difference in the gains and cost of search in the different labour market states.

Next, we provide a link between the observed search indicators \(\tilde{s}_j\) in (3.1) and the values \(\tilde{s}_j\) from (4.3) 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 (\# of applications). Let \(\epsilon_{lj}, l = e, u\) denote random errors, and let \(\tilde{s}_{lij}, l = e, u, j = 1, 2\) denote a dichotomous search indicator. We define the following relation:

\[
\tilde{s}_{lij} = 1 \quad \text{if} \quad \tilde{s}_{lij} := \tilde{s}_{lij} + \epsilon_{lj} > 0 \\
= 0 \quad \text{if} \quad \tilde{s}_{lij} := \tilde{s}_{lij} + \epsilon_{lj} \leq 0
\]  (4.6)

and

\[
\bar{s}_{lij} = \max\{0, \tilde{s}_{lij}\}, l = e, u, j = 1, 2
\]  (4.7)

In (4.6) \(\tilde{s}_{lij}\) represents the stochastic equivalent of the outcome of the marginal cost equals marginal returns condition: it deviates from the ‘true’ solution by the error term \(\epsilon_{lj}\), which may represent reporting error. Equivalently, in (4.7) \(\bar{s}_{lij}\) represents the latent optimal search intensity including a stochastic error. Equation (4.6) implicitly defines
the probability that someone in labour market state \( l \) reports the use of search channel \( j \) (i.e. \( \hat{s}_{lj} = 1 \)).

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 (i.e. 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 e.g. Winkelmann (2000)). The mean of this Poisson distribution should be the optimal number of applications, generated by the model. Accordingly, for searchers we specify

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

(4.8)

The mean number of application is given by \( m_l, l = e, u \), and it actually represents the optimal number of applications. As we will see, \( m_l \) is specified as a random variable itself, which explains the conditioning on \( m_l > 0 \) in the notation. How can we provide a link between the optimal number of applications \( m_l \) and model as we have presented is this far? We define optimal search intensity for search by applications \( m_l \) by

\[
\begin{align*}
\bar{s}_{l3} &= \ln(1 + m_l) \text{ with} \\
\hat{s}_{l3} &= \bar{s}_{l3} + \epsilon_{l3} \text{ and } \bar{s}_{l3}^* = \max\{0, \hat{s}_{l3}\}, l = e, u
\end{align*}
\]

(4.9)

while \( \hat{s}_{l3} \) follows from (4.3).

A few notes apply. First, note that the logarithmic relation between the latent search indicator \( \bar{s}_{l3}^* \) in (4.9) and the number of applications \( \hat{s}_{l3} \) is simply a matter of definition; up till (4.9) we had not provided any formal link between data and the latent search indicator; (4.9) provides this link. The logarithmic transformation in (4.9) is nothing more than a monotonous reparametrization.

Second, note that (4.9) implies that the job offer arrival rate is logarithmic in the number of applications.

Third, note that the condition \( m_l > 0 \) is equivalent to \( \hat{s}_{l3} > 0 \) by (4.9). Thus, for
searchers, the distribution of the number of applications is defined by (4.8), (4.9) and the condition that $m_l > 0$.

For nonsearchers, we assume that the Poisson distribution (4.8) does not apply. For them the condition $\tilde{s}_{l3} \leq 0$ holds. Summarizing we write

$$
\begin{align*}
\text{Searchers:} & & \tilde{s}_{l3} \sim \text{Poisson}(m_l), \tilde{s}_{l3} = 0, 1, 2, \ldots \quad \text{and} \quad \tilde{s}_{l3} > 0 \\
\text{Nonsearchers:} & & \tilde{s}_{l3} = 0 \quad \text{by} \quad \tilde{s}_{l3} \leq 0
\end{align*}
\quad (4.10)
$$

Note that (4.10) provides a natural distinction between observing zero applications for someone who reports to be a searcher and the absence of applications of a nonsearcher.

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:

$$
\epsilon_l \sim N(0, \Sigma_l), l = e, u \quad (4.11)
$$

with

$$
\Sigma_l = \begin{pmatrix}
1 & \sigma_{l,12} & \sigma_{l,13} \\
\sigma_{l,12} & 1 & \sigma_{l,23} \\
\sigma_{l,13} & \sigma_{l,23} & \sigma^2_{l,3}
\end{pmatrix}, l = e, u \quad (4.12)
$$

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 $\tilde{s}_l = \tilde{s}_l + \epsilon_l$, (4.11) 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 $\sigma^2_m$.

Finally, the layoff rate $\sigma$ is made dependent on individual characteristics $m$ by specifying $\sigma = \exp(\zeta'm)$.

### 4.2 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 section can be formulated. Readers with a nontechnical background may skip this section and go to the results of estimation immediately.

To construct the likelihood contribution for an observation \((t_1, \hat{s}, w_1^o, w_2^o)\) existing of duration \(t_1\), 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 \(t_1\), conditional on the value of the (latent) search intensity \(\bar{s}^*_l, l = e, u\) (defined in (4.6) and (4.9)); (ii) the density function of the latent search intensity \(\bar{s}^*_l, l = e, u\); (iii) the distribution of wages; (iv) the Poisson distribution for the observed number of applications (defined in (4.10)). 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 \(\theta_{ue}(\bar{s}^*_e)\) and job to job transitions by \(\theta_{ee}(\bar{s}^*_e)\) we have:

\[
\theta_{ue}(\bar{s}^*_e) = (\alpha_{t0} + \alpha_{t1} \bar{s}^*_l) \lambda_l \tilde{F}(x_l), l = e, u, x_u = \xi, x_e = w_1
\]

(4.13)

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 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 model structure 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 model structure in (4.13)).

The density functions of unemployment duration and job duration, conditional on search intensity, wages and unobserved heterogeneity,\textsuperscript{21} are

\begin{align*}
    f_u(t_u | \bar{s}^*_u) &= \theta_{ue}(\bar{s}^*_u) \exp\{-\theta_{ue}(\bar{s}^*_u)t_u\}, 0 < t_u < \infty \\
    f_e(t_e | \bar{s}^*_e) &= \theta_{ee}(\bar{s}^*_e) \exp\{-\theta_{ee}(\bar{s}^*_e) + \sigma\}t_e, 0 < t_e < \infty \\
    f_e(t_e | \bar{s}^*_e) &= \sigma \exp\{-\theta_{ee}(\bar{s}^*_e) + \sigma\}t_e, 0 < t_e < \infty
\end{align*}

job to job transitions

\begin{equation}
(4.14)
\end{equation}

employment to unemployment transitions

(ii) By (4.6) and (4.9) the latent search intensity \(\bar{s}^*_l, l = e, u\) is a function of \(\bar{s}_l\) for which we denoted the density function (conditional on unobserved heterogeneity and wages) by \(g(\bar{s}_l, \Sigma_l)\) in the previous subsection. The relation between \(\bar{s}_l\) and \(\bar{s}^*_l\) 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 \(\xi\): \(f(w_2)/F(\xi)\) 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 \(f(w_1)/F(\xi), w_1 > \xi\), zero elsewhere.\textsuperscript{22} At this point it is important to realize that for the employed the latent search intensity \(\bar{s}^*_e\) also depends on the current wage \(w_1\). If someone employed transits

\textsuperscript{21} Note that the conditioning on wages and unobserved heterogeneity runs through \(\bar{s}^*_l\). To keep notation simple, we do not express wages and unobserved heterogeneity explicitly in the notation.

\textsuperscript{22} 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 \(\bar{g}\), which we suppress in the notation.
into a new job, the model implies that the new wage $w_2$ must be higher than the old wage $w_1$. 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 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

$$\ln w_j^o = \ln w_j + \tilde{m}_j, \tilde{m}_j \sim N(0, \sigma_{m_j}^2), j = 1, 2$$

(4.15) 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 for searchers has already been discussed in (4.8) and (4.10). We will denote this distribution by $P(\hat{s}_{t|3}|m_l)$ below.

Completing the likelihood contributions now involves the multiplication of the various parts and the integration over the latent variables.

For an unemployed searcher with a completed duration $t_u$, a vector of search indicators $\hat{s}_u$ and an observed wage $w_2^o$ we have the following likelihood contribution:

$$\int_{A(\hat{s}_u)} f_u(t_u|\hat{s}_u^*, \Sigma_u)P(\hat{s}_{u|3}|m_u) \int_{\xi} g^o(w_2^o|w_2) \frac{f(w_2)}{F(\xi)} dw_2 d\tilde{s}_l, l = e, u$$

(4.16) In (4.16), the region of integration $A(\hat{s}_u)$ is defined by the observed search indicators through (4.6) and (4.10). Moreover, (4.6) and (4.9) define the dependence of $\tilde{s}_u^*$ and $m_u$ on the variable of integration $\hat{s}_u$.

The likelihood contributions for nonsearchers, right hand censored unemployment durations and for completed unemployment durations without an observation on the wage are straightforward simplifications from (4.16).

For an employed searcher, with completed job duration $t_e$, who is observed to have

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23 We could have explicitly denoted this in the notation by writing $m_u = m_u(\hat{s}_u)$ and $\tilde{s}_u^* = \tilde{s}_u^*(\hat{s}_u)$. 
an initial wage $w_1^0$, a new wage $w_2^0$ and search indicators $\tilde{s}_e$ the likelihood contribution is
\[
\int_{\xi} \int_{A(\tilde{s}_e)} f_e(t_e|\tilde{s}_e^*) g(\tilde{s}_e; \Sigma_e) P(\tilde{s}_e|\Sigma_e) \frac{1}{\int_{w_1} g^0(w_1^0|w_1^0) g^0(w_2^0|w_2) f(w_1) f(w_2)} d\tilde{s}_e d\tilde{s}_t d\tilde{w}_1
\]
(4.17)

Again, (4.6) and (4.9) define the dependence of $\tilde{s}_e^*$ and $m_e$ on the variable of integration $\tilde{s}_e$.

Moreover, the optimal search intensity depends on the initial wage $w_1$, by (2.3) and (4.3). For this reason, integration over the latent wage $w_1$ is done in the outer integral. Finally, note that in (4.16) and (4.17) we implicitly condition on unobserved heterogeneity $\tilde{q}$, defined in (4.2). 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 (4.16) and (4.17) by $\tilde{s}_t, \tilde{s}_t^*$ and $\xi$.

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 $\tilde{s}_t$.\footnote{In (4.16) and (4.17) the integration over accepted accepted wages $w_2$ can be handled without simulation.}

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

5 Estimation results

In this section we present the estimation results. From the tables it follows which variables we included in the various parts of the model.
5.1 Parameter estimates

The estimation results of the structural model are reported in the tables 5.1 through 5.4. The rate of time preference \( \rho \) has been fixed, such that on a yearly basis the discount rate is 5\%. 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 (4.16) and (4.17). In the tables a double (single) asterisk indicates significance at the 5\% (10\%) level.

Table 5.1 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 unemployed who are older than 25. Recall from table 3 that the mean age of unemployed nonsearchers is higher than the mean age of unemployed searchers. 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 incentive 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 Western, 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 economic and administrative sector have the highest lay-off rate, whereas individuals with the lower levels of education tend to have the higher layoff rates.

The lower part of table 5.1 contains the coefficient estimates of the various search indicators in the job offer arrival rate. For both the unemployed and the employed the 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 e.g. 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 5.2 shows the parameters of the cost of search function. Recall that a pa-
parameter $\gamma_{ij}$ has a negative impact on the marginal cost of search and consequently a
positive impact on the optimal search intensity. We find that unemployed with a larger
family search harder, which is plausible. The parameter estimate of $\gamma_{0u,j}, j = 1, ..., 3$ is
significant for all of the three search indicators. This parameter measures the impact of
returns to search on the optimal search intensity. Apparantly the returns to search are
important in determining 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 5.3 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 5.4 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 train-
ing obtain higher wage offers, ceteris paribus. Note that the standard 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 ob-
served hours is due to variation in wage offers while the other half is due to measurement
error.

5.2 Elasticities

Up till now we have only looked at the separate coefficient estimates. In order to gain
more insight in the implications of the model we computed several elasticities. Analytic
expressions for the elasticities are presented in appendix B. The elasticities have been
evaluated in the mean values of the observed characteristics of the unemployed and the employed (see table 3). The computed values of various elasticities are shown in table 6.

For the unemployed we computed the impact of the benefit level on the reservation wage. This quantifies the impact on of the benefit level on the decision to accept or 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 is the easiest to interpret. The computation of the elasticity is based on (B.4) in appendix D. We evaluate the elasticity in 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 (i.e. \( P(\hat{s}_{u3} > 0) \)) 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 intensity of search, 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

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25 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.

26 Standard errors have been computed to account for variation in the elasticities that is due to variation around the estimated parameter values.
probability will always go together. The value of the elasticity, however, provides insight in the effectiveness of search. We find that a 10% increase in the number of applications leads to an increase of 3.4% 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, so the impact of the benefit level on the hazard is not neglectable.

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 \( \lambda_u \). The elasticity takes the value 0.12 in the mean characteristics of the unemployed. This shows that the more effective way to stimulate nonsearchers to search is to improve their labour marker opportunities,\footnote{This may e.g. be achieved by schooling: table 5.1 showed that individuals with only general (nonspecialized) type of education have a significantly lower arrival rate, given everything else.} rather than to decrease the benefit level.

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 employed searchers and employed nonsearchers, both before and after a job-to-job transition. For searchers, the distribution of wage income after a transition looks quite similar to the wage distribution of nonsearchers before a transition. Thus, a transition of employed searchers is enough to make them similar to nonsearchers 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 nonsearchers 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,
applications of the employed have a smaller impact on a transition than applications of the unemployed.

5.3 Residual analysis

In the structural modeling of duration data, usually a lot of structure is imposed on the data, both by the imposition of economic theory and by the choice of functional forms. The strength of a structural model is that it enables us to distangle things like cost of search, returns to search, arrival rates, 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.\textsuperscript{28} 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\textsuperscript{29} 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 in the direction and the degree of the possible duration dependence. This may give us further insight in 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 C 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 figure 3a shows the Kaplan-Meier estimate of the distribution function of the residuals for the unemployed individuals. The straight line shows

\textsuperscript{28} A notable exception is Bloemen (1997).

\textsuperscript{29} Introducing nonstationarity in the model is technically complicated and numerically burdensome, see e.g. 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.
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.

Figure 3b 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 employed nonsearchers can be quite 
long: a stationary exponential distribution, like we use in the modeling, apparently 
cannot be consistent with this 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 re-
currence times, given survival up to a period which is as long as the backward recurrence 
time. Under the null hypothesis that model is specified correctly, the residuals based on 
forward recurrence times and on backward recurrence times each follow an exponential 
distribution with parameter 1.

The figures 4a and 4b show the Kaplan-Meier estimates based on the forward recur-
rence times for the unemployed and the employed respectively. The distribution of the 
residuals based on forward 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 still is evident.

Figures 5a and 5b show the Kaplan-Meier estimates of the distribution of the residuals 
based on backward recurrence times for the unemployed and employed, respectively. The 
plots are very similar to figures 3a and 3b. This suggests that the model reasonably 
manages to fit transitions (i.e. 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, figures 6a and 6b show the Kaplan-Meier estimates of the residuals of the employed (based on total duration) for employed searchers and employed nonsearchers separately. For the searchers (figure 6a), we do better than for the entire sample (figure 3b): the distribution function of the residual is closer to the exponential distribution. For the nonsearchers (figure 6b), the estimate of the distribution function is comparable to the estimate shown in figure 3b. Given that the employed nonsearchers form the vast majority of the sample of employed, the difference between figures 6 and 3 show that introducing the distinction between searchers and nonsearchers among the employed 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.

6 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 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 relative 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 difference 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 searchers and unemployed nonsearchers: the mean age of unemployed non-searchers in considerably higher than the mean age of unemployed searchers. 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 decrease 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.

For the employed who are married the cost of search is higher. 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 in both 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 the respect to the benefit level are -0.0012 and -0.00010 respectively. The estimates are significantly different from zero at the 5% level, but they also show that the impact of benefits on search is small. The elasticity the number of applications with respect to the exogenous part of the arrival rate (i.e. job opportunities, or effectiveness of search) is much higher, namely 0.12.

Combining these results with the estimated decrease of the arrival rate of the unemployed with age and the much higher mean age for the subsample of unemployed nonsearchers, compared to the subsample of unemployed searchers, suggests that the nonsearchers seem to be nonsearching due to a ‘discouraged worker effect’.

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 show by its standard error.

We also studied the generalized residuals of the model in order to gain insight in the fit of the model, and in particular, to see whether it reveals something about neglected duration dependence.
For the unemployed the residual analysis shows that there is probably neglected duration dependence. A plot of residuals based on forward recurrence times looks reasonably well, 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. A positive point that follows from the residual analysis is that the inclusion of search intensity in the model specification leads to an improvement in the model specification: not distinguishing searchers from nonsearchers would have led to an even worse fit. However, the inclusion of search intensity alone is not enough to explain the high survivor rates of the nonsearchers.
A 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 3.2 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

\[
f(t|s,w)f(s|w)g(w), 0 < t < \infty, 0 < s < \infty, 0 < w < \infty \quad (A.1)
\]

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. 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:\(^{30}\)

\[
h(p,t,s,w) = \frac{i(-p,l)f(t|s,w)f(s|w)g(w)}{\int_0^\infty \int_0^\infty \int_0^\infty \frac{i(-p,l)f(t|s,w)f(s|w)g(w)}{i(-p,l)F(p|s,w)f(s|w)g(w)d\bar{w}d\bar{s}d\bar{p}}} \quad (A.2)
\]

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

\[
h(t,s,w|p) = \frac{h(p,t,s,w)}{h(p)} \quad (A.3)
\]

in which

\[
h(p) = \int_0^\infty \int_0^\infty \int_0^\infty h(p,\bar{t},\bar{s},\bar{w})d\bar{t}d\bar{s}d\bar{w} \quad (A.4)
\]

\(^{30}\)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, i.e. the density conditional on backward recurrence times, unaffected.
Combining (A.3) and (A.4) with (A.2) yields the required density:

\[ h(t, s, w|p) = \int_0^\infty \int_0^\infty \frac{f(t|s,w)f(s|w)g(w)}{\int_0^\infty \int_0^\infty F(p|\hat{s},\hat{w})f(\hat{s}|\hat{w})g(\hat{w})d\hat{s}d\hat{w}} \, \text{dsdwdw} \]

\[ 0 < s < \infty \]

\[ p < t < \infty \]

\[ 0 < w < \infty \]

(B.5)

B Elasticities

In this section we presented the expressions for the elasticities that serve as a basis for the computation of the elasticities presented in section 5.

For the evaluation of the elasticities, first give the value function for someone employed:

\[ (\rho + \sigma)W(w) = u(w + \mu) - c_e(s) + \lambda_e(\alpha_{e0} + \alpha_{es}) \int_w^\infty [W(x) - W(w)]dF(x) + \sigma V \]  

(B.1)

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

\[ \frac{b \, d\xi}{\xi \, db} = \frac{\rho + \sigma + \theta_{ee}(\xi) \, b}{\rho + \sigma + \theta_{ue} \, \xi} \]

(B.2)

in which \( \theta_{ee}(\xi) \) represents the transition intensity of a job-to-job transition, evaluated in the reservation wage \( \xi \): \( \theta_{ee}(\xi) = (\alpha_{e0} + \alpha_{es}(\xi))\lambda_e \bar{F}(\xi) \). In the derivation of (B.2), use has been made of the derivative of the value function for someone employed in (B.1) with respect to the wage, \( W'(w) \):

\[ W'(w) = \frac{1}{\rho + \sigma + \theta_{ee}(w)} \]

(B.3)

Note that the sign of the elasticity in (B.2) 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 (2.2). In determining the derivative, use has been made of the derivative of \( \xi \) with respect to \( b \) (see (B.2)) and the
derivative of the value function $W'(w)$ in (B.3). This leads to the following expression for the elasticity:

$$\frac{b}{s_{u_j}} \frac{ds_{u_j}}{db} = -\frac{\alpha_{u_j} \lambda_u F(\xi)}{c_{u_j}(s_{u_j})} \frac{\rho + \sigma}{\rho + \sigma + \theta_{ue} s_{u_j}} b$$

(B.4)

Note that by the convexity of the cost of search function (assumption 2 in section 2) the sign of the second order derivative of the cost of search function is positive, so the sign of the elasticity (B.4) 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 (2.2), the derivative of the value function (B.3), the specification of the cost of search function (4.1), and the derivative of the reservation wage $\xi$ with respect to $\lambda_u$ that was obtained by differentiating (2.1). This results in the following expression for the elasticity:

$$\frac{\lambda_u}{s_{u_j}} \frac{ds_{u_j}}{d\lambda_u} = \gamma_{0u,j} \frac{\rho + \sigma}{\rho + \sigma + \theta_{ue} s_{u_j}} \frac{1}{s_{u_j}}$$

(B.5)

The sign of the elasticity in (B.5) 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 (2.2): 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 is tended to wait for a better offer). By (2.2), a higher reservation wage goes together with a lower level of search intensity. From (B.5) it follows that the positive effect dominates.\(^{31}\)

For employed individuals, we determined the effect of the current wage on the intensity to search. Use has been made of (B.3). This results in the following elasticity:

$$\frac{w}{s_{e_j}} \frac{ds_{e_j}}{dw} = -\frac{\alpha_{e_j} \lambda_e F(w)}{c_{e_j}(s_{e_j}(w)) (\rho + \sigma + \theta_{ee}(w))} \frac{w}{s_{e_j}}$$

(B.6)

\(^{31}\) In the expression for (B.5) we made use of the specification of the cost function in (4.1). It should be noted, however, that the specific functional form chosen in (4.1) is not the result of the positive sign of (B.5). Any other specification of cost of search that satisfies the regularity conditions (see assumption 2) will lead to a positive sign.
The sign of the elasticity (B.6) 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 $j$:

$$\frac{s_{uj} \theta_{ue}}{\theta_{ue} ds_{uj}} = \left[ \alpha_{uj} \lambda_u \bar{F}(\xi) + \frac{(\alpha_{u0} + \alpha_{u} s_{uj}) f(\xi) c_{uj}(s_{uj})(\rho + \sigma + \theta_{ue}(\xi))}{\alpha_{uj} \bar{F}(\xi)} \right] \frac{s_{uj}}{\theta_{ue}} \quad (B.7)$$

In the derivation of (B.7) use has been made of (B.3) and, for the determination of the relation between the reservation wage and the level of search intensity, of (2.2).

For job-to-job transitions, the elasticity is

$$\frac{s_{ej} \theta_{ee}}{\theta_{ee} ds_{ej}} = \left[ \alpha_{ej} \lambda_e \bar{F}(w) + \frac{(\alpha_{e0} + \alpha_{e} s_{ej}) f(w) c_{ej}(s_{ej})(\rho + \sigma + \theta_{ee}(w))}{\alpha_{ej} \bar{F}(w)} \right] \frac{s_{ej}}{\theta_{ee}} \quad (B.8)$$

## C. Generalized residuals

It is a well-known result in duration analysis (see e.g. Cox ann 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 non-parametric 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.

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 (4.16) for unemployed and (4.17) for 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 5) on the basis of this hazard.
References


Table 1: Observed transitions

<table>
<thead>
<tr>
<th></th>
<th>Employed 3266 observations</th>
<th>Unemployed 352 observations</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Searchers</td>
<td>Non-searchers</td>
</tr>
<tr>
<td># observations</td>
<td>500 (15%)</td>
<td>2766 (85%)</td>
</tr>
<tr>
<td>Transitions (transitions rate in %)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>into employment(^{32})</td>
<td>107 (21%)</td>
<td>142 (5%)</td>
</tr>
<tr>
<td>into unemployment</td>
<td>20 (4%)</td>
<td>165 (6%)</td>
</tr>
</tbody>
</table>

Table 2 Sample statistics search indicators

<table>
<thead>
<tr>
<th>indicator</th>
<th>Employed sample frequency</th>
<th>Unemployed sample frequency</th>
</tr>
</thead>
<tbody>
<tr>
<td>Searching seriously</td>
<td>47.8%</td>
<td>81.8%</td>
</tr>
<tr>
<td>Looking for work</td>
<td>74.6%</td>
<td>78.2%</td>
</tr>
<tr>
<td># applications past 2 months &gt; 0</td>
<td>56.5%</td>
<td>64.1%</td>
</tr>
<tr>
<td># applications past 2 months = 1</td>
<td>25.6%</td>
<td>16.3%</td>
</tr>
<tr>
<td># applications past 2 months = 2</td>
<td>13.4%</td>
<td>11.5%</td>
</tr>
<tr>
<td># applications past 2 months = 3</td>
<td>6.4%</td>
<td>9.3%</td>
</tr>
<tr>
<td># applications past 2 months = 4</td>
<td>3.8%</td>
<td>7.1%</td>
</tr>
<tr>
<td># applications past 2 months &gt;= 5</td>
<td>7.5%</td>
<td>19.9%</td>
</tr>
</tbody>
</table>

\(^{32}\) = Job to job transitions for employed. The percentages in the table indicate the number of transitions as a percentage of the number of observations in the specific subgroup.
<table>
<thead>
<tr>
<th>Table 3 Sample statistics income and background variables</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Employed (n=3266)</strong></td>
</tr>
<tr>
<td>variable</td>
</tr>
<tr>
<td>age</td>
</tr>
<tr>
<td>family size (persons)</td>
</tr>
<tr>
<td>wage before transition (guilders/week)</td>
</tr>
<tr>
<td>duration (months)</td>
</tr>
<tr>
<td>education level</td>
</tr>
<tr>
<td>Dutch nationality</td>
</tr>
<tr>
<td>region 1 (industrialized west)</td>
</tr>
<tr>
<td>region 2 (east)</td>
</tr>
<tr>
<td>region 3 (south)</td>
</tr>
<tr>
<td>region 4 (agricultural)</td>
</tr>
<tr>
<td>married</td>
</tr>
<tr>
<td>sector of education 1 (technical)</td>
</tr>
<tr>
<td>sector of education 2 (economic/administrative)</td>
</tr>
<tr>
<td>sector of education 3 (no specialization)</td>
</tr>
<tr>
<td>sector of education 4 (services)</td>
</tr>
<tr>
<td><strong>Unemployed (n=352)</strong></td>
</tr>
<tr>
<td>variable</td>
</tr>
<tr>
<td>age</td>
</tr>
<tr>
<td>family size (persons)</td>
</tr>
<tr>
<td>benefit income (guilders/week)</td>
</tr>
<tr>
<td>positive benefit income (guilders/week)</td>
</tr>
<tr>
<td>wage after transition into employment</td>
</tr>
<tr>
<td>duration (months)</td>
</tr>
<tr>
<td>education level</td>
</tr>
<tr>
<td>Dutch nationality</td>
</tr>
<tr>
<td>region 1 (industrialized west)</td>
</tr>
<tr>
<td>region 2 (east)</td>
</tr>
<tr>
<td>region 3 (south)</td>
</tr>
<tr>
<td>region 4 (agricultural)</td>
</tr>
<tr>
<td>married</td>
</tr>
<tr>
<td>sector of education 1 (technical)</td>
</tr>
<tr>
<td>sector of education 2 (economic/administrative)</td>
</tr>
<tr>
<td>sector of education 3 (no specialization)</td>
</tr>
<tr>
<td>sector of education 4 (services)</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Table 4 Wages before and after a job to job transition</th>
</tr>
</thead>
<tbody>
<tr>
<td><strong>Employed nonsearchers</strong></td>
</tr>
<tr>
<td>(both wages observed, n=100)</td>
</tr>
<tr>
<td>mean</td>
</tr>
<tr>
<td>25% quantile</td>
</tr>
<tr>
<td>median</td>
</tr>
<tr>
<td>75% quantile</td>
</tr>
<tr>
<td><strong>Employed searchers</strong></td>
</tr>
<tr>
<td>(both wages observed, n=95)</td>
</tr>
<tr>
<td>mean</td>
</tr>
<tr>
<td>25% quantile</td>
</tr>
<tr>
<td>median</td>
</tr>
<tr>
<td>75% quantile</td>
</tr>
</tbody>
</table>
Table 5.1 Estimates of the structural model
Arrival rates and the lay-off rate

<table>
<thead>
<tr>
<th>Variable</th>
<th>Arrival rate $\lambda_u$ of the unemployed</th>
<th>Arrival rate $\lambda_e$ of the employed</th>
<th>Layoff-rate</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>estimate</td>
<td>std. error</td>
<td>estimate</td>
</tr>
<tr>
<td>const</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>log(age/17)</td>
<td>6.7**</td>
<td>1.3</td>
<td>0.32</td>
</tr>
<tr>
<td>square of log(age/17)</td>
<td>-8.5**</td>
<td>1.0</td>
<td>-2.2**</td>
</tr>
<tr>
<td>sec1 (technical)</td>
<td>0.04</td>
<td>0.80</td>
<td>0.80</td>
</tr>
<tr>
<td>sec2 (econ/adm)</td>
<td>-0.55</td>
<td>0.62</td>
<td>0.15</td>
</tr>
<tr>
<td>sec3 (not specialized)</td>
<td>-2.30**</td>
<td>0.6</td>
<td>-1.4**</td>
</tr>
<tr>
<td>region1 (west)</td>
<td>0.40**</td>
<td>0.19</td>
<td>0.95**</td>
</tr>
<tr>
<td>region2 (east)</td>
<td>-0.23</td>
<td>0.18</td>
<td>0.17</td>
</tr>
<tr>
<td>region3 (south)</td>
<td>0.11</td>
<td>0.20</td>
<td>0.41**</td>
</tr>
<tr>
<td>educ1 (lowest)</td>
<td>0.68</td>
<td>0.52</td>
<td>0.17</td>
</tr>
<tr>
<td>educ2</td>
<td>0.49</td>
<td>0.56</td>
<td>0.34</td>
</tr>
<tr>
<td>educ3</td>
<td>0.48</td>
<td>0.59</td>
<td>0.06</td>
</tr>
<tr>
<td>marital status</td>
<td>0.22</td>
<td>0.18</td>
<td>0.99**</td>
</tr>
<tr>
<td>nationality</td>
<td>-1.7**</td>
<td>0.3</td>
<td>1.1**</td>
</tr>
</tbody>
</table>

EFFECTIVENESS OF SEARCH

<table>
<thead>
<tr>
<th>Variable</th>
<th>Unemployed ($\alpha_u$)</th>
<th>Employed ($\alpha_e$)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>estimate</td>
<td>std. error</td>
</tr>
<tr>
<td>intercept $\alpha_{1u}$</td>
<td>14.7**</td>
<td>4.7</td>
</tr>
<tr>
<td>attitude</td>
<td>2.2**</td>
<td>1.1</td>
</tr>
<tr>
<td>screening</td>
<td>1.8</td>
<td>1.2</td>
</tr>
<tr>
<td>applications</td>
<td>29.6**</td>
<td>7.9</td>
</tr>
</tbody>
</table>

Table 5.2 Estimates of the parameters of the cost of search function

<table>
<thead>
<tr>
<th>SEARCH INDICATOR $\gamma/q$</th>
<th>Unemployed</th>
<th>Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>estimate</td>
<td>std. error</td>
</tr>
<tr>
<td>$\gamma_{1}$ (constant)</td>
<td>-1.5**</td>
<td>0.7</td>
</tr>
<tr>
<td>$\gamma_{2}$ (log(family size))</td>
<td>0.13*</td>
<td>0.08</td>
</tr>
<tr>
<td>$\gamma_{3}$ (marital status)</td>
<td>-0.013</td>
<td>0.08</td>
</tr>
<tr>
<td>$\gamma_{4}$ (log(age/17))</td>
<td>-0.95*</td>
<td>0.53</td>
</tr>
<tr>
<td>$\gamma_{5}$ (square of log(age/17))</td>
<td>0.94**</td>
<td>0.48</td>
</tr>
</tbody>
</table>

EFFECT OF RETURNS OF SEARCH ON SEARCH INTENSITY

<table>
<thead>
<tr>
<th>$\psi_{1}$ (attitude)</th>
<th>$\psi_{2}$ (screening)</th>
<th>$\psi_{3}$ (applications)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_{10}$</td>
<td>0.90**</td>
<td>0.15</td>
</tr>
<tr>
<td>$\gamma_{12}$</td>
<td>0.86**</td>
<td>0.19</td>
</tr>
<tr>
<td>$\gamma_{13}$</td>
<td>0.98**</td>
<td>0.10</td>
</tr>
</tbody>
</table>

PARAMETER $\psi_{1}$

$\psi_{1}$ (screening) | 0.81 | 0.58 | 2.0** | 0.4 |
$\psi_{1}$ (applications) | 2.6** | 1.2 | 1.2** | 0.2 |

PARAMETER $\tau_{1}$ (UNOBSERVED HETEROGENEITY)

<table>
<thead>
<tr>
<th>$\tau_{1}$ (attitude)</th>
<th>$\tau_{2}$ (screening)</th>
<th>$\tau_{3}$ (applications)</th>
</tr>
</thead>
<tbody>
<tr>
<td>$\gamma_{11}$</td>
<td>0.63**</td>
<td>0.19</td>
</tr>
<tr>
<td>$\gamma_{12}$</td>
<td>0.89**</td>
<td>0.27</td>
</tr>
<tr>
<td>$\gamma_{13}$</td>
<td>0.79**</td>
<td>0.11</td>
</tr>
</tbody>
</table>
### Table 5.3 Estimates of the structural model
**Parameters of error distribution, $\Sigma_i, i = e, u$**

<table>
<thead>
<tr>
<th></th>
<th>Unemployed</th>
<th>Employed</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>estimate</td>
<td>standard error</td>
</tr>
<tr>
<td>$\sigma_{i,12}$ (cov. attitude-screening)</td>
<td>0.59**</td>
<td>0.09</td>
</tr>
<tr>
<td>$\sigma_{i,13}$ (cov. attitude-applications)</td>
<td>0.37**</td>
<td>0.07</td>
</tr>
<tr>
<td>$\sigma_{i,23}$ (cov. screening-applications)</td>
<td>0.38**</td>
<td>0.08</td>
</tr>
<tr>
<td>$\sigma_i$ (std dev. applications)</td>
<td>0.67**</td>
<td>0.06</td>
</tr>
</tbody>
</table>

### Table 5.4 Estimates of the structural model
**Parameters of wage offer distribution**

<table>
<thead>
<tr>
<th></th>
<th>estimate</th>
<th>standard error</th>
</tr>
</thead>
<tbody>
<tr>
<td>Constant</td>
<td>-11.1**</td>
<td>1.6</td>
</tr>
<tr>
<td>Log age</td>
<td>8.4**</td>
<td>1.0</td>
</tr>
<tr>
<td>Log age squared</td>
<td>-1.1**</td>
<td>0.1</td>
</tr>
<tr>
<td>educ1</td>
<td>-0.40**</td>
<td>0.08</td>
</tr>
<tr>
<td>educ2</td>
<td>-0.35**</td>
<td>0.07</td>
</tr>
<tr>
<td>educ3</td>
<td>-0.32**</td>
<td>0.08</td>
</tr>
<tr>
<td>educ4</td>
<td>-0.11**</td>
<td>0.03</td>
</tr>
<tr>
<td>sec1</td>
<td>-0.04</td>
<td>0.10</td>
</tr>
<tr>
<td>sec2</td>
<td>0.11</td>
<td>0.08</td>
</tr>
<tr>
<td>sec3</td>
<td>0.25**</td>
<td>0.08</td>
</tr>
<tr>
<td>$\tau$ (standard deviation)</td>
<td>0.39**</td>
<td>0.03</td>
</tr>
<tr>
<td>$\sigma_m$ (std dev meas. err.)</td>
<td>0.38**</td>
<td>0.002</td>
</tr>
</tbody>
</table>

### Table 6 Elasticities

<table>
<thead>
<tr>
<th>$\frac{\partial \ln y}{\partial \ln x}$</th>
<th>in mean characteristics</th>
<th>in mean characteristics</th>
<th>in mean characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td>$y$</td>
<td>x</td>
<td>nonsearchers</td>
<td>searchers</td>
</tr>
<tr>
<td>The unemployed</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Reservation wage</td>
<td>benefit level</td>
<td>0.072**</td>
<td>0.027**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.010)</td>
<td>(0.003)</td>
</tr>
<tr>
<td>Number of applications</td>
<td>benefit level</td>
<td>-0.0035**</td>
<td>-0.0022**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.0005)</td>
<td>(0.0003)</td>
</tr>
<tr>
<td>Probability of search</td>
<td>benefit level</td>
<td>-0.00014**</td>
<td>-0.00016**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.00004)</td>
<td>(0.00005)</td>
</tr>
<tr>
<td>Hazard (arrival rate)</td>
<td>number of applications</td>
<td>0.34**</td>
<td>0.36**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Hazard</td>
<td>benefit level</td>
<td>-0.41**</td>
<td>-0.21**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.04)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>Number of applications</td>
<td>arrival rate</td>
<td>0.16**</td>
<td>0.12**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.02)</td>
<td>(0.02)</td>
</tr>
<tr>
<td>The employed</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Number of applications</td>
<td>wage</td>
<td>-1.46</td>
<td>-0.12*</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(1.89)</td>
<td>(0.07)</td>
</tr>
<tr>
<td>Hazard (arrival rate)</td>
<td>number of applications</td>
<td>0.055**</td>
<td>0.011**</td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.016)</td>
<td>(0.002)</td>
</tr>
</tbody>
</table>
Figure 1: Kaplan-Meier vs duration

Figure 1: Kaplan-Meier of Unemployment Duration
Figure 2: Kaplan-Meier vs duration

Figure 2: Kaplan-Meier of Employment Duration
Figure 3: Distribution of Residuals
Figure 4a: Kaplan-Meier for the residuals of the unemployed

Figure 4b: Kaplan-Meier for the residuals of the employed

Figure 4: Distribution of forward residuals
Figure 5: Distribution of backward residuals
Figure 6: Distribution of residuals by search status