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# AN EMPIRICAL EQUILIBRIUM SEARCH MODEL OF THE LABOR MARKET

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In structural empirical models of labor market search, the distribution of wage offers is usually assumed to be exogenous. However, because in setting their wages profit-maximizing firms should consider the reservation wages of job seekers, the wage offer distribution is essentially endogenous. We investigate whether a proposed equilibrium search model, in which the wage offer distribution is endogenous, is able to describe observed labor market histories. We find that the distributions of job and unemployment spells are consistent with the data, and that the qualitative predictions of the model for the wages set by employers are confirmed by wage regressions. The model is estimated using panel data on unemployed and employed individuals. We distinguish between separate segments of the labor market, and we show that productivity heterogeneity is important to obtain an acceptable fit to the data. The results are used to estimate the degree of monopsony power of firms. Further, the effects of changes in the mandatory minimum wage are examined.

KEYWORDS: Search, equilibrium, labor market, wage dispersion.

## 1. INTRODUCTION

ECKSTEIN AND WOLPIN'S (1990) EMPIRICAL ANALYSIS of the Albrecht and Axell (1984) equilibrium search model is an important step forward in the structural analysis of labor market search. For the first time in an empirical study, labor market search is modelled as the outcome of optimal choices by both workers and employers. This improves on the structural partial models of job search in which the distribution of wage offers is exogenous. If workers take a labor supply decision given a wage offer, and firms set wages for vacancies, then current empirical models of job search are based on the assumptions that (i) in setting wages firms do not take the strategy of workers into account, and (ii) the resulting wage offers are dispersed.[2]

The optimal strategy of the workers usually has the reservation wage property. If employers know this and set wages, their wage offers must equal the reservation wage of some (group of) worker(s). In particular, if all job searchers

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[2]Structural empirical analyses of job search by the unemployed include Flinn and Heckman (1982), Wolpin (1987), and Van den Berg (1990a). Van den Berg (1992) estimates a structural model of job search by employed individuals. Devine and Kiefer (1991) and Wolpin (1995) survey the literature.

have a common reservation wage, then the equilibrium wage offer distribution is degenerate. A dispersed wage offer distribution therefore requires a dispersed distribution of reservation wages. Moreover, parameter changes that affect the reservation wages of job searchers also affect the wage offer distribution that they face.

The equality of wage offers and reservation wages affects both the key assumption that job seekers face a dispersed wage offer distribution, and the comparative-static analysis of parameter changes. An important question of the effect of unemployment benefits on job search by the unemployed cannot be answered satisfactorily, if, as assumed in partial job search models, employers cannot respond to changes in the behavior of job seekers. In an *equilibrium* search model the wage offer distribution is endogenous. It results from optimal wage setting by firms that take account of the responses by job seekers and other firms, and hence is affected by a change in unemployment income. The same applies to changes in the level of the minimum wage. An increase affects the wage offers of firms that made offers below the old level, and this in turn affects the wage offers of the other firms. Again an equilibrium specifies the effect of a change in the minimum wage on the whole wage offer distribution.

The fact that the wage offer distribution is determined by the model is convenient, since this distribution is essentially unobservable. If job seekers use a reservation wage strategy, then the distribution of accepted wages is the wage offer distribution truncated at the reservation wage. It is well known that one cannot recover the complete wage offer distribution from this truncated distribution of accepted wages (Flinn and Heckman (1982)).

The Albrecht-Axell model is not the only equilibrium search model that is amenable to estimation. Our empirical analysis of equilibrium search is based on a model proposed by Burdett and Mortensen (1998). There are some striking differences between these two models, and it should be stressed from the outset that the empirical models of Eckstein and Wolpin (1990) and the present paper are not nested. In the Albrecht-Axell model, only unemployed individuals search for jobs and job-to-job transitions or layoffs are not allowed, while in the Burdett-Mortensen model employed individuals search as well and job-to-job transitions and layoffs do occur. Because, as argued above, the wage offers of employers are equal to the reservation wages of searching workers, Albrecht and Axell (1984) and Eckstein and Wolpin (1990) require the unemployed to be heterogeneous in order to obtain a dispersed wage offer distribution. They assume that there are a finite number of worker types that differ in their value of nonmarket time, and that firms are heterogeneous with respect to their labor productivity. With these assumptions, the number of different reservation wages, and hence the number of points of support of the wage offer distribution, is finite. It is not surprising that most of the observed variation in wages is explained by the measurement error that they introduce to smooth the discrete wage offer distribution.

Of course, job-to-job transitions are common, and they are an important source of wage growth for employees (see, e.g., Topel and Ward (1992)). The possibility of on-the-job search changes the optimal search strategy of unemployed job seekers. Furthermore, since the reservation wage of an employed job seeker is equal to his current wage, allowing for on-the-job search extends the range of reservation wages, and hence of equilibrium wage offers. Indeed, Burdett and Mortensen (1998) show that if workers continuously search for a better-paying job (and face a risk of becoming unemployed during that quest), then the equilibrium wage offer distribution is dispersed, even if all workers and firms are identical. In the latter case they obtain explicit solutions for the equilibrium wage offer and earnings distributions.

The availability of an explicit solution is an advantage in the empirical analysis of the model. However, the actual solution has some unattractive features. In particular, the wage offer and earnings distribution[3] have increasing densities. This implication is at odds with all the evidence on the shape of the income distribution, which is closely related to the earnings distribution. It should however be stressed that the explicit solution refers to a homogeneous population of workers and firms. Allowing for observed and unobserved population heterogeneity makes the model more realistic and more able to give an acceptable fit to the data. The heterogeneity in our empirical version of the Burdett-Mortensen model is different from the heterogeneity in the Albrecht-Axell model. We consider a labor market that consists of a large number of segments. Every segment is a labor market of its own, and all workers and firms in a particular segment are identical. The segments differ according to the age, the educational level, and the occupational level of the workers and jobs. Besides these observed differences we allow for unobserved differences in the productivity of the jobs or other characteristics of the segment. Eckstein and Wolpin (1990), in their empirical analysis of the Albrecht-Axell model, consider a single labor market with unobserved differences in the value of leisure between workers and unobserved differences in productivity between firms (they do not have observed differences across workers or firms). So our treatment of population heterogeneity allows for between-market heterogeneity while Eckstein and Wolpin (1990) allow for within-market heterogeneity.

As we will show, the fit to the observed wage (offer) distribution improves if we allow for sufficient variation in the productivity of firms. Heterogeneity in productivity has an impact on the effect of changes in the minimum wage on the level of unemployment. In the homogeneous model, which has an equilibrium with monopsonistic features, the minimum wage does not affect the level of unemployment, except in the case that it exceeds the common productivity level. With heterogeneity in productivity, a small change in the minimum wage affects some of the many submarkets, and has an effect on the level of unemployment.

[3]The earnings distribution refers to the distribution of wages paid to a cross-section of individuals who are employed at a particular date. In the sequel we concentrate on full-time workers, and for these workers wages and earnings are equal. We use this somewhat confusing terminology to distinguish between wages offered and the wages that are paid to those who are currently employed.

Hence, our empirical model lets the data decide whether the comparative or the monopsonistic point of view is empirically more important.

We estimate the model by maximum likelihood, using panel data on unemployed and employed individuals. For most individuals in the data, multiple durations (like unemployment durations and job durations) are observed. In particular, for some respondents, we observe consecutive job durations and corresponding wages. The model implies that unemployment and job durations have mixed exponential distributions, and we test whether this holds in our data. Moreover, wage regressions confirm the qualitative predictions of the model for the distribution of wages. The estimation results imply that, on average, the arrival rate of job offers is only slightly larger when employed. We find that a small number of observed personal characteristics is sufficient to capture the heterogeneity in arrival and separation rates, but insufficient to capture heterogeneity in the productivity of firms. In the paper we propose and apply a formal decomposition of observed wage variation into the variation due to the different structural determinants as well as variation due to measurement errors. Contrary to Eckstein and Wolpin we find that a relatively small fraction of wage variation is explained by measurement error and that about a fifth is pure wage variation as generated by the presence of search frictions. We also use our results to estimate the degree of monopsony power of firms and the effects of changes in the legal minimum wage on the level of unemployment.

In another paper (Koning, Ridder, and Van den Berg (1995)) we calibrate a simplified version of the model in an attempt to distinguish between frictional and structural unemployment. For this distinction we had to assume arbitrarily that individuals who are unemployed during the whole observation period have never been and will never be employed. In the other paper we also assumed that the wage data are measured without error, which in turn forced us to omit all wage data below the legal minimum wage and to restrict attention to at most one job spell per respondent (see Sections 3 and 4 below; note that additional job spells provide valuable information for specification tests). In order to ensure that all observed wages exceeding the minimum wage could be explained by the simplified model version we had to adopt a continuous distribution of productivity with unbounded support. Another difference between the papers concerns the present focus on variation across educational, occupational, and age groups. Not surprisingly, it turns out to be essential to allow for such observed determinants of heterogeneity in the arrival rates of events, and by allowing for such observed determinants of heterogeneity in productivity we do not restrict the productivity distribution to be the same across segments with different observed characteristics.

The outline of the paper is as follows. Section 2 presents the model. We argue that it is consistent with a number of stylized facts. In Section 3 we discuss the data used to estimate the model. In Section 4 we derive the likelihood function. Section 5 contains the results. We also discuss some implications of the estimates and we examine the effects of changes in the mandatory minimum wage. Conclusions and some suggestions for further research are in Section 6.

## 2. THE EQUILIBRIUM SEARCH MODEL

### 2.1. *Theory*

In this section we present the equilibrium search model. First, we consider the model of a labor market with homogeneous workers and firms, as developed by Burdett and Mortensen (1998) (see also Mortensen (1990)). Later we shall indicate how we take account of heterogeneity of workers and firms.

We make the following assumptions:

ASSUMPTION A1: *There are continua of workers and firms with measures* $m$ *and* 1, *respectively.*

ASSUMPTION A2: *Workers receive job offers at rate* $\lambda_0$ *if unemployed and* $\lambda_1$ *if employed. A job offer is an i.i.d. drawing from a wage offer distribution with c.d.f.* $F(w)$. *An offer has to be accepted or rejected upon arrival. During tenure of a job, the wage is constant. The utility flow of being employed at a wage* $w$ *equals* $w$.

ASSUMPTION A3: *Job-worker matches break up at rate* $\delta$. *If this happens, the worker becomes unemployed. The utility flow of being unemployed is* $b$.

ASSUMPTION A4: *Firms have a linear production function and the marginal (= average) revenue product is* $p$. *A firm pays all its workers the same wage* $w$.

ASSUMPTION A5: *Workers maximize their expected wealth and firms maximize their expected steady-state profit flow.*

ASSUMPTION A6: *The firms cannot set their wage below the mandatory minimum wage* $\underline{w}_L$.

Under these assumptions the supply side of the model is equivalent to the standard job search model with search on the job (see, e.g., Mortensen (1986)). Thus, the optimal strategy of an unemployed individual has the reservation wage property. In the limiting case of zero discounting,[4] the reservation wage $r$ can be shown to be (see Mortensen and Neumann (1988))

$$(2.1)\qquad r = b + (\lambda_0 - \lambda_1)\int_r^\infty \frac{\overline{F}(w)}{\delta + \lambda_1 \overline{F}(w)}\,dw \qquad \text{with } \overline{F} = 1 - F.$$

Further, an employed individual accepts a wage offer if and only if it exceeds his current wage. So a worker is continuously searching for a better paying job, but

[4]A positive discount rate has to be added to $\delta$ in (2.1). The assumption of zero discounting is made to avoid complications in the profit maximization problem that must be solved by the firm (see below).

this effort may be frustrated by a spell of unemployment. The worker never quits a job to search for a better paying one while unemployed.

It is important to distinguish between the distribution of wages offered to job seekers, which is the *wage offer distribution* $F$, and the distribution of wages received by workers who are currently employed. The latter distribution is referred to as the *earnings distribution*, and we denote this distribution by $G$. Concentrate for the moment on the employed workers who receive a wage $w$ or less. There are $G(w)(m-u)$ such workers, where $u$ is the number of unemployed workers. The flow of workers to jobs with a wage that exceeds $w$ is equal to $\lambda_1 \bar{F}(w) G(w)(m-u)$ and the flow of workers into unemployment is $\delta G(w) \cdot (m-u)$. In a steady-state equilibrium this outflow must be balanced by an inflow from unemployment. This inflow equals $\lambda_0(F(w)-F(r))u$, where it is obvious that $F(r)=0$, because firms offering a wage below $r$ never attract any worker and therefore cannot survive. Hence, in a steady state we have the following relation between the earnings distribution and the wage offer distribution:

$$G(w) = \frac{F(w)}{\delta + \lambda_1 \bar{F}(w)} \cdot \frac{\lambda_0 u}{(m-u)}. \tag{2.2}$$

The steady-state unemployment rate $u/m$ follows by setting $w=\infty$ in (2.2), or, equivalently, by equating flows into and out of unemployment,

$$\frac{u}{m} = \frac{\delta}{\delta + \lambda_0}. \tag{2.3}$$

This can be used to simplify (2.2) to

$$G(w) = \frac{\delta \cdot F(w)}{\delta + \lambda_1 \bar{F}(w)}. \tag{2.4}$$

The flow of revenue $p$ generated by employing a worker must satisfy $b<p<\infty$, i.e., there must be a positive and finite gain from trade. A match between a worker and a firm has a net revenue flow of $p-b$. At the prevailing wage $w$, the firm receives the part $p-w$ of this flow, and the worker receives $w-b$. Recall that it is assumed that the wage paid by the firm is posted prior to the moment at which it contacts searching individuals, and that there is no bargaining over the wage.

We now focus on the behavior of the firms in more detail. The steady-state level of production is determined by the size of the steady-state workforce $l$ that is available to the firm. The latter number is determined by the wage $w$ set by the firm, by the reservation wage $r$ set by the unemployed individuals, and by the distribution $F$ of wages set by the other firms competing for the same workers (see Burdett and Mortensen (1998) for the general expression of $l(w; r, F)$). We assume that each firm sets a wage $w$ that maximizes its steady-state profit flow $\pi$, which equals $(p-w)l(w;r,F)$, given $r$ and $F$ and subject to the restriction that $w$ exceeds the mandatory minimum wage $\underline{w}_L$.[5] Hence, the firm does not react to random fluctuations in its workforce.[6] For firms to have a positive level of employment, we need $\underline{w}_L < p$.

A noncooperative steady-state equilibrium solution consists of a reservation wage $r$ and a wage offer distribution $F$ such that (i) $r$ satisfies (2.1) given $F$, and (ii) every $w$ in the support of $F$ maximizes the steady-state profit flow $(p-w)l(w;r,F)$. Burdett and Mortensen (1998) prove that there is a unique equilibrium, and they give a complete characterization of it.

First, the equilibrium $F$ is absolutely continuous, and therefore not degenerate. Suppose there were a mass of firms offering a wage $w$. Then, by offering a wage slightly higher than $w$, each of these firms could increase its labor force significantly, attracting workers that currently earn $w$, while suffering only a second order loss of profit per worker $p-w$. Hence, profits $\pi$ would increase. The assumption that search on the job is possible is crucial for this result. Secondly, it is not possible to have an equilibrium $F$ for which the lower bound $\underline{w}$ of the support exceeds both $r$ and $\underline{w}_L$, or an equilibrium $F$ with gaps in its support, because then firms offering $\underline{w}$ (firms at the upper boundary of a gap) can increase their profits by offering a wage equal to $\max(\underline{w}_L, r)$ (by offering a wage equal to the lower boundary of the gap).

We conclude that $F$ and $G$ have probability density functions $f$ and $g$ with support $[\underline{w}, \overline{w}]$, with

$$\underline{w} = \max(\underline{w}_L, r)$$

and $\overline{w}$ the upper bound of the support of $F$ and $G$ with $\overline{w} < p$. The measure of individuals earning a wage $w$ equals $g(w)(m-u)dw$, and the measure of firms offering a wage $w$ equals $f(w)dw$. Consequently, $l(w;r,F)$ equals

$$l(w;r,F) = \frac{g(w)dw}{f(w)dw}(m-u) = \frac{m\lambda_0\delta(\delta+\lambda_1)}{(\delta+\lambda_0)\left(\delta+\lambda_1\overline{F}(w)\right)^2} \quad \text{on } [\underline{w},\overline{w}]. \tag{2.5}$$

In the steady state a firm offering $\underline{w}$ has a positive workforce $l(w;r,F)$ equal to $m\lambda_0\delta/((\delta+\lambda_0)(\delta+\lambda_1))$. Of course, the employees, who were all previously unemployed, leave for the first job they locate at another firm. The steady-state profit rate of the firms paying $\underline{w}$ is $\pi = (p-\underline{w})l(\underline{w};r,F)$. In equilibrium all higher paying firms have the same profit rate. Substitution of (2.5) gives the equilibrium wage offer distribution

$$F(w) = \frac{\delta+\lambda_1}{\lambda_1}\cdot\left(1-\sqrt{\frac{p-w}{p-\underline{w}}}\right) \qquad \text{on} \quad [\underline{w},\overline{w}] \tag{2.6}$$

[5] In their model, Burdett and Mortensen (1998) do not allow for a minimum wage.

[6] The model becomes intractable if this is relaxed; see Wernerfelt (1988).

with corresponding density

$$f(w) = \frac{\delta+\lambda_1}{2\lambda_1\sqrt{p-\underline{w}}} \cdot \frac{1}{\sqrt{p-w}} \qquad \text{on} \quad [\underline{w}, \overline{w}]. \tag{2.7}$$

It follows from (2.6) and (2.1) that

$$\begin{aligned} r &= \frac{(\delta+\lambda_1)^2 \cdot b + (\lambda_0 - \lambda_1)\lambda_1 \cdot p + \delta_0(\lambda_0-\lambda_1)\cdot \underline{w}_L}{(\delta+\lambda_0)(\delta+\lambda_1)} \qquad \text{if} \quad r < \underline{w}_L, \\ r &= \frac{(\delta+\lambda_1)^2 \cdot b + (\lambda_0-\lambda_1)\lambda_1 \cdot p}{(\delta+\lambda_1)^2 + (\lambda_0-\lambda_1)\lambda_1} \qquad \text{if} \quad r \geq \underline{w}_L, \end{aligned} \tag{2.8}$$

$$\overline{w} = \left(\frac{\delta}{\delta+\lambda_1}\right)^2 \cdot \underline{w} + \left(1 - \left(\frac{\delta}{\delta+\lambda_1}\right)^2\right) \cdot p. \tag{2.9}$$

If $r \geq \underline{w}_L$ then $r$ and $\overline{w}$ are weighted averages of $b$ and $p$. Note that $r$ is smaller than $b$ if $\lambda_1$ is larger than $\lambda_0$. In that case, searching on a job with a wage equal to $b$ is more rewarding than searching while unemployed.

The function $l(w; r, F)$ increases in $w$, so there is a positive relation between the size of the firm and the wage it offers. A large (small) wage implies that the exit rate of workers at the firm is relatively small (large), and that a relatively large (small) fraction of all workers currently employed in the economy is willing to work at the firm. Hence, in terms of total profits of a firm, there is a trade-off between the profit per worker and the steady-state number of workers at the firm. In this respect, there is a strong similarity to "turnover costs" efficiency wage models (see, e.g., Stiglitz (1985) and Weiss (1991)). The maximum wage offer is strictly smaller than the productivity level $p$, which Burdett and Mortensen (1998) call the competitive equilibrium wage, i.e. the single equilibrium wage in the absence of search frictions. The search and wage-setting game has a monopsonistic equilibrium.

## 2.2. *Some Empirically Relevant Issues*

From (2.4), the equilibrium earnings density is

$$g(w) = \frac{\delta\sqrt{p-\underline{w}}}{2\lambda_1} \cdot \frac{1}{(p-w)^{3/2}} \qquad \text{on} \quad [\underline{w}, \overline{w}]. \tag{2.10}$$

Note that both $f$ and $g$ are increasing densities. The earnings distribution is related to the income distribution, and there is abundant empirical evidence that the income distribution does not have an increasing density. However, as noted above, the increasing densities are derived for a homogeneous labor market with identical workers and firms. To show that allowing for heterogeneous workers and/or firms indeed improves the fit to the observed wage offer and earnings distributions, we consider the following transformation of $w$:

$$y = \frac{p - w}{p - \underline{w}}, \tag{2.11}$$

so that the excess wage $w - \underline{w}$ satisfies

$$w - \underline{w} = (1 - y)(p - \underline{w}). \tag{2.12}$$

The density of $y$ is for the wage offer distribution

$$f_y(y) = \frac{1}{2(1-\eta)} y^{-1/2}, \qquad \eta^2 \leq y \leq 1, \tag{2.13}$$

and for the earnings distribution

$$g_y(y) = \frac{\eta}{2(1-\eta)} y^{-3/2}, \qquad \eta^2 \leq y \leq 1, \tag{2.14}$$

with $\eta = \delta/(\delta + \lambda_1)$. Equation (2.12) summarizes wage determination in the Burdett-Mortensen model. The excess wage $w - \underline{w}$ is a fraction of the excess productivity $p - \underline{w}$. This fraction is a random variable with a distribution that only depends on $\lambda_1/\delta$, the expected number of wage offers during a spell of employment (which is a spell that starts with the acceptance of a job from unemployment and ends with a layoff). This number is a measure of the speed at which the worker climbs the job (and wage) ladder, with $y = 1$ corresponding to the bottom of this ladder ($w = \underline{w}$), and $y = \eta^2$ to the top ($w = \overline{w}$). From (2.12) it follows that the moments of $w - \underline{w}$ in either the wage offer or the earnings distribution are the product of $(p - \underline{w})^n$ and an expression that only depends on $\eta$. By choosing an appropriate distribution of the productivity $p$, the moments of any observed wage offer or earnings distribution can be matched. Hence, we expect that an acceptable fit to the data will depend on allowance for sufficient heterogeneity in $p$. In subsection 4.2 we incorporate heterogeneity into the model.

From the expressions above it is straightforward to derive the distributions of the sojourn times in different states. The duration of unemployment has an exponential distribution with parameter $\lambda_0$. The duration of a job that pays a wage $w$ has an exponential distribution with parameter $\delta + \lambda_1 \overline{F}(w)$. Exit from this job into unemployment occurs with probability $\delta/(\delta + \lambda_1 \overline{F}(w))$ and exit into another job with probability $\lambda_1 \overline{F}(w)/(\delta + \lambda_1 \overline{F}(w))$. These distributions, as well as $G(w)$ and $F(w)$ itself, will be used in Section 4 to construct the likelihood function of the model. Note that if $r < \underline{w}_L$, then $r$ (and therefore $b$) enters none of the expressions of the distributions mentioned here.

Despite its apparent restrictiveness the model is consistent with results from previous empirical studies on unemployment durations and job durations in The Netherlands in the eighties. For example, the model implication that all jobs are acceptable to the unemployed is consistent with the finding from studies based on partial job search models that the acceptance probability of unemployed workers is close to 1 (see, e.g., Van den Berg (1990b); Devine and Kiefer (1991) survey the evidence for the US). The model also implies that a change of the benefit level does not affect unemployment. When $b$ increases, then, as in partial job search models, the unemployed individual's reservation wage increases. However, in the present model employers modify their wage offers in response to this, and the net result is that the exit rate out of unemployment does not change (as long as $b < p$). This is consistent with the findings of many structural and reduced-form empirical studies on unemployment duration based on data from The Netherlands (see a survey in Van den Berg (1990b)).

In empirical search models it is often found that the reservation wage is smaller than the benefits level (see, e.g., Narendranathan and Nickell (1985), Van den Berg (1990a), and Van den Berg (1990b)). This is usually attributed to the existence of a nonpecuniary disutility of being unemployed. The present model generates $r < b$ if the job offer arrival rate is larger in employment than in unemployment. Finally, studies based on the panel data used in this paper confirm that there is an inverse relation between the wage in a job and the exit rate from a job, holding other factors constant (see Lindeboom and Theeuwes (1991) and Van den Berg (1992)).[7]

The assumption that firms set wages deserves some discussion. There is an extensive literature on search and matching models in which firms and workers individualistically bargain over the wage, and, more generally, the rents of the match. The way in which these rents are split reflects the bargaining power of both parties (see Pissarides (1990) and Mortensen (1996) for overviews). If, in such a framework, workers are allowed to search on the job for other jobs with the same productivity, then a number of complications arise. An employed worker meeting another firm has a better fallback option than an unemployed worker meeting that firm. This would seem to imply that the subsequently bargained wage for the applicant who is already employed is higher than that for the unemployed applicant. However, the employed applicant can renegotiate with his current employer. To be short, such a bargaining framework would have to allow for complicated strategic behavior on both sides of the market, and it may be necessary to take account of the costs of bargaining. In addition, it is conceivable that the equilibrium is such that a given firm pays different wages to workers with identical productivity in identical jobs, just because these workers had different fallback options at the time they bargained over their wage. This would violate within-firm fairness constraints.[8] Manning (1993) argues that bargaining cost considerations make the wage setting assumption less restrictive

[7] Kiefer and Neumann (1993), Machin and Manning (1991), and Van den Berg and Ridder (1993) discuss the consistency of the model with some additional stylized facts, such as the relation between wage and firm size, the effects of a change in the minimum wage, and the fact that typical wage regressions can explain only a moderate part of total wage variation, even if many regressors are included.

[8] If it is imposed that all workers at a firm earn the maximum bargained wage among its workers, then obviously additional strategic interactions can be expected, and, in addition, wages will vary within individual job spells.

for anonymous markets with low-skilled workers than for markets with high-skilled workers.

It is important to stress, however, that the equilibrium wage solution in our model reflects the bargaining power of both sides of the market, and, as such, it shares some of the fundamentals of a bargaining framework. The way in which the value of the match is split between the worker and the firm varies randomly across firms, but the corresponding wage offer distribution shifts upward if the bargaining power of workers is increased by way of a decrease in search frictions for the employed or an increase in the mandatory minimum wage (if this exceeds the reservation wage). Also, in the absence of search frictions, wages converge to the competitive wage. If on-the-job search is impossible, then the wage converges to the minimum wage (if this exceeds the utility flow in unemployment), which can be interpreted as the outcome of a nation-wide bargain between the unemployed workers and the employers.

## 3. THE DATA

### 3.1. *The Sample*

For the estimation of the model we use data from the OSA[9] Labor Supply Panel Survey. This panel survey started in 1985. Presently four waves are available (April–May 1985, August–October 1986, August–October 1988, and August–November 1990).

In the OSA panel a random sample of Dutch households is followed over time. The survey concentrates on individuals who are between 15 and 61 years of age, and who are not full-time students. Therefore only households with at least one person in this category are included. All individuals (and in all cases the head of the household) in this category are interviewed. The first wave consists of 4020 individuals (in 2132 households). In 1990, 1384 (34%) of these individuals are still in the panel. In 1986, 1988, and 1990, refreshment samples were drawn, so that in 1990 the sample size was 4438 individuals.

In the OSA panel an effort is made to collect extensive information on the labor market histories of the individual respondents. From these labor market histories we obtain the sequence of labor market states occupied by the individuals and the sojourn times in these states. The following labor market positions are distinguished: employment (job-to-job changes are recorded), self-employment, unemployment, and "not in the labor force" (homemaker, full-time education, disabled, and other activities not related to the labor market). A number of variables that give a more detailed description of the various positions is also recorded, notably income (net wages in case of employment) and occupation. Part of the information is retrospective. For example, in the first wave in 1985 an attempt was made to reconstruct the labor market histories from January 1, 1980 until the data of interview in 1985. A number of

[9] Netherland Organization for Strategic Labour Market Research.

individual characteristics is recorded at the first interview of the respondent, and an attempt was made to keep track of changes in time-varying characteristics as family composition, marital status, and level of education.

In this paper we restrict attention to respondents who were at least participating in the first wave of the panel. Individuals who were self-employed for some period during the time span covered by the survey are omitted, since it is likely that the behavior of such individuals, at least in a certain period, deviates substantially from the behavior that the model intends to describe. For similar reasons, we do not use information on respondents who are observed to be working in a part-time job[10] or who are observed to be a nonparticipant for some period. An alternative approach would be to extend the model to include a state of nonparticipation, and allow for transitions to and from this state. Van den Berg and Ridder (1993) develop such a model. It turns out that the main features of the model of Section 2 are insensitive to the inclusion of such a state. Moreover, transitions to and from nonparticipation are rare in the data. Therefore, using information on such transitions in an extended model would, except for a number of imprecisely estimated nuisance parameters, probably not result in any gains. The restrictions reduce the number of labor market states to two: unemployment and full-time employment.

The indicated selection results in a sample of 1949 individuals, of which 217 (1732) were unemployed (employed) at the date of the first interview. In our sample, like in the full data set, 34% participates in all four waves of the panel, while 33% only participates in the first wave. Van den Berg and Lindeboom (1998) and Van den Berg, Lindeboom, and Ridder (1994) study the effect of attrition in the OSA data on the estimates of the transition rates between employment and unemployment and from one job to another. Although attrition is sometimes nonignorable, it does not have discernible effects on the estimates of these rates. In the present paper, to minimize the effect of selective attrition, we include information from respondents who temporarily dropped out of the panel survey and returned to the panel later. Upon returning, these respondents were interviewed about their whole labor market history from their previous interview onwards. In Koning, Ridder, and Van den Berg (1995) we do not use this additional information. The data set in that paper is basically a subset of the current data set. Most importantly, in the present paper we do not omit respondents with wage data below the legal minimum wage, and we include information on subsequent job spells. This allows for a check on the model. In particular, we can study the sensitivity of the estimates to the omission of further job spells.

In Table I the sample means of the variables are compared for the full sample as of April 1985 and the subsample that is used to estimate the equilibrium search model. The exclusion of respondents who at some moment are observed to be self-employed, nonparticipant, or part-time employee gives a sample that is somewhat younger, is more predominantly male, and has a slightly higher

[10] A job with a working week that is shorter than 35 hours is considered to be a part-time job.

TABLE I

COMPARISON OF FULL SAMPLE AS OF APRIL 1985 AND THE SUBSAMPLE USED IN THE ESTIMATION OF THE EQUILIBRIUM SEARCH MODEL

| | Full sample | | Subsample | |
|---|---|---|---|---|
| | Mean | Standard Dev. of Mean | Mean | Standard Dev. of Mean |
| Age | 37.9 | .19 | 34.8 | .23 |
| Male | .50 | .0079 | .76 | .010 |
| Education level | | | | |
| Primary/lower sec. | .45 | .0078 | .35 | .011 |
| Intermediate | .38 | .0077 | .42 | .011 |
| Higher | .13 | .0054 | .18 | .0087 |
| University | .035 | .0029 | .046 | .0047 |
| Years of schooling | 10.1 | .045 | 10.6 | .064 |
| Occupation level | | | | |
| Un/semi-skilled | .46 | .0079 | .29 | .010 |
| Skilled | .32 | .0074 | .41 | .011 |
| Semi-specialized | .078 | .0042 | .11 | .0072 |
| Specialized | .14 | .0054 | .19 | .0089 |
| Working week (hours) | 37.0 | .27 | 42.1 | .18 |
| Labor market position | | | | |
| Unemployed | .068 | .0040 | .11 | .0072 |
| Full-time job | .50 | .0078 | .89 | .0072 |
| Part-time job | .077 | .0042 | | |
| Self-employed | .044 | .0032 | | |
| Not-in-labor-force | .31 | .0073 | | |
| Number of spells | | | | |
| Unemployment | .12 | .0072 | .19 | .012 |
| Job | 1.08 | .016 | 1.51 | .021 |
| Other | .58 | .013 | | |
| Average spell (months) | | | | |
| Unemployment | 28.8 | 1.61 | 27.5 | 1.56 |
| Job | 70.3 | 1.39 | 71.1 | 1.42 |
| Other | 85.7 | 1.94 | | |
| Individual net income (Guilders/month) | 1758 | 18.4 | 2015 | 17.7 |
| Household net income (Guilders/month) | 2578 | 27.6 | 2706 | 32.6 |
| Marital status | | | | |
| Married/cohab. | .81 | .0062 | .76 | .010 |
| Single | .19 | .0062 | .24 | .010 |
| Number of observations | 4020 | | 1949 | |

*Notes:* The means for the full sample are computed from the available cases. The maximum number of available cases is 4020. For variables with missing observations the number of available cases is smaller.

Education level: Primary/lower secondary means that the attained level of education is at most lower secondary, either in the general stream (MAVO or at most 3 years of HAVO or VWO) or the vocational stream (LBO). Intermediate means that the attained education level is secondary, again either in the general stream (completed HAVO or VWO) or the vocational stream (MBO). Higher is the level attained after a higher vocational (HBO) or incomplete college training, and University refers to college graduates.

Occupation level: classification of Department of Social Affairs. The distinction between semi-specialized and specialized jobs is based on the required level of theoretical knowledge: considerable for semi-specialized and very considerable/scientific for specialized jobs.

level of education. Of course, the working week is significantly longer for our subsample. The occupational level is significantly higher. The largest omitted group concerns the nonparticipants, who constitute 31% of the full sample. The part-time employees and the self-employed constitute 8% and 4% of the full sample, respectively. Note that the fraction of unemployed among those who are either unemployed or hold a full-time job in the full sample in April 1985 (.12) does not differ significantly from the corresponding fraction in the subsample. The average number of unemployment and job spells is somewhat larger in the subsample, which is not surprising because these are the only types of spells observed in the subsample. The average spell lengths are almost equal in the two samples. Average net income is higher in the subsample.

Income changes at transitions before the date of the first interview (April 1985) are only recorded to lie in one of a few broad intervals, so income levels in states occupied before this date are reported inaccurately relative to income levels in states occupied at or after this date (in the latter cases we observe exact levels). Moreover, using the spells ending before the date of the first interview generates computational problems in the estimation, as will become clear in Section 4. To avoid these problems we do not use these spells, so the first spell used is the one that is ongoing at the date of the first interview. We use at most one subsequent spell besides this first spell, per individual.

### 3.2. *Descriptive Analyses*

After the selection made in the previous subsection we end up with 366 unemployment and 2941 job durations. Table II gives some descriptive statistics. The equilibrium search model as specified in Section 2 has strong implications for the distribution of unemployment spells and job spells given the wage earned in the job: both follow an exponential distribution, and the job duration hazard decreases with the wage. We check whether these implications are at odds with the duration data in a subsample by estimating reduced-form (mixed) proportional hazard models. We do not report empirical hazard rates, because the

TABLE II

UNEMPLOYMENT AND JOB DURATIONS: DESCRIPTIVE STATISTICS

| | Unemployment Durations | Job Durations |
|---|---|---|
| Number of spells | 366 | 2941 |
| Fraction censored | .30 | .42 |
| Fraction transition to | | |
| Other job | — | .91 |
| Unemployment | — | .09 |
| Mean duration (months) | 27.5 | 71.1 |
| Standard deviation | 27.1 | 84.5 |

TABLE III

PROPORTIONAL HAZARD MODELS FOR UNEMPLOYMENT SPELLS (STANDARD ERRORS IN PARENTHESES)

| | Exponential Model | | Two-point Unobs. Heterogeneity | | Unobs. Heterogeneity, Weibull Duration Dep. | |
|---|---|---|---|---|---|---|
| Education | | | | | | |
| Primary/lower sec. | | | | | | |
| Intermediate | −.21 | (.20) | −.31 | (.24) | −.39 | (.30) |
| Higher | .097 | (.30) | .045 | (.26) | .0086 | (.20) |
| University | .57 | (.56) | .47 | (.55) | .49 | (.65) |
| Age | | | | | | |
| −29 | | | | | | |
| 30–38 | −.46 | (.21) | −.49 | (.28) | −.71 | (.44) |
| 39– | −.65 | (.19) | −.63 | (.23) | −.80 | (.35) |
| Occupation level | | | | | | |
| Un/semi-skilled | | | | | | |
| Skilled | .081 | (.20) | .11 | (.21) | .087 | (.28) |
| Semi-specialized | −.79 | (.41) | −.77 | (.52) | −.95 | (.80) |
| Specialized | −.12 | (.47) | −.031 | (.20) | −.0005 | (.093) |
| Constant | −3.58 | (.18) | −2.56 | (.46) | −3.59 | (1.13) |
| Unobserved heterogeneity | | | | | | |
| $v_1$ | | | .28 | | .13 | |
| $v_2$ | | | 1.63 | (.32) | 1.55 | (.18) |
| $\Pr(v = v_2)$ | | | .53 | (2.7) | .61 | (.18) |
| Duration dependence | | | | | | |
| $\alpha$ | | | | | 1.39 | (3.8) |
| Log likelihood | −785.56 | | −780.42 | | −779.94 | |

sample is a stock sample,[11] and it is well-known that empirical hazard rates obtained from a stock sample are biased estimates of the underlying cohort hazard rates. Moreover, we want to know how the unemployment and job hazard rates vary over the sample, and we are interested in the relation between the wage in the current job and the job hazard. Finally, the distinction between unobserved heterogeneity and true duration dependence, as explanations of a decreasing empirical hazard, is important, because the equilibrium search model with heterogeneity that we will estimate (see Section 4) does allow for the first, but not for the second explanation.

The results of the reduced-form proportional hazard estimates are reported in Tables III and IV. The model is a standard mixed proportional hazard model with Weibull duration dependence with parameter $\alpha$, and a two-point discrete mixing distribution with points of support $v_1$ and $v_2$ and mean normalized at 1. Because it is our intention to give an impression of the over-all shape of the hazard rates, and the possibility to explain it by unobserved heterogeneity, it is not necessary to explore the shape of the hazard rates in great detail. The

[11] The sampling plan does not restrict the labor market position of the respondents at the date of the first interview, but if we consider only the job or unemployment durations we do obtain a stock sample of employed and unemployed, respectively.

TABLE IV

PROPORTIONAL HAZARD MODELS FOR JOB SPELLS
(STANDARD ERRORS IN PARENTHESES)

| | Exponential Model | | Two-point Unobs. Heterogeneity | | Unobs. Heterogeneity, Weibull Duration Dep. | |
|---|---|---|---|---|---|---|
| Education | | | | | | |
| Primary/lower sec. | | | | | | |
| Intermediate | .14 | (.086) | .15 | (.10) | .11 | (.087) |
| Higher | .42 | (.12) | .45 | (.15) | .32 | (.17) |
| University | .70 | (.19) | .80 | (.21) | .55 | (.27) |
| Age | | | | | | |
| −22 | | | | | | |
| 23–29 | −.25 | (.12) | −.24 | (.16) | −.18 | (.13) |
| 30–38 | −1.02 | (.14) | −1.07 | (.17) | −.78 | (.33) |
| 39− | −1.62 | (.16) | −1.72 | (.19) | −1.26 | (.51) |
| Occupation level | | | | | | |
| Un/semi-skilled | | | | | | |
| Skilled | .045 | (.064) | .029 | (.11) | .020 | (.080) |
| Semi-specialized | .13 | (.13) | .11 | (.16) | .096 | (.12) |
| Specialized | .20 | (.13) | .14 | (.16) | .13 | (.12) |
| Wage/1000 | −.21 | (.084) | −.21 | (.086) | −.14 | (.086) |
| Constant | −4.16 | (.16) | −3.52 | (.23) | −2.25 | (.80) |
| Unobserved heterogeneity | | | | | | |
| $v_1$ | | | .32 | | .68 | |
| $v_2$ | | | 1.40 | (.23) | 1.18 | (2.84) |
| $\Pr(v = v_2)$ | | | .63 | (.15) | .64 | (4.49) |
| Duration dependence | | | | | | |
| $\alpha$ | | | | | .72 | (.29) |
| Log likelihood | −4683.8 | | −4668.3 | | −4667.1 | |

estimates are obtained by maximum likelihood, and the likelihood function deals appropriately with the length bias induced by the stock sample. The estimates for the unemployment spells reported in Table III indicate that unemployment hazard decreases with age. There is a significant amount of unobserved heterogeneity. Further, the estimate of $\alpha$ does not differ significantly from 1, so there is no significant duration dependence. The implied expected unemployment spell for the reference group (primary/lower secondary education, younger than 29, un/semi-skilled job) is about 13 months. This is much smaller than the number reported in Table II, and the difference reflects the combined effect of censoring and length bias due to stock sampling. The estimation results for the job spells in Table IV show that the job hazard increases with the level of education and decreases with age.[12] There is also a negative relation with the wage rate. Again there is a significant degree of unobserved heterogeneity, and

[12] It should be noted that this does not provide information on the way in which $\lambda_1$, $\delta$, or $p$ vary with these observables. First, the job hazard depends on all these three parameters. Secondly, these parameters do not always have a monotone effect on this hazard. For example, if the reservation wage exceeds the mandatory minimum wage, then $\lambda_1$ may have a nonmonotone effect on the job-to-job transition rate.

no significant relation between the job hazard and the tenure of the job. The implied expected job duration for the reference group (primary/lower secondary education, younger than 22, un/semi-skilled job, wage equal to 2095 guilders/month) is about 52 months.

The results of the reduced-form duration analyses are in agreement with the predictions of the equilibrium search model as specified in Section 2. In particular, there is no evidence of significant duration dependence in our data. However, it is also clear that there is significant heterogeneity in our sample, and that in this respect the homogeneous model does not give a good description of the duration data. In subsection 4.1 we incorporate heterogeneity into the model.

It is important to note that the structural models that are estimated in the following sections are not nested in the reduced-form duration models. As a result, we cannot perform goodness-of-fit tests as in Eckstein and Wolpin (1990), who compare structurally estimated hazard rates to empirical hazard rates. Nevertheless, the reduced-form results can be used to gauge the descriptive performance of the structural models.

The equilibrium search model characterizes the joint distribution of unemployment/job durations and accepted/earned wages. In Table V we present some descriptive statistics for the wage data in the subsample. The average earned wage is always larger than the average accepted wage out of unemployment, and this is consistent with transitions to higher paying jobs. The average wage increases with age, education, and occupation level, although this pattern is less clear for the accepted wages because of the small number of observations. The minimum wage varies with age: it is lower for employees up to 23 years of age (in subsection 4.2 we explain in detail how we measure the minimum wage).

We now turn to the wage data below or at the minimum wage. A few percent of the wage observations are below the relevant mandatory minimum wage (see Table V). For the U.S., DiNardo, Fortin, and Lemieux (1996) show that during the past decades there has always been a positive fraction of workers who are paid less than the minimum wage. Such workers are in jobs that are not covered by minimum wage laws or in jobs at firms that do not comply with minimum wage laws. Given the strictness with which labor laws are applied in The Netherlands, it seems highly unlikely that the full-time workers in our sample reporting a wage below the minimum wage actually earn that wage. We therefore interpret such reported wages as being affected by measurement error (see subsection 4.1 below).

Figure 1 pictures kernel estimates of the wage densities. In particular, we plot the densities of the data on accepted wages and earned wages as of April 1985 for the age categories 16–22 and 23–61. As a first observation, the estimated density of the accepted wages is stochastically dominated by that of the earned wages, as is predicted by the theory. We do not truncate the wage densities at the minimum wage, and if a spike at the minimum wage is present in the wage data, then it should show up in these estimated densities. Clearly, from Figure 1, we do not observe such a spike. This result also holds if the data are stratified

TABLE V

ACCEPTED AND EARNED WAGES (GUILDERS / MONTH): DESCRIPTIVE STATISTICS

| | Net Wage Earned in April 1985 | | Accepted Wage Out of Unemployment | |
|---|---|---|---|---|
| | Mean | Stand. deviation | Mean | Stand. deviation |
| All | 2092 | 727 | 1696 | 322 |
| Education | | | | |
| Primary/lower sec. | 1816 | 869 | 1625 | 448 |
| Intermediate | 2022 | 948 | 1772 | 796 |
| Higher | 2519 | 1850 | 1762 | 603 |
| University | 2989 | 4960 | 1733 | 537 |
| Age | | | | |
| −22 | 1313 | 910 | 1355 | 913 |
| 23–29 | 1793 | 640 | 1726 | 508 |
| 30–38 | 2211 | 1130 | 1756 | 380 |
| 39– | 2465 | 1495 | 1776 | 700 |
| Occupation level | | | | |
| Un/semi-skilled | 1807 | 980 | 1739 | 365 |
| Skilled | 1903 | 789 | 1657 | 512 |
| Semi-specialized | 2234 | 1948 | 1875 | 497 |
| Specialized | 2771 | 2081 | 1736 | 477 |
| Minimum wage | | | | |
| −22 | 1000 | | 1000 | |
| 23– | 1450 | | 1450 | |
| Fraction with wage below minimum wage | | | | |
| −22 | .098 | | .0 | |
| 23– | .050 | | .11 | |
| Ratio of net wage to minimum | 1.48 | .48 | 1.23 | .23 |
| UI benefits | 1192 | | 1192 | |
| Ratio of net wage to UI benefits | 1.76 | .60 | 1.42 | .27 |
| # observations | 1614 | | 44 | |

further by age or level of education or if a smaller bandwidth is used than in Figure 1.[13] Van Soest and Kapteyn (1989) and Van Soest (1991), who use a different longitudinal panel survey from The Netherlands in the eighties to study wages, do not find evidence of such spikes either. One may argue that the presence of a spike in the raw wage data is obscured by measurement errors. We return to this in subsection 5.2.

[13] Let the wage data be grouped into 100 Guilder intervals. The fraction of employed respondents aged at or above 23 (below 23) who report a wage within the interval containing the minimum wage is 5% (14%). (It should be noted that more than 90% of the wages of respondents aged below 23 lie within an interval with a range of less than 1000 Guilders.) For individuals aged above 23, the subgroup with the highest percentage of responses in the interval containing the minimum wage is the group with the lowest level of education (7%). In any case, the kernel estimates do not display spikes, in the sense that if it is attempted to smooth bumps in the right-hand tail of the densities by choosing larger bandwidths, then bumps in the left-hand tail rapidly disappear.

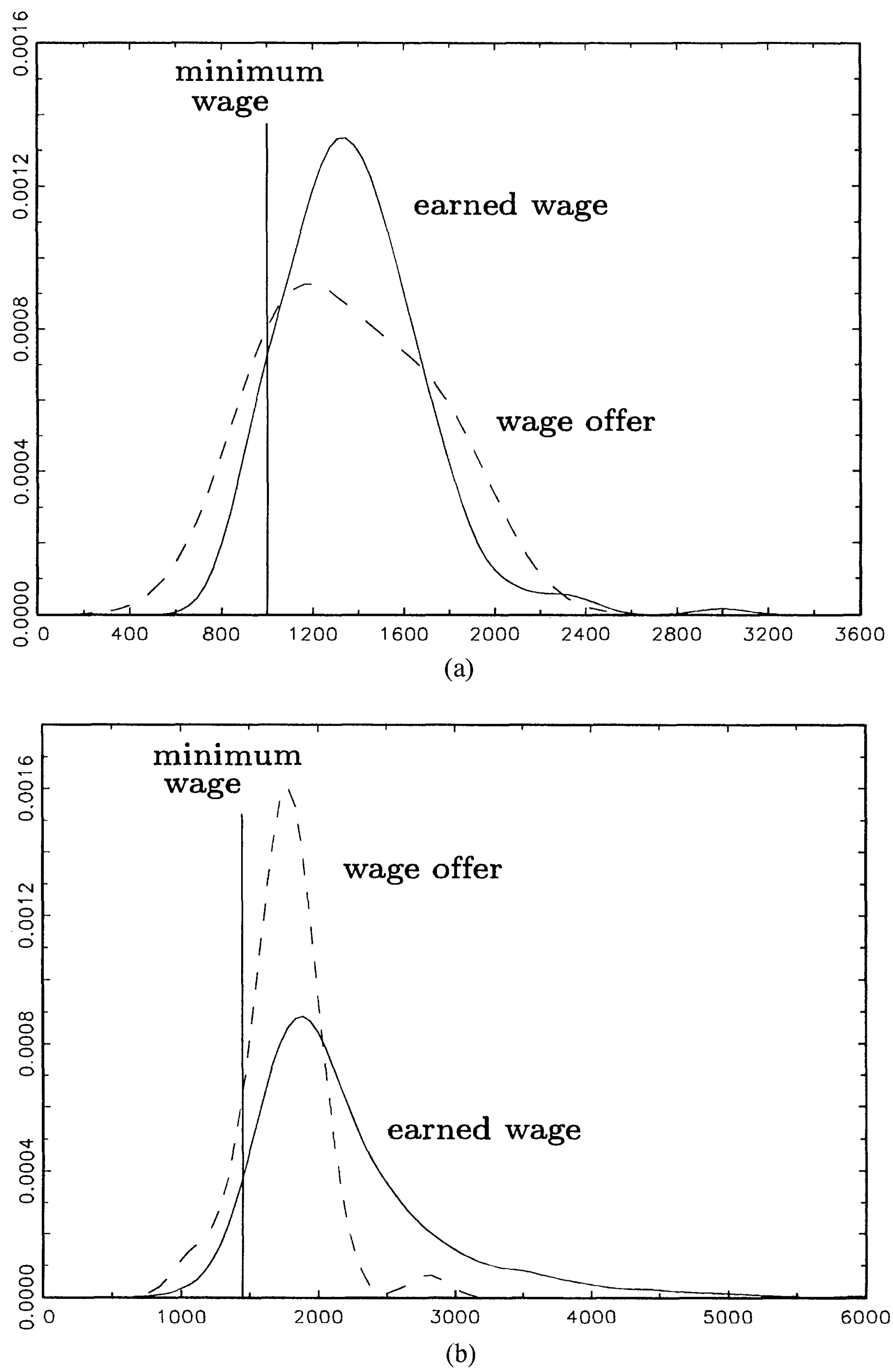


FIGURE 1.—Kernel estimates of wage offer and earnings densities for age −22 and 23− (standard normal kernel and bandwidth $1.06 s_w n^{-1/5}$ with $s_w$ the standard deviation of $w$). (a) Age −22. (b) Age 23−

Finally, because the equilibrium search model is concerned with the joint distribution of wages and durations, we computed the correlation coefficient of the residual unemployment duration as measured from the date of the first interview and the accepted wage from unemployment. This coefficient is .033, and is not significantly different from 0. This is in agreement with the homogeneous model that predicts a zero correlation between unemployment durations and wages accepted from unemployment.[14]

So far, $b$ has been interpreted somewhat vaguely as the full opportunity cost of employment. In the sequel we set $b$ equal to the unemployment benefit level. At the end of Section 4 we explain how we assign numerical values to $b$.

## 4. EMPIRICAL IMPLEMENTATION

### 4.1. *The Likelihood Function*

We estimate the model by maximum likelihood (ML), using the data described in Section 3. In this section we discuss some noteworthy issues related to the likelihood function and the empirical implementation. The Appendix to this paper contains a detailed derivation of individual likelihood contributions.

We allow for measurement errors in the wage data. Hartog and Van Ophem (1991) provide evidence for the presence of measurement errors in the wage data in the OSA panel. Here, this is particularly relevant because, as shown in Van den Berg and Ridder (1993), the dependence of the support of $F(w)$ and $G(w)$ on the parameters of the model implies that the ML estimates of the parameters are sensitive to measurement errors in the wage data. A similar problem arises in the structural estimation of partial job search models (see, e.g., Wolpin (1987)). To deal with these problems, we assume that the observed wage $\tilde{w}$ equals the true wage $w$ times an error term $\varepsilon$ which is i.i.d. across job spells and across individuals, and which is independent of all other random variables in the model. Note that allowing for measurement errors also prevents the log likelihood from equaling $-\infty$ if a transition from a job to a job with a lower wage is observed[15] or if a wage below the mandatory minimum wage is reported (recall the discussion on this in subsection 3.2). We assume that $\varepsilon$ has a log-normal distribution with mean 1 and $\text{var}(\log \varepsilon) = \sigma^2$.

A consequence of allowing for measurement errors is that the individual likelihood contribution contains an integral for each wage that is observed for the corresponding individual. These integrals have to be evaluated numerically. Moreover, at any job-to-job transition the true wage must increase, so that, conditional on the observed wages, the range of possible values of the measurement error in the new wage depends on the value of the measurement error in the previous wage. Because of this, the joint density of observed wages in consecutive job spells contains a multidimensional integral that is computationally demanding. For this reason we do not use information on events that occur

[14] Because of the complicated way in which some parameters affect $F$, the reduced-form analyses of relations between the duration spent in a state and the accepted wage after leaving that state do not give much insight into sources of heterogeneity. For example, if $\lambda_0 < \lambda_1$ and if there is unobserved heterogeneity in $p$, then the relation between the job duration and the wage in the next job (given the current wage) is nonmonotonous.

[15] In our sample, 11% of the observed job-to-job transitions result in a decrease of the observed wage.

after the completion of two consecutive job spells. As a consequence, the dimension of the numerical integral in the likelihood contribution is at most two. A further reduction of the dimension of the integral by deleting information on the job after the first job-to-job transition would cause a loss of valuable information on the parameters of the job-to-job transition rate.

A number of simple checks on the fit of the model specification can be performed. Suppose that the estimate of the standard deviation of $\varepsilon$ is relatively large. Then a large fraction of the variation in the wages cannot be explained by the model. Consequently, one may conclude that the model is not adequate. Further, by re-estimating the model using only subsets of the observed endogenous variables, various parts of the specification can be tested in a natural way.

It has been shown before that the model of Section 2 is identified from data on unemployment durations, job durations, destination states following exit out of a job, and accepted wage offers[16] (note that we observe more endogenous variables than these). Basically, $\lambda_0$ is identified from the unemployment durations, $\delta$ is identified from the job durations ending in a transition to unemployment, and $p$ and $\lambda_1$ are identified from the mean accepted wage offer and the job durations ending in a transition to another job. Given all this, $\sigma$ is identified from the variance of wage offers.

Because the measurement error in the wages makes the support of the distributions of observed wages independent of the parameters, the ML estimation of the model is standard. If there are no measurement errors, the support of $F$ and $G$ depends on unknown parameters, so ML estimators have nonstandard properties. Kiefer and Neumann (1993) suggest using order statistics to estimate the bounds of the support. The parameters in these bounds can then be estimated from these superconsistent estimates. We do not follow this suggestion because of the sensitivity of the resulting estimates to outliers and measurement errors, and because this method cannot deal easily with (un)observed population heterogeneity or with transitions to jobs with lower wages.

### 4.2. *Heterogeneity*

We introduce heterogeneity by assuming that there are separate labor markets (or segments of the labor market, or submarkets) for different types of individuals and firms. For example, there may be separate markets for individuals with different educational backgrounds. Furthermore, for each level of education, there may be separate markets for different age categories. To deal with this type of heterogeneity, the model can be estimated separately for each labor market, using only those individuals that belong to the labor market at hand. However, the number of individuals per market may be very small. In the empirical analysis below we distinguish separate labor markets by level of education, age, and occupation level (defined by the degree of complexity of the

[16]See Mortensen (1990), Kiefer and Neumann (1993), and Van den Berg and Ridder (1993) for details.

job). For each of these three variables we distinguish four levels, so that we have 64 segments.[17] Six of these do not contain any respondents. For only 34 segments we observe more than 10 individuals.

Instead of estimating separate models for the 58 (64 minus 6) segments, we assume that the deep structural parameters in the model ($p$, $\lambda_0$, $\lambda_1$, and $\delta$) vary over the different labor markets in a fairly regular way that can be captured by simple parametric functions. Then we can estimate the parameters using the data on all markets simultaneously. In other words, we estimate the models for all markets simultaneously. Let $x$ be the vector of age, education, and occupation dummies (and a constant, so $x$ contains 10 elements). We assume that $p$, $\lambda_0$, $\lambda_1$, and $\delta$ are log-linear functions of $x$,

$$\begin{aligned} &p = \exp(\beta_1' x), \qquad \lambda_0 = \exp(\beta_2' x), \\ &\lambda_1 = \exp(\beta_3' x), \qquad \delta = \exp(\beta_4' x). \end{aligned} \tag{4.1}$$

The only restriction in comparison to separate estimation for each market is that in $p$, $\lambda_0$, $\lambda_1$, and $\delta$ there are no interactions between age and educational and occupational level. In the estimation we merge the two highest levels of education and the two highest occupational levels in $\lambda_1$ and $\delta$ (so $\beta_3$ and $\beta_4$ contain eight free parameters), because of computational problems encountered when estimating the unrestricted version.[18]

We replicated the empirical analysis below using four type of industry dummies instead of the four occupation dummies, but the estimates of the corresponding parameters turned out to be insignificant while the other parameter estimates were similar to those reported below. Note that variables like gender, marital status, or nonwage income do not define separate labor markets, and hence cannot be included in $x$. Allowing structural parameters like $\lambda_1$ to depend on a range of personal characteristics that do not characterize different segments of the labor market introduces worker heterogeneity within a labor market, and the result is a different model with a different equilibrium wage offer distribution. So, not every parameterization of our model makes sense. It is obvious that the personal characteristics that are included in $x$ (notably age) are not immune to this criticism either. The segmentation assumption precludes individuals moving from one segment to another, but it also entails that firms in different segments do not compete. It would be a challenge to build equilibrium search models allowing for competing segments with workers who simultaneously search with different intensities in different segments. The prime reason

[17] We distinguish between the following levels of education: (i) primary/lower secondary education, (ii) intermediate education, (iii) higher education, (iv) university, and between the following levels of occupation: (i) un/semi-skilled, (ii) skilled, (iii) semi-specialized, (iv) specialized. See Table I for more detailed information on these categorizations.

[18] For the highest education and occupation categories, which are the smallest categories, transitions from employment to unemployment are rarely observed. Moreover, as will be shown below, the information in the wage data does not contribute much to the estimation of the arrival rate parameters.

for including age in the set of segment-defining characteristics is that the mandatory minimum wage is different for youths, so this enables us to study minimum wage effects more carefully across age groups.

The variables in $x$ divide the labor market into segments on the basis of observed characteristics. However, this segmentation may not be sufficiently detailed. For example, within each category defined by age and levels of education and occupation, there may be separate segments. They can be distinguished by unobserved heterogeneity variables $\upsilon$ affecting the structural parameters. It is important to include this into the model. In particular, as noted in Section 2, allowing for sufficient heterogeneity in the productivity level $p$ improves the fit to the wage data. We therefore replace the specification for $p$ in (4.1) by

$$p = \upsilon \cdot \exp(\beta_1' x). \tag{4.2}$$

We assume that $\upsilon$ has a discrete distribution with three unknown points of support. The family of discrete distributions is attractive for reasons of flexibility as well as for computational reasons. We experimented with additional points of support, but during the ML procedure these sometimes converged to existing ones while at other times they caused the $p$ for certain values of $x$ and $\upsilon$ to converge to $\underline{w}_L$.[19] We denote the three points of support by $\upsilon_1 < \upsilon_2 < \upsilon_3$, and the corresponding probabilities by $\exp(q_i)/(\Sigma_i \exp(q_i))$, with normalization $q_3 = 0$. The parameter in $\beta_1$ corresponding to the constant in $x$ is normalized to zero.

The distribution of $\upsilon$ does not depend on $x$, so that (4.2) effectively increases the number of segments by a factor equal to the number of points of support of $\upsilon$. Hence, each segment as defined by $x$ consists of three subsegments. As a consequence, $F$ and $G$ (conditional on $x$) are mixtures of $F$ and $G$ in the model without heterogeneity (see Eckstein and Wolpin (1995a) and Eckstein and Wolpin (1995b) for a similar approach in an equilibrium matching model). The likelihood is simply obtained by integrating the likelihood derived in subsection 4.1 over the discrete distribution of $\upsilon$.

In subsection 5.1 we also examine whether the other structural parameters depend on $\upsilon$. Those extensions turn out to be empirically uninteresting.

For each segment, the benefits level $b$ is taken to be the corresponding predicted value of a regression of the observed log unemployment benefits on the dummy variables defining the segments. Alternatively, one could treat $b$ as an unknown parameter with a parameterization analogous to (4.1). (Note however that if $r < \underline{w}_L$, then $b$ does not enter the likelihood contribution.) From the information in the survey, the net mandatory minimum wage $\underline{w}_L$ can be calculated for each respondent. The resulting values vary slightly within segments, mainly because the minimum wage for youths is relatively small. In the

[19] This can be interpreted as suggesting that in reality the location of the mass points of $\upsilon$ varies over the segments (i.e. is dependent on $x$), contrary to what is assumed.

empirical analysis, we take the sample average per segment. In Section 5 we argue that (within bounds) the way in which we assign values to $b$ and $\underline{w}_L$ does not alter the main results.

### 4.3. *Non-wage Job Characteristics*

Following virtually all of the literature on (equilibrium) job search, we have assumed that a job is fully characterized by its wage. This implies that the wage is the only job characteristic that matters to the employees, and that for the firm the cost of employing a worker is equal to the wage. It may be interesting to examine to what extent this counterfactual assumption can be relaxed without making the model or its empirical analysis intractable. Burdett and Mortensen (1998) consider the case in which firms on the same labor market differ in their cost of providing the nonwage characteristic. The resulting model (see Gronberg and Reed (1994) for a summary) is more or less equivalent to a model in which there is within-market productivity dispersion. Estimation of such a model would be beyond the scope of this paper.

In the remainder of this subsection we show that, under some specific assumptions, a model with nonwage characteristics can be developed that is observationally equivalent to our equilibrium search model with measurement errors in the wage data. We do not claim to present here the best way to incorporate nonwage characteristics. Rather, we intend to show that it is possible to include nonwage characteristics in a manageable way, and, more importantly, that our estimates may be less sensitive to the omission of nonwage characteristics than may be thought at first sight.

To make progress we consider the case in which provision of the nonwage attribute is exogenous to the equilibrium search model. To be more specific, we consider the case in which, for all values of the wage $w$ and all levels of the nonwage characteristic $z$, the monetary equivalent of the total utility of the job is equal to the total cost of employing the worker. Let the value of the job to the worker be $\xi$ and the per period cost of employing this worker be $c$; then we assume for all $w, z$,

$$\xi = c = k(w, z). \tag{4.3}$$

For convenience we assume that

$$k(b, z) = b, \qquad k(\underline{w}_L, z) = \underline{w}_L, \tag{4.4}$$

for all $z$, i.e. being unemployed or being in a minimum-wage job does not give nonmonetary rewards.

Under these assumptions, the analysis of Section 2 applies directly for $\xi$ rather than $w$. Hence, under the assumptions of this section, the model determines the distribution of the total value $\xi$, but not the division of $\xi$ into $w$ and $z$. A natural assumption is that $z$ follows some distribution with support

$(0,\infty)$, and that $w$ and $z$ are stochastically independent. In the sequel we shall specialize (4.3) to

$$\xi = w \cdot z. \tag{4.5}$$

By taking the logarithm of both sides of (4.5) it follows that the characteristic function, or moment generating function if it exists, of the distribution of the observed wages is equal to the ratio of the characteristic functions of $\xi$ and $z$. Only in special cases can we obtain an explicit expression for the wage distribution, and this is an obstacle in deriving the likelihood function for this model. Note that now the support of the distribution of $w$ is $(0,\infty)$. Hence, if there are nonwage job characteristics, we expect to observe wages below the minimum specified by the equilibrium search model.

Inclusion of a multiplicative measurement error does not alter the model. If the measurement error is stochastically independent of $w$ and $z$, then it can be shown that the distribution of $\xi$ is equal to that of $\tilde{w}\cdot z/\varepsilon$. Hence, the measurement error can be absorbed into the distribution of $z$. In general this does not lead to a model that is formally equivalent to the model with measurement error introduced above, because $\xi$ and $\varepsilon/z$ are dependent random variables. As a special case, if the distribution of $z$ is degenerate, then we obtain the measurement error model with a small modification: the measurement error is now $\varepsilon/z$, and $z$ is absorbed into the distribution of the measurement error.

We also obtain the measurement error model if we assume that the joint distribution of $w$ and $z$ is such that $\xi$ and $z$ are stochastically independent (use a change of variable to $1/z$). Note that such an assumption is hard to justify.

We conclude that the model can be extended to deal with nonwage job characteristics. If there is no dispersion in the level of the nonwage attribute, then we obtain the measurement error model that is estimated below. If the nonwage characteristic is dispersed, then in special cases we also obtain the measurement error model. In general, the extension of the support of the wage distribution is as in the measurement error model.

## 5. RESULTS

### 5.1. *Parameter Estimates and Their Implications*

We estimate the models by ML, using the BHHH algorithm with analytical derivatives. The parameter estimates for the basic model without unobserved heterogeneity are in Table VI, while the corresponding estimates for the model with unobserved heterogeneity in $p$ are in Table IX. Time and money are measured in months and Dutch Guilders, respectively. For the education, age, and occupation level dummies, the reference categories are the primary/lower secondary level of education, age 16–22, and the un/semi-skilled level of occupation, respectively. Given the parameter estimates, one can calculate estimates of $p, \lambda_0, \lambda_1, \delta, r, \overline{w}$, and the mean of $F(w)$ for each labor market

TABLE VI

ESTIMATES FOR THE EQUILIBRIUM SEARCH MODEL: OBSERVED HETEROGENEITY (STANDARD ERRORS IN PARENTHESES)

| Parameter | $p$ | $\lambda_0$ | $\lambda_1$ | $\delta$ |
|---|---|---|---|---|
| Constant | 7.17 (0.03) | −2.94 (0.14) | −2.23 (0.47) | −4.24 (0.14) |
| Intermediate educ. | 0.06 (0.02) | 0.31 (0.11) | 0.34 (0.27) | −0.02 (0.11) |
| Higher education | 0.16 (0.02) | 0.46 (0.16) | | |
| | | | 0.46 (0.32) | 0.22 (0.15) |
| University | 0.27 (0.03) | 0.37 (0.22) | | |
| Age category 23–29 | 0.24 (0.03) | −0.41 (0.16) | −0.26 (0.46) | −0.80 (0.14) |
| Age category 30–38 | 0.39 (0.03) | −0.95 (0.17) | −0.96 (0.46) | −1.56 (0.15) |
| Age category 39–70 | 0.47 (0.03) | −1.53 (0.16) | −1.67 (0.45) | −2.13 (0.14) |
| Skilled | 0.06 (0.02) | 0.05 (0.13) | −0.44 (0.34) | −0.02 (0.11) |
| Semi-specialized | 0.14 (0.02) | −0.16 (0.18) | | |
| | | | −0.61 (0.35) | 0.04 (0.15) |
| Specialized | 0.30 (0.02) | 0.25 (0.20) | | |
| $\sigma^2$ | 0.0447 (0.0013) | | | |
| Log likelihood = −26425 | | | | |

TABLE VII

CHARACTERISTICS OF THE EQUILIBRIUM: OBSERVED HETEROGENEITY

| Age Category: | 16–22 | 23–29 | 30–38 | 39–70 | Average |
|---|---|---|---|---|---|
| $p$ (Productivity) | 1435 | 1941 | 2353 | 2532 | 2208 |
| $\lambda_0$ (Arrival rate in unemployment) | 0.065 | 0.047 | 0.029 | 0.016 | 0.033 |
| $\lambda_1$ (Arrival rate in employment) | 0.095 | 0.075 | 0.037 | 0.018 | 0.047 |
| $\delta$ (Separation rate) | 0.014 | 0.007 | 0.003 | 0.002 | 0.005 |
| $r$ (Reservation wage) | 607 | 756 | 1038 | 1226 | 982 |
| $\overline{w}$ (Highest wage) | 1426 | 1937 | 2345 | 2521 | 2200 |
| $E_F(w)$ (Mean wage offer) | 1267 | 1761 | 2023 | 2153 | 1917 |
| $\underline{w}$ (Lowest wage) | 999 | 1449 | 1450 | 1506 | 1420 |
| $b$ (Benefits level) | 807 | 1120 | 1248 | 1320 | 1192 |
| $\mu$ (Monopsony power) | 0.13 | 0.10 | 0.16 | 0.17 | 0.14 |
| $u/m$ (Unemployment) | 0.18 | 0.13 | 0.10 | 0.11 | 0.12 |
| # Observations | 212 | 494 | 595 | 648 | 1949 |

segment. The sample averages of these estimates are listed in Table VII for the basic model and in Table X for the model with unobserved heterogeneity in $p$. Because the effect of age is particularly pronounced, we also list averages per age category.

Except for the estimates of $\sigma^2$ and (the distribution of) $p$, the parameter estimates in Table IX do not differ much from those in Table VI. It is important to note, however, that inclusion of unobserved heterogeneity in $p$ improves the fit of the model substantially. When going from the model without unobserved heterogeneity to the model in which $v$ has a discrete distribution with at most 2 points of support (which amounts to adding 2 parameters), the log likelihood increases 105 points (from $-26425$ to $-26320$). When increasing the maximum number of points of support from 2 to 3 (which again amounts to adding 2 parameters), the log likelihood increases a further 14 points. In the latter model, the estimate of $\sigma^2$ is about half of that in the model without unobserved heterogeneity. As a result, in the model with unobserved heterogeneity, it is estimated that only 5% of all observed wages are not within a range of 29% around the true wage. These results are reinforced below when we decompose total wage variation. Because of all this, the model with unobserved heterogeneity in $p$ is the preferred specification in the discussion below (it should be noted that many results carry over to the more restrictive specification).

Generally, the way in which the sample averages in Table X vary with age seems to be in accordance with intuition. All three rates $(\lambda_0, \lambda_1, \delta)$ are monotonically decreasing in age. For every age category, $\delta$ is smaller than $\lambda_0$ and $\lambda_1$, which do not differ much from each other. Because $\delta$ is much smaller than $\lambda_1$, $\overline{w}$ is very close to $p$. If $\delta/\lambda_1$ tends to zero, i.e. if the number of offers during a spell of employment is very large, workers climb the wage ladder with high speed, and the resulting competition between firms causes $G$ to tend to a degenerate distribution at $p$. In this case the wage offer distribution $F$ also shifts to the right, but $F$ does not tend to a degenerate distribution, nor does its probability mass become concentrated near $p$. Yet, if $\delta/\lambda_1$ tends to zero, then workers stay only for an infinitesimally short time at firms offering $w < \overline{w}$, and profits tend to zero.

Because in most segments $\lambda_0$ is fairly close to $\lambda_1$, search in employment is about as effective as in unemployment. This in turn implies that $r$ and $b$ generally do not differ much from each other. In other words, most unemployed individuals are willing to accept a job with a wage close to the benefits level. Further, in most segments, $r < \underline{w}_L$, so in general the lowest wage offer $\underline{w}$ equals the mandatory minimum wage. As a result, in most segments there holds that $r \approx b < \underline{w}_L = \underline{w} < \overline{w} < p$, although for each age category there are also segments with a different ordering.

The estimated distribution of $v$ (see Table IX) is skewed to the right. Given segment characteristics $x$, the fractions of workers affiliated to segments associated with $v = v_1$, $v = v_2$, and $v = v_3$ equal 81%, 16%, and 3%, respectively. The segments associated with $v_2$ ($v_3$) have values of $p$ that are 36% (95%) higher than that of the segments associated with $v_1$.

The equilibrium wage offer distribution implies that employers have monopsony power. For each segment we define the monopsony power index $\mu$ as

$$(5.1) \qquad \mu = \frac{p - E_F(w)}{E_F(w)} \qquad \text{with} \qquad E_F(w) = p - (p - \underline{w}) \cdot \frac{\left(\delta^2 + \delta\lambda_1 + \frac{1}{3}\lambda_1^2\right)}{(\delta + \lambda_1)^2}.$$

In traditional monopsony models of the labor market, $(p-w)/w$ is used as a measure of the monopsony power of the firm. In the present context, wages are dispersed, so (5.1) merely gives an indication of the average monopsony power of firms. Note that if search frictions in employment tend to zero ($\delta/\lambda_1 \downarrow 0$), then the index $\mu$ does not tend to zero but to $(p-\underline{w}_L)/(2p+\underline{w}_L)>0$. If, at the other extreme, search in employment is impossible ($\lambda_1 \downarrow 0$), and $b<\underline{w}_L$, then $\mu$ tends to $(p-\underline{w}_L)/\underline{w}_L$.

It should be noted that in traditional models as well as in the present model, $w/(p-w)$ equals the elasticity of the steady state workforce of the firm with respect to the wage offered by the firm (Machin and Manning (1991)). So, $\mu$ can also be interpreted as the relative increase in $w$ needed for a 1% increase in the workforce of the firm, evaluated at $w=E_F(w)$.

Monopsony power is not very strong in any segment. This can be explained by the fact that in general search frictions in employment are small, so individuals move relatively fast to jobs with high wages. Still, firms offer wages that are on average 13% below the competitive wage. Note that segments with $v=v_1$ have a value of $\mu$ which is generally smaller than the value of $\mu$ for segments with $v=v_2$ or $v=v_3$.

Tables VII and X also give the steady-state levels of unemployment $u/m$. Except for the age category 16–22 these are close to the national statistics for the mid-eighties. For young individuals the assumption of a constant inflow rate into employment prior to the date of the first interview (which follows from the assumption that the labor market is in equilibrium) may not hold, because these individuals may have left school shortly before that interview. In that case $\delta$ is underestimated from the employment durations ongoing at the date of the first interview, and $u/m$ is overestimated.

The results can be used to calculate other statistics than those presented in Tables VII and X. For example, $((\delta+\lambda_1)/\delta)^2$ equals the ratio $l(\overline{w})/l(\underline{w})$ of the workforces of the largest and smallest firms in a segment.

We performed some simple sensitivity checks on the specification of the model. First, we deleted the information on the accepted wages after a job-to-job transition. In the notation of the Appendix, this means that we set $d_{10}=1$ for all individuals, so information on behavior after such transitions is not used. If the distribution of accepted wages from a job would differ from the distribution of

TABLE VIII

DECOMPOSITION OF TOTAL VARIATION IN OBSERVABLE WAGE OFFERS

| Model: | Observed Heterogeneity | Observed and Unobserved Heterogeneity |
|---|---|---|
| Due to $\varepsilon$ | 44% | 23% |
| Due to $x$ | 37% | 33% |
| Due to $v$ in $p$ | — | 21% |
| Due to search frictions | 19% | 22% |

TABLE IX

ESTIMATES EQUILIBRIUM SEARCH MODEL: OBSERVED AND UNOBSERVED HETEROGENEITY (STANDARD ERRORS IN PARENTHESES)

| Parameter | $p$ | $\lambda_0$ | $\lambda_1$ | $\delta$ |
|---|---|---|---|---|
| Constant | 0 (−) | −2.92 (0.13) | −2.46 (0.37) | −4.21 (0.14) |
| Intermediate educ. | 0.06 (0.02) | 0.31 (0.10) | 0.28 (0.22) | −0.02 (0.11) |
| Higher education | 0.14 (0.02) | 0.51 (0.15) | 0.49 (0.28) | 0.21 (0.15) |
| University | 0.24 (0.03) | 0.53 (0.20) | | |
| Age category 23–29 | 0.25 (0.03) | −0.40 (0.16) | −0.40 (0.37) | −0.78 (0.14) |
| Age category 30–38 | 0.42 (0.03) | −0.95 (0.16) | −1.20 (0.36) | −1.52 (0.15) |
| Age category 39–70 | 0.47 (0.03) | −1.53 (0.15) | −1.75 (0.36) | −2.11 (0.14) |
| Skilled | 0.06 (0.02) | 0.05 (0.13) | −0.46 (0.26) | −0.00 (0.11) |
| Semi-specialized | 0.11 (0.02) | −0.19 (0.18) | −0.27 (0.29) | −0.01 (0.15) |
| Specialized | 0.26 (0.02) | 0.13 (0.18) | | |
| Log $v_1$ | 7.10 (0.03) | | $q_1$ | 3.35 (0.30) |
| Log $v_2$ | 7.41 (0.04) | | $q_2$ | 1.72 (0.31) |
| Log $v_3$ | 7.77 (0.05) | | $q_3$ | 0 (−) |
| $\sigma^2$ | 0.0220 (0.0013) | | | |
| Log likelihood = −26306 | | | | |

accepted wages from unemployment, then we would expect changes in the estimates. However, the estimates (not reported) do not differ much from those reported. The latter conclusion also holds for estimation results obtained for the model in which wage measurement errors are additive (so $\tilde{w} = w + \varepsilon$) and normally distributed.

Table VIII decomposes the total variation in observable wage offers into four components: (i) the variation due to wage measurement errors, (ii) the variation due to observed between-market heterogeneity in $p$, $\lambda_0$, $\lambda_1$, $\delta$, $b$, and $\underline{w}_L$,

TABLE X

CHARACTERISTICS OF THE EQUILIBRIUM: OBSERVED AND UNOBSERVED HETEROGENEITY

| Age Category: | 16–22 | 23–29 | 30–38 | 39–70 | Average |
|---|---|---|---|---|---|
| $p$ (Productivity) | 1446 | 1951 | 2392 | 2509 | 2216 |
| $\lambda_0$ (Arrival rate in unemployment) | 0.066 | 0.048 | 0.029 | 0.016 | 0.033 |
| $\lambda_1$ (Arrival rate in employment) | 0.075 | 0.055 | 0.025 | 0.015 | 0.035 |
| $\delta$ (Separation rate) | 0.015 | 0.007 | 0.003 | 0.002 | 0.005 |
| $r$ (Reservation wage) | 743 | 1022 | 1352 | 1400 | 1218 |
| $\overline{w}$ (Highest wage) | 1433 | 1944 | 2379 | 2495 | 2204 |
| $E_F(w)$ (Mean wage offer) | 1268 | 1762 | 2046 | 2130 | 1917 |
| $\underline{w}$ (Lowest wage) | 999 | 1450 | 1475 | 1502 | 1426 |
| $b$ (Benefits level) | 807 | 1120 | 1248 | 1320 | 1192 |
| $\mu$ (Monopsony power) | 0.13 | 0.10 | 0.16 | 0.17 | 0.14 |
| $u/m$ (Unemployment) | 0.19 | 0.13 | 0.11 | 0.11 | 0.12 |
| # Observations | 212 | 494 | 595 | 648 | 1949 |

(iii) the variation due to unobserved between-market heterogeneity in $p$, and (iv) the variation due to search frictions within markets. These components are defined by successive conditioning of var($\tilde{w}$) on $\varepsilon$, $x$, and $\upsilon$. In formula,

$$\begin{aligned}(5.2)\qquad \operatorname{var}(\tilde{w}) = {} & [E_x E_\upsilon E_F(w|x,\upsilon)]^2 \cdot \operatorname{var}_\varepsilon(\varepsilon) + E_\varepsilon(\varepsilon^2)\cdot \operatorname{var}_x(E_\upsilon E_F(w|x,\upsilon)) \\ & + E_\varepsilon(\varepsilon^2)\cdot E_x(\operatorname{var}_\upsilon(E_F(w|x,\upsilon))) \\ & + E_\varepsilon(\varepsilon^2)\cdot E_x E_\upsilon(\operatorname{var}_F(w|x,\upsilon)).\end{aligned}$$

To estimate the size of these four components we substitute the estimated $F$ and $\sigma^2$, the estimated distribution of $\upsilon$, and the empirical distribution of $x$, into the right-hand side of the equation above. Because $\tilde{w}$ is a nonlinear function of $\varepsilon$, $x$, and $\upsilon$, the results of the decomposition are not invariant with respect to the order of the successive conditioning of var($\tilde{w}$). However, it turns out that in our case the results are not sensitive to this order. It should also be noted that in our case almost all of the variation in the second component is due to variation in $p$ over $x$ (rather than variation in $\lambda_0$, $\lambda_1$, $\delta$, $b$, or $\underline{w}_L$ over $x$).

The wage offer variation due to search frictions amounts to only 22% of the total variation in observable wage offers. Recall that this is a consequence of the fact that the estimate of $\lambda_1/\delta$ is quite large. In the data, transitions from one job to another are much more frequently observed than transitions from a job to unemployment. Apparently, the information in the duration data on $\lambda_1$ and $\delta$ dominates the information in the wage data (Eckstein and Wolpin (1990) arrive at the same conclusion in the estimation of their equilibrium search model).

It is clear that the between-market variation due to unobserved heterogeneity $\upsilon$ in $p$ constitutes a substantial part of the wage variation. By comparing the results of the decomposition to those for the model without unobserved heterogeneity, it follows that in the latter model the variation due to unobserved heterogeneity in $p$ is erroneously attributed to measurement errors. As a result, the estimated variation due to measurement errors is much smaller in the model with unobserved heterogeneity in $p$ than in the model without unobserved heterogeneity.

It may be interesting to examine the fit of this model to the wage data in some more detail. The estimated earnings density $g$, appropriately mixed over $x$, $\upsilon$, and $\varepsilon$, fits the cross-sectional wage data at the first interview well. Now let us condition on $x$, i.e. let us consider segments with the same value of $x$. Generally the mean and variance of wage data given $x$ are well-predicted by mean and variance of the estimated distribution $G$, mixed over $\upsilon$ and $\varepsilon$. This is not surprising in light of the fact that the distribution of $\upsilon$ has five parameters. However, the predicted density function $g$, mixed over $\upsilon$ and $\varepsilon$, is multi-modal, with at most three modes, each mode corresponding to a particular value of $\upsilon$ (i.e. each mode is located close to the value of $p$ in the segment corresponding to a particular value of $\upsilon$). If we take $\varepsilon = 1$, i.e. if we disregard measurement errors, then the predicted density is saw-toothed with three spikes. These features generally are not reflected in the wage data for given $x$. However, as follows from equation (2.12), the wage data can be made to fit arbitrarily well by taking a sufficiently flexible functional form for $v$. In particular, the modes and spikes can be smoothed by assuming a continuous distribution for $v$.

We also estimated model versions in which we allow for unobserved between-market heterogeneity in the arrival rates $\lambda_0$, $\lambda_1$, and $\delta$. In subsection 3.2 we found significant unobserved heterogeneity in both the unemployment and job duration hazards. Allowing for unobserved heterogeneity in $p$ implies that there is unobserved heterogeneity in the job duration hazard. Hence, to allow for unobserved heterogeneity in both duration distributions (and therefore to improve the fit to the duration data), it is important to allow for unobserved heterogeneity in $\lambda_0$, but not necessarily in $\lambda_1$ or $\delta$.

In the structural estimation of the models that allow for unobserved between-market heterogeneity in the arrival rates, we took specifications analogous to (4.2), with discrete distributions for the unobserved heterogeneity terms. The results are in accordance with the reduced-form results mentioned in the previous paragraph. We found evidence for unobserved heterogeneity in $\lambda_0$ with two points of support. The log likelihood in the model that allows for unobserved heterogeneity in $\lambda_0$ (but not in $p$) is $-26415$. The other estimates are virtually identical to those in Table VI. As can be expected, this extension does not improve the fit to the wage data. The unobserved heterogeneity in $\lambda_0$ explains only 2% of the variation in observable wage offers. The ML estimates of the unobserved heterogeneity distributions for $\lambda_1$ and $\delta$ turned out to be degenerate. Hence, allowing for unobserved heterogeneity in $p$ seems to be sufficient to get an acceptable fit to the wage data.

The model does not allow for an unobserved component in $b$, let alone for unobserved heterogeneity in $b$. However, it is questionable whether such a generalization would improve the fit to the wage data. The value of $b$ affects $F$ and $G$ by way of the lower bound of their support. Given that the duration information dominates the wage information, and given that the resulting estimate of $\lambda_1/\delta$ is very large, there is virtually no probability mass in the left tails of $F$ and $G$. Consequently, changing the value of $b$ (within bounds) for some or all individuals will not affect the fit. Note that therefore small biases in the values of $b$ and $\underline{w}_L$ will not affect the fit either. For similar reasons, it is not clear whether allowing for unobserved within-market heterogeneity in the value of being unemployed would improve the fit to the wage data, in particular if most of these values would be close to $b$ (see also Eckstein and Wolpin (1990)). On the other hand, as will be argued below, such a generalization may generate different policy implications.

Under some restrictions, Eckstein and Wolpin's (1990) model can be estimated with (unemployment) duration data only. This provides a natural specification test. We cannot use such an approach, because in our model the job hazard depends on the wage. Note, for example, that if wages are integrated out of the likelihood function, then the latter does not depend on $p$. Also, if durations are integrated out, then the arrival rate parameters are not identified.

### 5.2. *Effect of a Change in the Minimum Wage*

It is interesting to examine the effect of an increase of the legal minimum wage on equilibrium unemployment in the present context. As mentioned in Burdett and Mortensen (1998), the imposition of a minimum wage $\underline{w}_L$ does not affect equilibrium unemployment as long as $\underline{w}_L < p$. A minimum wage exceeding the reservation wage $r$ merely redistributes part of the rent of the match from the firm to the worker, or, in other words, it decreases the monopsony power of the firm. In a segmented labor market consisting of segments with different productivity levels, the imposition of a minimum wage $\underline{w}_L$ exceeding the productivity level $p$ of a particular segment causes all firms in that segment to be unprofitable. All individuals associated with segments for which $p < \underline{w}_L$ are permanently unemployed (or, perhaps more accurately, are nonparticipant in the labor market).[20] So, in a segmented labor market the minimum wage reflects a trade-off between monopsony power and unemployment.

It turns out that a 25% increase of the legal minimum wage makes 7 segments unprofitable on a total of 174 segments (the data contain 58 different types of individuals in terms of their $x$ value, and for each $x$ value there are 3 possible $v$ values). These segments together contain 16% of all individuals (see Table XI). So, a 25% increase of the minimum wage makes 16% of the workers permanently unemployed. Most of the individuals affected by the 25% increase of $\underline{w}_L$ are between 22 and 30 years of age. Not surprisingly, this is also the age group for which the corresponding labor market segments display the weakest monopsony power $\mu$ of the firms. In those segments that do not become unprofitable, the wage distributions shift to the right.

[20] It should be noted that in Tables VII and IX for every segment the estimated value of $p$ exceeds $\underline{w}_L$.

TABLE XI

THE PERCENTAGE OF INDIVIDUALS BECOMING UNEMPLOYED WHEN THE MINIMUM WAGE IS INCREASED

| Model: | Observed Heterogeneity | Observed and Unobserved Heterogeneity |
|---|---|---|
| 10% Increase of $\underline{w}_L$: | | |
| Average | 0% | 3% |
| Age category 16–22 | 0% | 0% |
| Age category 23–29 | 0% | 10% |
| Age category 30–38 | 0% | 0% |
| Age category 39–70 | 0% | 0% |
| 25% Increase of $\underline{w}_L$: | | |
| Average | 11% | 16% |
| Age category 16–22 | 0% | 15% |
| Age category 23–29 | 42% | 56% |
| Age category 30–38 | 0% | 0% |
| Age category 39–70 | 0% | 0% |

Note that because the number of segments is finite, the size of the effect does not vary smoothly with the size of the change of $\underline{w}_L$.[21] The size of the effect depends on the distribution of the levels of $p$, and a smoother specification of this distribution would give smoother estimates of the effects of small changes of $\underline{w}_L$.

One of the major issues in the recent empirical literature on minimum wage effects concerns the presence of a spike in the wage density at the minimum wage (see Card and Krueger (1995)). A spike may indicate that the minimum wage constraint is binding, and that a substantial fraction of the workforce may be affected by a change in the minimum wage.[22] Recall from subsection 3.2 that our wage data densities do not display a spike at $\underline{w}_L$, and that this result is confirmed by other studies using different longitudinal survey data from The Netherlands in the eighties. It is conceivable that the presence of such a spike in the raw wage data is obscured by measurement errors. However, our empirical model does allow for measurement errors in wage data, and it is able to capture a spike at the minimum wage in the true wage densities (i.e., densities of wages without measurement errors). The latter can be seen as follows. If the productivity heterogeneity distribution has a mass point $p$ that is located close to the minimum wage $\underline{w}_L$, then the wage densities of the segments with this productivity $p$ would be concentrated in the tiny interval between $\underline{w}_L$ and $p$, and these densities would then display a spike very close to the minimum wage.

A large number of other studies, using data from different countries, have found evidence of spikes at the minimum wage. For a recent example see DiNardo, Fortin, and Lemieux (1996), who use U.S. data covering a long time span. From these data it seems that spikes are more important for females than for males, and that in any case they are of a temporary nature. Our sample consists primarily of males. Moreover, our model is an equilibrium model that may not be well fitted to describe movements from one equilibrium to another.

Suppose that the overall shape of the discrete distribution of $p$ just above $\underline{w}_L$ can be extrapolated to values of $p$ just below $\underline{w}_L$. Then our results suggest that unemployment of individuals aged in their twenties can be reduced substantially in the long run if their minimum wage is reduced by, say, 25%. (Such reasoning is similar to that applied in structural empirical analyses of partial job search models when addressing the effects of downward shifts in $b$.) This in turn suggests that the minimum wage is responsible for a certain amount of structural unemployment. Note that neither the model nor the data account for existing structural unemployment. It is well known that, in The Netherlands, structural unemployment is partly hidden in other social security programs like the disability program. In the data, such individuals are classified as nonparticipants. The data do not enable a distinction between (genuine) nonparticipants

[21] The smaller the change of $\underline{w}_L$, the smaller the proportionate effect on unemployment.

[22] However, in equilibrium search models, productivity levels are strictly larger than the corresponding wages. The distance between a productivity level and its corresponding average wage depends on the degree of frictions, which can only be reliably estimated from *duration* data.

by choice and structurally unemployed individuals. It should be noted that the unemployment percentages in the sample are close to the national statistics. This suggests that any existing structural unemployment is mostly hidden. It also suggests that the relatively high value of these observed unemployment percentages is mainly due to the fact that search frictions for the unemployed are relatively high. We cannot, however, preclude the possibility that there is hidden structural unemployment due to current minimum wages.

We conclude that in a labor market with considerable observed and unobserved heterogeneity in $p$, a uniform minimum wage can easily cause unemployment. This can only be avoided by making the minimum wage dependent on $p$, but such a policy would require observability of $p$ for all segments, as well as observation of the defining characteristics of all segments, which is obviously impossible. Imposing a minimum wage can make firms unprofitable in the Albrecht-Axell model as well. However, in the single labor market of that model, workers can move from low-productivity to high-productivity firms at no additional costs. In the heterogeneous Burdett-Mortensen model such shifts cannot occur, so that the two models represent polar cases. A synthesis of these models would improve our insight into the effect of the minimum wage on unemployment.

A change of the benefits level $b$ has the same qualitative implications for unemployment as a change of $\underline{w}_L$. If the new value of $b$ exceeds the productivity level $p$ of a particular segment, then all individuals in that segment become permanently unemployed. It turns out that even a 25% increase of the benefits levels in all segments keeps $b$ well below the corresponding values of $p$. So, moderate changes of $b$ do not affect unemployment. This is in line with the results cited in Section 2.

### 5.3. *Estimating the Returns to Education*

A final application of our model concerns the estimation of the returns to education. These are usually estimated from a cross-section of wages at a particular point in time. As convincingly argued by Eckstein and Wolpin (1995a), the returns to education should be estimated from the wage *offer* distribution because the latter is the distribution facing the individual searcher. In their model, the mean wage offer is smaller than the mean wage that is accepted, because individuals sometimes decide not to engage in a match. In our model, the mean wage offer is smaller than the mean wage in a cross-section of workers because of job-to-job transitions. In both models, the difference varies across individuals because individuals in different segments have different structural parameters.

We use the parameter estimates of Table IX to compute the mean wage offer for the four educational levels. The computation is rather simple if we use (2.12) and (2.13). The results are reported in Table XII (note that expressing the returns for *years* of schooling is not sensible here, because of the early assignment of children into one of a set of parallel educational streams). A

TABLE XII

RETURN TO EDUCATION: CROSS-SECTIONAL ESTIMATES (APRIL, 1985) AND ESTIMATES BASED ON THE STRUCTURALLY ESTIMATED MEAN WAGE OFFERS (DUTCH GUILDERS / MONTH)
RETURNS RELATIVE TO PRIMARY / LOWER SECONDARY LEVEL

| Education | Cross-Sectional Estimate (Standard Error) | Estimate from Structural Mean |
|---|---|---|
| Intermediate | 128.8 (31.9) | 98.0 |
| Higher | 347.2 (43.5) | 238.1 |
| University | 705.1 (68.7) | 410.0 |

*Notes:* Cross-sectional estimates are computed from a regression with age, occupation level, and education dummies as in Tables VI and IX. The structural estimates are obtained from the parameter estimates in Table IX.

comparison of the regression and structural estimates reveals that the cross-sectional estimates overestimate the return to education, in particular at advanced levels of education.

## 6. CONCLUSION

In this paper we have estimated the Burdett-Mortensen equilibrium search model of the labor market. In this model, the distributions of wage offers and earnings are endogenous and nondegenerate. We allowed for observed and unobserved heterogeneity across different segments of the labor market. It turned out that the possibility of on-the-job search has a distinctive effect on the equilibrium wage offer and earnings distributions. Because the job offer arrival rate while employed is much larger than the layoff rate, workers can climb the wage ladder with rather high speed, and as a result most wages within a particular segment are concentrated close to the marginal revenue product. As a consequence, search frictions explain about 20% of the variation in observable wage offers. Observed and unobserved heterogeneity in productivity levels across segments turn out to be the other main determinants of wages.

The results were used to examine the effects of changes in the mandatory minimum wage on unemployment. Because for most individuals aged in their twenties the productivity level is close to the present mandatory minimum wage, changing the latter has a large impact on the level of unemployment for those individuals.

The model explains most of the observed wage variation as due to either the process of labor market search or to heterogeneity in the parameters, in particular in $p$. Hence, we are more optimistic than Eckstein and Wolpin (1990) who conclude that in their model the wage variation is mainly "explained" by measurement error. Of course, a synthesis of the two models is desirable. Mortensen (1990) discusses such a synthesis. As argued in Section 5, empirical analysis of such a synthesis may increase our understanding of the effect of policy interventions like a change in the mandatory minimum wage. However, a potential problem is that uniqueness of equilibrium in the synthesis has not been proven.

Finally, it is clear the demand side of the model is not very realistic. In particular, the model assumes a stationary environment, and thus it does not incorporate external shocks that lead to the creation or destruction of jobs at existing firms. Although incorporation of this would make the model very complicated, it seems important to direct future research to this as well.

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## APPENDIX: THE LIKELIHOOD FUNCTION

In this Appendix we derive the individual contributions to the likelihood function in detail. Because the expressions depend critically on the labor market state occupied at the date of the first interview, we derive the contributions separately for individuals who are unemployed and individuals who are employed at that date. The first job or unemployment spell we use is the spell that is ongoing at the date of the first interview. In the sequel we invoke arguments analogous to those in Ridder (1984) to derive the exact distribution of such spells.

First, consider an individual who is unemployed at the date of the first interview. If the labor market is in equilibrium, then the probability of being unemployed at a randomly chosen date equals $\delta/(\delta+\lambda_0)$. Conditional on the individual being unemployed at the date of the first interview, the elapsed unemployment duration $t_{0b}$ and the residual unemployment duration $t_{0f}$ are i.i.d. and have an exponential distribution with parameter $\lambda_0$. Let $d_{0b}$ ($d_{0f}$) denote a dummy that is one if it is only known that the elapsed (residual) duration exceeds a certain value, i.e. is right-censored, and zero otherwise. The likelihood contribution of the events until and including the moment of exit out of unemployment or censoring is

$$\text{(A.1)} \qquad \mathscr{L}_0 = \frac{\delta}{\delta+\lambda_0}\cdot\lambda_0^{1-d_{0b}+1-d_{0f}}\cdot\exp(-\lambda_0(t_{0b}+t_{0f})).$$

All events occurring after exit out of unemployment are independent of the events up to exit. Consequently, their probability can be derived separately. The first relevant event is the realization of the wage $w$ in the accepted job. This is a random draw from the wage offer distribution $F(w)$. Conditional on $w$, the job duration $t_1$ has an exponential distribution with parameter $\delta+\lambda_1\overline{F}(w)$. Exit into unemployment occurs with probability $\delta/(\delta+\lambda_1\overline{F}(w))$ and exit into another job with probability $\lambda_1\overline{F}(w)/(\delta+\lambda_1\overline{F}(w))$.

As explained in the main text, we allow for measurement errors in the wage data. Specifically, we assume that the observed wage $\tilde{w}$ equals the true wage $w$ times an error term $\varepsilon$. Let $d_1$ denote a variable being one if $\tilde{w}$ is missing and zero otherwise. If $d_{0f}=1$ or $d_1=1$, then we do not follow the individual any further, so in that case (A.1) gives the total individual likelihood contribution. Let $d_2=1$ if $t_1$ is right-censored and $d_2=0$ otherwise, and let $d_3=1$ if the destination following exit out of the job is unknown and $d_3=0$ otherwise. Finally, let $d_4=1$ if the destination is another job and $d_4=0$ if the destination is unemployment. If $d_{0f}=0$ and $d_1=0$ and if the wages are measured without error, then the individual likelihood contribution $\mathscr{L}_1$ of the events between entry into employment and exit out of the first job equals

$$\mathscr{L}_1 = f(w)\cdot \exp(-(\delta+\lambda_1\bar{F}(w))\cdot t_1)\cdot(\delta+\lambda_1\bar{F}(w))^{d_3(1-d_2)} \cdot(\lambda_1\bar{F}(w))^{d_4(1-d_2)(1-d_3)}\cdot \delta^{(1-d_4)(1-d_3)(1-d_2)}$$

with $w \in \langle \underline{w}, \overline{w}\rangle$ (see Section 2 for the equations for $\underline{w}$, $\overline{w}$, $f(w)$, and $F(w)$).

Now let $\varepsilon$ have a distribution with density $h(\varepsilon)$. If $d_{0f}=0$ and $d_1=0$, then

$$\text{(A.2)}\qquad \mathscr{L}_1 = \int_{\tilde{w}/\overline{w}}^{\tilde{w}/\underline{w}} f(\tilde{w}/\varepsilon)\cdot \exp(-(\delta+\lambda_1\bar{F}(\tilde{w}/\varepsilon))\cdot t_1)\cdot(\delta+\lambda_1\bar{F}(\tilde{w}/\varepsilon))^{d_3(1-d_2)} \cdot(\lambda_1\bar{F}(\tilde{w}/\varepsilon))^{d_4(1-d_2)(1-d_3)}\cdot \delta^{(1-d_4)(1-d_3)(1-d_2)}\frac{1}{\varepsilon}\cdot h(\varepsilon)\,d\varepsilon$$

with $\tilde{w} \in \langle 0, \infty\rangle$.

To summarize, the total individual likelihood contribution for a respondent who is unemployed at the date of the first interview equals

$$\mathscr{L}_0 \cdot \mathscr{L}_1^{(1-d_{0f})(1-d_1)}.$$

It is possible to use information on events occurring after completion of $t_1$. However, for reasons explained in the main text, the joint density of observed wages in consecutive job spells contains a multidimensional integral that is computationally demanding. For only twenty three of the respondents who are unemployed at the first interview we observe more than one transition. Because of this, we have decided not to use information on events after exit from the first job after unemployment.

Now consider an individual who is employed at the date of the first interview. Under the assumptions made above, the probability of being employed at a randomly chosen date equals $\lambda_0/(\delta+\lambda_0)$. Given that the individual is employed at the date of the interview, his wage $w_1$ at that date is a random draw from the distribution $G(w)$ of paid wages. As before, we take $\tilde{w}_1 = w_1\cdot\varepsilon_1$. Let $d_5=1$ if $\tilde{w}_1$ is unobserved, and $d_5=0$ otherwise.[23] If $d_5=1$, then the likelihood contribution is $\lambda_0/(\delta+\lambda_0)$; otherwise it is constructed as follows.

Conditional on being employed in a job with a wage $w_1$ at the date of the first interview, the elapsed job duration $t_{1b}$ and the residual job duration $t_{1f}$ are i.i.d. and have an exponential distribution with parameter $\delta+\lambda_1\bar{F}(w_1)$. Exit into unemployment occurs with probability $\delta/(\delta+\lambda_1\bar{F}(w_1))$ and exit into another job with probability $\lambda_1\bar{F}(w_1)/(\delta+\lambda_1\bar{F}(w_1))$. Let $d_{6b}$ ($d_{6f}$) denote a variable being one if it is only known that the elapsed (residual) duration exceeds a certain value, i.e. is right-censored, and zero otherwise. Further, let $d_7=1$ if the destination following exit out of the job is unknown and $d_7=0$ otherwise, and let $d_8=1$ if the destination is another job and $d_8=0$ if it is unemployment.

Suppose that the destination is unemployment. The unemployment duration $t_0$ has an exponential distribution with parameter $\lambda_0$. We define $d_9=1$ if $t_0$ is right-censored, and $d_9=0$ otherwise. If the destination is another job, then the wage $w_2$ in the new job is a random draw from the wage offer distribution truncated from below at $w_1$, that is, from $F(w)/\bar{F}(w_1)$. Again, we set $\tilde{w}_2 = w_2\cdot\varepsilon_2$. The duration $t_2$ of the new job has an exponential distribution with parameter $\delta+\lambda_1\bar{F}(w_2)$. Exit into unemployment occurs with probability $\delta/(\delta+\lambda_1\bar{F}(w_2))$ and exit into another job with probability $\lambda_1\bar{F}(w_2)/(\delta+\lambda_1\bar{F}(w_2))$. We define dummy variables $d_{10}$, $d_{11}$, $d_{12}$, and $d_{13}$ that indicate whether $\tilde{w}_2$ is unobserved, whether $t_2$ is right-censored, whether the destination state is unobserved, and whether the destination state is another job. As explained in the main text, for computational reasons we do not use information on events that occur after the completion of a second spell.

[23] In the data, $d_5=0$ for 93% of the 1732 individuals employed at the date of the first interview.

If $d_5 = 0$, and if there is no measurement error, then the individual likelihood contribution equals

$$
\begin{aligned}
\text{(A.3)} \quad \mathscr{L} = {} & \frac{\lambda_0}{\delta+\lambda_0} \cdot g(w_1) \cdot (\delta + \lambda_1 \bar{F}(w_1))^{1-d_{6b}} \cdot \exp(-(\delta+\lambda_1\bar{F}(w_1)) \cdot (t_{1b}+t_{1f})) \\
& \cdot (\delta+\lambda_1\bar{F}(w_1))^{d_7(1-d_{6f})} \cdot [\delta \cdot \lambda_0^{(1-d_9)} \cdot \exp(-\lambda_0 t_0)]^{(1-d_8)(1-d_7)(1-d_{6f})} \\
& \cdot \Bigg[ \lambda_1 \bar{F}(w_1) \cdot \Bigg[ \frac{f(w_2)}{\bar{F}(w_1)} \cdot (\delta+\lambda_1\bar{F}(w_2))^{d_{12}(1-d_{11})} \\
& \qquad \cdot \exp(-(\delta+\lambda_1\bar{F}(w_2)) \cdot t_2) \cdot \delta^{(1-d_{13})(1-d_{12})(1-d_{11})} \\
& \qquad \cdot (\lambda_1 \bar{F}(w_2))^{d_{13}(1-d_{12})(1-d_{11})} \Bigg]^{(1-d_{10})} \Bigg]^{d_8(1-d_7)(1-d_{6f})}
\end{aligned}
$$

with $w_1 \in \langle \underline{w}, \overline{w} \rangle$ and $w_2 \in \langle w_1, \overline{w} \rangle$. Now let $\varepsilon_1$ and $\varepsilon_2$ be independent random drawings from the density $h(\varepsilon)$. If $d_5 = 0$ then $\mathscr{L}$ can be rewritten as in (A.2), with a bivariate integral over $\varepsilon_1$ (ranging from $\tilde{w}_1/\overline{w}$ to $\tilde{w}_1/\underline{w}$) and $\varepsilon_2$ (ranging from $\tilde{w}_1/\overline{w}$ to $\varepsilon_1\tilde{w}_2/\tilde{w}_1$) and with $0 < \tilde{w}_1, \tilde{w}_2 < \infty$. This bivariate integral must be computed numerically. Apart from the area of integration, the integral factorizes in two one-dimensional integrals. This can be exploited to increase the speed of the numerical calculation.[24]

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[24] The likelihood was programmed in Pascal. The univariate and bivariate integrals were evaluated using Gauss-Legendre quadrature after a transformation of the variable(s) of integration.

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