Estimating Measures of Labor Market Imperfection for Five OECD Countries, Using Aggregate Data in an Equilibrium Search Framework

Geert Ridder *

Gerard J. van den Berg †

September 22, 1998

Abstract

In this paper we define and estimate measures of labor market imperfection in the context of an equilibrium search and matching framework. The method uses readily available aggregate data on marginal distributions of unemployment and job durations and wages. We estimate an index of search frictions, the magnitude of structural and frictional unemployment, and the average monopsony power of firms, and we examine the effect of the minimum wage, unemployment benefits and search frictions on monopsony power. Estimation of some of the characteristics is invariant to the way in which wage determination is modeled. We perform separate empirical analyses for the USA, the UK, France, Germany and the Netherlands.

*Johns Hopkins University and Free University Amsterdam

†Free University Amsterdam, Tinbergen Institute and CEPR. E-mail: gberg@econ.vu.nl. Address: Department of Economics, Free University Amsterdam, De Boelelaan 1105, 1081 HV Amsterdam, The Netherlands.

Keywords: wages, search frictions, cross-country comparisons, unemployment, monopsony power, minimum wage.

We thank Niels de Visser for his excellent research assistance. Useful comments were provided by seminar participants at NYU, UPenn, Penn State, UCL, Johns Hopkins, and Tilburg, and by participants at the ESEM 1997 and SOLE 1998 conferences.

1 Introduction

Labor economists have accumulated evidence that is at odds with the view that the labor market is a standard competitive market, where in equilibrium the wage is equal to the value of the marginal product of the worker. This evidence shows that wages are positively related to the number of employees of the firm or establishment, even if one controls for productivity-related characteristics of the workers (Brown and Medoff (1989)), and that the wages in different industries differ persistently (Krueger and Summers (1988)). These deviations from the competitive equilibrium have been found for many countries. Evidence against the simple competitive model with a frictionless world is also provided by the fact that in many countries unemployment is persistent, and wage adjustments do not restore the balance between labor demand and supply (see e.g. Layard, Nickell and Jackman (1991) for a survey).

Recently, a literature has emerged that stresses the importance of labor market frictions and the resulting labor market flows, for understanding unemployment and wage determination (see Mortensen and Pissarides (1998) for a survey). The size of these flows is assumed to be affected by the behavior of employers and employees, who make their decisions with incomplete information on the opportunities in the market. The discovery of these opportunities is modelled as the outcome of a random process, *i.e.* random from the point of view of the individual employer or employee. The resulting delays are referred to as search frictions or informational frictions. Such models are consistent with the observed anomalies in wage determination, and also provide an explanation for persistent unemployment.

It is well-known that the presence of search frictions gives employers a certain amount of monopsony power. Basically, if firms pay wages that are strictly smaller than the value of the marginal product of the workers then it is still possible to maintain a positive workforce, because it takes time for the employees to find a better paying job. The monopsony power depends on a number of variables. First of all, if a mandatory minimum wage is imposed then in general the amount of monopsony power decreases. As long as the minimum wage (or, more generally, the institutional wage floor) does not exceed the productivity level, it merely redistributes part of the rents of the match from the firm to the worker. Secondly, if the amount of search frictions decreases for employed job seekers then this provides an incentive for a firm to pay higher wages, because otherwise the firms paying a higher wage than this firm would be able to increase their workforce substantially at the expense of this firm. At the other extreme, if workers for some reason cannot search on the job and if they have the same unemployment income, then it is optimal for wage-setting firms to offer a wage equal to the common reservation wage of the unemployed. Offering a higher wage does not increase their workforce, but it decreases their profits. The resulting equilibrium is then the same as in the model in which one firm is a monopsonist in the labor market: all firms offer a wage equal to the unemployment income (see Diamond (1971)).

The imposition of a minimum wage has the side-effect that it may induce structural unemployment. In a segmented labor market consisting of segments with different productivity levels, the imposition of a minimum wage exceeding the productivity level of a particular segment causes all firms in that segment to become unprofitable. All individuals associated with this segment then become permanently (or *structurally*) unemployed. This side-effect of the minimum wage, or wage floors in general, has widely been held responsible for at least part of the European unemployment problem. Indeed, the difference between the European and American labor markets is often phrased in terms of a choice between, on the one hand, low wages and low unemployment, and, on the other, high wages and high unemployment.

In this paper we examine the importance of labor market imperfections for a number of countries. In particular, we estimate for each country (1) an index of search frictions, (2) the amount of structural and frictional unemployment, and (3) the average monopsony power of firms. The index of search frictions is defined as the mean number of job offers that a worker receives during a spell of employment (that is, during a time period between two unemployment spells). The larger this number, the less frictions there are for employed workers. This number is of importance for wage determination: if it is large then it is relatively easy for workers to leave the firm for another firm, so it reflects the bargaining power of workers vis-à-vis employers. The average monopsony power is defined as the average fraction of labor productivity that is not paid to the worker. We use data from five OECD countries: Germany, the Netherlands, France, the United Kingdom and the USA.

In a way, the index of search frictions and the amount of frictional and structural unemployment measure the distance from a competitive market without frictions. For example, the amount of structural unemployment measures the quantity distortion induced by the wage floors in the economy. The monopsony power index then measures the extent to which employers exploit frictions when they set their wages, in the presence of a minimum wage. The actual value of this index can be contrasted to the value if on-the-job search is impossible, or if a minimum wage does not exist, or if frictions are absent (the competitive solution with zero monopsony power). It should be noted that in a world in which firms have to pay search costs and job investment costs, the absence of frictions may actually result in a less efficient equilibrium (see Caballero and Hammour (1996)).

Equilibrium search models provide a formal theoretical framework within which the issues at hand can be analyzed. By now, there is a substantial literature in which these models are developed (MacMinn (1980), Albrecht and Axell (1984), Mortensen (1990), Burdett and Mortensen (1998)), estimated (Eckstein and Wolpin (1990), Van den Berg and Ridder (1998), Koning, Ridder and Van den Berg (1995), Bowlus, Kiefer and Neumann (1995)) or both (Bontemps, Robin and Van den Berg (1999)). See Ridder and Van den Berg (1997) and Mortensen and Pissarides (1998) for surveys. In this paper we rely on equilibrium search models as an underlying theoretical framework. We will only be concerned with models which allow for search on the job and are able to generate equilibrium wage dispersion. In effect, these will all be generalizations of the basic model developed by Burdett and Mortensen (1998).

Full estimation of equilibrium search models with longitudinal labor force survey data is a non-trivial task and requires data of high quality covering long time spans, as is obvious from the empirical studies above. Such data are not readily available for every country. In this paper we show that the measures of interest (which are related to the fundamental parameters in equilibrium search models) can be estimated from aggregate data that are obtained from yearly cross-sectional surveys (such as the US Current Population Survey (CPS) and the EC Labor Force Surveys (LFS); these aggregate data are obtained from readily available OECD and EUROSTAT publications). This may come as a surprise, since equilibrium search models deal with interrelations between duration and wage variables, while aggregate data only contain information on the marginal distributions of wages and durations. For example, the models stipulate that the current wage and the wage offer distribution affect the exit rate out of a job, and that job offer arrival rates affect the shape of the wage offer distribution itself.

Thus, the methodological contribution of this paper is the demonstration that the measures of interest can be estimated from readily available aggregate data. This is useful if micro panel data are not available or if the scope of a study does not allow a detailed and sophisticated estimation of search models even though an evaluation of labor market imperfection is warranted. Moreover, given the high requirements of the quality of the longitudinal data and the relatively small number of observations and high attrition rate in most of those data, estimates from aggregate data derived from repeated cross-sections provide a useful comparison. Finally, and this is a subject for further research, empirical research on models with an endogenous contact rate requires a combination of time-series and cross-section information over a period that exceeds the observation period of most panel studies.

Our estimation method is sequential and it closely follows the relation between a certain measure and data on a particular variable. For example, we show that data on marginal job durations (that is, job durations that are not conditioned on the wage) allow us to estimate the index of search frictions, without the need to estimate other parameters simultaneously. In some instances we use all available degrees of freedom in the data, and it is perhaps more appropriate to describe our inferences as calibration instead of estimation[1]. The relation between a certain measure and data on a particular variable is often valid under a wide range of models. This means that we do not have to confine ourselves to one particular (equilibrium search) model. For example, estimation of the index of search frictions from marginal job duration data only requires that employed job seekers behave according to the partial on-the-job search model of repeated search. As a result, the methodological contribution of this paper stretches beyond the analysis of equilibrium search.

With additional assumptions, the estimates of the friction parameters are used to compute factual and counterfactual measures of the degree of monopsony power and to decompose wage variation into variation due to productivity differences and variation due to search frictions. These additional assumptions are on the nature of productivity variation, in particular whether these differences are associated with workers or with firms. To decide this issue we would need micro panel data, and for that reason we consider the two extreme cases (all productive differences are associated with workers and these workers operate on distinct labor markets, and all productive differences are associated with firms and there are no separate markets) to bound our estimates.

In section 2 we introduce the equilibrium search framework. The estimation procedure is described in sections 3-5. Section 6 discusses the data and the estimation results. Section 7 contains the conclusions. In the Appendix we discuss our approach in the light of alternative theories of labor markets with informational frictions.

[1]For that reason we do not report standard errors. In cases where there are fewer parameters than observations, these standard errors depend on the details of the sample design of the CPS and LFS, and these details are not available to us.

2 The theoretical framework

2.1 The basic Burdett-Mortensen equilibrium search model

We use extensions of the homogeneous equilibrium search model of Burdett and Mortensen (1998) and Mortensen (1990) to interpret the estimation results and occasionally derive empirical equations. It is thus useful to review this basic homogeneous model briefly. We should stress that we do not claim that this model gives an accurate description of the whole labor market. In subsection 2.2 we briefly discuss extensions of the basic model that are supposed to increase the degree of realism of the basic model, notably by allowing for heterogeneity. Most of these extensions have been developed in the recent literature (see references below).

The basic model considers a labor market consisting of a continuum of workers and firms. The measure of workers is denoted by m, and the measure of unemployed workers by u. The measure of firms is normalized to one.

The supply-side is equivalent to a standard partial job search model with on-the-job search (see Mortensen (1986)). Workers obtain wage offers, which are random drawings from the wage offer distribution $F(w)$, at an exogenous rate λ_0 when unemployed and λ_1 when employed. Whenever an offer arrives, the decision has to be made whether to accept it or to reject it and search further for a better offer. Layoffs accrue at the constant exogenous rate δ. The opportunity cost of employment is denoted by b and is assumed to be constant across individuals and to be inclusive of unemployment benefits. The optimal acceptance strategy for the unemployed is characterized by a reservation wage ϕ satisfying

$$\phi = b + (\lambda_0 - \lambda_1) \int_{\phi}^{\infty} \frac{1 - F(w)}{\delta + \lambda_1 (1 - F(w))} \mathrm{d}w \tag{1}$$

Employed workers accept any wage offer that exceeds their current wage. In sum, workers climb a job ladder to obtain higher wages, but this effort may be frustrated by a spell of (frictional) unemployment. Note that λ_1/δ equals the average number of job offers in a given spell of employment, since the average duration of a spell of employment is $1/\delta$, and job offers arrive according to a Poisson process with parameter λ_1. This quantity is of importance in the sequel.

Now consider the flows of workers. First, note that firms do not offer a wage below ϕ, so that all offers are acceptable for the unemployed. Consequently, the flow from unemployment to employment is $\lambda_0 u$. The flow from employment to unemployment is $\delta(m - u)$. In a steady state these flows are equal and the resulting rate of unemployed workers is

$$\frac{u}{m} = \frac{\delta}{\delta + \lambda_0} \tag{2}$$

Let the distribution of wages paid to a cross-section of employees have distribution function G. These wages are on average higher than the wages offered, because of the flow of employees to higher paying jobs. The stock of employees with a wage less or equal to w has measure $G(w)(m-u)$. The flow into this stock consists of unemployed who accept a wage less than or equal to w, and this flow is equal to $\lambda_0 F(w)u$ The flow out of this stock consists of those who become unemployed, $\delta G(w)(m-u)$ and those who receive a job offer that exceeds w, $\lambda_1(1-F(w))G(w)(m-u)$. In the steady state, the flows into and out of the stock are equal, so

$$G(w) = \frac{\delta F(w)}{\delta + \lambda_1(1-F(w))} \tag{3}$$

where we have substituted for u from equation (2).

From the two wage distributions we derive the steady-state supply of labor $l(w|F)$ to an employer setting a wage w, where we explicitly indicate its dependence on the wages offered by other firms. Somewhat loosely, one may say that this must equal the number of workers earning w in a steady state, divided by the number of firms paying w in the steady state. The equilibrium F and G cannot have a mass point, because then the workforce and the profits of a firm offering slightly more than the wage at the mass point would be substantially higher than the workforce and profits of the firms at the mass point. As a result,

$$l(w|F) = \frac{m\delta\lambda_0(\delta + \lambda_1)}{\delta + \lambda_0} \frac{1}{(\delta + \lambda_1(1-F(w)))^2} \tag{4}$$

where of course w has to exceed both ϕ and the mandatory or legal minimum wage, which is denoted by w_{min} (Van den Berg and Ridder (1998) extend the basic model by allowing for such a minimum wage). It is easily seen that l increases in w on the support of F, if $0 < \lambda_1 < \infty$.

Now consider optimal wage setting by the employer. We assume that the marginal value product p does not depend on the number of employees, *i.e.* we assume that the production function is linear in employment. Assume that $p > \max\{b, w_{min}\}$. The steady-state profit flow of the firm paying w equals $(p-w)l(w|F)$. The wage offer of the firm maximizes this profit flow, given F and given the behavior of workers. Burdett and Mortensen (1998) show that this game has a unique non-cooperative steady-state equilibrium solution, with

$$F(w) = \frac{\delta + \lambda_1}{\lambda_1}\left(1 - \sqrt{\frac{p-w}{p-\underline{w}}}\right) \tag{5}$$

F has support $(\underline{w}, \overline{w})$, with

$$\underline{w} = \max\{\phi, w_{min}\} \qquad \text{and}$$

$$\overline{w} = \left(\frac{\delta}{\delta+\lambda_1}\right)^2 \underline{w} + \left(1 - \left(\frac{\delta}{\delta+\lambda_1}\right)^2\right) p \tag{6}$$

Furthermore,

$$G(w) = \frac{\delta}{\lambda_1}\left(\sqrt{\frac{p-\underline{w}}{p-w}} - 1\right) \tag{7}$$

The equilibrium has some properties that are important for our purposes. First of all, wages are dispersed, and all workers face a non-degenerate wage offer distribution. As a result, job-to-job transitions do occur. Secondly, firms always offer wages that are smaller than their productivity level, so they do have a certain monopsony power. Thirdly, the lowest wage in the market is either the minimum wage or the reservation wage of the unemployed. The frictional unemployment rate u/m does not have a "choice" component. Consequently, it is fully determined by the magnitudes of the arrival rates λ_0 and δ. Finally, note that F and G only depend on λ_0, λ_1 and δ by way of the ratios λ_0/δ and λ_1/δ, which will be denoted by k_0 and k_1, respectively (λ_0 only affects wages by way of ϕ).

Because all workers and firms are identical, the presence of wage dispersion implies that the law of one price does not hold in equilibrium. However, we obtain the competitive equilibrium, in which all wages are equal to p, and the monopsonistic equilibrium, in which all wages are equal to $\max\{b, w_{min}\}$, as limits of the equilibrium solution. If λ_0 approaches infinity, *i.e.* if the unemployed find jobs instantaneously, then they can afford to be extremely selective with respect to wage offers. As a result, ϕ approaches p, and the wage offer and wage distributions are degenerate in p. If λ_1 approaches infinity, *i.e.* if the employed find jobs instantaneously, then workers instantaneously move to the top of the wage ladder, and the wage distribution G approaches the degenerate distribution at p. In this case ϕ does not approach p, and neither does F. However, this is irrelevant, because an unemployed worker, upon leaving unemployment, immediately moves to a wage p. As a result, firm profits are equal to zero (all this also holds if k_1 approaches infinity). At the other extreme, if λ_1 (or k_1) approaches zero, *i.e.* if the employed do not receive alternative job offers, then the distributions F and G are degenerate at $\max\{b, w_{min}\}$. In the (general) intermediate case, the wage (offer) distributions for larger k_1 first-order stochastically dominate the wage (offer) distributions for smaller k_1.[2]

In traditional monopsony models of the labor market, $(p-w)/w$ is used as a measure of the monopsony power of a firm paying w. The value of $(p-w)/w$ can be shown to equal the relative increase in w needed for a 1% increase in the workforce of the firm. The latter is also true for the present model (Boal and Ransom (1997)). In fact, we adopt $(p-w)/p$ as our measure of the monopsony power of a firm paying w. This is of course a monotone transformation of $(p-w)/w$. Note that in the present case wages are dispersed, so our measure of the monopsony power in the labor market has to be based on an average value (see section 5).

The basic equilibrium search model is a highly stylized model with strong implications for the distribution of unemployment and job spells. Are these predictions consistent with empirical evidence? Of course, not much should be expected from a model that assumes that all workers and firms are identical. In equilibrium, all job offers are acceptable to the unemployed, and the re-employment hazard is equal to the offer arrival rate. This is consistent with the empirical evidence in *e.g.* Devine and Kiefer (1991) and Van den Berg (1990). Although job search models originally were introduced as a potential explanation for the existence of unemployment, most empirical studies find that rejection of job offers is rare. Note that the homogeneous model does not allow for structural unemployment. The rate at which job spells end decreases with the wage. This is consistent with empirical evidence (Lindeboom and Theeuwes (1991)). In equilibrium there is a positive association between firm size and wage. Hence, the model is consistent with the employer size wage effect as well.[3] However, the actual solutions for the equilibrium wage (offer) distribution have increasing densities. This implication is at odds with the data. This means that the shapes of the empirical wage (offer) distributions are not explained by the model.

2.2 Extensions of the basic model

In this subsection we examine some extensions of the basic model. We focus in particular on heterogeneity in the firms' productivity levels p. As argued

[2]This is true if $\phi < w_{min}$. If $\phi > w_{min}$ and k_1 is not very small then an increase in k_1 decreases ϕ, so until ϕ decreases below w_{min}, the stochastic dominance is not of first order.

[3]See also Kiefer and Neumann (1993) and Ridder and Van den Berg (1997).

in Ridder and Van den Berg (1997) and Bontemps, Robin and Van den Berg (1999), heterogeneity in p is essential to obtain an acceptable fit to observed wages. We restrict attention to issues that are of importance for the measures of labor market imperfection. For sake of brevity we refer to the literature for details on the derivation of the equilibria and other properties. The maintained assumption is that all workers who are attached to a given labor market are homogeneous in terms of their opportunity cost of employment.

Van den Berg and Ridder (1998) estimate versions of the Burdett and Mortensen (1998) model in which the labor market is considered to consist of a large number of segments. Each segment is a separate labor market of its own, and workers and firms in a particular segment are homogeneous. The segments are defined by observed characteristics like occupation as well as by unobserved characteristics. Each segment has its productivity level p, and in each market the equilibrium is as in the basic model. Such *between-market* heterogeneity can be associated with the worker or with the firm. We shall not relate the productivity levels to characteristics of workers and/or firms that are observable in micro data. Our aggregate data do not allow us to make distinctions. We take the distribution function $\Phi(p)$ to describe how p is distributed across the individuals in the population.

Allowing for between-market heterogeneity in p enriches the model by adding the possibility of structural unemployment. In a given segment, as long as the minimum wage is lower than p, the level of unemployment is independent of the minimum wage. If w_{min} exceeds ϕ then a further increase in the minimum wage shifts the whole wage (offer) distribution upwards. That is, it redistributes the rents of the match by lowering the profits of all employers and raising the income of all workers. In effect, it decreases the monopsony power of firms. If the minimum wage exceeds the productivity p, firms will close, and all workers become permanently (structurally) unemployed. (The same holds if $b > p$, but this turns out to be empirically less relevant.)

The unemployment rate is equal to

$$\frac{u}{m} = \frac{\delta}{\delta + \lambda_0}(1 - \Phi(w_{min})) + \Phi(w_{min}) \tag{8}$$

The first term on the right-hand side of this equation reflects frictional unemployment and the second-term structural unemployment.

Now consider *within-market* heterogeneity in p. Mortensen (1990) and Bontemps, Robin and Van den Berg (1999) examine models in which firms that are active in a given labor market have different labor productivity levels p. As a result, workers are more productive in one firm than in another. This alters the equilibrium solution. Mortensen (1990) assumes that the distribution of productivities is discrete, whereas Bontemps, Robin and Van den Berg (1999) assume that this distribution is continuous. Without loss of generality we adopt the continuous case, because it provides more convenient expressions for the equilibrium solution. The model by Mortensen (1990) has been estimated by Bowlus, Kiefer and Neumann (1995). Bontemps, Robin and Van den Berg (1999) estimate their continuous model and show that it gives a perfect fit to the cross-sectional wage density for an appropriate choice of the productivity distribution.

The equilibrium is characterized as follows. As before, p is the marginal revenue of employing a worker, and p does not depend on the number of workers at the firm. The steady-state profit flow can again be expressed as $(p-w)l(w|F)$. It is important to stress that the expressions for ϕ and u/m and for $G(w)$ and $l(w|F)$ as a function of $F(w)$ are exactly the same as in equations (1), (2), (3) and (4) above. This is because worker behavior conditional on F is the same as in the basic model. We denote as $\underline{p}$ the lowest productivity of firms which make a non-negative profit and thus are active on the market, and as $\Gamma(p)$ the distribution of p among active firms. Obviously, $\underline{p} \geq \max\{\phi, w_{min}\}$ (note that the measure of active firms is endogenous). Bontemps, Robin and Van den Berg (1999) show that the non-cooperative steady-state equilibrium solution has the following properties. First of all, as in the basic model, $\underline{w} = \max\{\phi, w_{min}\}$. Secondly, the wage offer $w \equiv K(p)$ of a firm with productivity p equals

$$K(p) = p - \left[\frac{\underline{p} - \max\{\phi, w_{min}\}}{[1+k_1]^2} + \int_{\underline{p}}^{p} \frac{dx}{\left[1 + k_1 \overline{\Gamma}(x)\right]^2} \right] \left[1 + k_1 \overline{\Gamma}(p)\right]^2 \qquad (9)$$

Thus, more productive firms offer higher wages than less productive firms. By combining (9) with the reservation wage equation we obtain an expression for w given p, Γ, b, λ_0 and λ_1. By invoking $F(w) = \Gamma(K^{-1}(w))$, we also obtain the expression for $F(w)$. In general it is not possible to obtain closed-form expressions for $K(p), F(w)$ or $G(w)$. As a special case, if $\Gamma(p)$ is a uniform distribution or an exponential distribution then a closed-form expression for $K(p)$ can be derived. However, in the last case there is no closed-form solution for $K^{-1}(w)$, and therefore neither for $F(w)$.

In equilibrium, wages are dispersed, and all workers face a non-degenerate wage offer distribution. As a result, job-to-job transitions do occur. It is clear from equation (9) that the mapping $K(p)$ from productivities to wage offers depends on the size of the search frictions. Bontemps, Robin and Van den Berg (1999) show that in general, $K(p)$ increases in k_1. If $k_1 = 0$ then the distributions

F and G are degenerate at $\max\{b, w_{min}\}$.

Firms always offer wages that are smaller than their productivity level, so they do have a certain monopsony power. Productivity dispersion affects the distribution of this monopsony power across firms. In particular, dispersion favors high-productivity firms disproportionally relative to low-productivity firms, because any wage set by the latter necessarily lies in the narrow interval between the minimum wage and the low productivity level itself. If the minimum wage increases then unemployment is not affected in this model. Firms with a p below the old and the new minimum wage close down, and workers move to firms with higher p. Hence, in a labor market with only within market heterogeneity there is no structural unemployment.

It is straightforward to construct a model that allows for both within-market and between-market heterogeneity in p. For example, consider a labor market that consists of a number of segments, each of which has a within-market productivity distribution with a bounded support, while the support itself varies across segments. Then there is structural unemployment if the minimum wage exceeds the upper bound of the support of the productivity distribution for some segment. The distribution across segments of the upper bound of the support determines the amount of structural unemployment.

There are empirical facts that cannot be described by the equilibrium search models considered here. In labor economics there has been a lively debate on the positive relation between wages and labor market experience. The present model only allows for wage growth due to transitions from lower to higher paying jobs. Attempts have been made to construct an equilibrium search model in which firms offer a wage-tenure profile, but thus far the resulting models have unappealing empirical predictions (Burdett and Coles (1993)). It should be noted that Altonji and Williams (1997), in the most recent contribution to the descriptive empirical literature, convincingly argue that wage growth due to wage growth on the job is of a smaller order of magnitude than was suggested in some of the earlier work.

A low value of δ may be a result of stringent job protection laws, and thus may reflect an important source of labor market imperfection. For this reason, we do not focus exclusively on λ_1/δ as the index of search frictions, but we also examine the absolute value of λ_1 as a measure of these frictions. It should be noted that certain important features of the models (notably the equilibrium wage distributions) are invariant to allowing δ to be a function of the current wage; see Ridder and Van den Berg (1997).

A convenient feature of the equilibrium search models reviewed so far, is that they can easily deal with taxation of wage income. Let w be the gross wage, *i.e.*

the wage paid by the employer, and let w_N be the net after-tax wage received by the worker. With proportional taxation at rate τ and a fixed deductible d, we have

$$w_N = (1-\tau)w + \tau d \tag{10}$$

If the marginal tax rate is less than 1, the net wage increases with the gross wage, and the acceptance decisions of the workers are independent of the tax rate. Employees base their acceptance decisions on net wages, and a net wage offer exceeds the current net wage if and only if the gross wage offer exceeds the current gross wage. Hence, taxation has no effect on the wages set by the employers, and all expressions mentioned so far apply. The only difference concerns the reservation wage of the unemployed. If unemployment income is not taxed, and b is net unemployment income, then (1) holds after substitution of $(b-\tau d)/(1-\tau)$ for b, with ϕ the before tax reservation wage of the unemployed[4]. The before-tax reservation wage is the reservation wage that is used in the determination of the lower bound of the wage offer distribution. Note that the deductible d lowers the before-tax reservation wage of the unemployed. In our analysis we ignore variation in unemployment income b. Because on average $b < w_{min}$, unemployment due to rejection of job offers is predicted to be absent. Micro-simulation models suggest that there is variation in b (OECD (1997)), so that some unemployment may indeed be caused by high reservation wages. If that is true, then a deductible that is conditional upon employment, as the Earned Income Tax Credit in the US, may lower these high reservation wages. We shall explore this issue in future work.

In the empirical analysis we use both before and after tax wage data. Because the wages are set by employers, it is natural to focus on before-tax wages. In the estimation of the friction parameters we do not use wage data. The wage data are only used for the estimation of the monopsony index and the variance decomposition. However, with data on the (average) tax rate, it is easy to compute before-tax quantities.

[4]If unemployment income is taxed as wage income, the before-tax reservation wage is given by (1)

3 Inference on structural and frictional unemployment

In sections 3–5 we discuss inference on the measures of labor market imperfection using aggregate data. It is thus useful to start each section with a brief account of the type of aggregate data that are typically available. Section 6 discusses the data we actually use in more detail.

Inference on the index of search frictions and the average monopsony power builds on inference on unemployment, so we start with the latter. Aggregate unemployment data typically consist of (a) the unemployment rate, *i.e.* the size of the stock of unemployed as a fraction of the labor force, and (b) the frequency distribution of elapsed unemployment durations in the stock of unemployed. It is clear that the unemployment rate does not allow us to identify both structural and frictional unemployment. In the vein of subsection 2.2, the stock of unemployed consists of two groups: the structurally unemployed with zero exit rate, and the frictionally unemployed with exit rate λ_0. The latter group has a changing composition, whereas the former does not.

Let the structural unemployment rate (as a fraction of the labor force) be denoted by q. According to equation (8), q equals $\Phi(w_{min})$. The amount of structural unemployment as a fraction of total unemployment can then be expressed as $q/(u/m)$, which will be denoted by π. (Consequently, the structural and frictional unemployment rates can be expressed as $\pi u/m$ and $(1-\pi)u/m$, respectively.) Now consider a large sample from the stock of unemployed persons. A fraction π has a zero exit rate and infinite unemployment durations. A fraction $1-\pi$ has an exit rate equal to λ_0. An inflow sample of these frictionally unemployed has an unemployment duration distribution that is exponential with parameter λ_0. It is well known that the corresponding distribution of elapsed durations in the stock has the same distribution. We do not observe to what type an unemployed individual belongs. Consequently, the observed distribution $\Psi(t)$ of elapsed durations t in the stock is a mixture of a degenerate distribution with a single mass point at infinity and an exponential distribution with parameter λ_0. The survival function equals

$$\overline{\Psi}(t) \equiv 1 - \Psi(t) = \pi + (1-\pi)e^{-\lambda_0 t}$$

This is a discrete mixture of exponentials with two mass points, one of which is fixed at zero. Aggregate data provide observations on the fraction of unemployed in a finite number of duration intervals $[t_i, t_{i+1})$. The corresponding probabilities equal $\Psi(t_{i+1}) - \Psi(t_i)$. Thus, the parameters λ_0 and π (and therefore q) can be readily estimated.

Some comments are in order. First, in reality, no one has an infinite elapsed duration. The fraction π is estimated by comparing the fraction of unemployed in the last (open) duration interval to the fraction predicted by an exponential distribution with parameter λ_0 fitted to the earlier duration intervals. For most countries the open interval concerns durations that exceed two years, and it seems reasonable to assume that a fraction of those unemployed are structurally unemployed in the sense defined above. Secondly, it is clear that the model is overidentified, and specification tests can be applied. In particular, we can fit an unrestricted exponential mixture and compare its fit to the defective mixture in the model with structural unemployment. Thirdly, structurally unemployed individuals may be underrepresented in unemployment figures. These individuals will never find a job, so they may classify themselves as a nonparticipant when being questioned on their labor market state. Some of them may also be counted as disabled or retired (and as claiming disablement or retirement benefits), even though they are still able and willing to work. Their underrepresentation may have been less serious in the EC countries until 1992, because until that year unemployed individuals who were willing and able to work, but who were not looking for a job were counted as unemployed. Since 1992 these individuals are considered to be nonparticipants, as they have always been in the US. This problem cannot be solved by adding all nonparticipants to the unemployed, because the state of nonparticipation also includes individuals who are clearly not structurally unemployed. For example, it includes all mothers who are at home full time. The data do not enable a distinction between these different groups of nonparticipants. Therefore we cannot deal with this any further. In any case, the structural unemployment rate may be underestimated because of this, and the bias is likely to be larger in the US. Fourthly, the estimates of λ_0 and π will in general depend on the year from which the data are. In particular, they can be expected to vary over the business cycle. We investigate this by using data from several years.

Once λ_0 and π are estimated, it is trivial to obtain an estimate of δ by employing equation (8), which can be rewritten as

$$\frac{u}{m} = \pi\frac{u}{m} + (1 - \pi\frac{u}{m})\frac{\delta}{\delta + \lambda_0}$$

Given data on the unemployment rate u/m, an estimate of δ follows from this equation.

4 Inference on the index of search frictions

We use k_1, *i.e.* λ_1/δ, as our index of search frictions. This index equals the average number of job offers in a spell of employment. As shown above, it is informative on the speed at which workers climb the job ladder, and thus on the strength of the bargaining position of workers. Note that in all of the equilibrium models considered, $F(w)$ and $G(w)$ depend on λ_1 only by way of k_1. It is also interesting to know the value of λ_1 itself, as it is a structural parameter (note that the previous section provides an estimate of δ).

According to equilibrium search models, k_1 affects the wage (offer) distribution. However, it is obvious that data on the wage distribution G only do not suffice to identify k_1, and Van den Berg and Ridder (1993) show that estimation of k_1 is problematic even if data on both G and F are available. We therefore turn to data on job durations.

Aggregate data contain information on a number of variables that are related to job durations and flows into and out of jobs. All of these variables are unconditional on the wage in the job. In terms of the model this means that we have to integrate wages out of the job duration distribution. It is useful to derive some results before comparing the different pieces of information in the data.

4.1 The flow into employment

First of all, consider the flow of workers from unemployment into *employment* at a given point of time. We call this the *E-inflow.* More specifically, consider the job spells t_{uj} of a cohort of workers recruited from those who have just left unemployment for a job. We call a sample from this cohort an E-inflow sample of job durations. The distribution of t_{uj} given the wage w on the job is exponential with density (in the sequel φ denotes a density function)

$$\varphi(t_{uj}|w) = (\delta + \lambda_1 \overline{F}(w))e^{-(\delta+\lambda_1\overline{F}(w))t_{uj}} \tag{11}$$

The wage w is distributed according to $F(w)$, as we consider the inflow into employment and all unemployed workers accept any wage that is offered to them. After integration of (11) with respect to $dF(w)$ we obtain

Proposition 1 *If unemployed workers accept all job offers and employed workers accept any job with a wage higher than the current one, then the density of the job duration t_{uj} following inflow into employment equals*

$$\varphi(t_{uj}) = \frac{e^{-\delta t_{uj}}}{\delta k_1 t_{uj}^2}\left[1 + \delta t_{uj} - (1 + \delta(1 + k_1)t_{uj})e^{-\delta k_1 t_{uj}}\right]$$

irrespective of the wage offer distribution.

A number of comments is in order. First of all, the density above can be rewritten as

$$\varphi(t_{uj}) = \frac{1}{\lambda_1} \int_{\delta}^{\delta+\lambda_1} z e^{-z t_{uj}} dz \tag{12}$$

This highlights that the marginal density of t_{uj} is a mixture of exponentials *i.e.*, a mixture of distributions with constant hazards, with a uniform mixture distribution for the hazards with support on the interval $(\delta, \delta + \lambda_1)$. This is not surprising. The conditional hazard of t_{uj} given w is constant over the job duration. It is then mixed with respect to a determinant (w) of the conditional hazard. After a change of variable, the variable of integration can be interpreted as the job exit rate. The value of the conditional (on w) hazard ranges from δ to $\delta + \lambda_1$. These limiting values correspond to a job with a wage equal to $\overline{w}$ and a job with a wage equal to $\underline{w}$, respectively.

Now consider the hazard of the marginal distribution of t_{uj}. At the one extreme, at $t_{uj} = 0$, this equals $\delta + \frac{1}{2}\lambda_1$. This is plausible. The rate δ represents exit into unemployment, while for the individuals who just entered employment, on average half of the new jobs offered to them are acceptable. At the other extreme, when $t_{uj} \to \infty$, the hazard of t_{uj} converges to δ. This is plausible as well, because the longest job spells correspond to jobs with the highest wage in the market, for which the exit rate to jobs with even higher wages is zero. In between zero and infinity, the hazard of t_{uj} decreases monotonically, as the distribution of t_{uj} is a mixture of exponential distributions. Basically, jobs with lower wages end quicker because of transitions to higher paying jobs, so that the remaining jobs tend to have higher wages and lower exit rates.

The proposition above has far-reaching implications. Most importantly, the marginal job duration distribution does not depend on F, and therefore neither on the way it is determined. The result is thus valid under a wide range of models of wage determination, including equilibrium search models with any within-market and/or between-market heterogeneity, but also models in which workers *e.g.* simply get a constant fraction of productivity. In all of these cases, the resulting marginal job duration distribution does not depend on the determinants of F (like the productivity distribution). It is merely needed that workers accept jobs with a wage that exceeds the current wage, and that the unemployed accept any job offer. As we have seen in section 2, sufficient conditions for the latter are that workers are homogeneous in terms of their unemployment income, or that the minimum wage exceeds the reservation wage of the unemployed. In sum, the density of t_{uj} only depends on λ_1 and δ, or, equivalently, on k_1 and δ. The intuition behind this result is that workers' behavior merely focuses on the ordering of the current wage and the wage offer and not on the shape of the underlying wage offer distribution itself.

4.2 The flow into jobs

In general, aggregate data do not provide information on job durations following a transition from unemployment to employment. They do however often contain the grouped distribution of elapsed job durations in the stock of employed. In addition, they sometimes contain the fraction of newly created jobs that dissolve within a given time period (*the job separation rate for newly created jobs*). For expositional reasons, it is useful to start with the latter. So we consider the total flow of workers into *jobs* at a given point of time. We call this the *J-inflow*. To our knowledge, this flow has not been defined (or analyzed) before. It is crucial to understand that it is not the same as the E-inflow. This is because part of the flow into jobs consists of workers who already had (another) job. The previous job of these workers had a wage that was higher than the reservation wage of the unemployed. Consequently, the accepted wages in the J-inflow are on average higher than the accepted wages in the E-inflow.

Consider the job spells t_{*j} of a cohort of workers who just started in a new job after leaving unemployment or after leaving their previous job (J-inflow). We call this a J-inflow sample of job durations. The density of t_{*j} given the wage w on the job is of course the same as for t_{uj} given w,

$$\varphi(t_{*j}|w) = (\delta + \lambda_1 \overline{F}(w))e^{-(\delta+\lambda_1\overline{F}(w))t_{*j}} \tag{13}$$

We now need to determine the distribution of w in the J-inflow. At a given point in time, the fraction of frictionally unemployed workers is $\delta/(\delta+\lambda_0)$. This is a fraction of the workers that are active, *i.e.* of $(1-q)m$. Of these, $\lambda_0 dt$ receive a job offer in a small interval with length dt. The corresponding wage offer has density $f(w)$. Consequently, the joint probability density of the events of being unemployed, receiving a job offer and flowing into a job with wage w equals

$$\frac{\delta}{\delta+\lambda_0}\lambda_0 f(w) \tag{14}$$

At the same point of time, the fraction of employed workers is $\lambda_0/(\delta+\lambda_0)$. (Again, this is a fraction of the workers that are active, *i.e.* of $(1-q)m$.) The density of wages w_0 among them is $g(w_0)$, which is the density associated with

G. Of these workers, $\lambda_1 dt$ receive a job offer in a small interval with length dt. The corresponding wage offer has density $f(w)$. This offer is acceptable if $w > w_0$. Consequently, the joint probability density of the events of being employed, earning a wage w_0, receiving a job offer, accepting it, and subsequently earning a wage w equals

$$\frac{\lambda_0}{\delta+\lambda_0} g(w_0)\lambda_1 \overline{F}(w_0)\frac{f(w)}{\overline{F}(w_0)}\mathrm{I}(w_0 < w < \infty) \tag{15}$$

in which I(.) is the indicator function of the event between parentheses. By the law of total probability we add (14) and (15) to obtain the joint density of w and w_0. The density of w in the J-inflow follows by integration over w_0. In the steady-state, *i.e.* if worker flows in and out all states are equal, the density g can be expressed in terms of F and the frictional parameters (see equation (3) in subsection 2.1). As a result,

Proposition 2 *If unemployed workers accept all job offers and employed workers accept any job with a higher wage, and if worker flows are in equilibrium, then the density of accepted wages w in the inflow into jobs equals*

$$\varphi(w) = \frac{k_1}{\log(1+k_1)} \frac{f(w)}{1+k_1\overline{F}(w)} \tag{16}$$

Note that, as predicted, the corresponding distribution first-order stochastically dominates F.

We are now in a position to derive the marginal density of t_{*j}.

Proposition 3 *If unemployed workers accept all job offers and employed workers accept any job with a higher wage, and if worker flows are in equilibrium, then the density of job durations t_{*j} following the inflow into a job equals*

$$\varphi(t_{*j}) = \frac{1}{\log(1+k_1)} \frac{1}{t_{*j}} e^{-\delta t_{*j}} \left[1-e^{-\lambda_1 t_{*j}}\right] \tag{17}$$

irrespective of the wage offer distribution.

This result is qualitatively similar to the result in Proposition 1. First of all, the density above can be rewritten as

$$\varphi(t_{*j}) = \frac{1}{\log(1+k_1)} \int_{\delta}^{\delta+\lambda_1} \frac{1}{z} \left[z e^{-z t_{*j}}\right] dz \tag{18}$$

Thus, the marginal density of t_{*j} is again a mixture of exponentials, but now with a log-uniform mixture distribution for the hazard, with support on $(\delta, \delta + \lambda_1)$, [5]

$$\varphi(z) = \frac{1}{\log(1+k_1)} \frac{1}{z} \, \mathrm{I}(\delta < z < \delta + \lambda_1)$$

Now consider the hazard of the marginal distribution of t_{*j}. This hazard is equal to $\lambda_1 / \log(1+k_1)$ for $t_{*j} = 0$, and it converges to δ when $t_{*j} \to \infty$. In between, the hazard decreases monotonically, and this is of course again a consequence of the mixing introduced by integration over wages.

The marginal distribution of job durations t_{*j} does not depend on F, and therefore neither on the way it is determined. The result is therefore valid under a wide range of models of wage determination. The only additional assumption in comparison to the marginal distribution of job durations in the E-inflow is that flows of workers have to be in equilibrium.

4.3 The stock of employed

Next, we consider the distribution of elapsed job durations t_e in the stock of the employed. The stock of workers in *employment* at a given point of time is called the *E-stock*. The wages in the E-stock are on average higher than the accepted wages in the J-inflow. This is because, in a stock sample, high durations are overrepresented, and a high job duration corresponds to a high wage on the job. The distribution of elapsed job durations in this stock is easily derived from the density of complete job durations in the J-inflow, using the familiar relation between cohort and stock duration densities (see *e.g.* Ridder (1984))

$$\varphi(t_e) = \frac{\overline{\Phi}(t_{*j})}{\mathrm{E}(t_{*j})}$$

where $\overline{\Phi}$ and $\mathrm{E}(t_{*j})$ denote the survivor function and mean of the distribution of t_{*j}. As a result, under the same conditions as Proposition 3, and because

$$\mathrm{E}(t_{*j}) = \frac{1}{\delta} \frac{1}{\log(1+k_1)} \frac{k_1}{1+k_1},$$

Proposition 4 *If unemployed workers accept all job offers and employed workers accept any job with a higher wage, and if worker flows are in equilibrium, then the density of elapsed job durations in the stock of employed workers equals*

[5] A random variable z has a log-uniform distribution iff $\log z$ has a uniform distribution.

$$\varphi(t_e) = \frac{\delta(1+k_1)}{k_1} \int_{\delta}^{\delta(1+k_1)} \frac{1}{z}\, e^{-zt_e}\, dz \tag{19}$$

irrespective of the actual shape of the wage offer distribution.

Again, the result in the proposition is qualitatively similar to the result in Proposition 1. First of all, the density above can be rewritten as

$$\varphi(t_e) = \frac{\delta(1+k_1)}{k_1} \int_{\delta}^{\delta+\lambda_1} \frac{1}{z^2}\, ze^{-zt_e}\, dz \tag{20}$$

Thus, the marginal density of t_e is a mixture of exponentials with mixture density,

$$\varphi(z) = \frac{\delta(1+k_1)}{k_1} \frac{1}{z^2}\, \mathrm{I}(\delta < z < \delta + \lambda_1)$$

The hazard of the marginal distribution of t_e is equal to $\delta(1+k_1)(\log(1+k_1))/k_1$ at $t_e = 0$, converges to δ when $t_e \to \infty$, and decreases monotonically in between.

Again, the marginal distribution of job durations t_e does not depend on the wage offer distribution, and therefore has the same form for different models of wage determination. In sum, inference on k_1 and λ_1 using the marginal job duration distributions considered in this section is robust with respect to wages and their determination.[6]

In the Appendix to this paper we examine to what extent this is robust with respect to the model assumptions that were made. In the next subsection we compare the information content of different job duration data with respect to k_1 and λ_1.

4.4 Comparison of the information in different job duration distributions

It is useful to summarize some of the results of the previous subsections. The densities of wages in the E-inflow, the J-inflow and the E-stock are proportional to, respectively,

[6]In the E-stock, the wage is distributed according to $G(w)$, which under the assumption of equilibrium worker flows can be expressed in terms of F (see equation (3)). It is not difficult to show that the distribution of t_e given the wage w on the job is then exponential and is identical to the distribution of t_{uj} given w in the E-inflow. This justifies the practice in the descriptive empirical literature on job durations to assume exponentiality of the conditional distribution of elapsed job durations given the wage. To our knowledge our result has never been derived in the literature.

$$f(w), \qquad \frac{f(w)}{1+k_1\overline{F}(w)}, \qquad \frac{f(w)}{(1+k_1\overline{F}(w))^2}$$

The densities of job durations t in the E-inflow, the J-inflow and the E-stock are proportional to, respectively,

$$\int_\delta^{\delta+\lambda_1} \left[ze^{-zt}\right] dz, \qquad \int_\delta^{\delta+\lambda_1} \frac{1}{z} \left[ze^{-zt}\right] dz, \qquad \int_\delta^{\delta+\lambda_1} \frac{1}{z^2} \left[ze^{-zt}\right] dz$$

Because the distribution of wages in the J-inflow first-order stochastically dominates the distribution F of wages in the E-inflow, the marginal distribution of t_{*j} first-order stochastically dominates the marginal distribution of t_{uj}. Similarly, because the distribution of wages G in the E-stock first-order stochastically dominates the distribution of wages in the J-inflow, the marginal distribution of t_e first-order stochastically dominates the marginal distribution of t_{*j}.

The hazards of the three duration distributions all decrease, and they all converge to δ for long spells. The hazard of t_e at zero is smaller than the hazard of t_{*j} at zero, which in turn is smaller than the hazard of t_{uj} at zero. Let $\theta(.)$ be a generic symbol for a hazard. Then

$$\begin{array}{rrcl} \delta(1+k_1) & > \quad \theta_{uj}(0) & = & \delta(1+\frac{1}{2}k_1) \\ & > \quad \theta_{*j}(0) & = & \dfrac{\delta k_1}{\log(1+k_1)} \\ & > \quad \theta_e(0) & = & \dfrac{\delta(1+k_1)\log(1+k_1)}{k_1} \quad > \quad \delta \end{array}$$

For the average durations we obtain

$$\begin{array}{rrcl} \dfrac{1}{\delta}\dfrac{1}{1+\frac{1}{2}k_1} & < \quad \mathrm{E}(t_{uj}) & = & \dfrac{1}{\delta}\dfrac{\log(1+k_1)}{k_1} \\ & < \quad \mathrm{E}(t_{*j}) & = & \dfrac{1}{\delta}\dfrac{1}{\log(1+k_1)}\dfrac{k_1}{1+k_1} \\ & < \quad \mathrm{E}(t_e) & = & \dfrac{1}{\delta}\dfrac{1+\frac{1}{2}k_1}{1+k_1} \quad < \quad \dfrac{1}{\delta} \end{array}$$

The first inequality follows from the fact that the hazard of t_{uj} at zero equals $\delta + (1/2)\lambda_1$, and that this hazard is decreasing, so that the average duration exceeds the inverse of the hazard at zero. If $\lambda_1 = 0$ then all means are equal to $1/\delta$. If $\lambda_1 \to \infty$ then the first two means converge to zero whereas the third converges to $1/(2\delta)$. Thus, $1/(2\delta) < \mathrm{E}(t_e) < 1/\delta$, which is testable given an estimate of δ and an estimate of $\mathrm{E}(t_e)$.

We are now in a position to discuss the merits of different types of data on job durations. On average job spells are much longer than unemployment spells. To obtain a reasonable number of complete job spells, one must either rely on retrospective information on elapsed job spells, or one must follow a cohort during a long observation period. Retrospective information concerning a rather distant past is unreliable due to recall errors. Moreover, with aggregate data, the periods during which a cohort is followed are relatively short. Hence, in the latter case, a substantial fraction of all observations is censored. With censored data inference is usually based on the hazard rate of the assumed distribution. With aggregate data the empirical hazard can only be obtained for (relatively) short job spells. This limits, as we shall argue, our ability to obtain estimates of both λ_1 and δ, and it also makes us prefer one type of duration data over the others. It is clear that micro panel data, and in particular panel data with a long observation period, are more informative than the aggregate data that are typically available.

First, both λ_1 and δ are identified from each of the three duration distributions. It is instructive to consider the closed-form expression for $\theta_{uj}(t)$,

$$\theta_{uj}(t) = \delta + \frac{1}{t} - \frac{\lambda_1 e^{-\lambda_1 t}}{1 - e^{-\lambda_1 t}}$$

The job destruction rate δ determines the minimum *level* of the hazard. This level is the limit of the hazard for long job spells. As such spells are not observed due to censoring, the (censored) duration are not informative on δ. That is also true for the other two duration distributions. For that reason, we do not estimate both λ_1 and δ from the job duration data. Instead, we substitute the estimate obtained in section 3 in the job duration hazards, and we shall proceed as if δ were known.

Basically, for each of the three duration distributions, λ_1 is identified from the slope of the hazard rate. If λ_1 is large (small) then the hazard at zero is large (small) and the negative slope of the hazard is steep (flat). Ultimately, the hazard always converges to δ. Again, this is evident for the closed-form hazard $\theta_{uj}(t)$. Figure 1 shows this hazard for two different values of λ_1: 0.02 and 0.06, with δ equal to 0.01. If the unit of time is one month, then $\lambda_1 = 0.02$ corresponds to a small value whereas $\lambda_1 = 0.06$ corresponds to a reasonably large value, in the light of the estimates in micro-econometric studies (see Bontemps, Robin and Van den Berg (1999)). It is seen that both hazard rates are well above δ even at job durations of 25 years. This illustrates that it is not straightforward to make inferences on the value of δ from censored job duration data, even if the censoring is after 20 years. Also note that both hazard rates are almost equal for large durations. This illustrates that the information on λ_1 is in the short spells.

The difference between $\theta(0)$ and δ for certain job duration data thus provides a good measure of the information in these data on λ_1, and the ratio of this difference and δ therefore provides a good measure of the information on k_1. The smaller the latter relative difference for a certain duration variable, the more difficult it is to estimate the value of k_1. If the difference is very small then measurement errors in the data can have a huge impact on the estimate of k_1 (see below for an example). It follows that a random sample of t_{uj} is more informative than a random sample of t_{*j} which in turn is more informative than a random sample of t_e. From (22),

$$
\begin{aligned}
k_1 \quad &> \quad \frac{\theta_{uj}(0)-\delta}{\delta} \quad = \quad \frac{k_1}{2} \\
&> \quad \frac{\theta_{*j}(0)-\delta}{\delta} \quad = \quad \frac{k_1}{\log(1+k_1)} - 1 \\
&> \quad \frac{\theta_{e}(0)-\delta}{\delta} \quad = \quad \frac{(1+k_1)\log(1+k_1)}{k_1} - 1 \quad > \quad 0
\end{aligned}
$$

Note that these expressions only depend on k_1 and not (separately) on δ.

The aggregate data contain the grouped distribution of t_e (which includes $\theta_e(0)$) and a proxy for $\theta_{*j}(0)$. They also contain values of $\mathrm{E}(t_e)$. Figure 2 plots

$$
\frac{\theta_e(0)-\delta}{\delta} \quad \text{(Function A)}, \qquad \frac{\theta_{*j}(0)-\delta}{\delta} \quad \text{(Function B)}, \ \text{and}
$$

$$
\frac{\frac{1}{\delta}-\mathrm{E}(t_e)}{\frac{1}{\delta}} \quad \text{(Function C)}
$$

as functions of k_1. (The Function C normalizes $\mathrm{E}(t_e)$ in a similar way as the other functions, by specifying it as the relative deviation with respect to the model with $\lambda_1 = 0$.)

It turns out that Functions A and C are rather flat. This means that the corresponding data are not very informative on k_1. Minor measurement errors then have a major impact on the estimate. Consider for example the use of data on $\theta_e(0)$ (see Function A). If the observed $\theta_e(0)/\delta$ equals 2.2 then the implied k_1 equals 5.5. But if the observed $\theta_e(0)/\delta$ equals 2.4 then k_1 equals 7.4. Thus, a 9% increase in the observed variable leads to a 35% increase in the value of

k_1. Given the fact that published aggregate data are rounded and also contain other measurement errors, a 9% error in the value of an observable should not be considered as uncommon. The k_1 estimates based on Functions A and C turn out to be widely implausible in most cases. We conclude that only the data on $\theta_{*j}(0)$ are useful for our purposes.

Aggregate data also contain so-called "retention rates", which equal the fraction of jobs that do not dissolve in a given time period. The fraction of jobs that do dissolve in a given time period equals the over-all exit probability for the E-stock sample of workers. It is not difficult to see that in a steady state, if the time period is sufficiently small, this equals $\theta_e(0)$, that is, the fraction of the E-stock with jobs that have just been created. As a consequence, such data are not useful for our purposes either.

In the literature on job and worker flows, the "total worker reallocation rate" is defined as $\theta_e(0) + \delta$ (see Davis, Haltiwanger and Schuh (1996)). Basically, this measures the sum of the number of individuals who have just starting to work in a new job and the number of individuals who have just entered unemployment. Once k_1 and δ are estimated, it is straightforward to estimate this measure as well (it equals $\delta + \delta(1+k_1)\log(1+k_1)/k_1$). It can subsequently be decomposed into a component due to transitions into and out of employment and a component due to job-to-job transitions.

5 Inference on wages: average monopsony power and variance decomposition

We define the average monopsony power μ as follows,

$$\mu = \frac{\mathrm{E}(p-w)}{\mathrm{E}(p)} \tag{21}$$

in which we take expectations over individuals (instead of firms), so we examine monopsony power from the perspective of the worker. To quantify this measure, it does matter which model of wage determination is adopted. Consider the equilibrium search model with between-market heterogeneity in firms' productivities. In a homogeneous segment, in a cross-section of employed workers, wages are distributed according to $G(w)$ as specified in equation (7). As shown in *e.g.* Van den Berg and Ridder (1998), the cross-section distribution of wages in such a segment can be represented as

$$w = \underline{w}(p) + (1-y)(p - \underline{w}(p)) \tag{22}$$

where y is a random variable with

$$\mathrm{E}(y) = \psi = \frac{1}{1+k_1} \quad , \mathrm{Var}(y) = \frac{\psi(1-\psi)^2}{3} \tag{23}$$

The lowest wage $\underline{w}(p)$ may be a function of productivity p. In fact, we distinguish between two cases: (i) $\lambda_0 > \lambda_1$, (ii) $\lambda_0 \leq \lambda_1$. In all five countries the (average) unemployment benefits b are lower than the minimum wage, although the difference is small in *e.g.* Germany, and variation in b may reverse the inequality for a fraction of the workers. Case (i) applies to the EC countries, while case (ii) is relevant for the US. For case (i) the lowest wage is

$$\begin{aligned} \underline{w}(p) &= w_{min} &&, w_{min} \leq p \leq p_0 \\ &= \gamma b + (1-\gamma)p &&, p > p_0 \end{aligned} \tag{24}$$

with

$$p_0 = \frac{w_{min} - \gamma b}{1-\gamma} \tag{25}$$

$$\gamma = \frac{(1+k_1)^2}{(1+k_1)^2 + (k_0 - k_1)k_1} \tag{26}$$

For case (ii), for all p

$$\underline{w}(p) = w_{min} \tag{27}$$

In case (i), the lowest wage for the high productivity workers is equal to their reservation wage that is larger than the minimum wage. The minimum wage is the lowest wage for the low productivity workers. In case (ii) the offer arrival rate while employed exceeds the arrival rate for the unemployed. As a consequence, the reservation wage of the unemployed is smaller than unemployment income b (for all p), which in turn is smaller than the minimum wage. In case (i) the wage floor is the minimum wage (low productivity workers) or depends on unemployment benefits (high productivity workers). In case (ii) the wage floor is independent of unemployment benefits (as long as they do not exceed the minimum wage).

Substitution of equations (23) and (24) in (22) gives

$$\mu = \psi \frac{\mathrm{E}(p) - \mathrm{E}(\underline{w}(p))}{\mathrm{E}(p)} \tag{28}$$

Hence, the degree of monopsony is determined by the average of the lowest wage over all workers, and this is the only feature of the wage distribution that plays a role. Recall that in each segment $p > \underline{w}(p)$. In the limiting case where w_{min} equals p for each segment, the value of μ attains its minimum value 0. Similarly, if k_1 is infinite then $\mathrm{E}(w) = E(p)$ and again $\mu = 0$. If, on the other hand, $k_1 = 0$ and $\underline{w} = 0$ then μ attains its maximum value (which is 1), as a sensible measure of monopsony power should.

From equations (23) and (24)

$$\mathrm{E}(w|p) = (1-\psi)p + \psi\underline{w}(p) \tag{29}$$

$$\mathrm{Var}(w|p) = (p - \underline{w}(p))^2 \frac{\psi(1-\psi)^2}{3} \tag{30}$$

Taking the expectation with respect to p, we have

$$\mathrm{E}(w) = (1-\psi)\mathrm{E}(p) + \psi\mathrm{E}(\underline{w}(p)) \tag{31}$$

$$\mathrm{Var}(w) = \mathrm{E}(\mathrm{Var}(w|p)) + \mathrm{Var}(\mathrm{E}(w|p)) \tag{32}$$

In section 6, we fit a (lognormal) distribution to the grouped wage distribution. Next, we compute the mean and variance of the wage distribution. Finally, we determine the mean and variance of the productivity distribution by equating the estimated mean and variance to the expressions (32) and (33). In case (ii) we obtain closed form expressions

$$\mathrm{E}(p) = \frac{\mathrm{E}(w) - \psi w_{min}}{1-\psi} \tag{33}$$

$$\mathrm{Var}(p) = \frac{\mathrm{Var}(w) - (p - w_{min})^2 \frac{\psi(1-\psi)^2}{3}}{(1-\psi)^2} \tag{34}$$

In case (i), the result is a nonlinear system that involves the truncated moments $\mathrm{E}(p^k|p \geq p_0)$, $k = 1, 2$. If we choose a lognormal distribution for p, we obtain a nonlinear system in the parameters of this distribution, and this system can be solved numerically.

Equation (33) is the basis for a decomposition of wage variation. The first term on the right-hand side is associated with "pure wage variation" (failure of the law of one price due to positive and finite search frictions). The second term is associated with productivity dispersion. We shall compute the fraction of total wage dispersion due to the first term.[7] This is another measure for the distance to a competitive equilibrium. If search frictions in employment vanish ($\lambda_1 \to \infty$), then wages approach productivity levels, the labor market equilibrium approaches a competitive equilibrium, and the fraction of wage dispersion due to search frictions vanishes.

The estimated parameters of the productivity distribution can be used to compute a number of counterfactual monopsony indices. In particular, we consider (i) the effect of reducing unemployment benefits, while leaving the minimum wage unaffected, (ii) the effect of reducing the minimum wage, while leaving the unemployment benefits unaffected, (iii) the effect of eliminating both the minimum wage and unemployment benefits, and (iv) the effect of making search on the job impossible. Note that the estimated productivity distribution is truncated at the minimum wage. All counterfactuals that involve a reduction of the minimum wage below its current level must be interpreted with care. Although we have an estimate of the probability mass of the productivity distribution below the minimum wage, the reduction of the minimum wage extends the support of the distribution of p, and the effect of this extension on the monopsony index is ambiguous. We shall proceed as if the support is unaffected.

The assumption that workers are homogeneous in their unemployment income (or value of leisure) b is essential for the results on the monopsony power. An alternative approach would be to assume that b varies across segments in such a way that in all segments the reservation wage of the unemployed is smaller than the minimum wage w_{min}. If $\lambda_0 > \lambda_1$ then this amounts to assuming that b in segments with large p must be very small (in fact, if p has an unbounded support then b must strictly decrease in p for all sufficiently large p). If the lowest wage is always equal to w_{min} then the theoretical and empirical analysis of the monopsony power index is greatly facilitated. In the Appendix to this paper we provide details and results.

We have now developed a number of measures that summarize in different directions how far away the labor market is from the competitive steady-state equilibrium. In reality, an economy is affected by shocks, and high mobility also helps to absorb shocks that are sector-specific and induce reallocation (Davis,

[7] In case (ii) this equals

$$\frac{\psi \mathrm{E}(p-\underline{w})^2}{\psi \mathrm{E}(p-\underline{w})^2 + 3\mathrm{Var}(p)}$$

where expectations are taken with respect to the distribution of p across individuals. Note that if $\lambda_1 \to \infty$ then this converges to zero, whereas for finite nonnegative values of λ_1 this is strictly positive.

Haltiwanger and Schuh (1996)). This suggests that high values of λ_0, λ_1 and δ are advantageous in case of shocks. On the other hand, the theoretical literature on "job matching models" shows that it is possible to have an inefficiently high amount of mobility (see Pissarides (1990), Caballero and Hammour (1996) and Bertola and Caballero (1996)). When a firm creates a vacancy then it has to pay investment costs as well as search costs, and the way in which this affects worker and firm behavior is not necessarily efficient.[8] In the present paper we avoid the issue of efficiency. Note that, in the equilibrium search model with between-market heterogeneity, job-to-job mobility has no effect at all on efficiency, whereas in the within-market heterogeneity model, job-to-job transitions increase efficiency because they allow workers to move to higher-productivity firms.

6 Data and results

The data on labor market flows are from readily available OECD, EUROSTAT and US Department of Labor publications (see e.g. OECD (1993) and (1997)). Most of the data for the EC countries are obtained from the yearly Labor Force Surveys (LFS), a standardized survey that is conducted in all EC countries. The LFS is comparable to the Current Population Survey (CPS) from which the US data on labor market flows and wages are obtained. Unfortunately, the LFS does not collect data on wages, at least not for all countries. For the EC countries the frequency distribution of wages was obtained from other surveys. This makes these data less comparable than the data on labor market flows. In particular, we must deal with both before- and after-tax wage rates.

We examine five OECD countries: the Netherlands (NL), Germany (D), France (F), United Kingdom (UK) and the USA. Some summary statistics that characterize the labor markets in these five economies are reported in Table 1. We perform separate empirical analyses with data from different years, but the benchmark results are with data from 1990 or 1991. The aggregate data are not available in a uniform format, but fortunately our estimation procedure is flexible in that respect. We start with the inference on λ_0, structural unemployment, and δ. Next, we consider estimation of λ_1 from job duration data, and finally, inference on the wage distribution.

[8]The models considered in these references do not allow for job-to-job transitions, but such an extension would not invalidate this result.

6.1 Estimation of unemployment parameters

We use the following data:

Unemployment spells. The distributions of (elapsed) unemployment spells categorized in 6 intervals were obtained from the Labor Force Survey (NL, D, F, UK)[9][10]. The data are for the years 1983–94[11]. For the US the frequency distribution of (elapsed) unemployment spells was obtained from the Current Population Survey. In US DoL (1995) the spells are grouped in 4 intervals[12].

Unemployment rate. Unemployment rate as reported in LFS (NL, D, F, UK) and standardized unemployment rate as reported in US DoL (1995). Comparison with the standardized unemployment rates reported in the OECD Quarterly Labor Force Statistics (1997) shows that the LFS rates are almost equal to the OECD rates[13], except for the Netherlands where this only is true after 1991. Until that year the LFS rate is about 1.5% higher in that country.

The parameters λ_0 and π are estimated by quasi ML. The estimates obtained by maximizing the grouped duration likelihood are quasi MLE because neither the LFS, nor the CPS is a simple random sample. Although the estimators are consistent for a stratified sample, provided that the stratification variables are exogenous, the standard errors depend on the details of the sample design. Note that the grouped MLE is less sensitive to rounding errors in the unemployment durations. The estimate of δ is computed from the unemployment rate and the estimates of λ_0 and π (see section 3).

The estimation results are given in Tables 2, 3 and 4. We use data from the years 1990 and 1991 to estimate the friction parameters on the job, the monopsony index, and to decompose the wage variation. These years may be unrepresentative, and a comparison of the estimates of the unemployment parameters over a longer tine period may be informative. The design of the CPS in the US has not changed much during the years 1983–94[14]. The time-series of the parameters of

[9] The intervals are 0–3, 3–6, 6–12, 12–18, 18–24, and 24– months.

[10] From 1991 on the data are for East- and West-Germany, before that year only for West-Germany.

[11] For the Netherlands, the LFS did not record unemployment durations in 1984 and 1986.

[12] The intervals are less than 5 weeks (1.15 months), 5–14 weeks (1.15–3.44 months), 15–29 weeks (3.44–6.20 months), and 29– weeks (6.20– months).

[13] The OECD rates are yearly averages and the LFS rates measure unemployment in a reference week, which is a normal (no bank holidays) week in Spring.

[14] There has been a major overhaul in 1995. Data from 1995 and later are incomparable to data from earlier years.

the unemployment duration distribution, the structural unemployment rate, and the job destruction rate show gradual changes during 1983–94. During 1983–89 the unemployment rate fell by 45%, and unemployment increased and decreased again during 1990–1994. The parameters of the unemployment duration distribution (λ_0 and π) and the structural unemployment rate are clearly negatively (λ_0) and positively (π and structural unemployment rate) correlated with unemployment. The job destruction rate has a small downward trend during the observation period. The changes over time in the estimates are small.

The LFS, the EC counterpart of the CPS, started in 1983[15]. In 1992 there was a major overhaul that affected the unemployment data. In an attempt to conform to the International Labor Organization (ILO) guidelines, all persons who reported to be unemployed, but did not search actively for a job in a reference period, were no longer considered to be unemployed. The estimates of λ_0 and π change dramatically during the first four years of the LFS. The unemployment rate in the EC countries was essentially constant in those years. The job destruction rate is almost constant, as one would expect. After that initial period the estimates evolve more gradually until 1992. It is likely that the dramatic changes during the first four year are spurious. This suspicion is reinforced by the dramatic changes in the parameters in 1992. The change in the definition of unemployment eliminated a large fraction of the long-term unemployed. This is reflected by lower estimates of π. Except for the Netherlands, the change in definition did not lower the unemployment rate as one would expect. It is remarkable, that just as during the start of the LFS, there is a reversion to the pre–1992 parameter values. In 1996 the estimates for λ_0 are .0582 (NL), .0838 (D), .109 (F), and .123 (UK), and for π .12 (NL), .18 (D), .15 (F), and .21 (UK). It seems that the changes in the estimates during 1983–87 and 1992–94 are design effects. Note that the reunification of Germany did not affect the estimates for 1991 nearly as much.

If we concentrate on the period 1988–1991, a period of decreasing unemployment, we notice a number of differences between the five economies. The US has by far the most 'dynamic' labor market. The offer arrival rate is 5.5 times that in the UK that has the most dynamic labor market among the EC countries. The job destruction rate in the US is three times as large as that in the UK. The structural unemployment rate in the US is about a third of that in (West-)Germany that has the lowest rate in the EC. The total unemployment rates in (West-)Germany and the US were about the same during those years. The

[15]There was an LFS before 1983, but the results are not comparable between countries and years.

Netherlands has the highest level of structural unemployment, both as a fraction of total unemployment and as a fraction of the labor force. The job offer arrival rate in that country is close to that in the UK. The Netherlands also has by far the highest minimum wage (see Table 1). Except for the UK, there is a clear relation between the level of structural unemployment and the minimum wage, which is in line with the wage floor explanation of structural unemployment discussed in section 2. The relation between the estimates of the job destruction rate δ and the employment protection ranking of the OECD that reflects legal restrictions on lay-offs is even stronger. Less protection is associated with a larger job destruction rate.

6.2 Estimation of the index of search frictions

First, we discuss the available data:

Job spells. Job duration data are scarcer than data on unemployment durations. The LFS collects data on elapsed job durations, but these data are not published. Only in the 1990's the concern with perceived job insecurity has led to an effort to collect these data. OECD (1993) contains the frequency distribution of elapsed job durations, categorized in 6 intervals, for all five countries. These distributions are not directly comparable, because some have been obtained from special panel surveys (NL, D) and the other from the LFS (F, UK) or CPS (US)[16]. Table 5.5 in OECD (1997) contains more comparable data for all five economies. The distributions of elapsed job spells are obtained from the 1995 LFS (NL, D, F, UK)[17] and the 1996 CPS (US). For the Netherlands and Germany, the fraction of jobs with an elapsed duration of less than 1 year is much smaller than in the distribution derived from the micro panel data in OECD (1993). In the sequel we use the 1995/1996 data.

Separation rates. In subsection 4.4, we indicated that elapsed job duration data may not very informative on k_1. For that reason we also use separation rates of newly created jobs to estimate this index. The data on these separation rates are from OECD (1997). We mostly use the fraction of jobs with a duration less than a year that are dissolved within a year. In particular, Table 5.10 in OECD (1997) provides the separation rate from 1 year to 2 years, which is calculated as the difference between the number employed with tenure less than 1 year in 1994 and the number employed with tenure between 1 and 2 years in 1995, as a

[16]The data for NL and D are for 1990 and those for F, UK, and US for 1991.

[17]The LFS job tenure data are not published.

fraction of the former. In the estimates for the US, both numbers are from 1995. We denote the reported separation rate by s_1 (for ease of exposition, we use a year as the time unit in this exposition on the job spells).

First, we consider the information in the separation rates. According to subsection 4.4, these rates may contain more information than the incomplete job spells. Extraction of an estimate of k_1 from data on s_1 is non-trivial. First of all, the jobs sample is not a genuine J-inflow sample but rather a sample from the stock of jobs with a duration less than one year. Secondly, the exit rate out of jobs decreases within the interval considered. For these reasons, it is invalid to estimate $\theta_{*j}(0)$ from the equality $s_1 = 1 - \exp(-\theta_{*j}(0))$. To proceed, we have to derive the joint density in the E-stock of the elapsed job duration t_e and the residual (or remaining) job duration t_r. Note that $t_e + t_r$ equals the total job duration of a spell in the E-stock. The observation s_1 then equals

$$s_1 = \Pr(0 < t_r < 1 | 0 < t_e < 1)$$

By analogy to the derivations in Section 4 it is easy to show that the joint density of t_e, t_r is proportional to

$$\int_{\underline{w}}^{\overline{w}} \frac{k_1}{\log(1+k_1)} \frac{f(w)}{1+k_1\overline{F}(w)} e^{-(\delta+\lambda_1\overline{F}(w))t_e} (\delta + \lambda_1\overline{F}(w))\, e^{-(\delta+\lambda_1\overline{F}(w))t_r}\, dw$$

After some elaboration we obtain

$$s_1 = \Pr(0 < t_r < 1 | 0 < t_e < 1) = 1 - \frac{\int_\delta^{\delta+\lambda_1} \frac{1}{z^2} e^{-z}(1-e^{-z})dz}{\int_\delta^{\delta+\lambda_1} \frac{1}{z^2}(1-e^{-z})dz}$$

Some comments are in order. First, note that if $\lambda_1 \downarrow 0$ then $s_1 = 1 - \exp(-\delta)$, as is to be expected. This suggests that, to compare the information in s_1 to that in the normalized characteristics in subsection 4.4, one should examine $(s_1 - (1 - \exp(-\delta))/(1 - \exp(-\delta))$. A problem here is that this normalized version of s_1 still depends on δ. For most plausible values of δ, however, the graph of the normalized s_1 as a function of k_1 lies between the graphs of B and A in Figure 2. This means that s_1 is less informative than $\theta_{*j}(0)$ but more informative than $\theta_e(0)$.

In fact, the information in the separation rate $s_T \equiv \Pr(0 < t_r < T | 0 < t_e < T)$ converges to the information in $\theta_{*j}(0)$ if $T \downarrow 0$. It should also be noted that s_T is a strictly increasing function of λ_1, for any T, so λ_1 is identified from any s_T.

The estimation with s_1-data gives very implausible results for France and Germany. For both countries, the estimated k_1 is well above 20, which is much higher than for the other countries and also much higher than the estimate for France based on micro data, which is about 5 (Bontemps, Robin and Van den Berg (1999)). By comparing all data on job durations, it seems that F and D have an unexpectedly high fraction of jobs with a duration of less than or equal to a year. This is not compatible with the job duration distribution for higher durations, within our model framework. For France, Cohen, Lefranc and Saint-Paul (1997) convincingly argue that these are jobs with a predetermined fixed duration, mostly occupied by young workers. In particular, they argue that one can distinguish two types of job contracts: 1) with a predetermined fixed short duration, with low firing and dissolution costs, and low wages, mostly occupied by new entrants and other young workers and 2) with indeterminate long durations and high firing costs. Basically, the type-1 workers bear the full burden of the attempts to increase the labor market flexibility.

This suggests that the labor markets in these countries are heterogeneous with respect to the parameter δ, a suspicion that will be confirmed by the job tenure data. Instead of estimating a mixture over the job destruction rate we use data on separation rates s_T for higher T, since these may be less sensitive to the shape of the job duration density close to zero. Table 5.9 in OECD (1997) provides the retention rates from $0 - - < 5$ years to $5 - - < 10$ years of tenure. Retention rates are the mirror-image of separation rates. Here, they measure the fraction of workers with a tenure less than 5 years who are still with their employer 5 years later. This gives an observation of s_5. In effect, we compare 1980–1985 with 1985–1990.

The expression for s_5 is the same as for s_1, provided we replace δ and λ_1 by 5δ and $5\lambda_1$, respectively. This gives the reported results on k_1 and λ_1 for Germany and France, which are plausible and (for France) very close to the results found in micro studies. It is conceivable that the micro studies interpret part of the short-term temporary jobs as regular jobs. In that case one would perhaps expect a slightly lower λ_1 estimate than in the micro studies. In any case, our results suggest that it would also be important in micro studies to pay attention to the special nature of these short-term jobs.

There are no data on s_5 available for the Netherlands and the US. For the UK, the estimates based on s_5 are rather implausible. Table 5.10 in OECD (1997) also gives data on $s_{0.25}$. This gives similar problems for France and Germany as those based on s_1. Moreover, the results for the Netherlands now suffer from the same problem.

Next, we consider the distribution of elapsed job spells. The job destruction rate δ (or its mean) is fixed at the average over the years 1987–1991. Quasi-MLE of k_1 are implausibly small, and the fit is poor. The estimates are sensitive to small changes in the value of δ, but the fit is unaffected. This confirms that the elapsed job durations are uninformative on k_1. An acceptable fit is obtained if we set k_1 equal to the estimate obtained from the retention rates and assume that δ has a discrete distribution with two points of support. If these points are δ_1 and δ_2, and the proportion of δ_1-types in the J-inflow is equal to P, then the density of elapsed job spells is a mixture of densities of incomplete job spells (20) with fraction of δ_1-types equal to

$$\tilde{P} = \frac{\frac{P}{\delta_1}}{\frac{P}{\delta_1} + \frac{P}{\delta_2}}$$

The results are reported in Table 6. The mean of the distribution of the job destruction rate is set equal to the mean over the years 1987–1991 in Table 3. This mean is identified from the hazard of the tenure distribution at very long spells. Censoring and recall errors make an estimate based on the grouped spell distribution unreliable[18]. The results confirm the suspicions regarding the composition of the stock of jobs: a relatively small fraction is short-lived while the majority of jobs has a much lower destruction rate. The fraction of short-lived jobs in the J-inflow is larger.

A comparison of the arrival rates in Table 5 to the 87–91 average of the arrival rates in Table 2, shows that there is a positive relation between these rates. There is a marked difference between the EC countries, where the arrival rate in unemployment is larger than that in employment, and the US where the reverse inequality holds.

Note that total worker reallocation is of the same order of magnitude for France and the Netherlands, even though in the Netherlands the job offer arrival rate for the employed is substantially higher. In comparison to France, workers in the Netherlands move relatively quickly to high-wage jobs. However, δ is slightly smaller in the Netherlands, and as a result, workers stay longer in their high-wage jobs. As a result, the difference between the k_1 values of the two labor markets is not reflected in the cross-sectional reallocation rates, so that these rates may be uninformative on the mobility potential of the labor market.

This also shows in the results on the decomposition of the total worker reallocation rate. This decomposition is very stable across countries. The fraction

[18]Estimation of the hazard in the open interval on the (erroneous) assumption that elapsed job spells are exponentially distributed after 20 years, gives an estimate that is close to the average over 87–91, except for Germany and the US. The exponential tail estimate is larger than the average in Germany and smaller than the average in the US.

of reallocation due to transitions into and out of unemployment always lies in the 24%–32% (so the fraction due to job-to-job transitions always lies in the 68%–76% range).

6.3 Monopsony indices and decomposition of wage variation

Wage data. We use categorized data on before-tax monthly wages of full-time employees who worked during the whole year. For Germany the data refer to 1990 (source: Löhne und Gehälter, Statistisches Bundesamt, Fachserie 16, Table 12). For the Netherlands, the data are also for 1990. The source is Statistisch Jaarboek, 1993, Centraal Bureau voor de Statistiek, Table 31. The UK data refer to 1991 (Annual Abstract of Statistics, Central Statistical Office, Table 6.17). The US data are from the CPS and are for 1992. The French data are categorized after-tax wages for 1991 (Les salaires de 1991 à 1993 dans le secteur privé et semi-public, INSEE, 1994, Table 6). The minimum wage and unemployment benefits are taken from CPB (1995). They are converted to local currencies using the average exchange rate for the particular year, as published in Statistisch Jaarboek, 1994.

We compute the mean and variance of the wage distribution by fitting a lognormal distribution to the grouped wage data. Next, we compute the mean and variance of the productivity distribution by equating the estimated mean and variance to the expressions in section 5. The computation is different for the EC countries and the US, because in the former $\lambda_0 > \lambda_1$, while in the latter the reverse holds. The results for France are for the distribution of after-tax productivities (on the assumption the tax is nearly proportional, see section 2). All results are in local currencies.

Table 7 contains the estimates of the monopsony indices. The first row gives the fraction of workers for whom the lowest wage is equal to the minimum wage. The estimates of the monopsony index are in the second row. The next rows give counterfactual indices for $b = 0$, $w_{min} = 0$, $w_{min} = b = 0$, and $k_1 = 0$. Finally, we report the fraction of the wage variation due to search frictions.

For all countries the average monopsony power is small. It ranges from less than 1% in Germany to almost 5% in the UK. For this reason we only consider counterfactuals that increase the monopsony index. Elimination of unemployment benefits and of the minimum wage increases the monopsony indices to about 6% for the UK and the Netherlands, but the German index increases to only 1%. The insensitivity of the German index is due to the relatively high reservation wages of more productive (unemployed) workers (*i.e.* the parameter γ in equation (27) is relatively small), which in turn is due to a relatively large value of k_0. In the Netherlands and France the effect of a reduction in the unemployment benefits is somewhat larger than that of a reduction in the minimum wage. The fraction workers for who the minimum wage is binding is larger in these countries. Hence, a concentration near the minimum wage is not a good predictor of the effect of a reduction in the wage on monopsony power. A decrease in b affects not only low, but also higher productivity workers. The index for the counterfactual $k_1 = 0$ (the minimum wage is unchanged, because otherwise this index would be 1) shows convincingly that the main protection of workers against the monopsony power of firms is provided by the ability to move to higher paying jobs.

In all countries, the unemployment benefits and the minimum wage reduce the monopsony power of firms, *i.e.* make the labor market more like a competitive market where wages are equal to (marginal) products. The case of the Netherlands that has a high minimum wage and high unemployment benefits illustrates this point. Without these wage floors the labor market becomes more monopsonistic. However, the wage floors cause (structural) unemployment among less productive workers. Indeed, there are good reasons to suspect that structural unemployment in the Netherlands is even higher than our estimate, since many structurally unemployed are counted as non-participants on the labor market (they are in early retirement or in the disability program; see e.g. Koning, Ridder and Van den Berg (1995) and Van den Berg and Ridder (1998)). It should be noted that the estimates of k_1 for the Netherlands are very close to the estimates in micro studies (Van den Berg and Ridder (1998)). Our estimate of λ_0 is somewhat higher than in the micro studies, but this can be attributed to the fact that the micro studies do not allow for structural unemployment, whereas here we do.Although our model is too simple to allow for a welfare analysis of the minimum wage, it is clear that the argument that the minimum wage is needed to protect workers against monopsonistic employers is not convincing. Of course, our analysis does not allow for individual variation in the rate of job-to-job transitions, but on average these transitions seem to protect the workers sufficiently.

The case of Germany illustrates another mechanism to strengthen the position of workers relative to employers. The low job destruction rate in that country, that may well be a consequence of the high level of employment protection (see Table 1), increases the reservation wages of more productive workers and reduces the monopsony index.

Finally, we note that, as expected, most of the wage variation is not explained by search frictions, but by productivity variation. By this measure, the UK and US labor markets are close to competitive.

7 Conclusion

In this paper we have defined and estimated measures of labor market imperfection in the context of an equilibrium search and matching framework. The method uses readily available aggregate data on marginal distributions of unemployment and job durations and wages. Estimation of some of the characteristics is invariant to the way in which wage determination is modeled. The estimation results provide some insights into the performance of the labor markets in the USA, the UK, France, Germany and the Netherlands.

The data that we use in the calibration are collected yearly in the Current Population Survey (CPS) in the US and the Labor Force Survey (LFS) in EC countries. These surveys concentrate on labor market flows and wages. Our framework relates these seemingly unrelated data to key policy parameters as the level of unemployment benefits, the minimum wage, and the level of employment protection.

The accuracy of our estimates is limited by the availability of published aggregate data. For instance, the LFS collects job tenure data, but these are not routinely published. For the estimation of our index of search frictions it would be beneficial to have access to more detailed data on retention rates, *e.g.* retention rates by wage level or even tenure distributions by wage level. Another weak point is the estimate of the job destruction rate. Data on the fraction of job leavers who become unemployed would help in the estimation of that rate. Although the details of our model and the calibration may be criticized, we think that our approach directs attention to some key parameters that may help us understand the differences between labor markets.

Table 1: **Some characteristics of the labor markets in the five OECD countries**

	NL	D	F	UK	USA
Average standardized unemployment rate (1989–1993)	6.9	5.1	9.9	8.7	6.2
Monthly flow out of unempl. (% of unempl.; av. over 1985 and 1993)	6.6	7.6	3.6	7.7	39.4
Monthly flow into unempl. (% of empl.; av. over 1985 and 1993)	.26	.41	.33	.59	2.26
Monthly flow of hires (% of empl.; av. various years)	.99	2.63	2.42	–	5.38
Average wedge (%)	44	41	38	29	33
Minimum wage (max. of statutory and collective; Dutch guilders per year)	30833	21875	23750	15416	16607
Min. wage as frac. wage av. production worker	.57	.38	.63	.39	.35
Average minimum unempl. benefit (Dutch guilders per year)	25932	20862	16598	12670	12704
Employment protection ranking	3	5	4	2	1

Germany is West-Germany only; Average standardized unemployment rate, OECD (1995), p. 216; Monthly outflow from and inflow into unemployment, OECD (1995), p. 27–28; Monthly flow of new hires, OECD (1997), p. 166; Replacement rate, average wedge, minimum wage, wage average production worker, and minimum unemployment benefit (average of one-earner family with two children and single person), CPB (1995); employment protection ranking from OECD (1994), p. 74.

Table 2: **Offer arrival rate (per month) (λ_0) and average unemployment duration (months) of frictionally unemployed, for five OECD countries, 1983–94**

	NL		D		F		UK		US	
Year	λ_0	av. dur.	λ_0	av. dur.	λ_0	av. dur.	λ_0	av. dur.	λ_0	av. dur.
83	.0580	17.2	.0770	13.0	.0701	14.3	.0794	12.6	.405	2.5
84	–	–	.0712	14.0	.0782	12.8	.0947	10.6	.497	2.0
85	.0613	16.3	.0804	12.4	.0635	15.7	.0967	10.3	.527	1.9
86	–	–	.0825	12.1	.0713	14.0	.0988	10.1	.516	1.9
87	.110	9.1	.0940	10.6	.0723	13.8	.114	8.8	.534	1.9
88	.109	9.2	.0975	10.3	.0775	12.9	.124	8.1	.565	1.8
89	.113	8.9	.0896	11.2	.0789	12.7	.139	7.2	.599	1.7
90	.120	8.4	.0975	10.3	.0933	10.7	.156	6.4	.563	1.8
91	.128	7.8	.101	9.9	.0936	10.7	.153	6.5	.468	2.1
92	.0594	16.8	.0981	10.2	.116	8.6	.105	9.6	.420	2.4
93	.0478	21.0	.0851	11.8	.110	9.1	.0849	11.8	.442	2.3
94	.0664	15.1	.0797	12.6	.0957	10.4	.0950	10.5	.408	2.5

Table 3: **Fraction of unemployment that is structural (π) and job destruction rate (per month) (δ) for five OECD countries, 1983–94**

	NL		D		F		UK		US	
Year	π	δ	π	δ	π	δ	π	δ	π	δ
83	.000	.00783	.000	.00526	.010	.00595	.13	.00862	.17	.0357
84	–	–	.036	.00493	.076	.00759	.23	.00892	.15	.0342
85	.20	.00575	.15	.00504	.035	.00704	.24	.00956	.12	.0360
86	–	–	.19	.00471	.12	.00714	.23	.00992	.11	.0347
87	.24	.00923	.23	.00529	.15	.00754	.26	.0105	.11	.0315
88	.28	.00809	.23	.00504	.16	.00737	.27	.00899	.093	.0298
89	.30	.00766	.22	.00422	.16	.00701	.24	.00837	.076	.0310
90	.28	.00733	.22	.00391	.18	.00798	.22	.00912	.073	.0304
91	.26	.00750	.21	.00339	.16	.00792	.15	.0122	.080	.0309
92	.048	.00335	.047	.00629	.12	.0116	.092	.0102	.14	.0288
93	.00	.00321	.058	.00669	.089	.0129	.11	.00872	.15	.0274
94	.16	.00431	.092	.00689	.071	.0129	.19	.00829	.13	.0230

Table 4: **Total and structural unemployment rate (%), for five OECD countries, 1983–94**

	NL		D		F		UK		US	
Year	Total	Struct.	Total	Struct.	Total	Struct.	Total	Struct.	Total	Struct.
83	11.9	0.0	6.4	0.0	7.9	.1	11.1	1.4	9.6	1.6
84	12.4	–	6.7	.2	9.5	.7	10.9	2.5	7.5	1.1
85	10.5	2.1	6.9	1.0	10.3	.4	11.5	2.8	7.2	.9
86	10.0	–	6.6	1.3	10.2	1.2	11.5	2.6	7.0	.8
87	10.0	2.4	6.8	1.6	10.7	1.6	11.0	2.9	6.2	.7
88	9.4	2.6	6.3	1.4	10.2	1.6	9.0	2.4	5.5	.5
89	8.8	2.6	5.7	1.3	9.6	1.5	7.4	1.8	5.3	.4
90	7.8	2.2	4.9	1.1	9.4	1.7	7.0	1.5	5.5	.4
91	7.3	1.9	4.1	.9	9.2	1.5	8.6	1.3	6.7	.5
92	5.6	.3	6.3	.3	10.2	1.2	9.7	.9	7.4	1.0
93	6.3	0.0	7.7	.4	11.4	1.0	10.3	1.1	6.8	1.0
94	7.2	1.2	8.7	.8	12.7	.9	9.7	1.8	6.1	.8

Table 5: **Index of search frictions**

	λ_1	k_1	total worker reallocation
Netherlands	0.072	9.1	0.026
Germany	0.028	6.5	0.013
France	0.038	5.0	0.025
United Kingdom	0.13	13	0.047
United States	0.61	20	0.13

Table 6: **The distribution of the job destruction rate (mean fixed at average estimate 1987–91) and fitted and observed fractions, for five OECD countries, 1995**

	Distr. δ			Fitted (observed) fractions					
	δ_1	δ_2	frac. δ_1	0–1	1–2	2–5	5–10	10–20	20–
NL	.0763	.00481	.04	.163	.109	.220	.178	.126	.204
				(.163)	(.114)	(.204)	(.198)	(.118)	(.203)
D	.0225	.00362	.18	.155	.107	.204	.186	.178	.171
				(.161)	(.094)	(.220)	(.172)	(.184)	(.170)
F	.0509	.00361	.08	.136	.088	.182	.193	.201	.199
				(.150)	(.080)	(.177)	(.174)	(.233)	(.187)
UK	.107	.00526	.04	.189	.118	.226	.198	.165	.104
				(.196)	(.107)	(.195)	(.235)	(.173)	(.094)
US	.228	.00505	.11	.257	.107	.203	.179	.153	.102
				(.260)	(.085)	(.200)	(.198)	(.168)	(.090)

Table 7: **Fraction of workers for whom the lowest wage in the market is the minimum wage rather than the reservation wage of the unemployed, (counterfactual) monopsony power indices, and the fraction of wage variation due to search frictions**

	Germany	Netherlands	France	United Kingdom	United States
Frac. min. wage	.01	.07	.06	.01	1.
μ	.0068	.029	.025	.046	.036
$\mu_{b=0}$	.010	.034	.037	.046	.036
$\mu_{w_{min}=0}$	.0069	.031	.027	.047	.040
$\mu_{w_{min}=b=0}$	.011	.060	.046	.063	.053
$\mu_{k_1=0}$	.62	.44	.52	.69	.68
Frac. var. frictions					

References

Abbring, J.H. (1998), "Wage bargaining in job matching models with on-the-job search", Working paper, Free University Amsterdam, Amsterdam.

Albrecht, J.W. and B. Axell (1984), "An equilibrium model of search unemployment", *Journal of Political Economy*, 92, 824–840.

Altonji, J.G. and N. Williams (1997), "Do wages rise with job seniority? a reassessment", Working paper, Northwestern University, Evanston.

Bertola, G. and R.J. Caballero (1994), "Cross-sectional efficiency and labour hoarding in a matching model of unemployment", *Review of Economic Studies*, 61, 435–456.

Boal, W.M. and M.R. Ransom (1997), "Monopsony in the labor market", *Journal of Economic Literature*, 35, 86–112.

Bontemps, C., J.M. Robin, and G.J. van den Berg (1998), "An empirical equilibrium job search model with continuously distributed heterogeneity of workers' opportunity costs of employment and firms' productivities, and search on the job", Working paper, Tinbergen Institute, Amsterdam.

Bontemps, C., J.M. Robin, and G.J. van den Berg (1999), "Equilibrium search with continuous productivity dispersion: theory and non-parametric estimation", *International Economic Review*, forthcoming.

Bowlus, A.J., N.M. Kiefer, and G.R. Neumann (1995), "Estimation of equilibrium wage distributions with heterogeneity", *Journal of Applied Econometrics*, 10, S119–S131.

Brown, C. and J. Medoff (1989), "The employer size wage effect", *Journal of Political Economy*, 87, 1027–1059.

Burdett, K. and M.G. Coles (1993), "Equilibrium wage dynamics and firm growth in the steady-state", in J.C. van Ours et al., editor, *Labor Demand and Equilibrium Wage Formation*, North Holland, Amsterdam.

Burdett, K. and D.T. Mortensen (1998), "Wage differentials, employer size, and unemployment", *International Economic Review*, forthcoming.

Caballero, R.J. and M.L. Hammour (1996), "On the timing and efficiency of creative destruction", *Quarterly Journal of Economics*, 111, 805–852.

Cohen, D., A. Lefranc, and G. Saint-Paul (1997), "French unemployment: a transatlantic perspective", *Economic Policy*, 25, 267–285.

CPB (1995), “Replacement rates”, Working paper, Central Planning Bureau, The Hague.

Davis, S.J., J.C. Haltiwanger, and S. Schuh (1996), *Job Creation and Job Destruction*, MIT Press, Cambridge.

Devine, T.J. and N.M. Kiefer (1991), *Empirical Labor Economics*, Oxford University Press, Oxford.

Diamond, P.A. (1971), “A model of price adjustment”, *Journal of Economic Theory*, 3, 156–168.

Eckstein, Z. and K.I. Wolpin (1990), “Estimating a market equilibrium search model from panel data on individuals”, *Econometrica*, 58, 783–808.

Kiefer, N.M. and G.R. Neumann (1993), “Wage dispersion with homogeneity: the empirical equilibrium search model”, in H. Bunzel et al., editor, *Panel data and labor market analysis*, North Holland, Amsterdam.

Koning, P., G. Ridder, and G.J. van den Berg (1995), “Structural and frictional unemployment in an equilibrium search model with heterogeneous agents”, *Journal of Applied Econometrics*, 10, S133–S151.

Krueger, A.B. and L.H. Summers (1988), “Efficiency wages and the inter-industry wage structure”, *Econometrica*, 56, 259–293.

Layard, R., S. Nickell, and R. Jackman (1991), *Unemployment; Macroeconomic Performance and the Labour Market*, Oxford University Press, Oxford.

Lindeboom, M. and J. Theeuwes (1991), “Job duration in the Netherlands”, *Oxford Bulletin of Economics and Statistics*, 53, 243–264.

MacMinn, R.D. (1980), “Job search and the labor dropout problem reconsidered”, *Quarterly Journal of Economics*, 95, 69–87.

Mortensen, D.T. (1986), “Job search and labor market analysis”, in O. Ashenfelter and R. Layard, editors, *Handbook of Labor Economics*, North-Holland, Amsterdam.

Mortensen, D.T. (1990), “Equilibrium wage distributions: a synthesis”, in J. Hartog et al., editor, *Panel data and labour market studies*, North-Holland, Amsterdam.

Mortensen, D.T. (1994), “The cyclical behavior of job and worker flows”, *Journal of Economic Dynamics and Control*, 18, 1121–1142.

Mortensen, D.T. and C.A. Pissarides (1994), “Job creation and destruction in the theory of unemployment”, *Review of Economic Studies*, 61, 397–415.

Mortensen, D.T. and C.A. Pissarides (1998), "New developments in models of search in the labor market", in *Handbook of Labor Economics*, North-Holland, Amsterdam, forthcoming.

OECD (1993), *Employment Outlook 1993*, OECD, Paris.

OECD (1997), *Employment Outlook 1997*, OECD, Paris.

Pissarides, C.A. (1990), *Equilibrium Unemployment Theory*, Basil Blackwell, Oxford.

Pissarides, C.A. (1994), "Search unemployment with on-the-job search", *Review of Economic Studies*, 61, 457–475.

Ridder, G. (1984), "The distribution of single-spell duration data", in: G.R. Neumann and N. Westergård-Nielsen, editors, *Studies in labor market analysis*, Springer Verlag, Berlin.

Ridder, G. and G.J. van den Berg (1997), "Empirical equilibrium search models", in D.M. Kreps and K.F. Wallis, editors, *Advances in Economics and Econometrics: Theory and Applications*, Cambridge University Press, Cambridge.

Van den Berg, G.J. (1990), "Search behaviour, transitions to nonparticipation and the duration of unemployment", *Economic Journal*, 100, 842–865.

Van den Berg, G.J. and G. Ridder (1993), "Estimating an equilibrium search model from wage data", in H. Bunzel et al., editor, *Panel data and labor market analysis*, North Holland, Amsterdam.

Van den Berg, G.J. and G. Ridder (1998), "An empirical equilibrium search model of the labor market", *Econometrica*, forthcoming.

Appendix

Monopsony power index if the lowest wage is always equal to the minimum wage

We assume that all workers have $\phi < w_{min} = \underline{w}$, so, in terms of the classification used in Section 5, they are all in case (ii). As a result, $\mathrm{E}(w|p) = (1-\psi)p + \psi w_{min}$. By taking the expectation of this across all segments we obtain

$$\mathrm{E}(w) = (1-\psi)\mathrm{E}(p) + \psi w_{min} \tag{35}$$

with $\psi = 1/(1+k_1)$ and $\mathrm{E}(p)$ the mean of the distribution of p truncated at w_{min}. Equation (36) can be used to express $\mathrm{E}(p)$ in terms of the mean wage, the minimum wage, and the index k_1 of search frictions. This in turn can be substituted into (22) to obtain an estimate of μ.

As mentioned in Section 1, there are basically two factors preventing the employers to attain a monopoly profit: the minimum wage, and search on the job. The average monopsony power captures the combined effect of these two factors. Now let us examine the two counterfactual cases in which one of these two factors is absent. First, suppose there is no wage floor in the labor market (so there is no mandatory minimum wage, and $\underline{w} = 0$). At first sight it may seem to be impossible to obtain any results here, since we do not know the shape of the productivity density below the original minimum wage w_{min}, and we need that in order to calculate the new $\mathrm{E}(p)$. However, substitution of (36) with $w_{min} = 0$ into (22) gives $\mu_{\text{nowagefloor}} = 1/(1+k_1)$, which is identified. Moreover, this result holds for any distribution of p.

In the second counterfactual case, there is no search on the job (so $k_1 = 0$). Then all wages are equal to w_{min}, but the distribution of p in the labor market does not change. As a result, we can use our estimate of $\mathrm{E}(p)$ again. Substitution of this estimate and of $w \equiv w_{min}$ into (22) gives an estimate of $\mu_{k_1=0}$. In the following equations, the quantities on the right-hand sides refer to observed data and estimates based on observed data.

$$\mu = \frac{\mathrm{E}(w) - w_{min}}{(1+k_1)\mathrm{E}(w) - w_{min}}$$

$$\mu_{\text{nowagefloor}} = \frac{1}{1+k_1}$$

$$\mu_{k_1=0} = \frac{(1+k_1)(\mathrm{E}(w) - w_{min})}{(1+k_1)\mathrm{E}(w) - w_{min}}$$

Finally, recall that if there is no wage floor *and* search on the job is absent, then $\mu = 1$, whereas if there are no search frictions then $\mu = 0$.

By confronting the estimate of μ to those of $\mu_{\text{nowagefloor}}$ and $\mu_{k_1=0}$ we can quantify the relative importance of the minimum wage and search on the job in the actual monopsony power. Note that due to the nonlinear nature of the model, this is not an additive decomposition. In fact, the decomposition is multiplicative, as is obvious from the three expressions above. The estimation results are below.

Average monopsony power

	μ	$\mu_{\text{nowagefloor}}$	$\mu_{k_1=0}$
West Germany	0.08	0.13	0.57
Netherlands	0.04	0.10	0.45
France	0.07	0.17	0.43
United Kingdom	0.05	0.07	0.70
United States	0.03	0.05	0.72

Again, the actual average monopsony power does not vary much between the five countries. However, the decomposition of the average monopsony power enables a distinction into two groups of countries. For the UK and the US, the minimum wage is much less important as a tool to curb average monopsony power than the fact that job-to-job transitions are possible. For the other countries, the minimum wage is more important. However, for all countries, job-to-job transitions are more important than the minimum wage.

Alternative theoretical frameworks

We examine to what extent our measures of imperfection make sense in the context of other theories with informational frictions and search on the job, and to what extent the estimates are biased in the context of those theories. We will mostly focus on the index of search frictions and the estimation of λ_1.

First of all, Abbring (1998) extends the basic Pissarides (1990) job matching model by allowing for search on the job. In this model, the wage is determined in decentralized bargaining between worker and firm (a firm here equals a single vacancy or job). Given certain assumptions on the way a currently employed worker can negotiate with another firm, the equilibrium is such that all contacts result in a match. Each time an employed worker meets another firm, the worker moves to the new firm, and his wage increases. In this model, the hazard rate of the job duration distribution is simply equal to $\lambda_1 + \delta$, independently of the current wage. If this model is correct then our estimation method actually over-estimates λ_1. It should be noted that in this model (as well as in the models of the following paragraphs) the concepts of structural and frictional unemployment are still meaningful if the labor market consists of separate segments. The arrival rates λ_0 and λ_1 are endogenized in job matching models, so what we estimate are the actual values of contact rates. In the Abbring (1998) model, the monopsony power index in a single segment can be shown to be almost the same as before. The only difference concerns the fact that k_1 has to be replaced by βk_1, with β being the parameter that gives the part of the match surplus that goes to the worker.

Secondly, consider the model by Mortensen (1994), who extends the basic Pissarides (1990) model by allowing *1)* for stochastic idiosyncratic productivity shocks on the job[19] (this is actually the model in Mortensen and Pissarides (1994)) and *2)* for on-the-job search. In this model, new jobs are the most productive because they employ the latest technology. On-the-job search is somewhat more restricted than in Abbring (1998), since search by workers who are employed in a job with the highest productivity is ruled out. This means that a worker starts to search on the job after the moment that the productivity of his job experiences the first shock, which by definition is a negative shock. As a result, the job-to-job transition rate is zero for jobs with duration zero. The hazard of the job duration distribution starts at δ and then gradually increases. If this model is correct then our estimation method should produce an estimate of λ_1 equal to zero, or at least it would under-estimate the rate at which searching employed workers meet vacancies.

Thirdly, consider the model by Pissarides (1994). He extends the basic Pissarides (1990) model by distinguishing between two productivity levels and by allowing for on-the-job search. Again, search by workers in a job with the highest productivity is ruled out. In addition, job-searching workers in low-productivity jobs only consider matches with high-productivity firms. Both types of jobs allow for the accumulation of job-specific human capital. As a result, the only type of job-to-job transitions that occur are transitions from workers in a low-productivity job with a short elapsed duration to a high-productivity job. The job duration distribution is a mixture of an exponential distribution with parameter δ (these are the high-productivity jobs) and a distribution with a hazard that decreases until it reaches δ (these are the low-productivity jobs). It is dif-

[19] The models of section 2 can also be interpreted as allowing for such shocks. If a job has two possible productivity levels, one of which is unprofitable, then a drop in the productivity level results in a dismissal; this occurs at rate δ.

ficult to determine which model variable corresponds to λ_1. In any case, the arrival rate for searching employees depends crucially on the proportion of high- and low-productivity firms. In the models of Mortensen (1994) and Pissarides (1994), the wage is not constant in a job. This makes it difficult to derive a simple measure of monopsony power.

Finally, consider the extension of the Burdett and Mortensen (1998) equilibrium search model where workers are inherently within-market heterogeneous in their opportunity costs of leisure or their unemployment benefits (see Bontemps, Robin and Van den Berg (1998) for a model with within-market heterogeneity of both workers and firms). In this model, some unemployed workers reject some wage offers because they are lower than their reservation wage. As a result, employed individuals will on average reject more offers of new jobs than in the models of section 2. Our estimation method will then under-estimate λ_1.

The studies above vary widely in their predicted effect on the bias of the estimate of λ_1. The most we can say is that if this estimate is biased then it is not clear from the theoretical literature whether it is biased upward or downward. The measures of structural and frictional unemployment that we developed are however robust with respect to the alternative model specifications. For most studies, it is difficult to summarize the monopsony power in a transparent way.[20]

[20] In all fairness, it should be noted that most models mentioned in this subsection abstract from some of the phenomena that are observed in micro duration and transition data and that are incorporated in equilibrium search models. Some studies do not consider on-the-job search, whereas others make predictions on the job hazard rate as a function of tenure or the wage that are not commonly observed.

Figure 1. Job duration hazard in E−inflow

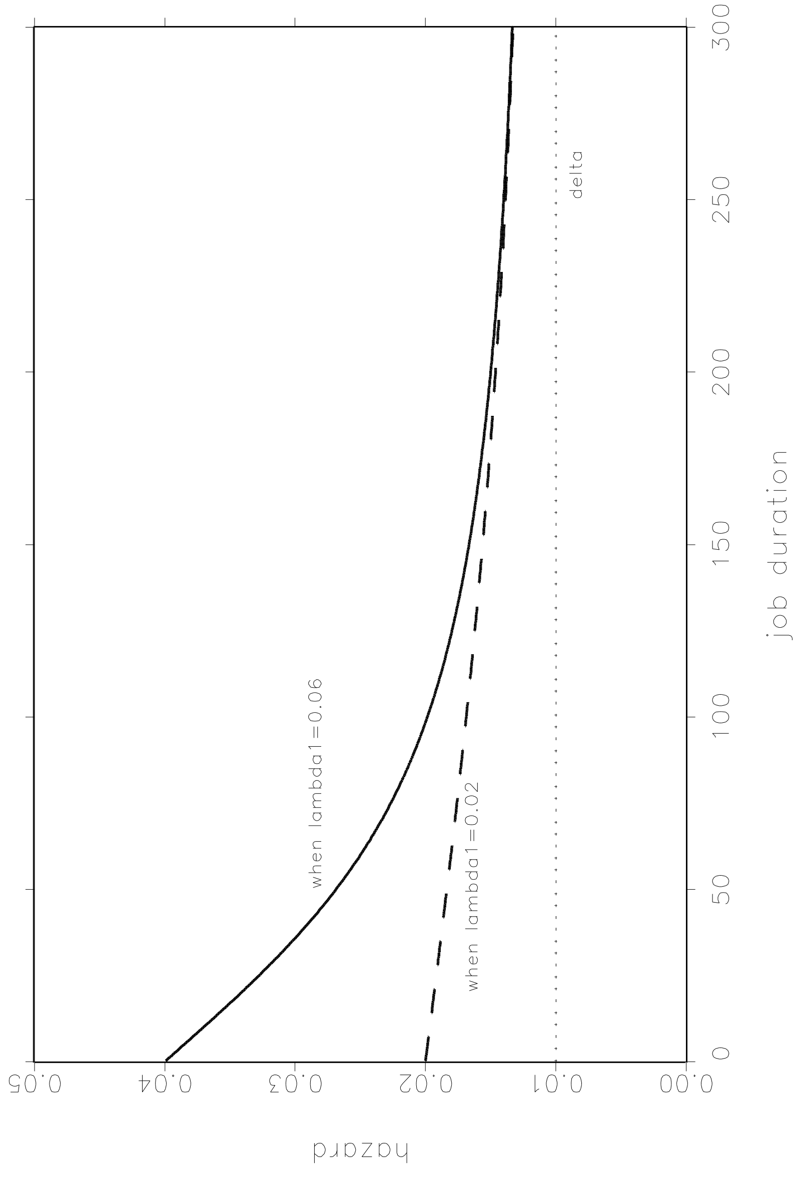

Figure 2. Observable relative theta(0) or E(t)