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Job Durations and the Job Search Model: A Two-Country, Multi-Sample Analysis*

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Abstract

This paper assesses whether a parsimonious partial equilibrium job search model with on-the-job search can reproduce observed job durations and transitions to other jobs and to nonemployment. We allow for unobserved heterogeneity across individuals in key structural parameters. Observed heterogeneity and life cycle effects are accounted for by estimating separate models for flow samples of labor market entrants and stock samples of mature workers with 10-11 years of experience, by stratifying on education length and by allowing for non-search related wage growth due to accumulation of labor market experience. We use comparable register based panel data for two countries, Denmark and Norway. All workers are followed for 6 years. The model fits observed job-to-job and job-to-nonemployment hazard functions well for most samples with a better fit for entrants than for mature workers, especially for the job-to-job hazard function. We find important differences in structural parameters between entrants and mature workers and we find that the Norwegian labor market is more frictional than the Danish labor market.

Keywords: Job Mobility, Job Durations.

JEL codes: J31, J63

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1 Introduction

The job search model stipulates that labor markets are frictional, in the sense that they are characterized by incomplete information about the location of vacancies and searching workers, and by transaction costs. This has two interrelated implications: first, jobs of different quality may co-exist in the same market (Burdett and Judd, 1983 and Burdett and Mortensen, 1998). Second, a worker's labor market career can be described as a continuous process of search for (better) jobs, both when unemployed and when employed (Burdett, 1978). The frictions are typically operationalized by shock processes that govern the frequencies of job offers and job destruction. It is standard to assume that: (i) events occur according to Poisson processes such that the duration between shocks is exponential distributed with a fixed rate parameter common across all individuals;[1] (ii) a job offer is a job quality or productivity (sometimes simply a wage) that is fixed over time and drawn from a known distribution.[2] Variants of this model framework have been applied to a variety of classic topics in labor economics: wage dispersion (Bontemps, Robin and van den Berg, 2000; Bunzel et al., 2001; Postel-Vinay and Robin, 2002; Mortensen, 2003; Christensen et al., 2005), income inequality (Flinn, 2002; Bowlus and Robin, 2004), individual wage dynamics and wage growth (Postel-Vinay and Turon, 2006; Bagger et al., 2006), discrimination (Bowlus and Eckstein, 2002) and the discouraged worker problem (van den Berg, 1990a; Rosholm and Toomet, 2005; Bloemen, 2005).

In this paper we are concerned with the adequacy of assuming that durations are exponential distributed. In particular, we investigate whether a job search model with exponential distributed durations between events can be made consistent with observed job hazard functions by introducing individual level heterogeneity in job destruction and job offer arrival rates. Observed heterogeneity is accounted for by stratification on education and by the use of two sample types: a flow sample of labor market entrants and a stock sample of "mature" workers with 10-11 years of experience at the time of sampling. Hence, a second contribution of this paper is to document the importance

[1] This assumption can be traced back to Mortensen (1970).

[2] In equilibrium search models this distribution is endogenized; in partial equilibrium models it is not. We are concerned with partial equilibrium models, although we compare some methods and results to applications of equilibrium models.

of life cycle effects in the job search model's structural parameters.[3] A third contribution is that we evaluate the job search model's performance using comparable data for two countries, Denmark and Norway. These countries are culturally and economically similar, but differ in terms of certain labor market institutions, most notably the strictness of Employment Protection Legislation (EPL). By using two different data sources we also obtain a more solid foundation for concluding on the importance of model structure versus data for goodness of fit. Some previous studies have examined cross-country differences in labor market structures within a job search model framework, see Flinn (2002), Ridder and van den Berg (2003), and Jolivet, Postel-Vinay and Robin (2006). To our knowledge we are the first to estimate structural job search models using Norwegian register based panels on individual labor market histories. Finally, we also consider heterogeneity across individuals and life cycle effects in wages, although these effects are of second order importance for this paper.

Compared to the number and range of applications of the job search model, and even though transitions between labor market states is at the core of this model, few works have addressed its ability to explain observed job durations. Bowlus and Seitz (2000) use PSID data for estimating an equilibrium search model and find that the model over-predicts average job durations, although this may stem form a very high rate of right-censoring. Bowlus, Kiefer and Neumann (2001) use NLSY data and an equilibrium model with heterogeneous firm productivity and identical workers, and also find that the model generates more long jobs than observed. Using data from the Dutch Socio-Economic Panel with self-reported job search activity, Bloemen (2005) estimates a model with endogenous search intensity, allowing for observed heterogeneity in job offer arrival rates and in search cost, in addition to unobserved heterogeneity in search cost. Bloemen finds that the model fails to fit the low exit rates at long durations. Rosholm and Svarer (2004) estimate a search model on Danish data endogenizing the decision to train workers, and find a poor fit to durations. Finally, Jolivet, Postel-Vinay and Robin (2006) use data for ten countries to estimate a job search model

[3] We do not formally consider non-stationary parameters (as is done in e.g. van den Berg, 1990b). Separating heterogeneity from structural duration dependence is an important empirical issue (Heckman, 1991), but not one that we will take on in this paper.

and conclude that "*... in some cases there seems to be more negative duration dependence in the data than the model can predict*" (p. 896). Hence, studies that have used different data sources, various age, education and gender groups, and different model specifications, arrive at the same conclusion: the job search model fails in fitting job durations and the data are likely to contain heterogeneity that has not been accounted for in the model.

We obtain more detailed insight into where the model may fail than previous studies by addressing the fit to destination-specific hazard functions within a competing risks framework (job-to-job and job-to-nonemployment), and by specifically considering the role of heterogeneity in generating acceptable fit to job durations. We find that the search model with heterogeneous parameters produces acceptable, though not perfect, fits to observed job-to-job and job-to-nonemployment hazard functions. The fit is better for entrants than for mature workers, especially for the job-to-job hazard function. Moreover, we find significant differences in structural parameters between entrants and mature workers, suggesting that life-cycle effects in structural parameters is an important empirical issue when applying the job search model to long panels. Finally, relative to Denmark, the Norwegian labor market is characterized by lower job offer arrival rates for both employed and nonemployed workers and higher job destruction risks. This pattern is stable across education groups and between samples of entrants and mature workers.

The remainder of the paper is organized as follows: section 2 presents the theoretical model. Section 3 contains a brief description of Danish and Norwegian EPL and wage setting institutions. Section 4 presents the data and section 5 develops the empirical model. The estimated models are discussed in section 6 and we evaluate goodness-of-fit in section 7. Section 8 concludes the paper. Appendices A, B and C provide technical details.

2 The job search model

Setup. The labor market consists of a demand side represented by a continuum of firms and a supply side represented by a continuum of workers. The measures of firms and workers are normalized to unity. Time is continuous and is discounted at a constant rate ρ. Without loss of

generality we state all income related variables in logs and assume that workers are endowed with an instantaneous utility function $u(\cdot)$ over log flow income. Workers can be either employed or nonemployed, i.e. we do not distinguish nonparticipation from unemployment and refer to these out-of-work states as nonemployment. We make no distinction between a firm and a job but refer to the demand side of the market as being populated by firms. Hence, workers and firms match one-to-one, but must engage in a search process to locate a potential match partner. Firms produce a multipurpose consumption good using a constant-returns-to-scale technology with labor as the only variable input. The matching process is such that nonemployed workers receive job offers at a Poisson rate λ_0 whereas employed workers receive job offers at rate λ_1. Existing jobs are destroyed at rate δ and workers retire (i.e. vanish from the model) at rate μ. To maintain a constant labor force we assume that nonemployed workers are born into the model at rate μ.[4] We treat job offer arrival rates, job destruction rates and retirement rates as fixed parameters from the perspective of workers. Workers cannot recall offers rejected in the past.

Wage setting and match quality. Firms post real log wage contracts of the form

$$w^*(a, x) = y(a) + x, \tag{1}$$

where $w^*(a, x)$ is the log wage, x is a time-invariant log match quality and $y(\cdot)$ is some function of the worker's experience $a \geq 0$ with $y(0) = 0$. Experience is assumed transferable across jobs and labor market states. Newborn workers have $a = 0$ and only employed workers accumulate experience. There is an experience level A after which the worker's productivity remains constant:

$$y(a) = \begin{cases} y(a) & 0 \leq a \leq A \\ y^* & a > A \end{cases} . \tag{2}$$

Nonemployment is treated as employment in a match of log quality b such that nonemployed workers receive log flow income $y(a) + b$.[5] Let F be the sampling distribution of log match qualities x on $[\underline{x}, \overline{x})$ with $\overline{x}$ possibly extending to ∞. In partial equilibrium we take F as given.[6]

[4] The constant retirement rate μ should be considered a technical assumption needed to secure the existence of proper steady state distributions needed for our analysis. See Appendix B.

[5] A partial justification for this assumption can be found in the fact that unemployment insurance depends on previous earnings in both Denmark and Norway.

[6] In a setup similar to ours, Burdett and Mortensen (1998) show that the unique Nash equilibrium offer distribution in a game where firms post match qualities, is continuous, non-degenerate and bounded from below.

The log-additivity of $y(a)$ and x in (1) simplify the characterization of workers' optimal strategies. One way of rationalizing (1) is to assume that firms post piece-rate contracts (following Barlevy, 2003 and Bagger et al., 2006). When a worker and a firm form a match, a fraction $\exp(\widetilde{x}) \in [0,1]$ of the match's produce is assigned to the worker. From the worker's perspective, a job offer is thus a draw from a distribution of piece-rates $\exp(\widetilde{x}) \in [0,1]$. Let the worker's productivity be $\exp(\widetilde{y}(a))$. Then, the log wage is a function of the piece-rate contract and labor market experience (through productivity): $w^*(\widetilde{x}, a) = \widetilde{y}(a) + \widetilde{x}$. Because piece-rates and productivity are not observed, $\widetilde{x}$ and $\widetilde{y}(a)$ are only identified up to scale and our wage equation (1) ensues by normalizing by $\exp(\widetilde{y}(0))$. That is, $y(a) = \widetilde{y}(a) - \widetilde{y}(0)$ and $x = \widetilde{x} + \widetilde{y}(0)$.

Labor market flows. Whereas job destructions and retirement shocks are exogenous to the workers, the decision of whether or not to accept a job offer is endogenous. Proposition 2.1 characterizes workers' optimal strategies.

Proposition 2.1 *A worker's optimal strategy has the reservation quality property. Let $\mathcal{V}_1(x,a)$ and $\mathcal{V}_0(a)$ be the expected present discounted value of employment in a match of log quality x and nonemployment, respectively, for a worker with experience a. Let $\mathcal{V}_1^*(x) \equiv \mathcal{V}_1(x,A)$ and $\mathcal{V}_0^* \equiv \mathcal{V}_0(A)$. For $0 \leq a < A$ the unemployed search reservation log quality $r^u(a)$ exists and solves:*

$$\mathcal{V}_1(r^u(a), a) = \mathcal{V}_0(a).$$

For $a \geq A$ the unemployed search reservation log quality $r^{u,*}$ exists and solves $\mathcal{V}_1^*(r^{u,*}) = \mathcal{V}_0^*$. It is defined by:

$$r^{u,*} = u^{-1}\left(u(y^* + b) + (\lambda_0 - \lambda_1)\int_{r^{u,*}}^{\overline{x}} \frac{\overline{F}(s)\,\mathbf{1}(s \geq \underline{x})}{\rho + \mu + \delta + \lambda_1 \overline{F}(s)}\, ds\right).$$

The on-the-job search reservation log quality $r^e(x)$ of a worker in a match of log quality x exists and is independent of the worker's labor market experience. It solves $\mathcal{V}_1(r^e(x), a) = \mathcal{V}_1(x,a)$ and $\mathcal{V}_1^*(r^e(x)) = \mathcal{V}_1^*(x)$ for $0 \leq a < A$ and $a \geq A$, respectively, and is given by the unit function:

$$r^e(x) = x.$$

Proof See Appendix A ■

Proposition 2.1 and the assumption of Poisson arrival rates generates a continuous time exponential competing risks duration model for job durations with three transitions: retirement (with hazard rate μ), job-to-nonemployment (hazard rate δ), and job-to-job transitions. The job-to-job hazard is the product of the arrival rate of offers λ_1 and the probability that the quality of the offer exceeds the worker's current match quality. Conditional on current log match quality x, the latter event occurs with probability $\overline{F}(x) \equiv 1 - F(x)$, producing the conditional job-to-job hazard rate $\lambda_1 \overline{F}(x)$.

Let T^{er}, T^{eu} and T^{ee} be the latent durations until retirement, job destruction and a job-to-job transition, respectively. In the absence of censoring, observed job duration $T^e = \min\{T^{er}, T^{eu}, T^{ee}\}$ with realization t^e.[7] Let D^{er}, D^{eu} and D^{ee} be binary random variables whose realizations d^{er}, d^{eu} and d^{ee} indicate transitions into retirement, nonemployment and another job, respectively. We will condition the data used for the empirical analysis on no retirement in the sample period. This is equivalent to conditioning on no retirement during each separate spell (that is, $d^{er} = 0$ for each job and nonemployment spell). To save on notation we do not make the condition $d^{er} = 0$ explicit. It follows that the joint density of (T^e, D^{eu}, D^{ee}), conditional on x (and $d^{er} = 0$), denoted $p^e(t^e, d^{eu}, d^{ee}|x)$, is a competing risks exponential distribution:

$$p^e(t^e, d^{eu}, d^{ee}|x) = \delta^{d^{eu}} [\lambda_1 \overline{F}(x)]^{d^{ee}} e^{-[\delta + \lambda_1 \overline{F}(x)]t^e}. \tag{3}$$

Let T^{ur} and T^{ue} be the latent durations until a nonemployed worker retires and transits into employment, and let D^{ur} and D^{ue} be binary random variables whose realizations d^{ur} and d^{ue} indicate transitions into retirement (hazard rate μ) and employment (hazard rate $\lambda_0 \overline{F}(r^u(a))$, respectively. We assume that nonemployed workers accept all job offers, implying that $\overline{F}(r^u(a)) = 1$ for all $a \geq 0$ such that the nonemployment-to-job hazard rate is λ_0. Hence, conditioning on no retirement in each nonemployment spell, in the absence of censoring, the joint density of observed nonemployment duration $T^u = T^{ue}$ (with realization t^u) and D^{ue}, is

$$p^u(t^u, d^{ue}) = \lambda_0^{d^{ue}} e^{-\lambda_0 t^u}. \tag{4}$$

[7] Random censoring is routinely handled in a competing risks framework. See for example Lancaster (1990).

The assumption that nonemployed workers accept all job offers relates to a fundamental identification problem of the partial equilibrium model: the reservation log match quality of nonemployed workers, $r^u(a)$, is an endogenous variable, whereas the match quality sampling distribution F is taken as exogenous. If $r^u(a)$ exceeds the lower point of the support of F, the left tail of F is never observed, leaving F nonparametrically unidentified (Flinn and Heckman, 1982). The assumption that $\overline{F}(r^u(a)) = 1$ for all $a \geq 0$ restricts the set of admissible match quality sampling distributions to those with an estimable lower point of support and also rules out endogenous quitting into nonemployment as it implies that $\mathcal{V}_1(x, a) > \mathcal{V}_0(a)$ for all $a \geq 0$ and $x \in [\underline{x}, \overline{x})$.[8]

Distribution of match qualities. In our empirical analysis we will use employment spells sampled from stock, i.e. jobs that are active on a given date. Due to the selection mechanism working through workers' reservation strategies (proposition 2.1), match qualities are not distributed according to F in such a sample. However, imposing a steady state on the model yields a set of balanced-flow restrictions that can be used for deriving the cross-section log match quality distribution conditional on experience. The labor market is in a steady state when the inflow and outflow to any given state or set of workers (e.g. nonemployment, workers with experience a, workers earning w or less, etc.) balance. We use a number of such steady state conditions to prove the following proposition:

Proposition 2.2 *The steady state distribution of log match qualities x in a cross section of workers with labor market experience a, $G(x|a)$, is:*

$$G(x|a) = \frac{F(x)}{\delta\lambda_0 + (\mu + \lambda_0)\lambda_1\overline{F}(x)} \left[\delta\lambda_0 + (\mu + \lambda_0)\lambda_1\overline{F}(x)e^{-[\mu+\delta+\lambda_1\overline{F}(x)]a}\right].$$

Proof See Appendix B ■

As a approaches 0, the distribution of match qualities $G(x|a)$ approaches $F(x)$: inexperienced workers have not yet had the time to climb the "job-ladder". Conversely, $G(x|a') > G(x|a'')$

[8] When introducing heterogeneous shock processes in a partial equilibrium setting as the one considered in this paper, one should also consider heterogeneity in the lower point of support of the sampling distribution F. We do so in the empirical analysis.

for $a' < a''$: the distribution of match qualities among more experienced workers stochastically dominates that of less experienced workers, because more experienced workers have made more job-to-job transitions since the latest nonemployment period, on average.

3 Institutions

When evaluating the ability of the job search model to reproduce observed transition rates it is important to confront the model with data on workers who act in different environments and to use different data sources. We do this using data for Denmark and Norway (described in detail in section 4). The two countries are similar in terms of income levels and the form and scope of welfare states, but differ in certain labor market institutions.

Employment protection An important difference between the labor markets of Denmark and Norway is the strictness of EPL. OECD (1999) compared EPL for a number of countries and ranked Denmark 7 and Norway 15 among 27 countries on overall strictness of protection against individual dismissal in the late 1990s (a higher rank indicates stricter EPL in the sense that workers are more protected). Norwegian EPL is particularly strict on the definition of "unfair dismissal", i.e. it is harder to fire individual employees in Norway than it is in Denmark and the other 27 countries. In Norway, individual dismissal requires some form of disloyalty or other breach of contract. Legal practice has established that individual lay-off for economic reasons is only allowed if the job has become redundant and the worker could not be retained in some other position. In Denmark it is generally possible to dismiss an individual worker whose job has become redundant. Reinstatement is more frequent in Norway and compensation for unfair dismissal slightly more generous. Severance payments are not required by law in Norway (but agreed for older workers in the private sector) or for blue collar workers in Denmark, but last up to three months for white-collar workers in Denmark.[9] Denmark also has longer notice periods for white-collar workers, whereas notice periods are similar for blue collar workers in Denmark and Norway (slightly longer for Norwegian blue-collar

[9] In our empirical analysis we will stratify the data according to educational attainment rather than using the blue collar/white collar distinction.

workers with long tenure). Both countries are in the middle of the distribution within the OECD for strictness of regulations of collective dismissals.

Wage setting Both countries are characterized by a high degree of centralization in wage setting and a high degree of coordination between employer and employee organizations. There is bargaining at several levels and at two year intervals, with collective agreements setting minimum standards for wage increases tied to education, formal skills and job types. Wages may increase above this amount through negotiation at lower levels. Mortensen (2003) asserts that 85 percent of all central agreements in Denmark in 1993 allowed for local (i.e. firm level) determination of wages and working conditions. This fraction is likely to have risen since then. In Norway, blue collar workers are typically covered by minimum wage agreements (with a wage drift due to local negotiations), whereas for white collar workers, only wage setting procedures and not wages per se are negotiated at the collective agreements. In 1994 the union densities were 76 and 58 in Denmark and Norway, respectively. However, due to wider coverage of non-members in Norway total coverage rates are similar, with 69 percent in Denmark and 74 percent in Norway (OECD, 1997).[10]

4 Data

The data used for the empirical analysis are based on two comprehensive matched employer-employee panel data sets from Denmark and Norway and contain information on wages, labor market transitions and worker characteristics.

Data for Denmark. The main source of the Danish data is a collection of individual labor market histories (spells) recorded on a weekly basis over the period 1985-2001 and covering the full Danish population aged 16-70 and all firms. The spell data are constructed from administrative registers with information on public transfers, earnings as well as start and end dates for all jobs reported by firms to the Danish Tax Authorities, and mandatory employer pension contributions. We supplement the spell data with annual background information on individuals (for this study:

[10] OECD (1997) mentions data problems and unionized workers working in non-covered firms as possible reasons that unionization exceeds coverage in Denmark.

educational attainment and experience) and firms (for this study: a public sector indicator) from IDA.[11] Labor market experience is deduced from mandatory pension payments related to the number of hours worked and dates back to 1964. Employers are identified both at the firm and establishment level. We construct job spells using the firm identifiers, i.e. we do not treat job changes between establishments within the same firm as labor market transitions. Because we are not specifically interested in the differences between unemployed and non-participating workers, we pool unemployment and nonparticipation together in the single state, nonemployment. We observe within-year average wages that are calculated from job-specific annual earnings and a rough calculation of the number of hours worked in each job (based on mandatory pension payments related to the number of hours worked). Hence, the wage measure incorporates bonus pay, overtime pay etc.

Data for Norway. The Norwegian data derive from administrative registers for firms, establishments and individuals. The data are collected by various authorities for different administrative purposes and cover the entire Norwegian population of persons and firms, with most information being available from 1992. Consistent use of establishment and person identifiers across registers facilitates linking of different data sets. The data sources used for constructing individual labor market histories are the employer-employee register and the LTO register, the Norwegian Tax Directorate's register of wage sums, available since 1995. The employer-employee register is part of the social security system, and employers report information on employment relationships to this register at the establishment level. Apart from very short jobs and self-employment, these data include all jobs in the Norwegian economy. We obtain information on annual earnings for each job from the LTO-register. All employers are required to report paid wages to the Tax Directorate with one report for each contract of employment each year and the reporting is done at the firm level. The earnings measure includes pecuniary compensation including bonuses and overtime pay. Working hours are coded in three intervals, resulting in errors in the calculated hourly wages. As with the Danish data, we define the Norwegian job spell data using the firm identifier, and define

[11] IDA: *Integreret Database for Arbejdsmarkedsforskning* is constructed and maintained by Statistics Denmark.

nonemployment periods as periods when not registered as employed. Actual labor market experience is calculated using individual earnings histories from 1967 onwards, see Hægeland (2001) for details. Length of highest completed education is taken from the National Education Database (NUDB).

4.1 Sample selection

We use the period 1997-2003 for the Norwegian data and 1995-2001 for the Danish data and restrict attention to men in order to not confound the analysis with fertility and household production issues usually deemed more relevant for women.[12] Both the Norwegian and the Danish data include information on highest completed education in a given year. We assume that labor market entry occurs the January 1 in the year following graduation from highest completed education. Because workers under 18 are subject to different rules regarding employment conditions and wages than adult workers, we do not use information on careers that occur before age 18. For individuals graduating from a highest completed education before turning 18, we re-define labor market entry to occur January 1 in the year the worker turns 19. Durations of the entry spells (employment or nonemployment) are measured from January 1 in the entry year irrespective of the actual starting date of the spell. These definitions of entry jobs are similar to those applied by Topel and Ward (1992). In order to narrow the data to a sample of workers who can be assumed to behave in accordance with the theoretical model, we exclude persons who disappear from our records, who are observed to be self-employed, who receive transfers related to disability or retirement, and who are observed in public sector jobs, any time during the data periods. This sample selection rule is similar to that applied by van den Berg and Ridder (1998) and Flinn (2002).

If a person is employed in the same firm during two separate periods that are less than 12 weeks apart we aggregate these jobs into a single job, thus interpreting the nonemployment spell as a temporary dismissal with behavior as if continuously employed. In both data sets there are a number of very short nonemployment spells (shorter than 4 weeks). We suspect that many of these spells are waiting periods when the start date of a new job has already been agreed.

[12] Because of errors in the 1996-data for Norway, we only use data from 1997

Consequently, we eliminate nonemployment periods shorter than four weeks and instead record a job-to-job transition. Bowlus, Kiefer and Neumann (2001) use a two-week threshold in a similar spell definition.

We stratify the data into three groups according to workers' education length: 7-10, 11-13 and 14-20 years, corresponding to lower secondary school, upper secondary school or tertiary education. For sake of brevity we refer to the three levels as low, medium and high education.

Wages. The theoretical model assumes a dynamically stable distribution of wage offers. This implies the absence of technological improvements and other macro shocks that might shift the wage distribution. We therefore trend the nominal wage observations in each stratum to the 2001 level by regressing wage observations on a set of year-dummies (and a constant), and retrieve the de-trended wage observations as the residuals (plus the constant). For the de-trending regression we use all jobs in the private sector for a sample of workers who satisfy the criteria for sample selection outlined above. We then ensure that the data are balanced across years by imposing a uniform age distribution in each year.[13] We remove the top and bottom 2.5 percent of wage observations in each year before wages are de-trended.

Labor market entrants. We sample a cohort of Danish workers who entered the labor market in 1996 (i.e. who graduated during 1995) and a cohort of Norwegian workers who entered in 1998 (graduating during 1997). All workers are followed for 6 years, i.e. until the end of 2001 and 2003, respectively. We impose two additional requirements on the samples of entrants: first, labor market experience at entry should be no more than 5 years (many workers accumulate experience before completing education). Second, age at entry cannot fall below years of education plus 5 (19 for workers entering the labor market before turning 18) and cannot exceed years of education plus 15.

Mature workers. The sample of mature workers consists of a cross section of workers who have between 10 and 11 years of labor market experience at a particular date. For the Danish sample

[13] To be precise, we randomly select 100 individuals in each age-year cell. In case 100 individuals cannot be selected for a given age-year cell we sample with replacement.

we take a cross section of workers in January 1, 1996. For the Norwegian sample we select workers at January 1, 1998. As with the labor market entrants all workers are followed for 6 years and an age requirement is imposed: age at sampling time cannot fall below years of education plus 15 and cannot exceed years of education plus 25.

Employment cycles. The likelihood function that we derive from the job search model is built using the notion of employment cycles. An employment cycle is a sequence of consecutive jobs where the first job in the cycle follows a transition from nonemployment, and the last job ends in either a transition back to nonemployment or in censoring. Inspection of both the Norwegian and the Danish data reveals that a non-trivial fraction of jobs end in the last week in December in each of the years covered by the samples (10-15 percent of jobs). The clustering occurs in both countries when employers fail to report start and ending dates of jobs. Although labor market mobility is likely to exhibit some seasonality, the clustering of job terminations is so pervasive that we decided to truncate employment cycles at entry to a job that ends in the last week of December. Note that we truncate employment cycles and not labor market histories, a practice that is in accordance with the search model's stipulation that nonemployment periods "reset" labor market histories.

For computational reasons (see section 5) we censor individual trajectories at exit from the third observed employment cycle,[14] and we censor the employment cycles at transition to the third job in the cycle (but record that a job-to-job transition occurred). Note that we do not censor jobs, apart from jobs that are ongoing at the end of the observation period. Also note that the censoring implies that some workers will have no employment spells. These workers contribute only to the identification of the parameter governing nonemployment-to-job transitions that is of no particular interest to us and are therefore discarded. Hence, the final samples consist of labor market histories with a maximum length of 6 years, covering up to three employment cycles, each of the observed employment cycles containing up to the two first jobs in the cycle.

[14]The third observed employment cycle may in reality be the fourth, fifth, etc. due to the truncation of cycles containing jobs ending in a last week of December. Given our model, where nonemployment periods neutralize all differences between workers, there is no difference between behavior and outcomes in a worker's third and subsequent employment cycles.

4.2 Descriptive analysis

The business cycle. We begin by briefly considering the state of the Danish and Norwegian labor markets during our sample periods. Figure 1 plots unemployment rates for men in Denmark and Norway 1994-2005. These numbers relate to the macro level of the labor market and are not representative for our samples due to the data manipulations and sample selection rules imposed above, but are still informative about the environment in which individuals in our sample act. The unemployment rate increased in Norway throughout the data period, whereas the Danish unemployment rate first decreased, then stabilized. Although the unemployment rates were not constant within our windows of observation, it may still be reasonable to assume steady state, as is done in order to derive the distribution of match qualities for mature workers. For instance, research by Jolivet, Postel-Vinay and Robin (2006) suggests that labor markets move rapidly from one steady state to another in response to external shocks.

< Figure 1 about here. >

Job durations and transitions. Table 1 describes the amount of data and transitions. There are only few workers in the lowest education groups, especially for entrants. Part of the reason is that we have excluded persons who retire from the labor market permanently. Remember that the number of cycles and the number of jobs are top-coded at three cycles per worker and two jobs per cycle, and that employment cycles are truncated at entry into a job with an end-date the last week of December. This makes it difficult to interpret differences between strata. Also note that any comparison of the raw numbers in Table 1 of entrants and mature workers is rendered difficult by the increase in average education levels between the cohorts.

< Table 1 about here. >

In our empirical model we will allow for heterogeneity between individuals in the job destruction rate δ and in the job offer arrival rate when employed, λ_1. Identification of this heterogeneity rests on the observation of multiple employment cycles (for δ), and multiple jobs within the same cycle (for λ_1) for the same individual. The numbers reported in Table 1 suggest that the number of

repeated spells are sufficiently high to estimate heterogeneity distributions.

We describe transition patterns in Figure 2 and Figure 3 using nonparametric kernel estimates of the transition specific hazard functions (Ramlau-Hansen, 1983). The hazard function estimates have been corrected for the downward bias near the boundary of the support (Nielsen, 1998). For entrants we plot the hazard function estimated on each entrant's first observed job (that is, we consider the flow of entry jobs), and for mature workers we plot the hazard function of jobs that were active at the time of sampling (that is, for a stock sample of jobs). The use of different samples makes it difficult to compare entrants and mature workers based on Figures 2 and 3. Neglected heterogeneity in duration models manifests itself as spurious duration dependence in the hazard function (see e.g. Lancaster, 1990). In single risk models the bias goes towards too much negative duration dependence. In competing risks it is not possible to sign the bias without restricting the distribution of unobservables. Estimates of the unconditional hazard function are thus indicative of unobserved heterogeneity in the parameters that govern the job destruction process and the empirical relevance of conditioning on a match quality in the job-to-job transition process. In fact, with homogenous λ_1 the job-to-job hazard function is a mixture of exponentials with the distribution of match qualities as the mixing distribution (Ridder and van den Berg, 2003).

< Figures 2 and 3 about here. >

The hazard functions are monotonically declining in all samples, except perhaps Danish high educated entrants. The negative duration dependence is most pronounced for entrants, the low-educated and for the job-to-nonemployment transitions. This supports the inclusion of heterogeneity in transition parameters. There is more duration dependence in the job-to-nonemployment hazard among entrants than among mature workers, and there is more duration dependence in the job-to-nonemployment hazard than in the job-to-job hazard. In fact, the hazard for transitions to nonemployment exceeds the hazard for direct job change at short durations for several samples (all but one Norwegian sample).

Overall, the job-to-job hazard rates are higher in Denmark and the job-to-nonemployment hazard lower, especially for entrants. Dale-Olsen and Rønningen (2000) conclude that flow rates

are higher in Denmark than in Norway, and in particular, Danish worker churning flow rates (worker flows over and above that needed for generating observed job flows) are larger than the Norwegian churning rates. Our data suggest that this is due to higher job-to-job mobility in Denmark. Given the stricter protection against individual dismissal and temporary employment in Norway we expected higher job-to-nonemployment mobility in Denmark. Differences in business cycles may be part of the explanation for the seemingly higher job destruction risk in Norway.

The hazard functions reveal that mobility decreases with education and that the bulk of this decrease is in terms of a reduced risk of nonemployment. Using Danish administrative register data similar to the data used here, Bunzel et al. (2001) report that the job destruction rate decreases with education level for workers aged under 30. This pattern is also in line with studies of displaced workers, where low educated workers face a higher risk of displacement. See e.g. the cross-country studies in Kuhn (2002) for international evidence.

Wages. Table 2 shows the means and standard deviations of the log-wage distribution in jobs that follow non-employment (and the first jobs observed for entrants).[15] Average starting wages increase with education and experience as expected. Between 39 and 55 percent of job-to-job transitions involve a wage cut. Jolivet, Postel-Vinay and Robin (2006) report frequencies of wage cuts within the same range, and van den Berg and Ridder (1998) report 11 percent (their footnote 15, p. 1202). The model presented in section 2 is in fact consistent with job-to-job transitions with wage cuts when $y'(a) < 0$. However, we expect $y(a)$ to be increasing and the experience effect is not likely to explain the observed level of wage cuts. The job search literature has pointed to a number of alternative explanations of job-to-job transitions with wage cuts. First, workers may accept a wage cut if they are compensated by higher expected future wage growth (like in Postel-Vinay and Robin, 2002). Second, workers who expect to be laid off or have received advanced notice of a lay-off may lower their reservation wage below their current wage. Third, there might be compensating differentials in wages: if workers value nonpecuniary job attributes, and if the ranking of jobs based on wages differs from the ranking based on wages and nonpecuniary attributes, then job-to-job

[15] The average exchange rate (DKK/NOK) was 92.6 in 2001.

transitions with wage cuts will occur. Fourth, it is likely that we measure hourly wages with error. We disregard structural explanations, and treat the wage cuts as a pure data issue. Hence, we maintain the assumptions of the basic model but allow for measurement error in wages in our empirical model.

5 The empirical specification

In this section we derive the likelihood function associated with the job search model of section 2 as the joint distribution of wages and destination-specific durations.[16] The data description demonstrated that wage observations are missing and that unobserved heterogeneity and measurement errors in wages are likely to be important. We adapt the empirical model to take these observations into account. We first specify functional forms for experience effects in wages, match quality distributions and introduce measurement errors. We then derive the likelihood function.

Experience effects, match quality and measurement errors. Individual log wages are additive in (normalized) individual log productivity $y(a)$, where a is years of experience, and a log match quality x. In the empirical implementation we specify $y(a)$ as a linear spline function with two knots, a_1^* and a_2^*:

$$y(a) = \begin{cases} \gamma_1 a & a \leq a_1^* \\ \gamma_1 a_1^* + (\gamma_1 + \gamma_2)a & a_1^* < a \leq a_2^* \\ \gamma_1 a_1^* + (\gamma_1 + \gamma_2)a_2^* + (\gamma_1 + \gamma_2 + \gamma_3)a & a \geq a_2^* \end{cases}, \tag{5}$$

The knots are set at 3 and 6 years for labor market entrants and at 12 and 14 years for mature workers. Whereas mature workers all have between 10 and 11 years of labor market experience when entering the sample, entrants have between 0 and 5 years of experience. Because we follow all workers for 6 years the range of experience values is 0-11 years for entrants and 10-17 years for mature workers. In order to treat pre-entry labor market experience similarly for entrants and mature workers (where we do not observe pre-entry experience) we assume that pre-entry experience

[16] Ridder and van den Berg (2003) develop unconditional inference techniques for the job search model's transition parameters where no restrictions are imposed on the distribution of match qualities. Their techniques are thus applicable in situations where one is unwilling to impose parametric restrictions on the sampling distribution F or where wage data are absent or seriously flawed. Although we utilize their ideas for jobs with missing wage data, we do estimate the wage and transition parameters jointly.

is as useful as post-entry experience in generating wage/productivity growth, and include pre-entry experience in our measure of experience. Equation (5) entails the implicit assumption that $A > 17$.

Next we need to parameterize the distribution of log match qualities F. Keeping in mind that we have restricted the set of admissible F's to have an estimable lower point of support, we assume that F is the three parameter Weibull distribution,

$$F(x) = 1 - e^{-\left(\frac{x-\alpha}{\nu}\right)^{\eta}}. \tag{6}$$

The Weibull distribution contains as a special case the truncated exponential distribution ($\eta = 1$), which in turn is equivalent to the Pareto distribution for match qualities in levels. It can also resemble the normal distribution.

As described above the calculated wages are surely infected by measurement error. We account for this in estimation.[17] Observed log wages w are given as

$$w = w^* + \varepsilon = y(a) + x + \varepsilon, \tag{7}$$

where ε is a classical log measurement error, i.e. independent of a and x and with $\varepsilon \sim \mathcal{N}(\xi, \sigma^2)$. Clearly, (α, ν, η) and (ξ, σ) are not separately identified from wage observations and we impose the normalization $\mathrm{E}[\exp(w)|a, x] = \exp(y(a) + x)$ implying that $\xi = -\sigma^2/2$. Hence, the density of observed log wages conditional on x and a is

$$h(w|a, x) = \phi\left(\frac{w - y(a) - x + \sigma^2/2}{\sigma}\right)\frac{1}{\sigma}, \tag{8}$$

where $\phi(\cdot)$ is the standard normal density.

A note on identification of the parameters in the match quality distribution is warranted here: our stock sample of mature workers all have 10-11 years of experience at the time of sampling. This implies that the first moment in the match quality distribution $F(x)$ for mature workers is unidentified, since it confounds the true mean of offered log match qualities $\alpha + \Gamma(1 + 1/\eta)/\nu$ with the effect of experience accumulated prior to stock sampling. $\Gamma(\cdot)$ is the gamma function.

[17] Previous studies have also accounted for measurement errors in job search models: Wolpin (1987), van den Berg and Ridder (1998), and Flinn (2002) use normal distributed errors, whereas Christensen and Kiefer (1994) and Bunzel et al. (2001) assume that errors are distributed according to Pearson type 5 distribution.

The likelihood function. Recall that an employment cycle is a sequence of consecutive job spells where the first job in the cycle follows a transition from nonemployment, and the last job ends in either a transition back to nonemployment or in censoring. Let subscripts $c = 1, ..., C$ represent a worker's employment cycles, and let $j = 1, ..., J_c$ represent the jobs within employment cycle c for each c. We have annual observations on wages and experience levels for each job, and let $k = 1, ..., K_{cj}$ for each c, j denote observations on job j in cycle c, where $K_{cj} \leq 6$. Furthermore, $C \leq 3$ because we have restricted the analysis to cover at most three employment cycles for a given individual, and $J_c \leq 2$ because we truncated employment cycles at entry into the third job in the cycle. A worker's nonemployment spells are indexed by $n = 1, ..., N \leq 4$.

Let $\{t^e_{cj}, d^{eu}_{cj}, d^{ee}_{cj}, \{w_{cjk}, a_{cjk}\}_{k=1}^{K_{cj}}\}$ be the data for a job of rank j in cycle c, and let $Q_{cj}(x)$ be the associated likelihood contribution, conditional on the log match quality x:

$$Q_{cj}(x) = p^e(t^e_{cj}, d^{eu}_{cj}, d^{ee}_{cj}|x) \times \left[\prod_{k=1}^{K_{cj}} h(w_{cjk}|a_{cjk}, x)^{m_{cjk}}\right], \tag{9}$$

where m_{cjk} takes the value 1 if w_{cjk} is non-missing and the value 0 otherwise. The first term on the right-hand side of (9) is the joint density of job durations and transition indicators, conditional on the match quality x. This is given by (3). The second term is the density of observed log wages, conditional on experience and the match quality x. The likelihood contribution of an unemployment spell is given by (4).

Log match quality is unobserved to the econometrician and is treated as a random effect. The assumption that nonemployed workers accept all job offers implies that the density of log match qualities in the first job of an employment cycle is $f(x)$, the sampling density of log match qualities. Because workers only move to better jobs, the density of log match qualities in the second job, conditional on the quality of the first job, is $f(x_2)/\overline{F}(x_1)$, with $x_2 > x_1$.

We assume that we observe the first job for every labor market entrant, such that the log quality of initial jobs is distributed according to $F(x)$. For mature workers who are employed at the sampling date, the stock sampling scheme, together with the assumption that the labor market for mature workers is at a steady state, implies that match qualities in mature workers' initial jobs are distributed according to $G(x|a^0)$ given by Proposition 2.2, where $a^0 \in [10, 11)$. Define s_c as an

indicator equal to 1 if the first job in the cycle was stock sampled and 0 otherwise, and let χ_c be an indicator equal to one if the cycle c has (at least) two jobs, zero otherwise. We can then write the unconditional likelihood contribution from an employment cycle with two observed jobs as

$$\int_{\alpha}^{\infty} Q_{c1}(x_1) \left[\int_{x_1}^{\infty} Q_{c2}(x_2) \frac{dF(x_2)}{\overline{F}(x_1)} \right]^{\chi_c} dG(x_1|a^0)^{s_c} \, dF(x_1)^{1-s_c}. \tag{10}$$

If the last job in a cycle has no wage observations the inner integral in (10) can be solved analytically (Ridder and van den Berg, 2003). Clearly, if none of the jobs in a cycle have wage observations the full likelihood contribution from that cycle admits a closed form solution. We solve remaining integrals by numerical integration using Gauss-Legendre quadrature techniques (see e.g. Judd, 1998), using 40 quadrature nodes in each dimension.

The descriptive statistics hinted at important unobserved heterogeneity in the job destruction rate δ and the job offer arrival rate λ_1. We incorporate this observation into the model using a random coefficient approach. Following the discrete distribution approach of Heckman and Singer (1984), a fraction $0 < \pi^v < 1$ of workers are of type v with parameters $(\delta^v, \lambda_1^v, \alpha^v)$, for $v = 1, .., V$, with $\sum_{v=1}^{V} \pi^v = 1$. We remind the reader that α is the lower point of support of F. The remaining parameters are common for all workers. We might interpret the discrete heterogeneity distribution as an approximation of an unknown heterogeneity distribution but we will use the worker type interpretation.[18] As the type of a worker cannot be conditioned upon, it is integrated out of the likelihood function. Hence, the structural parameter vector is $\xi = (\lambda_0, \nu, \eta, \gamma_1, \gamma_2, \gamma_3, \sigma, \{\delta^v, \lambda_1^v, \alpha^v; v = 1, 2, .., V\}, \{\pi^v; v = 1, 2, ..., V-1\})$ and the full likelihood contribution for an individual is

$$\mathcal{L}(\xi) = \sum_{v=1}^{V} \pi^v \prod_{n=1}^{N} p^u(t_n^u, d_n^{ue}) \prod_{c=1}^{C} \int_{\alpha^v}^{\infty} Q_{c1}^v(x_1) \times \left[\int_{x_1}^{\infty} Q_{c2}^v(x_2) \frac{dF^v(x_2)}{\overline{F}^v(x_1)} \right]^{\chi_c} dG^v(x_1|a^0)^{s_c} \, dF^v(x_1)^{1-s_c}, \tag{11}$$

where $p^u(\cdot, \cdot)$ is given by (4), and superscript v denotes that the object depends on the parameters that are specific for worker type v.

[18] We note that Gaure, Røed and Zhang (2007) show within a non-parametric mixed proportional hazards model with competing risks that different combinations of mass points and associated parameters may result in observationally equivalent distributions of random parameters. Hence, specific mass points are not identified, and a worker type interpretation not valid.

As noted above, our sample design implies that the retirement rate μ factors out of the conditional likelihood contribution (9). However, the retirement process has been maintained in the model to secure the existence of a proper distribution of experience, and thus of wages conditional on experience (see Appendix B), which enters the likelihood function for mature workers. We set μ equal to $1/(40 \times 12)$, such that the expected duration of a labor market career is 40 years.

6 Results

For each of our 12 samples, we have estimated the model without unobserved heterogeneity ($V = 1$), and with two and three worker types ($V = 2$ and $V = 3$) by maximizing the log-sum of the individual likelihood contributions (11). Table 3 reports the log likelihood values for all models. The null hypothesis of $V - 1$ worker types versus V types (for $V = 2, 3$) is on the boundary of the parameter space, invalidating the classical likelihood-based tests. Instead, we use the Akaike Information Criterion for model selection, also reported in Table 3. Among the estimated models, the preferred model features three worker types for every sample. Further estimation might show that a higher V is optimal for some samples but we stopped at three points in order to cap estimation time. The parameter estimates for the preferred models are presented in Table 4 and Table 5. Estimates for the rejected models can be obtained from the authors.

< Tables 3, 4 and 5 about here. >

Transitions. To ease comparison between the two countries and the different samples we frame the discussion of the estimated transition parameters in terms of expected durations between events. These are presented in Table 6. The type specific expected durations measured in months are $\mathrm{E}[T^{\lambda}|v] = 1/\lambda^v$ and $\mathrm{E}[T^{\delta}|v] = 1/\delta^v$ for job offers and job destructions, respectively. The population averaged expected durations between job offers and job destructions are $\mathrm{E}[T^{\lambda}] = \sum_{v=1}^{V} \pi^v/\lambda_1^v$ and $\mathrm{E}[T^{\delta}] = \sum_{v=1}^{V} \pi^v/\delta^v$.

< Table 6 about here. >

Consider first the expected durations between job offers. Table 6 shows that Norwegian labor market entrants can expect to wait approximately twice as long as their Danish counterparts for job

offers, whereas Norwegian mature workers' expected durations are only slightly longer than those of Danish mature workers. Eight out of eighteen type specific expected durations are 10 months or shorter among the Danish workers, whereas all of the Norwegian type specific durations exceed one year. Mature workers must wait longer than entrants, up to four times longer in Denmark. In other words, the frequency of job offers declines as workers age. This finding corroborates those of Bunzel et al. (2001) and Rosholm and Svarer (2004) on Danish data. Finally, durations increase with education among entrants, perhaps reflecting that education implies specialization and thus a thinner market for job search. The estimated job finding rates for nonemployed workers (λ_0) are almost twice as high in Denmark as in Norway, except among low educated workers (see Tables 4 and 5).

Turning now to the job destruction process, Table 6 reveals that Danish workers face a lower risk of job destruction than Norwegian workers, except for medium educated mature workers. A sizeable fraction of Danish workers face effectively no risk of job destruction. This is also true for Norway, albeit to a lesser extent.[19] Mature workers face considerably lower job destruction risk than entrants: durations between job destructions are between two and five times longer for mature workers than for entrants (omitting high educated Norwegians). Job destruction risk declines substantially with education in Denmark, and among Norwegian entrants.

The lower job offer arrival rates and higher job destruction rates in Norway are in line with the descriptive evidence from section 4 (Figures 2 and 3). However, given the lower degree of protection against dismissal in Denmark we might have expected job destruction to be more prevalent in Denmark vis-a-vis Norway. We offer here two possible (mutually consistent) explanations for the higher Norwegian job destruction rate: first, the worse development in the unemployment rate during the sample period in Norway is likely to inflate (deflate) the estimated job destruction (job offer) rates for Norway relative to Denmark. Indeed, a rise in unemployment has to come from rising job destruction or slower job finding (or both). Second, we cannot rule out that part of the cross-country difference in our estimated job destruction and job offer rates is driven by our definition

[19] A formal test of the null $\delta^v = 0$ is rejected for all types in all samples except for one type among medium educated Danish entrants.

of job-to-job transitions combined with differences in job offer arrival rates. Suspecting that many short nonemployment spells do not reflect genuine nonemployment, we eliminated nonemployment spells shorter than four weeks. This may lead us to overestimate λ_1 and underestimate δ.[20] If the job offer arrival rate for the nonemployed is higher in Denmark than in Norway, which it appears to be in our data, a larger share of genuinely nonemployed Danish workers (than of genuinely nonemployed Norwegian workers) find a new job within four weeks of leaving their previous job. This will induce a stronger downward (upward) bias in the estimated job destruction (job offer) rates in Denmark viz-a-viz Norway. Moreover, if workers on advance notice for lay-off receive job offers at a higher rate in Denmark than in Norway, which we would expect based on our estimates of λ_0 and λ_1, a higher fraction of Danish workers than Norwegian workers on advance notice will find a new job before entering nonemployment. This too will induce relative stronger downward (upward) bias in estimated job destruction (job offer) rate for Denmark. We note in passing that the advance notice period is longer in Denmark than in Norway for white collar workers. Although inconclusive, this discussion illustrates that differences in the true behavioral processes may lead to different impacts of the same data error in different samples.

Previous studies have found that gross job creation is substantially higher in Denmark than in Norway (which is consistent with our estimates of λ_1 and λ_0 in the two countries), whereas job destruction rates are similar or only slightly higher in Denmark. See Salvanes (1997, for manufacturing) and Dale-Olsen and Rønningen (2000, rates reported for whole economy, private sector, and manufacturing). Their data periods do not overlap ours.

Labor market friction index. Following Ridder and van den Berg (2003) we calculate the labor market friction index, $\kappa^v = \lambda_1^v/\delta^v$, and the average friction index $\kappa = \sum_{v=1}^{V} \pi^v \lambda_1^v/\delta^v$. κ^v measures the expected number of job offers during an employment spell for worker type v, and can be regarded as a summary measure of the degree of frictions in the labor market for this worker type, a large number indicating a low degree of frictions. All κ's, and most of the κ^v's, are in

[20] This bias is possibly smaller in absolute terms than the bias that would result from not eliminating short nonemployment spells.

the range of 1 to 10 for Norway. The κ's are larger for the Danish samples, between 6 and 26, which says that the Danish labor market is a low-friction labor market.[21] The labor markets of entrants are more frictional than those of comparable mature workers. This result is driven by job destruction rates that decline faster relative to the job finding rate as workers age. Moreover, high educated workers act in less frictional markets than do lower educated workers. Again, this result arises because job destruction rates decline more rapidly than job finding rates as one considers markets for progressively higher educated workers.

Match qualities. We imposed a three-parameter Weibull distribution on the sampling distribution of log match qualities. The Weibull distribution with shape parameter $\eta = 1$ is the exponential distribution. We reject the hypothesis $\eta = 1$ for all but one sample. Note that the negative estimates for the location parameters for high-education mature workers in Norway are not at odds with the model. These estimates merely imply that the lower bounds of the match offers are close to zero, but the shape of the estimated function ensures that offers "close to" zero occurs with very small probability: the first half-percentiles in the type-specific log match quality sampling distributions are 4.32, 4.66 and 5.03.

The wage equation delivers a natural decomposition of the variation of log wages, net of experience effects, into the three components: Within-type log match quality variance, between-type log match quality variance and measurement error variance,

$$\underbrace{\mathrm{Var}(x+\varepsilon)}_{\text{Total}} = \underbrace{\mathrm{E}[\mathrm{Var}(x|v)]}_{\text{Within-type}} + \underbrace{\mathrm{Var}(\mathrm{E}[x|v])}_{\text{Between-type}} + \underbrace{\mathrm{Var}(\varepsilon)}_{\text{Measurement error}}. \tag{12}$$

The decomposition is reported in Table 7. The identification of the measurement error process relies on differences between the predicted and actual relationship between wages and job transitions, most importantly the proportion of wage cuts in job-to-job transitions. However, as argued above, these wage cuts are rationalized in other (but similar) models, and our estimate of the measurement

[21] Our estimated κ's for Denmark are somewhat higher than what has been reported in previous studies: The estimates of Rosholm and Svarer (2004) imply friction indices in the range of 2 to 5 for a number of samples, and the equilibrium model of Bunzel et al. (2001) produces indices below 1 for most samples and models. Ridder and van den Berg (2003) estimate frictions indices in the range 1 to 5 for France, and Jolivet, Postel-Vinay and Robin (2006) report (modified) friction indices between 0.4 and 2 for a number of countries within a model with reallocation shocks. We know of no other studies that report labor market friction indices for Norway.

error process is likely to pick up effects of these other sources of between-job downward wage flexibility. Measurement errors account for 21 to 68 percent of log-wage variance, least for mature workers and high-educated workers. This is within the range of previous estimates using variants of job search models (but different data), see Wolpin (1987), Christensen and Kiefer (1994), van den Berg and Ridder (1998) and Flinn (2002). Table 7 shows no clear pattern concerning the relative importance of within-type and between-type dispersion.

< Table 7 about here. >

In addition to decomposing wage variance, we also calculate a measure of match quality dispersion, which affects the scope for wage growth through job search (of course, the total scope for gains through search also depends on λ_1 and λ_0). Table 7 reports our dispersion measure, the difference between the 10th and the 90th percentile in the distribution of log match quality offers. This difference is larger for the Norwegian samples, particularly for entrants, larger for mature workers than for entrants, and particularly small for Danish entrants. For example, according to our estimates a high educated Danish entrant gains 1 percent in match quality when moving from a match quality at the 10th percentile to a match quality at the 90th percentile. The corresponding figures for the remaining samples (excluding Danish entrants) in both Denmark and Norway are more plausible, between 25 and 50 percent. We stress that these numbers are closely related to the heterogeneity specification, and may not warrant a structural interpretation. In fact, with homogenous match sampling distributions, the scope for search would probably be larger for every sample, because larger variance in the match sampling distributions would be needed to fit the variance in wages.

Wage-experience profiles. In addition to wage gains through job mobility, the empirical model allows for non-search related wage growth tied to experience. Figure 4 shows the estimated wage-experience profiles. Overall, the returns to experience increase with education and are higher for entrants than for mature workers. This could be due to a higher rate of accumulation of human capital in the early years of careers, and confirms previous findings in Bagger et al., 2006. Figure 4

show similar experience effects in Denmark and Norway for low-educated[22] and medium educated workers, but faster wage growht for high-educated in Denmark than in Norway. This holds both for entrants and mature workers. Because our model is not explicitly intended for disentangling various sources of wage growth, we leave an analysis of wage growth and career earnings in Denmark and Norway for future studies.

< **Figure 4 about here.** >

Unobserved heterogeneity. The worker type fractions and associated parameters are estimated with good precision for most samples. The small sample of low-educated Norwegian entrants form a notable exception. Table 8 shows the correlations of the random parameters. Job destruction rates and job offer arrival rates are positively correlated in all samples but one and job offer arrival rates tend to be positively correlated with wage levels. This correlation hints at the need for modelling unobserved heterogeneity in order to estimate models with endogenous search effort (as in Christensen et al., 2005): if some workers have higher latent mobility and draw better match qualities than other workers, then we observe more job-to-job moves among high-wage jobs than predicted by a model that assumes identical workers. This may prohibit estimation of a well-behaved search cost function because endogenous search entails that search effort decreases in match quality.

< **Table 8 about here.** >

7 Goodness-of-fit

We now proceed with an assessment of the ability of the model to re-produce observed job durations and transitions, and wage distributions. The assessment of the fit to job durations is rendered difficult by the presence of right-censored durations and unobserved heterogeneity. We use goodness-of-fit analysis by visual inspection, comparing nonparametric unconditional hazard function estimates from the data to the corresponding model predicted hazard functions. Specifi-

[22]The very large experience effect for low-educated Norwegian entrants is most likely due to small sample size but may also derive from sample selection. Because we condition on staying in the labor force for six consecutive years, we have selected workers with more stable careers than the population. This composition effect may be more important for low-educated workers who are more likely to leave the labor force.

cally, we plot observed and predicted job-to-job hazard functions for labor market entrants including pointwise 95 percent confidence bands. The hazard rates implied by the model with homogenous workers ($V = 1$) are included for comparison.

The relevant hazard functions differ between entrants and mature workers due to differences in sampling schemes. For entrants we use the job duration for the first job of each worker, forming a single-spell flow sample of jobs. For mature workers we use the jobs that were active at the sampling time. These samples are identical to those used for producing Figures 2 and 3 in section 4. The theoretical hazard functions are derived in Appendix C. Note that these hazard rates are complicated because the composition of match qualities changes with elapsed duration, and because of heterogeneity, which implies that the composition of survivors changes as elapsed job duration increases. For mature workers, we face the additional problem of deriving the worker type composition in the initial stock sample of employed workers with a given level of experience.[23]

Fit to durations and transitions. Consider first the job-to-job hazard functions for labor market entrants. In terms of point estimates, Figure 5 shows that the predicted job-to-job hazard functions lie above the observed ones in all entrants-samples. Considering the degree of overlap between the confidence bands on the observed and the predicted hazard functions reveals a good fit to the job-to-job hazards for Danish medium and high educated entrants (and, trivially, for the very small sample of Norwegian low educated entrants). There is significant discrepancy between the data and the model prediction in the remaining entrant samples. However, the discrepancy is in terms of the level of the job-to-job hazard functions whereas we capture the amount of duration dependence fairly well in all samples. Not surprisingly, the model with unobserved heterogeneity outperforms the homogenous model in most samples.

Figure 6 displays job-to-nonemployment hazards for entrants. The fit is generally good, albeit with a tendency for over-prediction in terms of point estimates. The confidence bands of observed and predicted hazards overlap considerably, with medium educated Norwegian workers being the

[23] As the hazard functions for mature workers does not admit a closed form solution we resort to numerical integration in the computation using Gauss-Legendre quadratures with 40 nodes (Judd, 1998).

exception. In this latter sample, we significantly over-predict job-to-nonemployment transitions at low durations, but fit the hazard better at longer durations. Note that the heterogeneity specification does well in generating the observed sharp drop in job-to-nonemployment hazard functions within the first 24 months in the job (except for high educated Danes). The homogenous specification is, by construction, unable to match this feature of the data.

< Figures 5 and 6 about here. >

Figure 7 displays the job-to-job hazards for mature workers. Contrary to entrants, we under-predict mature workers' job-to-job hazard rates at all seniority levels and in all samples (except for seniority exceeding 70 and 50 months for Norwegian medium and high educated workers). Moreover, the confidence bands of observed and predicted job-to-job hazard functions do not overlap, except for low educated Norwegians. Our models for high educated mature workers also generate too little duration dependence in the job-to-job hazard function.

Turning now to the job-to-nonemployment hazard functions, Figure 8 shows that the model prediction tends to be above that obtained from the data. However, there is considerable overlap between predicted and observed job-to-nonemployment hazard functions' confidence bands in all mature samples, except low educated Danes. The model captures the flat job-to-nonemployment hazard function for Danish high educated mature workers.

< Figures 7 and 8 about here. >

Overall, we produce a better fit to both job-to-job and job-to-nonemployment hazard functions in the entrants samples as compared to the fit in samples of mature workers, albeit there is room for improvement in both types of samples. The improvement of the fit to hazard functions from allowing unobserved heterogeneity in parameters is particularly pronounced, and empirically important, for job-to-nonemployment transitions. Note that we have imposed a steady state assumption on the samples of mature workers, which may restrict the model's parameters in undesirable ways in terms of fitting transitions out of jobs. The steady state assumption was not imposed on the entrant models. Of course, any problem of fit may also reflect that the data generating processes contain more heterogeneity than we have allowed for. Finally, lack of fit could also point to

more fundamental mis-specifications. For example, the data generating process may feature job-reallocations unrelated to the quality of the job (Nagypal, 2008), or structural non-stationarity in the job mobility process. Indeed, the differences in the estimated structural parameters between entrants and mature workers suggest some sort of non-stationarity in the job mobility process. Differences in data, model specification and the goodness-of-fit measures make it difficult to compare our findings to those obtained in other studies (see references in the introduction).

Fit to wages. Let $\widetilde{W}$ be the log wage net of non-search related experience effects with realizations $\widetilde{w}$. The structure of the model (equations (5) and (7)) implies that

$$\widetilde{w} = x + \varepsilon = w - \widehat{\gamma}_1 a - \widehat{\gamma}_2 (a - a_1^*)\mathbf{1}(a > a_1^*) - \widehat{\gamma}_3 (a - a_2^*)\mathbf{1}(a > a_2^*). \tag{13}$$

where $(\widehat{\gamma}_1, \widehat{\gamma}_2, \widehat{\gamma}_3)$ are estimated parameters.

For entrants we focus on the distribution of $\widetilde{W}$ in the first job after entry. The distribution is a convolution of the type specific distributions of log match qualities $F^v(\cdot)$ and the distribution of log measurement errors $H_\varepsilon(\cdot)$:

$$\mathrm{P}[\widetilde{W} \leq \widetilde{w}] = \sum_{v=1}^{V} \pi^v \int_{-\infty}^{\widetilde{w}} \int_{\alpha^v}^{\infty} f^v(z) h_\varepsilon(s - z)\, dz\, ds, \tag{14}$$

Figure 9 shows a of plot (14) (in levels) obtained from the data and predicted using the estimated model. We also plot the averaged distribution of match qualities $\sum_{v=1}^{V} \pi^v F^v(x)$ in levels in the same graph, for illustration of the impact of measurement errors. The model fits observed distributions of match qualities well in all samples except for high educated Danes, but predicts too much mass in the lower end of the distributions. This may relate to truncation, as we have dropped the lowest 2.5 percent of wages. The assumption of a log normal distribution of measurement errors therefore cannot hold exactly.

< Figure 9 about here. >

For mature workers we focus on the distribution of $\widetilde{W}$ at the time of sampling. The distribution is obtained as

$$\mathrm{P}[\widetilde{W} \leq \widetilde{w}] = \sum_{v=1}^{V} \widetilde{\pi}^v \int_{-\infty}^{\widetilde{w}} \int_{\alpha^v}^{\infty} g^v(z|a^0) h_\varepsilon(s - z)\, dz\, ds, \tag{15}$$

where $g(x|a^0)$ is given by Proposition 2.2, $a^0 = 10.5$ years, and $\widetilde{\pi}^v$ is the steady state fraction of type v workers among the employed (see Appendix C for details). Figure 10 displays the data version and the predicted values of (15) together with the predicted steady state cross section match quality distribution $\sum_{v=1}^{V} \widetilde{\pi}^v G^v(x|a^0)$ (all in levels). Because the lower point of support in the sampling distribution of match qualities is unidentified (see section 5), we re-center the model prediction for mature workers at the observed average match quality. Figure 9 reveals that the fit to mature workers match distributions is good, even in the tails. In particular, Figure 9 does not indicate serious departures from the steady state assumption. This contrasts to the relatively poor fit to job-to-job hazard functions in mature samples. The overall good fit to observed match quality distributions across all samples suggests that the combination of the three-parameter Weibull distribution and normal measurement errors (in wage levels) is sufficiently flexible to accommodate the data.

< **Figure 10 about here.** >

8 Conclusion

We have shown that the assumption of exponential durations between events in a job search model can be reconciled with data on job durations and transitions when we allow for heterogeneity between individuals. The fit to duration and transition data is better in flow samples of labor market entrants than in stock samples of mature workers. This may indicate that the steady state restrictions imposed on the mature samples are not supported by the data, although the fit to steady state wage distributions is good. Unlike previous studies, we evaluate the fit to destination-specific hazard rates (job-to-job and job-to-nonemployment hazards). Both types of job hazards exhibit more negative duration dependence than can be accounted for with homogenous parameters. The heterogeneous model does very well in explaining the extent of duration dependence in both types of job hazards in most samples. That said, we observed a tendency to over-predict (under-predict) of the hazard functions among entrants (mature workers). The prediction error is non-negligible in some samples, in particular for mature workers' job-to-job transitions. This may indicate the

need for a richer heterogeneity specification but could also indicate more serious shortcomings of the estimated model.

In terms of differences between labor market entrants and mature workers (with 10 years of experience at the time of sampling) our results mirror previous findings regarding the change in labor market behavior and outcomes over the life cycle (Topel and Ward, 1992): labor market entrants are more mobile than mature workers, earn lower wages and have higher non-search related wage growth. Overall, labor market entrants act in labor markets that are more frictional than mature workers. Indeed, there are important differences in structural transition parameters between entrants and mature workers. This suggests that non-stationarity in parameters is an important empirical issue when applying the job search model to long panels, or when computing, say, permanent income measures from estimated models (see e.g. Flinn, 2002).

Finally, to our knowledge this paper represents the first estimation of a structural search model on Norwegian data. Relative to Denmark, the Norwegian labor market is characterized by lower job offer arrival rates for both employed and nonemployed workers, and higher job destruction risks. This pattern is stable across education groups and between samples of entrants and mature workers. The higher job destruction rate in Norway may partly reflect differences in business cycles, but puzzles us, given the stricter EPL in Norway. We offered an alternative explanation relating to sample selection but more research is required to further clarify this issue.

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APPENDIX

A Present discounted values and reservation strategies

The model's state space consists of the pair $(x, a) \in [\underline{x}, \overline{x}) \times \{0\} \cup \mathbb{R}^+$ for employed workers and $a \in \{0\} \cup \mathbb{R}^+$ for unemployed workers. Denote the expected present discounted value (EPDV) to a worker with experience $a \leq A$ of being in a match of quality x by $\mathcal{V}_1(x, a)$. The EPDV of employment in a match of quality x to a worker with experience $a > A$ is denoted by $\mathcal{V}_1^*(x) \equiv \mathcal{V}_1(x, A)$.[24] The worker's EPDV of being unemployed is denoted by $\mathcal{V}_0(a)$ when $a \leq A$ and $\mathcal{V}^*$ when $a > A$.

A.1 Stationary environment ($a > A$)

When $a > A$ the environment is stationary and the model reduces to the standard case which has been implemented and analyzed extensively elsewhere. We include it here for completeness.

Employed job search. The EPDV of employed search in a match of log quality x, $\mathcal{V}_1^*(x)$ is given as

$$(\rho + \mu + \delta)\mathcal{V}_1^*(x) = u(y^* + x) + \delta\mathcal{V}_0^* + \lambda_1 \int_{\underline{x}}^{\overline{x}} \max\{\mathcal{V}_1^*(z) - \mathcal{V}_1^*(x), 0\} dF(z). \tag{A1}$$

$\mathcal{V}_1^*(x)$ is everywhere increasing in x: Suppose there are $x', x'' \in (\underline{x}, \overline{x})$ such that $x' < x''$ and $\mathcal{V}_1^*(x') \geq \mathcal{V}_1^*(x'')$. Then, $u(y^* + x') + \lambda_1 \int_{\underline{x}}^{\overline{x}} \max\{\mathcal{V}_1^*(z) - \mathcal{V}_1^*(x'), 0\} dF(z) < u(y^* + x'') + \lambda_1 \int_{\underline{x}}^{\overline{x}} \max\{\mathcal{V}_1^*(z) - \mathcal{V}_1^*(x''), 0\} dF(z)$, thus producing the contradiction $\mathcal{V}_1^*(x') < \mathcal{V}_1^*(x'')$. As a consequence, employed workers invoke a simple reservation quality strategy: any alternative matches of higher (lower) quality than the worker's current match are accepted (rejected). Hence, when $a \geq A$ the reservation log quality of an employed worker is $r^e(x) = x$.

Now, (A1) can be restated (using integration by parts to simplify the integral) as

$$(\rho + \mu + \delta)\mathcal{V}_1^*(x) = u(y^* + x) + \delta\mathcal{V}_0^* + \lambda_1 \int_{x}^{\overline{x}} \frac{\overline{F}(z)}{\rho + \mu + \delta + \lambda_1 \overline{F}(z)} dz. \tag{A2}$$

Note that $\partial\mathcal{V}_1^*(x)/\partial x = 1/[\rho + \mu + \delta + \lambda_1 \overline{F}(x)] > 0$.

Unemployed job search. The structure of the model implies that the EPDV of unemployed search once the environment has become stationary is given by

$$(\rho + \mu)\mathcal{V}_0^* = u(y^* + b) + \lambda_0 \int_{\underline{x}}^{\overline{x}} \max\{\mathcal{V}_1^*(z) - \mathcal{V}_0^*, 0\} dF(z). \tag{A3}$$

Since $\mathcal{V}_1^*(x)$ is everywhere increasing in x and $\mathcal{V}_0^*$ is independent of x, the unemployed worker applies a reservation wage strategy and accepts all match offers of log quality $r^{u,*}$ or higher and rejects all offers with a quality below $r^{u,*}$, where $r^{u,*}$ is such that $\mathcal{V}_1^*(r^{u,*}) = \mathcal{V}_0^*$. This implies that

$$r^{u,*} = u^{-1}\left(u(y^* + b) + (\lambda_0 - \lambda_1) \int_{r^{u,*}}^{\overline{x}} \frac{\overline{F}(z)\,\mathbf{1}(z \geq \underline{x})}{\rho + \mu + \delta + \lambda_1 \overline{F}(z)} dz\right). \tag{A4}$$

[24] Recall that A is the experience level after which the workers productivity remains constant.

A.2 Non-stationary environment ($a \leq A$)

When $a \leq A$ a worker's wage still evolves according to labor market experience, making the environment nonstationary. Since the model's stochastic events occur according to Poisson processes, in any small time interval, the probability of each of the events is proportional to the length of that interval.[25]

Employed job search. Let da be the length of a small time interval. Then, the value of employed search for a worker with experience a in a match of log quality x, $\mathcal{V}_1(x,a)$, solves the functional equation:

$$\mathcal{V}_1(x,a) = \frac{1}{1+\rho da}\Bigg[u(y(a)+x)da + \delta da \mathcal{V}_0(a+da) \\ +\lambda_1 da \int_{\underline{x}}^{\overline{x}} \max\{\mathcal{V}_1(z,a+da), \mathcal{V}_1(x,a+da)\}dF(z) + (1-\mu da - \delta da - \lambda_1 da)\mathcal{V}_1(x,a+da)\Bigg]. \quad \text{(A5)}$$

Under the assumption that $\mathcal{V}_1(x,a)$ is increasing in x for all $a \leq A$, which we shall assert below, we can re-write (A5) in the following manner

$$\frac{\mathcal{V}_1(x,a+da) - \mathcal{V}_1(x,a)}{da} = [\mu + \delta + \lambda_1 \overline{F}(x)]\mathcal{V}_1(x,a+da) + \rho \mathcal{V}_1(x,a) \\ - u(y(a)+x) - \delta \mathcal{V}_0(a+da) - \lambda_1 \int_x^{\overline{x}} \mathcal{V}_1(z,a+da)dF(z), \quad \text{(A6)}$$

and taking the limit as $da \to 0$, and applying integration by parts, we obtain the following first order ordinary differential equation (ODE)

$$(\rho+\mu+\delta)\mathcal{V}_1(x,a) = u(y(a)+x) + \delta \mathcal{V}_0(a) + \lambda_1 \int_x^{\overline{x}} \frac{\partial \mathcal{V}_1(z,a)}{\partial z}\overline{F}(z)\,dz + \frac{\partial \mathcal{V}_1(x,a)}{\partial a}, \quad \text{(A7)}$$

Taking the derivative of (A7) with respect to x yields a first order ODE in x:

$$\frac{\partial^2 \mathcal{V}_1(x,a)}{\partial a \partial x} - [\rho+\mu+\delta+\lambda_1\overline{F}(x)]\frac{\partial \mathcal{V}_1(x,a)}{\partial x} = -u'(y(a)+x), \quad \text{(A8)}$$

which can be solved for $\partial \mathcal{V}_1(x,a)/\partial x$, using the terminal condition that $\partial \mathcal{V}_1(x,A)/\partial x = \partial \mathcal{V}_1^*(x)/\partial x = 1/[\rho+\mu+\delta+\lambda_1\overline{F}(x)]$ to pin down the constant of integration. Doing so produces

$$\frac{\partial \mathcal{V}_1(x,a)}{\partial x} = \frac{1}{\rho+\mu+\delta+\lambda_1\overline{F}(x)} \\ + \int_0^T e^{-[\rho+\mu+\delta+\lambda_1\overline{F}(x)](s-T)}u'(y(s)+x)\,ds - \int_0^t e^{-[\rho+\mu+\delta+\lambda_1\overline{F}(x)](s-t)}u'(y(s)+x)\,ds. \quad \text{(A9)}$$

Insofar that $u'(\cdot) \geq 0$, (A9) asserts that $\mathcal{V}_1(x,a)$ is indeed strictly increasing in x for all $a \leq A$. This implies that employed workers exercise a reservation quality strategy when conducting on-the-job search and that the on-the-job search reservation log quality for a worker employed in a match of log quality x is simply x. That is, $r^e(x) = x$ for $a < A$.

[25] Here, "small" is such that the probability of any two of the events occurring within the period is negligible.

Finally, solving (A7) for $\mathcal{V}_1(x,a)$, using $\mathcal{V}_1(x,A) = \mathcal{V}_1^*(x)$ to pin down the constant of integration, yields

$$\mathcal{V}_1(x,a) = \mathcal{V}_1^*(x) + \int_0^a e^{-[\rho+\mu+\delta](s-a)} B(x,s)\,ds - \int_0^A e^{-[\rho+\mu+\delta](s-A)} B(x,s)\,ds, \tag{A10}$$

where $V^*(x)$ is given by (A2),

$$B(x,a) = u(y(a)+x) + \delta U(a) + \lambda_1 \int_x^{\overline{x}} \frac{\partial \mathcal{V}_1(z,a)}{\partial z} \overline{F}(z)\,dz, \tag{A11}$$

and where $\mathcal{V}_1(x,a)/\partial x$ is given by (A9).

Unemployed job search. Again, consider a small time interval of length da. The structure of the model implies that the value of unemployed search $\mathcal{V}_0$ solves the functional equation[26]

$$\mathcal{V}_0(a) = \frac{1}{1+\rho da}\left[u(y(a)+b)da + \lambda_0 da \int_{\underline{x}}^{\overline{x}} \max\{\mathcal{V}_1(z,a) - \mathcal{V}_0(a)\} dF(z) + (1-\mu da - \lambda_0 da)\mathcal{V}_0(a)\right]. \tag{A12}$$

Since $\mathcal{V}_1(x,a)$ is strictly increasing in x for all a, and U is independent of x, the unemployed worker's problem has the reservation quality property: an unemployed worker accepts any job offer with a log match quality x above his or her reservation log quality $r^u(a)$ and rejects offers with quality falls short of $r^u(a)$, where $r^u(a)$ is defined by $\mathcal{V}_1(r^u(a),a) = \mathcal{V}_0(a)$. Hence, by integration by parts,

$$(\rho+\mu)\mathcal{V}_0(a) = u(y(a)+b) + \lambda_0 \int_{r^u(a)}^{\overline{x}} \frac{\partial \mathcal{V}_1(z,a)}{\partial z} \overline{F}(z)\,\mathbf{1}(z \geq \underline{x})\,dz. \tag{A13}$$

The model does not admit a closed form solution to the reservation log quality of unemployed job seekers.

B Steady state relations

Nonemployment rate. Let q denote the steady state nonemployment rate. Seeing that the measure of workers in the labor market is normalized to unity, q is also the stock of nonemployed workers. Balancing the inflow and outflow to this stock of workers we arrive at the following useful characterization of the steady state nonemployment rate:

$$\frac{q}{1-q} = \frac{\mu+\delta}{\lambda_0}. \tag{B1}$$

Experience. Recall that a denotes experience. Let $\ell_0(a)$ and $\ell_1(a)$ be the densities of experience a in a cross section of nonemployed and employed workers, respectively. Balancing the flows into and out of the stock of nonemployed workers with $a > 0$ years experience restrict $\ell_0(a)$ in the following way:

$$(\mu+\lambda_0)\ell_0(a)q = \delta\ell_1(a)(1-q). \tag{B2}$$

Likewise, balancing flows related to the stock of employed workers with $a + da > 0$ years of experience ($da > 0$ being "small"), yields

$$(1-q)\ell_1(a+da) = \ell_1(a)(1-q)\,(1-\mu da - \delta da) + \ell_0(a)q\lambda_0 da \tag{B3}$$

[26] Recall that experience remains constant during an unemployment spell.

Now, from (B2) and (B3) we obtain (using (B1))

$$\frac{\ell_1(a+da)-\ell_1(a)}{da} = -\frac{\mu(\mu+\delta+\lambda_0)}{\mu+\lambda_0}\ell_1(a) \tag{B4}$$

Taking the limit as $da \to 0$, and solving the resulting ODE, pinning down the constant of integration by the restriction $\int_0^\infty \ell_1(a)da = 1$, we find that experience among employed workers follows an exponential distribution:

$$\ell_1(a) = \frac{\mu(\mu+\delta+\lambda_0)}{\mu+\lambda_0} e^{-\frac{\mu(\mu+\delta+\lambda_0)}{\mu+\lambda_0}a}, \quad a > 0. \tag{B5}$$

For completeness, consider next the distribution of experience among the nonemployed. First note that the balancing flow condition for $a = 0$ implies that

$$\ell_0(0) = \frac{\mu(\mu+\delta+\lambda_0)}{(\mu+\delta)(\mu+\lambda_0)}. \tag{B6}$$

Then, using (B5) and (B1) in (B2), we find that

$$\ell_0(a) = \frac{\delta\lambda_0}{(\mu+\delta)(\mu+\lambda_0)}\,\ell_1(a), \quad a > 0. \tag{B7}$$

As a consistency check, notice that $\ell_0(0) + \lim_{a\to 0}\int_a^\infty \ell_0(\tau)\,da = 1$. Also notice that $\lim_{a\to 0}\ell_0(a) \neq \ell_0(0)$, so $\ell_0(a)$ has a mass-point at $a = 0$.

Match qualities conditional on experience. Let $G(x,a) = G(x|a)\ell_1(a)$ be the share of employed workers who have experience a and a log match quality less than x. The balanced flow equation for $G(x,a)$ is

$$(1-q)G(x,a+da) = (1-q)G(x,a)\left(1-\mu da-\delta da-\lambda_1 da\overline{F}(x)\right) + q\ell_0(a)\lambda_0 daF(x), \tag{B8}$$

for a "small" da. Substitute in (B1) and (B2) to find

$$\frac{G(x,a+da)-G(x,a)}{da} = \left(\mu+\delta+\lambda_1\overline{F}(x)\right)G(x,a) + \frac{\lambda_0\delta}{\mu+\lambda_0}F(x)\ell_1(a) \tag{B9}$$

Again, taking the limits of (B9) for $da \to 0$ results in an ODE that can be solved for $G(x,a)$. The constant of integration is determined using the initial condition that the cross section distribution of match qualities among labor market entrants is the sampling distribution of log match qualities: $\lim_{da\to 0} G(x|a) = F(x)$. Since $G(x,a) = G(x|a)\ell_1(a)$ we obtain the following expression for $G(x|a)$:

$$G(x|a) = \frac{F(x)}{\delta\lambda_0+(\mu+\lambda_0)\lambda_1\overline{F}(x)}\left[\delta\lambda_0+(\mu+\lambda_0)\lambda_1\overline{F}(x)e^{-[\mu+\delta+\lambda_1\overline{F}(x)]a}\right]. \tag{B10}$$

C Hazard functions

In this appendix we derive the unconditional job hazard functions as predicted by the theoretical model in our two types of cross section (i.e. single spell) samples: A flow sample of labor market entrants (subscript "E-flow") and a stock sample of mature workers (viz. workers with a^0 years of experience at the time of sampling, subscript "M-stock").

Flow of labor market entrants. By construction, all entrants eventually find a job and the distribution of intrinsic heterogeneity in the flow of labor market entrants at entry ($t = 0$) coincides with the distribution of intrinsic heterogeneity in the full population: types $(v^1, v^2, ..., v^V)$ with associated population distribution $(\pi^1, \pi^2, ..., \pi^V)$. Random matching and the maintained assumption that unemployed workers accept any job offer implies that the distribution of match qualities x among the flow of entrants of type v is $F^v(x)$ for $v = 1, 2, ..., V$.

Conditional on log match quality x, and conditional on not retiring (no μ-shock), the probability that a type v match survives until t is $e^{-[\delta^v + \lambda_1^v \overline{F}^v(x)]t}$. Because the distribution of log match qualities in the flow of entry jobs occupied by type v workers is $F^v(x)$, the unconditional type specific survival probability is

$$\int_{\underline{x}}^{\overline{x}} f^v(x) e^{-[\delta^v + \lambda_1^v \overline{F}^v(x)]t} dx = e^{-\delta^v t}[1 - e^{-\lambda^v t}]/\lambda^v t. \tag{C1}$$

Hence, the distribution of types in matches surviving seniority t, denoted by $\{\widetilde{\pi}^v_{\text{E-flow}}(t), v = 1, 2, ..., V\}$, is

$$\widetilde{\pi}^v_{\text{E-flow}}(t) = \frac{\pi^v e^{-\delta^v t}[1 - e^{-\lambda_1^v t}]/\lambda_1^v}{\sum_{s=1}^V \pi^s e^{-\delta^s t}[1 - e^{-\lambda_1^s t}]/\lambda_1^s} \text{ for } v = 1, 2, ..., V. \tag{C2}$$

Consider now the job-to-nonemployment hazard function. The type specific job-to-nonemployment hazard is constant at δ^v. Using (C2), it follows that the unconditional job-to-nonemployment hazard rate at seniority t, denoted $\theta^{eu}_{\text{E-flow}}(t)$, is

$$\theta^{eu}_{\text{E-flow}}(t) = \sum_{v=1}^V \widetilde{\pi}^v_{\text{E-flow}}(t)\delta^v. \tag{C3}$$

Next, consider the job-to-job hazard function. Conditional on type v and log match quality x, the job-to-job hazard rate is constant at $\lambda_1^v \overline{F}^v(x)$. To arrive at the unconditional job-to-job hazard we must therefore first integrate out the match qualities conditional on worker type v, and second, integrate over the relevant distribution of types (given by (C2)). The type specific density of log match qualities among matches that have survived until seniority t, denoted $f^v_{\text{E-flow}}(x|t)$ is easily derived. At seniority $t = 0$ the match quality density is $f^v(x)$. Conditional on log match quality x, a fraction $e^{-[\delta^v + \lambda_1^v \overline{F}^v(x)]t}$ of entry matches survive seniority t. Hence,

$$f^v_{\text{E-flow}}(x|t) = \frac{f^v(x) e^{-[\delta^v + \lambda_1^v \overline{F}^v(x)]t}}{\int_{\alpha^v}^{\overline{x}} f^v(x) e^{-[\delta^v + \lambda_1^v \overline{F}^v(x)]t} dx} = f^v(x) \frac{\lambda_1^v t e^{-\lambda_1^v \overline{F}^v(x) t}}{1 - e^{-\lambda_1^v t}}. \tag{C4}$$

Note that $\lim_{t \to 0} f^v_{\text{E-flow}}(x|t) = f^v(x)$: at zero seniority, no selection has taken place. Using (C4) to integrate out the distribution of match qualities from the type specific job-to-job hazard function, one obtains,

$$\theta^{ee,v}_{\text{E-flow}}(t) = \int_{\alpha^v}^{\overline{x}} \lambda_1^v \overline{F}^v(x) f^v_{\text{E-flow}}(x|t) dx = \frac{1}{t} - \frac{\lambda^v e^{-\lambda_1^v t}}{1 - e^{-\lambda_1^v t}}. \tag{C5}$$

Finally, using the marginal distribution of types in surviving matches at seniority t (C2), one obtains the unconditional job-to-job hazard function that can be confronted by the data:

$$\theta^{ee}_{\text{E-flow}}(t) = \sum_{v=1}^V \widetilde{\pi}^v_{\text{E-flow}}(t) \left[\frac{1}{t} - \frac{\lambda^v e^{-\lambda_1^v t}}{1 - e^{-\lambda_1^v t}} \right]. \tag{C6}$$

Stock of mature workers. The techniques applied to obtain the unconditional hazard functions for mature workers is similar to that applied above for labor market entrants. However, a couple of complications arise from the imposition of a steady state and the complicated structure of the cross section distribution of match qualities (see proposition 2.2).

The first complication has to do with the distribution of types among a cross section of employed workers when the labor market is in a steady state. Conditioning, as we do in the data, on individuals not leaving the sample (i.e. retire), the type specific employment rate is $\lambda_0/(\delta^v + \lambda_0)$ (see Appendix B). Hence, in steady state, the fraction of employed workers that are of type v is given as:

$$\widetilde{\pi}^v_{\text{M-stock}} = \frac{\pi^v \prod_{s\neq v}(\delta^s + \lambda_0)}{\sum_{r=1}^V \pi^r \prod_{s\neq r}(\delta^s + \lambda_0)}. \tag{C7}$$

The distribution of types among employed workers differ from the population distribution of types due to differential job destruction rates across types.

The next complication has to do with the derivation of the relevant heterogeneity distributions. At the time of sampling (i.e. at $t = 0$), the type specific distribution of log match qualities in the stock sampled mature workers is $G^v(x|a^0)$ (see proposition 2.2). The unconditional (on match quality) probability that a type v match survives seniority t is thus $\int_{\alpha^v}^{\overline{x}} e^{-[\delta^v+\lambda_1^v\overline{F}^v(x)]t} dG^v(x|a^0)$, which does not admit a closed form solution. The distribution of types in matches surviving seniority t, denoted by $\widetilde{\pi}^v_{\text{M-stock}}(t|a^0)$, is then obtained as

$$\widetilde{\pi}^v_{\text{M-stock}}(t|a^0) = \frac{\widetilde{\pi}^v_{\text{M-stock}} \int_{\alpha^v}^{\overline{x}} e^{-[\delta^v+\lambda_1^v\overline{F}^v(x)]t} dG^v(x|a^0)}{\sum_{s=1}^V \widetilde{\pi}^s_{\text{M-stock}} \int_{\alpha^s}^{\overline{x}} e^{-[\delta^s+\lambda_1^s\overline{F}^s(x)]t} dG^s(x|a^0)} \text{ for } v = 1, 2, ..., V, \tag{C8}$$

where $\widetilde{\pi}^v_{\text{M-stock}}$ is given by (C7).

The unconditional job-to-nonemployment hazard function for the stock sample of mature workers is

$$\theta^{eu}_{\text{M-stock}}(t|a^0) = \sum_{v=1}^V \widetilde{\pi}^v_{\text{M-stock}}(t|a^0)\delta^v, \tag{C9}$$

where $\widetilde{\pi}^v(t|a^0)$ is given by (C8).

To obtain the unconditional job-to-job hazard function we first need the density of log match quality conditional on elapsed seniority t and type, denoted $g^v_{\text{M-stock}}(x|t, a^0)$. At seniority $t = 0$ the match quality density is $g^v(x|a^0)$. Conditional on log match quality x, a fraction $e^{-[\delta^v+\lambda_1^v\overline{F}^v(x)]t}$ of stock sampled matches survives seniority t (again,this is also conditional on not retiring). Hence,

$$g^v_{\text{M-stock}}(x|t, a^0) = \frac{g^v(x|a^0)e^{-[\delta^v+\lambda_1^v\overline{F}^v(x)]t}}{\int_{\alpha^v}^{\overline{x}} g^v(x|a^0)e^{-[\delta^s+\lambda_1^v\overline{F}^v(x)]t}dx}. \tag{C10}$$

It follows that the type specific job-to-job hazard function is given by

$$\theta^{ee,v}_{\text{M-stock}}(t|a^0) = \int_{\alpha^v}^{\overline{x}} \lambda_1^v\overline{F}^v(x) g^v_{\text{M-stock}}(x|t, a^0)dx \text{ for } v = 1, 2, ..., V. \tag{C11}$$

The unconditional job-to-job hazard function is thus obtained as:

$$\theta^{ee}_{\text{M-stock}}(t|a^0) = \sum_{v=1}^V \widetilde{\pi}^v_{\text{M-stock}}(t|a^0)\theta^{ee,v}_{\text{M-stock}}(t|a^0) = \sum_{v=1}^V \widetilde{\pi}^v_{\text{M-stock}}(t|a^0) \int_{\alpha^v}^{\overline{x}} \lambda_1^v\overline{F}^v(x) g^v_{\text{M-stock}}(x|t, a^0)dx. \tag{C12}$$

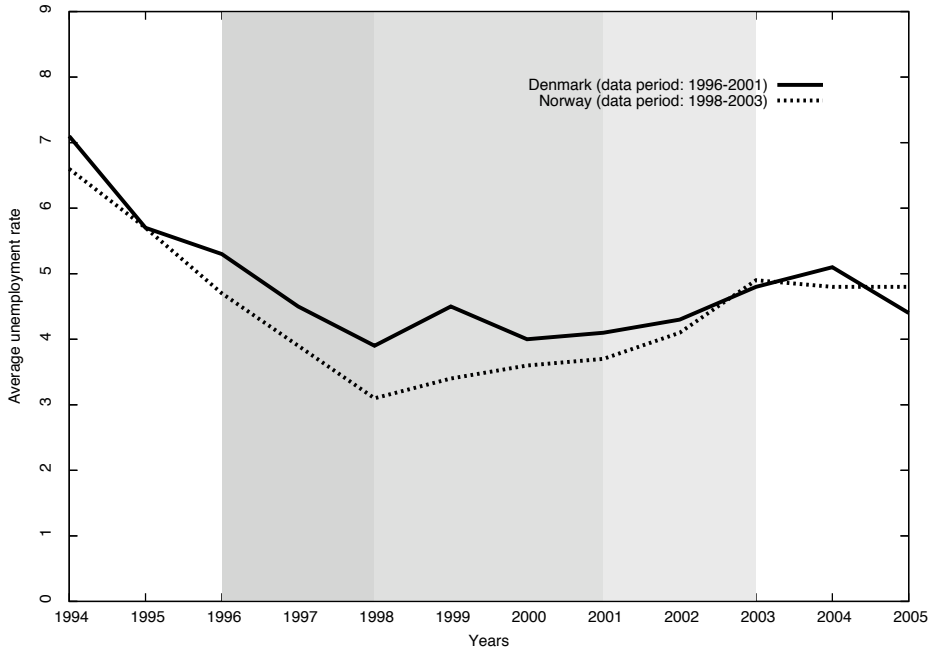

Figure 1: Average unemployment rate for men in Denmark and Norway (source: OECD Factbook 2007). Dark shaded area is Danish data period. Light shaded area is Norwegian data period.

Denmark	Low education		Medium education		High education	
	Ent.	Mat.	Ent.	Mat.	Ent.	Mat
Number of workers	816	2751	4232	8408	1101	1522
Number of workers with 1 employment cycle	425	2180	3312	7356	964	1443
Number of workers with 2 employment cycles	195	343	633	753	114	66
Number of workers with 3 employment cycles	196	228	287	299	23	13
Number of employment cycles	1403	3550	5439	9759	1261	1614
Number of employment cycles with 1 job	870	2246	2522	5678	624	969
Number of employment cycles with 2 jobs	533	1304	2917	4081	637	645
Number of jobs	1936	4854	8356	13840	1898	2259

Norway	Low education		Medium education		High education	
	Ent.	Mat.	Ent.	Mat.	Ent.	Mat
Number of workers	375	1301	8211	7846	2621	1701
Number of workers with 1 employment cycle	116	935	3957	6196	1779	1406
Number of workers with 2 employment cycles	126	263	2370	1209	616	258
Number of workers with 3 employment cycles	133	103	1884	441	226	37
Number of employment cycles	767	1770	14349	9937	3689	2033
Number of employment cycles with 1 job	583	1247	10285	6774	2457	1344
Number of employment cycles with 2 jobs	184	523	4064	3163	1232	689
Number of jobs	951	2293	18413	13100	4921	2722

Table 1: Summary statistics of observations and spells.

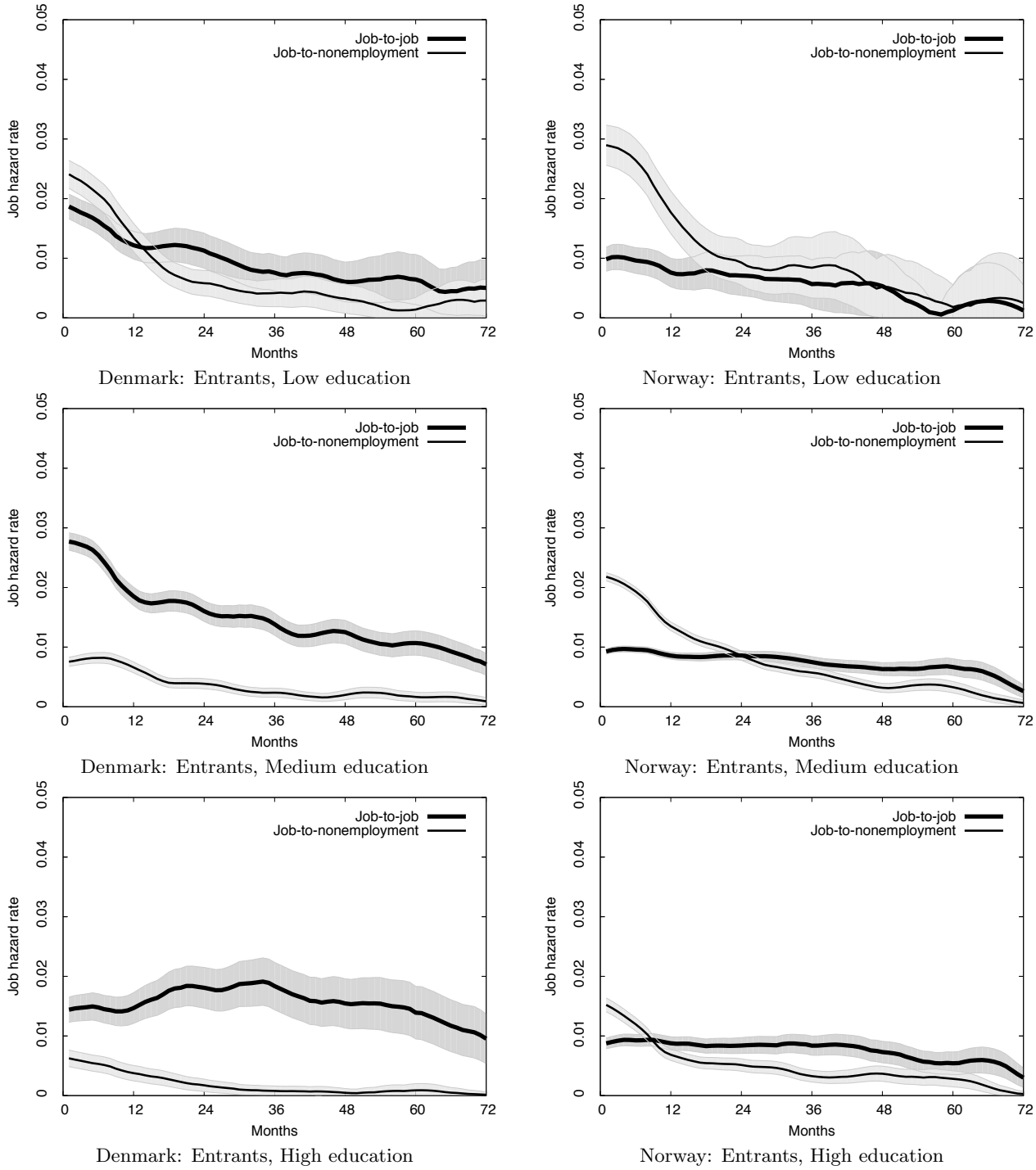

Figure 2: Smoothed monthly job hazard functions for entrants. Shaded areas are 95% point-wise confidence bands.

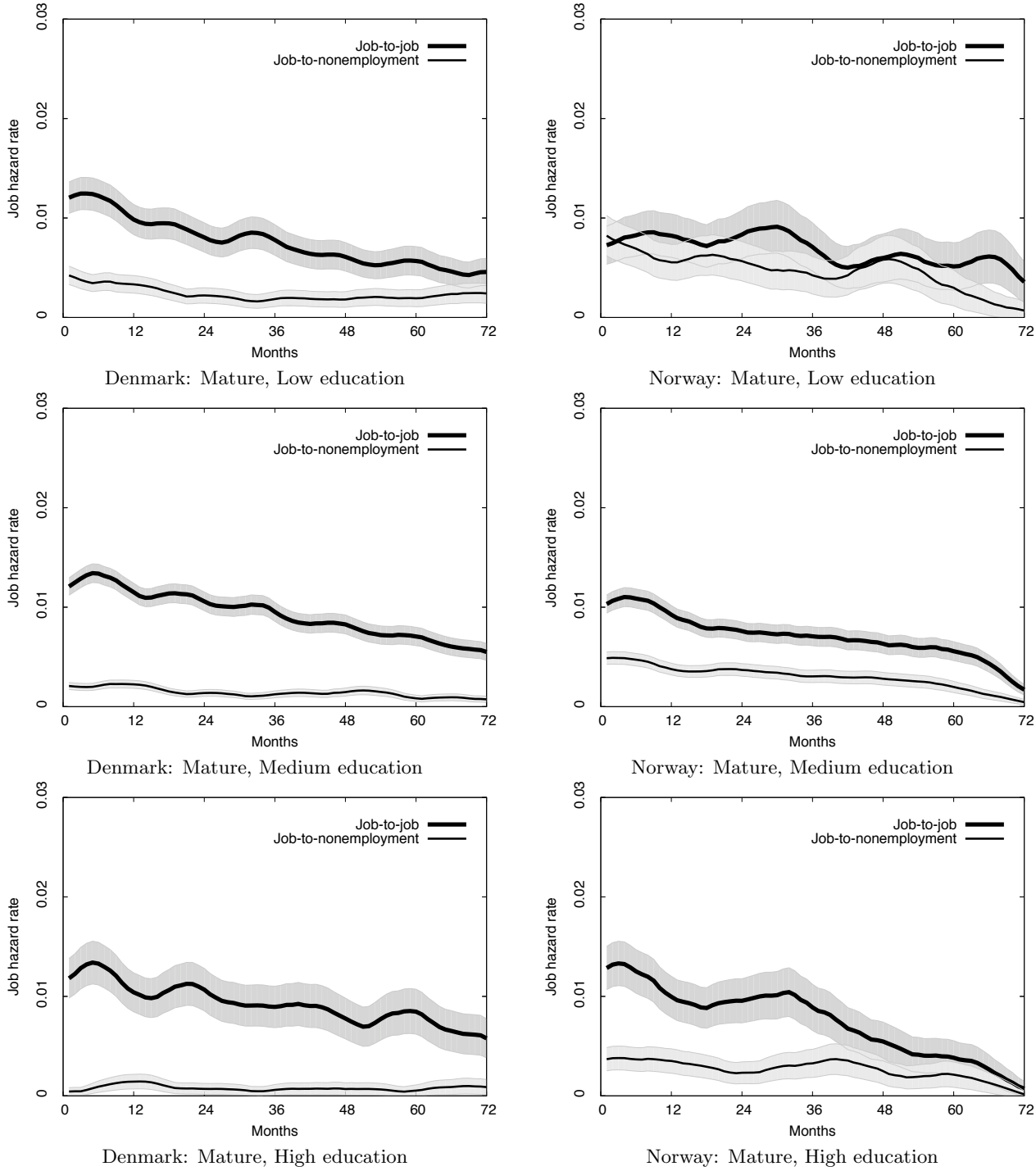

Figure 3: Smoothed monthly job hazard functions for mature workers. Shaded areas are 95% point-wise confidence bands.

Denmark	Low education		Medium education		High education	
	Ent.	Mat.	Ent.	Mat.	Ent.	Mat
Share of jobs with missing wage	0.19	0.06	0.10	0.05	0.06	0.04
Average log wage offer (log-DKK)	4.84	5.03	4.94	5.12	5.14	5.38
Std. dev. log wage offer	0.40	0.39	0.32	0.37	0.27	0.39
Share of jj-transitions with wage cut	0.43	0.42	0.47	0.49	0.55	0.53
Norway	**Low education**		**Medium education**		**High education**	
	Ent.	Mat.	Ent.	Mat.	Ent.	Mat
Share of jobs with missing wage	0.18	0.15	0.16	0.14	0.16	0.14
Average log wage offer (log-NOK)	4.62	4.87	4.69	4.92	4.94	5.27
Std. dev. log-wage offer	0.29	0.34	0.31	0.32	0.33	0.35
Share of jj-transitions with wage cut	0.49	0.43	0.42	0.39	0.41	0.39

Table 2: Summary statistics of wages.

Denmark	Low education		Medium education		High education	
	Ent.	Mat.	Ent.	Mat.	Ent.	Mat
Hom. parameters, 10 parameters						
Log-likelihood	−12422	−6349	−39900	−27004	−8545	−5515
Akaike Information Criterion	−24865	−12718	−79821	−54028	−17109	−11050
Het. parameters, 2 mass points, 14 pars.						
Log-likelihood	−12159	−6173	−38904	−26264	−8378	−5311
Akaike Information Criterion	−24346	−12375	−77837	−52556	−16784	−10651
Het. parameters, 3 mass points, 18 pars.						
Log-likelihood	−12083	−6126	−38686	−26049	−8276	−5254
Akaike Information Criterion	−24202	−12288	−77408	−52135	−16587	−10545

Norway	Low education		Medium education		High education	
	Ent.	Mat.	Ent.	Mat.	Ent.	Mat
Hom. parameters, 10 parameters						
Log-likelihood	−10887	−10718	−60012	−50370	−11459	−9957
Akaike Information Criterion	−21795	−21457	−120044	−100760	−22938	−19933
Het. parameters, 2 mass points, 14 pars.						
Log-likelihood	−10712	−10610	−59026	−49541	−11245	−9746
Akaike Information Criterion	−21452	−21248	−118079	−99110	−22518	−19520
Het. parameters, 3 mass points, 18 pars.						
Log-likelihood	−10679	−10501	−58844	−49000	−11120	−9658
Akaike Information Criterion	−21394	−21038	−117725	−98036	−22275	−19353

Table 3: Model selection.

	Low education		Medium education		High education	
	Ent.	Mat.	Ent.	Mat.	Ent.	Mat.
λ_0 (monthly nonemployment-to-job rate)	0.0583	0.0974	0.1238	0.1091	0.1089	0.0934
	(0.0018)	(0.0028)	(0.0027)	(0.0024)	(0.0050)	(0.0063)
δ^1 (monthly job destruction rate, type 1)	0.1543	0.0098	0.0001	0.0031	0.0024	0.0010
	(0.0255)	(0.0023)	(0.0004)	(0.0003)	(0.0005)	(0.0004)
δ^2 (monthly job destruction rate, type 2)	0.0987	0.0020	0.0540	0.0010	0.0099	0.0013
	(0.0139)	(0.0002)	(0.0048)	(0.0001)	(0.0025)	(0.0002)
δ^3 (monthly job destruction rate, type 3)	0.0011	0.0507	0.0027	0.0087	0.0029	0.0012
	(0.0051)	(0.0075)	(0.0002)	(0.0006)	(0.0008)	(0.0003)
λ_1^1 (monthly job offer arrival rate, type 1)	0.3475	0.1385	0.1018	0.0655	0.0521	0.0459
	(0.0569)	(0.0128)	(0.0098)	(0.0040)	(0.0032)	(0.0052)
λ_1^2 (monthly job offer arrival rate, type 2)	0.1298	0.0138	0.2543	0.0114	0.0999	0.0151
	(0.0166)	(0.0009)	(0.0157)	(0.0007)	(0.0142)	(0.0010)
λ_1^3 (monthly job offer arrival rate, type 3)	0.0615	0.1231	0.0369	0.1038	0.0440	0.0489
	(0.0077)	(0.0110)	(0.0016)	(0.0048)	(0.0047)	(0.0037)
η (sampling distribution, shape)	0.7546	1.5110	0.5869	1.9223	0.2068	6.9791
	(0.0956)	(0.0794)	(0.0371)	(0.0828)	(0.0444)	(1.7042)
ν (sampling distribution, scale)	0.0242	0.3138	0.0430	0.3299	0.0002	1.0128
	(0.0802)	(0.0179)	(0.0076)	(0.0136)	(0.0004)	(0.2258)
α^1 (sampling distribution, location, type 1)	5.2998	4.9984	4.9958	5.1702	5.0262	4.9567
	(0.0599)	(0.0254)	(0.0236)	(0.0149)	(0.0217)	(0.2198)
α^2 (sampling distribution, location, type 2)	4.6556	4.7523	4.8461	4.7332	5.3262	4.2837
	(0.0293)	(0.0155)	(0.0237)	(0.0122)	(0.0290)	(0.2249)
α^3 (sampling distribution, location, type 3)	4.7351	4.6210	4.7337	4.7553	4.7992	4.5390
	(0.0338)	(0.0217)	(0.0208)	(0.0143)	(0.0237)	(0.2232)
σ (std. dev. log measurement errors)	0.2899	0.2195	0.2325	0.2091	0.2116	0.1949
	(0.0050)	(0.0015)	(0.0014)	(0.0008)	(0.0023)	(0.0009)
γ_1 (parameter in experience spline fct.)	−0.0038	−0.0166	−0.0052	−0.0023	0.0590	0.0400
	(0.0099)	(0.0042)	(0.0072)	(0.0023)	(0.0080)	(0.0055)
γ_2 (parameter in experience spline fct.)	0.0377	0.0107	0.0511	0.0105	−0.0019	−0.0283
	(0.0146)	(0.0070)	(0.0085)	(0.0038)	(0.0102)	(0.0091)
γ_3 (parameter in experience spline fct.)	−0.0350	0.0124	−0.0287	−0.0015	−0.0231	0.0206
	(0.0252)	(0.0078)	(0.0036)	(0.0042)	(0.0063)	(0.0098)
π^1 (fraction, type 1)	0.1216	0.1624	0.2446	0.1540	0.5864	0.1193
	(0.4848)	(0.0726)	(0.1047)	(0.1108)	(0.0348)	(0.2903)
π^2 (fraction, type 2)	0.4555	0.6126	0.2634	0.5038	0.1255	0.5032
	(0.0128)	(0.0001)	(0.0852)	(0.0160)	(0.3145)	(0.0219)

Table 4: Estimation results—Denmark.

	Low education		Medium education		High education	
	Ent.	Mat.	Ent.	Mat.	Ent.	Mat.
λ_0 (monthly nonemployment-to-job rate)	0.0587	0.0433	0.0601	0.0446	0.0436	0.0357
	(0.0017)	(0.0016)	(0.0008)	(0.0008)	(0.0014)	(0.0015)
δ^1 (monthly job destruction rate, type 1)	0.0066	0.0029	0.0037	0.0379	0.0016	0.0044
	(0.0016)	(0.0011)	(0.0005)	(0.0029)	(0.0008)	(0.0004)
δ^2 (monthly job destruction rate, type 2)	0.0988	0.0385	0.0852	0.0010	0.0830	0.0031
	(0.0067)	(0.0086)	(0.0040)	(0.0002)	(0.0113)	(0.0004)
δ^3 (monthly job destruction rate, type 3)	0.0127	0.0084	0.0498	0.0067	0.0068	0.0050
	(0.0067)	(0.0012)	(0.0054)	(0.0004)	(0.0007)	(0.0008)
λ_1^1 (monthly job offer arrival rate, type 1)	0.0297	0.0128	0.0310	0.0537	0.0218	0.0136
	(0.0031)	(0.0019)	(0.0010)	(0.0034)	(0.0022)	(0.0012)
λ_1^2 (monthly job offer arrival rate, type 2)	0.0535	0.0674	0.0451	0.0135	0.0422	0.0271
	(0.0047)	(0.0148)	(0.0025)	(0.0005)	(0.0058)	(0.0022)
λ_1^3 (monthly job offer arrival rate, type 3)	0.0101	0.0314	0.0733	0.0415	0.0359	0.0339
	(0.0080)	(0.0042)	(0.0072)	(0.0022)	(0.0026)	(0.0042)
η (sampling distribution, shape)	0.5653	12.0823	3.6041	6.1328	1.1806	66.9472
	(0.0551)	(4.6769)	(0.5742)	(0.5161)	(0.1495)	(8.5866)
ν (sampling distribution, scale)	0.0568	2.1059	0.6038	1.0498	0.1975	9.8298
	(0.0152)	(0.7684)	(0.0834)	(0.0776)	(0.0333)	(1.2282)
α^1 (sampling distribution, location, type 1)	4.6384	2.7831	4.1397	3.7486	4.6421	−4.7676
	(0.0234)	(0.7661)	(0.0814)	(0.0763)	(0.0372)	(1.2279)
α^2 (sampling distribution, location, type 2)	4.5066	2.6667	4.0078	3.8971	4.4320	−4.4215
	(0.0162)	(0.7667)	(0.0800)	(0.0776)	(0.0286)	(1.2280)
α^3 (sampling distribution, location, type 3)	4.0541	3.2340	4.5264	4.2531	4.9648	−4.0505
	(0.0904)	(0.7653)	(0.0795)	(0.0762)	(0.0309)	(1.2278)
σ (std. dev. log measurement error)	0.2274	0.1860	0.2176	0.1644	0.1831	0.1625
	(0.0044)	(0.0022)	(0.0016)	(0.0007)	(0.0024)	(0.0016)
γ_1 (parameter in experience spline fct.)	0.0108	−0.0006	0.0285	−0.0031	0.0372	0.0066
	(0.0062)	(0.0051)	(0.0028)	(0.0021)	(0.0058)	(0.0044)
γ_2 (parameter in experience spline fct.)	0.0028	−0.0084	−0.0174	−0.0080	−0.0209	0.0108
	(0.0114)	(0.0085)	(0.0044)	(0.0034)	(0.0079)	(0.0071)
γ_3 (parameter in experience spline fct.)	0.0556	0.0412	−0.0007	0.0306	0.0174	0.0003
	(0.0364)	(0.0100)	(0.0056)	(0.0034)	(0.0071)	(0.0071)
π^1 (fraction, type 1)	0.3039	0.5392	0.4404	0.2173	0.3066	0.4021
	(2.6699)	(0.0137)	(0.0604)	(0.0069)	(0.0664)	(0.0116)
π^2 (fraction, type 2)	0.6814	0.2787	0.4546	0.5844	0.2587	0.4333
	(4.6423)	(0.0579)	(0.0637)	(0.0050)	(0.0944)	(0.0036)

Table 5: Estimation results—Norway.

Denmark	Low education		Medium education		High education	
	Ent.	Mat.	Ent.	Mat.	Ent.	Mat
$E[T^\lambda \mid \text{lowest } \lambda_1^v]$	16.3 (*0.42*)	72.4 (*0.61*)	27.0 (*0.49*)	87.4 (*0.50*)	22.7 (*0.2*)	66.3 (*0.50*)
$E[T^\lambda \mid \text{medium } \lambda_1^v]$	7.7 (*0.46*)	8.1 (*0.23*)	9.8 (*0.24*)	15.3 (*0.15*)	19.2 (*0.59*)	21.8 (*0.12*)
$E[T^\lambda \mid \text{highest } \lambda_1^v]$	2.9 (*0.12*)	7.2 (*0.16*)	3.9 (*0.26*)	9.6 (*0.34*)	10.0 (*0.13*)	20.5 (*0.38*)
$E[T^\lambda]$	10.7	47.3	16.8	49.7	19.1	43.7
$E[T^\delta \mid \text{lowest } \delta^v]$	197.4 (*0.42*)	509.9 (*0.61*)	∞ (*0.24*)	967.3 (*0.50*)	422.4 (*0.59*)	971.8 (*0.12*)
$E[T^\delta \mid \text{medium } \delta^v]$	10.1 (*0.46*)	102.3 (*0.16*)	366.3 (*0.49*)	324.0 (*0.15*)	346.9 (*0.29*)	818.3 (*0.38*)
$E[T^\delta \mid \text{highest } \delta^v]$	6.5 (*0.12*)	19.7 (*0.23*)	18.5 (*0.26*)	114.4 (*0.34*)	101.3 (*0.13*)	746.8 (*0.50*)
$E[T^\delta]$	88.9	333.4	244.6	576.4	360.4	800.6
Lowest κ^v	1.3 (*0.46*)	2.4 (*0.23*)	4.7 (*0.26*)	11.1 (*0.50*)	10.1 (*0.13*)	11.3 (*0.50*)
Medium κ^v	2.3 (*0.12*)	7.0 (*0.61*)	13.5 (*0.49*)	11.9 (*0.34*)	15.3 (*0.29*)	40.0 (*0.38*)
Highest κ^v	12.1 (*0.42*)	14.2 (*0.16*)	∞ (*0.24*)	21.2 (*0.15*)	22.0 (*0.59*)	44.6 (*0.12*)
κ	6.0	7.2	10.4	12.9	18.6	26.1

Norway	Low education		Medium education		High education	
	Ent.	Mat.	Ent.	Mat.	Ent.	Mat
$E[T^\lambda \mid \text{lowest } \lambda_1^v]$	99.0 (*0.01*)	78.1 (*0.54*)	32.3 (*0.44*)	74.3 (*0.58*)	45.9 (*0.31*)	73.6 (*0.40*)
$E[T^\lambda \mid \text{medium } \lambda_1^v]$	33.7 (*0.30*)	31.9 (*0.18*)	22.2 (*0.45*)	24.1 (*0.20*)	27.9 (*0.43*)	36.8 (*0.43*)
$E[T^\lambda \mid \text{highest } \lambda_1^v]$	18.7 (*0.68*)	14.8 (*0.28*)	13.6 (*0.11*)	18.6 (*0.22*)	23.7 (*0.26*)	29.5 (*0.16*)
$E[T^\lambda]$	24.4	52.1	25.7	52.2	32.3	50.4
$E[T^\delta \mid \text{lowest } \delta^v]$	150.7 (*0.30*)	347.0 (*0.54*)	272.3 (*0.44*)	1042.3 (*0.58*)	617.8 (*0.31*)	324.0 (*0.43*)
$E[T^\delta \mid \text{medium } \delta^v]$	78.7 (*0.01*)	119.4 (*0.18*)	20.1 (*0.11*)	149.0 (*0.20*)	147.3 (*0.43*)	226.2 (*0.40*)
$E[T^\delta \mid \text{highest } \delta^v]$	10.1 (*0.68*)	25.9 (*0.28*)	11.7 (*0.45*)	26.4 (*0.22*)	12.1 (*0.26*)	199.3 (*0.16*)
$E[T^\delta]$	53.8	216.1	127.4	644.4	256.6	264.2
Lowest κ^v	0.5 (*0.68*)	1.8 (*0.28*)	0.5 (*0.45*)	1.4 (*0.22*)	0.5 (*0.26*)	3.1 (*0.40*)
Medium κ^v	0.8 (*0.01*)	3.7 (*0.18*)	1.5 (*0.11*)	6.2 (*0.20*)	5.3 (*0.43*)	6.8 (*0.16*)
Highest κ^v	4.5 (*0.30*)	4.4 (*0.54*)	8.4 (*0.44*)	14.0 (*0.58*)	13.5 (*0.31*)	8.8 (*0.43*)
κ	1.7	3.6	4.1	9.7	6.6	6.2

Table 6: Expected durations until events, and friction index κ. Estimated worker type fractions π^v in parentheses.

Denmark	Low education		Medium education		High education	
	Ent.	Mat.	Ent.	Mat.	Ent.	Mat
Within-type, $\mathrm{E}[\mathrm{V}(\ln x \mid v)]$	0.016 (*0.116*)	0.036 (*0.371*)	0.015 (*0.182*)	0.025 (*0.271*)	0.069 (*0.496*)	0.026 (*0.230*)
Between-type, $\mathrm{V}(\mathrm{E}[\ln x \mid v])$	0.041 (*0.288*)	0.014 (*0.139*)	0.011 (*0.142*)	0.024 (*0.258*)	0.025 (*0.182*)	0.047 (*0.428*)
Measurement error, $\mathrm{V}(\ln \varepsilon)$	0.084 (*0.596*)	0.048 (*0.491*)	0.054 (*0.676*)	0.044 (*0.471*)	0.045 (*0.322*)	0.038 (*0.343*)
Total, $\mathrm{V}(\ln x + \ln \varepsilon)$	0.141 (*1.000*)	0.098 (*1.000*)	0.080 (*1.000*)	0.093 (*1.000*)	0.139 (*1.000*)	0.111 (*1.000*)
Log match quality range: $P_F^{90} - P_F^{10}$	0.072	0.474	0.177	0.407	0.011	0.408

Norway	Low education		Medium education		High education	
	Ent.	Mat.	Ent.	Mat.	Ent.	Mat
Within-type, $\mathrm{E}[\mathrm{V}(\ln x \mid v)]$	0.031 (*0.345*)	0.041 (*0.361*)	0.028 (*0.285*)	0.034 (*0.382*)	0.025 (*0.233*)	0.034 (*0.273*)
Between-type, $\mathrm{V}(\mathrm{E}[\ln x \mid v])$	0.007 (*0.080*)	0.038 (*0.336*)	0.023 (*0.235*)	0.029 (*0.317*)	0.049 (*0.457*)	0.065 (*0.517*)
Measurement error, $\mathrm{V}(\ln \varepsilon)$	0.052 (*0.575*)	0.035 (*0.303*)	0.047 (*0.480*)	0.027 (*0.301*)	0.034 (*0.310*)	0.026 (*0.211*)
Total, $\mathrm{V}(\ln x + \ln \varepsilon)$	0.090 (*1.000*)	0.114 (*1.000*)	0.099 (*1.000*)	0.090 (*1.000*)	0.108 (*1.000*)	0.125 (*1.000*)
Log match quality range: $P_F^{90} - P_F^{10}$	0.248	0.508	0.438	0.475	0.371	0.448

Table 7: Decomposition of log wage variance net of experience effects and range of log match qualities. Fraction of total variance in parentheses.

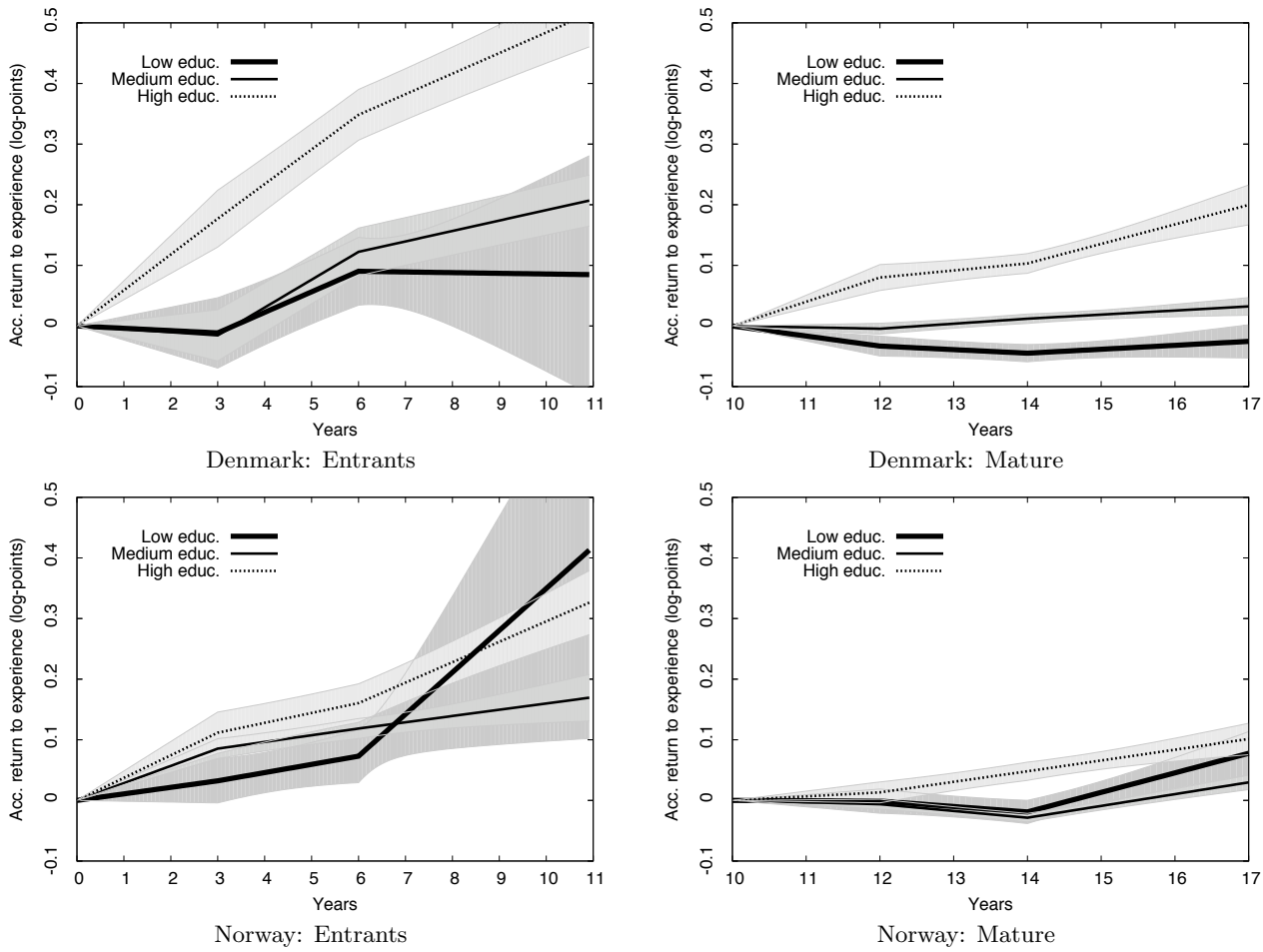

Figure 4: Estimated wage-experience profiles. Shaded areas are 95% point-wise confidence bands.

Denmark	Low education		Medium education		High education	
	Ent.	Mat.	Ent.	Mat.	Ent.	Mat
Corr(δ,λ_1)	0.90	0.53	0.94	0.94	0.98	−0.70
Corr(δ,α)	0.70	−0.66	−0.12	−0.21	0.88	−1.00
Corr(λ_1,α)	0.94	0.28	0.21	0.14	0.95	0.74
Norway	**Low education**		**Medium education**		**High education**	
	Ent.	Mat.	Ent.	Mat.	Ent.	Mat
Corr(δ,λ_1)	0.86	0.98	0.40	0.82	0.78	0.13
Corr(δ,α)	0.25	−0.54	−0.17	−0.62	−0.76	0.33
Corr(λ_1,α)	0.70	−0.37	0.84	−0.07	−0.18	0.98

Table 8: Correlations of random parameters between worker types.

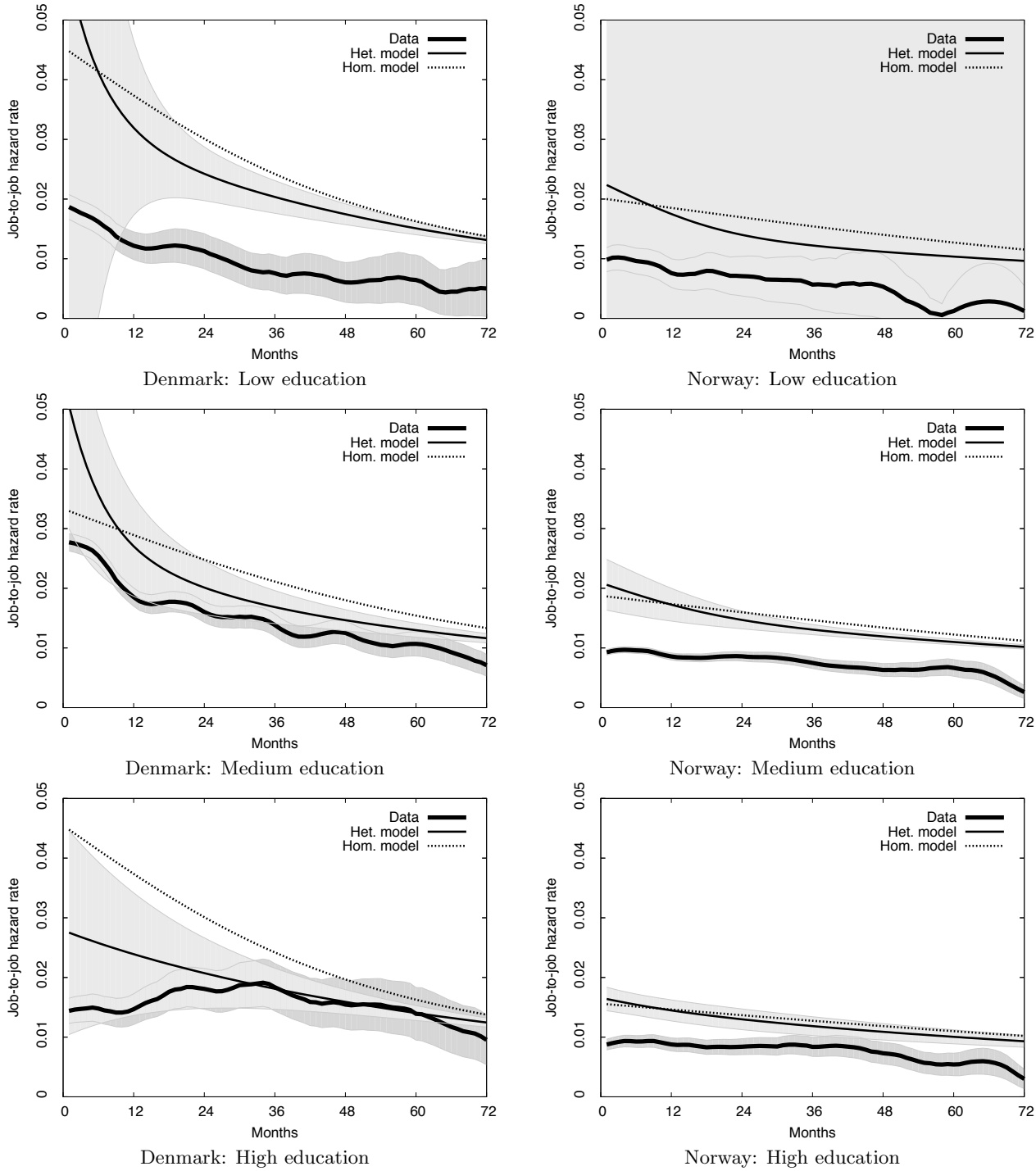

Figure 5: Fit: Job-to-job hazard functions for entrants. Shaded areas are 95% point-wise confidence bands (not shown for homogenous model).

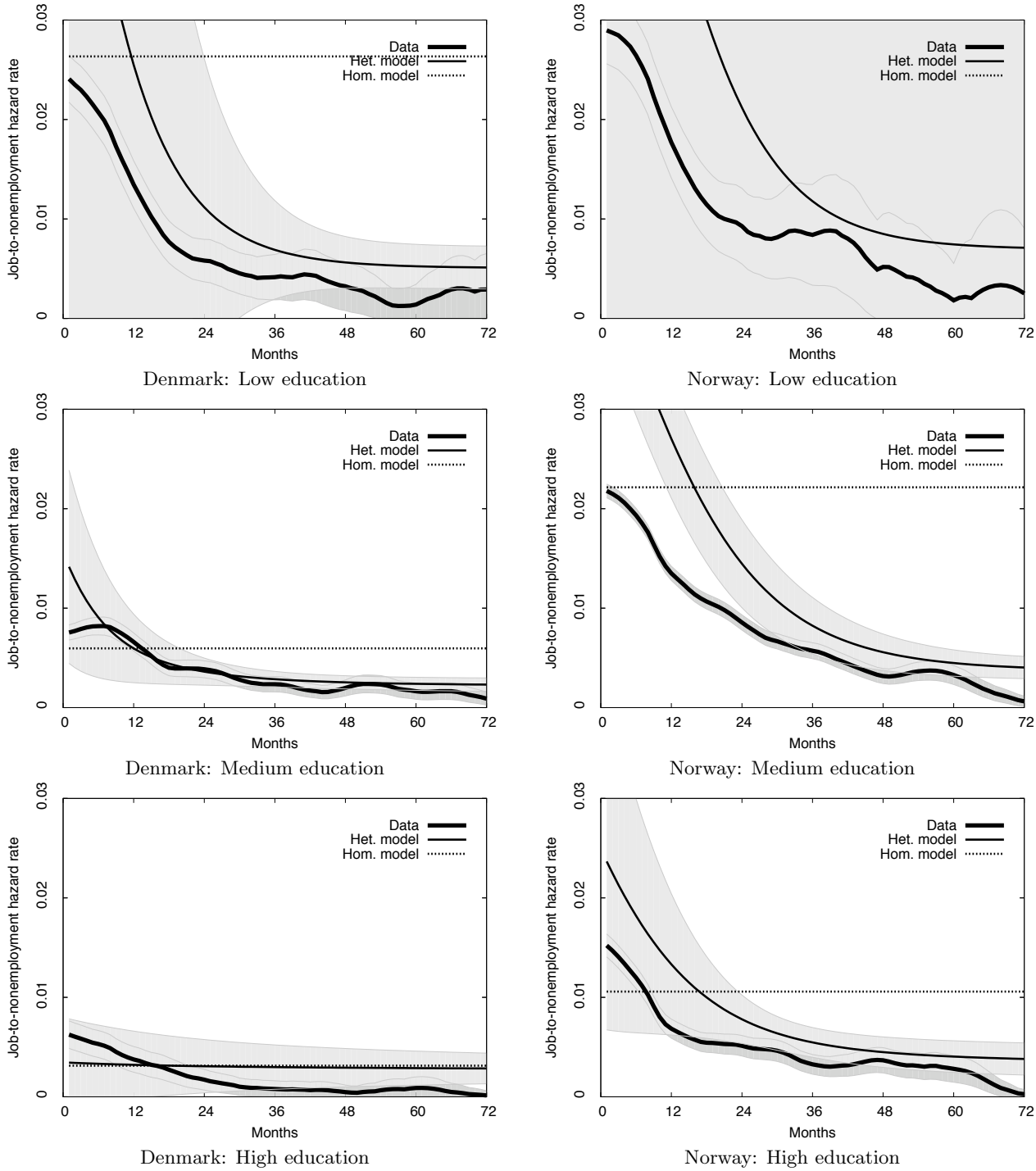

Figure 6: Fit: Job-to-nonemployment hazard functions for entrants. Shaded areas are 95% point-wise confidence bands (not shown for homogenous model).

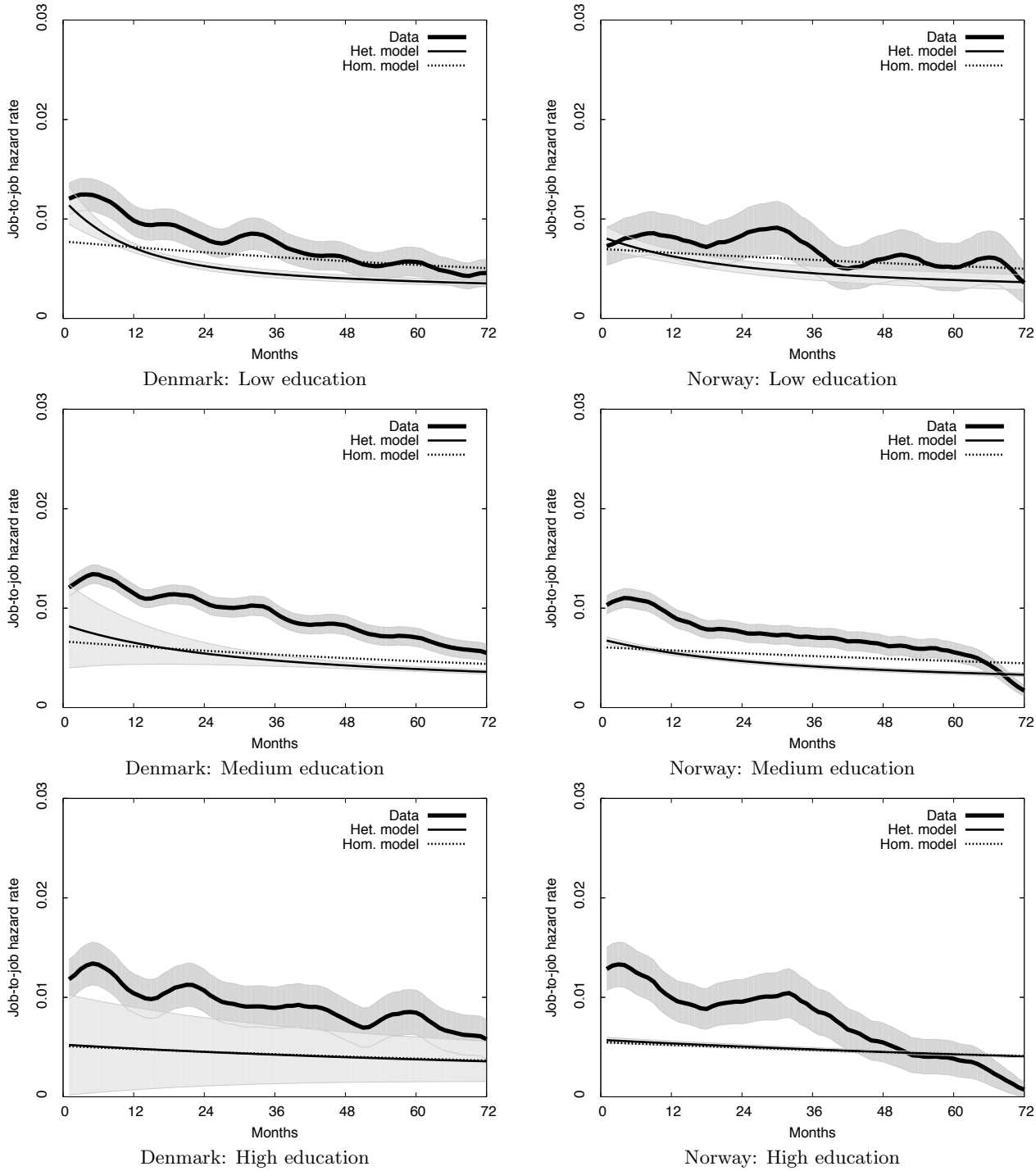

Figure 7: Fit: Job-to-job hazard functions for mature workers. Shaded areas are 95% point-wise confidence bands (not shown for homogenous model).

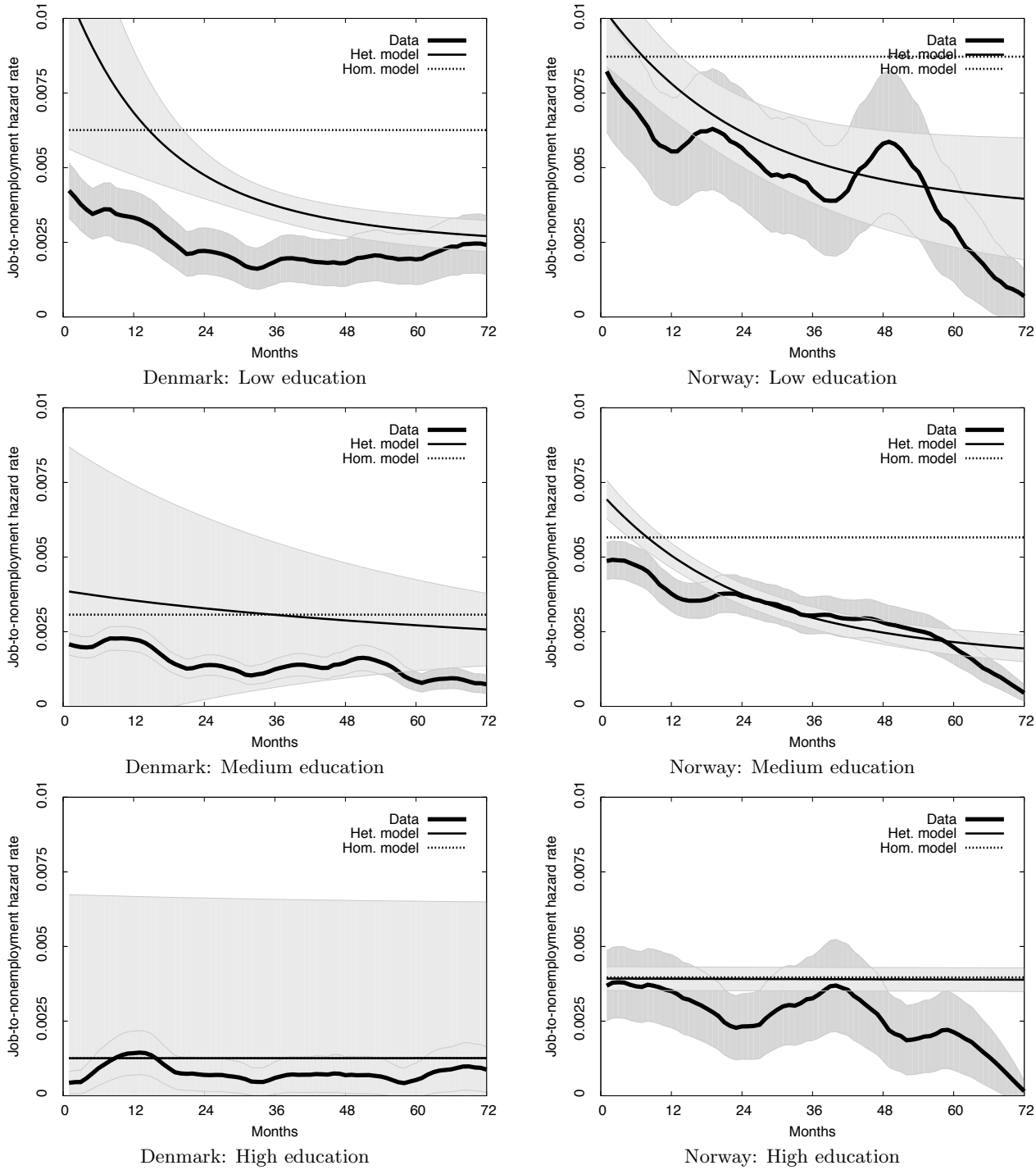

Figure 8: Fit: Job-to-nonemployment hazard functions for mature workers. Shaded areas are 95% point-wise confidence bands (not shown for homogenous model).

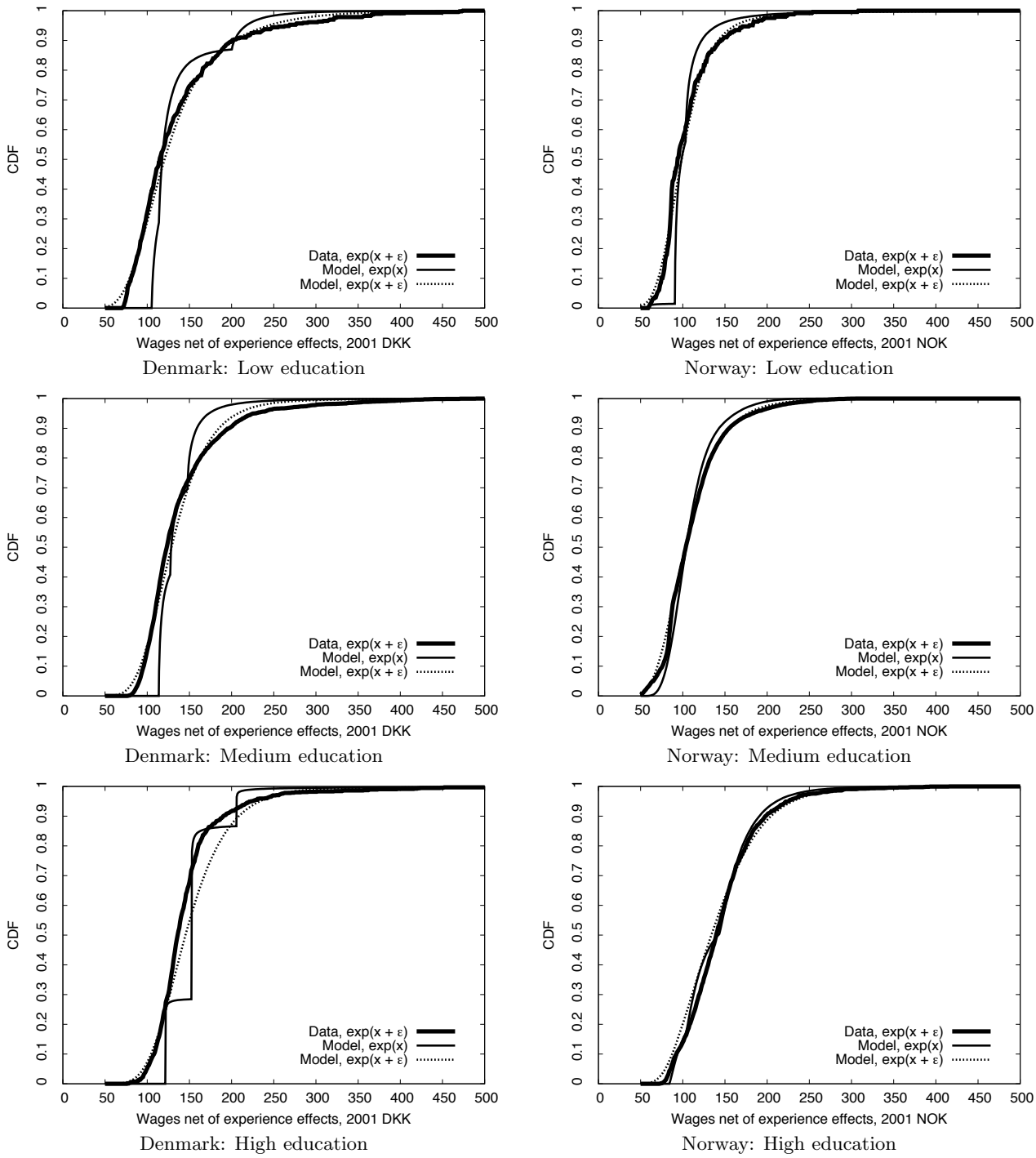

Figure 9: Fit: Sampling distributions of match qualities and wages (net of experience effects), for entrants.

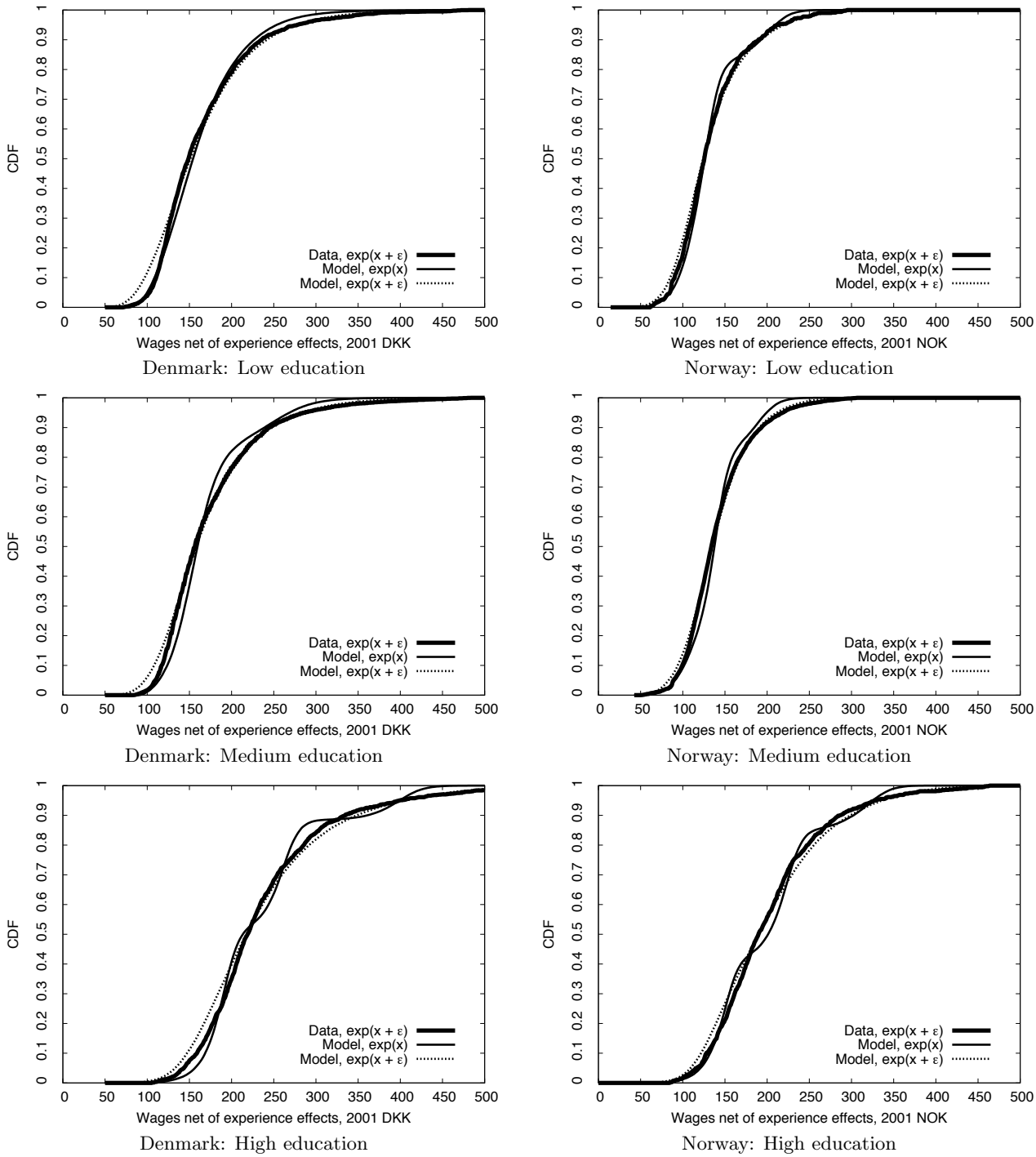

Figure 10: Fit: Steady distributions of match qualities and wages (net of experience effects) conditional on experience = 10.5 years for mature workers.