Search behaviour and unemployment income: evidence using Danish unemployment assistance data

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Abstract

Danish unemployment assistance increases by 70% when individual becomes 25 years old. This feature is used to identify the effect of income on the receipients of unemployment assistance. Competing-risks duration models are used. The semiparametric estimates cease to find any effect on the hazard rate around age 25. The parametric differences-in-differences estimate suggests the presence of a significant negative income effect for females, the effect for males is positive but insignificant. The income elasticity of the hazard rate into employment is -0.4 for females, the results for transitions to non-participation are insignificant.

1 Introduction

The economic theory predicts that a high level of unemployment compensation leads to longer unemployment spells. Subsidizing search makes unemployed individuals more choosy and less willing to accept low-wage jobs. Even more, if search intensity cannot be monitored (as is usually the case), the motivation to search a job will also be lower. Although unemployment duration unambiguously increases, welfare and efficiency issues are less clear. More search may lead to more efficient allocation of ressources and unemployment benefits may deter people for leaving the labour force[1].

There is a large literature investigating the effect of unemployment benefits level and entitlement on the search behaviour and the hazard rate of leaving the unemployment. The results in experimental setup basically confirm the search theory although there are some indication of risk-seeking behaviour and loss-aversion (Boone, Sadrieh, and van Ours, 2004). The empirical results reflect the fact that the real world is much more heterogeneous than the laboratory set-up. The evidence from US indicates that the effect of benefits on the out-from-unemployment hazard rate is indeed negative and significant (Card and

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[1]see Atkinson and Micklewright (1991) for an excellent review

Levine, 2000; Lee, 2000; Hotz, Mullin, and Scholz, 2002; Jurajda and Tannery, 2003), the elasticity of the hazard rate with respect to unemployment benefits is found to be between -0.3 (Lee, 2000) and -0.9 (Meyer, 1990). There is some evidence that the effect is heterogeneous (Grogger, 2002) and diminishing in time (Addison and Portugal, 2004).

In Europe, the results are even more mixed. Some studies have found no significant effect at all (Stancanelli, 1999; Puhani, 2000; Bratberg and Vaage, 2000) while according to the others the effect is negative and significant (Narendranathan and Stewart, 1993; Micklewright and Nagy, 1999; Carling, Holmlund, and Vejsiu, 2001; Gonzalo, 2002; Røed and Zhang, 2003). The corresponding elasticity estimates stretch from -0.1 (Arulampalam and Stewart, 1995) to -1.6 (Carling, Holmlund, and Vejsiu, 2001). There is also some mixed evidence of effect heterogeneity: according to Narendranathan and Stewart (1993) and Bover, Arellano, and Bentolila (2002) the negative effect of benefits diminishes quickly in time, while the other studies have found a constant effect (Røed and Zhang, 2003). The negative effect is stronger for younger workers (Arulampalam and Stewart, 1995; Carling, Holmlund, and Vejsiu, 2001) and during economic boom (Arulampalam and Stewart, 1995).

A fundamental problem of estimating the effect of unemployment benefits is the fact that the benefit level and entitlement may be endogeneous. In recent studies, it is common to use natural experiments, related with legislation and economic conditions in the particular labour market, in order to overcome the endogeneity problems. Examples include differences in benefit duration and level in time or space (Meyer, 1990; Card and Levine, 2000; Bratberg and Vaage, 2000), differet rules for fixed-term/permanent contracts (Bover, Arellano, and Bentolila, 2002) and the fact that the legislation may have some seasonal features like relationship between benefit level and the labour income in a particular *calendar* year (Røed and Zhang, 2003).

In the current analysis I use the age-dependence of unemployment assistance (UA) in Denmark as the identifying feature. In contrary to what has been used in most of the other studies, it may lead to an *increase* of benefits during the unemployment spell for individuals around age 25. Unemployment assistance is a cash transfer to unemployment people, it is distinct from unemployment benefits. The receivers of UA is a specific group of individuals where "weak" unemployed are significantly overrepresented. It is often considered that at least a part of them are not sensitive to neither active labour market policy nor income transfers.

The results are unstable. The parametric differences-in-differences model shows no significant income effect for males, for females the effect is significant and negative. Non-parametric methods reveal no indication of a discontinuity around age 25, the lower bounds for income elasticities of the hazard rates are found in this case to be around -0.3, not much different for different genders and for transitions into employment or non-participation. The results must be interpreted conditional on receiving unemployment assistance because corresponding selection effects are not investigated in the present study.

The paper is divided as follows: the next section describes the Danish unemployment insurance legislation with particular attention on the age depending unemployment assistance. The third section presents the econometric method; the fourth section describes the data and gives some descriptive statistics. Estimation results are given in the fifth section, and the last section is devoted to a brief discussion.

2 A short overview of Danish unemployment insurance legislation

Danish labour market is characterised by a generous and high level of income support for unemployment people. There are two types of transfers – unemployment benefits (UB) and unemployment assistance (UA). An unemployed individual may receive unemployment benefits if he or she fulfils certain requirements about membership of unemployment insurance system and previous employment. Certain types of education (in particular university and vocational education) count as well as employment for eligibility of UB. The level of the benefits is 90% of the previous wage. However, due to the presence of lower bound and a ceiling of the weekly benefits (correspondingly 2411 and 2940 DKK weekly in 2003), the variation in the size of the benefits is actually quite small.

The requirements for UA are less strict. It is required that an individual looses his or her income as a result of an "event" (e.g. a job loss, illness or divorce), and that he or she is actively searching for a new job. UA is not related to the previous income[2], it depends on age and family conditions only (Table 1). The age dependency of UA was introduced in 1994. The recipients were divided into four groups – individuals below 23 years (since 1995 25 years) living together with their parents; individuals of equal age living alone; individuals above 23 (later 25); and individuals responsible for children. The UA was different for different groups. In the case of the last group – individuals with dependent children – it was not depending on age. The other groups experienced a significant increase when they turned 23 (25). In particular, for individuals without children, UA increases from 4969 to 7711 DKK monthly when they turn 25 (in 2001).

However, not only UA but the active labour market policy too, depends on the age. Since 1994, individuals below 25 had to participate in an active labour market programme (ALMP) after 13 weeks of UA, while the older individuals had to do the same after 12 months (*lov om kommunal aktivering* 498, June 30, 1993). This policy was changed from 1st of July 1998[3] (*lov om aktiv socialpolitik* 455, 10/VI 1997) when the age boundary for early activation was increased to 30 years. Hence, between January 1994 and June 1995, and since July 1998, the discontinuity in UA payments does not coincide to the discontinuity in the participation requirements.

During participation in an ALMP, the assistance remains the same as before the participation for most types of ALMP. However, there are some exceptions (according to the the law 455/1997 §38, *lov om aktiv socialpolitik*):

- During the job-training in a private firm the individual receives ordinary salary for the particular job.
- During the job-training in the public sector, the individual receives salary which must not exceed 85.10 DKK hourly (about 3200 DKK weekly).

[2]During the period of 1/VII 1998 – 1/I 1999 (Introduced by law 455/1997 §25, stk. 3, 2. pkt. and abolished by law 1040 23/12/1998 §1) individuals below 25 could get the higher UA if their previous income exceeded a certain treshold during last 18 months.

[3]for individuals who started their UA-period before 1st of July, the old rules still applied.

Valid from	A	B	C	D	introduced by
Until 1994: base benefits + housing allowance + child allowance					
		age boundary 23 years:			
January 1st, 1994	2080	4251	6615	8825	Law 496, June 30, 1993
		age boundary 25 years:			
July 1st, 1995[a]	2080	4251	6615	8825	Law 1129, Dec. 21, 1994
April 1st, 1996	2238	4370	6615	8825	Law 1113, Dec. 20, 1995
July 1st, 1998	2195	4489	6998	9317	Law 980, Dec. 17, 1997
March 1st, 2001	2195	4969	7711	10245	Law 1087, Dec. 13, 2000

[a]Individuals who received UA before that date continued to receive the previous amount

Table 1: *Unemployment assistance (DKK monthly). A – individuals aged below 23 (25) and living together with their parents; B – individuals aged below 23 (25) and living alone; C – individuals 23 (25) years old and above; D – individuals responsible for children, and pregnant women from 12th week of pregnancy. Does not depend on age.*

- During individual job-training, UA must not be less than 40 DKK for one training hour. Outside of the training hours, UA is the same as without the participation.
- Local community may cover the costs, related with the participation, up to 1000 DKK in a month.[4]

According to the law 419/2003 (*lov om en aktiv beskæftigelsesindsats*), from July 1st, 2003 UA benefits during qualification-related ALMP-s (*vejledning og opkvalificering*) and work-place practice (*virksomhedspraktik*) are equal to the benefits before the participation. While employed with wage subsidies, the wage must correspond to the ordinary wage for the particular job (but not exceed 96.21 DKK hourly in public sector).

The discussion above suggests that UA depends on the age for individuals without children, except when in job-training. There are two ways to indentify the effect for spells which start not before July 1998. First, the individuals without the cildren can be used as a control group. Second, the discontinuity itself at age 25 can be used as the identifying feature. Analogous features existed 1994-1995 where the corresponding age boundary was 23 years.

3 The model

A natural way of investigating search behaviour is by using a hazard rate framework. In the current study I am looking at transitions from unemployment into employment and out of labour force. The hazard rate into employment can be described as a product of two probabilities – probability of receiving a job offer and probability of accepting the offer. An observable transition occurs if either the job offer is accepted or if the individual considers it no more worthwhile to continue the job-search. The corresponding events for transitions into non-participation can be defined analogously. Reduced-form duration models

[4]In "exceptional cases" up to 1500 DKK

draw conclusions based on the actual transitions and do not attempt to estimate the arrival rate and acceptance probability separately. The advantage of the reduced-form models is that they are significantly simpler to estimate, and the necessary assumptions and requirements for the data are relatively well-known. In order to disentangle the components of the hazard rate, one has to use more information and additional assumptions. Unfortunately, job offer rejections and reservation wages are not observed in common datasets, and hence various somewhat arbitrary assumptions are needed, the effect of which is not completely clear. However, although assumptions behind reduced-form models are more transparent, a corresponding arbitrariness arises when interpreting the results in structural context. In the current analysis I have chosen the latter way.

The effect of UA on the individual search behaviour is reflected by the dependence of the transition intensities on the age (see section 2). In particular, it should be reflected by a discontinuity around age 25 which is not present for individuals with children. As the hazard rate can depend on the age on several reasons, I have modelled the age effect in a flexible way using splines. Two types of models are estimated. First, I estimate a differences-in-differences model treating individuals without kids a the treatment group on those with kids as the control group. Second, I use just the discontinuity in the age effect for the treatment group as an estimate for the income effect.

3.1 Duration model

The duration analysis was performed using mixed proportional hazard (MPH) models in competing risks grouped data framework. Transitions from unemployment (U) into employment (E) and non-participation (N) were investigated. I am (somewhat loosely) calling the hazard rate (or transition intensity) the conditional probabilities of entering any of the final states. I do not distinguish between origin- and destination-specific hazard rates in the text.

I specify the model in grouped duration framework (Moon, 1991). The use of grouped durations is mainly motivated by the data availability (there is no direct daily or weekly information about labour market state). The second reason is that the use of grouped data does not impose a particular functional form onto the hazard rate. The differences in survival probability across the intervals are treated as unknown parameters, the shape of the hazard rate inside of the intervals remains unspecified. Previous research has indicated that this type of models are much more robust with respect to aggregation of duration than the flexible parametric specifications (Bergström and Edin, 1992). Unfortunately, simplifying assumptions are necessary in order to keep a competing risks model tractable. As in Moon (1991), I assume that only one event may occur during a time interval. The assumptions is innocuous if the length of the intervals is short.

Divide duration into L intervals: $[0, \tau_1), [\tau_1, \tau_2), \ldots, [\tau_{T-1}, \tau_L)$. Denote by n_i the interval, during which the individual i exited the unemployment, or during which the observation was censored. This is the only type of individual timing information we use. Denote further by $\boldsymbol{x}(n)$ the vector of individual and spell-specific characteristics during the interval n. I assume the covariates are constants during the intervals (most of the variables are recorded yearly anyway). I assume further that $\boldsymbol{x}(T)$ is an exogeneous process, in the sense as defined by Lancaster (1990, p. 28). Let v_i^m be the unobserved individual characteristics, specific to destination $m \in \{E, N\}$. I use a bivariate $K^E \times K^N$-point discrete distribution $\boldsymbol{v} \equiv (v^E, v^N)' \in \{v_1^E, v_2^E, \ldots, v_{K^E}^E\} \times \{v_1^N, v_2^N, \ldots, v_{K^N}^N\}$ where the realisation (v_k^E, v_l^N) has probability p_{kl}. I assume that the transition intensity into final state m, $\vartheta^m(\tau|\boldsymbol{x}, v^m)$ can be separated into duration-only depending term $\lambda^m(\tau)$ and covariate-only depending term $v^m\phi^m(\boldsymbol{x})$ (a MPH specification):

$$\vartheta^m(\tau|\boldsymbol{x}, v^m) = \lambda^m(\tau)\psi^m(\boldsymbol{x})v^m. \tag{1}$$

Additional crucial assumptions I do is that $\boldsymbol{v}$ is independent of $\boldsymbol{x}$ and has a finite mean (which I normalise to unity). These assumptions allow to indentify $\lambda^m(\tau)$, $\boldsymbol{\beta}^m$ and distribution of $\boldsymbol{v}$ (Elbers and Ridder, 1982; Heckman and Honoré, 1989; Abbring and van den Berg, 2003). Note that the parametric assumptions about $\phi(\boldsymbol{x}(T))$ and distribution of v are not strictly required for identification. In addition, time-varying covariates would allow us to drop either the assumption about the finite mean of v (Heckman and Taber, 1994) or proportionality assumption (Brinch, 2000). Even more, as I observe multiple spells for a certain number of individuals, most of the previous assumptions can be relaxed (Honoré, 1993; Abbring and van den Berg, 2003). However, those assumption simplify the estimation on finite samples.

I assume that only one event may occur during an interval, as discussed above. Probability that individual i stays in unemployment during the interval n can now be written, using the expression (1) for the transition intensities, as:

$$\begin{aligned} &S(n|\boldsymbol{x}_i(n), \boldsymbol{v}_i) = \\ &= \exp\left(-v_i^E \int_{\tau_{n-1}}^{\tau_n} \psi^E(\boldsymbol{x}_i(n))\lambda^E(s)\,\mathrm{d}s - v_i^N \int_{\tau_{n-1}}^{\tau_n} \psi^N(\boldsymbol{x}_i(n))\lambda^N(s)\,\mathrm{d}s\right) \equiv \\ &\equiv \exp(-v_i^E z_n^E(\boldsymbol{x}_i(n)) - v_i^N z_n^N(\boldsymbol{x}_i(n))) \end{aligned} \tag{2}$$

where $v_i^E z_n^E(\boldsymbol{x}_i(n))$ and $v_i^N z_n^N(\boldsymbol{x}_i(n))$, defined by the equation above, are the integrated destination specific hazard rates in the interval n. We define λ_n^m as:

$$\lambda_n^m(t_n - t_{n-1}) \equiv \int_{\tau_{n-1}}^{\tau_n} \lambda^m(s)\,\mathrm{d}s. \tag{3}$$

λ_n^m can can be interpreted as the average destination-m specific baseline hazard in the interval n. It is a free parameter and has to be estimated. This is a flexible way of specifying the baseline hazard. The number of intervals L may let to increase and the length of intervals may to decrease as the number of observations increases, and in this way a non-parametric estimator of the baseline hazard (BLH) can be achieved.

The contribution of the individual i who exits the initial state in the interval n_i, to the likelihood function, conditional on $\boldsymbol{X}(0, \tau_{n_i})$, the path of $\boldsymbol{x}_i$ until the end of the interval n_i, and $\boldsymbol{v}_i$, is

$$\begin{aligned} &\mathcal{L}(n_i|\boldsymbol{X}_i(0, \tau_{n_i}), \boldsymbol{v}_i) = \\ &= \left(1 - \mathrm{e}^{-v_i^E z_n^E(\boldsymbol{x}_i(n))}\right)^{\delta_i^E} \left(1 - \mathrm{e}^{-v_i^E z_n^N(\boldsymbol{x}_i(n))}\right)^{\delta_i^N} \prod_{l=1}^{n_i-1} \mathrm{e}^{-v_i^E z_l^E(\boldsymbol{x}_i(l)) - v_i^N z_l^N(\boldsymbol{x}_i(l))} \end{aligned} \tag{4}$$

where the δ_i^m indicates whether the particular observation ended with transition into state m. If there are N_i spells observed for the individual i, the corresponding log-likelihood contribution of her, conditional on the observed covariates $\boldsymbol{x}_i$ is

$$\ell(\cdot|\boldsymbol{x}_i(T)) = \log\left(\sum_{k=1}^{K} p_k \prod_{j=1}^{N_i} \mathcal{L}(n_{ij}|\boldsymbol{X}_{ij}(0,\tau_{n_{ij}}), \boldsymbol{v}_i^k)\right) \tag{5}$$

where n_{ij} is the exit interval of the j-th spell of the individual.

3.2 Income effect

Three different specifications for isolating the income effect are used.

The first one is a parametric differences-in-differences estimator where I treat the individuals without the children as the treatment group and those with children as the control group. I look at differences of the age effects around age 25 for those two groups. $\psi^m(\boldsymbol{x})$ in (1) is specified as

$$\begin{aligned}\psi^m(\boldsymbol{x}) = \exp\big[g^m(\mathit{age}) + \gamma_1^m \mathit{kids} + \gamma_2^m \mathit{female} \cdot \mathit{kids} +\\ + \gamma_3^m(\mathit{age} \geq \mathit{25}) \cdot (\mathit{no\ kids}) +\\ + \gamma_4^m(\mathit{Q1\ before}) \cdot (\mathit{no\ kids}) + \gamma_5^m(\mathit{Q2\ before}) \cdot (\mathit{no\ kids}) +\\ + \gamma_6^m(\mathit{Q3\ before}) \cdot (\mathit{no\ kids}) + \gamma_7^m(\mathit{Q4\ before}) \cdot (\mathit{no\ kids}) +\\ + \boldsymbol{\beta}^{m\prime}\boldsymbol{y}\big].\end{aligned} \tag{6}$$

Here $g^m(\mathit{age})$ is a flexible age effect (I specify it using splines). I allow for a duration-invariant difference between individuals with and without kids (γ_1^m), possibly different for males and females (γ_2^m). The income effect is reflected as a change in the difference between age effects for individuals with- and without kids (γ_3^m, note that specification "*no kids*" means that γ_3^m counts for the effect on the individuals without kids, i.e. those who experience a change in income). $\gamma_4^m - \gamma_7^m$ allow for an anticipation effect up to one year, *Q1 – Q4 before* means the respective number of quarters before turning 25. $\boldsymbol{y}$ are all other relevant covariates.

The second approach is less parametric. I am still using the individuals without children as the control group and those without children as the treatment group. However, in this time I model the difference between individuals with- and without children using in a flexible way, without imposing parametric restrictions related with age 25. $\psi^m(\boldsymbol{x})$ in (1) is specified as

$$\begin{aligned}\psi^m(\boldsymbol{x}) = \exp\big[g^m(\mathit{age}) + \gamma_1^m \mathit{kids} + \gamma_2^m \mathit{female} \cdot \mathit{kids} +\\ + g_1^m(\mathit{age}) \cdot (\mathit{no\ kids}) + \boldsymbol{\beta}^{m\prime}\boldsymbol{y}\big].\end{aligned} \tag{7}$$

The meaning of $g^m(\cdot)$, γ_1^m, γ_2^m and $\boldsymbol{y}$ is as before. The function $g_1^m(\cdot)$ allows the age effect to differ between individuals with- and without kids in a flexible way. In this way it allows to test whether the results from the previous specifications are robust if the corresponding parametric specification is dropped. I specify $g_1^m(\cdot)$ using the same base splines as for $g^m(\cdot)$.

The third approach does not use the treatment and control group approach. Instead, I am looking for a discontinuity in the age effect around the age 25. Because the 25th birthday is fully anticipated, the method is valid only if the anticipation effect is short. The current estimates for the length of anticipation effect (based on the decrease of benefits) are around 5-6 months (Narendranathan and Stewart, 1993; Carling, Holmlund, and Vejsiu, 2001). This may or may not be a problem, depending on the smoothness of the age effect. I specify the covariate-only depending terms $\psi^m(\boldsymbol{x})$ as

$$\psi^m(\boldsymbol{x}) = \exp\left(\boldsymbol{\beta}^{m\prime}\boldsymbol{y} + g^m(age)\right). \tag{8}$$

The function $g^m(\cdot)$ is specified in a flexible way in order to capture both the true age-dependence and the possible discontinuity at age 25. Two different types of $g^m(\cdot)$ are used: at first, I model the true age effect using splines and add a discontinuity (in $g(\cdot)$ and it's derivatives) at age 25. This specification allows to interpret the discontinuity variable as the true assistance effect. However, in using a pre-specified location for discontinuity, we do not allow for anticipation effect. Hence, the second specification uses only a flexible age effect without any discontinuity. The advantage is that in this way we "let data speak for itself" and do not impose any particular feature at the age 25. In this case I am looking for a rapid decrease (or increase) of the effect before and at age 25. The discontinuity is estimated as the difference between smoothed and not smoothed age effects. Smoothing is done regressing the estimated flexible effect on age and age^2 by OLS. The discontinuity should show up as a decrease (or increase) of the effect with respect to the trend around the age 25. Although in this way we impose less pre-determined features on the function g, the results are not so straightforward to interpret.

4 Data

4.1 Variables

The data set used in this study is a register based representative 10% sample of the Danish population aged 16-75 and covering the period 1981-2001, and corresponding labour-market histories. The data set is compiled from various administrative registries by the Danish Statistical Office. The sample is updated in such a way that it is representative in each of the years. The dataset includes demographic characteristics, income, labour market status, education and the location of residence. Data for most of the variables is collected once a year. Data for unemployment benefits and assistance include monthly duration of payments (number of days). Unfortunately the amount of the payments is available only on yearly basis. In order to find monthly benefits and wages, I have to relay on the corresponding duration data. It is obvious that no direct inference about benefit- or wage changes during a year can be made.

The sample was restricted for spells starting between July 1998 (due to the UA-related legislation, see section 2) and December 2001 (end of the dataset). The sample was further restricted for the age group 20 to 28 (as in the beginning of the spell). For each spell a local unemployment rate, based on the municipality of residence, is calculated. This is unemployment in the travel-to-work area, which is calculated based on commuting costs (not exceeding 90DKK daily). Possible mobility during unemployment spell is taken into account. In addition, regional dummies, defined by administrative borders, are used.

variable	description
age	age, measured in the beginning of year
female	gender
kids	children in the family
education: *primary* (reference group), *high school*, *university*	
danish	ethnicity, danish contrary to immigrant
single	family status, not married or co-habiting
experience	working experience, in years
ALMP	participation in an ALMP programm
local u	unemployment in the local commuting area
Copenhagen	residence in Copenhagen county
East-Sealand	Roskilde, Frederiksborg (capital area)
Western Jutland	Western-Jutland
quarterly dummies (*Q4* is the reference quarter)	
year dummies (*1998* is the reference year)	

Table 2: *The definition of the explanatory variables.*

	all			*age* $<$ *25*	*age* $\geq$ *25*
	min	mean	max	mean	mean
durations (in months):					
all	0.926	6.822	42.560	5.494	8.034
$U \rightarrow E$	0.933	5.778	37.567	4.894	6.655
$U \rightarrow N$	0.933	6.743	39.567	5.682	7.731
share of transitions:					
$U \rightarrow E$	0.000	0.427	1.000	0.446	0.410
$U \rightarrow N$	0.000	0.360	1.000	0.364	0.357
Individual- and spell-specific variables:					
age at beginning	21.037	24.603	28.878	22.687	26.353
age at end	21.122	25.164	31.211	23.139	27.013
female	0.000	0.500	1.000	0.503	0.498
kids	0.000	0.337	1.000	0.271	0.397
high school	0.000	0.347	1.000	0.315	0.376
university	0.000	0.018	1.000	0.002	0.032
danish	0.000	0.844	1.000	0.863	0.827
single	0.000	0.607	1.000	0.639	0.578
experience	0.000	2.301	11.000	1.824	2.737
ALMP	0.000	0.283	1.000	0.306	0.263
local u	0.030	0.051	0.124	0.052	0.051
Copenhagen	0.000	0.241	1.000	0.218	0.262
East-Sealand	0.000	0.074	1.000	0.083	0.065
Western Jutland	0.000	0.106	1.000	0.113	0.100
Number of obs		7450		3556	3894

Table 3: *Summary statistics for all spells, and spells for individuals below and above 25 year (at the beginning of the year when spell ends). Time-varying variables are measured in the beginning of the year when the spell ended.*

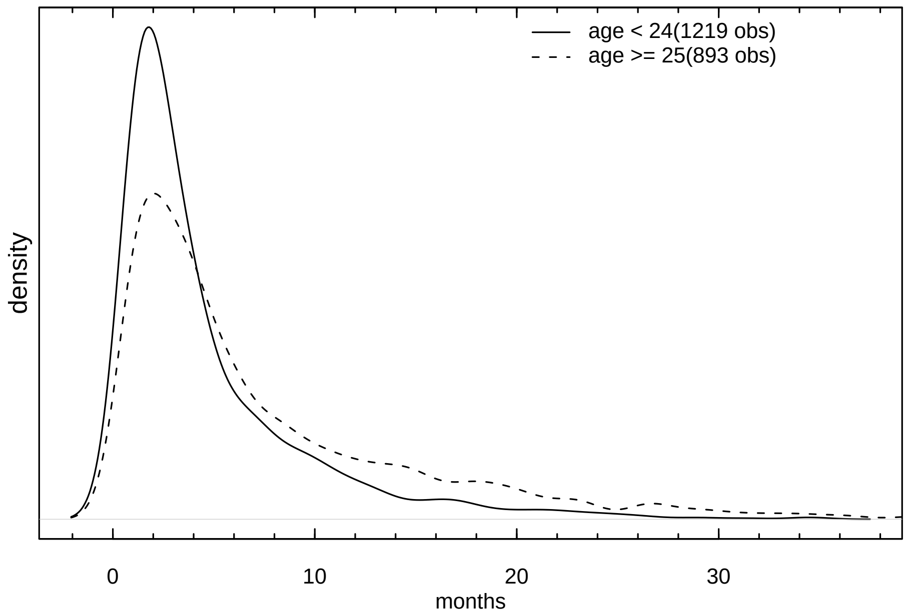

Figure 1: *Duration at which active labour market program (ALMP) participation starts. Kernel estimate of density. Note that only a part of the sample is activated.*

The definition of variables and a brief summary statistics are presented in the Tables 2 and 3. One can see that there are indeed differences between the age groups. In particular, the unemployment spells for individuals above 25 are two and a half months longer in average. The difference is smaller for the completed spells (1.8 and 2.0 months for $U \to E$ and $U \to N$ spells respectively). $U \to E$ transitions are a bit more common for the younger age group, the share of $U \to N$ transitions is almoust equal. We can see that the participation in ALMP-s is slightly more common among younger people. The differences in education and family characteristics between the age groups are as expected: older individuals have longer experience and education, they have more often children. Surprisingly, the share of married individuals is higher in the younger group. This is probably related with the fact that UA-receipients is a specific group of individuals. Members of the older age group are more often living in Copenhagen but less in East-Sealand and Western Jutland.

In order to check whether there is any differences in timing of ALMP-s for different age groups, I plot the distribution of durations when ALMP participation starts (Figure 1). The Figure suggest that the timing of ALMP-s is indeed similar for both age groups and hence there is no ALMP-related discontinuity at age 25.

The number of transitions according to age is presented in the Table 4. There are no special features around age 25. Starting from age 26, the share of censored observations increases and that of the completed $U \to E$ spells falls significant. The share of completed $U \to N$ spells is roughly constant.

This brief look above at the data suggests that older individuals are indeed slower to leave the unemployment. However, the tables reveal no visible effect around age 25.

	age									
	20	21	22	23	24	25	26	27	28	29
cens	0.19	0.19	0.22	0.20	0.19	0.20	0.22	0.26	0.28	0.47
E	0.54	0.53	0.50	0.47	0.51	0.48	0.47	0.45	0.39	0.24
N	0.27	0.28	0.28	0.33	0.31	0.32	0.31	0.29	0.33	0.29
# obs	592	872	780	659	588	610	632	409	75	17

Table 4: *Observed transitions from unemployment according to age and transition type.*

4.2 Relationship between UA and age

I demonstrate in this section that the actual payment to UA-receipients is in fact in compliance with the law. Current dataset includes only yearly information about income. Consequently the monthly level of UA tranfers must be found, combining the yearly payment data with corresponding duration. Note that the measurement errors in recorded spell durations result in the estimated income effect being upward biased, if the monthly or weekly benefits, derived in this way, were used. The bias does not arise if age is used as an instrument and the 25-year rule is fully implemented.

The information, whether the individuals are living together with parents, is not directly available and is not used in the current study.

A (kernel estimate of) distribution of the average monthly assistance is plotted in the Figure 2. Four maxima, corresponding to assistance in the Table 1, are clearly visible. The maximum around 2000 (DKK monthly) corresponds to individuals below 25 who are living together with their parents; next maximum slighly below 5000 represents those who are living alone; the third maximum around 7000 are those above 25, and the last maximum at 9000-10 000 corresponds to parents with children. Note that the first two maxima are present only for the younger age group while the third one only for the older group, in compliance with the Table 1. Not all the observations belong to one of the group. However, only part of the mass is located in the four maxima. The continuous part of the distribution may be related with different factors: individuals who experience a change in UA during the year (no direct information about those cases is available), errors in recorded duration and lower actual benefits due to other sources of family income.

In order to get an idea about the strength of the instrument, I ran a regression explaining unemployment assistance by age and other relevant variables. $\mathtt{1}(age \geq 25)$ is clearly a significant predictor of UA (Table 5). All the relevant coefficients are significant and of reasonable order. Note that I have not controlled for living together with parents due to data limitations. The regression includes a couple of irrelevant variables (according to the legislation) as well. *danish* turns out to be insignificant, the other are related with relatively small but significant effects. Why this is like that, is beyond the scope of the current study but selection effects are a possible explanation. The explanatory power of the instruments is not impressive ($R^2 = 0.23$). However, part of the problem lies in measurement errors which, in fact, makes the instrument more suitable than it appears.

How large effect on the hazard rate should we expect, based on these results?

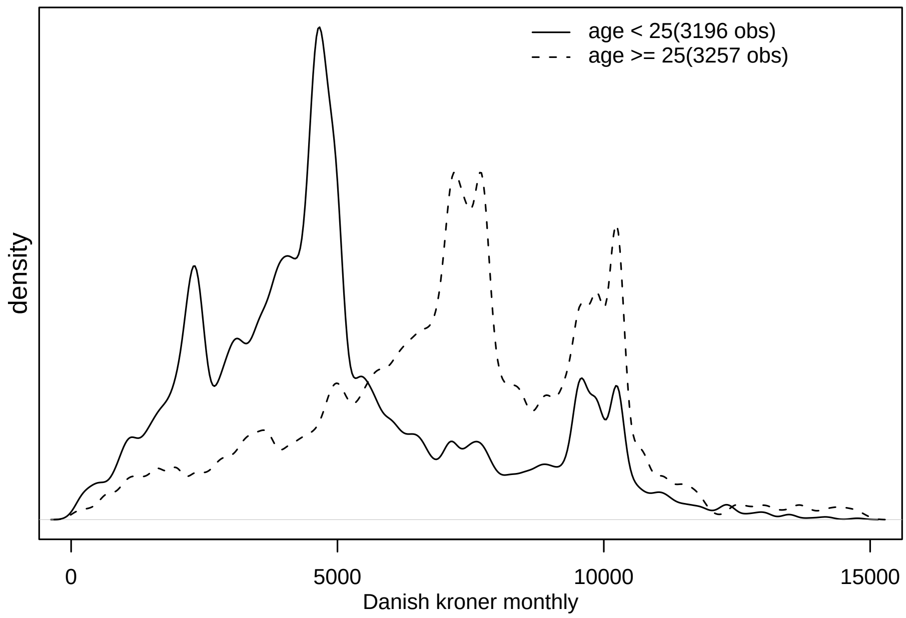

Figure 2: *Kernel estimate of the density of monthly unemployment benefits according to age. Yearly averages. Two age groups: 21-23 and 25-27 years.*

Table 5 suggests that the turning 25 is related with 70% pre-tax increase in UA in average (for individuals without kids). I follow the other studies like Carling, Holmlund, and Vejsiu (2001) and Røed and Zhang (2003) and ignore the tax-related issues. Using the estimate by Meyer (1990) for the elasticity of the hazard rate with respect to unemployment benefits (between -0.5 and -0.9), we would expect the multiplicative effect on the hazard rate (out from unemployment) to lie between $1 - 0.5 \times 0.7 \approx 0.55$ and $1 - 0.9 \times 0.7 \approx 0.3$. The effect on different destination specific hazard rates may differ.

4.3 Relationship between the hazard rate and age

Tables 3 and 4 suggest that there is difference between the age groups but there is no indication of a sharp effect at age 25. In this subsection, I present two simple plots. First, Kaplan-Meier hazard rates are given for two age groups, those below and those above 25. Second, I plot age density at the time of spell end. This is related with the age effect of the hazard rate as shown below.

Kaplan-Meier hazard rates into employment and non-participation are shown in the Figure 3. The hazard rates have a similar hump-shaped form for both age groups. However, they are significantly lower for the older group. This fits well with the Table 3. However, we cannot conclude that the effect is due a rapid fall near age 25.

A discontinuity in the hazard rate at age 25 results in a corresponding discontinuity in the age distribution at spell end as shown below. Assume for a while that we have a singe-risk no-censoring case. We look at $\vartheta(\tau|a)$, the hazard rate conditional on age and abstract on the other covariates except the age. The density of completed durations, conditional on the age at spell start can be

coefficient	estimate	stdd
constant	3765.09*	155.65
age $\geq$ *25*	2747.36*	108.63
kids	3331.29*	137.86
female	401.70*	91.06
danish	38.86	120.09
single	273.25*	93.18
high school	−395.21*	90.17
university	−658.55*	325.72
(age $\geq$ *25)*$\times$*kids*	−2195.22*	176.22
R^2	0.23	
# obs	6566	

Table 5: *Unemployment assistance as a function of* $\mathtt{1}(age \geq 24)$ *and other relevant variables.*

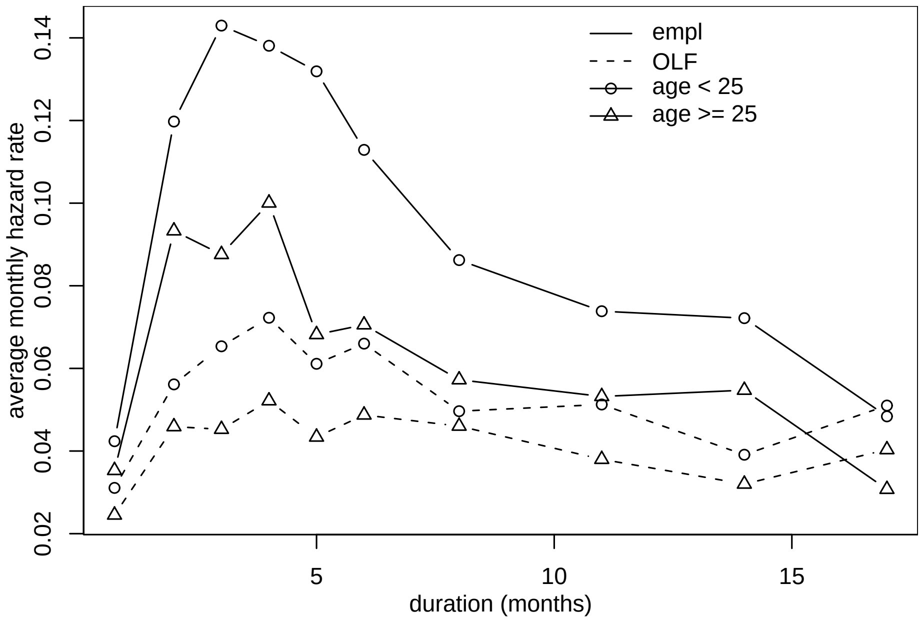

Figure 3: *Kaplan-Meier estimate of the transition intensities according to age.*

expressed as

$$f(\tau|a^0) = \vartheta(\tau|a^0 + \tau)\exp\left(-\int_0^\tau \vartheta(s|a^0 + s)ds\right). \tag{9}$$

Let $h(a)$ be the age density at spell start. The joint density of τ and a^0, $g(\tau, a^0)$, can now be written as

$$f(\tau, a^0) = g(\tau, a^1 - \tau) = f(\tau, a^1 - \tau)h(a^1 - \tau). \tag{10}$$

Integrating out duration results in the age density at spell end:

$$g(a^1) = \int_0^\infty \vartheta(\tau|a^1)\exp\left(-\int_0^\tau \vartheta(s|a^1 - \tau + s)ds\right) h(a^1 - \tau)\,\mathrm{d}\tau. \tag{11}$$

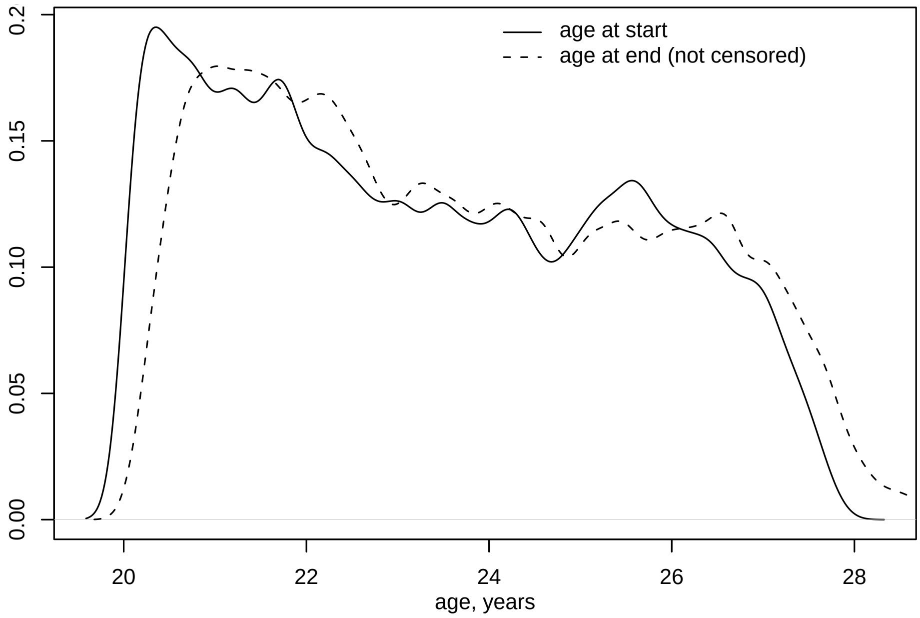

Figure 4: *A kernel estimate of age distribution at the start and end of spell.*

This function inherits the eventual discontinuities of $\vartheta(\tau|a)$ w.r.t. to a, given that $h(\cdot)$ is continuous at those points. Even more, if $\vartheta(\tau|a)$ is discontinuous at a^*,

$$\frac{\lim_{a \to a^*_-} g(a)}{\lim_{a \to a^*_+} g(a)} = \frac{\lim_{a \to a^*_-} \vartheta(\tau|a)}{\lim_{a \to a^*_+} \vartheta(\tau|a)}. \tag{12}$$

If we allow for multiple destinations and censoring, the result remains essentially the same, but (12) is not more valid.

The age density is plotted in the Figure 4. Both distributions are similar. Young individuals are slightly overrepresented among the completed spells. This fits with the lower transition hazard rate of the older age group, as discussed previously. However, there is no visible fall around age 25. The small gap is equal in for both distributions.

The conclusion of this exploratory analysis of hazard rate and age density is similar to that of Section 4.1. The older individuals have lower hazard rates out from unemployment. However, there seems to be no specific feature around the age 25.

5 Results

5.1 Age effect

5.1.1 Specification with discontinuity

I am looking for a sudden change in the age effect in the month when individuals turn 25, disregarding the anticipation effect. The age effect $g(a)$ was modelled using cubic splines with 4 internal distinct knots, two knots at age 25 in order to

	Males		Females		Pooled	
	$U \to E$	$U \to N$	$U \to E$	$U \to N$	$U \to E$	$U \to N$
coefficient	-0.02	0.19	0.75	0.29	0.44	0.21
stdd	0.36	0.41	0.47	0.78	0.29	0.38
			lower bounds:			
coefficient	-0.61	-0.49	-0.02	-0.99	-0.04	-0.41
income elasticity	-0.88	-0.69	-0.02	-1.42	-0.05	-0.58

Table 6: *Estimated discontinuities (income effects) at age 25, standard errors, and estimated 95% lower bounds for the effects and corresponding income elasticities.*

allow discontinuous derivatives (only for cubic splines), and an indicator $\mathtt{1}(a \geq 25)$. In the following, the indicator is interpreted as the income effect. The 95% lower bounds for the coefficient α were estimated as $bound = \alpha - \sigma_\alpha \cdot \mathrm{qnorm}(0.05)$ where σ_α is the standard deviation for α and qnorm is the normal quantile function. The corresponding elasticity can be found as

$$\varepsilon = \frac{\exp(\alpha) - 1}{1} \frac{b}{\Delta b} \approx \alpha \frac{b}{\Delta b} \approx \alpha / 0.7. \tag{13}$$

As the elasticity is a monotone transform of the coefficient, the relationship between lower bounds can be found similarily.

The estimated coefficients and estimates for 95% lower bounds of coefficients and corresponding income elasticities, are given in the Table 6. None of the effects are statistically significant. Most of the estimates are positive, in contrary to the theoretical predicitons, but the negative values cannot be excluded in none of the cases. However, the estimated lower bounds for $U \to E$ transitions for female and pooled samples are pretty close to zero.

The fact that the estimates are not robust suggests that the indicator variable may in fact be affected by the rest of the function $g(a)$. Figure 5 reveals that in most cases the discontinuity is not capturing a more or less permanent decrease (or increase) on the age effect, but rather a local feature. In particular, the large coefficient for female $U \to E$ transitions is cancelled by the decrease of the effect immidiately before and after the age 25. Hence we have to interpret the indicator together with the general path of the age effect.

The case with linear splines (Figure 6) seems to be somehow more stable. The general pattern of the effects is the same as in the Figure 5, except that the linear splines are more stable at boundary. The discontinuity, captured by the indicator variable, is quite small. The corresponding coefficient (Table 7) is smaller in the absolute value than for the cubic-spline specification. The estimated lower bound for elasticity is more stable and of the order between -0.3 and -0.5.

We can conclude that there is no indication of a distinct feature in the age effect around age 25. However, we cannot exclude the presence of weak effects corresponding to elasticity less than 0.3 in absolute value.

5.1.2 Specification without discontinuity

If the individuals react to the expected income increase only a short time in advance, and the income effect is large, the age effect should still show a feature

Figure 5: *Multiplicative age effect, cubic splines. Models with discontinuity.*

Figure 6: *Multiplicative age effect, linear splines. Models with discontinuity.*

around (or before) age 25. Such an effect can be cached by looking at comparing a flexible estimate of the age effect with a smooth one.

The results here are presented for $g(\cdot)$ specified by cubic splines with 7 distinct internal knots, put at the sample quantiles. The calculations with other types of base functions (dummies, polynomials and splines of different degree and with different number and placement of knots) gave qualitatively same results.

The age effect on the hazard rate is presented in the Figure 7. The waves, visible on the Figure, are related with the specification of the spline base. There is no indication of a distinct feature around the age 25. The age effect decreases rapidly between age 24 and 25 for both genders, but this seems not to be much different from its general behaviour.

To test the significance of the above mentioned features, I smoothed the effect by OLS as a quadratic function of age. The resulting differences with corresponding confidence intervals are plotted in the Figure 8. The figure confirms the previous impression. None of the features appear statistically significant. All the features on the Figure 7 are only marginally different from the quadratic

	Males		Females		Pooled	
	$U \to E$	$U \to N$	$U \to E$	$U \to N$	$U \to E$	$U \to N$
coefficient	-0.05	0.10	0.30	0.18	0.05	0.10
stdd	0.19	0.22	0.26	0.42	0.16	0.21
			lower bounds:			
lower bound	-0.36	-0.26	-0.14	-0.51	-0.21	-0.24
l.b. elasticity	-0.51	-0.37	-0.20	-0.73	-0.30	-0.34

Table 7: *Estimated discontinuities (income effects) at age 25, standard errors, and estimated 95% lower bounds for the effects and corresponding income elasticities.*

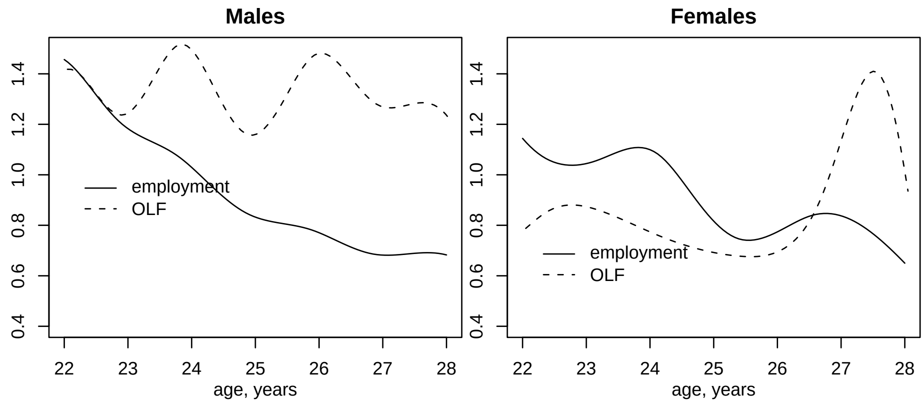

Figure 7: *Multiplicative age effect. Pooled sample, models without disconitnuity*

trend.

We can still estimate the absolute bounds of the elasticity based on the effect E and its standard error σ_E. Assuming the discontinuity must be smaller than twice of the width of the corresponding confidence band, the absolute bound for the elasticity is

$$|\varepsilon| \leq \frac{\frac{2 \cdot 1.96 \cdot \sigma_E}{E}}{0.7} \tag{14}$$

where $0.7 = \Delta b/b$ is the average increase in income at age 25. The corresponding bounds for males are 0.34 and 0.94 (for $U \to E$ and UI transitions respectively); for females 0.48 and 0.52; and for the pooled sample 0.20 and 0.44.

5.1.3 Parametric differences in differences estimate

The results, related with the income effect, for different samples (specification 6) are presented in the Table 8. The flexible age effect $g(\cdot)$ was specified as a 1st-order spline-function with 7 distinct internal knots.

In the following I discuss the $U \to E$ transition as almoust none of the $U \to N$ coefficients turned out to be significant. The results for the pooled sample follow the theoretical predictions. The income effect (*no kids* $\times$ *(age* $\geq$ *25)*) is negative and significant although the standard errors are large, the corresponding elasticity (-0.272) is close to more conservative estimates in the

Figure 8: *Difference of the estimated and smoothed age effects. Pointwise confidence bands are calculated with delta-method.*

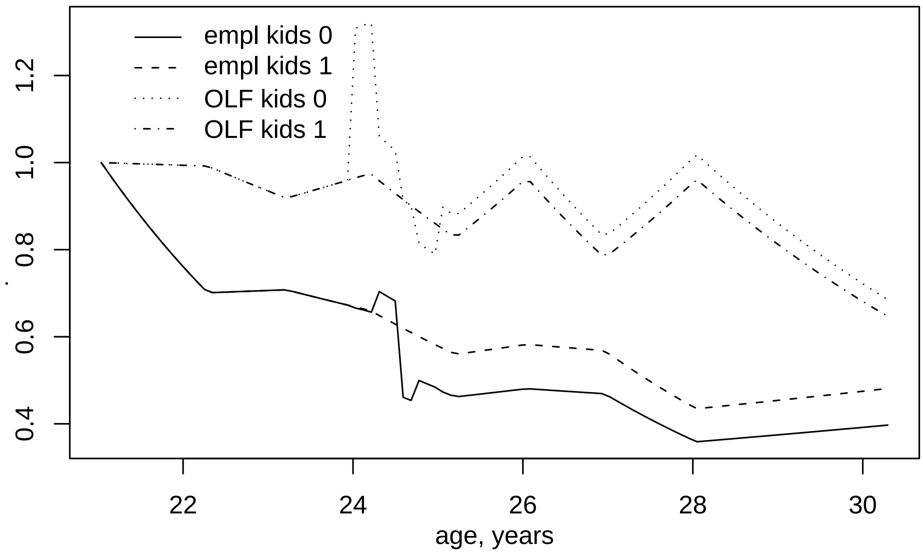

Figure 9: *Age effect. Pooled sample, parametric differences-in-differences estimate.*

literature. The anticipation effect is roughly as large as the income effect during the two preceeding quarters and close to zero before (not shown). However, all these effects are insignificant. The dependency of the hazard rate on age is plotted in the Figure 9. We see a fall in the age effect two quarters before the increase of UA benefits, at age around 24.5 years. The slight increase, preceeding this falll, is not significant. *kids* show well-known effect: the presence of children in leads females less inclined to take a job and more prone to leave the labour market while the effect on males is small.

However, the male subsample shows quite different results. The income effect (*no kids* $\times$ *(age* $\geq$ *25)*) is positive but not significant, the same is true

transition to:	employment		out of labour force	
	estimate	stdd	estimate	stdd
		Pooled sample		
no kids × *age >= 25*	−0.192*	0.083	0.058	0.084
elasticity	−0.272*	0.119	0.083	0.121
kids	−0.162	0.084	−0.062	0.101
female × *kids*	−0.590*	0.084	0.475*	0.101
Q1 before	−0.184	0.131	−0.086	0.161
Q2 before	−0.295	0.156	−0.001	0.154
LRT: $\chi^2(8)$	9.08		6.98	
		Males		
no kids × *age >= 25*	0.071	0.123	0.067	0.159
elasticity	0.107	0.177	0.094	0.227
kids	0.006	0.102	−0.087	0.138
Q1 before	−0.293	0.166	−0.218	0.208
Q2 before	−0.435*	0.194	−0.140	0.184
LRT: $\chi^2(8)$	12.030		4.918	
		Females		
no kids × *age >= 25*	−0.279*	0.121	0.091	0.129
elasticity	−0.403*	0.173	0.129	0.184
kids	−0.797*	0.098	0.488*	0.096
Q1 before	−0.059	0.226	0.071	0.260
Q2 before	0.024	0.281	0.196	0.338
LRT: $\chi^2(8)$	3.776		5.428	

Table 8: *Parametric differences-in-differences estimate*

for corresponding elasticity. The standard errors are larger than in the case of the pooled sample. Only the anticipation effect *Q2 before* is statistically significant. In contrary to males, the income effect for females is much larger, the corresponding elasticity is -0.403. None of the anticipation effect variables is significant.

These estimates above are subject to specific assumptions about treatment- and control group. In particular, I assume that the path of the age effect is the same for individuals with- and without children, when controlled for the time-invariant effect of kids, gender (and their cross effect), anticipation effect, and income. Put differently, the specification assumes a duration-invarant difference between those two groups. However, it is possible that the age effect of individuals with kids has a downward trend while that for those without kids has an upward trend. This results in decreasing inter-group difference and hence biases the estimates downwards.

In order to test the hypothesis, I allow the inter-group difference, after controlling for the effect above, to depend on the age in a flexible way, using a similar spline function as used for modelling $g(\cdot)$. Likelihood ratio test does not reject the hypothesis of a duration-invariant difference for any of the samples and any of the transitions (the 95% critical value for $\chi^2(8)$ is 15.51).

5.2 Other effects

In the Table 9, I report the the effect of individual- and spell-specific characteristics for models without discontinuity. The results for models with discontinuity

transition to:	employment		out of labour force	
	estimate	stdd	estimate	stdd
	Males			
danish	0.095	0.096	−0.035	0.095
high school	0.313*	0.055	−0.285*	0.083
university	1.085*	0.245	−1.324	0.690
experience	0.216*	0.014	−0.109*	0.022
ALMP	0.264*	0.072	0.036	0.087
local u (%, ×10)	−0.685*	0.267	−0.619	0.322
Copenhagen	0.298*	0.065	0.256*	0.079
East-Sealand	0.295*	0.111	0.003	0.149
Western Jutland	0.190*	0.096	−0.049	0.126
	Females			
danish	0.196	0.137	0.002	0.154
high school	0.610*	0.070	−0.295*	0.106
university	0.841*	0.222	−1.039*	0.514
experience	0.215*	0.019	−0.114*	0.043
ALMP	0.068	0.094	0.025	0.127
local u (%, ×10)	−0.483	0.365	0.283	0.508
Copenhagen	0.231*	0.080	0.396*	0.130
East-Sealand	0.398*	0.128	0.482*	0.207
Western Jutland	0.061	0.132	0.167	0.175

Table 9: *Estimated individual-specific coefficients and standard errors for females. The naive model. ∗ – statistically significant at 95% level.*

were almoust equal.

The ethnic danes have (insignificantly) higher $U \to E$ hazard rate. Education affects the transition intensity in an expected way: more education leads to faster transitions to jobs and less propensity to leave the labour force. The same is true for working experience (the coefficient corresponds to an additional year of experience). Males are more prone to find a job during ALMP-s, otherwise the effect is insignificant. Higher regional unemployment leads to lower escape rate from unemployment into employment, though the effect is significant only for males. In all regions which I have controlled by a dummy, $U \to E$ hazard rate is above the reference value. In addition, $U \to N$ hazard rate is higher in Copenhagen. There are some gender differences, though: the positive effect in Western Jutland is small and insignificant for female $U \to E$ transitions, in West-Sealand the female $U \to N$ effect is significant and positive.

6 Discussion

The results suggest that the females in the current sample are much more sensitive to financial incentives than males. Although not common, this result is far from unique (Achdut, Romanov, Toledano, and Zussman, 2004). The current sample, unemployment assistance recipients, contains significantly more "weak unemployed", individuals with low skills and low motivation. It may be the case that men who are falling to the last-resource security net have weak working motivation anyway. The females, in contrary, may be closer to the average population and more sensitive to incentives.

The 70% increase of unemployment assistance at the age 25 seems not to have a large effect on the transitions out from unemployment. The 25% fall in the female hazard rate correspond to elasticity -0.4, which is in line with other studies (Røed and Zhang, 2003).

The estimated anticipation effect contradicts the corresponding estimates of the main effect. Anticipation effect is significant only for males where the income effect is missing and the way around.

Unfortunately the corresponding semiparametric estimates are too noisy for any inference. The lower bounds of the effect are in line with the more conservative estimates in the literature.

The significance of local unemployment rate stresses the importance of the local labour demand. For females, the possible income effect (Table 8) corresponds to an increase in unemployment by 7%.

Current results cannot easily generalised to the whole labour market as they are based on a highly selective sample.

6.1 Future work

There are several additions planned to perform in the future:

- Take into account taxes
- -”- other income transfers
- -”- savings?
- Anticipation effect: theory and some simulation
- Control for living together with parents. The dataset does not include the direct family information for individuals more than 18 years old. However, it is possible to compare the addresses with the parents' addresses.
- Investigate effects related with selection into UA and having children. Is this the reason for negative coefficients for education in the Table 5?
- Some MC sensitivity analysis.
- If the people have savings/are not credic constrained... ?

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