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Estimation of competing risks duration models with unobserved heterogeneity using hsmlogit

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Abstract.

This article presents `hsmlogit`, a new Stata command that estimates multispells discrete time competing risks duration models with unobserved heterogeneity. `hsmlogit` allows for the estimation of one, two and up to three competing risks, as well as a maximum of five points of support for the identification of unobserved heterogeneity distribution ([Heckman and Singer, 1984]). The main contribution of `hsmlogit` is that allows for exploiting the richness of large longitudinal micro datasets, by estimating competing risks duration models, instead of one-risk models (such as `hshaz` and `hshaz2`), as well as it takes into account the presence of unobserved heterogeneity affecting transition rates. In addition to this, and taking into account the larger size of longitudinal micro datasets used for the estimation of discrete time duration models, `hsmlogit` also provides the algebraic expressions of both first and second order derivatives that, respectively, define the gradient vector and Hessian matrix, which significantly reduce time required to achieve model convergence.

Keywords: Duration analysis, Unobserved heterogeneity, `d2 ml` method, `hshaz`, `hshaz2`, `hsmlogit`, Hessian matrix, Multinomial Logit, Competing risks models

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1 Introduction

Empirical estudies on individual decisions have experienced an important increase in recent years due to the boost of large and rich longitudinal micro datasets put available to the research community. Specially for the field of empirical Labor Economics focused on the estimation of labor market transition rates, the recent availability of large longitudinal micro datasets allows for capturing the presence of unobserved heterogeneity (UH, hereafter) components that affect the estimated transition rates. However, an important number of these empirical estudies that incorporates the presence of UH mainly focused on one-risk duration models,[1] that analyze transition rates towards an only destination (for example, transitions from employment to unemployment, ignoring the existence of other destinations, such as inactivity, or finding another job). This article presents `hsmlogit`, a new Stata command that estimates multi-spells discrete time competing risks duration models with UH. `hsmlogit` allows for the estimation of one, two and up to three competing risks, as well as a maximum of five points of support for the identification of unobserved heterogeneity distribution ([Heckman and Singer, 1984]).

The main contribution of `hsmlogit` is that allows for exploiting the richness of large longitudinal micro datasets, by estimating competing risks duration models, instead of one-risk models (such as `hshaz` and `hshaz2`), as well as it takes into account the presence of unobserved heterogeneity affecting transition rates. In addition to this, and taking into account the larger size of longitudinal micro datasets used for the estimation of discrete time duration models, `hsmlogit` also provides the algebraic expressions of both first and second order derivatives that define the gradient vector and Hessian matrix, respectively, which significantly reduce time required to achieve model convergence [Gould et al., 2010].

The rest of the article estructures as follows: Section 2 describes the longitudinal database used to obtain estimation results; the econometric model and `hsmlogit` command syntax are explained, respectively, in Sections 3 and 4; Section 5 presents estimation results, and Section 6 shows the advantages of providing the algebraic expressions of both the gradient vector and Hessian matrix. Finally, Section 7 concludes.

2 Database: The Continuous Sample of Working Histories

I analyze a longitudinal sample of workers in the Spanish labor market that comes from the *Continuous Sample of Working Histories* database (CSWH, hereafter). The CSWH is a longitudinal database that provides the working histories records of more than one million people, who represent a 4% non-stratified random draw from a target population, composed of any person with a contribution relation with the Spanish Social Security Administration. It includes both wage workers and recipients of Social Security benefits, namely, unemployment benefits, disability, survivor pension and maternity leave.[2]

[1] An exception is the work presented in [Troncoso-Ponce, 2016], where a two-states multi-spells discrete time competing risks duration model with UH is estimated to analyze the effect of apprenticeship contracts in the Spanish labor market.

[2] [García-Pérez, 2008], [Lapuerta, 2010], [Arranz and García-Serrano, 2011] and [Arranz, García-Serrano and Hernanz, 2013] contain a deep exposition about features of CSWH as well as all necessary techniques to perform a duration analysis using working lives information.

The CSWH contains detailed information on each employment and unemployment episodes experienced by workers through their entire working histories. The information provided by the CSWH can be grouped into several categories: First, personal characteristics of workers (gender, age, nationality, educational level, residence place, and other personal characteristics). Second, job characteristics (type of labor contract, part-time coefficient, qualification level, and other job characteristics). Third, information on the employer (firm size, activity sector, and other firm characteristics). Furthermore, an important feature of the CSWH is that provides the beginning and termination dates of all employment and unemployment episodes, which takes special interest for duration analysis.

The estimation sample is composed of 48,246 low-educated and low-qualified young workers in the Spanish labor market for the period 2000-2014. The average age is 22.5 years-old, and 75.5% of them are males. The average number of employment episodes per worker is 8.9, lasting, on average, 7.13 months. Indeed, more than 25% of all employment episodes last 2 months or less, and only 5% last at least 24 months, which highlights the high turnover rate experienced by these workers. Multispell estimation sample has 1,316,611 observations. A `describe` output is shown below, describing the estimation sample's full varlist, as well as a `summarize` outuput to show the main descriptive statistics of the estimation sample's varlist.

Description of the estimation sample's varlist

```
. describe , fullnames

  obs:     1,316,611
 vars:            59                          29 Sep 2017 17:04
 size:   127,711,267
-----------------------------------------------------------------------------------------------------------
              storage   display    value
variable name   type    format     label      variable label
-----------------------------------------------------------------------------------------------------------

codind          long    %12.0g                id of individual
spell           int     %9.0g                 Sequential number of the employment episode
j               int     %9.0g                 Month of employment spell
exit3           byte    %8.0g      exit3      Exit from employment state (3 competing risks)
exit1           byte    %8.0g      exit1      Exit from employment state (1 only risk)
exit2           byte    %8.0g      exit2      Exit from employment state (2 competing risks)
cf              byte    %8.0g                 Apprenticeship contract (=1)
ct              byte    %8.0g                 Temporary contract (=1)
lnjemp          float   %9.0g                 Log(t)
lnjemp2         float   %9.0g                 Log(t)^2
lnjemp3         float   %9.0g                 Log(t)^3
month1          byte    %8.0g                 Month 1
month2          byte    %8.0g                 Month 2
month3          byte    %8.0g                 Month 3
month6          byte    %8.0g                 Month 6
month12         byte    %8.0g                 Month 12
month18         byte    %8.0g                 Month 18
month24         byte    %8.0g                 Month 24
month36         byte    %8.0g                 Month 36
month48         byte    %8.0g                 Month 48
female          byte    %8.0g                 Female (=1)
age16tv         byte    %9.0g                 Current age - 16
age16tv2        int     %9.0g                 (Current age - 16)^2
educcompul1     byte    %8.0g                 Education: Compulsory stage #1
educcompul2     byte    %8.0g                 Education: Compulsory stage #2
educless1       byte    %8.0g                 Education: Less than compulsory stage #1
educless2       byte    %8.0g                 Education: Less than compulsory stage #2
inmigra         byte    %8.0g                 Not Spanish nationality (=1)
manufactory     byte    %8.0g                 Economic sector: Manufacturing industry
highserv        byte    %8.0g                 Economic sector: High qualfied services
lowserv         byte    %8.0g                 Economic sector: Low qualfied services
comerce         byte    %8.0g                 Economic sector: Commerce
highqualif      byte    %8.0g                 Previous job: High qualification
midhighqualif   byte    %8.0g                 Previous job: Mid-High qualification
midlowqualif    byte    %8.0g                 Previous job: Mid-Low qualification
lowqualif       byte    %8.0g                 Previous job: Low qualification
prevunemp       byte    %9.0g                 Number of previous unemployment spells
prevtc          int     %9.0g                 Number of previous temporary contracts
unrate          double  %10.0g                Quarterly regional unemployment rate (Q.r.u.r.)
unratexlnjemp   float   %9.0g                 (Q.r.u.r.) x Log(t)
unratexlnjemp2  float   %9.0g                 (Q.r.u.r.) x Log(t)^2
gremployment    float   %9.0g                 Quarterly employment growth rate (Q.e.g.r.)
gremploymentxlnjemp
                float   %9.0g                 (Q.e.g.r.) x Log(t)
gremploymentxlnjemp2
                float   %9.0g                 (Q.e.g.r.) x Log(t)^2
andal           byte    %8.0g                 Spanish region: Andalucia
aragon          byte    %8.0g                 Spanish region: Aragon
astur           byte    %8.0g                 Spanish region: Asturias
balear          byte    %8.0g                 Spanish region: Baleares
```

```
canar           byte    %8.0g                  Spanish region: Canarias
cantab          byte    %8.0g                  Spanish region: Cantabria
castman         byte    %8.0g                  Spanish region: Castilla La Mancha
castleon        byte    %8.0g                  Spanish region: Castilla Leon
valenc          byte    %8.0g                  Spanish region: Valencia
extrem          byte    %8.0g                  Spanish region: Extremadura
galic           byte    %8.0g                  Spanish region: Galicia
murcia          byte    %8.0g                  Spanish region: Murcia
navarr          byte    %8.0g                  Spanish region: Navarra
vasco           byte    %8.0g                  Spanish region: Pais Vasco
rioja           byte    %8.0g                  Spanish region: La Rioja
-----------------------------------------------------------------------------------------------------------
Sorted by: codind  spell  j
```

Descriptive statistics of the estimation sample's varlist

```
. sum codind spell j exit* `varsaleE´
```

Variable	Obs	Mean	Std. Dev.	Min	Max
codind	1,316,611	3800765	2579758	1868	1.00e+07
spell	1,316,611	8.951002	13.46625	1	435
j	1,316,611	7.132385	9.23605	1	108
exit3	1,316,611	.3740976	.7186157	0	3
exit1	1,316,611	.2373564	.4254626	0	1
exit2	1,316,611	.369709	.7054998	0	2
cf	1,316,611	.16471	.3709188	0	1
ct	1,316,611	.83529	.3709188	0	1
lnjemp	1,316,611	1.407723	1.039737	0	4.682131
lnjemp2	1,316,611	3.062737	3.439172	0	21.92235
lnjemp3	1,316,611	7.66514	11.91313	0	102.6433
month1	1,316,611	.2119381	.4086814	0	1
month2	1,316,611	.1404713	.3474754	0	1
month3	1,316,611	.1057419	.3075072	0	1
month6	1,316,611	.054834	.227656	0	1
month12	1,316,611	.0209416	.1431891	0	1
month18	1,316,611	.0090034	.0944583	0	1
month24	1,316,611	.0052263	.072104	0	1
month36	1,316,611	.0014818	.0384661	0	1
month48	1,316,611	.0005301	.0230189	0	1
female	1,316,611	.2444549	.4297637	0	1
age16tv	1,316,611	5.573653	3.642791	0	22
age16tv2	1,316,611	44.33552	53.2066	0	484
educcompul1	1,316,611	.1649796	.3711623	0	1
educcompul2	1,316,611	.4394009	.4963143	0	1
educless1	1,316,611	.2096162	.4070349	0	1
educless2	1,316,611	.1860033	.3891095	0	1
inmigra	1,316,611	.1212887	.3264626	0	1
manufactory	1,316,611	.1599212	.3665331	0	1
highserv	1,316,611	.0580111	.2337645	0	1
lowserv	1,316,611	.1449327	.3520331	0	1
comerce	1,316,611	.1784703	.3829083	0	1
highqualif	1,316,611	.0061841	.0783953	0	1
midhighqua~f	1,316,611	.0349579	.1836734	0	1
midlowqualif	1,316,611	.3149009	.4644766	0	1
lowqualif	1,316,611	.6439571	.4788283	0	1
prevunemp	1,316,611	1.988224	2.428205	0	25
prevtc	1,316,611	5.621923	12.12324	0	431
unrate	1,316,611	11.85796	5.19547	3.9	36.87
unratexlnj~p	1,316,611	17.4539	17.60828	0	169.4221
unratexlnj~2	1,316,611	39.34931	58.8646	0	778.5148
gremployment	1,316,611	2.102568	3.801228	-14.00105	10.99764
gremployme~p	1,316,611	2.442792	7.083604	-62.03608	38.71074
gremployme~2	1,316,611	4.294824	19.12216	-274.8705	142.1837
andal	1,316,611	.2453321	.4302841	0	1
aragon	1,316,611	.0239395	.1528608	0	1

astur	1,316,611	.0198137	.1393599	0	1
balear	1,316,611	.0305026	.1719656	0	1
canar	1,316,611	.046025	.2095393	0	1
cantab	1,316,611	.013935	.1172214	0	1
castman	1,316,611	.0572325	.2322865	0	1
castleon	1,316,611	.0449579	.2072117	0	1
valenc	1,316,611	.1079005	.3102548	0	1
extrem	1,316,611	.0249443	.1559556	0	1
galic	1,316,611	.0732874	.2606078	0	1
murcia	1,316,611	.0322449	.1766499	0	1
navarr	1,316,611	.0085128	.0918711	0	1
vasco	1,316,611	.0262386	.1598441	0	1
rioja	1,316,611	.0053638	.0730411	0	1

3 Econometric model

This Section briefly describes the main features of the econometric models that will be estimated in Section 5. The main goal of this kind of models is to analyze duration spent by a population in a specific state (in this example, employment state), as well as to analyze the set of factors, observable and specially unobservable, that affect time spent in that state (see [Lancaster, 1992], [Allison, 1982] and [Jenkins, 1995]).

Let's consider an individual beginning an employment episode at time $T = 1$ (time T is measured in month intervals). The worker is observed monthly during the employment episode until either he/she exits to another modeled state (such as, unemployment, or finding a new job), or the observation window ends (right censored observations). Employment duration is analyzed by estimating the hazard rate out of employment at each observed month. Depending on the number of exits (i.e. risks) modeled by the command's user, `hsmlogit` can estimate two different functional forms for the hazard rate.

Single-risk models use a *Logit* functional form to characterize the hazard rate, given by the following expression:

$$h(t|x,\eta) = \frac{exp(\lambda(t) + x\beta + \eta)}{1 + exp(\lambda(t) + x\beta + \eta)} \quad (1)$$

And competing risks models use a *Multinomial Logit* functional form to characterize the hazard rates:

$$h_d(t|x_d,\eta) = \frac{exp(\lambda_d(t) + x_d\beta_d + \eta)}{1 + \sum_{d=1}^{D} exp(\lambda_d(t) + x_d\beta_d + \eta)} \quad (2)$$

Assuming that $h = \sum_{d=1}^{D} h_d$, where $d = 1, ..., D$ and $D = \{1, 2, 3\}$ depending on the total number of risks modeled by the command's user.

As the two expressions above show, the hazard rate at month $T = t$ depends on time (months) spent in the current unemployment state (i.e. duration dependence), captured by $\lambda(t)$, as well as on a set of covariates summarized by x vector, that may contain both time-fixed and time-varying covariates. Furthermore, the hazard rate also depends on an unobserved component given by η, that mesasures factors, such as job search effort, job networking, motivation, ability, etc, that are unobserved to the researcher and may affect the transition rate out of employment.

For the case of one-risk models, the contribution to the likelihood function of an individual i is given by the following expression:

$$L_i = \sum_{j=1}^{P} \pi_j \{ \prod_{t=1}^{T_i} \frac{h(T = t|\lambda(t), x_{it}, \eta_j)^{y_{it}}}{(1 - h(T = t|\lambda(t), x_{it}, \eta_j))^{(1-y_{it})}} S(T = t|\lambda(t), x_{it}, \eta_j)^{(1-y_{it})} \} \tag{3}$$

Where dependent variable $y_{it} = \{0, 1\}$ denotes a dummy variable that takes value 1 if worker i exits out from employment at month $T = t$, and takes value zero otherwise.[3] Expression given by $h(T = t|\lambda(t), x_{it}, \eta_j)$ denotes the hazard rate observed at month $T = t$, and $S(T = t|\lambda(t), x_{it}, \eta_j)$ denotes the survival rate observed at month $T = t$, that estimates the cummulative probability of being employed (from the month $T = 1$) until the month $T = t$, and that is given by the following expression:

$$S(T = t|\lambda(t), x_{it}, \eta_j) = \prod_{s=1}^{t} (1 - h(T = s|\lambda(s), x_{is}, \eta_j)) \tag{4}$$

As expressions 1 and 4 show, the hazard rate observed at month $T = t$ is conditional on the duration dependence $\lambda(t)$ and on the set of covariates x_{it}. And the survival rate at month $T = t$ is conditional on $\lambda(s)$ and on the set of covariates x_{is}, observed at months $s = 1, 2, ..., t$. Both the hazard and the survival rates also depend on belonging to the type of employed workers with unobserved characteristics given by η_j.[4]

The total likelihood function of single-risk models is given by:

$$L = \prod_{i=1}^{N} \sum_{j=1}^{P} \pi_j \{ \prod_{t=1}^{T_i} \frac{h(T = t|\lambda(t), x_{it}, \eta_j)^{y_{it}}}{(1 - h(T = t|\lambda(t), x_{it}, \eta_j))^{(1-y_{it})}} S(T = t|\lambda(t), x_{it}, \eta_j)^{(1-y_{it})} \} \tag{5}$$

`hsmlogit` command maximizes, using `d2 ml` method, the natural logarithm of L to estimate the model parameters.

[3]Dependent variable y_{it} refers to `dead(deadvar)` of `hsmlogit` command.

[4]It is assumed that unobserved characteristics do not vary with time and are not correlated to the rest of explanatory variables included in the specification of the hazard rate.

For the case of competing risks models, the contribution to the likelihood function of an individual i is given by the following expression:

$$L_i = \sum_{j=1}^{P} \pi_j \{ \prod_{t=1}^{T_i} \prod_{d=1}^{D} \{ h_d(T_d = t | \lambda_d(t), x_{it}^d, \eta_j)^{y_{it}^d} \} S(T = t-1 | \lambda(t), x_{it}, \eta_j)^{(1 - \sum_{d=1}^{D} y_{it}^d)} \} \tag{6}$$

Where $h_d(T_d = t|\lambda_d(t), x_{it}^d, \eta_j)$ denotes the hazard rate for the especific risk $d = 1, ..., D$ observed at month $T = t$, conditional on the duration dependence $\lambda_d(t)$, on the set of covariates x_{it}^d, and on belonging to the type of employed workers with unobserved characteristics given by η_j. Dependent variable $y_{it}^d = \{0, 1\}$, for $d = 1, ..., D$, denotes a dummy variable that takes value 1 if worker i exits out from employment towards the destination d at month $T_d = t$, and takes value zero otherwise.

Unlike single-risk models, the survival function for competing risks takes into account the all possible risks faced by the individual at month $T = t$, and therefore takes the following expression:

$$S(T = t-1 | \lambda(t-1), x_{it-1}, \eta_j) = \prod_{s=1}^{t-1} (1 - \sum_{d=1}^{D} h_d(T_d = s | \lambda_d(s), x_{is}^d, \eta_j)) \tag{7}$$

Similarly to single-risk models, the total likelihood function for competing risks is given by:

$$L = \prod_{i=1}^{N} \sum_{j=1}^{P} \pi_j \{ \prod_{t=1}^{T_i} \prod_{d=1}^{D} \{ h_d(T_d = t | \lambda_d(t), x_{it}^d, \eta_j)^{y_{it}^d} \} S(T = t-1 | \lambda(t), x_{it}, \eta_j)^{(1 - \sum_{d=1}^{D} y_{it}^d)} \} \tag{8}$$

And likewise single-risk models, `hsmlogit` command maximizes, also using `d2 ml` method, the natural logarithm of L to estimate the model parameters for competing risks models.

3.1 The non-parametric identification of the UH distribution

Regarding the estimation of UH distribution, we assume the existence of unobserved factors affecting hazard rates, that if are ignored, may lead to spurious duration dependence, captured by $\lambda(t)$ ([Van Den Berg, 2001]). A well known method to capture the effect of UH on the hazard rates is the proposed by [Heckman and Singer, 1984], by which the UH components are captured without imposing any parametric distribution function for the identification of UH distribution, but as a discrete mixture of several types of individuals with different values of UH components. Thus, it is assumed the presence of different types of workers who characterize themselves by having different levels of unobserved variables (such as, ability, cognitive and non cognitive skills, social and networking capabilities, etc.), captured by the set of parameters $\eta = \{\eta_1, \eta_2, ..., \eta_P\}$, that are estimated as regression's constant terms.[5] For each Type of worker j, characterized by η_j, an associated probability of being observed in the data, given by $\pi = \{\pi_1, \pi_2, ..., \pi_P\}$, is also estimated jointly with the rest of the model parameters. Finally, the non-parametric discrete UH distribution is the result of the combination of these Types of workers, whose different values of UH are given by the vector $\eta = \{\eta_1, \eta_2, ..., \eta_P\}$ and by their associated probabilities $\pi = \{\pi_1, \pi_2, ..., \pi_P\}$, are estimated jointly with the rest of the model parameters.

Furthermore, likewise `hshaz2` command, when more than two mass-points are especified by the command's user, `hsmlogit` also properly estimates mass-points probabilities using a *Multinomial Logit* function, rather than a *Logit* one, to compute the values of $(\pi_1, \pi_2, ..., \pi_P)$ (see [Troncoso-Ponce, 2017]). For example, when the UH distribution is characterized by five points of support, the mass probabilty parameteres computed by `hsmlogit` take the following expression: $\pi_j = \frac{e^{p_j}}{1+\sum_{l=2}^{5} e^{p_l}}$, for $j = 2, \ldots, 5$, and $\pi_1 = 1 - \sum_{l=2}^{5} \pi_l$. And for the computation of the standard errors of mass probability parameters, `hsmlogit` also provides to `_diparm()` command the algebraric expressions of the first order derivatives of each $\pi_j = \frac{e^{p_j}}{1+\sum_{l=2}^{L} e^{p_l}}$, for each $j = 1, 2, \ldots, P$, with respect to each p_l, with $l = 2, 3, \ldots, P$.

4 Command syntax

The `hsmlogit`'s command syntax follows the same design that `hshaz` and `hshaz2`'s. The only difference between `hsmlogit`'s command syntax and `hshaz2`'s is added by `dead`(*deadvar*) option. Unlike `hshaz2`, the `dead`(*deadvar*) option of `hsmlogit` command identifies whether the dependent variable typed by the command user in the `dead`(*deadvar*) option takes one, two or three risks. Therefore, `hsmlogit`, depending on the number of the values taken by the dependent variable, estimates, respectively, a single, a two, or a three competing risks duration model. The rest options of `hsmlogit`'s command syntax are the same that `hshaz2`'s (see [Troncoso-Ponce, 2017]).

The `hsmlogit` command syntax is:

`hsmlogit` *varlist* [*weight*] [*if exp*] [*in range*] [, `id(`*idvar*`)` `dead(`*deadvar*`)` `seq(`*seqvar*`)` `spell(`*spellvar*`)` `nmp(#)` `m2(#)` `p2(#)` `m3(#)` `p3(#)` `m4(#)` `p4(#)` `m5(#)` `p5(#)` `eform` `nocons` `nolog` `nobeta0` `level(#)` `maximize_options`]

[5] As previously mentioned, `hsmlogit` allows for the estimation of a maximum of five points of support (ie. Types of workers) for the identification of the UH distribution.

5 Estimation results

This Section shows results from the estimation of three duration models, each of them depends on the number of exits modeled. The first model, presented below in the first estimation output (**Single risk model with UH using hsmlogit**), simply estimates the transition rate out of employment without differentiating the destination state. The second one, shown below in the second estimation output (**Two competing risks model with UH using hsmlogit**), estimates a two risks duration model, by which the two modeled risks are: i) exiting to unemployment; and ii) a job-to-job transition to another employment. Finally, the third model, shown below in the third estimation output (**Three competing risks model with UH using hsmlogit**), allows for distinguishing the type of labor contract of the new employment found in the job-to-job transition. Specifically, the model differs between finding a fixed-term contract, and an open-ended one. Therefore, these three competing risks are: i) exiting to unemployment; ii) finding a fixed-term contract; and iii) finding an open-ended contract.

As mentioned in Section 3, the functional form of the hazard rate estimated in the first model is given by a *Logit* function, whereas the hazard rates of the second and third models are given by *Multinomial Logit* functions with two a three competing risks, respectively. The mentioned three tables with the estimation output show estimation results of fitting multispells duration models with two mass-points of unobserved heterogeneity.[6]

For the three estimated models, the set of covariates included in the specification of the hazard rates controls for the effect of: i) personal characteristics of the employed workers, such as, gender, age (`age16tv`) and squared age (`age16tv2`),[7] nationality,[8] and educational level[9]; ii) business cycle effects, by including the quarterly unemployment rate (`unrate`) and the product of the unemployment rate with the natural logarithm of the current employment spell (`unratexlnjemp`), and its squared (`unratexlnjemp2`); iv) a set of dummy variables that identify the Spanish regions (`andal-rioja`) to capture regional effects. Additionally to the duration dependence specification (using a three order polynomial of the natural logarithm of the duration of current employment spell), three dummy variables are included to identify months 6, 12, 18 and 24. These dummy variables are included to capture exit peaks related to the duration of temporary contracts in the Spanish labor market. Finally, to capture the effect of holding an apprenticeship contract on the employment exit

[6]All estimation results, with and without UH, shown in this article are available to the interested reader upon request.

[7]Age covariates measure the difference between the current age (time-varying age) with respect to the legal working age in the Spanish labor market, 16 years old.

[8]Nationality effect is captured using a dummy variable, called `inmigra`, that takes value one if the employed worker is not Spanish, and zero otherwise.

[9]The effect of educational level is captured by including two dummy variables: `educcompul1` and `educcompul2`. Dummy variable `educcompul1` (`educcompul2`) takes value one whether the worker has a primary (secondary) compulsory education degree, and takes zero otherwise.

rate, the dummy variable (`cf`) takes value one whether the worker is holding an apprenticeship contract, and takes value zero whether the worker has another type of temporary contract different from the apprenticeship one.[10] The regression coefficients not shown in the estimation output tables are omitted due to space reasons, and are available to the interested reader upon request.

[10]Hence, the regressions' constant term contains male native employed workers holding a temporary contract in the Spanish regions Madrid and Catalonia, with less than primary compulsory education.

Single risk model with UH using hsmlogit

```
. hsmlogit_v4 `varsaleE´ , id(codind) spell(spell) seq(j) d(exit1) nmp(2) difficult
Discrete time competing risks hazard model without frailty
Logistic regression                                 Number of obs   =    1316611
                                                    LR chi2(28)     =  131531.43
                                                    Prob > chi2     =     0.0000
Log likelihood = -655754.83                         Pseudo R2       =     0.0911
```

exit1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
cf	-.8912589	.0084509	-105.46	0.000	-.9078224	-.8746955
lnjemp	-1.886904	.018425	-102.41	0.000	-1.923016	-1.850791
lnjemp2	.9354424	.0114129	81.96	0.000	.9130735	.9578113
lnjemp3	-.1648652	.0024098	-68.41	0.000	-.1695883	-.1601421
age16tv	-.0211124	.0020584	-10.26	0.000	-.0251468	-.017078
age16tv2	.0003848	.0001402	2.75	0.006	.0001101	.0006595
educcompul2	-.0368489	.0044142	-8.35	0.000	-.0455005	-.0281973
manufactory	-.3241511	.0066488	-48.75	0.000	-.3371825	-.3111197
highserv	.1818382	.0088225	20.61	0.000	.1645465	.1991299
lowserv	.1175756	.0060339	19.49	0.000	.1057494	.1294018
unrate	.0002062	.0009034	0.23	0.819	-.0015644	.0019768
unratexlnj~p	.0090781	.0012325	7.37	0.000	.0066624	.0114938
unratexlnj~2	-.0033776	.0004145	-8.15	0.000	-.00419	-.0025653
_cons	.0830947	.0119988	6.93	0.000	.0595775	.1066118

```
Discrete time competing risks hazard model, with discrete mixture
Log likelihood =     -635096                        Number of obs      =  1,316,611
```

exit1	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
hazard						
cf	-.913632	.0092041	-99.26	0.000	-.9316717	-.8955923
lnjemp	-1.437325	.0194947	-73.73	0.000	-1.475534	-1.399116
lnjemp2	.7870148	.0118972	66.15	0.000	.7636968	.8103328
lnjemp3	-.1451242	.0024777	-58.57	0.000	-.1499804	-.1402681
age16tv	-.0277728	.0023687	-11.73	0.000	-.0324153	-.0231303
age16tv2	.0004827	.0001626	2.97	0.003	.000164	.0008014
educcompul2	-.0291969	.005713	-5.11	0.000	-.0403942	-.0179996
manufactory	-.3281004	.0074911	-43.80	0.000	-.3427826	-.3134182
highserv	.077762	.0100445	7.74	0.000	.0580751	.097449
lowserv	.0705415	.0068966	10.23	0.000	.0570244	.0840586
unrate	.0023788	.0010097	2.36	0.018	.0003999	.0043578
unratexlnjemp	.0099583	.0012989	7.67	0.000	.0074125	.0125041
unratexlnjemp2	-.0040484	.0004267	-9.49	0.000	-.0048848	-.0032121
_cons	-.4461856	.0145465	-30.67	0.000	-.4746963	-.417675
m2						
_cons	1.588835	.0089093	178.33	0.000	1.571373	1.606297
logitp2						
_cons	-1.742683	.0211864	-82.25	0.000	-1.784207	-1.701158
Prob. Type 1	.8510275	.002686	316.84	0.000	.8456859	.8562156
Prob. Type 2	.1489725	.002686	55.46	0.000	.1437844	.1543141

```
Note: m1 = 0
```

Two competing risks model with UH using hsmlogit

```
. hsmlogit_v4 `varsaleE´ , id(codind) spell(spell) seq(j) d(exit2) nmp(2) difficult
Discrete time competing risks hazard model without frailty

Multinomial logistic regression                   Number of obs   =    1316611
                                                  LR chi2(56)     =  149758.52
                                                  Prob > chi2     =     0.0000
Log likelihood = -861174.84                       Pseudo R2       =     0.0800

------------------------------------------------------------------------------
       exit2 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
EU           |
          cf |  -.7949866   .0109422   -72.65   0.000     -.816433   -.7735403
      lnjemp |  -.9706289   .0245682   -39.51   0.000    -1.018782    -.922476
     lnjemp2 |   .5054906   .0152706    33.10   0.000     .4755607    .5354205
     lnjemp3 |  -.1151439   .0033619   -34.25   0.000    -.1217332   -.1085547
    age16tv  |  -.0874133   .0026712   -32.72   0.000    -.0926488   -.0821778
    age16tv2 |   .0039427   .0001826    21.60   0.000     .0035849    .0043005
 educcompul2 |  -.1047359   .0060011   -17.45   0.000    -.1164979   -.0929739
 manufactory |  -.1986758   .0088302   -22.50   0.000    -.2159827   -.1813689
    highserv |   .2298115   .0118434    19.40   0.000     .2065989    .2530242
     lowserv |   .2196708   .0079353    27.68   0.000      .204118    .2352237
      unrate |   .0225876   .0012259    18.43   0.000     .0201849    .0249904
unratexlnj~p |  -.0009619   .0016357    -0.59   0.557    -.0041678    .0022441
unratexlnj~2 |   .0002686   .0005461     0.49   0.623    -.0008018    .0013389
       _cons |  -1.011903   .0163099   -62.04   0.000     -1.04387   -.9799364
-------------+----------------------------------------------------------------
EE           |
          cf |  -1.011942   .0122039   -82.92   0.000    -1.035861   -.9880226
      lnjemp |   -2.53216   .0241991  -104.64   0.000     -2.57959   -2.484731
     lnjemp2 |   1.255083   .0153547    81.74   0.000     1.224988    1.285178
     lnjemp3 |  -.2022639   .0031734   -63.74   0.000    -.2084836   -.1960442
    age16tv  |    .043099   .0027103    15.90   0.000      .037787    .0484111
    age16tv2 |  -.0031777    .000185   -17.18   0.000    -.0035402   -.0028152
 educcompul2 |   .0220555    .005569     3.96   0.000     .0111405    .0329705
 manufactory |  -.4401769   .0088543   -49.71   0.000    -.4575309   -.4228228
    highserv |   .1415707   .0109013    12.99   0.000     .1202046    .1629368
     lowserv |   .0282416   .0076963     3.67   0.000     .0131571    .0433262
      unrate |  -.0165131   .0010909   -15.14   0.000    -.0186511   -.0143751
unratexlnj~p |   .0118484   .0016218     7.31   0.000     .0086697    .0150271
unratexlnj~2 |  -.0052452   .0005698    -9.21   0.000     -.006362   -.0041284
       _cons |  -.3861184   .0145517   -26.53   0.000    -.4146391   -.3575977
------------------------------------------------------------------------------
(exit2==no exit is the base outcome)
```

Discrete time competing risks hazard model, with discrete mixture

Log likelihood = -840603.57 Number of obs = 1,316,611

exit2	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
hazard1						
cf	-.8244588	.0115585	-71.33	0.000	-.8471131	-.8018045
lnjemp	-.5313624	.0253333	-20.97	0.000	-.5810148	-.4817099
lnjemp2	.3610352	.01561	23.13	0.000	.3304402	.3916302
lnjemp3	-.0957306	.0034033	-28.13	0.000	-.102401	-.0890603
age16tv	-.0934056	.0028976	-32.24	0.000	-.0990848	-.0877263
age16tv2	.0039949	.0001992	20.06	0.000	.0036046	.0043852
educcompul2	-.0968852	.0069518	-13.94	0.000	-.1105105	-.08326
manufactory	-.211835	.0094664	-22.38	0.000	-.2303887	-.1932812
highserv	.1350418	.0127147	10.62	0.000	.1101215	.1599621
lowserv	.1745412	.0085626	20.38	0.000	.1577589	.1913235
unrate	.024601	.0013045	18.86	0.000	.0220443	.0271577
unratexlnjemp	.0004602	.0016838	0.27	0.785	-.0028401	.0037605
unratexlnjemp2	-.0005451	.0005548	-0.98	0.326	-.0016324	.0005422
_cons	-1.540267	.0182031	-84.62	0.000	-1.575944	-1.504589
hazard2						
cf	-1.02528	.0127572	-80.37	0.000	-1.050284	-1.000277
lnjemp	-2.078786	.0250507	-82.98	0.000	-2.127885	-2.029688
lnjemp2	1.107497	.015722	70.44	0.000	1.076683	1.138312
lnjemp3	-.1831092	.0032193	-56.88	0.000	-.1894189	-.1767995
age16tv	.038407	.0029839	12.87	0.000	.0325588	.0442553
age16tv2	-.0031854	.000205	-15.54	0.000	-.0035871	-.0027836
educcompul2	.0336721	.0067271	5.01	0.000	.0204872	.0468571
manufactory	-.4384897	.0095412	-45.96	0.000	-.45719	-.4197893
highserv	.0295985	.0119948	2.47	0.014	.006089	.0531079
lowserv	-.0230854	.0084529	-2.73	0.006	-.0396528	-.0065181
unrate	-.0144479	.0011802	-12.24	0.000	-.0167611	-.0121346
unratexlnjemp	.0123513	.0016725	7.38	0.000	.0090732	.0156294
unratexlnjemp2	-.0058043	.0005786	-10.03	0.000	-.0069384	-.0046703
_cons	-.9270718	.0167796	-55.25	0.000	-.9599592	-.8941844
m2						
_cons	1.584087	.0088521	178.95	0.000	1.566737	1.601437
logitp2						
_cons	-1.730903	.0210766	-82.12	0.000	-1.772212	-1.689593
Prob. Type 1	.8495279	.0026942	315.31	0.000	.8441707	.8547326
Prob. Type 2	.1504721	.0026942	55.85	0.000	.1452674	.1558293

Note: m1 = 0

Three competing risks with UH using hsmlogit

```
. hsmlogit_v4 `varsaleE´ , id(codind) spell(spell) seq(j) d(exit3) nmp(2) difficult
Discrete time competing risks hazard model without frailty

Multinomial logistic regression                   Number of obs   =    1316611
                                                  LR chi2(84)     =  160654.70
                                                  Prob > chi2     =     0.0000
Log likelihood = -881090.49                       Pseudo R2       =     0.0836

------------------------------------------------------------------------------
       exit3 |      Coef.   Std. Err.      z    P>|z|     [95% Conf. Interval]
-------------+----------------------------------------------------------------
EU           |
          cf |  -.7986611   .0109406   -73.00   0.000    -.8201043   -.7772179
      lnjemp |  -.9709934   .0245729   -39.51   0.000    -1.019155   -.9228314
     lnjemp2 |   .5069499   .0152775    33.18   0.000     .4770066    .5368933
     lnjemp3 |  -.1157149   .0033656   -34.38   0.000    -.1223114   -.1091185
     age16tv |  -.0881035   .0026718   -32.98   0.000    -.0933401   -.0828668
    age16tv2 |   .0039923   .0001826    21.86   0.000     .0036344    .0043502
  educcompul2 |   -.105202   .0060017   -17.53   0.000    -.1169652   -.0934388
  manufactory |  -.2006661   .0088305   -22.72   0.000    -.2179736   -.1833587
    highserv |   .2296968   .0118453    19.39   0.000     .2064804    .2529132
     lowserv |   .2180955   .0079363    27.48   0.000     .2025406    .2336503
      unrate |    .022578   .0012261    18.41   0.000     .0201749    .0249811
unratexlnj~p |  -.0011119   .0016364    -0.68   0.497    -.0043191    .0020953
       _cons |  -1.009577   .0163131   -61.89   0.000     -1.04155   -.9776039
-------------+----------------------------------------------------------------
ET           |
          cf |  -1.214204   .0134696   -90.14   0.000    -1.240604   -1.187804
      lnjemp |  -2.566013   .0252271  -101.72   0.000    -2.615457   -2.516569
     lnjemp2 |   1.310668   .0165322    79.28   0.000     1.278266    1.343071
     lnjemp3 |  -.2269325   .0035308   -64.27   0.000    -.2338528   -.2200123
     age16tv |   .0348604   .0027452    12.70   0.000     .0294799    .0402409
    age16tv2 |   -.002567   .0001871   -13.72   0.000    -.0029338   -.0022002
  educcompul2 |   .0164089   .0056687     2.89   0.004     .0052985    .0275193
  manufactory |  -.4715925   .0091037   -51.80   0.000    -.4894354   -.4537496
    highserv |   .1380367   .0110533    12.49   0.000     .1163726    .1597009
     lowserv |   .0082154   .0078295     1.05   0.294    -.0071302     .023561
      unrate |  -.0164156    .001101   -14.91   0.000    -.0185736   -.0142576
unratexlnj~p |   .0097402   .0016896     5.76   0.000     .0064288    .0130517
       _cons |  -.3760623   .0146951   -25.59   0.000    -.4048642   -.3472603
-------------+----------------------------------------------------------------
EP           |
          cf |   .7109967    .035604    19.97   0.000     .6412142    .7807791
      lnjemp |  -2.083359   .1148221   -18.14   0.000    -2.308406   -1.858312
     lnjemp2 |   1.077243    .056833    18.95   0.000     .9658519    1.188633
     lnjemp3 |  -.1234547   .0099939   -12.35   0.000    -.1430423   -.1038671
     age16tv |   .2424454   .0156192    15.52   0.000     .2118325    .2730584
    age16tv2 |  -.0191269   .0011496   -16.64   0.000    -.0213801   -.0168737
  educcompul2 |    .151788   .0268159     5.66   0.000     .0992299    .2043462
  manufactory |    .149392   .0355004     4.21   0.000     .0798125    .2189714
    highserv |   .2252933    .057029     3.95   0.000     .1135184    .3370681
     lowserv |   .5072968   .0360027    14.09   0.000     .4367328    .5778609
      unrate |  -.0802567   .0089966    -8.92   0.000    -.0978896   -.0626237
unratexlnj~p |   .0610449   .0089799     6.80   0.000     .0434446    .0786453
       _cons |  -4.808289   .1012222   -47.50   0.000    -5.006681   -4.609897
------------------------------------------------------------------------------
(exit3==no exit is the base outcome)
```

Discrete time competing risks hazard model, with discrete mixture

Log likelihood = -860570.7 Number of obs = 1,316,611

exit3	Coef.	Std. Err.	z	P>|z|	[95% Conf.	Interval]
hazard1						
cf	-.8317648	.0115702	-71.89	0.000	-.8544421	-.8090876
lnjemp	-.5323972	.0253395	-21.01	0.000	-.5820617	-.4827327
lnjemp2	.3637062	.0156171	23.29	0.000	.3330973	.3943152
lnjemp3	-.0965266	.0034067	-28.33	0.000	-.1032035	-.0898496
age16tv	-.0946958	.0028946	-32.71	0.000	-.1003691	-.0890224
age16tv2	.0041084	.0001986	20.68	0.000	.003719	.0044977
educcompul2	-.098385	.0069564	-14.14	0.000	-.1120192	-.0847508
manufactory	-.2151223	.0094659	-22.73	0.000	-.2336751	-.1965695
highserv	.1342664	.0127151	10.56	0.000	.1093452	.1591875
lowserv	.1714203	.0085664	20.01	0.000	.1546305	.1882101
unrate	.0246167	.0013044	18.87	0.000	.02206	.0271733
unratexlnjemp	.0002379	.0016847	0.14	0.888	-.003064	.0035398
_cons	-1.537957	.0182095	-84.46	0.000	-1.573647	-1.502267
hazard2						
cf	-1.230282	.0139993	-87.88	0.000	-1.25772	-1.202843
lnjemp	-2.109857	.0260808	-80.90	0.000	-2.160975	-2.05874
lnjemp2	1.161366	.0169049	68.70	0.000	1.128233	1.194499
lnjemp3	-.2072636	.0035771	-57.94	0.000	-.2142745	-.2002527
age16tv	.0294043	.0030183	9.74	0.000	.0234885	.0353201
age16tv2	-.002497	.000207	-12.06	0.000	-.0029027	-.0020913
educcompul2	.0270498	.0068402	3.95	0.000	.0136433	.0404563
manufactory	-.4710222	.0097941	-48.09	0.000	-.4902183	-.4518261
highserv	.023543	.0121529	1.94	0.053	-.0002762	.0473622
lowserv	-.0459738	.008593	-5.35	0.000	-.0628157	-.0291318
unrate	-.0143704	.0011898	-12.08	0.000	-.0167023	-.0120384
unratexlnjemp	.0101926	.0017401	5.86	0.000	.006782	.0136031
_cons	-.9171136	.0169239	-54.19	0.000	-.9502838	-.8839434
hazard3						
cf	.6758236	.0358259	18.86	0.000	.6056062	.7460411
lnjemp	-1.679314	.1147489	-14.63	0.000	-1.904217	-1.45441
lnjemp2	.9649278	.0568303	16.98	0.000	.8535425	1.076313
lnjemp3	-.1111428	.0099834	-11.13	0.000	-.13071	-.0915757
age16tv	.2357879	.0156333	15.08	0.000	.2051473	.2664286
age16tv2	-.0190263	.0011489	-16.56	0.000	-.0212781	-.0167745
educcompul2	.1549394	.0269799	5.74	0.000	.1020597	.2078191
manufactory	.134427	.035673	3.77	0.000	.0645092	.2043449
highserv	.1660599	.0571961	2.90	0.004	.0539576	.2781622
lowserv	.4844141	.0361505	13.40	0.000	.4135604	.5552679
unrate	-.0763687	.0089703	-8.51	0.000	-.0939502	-.0587873
unratexlnjemp	.0608414	.0089472	6.80	0.000	.0433051	.0783776
_cons	-5.338236	.101233	-52.73	0.000	-5.536649	-5.139823
m2						
_cons	1.583831	.0088365	179.24	0.000	1.566512	1.60115
logitp2						
_cons	-1.725456	.0210304	-82.05	0.000	-1.766674	-1.684237
Prob. Type 1	.8488302	.0026986	314.55	0.000	.8434647	.8540436
Prob. Type 2	.1511698	.0026986	56.02	0.000	.1459564	.1565353

Note: m1 = 0

The estimation exercise shown in this Section is addressed only to highlight the importance of allowing for modelling more than one single risk in a duration model that also takes into account the presence of UH. For that reason, analogously to [Troncoso-Ponce, 2017], the main purpose of these regressions is not intended to address a rigorous regression analysis to properly estimate the effect of a set of covariates on the probability of exiting out of employment. Therefore, in this Section, comments on detailed estimation results will be focused mainly on the impact of holding an apprenticeship contract (captured by the covariate `cf` in the three estimation outputs presented above) when we allow for modelling more than one single risk.

The single risk duration model estimates a statistically significant negative effect (-0.9136) of holding an apprenticeship contract on the probability of exiting out from the employment state, which may suggest that apprenticeship contracts last longer (ie. seem to be more stable) than regular fixed-term contracts. And when we allow for modelling two competing risks (exiting to unemployment, or a job-to-job transition to another job), the effect of apprenticeship contracts remain negative and statistically significant on both the two risks modeled: exiting to exit to unemployment (-0.8244), and a direct transition to another job (-1.0252).

However, interestingly, the estimated effect of apprenticeship contracts turns positive when we allow for modelling the job-to-job transition separately in two different, and mutually exclusive, destinations: i) a direct transition to a fixed-term contract; and i) a direct transition to an open-ended contract. As the third estimation output shows, apprenticeship contracts increase the probability of experiencing a job-to-job transition towards an open-ended contract (0.7109). The main reason of observing this possitive effect is the role played by public financial incentives addressed to the conversion of apprenticeship contracts into open-ended ones. Apprenticeship contracts in Spain benefit from public subsidies for the conversion into open-ended contracts. These subsidies mainly consist of a significant reduction in Social Security contributions paid by the employer during a maximun period of three years, from the starting date of conversion of the apprenticeship contract into an open-ended one. The main goal of these financial incentives is to favour employment stability, and to foster the accumulation of employment experience of apprentices by allowing them to put in practice the work-specific skills acquired during the apprenticeship period. Thus, the possitive coefficient found (0.7109) may be capturing the effect of these public financial incentives provided by Spanish policy makers addressed to the conversion of apprenticeship contracts into open-ended ones.

An axhaustive analysis of the apprenticeship contracts in the Spanish labor market is presented in [Troncoso-Ponce, 2016] and [Jansen and Troncoso-Ponce, 2017]. The first one estimates a multispell and multistate competing risks duration

Table 1: Interpretation of UH coefficients (three competing risks model)

	Prob.	Emp. to Unemp.	Emp. to Fixed-term	Emp. to Open-ended
Type I	84.88%	-1.537957	-0.9171136	-5.338236
Type II	15.12%	0.045874[a]	0.6667174[b]	-3.754405^c

[a] $(= -1.537957 + 1.583831)$ [b] $(= -0.9171136 + 1.583831)$ [c] $(= -5.338236 + 1.583831)$

model with UH especific to both each state and to each destination state, as well as a selection equation that estimates the transition rates to the entry into the labor market holding three different types of labor contract: an apprenticeship contract, a fixed-term contract, and an open-ended contract. The second, and more recent, work also estimates a multispell and multistate competing risks duration model with UH, but the selection equation consists of an initial conditions equation, rather than a transition rate equation, that controls for the effect of a set of observable covariates on the probability of having an apprenticeship contract just in the first employment spell of the individual's working life. Moreover, the empirical strategy followed in this work allows us to disentangle two types of effect: an instant effect, and a subsequent effect of apprenticeship contracts on the employment and unemployment transition rates.

5.1 Some insights on the interpretation of UH coefficients

Regarding the estimation and interpretation of UH coefficients, as we assume that η_1 is set to zero,[11] the estimated regression's constant terms (-1.537957, -0.9171136 and -5.338236, for the exit to unemployment, to a fixed-term, and to an open-ended contract, respectively) capture the UH component specific to Type I workers, whereas η_2 captures the unobserved differential effect of Type II workers with respect to Type I workers. Therefore, the estimated value of UH component specific to Type II workers are the result of the sum of the regression's constant terms and the estimated coefficient value of η_2.

Table 1 shows the estimated coefficients of the UH components of Type I and Type II workers from the estimation results of the three competing risks model. The estimation of the non-parametric UH distribution, characterized by the presence of two types of workers (two points of support), captures Type I and Type II workers who represent, respectively, 84.88% and 15.12% of the estimation sample. As Table 1 shows, Type II workers have unobserved characteristics that positively correlate to the employment hazard rates, which implies that Type II workers face employment transition rates (towards all the three

[11] It explains the footnote shown at the estimation output tables with the message "Note: m1 = 0", where m1 denotes UH component given by η_1. See also [Troncoso-Ponce, 2017] and `hshaz` command's official Stata helpfile.

modeled risks) higher than Type I workers'.

In conclusion, the estimation of not only a single or a two competing risks, but a three competing risks duration model has allowed for capturing a positive and statistically significant effect of apprenticeship contracts on the probability of transiting directly (via job-to-job) to an open-ended contract, that otherwise would have remained hidden to the empirical researcher if only one risk, or even two, would have been estimated. Furthermore, given the relevance of UH, and its non parametric identification, in discrete time duration models with multispell observations (see, for example, [Gaure, Roed and Zhang, 2007] and [Abbring and Van den Berg, 2004]), the new Stata command `hsmlogit` takes especial relevance, as allows for the estimation of discrete time competing risks duration models with UH.

6 The advantages of using ml d2 method

As mentioned in Section 1, `hsmlogit` provides the algebraic expressions of both the gradient vector and Hessian matrix, allowing for using `d2 ml` method to achieve the model convergence. An important advantage of programming the Hessian matrix is that allows applied researchers to deal with large longitudinal microdata sets (see for example [Troncoso-Ponce, 2017]). To show the savyings in estimation time, this Section presents time required to estimate multispell both single and competing risks duration models (with 2, 3 and 4 mass-points) using `d0`, `d1` and `d2 ml` methods,[12]. Comments in this Section will be focused only on the comparison between `d1` and `d2 ml` methods. The comparison between `d0` and `d2 ml` does reinforce the same conclusions obtained below.

Table 2 reports time spent[13] by each of the three `ml` methods in achieving the models' convergence.[14] Results from Table 2 highlight two relevant differences between `d1` and `d2 ml` methods: Firstly, `d2` method significantly reduces time required to achieve the all models convergence. Differences in time required seem to be less evident in the estimation of single risk models: for instance, for fitting the two mass-points model, `d2` (`d1`) method needs 46 seconds (6.28 minutes). However it becomes more important as both the number of risks and the number of mass-points increase: for fitting the three competing risks model with four mass-points, `d2` method only requires 8.02 minutes, whereas `d1` method needs 1.58 hours. On its part, `d0` method not even achieve the model convergence:

[12] The all estimations, whose time required are shown in Table 2, include a set of twenty eight covariates that, as results shown in Section 5, control for duration dependence, personal characteristics, type of labor contract, regional effects and economic cycle. The detailed estimation results are available upon request to the interested reader.

[13] I work with Stata 14.0 MP - Parallel edition 64 bits. The machine employed to obtain estimation results incorporates an Intel(R) Core(TM) i7-6700HQ CPU at 2.60 GHz, and 12 Gb RAM memory. The operating system is Windows 10 Home.

[14] In this sample composed of youth Spanish employees, the estimation of five points of support for the identification of the non-parametric unobserved heterogeneity distributuion is not possible, neither fitting single risk models, nor competing riks models.

Table 2: Time required for the estimation of multispell competing risks duration models (Sample size: 1,316,611 observations)

	Time (hh:mm:ss)				
	`d0` method	`d1` method	`d2` method	Diff.=`d1-d2`	Diff.=`d0-d2`
Single risk					
Two mass-points	1:37:59	0:06:28	0:00:46	0:05:42	1:32:17
Three mass-points	3:00:16	0:12:48	0:02:03	0:10:45	2:49:31
Four mass-points	18:02:16	0:21:01	0:06:52	0:14:09	17:48:07
Two risks					
Two mass-points	3:59:59	0:20:10	0:01:48	0:18:22	3:41:37
Three mass-points	7:58:44	0:37:28	0:04:00	0:33:28	7:25:16
Four mass-points	7:03:51	0:58:28	0:07:06	0:51:22	6:12:29
Three risks					
Two mass-points	3:45:53	0:40:09	0:03:19	0:36:50	3:09:03
Three mass-points	-	1:13:42	0:05:43	1:07:59	-
Four mass-points	-	1:58:29	0:08:02	1:50:27	-

after eleventh iteration, it gets into a backed up loop. Secondly, unlike `d2` method, time required by `d1` method to achieve the model convergence strongly dependes both on the number of exits modeled, and on the number of points of support for the identification of the UH. Table 2 shows that, using `d2` (`d1`) method, the difference in time spent between the less time-demanding model (the single risk model with two mass-points) and the most time-demanding model (the three competing risks with four mass-points) reaches 7.16 minutes (1.52 hours).

7 Concluding remarks

This article presents **`hsmlogit`**, a new Stata command that estimates multispells discrete time competing risks duration models with unobserved heterogeneity. **`hsmlogit`** allows for the estimation of one, two and up to three competing risks, as well as a maximum of five points of support for the identification of the non-parametric unobserved heterogeneity distribution [Heckman and Singer, 1984]. The relevance of modelling more than one risk has been highlighted by estimating the effect of apprenticeship contracts on a sample composed of low educated young workers in the Spanish labor market for the period 2000-2014. Thus, the estimation of a three competing risks duration model has been the only way to find out the potential effect of public financial incentives for the conversion of apprenticeship contracts into open-ended ones on the direct (via job-to-job) transition rates towards an open-ended contract. Moreover, since **`hsmlogit`** allows for the estimation of non-parametric UH distribution ([Heckman and Singer, 1984]), our results capture the presence of two types of workers with different values of unobserved characteristics that affect the estimated hazard rates.

Finally, `hsmlogit` provides the algebraic expressions of both the gradient vector and the Hessian matrix, which significantly reduces time required to achieve the model convergence, and also improves the standard errors' accuracy of the estimated coefficients. The possibility of estimating competing risks duration models with the presence of UH, along with time savyings provided by the use of `d2 ml` method may allow the applied researchers to easily and properly exploit the richness and complexity of large longitudinal microdata sets.

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