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Unemployment Duration among Immigrants and Natives: Unobserved Heterogeneity in a Multi-Spell Duration Model*

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Abstract

This paper studies whether the unemployment dynamics of immigrants differ from those of natives, paying special attention to the impact of accounting for unobserved heterogeneity among individuals. Using a large administrative data set for Spain, we estimate multiple-spell discrete duration models which disentangle unobserved heterogeneity from duration dependence. Specifically, we estimate random effects models assuming that the distribution of the effects is discrete with finite support, and fixed effects models in which the distribution of the unobserved effects is left unrestricted. Our results show the importance of accounting for unobserved heterogeneity and that mistaken policy implications can be derived due to improper treatment of unmeasured variables. We find that lack of control for unobserved heterogeneity leads to the conclusion that immigrant males have a higher probability of leaving unemployment than natives and that the negative effect of unemployment benefits for immigrants lasts longer than for natives. Nonetheless, the estimates which do control for unobserved heterogeneity show the opposite results.

Keywords: Duration models; Discrete choice; Multiple spells; Unobserved heterogeneity; Unemployment; Immigration.

JEL Classification: J64, J61, C23, C41, J65

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1 Introduction

During the last years, economists have paid considerable attention to the effects of immigration on natives' labor market outcomes (see Borjas, 2003, Ottaviano and Peri, 2006). Other strand of the literature has studied the assimilation process of immigrant workers as their residence in the host country lengthens, focusing basically on the speed of the "catch up" process of immigrant wages to those of natives (see Chiswick, 1986, LaLonde and Topel, 1992, Card, 2005). The economics literature concerning immigration has also shown that there are important differences between the labor market performance of native born and foreign born individuals (see Borjas, 1994). However, no much attention has been paid to the unemployment behavior of immigrants and, in particular, to whether the duration of their unemployment spells differs from those of natives. Considering that immigrants' use of public transfers, such as unemployment benefits, is of major policy concern, this is surprising.[1]

This paper contributes to this empirical literature by analyzing whether the unemployment duration path of immigrants differs from that of natives. It also studies the effect of unemployment insurance benefits on unemployment duration for both groups of workers. Our basic motivation is to facilitate the distinction between unobserved heterogeneity and true duration dependence in the exit rate from unemployment for immigrants and natives.

One of the major issues in the econometric analysis of individual unemployment durations is the distinction between what has been called "true" and "spurious" duration dependence (see Heckman, 1991). It is well known that improper treatment of unmeasured variables could give rise to a relationship between future and past unemployment due solely to uncontrolled heterogeneity. Moreover, the presence of unobserved heterogeneity might give an alterna-

[1] Some papers have studied how employment and unemployment probabilities differ between natives and immigrants (see Chiswick et al., 1997, Uhlendorff and Zimmermann, 2006). Others have looked at differences in welfare participation between immigrants and natives (see Borjas and Hilton, 1996, Hansen and Lofstrom, 1999)

tive explanation for the negative duration dependence typically observed in the data. The reason is that individuals with the highest hazards on average leave unemployment quickest so those who are still unemployed at high durations tend to have lower values of the unobserved variables and thus lower hazards. Therefore, if one ignores the presence of unobserved heterogeneity the estimated duration dependence will be too negative. In this paper, we analyze if the impact over the unemployment hazard rate of the unobserved heterogeneity differs among immigrants and natives.

We use a large administrative data set, the Spanish *Muestra Continua de Vidas Laborales* (MCVL), which contains information on approximately $1,1$ million people in the year 2005 and which covers their entire labor market history. This data set provides a clear advantage over other data sets used in the literature, since it offers information on multiple spells of unemployment for the same individual,[2] and this is crucial to disentangle unobserved heterogeneity from genuine duration dependence.

We apply discrete duration models to our multiple spell data for immigrants and natives separately. Specifically, we estimate by maximum likelihood random effects models assuming that the distribution of the unobserved heterogeneity is discrete with finite support (see Heckman and Singer, 1984). The support point approach with multiple spells allows for a better identification of the parameters of interest than when only a single spell is available for each individual. Nonetheless, in practice it is often difficult to find more than a few different mass points, which reflects a lack of informativeness about the distribution of the unobserved effects in the data. For that reason, we also estimate a fixed effects model in which the full distribution of the unobserved heterogeneity is left unrestricted and allowed to be dependent of the explanatory variables of the model. Following Frederiksen, Honoré and Hu (2007), we use the information on the multiple

[2] Hansen (2000) and Kalwij (2001) also use multiple spell data to study individuals' unemployment experiences.

spells for each worker to rule out the individual unobserved heterogeneity, in the spirit of the fixed effects discrete choice panel data models. We highlight the impact of leaving the distribution of the heterogeneity unrestricted on the estimation of the effect of unemployment benefits on unemployment duration.

Spain can be considered an interesting case for investigating these issues in the context of unemployment duration for immigrants and natives. It is one of the European countries where immigration flows during the last decade have increased most noticeably. The foreign-born population living in Spain surged from around 350 thousand (1% of the total population) in 1991 to more than 4.3 million (10% of total the population) in 2006. Over the period 2000-2005 immigration accounted for almost all of the increase of working-age population, and had noticeable macroeconomic effects not only on the size, but also on the composition of aggregate supply and aggregate demand, contributing to sustain a long-lasting economic expansion that started in the mid-nineties.

Our results show that mistaken policy implications can be derived due to improper treatment of unmeasured variables. We find that lack of control of unobserved heterogeneity leads to the conclusion that immigrant males have a higher probability of leaving unemployment than natives and that the negative effect of unemployment benefits for immigrants lasts longer than for natives. Nonetheless, the estimates which do control for unobserved heterogeneity show the opposite results. Moreover, we find that for some groups of workers (native females and immigrant males) it seems that there is a great deal more of unobserved heterogeneity than the one captured by a random effects model with three mass points, while for native males and immigrant females the results from the random effects and the fixed effects models are very similar. Since we have not estimated a structural model of duration, it is difficult for us to interpret which factors are behind the unobserved effects. Nonetheless, a possible explanation for the differences among groups is that unobserved heterogeneity mainly affects one component of the hazard rate, probably the acceptance behavior, for those individuals for whom the mass point distribution is enough to control for such heterogeneity. On the contrary, native females and immigrant males might have a more complex influence of such heterogeneity both over the arrival rate of job offers and the acceptance probability (see García-Pérez, 2006) and, hence, this is not totally captured by a discrete distribution with three mass points.

The paper is organized as follows. Section 2 formulates the econometric model and discusses the estimation procedures. Section 3 provides a brief review of the related literature, presents some background information about immigrants performance in the Spanish labor market, and describes the data. Section 4 reports and discusses the estimation results. Finally, Section 5 concludes.

2 Models and Estimators

We analyze the dependence of exit from unemployment on the length of time unemployed and on other variables by the estimation of duration models. At any point in time, an individual could be in any of two states: Unemployed or Employed. We estimate hazard rates between unemployment and employment for natives and immigrants separately by estimating the probability that an individual will leave unemployment during the next period, given that she has been unemployed for T periods. We treat duration (T) as a discrete variable.[3] For individual i the probability of a spell being completed by time $t+1$ given that it was still continuing at time t is given by

$$h_i(t) = \Pr(T_i = t \mid T_i \geq t, b_i(t), x_i(t)) = F(\alpha_0 + \alpha_1(t)b_i(t) + \alpha_2(t)x_i(t) + \gamma_i(t)). \tag{1}$$

Our analysis is conditional on $b_i(t)$, a dummy variable taking the value 1 if the individual receives unemployment benefits in period t. The history of benefit

[3] See Meyer (1995) for a survey of discrete-time reduced-form duration models.

entitlements is observed in our data. Therefore, we do not need to estimate a process for this variable and it is not necessary to treat it as endogenous. That is, the probability in (1) is conditional on the entire path of $b(t)$ and we do not need to allow for feedback from T, the unemployment duration, to future values of b (see Bover, Arellano & Bentolila, 2002, for a detailed discussion on this issue).

In addition to benefits, we also condition on a vector of exogenous variables $x_i(t)$, which includes a set of individual, sectorial and aggregate variables. $\gamma_i(t)$ is a parameter that captures duration dependence and is a function of the number of periods spent in unemployment. Specifically, we model duration dependence by a third order polynomial term in $\log t$. Finally, $F(\cdot)$ denotes the logistic cumulative distribution function.

2.1 Single-Spell Duration Data

For each individual, the data consist of one or more spells of unemployment. We first consider a single spell duration model and treat different spells for the same individual as independent spells of different individuals. This is a reasonable assumption in the absence of unobserved heterogeneity. Then, the log likelihood function for all spells of unemployment takes the form

$$\log L = \sum_{i=1}^{N} \sum_{t=1}^{\bar{t}} m_{it} \left\{ (1 - y_{it}) \log(1 - h_i(t)) + y_{it} \log h_i(t) \right\}, \tag{2}$$

where N is the number of unemployment spells in the sample, $\bar{t}$ is the largest observed duration, y_{it} takes the value 1 if an exit from the spell of unemployment is observed in period t and 0 if not or if the observation is censored at t. Variable m_{it} equals 1 if a spell of unemployment is observed during the period t and zero otherwise.

The model is estimated by Maximum Likelihood (ML). Notice that, since the hazard rate $h_i(t)$ in the likelihood function is simply a *logit* probability, estimation is equivalent to estimating a sequence of *logit* models (with crossequation restrictions)[4] defined on the surviving population at each duration (see Jenkins, 1995).

However, previous estimates may be biased by the presence of unobserved heterogeneity. Heckman (1991) argues that it is not a simple task to distinguish duration dependence from unobserved heterogeneity. Clearly, because of the presence of unobserved heterogeneity, the duration dependence in the observed hazard function is more negative than otherwise since the individuals with the highest hazards on average leave unemployment quickest. A version of the previous model allowing for unobserved heterogeneity is given by

$$h_i(t,\eta_i) = \Pr(T_i = t \mid T_i \geq t, b_i(t), x_i(t), \eta_i) = F(\alpha_0 + \alpha_1(t)b(t) + \alpha_2(t)x_i(t) + \gamma_i(t) + \eta_i), \tag{3}$$

where the hazard is conditional on the unobserved heterogeneity, η_i. Again, assuming independence over the individual spells, the log-likelihood function is

$$\log L = \sum_{i=1}^{N} \int \sum_{t=1}^{\bar{t}} \left[m_{it} \left\{ (1-y_{it}) \log(1-h_i(t)) + y_{it} \log h_i(t) \right\} \right] d\mu(\eta), \tag{4}$$

where $\mu(\eta)$ is the unknown distribution of the unobserved heterogeneity.

As is usual in this type of models, the initial time does not correspond to the date of entry into the labor market for all the individuals in the sample. The beginning of the labor market process, from the end of schooling up to the state occupied on the initial period, is unobserved for the econometrician and possibly correlated with η_i. Consequently we have to consider the problem of initial conditions.

Two approaches can be used in order to solve this problem (see Hsiao, 1986). The first approach is to use the joint distribution of all outcomes -including that in the initial time period- conditional on unobserved heterogeneity. As Wooldridge (2005) points out, the main complication with this approach is specifying the distribution of the initial condition given unobserved heterogeneity.

[4] Specifically, in our estimates we impose $\alpha_2(t) = \alpha_2$ for all regressors but the ones measuring age, qualification and the business cycle.

For the dynamic probit model with covariates, Heckman (1981) proposed approximating the conditional distribution of the initial condition. This avoids the practical problem of not being able to find the conditional distribution of the initial value. But this approach is computationally cumbersome. The other method is proposed by Wooldridge (2005) and consists in modeling the unobserved heterogeneity conditionally on the initial condition (and the exogenous variables in all time periods) and to specify the unconditional distribution of unobserved factors. In this paper we consider this method, because it is flexible and simple to implement since the likelihood of interest has the same structure as in the standard random effects model, except that the explanatory variables at each time includes the initial condition. So we can add it as an additional explanatory variable and use our standard random effects model to estimate the parameters of interest. Specifically, we will condition on the number of months the individuals have been employed before we observe their labor market status in our sample.[5]

Previous likelihood function (4) is a typical form of the statistical mixture model. The problem of how to control for the unobserved mixing distribution $\mu(\eta)$ has been addressed extensively in the literature. Standard approaches require making strong and arbitrary assumptions about distribution functions for population heterogeneity η. A popular choice is the family of Gamma distributions. This stems from analytic tractability[6] although it suffers from the typical estimation bias due to an incorrect parametrization of $\mu(\eta)$.[7]

Heckman and Singer (1984) propose controlling for unobserved heterogeneity without explicitly specifying a parametric distribution for heterogeneity. They

[5] Notice that η_i should also be correlated with the set of individual exogenous characteristics in all time periods. This means that the variables $x_i(1), ..., x_i(T)$ should also be added to the list of explanatory variables to allow for such correlation. Nonetheless, in our application all the exogenous variables potentially correlated with the unobserved heterogeneity are time-constant.

[6] See Abbring and Van den Berg (1998) for a justification for the choice of the family of Gamma distributions.

[7] Moreover, Heckman and Singer (1984) show that the problem of overparametrization can lead to the observational equivalence of two different sets of distributions.

adopted a semi-parametric approach to identify the unobserved distribution from a mixed distribution assuming that η_i is a random effect independent of all individual characteristics, although correlated with $\gamma_i(t)$. For discrete duration models, the only assumption is that the distribution of the unobserved heterogeneity has a finite mean.

Therefore, assuming that the random variable η_i is discrete with finite support given by r mass points $s_1, ..., s_r$, and the corresponding probability mass $\Pr(\eta_i = s_\ell) = P_\ell$, the likelihood in this case is

$$\log L = \sum_{i=1}^{N} \sum_{\ell=1}^{r} \sum_{t=1}^{\bar{t}} \left[m_{it} \left\{ (1 - y_{it}) \log(1 - h_i(t, s_\ell)) + y_{it} \log h_i(t, s_\ell) \right\} \right] \Pr(\eta_i = s_\ell), \tag{5}$$

where

$$h_i(t, s_\ell) = F(\alpha_0 + \alpha_1(t) b_i(t) + \alpha_2(t) x_i(t) + \gamma_i(t) + s_\ell). \tag{6}$$

The idea is that if the number of points of support increases, then any true underlying distribution for the unobserved heterogeneity can be approximated well. Nonetheless, in practice it is often difficult to find more than a few different mass points.[8] This fact reflects a lack of informativeness on the distribution of the unobserved heterogeneity in the data, especially when only single spell data on durations are available.[9]

The availability of data on multiple spells for the same individual is crucial for identifying the parameters of interest in a duration model in the presence of unobserved heterogeneity. In this case, the support point approach by Heckman and Singer (1984) allows for a better identification than when only a single spell is available for each individual. Moreover, the availability of multiple spells allows us to transform the model to rule out the individual unobserved effects, in the spirit of the fixed effects discrete choice panel data models. Next section outlines both methods for multiple spell data.

[8] In our estimates we impose the number of mass points to be equal to three.

[9] Another drawback of this approach is that the distributional properties of the estimators are still unknown. Moreover, it is computationally expensive.

2.2 Multi-Spell Duration Data

2.2.1 Random Effects Estimator

Multivariate duration data occur when several spells are observed for each individual in the sample. In this case it is possible to look into possible dependence across spells for the same individual. This topic has been first discussed by Kalbfleisch and Prentice (1980).[10]

Notice that if the hazard rate allows for unobserved heterogeneity and multiple-spell data are available, we should estimate jointly durations in unemployment and in employment, since the unobserved heterogeneity is, in general, correlated across different types of spells. Therefore, accounting for the two states, unemployment (u) and employment (e), the model is defined by

$$h_i^k(t, \eta_i^k) = F(\alpha_0^k + \alpha_1^k(t) b_i(t) + \alpha_2^k(t) x_i(t) + \gamma_i^k(t) + \eta_i^k), \qquad k = u, e, \tag{7}$$

where $\eta_i^e = \delta \eta_i^u$. That is, we assume that for each individual the unobserved heterogeneity component is the same in all spells of the same type, and only differs across types of spells by a constant, δ.

Since employment and unemployment spells cannot be treated separately, we need to specify the likelihood function for all spells and integrate out the random effects (see Cheser and Lancaster, 1983, for a detailed discussion). Thus, following the support point approach by Heckman and Singer (1984), the likelihood function takes the form:

$$\log L = \sum_{i=1}^{N} \sum_{\ell=1}^{r} \sum_{t=1}^{\bar{t}} \left\{ \begin{array}{c} \left[u_{it} \left\{(1 - y_{it}^u) \log(1 - h_i^u(t, s_\ell^u)) + y_{it}^u \log h_i^u(t, s_\ell)\right\}\right] \Pr(\eta_i^u = s_\ell^u) + \\ \left[e_{it} \left\{(1 - y_{it}^e) \log(1 - h_i^e(t, s_\ell)) + y_{it}^e \log h_i^e(t, s_\ell^e)\right\}\right] \Pr(\eta_i^e = s_\ell^e) \end{array} \right\}, \tag{8}$$

where $u_{it} = 1$ if during the period t a spell of unemployment is observed and zero otherwise, and $e_{it} = 1$ if during the period t a spell of employment is observed and zero otherwise.

[10] Empirical analysis of models with multiple-spell duration data are for instance Newman and McCullogh (1984), Lillard and Panis (1996), Rudder and Tunali (1999) or Kalwij (2004).

2.2.2 Fixed-Effects Estimator

If more than one observation is available for each duration, then it is possible to identify the model without imposing untestable assumptions of the unobserved heterogeneity distribution. The idea, loosely speaking, is that in this case, the duration analysis becomes similar to the standard dynamic panel data analysis, where one can get rid of the so called "fixed-effects" before estimating the other parameters.

The fixed effects approach has been scarcely used in duration analysis. Frederiksen *et al.* (2007) proposed a method to estimate discrete time duration models allowing for group level heterogeneity in models for single and multiple spells. We follow this approach to estimate a fixed effects model in a multiple spell framework.[11] That is, in our application the grouping results from multiple spells for the same individual. We consider the parametric version of their model[12] and, as in previous sections, we assume a conditional logistic distribution.

The model is in the spirit of the fixed-effects panel data model, in which the distribution of the individual effect is left unrestricted and allowed to be correlated with the explanatory variables. This is attractive since it ensures that the conditional distribution of the individual effects does not play any role in identifying the parameters of interest. Moreover, notice that within this approach consistent estimators of the parameters of interest are available without assumptions on the initial conditions since it is possible to find an objective function that eliminates the unobserved effects.

To see how the approach works, it is useful to formulate the model as a discrete choice model. We use $y_{ijt}^{k} = 1$ to denote that the individual i during

[11] Ridder and Tunali (1999) also follow a fixed effects approach but it only works when durations are continuous.

[12] Frederiksen *et al.* (2007) also proposed semi-parametric versions of the model.

the spell j leaves the state k in period t. The model is

$$y_{ijt}^k = 1(\alpha_0^k + \alpha_1^k(t)b_{ij}(t) + \alpha_2^k(t)x_{ij}(t) + \gamma_{ij}^k(t) + \eta_i^k + \varepsilon_{ijt}^k \geq 0), \qquad k = u, e \quad (9)$$

In the spirit of linear panel data models, the proposed estimation technique is based on the observations for which the number of spells per individual, J_i, is larger than 1.[13] It is possible to construct conditional statements and to get rid off the unobserved heterogeneity by using only the spells of unemployment or only the spells of employment. Therefore, within this framework, it is not necessary to jointly model the spells of unemployment and employment in order to get consistent estimates of the parameters of interest. Thus, given that our main interest is the process for unemployment, we will drop out the unobserved heterogeneity by using only spells of unemployment for each individual.

For simplicity and to fix ideas, let's assume that the number of spells for all individuals is $J = 2$ and that $\alpha_1^u(t) = \alpha_1^u$ and $\alpha_2^u(t) = \alpha_2^u$. What we do to eliminate the unobserved heterogeneity is to compare first to second spells for each individual and each period, t. That is, we compare y_{i2t}^u to y_{i1t}^u assuming that the individual specific effect, η_i, does not depend on the spell number. Notice that only variables which depend on the spell number are identified and those constant across spells for the same individual are also dropped. Specifically, within this framework the duration dependence is not identified, although interactions between the explanatory variables and the duration dependence can be identified.

Frederiksen *et al.* (2007) assume that the $\varepsilon_{ijt}'s$ are logistically distributed and their framework allows for feedback from the $\varepsilon's$ to future values of the explanatory variables. That is, the explanatory variables can be predetermined. In our application the only explanatory variable which could be considered as predetermined as opposed to strictly exogenous is the indicator of benefits, b.

[13] One could think that this could give rise to an endogenous self-selection problem. In order to check for that, we have estimated the model which does not account for unobserved effects only with the individuals with two or more spells. Our results basically hold.

Nonetheless, since we observe data for benefits after the spells end (the benefit entitlement is also observed in our data) we can condition on past, current and future values of this variable. In this case, it can be treated as exogenous and therefore we do not need to specify the feedback from ε to future values of b in order to get consistent estimates of the parameters of interest.

Under the previous assumption (and assuming $J = 2$), Frederiksen *et al.* (2007) show that it is possible to construct conditional statements (see Lemma 1, page 1018) and that one can estimate the parameters of interest by maximizing

$$\sum_{i=1}^{N} \sum_{t_1=1}^{\bar{t}} \sum_{t_2=1}^{\bar{t}} \{1(T_{1i} = t_1, T_{2i} > t_2) + 1(T_{1i} > t_1, T_{2i} = t_2)\} \tag{10}$$
$$\times \log \left(\frac{\exp((b_{i1}(t_1) - b_{i2}(t_2))\alpha_1^u + (x_{i1}(t_1) - x_{i2}(t_2))\alpha_2^u)^{1(T_{1i}=t_1, T_{2i}>t_2)}}{1 + \exp((b_{i1}(t_1) - b_{i2}(t_2))\alpha_1^u + (x_{i1}(t_1) - x_{i2}(t_2))\alpha_2^u)} \right).$$

A similar approach can be used when there are more than two spells for each individual and when the α parameters do vary with the duration (see Frederiksen *et al.*, 2007, for details).

3 Estimating Unemployment Duration among Immigrants and Natives

3.1 Unemployment and the Use of Unemployment Benefits

Some early studies have analyzed the evolution of unemployment for immigrants and natives. For example, Chiswick, Cohen and Zach (1997) find for the US that immigrants had some initial difficulty finding work, but their employment and unemployment rates quickly attained levels comparable to those of native-born. Carlin, Edin, Harkman and Holmlund (1996) examine transitions out of unemployment in Sweden and find that immigrants enter into employment at a 30% lower rate than Swedish citizens. Hansen (2000) finds for Sweden that a substantial proportion of the observed differences in unemployment spells between natives and immigrants can be explained by differences in accumulated human capital and unemployment compensation. Uhlendorf and Zimmerman

(2006) study the German case and find that immigrants stay unemployed longer than natives. However, once immigrants find a new job, they do not observe differences in the employment stability compared to natives.[14]

For Spain, evidence from the Labor Force Survey (EPA) shows that throughout the period 2003-2007, the unemployment rates among immigrants are about 3 percentage points higher than for natives (see Table 1). It is worth noting that the difference in unemployment rates decreased up to 2006 and in 2007 increased again. Table 2 provides the percentage of individuals according to the duration of their unemployment spells. Unemployment tends to be longer for natives than for immigrants, especially for males. Since 2005, more than 50% of all unemployed stayed in that state for less than 6 months, with women, especially natives, being those with longer unemployment spells.

There is also an increasing concern about the impact of immigration on the costs of welfare. The available empirical evidence suggests that an increasing number of immigrants are beneficiaries of welfare programs. There is little evidence in the literature on this issue, especially for Europe. Borjas and Hilton (1996) find that in the US the immigrant-native difference in the probability of receiving cash benefits is small, but the gap widens once other programs are included in the analysis. Blau (1984) compares the receipt of transfers by families headed by immigrants and those headed by native-born Americans. Her main finding is that when age and other factors are held constant, immigrant families are less likely to rely on welfare than native families and their receipts from social insurance programs are found to be only slightly higher. For Canada, Baker and Benjamin (1995) find that immigrants have lower participation rates in Unemployment Insurance and Social Assistance than natives. They also find that "assimilation" leads to greater participation in both programs. Hansen and Lofstrom (2003) find for Sweden that immigrants use welfare to a greater

[14] Many of these papers do not control for unobserved heterogeneity nor allow for a different effect of explanatory variables on transitions for natives and immigrants.

extent than natives and that differences cannot be explained by observable characteristics. They also find that welfare participation decreases with time spent in Sweden.

In this paper we only focus on the receipt of unemployment benefits. Second panel of Table 1 shows the figures coming from the EPA. We can see that the use of unemployment benefits among immigrants has increased considerably since 2003. On average, the increase for natives has been 3.4 and 4.6 percentage points for males and females respectively, while for immigrants these figures rise by 14 and 11.7 percentage points.

3.2 The Data Set

We use administrative data from the *Muestra Continua de Vidas Laborales* (MCVL). This data set is based on a random draw from the Social Security archives. It provides a sample of 4% among all the affiliated workers, working or not, and pensioners in the year 2005. The MCVL reports information for about $1,1$ million people on their personal characteristics and employment and unemployment spells throughout their entire labor history. Specifically, the exact date when each job begins and ends is known.

Periods of non-employment can be identified from the dates when the firm does not pay Social Security contributions for the worker. We can distinguish non-employment spells in which the worker receives Unemployment Benefits (those in which payroll taxes are paid) from those which correspond to both periods of unemployment without benefits or periods of inactivity (those in which worker contributions to Social Security are not paid). We will use the term unemployment to name all these spells in which the worker does not work within a firm. Moreover, we know whether the Unemployment Benefits are contributive (corresponding to the Unemployment Insurance system, which pays benefits to workers who have previously contributed when employed) or assistance ones (corresponding to the Unemployment Assistance system, which pays to workers who have exhausted previous ones or do not qualify for receiving them).[15] Given that we have the complete labor history of the worker, we can also get the entitlement period for the benefit spells.

The main shortcoming of this data set is the lack of some personal or family characteristics, such as marital status or number of children, which could be important to determine, for example, the exact amount the worker can get from Unemployment Benefits. Another important caveat is that we cannot measure the educational level of the worker, but only the qualification level of the previous job held. Hence, our measure of qualification has to be taken with caution as it does not reflect the actual level of qualification of the worker but the one corresponding to the job she previously occupied.

Our initial sample included information about 381,894 men (347,070 natives and 24,824 immigrants) and 283,081 women (268,134 natives and 14,947 immigrants). Throughout this paper we consider as immigrants those individuals residing in Spain with a nationality not belonging to any of the European Union (as of 1995) countries. Our final sample includes men and women aged 19 to 62 who were unemployed at some point during the period 1995-2005. We have restricted our sample to start in 1995 since some relevant characteristics are missing before that date. After filtering the sample and applying some homogeneity restrictions (see Appendix), we end up with 405,731 native unemployed workers (215,609 males and 190,122 females) and 32,089 immigrants (21,393 males and 10,696 females).

Table 3 presents the structure of our data according to the number of spells of unemployment per individual and the duration of each spell. More than 73% of native workers have two unemployment spells or more and almost 60% of immigrant females and 64% of immigrant males experience unemployment at least twice. Hence, we have on average around 4 unemployment spells per

[15] See Bover *et al.,* (2002) for details.

native worker and around 3 per immigrants. Regarding unemployment duration, more than 70% of all completed unemployment spells last less than 6 months. Moreover, average duration for completed spells are lower for immigrant males (3.29 months) and larger for native females (4.73 months). The comparison of these figures from our data set and the corresponding ones from the EPA (see Table 2) shows that in our sample, considering both completed and censored spells,[16] there is a higher proportion of short unemployment spells, which makes sense given the quarterly structure of the Spanish Labor Force Survey.

The explanatory variables used in the estimations are described in the Appendix and summary statistics are presented in Table 4. We can see that more than 30% of native workers receive unemployment benefits when starting their unemployment spells, with this rate being much lower for immigrants (around 17%). Table 5 shows that the majority of benefits receipt is on a contributive basis and that the most likely entitlement duration is 1-8 months, especially for native workers. The incidence of Unemployment Assistance is much higher among women, specially immigrants. We can also observe that for censored unemployment spells the incidence of large entitlement periods and unemployment assistance is more important than for completed spells. It is interesting to note that immigrant workers, especially women, show a higher percentage of entitlement spells of intermediate duration.[17]

There are important differences among native and immigrant workers according to the sector where they previously worked (see Table 4). Most workers in both groups worked in market services but an important percentage of immigrant males worked in the construction sector. The largest percentage of unemployment spells are observed in the youngest category we consider (be-

[16] In the Labor Force Survey it is not possible to measure the exact duration for very small unemployment spells. Furthermore, it is only possible to measure duration of ongoing spells, not of the completed ones.

[17] For a number of spells we observe in the data that the worker receives both, unemployment benefits and unemployment assistance This is the reason why the percentage in the columns do not add up exactly to 100.

tween 19 and 30 years old), although immigrants also show a large percentage of unemployment spells in the 31-44 age range. Previous job qualification requirements are lower for immigrants than for natives. Regarding other characteristics related to the previous job held, the majority of workers leave the job for non-voluntary reasons, they were working at firms with less than 250 employees and created years before the worker was hired ("old firms"). Less than 10% of males and 13% of females were previously working on a permanent basis, and the incidence of part-time employment is small among males but much larger for females. The variable "*Same Employer*" measures whether the unemployed worker returns, after leaving unemployment, to the same firm where she was working in his last job. It is usual in the Spanish labor market for firms to fire workers in "bad" times and hire them again afterwards to save on labor costs. Table 4 shows that this hiring policy is more frequent among native workers (26.6% for males and 36.6% for females) than among immigrants. Finally, the majority of immigrant males come from Africa whereas, in the case of females, the origin is more likely to be Latin-America (see Table 6).

3.3 Empirical Hazards

In order to get an idea of the shape of the distribution of durations, we present the evolution over time of the sample probability of leaving unemployment. That is, we compute the number of exits from unemployment in each month divided by the population still in unemployment at the beginning of that month. This probability is displayed in Figure 1. We can see that there is a negative duration dependence in all cases. The hazard decreases rapidly up to the sixth month of unemployment. After that moment it is more or less constant. Immigrant males are more likely to exit from unemployment than native males up to the ninth month. Nonetheless, from that period on, the differences between both groups are reduced. The behavior of immigrant females is quite similar to that of native females from the beginning of the unemployment spell.

Figure 2 represents the effect on the empirical hazards of benefit receipt in a given month. We can see that individuals not receiving benefits have a higher hazard than those receiving benefits, with this difference being in general greater for immigrants than for natives.

4 Estimation Results

In this section we report the estimates from the different models described in the previous section for natives and immigrants separately. The estimation results are reported in Tables 7 and 8. We compare the results from a logit model which does not account for the effect of unobserved heterogeneity (Logit without UH) to those of the Heckman-Singer (HS) and fixed effects (FE) models, which control for the presence of unobserved heterogeneity and exploit the availability of multiple spell data.[18] We first discuss duration dependence and then take in turn the effect of unemployment benefits. Finally, we discuss the effect of other variables. The qualitative impact of the variables are discussed in terms of the sign and statistical significance of the estimated coefficients. In order to assess the economic significance of the effects we also report predicted hazards for some individual types.

4.1 Duration Dependence

We capture duration dependence by a third order polynomial of log duration. We also introduce as regressors interactions of the dummy for the receipt of unemployment benefits, age, qualification, and the employment growth rate with logged duration. Notice that in the fixed effects model the effect of duration is not identified, since it is constant across spells and, therefore, it has been dropped. Nonetheless, as mentioned above, the interactions between logged

[18] For the Heckman-Singer model we only report the estimates corresponding to the hazard of leaving unemployment. The estimates on the employment process, available upon request, show basically a larger exit from employment among female workers than among males. We do not find substantial differences among natives and immigrants, although the procyclical pattern of this hazard is much larger for immigrants.

duration and explanatory variables which do vary across spells, are identified.[19]

The results indicate a non-monotonic duration dependence in all cases. As expected, the coefficient for the *log Dur* variable is in general smaller once unobserved heterogeneity is accounted for. Specifically, we find that for natives, both males and females, the difference in the coefficient of the *log Dur* variable between the standard logit and the HS model is larger that among immigrants. The pattern of the predicted hazards are shown in Figures 3 and 4 for an individual with the average characteristics of our sample. We can see that the hazard of leaving unemployment decreases rapidly with elapsed duration, as is usually obtained in previous literature (see for instance Bover *et al.*, 2002).

The comparison between natives and immigrants show that for females the duration dependence is very similar at all durations in both models. For males, we do find substantial differences between natives and immigrants. The predicted hazard which does not control for unobserved heterogeneity (Figure 3) shows that immigrant males have a higher probability of leaving unemployment than natives up to one year, and afterwards the behavior of both groups of individuals becomes similar. Nonetheless, the estimates which do control for unobserved heterogeneity (Figure 4) show the opposite result: native males have a higher probability of leaving unemployment than immigrants since the fourth month. This result shows the importance of accounting for unobserved effects. Actually, what we obtain is that the predicted hazards with and without control for unobserved heterogeneity are basically the same for immigrants (both males and females) and native females, but for native males we do find more differences. For example, a native male who has remained unemployed for at least ten months has a probability of leaving unemployment during his tenth month of unemployment of approximately 11% according to the standard logit

[19] The results are based on the assumption that there is no feedback from one individual's spell to the future explanatory variables of other spells for the same individual. We have also estimated the model allowing for a certain level of feedback, and the results, available upon request, do not change.

model and of 17% according to the HS model, while for immigrant males the predicted hazards are about 12% in both models.

Since predicted hazards in Figures 3 and 4 are computed for an individual with the average characteristics of each sample, one could think that the differences among groups are due to the fact that we compare very heterogeneous individuals, since natives and immigrants have different observed characteristics. In order to check for that, we have compared a more homogeneous group of individuals and computed the predicted hazards for individuals with the same age and qualification.[20] Figures 5 and 6 show the results for the youngest and less qualified workers. This is the group with the largest number of observations (around 28% of the sample for immigrants, and 24 % and 33% for native females and males respectively). These figures show a similar pattern than the ones obtained for the average worker. So this result seems to reflect more structural differences among both worker groups.

4.2 Unemployment Benefits

Figures 7 and 8 show that the receipt of unemployment benefits reduces the hazard of leaving unemployment, and that the reduction in the hazard is smaller as duration increases (as indicated by the positive coefficient on the interaction between the dummy for benefit receipt and *log Dur)*. This result holds for all groups of individuals and models considered.

When unobserved heterogeneity is not controlled for (see Figure 7), the difference of the effect of receiving unemployment benefits on the hazard of leaving unemployment becomes zero after nine months of unemployment for natives, while for immigrants this figure rises up to twelve months of unemployment approximately. Therefore, according to these results which do not account for unobserved effects, we could conclude that the negative effect of unemployment

[20] In order to capture better the heterogeneity among immigrants, we have also included in the specification four dummy variables which take the value 1 if the worker has his first spell in a year in which an immigrant legalization took place in Spain (years 1996, 2000, 2001, and 2005).

benefits for immigrants lasts longer than for natives. However, the HS model shows that for native males this difference narrows after fifteen months of unemployment, while for immigrants and native females the HS and the standard logit model provide similar results. Again, as for the duration dependence, it seems crucial to control for unobserved heterogeneity in order to obtain an accurate estimate on the effect of benefits. According to the results, this effect is more important for native males, for whom receiving unemployment benefits affects their reservation wages much longer, and thus, their acceptance behavior.

In order to compare the magnitude of the estimated coefficients in the three models considered, Figure 9 displays the odd ratio of the effect of benefits on the hazard of leaving unemployment for individuals with a benefit entitlement equal to 24 months. We find that for native males and immigrant females, the differences between the HS and the fixed effects models are very small and both estimates reduce the negative effect of unemployment benefits considerably with respect to the standard logit model. On the other hand, for native females and immigrant males, standard logit and HS estimates provide similar results, while fixed effects estimates of the effect of benefits are smaller than the ones obtained from the other two models. This result suggests that for native females and immigrant males there is a great deal more of unobserved heterogeneity than the one captured by a HS model with three mass points, while for native males and immigrant females it seems enough to account for heterogeneity with a mass point distribution.

Concerning the effect of the benefit entitlement duration, the estimates show higher exit rates for individuals with smaller entitlement to benefits. Therefore, there is an additional disincentive effect of benefits, beyond the direct effect of the receipt of this type of unemployment compensation. Finally, it is worth mentioning that the differential effect of the receipt of unemployment subsidies is positive for immigrants, while it is negative for natives. A possible explanation is that probably the immigrants have less access to other sources of income and, thus, the level of benefits affects their acceptance behavior a lot.[21]

4.3 Other Characteristics

We obtain that for immigrants and for native females, the hazard rate decreases with age. For native males, the hazard of older workers is lower than that of younger and middle-age workers, and it is highest for the latter ones. There is also evidence of negative duration dependence for older workers (captured by the interaction between age dummies and *log Dur*). As to qualification, having a high level increases the hazard only for natives, while for immigrants reduces it. We also find that working part-time has a negative effect for all workers, with this effect being greater for males than for females. As to the origin of immigrants, the estimates suggest higher exit rates for Latin-American and lower ones for Asian workers.

Finally, the sample period considered in this paper corresponds to a period of expansion in the Spanish economy.[22] Therefore, it is difficult to infer conclusions about the effect of the business cycle. Nonetheless, since it is measured through the regional employment growth rate, we can exploit the regional and the time variation to obtain an indicator of aggregate effects. Our results show a negative relationship, although it decreases with duration in unemployment (notice the positive coefficient on the interaction between the employment growth rate and $\log Dur$). That is, it seems that for short term unemployed the hazard rate is smaller during expansions, while for long term unemployed the effect is the opposite. In this case, the effect is stronger for immigrants than for natives.

[21] Unemployment Subsidies in Spain pays a much lower amount than contributive benefits.

[22] Data up to 2008 will be available in 2009. This will allow us to analyze business cycle effects more properly since the data will cover a period of recession.

5 Discussion of the Results and Concluding Remarks

This paper studies to what extent the unemployment duration path of immigrants differs from that of natives, once differences in observable and unobservable heterogeneity are accounted for. The main contributions of the paper are twofold. On the one hand we use a large administrative data set which contains information on multiple spell data. This allows us to estimate discrete duration models which disentangle unobserved heterogeneity from duration dependence. We estimate random effects models assuming that the distribution of the effects is discrete with finite support. On the other hand, since the availability of multiple spells allows us to transform the model to rule out the individual unobserved effects, we also estimate fixed effects models and highlight the importance of leaving the distribution of the effects unrestricted in order to obtain an accurate estimate of the effect of unemployment benefits. Our main results can be summarized as follows.

(i) There is a negative unemployment duration dependence in all cases. For females, we find similar duration behavior for natives and immigrants. For males, we do find substantial differences between both groups of workers. The predicted hazard which does not control for unobserved heterogeneity, shows that immigrant males have a higher probability of leaving unemployment than natives. Nonetheless, the estimates which do control for unobserved heterogeneity show the opposite result: native males have a higher probability of leaving unemployment than immigrants.

(ii) Receiving unemployment benefits reduces the hazard of leaving unemployment, and the reduction falls as duration increases. When unobserved heterogeneity is not controlled for, the difference in the hazard of leaving unemployment between individuals who receive and who do not receive benefits becomes zero after nine months of unemployment for natives, while for immigrants this figure goes up to twelve months of unemployment approximately. Therefore, according to these results which do not account for unobserved effects, we would conclude that the negative effect of unemployment benefits for immigrants lasts longer than for natives. However, the estimates which do account for unobserved effects show that for native males this difference narrows after fifteen months of unemployment, while for immigrant males and native females both types of models provide similar results.

(iii) We do not find substantial differences in the estimated effect of benefits from the random effects and the fixed effects models for native males and immigrant females. Nonetheless, for native females and immigrant males, estimates without control for unobserved heterogeneity and random effects estimates do provide very similar results, while fixed effects estimates are lower than the previous ones. This result suggests that for native females and immigrant males there is a great deal more of unobserved heterogeneity than the one captured by a random effects model with three mass points, while for native males and immigrant females it seems enough to account for heterogeneity with a mass point distribution. This result could reflect a more complex influence of the unobserved heterogeneity over the unemployment hazard rate for the former groups.

Given previous results, it seems that it is important to accounting for unobserved effects and that mistaken policy implications can be derived due to improper treatment of unmeasured variables. Our estimation strategy makes it difficult to interpret which factors are behind the unobserved heterogeneity, since we have not estimated a structural model of duration. Nonetheless, a possible explanation for the differences among groups is that the unobserved heterogeneity mainly affects one component of the hazard rate, probably the acceptance behavior, for those individuals for whom the mass point distribution is enough to control for such heterogeneity. On the contrary, native females and immigrant males might have a more complex influence of such heterogeneity over both the arrival rate of job offers and the acceptance probability (see García-Pérez, 2006) and, hence, this is not totally captured by a discrete distribution with three mass points.

To obtain certain evidence in favour of this interpretation, we have performed estimates only for those individuals who never receive unemployment benefits. The idea is that this group of workers should have a low reservation wage and, therefore, there could be no much unobserved heterogeneity affecting their acceptance behavior. What we have found is that the estimation of the mass points in the HS model for immigrant males and native females are very different from the estimates with the whole sample, while for immigrant females and native males the estimates of the mass points are very similar in both cases. This result suggests that for the latter group, the unobserved heterogeneity affects basically the arrival rate of offers, and not much their acceptance behavior, while for immigrant males and native females the heterogeneity probably affects both the arrival rate of offers and the acceptance behavior. One could think that for native males, the unobserved factors could be related to search efforts or other factors affecting the demand for labor. In the case of immigrant males, it seems that some additional unobserved factors which affect their acceptance behavior, are not properly accounted for in our estimates. For instance, unobservable differences among natives and immigrants could reflect differences in the institutional design affecting both groups of workers. The fact that immigrants have to renew their work permits could affect their search behavior, which differs in this respect from that of natives.

Finally, it is worth mentioning the possible problem of endogenous attrition in our multiple spell data. Formally speaking, the problem is similar to having an unbalanced panel in the context of panel data models. That is, if there are reasons to believe that the probability of dropping out of the panel of durations is related to the rate at which a job is found, then the estimator of the rate at which individuals become employed will generally be inconsistent. To check if our basic results are affected by this problem, we have estimated the logit model which does not account for unobserved heterogeneity selecting the sample of individuals with just one spell of unemployment. Our results show that, as expected, their hazard rate are smaller, but the effect of duration, unemployment benefits and the comparison between immigrants and natives do not change. Future research will investigate this issue in more detail.

Appendix: Database Description

The MCVL offers an enormous amount of information on the labor history of all workers in the sample. In some cases, we observe more than one register for each contract held by the worker. In others, the same job in the same firm may be represented by different registers. This makes it necessary to take some decisions about what we call an "employment spell". Therefore, we have applied some criteria to unify different registers when they refer to the same employment spell. In order to eliminate simultaneous employment spells, that is, when the individual is working in two firms at the same time, we keep only the information about the longest spell. Furthermore, we have also unified each two registers when they correspond to one contract that begins before the previous one has finished.

In order to work with a relatively homogeneous sample of workers, we consider only labor histories of workers within the so-called "Régimen General", that is, regular workers being paid by a firm. Thus, we exclude self-employed and workers in agriculture. We keep only workers aged between 19 and 62 years old and study only unemployment spells whose duration is greater than 15 days given that in Spain smaller durations correspond basically to job-to-job movements. Finally, we do not include those unemployment spells for which information about qualification or about the contract type of the previous job is missing.[23] The step-by-step selection of our sample and the variables definition are illustrated in the following tables.

[23] The type of contract is missing in the majority of unemployment spells beginning before 1995. Hence, we have also dropped the spells that begin before that year.

Sample Selection

	Natives		Immigrants	
	Males	Females	Males	Females
Nº. Individuals (initial sample)	347,070	268,134	24,824	14,947
Nº. Spells (initial sample)	1.209,584	968,814	82,255	39,792
Nº. spells dropped due to:				
Working in agriculture	56,652	42,676	9,445	8,675
Age below 19 or above 62	91,299	59,254	505	520
Unemployed before 1995	65,723	31,960	351	75
Unemployment duration < 15 days	38,702	29,393	1,750	596
Not working in the General Regime	23,394	8,249	2,607	1,879
No information about occupation	3,923	1,947	2	2
No information about contract type	28,724	23,704	568	137
Nº Individuals (final sample)	215,609	190,122	21,393	10,696
Nº Spells (final sample)	903,639 74.71%	773,447 79.83%	67,077 81.55%	28,175 70.84%

Variables Definition

Variable Name	Definition
Unempl. Benefits	The worker is receiving unemployment benefits in the current period
Entitlement4	The entitlement period of the ongoing spell is between 1 and 4 months
Entitlement8	The entitlement period of the ongoing spell is between 5 and 8 months
Entitlement12	The entitlement period of the ongoing spell is between 9 and 12 months
Entitlement24	The entitlement period of the ongoing spell is between 13 and 24 months
Unempl. Subsidy	Unemployment benefits are of the assistance type
Industry	Sector of activity in the previous job
Construction	Sector of activity in the previous job
Non-market services	Sector of activity in the previous job
Δ Empl. rate	Annual growth rate of employed population in the corresponding region and period
High Occupation	Occupation held in the previous job
Intermediate Occupation	Occupation held in the previous job
Age 31-44	The age in the current period belongs to the interval 31-44
Age 45-62	The age in the current period belongs to the interval 45-62
New EU countries	The country of origin is one of the new East. Europ. countries that belongs to the EU
Rest of Europe	The country of origin is another European country not belonging to the EU
Latin-America	The country of origin is one from Latin-America
Asia	The country of origin is one from Asia
Fired	Non voluntary exit from the previous job
Firm≥250 workers	The previous firm of the worker had more than 250 workers
New Firm	The worker's previous firm was created one year before the worker was hired or less
THA	Coming from a Temporary Help Agency
Permanent contract	The previous job of the worker was under a permanent contract
Part-time job	The previous job of the worker was under a part-time contract
Total empl.	Nº months of employment before the first observation in our sample
Same Employer	Same employer in the following job as in the pervious one
Private firm	The previous firm did not belong to the Public sector

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Table 1: Unemployment Rates and Unemployment Benefits Use

	Natives		Immigrants	
	Males	Females	Males	Females
Unemployment Rates				
2003	8.02	14.44	11.57	18.67
2004	7.78	14.10	10.95	18.44
2005	6.20	10.98	8.69	12.64
2006	5.71	10.64	8.15	13.90
2007	5.70	9.76	9.33	14.48
Unempl. Benefits Use*				
2003	28.47	17.89	6.90	3.62
2004	29.63	19.11	12.45	8.91
2005	32.05	19.62	16.77	6.51
2006	32.15	22.66	22.75	12.31
2007	31.86	22.54	20.89	15.38

Source: Labour Force Survey, 3rd term.

*Percentage of unemployed workers receiving Unemployment Benefits

Table 2: Ongoing Unemployment Duration

	Natives		Immigrants	
	Males	Females	Males	Females
2003				
1-6 months	44.43*	35.09	49.85	40.90
6-12 months	20.51	20.54	20.78	22.30
+12 months	35.07	44.39	29.37	36.81
2004				
1-6 months	45.57	37.20	44.20	51.78
6-12 months	21.20	20.97	27.57	20.47
+12 months	33.23	41.84	28.23	27.75
2005				
1-6 months	57.62	51.32	67.38	53.86
6-12 months	12.81	13.72	13.76	17.21
+12 months	29.57	34.97	18.85	28.92
2006				
1-6 months	59.58	53.70	74.29	62.89
6-12 months	13.23	14.07	10.9	11.58
+12 months	27.20	32.23	14.81	25.51
2007				
1-6 months	60.61	55.75	70.02	70.02
6-12 months	14.24	14.09	12.44	14.65
+12 months	25.15	30.16	17.54	15.34

Source: Labour Force Survey.

*Percentage of unemployed individuals per group and year

Table 3: Number of Unemployment Spells per Individual and Unemployment Duration

	Natives		Immigrants	
	Males	Females	Males	Females
Number of spells per individual				
1	26.62*	26.37	35.86	41.19
2-4	40.46	41.57	41.51	43.02
5-9	23.77	24.00	19.29	14.33
10 or more	9.15	8.06	3.34	1.46
Unempl. Duration. All spells				
1-6 months	71.50*	67.19	75.51	67.72
6-12 months	13.70	14.38	8.58	10.75
+12 months	14.81	18.43	15.91	21.57
Unempl. Duration. Completed spells				
1-6 months	76.13*	72.87	83.93	77.57
6-12 months	14.58	15.59	9.53	12.32
+12 months	9.29	11.59	6.54	10.11

Source: MCVL

*Percentage of individuals per group

Table 4: Descriptive Statistics

	Natives		Immigrants	
	% Males	% Females	% Males	% Females
With Unemployment Benefits	32.10	30.48	17.80	16.40
Sector: Industry	13.45	10.80	11.22	8.16
Construction	30.45	1.71	46.23	3.04
Non-market services	12.99	26.82	3.81	10.98
Market services	56.66	71.37	49.84	85.90
High Occupation	14.34	23.53	4.84	10.44
Intermediate Occupation	35.91	33.40	26.96	25.08
Low Occupation	49.75	43.08	68.20	64.48
Age 19-30	70.73	70.06	53.95	56.36
Age 31-44	29.13	29.83	45.95	43.55
Age 45-62	13.45	11.11	10.57	9.27
Non voluntary exit from previous job	83.87	87.05	67.83	69.14
Firm$\geq$250 workers	12.98	21.67	8.08	15.44
Old Firm	74.50	80.40	67.78	77.55
Coming from a Temp. Help Agency	9.67	8.94	7.77	9.58
Permanent contract	9.75	13.10	9.05	13.83
Part-time job	13.54	32.32	11.20	34.17
Total empl. (N^o months)	52.14	24.25	2.37	1.17
Same Employer in the following job	26.61	36.62	18.25	19.06
Private firm	93.22	85.20	99.31	98.41
No. of Spells	903,639	773,447	67,077	28,175

Table 5: Type of Unemployment Benefits

	Natives		Immigrants	
	Males	Females	Males	Females
Nº. Completed Spells of Unemployment	283,382	227,526	11,840	4,566
Contributive Unempl. benefits (%)	81.75	73.68	88.23	71.51
Entitlement 1-4 months	30.83	32.09	29.20	24.86
Entitlement 5-8 months	18.92	17.01	28.68	24.84
Entitlement 9-12 months	10.67	8.96	14.44	11.80
Entitlement 13-24 months	21.23	15.46	15.80	9.92
Entitlement >24 months	0.10	0.16	0.11	0.09
Unemployment Assistance (%)	21.83	29.03	13.78	31.71
Nº Censored Spells of Unemployment	6,729	8,257	100	54
Contributive Unempl. benefits (%)	54.75	51.29	68	55.56
Entitlement 1-4 months	12.77	12.58	1.00	9.26
Entitlement 5-8 months	12.08	12.17	12.00	12.96
Entitlement 9-12 months	8.31	7.93	3.00	7.41
Entitlement 13-24 months	33.36	30.50	29.00	27.78
Entitlement >24 months	3.48	2.11	32.00	5.56
Unemployment Assistance (%)	45.25	48.71	32.00	44.44

Table 6: Immigrants in the Estimation Sample by Country of Origin

	Males (%)	Females (%)
New EU countries	9.37	10.57
Rest of Europe	4.03	6.11
Africa	45.57	17.64
Latin-America	31.70	59.47
Asia	8.93	5.74
No. Spells	67,077	28,175

Table 7: ML Estimates. Males

	Immigrants			Natives		
	Logit without UH	HS	FE	Logit without UH	HS	FE
log Dur	-1,635	-1,630	-	-2,144	-1,918	-
	(0,042)	(0,043)		(0,010)	(0,035)	
(log Dur)^2	0,619	0,632	-	1,031	1,006	-
	(0,042)	(0,042)		(0,009)	(0,032)	
(log Dur)^3	-0,122	-0,123	-	-0,194	-0,184	-
	(0,010)	(0,010)		(0,002)	(0,007)	
U. Benefits	-1,606	-1,604	-1,487	-1,155	-1,364	-1,242
	(0,033)	(0,033)	(0,060)	(0,006)	(0,024)	(0,011)
U. Benefits$x$ logDur	0,529	0,522	0,516	0,394	0,404	0,492
	(0,019)	(0,020)	(0,038)	(0,003)	(0,013)	(0,007)
Entitlement4	0,571	0,574	0,028	0,637	0,288	0,178
	(0,031)	(0,032)	(0,058)	(0,006)	(0,025)	(0,009)
Entitlement8	0,448	0,475	-0,240	0,383	0,541	-0,150
	(0,032)	(0,032)	(0,060)	(0,006)	(0,022)	(0,011)
Entitlement12	0,331	0,394	-0,339	0,321	0,248	-0,216
	(0,040)	(0,040)	(0,072)	(0,008)	(0,032)	(0,013)
Entitlement24	0,158	0,267	-0,350	0,230	0,138	-0,296
	(0,040)	(0,041)	(0,071)	(0,007)	(0,029)	(0,012)
U. Assitance	0,105	0,076	-0,117	-0,151	-0,233	-0,377
	(0,034)	(0,035)	(0,062)	(0,006)	(0,023)	(0,010)
Δ Empl. rate	-4,049	-3,879	-3,490	-1,276	-0,700	-0,475
	(0,358)	(0,363)	(0,502)	(0,089)	(0,319)	(0,127)
Δ Empl. rate$x$ logDur	1,900	1,942	1,140	0,394	0,404	0,492
	(0,310)	(0,314)	(0,592)	(0,003)	(0,013)	(0,007)
Age 31-44	-0,022	-0,001	0,048	0,125	0,158	0,180
	(0,011)	(0,012)	(0,037)	(0,005)	(0,020)	(0,012)
Age 45-64	-0,067	-0,026	0,135	-0,079	-0,034	0,167
	(0,025)	(0,026)	(0,087)	(0,007)	(0,033)	(0,022)
Age 45-64x logDur	-0,045	-0,044	-0,023	-0,190	-0,186	-0,026
	(0,020)	(0,020)	(0,080)	(0,004)	(0,015)	(0,020)
Industry	0,026	0,030	-0,043	0,043	0,062	-0,015
	(0,019)	(0,019)	(0,035)	(0,004)	(0,018)	(0,008)
Construction	0,198	0,195	0,040	0,199	0,185	0,085
	(0,013)	(0,014)	(0,027)	(0,003)	(0,015)	(0,007)
Non-market services	-0,145	-0,204	-0,038	-0,004	-0,015	0,011
	(0,030)	(0,031)	(0,054)	(0,005)	(0,021)	(0,009)
New EU countries	0,090	0,095	-	-	-	-
	(0,020)	(0,022)				
Rest Europe	0,018	0,029	-	-	-	-
	(0,028)	(0,030)				
Latin-America	0,1961	0,197	-	-	-	-
	(0,013)	(0,014)				
Asia	-0,055	-0,061	-	-	-	-
	(0,020)	(0,022)				

Note: Numbers in brackets are st. errors.

Table 7(Cont.): ML Estimates. Males

	Immigrants			Natives		
	Logit without UH	HS	FE	Logit without UH	HS	FE
Private firm	0,176	-0,107	-0,012	0,200	0,220	0,181
	(0,069)	(0,047)	(0,125)	(0,006)	(0,027)	(0,012)
Same Employer	0,748	0,792	0,814	0,798	0,964	0,839
	(0,014)	(0,015)	(0,023)	(0,003)	(0,012)	(0,005)
Firm$\geq$250 workers	0,003	-0,013	-0,039	0,029	0,047	0,053
	(0,023)	(0,024)	(0,038)	(0,004)	(0,017)	(0,007)
New firm	-0,021	-0,024	0,012	-0,004	-0,019	-0,028
	(0,012)	(0,012)	(0,018)	(0,003)	(0,011)	(0,004)
Fired	0,040	0,013	0,037	0,032	0,017	0,009
	(0,012)	(0,013)	(0,019)	(0,004)	(0,014)	(0,006)
T. Help Agency	0,409	0,414	0,332	0,262	0,249	0,208
	(0,026)	(0,027)	(0,042)	(0,005)	(0,021)	(0,008)
High qualification	-0,164	-0,166	-0,129	0,022	-0,002	0,082
	(0,026)	(0,027)	(0,046)	(0,006)	(0,023)	(0,011)
Interm. qualification	0,124	0,112	-0,003	0,196	0,171	0,088
	(0,017)	(0,017)	(0,028)	(0,004)	(0,016)	(0,007)
Interm. qualif.x logDur	-0,081	-0,073	-0,005	-0,070	-0,053	-0,005
	(0,014)	(0,015)	(0,034)	(0,003)	(0,011)	(0,006)
Permanent contract	-0,257	-0,252	-0,239	-0,230	-0,227	-0,118
	(0,019)	(0,020)	(0,033)	(0,005)	(0,019)	(0,008)
Part-time	-0,219	-0,205	-0,089	-0,289	-0,284	-0,134
	(0,018)	(0,018)	(0,030)	(0,004)	(0,015)	(0,006)
Total empl.	-0,001	-0,002	-	0,001	0,001	-
	(0,0004)	(0,0004)		(0,000)	(0,000)	
Constant	-0,655	0,146	-	-0,861	0,366	-
	(0,074)	(0,047)		(0,000)	(0,055)	
P_1	-	-2,157	-	-	-1,166	-
		(0,163)			(0,109)	
P_2	-	-0,5176	-	-	0,1754	-
		(0,117)			(0,057)	
s_2	-	-0,7438	-	-	-0,779	-
		(0,067)			(0,044)	
s_3	-	-0,310	-	-	-1,796	-
		(0,045)			(0,043)	
δ	-	1,833	-	-	0,029	-
		(0,166)			(0,018)	
N^o Obs.		202,983			3,914,780	
Log Lik.	-103.394	-274.046	-29.395	-1.707.565	-369.958	-526.962

Note: Seasonal and regularization dummies included.

Table 8: ML Estimates. Females

	Immigrants			Natives		
	Logit without UH	HS	FE	Logit without UH	HS	FE
log Dur	-1,698	-1,657	-	-1,632	-1,498	-
	(0,063)	(0,065)		(0,011)	(0,037)	
$(\log \text{Dur})^2$	0,651	0,666	-	0,683	0,639	-
	(0,060)	(0,061)		(0,009)	(0,032)	
$(\log \text{Dur})^3$	-0,121	-0,118	-	-0,1271	-0,115	-
	(0,014)	(0,015)		(0,002)	(0,007)	
U. Benefits	-1,698	-1,736	-1,654	-1,083	-1,183	-1,132
	(0,051)	(0,053)	(0,094)	(0,007)	(0,024)	(0,012)
U. Benefits$x$ logDur	0,545	0,543	0,680	0,375	0,410	0,449
	(0,032)	(0,033)	(0,062)	(0,004)	(0,013)	(0,007)
Entitlement4	0,454	0,470	-0,051	0,603	0,439	0,250
	(0,047)	(0,052)	(0,091)	(0,006)	(0,025)	(0,010)
Entitlement8	0,490	0,498	-0,20	0,371	0,671	-0,050
	(0,048)	(0,052)	(0,094)	(0,007)	(0,022)	(0,012)
Entitlement12	0,260	0,347	-0,353	0,291	0,401	-0,188
	(0,066)	(0,071)	(0,127)	(0,009)	(0,033)	(0,015)
Entitlement24	0,09	0,232	-0,479	0,026	0,098	-0,453
	(0,073)	(0,078)	(0,143)	(0,008)	(0,030)	(0,015)
U. Assitance	0,135	0,079	-0,195	-0,119	-0,156	-0,263
	(0,042)	(0,045)	(0,082)	(0,006)	(0,021)	(0,010)
Δ Empl. rate	-4,507	-4,473	-3,542	-2,166	-2,226	-1,053
	(0,577)	(0,611)	(0,868)	(0,098)	(0,337)	(0,142)
Δ Empl. rate$x$ logDur	2,969	3,029	1,061	0,375	0,410	0,449
	(0,443)	(0,465)	(0,881)	(0,004)	(0,013)	(0,007)
Age 31-44	-0,019	-0,015	-0,001	-0,036	-0,051	0,137
	(0,017)	(0,020)	(0,063)	(0,005)	(0,019)	(0,013)
Age 45-64	-0,132	-0,136	-0,220	-0,159	-0,173	0,419
	(0,041)	(0,046)	(0,181)	(0,007)	(0,029)	(0,026)
Age 45-64x logDur	0,027	0,037	0,106	-0,052	-0,014	0,047
	(0,030)	(0,032)	(0,158)	(0,005)	(0,016)	(0,022)
Industry	-0,104	-0,104	0,013	0,024	0,004	-0,005
	(0,030)	(0,034)	(0,063)	(0,005)	(0,018)	(0,010)
Construction	-0,047	-0,085	-0,166	-0,232	-0,292	-0,052
	(0,049)	(0,056)	(0,107)	(0,011)	(0,040)	(0,020)
Non-market services	-0,074	-0,142	0,027	0,019	-0,024	0,069
	(0,028)	(0,032)	(0,057)	(0,004)	(0,016)	(0,008)
New EU countries	0,112	0,100	-	-	-	-
	(0,032)	(0,040)				
Rest Europe	-0,009	-0,025	-	-	-	-
	(0,038)	(0,046)				
Latin-America	0,148	0,131	-	-	-	-
	(0,022)	(0,028)				
Asia	0,013	-0,011	-	-	-	-
	(0,040)	(0,048)				

Table 8(Cont.): ML Estimates. Females

	Immigrants			Natives		
	Logit without UH	HS	FE	Logit without UH	HS	FE
Private firm	0,359	0,058	0,050	0,085	0,018	0,106
	(0,067)	(0,071)	(0,140)	(0,005)	(0,020)	(0,011)
Same Employer	0,923	1,025	1,070	0,958	1,004	0,915
	(0,021)	(0,026)	(0,038)	(0,003)	(0,012)	(0,005)
Firm≥250 workers	0,092	0,069	-0,051	0,115	0,091	0,090
	(0,025)	(0,027)	(0,044)	(0,003)	(0,013)	(0,006)
New firm	-0,069	-0,073	-0,002	-0,040	-0,040	-0,049
	(0,020)	(0,021)	(0,033)	(0,003)	(0,012)	(0,005)
Fired	0,111	0,069	0,081	0,108	0,007	0,046
	(0,019)	(0,021)	(0,032)	(0,004)	(0,016)	(0,007)
T. Help Agency	0,266	0,274	0,285	0,297	0,313	0,226
	(0,032)	(0,035)	(0,054)	(0,005)	(0,020)	(0,009)
High qualification	-0,047	-0,077	-0,024	0,176	0,128	0,118
	(0,028)	(0,031)	(0,054)	(0,005)	(0,021)	(0,011)
Interm. qualification	0,048	0,040	0,003	0,141	0,124	0,107
	(0,027)	(0,029)	(0,045)	(0,005)	(0,018)	(0,008)
Interm. qualif.x logDur	-0,046	-0,046	-0,052	-0,037	-0,031	-0,031
	(0,021)	(0,022)	(0,047)	(0,003)	(0,011)	(0,007)
Permanent contract	-0,194	-0,188	-0,176	-0,141	-0,1546	-0,102
	(0,024)	(0,027)	(0,044)	(0,004)	(0,016)	(0,008)
Part-time	-0,163	-0,153	-0,023	-0,159	-0,123	-0,047
	(0,017)	(0,019)	(0,031)	(0,003)	(0,011)	(0,005)
Total empl.	-0,004	-0,004	-	0,0007	0,0002	-
	(0,001)	(0,001)		(0,000)	(0,000)	
Constant	-1,165	0,515	-	-1,069	0,433	-
	(0,078)	(0,132)		(0,009)	(0,046)	
P_1	-	-3,228	-	-	-2,750	-
		(0,248)			(0,112)	
P_2	-	-0,413	-	-	-0,517	-
		(0,198)			(0,042)	
s_2	-	-1,459	-	-	-0,635	-
		(0,098)			(0,042)	
s_3	-	-0,645	-	-	-1,388	-
		(0,080)			(0,047)	
δ	-	0,797	-	-	0,617	-
		(0,081)			(0,032)	
N^o Obs.		107,318			3,841,816	
Log Lik.	-47.176	-109.959	-10.911	-1.547.628	-305.880	-449.760

Note: Seasonal Seasonal and regularization dummies included.

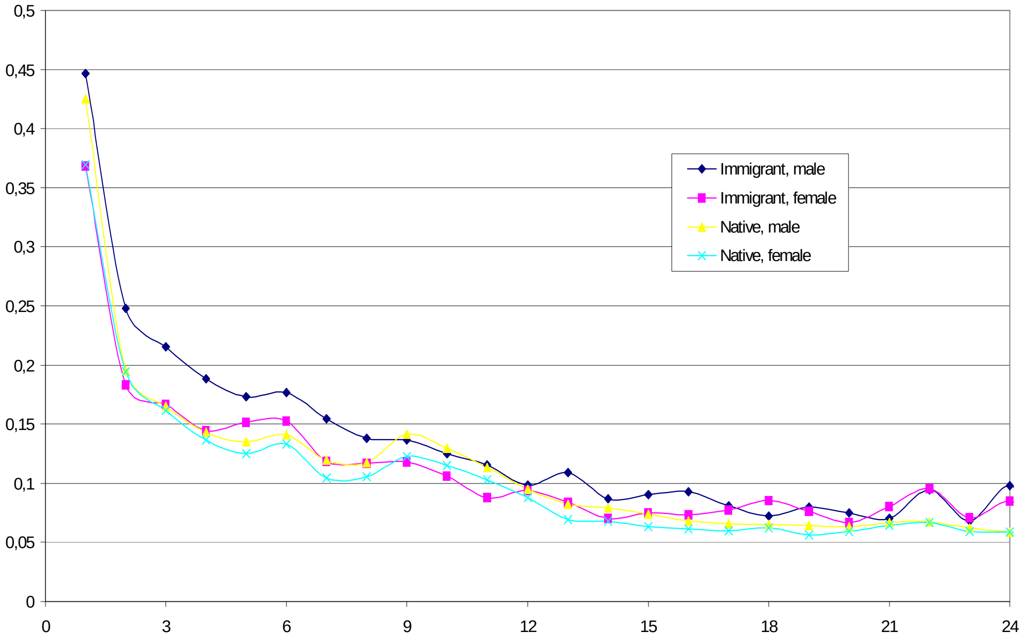

Figure 1: Empirical Hazards.

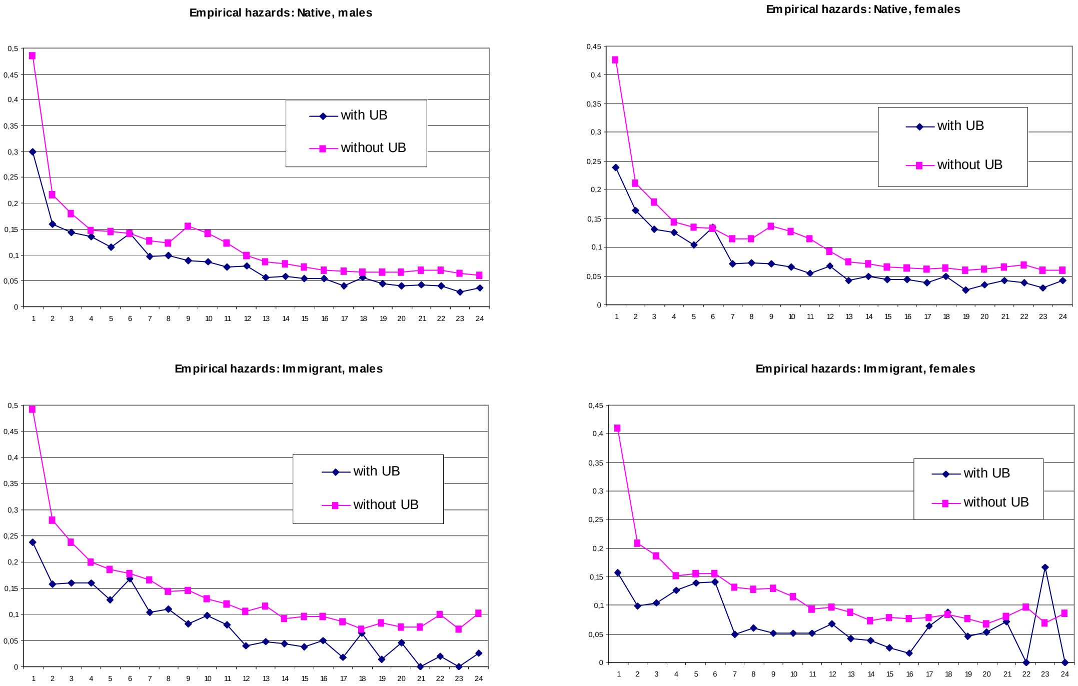

Figure 2: Empirical Hazards and Benefits.

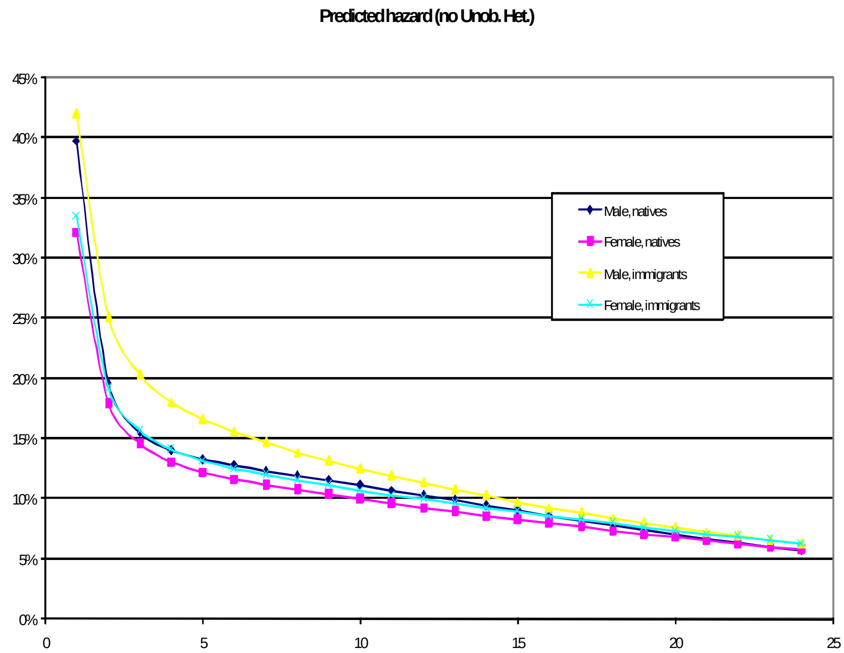

Figure 3: Predicted Hazards. Standard Logit Model (without unobs. het)

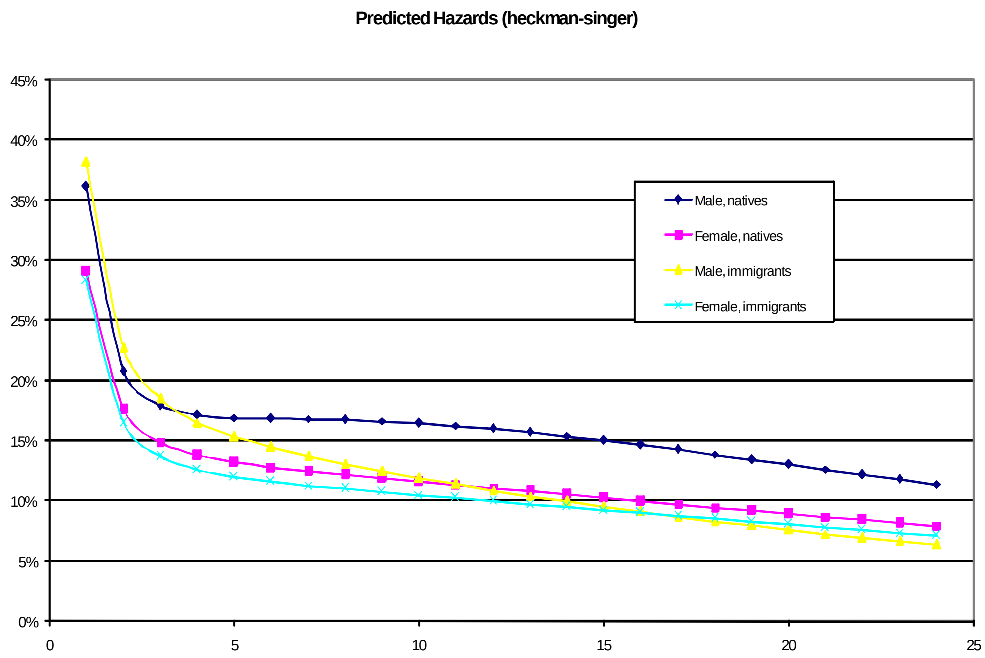

Figure 4: Predicted Hazards. HS model.

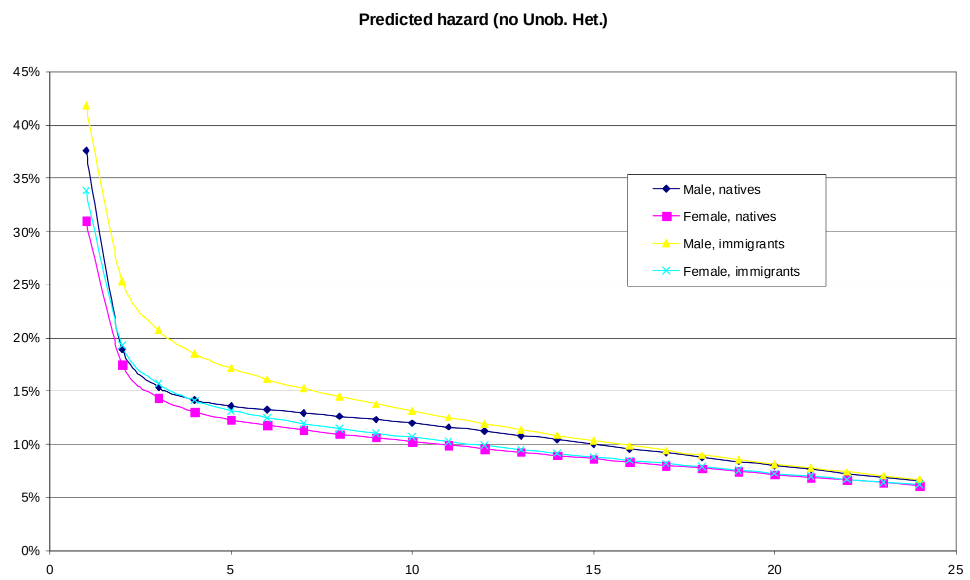

Figure 5: Predicted Hazards. Standard Logit for youngest and less qualified.

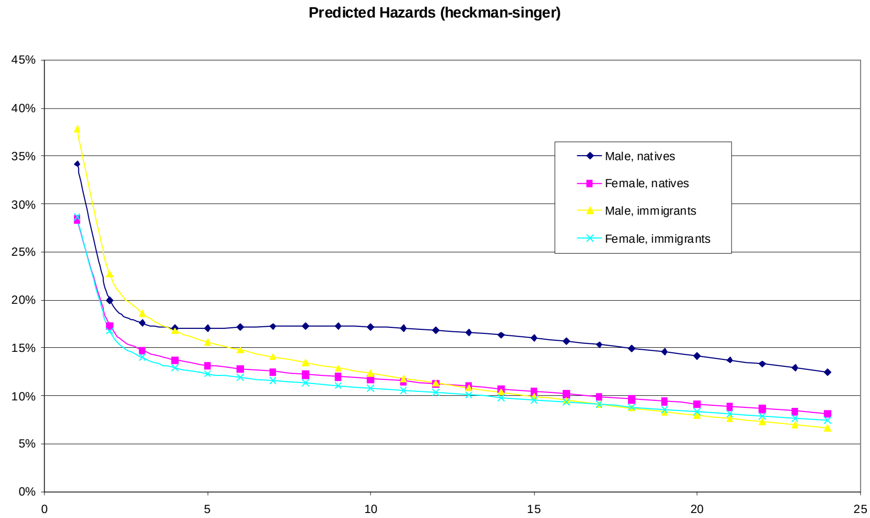

Figure 6: Predicted Hazards. HS for youngest and less qualified.

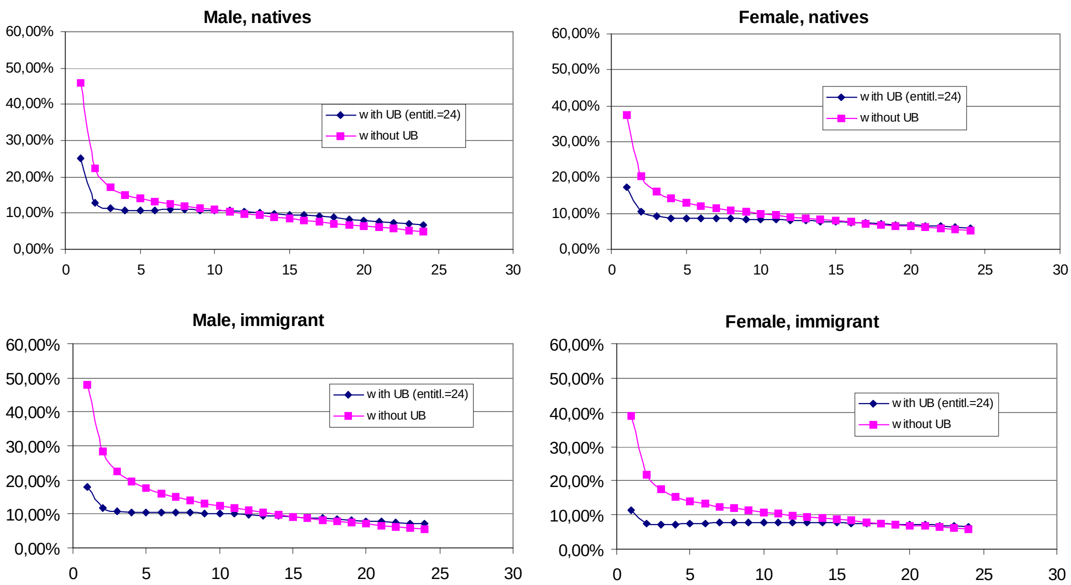

Figure 7: Predicted Hazards by UB. Standard logit model (without unobs. het).

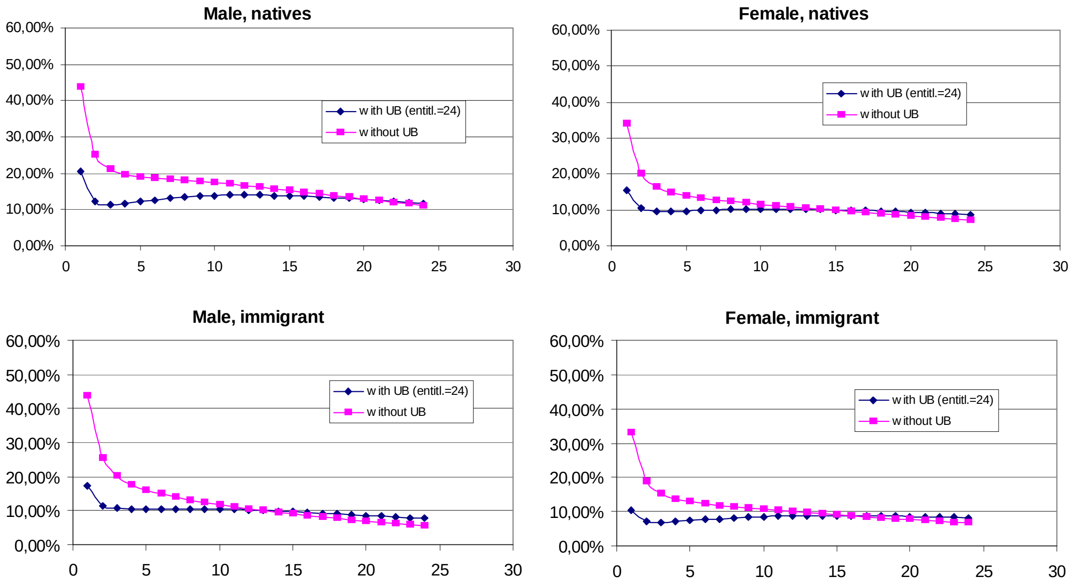

Figure 8: Predicted Hazards by UB. HS model

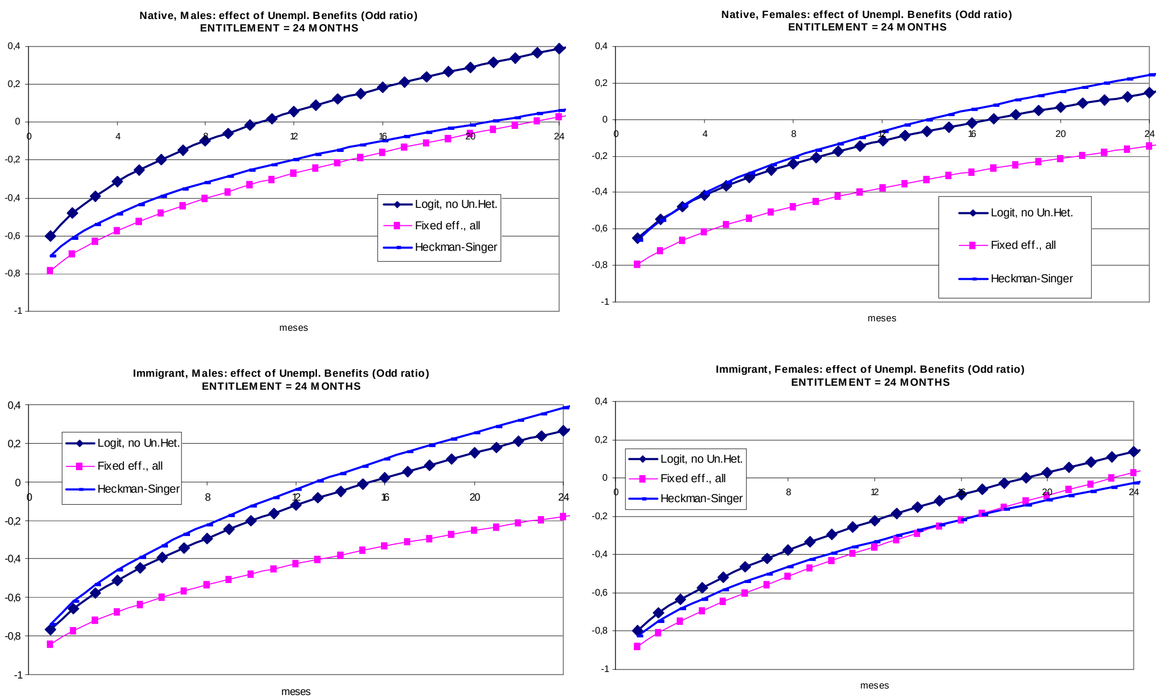

Figure 9: Effect of U. Benefits (odd ratio). Entitlement 24 months.