THE EFFECTS OF DEMOGRAPHIC FACTORS ON WELFARE DURATION: EVIDENCE FROM SPAIN

Luis Ayala[1]
Magdalena Rodríguez[2]

[1] *Facultad de Ciencias Jurídicas y Sociales, Universidad Rey Juan Carlos, Paseo Artilleros s/n, 28032 Madrid, SPAIN, layala@fcjs.urjc.es*
[2]*Instituto de Estudios Fiscales, Cardenal Herrera Oria, 378, 28035 Madrid, SPAIN, magdalena.rodriguez@ief.minhac.es.*

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ABSTRACT

The primary goal of this study is to explain some of the main features of the dynamics of welfare programs in Spain. An attempt is made to answer two fundamental questions: Firstly, what socio-economic characteristics determine longer spells in the program? Secondly, how does the probability of exiting the program vary as people remain for longer periods? The main determinants of spell durations are analysed using parametric models. The effects of unobserved heterogeneity on spell durations are also estimated and competing risks models for different ways of exiting the programs are developed. The results show different kinds of recipients depending on their possibilities of entering the labour market. The most important variable explaining duration is belonging to an ethnic minority. We also prove that there is a moderate degree of duration dependence, even when unobserved heterogeneity is controlled. Lastly, we carry out different tests to assess lineal convergence in time of the different ways of exiting the program. Results clearly show a striking similarity between the profiles of exits from the program for successful reasons and those due to fraud. Exits from the program caused by administrative reasons behave in a clearly different way.

JEL: I30, I38, C41

Key words: welfare, poverty, survival analysis, unobserved heterogeneity.

INTRODUCTION[1]

The interest for the dynamic aspects of Social Assistance has grown considerably in recent years. On the one hand, it seems necessary to differentiate between long-term and short-term spells to design public intervention more precisely. On the other hand, there is a growing conviction that these programs favour behaviour leading to dependency on public welfare, and consequently a reduction in the intensity of job search. As a result, most OECD countries have put restrictive reforms into effect, establishing stricter time limits and imposing more onerous obligations on those receiving benefits. The latter, among others, include participation in training activities or the obligation to accept job offers.

The scope of these reforms contrasts with a general lack of knowledge about the processes that determine the duration of welfare spells. There is no exact knowledge about the factors that determine households with similar characteristics remaining in the programs for longer or shorter spells, nor have the causes that lead to chronification been completely identified. The availability of new longitudinal databases has been accompanied by important advances in analytical methods. The result is a body of techniques and hypotheses that are considerably more solid that the ones available previously.

Due to the lack of studies that look into the duration of welfare programs, the aim of this study is to use this body of techniques and hypotheses to try to explain some of the main features of the dynamics of these programs in Spain[2]. The data from the Minimum Income program of the Madrid Regional Government (IMI) will be used to such an effect. This is an "average" program within the complex mosaic of regional schemes existing in Spain, which would allow some conclusions to be extrapolated for other regional programs. An attempt is made to answer two fundamental questions. Firstly, what socio-economic characteristics determine longer spells in the program? Secondly, how does the probability of exiting the program vary as people remain for longer periods? The answer to the first question would allow us to confirm differences in the pace of households with different characteristics entering and exiting the program. The second answer would provide information on whether or not dependency chains exist caused by how public sector intervention is carried out.

The structure of the study is as follows. The main theoretical grounds that allow us to understand the dynamics of these programs are set out in the first section. The data used in this study is then

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[2] The same cannot be said for poverty durations or entry and exit transitions into and out of poverty. See Cantó (1999 and 2001).

analysed. An initial approach to duration analysis is made in the third section by means of a non-parametric estimation. In the fourth section, the main determinants of spell durations are analysed using parametric models. The effects of unobserved heterogeneity on spell durations are also estimated and different explicative models for different ways of exiting the programs are developed. The study ends with a brief list of conclusions.

1. THEORETICAL FRAMEWORK

1.1. *Welfare Duration: Basic Concepts*

The notion of dependency on welfare programs refers back to a varied range of interpretations. It is commonly accepted that it refers to a prolonged need for Social Assistance. Other interpretations, however, incorporate value judgements and see welfare dependency as a lack of self-sufficiency. While the first interpretation refers to an analysis of the duration of welfare spells, the second evokes the existence of a complex set of social and cultural values. For instance, that is how it is set out by the Expectancy Models and Underclass literature. According to these, there are groups that share specific social values, such as the habit of taking part in these programs, as well as a strong inter-generational component that transmits social norms favouring dependency[3]. Following the lines set out by most of the previous literature, we will focus our attention on the first interpretation. From this standpoint, the key variable is the duration of welfare spells (T), along with its corresponding density $f(t)$ and cumulative distribution $F(t)$ functions, given the probability of exiting the programs after participation for a specific period. The survival function is given by the complement of the distribution function:

$$S(t) = \Pr\{T > t\} = 1 - F(t) = \int_t^{\infty} f(x)dx \qquad (1)$$

while the hazard function, or probability of abandoning the program, is given by:

$$l(t) = \lim_{dt \to 0} \frac{\Pr\{t < T \le t + dt \,|\, T > t\}}{dt} \qquad (2)$$

where the numerator is the conditional probability that the event will occur in the interval (t, $t+dt$), given that it has not occurred before, while the denominator represents the interval length. Given that $l(t)=f(t)/(1-F(t))$, if we integrate:

[3] Different studies confirm transmission across generations of welfare program participation. See Pepper (2000) and Gottschalk (1996).

$$S(t) = \exp\left(-\int_0^t l(u)du \right) \qquad \text{and} \qquad f(t) = l(t)\exp\left(-\int_0^t l(u)du \right) \tag{3}$$

Selecting a hazard function is subject to the assumptions made on the distribution of durations. As will be seen, the profile of durations will depend on this, as will possible inferences on the effect the length of durations could have on the chances of exiting the program.

Various questions arise related to survival in welfare programs[4]. The first of these is the difference between "definitive" exits from the program and transitory ones. Different studies demonstrate the possibility of *re-entries*[5]. Some authors estimate duration by considering the time a welfare claimant stays in the program as the sum of multiple spells during a fixed time interval (Gottschalk y Moffitt, 1994). If we can observe the time spent in the programme (T_D) as well as the time spent outside it, a dependency indicator incorporating multiple spells could be:

$$y_i = \frac{T_{D_i}}{T_{D_i} + T_{F\,i}} \tag{4}$$

However, certain problems arise with such an option. If each spell is aggregated, it is impossible to distinguish whether dependency is a result of long-term participation, with a possible skills deterioration and changes in motivation, or if it is due to various short spells as the recipient enter and exit the labour market. Furthermore, household characteristics may vary each time a claimant re-enters the program.

A second question concerns the existence of incomplete information on the time spent in the program before the information was gathered (left censoring) and on the future participation of households that are presently receiving benefits (right censoring). Our administrative records allow us to have access to complete historical series, thus eliminating left censoring. A way of dealing with right censoring is to include variables that provide information on the existence of censoring in the survival and hazard functions.

A third question is the distinction between *durations of welfare for those beginning a spell and those on welfare at a point in time*. The general question is would a different response be obtained if

[4] Some authors suggest the need of adding other indicative dimensions to welfare dependency. A prolonged period of claiming benefit that only makes a small contribution to household income could happen. Gottschalk and Moffitt (1994) defined an alternative measure: $TWI = \sum_{i=1}^{n} \left(\frac{1}{n} \cdot \frac{y_i^w}{\sum_i y_i^f} \right)$. It averages out for the whole population the weight that welfare income (y^w) has for each household with regard to the sum of all its different sources of income (y^f).

[5] Calculations made by Duclos *et al.* (1999) reveal that somewhat more the 40% of recipients in Canada leaving the programs return within two years. Blank y Ruggles (1994) find a 50% for the United States.

dependency relationships are established depending on which distribution is taken as a reference. Concerning the former, if the percentage of households (D(t)) whose spells in the program have lasted exactly t units of time is known, we can obtain the percentage of claimants with durations equivalent to that same period. As Duclos *et al.* (1999) point out this percentage is the product of the percentage of households that remained within the program in period *t-1* and the conditional probability of not receiving the benefit during period t:

$$D(1) = l(1), D(2) = l(2)[1 - D(1)], \ldots, D(t) = l(t)\left[1 - \sum_{j=1}^{t-1} D(j)\right] \tag{5}$$

In the case of ongoing recipients, the reasoning is different. The percentage of current recipients that will exit the program after taking part in it during period t is:

$$F(t) = \frac{tD(t)}{\sum_{j=1}^{\infty} jD(j)} \tag{6}$$

Bane and Ellwood (1994) use a very illuminating example to assess the implication of the double distribution. If we were to observe the ill entering and exiting the doors of a hospital for some time, we would find that most of those that enter do so to leave the hospital in generally short periods of time. If, however, we were to enter into the hospital wards, we would find a large percentage of ill people there that have been in hospital for a much longer period due to chronic illnesses. The implications of this for the programs under study are clear. Most of the expenditure is taken up by recipients with longer spells in the programs despite the fact that they only make up a relatively small percentage of all those who have at some point taken part in them[6].

The last relevant issue is selecting the *accounting period*. As Ashworth and Walker point out (1994), the use or monthly or annual data is crucial when analysing welfare durations. If the period under observation is brief, only a small percentage of the population that enters a program in a specific state will be included in the set selected. The extensive review carried out by Moffitt (1992) revealed that estimated durations are systematically shorter when monthly data is used.

1.2. *The Determinants of Welfare Duration*

The interest aroused by matters related to welfare dependency leads us to estimate not only the duration of participation spells but also the factors determining their lengthening. It is possible to

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[6] It could be objected that if only current recipients are taken into consideration, the existence of a steady state is accepted. If there are cyclical changes, however, the composition of welfare rolls in an economic boom (higher relative presence of chronic claimants) could be very different from that in an economic slowdown.

associate a vector of the households' socio-economic characteristics (X) to the hazard function that could have an influence on the chances of moving on to other situations outside the program:

$$l(t, X) = \lim_{dt \to 0} \frac{\Pr\{t < T \leq t + dt \mid T > t, X\}}{dt} \tag{7}$$

The theoretical foundations to explain welfare duration is much more limited than the attempts to explain other dynamic processes. The available studies essentially use a combination of *search* and *take-up* models. Durations depend on entry and exit decisions, which can be specified by means of normal supply equations with non-lineal budgetary constraints and cost functions. The key issue is the utility provided by the different income and leisure combinations resulting from benefits and labour market opportunities, both of which are affected by the socio-economic characteristics of each household. Moffitt (2001) defines a simple system of entry (E_t) and exit (O_t) equations with this reasoning. For households not taking part in the program at *t-1*, the entry function is determined by:

$$E_t^* = U\{w_t(1-t), y_t(1-t)+G\} - U(w_t, y_t) - C_V - C_E \tag{8}$$

where w_t represents the income the household could obtain in the labour market, y_t other income, t the earnings disregard and G is the guarantee level. The costs associated to the decision of taking part in the program can vary (C_V), —costs of applying for the benefit, time costs, the obligation of taking part in training activities or social stigma— or fixed as a result of moving onto welfare. It is simple to deduce that $E_t=1$ if $E_t^*>0$, and $E_t=0$ if $E_t^*\leq 0$.

The exit equation uses the same parameters, with the inclusion now of the costs associated with the decision to exit the welfare program (C_S):

$$O_t^* = U(w_t, y_t) - U\{w_t(1-t), y_t(1-t)+G\} - C_V - C_S \tag{9}$$

As in the previous case, $O_t=1$ if $O_t^*>0$, and $O_t= 0$ if $O_t^*\leq 0$. Given this utility structure of entry and exit decisions, entry rates are increasing in G. Likewise there is a lower probability if the implict tax burden on income derived from other sources is increased, or if employment and earnings opportunities improve:

$$\frac{\partial E_t^*}{\partial G} > 0,\ \frac{\partial E_t^*}{\partial t} < 0,\ \frac{\partial E_t^*}{\partial w} < 0\ ,\ \frac{\partial O_t^*}{\partial G} < 0,\ \frac{\partial O_t^*}{\partial t} > 0,\ \frac{\partial O_t^*}{\partial w} > 0 \tag{10}$$

It is generally believed that there are important differences in earnings opportunities between short and long-spell recipients[7]. In practice, however, numerous studies have revealed that different socio-economic characteristics have a very varied influence on recipients despite the fact that changes in program parameters and in macroeconomic conditions are relevant to explain entries into and exits from these programs.

This partially blurs the conclusion that changes in the job market play a decisive role in the duration of welfare spells in these programs. O'Neill *et al.* (1987) calculated the opportunity costs of taking part in these programs by taking into account potential earnings and working hours. The variables behaved in accordance with the previous assumption. Blank (1989) found that changes in unemployment have an influence on the possibility of exiting these programs, but that it was not significant. Hoynes and MaCurdy (1994) introduced alternative specifications of earnings opportunities and found that their variations affect short-term spells, although they hardly had any influence at all on longer spells. Sandefur and Cook (1997) confirmed the existence of a link between job market conditions and the probability of exiting the programs. However, this link was very tenuous and had less importance than demographic variables. In the case of Canada, Fortin *et al.* (1999) took into account much wider dimensions of the labour variables to find that there is a negative relationship between the probability of exiting these programs and the evolution of the unemployment rate. The coefficients were much lower than those for some demographic variables. Finally, Gottschalk (1997) attempted to offer an alternative specification by including other variables and using different dependency measures. He also found that unemployment had a limited influence on duration and detected notable differences among demographic groups.

The pressing question is what can explain welfare duration if it is not changes in the labour market. Moffit's (1992) review reveals that the models that obtain the best results were those that focused their analyses on households' socio-demographic characteristics. It therefore seems necessary to try to identify which of these characteristics could be the ones that have the greatest influence on the duration of spells.

It seems evident that changes in the labour market affect each household differently depending on its *educational and employability levels*. As transition into employment is one of the most common causes for exiting the programs, the recipients with the greatest chances of entering the labour market are also those that have the greatest probability of enduring shorter spells. This ability can be measured by different variables such as the working situation at the moment of entering the program or his/her educational qualifications (Barret, 2000). According to signalling theories, recipients with better qualifications offer employers greater possibilities of settling into jobs well.

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[7] An increase in durations of those already in the program would be expected if G increases. In addition, the number of new entries would increase. However, as Stewart and Dooley (1999) have pointed out, it could happen that mean durations would decrease if this last effect increases the number of households with shorter spells.

Sufficient information also exists concerning the singularity of the demographic characteristics of households receiving welfare. In various countries, single-parent households and people living alone tend to have longer than average spells (Heikkilä *et al.*, 2001). Regarding other variables such as age, the evidence is more tenuous and the assumptions more complex. For older people, arguments exist that foresee both shorter spells (access to other benefits) as well as more prolonged spells (large retraining difficulties and the difficulty of adapting qualifications to fit in with labour market demands). Recipients' gender can also be a determining factor given the greater obstacles women have to face to find a job. Nevertheless, certain kinds of low-paid jobs, particularly those that are rife in the black economy like domestic housework and cleaning activities, tend to be done by women. Household size is also relevant. The greater the number of members there are in a household, the more difficult it is to reach an income level enough to meet the family's needs. At the other end of the spectrum, people living alone could be suffering from difficulties in establishing personal relationships that limit their possibilities of social integration.

Lastly, the chances of obtaining income from other sources are also linked to the presence of *social problems*. Having had a criminal background, for instance, can be a disincentive to being taken on by an employer. It also seems clear that drug or alcohol abuse and the development of social alienation reduce the possibilities of entering the labour market.

1.3. *Duration Dependence vs. Unobserved Heterogeneity*

The concern for verifying the possible generation of dependency situations obliges us to take a comprehensive look into the relationship between the length of spells in programs and changes in the exit rates. There is positive duration dependence if $d\lambda(t)/d(t)>0$ and negative duration dependence if $d\lambda(t)/d(t)<0$. The argument that duration dependence exists has inspired most of recent reforms of welfare programmes. The belief that taking part at a given moment in time affects individuals' preferences or opportunities has been interpreted in some countries as a guarantee of automatic future participations.

There are various reasons that could explain this relationship. A prolonged spell could lead to a worsening of an individual's qualifications, therefore making access to the job market difficult. At the same time, duration acts as a signal to employers, who are less likely to take on individuals that have suffered a prolonged dependency on these benefits. Using up other sources of income, like savings or assets, can also make dependency on this economic safety net. Other more controversial arguments allude to changes in demographic habits that can lead to continuously relying on benefit. Reasons related to basic model parameters also exist. Lengthy spells may alter income and leisure effects by displacing the utility curve. Alternatively, the social stigma associated with taking part in such programs is reduced as the households taking part in them come to terms with their circumstance as a long-term situation.

The possibility of taking recipients' unobserved differences into account is necessary in order to assess any possible duration dependence (Kiefer, 1998 and Lancaster, 1990). If these are important, duration dependence could turn out to be a spurious result. Recipients could have different skills or motives that could make exiting these programs easier for a segment of the population, the weight of the population encountering the greatest difficulties would therefore increase with time. It seems logical to think, for instance, that individuals with the greatest human capital, a variable that cannot always be measured, will have shorter spells than individuals lacking in training. The latter would consequently have less possibilities of exiting these programs[8].

Unmeasured heterogeneity tends to produce hazard functions that decrease with time, even when the number of exits do not decrease for any individual of the sample (Heckman y Singer, 1985). There are different procedures to analyse possible duration dependence by controlling unobserved heterogeneity in duration models[9]. If q is a vector of unobserved variables and X a set of observed variables, the distribution function can be defined as:

$$F(t, X, q) = \exp\left(-\int_0^t l(u, X_u \mid q)du\right) g(q)d(q) \qquad (11)$$

where $g(q)$ is the distribution of unobserved variables. The lack of information on the appropriate characterisation of this function often makes if necessary to make different assumptions. The results are therefore sensitive to the decisions thus taken (Heckman y Singer, 1984).

Various studies have included different assumptions on the distribution of heterogeneity in these programs and duration dependence. Most of the studies reveal that the latter exists, although it is very concentrated in specific segments. Bane and Ellwood (1983) found a negative relationship between duration and exits from these programs in a ground-breaking study. Blank (1989) specified different models that included dependence duration and heterogeneity to find two clearly differentiated groups. One of these was made up of individuals with initially high exit rates that subsequently decreased and another group with low but constant rates. A similar conclusion was reached by Moffit (1992) based on a review of most of the available studies. Sandefur and Cook (1997) developed different contrasts to also find that the likelihood of exiting these programs is lower as duration increases. The development of conditional fixed-effect logit models allowed Chay *et al.* (1999) to find state dependence[10]. Green y Warburton (2001) calculated a model with experimental data that enabled them to have a control group in order to examine the correlation

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[8] Moffitt (2001) refutes this interpretation. According to his calculations, temporary and chronic recipients' job opportunities are not on average very different. The difference could lie in the fact that the former have a greater variance, or in the different ability of each group to meet administrative obligations.

[9] See Elbers y Ridder (1982), Chamberlain (1985), Heckman and Singer (1984), Honoré (1990) , Horowitz (1999) and Chay, *et. al.* (1999), among others.

[10] In addition, their results show an aggregation bias derived from the use of quarterly or annual data, which smoothen out duration dependence notably.

between present and future participation. Once again, their results revealed the existence of two groups. One can talk about the formation of dependency chains in the medium-term for one of these groups while for the other larger group, however, behavioural changes resulting from participating in these programs could not be confirmed [11].

1.4. *Duration and Alternative Exits from the Programs*

There are different ways of exiting welfare programs. There are remarkable differences, for instance, if exit results of finding a job from exiting because a recipient has not complied with administrative obligations. For some households, like single-parent households, another common reason for leaving is finding a stable family situation. It is necessary to develop analytical models that take this diversity into account. Econometric theory offers relatively simple responses. If j= 1,..., J is a variable that provides information on the type of exit corresponding to each household i, the hazard function for that household is:

$$l_{ij}(t) = \lim_{dt \to 0} \frac{\Pr\{t < T_i \leq t + dt, J_i = j \mid T > t\}}{dt}, \quad j = 1,..., J \tag{12}$$

Assuming the different ways of exiting the program are independent, the hazard rate for the whole set of recipients would be the sum of each specific hazard:

$$l(t) = l_1(t) + l_2(t) + \ldots + l_J(t) = \sum_j l_j(t) \tag{13}$$

In practice, however, it is not easy to clearly differentiate each type of exit. The classifications may turn out to be arbitrary and end up being sensitive to a particular analysis' political aims.

2. DATA

2.1. *The IMI's Administrative Records*

The data source used in this study are the administrative records on recipients of the Madrid Regional Government's Minimum Income program (IMI). The eligibility conditions are normal for this type of programs. There is an upper age limit (65 years of age, at which age claimants can benefit from the national non-contributory pension scheme) and a lower age limit (25 years of age, except for claimants with dependent children). Along with these, there is a time prerequisite for households to have already been formed in order to prevent the formation of fictitious family units solely aimed at receiving the benefit. Another legal requirement is being officially registered in the

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[11] The results for the United States were repeated for other countries, like Canada (Barret and Cragg, 1998, and

Madrid region as a resident. This requirement is compatible with people from other nationalities claiming the benefit. Lastly, the benefit is calculated differentially depending on the scale set for each kind of household. No major changes have been introduced since the IMI was implemented, which suggests that special attention should be paid to the households' socio-demographic characteristics when explaining durations within the program.

The processing of the administrative records allows us to access over 50,000 spells, with abundant information on each household's characteristics. Most of the variables contained in the database coincide with the ones highlighted by different studies as the best to analyse welfare populations (Mainieri y Danziger, 2001 y Goerge y Boo Lee, 2001)[12]. However, the fact that these administrative records were designed to cover management needs has made it necessary to cleaning and re-sort the data. Different administrative files have been merged, original variables have been treated by cross-checking fields, control variables have been added and new variables have been created in order to make the information suitable for the study's aims.

In order to build-up a suitable file to analyse duration, it was necessary to make different suppositions and adopt alternative decisions concerning how to define entries into and exits from the program, as well as semester-long spells. After eliminating inconsistencies in the dates recorded, the moment the first benefit was paid out was considered as the entry date into the program. The exit date was considered as the last date an annotation was made on the claimant's monitoring file. A chronological sequence of 23 semesters was defined (from the second half of 1990 to the second half of 2001) to contrast possible trajectory inconsistencies in the program inferred from the records. Lastly, different assumptions were made on the exact number of semesters each household remained in the program. Another variable was added indicating the data quality for each record.

2.2. *Analysis of Recipients*

A descriptive analysis of the IMI data allows us to have a preliminary assessment of the characteristics of participating households. Remembering the notion expressed above concerning two reference distributions, the tables and comments differentiate between the households that had a spell in the program at some time between 1990 and 2001 and the households that are presently receiving benefits. Almost fifty thousand spells are available, which are divided into the approximately 42,000 observations that correspond to already dosed claimant files and 7,500 ongoing participants.

Stewart and Dooley, 1999).

[12] The database offers information on beggary and prostitution problems. It also includes the homeless, a group which by definition is absent from all surveys based on census information.

The data on age shows a larger presence of middle-aged individuals among households' heads (Table 1). Concerning the differences between former and ongoing recipients, the lower proportion of young people and the greater presence of individuals over 55 in the former stand out. This is due to the transfer of recipients to the national non-contributory pension scheme at the age of 65. The relative frequencies of recipients' gender suggest that the program has been increasingly used by women. Women represent almost two-thirds of current spells and around 60% of former participants. Regarding *household size and type*, small households stand out in general. People living alone make up a third of total households and have gained in relative weight over time. The presence of single-parent households is also striking, accounting for almost 40% of all cases. While the percentage of single-parent households is common to other European countries, the high figures for people living alone is a differentiating feature of the program being analysed.

A final set of variables provides information on different *social problems* that accompany the lack of income. Various studies on the living conditions of the poor have made it clear that there is a notable incidence of multiple social pathologies in groups suffering from extreme poverty (EDIS *et al.,* 1998). Five types of social problems stand out among IMI recipients. The first is related to health problems, be they general health problems or those derived from the consumption of drugs and alcohol, as well as from mental illnesses. Another group constitutes social pathologies arising from insolvency in situations of debt, including non-payment for dwellings. A third problem involves belonging to an ethnic minority[13]. There is also a large percentage of recipients suffering from severe mental health problems that limit their chances of becoming economically self-sufficient. A final problem is the development of behaviour associated with social alienation, such as begging or prostitution, although this group is not really relevant in quantitative terms.

3. A NON-PARAMETRIC ANALYSIS OF WELFARE DURATION

The debate on the existence of dependency chains associated to prolonged spells in welfare refers back to the analysis of the duration of each spell. As was mentioned previously, there may well be substantial differences in the possible conclusions depending on whether a longitudinal or a cross-sectional approach is taken. Table 2 shows the differences in the average durations of households beginning a spell and ongoing recipients. In the case of spells that have come to an end, the data reveals a notable concentration of recipients in shorter time intervals. The cross-section distribution shows a profile that is relatively similar, although there are some differences. Though the percentages are higher in the first two intervals the figures are lower than those of the first column, while just the opposite happens with longer-term spells.

The results are considerably lower than the ones estimated for the United States (Pavetti, 1993, and Bane and Ellwood, 1994), Canada (Duclos, et. al., 1999) and for other central and northern

European countries (Heikkilä *et al*., 2001). This suggests that one should put the possible critiques on dependency generation within the IMI program into some sort of perspective. Nevertheless, any inferences should be made with great care. On the one hand, because the few years the program has been in operation makes it difficult to compare it with programs that have been going on for a much longer time and, on the other, because the institutional characteristics of these programs differ considerably, particularly the IMI's low benefit and replacement rates.

Non-parametric estimation procedures allow us to define a preliminary set of characteristics that are potentially linked with program duration. The most common tool to do this is the Kaplan-Meier estimator, which is defined as follows:

$$\hat{S}(t) = \prod_{j|t_j \leq t} \left(\frac{n_j - d_j}{n_j} \right) \tag{14}$$

where n_j represents the households that remain within the program and d_j those that exit it. To represent the programs' hazard function resulting from applying the estimator, we have chosen to apply a Kernel smoothing procedure. Given its properties for estimating hazard functions, we used the algorithm proposed by Ramlau-Hansen (1983)[14].

The exit function corresponding the different *age groups* allows us to find the main differences in extreme cases (Figure 1). *Gender* does not seem to be a clearly differentiating factor for duration. Only when combined with other characteristics, such as the presence of other adults or family burdens, does it appear to be a determining factor for lower probabilities of exiting the program. Results for *household size* reveal that the probabilities of exiting are generally higher for smaller households, apart from households made up of a single individual. Something similar can be said for the *number of children*. Exit rates are consistently lower as this number increases. The hazard functions for *household type* also show relevant differences. Exit rates are lower for single-parent households and people living alone. The hazard profiles for *educational qualifications* reveal a lineal relationship, except for the final ascending curve for those possessing secondary school qualifications. The results on *labour force status and employability* confirm a lineal profile in the groups having the greatest chance of finding employment, as well as constant exit rates for the groups that find greatest difficulties in accessing the job market when their spells in the program are prolonged.

The data on *social problems* reflect the different incidence of each specific kind of problem (Figure 2). In most cases, the curves are below that for the rest of the population, except for households suffering from alcohol consumption and drug abuse. For these cases, problems related to

[13] Belonging to an ethnic minority is not in itself a social problem. It is regarded as such in so far as belonging to an ethnic minority limits a person's possibilities of social integration.

performing administrative requirements help to explain the fact that their exit rates are higher than what would be expected due to the problems they encounter in finding stable employment. The most striking feature among the wide range of social difficulties is the distance separating the hazard function of households belonging to an ethnic minority from the rest of the population.

A way of assessing the varying incidence of the above-mentioned variables are contrasts that measure the similarity of the survival functions for different population categories. Under the null hypothesis for identical hazard functions, statistics can be calculated that measure differences between observed exits and their expected values:

$$\sum_{j=1}^{r}(d_{ij}-e_{ij}) \tag{15}$$

where d_{ij} represents the number of exits of group i at moment j, while e_{ij} is the number of expected exits. Different indicators are based on this function, although the weighting used for calculation differs. The most common are the *log rank*, which does not use weightings, and the *Wilcoxon Test* in which the number of cases is the basis of weighting. Both contrasts allow us to identify which variables have the greatest influence in estimated durations by examining the individual contribution to the c^2 (Table 3).

Except for the case of alcohol consumption, practically all the variables are significant to 99%. Although both tests do show some differences in how the variables are ordered by explicative capacity, they coincide in identifying employability (with a negative effect on duration) and belonging to an ethnic minority (with a positive effect on duration) as the main determining factors. Household type and size also seem to be key factors. The data points to the fact that people living alone, single-parent households and large families have a greater chance of spending longer spells in welfare programs. Educational levels also provide relevant information on durations, although it is less important with the Wilcoxon test. Just the opposite happens with the claimant's gender and mental health problems. Apart from belonging to an ethnic minority, the non-parametric contrasts do not seem to give any great explicative capacity to most of the social problems despite the fact that they are significant variables.

4.THE DETERMINANTS OF WELFARE DURATION: A PARAMETRIC APPROACH

The non-parametric study of duration in the program allows us to identify some of the household characteristics that are linked to a greater chance of remaining in it. In order to be able to predict duration values and quantify the factors that determine them in probability terms, we will use

[14] The filter is defined as $\bar{l}(t)=\frac{1}{b}\int_0^1 K\left(\frac{t-s}{b}\right)d\bar{b}(s)$, being b>0.

parametric models. As in the case above, we will focus our attention on the socio-demographic characteristics of households taking part in the program. The main reason for this is the lack of any great regulatory changes, unlike those seen in other countries that have had a decisive influence on designing explicative models[15]. Following Blank (1989), we will take *households' characteristics at the moment of entering into the program* as a reference. To assess the sensitivity of the models estimated to the treatment given to re-entries to the program, other specifications will be added.

A second methodological decision is the response given to the *censoring problem*. More than seven thousand households remained in the program when the data was gathered. Should censoring exist, the conventional framework of a regression analysis, which assumes that the dependent variable —duration in the program— is the sum of the explicative variables' effects and a random variable that is normally distributed, is not very appropriate[16]. For this very reason, the different models are estimated by maximum likelihood. As was mentioned before, the way of incorporating censoring to the likelihood in duration models is relatively simple[17]. Let us suppose information exists on n number of independent individuals ($i=1,\dots,n$) that have gone through or remain in the program and that $\boldsymbol{d_i}$ is a representative variable for censoring. The contribution made by each household to the likelihood function can be calculated by means of a relationship like:

$$L = \prod_{i=1}^{n} L_i = \prod_{i} l(t_i)^{d_i} S(t_i) \tag{16}$$

The last option to be made before specifying the models is the need to define the most suitable *distribution* for *t*. It is well known that the results of duration models are very sensitive to decisions taken concerning the form of the distribution. The scope of the IMI program's database improves the analysis' options. The flexibility of semi-parametric models and the ease with which they are calculated has led their use to be extended to duration analyses for most welfare benefits. We have chosen to use a parametric model with a log-normal distribution given that the contrasts carried out confirm that it is the most suitable functional form for the data being used. Other models are also calculated to contrast the sensitivity of the estimated durations to the option chosen.

4.1. *Estimating the Model*

The diversity of possible functions in a parametric model makes it necessary to broach the issue of setting a selection criterion. It has frequently been the case that Weibull type functions have been used to analyse the duration on welfare programs (Blank 1989, and Sandefur and Cook, 1997).

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15 See Ayala and Pérez (2003) for an analysis on the relationships among the economic cycle, parameter changes of welfare programs and demand for the IMI.

16 Some authors have proposed using OLS to analyse survival with censored data (Lawless, 1982). Apart from the obvious theoretical difficulties of justifying the hypothesis' specification, results have very high standard errors.

17 See Klein and Moeschberger (1997) for a detailed treatment of the application of parametric duration models to censored data.

These assume the hazard rate increases or decreases monotonically over time. Although it has the advantage of being easy mathematically, this function does not necessarily have to be the most suitable for duration in the IMI. A simple optimum function selection method is the one proposed by Klein and Moeschberger (1997), which uses the slope of the survival function as a criterion:

- if the distribution is exponential with a survival function $\{S=\exp[-gt], \gamma>0, t\geq 0\}$, the graphical representation of (- log $\hat{S}(t)$) *versus* t is a straight line
- if it is a Weibull type distribution with a survival function $\{S=\exp[-\gamma t^{p}], p, \gamma>0, t\geq 0\}$, the graphical representation of (- log $\hat{S}(t)$) *versus* log (t) is a straight line
- if the distribution is log-normal with a survival function $\{S=1-\Phi\left[\frac{\ln t-m}{s}\right]$, $\sigma>0$, $t\geq 0$, Φ being a normal distribution function, the graphical representation of Φ^{-1} [1- $\hat{S}(t)$] *versus* log(t) is a straight line
- if the distribution is log-logistic with a survival function $\{S=\frac{1}{1+gt^{a}}$, $\gamma>0, t\geq 0\}$, the graphical representation of [(1- $\hat{S}(t)$) / ($\hat{S}(t)$)] *versus* log(t) is a straight line.

The different contrasts confirm that a log-normal distribution is the one that best fits in with the IMI program (Figure 3). To check the results with other distributions, we also estimate a Weibull-type model.

The log-normal distribution's hazard rate is given by the relationship between the density and survival functions:

$$l(t)=\frac{f(t)}{S(t)} \tag{17}$$

These are respectively:

$$f(t)=\frac{\exp\left[-\frac{1}{2}\left(\frac{\ln t-m}{s}\right)^{2}\right]}{t(2p)^{1/2}s}=f\left(\frac{\ln t-m}{s}\right)/t \qquad \text{and} \qquad S(t)=1-\Phi\left[\frac{\ln t-m}{s}\right] \tag{18}$$

In a log-normal time distribution, the probability of abandoning the program is conditional upon a vector of household characteristics (X) that can be expressed as a regression model in which the dependent variable is the hazard logarithm:

$$\log\ l(t)=\log\ l_{0}(t\, e^{bx})-bx \tag{19}$$

The characteristics chosen for the basic model include: the age of the head, employability, the number of simultaneous social problems, educational level, the household size, the number of children and four dummy variables (indicating the recipient's sex, whether it is a single-parent household, an individual living alone or belongs to an ethnic minority). A second model adds the existence or not of different social problems to these variables, including mental health problems, prostitution, non-payment for dwellings and drug consumption.

The hazard rate for a Weibull-type distribution is expressed as $l(t)= gpt^{p-1}$, while the survival function is $S(t)= \exp(-gt^{p-1})$. If we transform time into logarithms, $Y=\ln t$, the survival function can be expressed as $S(y)= \exp(-l e^{py})$. Y may take on the form of a log-lineal model redefining parameters as $l=\exp(-m/s)$ y $s=1/p$:

$$Y= \ln t = m + s W \tag{20}$$

with $f_W(w)=\exp(w-e^{w})$ y $S_w(w)=\exp(-e^{w})$ being, respectively, the density and survival functions of W. The likelihood function when there is right censoring is given by:

$$L=\prod_{j=1}^{n}\left[\frac{1}{s}f_w\left(\frac{y-m}{s}\right)\right]^{d}\left[S_w\left(\frac{y-m}{s}\right)\right]^{(1-d)} \tag{21}$$

With the same vector of characteristics $\boldsymbol{X}$ as in the previous case the hazard function is:

$$l(t\,|\,x)= \exp(bx)\, gpt^{p-1}[x \exp(bx)] \tag{22}$$

The results obtained from applying the log-normal model to the IMI data offer up a highly satisfactory fit (Table 4). The overall significance level is very high and all the coefficients are significant at the 99%. The likelihood tests confirm that the log-normal model has a better fit than the model with a Weibull-type distribution. In general terms, the model estimated confirms the conclusions deduced from the non-parametric analysis. Belonging to an ethnic minority and especially employability appear, with different signs, to be the main determining factors for duration in the program. The remaining factors show the expected signs. Higher educational levels have a negative effect on duration. Greater difficulties are also encountered in exiting the program when different social problems exist simultaneously or when we are dealing with individuals living alone or single-parent households. Female claimants have a lesser chance of exiting the program.

More doubts arise when we consider the opposite effects obtained for household size and number of children. Although the differences are not very marked, it seems obvious that there would be more children in large households. To interpret this correctly, one must take into account the uniqueness of people living alone which could bias the coefficient corresponding to the household size. The information on social problems adds some relevant qualitative elements. The coefficients are significant, although the fit improves by very little. Social isolation turns out to be a factor that limits exiting the program and expected duration is considerably higher when there are problems associated with prostitution, despite the fact that the actual number of cases is very low. Coefficients for problems concerning the non-payment of dwellings and drug abuse have the opposite effect. As will be seen below, difficulties in completing the necessary administrative monitoring forms in order to receive the benefit may have an influence on this.

The results therefore appear to be consistent with the preliminary hypotheses. Given that employability turns out to be a decisive factor for remaining within welfare programs, it seems necessary to design training strategies that would increase the chances of a large percentage of recipients of finding employment. It can also be deduced from the results that investing in training and recycling measures should essentially be focused on the segments lying between the total incapacity for work and the temporarily unemployed. At these two extremes, the program's function should be to maintain income. It is to be expected that the former of these groups will be chronified in the program, while the individuals who can work will not take long to exit it.

The results also suggest performing specific actions aimed at particular groups. Single-parent families should receive complementary benefits to ensure their level of income while a very different problem is that suffered by people living alone. Their lack of social relationships should be offset by individualised measures. In the case of ethnic minorities, the problem of incorporating culturally differentiated groups into the labour market and the difficulties of changing very deeply rooted and socially determined patterns of reproduction make if very difficult for these groups to exit the programs.

A doubt remains, however, if any of the methodological decisions taken could have had an influence on the direction or value of the coefficients. The two most controversial decisions are how re-entries are dealt with and the cleaning of the data necessary to quantify durations. According to Stewart and Dooley (1999), a possibility would be to include re-entries as an explicative variable. Shorter durations are to be expected *a priori* as this number increases. The results of the basic model including re-entries are very similar to the results obtained without considering this variable (Table 5). The coefficient's sign is what was expected, although not very relevant quantitatively. The remaining variables do not change substantially. The coefficients for age, gender and people living alone are slightly higher, but the standard errors are greater.

A way of assessing the sensitivity of the basic model's results to the decisions taken when the information contained in the records show inconsistencies in temporal sequences is to compare the results with those obtained if only data without cleaning assumptions are included. The results reveal some changes when they are compared to those of the initial estimation, although the signs of the coefficients do not change (Table 6). The ranking of the variables does not change substantially, although the weight of some of them, such as recipient's gender, single-parent households and belonging to an ethnic minority, do increase. The errors are, in any case, much greater than in the initial specification and a fair number of variables lose statistical significance, including most social problems.

4.2. *Duration Dependence and Unobserved Heterogeneity*

Apart from offering information on the determining factors for spell durations in the IMI, the estimations of the previous section allow us to respond to the second type of questions initially broached. These include: does the probability of leaving the program diminish as duration gets longer? What is the sign, if it exists, of duration dependence? The hazard function for abandoning the IMI program for the average value of the lineal predictor $x\beta$'s (Figure 4) can be drawn from the basic model estimated with the chosen variables. The probability of exiting increases rapidly for spells less than two years, its pace of increase slows down until the third and from that moment on it decreases.

In order to accept the hypothesis of a decreasing number of exits as duration increases, it is necessary to analyse if there is any relevant information that has not been taken into account when the models were designed. If unobserved heterogeneity in time distributions exists, it is possible that the inferences on the scope of duration dependence are subject to error. Different studies have pointed out that it is probable that there is a bias that lowers estimated dependence under these conditions. As was explained above, there are various arguments that could account for the existence of different forms of heterogeneity that are difficult to observe in welfare programs.

Among the procedures that are available to monitor the scope of unobserved heterogeneity, the most normally used is to incorporate a common random effect into the previous model. This effect multiplies the hazard rates of all the members belonging to a specific sub-group. An attempt is made to make the analysis conditional upon an unobserved variable with a distribution that is independent of the explicative variables under consideration[18]:

$$\lambda(t \mid \alpha) = \alpha\,\lambda(t) \qquad (23)$$

where α is some random positive quantity assumed to have mean one and variance θ. Households with $\alpha > 1$ will have a greater likelihood of leaving the program earlier due to unobserved characteristics, while just the opposite is true if $\alpha < 1$. The individual conditional survival function is as follows:

[18] See Gutierrez (2000) for a detailed revision of these models and computational methods to take account of heterogeneity in parametric estimations.

$$S(t \mid a)=\{S(t)\}^{\alpha} \tag{24}$$

where $S(t)$ can take on different specifications. The survival function for the whole population is obtained by integrating out the a): Being g(a)the density function:

$$S_q(t) = \int_0^{\infty} \{S(t)\}^a \, g(a)da \tag{25}$$

The fundamental question resides in the distribution chosen for a. Since Lancaster's ground-breaking study (1979), there has been a clear trend of using the gamma function. Its justification lies in the ease of programming it and the way it fits in well with models that use simple explicit expression functions. When a is distributed as a gamma with men one and variance q is:

$$g(a) = \frac{a^{1/(q-1)} \exp(-a/q)}{\Gamma(1/q)q^{1/q}} \tag{26}$$

Therefore the survival function becomes:

$$S_q(t)= [1 - q \ln\{S(t)\}]^{-1/q} \tag{27}$$

As in the case of the models with no control of heterogeneity, the likelihood function is comprised of a combination of former and censored recipients:

$$\ln L = \ln \prod_{i=1}^{n} \frac{\{S_{qi}(t_i)\}^{1-d_i}\{f_{qi}(t_i)\}^{d_i}}{S_{qi}(t_{0i})} = \sum_{i=1}^{n} \left[\ln\{S_{qi}(t_i)\} - \ln\{S_{qi}(t_{qi}\} + d_i \, l_{qi}(t_i)\right] \tag{28}$$

The use of this procedure to analyse the duration of welfare programs has been placed into question by various authors. Some of the criticisms are due to conceptual difficulties. It is possible that continued participation in the program could cause changes in unobserved variables such as individuals' motivation (Blank, 1989). In that case, an attempt to correct heterogeneity not only would eliminate the bias of the duration dependence estimation but also introduce other biases. From a strictly methodological standpoint, generalising the use of a specific form for the distribution of heterogeneity –mainly the gamma function– has also been challenged. Various authors have checked the sensitivity of results against incorrect distribution specifications. They propose a non-parametric maximum likelihood estimator to minimise the consequences of opting for a specific form of distribution.[19]. Various studies conducted in Spain use this procedure to

[19] It is possible to approach the distribution of unknown probability be means of a parameter vector that represents the finite set of distribution values and estimate the probability associated with each of these values.

analyse the effects of unemployment benefits on the duration of unemployment[20]. Nevertheless, some recent studies show the relevance of using the gamma function to correct unobserved heterogeneity. Abbring y Van den Berg (2001) found that the distribution of survivors converge on a gamma distribution for a very large range of distributions.

In order to measure the sensitivity of the gamma distribution option, we also estimate another model that uses an inverse Gaussian distribution. When α follows this distribution:

$$g(a) = \left(\frac{1}{2pqa^3} \right)^{\frac{1}{2}} \exp\left\{ -\frac{1}{2q} \left(a - 2 + \frac{1}{a} \right) \right\} \tag{29}$$

and the resulting survival function is:

$$S_q(t) = \exp\left\{ \frac{1}{q} \left(1 - [1 - 2q \ln\{S(t)\}]^{\frac{1}{2}} \right) \right\} \tag{30}$$

The most significant conclusion that can be reached from estimating this new model is the absence of any great changes in the coefficients calculated (Table 6). In general terms, these decrease, except for age. The higher coefficient of people living alone is the only relevant change. Something similar happens with the models that use a Weibull-type specification, although changes are more visible. These include the greater effect for female recipients. There is likewise very little change in the coefficients regardless of whether the gamma or the inverse Gaussian are used.

The results for the specification using a Weibull-type function appear to point to the presence of an individual unobserved effect. The estimated parameter ($\hat{q}$) is high and significant and p increases significantly, indicating a growing probability of abandoning the program. Nevertheless, this result could be due to the fact that a homogenous population exists that does not fit in with the Weibull's monotonous hazard profile. Such is the case if there are homogenous households with a hazard function that first increases and then diminishes like the log-normal that seems to fit in with IMI's spells. When adopting the monotonous hypothesis the correction models calculated for heterogeneity therefore assign a high value to it. Proof of this is that heterogeneity is much less relevant in the log-normal model, although there appears to be slight hints of it.

4.3. *Multiple Exits from the Program*

It has been implicitly considered in the calculations carried out that exits from the IMI are homogeneous. In practice, however, there are different ways of leaving the program. Exits caused

[20] See Bover *et al.* (1996), Ahn and García Pérez (1999), and Arranz y Muro (2002), among others.

by the fact that a recipient has taken part in public-funded training initiatives are very different from being expelled from the program for not fulfilling administrative obligations. Likewise, it is not very difficult to imagine that the processes that explain individuals exiting the program because they suffer from drug abuse problems, lack a fixed address or encounter difficulties when filling out administrative forms, differ considerably from those for individuals above 55 years of age who leave the program upon reaching 65 to benefit from the national non-contributory system.

Differentiating the determining factors for each kind of exit thus seems to be relevant. The IMI records offer comprehensive information on the causes behind each exit. It is possible to group them together into three types. The most important of these could be classified as "successful" exits. According to the records' codes, earning income above the minimum requirement, completing objectives agreed upon or recipients voluntarily abandoning the program could all be grouped together under this kind of exit. A second group is linked to being expelled from the program for not satisfying the commitments undertaken. These could include not meeting integration contract commitments, inadequate use of benefits, not taking children to school, fraud, not giving notice of changes, rejecting to take part in job insertion initiatives or being excluded from integration projects. A third group of causes could be classified as "administrative". They include becoming 65, moving out of the Madrid region, death or being committed to prison.

The first basic question that arises is to identify the factors that determine duration for each type of exit. The second question is to contrast the level of similarity in the profile of each destination. Econometric theory offers sufficiently contrasted responses to study both these questions. Under certain circumstances, such as the lack of correlation among unobserved factors that affect each kind of exit and the need to treat as censored exists different from the ones analysed, the overall hazard rate can be expressed as the sum of the hazards corresponding to each exit. If j= 1,..., J is the type of exit, specific survival functions can be defined as:

$$S_j(t) = \exp\left\{-\int_0^t \lambda_j(u)du\right\} \tag{31}$$

The hazard rate can be disaggregated as the sum of each specific hazard:

$$\lambda(t) = \lambda_1(t) + \lambda_2(t) + \lambda_3(t) = \sum_j \lambda_j(t) \tag{32}$$

The specific hazard for each exit can be calculated with the same procedures used to determine the factors behind the program's overall duration:

$$\log \lambda_{ij}(t) = \alpha_j(t) + \beta_j x_i(t) \tag{33}$$

The multiple exit model's likelihood can be decomposed as the sum of partial contributions.

Estimating the log-normal model by possible destinations reveals the existence of different determining factors for each case (Table 7). Due to the fact that people access the non-contributory pension scheme at 65, age is a considerably more decisive factor for administrative reasons than for the others. Belonging to an ethnic minority has a greater effect on lengthening duration for exits due to fraud than in the rest of the exits, where even has an opposite effect from the one seen in the general model. It must be taken into account that the multiple exit model excludes households that are presently receiving benefits, which could include those with the most prolonged spells. The only variables that maintain their sign and statistical significance are employability and the number of children.

Reviewing the determining factors for each kind of hazard allows us to approach the second question we posed. Can we talk about radically different explicative models for each type of hazard? This question can be reformulated as whether durations differ lineally in time depending on the causes for exiting the program. Some statistical contrast on the similarity of the hazard functions is needed to answer it. A criterion is the proportionality of the functions. If the probability of exiting the program for "successful" reasons changes over time, the hazard corresponding to exits due to fraud or for administrative reasons should also change:

$$l_j(t) = w_j\, l(t) \qquad j=1,\ldots,3 \tag{34}$$

where w_j is a constant representing proportionality .

Figure 5 shows the hazard functions obtained by means of the Kaplan-Meier estimator with the Kernel smoothing described above. The probability of leaving the program in "successful" and "exits due to fraud" is relatively stable with moderate growth. There is a slight peak when a spell exceeds one hundred months. The profile for exits due to administrative reasons is very different. It is relatively stable and decreasing, and crosses the other two curves.

Parametric methods can also be used to estimate the similarity or divergence of the hazard functions. A possible way of doing this is using proportionality contrasts[21]. Cox and Oakes (1984) set out the procedure for contrasting a model with only two types of exit::

$$\log\ l_j(t) = a_0(t) + a_j + b_j(t) \qquad j=1,2 \tag{35}$$

The proportionality hypothesis is met if $b_j = b$, $\forall\, j$. When $b_j \neq b$, the *log*(hazard) of each exit diverge lineally in time. In this way, a logistic regression can be estimated for each kind of exit with time as

[21] Another alternative approach would be to use techniques that attempt to prove the equality of the coefficients estimated (Narendranathan and Stewart, 1991).

an explicative variable. If the number of kinds of exits is greater than two, as is the case with the IMI, the solution is a multinomial logit.

Table 8 gathers the results of calculating the contrasts proposed by Cox and Oakes for the three possible ways of exiting the IMI. An ANOVA analysis confirms that time has a highly significant effect, which implies rejecting the hypothesis of proportionality. The coefficients in the second table show which hazard functions meet the hypothesis and which do not. There are two clearly different processes. On the one hand, the coefficient for successful exits and exits due to fraud is almost zero. Furthermore, χ^2 has a very low value, far from the statistical significance requirements. Thus, the proportionality hypothesis cannot be rejected. The hazard function for both ways of exiting the program is similar. On the other hand, the same cannot be said for the parameter showing the relationship between exits caused by administrative reasons and those due to fraud. The coefficient is much higher, and the high level of significance allows us to reject the proportionality hypothesis. The probability of exiting the IMI for administrative reasons decreases much more quickly over time than is the case for exits due to fraud.

The results therefore seem to confirm the existence of a specific hazard function for exits due to administrative reasons, as well as showing the similarity of the processes that determine the "successful" exits and those "due to fraud". This similarity places into question the commonly held view that exits due to fraud are clearly differentiated from exits derived from meeting economic self-sufficiency objectives. A proportion of the exits due to fraud could hide improvements in the economic situation of these recipients. Compared to the lack of sanctioning mechanisms, incentives exist that lengthen the time the benefit can be enjoyed.

5. CONCLUSION

Over the last decade, welfare benefits have been at the centre of the debates focused on the reform of income maintenance programs. The reforms put into effect have introduced more restrictive access conditions and have sought to find a closer link between receiving the benefit and working in order to reduce chronification. This study has made an attempt to examine the determining factors behind spell duration in these programs in Spain based on an average minimum income program. All the contrasts carried out coincide in pointing out that belonging to an ethnic minority and employability are the main determining factors leading to lengthened spells. These results are coherent with the theoretical framework that was set out, which gave a significant weight to demographic characteristics to explain welfare duration. In addition, they are also statistically consistent, as can be seen both from the fact that they meet the requirements of the log-normal parametric model as well as from their robustness in the face of alternative specifications.

The implications derived from the results are of interest. There are different kinds of recipients depending on their possibilities of entering the labour market. These need to be dealt with differently. An important segment of households accesses the program temporarily. The best course of action for these households is to ensure a basic level of income rather than paying out large sums in training processes due to the likelihood that they will leave the program in the short-term. For very different reasons, the same solution also seems logical for people who are totally unfit for employment. The different sections of the study have shown the great barriers this group –with a much higher probability of chronification than the other groups– encounters to exit the program successfully by finding work.

This study has also proved that there is a certain degree of duration dependence. The fit of the log-normal model to the dynamics of the program confirms that the exit patterns have a very characteristic profile. The probability of abandoning the program increases during the first three years and is then reduced gradually from this threshold. In any event, the pace of reduction in the hazard rate is more gradual than its initial upward curve. These results are confirmed when unobserved heterogeneity is monitored. It seems to have little effect due to the large number of variables and the inclusion of very detailed information on household characteristics.

Lastly, the study shows there is a need to differentiate among the factors that affect each type of exits from the program. Households leave the program for very different reasons. The contrasts carried out to assess lineal convergence in time of the different ways of exiting the program clearly show a striking similarity between the profiles of exits from the program for successful reasons and those due to fraud. Exits from the program caused by administrative reasons behave in a clearly different way. This result warns against making excessively restrictive classifications that consider the first two types of exits as different.

Making use of administrative records can therefore serve to provide abundant quantitative information for the debates on welfare program reforms, as well as more detailed knowledge on the dynamics of taking part in such programs. Characterising the processes that determine welfare duration should contribute to improve any initial diagnoses made before reforms are put into place. They should also help design more suitable social insertion investments that accompany minimum income programs.

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Table 1
Socio-Economic Characteristics of IMI Recipients
(*frequency distribution*)

	Households beginning a spell	*Households on welfare at a point in time*
AGE		
<26	6,7	11,4
26-35	30,9	29,5
36-45	28,7	26,5
46-55	18,0	19,6
56-65	15,7	12,9
GENDER		
Males	40,3	34,2
Females	59,7	65,6
HOUSEHOLD SIZE		
1 person	25,8	33,4
2 people	20,6	21,1
3 people	20,2	18,6
4 people	15,5	12,1
5 people	8,9	7,6
6 people	4,7	3,9
7 people	2,2	1,9
8 or more people	2,0	1,3
HOUSEHOLD TYPE		
Single person	25,8	33,4
Single-parent household	31,6	37,6
Other households with children	20,1	12,0
Other households without children	22,5	17,0
EDUCATION		
Does not read or write	10,3	13,6
No academic qualifications (only reads and writes)	20,6	21,6
Primary Education	36,7	35,5
Middle School Education	18,1	15,8
Secondary Education	6,6	6,6
Level 1 Vocational Training	2,9	2,3
Level 2 Vocational Training	1,7	1,4
University Degree	1,3	1,3
Post-Graduate Degree	1,5	1,8
LABOUR FORCE STATUS		
Employed	18,0	13,5
Unemployed	59,1	69,0
Inactive	22,9	17,5
EMPLOYABILITY		
Totally unfit for normal work	9,6	8,0
Needs process of social / health recuperation	23,8	37,3
Unemployed needing training / education	21,1	25,4
Could access employment now	32,4	21,3
Does work on hidden economy or equivalent activity	8,3	7,0
Does normal work or equivalent activity	4,8	1,1

TABLE 1 (continued)

SOCIAL PROBLEMS[1]		
Drug abuse	5,0	6,0
Alcohol abuse	4,8	4,7
Other mental health problems	8,8	10,9
Other serious health problems	14,9	18,1
Non-payment of dwelling, eviction	6,3	7,0
Debt accumulation, non-payment	9,7	9,4
Beggary	0,8	1,2
Prostitution	0,4	0,7
Social isolation	10,8	15,9
Ethnic minority	11,7	23,2

[1]The categories appearing in social problems are non-excluding dummy variables. A household can therefore suffer from more than one problem. The figures show percentages of recipients affected by each problem.

Table 2
Distribution of Spells

	Households beginning a spell	*Households on welfare at a point in time*
< 1 year	6,1	16,6
1 to 2 years	60,8	37,5
3 to 4 years	16,2	13,0
5 to 6 years	8,6	11,3
7 to 8 years	3,9	6,9
9 to 10 years	2,0	5,6
> 10 years	2,3	9,3
TOTAL	100,0	100,0

Table 3
Non-Parametric Tests

	Sign of the Coefficient	Wilcoxon Test		Log-rank	
		Δc^2	Pr > Δc^2	Δc^2	Pr > Δc^2
Employability	-	1302,1	< .0001	934,7	< .0001
Éthnic Minority	+	1173,5	< .0001	826,0	< .0001
Females	+	214,9	< .0001	67,5	< .0001
Single Person	+	169,0	< .0001	207,0	< .0001
Severe Mental Health Problems	+	166,8	< .0001	68,9	< .0001
Educational Level	-	122,5	< .0001	138,6	< .0001
Number of Children	+	107,7	< .0001	12,9	0.0003
Single-Parent	+	101,7	< .0001	125,5	< .0001
Age	+	40,6	< .0001	13,1	< .0003
Household Size	-	23,7	< .0001	98,0	< .0001
Number of Problems	+	18,7	< .0001	15,8	< .0001
Non-Payment of Dwelling	-	12,6	0.0004	10,3	0.0013
Drug Abuse	-	12,3	0.0005	7,2	0.0073
Prostitution	+	6,5	0.0107	7,6	0.0042
Alcohol Abuse	+	4,3	0.0373	0,1	0.8245

Table 4
Results of Parametric Models

	Log-normal		Weibull	
Constant	3,480***	3,477***	3,869***	3,859***
	(0,0343)	(0,0344)	(0,0343)	(0,0344)
Age Group	0,026***	0,023***	0,021***	0,019***
	(0,0043)	(0,0044)	(0,0044)	(0,0044)
Employability	-0,118***	-0,117***	-0,109***	-0,107***
	(0,0046)	(0,0047)	(0,0047)	(0,0048)
Number of Problems	0,040***	0,039***	0,040***	0,041***
	(0,0052)	(0,0069)	(0,0054)	(0,0070)
Educational Level	-0,054***	-0,053***	-0,074***	-0,073***
	(0,0049)	(0,0048)	(0,0048)	(0,0048)
Females	0,102***	0,104***	0,080***	0,082***
	(0,0095)	(0,0095)	(0,0096)	(0,0096)
Single-Parent Household	0,102***	0,098***	0,109***	0,106***
	(0,0127)	(0,0127)	(0,0128)	(0,0128)
Single Person	0,087***	0,071***	0,126***	0,110***
	(0,0127)	(0,0147)	(0,0142)	(0,0144)
Ethnic Minority	0,420***	0,420***	0,461***	0,459***
	(0,0151)	(0,0156)	(0,0165)	(0,0170)
Number of Members	-0,063***	-0,060***	-0,065***	-0,062***
	(0,0053)	(0,0053)	(0,0050)	(0,0050)
Number of Children	0,078***	0,077***	0,091***	0,090***
	(0,0067)	(0,0067)	(0,0065)	(0,0065)
Prostitution		0,180**		0,250***
		(0,0607)		(0,0651)
Non-Payment of Dwelling		-0,069***		-0,074***
		(0,0174)		(0,0176)
Drug Abuse		-0,077***		-0,067***
		(0,0185)		(0,0188)
Social Isolation		0,081***		0,071***
		(0,0141)		(0,0142)
Scale	0,6574	0,6560	0,6189	0,6179
p			1,6159	1,6185
Log L	-24757,1	-24710,4	-26881,4	-26838,3

Standard errors in brackets. ***Significance at 99%, **Significance at 95%.

Table 5
Sensitivity Analysis

	Basic Model		*Model with Re-Entries*		*Model with uncleaned records for duration*	
Age Group	3,480***	3,477***	3,466***	3,462***	3,640***	3,617***
	(0,0343)	(0,0344)	(0,0511)	(0,0512)	(0,0910)	(0,0914)
Employability	0,026***	0,023***	0,036***	0,032***	0,022*	0,021*
	(0,0043)	(0,0044)	(0,0049)	(0,0050)	(0,0115)	(0,0117)
Number of Problems	-0,118***	-0,117***	-0,114***	-0,113***	-0,165***	-0,165***
	(0,0046)	(0,0047)	(0,0053)	(0,0054)	(0,0126)	(0,0128)
Educational Level	0,040***	0,039***	0,041***	0,041***	0,077***	0,049***
	(0,0052)	(0,0069)	(0,0061)	(0,0080)	(0,0138)	(0,0182)
Age Group	-0,054***	-0,053***	-0,056***	-0,055***	-0,077***	-0,074**
	(0,0049)	(0,0048)	(0,0055)	(0,0055)	(0,0129)	(0,0128)
Females	0,102***	0,104***	0,113***	0,115***	0,183***	0,192***
	(0,0095)	(0,0095)	(0,0109)	(0,0109)	(0,0247)	(0,0247)
Single-Parent Household	0,102***	0,098***	0,107***	0,103***	0,209***	0,200***
	(0,0127)	(0,0127)	(0,0152)	(0,0152)	(0,0332)	(0,0332)
Single Person	0,087***	0,071***	0,098***	0,083***	0,178***	0,145***
	(0,0127)	(0,0147)	(0,0168)	(0,0170)	(0,0383)	(0,0387)
Ethnic Minority	0,420***	0,420***	0,429***	0,423***	0,781***	0,805***
	(0,0151)	(0,0156)	(0,0193)	(0,0199)	(0,0388)	(0,0402)
Number of Members	-0,063***	-0,060***	-0,060***	-0,056***	-0,107***	-0,101***
	(0,0053)	(0,0053)	(0,0065)	(0,0065)	(0,0139)	(0,0139)
Number of Children	0,078***	0,077***	0,073***	0,071***	0,078***	0,076***
	(0,0067)	(0,0067)	(0,0082)	(0,0082)	(0,0174)	(0,0174)
Prostitution		0,180**		0,150**		0,264
		(0,0607)		(0,0696)		(0,1769)
Non-Payment of Dwelling		-0,069***		-0,070***		-0,050
		(0,0174)		(0,0203)		(0,0456)
Drug Dependency		-0,077***		-0,085***		-0,028
		(0,0185)		(0,0216)		(0,0476)
Social Isolation		0,081***		0,079***		0,183***
		(0,0141)		(0,0160)		(0,0372)
Re-Entries			-0,057*	-0,053*		
			(0,0319)	(0,0319)		
Escala	0,6574	0,6560	0,6552	0,6539	0,8780	0,8752
Log L	-24757,1	-24710,4	-18443,1	-18407,8	-7593,2	-7576,3

Standard errors in brackets.
***Significance at 99% ; **Significance at 95%; *Significance at 90%.

Table 6
Results of the Parametric Models with Unobserved Heterogeneity

	Log-normal		Weibull	
	Gamma	Inverse Gaussian	Gamma	Inverse Gaussian
Age Group	3,327***	3,305***	3,237***	3,379***
	(0,0320)	(0,0322)	(0,0458)	(0,0330)
Employability	0,025***	0,024***	0,027***	0,020***
	(0,0043)	(0,0043)	(0,0043)	(0,0044)
Number of Problems	-0,119***	-0,119***	-0,123***	-0,112***
	(0,0046)	(0,0046)	(0,0046)	(0,0048)
Educational Level	0,038***	0,038***	0,039***	0,040***
	(0,0068)	(0,0068)	(0,0067)	(0,0069)
Age Group	-0,044***	-0,044***	-0,043***	-0,064***
	(0,0048)	(0,0048)	(0,0048)	(0,0048)
Females	0,111***	0,111***	0,113***	0,093***
	(0,0093)	(0,0093)	(0,0093)	(0,0095)
Single-Parent Household	0,093***	0,092***	0,091***	0,102***
	(0,0125)	(0,0124)	(0,0125)	(0,0128)
Single Person	0,055***	0,054***	0,049***	0,093***
	(0,0146)	(0,0146)	(0,0146)	(0,0146)
Ethnic Minority	0,400***	0,393***	0,391***	0,441***
	(0,0154)	(0,0153)	(0,0157)	(0,0163)
Number of Members	-0,058***	-0,057***	-0,059***	-0,061***
	(0,0053)	(0,0053)	(0,0053)	(0,0052)
Number of Children	0,070***	0,069***	0,071***	0,085***
	(0,0067)	(0,0067)	(0,0067)	(0,0066)
Prostitution	0,154**	0,153***	0,142**	0,217***
	(0,0598)	(0,0593)	(0,0606)	(0,0624)
Non-Payment of Dwelling	-0,067***	-0,057***	-0,068***	-0,072***
	(0,0171)	(0,0053)	(0,0170)	(0,0175)
Drug Dependency	-0,077***	-0,077***	-0,077***	-0,072***
	(0,0181)	(0,0181)	(0,0180)	(0,0187)
Social Isolation	0,082***	0,082***	0,079***	0,076***
	(0,0139)	(0,0139)	(0,0138)	(0,0142)
θ	0,2457	0,3787	1,9348	2,7299
	(0,0153)	(0,0304)	(0,0527)	(0,0227)
Scale	0,5788	0,5624	0,2947	0,3986
P			3,3931	2,5086
Log L	-24553,6	-24538,7	-24688,9	-25502,7

Standard errors in brackets.
***Significance at 99% ; **Significance at 95%; *Significance at 90%.

Table 7
Results of the Multiple Exits Model

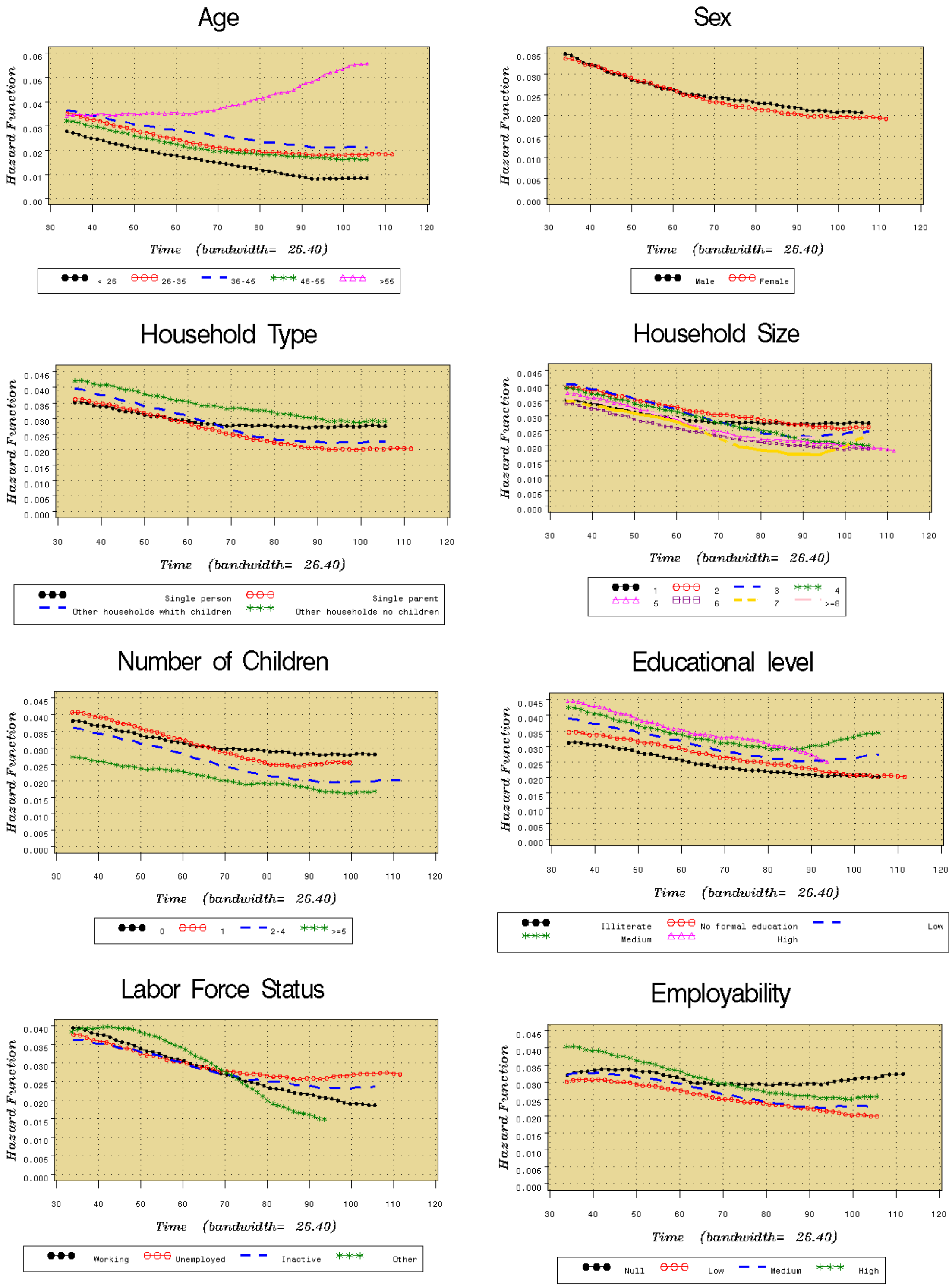
	"Administrative" Exit	*Exit due to "Fraud"*	*"Successful" Exit*
Age Group	2,386***	2,921***	2,800***
	(0,0583)	(0,0359)	(0,0433)
Employability	0,125***	-0,033***	0,002
	(0,0072)	(0,0053)	(0,0055)
Number of Problems	-0,087***	-0,034***	-0,062***
	(0,0076)	(0,0058)	(0,0059)
Educational Level	0,009	0,018**	0,061***
	(0,0112)	(0,0083)	(0,0085)
Age Group	-0,006	-0,006***	-0,003
	(0,0080)	(0,0015)	(0,0061)
Females	0,025*	-0,008	0,066***
	(0,0154)	(0,0113)	(0,0118)
Single-Parent Household	-0,009	0,026*	0,034**
	(0,022)	(0,0147)	(0,0160)
Single Person	-0,046*	-0,041**	-0,008
	(0,0243)	(0,0178)	(0,0185)
Ethnic Minority	-0,146***	0,073***	-0,269***
	(0,0284)	(0,0175)	(0,0209)
Number of Members	-0,088***	0,008	-0,024***
	(0,0097)	(0,0062)	(0,0068)
Number of Children	0,070***	0,024***	0,037***
	(0,0122)	(0,0078)	(0,0086)
Prostitution	-0,066	0,052	-0,155*
	(0,1030)	(0,0739)	(0,0805)
Non-Payment of Dwelling	-0,051*	-0,038*	-0,150***
	(0,0289)	(0,0204)	(0,0218)
Drug Dependency	-0,163***	-0,083***	-0,196***
	(0,0313)	(0,0216)	(0,0230)
Social Isolation	0,066***	0,051***	-0,026
	(0,0224)	(0,0172)	(0,0175)
Scale	0,8211	0,6745	0,7016
Log L	-15271,2	-18449,6	-18798,9

Standard errors in brackets.
***Significant to 99% ; **Significant to 95%; *Significant to 90%.

Table 8
Estimation of the Time Lineal Divergence Hypothesis

Variance Analysis			
	DF	χ^2	Pr > χ^2
Constant	2	4630,4	<0,0001
T	2	1935,5	<0,0001
Maximum Likelihood Estimation			
Parameter	Coefficient	χ^2	Pr > χ^2
Constant (sucful./fraud)	-0,212	104,6	<0,0001
	(0,0207)		
Constante (admin./fraud)	-1,759	4414,3	<0,0001
	(0,0265)		
T (Sucsful./fraud)	0,001	2,5	0,1141
	(0,0007)		
T (admin./fraud)	0,028	1581,0	<0,0001
	(0,0007)		

Figure 1



Age
Hazard Function
Time (bandwidth= 26.40)
< 26
26-35
36-45
46-55
>55
Sex
Male
Female
Household Type
Single person
Single parent
Other households whith children
Other households no children
Household Size
1
2
3
4
5
6
7
>=8
Number of Children
0
1
2-4
>=5
Educational level
Illiterate
No formal education
Low
Medium
High
Labor Force Status
Working
Unemployed
Inactive
Other
Employability
Null
Low
Medium
High

Figure 2

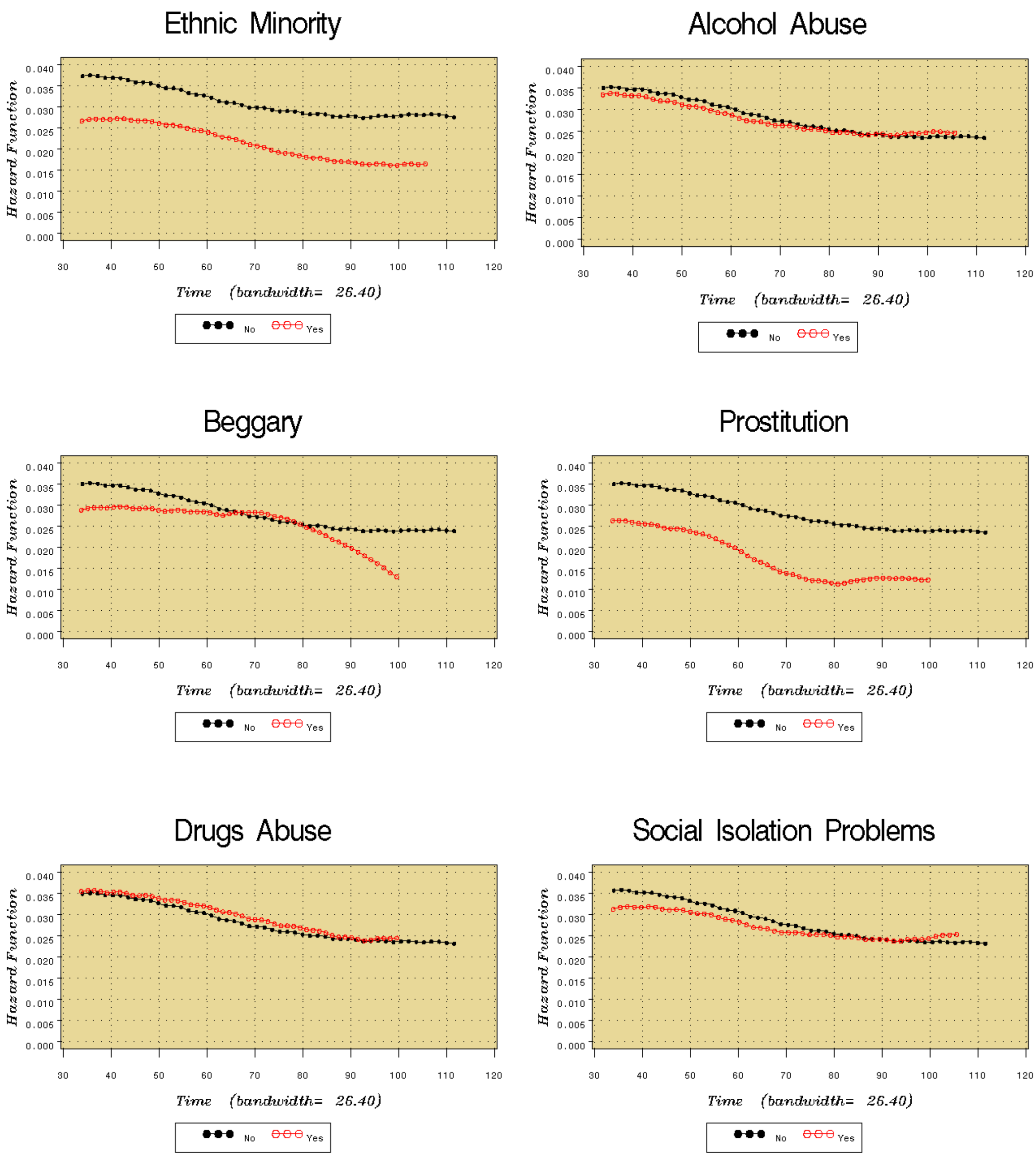

Ethnic Minority
Alcohol Abuse
Beggary
Prostitution
Drugs Abuse
Social Isolation Problems
Hazard Function
0.000
0.005
0.010
0.015
0.020
0.025
0.030
0.035
0.040
30
40
50
60
70
80
90
100
110
120
Time (bandwidth= 26.40)
No
Yes

Figure 3
Graphical Diagnostics: Discriminate Between Different Probability Distributions

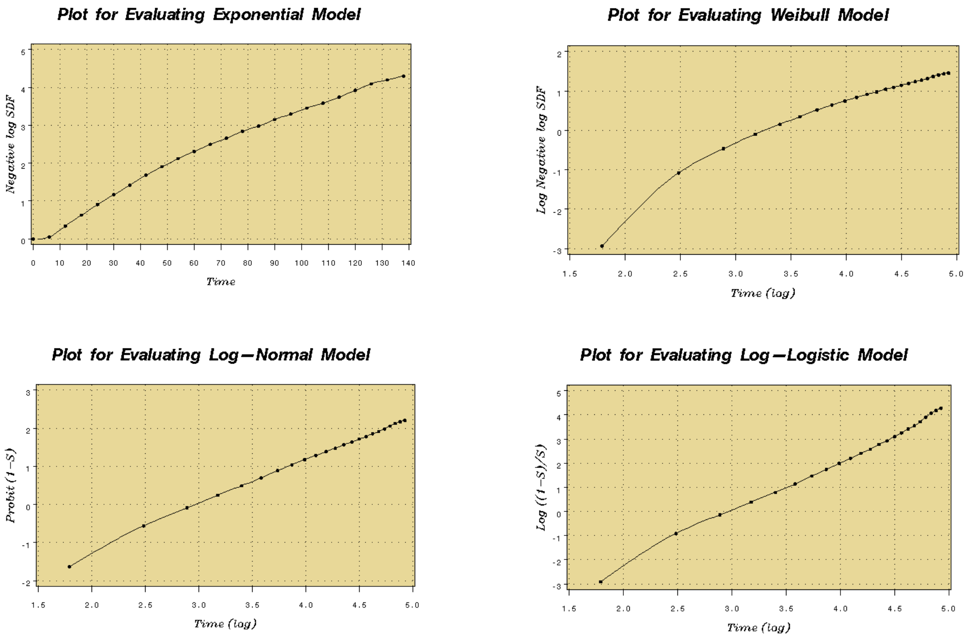


Figure 4
Graph of Hazard Function for IMI Data. Predicted Survival Times

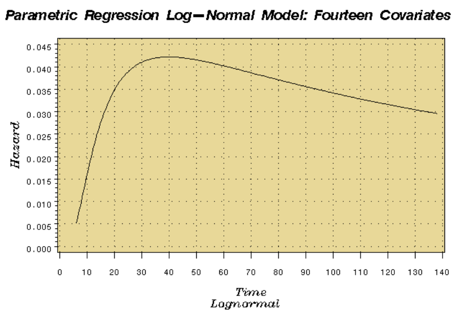


Figure 5
Competing Risk Model