Mobility of Married Women

Non-Parametric Analysis of

Labour Force Transitions in Spain

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January 1997

Abstract

This paper analyses the dynamics of wives' labour force participation in Spain during the late 1980s from a non-parametric descriptive perspective. This research is motivated by two basic facts: One, there is evidence that female labour supply behaviour in Spain is changing since the late 1980s. Two, while the analysis of participation stocks is covered in the literature, there is no published research on mobility or flows. In the first part of this paper there is a description of the three-monts' transition rates over two-waves. The underlying assumption is the First Order Markov Hypothesis. In the second part, the Markov assumption is questioned. This is done by carrying out an analysis of survival over 7 waves in which re-entries are ignored. Moreover, there is also an analysis of mobility contingent on past labour market state, which includes re-entries in the analysis. This allows me to study the likelihood of relapsing in a particular state, or the likelihood of surviving contingent on past labour market states. The results are interesting because they reveal features of female labour market behaviour unknown to date.

Acknowledgments

I thank John Micklewright for his advise, especially during the first stage of this research. I also thank Alfonso Alba-Ramírez, John Ermisch, Siv Gustafsson and Robert Waldmann for their interesting comments. Finally, I thank IGIER and the European University Institute for providing me the best working conditions. All errors are mine.

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1. Introduction

The objective of this paper is to shed some light on labour market mobility of Spanish married women, and to explore how transitions (flows) help to understand participation (stocks). This is done with a non-parametric analysis of transition rates.

There are several reasons why the study of the dynamics of participation is important. Historically, Spanish female labour force participation is the lowest among OECD countries. Since 1985, participation of women aged 25 to 45 experienced a significant growth, which has been under-studied to date. Some authors conclude that this significant growth is due to a structural change regarding female labour market behaviour (Arellano and Bover (1994), Martínez-Granado (1994), and Adam (1996a)).[1] However, participation levels are still the lowest in the OECD, which suggests that this changing behaviour (if at all) does not affect all women.

The economic implications of a transition from a traditional behaviour (where typically women withdraw from the labour force after marriage or childbirth) to a modernized behaviour (where typically women stay in the labour force over the life-cycle except, maybe, during the first years of childbearing) are surely under-estimated. Just to give some examples, one implication is that the proportion of dual-earner households in the Spanish economy will increase. This requires a re-thinking of Spanish family policies (i.e. income taxes, pension system, SS system). Moreover, consumption patterns are likely to change and an increase in the demand for (public and private) services is expected (eating out, laundries, childcare, care for elders, etc.).

While the evolution of female participation levels (stocks) is documented in the literature, there is no published research on female mobility (flows). What is the level of mobility? How do labour stocks and flows relate to each other? Does the analysis of flows help to understand stocks? Throughout a descriptive analysis of transitions, this paper contributes to understand labour force participation of wives in Spain during the late 1980s. The choice of married women is imposed by the data.

The distinction between labour force "stocks" and "flows" has extremely important policy implications. For instance, wives' participation rate is approximately 25% in 1990.[2] This rate can either characterize a population where every wife participates only one quarter each year, or by a population where 25% of wives always participate and the remaining 75% never participate. These two extremes reflect completely different pictures: a world with high mobility versus a completely static world. The efficiency of a given policy may differ from one world to another. For example, assume the objective of a policy maker is to save the welfare state. Suppose the balance of the welfare state in that country is seriously menaced because of low activity rates and low fertility (like in Spain). There are two choices: one, to set up a policy that promotes activity; and two, to set up a policy that promotes fertility. If we are in a world with high mobility, then the promotion of activity is not going to help the welfare state to balance because contributions to SS during only one quarter usualy tend to turn into negative income taxes. The promotion of fertility is likely to be less effective in a world with high mobility than in a world with low mobility (and low activity rates like, say, 25%). Concerning unemployment policies, the stock-flow spectrum of unemployment is also important for policy design. The impact on inequality and income distribution differs substantialy if there are 100 unemployed individuals during one day than one person unemployed for 100 days.

How large are female labour market flows in Spain? Table 1 shows an international comparison of transition rates. It shows that in Spain labour force inflow and outflow rates are among the lowest in the EC. That is, Spain has the lowest proportion of active women who change status and the lowest proportion of inactive women who change status (after Belgium). However, the employment outflow and inflow rates (the

[1] Some indicators of this structural change (observed since the early 1980s) are: (i) increasing demand for female employment (especially in services) and female real wages' growth, (ii) increasing female participation after marriage and childbirth, (iii) increasing female education, etc.

[2] Source: Encuesta Continua de Presupuestos Familiares, first quarter.

proportion of employed women who quit working and the proportion of non-working women who find jobs) are close to the EC average. Thus, this suggests that while there is very little mobility in and out of the labour force, mobility in and out of employment is more frequent.

Table 1
Employment and Labour Force Transition Rates (%)
in Selected European Countries, 1989

	Employment			Labour Force	
	Inflow	Outflow		Inflow	Outflow
Netherlands	14.8	7.6	Netherlands	18.4	5.6
UK	11.5	7.5	UK	12.3	6.1
Denmark	10.8	11.7	Denmark	8.4	7.1
France	7.2	9.6	Ireland	7.9	4.6
Spain	5.6	8.6	France	7.1	7.6
Ireland	5.1	6.9	Greece	5.1	3.2
Portugal	4.3	5.6	Germany	4.1	7.1
Germany	3.3	5.4	Portugal	3.3	4.9
Belgium	3.1	3.8	Spain	3.2	4.6
Greece	2.8	4.7	Belgium	2.9	3.4
EC average	*6.9*	*7.1*		*7.3*	*5.4*

Notes: (1) Italy is not reported due to lack of data.
(2) Inflow and outflow rates are calculated in a yearly basis.
(3) All women of working age. The denominator in the outflow rates is the participation cases one year before, and the denominator in the inflow rates is the non-participation cases one year before.
Source: My own calculations form Eurostat Labour Force Surveys. I thank Lene Meyer at Eurostat for providing me with the raw data.

This paper is organized as follows. Section 2 defines the estimates of non-parametric Transition Rates. Section 3 discusses transition rates over two waves. Section 3.1 describes the sub-sample and Section 3.2 analyses the estimated moves into and out of the labour force. Section 3.4 analyses the estimated gross outflows from employment and unemployment and their destinations. Section 4 is devoted to a multi-wave analysis of transitions, which allows to question the assumptions underlying the results of Section 3 (i.e. First Order Markov Assumptions). Section 4.1 defines 'predicted' transition rates under the Markov Assumption. Subsequently, Section 4.2 analyses the survival of every labour market state over 7 waves, and compares the 'actual' and 'predicted' transition rates. This gives a dynamic picture of every labour market state and the effect of past history. Finally, Section 5 explores re-entries to previously labour market states with an analysis of mobility over 3 waves. The Appendix includes the figures supporting the results discussed throughout the article.

2. Definition of Non-parametric Transition Rate Estimates

Transition Rates by age can be estimated non-parametrically: the fraction of individuals in state x at age a who move to state y over one period. This gives an approximation of the hazard of exiting from x to y for homogenous groups of individuals (age groups). To simplify, the subindex a that refers to the age group will be ignored in the definitions of transition rates given in this section. However, any transition rate here described can be equally defined for a particular age group.

Let us start by introducing a sequence of useful definitions. Let us assume there are three labour market states: *x*, *y* and *z*. Let S_x^t be the number of individuals who are in state x at time t, let S_x be the sum of S_x^t over time, for $t = 1,\ldots T$, let S^t be the sample size at time t (i.e. the total number of individuals at t occupying any state x, y or z) and let S be the sum of sample sizes over time, for $t=1,\ldots T$. Let $S_{y/x}^{t,t+1}$ be the number of individuals in state x at time t who are in state y at time $t+1$. Then, the ***Transition Rate*** $\tau_{xy}^{t,t+1}$ from state x to y, from t to $t+1$ is:

$$\tau_{xy}^{t,t+1} = \frac{S_{y/x}^{t,t+1}}{S_x^t} \tag{1}$$

Note that this simple non-parametric definition does not involve past history. Rather, only two periods are involved: the *origin period* and the *destination period*. In practical terms, this definition actually refers to *Three-month Transition Rates* because the longitudinal data set used in this article (ECPF) gives quarterly information.

In unbalanced panel data sets, like the ECPF, sample sizes are not the same over the panel quarters (i.e S^t is not equal to S^q for all t different from q, $t,q=1,...T$).[3] In this case the overall transition rate across periods is not a simple average of transition rates. One needs to use weighted averages, where the weights are, for any transition, the number of individuals in the origin state, S_x^t. Thus, the ***Average Transition Rate*** τ_{xy} is:

$$\tau_{xy} = \frac{\tau_{xy}^{12} S_x^1 + \tau_{xy}^{23} S_x^2 + \ldots + \tau_{xy}^{T\text{-}1,T} S_x^{T\text{-}1}}{S_x^1 + S_x^2 + \ldots + S_x^{T\text{-}1}} = \frac{\Sigma\, \tau_{xy}^{t,t+1} S_x^t}{\Sigma\, S_x^t} \tag{2}$$

where $t = 1...T\text{-}1$. Now, using (1), expression (2) can be decomposed as follows:

$$\tau_{xy} = \frac{S_{y/x}^{12} + S_{y/x}^{23} + \ldots + S_{y/x}^{T\text{-}1,T}}{S_x^1 + S_x^2 + \ldots + S_x^{T\text{-}1}} \tag{3}$$

This leads to a nice definition of the *Average Transition Rate*, as the number of changes from x to y as a proportion of the total number of cases where x is occupied in the origin period of the transition. That is,

$$\tau_{xy} = \frac{S_{y/x}}{S_x} \tag{4}$$

where $S_{y/x} = S_{y/x}^{12} + S_{y/x}^{23} + ... + S_{y/x}^{T\text{-}1,T}$ and $S_x = S_x^1 + S_x^2 + ... + S_x^{T\text{-}1}$. As an extension, I define two additional rates. The ***Average Exit Transition Rate*** from, say, state x is:

$$\tau_{x*} = \frac{\Sigma(\tau_{xy}^{t,t+1} + \tau_{xz}^{t,t+1}) S_x^t}{\Sigma\, S_x^t} \tag{5}$$

for $t=1,...T\text{-}1$. This expression can be transformed using a procedure similar to that used to obtain τ_{xy}:

$$\tau_{x*} = \frac{S_{y/x} + S_{z/x}}{S_x} \tag{6}$$

[3] In most longitudinal data sets (including the ECPF), unbalance is normally due to attrition. Some causes of attrition are non-response, impossibility to allocate the individual units, migration of the individual units, etc.

In other words, τ_{x*} is the number of individuals ever exiting state x as a proportion of the total number of individuals ever occupying state x over the sample time periods from $t=1,...T$. Similarly, the ***Average Entry Transition Rate*** to, say, state x is defined as follows:

$$\tau_{*x} = \frac{S_{x/y} + S_{x/z}}{S_y + S_z} = \frac{\Sigma\, \tau_{yx}^{t,t+1} S_y^t + \Sigma\, \tau_{zx}^{t,t+1} S_z^t}{\Sigma\, S_y^t + \Sigma\, S_z^t} \qquad (7)$$

for $t=1,...T-1$. That is, τ_{*x} is the number of individuals ever entering state x as a proportion of the total number of individuals ever occupying states other than x over the sample periods $t=1,...T$. In what follows, the analysis is based on the use of Average Transition Rates τ_{xy} Average Entry Rates τ_{*x} and Average Exit Rates τ_{x*}.

3. Transition Rates Over Two Waves

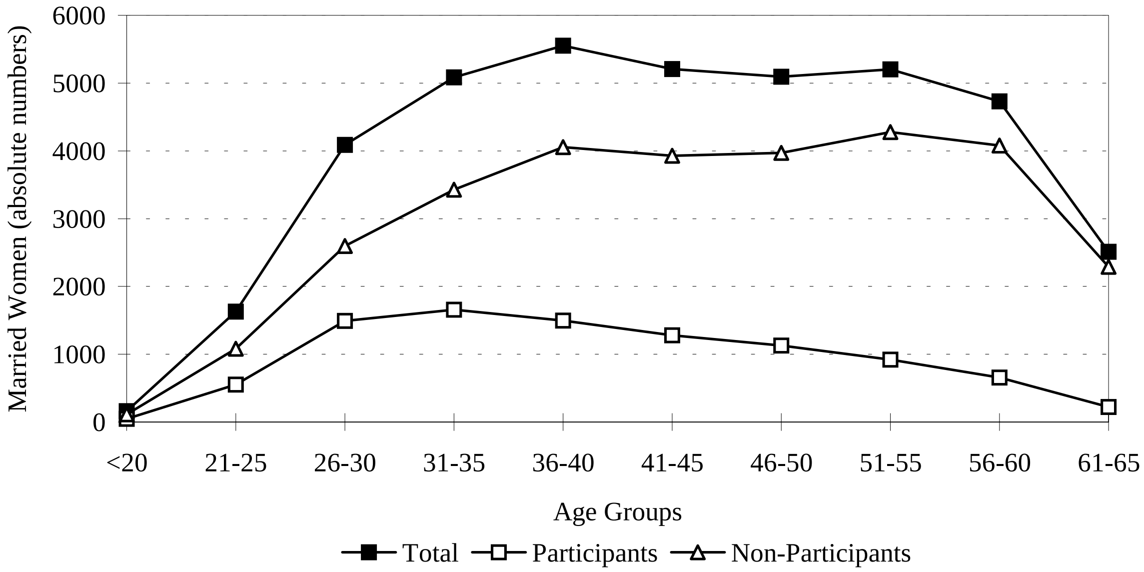
In this section I describe the obtained non-parametric estimates of transition rates over two waves. Only transitions of interest are discussed, being the objective to give a picture of married women's labour market flows.

3.1 Sub-sample and Sample Sizes

The ECPF (Spanish Income and Expenditure Survey) is a rotating panel with a quarterly (theoretical) sample of 3,200 households. In theory, households are interviewed for 8 consecutive quarters and then replaced by households selected using the same random criteria. However, due to attrition, only 15% of the households respond to the 8th interview, 25% respond to the 7th interview, 35% to the 6th interview, etc. In this article, I use the ECPF quarters from 1985:1 to 1990:4 (i.e 24 quarters). After sample selection, the ECPF sub-sample contains every household headed by (married) couples where the wife is of working age i.e. younger than 65. A drawback of conditioning sample selection on marriage in all periods is that it affects the obtained transition rates. See Adam (1996c) for details about the ECPF and its uses for labour market research and the effects of this sample selection.

To obtain flow estimates on the basis of three-month transitions, I select all successive pairs of observations in the panel. With this strategy, I obtain 39,260 three-month transitions related to 51,551 households. A consequence of exploiting the data in this way is that households that collaborate only once with the ECPF sub-sample are not included because they do not partake in any transition. Furthermore, transitions that are not made within three months are not included in the sub-sample because the six-months transition probability is different than the three-months probability.[4]

Figure 1a
Distribution of Married Women by Age
in the Origin Wave (S) and by Origin State (S_x)

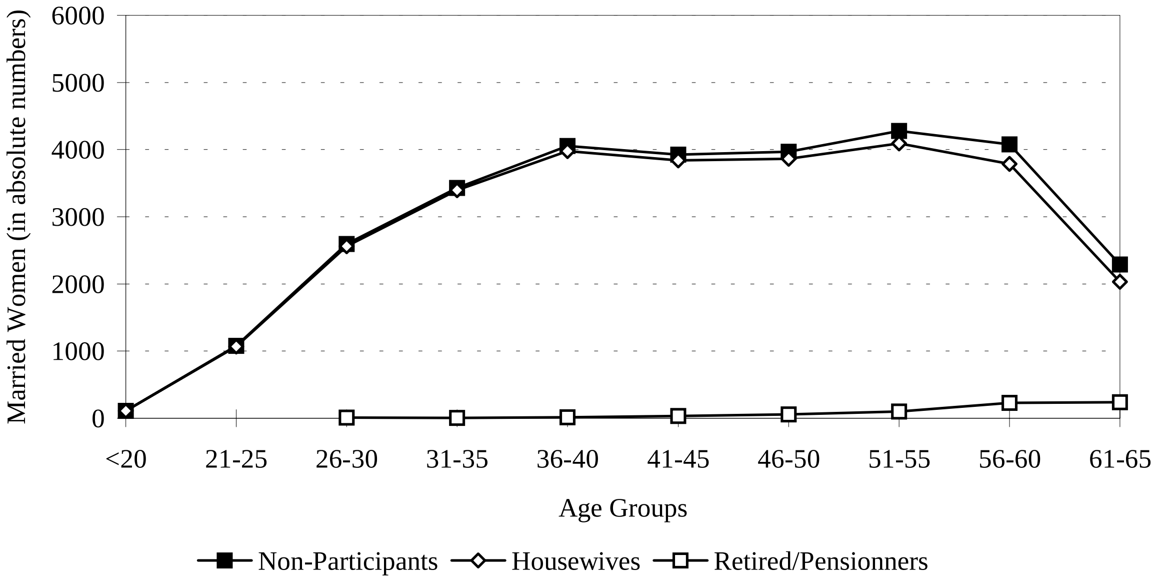


A description of the S_x's is reported now to give an picture of the sample sizes used as weights for the calculation of transition rate estimates. Figure 1a shows the distribution of participators and non-participators by age in absolute numbers. Recall

[4] The probability of moving from one state to another over six months is the sum of the combination of the products of all pairs of three-month transition probabilities with the same origin and destination states. In other words, let us define $p_{ij}^{1,2}$ as the probability of moving from state i to state j from period 1 to period 2 ($i,j = x,y,z$). Now, the probability over 3 periods of, say, moving from state x to state y is: $\tau_{xy}^{1,3} = (\tau_{xx}^{1,2} \times \tau_{xy}^{2,3}) + (\tau_{xy}^{1,2} \times \tau_{yy}^{2,3}) + (\tau_{xz}^{1,2} \times \tau_{zy}^{2,3})$

that the sub-sample has 39,260 observations in the origin state. The proportion of non-participators is larger by far (particularly after the age of 30). This difference is so big that even for the 26-30 age group (which has one of the largest pool of participators and one of the smallest pool of non-participators), the pool of non-participators is twice as large as the pool of participators. For the groups aged more than 30, the ratio of non-participators' to participators' pools increases with age: 2.2, 2.8, 2.9, 3.3, 4.3 and 5 for the age groups 31-35, 36-40, 41-45, 46-50, 51-55 and >56 respectively.

Figure 1b
Distribution of Married Women by Age
by Origin State (S_x), for Non-Participants

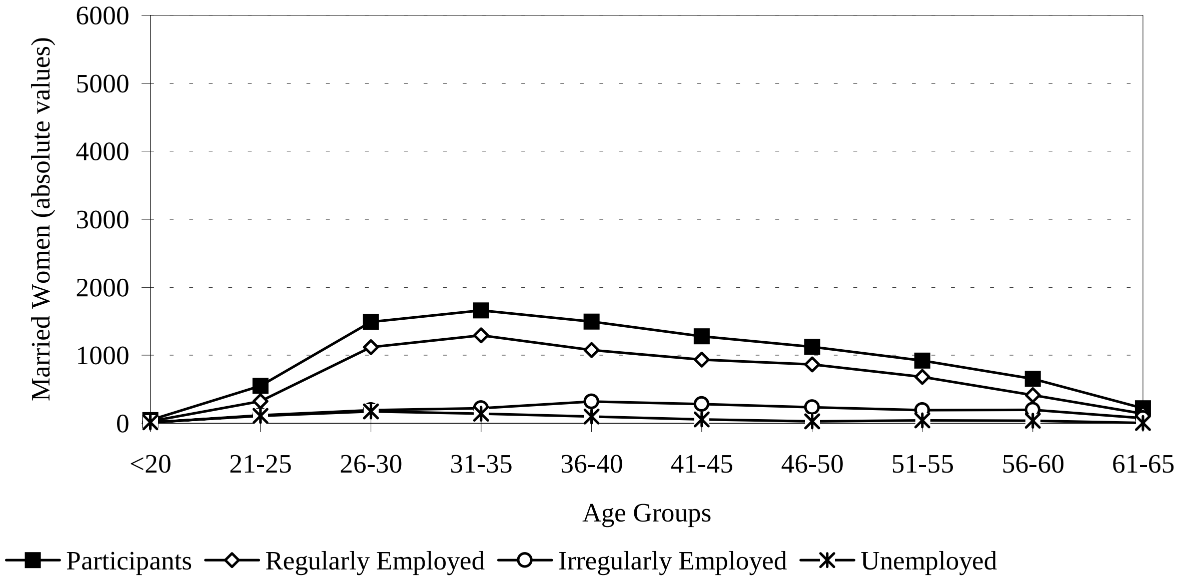


Figures 1b and 1c show the distribution of the non-participation and participation pools (in absolute values).[5] "Housewives" completely dominate non-participation. "Retired or pensioners" are an insignificant proportion in the non-participation pool, even among the oldest groups. In the participation pool, the most represented category is "regular employment". The number of "irregular employed" and "unemployed" are very small compared to "regular employed". A clear pattern

[5] The ECPF labour market states are: regular employment, irregular employment and unemployment. The distinction between "regular" and "irregular" employment given by the ECPF handbook is: Regular employment implies working more than 1/3 of the "normal working hours" and irregular employment implies working less than 1/3 of the "normal working hours".

emerges: Unemployment rates are not significantly different from irregular employment rates for younger wives, but are significantly lower after the age of 31-35. Finally, the general conclusion from Figures 1a, 1b and 1c is that in the ECPF subsample there is a huge proportion of housewives. This conclusion is re-affirmed if one performs international comparisons: none of the OECD countries has such a large proportion of housewives. The remaining wives are mainly distributed as regularly employed. There are smaller groups, namely irregularly employed and unemployed.

Figure 1c
Distribution of Married Women by Age
by Origin State (S_x), for Participants



Therefore, due to its large sample size, the non-participating pool takes a relevant place in the analysis of this article. I first discuss the flows into and out of the labour force and then the flows within the labour force. Normally, moves into and out of the labour force are different from moves within the labour force. However, in the case of married women the labour force frontier might be ambiguous, especially in a country with such a high proportion of housewives combined with a really high unemployment rate.

Because of small sample sizes of some labour market states, I use the standard errors associated with each transition rate to construct confidence intervals for a significance level of 0.05. This shall give a better assessment of the results. The confidence intervals are constructed using contingency tables' procedures, based on χ-squared statistics.

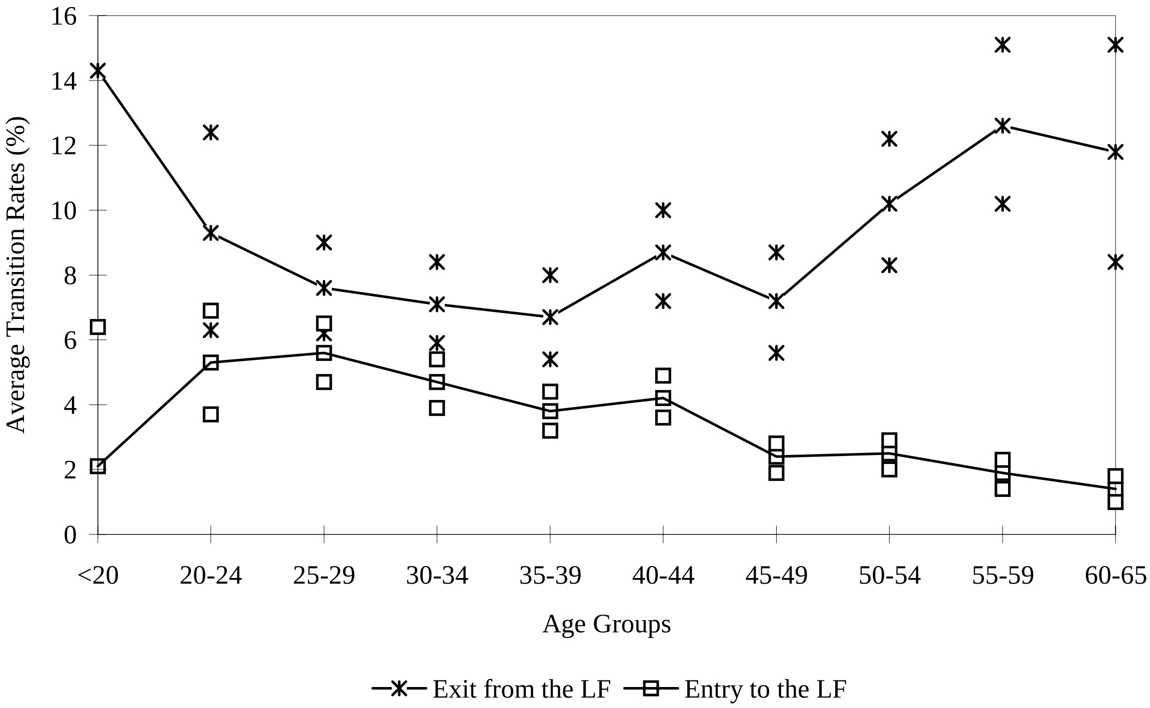
3.2 Moves Into and Out of the Labour Force

What is the hazard that active married women exit the labour force? And what is the hazard that inactive married women enter the labour force? Figure 2 shows the Exit from the Labour Force Average Transition Rates and the Entry to the Labour Force Average Transition Rates by age. Standard errors and confidence intervals are also reported. Table A1 in the Appendix shows the raw figures. Note that the transition rates of Figure 2 cannot be compared with those shown in Table 1, which are yearly (not quarterly) transition rates of all women (married and unmarried) of working age (taken from the EPA-1989). The correct comparison requires the use of quarterly information. The labour force transition rates obtained from the EPA-1989:2-3 (for married women aged 16-54) are similar to those obtained with the ECPF. The entry rate is 4.1% with the EPA and 3.2% with the ECPF. The exit rate is 5.6% with the EPA and 8.4% with the ECPF. In fact, given the sub-samples used, the fact that the exit rate is lower and the entry rate is higher with the EPA makes sense.

The hazard of entry into the labour force has a smoothly decreasing pattern after the age of 25-29. The confidence intervals show that, despite the low entry rates, these are significantly different from zero (except for ages below 20). In addition, each rate is significantly different ten years ahead, although some rates are not significantly different at five year intervals. The pattern of entry flows is thus very intuitive: the highest hazard is at the age of 25-30 (after studies and before fertile age), and beyond decreases smoothly with age, reaching levels close to zero at the age of 65.[6]

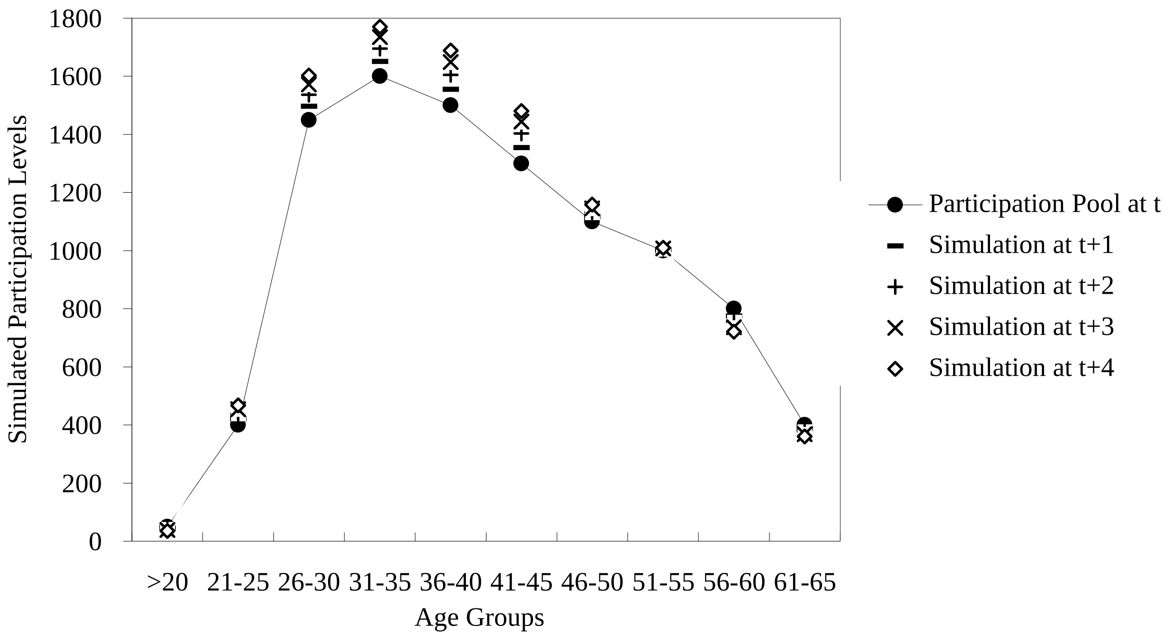
[6] Recall that the average age of women's first childbirth has increased in Spain during the 1980s, and is now at 30 on average.

Figure 2
Exit from and Entry to the Labour Force
Average Transition Rates



The hazard of exit from the labour force follows a flat u-curve. It slightly decreases for the young groups aged 25-29 to 35-39 (for younger groups the confidence interval is so wide that conclusions are difficult to draw). After the age of 35-39 the exit hazard increases with age (except for the age group 45-49). In general, at ten year intervals the exit rates are significantly different from each other. The pattern of exit flows is also very intuitive. There are two main life-cycle periods with higher exit likelihood: the early age of marriage, childbirth and post-studies and the late age of pre-retirement. Note that the confidence intervals of the exit rates are much broader than those of the entry rates, due to smaller sample sizes. As Table A1 in the Appendix shows, in the overall sample there are 748 exit cases (out of 9,580) and 958 entry cases (out of 29,805). Comparing hazards, the exit hazard is systematically and significantly higher than the entry hazard for any age group (except for the ages below 20) at a 0.05 significance level, and the difference increases with age. The older the women, the more likely to exit and less likely to enter. The group with highest mobility is the 40-44 age group. in sum, exit rates are greater than entry rates for any age group. This would appear to suggest *falling* participation in all age groups, a rather counter intuitive result, considering the female labour force growth during the 1980s, also among married women, as described in Section 1. However, despite low entry rates and high exit rates, labour force inflows are larger than outflows (except the group <19 and >55), simply because the non-participation pool is large and the participation pool is small.[7] In other words, 3.2% of 29,805 cases is a larger number than 8.4% of 9,580 cases.

Figure 3
Simulation of Participation Levels



In Figure 3 shows four simulations of participation profiles obtained from the transition rate estimates. The first simulation (i.e for time *t+1*) is obtained by applying the transition rate estimates to the participation pool at time *t* (i.e. wave 1 in the ECPF sub-sample). The second simulation (i.e. for time *t+2*) is obtained by applying the transition rate estimates to the participation profile obtained from the first simulation for *t+1*. In the third and fourth simulations are calculated by applying the same procedure to obtain the participation profiles at *t+3* and *t+4*. Figure 3 shows that the participation pattern is *not* falling. Even more interesting, the growing participation pattern is due to the increasing presence of women of fertile and post-fertile age in the

[7] See Table A1 in the Appendix for the absolute figures of labour force inflows and outflows by age.

labour force.[8] Of course this simulation does not account for entries of new cohorts into the labour force, which surely would inflate the participation pattern even more.

Figure 4
Entry to the Labour Force, by Destination State
Average Transition Rates

Moves Into the Labour Force by Destination State.

Consider now the flows into the labour force. What fraction enter as unemployed and what fraction enter as employed?[9] Figure 4 shows the Average Entry to the Labour Force (LF hereafter) Rates by two destination states i.e. the transition rates from out-of-the-labour-force (OLF hereafter) to employment and to unemployment (see Table A2 for the raw figures).[10] While the entry to employment rate tends to decrease with age, the entry to unemployment rate is very low and flat, especially after the age of 30, which is significantly not different from zero. In fact,

[8] Note that this result is consistent with the hypothesis raised in Adam (1996a), which stands that there is a structural change concerning women's attachment to the labour market in Spain, reflected in their working intentions over the life-cycle. Adam (1996a, 1996b) shows that permanent withdrawals from the labour force after childbirth are less and less frequent among Spanish women.

[9] Note that, in principle, entering the labour force as unemployed does not involve unemployment benefit entitlement although registration at the unemployment office is a possibility.

[10] I do not include all ECPF labour market categories for simplification.

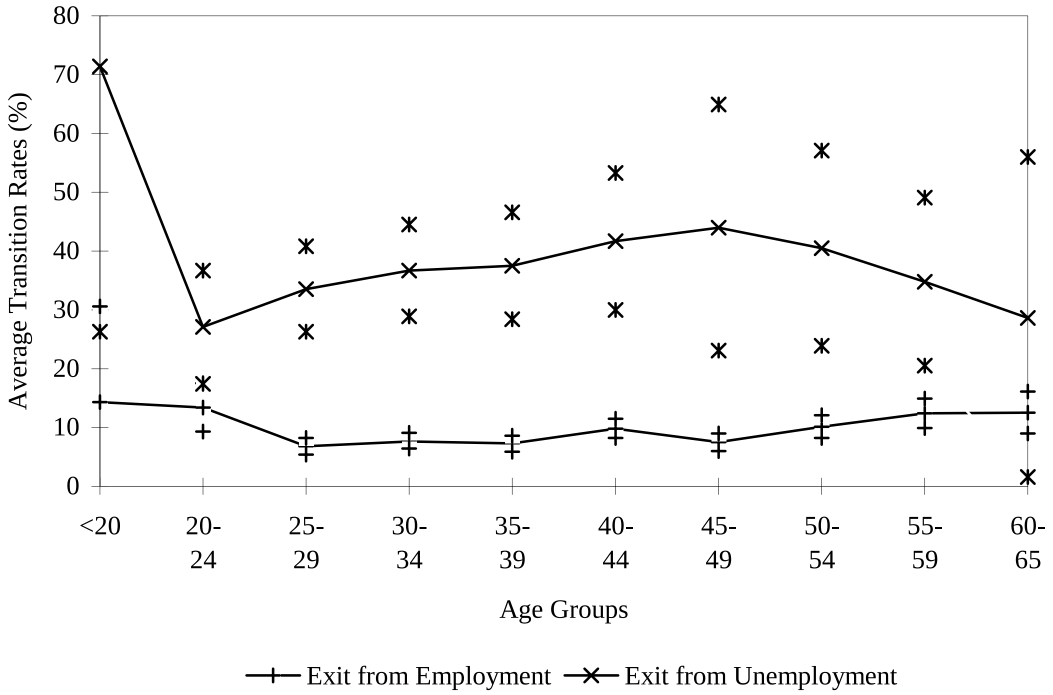
there are very few cases related to transitions from OLF to unemployment (see Table A2). Thus, labour force inflows are dominated by job-finders.

Figure 5
Exit from the Labour force, by Origin State
Average Transition Rates

Moves Out of the Labour Force, by Origin State

Figure 5 shows the Average Exit from the LF Transition Rates by origin state. That is, the proportion of participants that exit from the LF, the proportion of employed that exit from the LF and the proportion of unemployed that exit from the LF. Thus, the sum of the two latter do not add up to the former rate, unlike in Figure 4. Note that the scaling of Figure 5 (and Figure 6 to 8) is different from that of the previous figures. As an indication of the size of the transition rates, note that the exit from the LF rates reported in Figure 5 are also reported in Figure 2. Two interesting results emerge from Figure 5. One, the employment to OLF rates are systematically lower than the unemployment to OLF rates, except for the groups younger than 24 and older than 55 (where the sample sizes are very small). Two, employment to OLF rates are significantly not different than exit the LF transition rates. This suggests that exits from the LF are dominated by job-leavers. Indeed, because the number of unemployed is quite low in the ECPF (as reflected through the confidence intervals) the volume of these flows is very low, compared to the flow from employment to OLF.

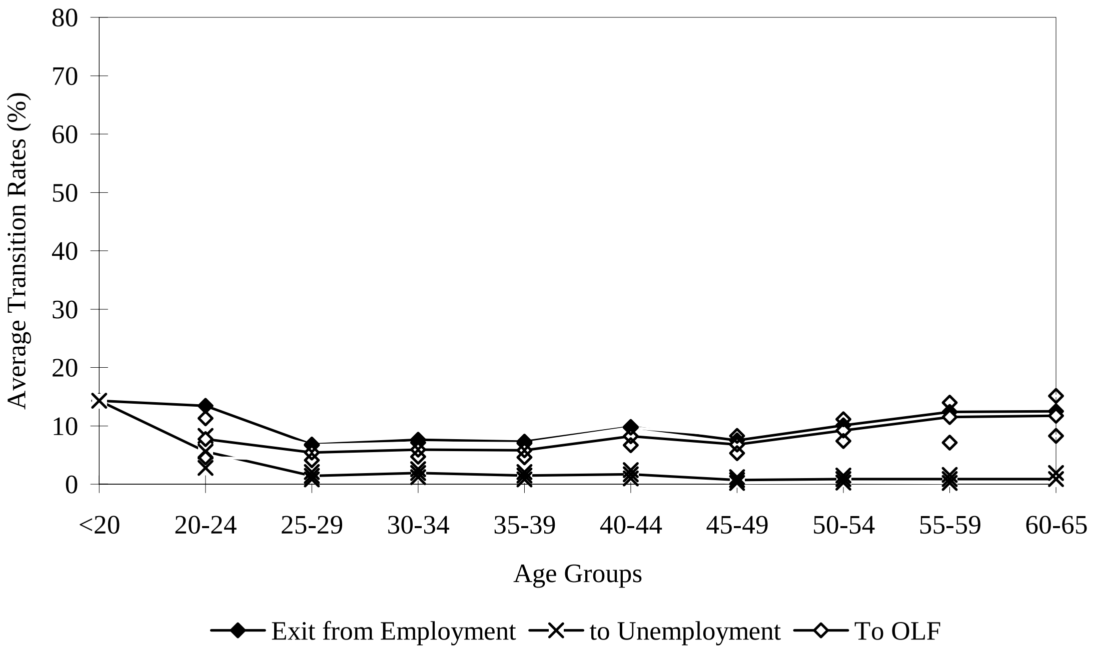
Figure 6
Exit from Employment and Exit from Unemployment
Average Transition Rates



3.3 Moves from Employment and Unemployment

Figure 6 reports the hazard of exiting employment and exiting unemployment. As an indication of the size of the reported rates (recall the change in the scaling), note that the rates presented in Figure 2 fall below the exit from employment rates reported in Figure 6. Thus, the hazard of exiting unemployment is far higher than the hazard of exiting employment (although the difference decreases with age). In other words, a huge proportion of unemployed (36% in average) compared to employed (9% in average) are likely to exit in a three month period. In relative terms, the unemployment state thus appears as an infrequent state among married women, given the small stock of unemployed, given the small proportion of LF entries with a destination into the unemployment state, and given the high hazard of exit. By contrast, the employment state appears to be more stable, given the relatively larger stock, the larger proportion of LF inflows with a destination into employment and the relatively low hazard of exit.

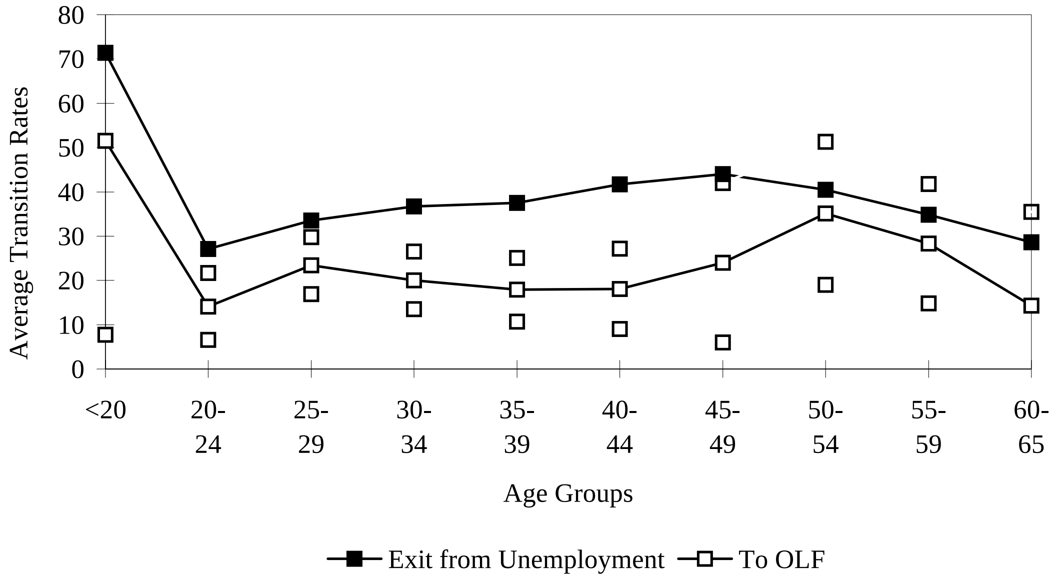
Figure 7
Exit from Employment by Destination State
Average Transition Rates



Now, let us examine the destination state of these flows. Figure 7 shows the Average Exit From Employment Rates by destination and age. As age increases, employment outflows are more and more likely to result in withdrawals from the LF (as opposed to unemployment). These differences in the destination state are significant at a 0.025 significance level (excluding the ages below 25). Comparing the hazard of "exit from employment" with the hazard of "exit from employment to OLF", these are not significantly different, which is consistent with the results of Figure 5.

Consider now the group who exits unemployment. Figure 8 shows the exit unemployment rates, the transition rates from unemployment to employment (top figure) and from unemployment to OLF (bottom figure) by age. Despite the high rates, these are difficult to interpret because of the large confidence intervals due to small sample sizes. One can, however, draw the following conclusions. On the one hand, for the age groups 30-50 the exits from unemployment to OLF are not significantly different from the exits from unemployment to employment, Thus, the exit unemployment rate is not dominated by either of the two destination states. On the other hand, after the age of 50 and before the age of 29 exits from unemployment are clearly dominated by withdrawals from the LF.

Figure 8
Exit from Unemployment by Destination State
Average Transition Rates



In summary, the analysis of mobility over two waves shows:

(1) The hazard of exit from the LF (8.4% of the LF on average) is higher than the hazard of entry to the LF (3.2% of the non-participants on average) for any age group. This difference increases with age from a 2 percentage points difference at the age of 25-29 to more than 10 percentage points difference at the age of 60-65. However, in absolute terms inflows are larger than outflows which led to an overall increase in the LF. Moreover, LF inflows and outflows are mainly driven by employment inflows and outflows.

(2) Despite employment flows being larger than unemployment flows (in absolute values), the hazard of exit from unemployment (36% in average) is systematically higher than the hazard of exit from employment (9% in average), with a likely destination to OLF in 90% of the cases.

(3) Exits from unemployment are more complicated: for ages below 45-49, unemployment outflows mainly turn into employment inflows, while after the age of 49 these turn into LF outflows.

4. Multi-wave Analysis of Transitions

The analysis of transitions of the previous section is based on the First-Order Markov Assumption. Under Markov assumption, transitions between states are independent of time and are not dependent on which state was occupied before. In this section, I attempt to relax this assumption. So, the question posed is whether the hazard of exit from state *x* is affected by the length of time occupied in *x*, and by the state occupied before occupying *x*. To do this, I first take a sample of women observed over a long length of time and analyze whether the hazard of staying in the origin state is constant over time or rather increases with time. That is, I compare the actual survival rates over seven waves (ignoring re-entries to the origin state) with the predicted pattern under the First-Order Markov Assumption. Secondly, I take a sample of women observed over three waves and analyze the relationship between current and past labour market moves. The sample sizes in the multi-wave analysis decrease substantially due to the exclusion of households observed for a short period. This reduces significantly the size of the standard errors estimates. To avoid problems of representatives and missing cases for a large number of cells, age as a factor is not considered in the multi-wave analysis.

4.1 Predicted Transition Rates Under the First-Order Markov Assumption

Under the First-Order Markov Assumption, past history does not affect the probability of leaving this state, this probability is constant over time and is the same for all individuals within an homogeneous group. Thus, under this assumption the ***Predicted Transition Rates (Pτ)*** over two waves are the same for all waves, for a particular homogeneous group:

$$P\tau_{xy}^{t,t+1} \;=\; P\tau_{xy}^{s,s+1} \;=\; C_{xy} \qquad t,s = 1,\ldots.T \tag{10}$$

where C_{xy}, is a constant, which is different for any combination of origin and destination states.[11] This property leads to very convenient definitions of predicted transition rates over *more than two waves*. For example, the Predicted Exit Transition Rate (from state x to any possible state $*$, where $*$ refers to any state different from x) over $K+1$ waves is:

$$\begin{aligned} P\tau_{x*}^{t,t+K} &= (C_{xx})^{K}\ C_{x*}\ (C_{**})^{K-K} + (C_{xx})^{K-1}\ C_{x*}\ (C_{**})^{K-K+1} + \ldots + (C_{xx})^{K-K}\ C_{x*}\ (C_{**})^{K} \\ &= \textstyle\sum_{j=0}^{K} (C_{xx})^{K-j}\ C_{x*}\ (C_{**})^{j} \end{aligned} \tag{11}$$

where $K \leq T\text{-}t$. The ***Predicted Survival Rate over $K+1$ waves*** (i.e the probability of not making any transition and hence staying in x) under the Markov Assumption is simply the product of two-wave transitions by the number of transitions (K):[12]

[11] Note that this definition implicitly involves four assumptions: (1) transitions between states are independent of time; (2) transitions are not dependent on which state was occupied before *t*; (3) *t* is taken to be discrete; (4) only one movement can occur in a unit of time.

[12] I shall call Survival Rate to the proportion of individuals still in a certain state over one period. In labour economics literature and in international organizations' reports this rate is called *Retention Rate* when it refers to employment state. However, because I use it for all states including housewives (in which case "retention rates" does not sound appropriate in english), I decided to change the name.

$$P\tau_{xx}^{t,t+K} = P\tau_{xx}^{t,t+1} \,.\, P\tau_{xx}^{t+1,t+2} \,.\, \ldots . \,.\, P\tau_{xx}^{t+K-1,t+K} = (C_{xx})^K \qquad (12)$$

Then, the formula for the ***Predicted Exit Transition Rates over K+1 waves*** of (11) can be rearranged using equation (12):

$$P\tau_{x*}^{t,t+K} = 1 - P\tau_{xx}^{t,t+K} = 1 - (C_{xx})^K \qquad (13)$$

In this context (where a First-Order Markov Process is assumed) any transition rate over any number of waves can be very easily simulated by using C_{xy} for any x and y. The simulated transition rates have the property of decreasing as the time period of the transition increases:

$$P\tau_{x*}^{t,t+K} > P\tau_{x*}^{t,t+Q} \quad \text{for any } K < Q, \text{ and } K < T - t,\ Q < T - t \qquad (14)$$

because

$$(C_{x*})^K > (C_{x*})^Q \quad \text{given that } C_{x*} < 1 \text{ for any } x \qquad (15)$$

Define the ***Predicted Survival Curve for State x*** as the curve obtained after plotting every predicted survival rate over $K+1$ waves for every value of K, and for the N_x individuals occupying state x in wave 1. Define ***Actual Survival Curve for State x*** as the curve of actual survival rates obtained over $K+1$ waves for every value of K and for the N_x individuals occupying state x in wave 1. Then, C_{xx} is calculated based on $\tau_{xx}^{1,2}$ i.e $C_{xx}=\tau_{xx}^{1,2}$. The predicted survival curve can be compared with the actual survival curve, being the following the main properties:

(1) Both curves are decreasing functions over time (see expression (14)).

(2) In the first two waves both curves take the same value because the predicted survival rate is calculated based on the actual: in the first wave both curves take a value of 100, and in the second both take the value of the survival rate from the first to the second wave.

(3) After the second wave, if the actual curve is systematically higher than the predicted curve, it means that the more one individual stays in a particular

state, the less likely he / she is to exit. Hence, there is an influence of past history, and thus the assumption of constant transition rates over time is rejected.

The *effect of past history* can then be measured by using these curves. Define an index which takes value 0 if there is no effect of past history and value 1 if there is a deterministic situation in which there is total effect of past history (i.e individuals that occupy any state have a zero probability of exiting it). Then, the lower bound can be derived from the Predicted Survival curve. The upper bound can be derived as the value of an imaginary curve reflecting the situation where the hazard of exit is null after the second wave. This is a completely flat curve (i.e slope equals zero) with intercept C_{xx}. Now, the position of the Actual Survival curve relative to these two bounds is a possible index of past history effect. Define the **Index of Past History Effect (θ)** for finite samples with discrete time and, say, $K+1$ waves, as follows:

$$\theta = \frac{\sum_{t=2}^{K} \dfrac{\tau_{xx}^{t,t+1} - (C_{xx})^t}{C_{xx} - (C_{xx})^t}}{K-2} \tag{16}$$

This is the average sum of actual survival rates relative to the two bounds after wave 1. This index has the following properties:

(1) $1 > \theta > 0$

(2) If $\theta=1$ then there is total effect of past history (i.e, $\tau_{x*}^{t,t+1}=0$ for any $t>1$).

(3) If $\theta=0$ then there is no effect of past history (i.e $\tau_{xx}^{t,t+1}=C_{xx}$ for all t)

Thus, the higher θ the higher the effect of past history. Note that with continuous time this index measures the area between the actual and predicted curves relative to the area between the flat curve and the predicted curve. The simplicity of this index involves certain drawbacks. Nevertheless it is sufficient for the purpose of ordering the states according to the effect of past history.

4.2 Survival Rates: Analysis Over Seven Waves

To examine how past history affects the hazard of exit, I select households that stay in the survey for a sufficiently long time period. Then, I examine the hazard of survival at the origin state occupied in the first wave, ignoring re-entries to the origin state because they are not comparable. I use a sub-sample of households that respond to 7 consecutive interviews.[13] The criteria used for sample selection is to maximize both the number of consecutive waves and the sample size. The sub-sample of 7 consecutive interviews is preferable to that of 8 consecutive interviews because of the gain in terms of sample size (4,348 households versus 1,655 households), despite the loss of one time period. The distribution of labour market states in the first wave is: 17.5% is in regular employment, 5.1% is in irregular employment, 1.7% is in unemployment, and 73.7% are housewives. Thus, 75.7% are OLF, 22.6% are employed and 1.7% are unemployed wives.

Figures 9 to 14 (see Table A5 in the Appendix for the original figures) show the actual and predicted survival rates over 7 waves for different labour market states. Each figure is based on the sub-sample of wives occupying the origin state in wave 1. Entries and re-entries to the origin state in subsequent waves are ignored. For example, in Figure 9, the curve of survival OLF has been calculated using the subsample of wives who are OLF in the first wave, and who are observed in 7 consecutive waves. As soon as they change status they are dropped from the sub-sample. In the case they re-enter OLF, they would not be re-included in the sub-sample. The following labour market states are considered: regular employment, irregular employment, unemployment, housewives, OLF and in-the-labour-force. Three important (and expected) results emerge from Figures 9 to 14:

(1) Actual curves are systematically above predicted curves for all labour market states, indicating a positive effect of past history on the likelihood to survive. Thus, the more time individuals occupy a state, the lower the hazard of

[13] Recall that, in theory, ECPF households are interviewed for 8 consecutive quarters. However, due to attrition only 15% of the sample respond to 8 interviews, and only 25% respond to 7 interviews (before sample selection).

exiting such states. This is a general finding in labour economics literature (Blumen *et al.* 1955, Heckman and Willis, 1977).

(2) There is a clear distinction among two groups of states: those with high (predicted and actual) survival, reflected in flatter curves, and those with low (predicted and actual) survival, reflected in rapidly decreasing curves. Unemployment and irregular employment are the two states with low survival. In both cases, the predicted survival curve tend to zero in the 8th wave, while the actual curve only tends to zero (if at all) in the long-run. Regular employment and housewives are the two states with high survival, being housewives the state with higher survival of the two.

(3) The state with greater effect of past history is housewives, with an index θ=0.49. Regular employment follows with θ=0.44, irregular employment (with θ=0.34) and lastly unemployment (with θ = 0.26).

Figure 9
Wives Remaining Out of the Labour Force
Actual versus Predicted Rates

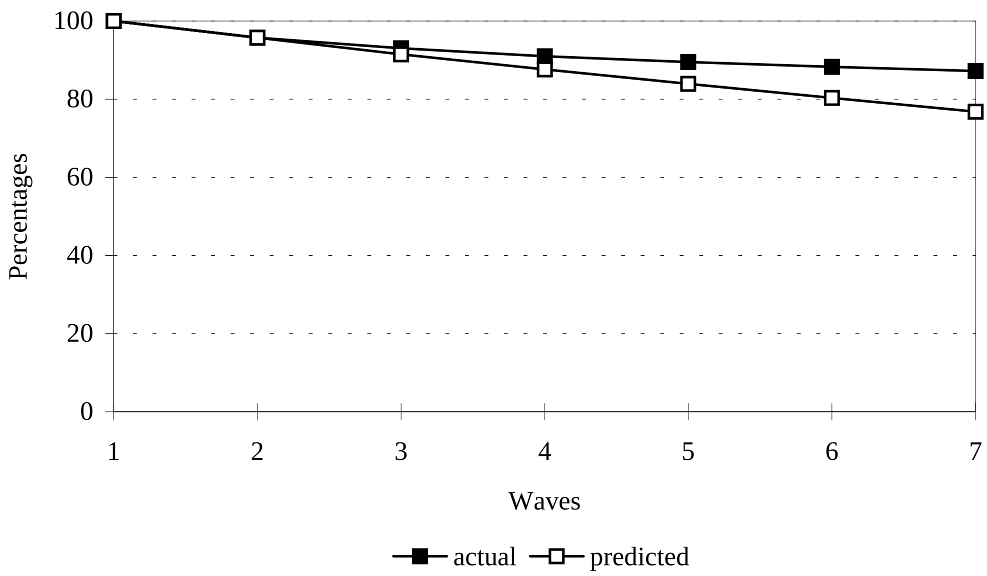


Figure 10
Wives Remaining In the Labour Force
Actual versus Predicted Rates

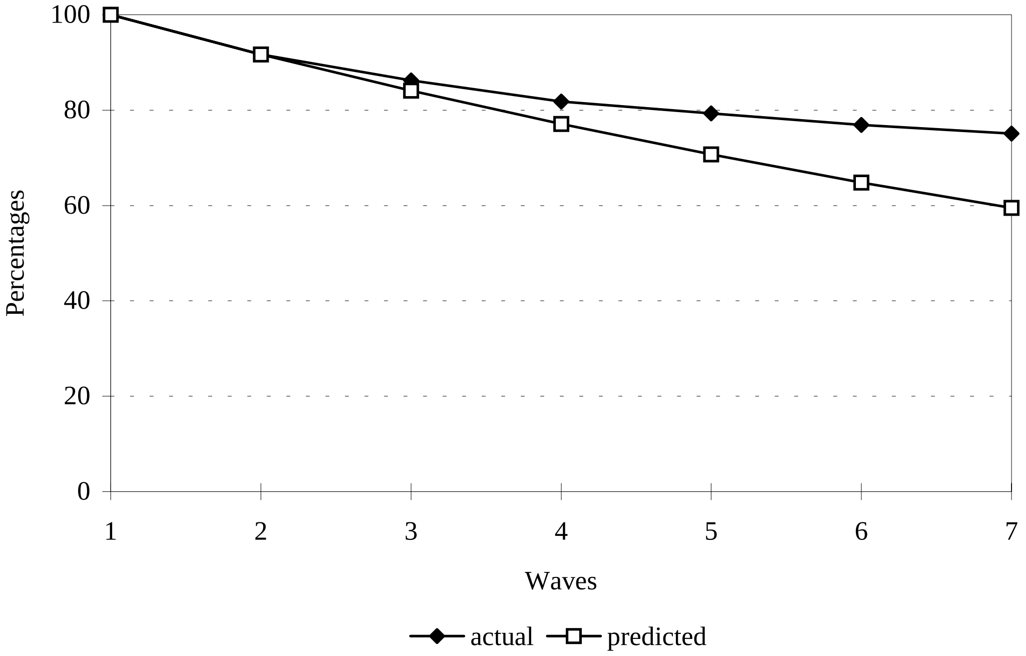


Figure 11
Wives Remaining as Housewives
Actual versus Predicted Rates

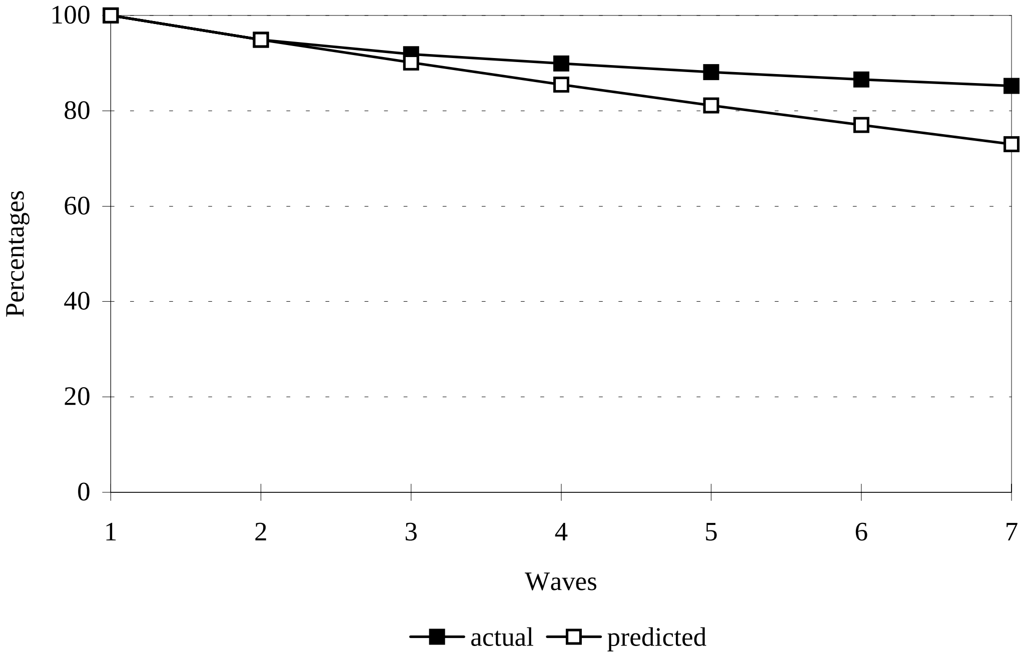


Figure 12
Wives Remaining in Regular Employment
Actual versus Predicted Rates

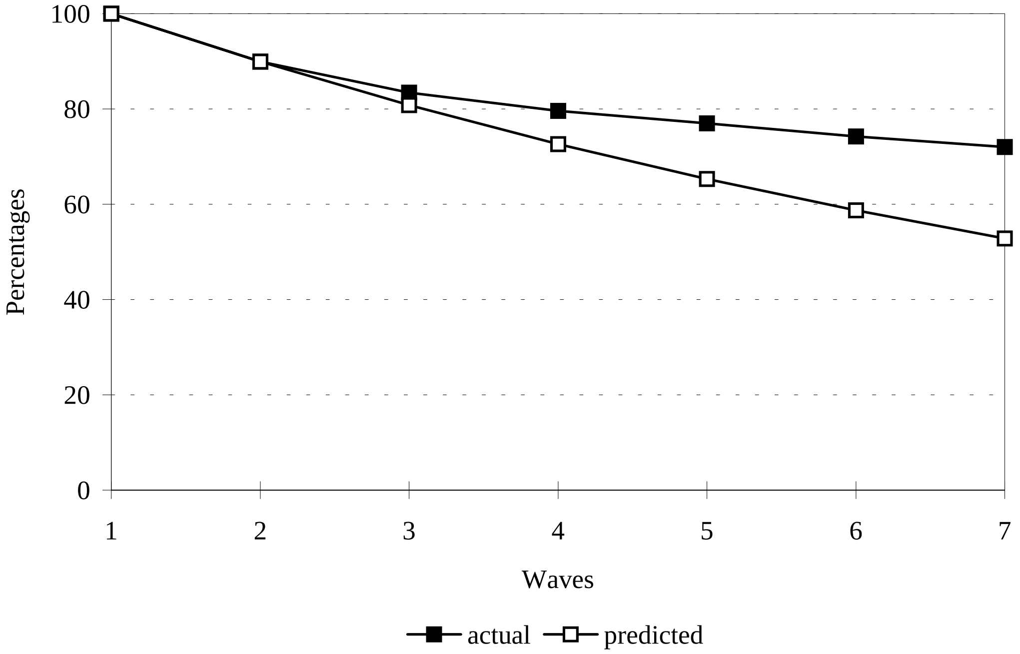


Figure 13
Wives Remaining in Unemployment
Actual versus Predicted Rates

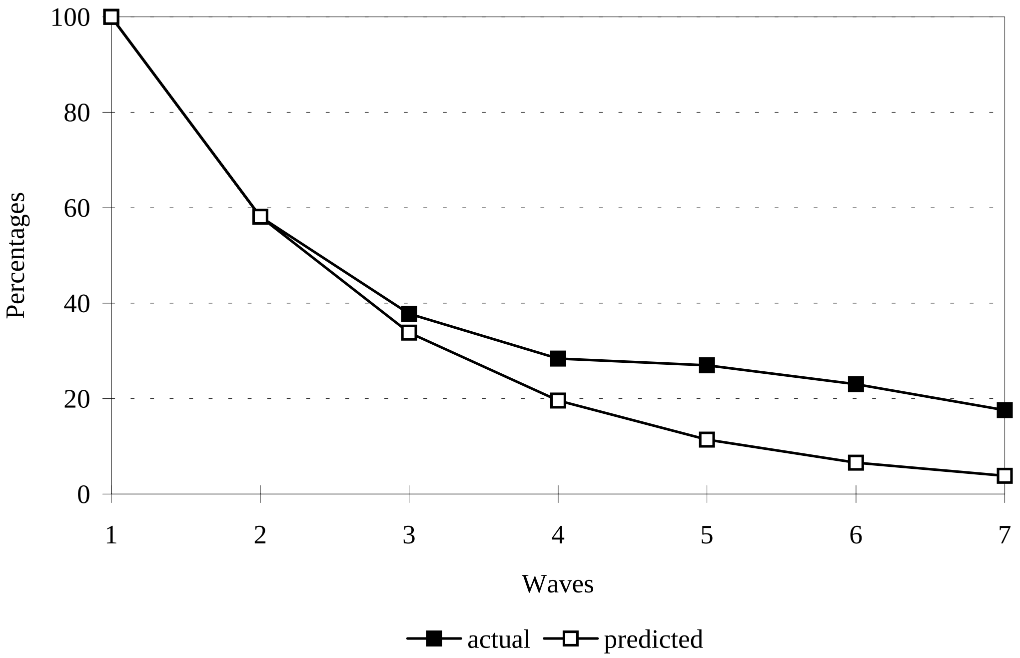
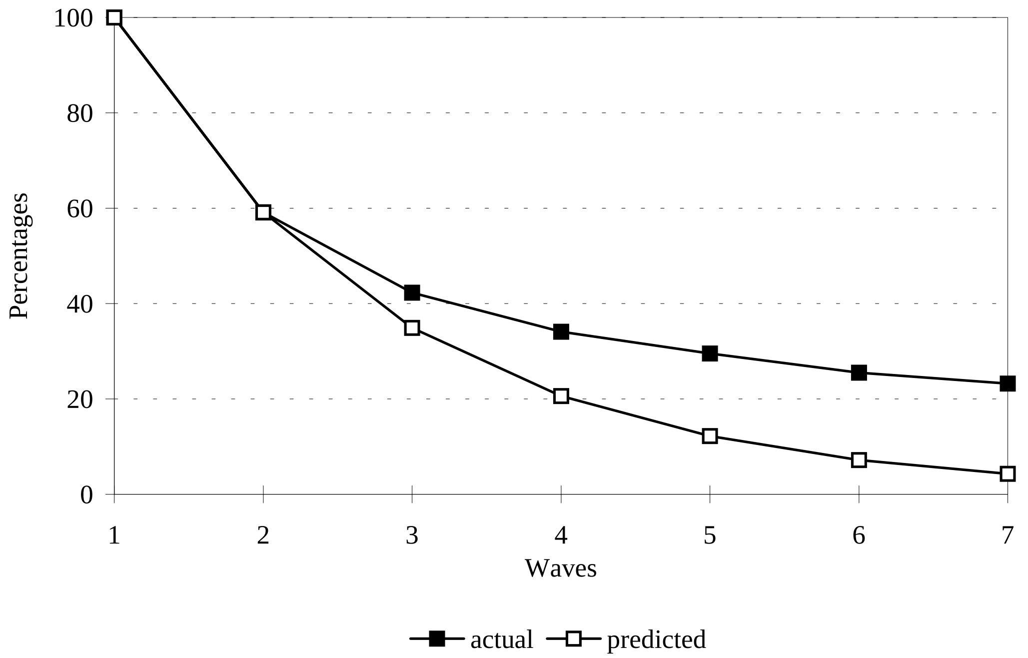


Figure 14
Wives Remaining in Irregular Employment
Actual versus Predicted Rates



Comparing the survival of participants and non-participants (Figures 9 and 10), the group of non-participants has a more stable profile than the group of participants, although both are very stable. Non-participants have a higher rate of survival and its index of time dependence is $\theta=0.46$, while among participants the same index is $\theta=0.39$. That is, the average LF outflow after the second wave is 39% lower than from the first to the second wave, while the average LF inflow after the second wave is 46% lower than from the first to the second wave. Therefore, flows into and out of the LF are rather scarce, and individuals in each pool are quite stable (which, is consistent with the results obtained from the two-wave analysis).

Housewives are by far the most stable group of them all (see Figure 11). The actual survival rate is the highest; 95% of housewives in wave 1 stay as housewives in wave 2. The effect of past history is also extremely high; average housewives' outflow after the second wave is 50% lower than that observed from waves 1 to 2. Indeed, the actual survival curve is almost flat. Despite of being also quite stable, the group of regularly employed is less stable than housewives (Figure 12). Nineteen percent of regular employment in wave 1 stay as such in wave 2. There is also less effect of past history. The average regular employment outflow after the second wave is 44% lower than that observed from waves 1 to 2.

Unemployment and irregular employment (Figures 13 and 14) present a completely different picture. The actual survival rate from waves 1 to 2 is very similar in both cases (58.1% and 59.1%), a rather low rate compared to that of housewives and regular employment. The effect of past history among irregularly employed is larger than among unemployed. In particular, the average irregular employment outflow after the first wave is 34% lower than that observed from waves 1 to 2 (i.e 10 percentage points less than that found for regular employment), while in the case of unemployment is 26%. ThUS, despite the low mobility into and out of the LF, mobility within the LF presents a rather different picture.

Of course, the incidence and evaluation of these results depends on the nature of the labour market state, the policy targets and the subjectivity of the analyst. For example, is high immobility of housewives good or bad? Labour economics theory does not give a straightforward answer to this question as easily as to the question of whether unemployment entrapment is good or bad. However, there is some agreement that a certain level of participation is desirable in any economy. For instance, Dolado and Jimeno (1995) affirm that Spanish activity rates are too low to achieve the requirements for EC convergence. So, if the policy objective is to achieve high levels of LF participation, then the high proportion of housewives should be worrying, and the high rate of housewives' survival should be even more worrying phenomenon.

There is a general consensus that unemployment entrapment is not desirable in any economy. As expected, this rate decreases significantly if one uses a yearly base (48.4%) rather than a monthly rate (58%). In other words, only 58% of the unemployed wives in one period are unemployed three months later, while 48.4% are unemployed one year later. This figure appears 20 percentage points higher (67.8%, using the EPA-1988/89) if one considers all women of working age. This suggests that married women tend to "survive" shorter in unemployment than average women. Using this data for all women of working age, one can carry out international comparisons which are useful to assess how large the obtained rates are. Table 2 shows that women of working age in Spain present the highest retainment rate into unemployment (proportion of unemployed in 1988 who are still unemployed exactly one year later) among OECD countries, after Belgium. Thus, the results are not very encouraging.

Table 2
Unemployment Retainment Rates (yearly) in selected EC countries

Belgium	73.1%	Greece	36.8%
Spain	67.8%	Denmark	32.5%
Portugal	49.7%	Ireland	29.6%
Germany	47.8%	UK	25.0%
France	47.0%	Netherlands	13.0%

Source: My own calculations using the *Eurostat Labour Force Survey (1989).*

With respect to employment, survival contingent on tenure should in principle be desirable unless it reflects the impossibility of the unemployed and irregularly employed of moving to regular employment. The results show a greater effect of past history in regular employment than in irregular employment. Moreover, there is more entrapment in irregular employment than in unemployment. Of course, the evaluation of whether this result is good or not depends very much on the destination state. The picture changes significantly if the destination state is a regular job, rather than unemployment or irregular jobs. Thus, to complete the multi-wave analysis a discussion of the destination states is needed. In the following sub-section, transition rates contingent on past labour market states are evaluated.

4.3 Mobility Contingent on Past States: Analysis Over Three Waves

Previous labour market states may well influence the hazard of moving out of the current state. Put in another way, given a transition from x to y, the probability of either staying in y, moving back to x, or moving to another state z in the next period may well differ according to the nature of the origin state x, the nature of the destination state *y*, and the nature of the alternative state *z*. The importance of past history can be uncovered by decomposing the change between states from *t* to *t+1* so that the previous change from *t-1* to *t* may also be distinguished. This allows us to see the relationship between actual moves or states and past labour market states or moves. To carry out this analysis, an ECPF sub-sample of households that respond to three consecutive interviews is used. The advantage of this sub-sample with respect to the 7-waves' sub-sample is that there is an increase in sample size and thus the precision of the estimates. With the 3-wave sample, there is indeed a significant gain in terms of observations: 29,101 observations are available. The labour market state distribution in the first wave of this subsample is: 17.5% are in regular employment, 4.8% are in irregular employment, 1.8% are unemployed and 73.4% are housewives (thus, 75.9% are non-participants).

Table 3
Mobility Over Three Waves

Labour Market State at: *t-1*	*t*	*Labour Market State at t+1:* X	Y	Z	
	X	f(xxx)	f(xxy)	f(xxz)	f(xx*)
Y		f(yxx)	f(yxy)	f(yxz)	f(yx*)
Z		f(zxx)	f(zxy)	f(zxz)	f(zx*)
		f(*xx)	f(*xy)	f(*xz)	f(*x*)
X	Y	f(xyx)	f(xyy)	f(xyz)	f(xy*)
Y		f(yyx)	f(yyy)	f(yyz)	f(yy*)
Z		f(zyx)	f(zyy)	f(zyz)	f(zy*)
		f(*yx)	f(*yy)	f(*yz)	f(*y*)
X	Z	f(xzx)	f(xzy)	f(xzz)	f(xz*)
Y		f(yzx)	f(yzy)	f(yzz)	f(yz*)
Z		f(zzx)	f(zzy)	f(zzz)	f(xz*)
		f(*zx)	f(*zy)	f(*zz)	f(*z*)

In decomposing transitions over three waves into two transitions I construct a transition matrix, like the theoretical one presented in Table 3, where the rows report labour market changes from *t-1* to *t* and the columns report the actual state at *t+1*. This matrix is divided into *n* sub-matrices, where *n* equals the number of labour market states, and is the same for all *t* (in the case of Table 3, *n*=3 because there are three states: *x*, *y* and *z*). I shall call each sub-matrix by the name of the state occupied at time *t*. Now look at the *x sub-matrix*, which corresponds to all wives occupying state *x* at *t*. The first row shows the distribution of labour market states at *t+1* among all women who stayed in state *x* at *t-1* and *t*, i.e the frequencies *f(xxx), f(xxy)* and *f(xxz)*. Similarly, the second row shows the labour market states' distribution at *t+1* among all women who made a transition from *y* to *x* from *t-1* to *t*, i.e the frequencies *f(yxx), f(yxy)* and *f(yxz)*. By analogy, the first column shows the distribution of wives occupying state *x* at time *t+1* by all different types of past histories recorded from *t-1* to *t*, i.e *f(xxx), f(yxx)* and *f(zxx)*. Thus, the column totals report the distribution of exit transitions from *t* to *t+1* by destination state, i.e f(*xx), f(*xy), etc, and the row totals report the distribution of entry transitions from *t-1* to *t* by origin state, i.e f(xx*), f(yx*), etc. The diagonal cells (excluding the first cell) report the cases where there is a relapse. Namely a move back to the same state occupied at *t-1* like *f(yxy), f(zxz)*.

Using this matrix one can easily evaluate the hazard of survival and the hazard of relapse to previous states over three waves. By taking row percentages, the x-sub-matrix of frequencies gives the *hazard of a particular state given a transition to x*. This allows us to calculate all types of hazards like, for example, the hazard of survival in *x* given a two period survival. This **Survival Rate (SR) in x** is:

$$SR_{xxx} = \frac{f(xxx)}{f(xx^*)} \tag{17}$$

Similarly, the hazard of survival in *x* given a transition from *y* is:

$$SR_{yxx} = \frac{f(yxx)}{f(yx^*)} \tag{18}$$

This rate allows us to calculate the likelihood of survival by origin, and compare whether someone coming from *y* is more likely to stay in *x* than someone coming from *z*. One can also calculate the **Relapse Rates**, say, into *y* from *x*:

$$RR_{yxy} = \frac{f(yxy)}{f(yx^{*})} \tag{19}$$

Thus, one can calculate the likelihood of falling back to a certain state by different states occupied at *t*, and then see, for instance, whether individuals who exit *y* are more likely to relapse into *y*, had they moved to *z* instead of *x*. One can also compare the relapse rates and evaluate which states are more prone to backsliding. In view of the results obtained in the previous sections, one expects the Survival Rates to be larger than the Relapse Rates in the regular employment sub-matrix and the OLF sub-matrix. In the irregular employment and unemployment sub-matrices, the relationship between Survival Rates and Relapse Rates is less predictable, and probably depends on the nature of the states at *t-1* and *t+1*.

Table 4 reports the actual figures (row percentages) corresponding to the three-wave transition matrix described above, where four labour market states are considered: OLF, regular employment, irregular employment and unemployment. All entries based on samples of size more than 100 are in bold, all based on sizes greater than 50 but less than 100 are in italics and all based on sizes less than 50 in both italics and asterisk, e.g *50.0**. See Table A6 for the row matrix, with 16 rows and 4 columns.

Let us start with the OLF sub-matrix. *Survival Rates* from *t* to *t+1* (first column) are greater than any other rate in the same row: non-participating wives are more likely to stay than exit, no matter what the previous labour market state was. Of course, the likelihood is higher for those who were previously non-participants, for whom the likelihood of surviving a third period in the same state is 97.7%. Otherwise, the group with higher likelihood of surviving in inactivity is the group of previously unemployed (74.5%) and previously irregularly employed (73.4%), followed by the group of previously regularly employed (66%). As expected, Survival Rates are higher than *Relapse Rates* (diagonal entries). Among the previously regular employed wives who exit from the LF, 21% return back to regular employment one period later (7.3% return as irregularly employed, 5.7% as unemployed and 65.9% remain OLF). In the case of the irregular employed who exit from the LF, 19% return back to irregular employment. Finally, 19 out of 105 unemployed who exit return as unemployed.

Concerning the regular-employment sub-matrix, *Survival Rates* from t to $t+1$ (second column) are greater than any other rate in the same row: wives in regular employment are more likely to stay than to exit. The likelihood is higher for those previously occupied as regularly employed, for whom the likelihood of surviving a third period in the same state is 93.4%. Otherwise, the group with higher likelihood of surviving in regular-employment is the group of previously irregularly employed (62.8%), followed by the group of previously non-participants (56.9%) and by the group of previously unemployed (54.4%). Interestingly, previously unemployed have a lower likelihood of survival in regular employment than previously non-participants. As expected, Survival Rates are higher than *Relapse Rates* (diagonal entries, RE sub-matrix). Previously irregularly employed have a Relapse Rate of 29.7%, meaning that wives who make a transition from irregular to regular employment have a 29.7% chance of falling back to irregular employment in the next period. The hazard of relapse is a bit lower in the case of OLF (26.9%) and unemployed (26.3%) wives. In addition, note that 44 wives out of 364 (12.1%) who moved from OLF to regular employment are in irregular employment one wave later. A similar proportion move to OLF after a transition from unemployment to regular employment. Finally, note that 3.1% of wives who stay in regular employment for two periods move to OLF.

Comparing the RE sub-matrix with the OLF sub-matrix, the OLF Survival Rate from $t-1$ to t and $t+1$ is greater than the RE Survival Rate (97.7% versus 93.4%): women who stay as non-participants for two periods are more likely to survive as non-participants than women who stay as regular employed for two periods are likely to survive as regular employed. In addition, Survival Rates in inactivity are higher no matter what the previous state was. However, Relapse rates in the OLF sub-matrix are lower than in the RE sub-matrix, meaning that the probability of falling back into previous states is lower if one enters inactivity than regular employment.

Table 4
Mobility Over Three Waves
(Row Percentages)

Labour Market Transition from *t-1* to *t*		*Labour Market State at t+1:* OLF	RE	IE	U	
OLF		**97.7**	**1.1**	**0.9**	*0.3*	100
RE	OLF	**65.9**	*21.1*	*7.3**	*5.7**	100
IE		**73.4**	*5.6**	*19.0**	*2.0**	100
U		**74.5**	*3.6**	*3.6**	*18.2**	100
Total		**97.0**	**1.4**	**1.2**	*0.4*	
OLF		*26.9*	**56.9**	*12.1**	*4.1**	100
RE	RE	**3.1**	**93.4**	**2.7**	*0.9**	100
IE		*6.5**	**62.8**	*29.7*	*1.0**	100
U		*12.3**	*54.4**	*7.0**	*26.3**	100
Total		**5.0**	**88.7**	**4.9**	*1.4*	
OLF		*32.8*	*16.7**	**48.4**	*2.1**	100
RE	IE	*9.8**	**47.7**	**40.9**	*1.5**	100
IE		*10.4*	**13.7**	**74.9**	*1.1**	100
U		*18.8**	*12.5**	*37.5**	*31.3**	100
Total		**14.7**	**20.6**	**62.8**	*1.7**	
OLF		*38.0**	*6.5**	*3.3**	*52.2**	100
RE	U	*15.6**	*32.8**	*3.1**	*48.4**	100
IE		*29.2**	*20.8**	*20.8**	*29.2**	100
U		*15.5**	*8.8**	*2.4**	*76.2*	100
Total		**18.3**	*12.0*	*3.5**	**66.1**	

Notes: (1) The definitions of labour market states are: OLF is "out of the labour force", RE is "regularly employed", IE is "irregularly employed" and U is "unemployed".
(2) This table was obtained by calculating the column percentages of Table A6 in the Appendix. For example, the first cell tells that 97.7% of individuals who stayed as non-participants at t-1 and t are actually non-participants also at t+1.
(3) Some entries of this table are based on tiny sample sizes. To indicate which entries are based on a small sample and which on a very small sample the entries are in three different ways: Entries in bold are based on samples bigger than 100, entries in italics are based on samples smaller than 100, and entries both in italics and an asterisk are based on samples less than 50 (e.g *50.0**).

Concerning the irregular-employment sub-matrix, *Survival Rates* from *t-1* to *t* (third column) are lower than the survival rates in the RE and the OLF sub-matrices. In particular, the *Survival Rate* from *t-1* to *t* and *t+1* of irregular employment (75%) is, as expected, lower than that of OLF and regular employment (97.7% and 93.4% respectively), but equal to that for unemployment (76.2%). Women who stay as irregularly employed for two periods are less likely to survive as irregularly employed that women who stay as regularly employed or inactive are to survive. Moreover, the hazard of stay as irregular employed is higher for previously inactive wives (48.4%) than for previously regularly employed (40.9%), which in turn is higher than for previously unemployed wives (37.5%). More interesting, for previously regularly employed, the hazard of falling back to regular employment is higher than the hazard of staying as irregularly employed. In general, relapse rates are quite large (at least much larger than those found in the regular employment and OLF sub-matrices). Indeed, a large proportion (33%) of previously non-participating wives who moved to irregularly employment return back to OLF after one period, compared to 48.4% who stay as irregular employed for another period.

Concerning the unemployment sub-matrix, due to small sample sizes, not much discussion is provided on this sub-matrix. Although survival rates are higher than relapse rates, they are quite similar. Moreover, 48.4% of wives who moved from regular employment to unemployment stay after one period, a large proportion (32.8%) relapse. Similarly, while 52.2% of wives moved from OLF to unemployment, 38% stayed for another period.

Summarizing, the different results obtained in this section are consistent. The following conclusions can be drawn from Table 4:

(1) The hazard of surviving in inactivity or in regular employment is larger than the hazard of surviving in unemployment or irregular employment.

(2) The lowest relapse rates are those from OLF.

(3) The hazard of relapsing into regular employment is higher among irregularly employed (47.7%) than among unemployed (32.8%), which is in turn higher than among non-participants (21.1%).

(4) The hazard of relapsing into irregular employment is higher for regularly employed (29.7%) than for non-participating wives (19.0%). For the unemployed there are too few cases to draw conclusions.

(5) The hazard of relapsing into inactivity is similar for unemployed (38%), for the irregularly employed (32.8%) and for the regularly employed (26.9%).

(6) The likelihood of keeping regular employment is higher among previously irregularly employed (62.8%) than among previously non-participating wives (36.9%), which in turn is higher than among unemployed (54.4%).

(7) The hazard of staying in irregular employment is higher among previously non-participating wives (48.4%) than among previously regularly employed (40.9%) as the latter move back to regular employment in 47.7% of the cases.

(8) The hazard of staying unemployed is higher among previously non-participating wives (52.2%) than among previously regularly employed wives (48.4%). Note that in this case a great proportion move back to the previous labour market state: 32.8% of previously regularly employed and 38% of previously inactive wives actually relapse.

(9) The hazard to stay inactive is higher among previously unemployed (74.5%) or irregular employed (73.4%) than among previously regular employed (65.9%).

To conclude, among all states, OLF is caracterized for its 'retaining' nature in the sense that individuals occupying this state are unlikely to exit and if so, they are very likely to fall back into inactivity, no matter what the destination state is. Among inactive wives that enter into the LF, the likelihood of staying is similar if they accept regular jobs, irregular jobs or enter as unemployed. To a lesser extent, regular employment is also caracterized for its 'retaining' nature. Individuals who enter regular employment are less likely to exit than individuals who enter other LF states (excluding OLF). However, the caracteristics of this state are more complex. Losers of regular employment are more likely to recover their regular jobs if they keep a link with the LF i.e. either as irregularly employed or as unemployed. Finders of regular employment are more likely to stay if they were attached to the workforce as irregularly employed in the previous period. Thus, previous work experience increases the hazard of keeping a regular job more than previous inactivity or unemployment. Concerning irregular employment, entrapment into this state is more likely among previously inactive wives than among previously regularly employed. Thus, again, previous experience raises the hazard of being regular employment.

5. Conclusions

The analysis of wives' mobility of this paper describes the size and direction of the labour market flows among Spanish married women, and contributes to understand LF participation. As a general conclusion, it has been shown that the the large pool of non-participator wives is very unmobile and stable or, in other words, very unlikely to change status. The pool of regularly employed is also stable but to a lesser extent. To the contrary, irregularly employed and unemployed are extremely mobile and unstable, experiencing high rotation back and forth. The two-wave analysis of transitions shows that:

(1) Wives below 35-39 are more likely to exit than enter. This difference is constant over age (with the exception of the younger groups). In the main, LF inflows and outflows are characterized for employment outflows and inflows. Nevertheless, the hazard of exit from unemployment are greater than the hazard of exit from employment. The difference between the two hazards increases with age. The most likely destination of employment leavers is OLF, while unemployment outflows are mainly due to jobfindings.

(2) Wives above 39: As with youngers groups, active wives are more likely to exit the LF than inactive wives to enter. This difference increases considerably with age. Despite the fact that most LF inflows and outflows are characterized by employment inflows and outflows, the hazard of exit from unemployment is far larger than the hazard of exit from employment. The most likely destination of employment leavers is OLF, while the likely destination of unemployment leavers is employment for wives below 45-49 and OLF for wives older than 49.

(3) In absolute values, the LF inflow is larger than the outflow for women aged 30 to 55. This suggests an evolution of the life-cycle participation pattern towards a modern profile as in other Northern European countries. Unemployed are more likely to exit than the employed. However, in absolute values the employment outflow is greater than the unemployment outflow.

The multi-wave analysis reveals further information on wives' transitions, although inference for different age groups has not been made due to small sample sizes. Considering all labour market states, non-participating wives (particularly housewives) are by far the most stable and state-dependent group of all. Wives occupying non-participation are unlikely to exit (although previously regularly employed have a better chance) and if so, they are very likely to fall back into inactivity, no matter what the destination state is. Among inactive wives that enter into the LF, the likelihood of staying is similar if they accept regular jobs, irregular jobs or enter as unemployed. Once wives enter non-participation, the likelihood of an inmediate re-entry to the LF is 19.4%. This is lower than the likelihood of relapsing after leaving non-participation: 32.6% of exits from non-participation become withdrawals after one quarter.

The regularly employed group (working more than 1/3 of the normal working hours) is also very stable and highly state-dependent. Losers of regular employeemnt are more likely to recover their regular jobs if they keep a link with the LF i.e. either as irregularly employed or as unemployed. Finders of regular employment are more likely to stay if they were attached to the workforce as irregularly employed in the previous period. Thus, previous work experience increases the hazard of keeping a regular job more than previous inactivity or unemployment. The likelihood of an inmediate exit once wives enter regular employment is 27.6% and the likelihood of relapsing after leaving regular employment is 33.8%. Note that comparing with non-participation, the size of these rates reverse.

Unemployment and irregular employment appear as quite unstable states, despite the existence of fairly high state dependence. Considering all wives who exit irregular employment, 23.2% of them actually fall back after one period, while 37.7% of those entering irregular employment leave this state after one quarter. Entrapment into this state is more likely among previously inanctive wives than among previously regularly employed wives. Thus, again, previous experience raises the likelihood of reaching regular employment. For the unemployment case, it is difficult to draw conclusions due to the small number of cases, however, the hazard of exiting unemployment one period after entering seems to be higher than the hazard of moving back after an exit.

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Statistical Appendix

Table A.1
Exit from and Entry to the Labour Force
Average Transition Rates

	Exit Rates			Entry Rates		
Age Groups	Rates	SE	NO	Rates	SE	NO
≤ 19	14.3	(0.067)	5	2.1	(0.021)	2
20-24	9.3	(0.016)	47	5.3	(0.008)	63
25-29	7.6	(0.007)	122	5.6	(0.005)	145
30-34	7.1	(0.006)	107	4.7	(0.004)	146
35-39	6.7	(0.006)	112	3.8	(0.003)	150
40-44	8.7	(0.008)	108	4.2	(0.003)	156
45-49	7.2	(0.008)	83	2.4	(0.002)	90
50-54	10.2	(0.010)	96	2.5	(0.002)	113
55-59	12.6	(0.013)	81	1.9	(0.002)	67
60-65	11.8	(0.017)	28	1.4	(0.002)	26
Total	8.4	(0.003)	789	3.2	(0.001)	958

Notes: (1) Standard Errors in brackets (*). NO: Number of Observations.
(2) Exit Rates are calculated as the proportion of married women in the labour force at time t who withdraw at t+1. Entry Rates are calculated as the proportion of inactive married women at t who are active at t+1.
(3) Figures obtained from the two-wave subsample of 39,959 households. The sample sizes at time t are: 9,580 participant and 30,379 non-participant married women.

Table A.2
Entry to the Labour Force (Inactive Women)
Average Transition Rates

	Entry the Labour Force	*of which:* Entry Employment			Entry Unemployment		
	Rates	Rates	SE	Number Obs	Rates	SE	Number Obs
≤ 19	2.1	2.1	(.021)	2			0
20-24	5.3	4.1	(.007)	50	1.2	(.004)	13
25-29	5.6	4.4	(.004)	114	1.2	(.002)	31
30-34	4.7	3.9	(.003)	125	0.7	(.002)	21
35-39	3.8	3.1	(.003)	120	0.7	(.001)	30
40-44	4.2	3.7	(.003)	139	0.6	(.001)	17
45-49	2.4	2.2	(.002)	83	0.1	(.001)	7
50-54	2.5	2.3	(.002)	105	0.2	(.001)	8
55-59	1.9	1.6	(.002)	61	0.2	(.001)	6
60-65	1.4	1.3	(.002)	24	0.1	(.001)	2
Total	3.2	2.8	(.001)	823	0.5	(.000)	135

Notes: (1) Standard Errors in brackets (*).
(2) Entry Rates are the proportion of inactive married women at t who are active at t+1.
(3) Figures obtained from the two-wave subsample. The sample size at time t is 29,805 non-participant married women.

Table A.3

Exit from the Labour Force (Women in the Labour Force)

Average Transition Rates

	Exit from the Labour Force	*from:* Employment			Unemployment		
	Rates	Rates	SE	Number Obs	Rates	SE	Number Obs
≤ 19	14.3	-		1			4
20-24	9.3	7.8	(.016)	30	14.1	(.038)	17
25-29	7.6	5.4	(.007)	80	23.4	(.033)	42
30-34	7.1	5.9	(.006)	81	20.0	(.033)	26
35-39	6.7	5.8	(.006)	91	17.9	(.036)	21
40-44	8.7	8.2	(.008)	99	18.1	(.046)	9
45-49	7.2	6.8	(.008)	72	24.0	(.087)	11
50-54	10.2	9.2	(.010)	84	35.1	(.080)	12
55-59	12.6	11.5	(.012)	73	28.3	(.067)	8
60-65	11.8	11.7	(.017)	26	14.3	(.097)	2
Total	8.4	7.3	(.003)	637	21.3	(.0153)	152

Notes: (1) Standard Errors in brackets (*).

(2) Exit Rates are calculated as the proportion of married women in the labour force at t who withdraw at t+1.

(3) Figures obtained from the two-wave subsample. The sample size at time t is 9,580 participant married women.

Table A.4
Exit Employment and Exit Unemployment
Average Transition Rates

Exit Employment

	Total			to Unemployment			to Non-Participation		
	Rates	SE	NO	Rates	SE	NO	Rates	SE	NO
≤ 19	14.3	(.078)	7	14.3	(.078)	6	-		1
20-24	13.4	(.021)	45	5.6	(.014)	15	7.7	(.016)	30
25-29	6.8	(.007)	101	1.4	(.003)	21	5.4	(.007)	80
30-34	7.6	(.007)	110	1.9	(.004)	29	5.9	(.006)	81
35-39	7.3	(.007)	108	1.5	(.003)	17	5.8	(.006)	91
40-44	9.8	(.008)	121	1.7	(.004)	22	8.2	(.008)	99
45-49	7.5	(.008)	78	0.7	(.003)	6	6.8	(.008)	72
50-54	10.1	(.010)	91	0.9	(.003)	7	9.2	(.010)	84
55-59	12.4	(.013)	79	0.9	(.004)	6	11.5	(.012)	73
60-65	12.5	(.018)	28	0.9	(.005)	2	11.7	(.017)	26
Total	8.8	(.003)	768	1.5	(.001)	131	7.3	(.003)	637

Exit Unemployment

	Total			to Employment			to Non-Participation		
	Rates	SE	NO	Rates	SE	NO	Rates	SE	NO
≤19	71.4	(.185)	8	14.3	(.143)	4	51.5	(.202)	4
20-24	27.1	(.049)	29	12.9	(.063)	12	14.1	(.038)	17
25-29	33.5	(.037)	61	10.2	(.024)	19	23.4	(.033)	42
30-34	36.7	(.040)	51	16.7	(.031)	25	20.0	(.032)	26
35-39	37.5	(.046)	39	19.6	(.038)	19	17.9	(.036)	21
40-44	41.7	(.059)	27	23.6	(.050)	18	18.1	(.045)	9
45-49	44.0	(.101)	14	20.0	(.082)	3	24.0	(.087)	11
50-54	40.5	(.082)	13	5.4	(.038)	1	35.1	(.079)	12
55-59	34.8	(.071)	12	6.5	(.037)	4	28.3	(.067)	8
60-65	28.6	(.125)	3	14.3	(.097)	1	14.3	(.097)	2
Total	35.9	(.018)	257	14.7	(.013)	105	21.3	(.015)	152

Notes: (1) Standard Errors (SE) in brackets (*). NO: Number of observations.
(2) Exit Rates are calculated as the proportion of married women in the labour force at t who withdraw at t+1. Entry Rates are calculated as the proportion of inactive married women at t who are active at t+1.
(3) Figures obtained from the two-wave subsample. The sample size is 8,732 employed married women, and 715 unemployed married women at time t.

Table A.5

Women Remaining in the Origin State over Seven Waves (Ignoring Re-entries)
Actual and Predicted (Under Markov Assumption) Percentages

Actual Percentage (Ignoring Re-entries)

	Regular Employment		Irregular Employment		Unemployment		Housewives		OLF	Participant in the LF
Waves	Total	SR	Total	SR	Total	SR	Total	SR	SR	SR
1	760	100	220	100	74	100	3,201	100	100	100
2	683	89.9	130	59.1	43	58.1	3,039	94.9	95.7	91.7
3	634	83.4	93	42.3	28	37.8	2,942	91.9	93.0	86.2
4	605	79.6	75	34.1	21	28.4	2,873	89.9	91.0	81.8
5	585	77.0	65	29.5	20	27.0	2,821	88.1	89.5	79.3
6	564	74.2	56	25.5	17	23.0	2,771	86.6	88.3	76.9
7	547	72.0	51	23.2	13	17.6	2,728	85.2	87.2	75.1

Predicted Percentage Under Markov Assumption (Ignoring Re-entries)

	Regular Employment	Irregular Employment	Unemployment	Housewives	OLF	Participant in the LF
Waves	SR	SR	SR	SR	SR	SR
1	100	100	100	100	100	100
2	89.9	59.1	58.1	94.9	91.7	91.7
3	80.8	34.9	33.8	90.1	84.1	84.1
4	72.6	20.6	19.6	85.5	77.1	77.1
5	65.3	12.2	11.4	81.1	70.7	70.7
6	58.7	7.2	6.6	77.0	64.8	64.8
7	52.8	4.3	3.8	73.0	59.5	59.5

Notes: (1) SR is the "Stay Transition Rate". OLF is the "Out of the Labour Force" state. LF is the "Labour Force".
(2) Figures obtained from seven-wave ECPF sub-sample. The sample size is 4,355 households.

Table A.6
Labour Market Flows Over Three Waves

State Occupied in:		State Occupied in Wave 3:				
Wave 1	Wave 2	RE	IE	U	OLF	Total
RE	RE	4,215	120	41	139	4,515
	IE	126	108	4	26	264
	U	21	2	31	10	64
	OLF	54	18	15	168	261
	Totals	4,417	249	91	347	5,104
IE	RE	184	87	3	19	293
	IE	116	636	9	88	849
	U	5	5	7	7	24
	OLF	14	47	5	175	241
	Totals	319	775	24	289	1,407
U	RE	31	4	15	7	57
	IE	2	6	5	3	16
	U	29	8	250	41	328
	OLF	4	4	19	78	105
	Totals	66	22	290	133	511
OLF	RE	207	44	15	98	364
	IE	48	139	6	94	287
	U	6	3	48	35	92
	OLF	242	183	57	20,846	21,329
	Totals	504	369	126	21,073	22,072

Notes: (1) The labour market states are as defined in Chapter 2:

RE Regular Employment (working more than 1/3 of the normal working hours)
IE Irregular Employment (working less than 1/3 of the normal working hours)
U Unemployment
OLF Out of the Labour Force (includes housewife, retired/pensioner and "others")

(2) Figures obtained from the three-waves' subsample.

Table A.7

Labour Market Flows Over Three Waves

Regular Employment at Wave 2

Labour Market State in Wave 1	Labour Market State in Wave 3				
	RE	IE	U	OLF	Total
RE	4,215	120	41	139	4,515
	90.9	**47.1**	**55.4**	**54.1**	**86.3**
IE	184	87	3	19	293
	4.0	**34.1**	**4.1**	**7.4**	**5.6**
U	31	4	15	7	57
	0.7	**1.6**	**20.3**	**2.7**	**1.1**
OLF	207	44	15	98	364
	4.5	**17.3**	**20.3**	**38.1**	**7.0**
Total	4,637	255	74	257	5,229
	88.7	**4.9**	**1.4**	**4.9**	

Notes: (1) The upper figures in the cells are the numbers, and the lower figures (in bold) are the column percentages. (2) Figures obtained from the three-wave subsample.

Table A.8

Labour Market Flows Over Three Waves

Irregular Employment at Wave 2

Labour Market State in Wave 1	Labour Market State in Wave 3				
	RE	IE	U	OLF	Total
RE	126	108	4	26	264
	43.2	**12.1**	**16.6**	**12.3**	**18.6**
IE	116	636	9	88	849
	39.7	**71.5**	**37.5**	**41.7**	**60.0**
U	2	6	5	3	16
	0.7	**0.7**	**20.8**	**1.4**	**1.1**
OLF	48	139	6	94	287
	16.4	**15.6**	**25.0**	**44.5**	**20.3**
Total	292	889	24	211	1,416
	20.6	**62.8**	**1.6**	**14.9**	

Notes: (1) The upper figures in the cells are the numbers, and the lower figures (in bold) are the column percentages. (2) Figures obtained from the three-wave subsample.

Table A.9

Labour Market Flows Over Three Waves

Unemployment at Wave 2

Labour Market State in Wave 1	Labour Market State in Wave 3: RE	IE	U	OLF	Total
RE	21	2	31	10	64
	34.4	**11.1**	**9.2**	**10.8**	**12.6**
IE	5	5	7	7	24
	8.2	**27.8**	**2.1**	**7.5**	**4.7**
U	29	8	250	41	328
	47.5	**44.4**	**74.4**	**44.1**	**64.6**
OLF	6	3	48	35	92
	9.8	**72.2**	**14.3**	**37.6**	**18.1**
Total	61	18	336	93	508
	12.0	**3.5**	**66.1**	**18.3**	

Notes: (1) The upper figures in the cells are the numbers, and the lower figures (in bold) are the column percentages. (2) Figures obtained from the three-wave subsample.

Table A.4.10

Labour Market Flows Over Three Waves

Out-of-the-Labour-Force at Wave 2

Labour Market State in Wave 1	Labour Market State in Wave 3: RE	IE	U	OLF	Total
RE	55	19	15	172	261
	17.5	**7.5**	**15.5**	**0.8**	**1.2**
IE	14	47	5	175	241
	4.4	**18.6**	**5.2**	**0.8**	**1.1**
U	4	4	20	441	447
	1.3	**1.6**	**20.6**	**2.0**	**2.0**
OLF	243	183	57	20,846	21,329
	77.1	**72.3**	**58.8**	**95.4**	**97.2**
Total	316	253	97	21,275	21,941
	1.4	**1.2**	**0.4**	**97.0**	

Notes: (1) The upper figures in the cells are the numbers, and the lower figures (in bold) are the column percentages. (2) Figures obtained from the three-wave subsample.