# Analising labour market mobility: some empirical 

 applicationsby

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Thesis submitted for the degree of Doctor of Philosophy (Ph.D.)
in February, 1998,
at

University College London
University of London

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To my parents

A mis padres

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#### Abstract

This thesis analyses different labour market aspects using microeconometric techniques, relating individual labour supply and mobility (jobs or occupation).

Chapter 2 provides empirical evidence, using US data, on testing the assumption that considers individuals freely decide the number of hours they work at a given wage. Change in hours equations are estimated for individuals that change job and for those that stay in the same one using a GMM estimator. By comparing the variance (after controlling by observable heterogeneity) of the change in hours for individuals that move from their job and for those who stay in two consecutive periods, we can conclude that the dispersion in hours for those who move is significantly higher than for those who stay. The main conclusion is that some other factors besides personal characteristics and wages are behind movements between jobs and that traditional life-cycle labour supply models are misspecified.

Chapter 3 investigates the characteristics and economic factors that determine self-employment decisions in UK. A multiple state transition model with unobservable heterogeneity is estimated, describing transitions in and out of three possible labour market states: self-employment, paid employment and unemployment. Results are consistent with the hypothesis of a deterioration of the labour market conditions generating an increase in the self-employment rates in adverse economic conditions. However, unemployment duration generates a loss on human capital that reduce the probabilities of switching to self-employment as well as to employment. It appears also that family background and education play an important role in determining the transition probabilities. Medium level educated individuals are the most likely to become selfemployed.

Using the same of techniques, Chapter 4 analyses labour market transitions jointly for married couples. This chapter investigates the effect of husbands' unemployment spells on wives' participation decisions. The aim is to clarify whether an added worker effect can be found in the UK labour market, that is, whether wives' labour force participation increases when their husbands become unemployed. A small but significant added worker effect is found for a subgroup of households. Women highly attached to the labour market (young, educated, participating before marriage and without children) married to men low or medium level educated are likely to enter the labour force when their husbands become unemployed. The data support the existence of complementarities between leisure of husband and wife.


## Acknowledgments

My foremost thanks are due to Richard Blundell and Costas Meghir for their supervision and encouragement over the last four years. I also would also like to thank Manuel Arellano not only for his advice and helpful comments but also for his kind readiness to help whenever asked. My thanks should also go to Christian Dustman, Adriaan Kalwij, Jose María Labeaga and Frank Windmeijer for their help and suggestions at various stages. Part of this research has also benefited from comments and suggestions of Cati Martínez, María Rochina, Juan Sanchis and Amparo Sanchis. I am most grateful to them. Special thanks are due to Jan Eeckhout, Maria Iacovou, Txuni López and Gustavo Nombela for their constant support and encouragement.

I want to express my thanks to all members of the Economics Department of University College London where I have found a very friendly and encouraging environment.

Financial support from the Bank of Spain is also greatly acknowledged. Some of the data used in this thesis was made available trhough the ESRC Data Archive. The ESRC Data Archive does not bear any responsability for the analysis or the interpretacion of the data reported here.

However, my deepest gratitude is owed to my parents, Carlos and Goya, my brothers, Carlos and Aitor, and my sister, Arantza. Their love, help and understanding has taken me where I am now.

## Chapter 1

## Introduction

The aim of this thesis is to empirically analyse three different topics related to mobility. Chapter 2, specifically, deals with a microeconometric model of labour supply and hours constraints for the US, taking into account the differences between individuals who stay in the same job two consecutive periods and individuals who change job. A neoclasical framework is chosen to implement this analysis. Given participation on the labour market, Chapter 3 estimates a model coherent with search and on-the-job search to analyse self-employment decisions in the UK. Chapter 4 investigates the existence of an added worker effect for the British economy, based on Burdett and Mortensen (1978) extension of the search model. Chapter 5 presents the summary and main conclusions of the thesis.

Let us briefly summarise the contents of each chapter. Chapter 2 considers a model which reveals information about labour supply preferences from those individuals who move jobs. Those who do not move may be constrained on their hours of work choices. A labour mobility model with endogenous regimes is considered then.

Labour mobility is a pervasive feature of market economies. Different tools are at disposal of the economist to analyse labour supply behaviour and mobility decisions. The most traditional is the theory of time allocation and it has become the principal
instrument to interpret labour force participation and labour supply. This theory assumes that individuals have perfect control about his/her labour market experience. It may be well suited to analyse the effects of wage rates, non-labour income or wealth and other demographic characteristics of the labour supply decisions. But precisely its emphasis on unilateral and fully informed choices makes it unable to explain important features of the typical individual's experience in the labour market. Two important examples are the experience of unemployment and job turnover.

The theory of job search was developed as a complement to the neoclassical theoretical framework. Basic assumption here is that individuals face imperfect information about wage rates and job locations within an uncertain environment. The original model and its extensions can be used to derive implications for distribution of completed spells of search unemployment, completed job spells lengths and time path of earnings as Mortensen (1986) points out. However the possibility that the worker may lose his job or decide to leave the labour force is ignored.

The availability of panels on individual work histories requires a dynamic model allowing for uncertainty of duration of both employment and unemployment periods. Then, labour market histories are best described as realisations of a stochastic process due to uncertainties concerning the magnitude, timing and frequency of job offers and duration of jobs. Future participation emerges here as the realisation of this stochastic process partially controlled by the worker's strategy, optimally derived through the maximisation of his life time utility (as in Burdett and Mortensen (1978)).

In regard to Chapter 2, the traditional labour supply models assume that workers are always in their supply curves. Individuals can freely choose the amount of hours they want to work or alternatively they can change job at no cost into another one which offers their desiderd amount of working hours. In the presence of a reservation rule governing the acceptance of a job, as in the search models, this theory implies that the supply of working time depends solely on the highest wage available in the market and on workers' nonlabour income. This job can be found at no cost.

Several models have been developed to incorporate constraints on working hours. Ham (1982), among the first generation of studies, allows for some censoring in worked hours due to hours constraints. More recently and in the same line, Stwart and Swaffield (1997) estimate a double censored model for the UK. More structural approaches are undertaken by Rosen (1976) or Biddle and Zarkin (1989) with models in which the employer offer is a package hours-wage. In these models, wages influence hours and hours influence wages.

However, only a few studies are concerned with the nature of the restrictions. Altonji and Paxson (1986) propose a simple test of hours constraints within jobs. They also check for the existence of some mobility costs which prevent workers from changing jobs when they are off their labour supply curve. If individuals are always in their supply curves, the hours of work should not vary more across jobs than within jobs. In addition, the behaviour of the individuals that were (exogenously) layoff from their jobs, should be similar to the behaviour of individuals who stay in the same job two consecutive periods in the absence of mobility costs. They have found that hours vary significantly more between jobs that within jobs, whether the worker voluntary moves or is layoff. Their conclusion is that some workers face hours constraints and cannot change jobs at no cost.

Chapter 2 uses this approach to estimate a life-cycle labour supply model under uncertainty, with the important additional assumption of endogeneity of job changes. A subsample of the National Longitudinal Survey of Youth (NLSY) is used on the analysis. That enable us to distinguish whether the degree of adjustment for individuals who stay in their job is different from the adjustment for individuals who change jobs. Results reveal that the neoclasical approach fails to explain movements between jobs and traditional wage elasticities may better be reflecting contracting arrangements between workers and firms.

Given the inability of the traditional theory to explain movements between jobs or unemployment spells, the remain of the thesis, also concerned with mobility, will use a
search approach. For the British economy, two important topics are tackled in Chapter 3 and 4: self-employment and female participation on the labour market.

Chapter 3 is concerned with the empirical determination of some of the characteristics and economic factors that drive self-employment decisions. Selfemployment rates have experienced a sharp increase in almost all OECD countries in recent decades ( $15 \%$ of the workforce was self-employed in March 1989 in the UK). Many governments, including the British, undertake programs to promote entrepreneurship although there is not consistent empirical evidence about the reasons behind this rise in self-employment rates.

Self-employment is viewed in most of the literature as an alternative to paid employment (leaving aside liquidity constraints considerations). Therefore transitions to and from self-employment may be seen as a result of the process of on-the-job search. Search theory has focused its attention mainly on unemployment and the flow from unemployment into employment, although other important flows, as the ones from and to self-employment, can be analysed in this framework.

Two types of "jobs" are defined: self-employment and paid employment. Under this definition, job-to-job transitions are considered alongside with to and from unemployment transitions. Blundell et al. (1995) use this approach to model upward mobility and self-employment transitions. Mortensen (1986) presents a revision of the theoretical background for this type of literature and Devine and Kiefer (1991) extensively revise its empirical applications although there are not many to analyse job-to-job movements. The simplest on-the-job search theory supposes that when workers accept a job at a given wage they may continue the search. Implications are that workers in low wage jobs will have higher acceptance probabilities and face greater gains from search. Workers in high wage jobs may simply wait a longer period of time to get a better offer.

Deeply controversial but of special interest, is to determine the effect of business cycle and unemployment experience on self-employment decisions. Empirical literature does not reach an agreement in this respect. Some authors support the theory of an
encouraging effect of economic conditions. Good economic conditions would encourage individuals to start up a business because the expected returns from self-employment are higher and the probability of failure lower. Blanchflower and Oswald (1991) or Taylor (1996) have found that effect for the UK. Other authors argue that unemployment and adverse economic conditions reduce the opportunity cost of becoming self-employed. Individuals can see self-employment as a way of avoiding unemployment when the probability of finding a paid job decreases. In this line Alba-Ramirez and Freeman (1994), Evans and Leighton (1989) or Acs et al. (1994), provide evidence for Spain, the US and a panel of OECD countries.

None of the previous studies discern clearly between the effect of economic conditions and of individual unemployment experience. The on-the-job search approach followed in this Chapter, allows us to disentangle these two effects in a natural way for the UK, using a subsample of the British Household Panel Survey (BHPS).

As mentioned above, the search theory does not account for the probability of withdrawal from the labour force. Chapter 4 focused precisely on the relationship between unemployment and participation decisions of males and females in the UK. A widespread deterioration on employment opportunities results in discouraged workers that drop out of the labour force. However, additional labour force participants (secondary workers, and in particular wives who would be otherwise out of the labour force) may appear in families whose employed members experience unemployment. This latter effect is known in the literature as the added worker effect. There is evidence with aggregate that the discouraged worker dominates the added worker effect but at an individual household level evidence is less clear cut.

In order to account for market imperfections responsible for discouragement, the search framework adopted in previous chapter has to be extended, as in Burdett and Mortensen (1978) mentioned above. They develop a household decision model of optimal behaviour under uncertainty, allowing for dependence of one person's strategy on the employment status of other household members. It is then the perfect instrument to analyse topics as the added worker effect.

A striking feature of the British labour market, also present in other OECD countries, is the low participation rates for wives of unemployed individuals. During 1987-89, the participation rate for the wives of employed men amounted to $71 \%$ whilst only to $28 \%$ for those married to an unemployed man. A great deal of literature has been devoted to explain such a big difference. In general, studies at a household level fail to find any added worker effect. This fact, not important at an aggregate level, creates contradictions with the theory at a household level.

Different explanations have been given in order to reconcile theory and empirical findings. First of all, the added worker effect is theoretically clear when assuming sustituibility between the leisure of the husband and the wife. Therefore, one of the reasons for which not any added worker effect was found could be the existence of strong complementarities in leisure. Pudney and Thomas (1992), among others, have found evidence to support this theory for the UK.

The disincentive effects of the benefit system have also been well studied. A social security system in which benefits are means-tested, as some of the British, would produce a disincentive for the wife of an unemployed man to participate in the labour force. Pudney and Thomas (1992), Garcia $(1989,1991)$ or Dilnott and Kell (1989) provide evidence at this respect. However, their conclusion is that this effect explains only a small part of the differences in participation rates.

A social stigma attached to an unemployed man who is seen as supported by his wife's earnings could also originate low participation rates for unemployed husband's wives.

Chapter 4 concentrates on the effect of common observable (age, education) and unobservable characteristics (as local labour market conditions in this study) for the couple that could explain the differences in participation mentioned above, using Burdett and Mortensen (1979) framework. Unobserved common factors affecting members of the household imply that the labour force states of husband and wife have to be modelled as the outcome of a joint process. Therefore husband's and wife's labour decisions are endogenous and influence one each other.

Davies et al. (1992) provide some evidence in this topic for UK considering the husband's job status exogenous. They suggest that the heterogeneous nature of the observed sample could produce a spurious state dependence relationship. In other words, it is probably the case that the wives of unemployed men that are out of the labour force, would be out of the labour force simply due to their personal characteristics. Lundberg (1985) also shows some evidence of assortative matting. A small but significant added worker effect is found after controlling by common observable characteristics.

Chapter 4 extends previous studies by allowing both endogeneity of the husband's job status and a correction for unobservable characteristics that could affect household members. Data from the BHPS is used in the study.

Finally, in Chapter 5 we summarise the results and main conclusions derived from the research developed in the thesis.

## Chapter 2

## Testing labour supply and hours constraints

### 2.1. Introduction


#### Abstract

A basic assumption of an important stream of labour supply literature is that each employer is indifferent to the number of hours his/her employees choose to work. A possible reinterpretation of this assumption would be that workers face a wide range of job options, with each job being paid the same wage rate but demanding different number of hours. Within this framework, labour supply is determined by a set of personal characteristics and wages. These are the only job specific characteristic that affect the number of hours an individual works. Therefore, under both interpretations, workers freely choose the amount of hours they want to work at a given wage and they should be in their labour supply curves at every point in time. Several authors have criticised this assumption for excluding hours constraints and simplifying dynamics ${ }^{1}$.

The aim of this chapter is to provide additional empirical evidence on whether this classical life-cycle labour supply theory can satisfactorily explain changes in working


[^0]hours between jobs, that is, to check whether or not individuals face hours constraints. If workers may freely vary the amount of hours supplied on a given job and labour supply largely depends on personal characteristics, we should not expect hours to vary more across jobs than within jobs. On the other hand, if labour supply depends on job-specific characteristics or the preferences of the employer on working hours play an important role, such differences in the variances of hours between jobs and within jobs will be present. Behavioural differences among those who change job voluntarily and those who are layoff ${ }^{2}$ are considered alongside with differences among workers that change job and workers that do not move.

The starting point is Altonji and Paxson (1986). Using data from the Panel Study of Income Dynamics (PSID) and the Quality of Employment Survey (QES) they find that the variance of changes in hours is between two and four times larger for those who have switched job than for those who are in the same job during two consecutive years. They also find that the data was inconsistent with a model in which hours in a given job are determined by the employer, but each worker can cheaply move to another job offering an amount of hours equal to the individual optimal level. Their conclusion is that two structural interpretations, or a mixture of both, can be held in view of the results: either individuals are constrained in hours that, as wages, are determined by the employer or, alternatively, many non wage labour supply determinants are job specific and vary greatly across jobs. In other words, characteristics of the job held have a large influence on the amount of hours that individuals work.

There are several shortcomings in their paper that motivate further research. First, Altonji and Paxson consider the decision of changing job as exogenous. This may generate biased parameter estimates and, therefore, biased estimates for the relevant variances of changes in hours ${ }^{3}$. Secondly, the PSID presents serious difficulties to identify job changes and the variable "hours" is subjected to great measurement error.

[^1]Finally, more efficient estimates can be proposed using the longitudinal nature of the data.

In this chapter we try to overcome the problems referred above. Instead of using the PSID, we use the National Longitudinal Survey of Youth (NLSYTH) from 1985 to 1991 for the US. This survey identifies without ambiguity movements between jobs and hours of work. Consistent and more efficient estimates under the presence of individual heterogeneity are computed, using the Generalised Method of Moments (GMM) as estimation method. Endogeneity of movements may bias estimates if not properly controlled. This method allow us to estimate and test a model with switching regimes that accounts for endogenity of the decision to change job.

In previous empirical work Abowd and Card (1989) study the covariance structure of earnings and hours changes. They also question the life-cycle model interpretation of labour supply which implies that changes in productivity influence earnings more than hours. Their result suggests that most changes in earnings and hours occur at fixed hourly wage rates, with earnings and hours covarying proportionally.

Biddle (1988) and Ball (1990) find evidence of misspecification in life-cycle labour supply models. Intertemporal elasticities computed using constrained individuals may reflec contracting arrangements between workers and firms that move workers off their labour supply curves. Intertemporal elasticities computed using only unconstrained workers are more likely to represent workers' labour supply preferences.

Several authors have tried to incorporate hours constraints explicitly in estimation. Ham (1982) extended the traditional tobit type model for working hours by introducing censoring due to under or overemployment. Stewart and Swaffield (1997) also estimate a double censored model for the UK. An alternative "structural" model is the hours-wage offer models where wages influence hours and hours, simultaneously, influence wages (e.g., Rosen, 1976, or Biddle and Zarkin, 1989).

In other direction, we can see on the job search models with hours constraints (see Kiefer, 1987). These models require information on movements between jobs but are otherwise static; i.e., they do not consider learning about unobservable characteristics
by either the employer or the employee. Information on duration, hours-wage evolution and layoffs and quits for each job, opens up the possibility of allowing identification of matching processes. However, matching models have typically had nothing to say about hours determination.

The structure of the chapter is as follows. Section 2.2 contains a description of the empirical model and the estimation method. Section 2.3 presents data and sample design. Finally, Section 2.4 outlines the estimation results and Section 2.5 states the conclusions.

### 2.2. Empirical Model

This section introduces an empirically tractable model of labour supply compatible with the life-cycle theory and allowing for the presence of individual fixed effects. We also present the implications of hours constraints derived from the model and the basic specification to be estimated.

### 2.2.1. Labour supply and fixed effects

Let us consider an individual with a life time horizon $T$, who has a utility function in period $t$ depending on consumption, $C_{t}$, hours of work, $h_{t}$, and conditional on a set of demographic characteristics, $Z_{t}$. At period $t$ the individual maximises his lifetime utility, that is, the discounted sum of his by period instantaneous utilities,

$$
\begin{align*}
& \max _{C_{t}, h_{t}, A_{t}} E_{t} \sum_{k=t}^{T} \frac{1}{\left(1+\rho_{k}\right)} U_{k}\left(C_{t}, h_{t} \mid Z_{t}\right)=U_{t}(.)  \tag{2.1}\\
&+\frac{1}{\left(1+\rho_{t}\right)} E_{t} \sum_{k=t+1}^{T} \frac{1}{\left(1+\rho_{k}\right)} U_{k}(.)
\end{align*}
$$

subject to the asset accumulation constraint

$$
\begin{equation*}
A_{t}=\left(1+r_{t}\right) A_{(t-1)}+w_{t} h_{t}-C_{t} \tag{2.2}
\end{equation*}
$$

where $w_{t}$ and $r_{t}$ are real wages and interest rate, respectively; $A_{t}$ are the assets at the end of period $t$ and $\rho_{t}$ denotes the rate of time preference. The expectations operator $E_{t}$ is taken over future uncertain wages and interest rates. The time dependence of the utility reflects the influence of predetermined shifter variables on life-cycle preferences ${ }^{4}$.

Using Bellman's principle, we can define

$$
\begin{equation*}
V_{t+1}\left(A_{t}\right)=\max E_{t+1}\left\{\sum_{k=t+1}^{T} \frac{1}{\left(1+\rho_{k}\right)} U_{k}\right\} \tag{2.3}
\end{equation*}
$$

Then at period $t$ the individual maximisation problem can be written as follows:

$$
\begin{equation*}
V_{t}=\max _{C_{t}, h_{t}, A_{t}} U_{t}+\frac{1}{1+\rho_{t}} E_{t} V_{t+1}\left(A_{t}\right) \tag{2.4}
\end{equation*}
$$

under restriction (2.2).
For every period, first order conditions for an interior solution are:

$$
\begin{equation*}
\frac{\partial U_{t}}{\partial C_{t}}=\lambda_{t} \tag{2.5}
\end{equation*}
$$

$$
\begin{equation*}
\frac{\partial \mathrm{U}_{\mathrm{t}}}{\partial \mathrm{~h}_{\mathrm{t}}}=-\lambda_{t} w_{t} \tag{2.6}
\end{equation*}
$$

[^2]\[

$$
\begin{equation*}
\lambda_{t}=E_{t}\left\{\frac{1+r_{t+1}}{1+\rho_{t+1}} \lambda_{t+1}\right\} \tag{2.7}
\end{equation*}
$$

\]

Equation (2.7) implies that the individual chooses savings in such a way that his discounted expected marginal utility of wealth remains constant over time. Assuming no uncertainty about interest rate and discount factor, expression (2.7) can be written as

$$
\begin{equation*}
\frac{1+r_{t+1}}{1+\rho_{t+1}} \lambda_{t+1}=\lambda_{t}\left(1+e_{t+1}\right) \tag{2.8}
\end{equation*}
$$

$$
\text { where } E_{t}\left(e_{t+1}\right)=0
$$

$e_{t+1}$ reflects all unanticipated news gathered in period $t+1$. Expression (2.8) ensures $\lambda$ being positive for all $t$ and leads to the approximation

$$
\begin{equation*}
\ln \lambda_{t+1} \approx \ln \lambda_{t}+\rho_{t+1}-r_{t+1}+e_{t+1} \quad t, \ldots \ldots . T \tag{2.9}
\end{equation*}
$$

Therefore the means of all future values of $\lambda$ are revised to account for all forecasting errors at the time they are realised. So, at the start of the life-cycle the consumer sets $\lambda_{0}$ which takes into account all the information on future values of the variables available at that time. According to equation (2.7) $\lambda_{\mathrm{t}}$ is revised over time as new information is acquired.

Solving equations (2.5) to (2.7) for consumption and hours of work, conditional on $\lambda$ for each period, the solutions are the so called Frisch or $\lambda$-constant demand functions:

$$
\begin{align*}
& C_{t}=C\left(\lambda_{t}, w_{t} ; Z_{t}\right)  \tag{2.10}\\
& h_{t}=h\left(\lambda_{t}, w_{t} ; Z_{t}\right) \tag{2.11}
\end{align*}
$$

where $\lambda$ acts as a summary of between period allocations and is individual specific. It is therefore an appropriate conditioning variable although not observable in equations (2.10) and (2.11). However, assuming some restrictions about the form of within period preferences, $\lambda$ can be treated as an unobservable individual fixed effect suitable of being differenced out in the supply and demand equations, provided that these are linear in the logarithm of $\lambda_{t}{ }^{5}$. From this $\lambda$-constant demands we can compute $\lambda$-constant elasticities. They reflect fully anticipated movements along the wage profile ${ }^{6}$.

We assume the familiar log-linear specification for the previous labour supply equation ${ }^{7}$. Recovering individual subscripts and conditining on wages, personal characteristics and the marginal utility of wealth, an expression for equation (2.11) is:

$$
\begin{equation*}
E\left(h_{i j t} \mid x_{i}, x_{i t}, w_{i j t}, \lambda_{i t}\right)=\alpha_{0}+\alpha_{1}^{\prime} x_{i}+\alpha_{2}^{\prime} x_{i t}+\alpha_{3} w_{i j t}+\ln \lambda_{i t} \tag{2.12}
\end{equation*}
$$

or

$$
\begin{equation*}
h_{i j t}=\alpha_{0}+\alpha_{1}^{\prime} x_{i}+\alpha_{2}^{\prime} x_{i t}+\alpha_{3} w_{i j t}+\ln \lambda_{i t}+\varepsilon_{i j t} \tag{2.13}
\end{equation*}
$$

where $h_{i j t}$ is the $\log$ of worked hours; $w_{\mathrm{ijt}}$ is the $\log$ of real wage rate; $x_{i}$ is a set of labour supply determinants fixed over time (race, sex, education and the like); $x_{i t}$ is a set of time variant characteristics (marital status, number of children, non labour income); $\lambda_{\mathrm{it}}$ is the individual specific marginal utility of wealth and $\varepsilon_{\mathrm{ijt}}$ is a white noise error term.

Taking first differences in (2.13) all the characteristics fixed over time cancel out and we get an empirically tractable equation,

$$
\begin{equation*}
\Delta h_{i j t}=\alpha_{2}{ }^{\prime} \Delta x_{i t}+\alpha_{3} \Delta \ln w_{i j t}+\Delta \varepsilon_{i j t}+v_{i j t} \tag{2.14}
\end{equation*}
$$

[^3]$\nu_{\mathrm{ijt}}$ is an error component that includes $e_{t}$ from equation (2.8), that is, all unanticipated components of wage and demographic variables.

### 2.2.2. Movements between jobs and hours constraints

The model presented above, in the same way that most of the conventional labour supply models, assumes that workers can freely choose the number of hours they want to work. Alternatively, hours are determined by employer preferences but workers can move at zero cost towards firms offering the amount of hours they desire to work. There is a continuos of firms offering the whole range of possible hours of work. Both interpretations are coherent with traditional labour supply models. Hours' choices are primarily influenced by wage rates and personal preferences but not by other job specific characteristics. Moreover, each individual would be in his/her labour supply curve at every point in time. However, implications for mobility from both interpretations are very different.

Focusing on the first interpretation, we should not expect hours to vary more across jobs than within jobs ${ }^{8}$. Finding a higher variance of the change in hours for people who move from one job to another (movers) would suggest that individuals staying in the same job (stayers) are constrained in the number of hours they can choose to work and that they are off their supply curves. It could be the case that personal characteristics or wages vary more among movers than among stayers. In this situation the variances of the change in hours would differ, but this difference should vanish once we correct hours for those more variable characteristics.

If the second interpretation is the correct one and changing jobs has no cost, the variance of the change in hours would be bigger for movers than for stayers, just because every individual has to move to change hours. To test whether this interpretation is coherent with the data, as Altonji and Paxson (1986) suggest, we can distinguish

[^4]between job changes resulting from layoffs and other type of job changes. If layoffs (e.g., plant closings) are exogenous events to the individual decision process and preferences, then workers that experience a layoff will pick new jobs offering an hours level similar to their previous job. Therefore, the variance in the change in hours, once corrected by wages and personal characteristics, should be similar for stayers and for this subset of movers.

Analytically, consider the model presented in previous section, in particular equation (2.14). We can distiguish two subgroups of people: the ones that change job between $t$ and $t-1$ and the ones that stay at the same job.

Lets assume, as starting point, that movements are exogenous and that the variance for both subgroups is the same, that is,

$$
\begin{align*}
& E\left(u_{i j t} S_{i j t}\right)=0  \tag{2.15}\\
& E\left(u_{i j t} \mid S_{i t}=1\right)=E\left(u_{i j t} \mid S_{i t}=0\right)=E\left(u_{i j t}\right)
\end{align*}
$$

where $u_{i j t}=\Delta \varepsilon_{i j t}+v_{i j t}$, from equation (2.14), and $S_{i t}$ is a dummy variable that equals one if the individual stayed in the same job between $t$ and $t-1$. Equation (2.14) will hold for each subgroup of individuals, movers and stayers:

$$
\begin{gather*}
\Delta h_{i j t}^{s}=\alpha_{2}{ }^{\prime} \Delta x_{i t}^{s}+\alpha_{3}\left(w_{i j t}-w_{i j t-1}\right)+u_{i j t}^{s}  \tag{2.16}\\
\Delta h_{i j t}^{m}=\beta_{2}{ }^{\prime} \Delta x_{i t}^{m}+\beta_{3}\left(w_{i j t}-w_{i j t^{\prime} t-1}\right)+u_{i j t}^{m} \tag{2.17}
\end{gather*}
$$

where $u_{i j t}^{s}=\Delta e_{i j t}^{s}+v_{i j t}^{s}$ and $u_{i j t}^{m}=\Delta e_{i j t}^{m}+v_{i j t}^{m} ; i$ denotes individual, $j$ job and $t$ time. $m$ refers to movers and $s$ to stayers. For movers, wage in period $t$ correponds to job $j$ and wage in period $t$ - 1 to job $j^{\prime}$, being $j$ different from $j^{\prime}$.

We should expect that movers and stayers behave in the same way, so the parameters of interest must be equal for both subgroups ( $\alpha_{2}=\beta_{2}$ and $\alpha_{3}=\beta_{3}$ ). In addition, if the $u$ 's are distributed with constant variance for all individuals, movers or stayers, $\operatorname{var}\left(\Delta h_{i j t}^{s}\right)$ may be different from $\operatorname{var}\left(\Delta h_{i j t}^{m}\right)$, when personal characteristics or wages are more variable for one subgroup than for the other, but the variance of the adjusted change in hours should be the same. That is:

$$
\operatorname{var}\left(\Delta h_{i j t}^{s}-\alpha_{2}^{\prime} \Delta x_{i t}^{s}-\alpha_{3} \Delta w_{i j t}\right)-\operatorname{var}\left(\Delta h_{i j t}^{m}-\beta_{2}^{\prime} \Delta x_{i t}^{m}-\beta_{3}\left(w_{\mathrm{ijt}}-w_{\mathrm{ij} \mathrm{ij}^{\prime}-1-1}\right)\right) \approx 0
$$

or, more compactly,

$$
\begin{equation*}
\operatorname{var}\left(u_{i j t}^{s}\right)-\operatorname{var}\left(u_{i j t}^{m}\right) \approx 0 \tag{2.19}
\end{equation*}
$$

Assuming homoscedasticity on the $u$ 's distribution means that movers and stayers have the same preferences for hours; movers do not have more variable preferences for hours. If our model is well specified, that is, if we have included all variables that may differ between movers and stayers, constant variance on $u$ 's would imply constant variance on both its components, $\varepsilon$ and $v$. This assumption is quite strong. Abowd and Card (1985) found some evidence against it. Even though, the point is whether all differences in the variance can be explained by differences in tastes. Altonji and Paxson (1986) found that this is not the case. We try to minimise the impact of heterogeneity by the selection of the sample as stated in Section 2.4, although consistent estimates under heteroscedasticity are obtained ${ }^{9}$.

[^5]A different behaviour for stayers than for movers would be inconsistent with conventional life-cycle labour supply theory. Therefore estimation of equations (2.18) and (2.19) cast some interest by itself and is the first step on our analysis.

Estimation of both equations separately would give consistent parameter estimates under the null hypothesis of exogeneity of the movements. However, if the decision of changing job is correlated with some unobservable characteristic affecting preferences, stayers may show higher preference for stability. If so, estimates may be biased. Therefore possible endogeneity of movements has to be tested.

Nevertheless, whether $S_{i t}$ is endogenous or exogenous, estimation of

$$
\begin{equation*}
E\left(\Delta h_{i j t} \mid x_{i}, x_{i t}, w_{i j t}\right)=E\left(S_{i t} \Delta h_{i j t}^{s}+\left(1-S_{i t}\right) \Delta h_{i j t}^{m} \mid x_{i}, x_{i t}, w_{i j t}, S_{i t}\right) \tag{2.20}
\end{equation*}
$$

would give us consistent estimates of the parameters of interest. If endogenous, $S_{\text {it }}$ should be instrumented in estimation. Replacing expressions (2.16) and (2.17) in (2.20), the final equation to estimate is:

$$
\begin{align*}
\Delta h_{i j t}=\beta_{0}+ & \left(\alpha_{0}-\beta_{0}\right) S_{i t}+\beta_{2} \Delta x_{i t}+\left(\alpha_{2}-\beta_{2}\right) S_{i t} \Delta x_{i t}+ \\
& +\beta_{3} \Delta w_{\mathrm{ijt}}+\left(\alpha_{3}-\beta_{3}\right) S_{i t} \Delta w_{\mathrm{ijt}}+u_{\mathrm{ijt}} \tag{2.21}
\end{align*}
$$

In the easiest case, if there are no differences in the parameters for stayers and for movers, the coefficients on $\mathrm{S}_{\mathrm{it}}$ and cross-products will cancel out. Under this hypothesis, to estimate only one equation with all movers and stayers will be sufficient to recover consistency whereas this is a strong restriction to impose on the data. If coefficients are different for both subgroups of individuals, equation (2.21) has to be estimated and requires $S_{i t}$ to be appropriately instrumented.

Identical coefficients for both groups and endogeneity of the movements are two interesting hypotheses to test. Equation (2.21), without imposing any restriction on the coefficients, is estimated alongside with equations (2.16) and (2.17) separately and
results are compared. The estimation method and the implementation of different tests for the model specification are presented in Section 2.3 below.

### 2.3. Estimation Method

This section introduces the estimation method used, the Generalised Method of Moments (GMM), and compare it with Two Stage Least Squares (2SLS). We also present tests to check for the specification of the model.

### 2.3.1 The GMM estimator

Given equations (2.16), (2.17) and (2.20) and a panel of individual observations, we can pool all individuals and periods and consider the sample a cross-section, if parameters remained constant during the whole observation period. This increases the sample size and it gives us consistent estimates under the maintained assumptions.

From previous section, the error term $u_{i j t}$ has two components: $v_{i j t}$, that included all unanticipated components of the explanatory variables for which there were some uncertainty in period $t$; and $\Delta \varepsilon_{i j}$, reflecting a pure exogenous shock received by the individual at moment $t$. Consequently, some correlation may be present between the explanatory variables dated on $t$ for which there were some uncertainty in $t-1$ and the first component of the error term. Variables susceptible of such correlation are wages and other income $\left(E\left(w_{i j t} v_{i j t}\right) \neq 0\right.$ and $\left.E\left(o t i n c ~ i j t ~ v_{i j t}\right) \neq 0\right)$. Moreover, if some of these variables are generated endogenously in the model (as it certainly happens with wages) they may also be correlated with the contemporaneous exogenous shock $\left(E\left(w_{i j t} \varepsilon_{i j t}\right) \neq 0\right)$. We have to find instruments highly correlated with the explanatory variables but uncorrelated with the error term. In doing so, the longitudinal nature of the data is useful. The same endogenous variables lagged two or more periods are valid instruments. Arellano-Bond type instruments, exploiting all possible past information, are
used in the estimation. A description of the type of instrument used is presented in Appendix B.

The Generalised Method of Moments (GMM) gives consistent estimates of the parameters of interest and more efficient than the simple IV estimator. In this particular case, the IV would be equivalent to Two Stage Least Squares estimator (2SLS).

Lets consider a general equation to be estimated,

$$
\begin{equation*}
y_{i}=x_{i}^{\prime} \vartheta+u_{i} \quad i=1 \ldots N \tag{2.22}
\end{equation*}
$$

alongside with a set of instruments, $z_{i}$, correlated with the explanatory variables but uncorrelated with the error term $\left(E\left(z_{i} u_{i}\right)=0\right) . z_{i}$ is a vector of $r$ instruments, where the number of instruments in greater than the number of parameters to estimate, $k$.

Using an i.i.d. sample of N individuals, an estimate of the parameters is $c$, the solution to

$$
\begin{equation*}
b_{N}(c)=1 / N \sum_{i=1}^{N} z_{i}\left(y_{i}-x_{i}^{\prime} c\right)=1 / N Z^{\prime}(y-X c) \tag{2.23}
\end{equation*}
$$

As the number of instruments is greater than the number of parameters to estimate, there is no unique solution for (2.23). Therefore, an estimator of $\vartheta$, should minimise:

$$
\begin{equation*}
b_{N}(c)^{\prime} A_{N} b_{N}(c)=(y-X c)^{\prime} Z A_{N} Z^{\prime}(y-X c) \frac{1}{N^{2}} \tag{2.24}
\end{equation*}
$$

where $A_{N}$ is a matrix of weights and $Z=\left[\begin{array}{c}z_{1}^{\prime} \\ \cdot \\ z_{N}^{\prime}\end{array}\right]$, is the matrix of instruments. If $A_{N}=\left[\frac{Z^{\prime} Z}{N}\right]^{-1}$, the argument that minimise (2.24) is the familiar 2SLS estimator that would consistently estimate $\vartheta$

$$
\begin{equation*}
\hat{\vartheta}_{2 S L S}=\left[\left(X^{\prime} Z\right)\left(Z^{\prime} Z\right)^{-1}\left(Z^{\prime} X\right)\right]^{-1}\left(X^{\prime} Z\right)\left(Z^{\prime} Z\right)^{-1}\left(Z^{\prime} Y\right) \tag{2.25}
\end{equation*}
$$

A heteroscedasticity consistent estimate of the asymptotic variance is:

$$
\begin{align*}
\frac{\hat{W}}{N}= & N\left(X^{\prime} Z\left(Z^{\prime} Z\right)^{-1} Z^{\prime} X\right)^{-1} X^{\prime} Z\left(Z^{\prime} Z\right)^{-1} \\
& \left(\frac{1}{N} \sum_{i=1}^{N} \hat{u}_{i}^{2} z_{i} z_{i}^{\prime}\right)\left(Z^{\prime} Z\right)^{-1} Z^{\prime} X\left(X^{\prime} Z\left(Z^{\prime} Z\right)^{-1} Z^{\prime} X\right)^{-1} \tag{2.26}
\end{align*}
$$

However, under the null hypothesis of heteroscedastic errors, 2SLS is not optimum among the GMM class, given the set of instruments $Z$. Therefore, when $E\left(u_{i} \mid z_{i}\right)=\sigma_{i}$, $A_{N}$ is optimally chosen as $A_{N}=\left(\sum_{i} \hat{u}_{i}^{2} z_{i} z_{i}^{\prime}\right)^{-1}$, where $\hat{u}_{i}$ are the residuals from a consistent first stage estimation as in $(2.25)^{10}$. That would give us the more efficient estimate among the GMM class for which $E\left(z_{i} u_{i}\right)=0^{11}$,

$$
\begin{equation*}
\tilde{\vartheta}_{G M M}=\left[\left(X^{\prime} Z\right)\left(\sum \hat{u}_{i}^{2} z_{i} z_{i}^{\prime}\right)^{-1}\left(Z^{\prime} X\right)\right]^{-1}\left(X^{\prime} Z\right)\left(\sum \hat{u}_{i}^{2} z_{i} z_{i}^{\prime}\right)^{-1}\left(Z^{\prime} Y\right) \tag{2.27}
\end{equation*}
$$

Estimates presented in the Section 2.5 correspond to the type of robust estimators defined by (2.27). Standard errors are computed using (2.26).

[^6]
### 2.3.2. Testing model specification

Endogeneity of the explanatory variables in equations (2.16), (2.17) and (2.20) does not have to be assumed. Along with endogeneity of movements in equation (2.20) it may be tested. This section introduces two types of specification tests: firstly an endogeneity test is derived and secondly, a test for the adequacy of the instruments is presented.

Lets start with the endogeneity test. Two estimators, both consistent under some null hypothesis, should yield similar sets of estimates of the parameters of interest. Consider again the general equation (2.22). Let $Z_{I}$ and $Z_{2}$ be two sets of instruments, where $Z_{2}=\left\{Z_{l}, Z^{*}\right\}$, that is, $Z_{2}$ contains the same instruments than $Z_{l}$ plus an extra set of instruments, $Z^{*}$ that may be correlated with the error term.

With $Z_{l}$ we can construct a GMM estimator as in (2.27) and will get a consistent estimate, $\hat{\vartheta}_{1}$, of the true parameter vector $\vartheta_{1}$. The use of $Z_{2}$ may yield more efficient estimates only if it is uncorrelated with the error term. Applying the GMM method, with $Z_{2}$, we obtain an estimate, $\hat{\vartheta}_{2}$, of the parameter vector $\vartheta_{2}$. The relevant test can be written as:
$H_{0}: Z^{*}$ is exogenous with respect to the error term.
$H_{l}: Z^{*}$ is not exogenous with respect to the error term.

Under the null hypothesis, $\vartheta_{2}=\vartheta_{1}$. The test can be written more specifically using the estimates of these parameters as,

$$
\begin{aligned}
& H_{0}: \hat{\vartheta}_{2}=\hat{\vartheta}_{1} \\
& H_{1}: \hat{\vartheta}_{2} \neq \hat{\vartheta}_{1}
\end{aligned}
$$

and a Wald test for the difference of both estimates can be implemented, using the covariance matrix for the vector $\left(\hat{\vartheta}_{2}, \hat{\vartheta}_{1}\right)$.

When both estimators are consistent but only one is efficient under the null hypothesis, that test reduces to the Hausman test ${ }^{12}$, where the covariance matrix is $\operatorname{var}\left(\hat{\vartheta}_{2}, \hat{\vartheta}_{1}\right)=\operatorname{var}\left(\hat{\vartheta}_{2}\right)+\operatorname{var}\left(\hat{\vartheta}_{1}\right)$. However, in the present case, $\hat{\vartheta}_{2}$ need not to be efficient under the null, therefore this simplification can not be used. Mroz (1987) ${ }^{13}$ provides an estimator for the covariance matrix that does not rely on either the normality or homoscedasticity of the disturbances and it takes into account the correlation between the two sets of instruments. Therefore, the final test we will use has the following form:

$$
\begin{equation*}
W=\left(\hat{\vartheta}_{2}-\hat{\vartheta}_{1}\right)^{\prime}\left(\operatorname{var}\left(\hat{\vartheta}_{2}-\hat{\vartheta}_{1}\right)\right)^{-1}\left(\hat{\vartheta}_{2}-\hat{\vartheta}_{1}\right) \longrightarrow \chi_{k}^{2} \tag{2.28}
\end{equation*}
$$

where $k$ is the number of parameters of interest and therefore the number of restrictions we are imposing. The actual form for the covariance matrix appears in Appendix B. $W$ is used to test endogeneity of movements as well as endogeneity of wages and other income.

Once endogeneity is tested, the adequacy of the instruments used can also be tested. Fort doing so a Sargan test is implemented. When the number of instruments, $r$, is greater than the number of parameters to estimate, $k$, the constraints implied by the econometric specification can be tested. Estimation of $\vartheta$ in (2.22) equals zero $k$ linear combinations of the $r$ ortogonality conditions defined by (2.23) over the sample. Therefore, there must be $r-k$ linear combinations that are approximately equal to zero but are not zero. The following test can be derived from previous observation,

$$
\begin{equation*}
N S(\hat{\vartheta})=\left(Z^{\prime}(Y-X \hat{\vartheta})\right)^{\prime}\left(\sum_{i=1}^{N} \hat{u}_{i}^{2} z_{i} z_{i}^{\prime}\right)^{-1}(Y-X \hat{\vartheta}) Z \longrightarrow \chi_{r-k}^{2} \tag{2.29}
\end{equation*}
$$

[^7]A small value for this test indicates that the instruments used are accepted, in the sense that the restrictions they impose are close to zero.

A variation of this test can be used to test additional instruments. Consider two sets of instruments, $Z_{l}$, that contains $r_{1}$ instruments, and $Z_{2}$, that contains $r_{2}$. Z would be the union of both sets and will have $r=r_{1}+r_{2}$ instruments. Using $Z_{l}$ an estimate $\hat{\vartheta}_{1}$ of $\vartheta$ is obtained, using $Z_{2}$ an estimate $\hat{\vartheta}_{2}$ and using $Z$ an estimate $\hat{\vartheta}$. If the restrictions implied by the use of $Z_{l}$ have been accepted via their corresponding Sargan test, $N S_{1}\left(\hat{\vartheta}_{1}\right)$, or they are considered valid a priori, a statistic, $S D T$ (incremental Sargan test), can be constructed to test the additional restrictions implied by the use of $Z_{2}$ :

$$
S T D=N S(\hat{\vartheta})-N S_{1}\left(\hat{\vartheta}_{1}\right) \longrightarrow \chi_{r-r 1}^{2} \equiv \chi_{r 2}^{2}
$$

### 2.4. Data

Distinguish between movers and stayers requires detailed information on job changes as well as on personal characteristics and wages during a reasonably long period. This is the kind of information that the National Longitudinal Survey of Youth (NLSY) collects. This is a longitudinal survey conducted by the US Bureau of the Census and NORC-University over a population of 12,686 young men and women who where among 14 and 22 years old in 1979 when it started. At the beginning, military youth and civilian Hispanics, black and economically disadvantaged white youth were oversampled, but since 1985 the military oversample disappeared and 1643 individuals of the oversampled civilian population were dropped out in 1991. The last available wave is from 1991.

Using the NLSY had some advantages over the use of the PSID. The last one presents serious difficulties to identify job changes: it generally provides no employer codes that uniquely identify jobs. Researchers must rely on reported tenure to infer job
changes. Measurement error in tenure responses can lead to incorrect inferences ${ }^{14}$. In addition, the variable hours refer to the full calendar before the interview. Then if a job change occurs in this period, hours can refer to a mixture of hours worked on two sequential jobs. To avoid this problem, Altonji and Paxson, try to construct a variable that measures unambiguously either within jobs or between job hours' changes using the hours changes over a three year gap.

Alternatively, in the NLSY all variables refer to employer code. It provides information for, at most, five jobs by individual and year: starting and finishing dates of contract, hours worked, hourly rate of pay, tenure and so. That allows us to construct a complete work history for each individual and job changes can then be identified. Hours can in this case be measured without ambiguity.

An additional advantage of the NLSY is that it collects information for a particular cohort of the population, those who were born between 1957 and 1965, which are more likely to have the same preferences (discount rates, for example), reducing possible heterogeneity. To concentrate on prime age males, highly attached to the labour market, allow us to disregard participation decisions.

Information for the current or most recent job is more detailed than for other jobs (e.g., hours per year worked), therefore all variables will refer to this job. Then, for example, the variable hours91 is the number of hours worked in the current or most recent job during 1991. A stayer is a worker who has not changed his current or most important job between two consecutive years. Movers can be either layoffs or can change job for any other reason.

The period chosen for the analysis is seven years, short enough to assume stability on the parameters of interest and long enough to be able to reach some conclusions. We select a subsample of males continuously interviewed between 1985 and 1991. The subsample contains individuals that reported positive hours of work and wages for every year and that gave valid answers for the rest of variables included in the analysis. In principle, as we want to test hours restrictions, workers holding more than

[^8]one job in any year would also be dropped. Self-employed individuals are neither used in the estimation. That leave us with a sample of 974 individuals per year. Although we have seven years of data, due to the nature of instruments we are forced to use, only five years, from 1987 to 1991, are finally included in estimation ${ }^{15}$. Data for 1985 and 1986 will be used to instrument endogenous variables.

A total of 4870 individual observations constitute the final sample. Of those, approximately $78 \%$ are stayers (3806), $17.5 \%$ mover not layoffs ( 851 ) and $4.4 \%$ movers that experience a layoff (213). It is interesting to point out that $35.5 \%$ of the sample did not change job during the whole period 1985-1991, and an extra $25 \%$ did it only once. This may indicate either that everyone is in his labour supply curve or that moving jobs has some costs.

Along with hourly wage rates, other variables included in the analysis are those which can influence hours of work and change over time. Following the traditional labour supply theory such variables should relate personal characteristics rather than job characteristics. Therefore changes on health status, number of children, marital status and other income are selected. Appendix A provides a detailed explanation of the construction and definition of the relevant variables, and their mean and standard deviation for the selected sample are shown in Table 2.A.1.

Although the survey collects alternative measures for hours (hours per day, per week and per year), we choose hours per year because it is the more flexible. An individual may be constrained in the number of hours he works per day but in compensation he can have days or weeks off.
Figure 2.1 shows cleary that dispersion of the change in hours among stayers is far below dispersion of movers. This graph represents the distribution of the change in yearly worked hours over the sample. It distinguishes among the three types of workers

[^9]

Figure 2.1: Histogram of change in hours per year by individual type.


Figure 2.2: Histogram of change in hourly rate of pay by indi vidual type.

[^10]we are studying, namely stayers, movers that were layoff and movers that were not layoff. Actually, $48 \%$ of stayers did not change hours at all while only $12.7 \%$ of movers did not ( $13.75 \%$ if they quit the job and $8.45 \%$ if they were layoff).

From this figure, dispersion for layoff movers is higher than for stayers. Although this finding supports the idea of job changes having some cost, some caution should be taken given that no correction has been made for wages or personal characteristics. Figure 2.2 presents the corresponding distribution of the changes in the hourly rate of pay over the sample. Wages are also more variable among movers (of both types) than among stayers. Therefore correcting for factors such as wages is necessary before reaching any conclusion.

### 2.5. Empirical results

Estimates for the change in hours equations for movers and stayers separately are presented in Table 2.1 (equations (2.16) and (2.17)). For movers, different equations are also estimate for movers that experience a layoff and for movers not layoff, in spite of the reduced sample size for the first subset. Explanatory variables for the change in hours are: two dummies accounting for change in health status (uphlth and dwhlth), change in marital status, change in the number of children, change in other income and change in hourly rate of pay.

Due to the error structure in (2.16) and (2.17) valid instruments for wages are dated two periods before current period. That is why the data on 1986 and 1985 cannot be used as additional observations in estimation. Some broad occupational dummies are also included as instruments (professional and non manual workers, as defined in Appendix A). Occupation is a variable highly correlated with wages but it is also likely to be endogenous. Then lagged values of these dummies are used for estimation purposes. Arellano and Bond type instruments are used, exploiting all possible instruments for
every year ${ }^{16}$. The change in wages for 1991 is instrumented with the hourly rate of pay (in levels) for $1989,1988,1987,1986,1985$; change for 1990 is instrumented with 1988 , 1987, 1986, 1985's hourly rate of pay, and so on.

Other income is considered exogenous in this specification. As it can be seen in the bottom line of Table 2.1 , for any of the four subgroups, the null hypothesis of exogeneity is rejected, using a $\chi^{2}$ test as defined by (2.28). However, lagged values of other income are also included as additional instruments, jointly with the current change in the variable. Applying the incremental Sargan test, we do not reject the validity of this additional set in any of the cases and some precision is gained in the estimates.

Most of the variables in Table 2.1 are unsurprisingly no significant. In general, children and marital status are never very significant for men. About the variable other income, it is necessary to remember that the oldest individual in the sample is 34 years old. Changes in health status are marginally significant for some of the groups. If there is some improvement in health, individuals tend to work more than in the previous year, especially if they are stayers or movers who were layoff.

Regarding the wage coefficient, lets first concentrate on the subsamples of movers. As it should be expected, a positive coefficient for wages is obtained ${ }^{17}$. The higher the wage of this year is with respect to the previous, the more hours the individual works this year with respect to the previous. However the coefficient is very imprecise, especially when we split the sample of movers in the two subgroups. For stayers also a positive wage elasticity is implied. As we will see from estimation of equation (2.20), equality of coefficients for movers and stayers would be rejected.

First column of Table 2.3 shows that the variance of the change in hours is greater for movers (both layoff and not layoff) than for stayers. In that column, variances are not corrected by the possible variation of other variables, such as wages. Estimation of equations (2.16) and (2.17) enables us to adjust the change in hours for the change in

[^11]observable factors. Column two of the same table shows that even adjusting by all the factors that can be more variable for movers than for stayers (Table 2.2), the differences in the variance of the change in hours between movers and stayers are high and significant. Our estimates are a little bit higher than those found by Altonji and Paxson (1986), but also the sample we select is slightly different: we concentrate only on prime age males. The variance in hours is 5.5 times bigger for all movers than for stayers (4.8 times if they where not layoff and 6.4 times if they experience a layoff). This suggests that some constraint in the hours an individual can work must exist or that the hours of work are influenced by other factors appart from personal characteristics.

Table 2.1: Change in hours equation by individual type

|  | Stayers | Movers | M.not layoff | M.layoff |
| :--- | :---: | :---: | :---: | :---: |
| Intercept | 0.017 | -0.066 | -0.023 | -0.135 |
|  | $(0.006)$ | $(0.024)$ | $(0.026)$ | $(0.054)$ |
| $\Delta$ wage | 0.229 | 0.386 | 0.242 | 0.468 |
|  | $(0.106)$ | $(0.169)$ | $(0.172)$ | $(0.326)$ |
| Uphlth | 0.088 | 0.387 | 0.166 | 1.430 |
|  | $(0.063)$ | $(0.171)$ | $(0.148)$ | $(0.969)$ |
| Dwhlth | -0.053 | 0.034 | 0.104 | -0.915 |
|  | $(0.045)$ | $(0.319)$ | $(0.277)$ | $(0.727)$ |
| $\Delta$ children | 0.011 | -0.008 | -0.033 | 0.018 |
|  | $(0.013)$ | $(0.061)$ | $(0.062)$ | $(0.155)$ |
| $\Delta$ marital status | 0.012 | 0.033 | 0.031 | 0.102 |
|  | $(0.020)$ | $(0.058)$ | $(0.061)$ | $(0.177)$ |
| $\Delta$ otinc | 0.0002 | -0.008 | -0.010 | 0.008 |
|  | $(0.001)$ | $(0.009)$ | $(0.010)$ | $(0.019)$ |
| Observations | 3806 | 1064 | 851 | 213 |
| R | 0.077 | 0.078 | 0.039 | 0.104 |
| Sargan test | 55.64 | 38.94 | 39.23 | 39.03 |
| (p-value) | $(0.041)$ | $(0.473)$ | $(0.459)$ | $(0.152)$ |
| $W$ (Income) | 0.002 | 2.502 | 2.206 | 0.493 |
| (p-value) | $(1.000)$ | $(0.927)$ | $(0.948)$ | $(0.152)$ |
| Nos E |  |  |  |  |

Notes: Estimation Method: GMM. Standard errors in brackets.
Instruments include a constant, $\Delta$ marital status, $\Delta$ children, dwhlth, uphlth and $\Delta$ otinc plus ArellanoBond type instruments with lagged values of otinc and wages dated $t-2$ and backwards (see Appendix B for an explanation of this kind of instruments), and two occupational dummies (as defined in the Appendix A) dated in $t-1$.
None of the movers experience a layoff during 1988. Instruments used in estimation for this subgroup are adjusted by this fact. W(Income): Exogeneity test for income.

The hypothesis of movers having more variable preferences and the possibility of moving jobs at no cost do not seem to be coherent with the data if we compare the behaviour of stayers and movers that were layoff. As explained in previous section, we should expect that if layoffs are exogenous, as it seems quite plausible, stayers and layoffs behave in the same way. However, that is not the case when comparing the variances of their change in hours of work. Layoffs have an even greater variance, both unadjusted and adjusted, than the rest of movers ${ }^{18}$. Some caution has to be taken with this result due to the small sample size for layoffs.

Previous results are consistent only under the restrictive assumptions that movements between jobs are exogenous and that the error term is equally distributed across individual types. These are strong assumptions that should be tested because there could be some sample selection bias on the estimates. To do so we estimate equation (2.20) under endogeneity and exogeneity of the movements and compare the results.

Estimates of equation (2.20) under both hypotheses are presented in Table 2.2. Only movers that were not layoff are included in the estimation, although inclusion of the 213 layoffs does not change results, only reinforces them as can be seen in Table 2.C. 1 in Appendix C.

First, we discuss the specification of both hypotheses. Columns of Table 2.2 are estimated for other income exogenous and wages endogenous. Testing exogeneity of income we get an statistic $\mathrm{W}=7.881$ if movements exogenous and $\mathrm{W}=2.634$ if movements endogenous, both of them following a $\chi^{2}$ distribution with 12 degrees of freedom. Therefore we can not reject exogeneity of income in any of the specifications. Instruments for the change in other income and its cross product with the dummy Stay include, along with the current change, all possible lagged values and the product of those and the instrument for the variable Stay. Testing this additional set of instruments, they are not rejected ${ }^{19}$.

[^12]Table 2.2: Change in hours pooling individuals
(excluding layoffs).

|  | Stay exogenous | Stay endogenous |
| :--- | :---: | :---: |
| Intercept | -0.044 | 0.181 |
|  | $(0.026)$ | $(0.072)$ |
| Stay | 0.055 | -0.194 |
|  | $(0.027)$ | $(0.080)$ |
| $\Delta$ wage | 0.492 | 0.518 |
|  | $(0.165)$ | $(0.273)$ |
| $\Delta$ wage x Stay | -0.452 | -0.654 |
|  | $(0.203)$ | $(0.298)$ |
| $\Delta$ otinc | -0.011 | 0.051 |
|  | $(0.010)$ | $(0.036)$ |
| $\Delta$ otinc x Stay | 0.011 | -0.057 |
|  | $(0.010)$ | $(0.040)$ |
| $\Delta$ marital status | 0.025 | -0.206 |
|  | $(0.064)$ | $(0.283)$ |
| $\Delta$ marital status x Stay | -0.002 | 0.257 |
|  | $(0.066)$ | $(0.346)$ |
| Uphlth | 0.157 | 0.183 |
|  | $(0.150)$ | $(0.307)$ |
| Uphlth x Stay | -0.073 | -0.098 |
|  | $(0.163)$ | $(0.376)$ |
| Dwhlth | 0.174 | -0.013 |
|  | $(0.295)$ | $(0.671)$ |
| Dwhlth x Stay | -0.206 | -0.001 |
| $\mathrm{R}^{2}$ | $(0.299)$ | $(0.739)$ |
| Sargan test | 0.078 | 0.146 |
| (p-value) | 193.6 | 87.28 |
| $W$ (Income) | $\left(5.02 e^{-5}\right)$ | $(0.221)$ |
| (p-value) | 7.881 | 2.634 |
| W(wages) | $(0.794)$ | $(0.998)$ |
| (p-value) | 350.2 | 30.07 |
| W(Stay) | $(0.000)$ | $(0.003)$ |
| (p-value) |  |  |
| Observations |  |  |
| Noes: |  |  |

Notes: Estimation method: GMM. Standard errors in brackets. Common instruments to both specifications: constant, $\Delta$ marital status, $\Delta$ children, dwhlth, uphlth and $\Delta$ otinc plus Arellano-Bond type instruments with lagged values of otinc and wages dated $t-2$ and backwards, and two occupational dummies dated in $t-1$. Specific instruments for column 2: Stay instrumented with lagged value of Stay, Stay $_{\mathrm{t}-1}$, and cross products StayxVariable, are instrumented with the cross product of Stay ${ }_{t-1}$ and the corresponding instrument for the Variable. Specific instruments for column l: Stay instrumented with itself, and cross products StayxVariable, are instrumented with the cross product of Stay and the corresponding instrument for the Variable. They include also all instruments in column 2.
$W$ (Income): exogeneity test for income; $W$ (wages): exogeneity test for wages; $W$ (Stay): exogeneity test for movements.

Conversely, wages can not be considered as exogenous (from $W$ (wages) in Table 2.2) in any of the specifications. They are instrumented with two periods lagged values, two occupational dummies and the product of the instrument chosen for Stay and all previous instruments.

The only difference between the two columns of Table 2.2 is that in the first one, the variable Stay is exogenous, and therefore instrumented by itself. Second column considers Stay endogenous and it is instrumented with its one period lagged value. Stay equals 1 if the individual did not change job between $t-1$ and $t$ and thus Stay $_{t-1}$ equals 1 if the worker did not move between $t-2$ and $t-1$. Therefore, even if Stay is endogenous, Stay $_{\mathrm{t}-1}$ would be correlated with $\varepsilon_{\mathrm{t}-2}$, but most probably uncorrelated with $\varepsilon_{\mathrm{t}-1}$ or any of the components of $u_{t}$, being a valid instrument for Stay ${ }^{20}$.

From Table 2.2, results under both specifications are quite different. In the specification that assumes exogeneity of movements, hours respond to wage changes more for movers than for stayers ( $\beta_{1}=0.519$ and $\alpha_{1}=0.041$ ), but both elasticities are positive. Hours constraints affecting stayers would be coherent with this finding ${ }^{21}$.

The variable Stay is positive and highly significant, indicating that the change in hours is, in mean, bigger for stayers than for movers. However, although significant, its effect is rather small. None of the remaining variables has any significant effect on the change in hours of work. When we compare this results with the separate equations for each group, we see that they are quite different, suggesting that the assumption of the error term being homoscedastic for both groups is quite strong. Therefore estimates in Table 2.1 will be most probably biased.

When we allow for endogeneity of movements, results change quite significantly. First of all, the coefficient on wages for stayers implied by the second column of Table 2.2 is $\alpha_{1}=-0.137$ although it is not significantly different from zero ${ }^{22}$. These results

[^13]contradict Altonji and Paxson (1986). They are quite similar to those of Ham (1986), where he estimates a labour supply equation similar to ours and allowing for hours constraints in the form of unemployment or underemployment to be endogenous. He found that this misspecification of the labour supply is consistent to different tests about the functional form, the omission of variables and the error structure assumed in the hours equation. That coefficient could imply that those restricted individuals are off they labour supply function. In that case, labour elasticities may better be reflecting contracting arrangements between workers and firms ${ }^{23}$.

Imposing equal coefficients for movers and for stayers, an intertemporal elasticity estimate of 0.359 is found. This figure is in line with previous results for the US. MaCurdy (1981) found an elasticity of 0.15 for white married men using a sample of the PSID from 1968 to 1977 . Altonji (1986) got a higher elasticity ( 0.267 ) by including age in the regression. More recently Zabel (1997) replicated Altonji's result for married white men aged 25 to 45 in 1968, using the PSID from 1968 to 1987. Our estimated elasticity is somehow larger, but the selected sample we use is also slightly different: prime age males, married and unmarried, may show a higher wage elasticity. However, given the results when we split the sample between movers and stayers (Table 2.2), this restriction seems quite strong.

Regarding the rest of the parameters, the coefficient for the dummy Stay changes sing and its effect is bigger than in previous specification. Therefore, the change in hours is now bigger for movers than for stayers, as it should be expected under hours constraints. Other income becomes now marginally significant, at least for movers, and it positively affects the number of hours worked. The remaining variables do not have any effect as in previous specifications.

Testing exogeneity of movements produces a test $W=181.9$ distributed as a $\chi^{2}$ with 33 d.o.f. The null hypothesis of exogeneity is clearly rejected. Therefore specification with movements endogenous is preferred and the estimation of the separated equations is not valid any more.

[^14]Table 2.3: Variance of changes in hours

|  | Unadjusted | Adjusted: estimates Table 2.1 | Adjusted: estimates Table 2.2, column 1 | Adjusted: estimates Table 2.2, column 2 | Adjusted: estimates Table 2.C.1, column 2 |
| :---: | :---: | :---: | :---: | :---: | :---: |
| Stayers | $\begin{gathered} \hline 0.075 \\ (0.008) \end{gathered}$ | $\begin{gathered} \hline 0.085 \\ (0.008) \end{gathered}$ | $\begin{gathered} 0.076 \\ (0.008) \end{gathered}$ | $\begin{gathered} \hline 0.076 \\ (0.008) \end{gathered}$ | $\begin{gathered} \hline 0.079 \\ (0.008) \end{gathered}$ |
| Movers | $\begin{gathered} 0.438 \\ (0.037) \end{gathered}$ | $\begin{gathered} 0.466 \\ (0.038) \end{gathered}$ |  | - | $\begin{gathered} 0.540 \\ (0.045) \end{gathered}$ |
| Not Layoff | $\begin{gathered} 0.402 \\ (0.039) \end{gathered}$ | $\begin{gathered} 0.414 \\ (0.040) \end{gathered}$ | $\begin{gathered} 0.454 \\ (0.042) \end{gathered}$ | $\begin{gathered} 0.481 \\ (0.046) \end{gathered}$ | - |
| Layoff | $\begin{gathered} 0.537 \\ (0.096) \\ \hline \end{gathered}$ | $\begin{gathered} 0.540 \\ (0.096) \\ \hline \end{gathered}$ | - | - | - |
| Difference move-stay | $\begin{gathered} 0.363 \\ (0.038) \end{gathered}$ | $\begin{gathered} 0.381 \\ (0.039) \end{gathered}$ | - | - | $\begin{gathered} \hline 0.461 \\ (0.046) \end{gathered}$ |
| Diff. not | 0.327 | 0.329 | 0.378 | 0.405 | - |
| layoff-stay | (0.040) | (0.041) | (0.043) | (0.047) |  |
| Diff. layoffstay | $\begin{gathered} 0.462 \\ (0.096) \\ \hline \end{gathered}$ | $\begin{array}{r} 0.455 \\ (0.096) \\ \hline \hline \end{array}$ |  | - | - |
| Notes: Standard errors in brackets. Standard errors are computed est $\operatorname{var}\left(\hat{\sigma}^{2}\right)=\frac{1 / n \sum w_{i}^{4}-\hat{\sigma}^{4}}{n}$, where $w_{i}$ is the variable in deviations from the mean. |  |  |  |  |  |

Implications of using an invalid specification on the variance of the change in hours can be seen in Table 2.3. Column 3 gives the estimation for the variance of the change in hours adjusted according to the final valid specification (movements endogenous). We see that the difference for the variance of the change in hours between movers and stayers was underestimated when using the separated equations or considering movements exogenous. The variance for stayers is smaller and the one for movers is higher than under the simplifying. The variance for movers is around 6.3 times higher than for stayers, which is well over the results obtained by Altonji and Paxson (1986).

As mentioned above, results do not change by the use of the whole set of movers (including layoffs). If anything, they become reinforced (see Table 2.C.1), which suggest that layoffs do not behave at all as stayers. That corroborates the hypothesis that job changes are not free for individuals and therefore is not the case that they can move jobs and remain in their labour supply curve. Column 4 of Table 2.3 shows the variance of the
change in hours obtained when using the whole sample of movers: this is around 6.8 times bigger for movers than for stayers.

### 2.6. Conclusions

This chapter provides empirical evidence on the assumption that individuals freely decide the number of hours they work at a given wage, using US data on prime age males. If this assumption holds, the behaviour of individuals who change jobs should be similar, once personal characteristics have been corrected for, to the behaviour of individuals that remain in the same job. In other words, the variance of the change in hours for individuals that move should be statistically equal to the variance of the change in hours for individuals that stay. If this assumption does not hold, differences in the variance of the change in hours would appear higher for movers than for stayers. This is because they move, among other reasons, to adjust the number of hours they work.

Taking advantage of the longitudinal nature of the data and by using GMM, we estimate a labour supply equation which is consistent with a life-cycle labour supply model under uncertainty. In this context, the endogeneity of movements is crucial to get consistent estimates.

We find that the variance of the change in hours is more than six times higher for movers than for stayers. This figures are somehow higher than previous estimates (see Altonji and Paxson ,1986). Invalid specification of the model (i. e., the assumption of homogeneity between movers and stayers or the assumptio of exogeneity of the movements) leads to downward biases on the estimated variance.

Taking into account the behaviour of stayers and layoffs, data does not seem compatible with a model in which individuals can change jobs at no cost. If that was the case and layoffs are considered exogenous, stayers and layoffs should behave similarly. However, the behaviour of the layoffs is more similar to the behaviour of other movers
than to the stayers. Some caution has to be taken with this result due to the small amount of individuals that were layoff during the sampling period.

The results suggest that, at least for prime age males, the standard approach to estimate labour supply functions, which does not take into account the possibility of some groups of individuals being off their labour supply curves, leads to estimate an equation that is misspecified. Previous positive and quite large estimates for intertemporal labour supply elasticities using similar models (Zabel, 1997, MaCurdy, 1981, or Altonji, 1986) were found under the assumption of no constraints in the amount of hours the individual works. In general, wage elasticities for the constrained group are overestimated if the possibility of constraints is not considered. It is specially important to allow for endogeneity of the movements across jobs. It seems quite possible, that a more complex labour supply model incorporating job characteristics or employer preferences, would reflect better what is detected in the data. These findings are in the line of those of Ham (1986), Biddle (1988) or Ball (1990).

In this Chapter, we have focused on the group of individuals that are more likely constrained in the number of hours they work. Individuals holding more than one job were not considered here. It remains to be said whether the apparently constrained individuals may take second jobs to avoid their hours constraints, although this is out of the scope of this study.

### 2.7. Appendix A: variable description

Dwhlth: dummy variable that equals 1 if in period $t-1$ the individual did not have health limitations but he has them on $t$. Uphlth: dummy variable that equals one if individual had some health limitations in $t-1$ but he does not have them in period $t$.
$\Delta$ Children: dummy variable that equals one if the individual did have a child between $t-1$ and $t$.
$\Delta$ Marital Status: dummy variable that equals one if the individual married between $t-1$ and $t$. Different specifications were used to account also for marital disruptions but did not make any difference in estimates.

Wage: wages are measured as real hourly rate of pay in the current or most recent job for every year. They are deflated by the USA IPC for all items and therefore are constant at 1991 prices. It is a created variable constructed from the answers to two questions and the variable of hours relevant in each case:

Q1. How much do you usually earn at that job?
Q2. Was that per day, per hour, per week or what?
Around $40 \%$ of the individual answered per hour in Q2, $15 \%$ per week and $20 \%$ per year for every year. Then it can be subject to some measurement error.

Hours/year: this variable is constructed as hours per week times weeks per year worked in the current or most recent job.

Otinc: this variable measures annual before taxes income from other sources but paid work, in the household. It is also deflated by the USA IPC for all items. We created this variable as the sum of a set of variables referring other household sources of income:

- Annual income from UC benefits for the respondent or his wife.
- Annual income from child support for the respondent or his wife.
- Annual income from AFDC for the respondent or his wife.
- Annual income from SSI for the respondent or his wife.
- Annual income from veteran benefits, workers' compensation or disability for the respondent or his wife.
- Annual income from welfare for the partner (not wife).
- Annual income from welfare for other family members.
- Wife or partner's income (gross) from wages or farm/business.
- Annual income from regular sources for other family members.
- Hours per year are hours per week times weeks per year.
- Income from other sources (interest, dividends,...).

Occupation: two broad occupational dummies are constructed as additional instruments for wages. Ocup1 equals one if the individual is a professional and Ocup2 equals 1 if the individual is a non manual worker (services, sales, farm, clerical workers). The 70 Census (three digit decomposition) is use in their construction.
Stayer: individual that stayed in the same job between period $t-1$ and $t$.
Stay: dummy variable that equals one if the individual was employed by the same employer in his current or most important job between period $t-I$ and $t$.

Mover: individual that changed his most important or recent job between $t-1$ and $t$.
Layoff: individual that changes job because, as stated by himself, he was either layoff ( $62.91 \%$ ) or the plant where he worked closed $(10.8 \%)$ or he was discharged or fired (26.29\%).

Table 2.A.1: Mean of the relevant variables by individual type

| Variables | Stayers | Movers | Mov. not layoff | Movers layoff |
| :--- | :---: | :---: | :---: | :---: |
| Hours/year | 2212.09 | 1854.10 | 1918.03 | 1598.72 |
|  | $(410.297)$ | $(720.410)$ | $(711.826)$ | $(699.120)$ |
| Hours/week | 43.342 | 42.565 | 43.154 | 40.211 |
|  | $(7.345)$ | $(10.041)$ | $(9.980)$ | $(9.962)$ |
| Weeks/year | 51.030 | 43.244 | 44.170 | 39.545 |
|  | $(3.977)$ | $(12.433)$ | $(12.036)$ | $(13.308)$ |
| Wage/hour | 12.101 | 9.620 | 9.798 | 8.908 |
|  | $(5.285)$ | $(4.994)$ | $(5.057)$ | $(4.675)$ |
| Otinc. x 10-4 | 1.199 | 1.178 | 1.185 | 1.151 |
|  | $(2.738)$ | $(2.143)$ | $(2.180)$ | $(1.994)$ |
| $\Delta \ln$ (hours/year) | 0.036 | -0.029 | 0.019 | -0.224 |
|  | $(0.274)$ | $(0.662)$ | $(0.634)$ | $(0.733)$ |
| $\Delta \ln$ (wage) | 0.030 | 0.054 | 0.075 | 0.016 |
|  | $(0.366)$ | $(0.497)$ | $(0.517)$ | $(0.477)$ |
| $\Delta$ (otinc 10 $0^{-4}$ ) | 0.092 | 0.171 | 0.145 | 0.277 |
|  | $(3.461)$ | $(2.459)$ | $(2.550)$ | $(2.059)$ |
| $\Delta$ Children | 0.124 | 0.105 | 0.113 | 0.075 |
|  | $(0.330)$ | $(0.307)$ | $(0.316)$ | $(0.264)$ |
| $\Delta$ Marital status | 0.042 | 0.046 | 0.049 | 0.033 |
| • | $(0.201)$ | $(0.210)$ | $(0.217)$ | $(0.179)$ |
| Uphlth | 0.013 | 0.025 | 0.009 |  |
|  | $(0.112)$ | $(0.155)$ | $(0.097)$ |  |
| Dwnhlth | 0.015 | 0.012 | 0.014 |  |
|  | $(0.122)$ | $(0.012$ | $(0.118)$ |  |
| Observations | 3806 | 1064 | 213 |  |

[^15]
### 2.8. Appendix B: Some technical questions.

### 2.8.1. Instruments Structure

Imagine we only have information from 1988 to 1991. Arellano-Bond type instruments use all past information in the more efficient possible way. Therefore, due to the structure of the error term in Section 2.2, endogenous observations of year $t$ would be instrumented with observations of the variable dated $t-2$ and backwards. That is, observations corresponding to 1991, would be instrumented by observations in 1989 and 1988, in this case, and observations corresponding to 1990 would be instrumented with the variables dated in 1988. Lets consider wages. Valid instruments in this example are w1, w2, w3, constructed as below.

| $T$ | $N$ | $\Delta w$ | $w 1$ | $w 2$ | $w 3$ |
| :---: | :---: | :---: | :---: | :---: | :---: |
| 91 | 1 | $\left(w_{91}-w_{90}\right)_{1}$ | $\left(w_{89}\right)_{1}$ | $\left(w_{88}\right)_{1}$ | 0 |
| 91 | 2 | $\left(w_{91}-w_{90}\right)_{2}$ | $\left(w_{89}\right)_{2}$ | $\left(w_{88}\right)_{2}$ | 0 |
| $\cdot$ | $\cdot$ | $\cdot$ | $\cdot$ | $\cdot$ | $\cdot$ |
| $\cdot$ | $\cdot$ | $\cdot$ | $\cdot$ | $\cdot$ | $\cdot$ |
| 91 | $N$ | $\left(w_{91}-w_{90}\right)_{\mathrm{N}}$ | $\left(w_{89}\right)_{\mathrm{N}}$ | $\left(w_{88}\right)_{\mathrm{N}}$ | 0 |
| 90 | 1 | $\left(w_{90}-w_{89}\right)_{1}$ | 0 | 0 | $\left(w_{88}\right)_{1}$ |
| 90 | 2 | $\left(w_{90}-w_{89}\right)_{2}$ | 0 | 0 | $\left(w_{88}\right)_{2}$ |
| $\cdot$ | $\cdot$ | $\cdot$ | $\cdot$ | $\cdot$ | $\cdot$ |
| $\cdot$ | $\cdot$ | $\cdot$ | $\cdot$ | $\cdot$ | $\cdot$ |
| 90 | $N$ | $\left(w_{90}-w_{89}\right)_{\mathrm{N}}$ | 0 | 0 | $\left(w_{88}\right)_{\mathrm{N}}$ |

where T and N represent respectively time and individual to which the observation corresponds. $\Delta \mathrm{w}$ is the variable to be instrumented.

### 2.8.2. Covariance matrix for correlated estimators

Section 2.3 introduced a test for the possible endogeneity of some of the explanatory variables. Given the form of the objective functions from equation (2.24) and from Mroz (1987), the covariance matrix of a vector $\left(\hat{\vartheta}_{1}, \hat{\vartheta}_{2}\right)$ has the following expression:

$$
\operatorname{var}\left(\hat{\vartheta}_{1}, \hat{\vartheta}_{2}\right)=A^{-1} B^{\prime} C B A^{-1}
$$

where

$$
\begin{aligned}
& A=\left[\begin{array}{cc}
X^{\prime} Z_{1}\left(Z_{1}^{\prime} Z_{1}\right)^{-1} Z_{1}^{\prime} X & 0 \\
0 & X^{\prime} Z_{2}\left(Z_{2}^{\prime} Z_{2}\right)^{-1} Z_{2}^{\prime} X
\end{array}\right] \\
& B=\left[\begin{array}{cc}
X^{\prime} Z_{1}\left(Z_{1}^{\prime} Z_{1}\right)^{-1} & 0 \\
0 & X^{\prime} Z_{2}\left(Z_{2}^{\prime} Z_{2}\right)^{-1}
\end{array}\right] \\
& C=\left[\begin{array}{cc}
\sum_{i=1}^{N} \hat{u}_{1 i}^{2} z_{1 i} z_{1 i}^{\prime} & \sum_{i=1}^{N} \hat{u}_{1 i} \hat{u}_{2 i} z_{1 i} z_{2 i}^{\prime} \\
\sum_{i=1}^{N} \hat{u}_{1 i} \hat{u}_{2 i} z_{1 i} z_{2 i}^{\prime} & \sum_{i=1}^{N} \hat{u}_{2 i}^{2} z_{2 i} z_{2 i}^{\prime}
\end{array}\right]
\end{aligned}
$$

### 2.9. Appendix C: Results using all movers.

Table 2.C.1: Change in hours pooling individuals.
(including all movers)

|  | Stay exogenous | Stay endogenous |
| :---: | :---: | :---: |
| Intercept | $\begin{gathered} -0.079 \\ (0.023) \end{gathered}$ | $\begin{gathered} 0.148 \\ (0.060) \end{gathered}$ |
| Stay | $\begin{gathered} 0.090 \\ (0.024) \end{gathered}$ | $\begin{aligned} & -0.171 \\ & (0.069) \end{aligned}$ |
| $\Delta$ wage | $\begin{gathered} 0.574 \\ (0.157) \end{gathered}$ | $\begin{gathered} 0.570 \\ (0.241) \end{gathered}$ |
| $\Delta$ wage x Stay | $\begin{gathered} -0.521 \\ (0.198) \end{gathered}$ | $\begin{gathered} -0.773 \\ (0.286) \end{gathered}$ |
| $\Delta$ otinc | $\begin{gathered} -0.007 \\ (0.009) \end{gathered}$ | $\begin{gathered} 0.071 \\ (0.036) \end{gathered}$ |
| $\Delta$ otinc x Stay | $\begin{gathered} 0.007 \\ (0.009) \end{gathered}$ | $\begin{gathered} -0.080 \\ (0.040) \end{gathered}$ |
| $\Delta$ marital status | $\begin{gathered} 0.048 \\ (0.060) \end{gathered}$ | $\begin{gathered} -0.339 \\ (0.249) \end{gathered}$ |
| $\Delta$ marital status x Stay | $\begin{gathered} -0.023 \\ (0.062) \end{gathered}$ | $\begin{gathered} 0.449 \\ (0.314) \end{gathered}$ |
| Uphlth | $\begin{gathered} 0.283 \\ (0.173) \end{gathered}$ | $\begin{gathered} 0.383 \\ (0.344) \end{gathered}$ |
| Uphlth x Stay | $\begin{gathered} -0.211 \\ (0.184) \end{gathered}$ | $\begin{gathered} -0.336 \\ (0.431) \end{gathered}$ |
| Dwhlth | $\begin{gathered} 0.009 \\ (0.328) \end{gathered}$ | $\begin{gathered} -0.103 \\ (0.828) \end{gathered}$ |
| Dwhlth x Stay | $\begin{gathered} -0.054 \\ (0.331) \\ \hline \end{gathered}$ | $\begin{array}{r} 0.057 \\ (0.985) \\ \hline \end{array}$ |
| $\mathrm{R}^{2}$ | 0.100 | 0.166 |
| Sargan test (p-value) | $\begin{gathered} 198.7 \\ \left(1.81 e^{-5}\right) \end{gathered}$ | $\begin{gathered} 84.38 \\ (0.291) \end{gathered}$ |
| W(Stay) <br> (p-value) |  |  |
| Observations |  |  |

Notes: Estimation method: GMM. Standard errors in brackets. Common instruments to both specifications: constant, $\Delta$ marital status, $\Delta$ children, dwhlth, uphlth and $\Delta$ otinc plus Arellano-Bond type instruments with lagged values of otinc and wages dated $t-2$ and backwards, and two occupational dummies dated in $t-1$. Specific instruments for column 2: Stay instrumented with lagged value of Stay, Stay $_{t-1}$, and cross products StayxVariable, are instrumented with the cross product of Stay $_{t-1}$ and the corresponding instrument for the Variable. Specific instruments for column 1: Stay instrumented with itself, and cross products StayxVariable, are instrumented with the cross product of Stay and the corresponding instrument for the Variable. It includes also all instruments in column 2. W(Stay): exogeneity test for movements.

## Chapter 3

## Self-Employment and Labour Market Transitions: a Multiple State Model.

### 3.1. Introduction

Self-employment in the UK (and in general in all OECD countries) has experienced a sharp increase during the late 70's and 80's. In March 1980, 10\% of the workforce was self-employed. This figure increased to $15 \%$ in March 1989, according to the Department of Employment. Meanwhile, programs to promote and support start-up and expansion of small businesses have been carried out by the government. In spite of the growth of self-employment and of the policies to promote it, there is little empirical evidence, particularly for the UK, of the characteristics that motivate an individual to become self-employed.

The purpose of this chapter is to add some empirical evidence of the characteristics and economic factors that determine self-employment decisions in UK. It has been recently argued that self-employment growth is the result of a labour market deterioration. Difficulties in finding a job generate the increases on self-employment
figures rather than changes in personal characteristics, such as education, financial conditions or even unobserved skills. Consequently, an interesting question to answer is to analyse whether the probabilities of transition into self-employment are higher for unemployed people than for employees, after controlling for personal characteristics.

Most of the related empirical work relies on the hypothesis that capital markets are perfect and any individual can borrow and lend any amount of money at current interest rates. ${ }^{1}$ In this context, self-employment is considered as an alternative to paid employment. These studies have usually been focused on the differential between expected earnings and wages. The econometrician observes whether an individual is selfemployed or not. Thus, the usual approach is to estimate a structural or reduced form binary choice model (probit or logit). This is the approach followed by Ress and Shah (1985) and more recently by Blundell et al. (1995) using British data. They also consider the influence of demographic characteristics on the probability of becoming selfemployed, namely education, marital status, region, race, number of children and health. Evans and Leighton (1989) use the same approach for the United States.

The effect of unemployment on the probability of becoming self-employed is not clear in the literature, though. Two opposite results have been found. On the one side Blanchflower and Oswald (1991) or Taylor (1996) provide evidence for UK, supporting a negative relationship between unemployment rates and entering self-employment. Good economic conditions (lower risk of failure or higher probability of finding an alternative job in the event of failure) would encourage individuals to start their own business. On the other side, Alba-Ramirez and Freeman (1994) or Evans and Leighton (1989) find, that the longer one individual has been unemployed the higher is his probability of becoming self-employed for Spain and the US respectively. Individuals see self-employment as a way of avoiding unemployment when the probability of finding a

[^16]paid job decreases ${ }^{2}$. Acs et al. (1994), using a panel of OECD countries, find that a $10 \%$ increase in the unemployment rate produces a $1.5 \%$ increase in the self-employment rate.

Previous empirical work has several limitations. On the one side, some authors, in estimating a binary choice model upon the stock of self-employed individuals, mix up entry and exit decisions (as Blanchflower and Oswald (1991) or Taylor (1996)). If unemployment leads individuals more likely to enter self-employment but also to exit that state, the final effect is going to be a mixture of both. Its sign will depend on the relative inflows and outflows.

To avoid this problem Evans and Leighton (1989) or Alba-Ramírez and Freeman (1994) constraint their studies to a particular group of individuals, wage workers, and look at exit rates towards self-employment. Only for this subgroup their results hold. The effects can be different for unemployed individuals; if working is an endogenous decision, as it is, results can be subjected to sample selection bias. In addition, some variables as previous unemployment experience, are likely to be endogenous. None of the previous studies addresses the analysis of the effect of general economic conditions jointly with individual unemployment spells.

A natural approach to model self-employment decisions consists of looking at individual work histories and considering self-employment an additional labour market state. Transitions among different states can be constructed and analysed ${ }^{3}$ then. In this Chapter three possible labour market states would be considered: self-employment, paid employment and unemployment. We estimate reduced form parametric transition probabilities from and to any of the three possible states, using a multiple state transition econometric framework. Due to tastes' differences or ability or what can be called "entrepreneurial spirit", the presence of unobservable heterogeneity among individuals

[^17]seems quite likely in this context. As a result we also estimate the model under this hypothesis in order to compare the results.

This approach helps us to overcome some of the limitations of previous literature. First, it allows us to consider entry and exit decisions separately. Unemployment duration arises naturally in this framework, avoiding possible endogeneity and selection bias. In addition it enables comparisons of the probability of becoming self-employed between unemployed and employed individuals.

Data used in this Chapter is a subsample of males drawn from the British Household Panel Survey (BHPS). This survey contains a retrospective work history questionnaire recording all job spells for each individual in the house since they left school.

The Chapter outline is as follows. Section 3.2 describes the model specification and discusses the estimation of the transition probabilities. Section 3.3 presents the data used for the analysis and in section 3.4 the estimation results are discussed. Section 3.5 states the main conclusions of the analysis.

### 3.2. Model specification

We distinguish three different possible states in our model: unemployment, wage-work and self-employment. Self-employment is considered as an alternative to paid employment. Movements from and to "out of the labour force" are not considered here. An individual can move from any of these states (source state, denoted by the first subscript) to the others (destination state, denoted by the second subscript) at any time. Six types of transition can then be defined as shown in Table 3.1 below.

This specification of the model is coherent with on-the-job search theories. Unemployed individuals devote some of their time searching for jobs. But, once they accept a job and start working (as paid workers or self-employed) they continue to
search for a better job. Two types of "jobs" are considered here: paid work and selfemployment ${ }^{4}$.

Transition intensities are defined as the probability of departure from state $k$ to state $l$ in the short interval $(t, t+\partial t)$ and are denoted as $\theta_{k l}(t \mid Z ; \beta)$, where $Z$ is a set of observable and unobservable individual characteristics ( $X$ and $v$ respectively) and $\beta$ is a set of unknown parameters to estimate. $t$, the elapsed duration, is measured in months. In particular, the following functional form represents the transition intensities:

$$
\begin{equation*}
\theta_{k l}(t \mid Z ; \beta)=\exp \left\{g_{k l}(t)+X \beta_{k l}+\delta_{k l} v\right\} \tag{3.1}
\end{equation*}
$$

where $g_{k l}(t)$ is a function of time spent in state $k$, before departure towards $l$. This specification allows for a flexible and non-monotonic relation between elapsed duration and the hazard function. Its functional form will be discussed in Section 3.4.2. The set $\beta$, includes all parameters of interest in $g(),. \beta_{k l}$ and $\delta_{k l}$, for all possible $(k, l)$. An unobservable individual fixed effect is denoted by $v$ which would be correlated with the time spent in each state. It can reflect differences in tastes for working or starting up a business. The estimation of parameters specific to every state allows state dependence along with duration dependence. Finally, $X$ is a set of demand conditions and demographic variables.

Table 3.1: Possible transition intensities.

|  | Destination State |  |  |
| :--- | :---: | :---: | :---: |
| Source State | Self-Employment | Employment | Unemployment |
| Self-Employment | ----- | $\theta_{\text {see }}(t \mid Z ; \beta)$ | $\theta_{\text {seu }}(t \mid Z ; \beta)$ |
| Employment | $\theta_{\text {ese }}(t \mid Z ; \beta)$ | $-\cdots---$ | $\theta_{\text {eu }}(t \mid Z ; \beta)$ |
| Unemployment | $\theta_{\text {use }}(t \mid Z ; \beta)$ | $\theta_{u e}(t \mid Z ; \beta)$ | ----- |

[^18][^19]Therefore the contribution to the likelihood function for each individual and completed spell is the probability of surviving in state $k$ until $t$ (survival function) times the probability of moving from $k$ to $l$ in $t$ (transition intensity),

$$
\begin{equation*}
P_{k l}(t \mid Z ; \beta)=\exp \left\{-\Theta_{k}(t \mid Z ; \beta)\right\} \theta_{k l}(t \mid Z ; \beta) \tag{3.2}
\end{equation*}
$$

where $\Theta_{k}$ is the corresponding integrated hazard function $\left(\Theta_{k l}=\int_{0}^{t} \sum_{l \neq k} \theta_{k l}(s \mid Z ; \beta) \partial s\right)$. For each individual, the data consist of one or more spells in every state. Not every spell is complete by the time of the interview. Hence it is necessary to account for right censored spells. The contribution to the likelihood function of an incomplete spell is the survivor function, that is

$$
\begin{equation*}
\bar{F}_{k}(t \mid X ; \beta)=\exp \left\{-\Theta_{k}(t \mid X ; \beta)\right\} \tag{3.3}
\end{equation*}
$$

Assuming that $v$ equals zero for all individuals i. e. there is no unobserved heterogeneity, the likelihood function for an individual with a sequence of spells $\left\{t_{1}\right.$, $\left.t_{2}, \ldots, t_{C i}\right\}$, would be,

$$
\begin{equation*}
L_{i}\left(\beta \mid t_{i 1}, \ldots, t_{i C_{i}}\right)=\left(\prod_{c=1}^{c_{i}} \prod_{k} \prod_{l \neq k} P_{k l}\left(t_{c} \mid X_{i}^{c} ; \beta\right)^{d_{i k}}\right)\left(\prod_{c=1}^{c_{i}} \prod_{l} \bar{F}_{k}\left(t_{c} \mid X_{i} ; \beta\right)^{s_{k}^{c}}\right) \tag{3.4}
\end{equation*}
$$

where $d_{k l}^{c}$ is an indicator variable which equals 1 if the individual exited state $k$ towards state $l$ in the $c$ th spell; $s_{k}^{c}$ is a dummy which equals one if the $c$ th spell is incomplete and the individual did not move from state $k$.

Taking logs and considering a sample of $N$ i.i.d. individuals the log-likelihood function is given by ${ }^{5}$

[^20]\[

$$
\begin{equation*}
\log L=\sum_{i=1}^{N} \sum_{c=1}^{c_{i}} \sum_{k}\left[\left(\sum_{l \neq k} d_{k l}^{c} P_{k l}\left(t_{c} \mid X_{i} ; \beta\right)\right)+s_{k}^{c} \bar{F}\left(t_{c} \mid X_{i} ; \beta\right)\right] \tag{3.5}
\end{equation*}
$$

\]

In the presence of unobservable heterogeneity among the individuals the model becomes more complicated. The individual fixed effect, denoted by $v_{i}$, is an unobservable variable that varies over the population. Therefore, we cannot condition the individual probabilities on $v_{i}$ and use it as an additional explanatory variable. To get the unconditional probabilities it is necessary to integrate $v_{i}$ over all its possible values. In this case the individual likelihood takes the form

$$
\begin{align*}
& L_{i}\left(\beta \mid t_{i 1}, \ldots, t_{i c_{i}}, X_{i}\right)= \\
& \quad \int_{-\infty}^{\infty}\left\{\left(\prod_{c=1}^{c_{i}} \prod_{k} \prod_{l \neq k} P_{k l}\left(t_{c} \mid X_{i}^{c} ; \beta\right)^{d_{k l}^{c_{k}}}\right)\left(\prod_{c=1}^{c_{i}} \prod_{l} \bar{F}_{k}\left(t_{c} \mid X_{i} ; \beta\right)^{s_{k}^{c}}\right)\right\} h\left(v_{i}\right) d v_{i} \tag{3.6}
\end{align*}
$$

where $h\left(v_{i}\right)$ is the unknown distribution function of the individual effect. The loglikelihood function for all individuals would then be,

$$
\begin{equation*}
\log L=\sum_{i=1}^{N} L_{i}\left(\beta \mid t_{i 1}, \ldots, t_{i C_{i}}, X_{i}\right) \tag{3.7}
\end{equation*}
$$

The distribution of the unobserved heterogeneity could be fully specified and the previous equation estimated by maximum likelihood. However, Heckman and Singer (1984) pointed out that misleading results can be obtain by using these procedures when the chosen distribution for unobservables is not the right one. Therefore we alternatively use the Non-Parametric Maximum Likelihood Estimator (NPMLE) proposed by both authors which does not require any distributional assumption. This procedure approximates the distribution function of unobservables, $h(v)$, with a finite mixture distribution. The points of support of this finite distribution are the unknown values
$v_{l}, \ldots, v_{M}$ to which the $M$ unknown probabilities are attached. Then, the contribution to the likelihood of an individual becomes:

$$
\begin{align*}
& L_{i}\left(\beta, v, \pi \mid t_{i 1}, \ldots, t_{i c_{i}}, X_{i}\right)= \\
& \quad \sum_{\mathrm{m}=1}^{\mathrm{M}}\left\{\left(\prod_{c=1}^{c_{i}} \prod_{k} \prod_{l \neq k} P_{k l}\left(t_{c} \mid X_{i}^{c}, v_{m} ; \beta\right)^{d_{k l}^{c}}\right)\left(\prod_{c=1}^{c_{i}} \prod_{l} \bar{F}_{k}\left(t_{c} \mid X_{i}, v_{m} ; \beta\right)^{s_{k}}\right)\right\} \pi_{m} \tag{3.8}
\end{align*}
$$

being the log-likelihood function its summation over all individuals. The points of support as well as the probabilities assigned to each of them are now parameters of interest to be estimated by the EM-algorithm (see Appendix B for description of implementation). The function is maximised at different number of support points until the parameters of the criterion function relatively stable ${ }^{6}$.

### 3.3. Data Description

The data used in this analysis is obtained from the British Household Panel Survey (BHPS). This is an annual survey carried out by the ESRC Research Centre on Micro-social Change since 1991. At the moment of starting the research, three data waves are available. The survey is conducted over a nationally representative sample of at least 5000 households, making a total of approximately 10000 individual interviews. Data is collected at an individual and household level including information about household organisation, labour market, income and wealth, housing, health and socioeconomic values.

The Second Wave (1992) contains some additional records that do not appear in the First Wave relating individual's past history: marriage, cohabitation, children and employment status. In particular, it collects information about employment status spells

[^21]since the respondent first left full time education. The dates at which each spell began and ended as well as its length are recorded. This information enables us to estimate the model proposed in Section 3.2. Demographic information can be obtained from the main record.

We select a subsample of working age males at the interview date, that is aged between 16 and 65 years old by the first of December of 1992. Males who were not directly interviewed (somebody else in the household answered the questionnaire on their behalf) are not considered here: no answers for the additional questionnaires are provided for these individuals. We also dropped men who were out of the labour market (full time students, retired or out of the labour market for other reasons) at some point in their work histories. That avoids initial condition problems and also mixing decisions of early retirement. No differences are made between full time and part time work: both are considered employment. Within paid employment, no job-to-job transitions are considered.

All the previous conditions are fulfilled by 1978 individuals providing 4227 complete or incomplete employment status spells. Table 3.2 reports the number of observations for each possible transition, being the last spell for each individual incomplete.

The variables used in the estimation can be classified in two groups: demographic variables relating the individual and demand side variables referring to general economic conditions. In the first group, we include age at the beginning of the spell, four educational dummies and two dummy variables reflecting the family background of the individual: whether his mother and his father were self-employed when the individual was fourteen years old. In the second group, the final specification includes the National Unemployment Rate at the beginning of the spell that accounts for business cycle changes ${ }^{7}$. Variables as vacancies or GDP were also tried but were not found significant so that they are not included in the final specification. Those figures have been taken

[^22]from the Department of Employment. Table 3.A. 1 in Appendix A reports the mean and standard deviation for the relevant variables.

Table 3.2: Number of observations per possible transition.

|  | Destination State |  |  |  |
| :--- | :---: | :---: | :---: | :---: |
| Source State | Self-Employment | Employment | Unemployment | Censored |
| Self-Employment | ----- | 138 | 75 | 335 |
| Employment | 408 | ----- | 791 | 1467 |
| Unemployment | 91 | 746 | ----- | 176 |

### 3.4. Empirical Results

### 3.4.1. Non-Parametric Analysis

Before presenting the model estimates we describe survival probabilities in the labour market using non-parametric techniques. Figures 3.1 to 3.3 show Kaplan-Meier estimates of the survival probabilities for each possible source state conditioned on destination state.

Figure 3.1 shows survival probabilities in employment and unemployment for individuals who move to self-employment. Figure 3.2 presents the survival probabilities in self-employment and unemployment for individuals who move to employment. The pattern in both figures is similar: the probability of survival is lower if the origin state is unemployment, as expected. This just shows that unemployment is not individually considered as a definitive state. Nevertheless, it is worth to note that the survival probability decreases faster for self-employed individuals than for employees. There are different explanations for this finding.

Figure 3.1. Kaplan-Meier Survival curves: transition to self-employment from unemployment and paid employment


Figure 3.2. Kaplan-Meier Survival curves: transition to paid employment from unemployment and self-employment


Note: the survival function is computed as $\bar{F}(t)=1-\frac{\text { number of individuals leaving before } t}{N}$.

Figure 3.3. Kaplan-Meier Survival curves: transition to unemployment from selfemployment and paid employment


First, it can reflect the higher risk of self-employment, being more difficult to survive. Second, survival in employment would be higher in the presence of liquidity constraints to allow the individual to earn the capital necessary to start a business. Finally, the idea of a deterioration of the labour market could be supported by this data, in the sense that self-employment is used as a temporary state better than being unemployed, before jumping again into paid employment.

Figure 3.3 shows the survival probabilities for unemployed people and displays a steeper curve for those who came from self-employment, suggesting again that selfemployment is used to avoid unemployment when finding a job becomes difficult.

This analysis does not take into account either personal or demand side characteristics. Determining whether the stated differences can be explained by differences in characteristics is the next point to discuss.

### 3.4.2. Parametric estimation.

The previous analysis clearly shows that duration and state dependence are two important factors to explain mobility between different states. The longer an enterprise has been running the higher its probability of survival, through a reputation effect or because it has access to more resources than when it first started. The duration dependence comes through a tenure or experience effect for employess and through a loss in human capital for those unemployed. This is why in Section 3.2 our model includes a flexible function of elapsed duration, $h_{k l}(t)$, to control for duration dependence. We include the $\log$ and the $\log$ of tenure square ${ }^{8}$ as regressors:

$$
h_{k l}(t)=\alpha_{1 k l} \ln (t)+\alpha_{2 k l}(\ln (t))^{2}
$$

This specification generalises the traditional Weibull proportional hazard allowing non monotonic variation with respect to duration. So if $\alpha_{2 k l}<0$, the transition intensity has a maximum level when $\ln (t)=-\alpha_{1 k l} / \alpha_{2 l k}$. If $\alpha_{2 k l}>0$, this level corresponds to a minimum and if $\alpha_{2 k l}=0$ for all $k$ and $l$, the transition intensities are a monotonically increasing or decreasing function in $t$ (Weibull specification).

The specification also includes three types of explanatory variables: demographic (four educational variables, age and age square), family background (two dummy variables taking value one if each of the individual parents were self-employed when he was 14) and demand side conditions (National Unemployment Rate, NUR). Education in this context can act jointly with duration as a proxy for the individual wage. The unemployment rate tries to pick up changes in the general economic conditions altering the probabilities of layoff and job arrival rates and therefore the individuals' possibility of choice.

[^23]Unobserved heterogeneity is explicitly modelled accounting for the differences in ability among individuals and it is uncorrelated with the rest of explanatory variables. Two types of individuals are considered and therefore two support points are used in the estimation of the model proposed in Section 3.2.

Tables 3.3 and 3.4 show the results of this basic specification without and with corrections for unobserved heterogeneity, respectively. Estimates of the parameters of interest are similar in both cases, with the biggest differences lying in the duration parameters. In general, they are overestimated when ignoring unobservable heterogeneity. In what follows we would refer to Table 3.4, although the same conclusions can be drawn from Table $3.3^{9}$.

Education seems to play an important role in determining transitions between states. As it should be expected, the more educated an individual is the lower his probability of becoming unemployed. It also is interesting to point out that people with a medium level of education (A-levels and O-levels) are more likely to become selfemployed, whether they come from unemployment or paid employment. Moreover they are the less likely to become unemployed once in self-employment. This contradicts to some extend previous findings that suggest that self-employed people are poor wage earners and misfit for paid work ${ }^{10}$.

It is interesting to point out that the higher educated individuals are reluctant to become self-employed if they are actually employed. They are more willing to do so once they are unemployed (High Degree has a positive and significant effect on the transition probability from unemployment to self-employment). This can reflect the higher opportunity cost (in terms of wages) that this group of individuals face.

[^24]Table 3.3. Maximum Likelihood estimates for the transition equations; without controls for unobserved heterogeneity.

|  | E to U | E to SE | U to E | U to SE | SE to E | SE to U |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| High Degree | -0.686 | -0.117 | 0.779 | 0.648 | 0.501 | -0.424 |
|  | $(0.157)$ | $(0.208)$ | $(0.172)$ | $(0.529)$ | $(0.378)$ | $(0.456)$ |
| A-Levels | -0.384 | 0.367 | 0.769 | 0.977 | 0.422 | -1.038 |
|  | $(0.195)$ | $(0.228)$ | $(0.218)$ | $(0.631)$ | $(0.414)$ | $(0.640)$ |
| O-Levels | -0.154 | 0.211 | 0.602 | 0.872 | 0.118 | -0.420 |
|  | $(0.156)$ | $(0.207)$ | $(0.193)$ | $(0.561)$ | $(0.386)$ | $(0.453)$ |
| Other qualific. | -0.289 | 0.125 | -0.122 | -0.165 | 0.511 | -0.851 |
|  | $(0.306)$ | $(0.328)$ | $(0.404)$ | $(1.392)$ | $(0.643)$ | $(3.293)$ |
| Mother SE | 0.057 | 0.333 | -0.157 | 0.503 | 0.549 | -0.067 |
|  | $(0.265)$ | $(0.274)$ | $(0.378)$ | $(0.583)$ | $(0.387)$ | $(1.226)$ |
| Father SE | 0.071 | 0.583 | -0.126 | 0.549 | -0.356 | 0.193 |
|  | $(0.159)$ | $(0.168)$ | $(0.177)$ | $(0.360)$ | $(0.316)$ | $(0.383)$ |
| Age | 0.341 | 1.729 | -0.241 | 1.969 | -0.839 | -0.404 |
|  | $(0.382)$ | $(0.771)$ | $(0.395)$ | $(1.329)$ | $(0.988)$ | $(1.437)$ |
| Age Squared | -0.050 | -0.281 | 0.010 | -0.242 | 0.080 | 0.018 |
|  | $(0.058)$ | $(0.144)$ | $(0.055)$ | $(0.178)$ | $(0.156)$ | $(0.230)$ |
| NUR | 0.165 | 0.039 | -0.028 | 0.159 | 0.025 | 0.177 |
|  | $(0.020)$ | $(0.028)$ | $(0.026)$ | $(0.074)$ | $(0.038)$ | $(0.064)$ |
| ln(duration/l2) | -0.143 | 0.328 | -0.617 | -0.401 | 0.134 | -0.364 |
|  | $(0.084)$ | $(0.127)$ | $(0.114)$ | $(0.252)$ | $(0.201)$ | $(0.159)$ |
| (ln(duration/12)) | 0.050 | -0.044 | -0.246 | -0.188 | -0.262 | -0.077 |
| Intercept | $(0.028)$ | $(0.040)$ | $(0.051)$ | $(0.130)$ | $(0.079)$ | $(0.100)$ |
|  | -4.604 | -7.415 | 0.186 | -7.729 | -1.565 | -3.311 |
| Log-likelihood | $(0.552)$ | $(0.941)$ | $(0.680)$ | $(2.379)$ | $(1.496)$ | $(2.052)$ |
| Observations |  |  | -7777 |  |  |  |

Note: Standard errors (computed from the inverse of the information matrix) in brackets. SE denotes self-employment, E employment and U unemployment. Age is measured at the beginning of the spell. NUR is National Unemployment Rate.

The effect of age differs depending on the transition considered. In general, it is not significant but it positively affects (a decreasing rate) the probability of becoming self-employed. This effect is higher for those individuals that come from unemployment. This result is again coherent with the theory of liquidity constraints. An individual needs to have some wealth before starting up a business. If he is unemployed he would need a longer period of time to achieve this goal.

Table 3.4. Maximum Likelihood estimates for the transition equations; controlling for unobserved heterogeneity (NPMLE)

|  | E to U | E to SE | U to E | U to SE | SE to E | SE to U |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| High Degree | -0.620 | -0.144 | 0.773 | 0.648 | 0.494 | -0.318 |
|  | $(0.114)$ | $(0.156)$ | $(0.108)$ | $(0.312)$ | $(0.264)$ | $(0.374)$ |
| A-Levels | -0.340 | 0.340 | 0.775 | 0.982 | 0.411 | -0.975 |
|  | $(0.146)$ | $(0.142)$ | $(0.133)$ | $(0.435)$ | $(0.278)$ | $(0.534)$ |
| O-Levels | -0.085 | 0.152 | 0.606 | 0.860 | 0.079 | -0.148 |
|  | $(0.109)$ | $(0.155)$ | $(0.109)$ | $(0.291)$ | $(0.271)$ | $(0.418)$ |
| Other qualific. | -0.226 | 0.088 | -0.115 | -0.169 | 0.498 | -0.835 |
|  | $(0.218)$ | $(0.288)$ | $(0.215)$ | $(0.818)$ | $(0.414)$ | $(1.539)$ |
| Mother SE | 0.071 | 0.340 | -0.187 | 0.501 | 0.563 | -0.067 |
|  | $(0.210)$ | $(0.249)$ | $(0.263)$ | $(0.433)$ | $(0.319)$ | $(0.663)$ |
| Father SE | 0.073 | 0.592 | -0.116 | 0.522 | -0.366 | 0.312 |
|  | $(0.120)$ | $(0.139)$ | $(0.127)$ | $(0.297)$ | $(0.236)$ | $(0.346)$ |
| Age | 0.325 | 1.476 | -0.214 | 1.982 | -0.982 | 0.049 |
|  | $(0.277)$ | $(0.644)$ | $(0.235)$ | $(0.829)$ | $(0.829)$ | $(1.379)$ |
| Age Squared | -0.055 | -0.224 | 0.007 | -0.245 | 0.099 | -0.047 |
|  | $(0.043)$ | $(0.117)$ | $(0.034)$ | $(0.116)$ | $(0.132)$ | $(0.222)$ |
| NUR | 0.163 | 0.043 | -0.029 | 0.164 | 0.030 | 0.143 |
|  | $(0.014)$ | $(0.021)$ | $(0.015)$ | $(0.061)$ | $(0.30)$ | $(0.059)$ |
| ln(duration/12) | -0.124 | 0.293 | -0.662 | -0.413 | 0.123 | -0.325 |
|  | $(0.040)$ | $(0.120)$ | $(0.062)$ | $(0.154)$ | $(0.169)$ | $(0.151)$ |
| ln(duration/12)) | 0.048 | -0.036 | -0.246 | -0.188 | -0.262 | -0.077 |
|  | $(0.016)$ | $(0.037)$ | $(0.028)$ | $(0.087)$ | $(0.072)$ | $(0.082)$ |
| Unobs.heter. | 1.000 | -0.715 | -0.221 | 0.696 | -0.290 | 2.176 |
|  | --- | $(0.268)$ | $(0.153)$ | $(1.279)$ | $(0.249)$ | $(1.427)$ |
| Intercept | -4.198 | -7.791 | 0.093 | -7.705 | -1.656 | -3.041 |
|  | $(0.394)$ | $(0.842)$ | $(0.382)$ | $(1.418)$ | $(1.210)$ | $(2.034)$ |
| Log-likelihood |  |  | -7470 |  |  |  |
| Observations |  |  | 4227 |  |  |  |

Notes: Standard errors (computed from the inverse of the information matrix) in brackets. SE denotes self-employment, E employment and U unemployment. Age is measured at the beginning of the spell. NUR is National Unemployment Rate.
Two support Points: $\mathrm{v}_{1}=0$ with probability $\mathrm{p}_{1}=0.57$ and $\mathrm{v}_{2}=-1.691(0.363)$ with probability $\mathrm{p}_{2}=0.43$. The heterogeneity coefficient for the transition from E to U is normalise to one for identification.

Family background variables also have the expected sign. The probability of becoming self-employed is higher if one of the parents was self-employed (especially the father). Whether this happens because the individual keeps on running a family business or due to the effect of the environment in which he grew up, can not be separated given the characteristics of the data.

The effect of the national unemployment rate suggests that individuals are more likely to move towards self-employment when the economic situation worsens. This effect is much bigger if the individual is unemployed. The chances of getting a job decrease and the individual chooses to avoid unemployment by becoming self-employed. Therefore, the data seems to support to some extend the deterioration of the labour market theory as an explanation of the increase in self-employment rates.

Regarding elapsed duration variables, the null hypothesis of a monotone specification for the hazard rate is rejected (the Wald test statistic is 606.59 and distributed as a $\left.\chi^{2}(6)\right)$. The variables have also the expected sign. The longer an individual stays unemployed the lower the probabilities he has of moving towards employment or self-employment due to the loss of human capital. Employment duration has a positive effect on the probability of becoming self-employed at a decreasing rate although not significant. This result it is in line with the age effect (pointing to liquidity constraints). It could also show that people who have been longer in the labour market have more chances of picking up possibilities of starting a business. Tenure in selfemployment increases the probability of moving towards employment though the effect is smaller and less precise than the previous one. On the other hand, it reduces the probability of unemployment. We would expect that the longer an enterprise has been settled the higher its chances of survival and therefore the lower the probability that the individual ends up being unemployed.

Referring to the unobservable heterogeneity, one possible interpretation of the results (given the restrictions on the estimation procedure and the sign of the estimates) would be that if the individual effect is zero, the individual would have low ability, and if it is negative the individual would have high ability. Then, able individuals are more likely to become employed or self-employed and less likely to become unemployed.

An alternative specification is presented in Tables 3.B.1 and 3.B. 2 allowing for lagged duration dependence ${ }^{11}$. The basic results hold though the precision of some of the

[^25]estimates worsens a little. The most interesting result (with and without controls for heterogeneity) is that the previous self-employment experience pays, in the sense of increasing the probability of becoming self-employed, only if the individual is employed. If the individual is unemployed there is no effect, which again support the idea that individuals enter self-employment to avoid unemployment.

It is also important the fact that previous unemployment experience has a positive effect in the entry to self-employment if the individual is employed not if he is unemployed. This is exactly what Evans and Leighton (1989) found with a sample of workers from USA. Previous unemployment experience has in addition a positive effect on the transition from self-employment to employment. That suggests again that individuals coming from unemployment use self-employment as a temporary situation or they are less successful than the rest of self-employed workers.

Results from Tables 3.3 and 3.4 can be quite difficult to interpret in terms of transition probabilities from one state to other. Therefore Figures 3.4 to 3.8 highlight to what extent the transition intensities differ between individuals with different characteristics. Figure 3.4 shows the transitions into self-employment by source state and individual type. Employed are more likely to become self-employed than unemployed individuals with the same characteristics and in both cases this probability decreases with duration. This could be originated either by the presence of liquidity constraints (some capital is necessary to start a business and it is more difficult to earn the money if unemployed) or by the fact that employed people have more information about business opportunities. An interesting effect is that the more able individuals are more likely to enter self-employment but only if the source state is employment. If they are unemployed less able individuals are the ones with more chances to enter self-employment. Deterioration of labour market conditions could originate such an effect. Among the unemployed, the more able ones would find a job in paid employment, whereas the less able would not find any and therefore choose to be self-employed to avoid unemployment.

Figures 3.5 and 3.6 show transitions into self-employment for employed and unemployed people by education. Behaviour patterns are very different. Employed individuals have the lower probability of becoming self-employed during the first three years on their job. Afterwards their probability is the highest compared to the rest of the groups. For unemployed people, the transition probability curves are inversely related to the level of education. If the source state is unemployment, it is true that the less qualified individuals and therefore the ones who were probably receiving low wages before, are the ones switching to self-employment ${ }^{12}$. This finding does not hold for individuals whose source state is employment.

To conclude, Figures 3.7 and 3.8 show transition probabilities into selfemployment by source state, ability of the individual and National Unemployment Rate (NUR). The purpose of these figures is to clarify the effect of general economic conditions on the probability of becoming self-employed. We take the NUR of late seventies (around 3\%) and the corresponding to late eighties (around 10\%) to see if that change can explain to some extent the high increase in self-employed population during the last twenty years. Figure 3.7 shows the transition probabilities for employed people. It is important to note that the probability of becoming self-employed increases in a higher proportion for the more able individuals, given an increase in the unemployment rate. On the contrary, for unemployed individuals (Figure 3.8) the increase in the probability of self-employment is much higher for those less able. For both groups the increment in the probability is quite high if compare for example with the effect of education.

### 3.5. Conclusions

This Chapter describes in some detail transitions from and to paid work, selfemployment and unemployment. We use a multiple state transition model with

[^26]unobservable heterogeneity to asses the importance of some demographic variables along with time varying economic conditions. Distribution of unobservables is approximated with a discrete function, whose support points and probabilities are computed using the Heckman and Singer approach through an EM algorithm.

The main purpose of the Chapter is to determine the effect of unemployment on the probability of becoming self-employed. The results from previous section show that worse economic conditions, that is, higher unemployment rates, push individuals towards self-employment. The mechanism driving unemployed and employed individuals to selfemployment is anyhow different. Less able unemployed with lower chances to find a job choose self-employment to escape from unemployment. For employed people the pattern reverses: adverse economic conditions, as precariousness of their jobs or poor career perspectives, incentive more able individuals to start up a business.

However the longer an individual has been unemployed, the lower are his chances of switching to self-employment due to loss of human capital or lack of information about opportunities of starting an enterprise.

The model compounds the analysis of the effect of general economic conditions and individual unemployment experience. The results encompass previous findings. Evans and Leighton (1989) or Alba-Ramirez and Freeman (1994) find that previous experience of unemployment increases the probability of workers entering selfemployment. Acs et al. (1994) find that unemployment rates increase the probability of becoming self-employed. Our model confirms these results and extends them in a natural way to unemployed individuals, considering also exit rates from self-employment for both groups.

Therefore, data in this analysis supports the theory of a deterioration of labour market conditions as fundamental to explain the growth in self-employment rates in the last two decades. Bad economic conditions have a positive effect on self-employment rates (through reduction of its opportunity cost). This encouraging effect dominates the negative effect implied by the reduction of the expected returns from self-employment.

Some other interesting results refer to family background variables effect in selfemployment transitions. Although having a self-employed mother increases the probability of becoming self-employed, the effect of the father status is stronger and better defined; both prevent from becoming unemployed.

Data would also be consistent with the presence of liquidity constraints (through age and duration effects) although the simplicity of the model makes impossible to test this hypothesis. An interesting extension would be to allow for an explicit test of this hypothesis, besides some wage/earnings' effect, using a more structural model. This is far beyond the scope of the present Chapter and therefore left for future research.

Figure 3.4: Transition from Employment and Unemployment to Self-Employment (by individual type)


Note: estimates used to compute transition probabilities from Table 3.4.

Figure 3.5: Transition from Employment to Self-Employment (by education).


Figure 3.6: Transition from Unemployment to Self-Employment (by education).


Note: estimates used to compute transition probabilities from Table 3.4.

Figure 3.7: Transition from Employment to Self-Employment (increase in the National Unemployment Rate).


Figure 3.8: Transition from Unemployment to Self-Employment (increase in the National Unemployment Rate)


Note: estimates used to compute transition probabilities from Table 3.4.

### 3.6. Appendix A: Variable description

Table 3.A.1: Sample statistics for the relevant variables (1978 individuals, 4227 spells).

|  | Observations | $\begin{gathered} \text { Mean } \\ \text { (Std.dev.) } \end{gathered}$ |
| :---: | :---: | :---: |
| DURATION |  |  |
| Self-Employment (SE) | 213 | $\begin{gathered} 55.038 \\ (61.866) \end{gathered}$ |
| Employment (E) | 1199 | $\begin{gathered} 125.818 \\ (120.902) \end{gathered}$ |
| Unemployment (U) | 837 | $\begin{gathered} 9.931 \\ (17.136) \\ \hline \end{gathered}$ |
| AGE | 1978 | $\begin{gathered} \hline 37.951 \\ (10.932) \\ \hline \end{gathered}$ |
| AGE beginning spell Self-Employment | 4227 | $\begin{aligned} & 24.668 \\ & (9.807) \end{aligned}$ |
| Employment | 548 | $\begin{aligned} & 30.757 \\ & (9.095) \end{aligned}$ |
| Unemployment | 2666 | $\begin{aligned} & 21.590 \\ & (8.095) \end{aligned}$ |
|  | 1013 | $\begin{gathered} 29.473 \\ (10.780) \\ \hline \end{gathered}$ |
| High Degree |  | $\begin{gathered} 0.341 \\ (0.474) \end{gathered}$ |
| A levels |  | $\begin{gathered} 0.147 \\ (0.354) \end{gathered}$ |
| O levels | 1978 | $\begin{gathered} 0.261 \\ (0.439) \end{gathered}$ |
| Other qualif. |  | $\begin{gathered} 0.042 \\ (0.201) \end{gathered}$ |
| No qualif. |  | $\begin{gathered} 0.209 \\ (0.407) \\ \hline \end{gathered}$ |
| Mother SE | 1978 | $\begin{gathered} 0.034 \\ (0.182) \end{gathered}$ |
| Father SE |  | $\begin{gathered} 0.131 \\ (0.337) \\ \hline \end{gathered}$ |
| NUR | 4227 | $\begin{array}{r} 6.113 \\ (3.509) \\ \hline \end{array}$ |

Notes: duration is measured in months. Right censored observations are not considered in computing its mean and standard deviation. Age is age at the interview date (around 12/92). NUR is National Unemployment Rate at the beginning of the spell.

### 3.7. Appendix B: EM algorithm

Section 3.2 introduces the likelihood function to estimate. Simplifying notation in equation (3.8), the final likelihood function for the whole sample is

$$
\begin{equation*}
L\left(\beta, \nu, \pi \mid \mathbf{t}, X_{i}\right)=\sum_{i}\left[\ln \sum_{m=1}^{M} f_{i}\left(\mathbf{t} \mid X_{i}, \nu_{m}, \beta\right) \pi_{m}\right] \tag{3.9}
\end{equation*}
$$

where $f($.$) , is the contribution to the likelihood for each individual, conditional on v_{m} ; \mathbf{t}$ is a vector of duration in every spell, for each individual; $\beta$ is the vector of all parameters of interest; $X_{i}$ is a vector of individual characteristics and $\pi_{m}$ is the probability attached to every mass point $v_{m}$.

Taking derivatives in (3.9) with respect to $\beta$ and rearranging terms we obtain,

$$
\begin{equation*}
\frac{\partial L(.)}{\partial \beta}=\sum_{i} \frac{\partial \ln \left(f_{i}\left(. \mid v_{m}\right)\right.}{\partial \beta} \hat{\pi}_{m} \tag{3.10}
\end{equation*}
$$

where

$$
\begin{equation*}
\hat{\pi}_{m}=\frac{f_{i}\left(. \mid v_{m}\right) \pi_{m}}{\sum_{m} f_{i}\left(. \mid v_{m}\right) \pi_{m}} \tag{3.11}
\end{equation*}
$$

The EM algorithm has two stages: expectation and maximisation. Giving initial values for all parameters of interest, including $v_{m}$ and $\pi_{m}$, in the first stage we compute the probabilities $\hat{\pi}_{m}$ according to (3.11) and in the second stage we maximise the log likelihood function $L($.$) with respect to \beta$ and $v_{m}$, obtaining $L_{l}($.$) ; we will then update$ $\hat{\pi}_{m}$ recomputing (3.11) and so forth. This procedure produces a local optimum for $L$ (.) and the estimated values for the mass point probabilities are constrained to be in the unit interval (Heckman and Singer $(1982,1984)$ ).

To guard against failure to locate a global optimum a variety of starting values is used in the implementation of the EM algorithm.

### 3.8. Appendix $C$ : Results using experience

Table 3.C.1: Maximum Likelihood estimates for the transition equations; without controls for unobserved heterogeneity.

|  | $\begin{gathered} \hline \text { E to } \\ \mathrm{U} \end{gathered}$ | E to SE | $\begin{gathered} \hline \mathrm{U} \text { to } \\ \mathrm{E} \end{gathered}$ | U to SE | SE to E | SE to U |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| High Degree | $\begin{aligned} & -0.390 \\ & (0.172) \end{aligned}$ | $\begin{aligned} & -0.025 \\ & (0.205) \end{aligned}$ | $\begin{gathered} 0.761 \\ (0.172) \end{gathered}$ | $\begin{gathered} \hline 0.659 \\ (0.540) \end{gathered}$ | $\begin{gathered} 0.617 \\ (0.386) \end{gathered}$ | $\begin{gathered} -0.144 \\ (0.469) \end{gathered}$ |
| A-Levels | $\begin{gathered} -0.126 \\ (0.211) \end{gathered}$ | $\begin{gathered} 0.384 \\ (0.229) \end{gathered}$ | $\begin{gathered} 0.750 \\ (0.216) \end{gathered}$ | $\begin{gathered} 0.982 \\ (0.645) \end{gathered}$ | $\begin{gathered} 0.445 \\ (0.427) \end{gathered}$ | $\begin{aligned} & -0.799 \\ & (0.656) \end{aligned}$ |
| O-Levels | $\begin{gathered} 0.018 \\ (0.170) \end{gathered}$ | $\begin{gathered} 0.275 \\ (0.210) \end{gathered}$ | $\begin{gathered} 0.612 \\ (0.201) \end{gathered}$ | $\begin{gathered} 0.977 \\ (0.583) \end{gathered}$ | $\begin{gathered} 0.167 \\ (0.404) \end{gathered}$ | $\begin{aligned} & -0.136 \\ & (0.492) \end{aligned}$ |
| Other Qualification | $\begin{aligned} & -0.024 \\ & (0.332) \end{aligned}$ | $\begin{gathered} 0.349 \\ (0.342) \end{gathered}$ | $\begin{aligned} & -0.184 \\ & (0.391) \end{aligned}$ | $\begin{gathered} -0.169 \\ (1.447) \end{gathered}$ | $\begin{gathered} 0.393 \\ (0.636) \end{gathered}$ | $\begin{aligned} & -1.208 \\ & (5.719) \end{aligned}$ |
| Mother SE | $\begin{aligned} & -0.380 \\ & (0.294) \end{aligned}$ | $\begin{gathered} 0.406 \\ (0.293) \end{gathered}$ | $\begin{gathered} -0.140 \\ (0.338) \end{gathered}$ | $\begin{gathered} 0.661 \\ (0.715) \end{gathered}$ | $\begin{gathered} 0.549 \\ (0.402) \end{gathered}$ | $\begin{gathered} -0.034 \\ (1.702) \end{gathered}$ |
| Father SE | $\begin{gathered} 0.043 \\ (0.171) \end{gathered}$ | $\begin{gathered} 0.529 \\ (0.171) \end{gathered}$ | $\begin{aligned} & -0.086 \\ & (0.184) \end{aligned}$ | $\begin{gathered} 0.480 \\ (0.365) \end{gathered}$ | $\begin{aligned} & -0.482 \\ & (0.331) \end{aligned}$ | $\begin{gathered} 0.228 \\ (0.414) \end{gathered}$ |
| Age | $\begin{gathered} 0.278 \\ (0.390) \end{gathered}$ | $\begin{gathered} 2.939 \\ (0.723) \end{gathered}$ | $\begin{aligned} & -0.266 \\ & (0.385) \end{aligned}$ | $\begin{gathered} 1.926 \\ (1.411) \end{gathered}$ | $\begin{aligned} & -0.728 \\ & (1.037) \end{aligned}$ | $\begin{aligned} & -0.226 \\ & (1.589) \end{aligned}$ |
| Age Squared | $\begin{aligned} & -0.090 \\ & (0.060) \end{aligned}$ | $\begin{aligned} & -0.569 \\ & (0.135) \end{aligned}$ | $\begin{gathered} -0.010 \\ (0.053) \end{gathered}$ | $\begin{gathered} -0.241 \\ (0.185) \end{gathered}$ | $\begin{gathered} 0.003 \\ (0.162) \end{gathered}$ | $\begin{gathered} -0.012 \\ (0.260) \end{gathered}$ |
| NUR | $\begin{gathered} 0.202 \\ (0.021) \end{gathered}$ | $\begin{gathered} 0.073 \\ (0.027) \end{gathered}$ | $\begin{aligned} & -0.020 \\ & (0.025) \end{aligned}$ | $\begin{gathered} 0.165 \\ (0.077) \end{gathered}$ | $\begin{gathered} 0.051 \\ (0.040) \end{gathered}$ | $\begin{gathered} 0.173 \\ (0.070) \end{gathered}$ |
| $\ln ($ duration $/ 12)$ | $\begin{gathered} -0.133 \\ (0.085) \end{gathered}$ | $\begin{gathered} 0.343 \\ (0.124) \end{gathered}$ | $\begin{aligned} & -0.639 \\ & (0.116) \end{aligned}$ | $\begin{aligned} & -0.370 \\ & (0.268) \end{aligned}$ | $\begin{gathered} 0.140 \\ (0.206) \end{gathered}$ | $\begin{aligned} & -0.350 \\ & (0.163) \end{aligned}$ |
| $(\ln (\text { duration } / 12))^{2}$ | $\begin{gathered} 0.052 \\ (0.029) \end{gathered}$ | $\begin{gathered} -0.032 \\ (0.041) \end{gathered}$ | $\begin{gathered} -0.244 \\ (0.053) \end{gathered}$ | $\begin{aligned} & -0.184 \\ & (0.139) \end{aligned}$ | $\begin{gathered} -0.249 \\ (0.082) \end{gathered}$ | $\begin{gathered} -0.073 \\ (0.117) \end{gathered}$ |
| Prev.SE.Exp. | $\begin{gathered} 0.153 \\ (0.345) \end{gathered}$ | $\begin{gathered} 2.409 \\ (0.270) \end{gathered}$ | $\begin{aligned} & -0.458 \\ & (0.521) \end{aligned}$ | $\begin{gathered} 0.568 \\ (0.911) \end{gathered}$ | $\begin{gathered} 0.504 \\ (0.494) \end{gathered}$ | $\begin{gathered} 0.727 \\ (0.577) \end{gathered}$ |
| Prev.Empl.Exp. | $\begin{gathered} 0.168 \\ (0.018) \end{gathered}$ | $\begin{gathered} -0.149 \\ (0.177) \end{gathered}$ | $\begin{aligned} & -0.135 \\ & (0.069) \end{aligned}$ | $\begin{aligned} & -0.106 \\ & (0.140) \end{aligned}$ | $\begin{gathered} -0.094 \\ (0.455) \end{gathered}$ | $\begin{gathered} 0.285 \\ (0.183) \end{gathered}$ |
| Prev.Unemp.Exp. | $\begin{gathered} 0.042 \\ (0.006) \end{gathered}$ | $\begin{gathered} 0.031 \\ (0.008) \end{gathered}$ | $\begin{gathered} 0.023 \\ (0.009) \end{gathered}$ | $\begin{aligned} & 0.0004 \\ & (0.020) \end{aligned}$ | $\begin{gathered} 0.060 \\ (0.021) \end{gathered}$ | $\begin{gathered} 0.008 \\ (0.027) \end{gathered}$ |
| Intercept | $\begin{gathered} -4.963 \\ (0.570) \\ \hline \end{gathered}$ | $\begin{gathered} -9.084 \\ (0.917) \\ \hline \end{gathered}$ | $\begin{gathered} 0.344 \\ (0.667) \\ \hline \end{gathered}$ | $\begin{gathered} -7.609 \\ (2.517) \\ \hline \end{gathered}$ | $\begin{gathered} -1.908 \\ (1.593) \\ \hline \end{gathered}$ | $\begin{gathered} -3.975 \\ (2.267) \\ \hline \end{gathered}$ |
| Log-likelihood Observations | -7577 |  |  |  |  | 4227 |

Note: Standard errors (computed from the inverse of the information matrix) in brackets. SE denotes self-employment, E employment and $U$ unemployment. Age is measured at the beginning of the spell. NUR is National Unemployment Rate.

Table 3.C.2: Maximum Likelihood estimates for the transition equations controlling for unobserved heterogeneity (NPMLE).

|  | E to U | E to SE | U to E | U to SE | SE to E | SE to U |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| High Degree | -0.356 | -0.042 | 0.762 | 0.655 | 0.620 | -0.079 |
|  | $(0.121)$ | $(0.179)$ | $(0.111)$ | $(0.336)$ | $(0.282)$ | $(0.411)$ |
| A-Levels | -0.099 | 0.371 | 0.754 | 0.988 | 0.461 | -0.750 |
|  | $(0.151)$ | $(0.198)$ | $(0.135)$ | $(0.476)$ | $(0.299)$ | $(0.572)$ |
| O-Levels | 0.039 | 0.211 | 0.615 | 0.970 | 0.140 | 0.079 |
|  | $(0.116)$ | $(0.175)$ | $(0.113)$ | $(0.319)$ | $(0.291)$ | $(0.437)$ |
| Other qualific. | -0.001 | 0.327 | -0.180 | -0.189 | 0.360 | -1.040 |
|  | $(0.226)$ | $(0.326)$ | $(0.208)$ | $(0.853)$ | $(0.438)$ | $(1.631)$ |
| Mother SE | -0.307 | 0.388 | -0.142 | 0.685 | 0.596 | -0.057 |
|  | $(0.207)$ | $(0.304)$ | $(0.257)$ | $(0.486)$ | $(0.347)$ | $(0.760)$ |
| Father SE | 0.042 | 0.550 | -0.086 | 0.438 | -0.478 | 0.303 |
|  | $(0.123)$ | $(0.163)$ | $(0.132)$ | $(0.328)$ | $(0.283)$ | $(0.378)$ |
| Age | 0.071 | 2.798 | -0.236 | 1.953 | -0.949 | 0.260 |
|  | $(0.272)$ | $(0.607)$ | $(0.227)$ | $(0.892)$ | $(0.856)$ | $(1.544)$ |
| Age Squared | -0.056 | -0.551 | -0.014 | -0.245 | 0.036 | -0.078 |
|  | $(0.043)$ | $(0.108)$ | $(0.033)$ | $(0.122)$ | $(0.132)$ | $(0.256)$ |
| NUR | 0.199 | 0.083 | -0.020 | 0.163 | 0.055 | 0.151 |
|  | $(0.014)$ | $(0.023)$ | $(0.015)$ | $(0.063)$ | $(0.032)$ | $(0.062)$ |
| ln(duration/12) | -0.123 | 0.318 | -0.639 | -0.359 | 0.138 | -0.328 |
|  | $(0.043)$ | $(0.126)$ | $(0.059)$ | $(0.173)$ | $(0.177)$ | $(0.165)$ |
| (ln(duration/12)) | 0.047 | -0.013 | -0.243 | -0.181 | -0.244 | -0.082 |
|  | $(0.012)$ | $(0.040)$ | $(0.028)$ | $(0.091)$ | $(0.080)$ | $(0.096)$ |
| Prev.SE Exp. | 0.341 | 2.571 | -0.454 | 0.556 | 0.534 | 0.483 |
| Prev.Empl.Exp. | $(0.356)$ | $(0.299)$ | $(0.612)$ | $(0.660)$ | $(0.435)$ | $(0.660)$ |
| Prev.Unemp.Exp. | 0.204 | -0.052 | -0.135 | -0.121 | 0.030 | 0.152 |
| Unobs. heter. | $(0.018)$ | $(0.087)$ | $(0.033)$ | $(0.101)$ | $(0.325)$ | $(0.147)$ |
| Intercept | 0.037 | 0.033 | 0.023 | -0.001 | 0.061 | 0.002 |
|  | $(0.005)$ | $(0.008)$ | $(0.006)$ | $(0.017)$ | $(0.017)$ | $(0.026)$ |
| Log-likelihood | 1.000 | -1.228 | 0.021 | 0.841 | -0.489 | 2.358 |
| Observations | --- | $(0.440)$ | $(0.231)$ | $(1.072)$ | $(0.380)$ | $(1.222)$ |
|  | -4.46 | -9.787 | 0.300 | -7.509 | -2.041 | -3.782 |
|  | $(0.374)$ | $(0.820)$ | $(0.375)$ | $(1.532)$ | $(1.243)$ | $(2.226)$ |
|  |  |  | -7315 |  |  |  |
|  |  |  | 4227 |  |  |  |

Notes: Standard errors (computed from the inverse of the information matrix) in brackets. SE denotes self-employment, E employment and $U$ unemployment. Age is measured at the beginning of the spell. NUR is National Unemployment Rate.
Two support Points: $\mathrm{v}_{1}=0$ with probability $\mathrm{p}_{1}=0.65$ and $\mathrm{v}_{2}=-1.296(0.323)$ with probability $\mathrm{p}_{2}=0.35$. The heterogeneity coefficient for the transition from E to U is normalise to one for identification.

## Chapter 4

## Added worker effect: the case of female labour force participation for the UK

### 4.1. Introduction

Labour market behaviour of married couples is clearly influenced by family factors. It also appears that many labour market transitions of married workers occur in response to job moves by their spouses ${ }^{1}$. The individual decision problem is here generalised to a family level, the family being the decision-maker that maximises a joint utility function.

Within this framework, one of the topics that has attracted more interest among economists is the so called "added worker" effect. The term refers to a temporary increase in the labour supply or in the participation rate of secondary workers within the household (usually the wife) in response to an unemployment spell suffered by the head of the household. In general, the idea behind it is that, if during a recession the husband becomes unemployed (in other words, the husband's market productivity declines, at

[^27]least temporarily), in order to maintain the family's prior level of utility, the family as a whole may decide that the wife should look for a job, while the husband remains unemployed. Then she would become an added member of the labour force.

However, against this theoretical prediction, the opposite effect is found for a variety of countries ${ }^{2}$ : women married to unemployed men tend to have lower participation rates than those married to employed men. This is the case for the UK, where during 1987-89 $71 \%$ of women married to employed men were participating compared with only $28 \%$ of those married to an unemployed man ${ }^{3}$. It is important to point out that it is a common finding that wives of men who became unemployed were less likely to have been employed than wives in general ${ }^{4}$.

The purpose of this chapter is to shed some light on the reasons for these low participation rates of women married to unemployed men in the UK. We address the problem in a simple way by looking at household job status transitions. The focus here is to analyse the effect of common observable and unobservable characteristics ("assortative mating") on these transition rates. If men prone to be unemployed tend to marry women with a set of characteristics which make them more likely to withdraw from the labour market, the result would be an apparent fall in participation for wives of unemployed men. Therefore, by modelling jointly the labour force states of husband and wife and after controlling for these observed and unobserved characteristics, we should be able to establish whether there is any added worker effect in the British economy.

Most of the existent empirical literature treats the husband job status as exogenous (or predetermined) and analyse labour force decisions of wives. That is the case of Maloney (1985), Bell and Wright (1990), Giannelli and Micklewright (1995), Davies et al. (1992) or Pudney and Thomas (1992). Some authors, however, model a joint household decision problem but do not allow for unobservable characteristics to influence the labour force status of both partners (see Zimmer, 1992, Lundberg, 1985, or

[^28]Theeuwes, 1981). It should be noted that even if the husband job situation is predetermined, the presence of some unobservable characteristics highly correlated between husbands and wives ${ }^{5}$ would make necessary to model their labour market decisions as the outcome of a joint process.

Previous literature has tried to explain the lower (aggregate) participation rates of women married to unemployed men using different hypotheses, in principle as plausible as, or even coexisting with, the added worker theory. On the one hand the husband is more likely to lose his job because of a widespread deterioration in employment opportunities. This would produce an important fall in the expected wages that an individual without a job may receive. Real wages would decrease due to an excess of labour supply over demand and the probability of getting a job in a recession would also fall. This double effect (the discouraged worker effect) induces some individuals (in this case wives) to exit from the labour force or restrains them from entering it. Both effects may in principle coexist: added and discouraged workers will affect different groups of people. The aggregate outcome will depend upon which group predominates ${ }^{6}$.

A second hypothesis that could produce lower participation rates for women married to unemployed men is the complementarity of husband's and wife's non-labour market time. If a higher proportion of non-market time is pure leisure (as opposite to reproductive work), this complementarity is conceivable ${ }^{7}$. If strong complementarities between husband's and wife's leisure exist, the effect of an unemployment spell of the husband is not as clear as in the case when there is sustituibility.

[^29]Some authors ${ }^{8}$ have argued that there exists a social stigma attached to unemployed men when their wives work. Therefore, there may be a reluctance for wives of unemployed men to work because this could damage their husbands' self-esteem.

For the UK, many authors (García, 1989, 1991, Dilnott and Kell, 1990, or Pudney and Thomas, 1992) have drawn attention to de disincentive effects of the benefit system. A social security system based on means-testing benefits (as is the case for a part of the British system) would have a disincentive effect on the participation rates of the wives of unemployed men. However, in general, they have found that only a small part of the difference between the labour force participation of the wives of employed versus the wives of unemployed husbands can be explain by this disincentive effect.

This Chapter deals with the correction of the endogeneity and joint determination of the labour market decisions for the couple, correcting for observable and unobservable characteristics. We disregard the analysis of the security system disincentive effect which has been well studied in the literature.

In the case of a single individual, flows between states can be considered and reduced form equations proposed (controlling for observable and unobservable heterogeneity $)^{9}$. This framework can be extended to a family context in which now the state space has expanded so that instead of individual states we consider family states. Reduced form parametric transition probabilities from and to any of the possible states can then be estimated, using a multiple state transition econometric framework. The advantage of this approach is that it presents a dynamic view of the labour market decisions and incorporates the possibility of lagged adjustments. To change labour market status takes time and the response of the wife participation to the labour market state of the husband may be subject to adjustment delays.

The data used here is a subsample of couples drawn from the British Household Panel Survey (BHPS), using the four waves available and the retrospective work history questionnaire.

[^30]The chapter is structured as follows. Section 4.2 describes the model specification and discusses the estimation of the transition probabilities. Section 4.3 presents the data used for the analysis and in section 4.4 the estimation results are discussed. Section 4.5 states the main conclusions of the analysis.

### 4.2. Model Specification

### 4.2.1. Theoretical background

As stated in the previous section, the added worker effect is a temporary change in labour supply behaviour. This effect has two components: an increase in the number of hours the wife actually works and a change in her willingness to work, that is, in her decision to participate in the labour market. Labour demand restrictions may imply that it is not always possible to change the number of hours and individual works (or to change job), as it was seen in Chapter 2. This would not mean that there is no effect of the husband's unemployment on the labour supply decisions of the wife. Her decisions to enter or exit the labour force can be affected. Therefore, we abstract here from the effect on hours of work and would concentrate on how the participation decisions vary.

Given the uncertainties concerning the magnitude, timing and frequency of job offers and the duration of jobs, labour market histories are best described as realisations of a stochastic process. Within this framework, flow rates between labour market states are the object of study. The theoretical model behind this approach was proposed by Burdett and Mortensen (1978) and applied to the analysis of the added worker effect by Lundberg (1981, 1985). It would be briefly outlined bellow.

Let a two-person household maximise the expected value of their life-time utility, that is, the discounted sum of their utility flow in each period. Lets assume the utility flow is a concave function, $U\left(x_{t}, l_{m}, l_{f}\right)$ where $x_{t}$ is the household commodity
consumption in period $t$, and $l_{f t}$ and $l_{m t}$ are the fractions of time devoted to leisure by the husband and the wife, respectively.

In principle, lets suppose that there are three possible states for each member of a couple: unemployment (U), employment (E) or out of the labour force (NP). Employment requires to devote to work a fixed fraction of available time, $h_{i}$. Unemployment requires an extra fraction, $s_{i}<h_{i}$, to be spend on job search. Each employed person receives a wage, $w_{i}$. This wage, jointly with the nonlabour income, determines the budget constraint in each period. Job offers only arrive to unemployed individuals and they consist of a wage drawn from a known distribution that may vary across individuals.

In such a setting the allocation of time and income is completely determined by the state occupied. Therefore, the household's optimal strategy, maximising the utility flow, can be derived by comparing the expected utility associated with occupying alternative states.

Lundberg (1985) shows that given the husband status, the household's strategy will partly consists of two reservation wage functions depending on the husband's wage. The first one equates the value of the wife's employment to the value of unemployment. The second equates the value of the wife's employment to the value of nonparticipation. Jointly, both wages determine participation and acceptance decisions for the wife.

The added worker effect appears when analysing how the husband's wage alters these two reservation wages. If leisure for both household members are substitutes, it can be shown that the change in the second reservation wage due to a change in the husband's wage is greater than the change in the first reservation wage, both changes being positive. This means that, an increase in the husband's wage increases both reservation wages of the wife, making her less likely to participate in the labour force, and should she participate, less likely to accept a job offer. Therefore, a wife would be more likely to search for work and to accept a given wage offer if her husband is unemployed. However this effect will not be clear when the leisure times of both
members are not substitutes. Therefore, one reason for not finding any added worker effect could be the existence of strong complementarities in leisure.

The main result of the previous model is that both reservation wages (the value of unemployment and the value of nonparticipation) are lower for wives whose husbands are not employed. Three implications can then be inferred concerning transition rates:
1.Employed wives are less likely to leave employment when their husbands are unemployed.
2.Wives non participating are more likely to enter the labour force when their husbands are unemployed.
3.Unemployed wives will find more jobs acceptable and become employed more rapidly when their husbands are unemployed.

From the previous model, a way to take into account joint labour supply decisions for husbands and wives in the household is to consider the set of possible states the household can be in. If each individual of the household may be in three different states, as it was explained before, the household as a whole may be in nine different states: husband working - wife working, husband working - wife unemployed, husband working - wife non participating and so on. Transitions from and to any of these nine states (72 in total) can be constructed and compared to analyse the presence of an added worker effect.

Given the nature of our data, it is not possible to estimate the complete model so then we restrict the number of possible transitions by individual. As the focus in this chapter is to study the effect of husband's job status on wives' participation probabilities, we consider only two possible states per individual. The husband may be either working (W) or not working (NW) and the wife may be participating (P) or non participating (NP). Table 1 shows the household transition matrix resulting from this specification.

Next section describes the reduced form transition probabilities and the econometric methodology proposed for their estimation.

Table 4.1: Possible transition intensities.

|  | Destination State |  |  |  |  |  |  |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Source State | W-P | W-NP |  |  |  | NW-P | NW-NP |
| W-P | - | $\vartheta_{W P-W N P}(t / Z ; \beta)$ | $\vartheta_{W P-N W P}(t / Z ; \beta)$ | $\vartheta_{W P-N W N P}(t / Z ; \beta)$ |  |  |  |
| W-NP | $\vartheta_{W N P-W P}(t / Z ; \beta)$ | - | $\vartheta_{W N P-N W P}(t / Z ; \beta)$ | $\vartheta_{W N P-N W N P}(t / Z ; \beta)$ |  |  |  |
| NW-P | $\vartheta_{N W P-W P}(t / Z ; \beta)$ | $\vartheta_{N W P-W N P}(t / Z ; \beta)$ | - | $\vartheta_{N W P-N W N P}(t / Z ; \beta)$ |  |  |  |
| NW-NP | $\vartheta_{N W N P-W P}(t / Z ; \beta)$ | $\vartheta_{N W N P-W N P}(t / Z ; \beta ;$ | $\vartheta_{N W N P-N W P}(t / Z ; \beta$ |  |  |  |  |

Notes: First letter indicates husband status (W for working and NW for non working) and the second one wife status ( P for participating and NP for nonparticipating ). The intensities depend on the duration spend on a given status and are conditional on a set of observable and unobservable variables ( $Z$ ). $\beta$ are the parameters of interest.

### 4.2.2 Econometric specification

The econometric specification of the model follows the same patterns of the one used in Chapter 3, that is, a continuos time hazard model of transition rates among the four possible household labour states. Each of the transition intensities appearing in Table 1 are defined as the probability of departure from state $k$ to state $l$ in the short interval ( $t, t+\delta t$ ). They depend on $Z$, a set of observable and unobservable individual characteristics ( $X$ and $v$ respectively; some $X$ can vary over time), on a set of unknown parameters to estimate, $\beta$, and on the elapsed duration, measured in months, $t$. A flexible functional form is selected to represent transition intensities, allowing for duration and state dependence:

$$
\begin{equation*}
\theta_{k l}(t \mid Z ; \beta)=\exp \left\{g_{k l}(t)+X \beta_{k l}+\delta_{k l} v\right\} \tag{4.1}
\end{equation*}
$$

where $g_{k l}(t)$ is a function of time spend on state $k$, before departure towards $l$. If not allowing for occurrence or lagged duration dependence ${ }^{10}$, the process is a continuos time semi-Markov process. Both possibilities would be explored in the empirical implementation. $\beta$ includes all parameters to estimate in the model, that is, all the $\beta_{k l}$, all the $\delta_{\mathrm{kl}}$ and the parameters implicit in $g_{k l}(t)$.

The household fixed effect, $v$, varies over the population according to an unknown distribution function $h\left(v_{i}\right)$. This fixed effect reflects that there may be unobservable characteristics affecting couples and altering the transition probabilities. It can reflect the tastes for working of the couple and to some extend, it would control for the possibility of assortative mating or some type of aggregate shocks (e.g., local labour market conditions).

In principle, twelve of such transition intensities should be defined. However, as the model is on continuos time, some restrictions may be imposed. In continuos time the probability of two events occurring at exactly the same time is zero. Therefore four out of the twelve probabilities would be zero, namely, the probabilities of the transitions from WP to NWNP, from WNP to NWP, from NWP to WNP and from NWNP to WP. That leave us with eight positive probabilities to estimate.

For each household, data consists on one or more spells in every state, some of them incomplete ${ }^{11}$. The probability of departure from $k$ to $l$ at any point in time $t$ is its transition intensity, that is, the probability of departure from state $k$ to state $l$ in the short interval ( $t, t+\delta t$ ), times the survivor function (the probability of surviving in state $k$ until time $t$ ):

$$
\begin{equation*}
P_{k l}(t \mid Z ; \beta)=\theta_{k l}(t \mid Z ; \beta) \bar{F}(t \mid Z ; \beta)=\theta_{k l}(t \mid Z ; \beta) \exp \left\{-\Theta_{k}(t \mid Z ; \beta)\right\} \tag{4.2}
\end{equation*}
$$

[^31]where $\Theta_{k}$ is the corresponding integrated hazard function $\left(\Theta_{k l}=\int_{0}^{t} \sum_{l \neq k} \theta_{k l}(s \mid Z ; \beta) \partial s\right)$. Equation (4.2) is the contribution to the likelihood function for each individual and completed spell. If the spell is incomplete, the contribution to the likelihood function would be just the survivor function.

The individual likelihood function for an individual with a sequence of spells $\left\{t_{1}, t_{2}, \ldots t_{C_{i}}\right\}$, once $v_{i}$ has been integrated over all its possible values given its density function, $d\left(v_{i}\right)$, is:

$$
\begin{align*}
& L_{i}\left(\beta \mid t_{i 1}, \ldots, t_{i C_{i}}, X_{i}\right)=  \tag{4.3}\\
& \quad \int_{-\infty}^{\infty}\left\{\left(\prod_{c=1}^{c_{i}} \prod_{k} \prod_{l \neq k} P_{k l}\left(t_{c} \mid X_{i}^{c} ; \beta\right)^{d_{k i}}\right)\left(\prod_{c=1}^{c_{i}} \prod_{l} \bar{F}_{k}\left(t_{c} \mid X_{i} ; \beta\right)^{s_{k}}\right)\right\} d\left(v_{i}\right) d v_{i}
\end{align*}
$$

where $d_{k l}^{c}$ is an indicator variable which equals one if the household exited state $k$ towards state $l$ in the $c$ th spell and $s_{k}^{c}$ is a dummy which equals one if the $c$ th spell is incomplete and the household did not move from state $k$.

The log likelihood for the whole sample would then be,

$$
\begin{equation*}
\log L=\sum_{i=1}^{N} L_{i}\left(\beta \mid t_{i 1}, \ldots, t_{i c_{i}}, X_{i}\right) \tag{4.4}
\end{equation*}
$$

As in the previous chapter a Non-Parametric Maximum Likelihood Estimator (NPMLE), which does not require any distributional assumption, would be used to estimate the likelihood function. The distribution function of unobservables, $d(v)$ is approximated with a finite mixture distribution with $v_{l}, \ldots, v_{M}$ unknown support points to which M unknown probabilities are attached. Then the contribution to the likelihood of a household becomes:
$L_{i}\left(\beta, v, \pi \mid t_{i 1}, \ldots, t_{i C_{i}}, X_{i}\right)=$

$$
\begin{equation*}
\sum_{\mathrm{m}=1}^{\mathrm{M}}\left\{\left(\prod_{c=1}^{c_{i}} \prod_{k} \prod_{l \neq k} P_{k l}\left(t_{c} \mid X_{i}^{c}, v_{m} ; \beta\right)^{d_{k l}^{c}}\right)\left(\prod_{c=1}^{c_{i}} \prod_{l} \bar{F}_{k}\left(t_{c} \mid X_{i}, v_{m} ; \beta\right)^{s_{k}^{c}}\right)\right\} \pi_{m} \tag{4.5}
\end{equation*}
$$

the log-likelihood function being its summation over all individuals. The points of support as well as the probabilities assigned to each of them are now parameters of interest to be estimated by an EM-algorithm. The function is maximised for different number of support points until the parameters of the criterion function remain relatively stable.

Once the parameters have been estimated, a comparison among different pairs of transition probabilities would provide some information on the existence or absence of an added worker effect in the economy. The theoretical model presented before established that women married to unemployed men should have lower reservation wages (for unemployment and for nonparticipation). For our econometric specification, two hypotheses can be used to test the existence of an added worker effect:

$$
\begin{aligned}
& 1 . \vartheta_{W P-W N P}(t / Z ; \beta)>\vartheta_{N W P-N W N P}(t / Z ; \beta) \\
& 2 . \vartheta_{W N P-W P}(t / Z ; \beta)<\vartheta_{N W N P-N W P}(t / Z ; \beta)
\end{aligned}
$$

The first hypothesis implies that wives already participating would be less likely to get out of the labour market if their husbands are not working. The second hypothesis implies that non participating women married to unemployed men are more likely to enter the labour force than the ones married to employed men, due to their lower reservation wage. These points are discussed in Section 4.4, but before that, a description of the data and its characteristics is presented in Section 4.3.

### 4.3. Data Description

The data used in this Chapter is a subsample from the British Household Panel Survey (BHPS). This is an annual survey carried out by the ESRC Research Centre on Micro-social Change since 1991. It is a nationally representative sample collecting information of at least 5000 households (approximately 10000 individual interviews). Data is collected at both individual and household level. Information on marriage history is collected individually in an additional questionnaire corresponding to the Second Wave (1992): year of marriage and cohabitation, previous marriages, etc. Also for this wave a detailed employment status questionnaire was filled by each individual in the household.

Implementation of the model described in Section 4.2 requires information on marriage and job histories for each couple. Therefore this Second Wave of the BHPS would be the starting point. For all couples that where interviewed during 1992, data on the retrospective questionnaire is combined with the employment status data available for each wave. Data from the Second to the Fourth Wave, the last available at the moment, is used.

We select all couples that were married or cohabiting at the moment of collecting the Second Wave, and that remained married until the end of the period of observation ${ }^{12}$. Only couples in which husband and wife are of working age (males between 16 and 65 years old and females between 16 and 60 years old) are considered in the analysis. For every husband we have a series of working and non working spells ${ }^{13}$ and for every wife a series of participation and not participation spells, from the moment they married to the last interview date. For the couple as a whole, spells are constructed as shown in Figure 4.1. Every couple's spell since marriage is used in the analysis.

[^32]Figure 4.1: Household's Job Status

| Marriage <br> Date: $t_{0}$ | Husband's Job Status |  |  | Household Status |
| :---: | :---: | :---: | :---: | :---: |
|  | W |  |  |  |
|  |  | NWP |  |  |
|  | WP | NWP | NWNP |  |
|  | $P$ | Job St |  |  |

Notes: First letter indicates husband status (W for working and NW for non working) and the second one wife status ( P for participating and NP for nonparticipating).

After dropping those couples with missing or invalid values in some of the relevant variables, the final sample includes 1876 couples with 6657 complete and incomplete spells. Table 4.2 presents the number of observations for each possible transition. As stated in Section 2.2, some of these transitions should be zero, on theoretical grounds, but in the sample a small number of households make such transitions. This is due to the fact that employment history information is collected in monthly basis ${ }^{14}$. Those spells would not be considered in the analysis leaving us with 6502 valid spells.

Table 4.2: Observations per transition intensity ${ }^{15}$.
1876 couples ( 6502 valid complete and incomplete spells).
Destination State

| Source State | W-P | W-NP | NW-P | NW-NP | Censored |
| :--- | :---: | :---: | :---: | :---: | :---: |
| W-P | ---- | 1375 | 576 | 23 | 1202 |
| W-NP | 1396 | ---- | 7 | 377 | 342 |
| NW-P | 492 | 8 | ---- | 86 | 139 |
| NW-NP | 17 | 292 | 67 | ---- | 167 |

Notes: First letter indicates husband status (W for working and NW for non working) and the second one wife status ( P for participating and NP for nonparticipating ).

[^33]It is interesting to point out that in 1992, for the selected sample, $76.2 \%$ of women married to working husbands were participating in the labour market. Only $42.6 \%$ of women were participating if their husbands were not working. That result follows the usual pattern found in previous years for the British economy (see Pudney and Thomas, 1992, or Giannelli and Micklewright, 1995). However, this measure is just an aggregation and is purely static. If the wife decides to participate during a short period within two years it would not be reflected in this type of figures and would be considered as not participating. When taking into account movements between states, the pattern is somehow different. For $59.8 \%$ of the spells in which the husband was working, the wife was participating; for spells in which the husband was not working, the wife participates in $57.7 \%$ of the cases ${ }^{16}$. These percentages are quite similar, suggesting that previous measures do not take into account the dynamics behind labour market decisions of couples. Concentrating only on couples that actually change state at some point, the effect even reverses. The higher participation rate is for those spells in which the husband is not working: $58.4 \%$ of wives with an unemployed husband participate while $57.2 \%$ participate if their husband is working. This is an interesting point since it opens the possibility of an added worker effect, at least for a particular group of individuals, namely, the more mobile. It also seems important to consider a more dynamic vision of participation decisions allowing for short periods of participation.

Before presenting the parametric model estimates, it is worthy to describe survival probabilities using non-parametric techniques. Comparisons between KaplanMeier estimates of the possible survival probabilities are presented in Figures 4.2 to 4.5 .

Figure 4.2 and 4.3 present survival probabilities for transitions in which the change of status of the household is due to a change in the labour market decision of the wife. Both these transitions are the ones we need to analyse the added worker effect. Figure 4.2, shows the survivor functions for the transition from WP to WNP and for the transition from NWP to NWNP.

[^34]Figure 4.2


Figure 4.3
Kaplan-Meier survival estimates, by type of transition


Notes: First letter indicates husband status (W for working and NW for non working) and the second one wife status ( P for participating and NP for nonparticipating ).

Figure 4.4


Figure 4.5
Kaplan-Meier survival estimates, by type of transition


Notes: First letter indicates husband status (W for working and NW for non working) and the second one wife status ( P for participating and NP for nonparticipating ).

A comparison of both survival probabilities gives us a measure of whether the likelihood for a participating wife to withdraw from the labour market is higher if the husband is working. We see that the survival probability in participation declines faster if the husband is not working than if the husband is working. This effect is the opposite to the expected if there is an added worker effect. Different explanations are coherent with this finding. Some degree of complementarity between the leisure of the members of the couple could generate such an effect. Also if the discouraged worker effect is important, unemployed wives would tend to drop from the labour force more when conditions are worse. That can be reflected in the fact that their husbands lost their jobs. Other explanations as the disincentive role of benefits would produce the same result.

Figure 4.3 shows the survival estimates for the transition from WNP to WP and the transition from NWNP to NWP. This figure reflects whether wives of unemployed men have a higher probability of participating, which again would correspond to the presence of an added worker effect. It shows that the survival in non participation when the husband is not working decreases faster than the survival when he is working. That is, wives of unemployed men tend to transit faster to participation than wives of employed men, which is consistent with the presence of an added worker effect.

Figures 4.4 and 4.5 compare transitions from a husband working to not working and viceversa, given the wife's participation status. Figure 4.4 shows the same effect than in Figure 4.2. If the wife is not participating in the labour market the probability that the husband remains working is smaller than the same probability if the wife is participating. Figure 4.5 shows that if the wife is participating the probability that the husband survives non working is smaller. This could be reflecting that wife's participation provides some type of information concerning job possibilities and labour market conditions that can be transferred to the husband, making him more likely to find a job. In any case, the differences in the survival probabilities for men, given their wives' participation status, are smaller than the differences found for women, given their husband's job status.

Differences observed in figures 4.2 to 4.5 could be due to observable differences among households, since Kaplan-Meier estimates do not correct for any characteristic. Relevant characteristics by spell are collected in Table 4.A. 1 in Appendix A. Some differences in the variables are quite important depending on the type of transition as age, education, children or previous unemployment experiences of the husband.

The next section controls for all these characteristics and for unobservables, which could be determining the transitions. From the previous analysis a clear conclusion may be inferred: given that survival probabilities behave differently depending on the state occupied, in the final specification we should allow for state dependence.

The model estimated is a reduced form that can be consider as an approximation to the dynamic structural model proposed in section 4.2.1. Explanatory variables fall into three categories: demographic characteristics, lagged endogenous variables and business cycle variables. Variables in the first group (age, education and children in the household) can be associated to labour supply preferences. Given that wages are not included in the analysis, age and education also approximate their effect.

Lagged endogenous variables, once controlling by unobservable heterogeneity, may be interpreted in terms of state dependence in preferences or constraints. Current duration of the spell and its square are included along with splines at three months that allow for changes in the shape of the transition probabilities from the third month onwards. Husband's past record of unemployment may affect household preferences and therefore is also included as explanatory variable. In addition, to try to control for initial conditions problem (employment and participation histories for husband and wife started before the marriage), variables relating work and participation experience before marrying are included. In the final specification, the job status of each member before marriage (participation or non participation, for wives, and working or not working, for husbands) was enough to summarise these initial conditions. Other variables summarising duration of those spells were also tried and found not significant.

To control for business cycle effects the rate of change of the GDP at the beginning of the spell is included as explanatory variable. Appendix A gives a detailed description of all the variables and the way they enter transition intensities.

### 4.4. Results

In this section we present parametric results for the specification proposed in Section 4.2. Table 4.3 shows estimates of the $\beta$ 's for the model where two support points are included to account for unobservable heterogeneity. Including three support points did not alter the estimates. The inclusion of unobserved heterogeneity improves substantially the log likelihood and it seems important to analyse household job status decisions ${ }^{17}$.

Predicted hazard rates for a baseline case and variations around the baseline are given in Table $4.4^{18}$. Coefficient estimates in Table 4.3 are difficult to interpret in isolation. They reflect transition intensities and we are interested in probabilities to leave a given state in the interval between month $t-1$ and month $t$, given survival to $t-1$. Therefore, discussion would be focused on Table 4.4.

The first thing to notice in Table 4.4 is that the probability of a transition $\mathrm{NWP} \rightarrow \mathrm{WP}$ is much higher than any of the rest, for all possible changes in demographic variables. Several explanations are consistent with this fact. First, unemployment spells for husbands tend to be short and some kind of insider information may be used when the wife is attached to the labour market making easier for the husband to find a job. However this insider information theory is not symmetric: the probability of WNP $\rightarrow$ WP is, in general, quite small and smaller than the probability of NWNP $\rightarrow$ NWP, at least for some household types.

[^35]Table 4.3: Maximum Likelihood estimates for the transition equations (NPMLE estimation method)

|  | $\begin{aligned} & \hline \hline \text { WP } \\ & \overrightarrow{\text { WNP }} \end{aligned}$ | $\begin{aligned} & \mathrm{WP} \\ & \overrightarrow{\mathrm{NWP}} \end{aligned}$ | $\begin{aligned} & \hline \hline \text { WNP } \\ & \overrightarrow{\text { WP }} \end{aligned}$ | $\begin{aligned} & \hline \hline \text { WNP } \\ & \overrightarrow{\text { NWNP }} \end{aligned}$ | $\begin{aligned} & \text { NWP } \\ & \overrightarrow{\text { WP }} \end{aligned}$ | $\begin{aligned} & \hline \hline \text { NWP } \\ & \overrightarrow{~ N W N P ~} \end{aligned}$ | $\begin{aligned} & \mathrm{NWNP} \\ & \overrightarrow{\text { WNP }} \end{aligned}$ | $\begin{aligned} & \hline \hline \text { NWNP } \\ & \overrightarrow{\text { NWP }} \end{aligned}$ |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| Intercept | $\begin{aligned} & -1.810 \\ & (0.167) \end{aligned}$ | $\begin{aligned} & -2.804 \\ & (0.251) \end{aligned}$ | $\begin{gathered} -2.319 \\ (0.149) \end{gathered}$ | $\begin{gathered} -2448 \\ (0.306) \end{gathered}$ | $\begin{aligned} & \hline-1.383 \\ & (0.366) \end{aligned}$ | $\begin{aligned} & \hline-2.383 \\ & (0.604) \end{aligned}$ | $\begin{gathered} \hline-2.368 \\ (0.335) \end{gathered}$ | $\begin{array}{r} \hline-3.256 \\ (0.732) \end{array}$ |
| $\operatorname{Ln}(\mathrm{t})$ | $\begin{aligned} & -1.157 \\ & (0.205) \end{aligned}$ | $\begin{aligned} & -1.821 \\ & (0.332) \end{aligned}$ | $\begin{aligned} & -1.246 \\ & (0.274) \end{aligned}$ | $\begin{array}{r} -0.966 \\ (0.370) \end{array}$ | $\begin{gathered} -1.678 \\ (0.186) \end{gathered}$ | $\begin{aligned} & -1.144 \\ & (0.713) \end{aligned}$ | $\begin{aligned} & -0.861 \\ & (0.259) \end{aligned}$ | $\begin{array}{r} -0.931 \\ (0.827) \end{array}$ |
| $\operatorname{Ln}(\mathrm{t})^{2}$ | $\begin{aligned} & -0.465 \\ & (0.090) \end{aligned}$ | $\begin{aligned} & -0.670 \\ & (0.151) \end{aligned}$ | $\begin{aligned} & -0.597 \\ & (0.132) \end{aligned}$ | $\begin{gathered} -0.347 \\ (0.155) \end{gathered}$ | $\begin{array}{r} -0.562 \\ (0.075) \end{array}$ | $\begin{aligned} & -0.376 \\ & (0.315) \end{aligned}$ | $\begin{aligned} & -0.286 \\ & (0.097) \end{aligned}$ | $\begin{gathered} -0.269 \\ (0.347) \end{gathered}$ |
| $\mathrm{D} \ln (\mathrm{t})$ | $\begin{gathered} 0.854 \\ (0.208) \end{gathered}$ | $\begin{gathered} 1.452 \\ (0.354) \end{gathered}$ | $\begin{gathered} 1.043 \\ (0.282) \end{gathered}$ | $\begin{gathered} 0.729 \\ (0.395) \end{gathered}$ | $\begin{gathered} 1.042 \\ (0.198) \end{gathered}$ | $\begin{gathered} 1.078 \\ (0.737) \end{gathered}$ | $\begin{gathered} 0.635 \\ (0.270) \end{gathered}$ | $\begin{gathered} 0.789 \\ (0.852) \end{gathered}$ |
| $\mathrm{D} \ln (\mathrm{t})^{2}$ | $\begin{gathered} 0.184 \\ (0.094) \end{gathered}$ | $\begin{gathered} 0.843 \\ (0.155) \end{gathered}$ | $\begin{gathered} 0.671 \\ (0.135) \end{gathered}$ | $\begin{gathered} 0.485 \\ (0.162) \end{gathered}$ | $\begin{gathered} 0.333 \\ (0.140) \end{gathered}$ | $\begin{gathered} 0.320 \\ (0.349) \end{gathered}$ | $\begin{aligned} & -0.093 \\ & (0.174) \end{aligned}$ | $\begin{gathered} 0.206 \\ (0.418) \end{gathered}$ |
| Child<4 | $\begin{aligned} & -0.135 \\ & (0.059) \end{aligned}$ | $\begin{aligned} & -0.389 \\ & (0.122) \end{aligned}$ | $\begin{gathered} 0.148 \\ (0.072) \end{gathered}$ | $\begin{gathered} 0.260 \\ (0.135) \end{gathered}$ | $\begin{aligned} & -0.176 \\ & (0.175) \end{aligned}$ | $\begin{gathered} 0.445 \\ (0.340) \end{gathered}$ | $\begin{gathered} 0.056 \\ (0.194) \end{gathered}$ | $\begin{aligned} & -0.501 \\ & (0.359) \end{aligned}$ |
| Chl. bt. spells | $\begin{gathered} 2.817 \\ (0.066) \end{gathered}$ | $\begin{aligned} & -0.155 \\ & (0.161) \end{aligned}$ | $\begin{aligned} & -0.082 \\ & (0.082) \end{aligned}$ | $\begin{gathered} -0.087 \\ (0.163) \end{gathered}$ | $\begin{aligned} & -0.437 \\ & (0.491) \end{aligned}$ | $\begin{gathered} 1.885 \\ (0.428) \end{gathered}$ | $\begin{gathered} -0.160 \\ (0.251) \end{gathered}$ | $\begin{gathered} -0.221 \\ (0.516) \end{gathered}$ |
| Unexp | $\begin{gathered} 0.004 \\ (0.004) \end{gathered}$ | $\begin{gathered} 0.007 \\ (0.003) \end{gathered}$ | $\begin{aligned} & -0.002 \\ & (0.002) \end{aligned}$ | $\begin{gathered} 0.008 \\ (0.004) \end{gathered}$ | $\begin{aligned} & -0.010 \\ & (0.005) \end{aligned}$ | $\begin{gathered} 0.008 \\ (0.005) \end{gathered}$ | $\begin{aligned} & -0.007 \\ & (0.007) \end{aligned}$ | $\begin{gathered} -0.001 \\ (0.008) \end{gathered}$ |
| Hwork | $\begin{aligned} & -0.707 \\ & (0.123) \end{aligned}$ | $\begin{aligned} & -0.434 \\ & (0.163) \end{aligned}$ | $\begin{aligned} & -0.062 \\ & (0.107) \end{aligned}$ | $\begin{aligned} & -0.740 \\ & (0.187) \end{aligned}$ | $\begin{gathered} 0.329 \\ (0.206) \end{gathered}$ | $\begin{aligned} & -0.340 \\ & (0.373) \end{aligned}$ | $\begin{gathered} 0.308 \\ (0.196) \end{gathered}$ | $\begin{gathered} -0.073 \\ (0.380) \end{gathered}$ |
| Wpart | $\begin{aligned} & -0.057 \\ & (0.089) \end{aligned}$ | $\begin{aligned} & -0.193 \\ & (0.146) \end{aligned}$ | $\begin{gathered} 0.211 \\ (0.084) \end{gathered}$ | $\begin{gathered} -0.679 \\ (0.146) \end{gathered}$ | $\begin{gathered} 0.157 \\ (0.202) \end{gathered}$ | $\begin{aligned} & -0.107 \\ & (0.452) \end{aligned}$ | $\begin{gathered} 0.280 \\ (0.186) \end{gathered}$ | $\begin{gathered} 0.459 \\ (0.347) \end{gathered}$ |
| GDPI | $\begin{gathered} -0.054 \\ (0.047) \end{gathered}$ | $\begin{aligned} & -0.109 \\ & (0.091) \end{aligned}$ | $\begin{aligned} & -0.092 \\ & (0.050) \end{aligned}$ | $\begin{gathered} 0.010 \\ (0.123) \end{gathered}$ | $\begin{gathered} 0.034 \\ (0.148) \end{gathered}$ | $\begin{gathered} 0.040 \\ (0.388) \end{gathered}$ | $\begin{gathered} 0.079 \\ (0.178) \end{gathered}$ | $\begin{aligned} & -0.595 \\ & (0.523) \end{aligned}$ |
| H. Age | $\begin{gathered} 0.015 \\ (0.007) \end{gathered}$ | $\begin{gathered} 0.017 \\ (0.010) \end{gathered}$ | $\begin{gathered} 0.002 \\ (0.008) \end{gathered}$ | $\begin{gathered} 0.010 \\ (0.013) \end{gathered}$ | $\begin{array}{r} -0.046 \\ (0.011) \end{array}$ | $\begin{gathered} 0.036 \\ (0.033) \end{gathered}$ | $\begin{aligned} & -0.032 \\ & (0.016) \end{aligned}$ | $\begin{aligned} & -0.007 \\ & (0.040) \end{aligned}$ |
| W. Age | $\begin{aligned} & -0.045 \\ & (0.008) \end{aligned}$ | $\begin{gathered} 0.037 \\ (0.011) \end{gathered}$ | $\begin{gathered} 0.026 \\ (0.009) \end{gathered}$ | $\begin{gathered} 0.067 \\ (0.015) \end{gathered}$ | $\begin{gathered} 0.029 \\ (0.014) \end{gathered}$ | $\begin{gathered} -0.010 \\ (0.033) \end{gathered}$ | $\begin{gathered} -0.018 \\ (0.017) \end{gathered}$ | $\begin{aligned} & -0.005 \\ & (0.039) \end{aligned}$ |
| H. Edl | $\begin{gathered} 0.416 \\ (0.071) \end{gathered}$ | $\begin{gathered} -0.373 \\ (0.117) \end{gathered}$ | $\begin{aligned} & -0.050 \\ & (0.074) \end{aligned}$ | $\begin{aligned} & -0.632 \\ & (0.166) \end{aligned}$ | $\begin{gathered} 0.214 \\ (0.139) \end{gathered}$ | $\begin{aligned} & -0.008 \\ & (0.440) \end{aligned}$ | $\begin{gathered} 0.949 \\ (0.218) \end{gathered}$ | $\begin{aligned} & -0.616 \\ & (0.563) \end{aligned}$ |
| H. Ed2 | $\begin{gathered} 0.413 \\ (0.072) \end{gathered}$ | $\begin{aligned} & -0.162 \\ & (0.108) \end{aligned}$ | $\begin{gathered} 0.071 \\ (0.071) \end{gathered}$ | $\begin{gathered} -0.296 \\ (0.147) \end{gathered}$ | $\begin{gathered} 0.186 \\ (0.137) \end{gathered}$ | $\begin{aligned} & -0.114 \\ & (0.348) \end{aligned}$ | $\begin{gathered} 0.464 \\ (0.185) \end{gathered}$ | $\begin{aligned} & -0.101 \\ & (0.411) \end{aligned}$ |
| W. Ed1 | $\begin{aligned} & -0.660 \\ & (0.073) \end{aligned}$ | $\begin{aligned} & -0.114 \\ & (0.124) \end{aligned}$ | $\begin{gathered} 0.408 \\ (0.072) \end{gathered}$ | $\begin{aligned} & -0.316 \\ & (0.192) \end{aligned}$ | $\begin{gathered} 0.062 \\ (0.147) \end{gathered}$ | $\begin{aligned} & -0.023 \\ & (0.441) \end{aligned}$ | $\begin{gathered} 0.334 \\ (0.231) \end{gathered}$ | $\begin{gathered} 0.745 \\ (0.541) \end{gathered}$ |
| W. Ed2 | $\begin{gathered} -0.377 \\ (0.065) \end{gathered}$ | $\begin{aligned} & -0.182 \\ & (0.111) \end{aligned}$ | $\begin{gathered} 0.008 \\ (0.068) \end{gathered}$ | $\begin{aligned} & -0.058 \\ & (0.144) \end{aligned}$ | $\begin{gathered} 0.112 \\ (0.130) \end{gathered}$ | $\begin{gathered} 0.497 \\ (0.315) \end{gathered}$ | $\begin{gathered} 0.118 \\ (0.176) \end{gathered}$ | $\begin{gathered} 0.461 \\ (0.423) \end{gathered}$ |
| Cohort2 | $\begin{aligned} & -0.356 \\ & (0.080) \end{aligned}$ | $\begin{gathered} 0.432 \\ (0.142) \end{gathered}$ | $\begin{gathered} 0.420 \\ (0.082) \end{gathered}$ | $\begin{gathered} 0.186 \\ (0.200) \end{gathered}$ | $\begin{gathered} 0.321 \\ (0.165) \end{gathered}$ | $\begin{aligned} & -0.908 \\ & (0.433) \end{aligned}$ | $\begin{gathered} 0.562 \\ (0.249) \end{gathered}$ | $\begin{gathered} 0.714 \\ (0.540) \end{gathered}$ |
| Cohort3 | $\begin{aligned} & -0.448 \\ & (0.089) \end{aligned}$ | $\begin{gathered} 1.082 \\ (0.166) \end{gathered}$ | $\begin{gathered} 0.805 \\ (0.095) \end{gathered}$ | $\begin{gathered} 0.931 \\ (0.218) \end{gathered}$ | $\begin{gathered} 0.632 \\ (0.208) \end{gathered}$ | $\begin{aligned} & -0.392 \\ & (0.471) \end{aligned}$ | $\begin{gathered} 0.200 \\ (0.275) \end{gathered}$ | $\begin{gathered} 1.452 \\ (0.543) \end{gathered}$ |
| Cohort4 | $\begin{gathered} -0.967 \\ (0.106) \end{gathered}$ | $\begin{gathered} 1.346 \\ (0.203) \end{gathered}$ | $\begin{gathered} 0.932 \\ (0.119) \end{gathered}$ | $\begin{gathered} 2.090 \\ (0.231) \end{gathered}$ | $\begin{gathered} 0.202 \\ (0.273) \end{gathered}$ | $\begin{gathered} 0.012 \\ (0.527) \end{gathered}$ | $\begin{gathered} 0.090 \\ (0.284) \end{gathered}$ | $\begin{gathered} 1.219 \\ (0.643) \end{gathered}$ |
| Unob. het. | 1.000 | $\begin{array}{r} -0.379 \\ (0.202) \\ \hline \end{array}$ | $\begin{aligned} & -0.105 \\ & (0.048) \\ & \hline \end{aligned}$ | $\begin{gathered} 0.416 \\ (0.101) \\ \hline \end{gathered}$ | $\begin{gathered} -0.545 \\ (0.218) \\ \hline \end{gathered}$ | $\begin{gathered} 0.383 \\ (0.278) \\ \hline \end{gathered}$ | $\begin{gathered} 0.368 \\ (0.127) \\ \hline \end{gathered}$ | $\begin{aligned} & -0.053 \\ & (0.322) \\ & \hline \end{aligned}$ |

Observat.
Log-likel. -12610.69
Notes: First letter indicates husband status (W for working and NW for non working) and the second one wife status ( P for participating and NP for nonparticipating ). Standard errors in brackets. Data description in Appendix A. Two support points included: $\mathrm{v}_{1}=0$ with probability $\mathrm{p}_{1}=0.81$ and $\mathrm{v}_{2}=1.891$ with probability $\mathrm{p}_{2}=0.19$.

Table 4.4: Simulated transition probabilities

|  | WP $\rightarrow$ <br> WNP | $\begin{aligned} & \text { WP } \\ & \rightarrow \\ & \text { NWP } \end{aligned}$ | $\begin{aligned} & \text { WNP } \\ & \rightarrow \\ & \text { WP } \end{aligned}$ | $\begin{aligned} & \text { WNP } \\ & \rightarrow \\ & \text { NWNP } \end{aligned}$ | $\begin{aligned} & \text { NWP } \\ & \rightarrow \\ & \text { WP } \end{aligned}$ | $\begin{aligned} & \text { NWP } \\ & \rightarrow \\ & \text { NWNP } \end{aligned}$ | NWNP $\rightarrow$ <br> WNP | NWNP <br> $\rightarrow$ <br> NWP |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
| (1) | 0.036 | 0.013 | 0.029 | 0.006 | 0.184 | 0.011 | 0.072 | 0.038 |
| Child<4 =1 | 0.032 | 0.009 | 0.034 | 0.008 | 0.165 | 0.017 | 0.078 | 0.024 |
| Ch. bt $\mathrm{sp}=1$ | 0.600 | 0.011 | 0.027 | 0.005 | 0.119 | 0.071 | 0.061 | 0.031 |
| Unexp = 3 | 0.036 | 0.013 | 0.029 | 0.006 | 0.181 | 0.011 | 0.070 | 0.038 |
| $=12$ | 0.037 | 0.014 | 0.029 | 0.007 | 0.172 | 0.012 | 0.067 | 0.038 |
| $=48$ | 0.043 | 0.018 | 0.027 | 0.009 | 0.135 | 0.017 | 0.054 | 0.038 |
| Hwork $=0$ | 0.065 | 0.020 | 0.031 | 0.012 | 0.151 | 0.016 | 0.056 | 0.042 |
| Wpart $=0$ | 0.038 | 0.016 | 0.024 | 0.012 | 0.168 | 0.012 | 0.059 | 0.026 |
| GDP $=0$ | 0.037 | 0.014 | 0.031 | 0.006 | 0.182 | 0.011 | 0.068 | 0.050 |
| $=10$ | 0.035 | 0.012 | 0.028 | 0.006 | 0.185 | 0.011 | 0.076 | 0.029 |
| H. Age $=25$ | 0.033 | 0.012 | 0.029 | 0.006 | 0.212 | 0.008 | 0.085 | 0.038 |
| $=45$ | 0.043 | 0.016 | 0.030 | 0.007 | 0.125 | 0.019 | 0.052 | 0.037 |
| $=60$ | 0.051 | 0.021 | 0.031 | 0.008 | 0.070 | 0.034 | 0.034 | 0.035 |
| W.Age $=20$ | 0.051 | 0.009 | 0.023 | 0.003 | 0.158 | 0.012 | 0.081 | 0.039 |
| $=40$ | 0.022 | 0.020 | 0.038 | 0.012 | 0.211 | 0.009 | 0.062 | 0.037 |
| $=55$ | 0.009 | 0.040 | 0.059 | 0.042 | 0.227 | 0.006 | 0.046 | 0.036 |
| Cohort 1 | 0.053 | 0.004 | 0.013 | 0.002 | 0.122 | 0.018 | 0.069 | 0.010 |
| Cohort2 | 0.039 | 0.007 | 0.020 | 0.003 | 0.155 | 0.007 | 0.099 | 0.018 |
| Cohort4 | 0.022 | 0.017 | 0.033 | 0.018 | 0.141 | 0.017 | 0.067 | 0.031 |
| H. Ed0 | 0.025 | 0.015 | 0.027 | 0.008 | 0.166 | 0.013 | 0.049 | 0.044 |
| H. Ed 1 | 0.036 | 0.010 | 0.026 | 0.004 | 0.186 | 0.012 | 0.107 | 0.022 |
| W. Ed0 | 0.049 | 0.016 | 0.029 | 0.006 | 0.174 | 0.007 | 0.068 | 0.025 |
| W. Ed1 | 0.027 | 0.014 | 0.043 | 0.005 | 0.180 | 0.007 | 0.083 | 0.047 |

Note: first row (1) corresponds to the reference group: a couple with no children in which the husband was working and the wife was participating before marriage and medium level educated ( A or O levels). Husband's age is 32 and wife's age 29 (sample means). The wife belongs to the third cohort (she was born between 1951 and 1960) and GDP is set to $5 \%$. Previous unemployment experience for the husband is zero. Duration equals three months. Unobserved heterogeneity is integrated out. Edl reflects more than higher education and Ed0 less than higher education.

Second, it could also be reflecting the existence of a social stigma as mentioned above: unemployed men do not want to be supported by their wives. In this case the probability of NWP $\rightarrow$ NWNP should be higher than WP $\rightarrow$ WNP, unless a strong income
effect, associated with husbands' earnings, increases the latter probability and reduces the former. Data, in general terms, supports the existence of a strong income effect that is one of the implications of the added worker effect as explained in Section 4.2.1.

Children have a significant effect on most of the transition intensities. Especially important is the fact of having a child in the middle of the spell which increases, as expected, the wife probability of withdrawing from the labour market. This increase is very important, ranging between seven (for wives of unemployed men) and eighteen times (for wives of working men). Less significant is the negative effect on the probability of the wife entering the labour market and the husband leaving his job. Having a child reduces the probability of finding a job, whether the spouse is participating or not in the labour market, although not significantly.

The dummy for the presence of children younger than four years old in the household produces some mixed effects. It increases the probability for the wife going from participation to non participation and decreases the probability of the reverse when the husband is unemployed, as expected (Pudney and Thomas, 1992, find the same effect). However the opposite occurs, at a lower scale, when the husband is working. Combining that effect with the strong effect of having a child in the middle of the spell, that could be reflecting that these women are more attached to the labour market. They come back to participate as soon as they can after having a child.

About the effect of lagged unemployment experience (occurrence dependence), it reduces the probabilities of the husband going from a non working spell to a working one (human capital deterioration). It also lowers the probability that the wife participates on the labour market when she was not already participating (disincentive effect). Symmetrically, it increases the probabilities of the husband becoming unemployed and of the wife withdrawing from the labour market if she was participating. Some degree of complementarity between leisure for the couple ${ }^{19}$ or a strong disincentive effect could explain these increases. Short unemployment spells do not have a great impact but long

[^36]periods of not working (for example, 2 years) produce significant changes in the probabilities of $50 \%$ and even more in some cases, e.g., NWP $\rightarrow$ NWNP. The only transition for which there is no effect is NWNP $\rightarrow$ NWP.

Job status before marriage is also an important determinant for most of the transitions. In general, the effect of the husband being unemployed before marriage goes in the same direction that his previous unemployment experience, although this effect is greater. This is probably because it denotes the group of individuals less attached to the labour market. With respect to the effect of the wife not participating in the labour market before marriage, it prevents women for entering the labour market if they are out of it and increases their probabilities of exiting the labour market if they are participating, for any status their husbands are in. It also increases the probability of the husband giving up his job and decreases his probability of finding a job. Again the theory of complementarities between leisure seems quite possible for this group of households less attached to the labour market.

The effect of the business cycle variable, GDP, is quite small and not significant ${ }^{20}$. Bearing this in mind, it seems that in good economic conditions the husband is more likely to find a job if unemployed or to keep it if employed. Its effect on women's participation is that their probability of participating if they are not is lower in good economic conditions, which supports the existence of an added worker effect.

Husband's and wife's age ${ }^{21}$ are determinant factors for most of the transitions. The older the husband, given his wife's age, the most probable that she withdraws from the labour market. On the other hand, the older the wife, given her husband's age, the less likely is that she leaves the labour market if she is already participating. If she is not participating the effect is more imprecise. Regarding the husband transitions, the older he or his wife the more likely that he leaves his job. His probabilities of finding a new job also decrease with age. However, if his wife participates in the labour market and he is

[^37]unemployed, the older he becomes the higher the probability that he starts working. These effects are consistent with complementarities in leisure.

The cohort effect is one of the best defined. Cohort affects especially household transitions made by the wife. For younger cohorts the probability of a participating wife to go out of the labour force is lower. The probability of a non participating wife to start participating is higher for these cohorts than for older ones, whichever the job status of the husband is. This reflects the more recent incorporation of women to the labour market. The cohort effect is specially important for the NWNP $\rightarrow$ NWP transition.

Regarding education, more educated men are more likely to keep their job or to find one if unemployed. More educated women are more likely to continue participating or to participate if they were not, whichever the status of their spouses. Husband education increases the probability of WP $\rightarrow \mathrm{WNP}$. If educational dummies are proxies for wages, this reflects a pure income effect, as mentioned above. It also reduces quite significantly the probability of NWNP $\rightarrow$ NWP, maybe because for these men is easier to find a job. Women's education increases the probabilities of the husband finding a job and reduces the probability of him leaving his job. Again, that could be caused by the existence of a social stigma.

Duration effects can be better seen in Figures 4.6 to 4.9 due to the complex pattern that the model specification implies. These Figures simulate transition probabilities for the reference group and compare them as in the Kaplan-Meier estimates from previous section. Testing differences in the coefficients for the transition intensities in Table 4.3 for every pair of transitions considered below we strongly reject the null hypothesis of equality ${ }^{22}$

Figure 4.6 shows the transition probabilities from WP to WNP and from NWP to NWNP for the reference group. If the husband is unemployed, transition of his wife

[^38]towards non participation occurs quite early, during the three first months ${ }^{23}$. This is different from previous findings by Pudney and Thomas (1992) or Davies et al. (1992) that suggested a considerable time of adjustment. In their works they considered husband status exogenous, which could be generating some bias, and they deal with female employment that is slower to adjust than participation. More important is that wives of unemployed men are less likely to leave participation than wives of employed men as predicted for the model in Section 4.2.1. That holds for every demographic group considered in Table 4.4, although differences become smaller with age of the husband or the wife (possible complementarities).

Figure 4.7 compares transitions from wife's non participation to participation, conditional on her husband's job status. Movements in response of husband job status occur within the first months, at least for the case in which the husband is unemployed. Some caution must be taken with this simulation because the time effect is very imprecisely estimated ${ }^{24}$. If there is any added worker effect wives of unemployed men will tend to transit towards participation with higher probability than wives of employed men. Looking at the figure, we see that this is true only for short husband's unemployment spells. In addition, this effect only holds for some demographic groups as the younger cohorts, with wives highly attached to the labour market (wife participating before marriage), educated and young, without children and especially when economic conditions are adverse. Also, the less educated the husband the higher the difference between both transitions. This shows that only among the group of women that behave more like men in terms on labour market decisions an added worker effect can be found. In this case, maybe is not that accurate to consider women as secondary workers.

Figure 4.8 shows transitions from husband's unemployment to employment, given wife's participation status. The duration effect is quite small here but strongly significant,

[^39]reflecting that unemployment spells of the husband tend to be short. Transition to work if the wife is participating has always higher probability than if the wife is out of the labour market. The existence of a social stigma, insider information or complementarities on leisure, as mentioned above, would produce such an effect.

To conclude, in Figure 4.9, husband's probability of transition from working to non working given his wife status decline sharply with duration (coefficients in Table 4.3 are highly significant) reflecting an experience effect. The probability of giving up work when the wife is participating is higher than when she is out of the labour market, and that is true for all demographic groups but the older cohorts. The effect is probably due to a pure income effect. These probabilities never go completely to zero which shows that as tenure increases there is always a possibility of losing the job or retiring.

### 4.5 Conclusions

This Chapter proposes a dynamic model of household labour supply under uncertainty. The model is estimated with duration techniques to investigate the existence of an added worker effect for the British economy. The main difference with previous literature is that it endogenise husband employment decision instead of taking his job status as predetermined. Also duration, state and occurrence dependence are considered alongside with controls for observable and unobservable heterogeneity. A reduced form model is estimated for a subsample of married couples from the British Household Panel Survey, using semiparametric techniques as proposed by Heckman and Singer $(1982,1984)$. The added worker effect is restated in terms of changes in transition probabilities among labour force states when one family member becomes unemployed.

Considering a dynamic model that accounts for movements within years is important since usual figures of wives' participation rates given husband's job status do not account for short participation spells, that are of considerable importance. Results show that job status of the spouse has influence on the labour market decisions of each
individual, male or female. Therefore, allowing endogeneity of job status for both household members is important to avoid selectivity bias.

In this context, the added worker effect can be decomposed in two effects. On one side the probability of the wife withdrawing from the labour market should be lower if the husband is unemployed. On the other, the probability of the wife entering the labour market should be higher if her husband is unemployed. Results confirm clearly the existence of the first effect. However, the second effect is only present for some household types. Households with wives highly attached to the labour market (young, educated, in the labour force before marrying, without children), born after 1950 and with medium or low level educated husbands, present a small added worker effect when the husband's unemployment spell is relatively short. That would affect approximately $8 \%$ of the total number of spells considered in the study. The less attached to the labour market the husband is (the higher his probabilities of being not working), the stronger the effect. It also seems that the effect is higher in adverse economic conditions, as expected, though this is not well defined in the estimation.

Data is coherent with complementarities between the leisure of the couple. Existence of a social stigma affecting specially older cohorts will explain some of the results. Pudney and Thomas (1992) reach also this conclusion. The effect of such complementarities is to reduce the added worker effect size. That is why in aggregate terms the added worker effect dilutes. After controlling for observed and unobserved heterogeneity, previous results show that there is not clear causality between husband's unemployment and low participation rates for wives.

Results generalise some previous studies. For the UK, Davies et al. (1992) found that unemployment duration of the husband higher than one year, reduces significantly the probability of the wife being employed. That is consistent with our results although we also find a positive effect on the transition to participation if the unemployment spell of the husband is shorter than three months. Lundberg (1985), following a similar approach to ours, i. e. considering husband status endogenous, found also a small but significant added worker effect for white families.

Although a reduced form model is estimated, it is useful to highlight differences among households and to isolate groups for which there exists an added worker effect. A structural version of the model would be interesting to estimate. However the nature of the data does not allow for such complexity, due to the lack of information on wages, benefits or regional characteristics for every spell.

Figure 4.6: Transitions from P to NP by husband's job status


Figure 4.7: Transitions from NP to $P$, by husband's job status


Notes: First letter indicates husband status (W for working and NW for non working) and the second one wife status (P for participating and NP for nonparticipating )

Figure 4.8: Transitions from NW to W, by wife's job status


Figure 4.9: Transitions from W to NW, by wife's job status


Notes: First letter indicates husband status (W for working and NW for non working) and the second one wife status (P for participating and NP for nonparticipating )

### 4.6 Appendix A: Variable description

Most of the variables used in the estimation are measured at the beginning of the spell. Only the variable that measures the effect of having a child during the spell is allowed to change, by definition, during the spell.

Tenure: a flexible specification is chosen for this variable, measured in months. We include not only tenure and tenure squared, but also we allow for an spline at 3 months. The spline reflects changes in the couple's behaviour, especially of unemployed men's wives. The spline allows for a change in the shape of a quadratic, non monotonic, specification from the third month onwards. These variables are called in the analysis $\ln (t)$ and $\ln (t)^{2}$, for the $\log$ of tenure and the $\log$ squared respectively, and $\operatorname{Dn}(\mathbf{t})$ and $\mathbf{D} \ln (\mathbf{t})^{\mathbf{2}}$, for their corresponding spline at three months.
Children: after several possible specifications, two variables relating children were included. Child<4 is a dummy variable that indicates whether the youngest child in the household is younger than four years or not. Chl. bt. spells is a variable that indicates whether the wife was pregnant of more than 5 months or did have a child in the middle of one spell. This variable, by definition, varies during the spell for households in which a pregnancy or birth was produced.

GDP: this variable tries to measure to some extend the effect of the business cycle. It is measured at the beginning of the spell and it is actually the GDP rate of change between two consecutive years. Other variables, such as unemployment rate or number of vacancies, where also tried, although they do not appear in the final specification.

Education: two variables relating education are include for each member of the household. If they are preceded by H they correspond to the husband and to the wife if preceded by W. Ed1 is a dummy variable that takes value 1 if the individual has more than higher education and zero otherwise. Ed2 takes value 1 if the individual has A levels or O levels.

Age: age at the beginning of the spells is included for husband and wife of every household. The variables are measured in deviations from their means (that is 36 years for husbands and 33 for wives).

Cohort: three cohort variables were included in the estimation to take into account changes in women's behaviour in the last decades. Cohort1 (the omitted group) takes value 1 if the wife was born before 1941. Cohort2 takes value one for households in which the wife was born between 1941 and 1950. Cohort3 equals one for wives born between 1951 and 1960. Cohort4 would be one if the wife was born after 1961.

Previous Unemployment Experience: this is a cumulative variable that measures the number of months the husband has been unemployed since the couple married until the present spell. In the analysis it is called Unexp.

Job Status Before Marriage: to control to some extend initial conditions problem due to the job history of the household members before marriage, estimates are conditioned on husband and wife job status before marrying. Two dummy variables are included: Hwork that equals 1 if the husband was working in his employment spell just before marriage date and Wpart that equals 1 if the wife was participating before marrying. Duration of these spells was also tried as explanatory variable, but these two dummies seemed enough to control for this initial conditions problem.

Table 4.A.1: Relevant characteristics by spell


## Chapter 5

## Conclusions

This thesis has dealt with three relevant labour mobility topics, namely, restrictions in the number of hours of work (Chapter 2), self-employment decisions (Chapter 3) and household labour supply decisions (Chapter 3).

Chapter 2 uses a neoclassical framework to investigate the presence of hours constraints. In order to do that, the behaviour of individuals that stay in the same job for two consecutive periods is compared with the behaviour of individuals that change job. The traditional theory predicts no differences between both groups: all of them will be in their labour supply curve at every point in time. The results show that this assumption does not hold for a subsample of prime age males drawn from the NLSY. On the one side, the variance for the change of hours of work, after controlling for a set of personal characteristics, is greater for individuals that move than for individuals that stay in the same job. This suggests that individuals face some type of restriction on the number of hours they can work. A model accounting for employer preferences or influenced by job specific characteristics may be coherent with this finding.

On the other side, homoscedasticity among stayers and movers and exogeneity of job changes proved to be strong assumptions to maintain. A labour supply equation
under endogenous switching between jobs and controlling for heterogeneity is the preferred specification after several misspecification tests. The main result concerns the elasticity of substitution. Not considering hours constraints in estimation tends to upwards bias elasticities. The neoclassical labour supply approach seems to be misspecified for the constrained group of workers once the restrictions are included and endogeneity of the movements is allowed. The coefficient of wages may be reflecting agreements between the employee and the employer more than wage elasticities for the constrained group of workers. An interesting extension of this study would be to analyse the decision of dual job holding as a way of avoiding hours restrictions.

Chapter 3 analyses self-employment decisions for the UK using a subsample of males from the BHPS. Self-employment is defined as an alternative to paid work. A multiple state transition model with duration and state dependence controlling by unobserved heterogeneity is estimated. Reduced form transitions from unemployment and employment into self-employment are computed and compared avoiding the sample selection bias of previous studies. The model compounds the analysis of the effect of general economic conditions and individual unemployment experience.

Unobserved heterogeneity turns out to be an important factor in determining transitions among the states alongside with education, family background and general economic conditions. The mechanisms driving unemployed and employed individuals towards self-employment are somehow different. Among employees, more able individuals are more likely to start up a business if economic conditions are adverse. The pattern reverses for unemployed, being the less able the more likely to become selfemployed. However the longer an individual has been unemployed, the lower are his possibilities of switching towards self-employment due to a loss of human capital. This supports the theory of a deterioration of the labour market conditions as the factor behind the important rises in self-employment rates during the last decades.

By deterioration of the labour market we mean that individuals optimally would like to have a paid job, but because this is not possible they rather have to become selfemployed than to remain unemployed. This finding is consistent with on-the-job search
theories which predict that low wage earners (here proxied by education or unemployment experience) will have higher job acceptance probabilities and that high wage earners will wait a longer period of time to get a better job.

No attempt is made of investigating the effect on self-employment of liquidity constraints. New waves of the BHPS, in particular an additional questionnaire relating assets, could allow for estimation of a structural model incorporating those constraints.

Chapter 4 focus on the analysis of the added worker effect for the UK, using a subsample of married or cohabiting couples from the BHPS. A reduced form model consistent with life-cycle maximisation is proposed. The model considers job status of the husband and the wife as endogenous and allows for unobservable heterogeneity.

Household states can be constructed combining husband's and wife's states and trasitions from and to any of them are analysed. The added worker effect is identified by comparing the transitions towards participation of the wives by their husband's status and their transitions towards non participation also by their husband's status.

A small but significant added worker effect is found for a subgroup of households. Women strongly attached to the labour market whose husbands are medium or low educated respond to short unemployment spells of their husbands by participating in the labour market, especially in adverse economic conditions.

Strong complementarities between the leisure times of the husband and the wife and the existence of a social stigma for the older cohorts dilute the added worker effect on aggregate. This partially explains the reason why women married to unemployed men tend to participate less in the labour market.

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[^0]:    ${ }^{1}$ See Altonji and Paxson (1986, 1988, 1992), Biddle and Zarkin (1989), Ham (1982, 1986), Biddle (1988), Tummers and Woittiez (1991), Dickens and Lundberg (1993), Ball (1990), Kanh and Lang (1991) or Stewart and Swffield (1997) among others.

[^1]:    ${ }^{2}$ Layoffs are considered to be exogenous events.
    ${ }^{3}$ They use weighted two-stage least squares to correct for heteroscedasticity associated with the fact that the variance of the error component depends on whether or not the job changes. However it does not correct for the possible inconsistency of the parameter estimates.

[^2]:    ${ }^{4}$ All variables are individually indexed. For simplicity of the exposition the individual subscript is dropped.

[^3]:    ${ }^{5}$ Heckman and MaCurdy (1980) assumed additive separability of leisure and consumption in the direct utility function while Browning, Deaton and Irish (1985) relaxed this assumption.
    ${ }^{6}$ See Blundell and Walker (1986) for a detailed discussion of this type of demand functions.
    ${ }^{7}$ See Ham (1986) for similar a specification.

[^4]:    ${ }^{8}$ Altonji and Paxson (1986) follow this approach.

[^5]:    ${ }^{9}$ Here, again, the distinction between layoff movers and quitters may help: workers that experiment an exogenous layoff should have the same preferences than stayers. Therefore if differences are found also between these two groups they can not be just attributable to heterogeneity

[^6]:    ${ }^{10}$ See Arellano and Bond (1991).
    ${ }^{11}$ There can be other set of instruments more efficient. That is why (2.27) is efficient only conditional on the set of instruments used.

[^7]:    ${ }^{12}$ Hausman (1978).
    ${ }^{13}$ He follows White (1982) and MaCurdy and Mroz (1984).

[^8]:    ${ }^{14}$ See Brown and Light (1992) for detailed discussion.

[^9]:    ${ }^{15}$ See Section 2.3.1.

[^10]:    Note: see Section 2.4 and Appendix A for sample sizes and variable description.

[^11]:    ${ }^{16}$ See Appendix 2.B for detailed description of the instruments.
    ${ }^{17}$ The wage coefficient in this model represents in this context the intertemporal labour supply elasticity, that is, the elasticity with respect to the current wage holding constant wages in other periods.

[^12]:    ${ }^{18}$ Altonji and Paxson (1986) found the same result.
    ${ }^{19}$ With an incremental Sargan test, $\mathrm{S} 1=23.57$, distributed as a $\chi^{2}$ with 30 d.o.f., we can not reject the use of these additional instruments. This figure correspond to the specification that consider movements endogenous.

[^13]:    ${ }^{20}$ An exogeneity test for Stay ${ }_{1-1}$ was performed and gave a value of $\mathrm{W}=3.061$. The statistic is distributed as a $\chi^{2}$ with 31 d.o.f, and therefore the null hypothesis of exogeneity of the instrument could not be rejected.
    ${ }^{21}$ This is the opposite that Altonji and Paxson (1986) found. For the more clear measure of change in hours (based on a three year gap period), the coefficient for stayers is more or less of the same range than ours but it is not different for movers. For some other measures of the change in hours they found a negative coefficient for movers.
    ${ }^{22}$ A Wald test of $H_{0}: \alpha_{1}=0$, gave a value $\mathrm{W}=1.229$ distributed as a $\chi^{2}$ with a d.o.f.

[^14]:    ${ }^{23}$ See Biddle (1988).

[^15]:    Note: Standard errors in brackets.

[^16]:    ${ }^{1}$ See Evans and Jovanovic (1989), Holtz-Eakin et al. (1994a, 1994b) or Blanchflower and Oswald (1990) for an analysis of self-employment decisions under liquidity constraints. The first two papers refer to the American labour market while the third one relates the UK.

[^17]:    ${ }^{2}$ All these papers use the approach discussed above.
    ${ }^{3}$ Not many applications refer to transitions between labour market states including self-employment applications. Magnac and Robin (1991) estimate a reduced-form model of labour market transitions using discrete and tenure data for France. The aim of their paper is closely related to Chapter 3, with the difference that continuous records are available for the UK, which allows us to construct a more complex model.

[^18]:    Note: U denotes unemployment, E paid employment and SE self-employment.

[^19]:    ${ }^{4}$ Blundell et al. (1995) use a similar approach to analyse upwards and self-employment transitions.

[^20]:    ${ }^{5}$ For a step-by-step derivation of the likelihood function with and without unobserved heterogeneity, see Lancaster(1990)

[^21]:    ${ }^{6}$ The basic specification includes two support points. A possible interpretation for this model specification is to think of two individual types: high ability and low ability ones. Those support points can also represent aggregate shocks with different effects over the population.

[^22]:    ${ }^{7}$ The probability of having a successful enterprise is not the same if it was started in a good or bad period of the economic cycle.

[^23]:    ${ }^{8}$ Alternative specifications were tried, including splines for the square term and dummies for duration shorter than 6 months or greater than one year, but they seemed to fit worse the data.

[^24]:    ${ }^{9}$ A likelihood ration test of the joint hypothesis that all parameters related to heterogeneity are zero give us a value of 614 , distributed as $\chi^{2}$ with 10 d.o.f. The null hypothesis is clearly rejected.
    ${ }^{10}$ See Ress and Shah (1985) or Evans and Leighton (1989).

[^25]:    ${ }^{11}$ Flinn and Heckman (1982) point out that lagged spell values can be introduced as explanatory variables.

[^26]:    ${ }^{12}$ See Evans and Leighton(1989).

[^27]:    ${ }^{1}$ Lundberg (1985, 1988), Maloney (1987,1991), Shaw(1987), Blau et al.(1988) or Zimmer(1992), among others, gave empirical evidence in this respect.

[^28]:    ${ }^{2}$ See Cooke (1987), Giannelli and Micklewright (1995) or Pudney and Thomas (1992) for figures.
    ${ }^{3}$ Figures using cross-sectional data.
    ${ }^{4}$ Moylan et al. (1984).

[^29]:    ${ }^{5}$ In this respect Maloney (1991) points out that "personnel psychologists have found that the correlation in cognitive ability between spouses ( 0.9 ) is higher than the correlation between siblings, and between parents and their offspring".
    ${ }^{6}$ If the added worker effect is bigger and all these added workers have more problems to find a job (as Lundberg, 1985, suggests), the published unemployment rates during a recession will become swollen by these individuals that otherwise would not be in the labour force.
    ${ }^{7}$ See Lundberg (1988), Segura (1996) or Pudney and Thomas (1992) for empirical evidence on leisure time complementarity, for USA, Spain and the UK, respectively.

[^30]:    ${ }^{8}$ Barrere-Maurisson et al. (1985) discuss that hypothesis using French data.
    ${ }^{9}$ See Chapter 3.

[^31]:    ${ }^{10}$ Occurrence dependence exists when the transition probabilities depend upon previous entries to state 1 ; lagged duration dependence when they depend on the lengths of previous visits to state 1 or to other states.
    ${ }^{11}$ Incomplete spells are those that have not finish at the interview date. They are therefore right censored.

[^32]:    ${ }^{12}$ Marriage formation and disruption is not studied here and is consider as exogenous to the labour market decisions.
    ${ }^{13}$ Out of the labour force spells for husbands are considered as non working spells. Less than $4 \%$ of husbands where in that situation for the selected sample and for most of them it was a temporary situation, being therefore indistinguishable from unemployment spells.

[^33]:    ${ }^{14}$ These transitions could be modelled as the product of two of the valid ones, although it complicates even more the estimation: $P(W P$ to $N W N P)=P(W P$ to WNP) $P(W N P$ to NWNP). However, given the reduced number of observations on those cells, this decomposition is not used in the empirical implementation.
    ${ }^{15}$ Given the small sample size for some of the transitions, results are not always well defined and have to be taken with some caution. New Waves of the BHPS will help to overcome this problem.

[^34]:    ${ }^{16}$ These figures do not weight for the duration of the spells.

[^35]:    ${ }^{17}$ A likelihood ratio test for testing the null hypothesis of no effect of unobservable heterogeneity gives an statistic of 842.14 distributed as a $\chi^{2}$ with 14 d.o.f.
    ${ }^{18}$ Simulations are calculated by integrating over the estimated heterogeneity distribution.

[^36]:    ${ }^{19}$ Pudney and Thomas (1992) support that theory in their paper.

[^37]:    ${ }^{20}$ A problem with this variable can be that is measured at the beginning of the spell and therefore is not measuring correctly the business cycle effect.
    ${ }^{21}$ Given age at the beginning of the spell, duration reflects both age and duration in the state. Therefore, the presence of quadratic terms in age does not seem necessary.

[^38]:    ${ }^{22}$ Testing transitions in Figure 4.6 a Wald test of $W=67.58$ is obtained. For transitions in Figure 4.7, $W=436.09$. For transitions in Figure 4.8, $\mathrm{W}=56.76$. For transitions in Figure $4.8 \mathrm{~W}=50.20$. All of them are distributed as $\chi^{2} \mathrm{~s}$ with 20 d.o.f.

[^39]:    ${ }^{23}$ Testing the significance of the duration spline for the transition from NWP to NWNP a Wald statistic of 2.25 distributed as a $\chi^{2}$ with 2 d.o.f. and the null hypothesis can not be rejected. However, testing the significance of the $\log$ of the duration and its square we get $\mathrm{W}=4.76$ with the same distribution: the null hypothesis of no effect of these duration variables can be rejected at $10 \%$ but not at $5 \%$ significance level.
    ${ }^{24}$ That is probably due to the small size of the sample used in estimation that makes a transition from NWNP to NWP. Additional Waves of the BHPS will help to overcome this problem.

