The Dynamics of Household Membership and Labour Supply Decisions of Young Adults in Britain: A Panel Data Approach*

Sarkis Manoukian
Institute for Social and Economic Research, University of Essex.

This Draft: February, 2010

Abstract

This paper examines the determinants of the decision to leave home and the decision to work of young adults in Britain. These behavioural outcomes are jointly modelled using a bivariate dynamic setting that accounts for unobserved heterogeneity estimated on the first fifteen waves of the British Household Panel Survey. We augment previous research by examining the effect of current parental labour supply which could affect young adults' decisions through time spent in the household rather than income. Results show that, for men, parental labour supply rather than current parental income affects the two decisions. Strong gender differences emerge from this analysis where unobserved factors seem more important for women and men tend to be affected by parental characteristics more. Furthermore a model with age interactions shows ageing changes the process more for men than women. On methodological grounds, this paper shows that the two decisions are highly correlated and should therefore be studied jointly but separately for men and women.

JEL Classification: D10; J22;C15;C33

Keywords: Household formation; leaving home; labour supply; BHPS; panel data; bivariate dynamic random effects probit.

---

* I thank Dr Mark Bryan (ISER) for his comments and Prof. Shigeki Kano (Osaka University) for providing the maximisation code for the model used in this paper.

1. Introduction

The study of household formation[1] in microeconomics offers various insights about important choices in early adult life. Two of these are probably the most important decisions a young adult must undertake, the choice of living arrangements and the choice to enter the labour market for the first time. In this chapter we show that these two decisions are related and one should be examined in the presence of the other. Intuitively this seems plausible since normally deciding to exit the parental home would involve costs that can be met by paid employment. On the other hand, deciding to have a career in the labour market may necessitate moving to a location other than the parental one. It is difficult to distinguish between the two cases but in this work we employ a model that takes into account the simultaneity of the two choices.

In general there has been limited success in explaining the underlying causes behind the change in household formation dynamics observed in the last decade in the UK. There are many research questions that remained unanswered in the literature and some of them involve the interaction of the housing market with household formation; it is ironic that Borsch-Supan (1986) had similar research aims more than twenty years ago, he wonders if the "current" rise in house prices negatively affects household formation and also if adult offspring stay with the parents longer when the cost of housing rises. The same research question was addressed by others as well (e.g. Ermisch, 1999). Another important issue that has remained unresolved is the way household formation interacts with the labour market and labour supply decisions taken by young adults. McElroy (1985), in a pioneering paper, attempted to test

[1] In this chapter the terms household formation, leaving home or household membership decisions are used interchangeably.

empirically a theoretical model that incorporated the decision of young white males to leave the parental home along with their decision to find work in the labour market. One of the aims of this study is to combine the above two different research questions into one study by allowing for unobserved heterogeneity between individuals, dynamics and parental characteristics.

The importance of young adults' household formation decisions should not be underestimated since it affects future housing demand, saving and equity accumulation patterns and even population growth. Similarly the decision to enter the labour market affects employment levels and future productivity in the economy. In this work it is assumed that the decision to leave the parental home and the decision to look for a job or not is jointly determined by the economic agents. This assumption is based on the fact that major labour market institutional differences across countries are reflected in the decisions of young adults to stay with their parents for longer (Fogli, 2004). Southern European countries with high employment protection laws and lower employment levels across young people show increased percentages of young adult staying longer with their parents. On the other hand, Anglo-Saxon countries, as the least regulated countries and according to some with lower unemployment levels for young adults due to the liberalised labour market, have much lower coresidence percentages of young adults with their parents (Fogli, 2004).

This suggests that there must be at least some connection between the labour market and the residence decision for a young adult. This relationship between poor labour market conditions and a large percentage of "late leavers" is mostly an issue of Southern European countries since the UK enjoyed favourable economic conditions and relatively low unemployment rates among young people in the decade leading to 2008. Studying the determinants of this process will allow an improved understanding during today's unfavourable conditions with falling employment levels among the youth and diminishing economic activity (The Economist, 2009).

The determinants of household formation in the UK can also prove to be useful in any policy decisions aiming at young adults entering the labour market or looking into leaving the parental home to get onto the property ladder. McElroy's (1985) seminal paper main find is that families act as unemployment insurance for the young person still residing at home. This is a plausible scenario but possibly not the whole truth since in many countries the data show that many young adults still at home have a job. In Spain according to Granado-Castillo (2002) this number reaches 50% and in the UK this number reaches more than 80%[2]. This suggests there must be an extra dimension in the role the family home plays for young adults in the UK, also that the labour market plays an important role but also other factors must be at work in determining whether a young person will coreside with parents or not.

Ermisch (1999) considered the housing market as an important determinant of household formation in the UK along with personal incomes. House prices were found to have a negative effect on the probability of living apart and incomes a positive effect. The inclusion of housing prices may seem odd since children wishing to live alone would not necessarily look into becoming homeowners right away. However, anyone hoping to live alone will have to incur some housing costs and house prices are a good proxy for this expenditure. In this paper the same view is upheld with the adjustment of explicitly endogenising labour supply decisions. Ermisch did not look into labour supply decisions and young adult incomes, even though a central theme of his paper, were taken as exogenously given. According to his findings both parental income and personal income are major determinants in

[2] Source: Author's dataset created from the BHPS

household formation in the UK. Here we can only confirm the importance of house prices but not parental incomes as mentioned earlier.

As far as parental incomes or parental labour status is concerned, a common finding in McElroy (1985), Granado-Castillo (2002) and Diaz and Guillo (2005) is that the mother's labour status seems to matter more than the father's. This could be because children raised in families in which the mother is employed show greater labour market attachment, at least in Spain (Anh and Ugidos, 1996: Sanches & Prat, 1996). Also separately to the maternal effect, children who start working early have greater opportunities to leave the parental home than their unemployed peers. There seem to be no previous studies that analyse the above using UK data, even though similar behaviour has been recognised in the US. In this paper the effect of the mother's employment status will be tested on the probability of living apart and working for a young adult along with housing and general labour market effects mentioned earlier.

Another common issue in the various theoretical models about household formation is the public good aspect of housing. Theoretical models in the literature usually depict the decision to leave the parental home as a game between parents and children. When labour supply decisions are included (McElroy, 1985; Diaz and Guillo, 2005) the young adult (when coresiding) has the option of working or staying at home to enjoy housing consumption determined by the parents. In McElroy the reservation wage decreases with the mother's wage among other things[3]. Diaz and Guillo (2005) extend McElroy's model by including production of a public good[4] when the mother is not working that the child can consume by staying at home. According to this view the incentive to look for a job is related to the labour status of

[3] The same is true for the indirect utility function when coresiding.
[4] The mother produces the public good when not working and this is called consumption of housing in Ermisch 1999.

the mother but this relationship is not straightforward. If the mother is employed there is less of the home public good to be consumed so the child might decide to leave the parental home. On the other hand, there is more family income which could lead the child to stay, since in their model the effort to look for a job depends on the other family members' labour status too.

The determinants of young adults' household membership choices along with their labour supply decisions will be investigated in the present thesis. A summary of the most important published work in the last twenty years or so follows in the next section. Then the theory behind household formation is explained in more detail followed by the description of the econometric model followed by the empirical results.

2. Literature Review

One of the oldest and most frequently cited papers in the literature of household formation was published by McElroy in 1985. The aim of this paper was twofold, one to show that the option of living in the parental household as an adult youth serves as unemployment insurance and second, to illustrate the general characteristics of the empirically observable differences between bargained and individual decision making (McElroy, 1985). The author acknowledges that a dynamic approach would be more suitable if technology allowed estimating a theoretically based maximising model of jointly determined decisions (McElroy, 1985).

A cross-sectional empirical approach is used by McElroy to test the assumption that the parental household should act as insurance in the case of utility loss by a labour market setback. The sample included only observations on families with white, never married, out-of-school sons in the age range of 19–24. Parental income and assets were included in the explanatory variables in both cases of living with parents or not. Students were dropped from the analysis and observations of youth living independently and not working were also excluded. The results confirm the hypothesis family provides unemployment insurance as a minimal utility level in the face of poor market opportunities (McElroy, 1985). This means a young man could be supported by his family when unemployed and it is a first indication that the decision to stay at the parental home is linked with his labour market attachment.

Another paper to examine the transition from a framework in which there is a individual budget constraint to one where there is an family budget constraint, as the authors themselves point out, was published in 1993 by Rosenzweig and Wolpin. The main focus of the paper is intergenerational support in families and how families pool resources. In the term intergenerational support the authors include monetary transfers, human capital investments and coresidence decisions. They argue the individual in many cases faces not an individual budget constraint depending on just his/her own earnings when not living with his/her family but consists of a set of rules determining how his/her family pools resources even in cases when they live apart (Rosenzweig & Wolpin, 1993).

In the results the father's income has opposite effects on coresidence in the two methods used. With the simple logit it has a positive and significant effect, while when employing fixed-effects this effect becomes negative and significant. Since the fixed-effects approach eradicates unobserved time persistent effects the estimates are consistent where in the simple logit they are not. This indicates that privacy is a normal good for fathers who would help their children move out using financial transfers (Rosenzweig & Wolpin, 1993). In general parental support is viewed as a consumption smoothing helping tool either as a monetary transfer or in the form of shared residence. Future anticipated earnings of the offspring determine the decision of the parents to support their children, low future earnings increase the likelihood of transfers when living apart and support may take the form of coresidence if current earnings are low as well. In contrast, current human capital investments increase future earnings and lower the likelihood of current transfers; in this case support most commonly takes the form of coresidence.

Ermisch (1999) tests an economic theory of the decision of young adults to leave their parental home, he introduces house prices as a major influence in this decision, in contrast to the above papers where housing costs are ignored altogether. Ermisch argues that personal incomes of the parents and the child should be included in any empirical model, as well as some measure of the cost of housing. His theoretical model predicts that parental income should have a negative effect on the decision to live apart while the child's income should have the opposite effect. In addition higher parental income and lower child income increases the probability that financial transfers are given in either state. If financial transfers are only made when living apart higher parental income increases the chances of coresidence since financial assistance to the child is made cheaper by the public good aspect of housing. In other words a pound transferred when coresiding would cost to the parents less than a pound. When parents do not make financial transfers, higher parental income increases the chance of coresidence because it increases the amount of total housing consumption relative to when living apart; the opposite it true in the case the child has higher income than the parents.

In the above static framework, young adults compare utilities in the two states to decide their living arrangements. However, Ermisch argues that a dynamic application of the theoretical model is more desirable because estimates based on "static" states reflect the combined impacts on both inflows and outflows from a particular living arrangement. By using the first five waves of the BHPS along with government data for the price of housing in the UK Ermisch estimates two specifications, one static and one dynamic.

The dependent variable employed in the dynamic case is a dummy that takes the value one if the individual is observed to live with parents at year t-1 and is observed to live apart in year t and otherwise zero. The coefficients of the probit regression show that tighter housing markets significantly retard home leaving and particularly discourage the formation of partnerships. Other key results show that an unemployment spell increases the chances of young people leaving the parental home, a striking result that shows the importance of understanding the effect of the labour market on household formation. Ermisch regards this result as consistent with the theory that unemployed young people will move elsewhere to find a job. Incomes of parents and children have the opposite effect on household formation with parental income having a negative effect as has the presence of both parents in the household.

Borsch-Supan (1986) used a cross-sectional approach to test the effect of housing costs on household formation. As a housing cost this author includes rent costs and other costs that apply to homeowners as opposed to Ermisch's approach which included only housing prices that mainly affect the decision to purchase or not. In addition Borsch-Supan's model evaluates the effects a housing voucher program employed in the USA. One interesting result in this paper is the fact that young adults take into account out of pocket costs (including maintenance costs, bills, taxes etc) when deciding their living arrangements, more than any expected asset returns when they become homeowners. That would mean that a bullish housing market would do more to deter new entrants even though expected returns from investing would be high. This behaviour may seem irrational according to some economic models. In general this paper established household formation as an important mechanism that affects but is also affected by the housing market and challenged the traditional view that household formation is exogenous. Its main drawback is the cross-sectional approach that does not allow for any analysis of second round market effects as the author himself admits.

Haurin et al (1997) investigated the relationship of household formation with marriage and childbearing decisions and how these decisions are affected by the cost of living independently. Their hypothesis was that marriage and childbearing are endogenous decisions taken together with the decision to live independently from the parental home, and that the ability to pay the cost of independent living should influence these decisions. They tested the above using Australian data and a multiequation approach to account for the various endogenous choices faced by individuals.

The authors investigate the effect of the cost of living on the decision to leave the parental home and the decision to live alone, married or with a group of unrelated adults. In order to estimate the cost of living they use data on real rental prices for houses in major metropolitan areas of Australia assuming that most young adults rent rather than buy a house when they leave the parental nest. It is interesting to note that they do not find a significant effect of rental costs on the probability of residing outside the parental household but find a significant effect on the decision to live independently or with a group of unrelated adults. This effect is negative which means higher housing costs make living alone less probable. In addition to the housing cost marriage or partnership significantly increases the chances to live alone as opposed with unrelated adults.

In a cross-sectional study about the decisions of Spanish young adults Granado and Castillo (2002) use a simultaneous equations model to analyse the decision to form a new household, work and the decision to continue studying. The authors believe that the young decide simultaneously the above decisions and they test the endogeneity and simultaneity of the three decisions. Their main results include that parents in Spain support their children through coresidence when they are studying or unemployed, living alone increases the chances for the child to be employed, living in a big city as opposed to a small town increases the propensity to form a new household for the young adult, finally unemployment has a direct negative effect on both propensities to study and work. The above papers provided the motivation for this work, a theoretical discussion of factors influencing these decisions follows in the next section.

3. Theoretical Discussion

A simple theoretical framework can be developed by making some basic assumptions about young adults' decision process. This can be done in the spirit of McElroy (1981) and Ermisch (1999). The first assumption is that the child will decide about his/her living arrangements by comparing utility of living alone or with parents. The second assumption is that the decision to work is simultaneously determined with the decision to leave the parental home and the two decisions are determined by observable parental and personal characteristics and other unobservables such as a taste for independence. Parental characteristics include total parental income and parental labour supply, among other things. Privacy costs are not observed but assumed to rise with age and education both observable in the data used.

As mentioned earlier in most theoretical models in the literature the parents have an active role in the children's decision to leave the parental home. Usually by providing transfers, they can influence this decision according to their own preferences for cohabitation. This is especially true of the literature covering southern European countries where intergenerational financial transfers and high cohabitation rates are very common (e.g. Manacorda & Moretti, 2006; Becker et al, 2005). According to Guiliano (2006) the above difference is attributed to a varying level of family ties between Northern and Southern Europe. This is a cultural difference and her claim is supported by empirical data. In Alesina and Guiliano (2007) the Northern type of family is strongly associated with high levels of trust and more acceptance of changes or new ideas.

What is of interest here is that Guilliano describes Northern families including UK ones as a weak family type, "a family characterized by people who are not reliant on their children in old age and by youth who detach themselves from their parents at a relatively early age" Guiliano (2006). This is the main reason parents have a passive role in the theoretical model below and the same assumption is being made in the empirical part of this paper as well. The young adults' decision process is a function of parental characteristics but the parents in UK are assumed to have minimal interference in their children's decision to cohabitate and work. This removes the need for the parental indirect utility to be specified separately.

The above imply the young adult will be presented with the following four choices: (1) Living in the parental home and not working, (2) living in the parental home and working, (3) living alone and working, (4) living alone and not working. Each of these four different states V_i, i =1,..,4, give to the youth some indirect utility that is given here by the following linear equations:

(1) $V_1 = X\beta_1^1 - Z\beta_2^1 - \varepsilon_w + \varepsilon_h$

(2) $V_2 = X\beta_1^1 + Z\beta_2^2 + \varepsilon_w + \varepsilon_h$

(3) $V_3 = -X\beta_2^1 - Z\beta_2^2 + \varepsilon_w - \varepsilon_h$

(4) $V_4 = -X\beta_2^1 - Z\beta_2^1 - \varepsilon_w - \varepsilon_h$

Here X denotes personal and parental characteristics that affect the utility derived from the housing membership decision; Z indicates personal and parental characteristics that affect utility from working. We assume utility is "additive" from the two decisions which means you get some utility from leaving at home and in addition some from your labour market status. Furthermore, Z and X[5] could overlap and may include information on parental earnings, personal income, parental income, parental labour market status, personal characteristics such as age and education, the

[5] Z and X are merged into x in the next section.

price of housing and labour market conditions. The βs[6] reflect the effect of these characteristics on the utility attained when occupying one of the four states. It is clear that in equations (1) and (2) β_1^1 corresponds to the utility obtained by staying in the parental home, we therefore restrict this coefficient to be the same in the two equations. What changes between (1) and (2) is the decision to work. Total utility is different between the two states but we assume that the "partial" utility obtained by staying at the parental home is the same irrespective of the other decision. The same reasoning applies to the utility gained when being employed. The ε_h and ε_w, represent among other things, tastes for privacy and spending time at work. In this way the individual will choose the state that offers the highest indirect utility in a similar manner to Ermisch (1999) and McElroy (1985). For example the child will decide to live at home and be unemployed if the following three conditions are satisfied: $V_1 > V_2$ and $V_1 > V_3$ and $V_1 > V_4$ which amount to:

- $V_1 > V_2 \Rightarrow Z(-\beta_2^2 - \beta_2^1) - 2\varepsilon_w > 0$
- $V_1 > V_3 \Rightarrow X(\beta_1^1 + \beta_2^1) + Z(-\beta_2^2 - \beta_2^1) - 2(\varepsilon_w - \varepsilon_h) > 0$
- $V_1 > V_4 \Rightarrow X(\beta_1^1 - \beta_2^1) - 2\varepsilon_h > 0$

It is clear that if the first and third conditions are satisfied then the second must be satisfied too. Thus, the choice to stay with the parents and not work can be simplified into the following:

$\varepsilon'_w < -Z\beta_2$

$\varepsilon'_h > X\beta_1$

Where:

$\varepsilon'_w = 2\varepsilon_w \qquad \beta_2 = \beta_2^1 + \beta_2^2$

[6] Please note that these βs are not the same as in the next section econometric models. Please see the relationship between them in the derivation of the econometric model below.

$\varepsilon'_h = 2\varepsilon_h \qquad \beta_1 = -\beta_1^1 - \beta_1^2$

Similarly the young adult will decide to live with his parents and work if:

- $V_2 > V_1 \Rightarrow Z(\beta_2^2 + \beta_2^1) + 2\varepsilon_w > 0$
- $V_2 > V_3 \Rightarrow X(\beta_1^1 + \beta_2^1) + 2\varepsilon_h > 0$
- $V_1 > V_4 \Rightarrow X(\beta_1^1 + \beta_2^1) + Z(\beta_2^2 + \beta_2^1) + 2(\varepsilon_w + \varepsilon_h) > 0$

This can be written as:

$\varepsilon'_w > -Z\beta_2$

$\varepsilon'_h > X\beta_1$

The child will leave the parental home and work if:

- $V_3 > V_1 \Rightarrow X(-\beta_1^1 - \beta_2^1) + Z(\beta_2^2 + \beta_2^1) + 2(-\varepsilon_w + \varepsilon_h) > 0$
- $V_3 > V_2 \Rightarrow X(-\beta_1^1 - \beta_2^1) - 2\varepsilon_h > 0$
- $V_3 > V_4 \Rightarrow Z(\beta_2^2 + \beta_2^1) + 2\varepsilon_w > 0$

This can be written as:

$\varepsilon'_w > -Z\beta_2$

$\varepsilon'_h < X\beta_1$

Finally the child will leave the parental home and not work if:

- $V_4 > V_1 \Rightarrow X(-\beta_1^1 - \beta_2^1) - 2\varepsilon_h > 0$
- $V_4 > V_2 \Rightarrow X(-\beta_1^1 - \beta_2^1) + Z(-\beta_2^2 - \beta_2^1) + 2(-\varepsilon_w - \varepsilon_h) > 0$
- $V_4 > V_3 \Rightarrow Z(-\beta_2^2 - \beta_2^1) - 2\varepsilon_w > 0$

This can be written as:

$\varepsilon'_w < -Z\beta_2$

$\varepsilon'_h < X\beta_1$

This set of conditions suggests that the model can be estimate in bivariate choice framework. If we assume that ε'_w and ε'_h are normally distributed with a normalised variance to 1, conditions (1) to (4) are those implied by a bivariate probit:

$$y_w^* = Z\beta_2 + \varepsilon_w^{'}$$
$$y_h^* = X\beta_1 + \varepsilon_h^{'}$$

where: $$\begin{cases} y_w = 1 \;\; if \;\; y_w^* > 0 \\ y_h = 1 \;\; if \;\; y_h^* > 0 \end{cases}$$

These decisions are assumed to be influenced by the same characteristics but clearly the mechanics would be different for each decision resulting in varying magnitudes. The above equations can be altered to take into account dynamics by adding last year's state in the indirect utilities.

The decision to work could be modelled more extensively as a job search effort with a probabilistic distribution of the chances of getting a job. Even though this would make the theoretical analysis more realistic this is not the main focus of this paper. Furthermore, in the period analysed the UK enjoyed historically very low unemployment levels and for this reason it is being assumed that the young adults can enter the labour market if they wish and this should be a function of their personal and family characteristics. This argument is not to say that being a youth in London is the same as being one in the North East or Glasgow in respect to labour market opportunities. There would be local differences of course and to control for possible effects of local labour markets, we include the local unemployment rate in *Z*.

In the next section the econometric methods used will be presented and analysed. The stylized theoretical model will form the basis of the econometric models considered next.

4. Econometric Models

Following the theoretical model of the previous section the young adults are assumed to jointly determine whether to leave to parental home and whether to enter into the labour market. This process is modelled in a bivariate discrete-choice framework. We estimate two models. The first is a reduced form static model intended to highlight the main correlates of leaving the parental home and getting a job. The second[7] is a dynamic model which allows current residential and work status to depend on their previous status (state dependence). In addition it allows for the examination of the interaction of the two decisions (cross-state dependence). Both models allow correlation of unobservable factors affecting the two decisions. In what follows we describe the very basics of the first simple static model and go on to more detail on the second structural model.

The two binary dependent variables y_j for choice j (j=1,2) are modelled in terms of continuous latent variables y_j^* as given in the following equations:

$$y_{1it}^* = \mathbf{x}_{1it}\beta_1 + \varepsilon_{1it} \quad (5) \qquad corr(\varepsilon_{1it}, \varepsilon_{2it}) = \rho$$
$$y_{2it}^* = \mathbf{x}_{2it}\beta_2 + \varepsilon_{2it} \quad (6)$$

$$y_{jit} = \begin{cases} 1 & if\ y_{jit}^* > 0 \\ 0 & otherwise\ , \end{cases} \qquad j = 1,2;\ i = 1,\ldots N;\ t = 1,\ldots T.$$

The dependent variables indicate being at a specific state, y_{1t} = 1 if the young adult is living without any of his/her parents, y_{1t} = 0 otherwise; y_{2t} = 1 if the young adult is employed, y_{2t} =0 otherwise. The vector **x** includes observed explanatory variables such as personal and parental characteristics, which are the same in the two equations with the exception that house prices and regional unemployment data are

[7] It is second only in terms of presentation in this section. It is actually the main model of this chapter.

only included in equation (5) and (6) respectively. The reason for this is that house prices generally affect leaving home decisions where the unemployment rate should help to control for labour market conditions which affect somewhat the labour supply decision. The bivariate probit model does not necessitate the use of indentifying restrictions (Greene, 2008) so house prices and the unemployment rate do not act as indentifying parameters here.

The vectors β_1 and β_2 are parameters to be estimated, and show how characteristics such as income are related to living away from home and working. The parameter ρ captures the correlation of the remaining unobserved influences ε_{jit} on the two decisions such as taste for independence, after controlling for observed factors. This is a static setting which does not fully exploit the panel dimension. However, the results of this model could be an initial indication of a correlation between the two decisions. They will also be used as a benchmark or comparison with the results of the dynamic bivariate discrete-choice model shown next. The main variables of interest are parental and personal characteristics and their effects on the decisions of male and female young adults.

The second model is a bivariate dynamic probit model with unobserved heterogeneity, adapted from Alessie et al (2004) and Stewart (2007). This is the main model of this chapter and it explicitly accounts for the effect of being at a specific state in year t-1, namely state dependence, as well as the dependence of each decision on the previous outcome of the other decision, cross-state dependence. This model extends the original dynamic probit with unobserved heterogeneity proposed by Heckman (1981). Heckman's model is univariate so in effect what is the main difference here is that we add a second equation. The rest of the main features explained below remain basically the same. Heckman proposed a model that would take into account the lagged state of the dependent variable and the heterogeneity between individuals that cannot be observed in the data. As mentioned above state dependence can be defined as a behavioural change due to experiencing an event in the past. This behavioural change will be due to the event itself and not due to some unobserved preference. For example two identical individuals, different only in the sense that one experienced an event and the other not, would act differently in the future. Or two individuals that experienced the same event would act differently because there are unobserved differences between them like ability or preferences[8].

A good example also relevant to this work is given in Heckman's (1981) original work. In research concerning dynamics of women's labour supply state dependence would mean that by being employed the previous year a woman would probably see her wages increase due to work experience and this would reinforce her labour supply. This is in contrast to assuming that exit and entry into the labour market is random. On the other hand this state dependence would be overstated if unobserved heterogeneity between women was not properly modelled. This is why it is important to take into account unobserved permanent factors when analysing dynamics. Here we employ a similar model with dynamics with the addition of a second equation and the resulting cross dynamics between the two discrete choices of interest. The econometric model can be written as:

$$y_{1it}^{*} = \mathbf{x}_{1it}\beta_1 + y_{1it-1}\gamma_{11} + y_{2it-1}\gamma_{12} + \alpha_{1i} + u_{1it} \quad (7)$$
$$y_{2it}^{*} = \mathbf{x}_{2it}\beta_2 + y_{1it-1}\gamma_{21} + y_{2it-1}\gamma_{22} + \alpha_{2i} + u_{2it} \quad (8)$$

$$y_{jit} = \begin{cases} 1 & if\ y_{jit}^{*} > 0 \\ 0 & otherwise\ , \end{cases} \qquad j = 1,2;\ i = 1,...N;\ t = 1,...T.$$

The y_{jit} are the same as in the static model above, X_{jit} are Kx1 matrices of observed characteristics, α_{ji} represent time invariant individual random effects

[8] This is linked to the concept of spurious state dependence, please see below for an explanation.

(unobserved heterogeneity). These capture personal characteristics or traits that stay constant over time, like individual ability. The error term ε_{jit} for equations (7) and (8) has the following random effects structure:

$\varepsilon_{jit} = \alpha_{ji} + u_{jit},\ j = 1,2$ (9)

We assume here that, conditional on the observed regressors, ε_{jit} is bivariate normal with zero mean and covariance matrix:

$$\begin{bmatrix} \varepsilon_{1it} \\ \varepsilon_{2it} \end{bmatrix} = Normal\left(0_2, \begin{bmatrix} 1+\sigma_\alpha^2 & \sigma_{\alpha1}\sigma_{\alpha2}\rho_a + \rho_\varepsilon \\ \sigma_{\alpha1}\sigma_{\alpha2}\rho_a + \rho_\varepsilon & 1+\sigma_\alpha^2 \end{bmatrix}\right), \qquad t = 0,1,\ldots,T$$

with $Cov(\varepsilon_{jit}, \varepsilon_{jis}) = E(\varepsilon_{jit}\varepsilon_{jis}) = \sigma_{\alpha j}^2 \big/ (1+\sigma_{\alpha j}^2), t \neq s,\ j = 1,2.$

The covariance of the random effects is given by $\sigma_{\alpha1}\sigma_{\alpha2}\rho_a$ where σ_α denotes the standard deviation of the random effect for the two equations respectively. The time variant stochastic elements u_{jit} have $E[u_{1it}, u_{2it}] = \rho_\varepsilon$ and their variance is normalised to unity with the intention of identifying the time invariant parameters (Kano, 2008). Finally, as it can be seen both lagged dependent variables cross-appear in equations (7)-(8) and this is what makes this model more interesting. The coefficients of interest are γ_{12} and γ_{22}; γ_{12} would reveal if being employed in year t-1 would affect the state occupancy in respect to household membership in year t and vice versa for γ_{22}. According to Allesie if $\gamma_{12} = 0$ then the bivariate format is not necessary since equation (7) can be estimated on its own using the standard univariate probit with state dependence. Similarly, if $\gamma_{21} = 0$ equation (8) can be estimated as a univariate model. If y_{2it-1} enters the first equation, i.e. $\gamma_{12} \neq 0$, but the random effects and the stochastic elements are independent between the two equations (ρ_ε=0, ρ_α=0) then the univariate model can be used with y_{2it-1} as a weakly exogenous regressor (Alessie, 2004). The nature of the two dependent variables (household membership, having a job) is such that we would expect some form of state dependence. The main question is the magnitude of γ_{12}, γ_{21}.

By using the Alessie model we can distinguish between true state dependence and spurious state dependence. True state dependence can be defined as persisting in a particular state; in our case could be living with the parents, because of some observable reason such as the cost of moving out. Spurious state dependence is when there is persistence due to some unobservable reason, for example staying at the parental home because of a private taste for cohabitating with the parents. If the individual random effect is ignored then it could be the case that the $\hat{\gamma}$ estimates will not capture genuine state dependence but spurious state dependence (Alessie, 2004). Formally true state dependence exists when the serial correlation between states, as captured by the γ coefficients, is due to causality. Alternatively, persisting in one state could be the effect of individual unobserved heterogeneity rather than due to occupancy in that state at t-1, or spurious state dependence.

4.1 Estimation:

In this subsection the estimation of the model is presented along with the solution for the so-called initial conditions problem. Much of this discussion follows Kano (2008) and Alessie et al (2001). When a discrete time-discrete data stochastic process is estimated the problem of initial conditions arises. As Heckman explains: "before parameters generating a stochastic process with dependence can be estimated the process must be somehow initialised" (Heckman, 1981). We could treat the beginning of this process as exogenous but that would imply the disturbances that generate the process are serially independent or that a genuinely new process is observed from the beginning. In our case we could have argued that the process of leaving home and finding a job is new for all teenagers since everybody starts life at home and unemployed and this is not correlated with the disturbances. However, in this case the initial conditions problem arises from the fact we do not observe all individuals from age 16 onwards. This is a data collection issue and can be dealt with in two ways (Arulampalan and Stewart, 2009).

The initial conditions problem can be tackled by using a two-step approach such as Heckman's (1981) estimator or Orme's (1997, 2001) approximation. Heckman models the process that generated the initial values observed in the data by specifying an auxiliary equation and then estimates using all the observations allowing for correlation between the initial and main equations. Orme's approach is in the spirit of Heckman's estimator and it involves two steps as well. He uses an approximation to substitute the random effect α in equations (7), (8) with another unobservable factor that is not correlated with the initial observation y_0. This first step is similar with Heckman's initial process equation. Then he goes on to estimate the model as a normal random effects probit using standard software[9].

A second way of estimating the model and solving the problem of correlation of the initial values with the unobserved random effect is Wooldridge's conditional maximum likelihood estimator (Wooldridge, 2005). Wooldridge actually does the opposite than Heckman so instead of specifying and equation modelling the process that created the initial value y_1 conditional on the random effect he models the random effect α as a function of the initial values. This can be written as:

$$a_i = y_{1i0}\kappa_{11} + y_{2i0}\kappa 12 + z_{i0}\zeta + \alpha_i \quad (10)$$

The z_{i0} can include the same variables as in **x** above. Then he replaces the random effect in (7), (8) with the specification in (10). The resulting regression does not suffer

[9] For more details of these two methods see Heckman (1981), Orme (1997) and Arulampalan and Stewart (2009).

from the problem of endogenous regressors and can be estimated using standard software[10].

Alessie (2004) used a method proposed by Heckman (1981) which is described by Wooldridge as approximating the conditional distribution of the initial condition. In practice it would mean adding a third equation accounting for the initial conditions of our bivariate dynamic probit which would be a bivariate version of Heckman (1981). This is computationally more difficult than necessary for obtaining the parameters estimates and simplicity is the main reason the solution proposed by Wooldridge is used. Two variables y_{1io} and y_{2io} are added in both equations, which contain the value of the dependent variables at the first wave. In practice we copy the initial living arrangement and labour market status at every wave. This means that we model the distribution of the unobserved effects conditional on the initial value and the rest exogenous covariates (Wooldridge, 2005). The Wooldridge approach is more flexible and computationally much simpler.

Equations (7) and (8) now become:

$$y^*_{1it} = x'_{1it}\beta_1 + y_{1,i,t-1}\gamma_{11} + y_{2,i,t-1}\gamma_{12} + y_{1i0}\kappa_{11} + y_{2i0}\kappa_{12} + \alpha_{1i} + u_{1it} \qquad (11)$$
$$y^*_{2it} = x'_{2it}\beta_2 + y_{1,i,t-1}\gamma_{21} + y_{2,i,t-1}\gamma_{22} + y_{1i0}\kappa_{21} + y_{2i0}\kappa_{22} + \alpha_{2i} + u_{2it} \qquad (12)$$

$$y_{jit} = \begin{cases} 1 & if\ y^*_{jit} > 0 \\ 0 & otherwise\ , \end{cases} \qquad j = 1,2;\ i = 1,\dots N;\ t = 1,\dots T.$$

Here κ_{ij} refers to the estimated effect of the initial condition of an individual. Please also note the random effect α is not the same as in equations (7) (8) but it is the one specified in (10). Based on the model, we construct the likelihood function and then outline the estimation methods available.

[10] This is true only in the "simple" univariate case and not in the bivariate probit model employed here which requires programming irrespective of the method used.

In order to simplify the presentation we to group the parameters into 1xK vectors $\xi_{jit} = [y_{1i,t-1}, y_{2it-1}, x_{jit}, y_{1i0}, y_{2i0}]$, j = 1,2 and the coefficients into Kx1 vectors $\theta_j = [\gamma_{j1}, \gamma_{j2}, \beta_j, \kappa_{1j}, \kappa_{2j}]'$, j = 1,2. The probability that a young adult i in period t is out of the parental home and employed, or that both dependent variables are equal to 1, is given by:

$$\Pr(y_{1it} = 1, y_{2it} = 1 \mid \xi_{1it}, \xi_{2it}, \alpha_{1i}, \alpha_{2i}) = \Phi_2\,[(\xi_{1it}\theta_1 + \alpha_{1i}), (\xi_{2it}\theta_2 + \alpha_{2i}); \rho_\varepsilon],$$

where $\Phi_2(\cdot,\cdot;\cdot)$ is the cumulative distribution function of the bivariate standard normal distribution. Similarly, the probabilities of the other three combinations of the dependent variables values are:

$$\Pr(y_{1it} = 1, y_{2it} = 0 \mid \xi_{1it}, \xi_{2it}, \alpha_{1i}, \alpha_{2i}) = \Phi_2\,[(\xi_{1it}\theta_1 + \alpha_{1i}), -(\xi_{2it}\theta_2 + \alpha_{2i}); -\rho_\varepsilon],$$

$$\Pr(y_{1it} = 0, y_{2it} = 1 \mid \xi_{1it}, \xi_{2it}, \alpha_{1i}, \alpha_{2i}) = \Phi_2\,[-(\xi_{1it}\theta_1 + \alpha_{1i}), (\xi_{2it}\theta_2 + \alpha_{2i}); -\rho_\varepsilon],$$

$$\Pr(y_{1it} = 0, y_{2it} = 0 \mid \xi_{1it}, \xi_{2it}, \alpha_{1i}, \alpha_{2i}) = \Phi_2\,[-(\xi_{1it}\theta_1 + \alpha_{1i}), -(\xi_{2it}\theta_2 + \alpha_{2i}); \rho_\varepsilon].$$

The probability mass function[11] of the outcomes for individual i at time t can be written as:

$$f(y_{1it}, y_{2it} \mid \xi_{1it}, \xi_{2it}, \alpha_{1i}, \alpha_{2i}) = \Phi_2\,[q_{1it}(\xi_{1it}\theta_1 + \alpha_{1i}), q_{2it}(\xi_{2it}\theta_1 + \alpha_{2i}); q_{1it}q_{2it}\rho_\varepsilon],$$

where $q_{jit} = 2y_{jit} - 1$, j = 1,2.

By the conditional independence assumption on $\{(y_{1i1}, y_{2i1})(y_{1i2}, y_{2i2}), \ldots, (y_{1iT}, y_{2iT})\}$, their joint density for individual i can be expressed as:

$$\prod_{t=1}^{T} f\,(y_{1it}, y_{2it} \mid \xi_{1it}, \xi_{2it}, \alpha_{1i}, \alpha_{2i}) = \prod_{t=1}^{T} \Phi\,[q_{1it}(\xi_{1it}\theta_1 + \alpha_{1i}), q_{2it}(\xi_{2it}\theta_1 + \alpha_{2i}); q_{1it}q_{2it}\rho_\varepsilon].$$

And finally since α_{1i} and α_{2i} are distributed bivariate normal and the parameters to be estimated are given by $\boldsymbol{\theta} = [\theta_1\ \theta_2\ \sigma^2_{\alpha1}\ \sigma^2_{\alpha2}\ \rho_\alpha\ \rho_\varepsilon]$ the unconditional likelihood is:

---

[11] In probability theory, a **probability mass function** (**pmf**) is a function that gives the probability that a discrete random variable is exactly equal to some value. A pmf differs from a probability density function (pdf) in that the values of a pdf, defined only for continuous random variables, are not probabilities as such. Instead, the integral of a pdf over a range of possible values (a, b] gives the probability of the random variable falling within that range.

$$\ell_i(\boldsymbol{\theta}) = \int_{\alpha 1}\int_{\alpha 2} \prod_{t=1}^{T} \Phi\,[q_{1it}(\xi_{1it}\theta_1+\alpha_{1i}),q_{2it}(\xi_{2it}\theta_1+\alpha_{2i});q_{1it}q_{2it}\rho_\varepsilon]\; h(\alpha_1,\alpha_2)d\alpha_1 d\alpha_2,$$

where $h(\alpha_1,\alpha_2)$ is the assumed distribution of the random effects, in this case the bivariate normal distribution with variances ($\sigma^2_{\alpha 1}$ $\sigma^2_{\alpha 2}$) and correlation ρ_α. The log-likelihood for the sample of N individuals is given by:

$$\log \mathrm{L}(\boldsymbol{\theta}) = \sum_{i=1}^{N} \log \ell_i\,(\boldsymbol{\theta})$$

The above likelihood function is intractable since it contains a summation of double integrals. At this point there are two options a researcher can follow (Haan & Uhlendorff, 2006). The model can either be estimated by adaptive quadrature or by maximum simulated likelihood. In order to employ adaptive quadrature for the Alessie (2004) model employed here one may use the Stata program gllamm which can solve integration problems containing double integrals by approximation techniques such as adaptive quadrature. One advantage of the gllamm routine is that it can also be employed in a semi-parametric specification using mass-points. In this way the problem of imposing a distribution on the random effects can be avoided. (Clark and Etile, 2006).

The other option, followed in this work, is the method of maximum simulated likelihood (MSL) based on Halton sequences. This technique was proposed by Train (1999) and became more widely known after Train (2003). MSL is used to calculate the probability an agent will choose an action, e.g. moving out of the parental home and getting a job. This probability is an integral of an indicator for the outcome of this behavioural process over all possible values of the unobserved factors. To calculate this probability the integral must be evaluated but instead of solving the integral analytically it can be approximated through simulation (Train, 2003). The way MSL works is by drawing R values from the distribution of the unobserved heterogeneity per individual i. Since we have two equations we generate R bivariate normal random variables: $\{(\alpha^1_{1i}, \alpha^1_{2i}), (\alpha^2_{1i}, \alpha^2_{2i}),..., (\alpha^R_{1i}, \alpha^R_{2i})\}$. For given values of (θ_1, θ_2) the approximation of the individual likelihood is the average of the R draws:

$$\tilde{\ell}_i(\boldsymbol{\theta}) = \frac{1}{R}\sum_{\alpha_{1i}^{(r)}:r=1}^{R}\sum_{\alpha_{2i}^{(r)}:r=1}^{R}\left\{\prod_{t=1}^{T}\Phi\left[q_{1it}(\xi_{1it}\theta_1+\alpha^r{}_{1i}),q_{2it}(\xi_{2it}\theta_1+\alpha^r{}_{2i});q_{1it}q_{2it}\rho_\varepsilon\right]\right\}$$

Halton draws are a more efficient way of simulating higher dimension integrals than simple pseudo-random draws. Train reports that 100 Halton draws have a lower simulation error than 1000 random draws and the same result is reported by Capellari and Jenkins (2006). Capellari and Jenkins (2006) provide examples of applications that MSL based on Halton sequences can be used. The Halton sequence generator and the algorithm (including the maximisation code) used in this chapter were written in OX by Kano (2008)[12]. The above model was estimated with 200 Halton draws since the results did not change after this number and there is a low number of individuals on this work. Train (2003) shows that the MSL is equivalent to the classical maximum likelihood as $\sqrt{\mathrm{N}}/R \rightarrow 0$. All models presented above have been run on male and female young adults separately.

[12] These may only be provided from the author himself upon request but a strong knowledge of OX or C++ is required in order to be applied to a dataset. Please be advised that estimation is very slow and time increases with the number of individuals, observations, Halton draws and parameters to be estimated.

5. Data

We use individual level data from the British Household Panel Survey (BHPS). The BHPS is considered to be nationally near-representative starting with approximately 10,000 original members, belonging to about 5,500 households, interviewed annually every September. Individuals that have left their original household are interviewed too along with all adults in the new household[13]. This is done to ensure the survey remains representative. The same is true for children that have reached age 16 in all households in the survey. The respondents answer a range of questions including income, labour market status, education, health and on other socioeconomic indicators at every wave. Any changes that have occurred in the time between interviews are also recorded in the survey.

The first fifteen waves are being used for this research in the period from 1991 to 2005. The studied population is young people aged 16-32. These limits where chosen since the legal age a child is allowed to leave home is 16 and 32 was a reasonable limit that fits the description young adult. Other studies had a higher upper limit up to 34 (Guiliano, 2006) or 36 (Klasen and Woolard, 2008), while Ermisch (1999) kept the upper age limit at 30, probably because young adults in Britain tend to leave earlier than the elsewhere in Europe. We decided to raise the limit to 32 since we believe young adults these days may stay longer at the parental home. Observations added later from the BHPS extension samples are not being used here. Proxy respondents are also dropped from the analysis but these were only a small fraction of the sample. Single wave observations were dropped from the data since dynamic specifications require at least two consecutive waves.

[13] Ermisch (1996) shows that bias from sample attrition of those who leave their parental home is likely to be small.

Furthermore, dynamic analysis requires a compact panel. This means that observations of a given individual must be consecutive and all gaps must be eliminated. Standard practice in the research literature is to drop all individuals with gaps in order to simplify the analysis. This practice was avoided in this paper because it would mean the loss of perfectly good information. For example an individual who is followed from 1991 for thirteen waves, but then is missing in wave fourteen and then comes back to the survey at wave fifteen would be dropped completely with the above method. In this work we follow the method of keeping the longest consecutive spell. Thus, only one observation –wave fifteen– of that individual would be dropped from the analysis. In this way sample size remained at reasonable levels permitting the use of simulated estimation. Furthermore, by keeping the longest spell we ensure that students are excluded from our sample. We only included individuals that have finished their studies and are back home. The main reason for this is that in the UK it is common to attend University away from home and then come back after the three year period of undergraduate studies. Since, we are only interested in permanent exit this would create an upward bias in our leaving home dependent variable because more individuals would appear exiting the parental home.

Following Ermisch (1999), parental characteristics are included in the analysis. These are current parental labour supply, labour and non-labour incomes. Parental characteristics should not be confused with parental background variables like past employment or education. In the BHPS parental background would mean information about the parents when the respondent was fourteen. We are interested here in current incomes and labour supply decisions of the parents to identify any effect on their children's decisions. In order to have this information the child must be residing with his/her parents in the survey for at least one wave. This had the effect of losing roughly 50% of the observations. Since we are interested here in leaving home decisions, among other things, it seemed natural to include in the analysis only those that had the option of leaving or staying in the parental home at some point in the survey. The above sample selection criteria resulted in 767 young men and 648 young women being observed for a minimum of two waves each. The average spell was 6.1 waves for males and 6 waves for females.

In addition to the BHPS data, house price data are used in this chapter. The nature of this analysis requires a representative dataset that is compiled independently by a Building Society or from the National Statistics Office. Rainer and Smith (2008) use real annual average house prices for semi-detached properties from the Halifax House Price Index (HHPI) across 65 counties over the sample period. We follow their approach here and we link the BHPS dataset with the Halifax data in the same way as in Rainer and Smith[14]. All prices and incomes have been deflated by the Current Price Index (CPI) which was preferred to the retail price index (RPI). The CPI does not include housing costs and it was thought more suitable as a deflator of house prices. Rental costs are not included in the survey because according to our knowledge there is no high quality information on Rental Prices in the UK.

Table 1 summarizes the main variables used in this chapter across the period studied. Out of the parental home and having a job are the dependent variables of this study. Figure 1 shows the percentage of young adults that have left the parental home according to the age across all the period studied. Women tend to leave earlier and in greater numbers than men and this can be seen in this graph too. By the age of 30 about 80% of women live outside the parental home but for men this number is less than 75%. Back in Table 1 now it is immediately clear that there are more women

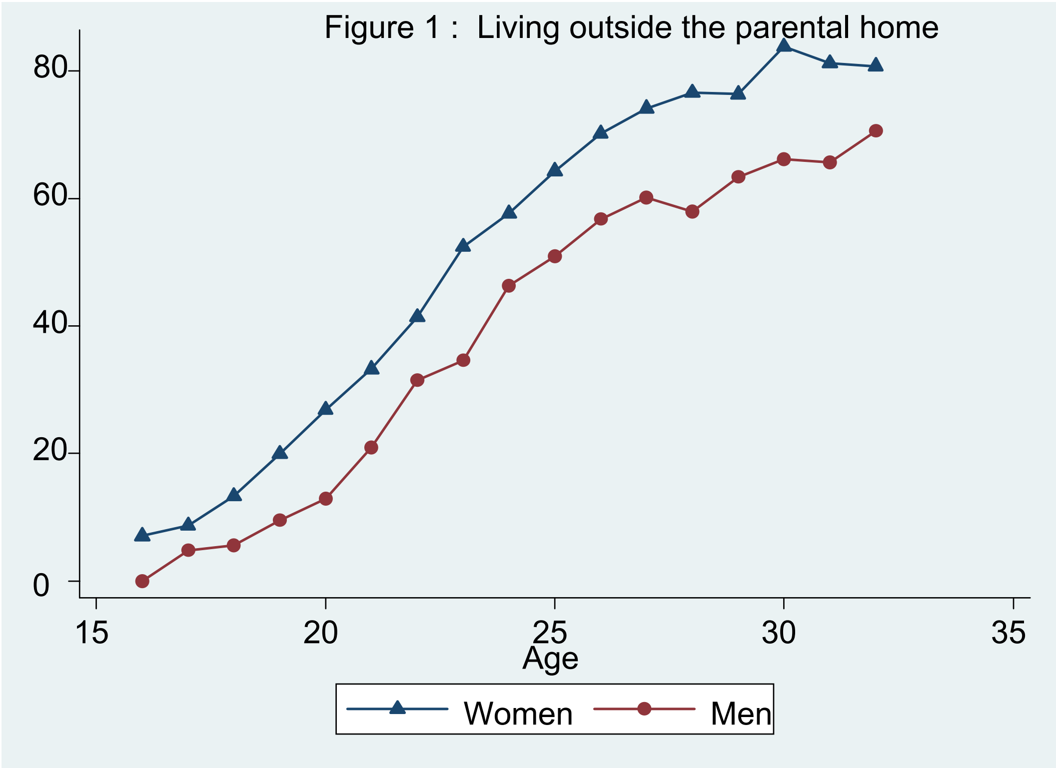
[14] The logarithmic scale of house prices' shocks is not being used here; see Rainer and Smith (2008) for more details on that.

living outside the parental home than men in our sample; about half the women in the sample have left the parental home (37% for men). The men have the edge in labour supply but only slightly with the difference being around six percentage points. Parental earnings are defined as monthly labour income and the non-labour income variables include income from all other sources except work.

Table 1
Means of main variables 1991-2006

Variable	Men	Women
Individuals	767	648
Out of the parental home	0.37	0.50
Has Job	0.87	0.81
Age	23.61	23.50
Father’s Earnings per month	960.00	1112.00
Mother’s Earnings per month	640.00	647.00
Parental Non-Labour Income	290.00	300.00
Non Labour Income	40.00	100.00
Lower than A levels	0.63	0.61
Race "white"	0.95	0.95
Has child 0-2 years old	0.07	0.13
Has child 3-4 years old	0.05	0.08
Lives in Urban Area	0.78	0.79
House Prices ‘000	1.09	1.21
Unemloyment Rate	0.05	0.03
Both Parents Work	0.40	0.46
Father Works Only	0.14	0.13
Mother Works Only	0.27	0.21

The non-labour incomes are all measured monthly. House prices are measured in thousands which means the average house would be valued over £100,000. The education variable shows that more than 60% of both genders have completed education up to GCSE’s or the old “O” levels. About 95% of our sample is of a “white” background and 78% live in highly populated “urban” areas.



In the next section we present the model estimates and discuss the implications of our results.

6. Model Estimates

In this section two main groups of estimates are presented. The first is the static specification presented in the beginning of section four. Then, we present the main results from the dynamic bivariate probit with random effects, adapted from Alessie (2004). Finally, a model with age interactions is presented at the end.

6.1 Static Model

This is a descriptive model that omits dynamics and does not account for heterogeneity between individuals. It is being used to obtain benchmark estimates of the associations between characteristics and outcomes[15]. In table 2 the results of the static bivariate probit are presented for both genders. The full estimation specification can be found in the appendix[16] containing all region and time dummies, these were left out here in order to focus on the main covariates of interest. The model was estimated by maximum likelihood using the biprobit routine in Stata. For the males the correlation ρ of the two equations (see section 4) is positive and significant (0.15). This is a first indication that the two equations are correlated and in this static setting it seems that having a job in year t would likely mean that you would live outside the parental home too. Furthermore, the two decisions do not seem highly interrelated in the female subsample as captured by the insignificant correlation between the error terms of the two equations. It would be interesting to see the correlations when unobserved heterogeneity is taken into account.

The results reveal other differences too; the mother seems to be slightly more important for the males, a finding echoed in Mayer (2002). In the male sample,

[15] Please see section 6.2 for the main model.
[16] The appendix is not included in this draft but can be provided upon request.

equation of household membership, the coefficient on mother's income is positive and significantly different than zero and positive at the 5% significance level.

Table 2: Static Bivariate Model of Living Away from Home and Working

	Males		Females	
	Living Away from Home			
Covariates[b]	Coeff.	Z-Score[a]	Coeff.	Z-Score[a]
Houseprices	-0.370**	-2.08	-0.280	-1.55
Age	0.664***	5.93	0.628***	6.04
Age Squared	-0.011***	-4.78	-0.010***	-4.61
Father's Income	0.041	1.26	0.018	0.61
Mother's Income	0.113**	2.10	0.020	0.33
Parental non-Lab Income	-0.044	-0.63	0.103	1.31
Non-Lab Income	0.032	0.34	0.112	1.11
Father Works only	0.066	0.44	-0.087	-0.51
Mother Works only	0.279**	2.01	0.279**	1.95
Both Par. Work	-0.295**	-2.04	-0.114	-0.79
Low Education	-0.225**	-2.33	-0.070	-0.73
Is White	0.341	1.33	0.568**	2.05
Children 0-2	1.112***	7.71	0.653***	6.41
Children 3-4	1.052***	5.37	0.669***	5.10
Urban	0.527***	4.36	0.316***	2.76
Constant	-11.236***	-7.78	-11.236***	-8.39
	Working			
Unemployment	-1.315	-0.43	-5.372*	-1.69
Age	0.053	0.47	0.282***	3.27
Age Squared	0.000	0.06	-0.005**	-2.52
Father's Income	0.117*	1.81	-0.028	-1.12
Mother's Income	-0.037	-0.60	-0.031	-0.56
Parental non-Lab Income	-0.968***	-10.85	-0.754***	-8.76
Non-Lab Income	0.390***	3.39	0.141	1.31
Father Works only	0.534***	2.91	0.449**	2.66
Mother Works only	0.890***	6.11	0.293**	2.18
Both Par. Work	0.633***	3.50	0.598***	4.41
Low Education	-0.512***	-4.51	-0.251**	-2.49
Is White	0.234	1.23	0.528**	2.26
Children 0-2	-0.173	-1.36	-1.046***	-12.04
Children 3-4	-0.004	-0.03	-0.908***	-8.79
Urban	0.105	0.82	0.100	1.00
Constant	-0.051	-0.04	-2.441**	-2.24
Correlation ρ	0.149***	3.24	-0.072	-1.16
No. of Obs.; No of people	3884 ;767		3897;648	

[a]Ratio of Coefficient to Asymptotic Standard error (adjusted for clustering on individuals).
[b]All models include 11 regional and 13 time dummy variables.
* p<0.10, ** p<0.05, *** p<0.01.

This means that a higher mother's income increases the likelihood a young man is away from home. In the female sample parental incomes do not seem to have an effect in either of the two equations, what matters is the labour supply of the father which increases the probability of living away from home and of working (though the coefficient is only significant at the 10% level in the work equation). The parental labour supply dummies were constructed in a way that the coefficients should be compared with the base case of neither parent working. The distinction between part-time and full-time work of the two parents was examined but the coefficients were not statistically different from each other. Therefore the parental part-time and full-time labour supply dummies were combined.

One other factor that seems to matter is house prices which have a negative effect on the household membership outcome for both genders even though not precisely estimated for the women. Thus, we can confirm the finding of Ermisch and others that higher house prices reduce the rate of departure from the parental home (Ermisch, 1999). In this work house price data are linked directly to the county individuals reside into, rather than linked to the broad region as in Ermisch. We also include eleven region dummies with the base case being the South East as opposed to Ermisch's ten. Still, we get a similar picture with Ermisch so according to our results if house prices remain expensive compared with their historical values[17] we expect young adults to stay longer with their parents.

Education and race seem to play a role as well. For example, a white young woman who has at least "A" levels is significantly more likely to have a job and live outside the parental home. The same could be said for men with the exception of race which seems to have a minimal effect on labour market opportunities for this sample

[17] Something that was confirmed in January 2010 when average UK house prices seemed to recover their losses of the previous two years according to Nationwide's latest report.

in this static setting where unobserved heterogeneity is not taken into account. One of the aims of this study is to identify if these results persist when dynamics are taken into account and unobserved heterogeneity is included in the form of a random effects specification.

6.2 Dynamic Random Effects Model

We now turn to the dynamic bivariate model which explicitly allows for several structural features of the decision to leave home and start work. First it models the dependence of each decision on previous year outcome (state dependence). Second, it allows the home leaving and work decisions to affect each other (cross-state dependence). Third, it accounts for unobserved factors that may affect both decisions and also be correlated. Estimation follows Alessie et al (2004) and the initial conditions treatment of Wooldridge (2005)[18]. The model was estimated using the OX routine[19] maxBFGS which employs a quasi-Newton maximisation method. A restricted version of the Alessie model was estimated too[20], it is the univariate case where $\rho_\alpha=\rho_\varepsilon=0$. This model was estimated using the Stata xtprobit command with the default number of quadrature points and the Broyden, Fletcher, Goldfarb, and Shanno (BFGS) maximisation technique. In the males subsample a likelihood ratio test of the restrictions yields a statistic of 21.36, distributed as a $\chi^2(2)$. This is higher than the 99% critical value and the restricted model is rejected[21]. In what follows the estimation results of males will be presented first and then females followed by a comparison of the two. Finally a model with interactions is presented to investigate further the effect of age in respect to our dependent variables. The purpose of that is to investigate what is the effect of age on the two decisions. For example, is it the

[18] For the estimation procedure and the model specification please refer to section 4.
[19] See OX documentation for more information (Doornik, 2007).
[20] Not included in this draft but available upon request.
[21] This test can be done by comparing the two likelihoods of the restricted model with the likelihood of the unrestricted model.

same to leave the parental home when someone is 19 years old and 27 years old and if not how age affects the individuals?

The bivariate dynamic probit specification with random effects is a major improvement on the previous static model. Here we take full advantage of the panel dimension of the data and understand the way dynamics work in the presence of unobserved heterogeneity for both decisions. To our knowledge, this has never been done before in the literature of household formation and is one of the main contributions of this chapter. The Alessie model not only allows identifying the effect of state dependence (see section 4 for an explanation of these concepts) but also cross-state dependence. In this way we are a step closer in determining the interrelation of the two decisions. The correlation of the random effects together with the cross-state dependence coefficients will shed some light on this issue.

The results, presented in Table 3, in the dynamic random effects models have certain similarities with the pooled model. For example, house prices as expected remained significant and negative in all specifications for both genders. However, in the presence of dynamics and unobserved heterogeneity we see that other major covariates of interest, e.g. parental incomes, lose predictive strength. Parental incomes were not significant in any of the specifications that accounted for unobserved heterogeneity

Table 3: Dynamic Bivariate Model with Random Effects

	Males		**Females**	
		Leaving Home		
Covariates[b]	Coeff.	Z-Score[a]	Coeff.	Z-Score[a]
Left Parental Home$_{t-1}$	2.252***	22.98	2.104***	19.05
Has a job$_{t-1}$	0.041	0.37	-0.015	-0.11
Houseprices	-0.316**	-2.22	-0.307*	-1.69
Age	0.366***	3.61	0.342***	2.92
Age Squared	-0.006***	-2.89	-0.005**	-2.15
Father's Income	0.064	1.57	0.041	0.93
Mother's Income	0.078	1.58	-0.059	-0.96
Parental non-Lab Income	0.098	1.18	0.101	1.04

Non-Lab Income	0.005	0.07	0.086	1.06
Father Works only	-0.023	-0.17	-0.127	-0.81
Mother Works only	0.199*	1.67	-0.089	-0.54
Both Par. Work	-0.242*	-1.84	0.044	0.31
Low Education	-0.172**	-2.23	-0.168*	-1.87
Is White	0.177	1.11	0.826***	3.93
Children 0-2	1.051***	7.20	0.568***	4.65
Children 3-4	0.767***	3.83	0.414***	2.63
Urban	0.466***	4.82	0.408***	3.85
Left Parental Home at t =1	0.328**	1.97	0.639***	3.36
Has job at t =1	0.060	0.60	-0.006	-0.05
Constant	-7.071***	-5.52	-7.024***	-4.71
		Working		
Left Parental Home$_{t-1}$	0.032	0.21	-0.450***	-3.19
Has a job$_{t-1}$	0.408***	2.95	1.034***	8.56
Unemployment	-4.422	-1.04	-5.828	-1.51
Age	-0.003	-0.02	0.346***	2.70
Age Squared	0.001	0.41	-0.006**	-2.24
Father's Income	0.064	0.75	0.008	0.21
Mother's Income	-0.018	-0.29	0.008	0.10
Parental non-Lab Income	0.306**	2.14	0.151	1.26
Non-Lab Income	-1.237***	-10.06	-0.878***	-7.62
Father Works only	0.505**	2.11	0.266	1.54
Mother Works only	0.529***	2.84	0.084	0.47
Both Par. Work	0.489**	2.09	0.119	0.72
Low Education	-0.496***	-3.22	-0.427***	-3.59
Is White	0.461	1.64	0.477**	1.98
Children 0-2	-0.298*	-1.67	-1.021***	-9.16
Children 3-4	-0.232	-1.01	-0.569***	-4.35
Urban	-0.034	-0.21	0.272**	2.14
Left Parental Home at t =1	0.055	0.21	-5.828	-1.51
Has job at t =1	1.414***	6.70	0.009	0.06
Constant	0.196	0.11	-3.705**	-2.27
Variance α Leaving Home	0.405***	4.46	0.508***	4.81
Variance α Working	1.216***	9.12	0.898***	7.38
Correlation ρ_α	0.176*	1.65	0.692***	3.66
Correlation ρ_ε	0.252***	2.92	-0.187**	-2.22
No. of Obs.; No of people	3884 ;767		3897;648	
Average Periods	6.06		6.01	
Draws per individual	200		200	
Log-Likelihood	-1886.32		-1808.5	

[a]Ratio of Coefficient to Asymptotic Standard error.
[b]All models include 11 regional and 13 time dummy variables.
* p<0.10, ** p<0.05, *** p<0.01.

between individuals. These models confirmed however that parental labour supply is important in influencing outcomes. Since we did not find a positive or negative effect of parental incomes on outcomes parental labour supply should affect outcomes through the time spent by the parents in the household.

Specifically for young men, if either or both parents are working increases the likelihood of being employed in this dynamic specification and in the presence of random effects. Men's decision to leave the parental home is also affected by parental labour supply. To elaborate on this, if both parents are present in the household and employed there is a negative influence on leaving home. If this effect is through parental income then it could be interpreted based on the Ermisch (2003) altruistic model which predicts a negative effect of parental income on leaving home. Effectively the parents would be paying their children to stay home. This assumes children and parents have opposite tastes and the parents a taste for cohabitation. However, parental income is controlled for here separately and has no effect, so a second explanation could be that children whose both parents are away from the home longer due to work obligations leave the parental home later in life[22]. Thirdly, looking at this from the base case point of view (both parents do not work), it could mean the child needs to leave earlier to find better opportunities elsewhere or because the parents cannot support the child financially. Finally, if the labour supply of the father is zero either because he is not working or it is a single (working) mother family then young men tend to leave earlier. We controlled for this difference by adding a dummy equal to one –not included here- if the father is missing or is indeed zero but this did not change the results.

The static model indicated the two decisions are jointly determined for young men. This was captured by the positive and significant correlation ρ between the stochastic elements of the two equations. This tells us that random shocks which

[22] This could be due to the fact the children have more time to enjoy the public good aspect of housing on their own.

affect household formation should affect labour supply decisions in a similar manner. At least this should be the case for young men residing in Britain assuming the sample used here is representative of British society. By using the Alessie (2004) model we augment the static model with the notion of state dependence and unobserved heterogeneity as described in section 4.

What is of interest here is to observe the direction of the correlation of the random, individual-specific, unobserved heterogeneity components of the two equations. The results are shown in table 3, the correlation is denoted as ρ_α and we see is positive and significant, albeit only at the 10% significance level. This shows that for young men random shocks and individual-specific time-fixed random effects may affect the two decisions in the same way. This low correlation (ρ_α=0.18) was unexpected since the static model indicated the two decisions were more related in the men's sample. This could be an indication that in the specific sample used the two decisions are exogenous and specifically the cross-state dependence terms; leading to a specification similar to the restricted model where $\rho_\alpha = 0$. However, this is not the case here since the transitory components are significantly correlated, $\rho_\varepsilon = 0.25$. There is an indication of a very strong state dependence in both equations but the two cross-state dependence terms are not significantly different than zero. This is investigated more in the models with interactions to see the effect of age on this. Perhaps the decision to work changes as the young adults get closer to 30 years old and the way this is related to the decision to leave the parental home.

The results for young women are shown in the left-hand columns of Table 3. It is immediately noticeable that the correlation of the random effects is positive and strongly significant standing at 0.69. On the other hand the correlation of the transient errors is negative and significant (ρ_ε = -0.19). This is in contrast to the static model which did not capture any correlation between the two equations. So a "shock" which makes a young woman more likely to stay at the parental home makes her less likely to work. An example could be pregnancy at a relatively young age which would cause a young woman to stop working and reduce the probability of moving at the same time. It seems that adding dynamics and accounting for unobserved heterogeneity is essential to explain household formation and labour supply decisions for young women in contemporary British society. The static pooled model showed the two decisions are correlated for males rather than females; in the bivariate dynamic case this is not clear. There is a smaller correlation of the random effects for young men and the cross-state dependence terms are not significant. In the females sample we see that living outside the parental home in year t-1 has a negative effect on the labour market outcomes in year t.

Parental labour market characteristics do not seem to matter for young women in the dynamic model since none of the coefficients are statistically different from zero. What seems to matter most are personal characteristics such as education, the presence of children and race. This is a similar finding to Le Blanc and Wolff (2006) where they find a lower effect of parental incomes in a sample of eleven European countries. Living in an urban area is also significant and positive in both equations. The initial and cross-initial conditions terms were added to account for the fact the longest spells were kept in the sample. This meant not necessarily the first observation or the first wave of the panel were included as explained in section 5. These terms behaved in the same way for males and females. Only the initial conditions and not the cross-initial ones were significant at every specification used.

After observing all the results it can be seen that the two decisions should be examined together and are related for both males and females. Accounting for state-dependence is important and same can be said for unobserved heterogeneity. Young men seem to be affected more by parental labour market characteristics than women. The main findings are that a working mother increases the possibility her son will live independently but living in two parent family where both parents work would delay the exit from home. Working parents increase the chances a young man is in paid employment. Other results include the confirmation of the finding in Granado and Castillo (2002) that living in an urban area increases the probability of living outside the parental home for both sexes; and increases the chances of working for women only. Young women's unobservables like ability or personal tastes that do not vary over time are highly correlated in the two decisions. This is in contrast with young men where the correlation seems weak and definitely much smaller. It would be interesting to examine this further using data from another European country or from the US.

6.3 A Model with Age Interactions.

The effect of age on state dependence is examined for both genders by adding interactions of the lagged dependent variables with age. The results are shown in Table 4 for the men and Table 5 for the women. The addition of the interaction terms reveals a possible relationship between the two decisions and age. The reason for using only a linear specification, i.e. no interaction with quadratic age, is that it seems the relationship between age and having a job for young men is linear. Adding the quadratic interaction made all main coefficients insignificant and it was dropped from the analysis.

By looking at the results one can see at once that the γ coefficients are statistically significant, including the cross-state dependence terms. A possible interpretation of this is that age has an effect on the two dependent variables, it is different being 19 and in the parental home than being 29 and in the parental home. The same is true for having a job and probably as mentioned above the relationship of the decision to work with living in the parental home changes as a young man grows up.

Table 4: Dynamic Bivariate Model with Interactions for Young Men.

	Leaving Home		**Work**	
Covariates[b]	Coeff.	Z-Score[a]	Coeff.	Z-Score[a]
Left Parental Home$_{t-1}$	2.218***	22.07	-2.781***	-3.40
Has a job$_{t-1}$	-1.821***	-3.38	0.414***	2.96
Hasjob$_{t-1}$*Age	0.084***	3.52	N/A	N/A
Left Parental Home$_{t-1}$*Age	N/A	N/A	0.119***	3.50
House Prices	-0.319**	-2.20	N/A	N/A
Unemployment	N/A	N/A	-4.486	-1.05
Age	0.371***	3.58	0.205	1.29
Age Squared	-0.007***	-3.46	-0.004	-1.11
Father's Income	0.069*	1.63	0.066	0.77
Mother's Income	0.077	1.53	-0.028	-0.44
Parental non-Lab Income	0.092	1.08	0.271*	1.89
Non-Lab Income	0.014	0.21	-1.246***	-9.95
Father Works only	0.205*	1.69	0.513***	2.77
Mother Works only	-0.237*	-1.76	0.515**	1.96
Both Par. Work	-0.028	-0.20	0.454**	2.10
Low Education	-0.159**	-2.00	-0.490***	-3.20
Is White	0.160	0.98	0.448*	1.63
Children 0-2	1.057***	7.16	-0.284*	-1.58
Children 3-4	0.787***	3.87	-0.276	-1.18
Urban	0.471***	4.75	-0.010	-0.06
Left Parental Home at t =1	0.377**	2.21	0.062	0.22
Has job at t =1	0.065	0.63	1.372***	6.50
Constant	-6.428***	-4.86	-1.823	-0.97
Variance α Leaving Home		0.443***		
Variance α Working		1.211***		
Correlation ρ_α		0.161*		
Correlation ρ_ε		0.214**		
No. of Obs.; No of people		3884;767		
Average Periods		6.06		
Draws per individual		200		
Log-Likelihood		-1873.98		

[a]Ratio of Coefficient to Asymptotic Standard error.
[b]All models include 11 regional and 13 time dummy variables.
* p<0.10, ** p<0.05, *** p<0.01.

We see in the household formation equation the cross–state dependence term, having a job in year t-1 has a strong negative effect which becomes positive after the age of 22. So having a job when very young means you will probably stay at home the next year but getting a job after 22, which probably would involve a higher salary after university studies perhaps, has a positive effect on departures[23].

Table 5: Dynamic Bivariate Model with Interactions for Young Women.

	Leaving Home		**Work**	
Covariates[b]	Coeff.	Z-Score[a]	Coeff.	Z-Score[a]
Left Parental Home$_{t\text{-}1}$	2.104***	18.97	-0.768	-1.20
Has a job$_{t\text{-}1}$	-0.050	-0.09	1.036***	8.57
Hasjob$_{t\text{-}1}$*Age	0.002	0.07	N/A	N/A
Left Parental Home$_{t\text{-}1}$*Age	N/A	N/A	0.014	0.51
House Prices	-0.308**	-1.69	N/A	N/A
Unemployment	N/A	N/A	-5.942	-1.55
Age	0.343***	2.91	0.374***	2.70
Age Squared	-0.005**	-2.16	-0.006**	-2.23
Father's Income	0.041	0.93	0.008	0.21
Mother's Income	-0.059	-0.96	0.008	0.12
Parental non-Lab Income	0.101	1.03	0.149	1.25
Non-Lab Income	0.087	1.06	-0.878***	-7.62
Father Works only	-0.089	-0.54	0.080	0.45
Mother Works only	0.043	0.31	0.116	0.71
Both Par. Work	-0.127	-0.82	0.259	1.50
Low Education	-0.167*	-1.85	-0.425***	-3.58
Is White	0.826***	3.91	0.471**	1.96
Children 0-2	0.567***	4.63	-1.017***	-9.12
Children 3-4	0.415***	2.63	-0.568***	-4.34
Urban	0.410***	3.85	0.276**	2.17
Left Parental Home at t =1	0.641***	3.36	0.006	0.04
Has job at t =1	-0.008	-0.06	0.634***	3.94
Constant	-7.032***	-4.58	-3.955**	-2.33
Variance α Leaving Home		0.511***		
Variance α Working		0.889***		
Correlation ρ_α		0.683***		
Correlation ρ_ε		-0.188**		
No. of Obs.; No of people		3897; 648		
Average Periods		6.01		
Draws per individual		200		
Log-Likelihood		-1808.37		

[a]Ratio of Coefficient to Asymptotic Standard error.
[b]All models include 11 regional and 13 time dummy variables.
* p<0.10, ** p<0.05, *** p<0.01.

[23] The age where this becomes positive can be calculated as follows. The effect on the dependent variable becoming 1 is : $0 \rightarrow 1 = \gamma_1 home_{t\text{-}1} + \gamma_2 home_{t\text{-}1} * age \Rightarrow age = \gamma_1 / -\gamma_2$. This reasoning can be applied in both equations and effectively one needs to take the ratio of the two coefficients: the lagged cross-dependent variable and the age interaction term.

In the labour supply equation living without your parents at time *t*-1 has a negative effect on having a job but this becomes positive after 23 years old. This is a first indication of perhaps an optimal age of living the parental home on future labour market outcomes. This model tells us a young man should have better chances of being employed if he had left the parental home after the age of 23.

This model with the interaction terms seems to explain better the dynamics of household formation and labour supply of young men in Britain. The cross-effects are all significant and in comparison with the model without interactions produced more meaningful results proving our earlier intuition that age matters for men was correct. The rest of the results did not change in the presence of the three interaction terms. The same exercise was undertaken in the female sample with the results reported on Table 5.

Here the interactions do not add anything new to the model estimated earlier. The cross-effects become insignificant and the interaction terms are not significant. This can be explained using differences in maturity between men and women during post-teen development. Women mature earlier than men and their decision making is not affected so much by age as for men where the change is more substantial. At least this is the prediction of this model. In general this is another indication of strong gender differences and for the need of a separate approach or at least a two sample approach when studying the household membership and labour supply decisions of young adults in Britain.

7. Conclusions

In this chapter we employ a bivariate dynamic model that takes into account unobserved heterogeneity across individuals to investigate the determinants of leaving home and labour supply decisions of young men and women in Britain. We find strong evidence of gender differences in both the relationship between the two decisions and the way these are affected by parental characteristics. Furthermore, current parental incomes do not have a strong effect or in most cases they do not have an effect at all. We augment previous research done on this area by examining the effect of current parental labour supply which could affect young adults' decisions through time spent in the household rather than income. Interestingly the mothers seem to influence the sons and the fathers influence the daughters even though the latter is not as strong. The model with age interactions shows the process changes for young men as they grow up. There is an indication that men who leave the parental home or have a job after the age of 23 have better outcomes. By using a static setting which pools all observations together we show that unobserved heterogeneity is important and in a similar manner (using a restricted model) we get a strong indication the two decisions should be considered jointly rather than on each own. To our knowledge this chapter presents a unique combination of features never done before in the literature of leaving home.

8. Bibliography

Ahn, N., and Ugidos, A., (1996). The Effects of the Labour Market Situation of Parents on Children: Inheritance of Unemployment, *Investigationes Econòmica*s, **20(1)**, 23-41.

Alesina, A., and Giuliano, P., (2007). The Power of the Family, *Discussion Paper*, **2750**, IZA

Alessie, R., Hochguertel, S., and van Soest, A., (2001). Ownership of Stocks and Mutual Funds: A Panel Data Analysis, *CentER for Economic Research*, Tilburg University, discussion paper no. 2001-94.

Alessie, R., Hochguertel, S., and van Soest, A., (2004). Ownership of Stocks and Mutual Funds: A Panel Data Analysis, *The Review of Economics and Statistics*, **86(3)**, 783-796

Arulampalam, W., and Stewart M. B., (2009). Simplified Implementation of the Heckman Estimator of the Dynamic Probit Model and a Comparison with Alternative Estimators, *Oxford Bulletin of Economics and Statistics*, **71 (5)**, 659-681.

Becker, O. S., Bentolila, S., Fernandes, A., and Ichino, A., (2005). Youth Emancipation and Perceived Job Insecurity of Parents and Children, *Discussion Paper*, **1836**, IZA

Borsch-Supan, A., (1986). Household Formation, Housing Prices, and Public Policy Impacts, *Journal of Public Economics*, **30**, 145-164.

Cappelari, L., and Jenkins, S. P., (2006). Calculation of Multivariate Normal Probabilities by Simulation, with Applications to Maximum Simulated Likelihood Estimation, *The Stata Journal*, **6**, 156-189.

Clark, A., and Etile, F., (2006). Don't Give up on me Baby: Spousal Correlation in Smoking Behaviour, *Journal of Health Economics*, **25(5)**, 958-978.

Diaz, A., and Guillo, M. D., (2005). Family Ties and Labour Supply, *Investigationes Econòmica*s, **29(2)**, 289-329.

Doornik, J. A., (2007), *Ox: An Object-Oriented Matrix Language*. London, UK: Timberlake Consultants Press.

Economist, (2009), *Out of work and out of luck*, The Economist, printed 4th June.

Ermisch, J., (1999). Prices, Parents, and Young People's Household Formation, *Journal of Urban Economics*, **45**, 47-41.

Ermisch, J., (2003). *An Economic Analysis of the Family*, Princeton University Press.

Fogli, A., (2004). Endogenous Labour Market Rigidities and Family Ties, *Working Paper*, NYU Stern School of Business.

Greene, W. H., (2008). *Econometric Analysis*, **6th ed.**, Prentice-Hall.

Giuliano, P., (2006). Living Arrangements in Western Europe: Does Cultural Origin Matter? *Working Paper*, **no. 2042**, IZA

Haan, P., and Uhlendorff, A., (2006). Estimation of Multinomial Logit Models with Unobserved Heterogeneteity Using Maximum Simulated Likelihood, *The Stata Journal*, **6**, 229-245.

Haurin, R. J., Haurin, D. R., Hendershott, P. H. and Bourassa, S. C., (1997). Home or Alone: the Costs of Independent Living for Youth, *Social Science Research*, **26**, 135-152.

Heckman, J. J., (1981). The Incidental Parameters Problem and the Problem of Initial Conditions in Estimating a Discrete Time-Discrete Data Stochastic Process. In Manski C. F., and McFadden D.L., (Eds.), *Structural Analysis of Discrete Panel Data with Econometric Applications*, **Ch 4**, 179-195. MIT Press.

Heckman, J. J., (1981). Heterogeneity and State Dependence, in S Rosen (ed.), *Conference on Labor Markets*, University of Chicago Press, Chicago.

Kano, S., (2008). Like Husband, Like Wife: A Bivariate Dynamic Probit Analysis of Spousal Obesities, *Unpublished Paper*, College of Economics, Osaka Prefecture University, Japan.

Klasen, S., and Woolard, I., (2008). Surviving Unemployment Without State Support: Unemployment and Household Formation in South Africa, *Journal of African Economies*, **18(1)**, 1-51.

Le Blanc, D., and Wolff, F. C, (2006). Leaving the Parental Home: The Role of Parents and Children's Incomes. *Review of Economics of the Household*, **4**, 53-73.

Manacorda, M., and Moretti, E., (2007). Why do Most Italian Young Men Live with Their Parents? Intergenerational Transfers and Household Structure, *Journal of the European Economic Association*, **4 (4)**, 800–829.

Martinez-Granado, M., and Ruiz-Castillo, J (2002). The decisions of the Spanish youth: A cross-section study, *Journal of Population Economics*, **15**, 305-330.

Mayer, E. S., (2002). The Influence of Parental Incomes on Children's Outcomes, *Knowledge Management Group*, Ministry of Social Development, New Zealand.

McElroy, M. B. and Horney M. J., (1981). Nash-Bargained Household Decsions: Towards a Generalization of the Theory of Demand, *International Economic Review*, **22 (2)**, 333-349.

McElroy, M. B., (1985). The Joint Determination of Household Membership and Market Work: The Case of Young Men, *Journal of Labor Economics*, **3 (3)**, 293-316.

Orme, C. D., (1997). The initial conditions problem and two-step estimation in discrete panel data models, *mimeo*, University of Manchester.

Rosenzweig, M. R. and Wolpin, K. I., (1993). Intergenerational Support and the Life-Cycle Incomes of Young Men and Their Parents: Human Capital Investments, Coresidence, and Intergenerational Financial Transfers, *Journal of Labor Economics*, **11 (1)**, 84-112.

Rainer, H., and Smith, I., (2008). Staying Together for the Sake of the Home? House Price Shocks and Partnership Dissolution in the UK, *ISER Working Paper*, **No. 2008-31**, ISER.

Stewart, M. B., (2007). The Interrelated Dynamics of Unemployment and Low-Wage Employment, *Journal of Applied Econometrics*, **22(3)**, 511-531.

Train, K., (1999). Halton Sequences for Mixed Logit, *Working Paper*, Department of Economics, University of California, Berkeley

Train, K., (2003). *Discrete Choice Models Using Simulation*, Cambridge University Press, Cambridge, UK.

Wooldridge, J. M., (2005). Simple Solutions to the Initial Conditions Problem in Dynamic, Nonlinear Panel Data Models with Unobserved Heterogeneity, *Journal of Applied Econometrics*, **20(1)**, 39-54.