THE MEANS TESTING OF BENEFITS AND THE LABOUR SUPPLY OF THE WIVES OF UNEMPLOYED MEN: RESULTS FROM A MOVER-STAYER MODEL

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Abstract

Women married to unemployed men in Britain have lower participation rates than those married to employed men. Possible reasons include (1) husbands and wives facing similar unfavourable local labour market conditions, (2) their both having characteristics which make it more likely that they will be unemployed, and (3) the means testing of benefit income, which creates a disincentive for the wife to work. These issues are investigated using a British survey of unemployed men and their families. Econometric results from a Mover-Stayer model indicate a limited effect of means testing on the labour supply of the wives.

Keywords: Labour Supply, Disincentives, Benefit System.

JEL Classification: J22, J65, H31, I38.

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1. Introduction

It has often been noted that the wives of unemployed men work significantly less than the wives of employed men in many countries for which data are available, as illustrated in Table 1.

Table 1 about here

The table shows that, with the exception of Italy, the wives of unemployed men work less than the wives of employed men, even though a text-book account of labour supply would predict a woman's husband becoming unemployed to have an 'added-worker effect' (AWE) on her labour supply, and indeed on the labour supply of other household members.

There are several explanations as to why the AWE might be absent, outweighed, or fail to translate into an increase in the employment of wives of unemployed men. These include:

- Spouses live in the same place, so the shock to the local labour market that caused the husband's unemployment may also make it less likely that his wife is in work, either by constraining her labour supply, or by making it more likely that she is a discouraged worker.

- There may be ‘assortative mating’,[1] whereby marriage sorts individuals according to characteristics that are relevant to their labour supply, such as level of education and taste for labour market work. If similar characteristics are important, then the type of man who is more likely to be unemployed is also likely to be married to the type of woman who is unlikely to be employed.
- Leisure times of husband and wife may be complements rather than substitutes, so that the AWE may be outweighed. This may be particularly relevant for older couples, if they regard a husband’s unemployment as early retirement, albeit unplanned.
- Women may be very reluctant to take over the role of the ‘breadwinner’ in the household. McKee and Bell (1985) report that, in their interviews with couples in which the husband was unemployed, both husbands and wives mentioned, and indeed became emotional at the prospect of wives becoming the chief breadwinner, with stereotypes of the ‘kept man’ often mentioned.
- Women may take their decisions according to dynamic rather than just static considerations. It may be reasonable for a woman to continue not to participate in the labour market if she believes that her husband’s unemployment will not last long enough to justify the transactions costs associated with finding a job, only to give it up again when he returns to work and the household situation is back to normal.

[1] In support of the hypothesis of assortative mating, Maloney (1991) reports that the correlation in cognitive ability between spouses is 0.9, which is higher than the correlation between siblings, or between parents and children.

- Also in a dynamic context, there may be delays in putting into effect changes in desired labour supply, since it usually takes time to find a job, particularly if it is also necessary to make alternative child-care arrangements.
- The provision of Unemployment Insurance (UI), which insures individuals against the loss of income in the case of their becoming unemployed, replaces income, thus reducing the AWE.
- Social security systems that provide benefits in the case of unemployment which are means tested against family income may generate disincentives to work for a spouse that are unrelated to the benefit's function of replacing lost income.

It is this last explanation of the absence of an AWE which has been the focus of the attention of much of the literature that exists to date on the labour supply of the wives of unemployed men, because of the policy implications. The possibility that the administrative rules governing the entitlement to benefit income may discourage women from entering the labour market in order to offset the loss of household income, or, worse, encourage working women to leave the labour market, is an unhappy one, suggesting that these rules may increase the likelihood that a spell of unemployment entails long-term poverty.

The British case is particularly interesting for two reasons. First, the difference in the labour supply of wives according to the labour supply status of their husbands is particularly high in Britain. The 14 point difference shown in Table 1 is actually in the lower range of employment gap estimates. Thus, for example, Labour Force Survey data from 1985 indicate a difference of 27 points and Pudney and Thomas (1992, 1993) note an employment difference of 43 points in the 1989 General Household Survey, with 71% of women married to employed men in work, compared to just 28% of wives of unemployed men.

A second reason why Britain is interesting is because of its benefit system. First, the degree of means testing that has applied in Britain has always been high. Moreover, the system has recently been changed according to proposals which came into force in late 1996 in a way that extends the means testing of benefits further. If it is the case that means testing has been an important disincentive to work for the wives of the unemployed in the past, then these changes to the system, described below, can be expected to widen the gap in employment between these two groups of women even further. The implications of the further concentration of unemployment and non-participation in the labour force into particular households, in a country where income inequality has been increasing since the 1980's, are clear.[2]

The remainder of the paper proceeds as follows. Section 2 outlines the British benefit system and the results of the existing literature on the importance of the means testing of benefits in explaining the participation gap. Section 3 describes the Living Standards During Unemployment survey used to analyse the issue in this paper, and provides some preliminary evidence of the reactions of women to their husbands' unemployment. Section 4 introduces the econometric framework used to analyse the data, the Mover-Stayer model, together with modifications proposed to improve the efficiency of the estimator. Section 5 reports and discusses the econometric results obtained. Section 6 concludes.

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[2] Gregg and Wadsworth (1996) document the increasing polarization between workless households and other households in OECD countries and conclude that, for the UK, most of this polarization can be attributed to the increasing numbers of household types with an incidence of worklessness that is typically high, such as single parent families. Nonetheless, a higher than average proportion of increased polarization was found to be due to increases *within* household types in the UK.

2. The British Benefit System

The system as it operated in 1983-84 is first described, as this is the period during which the data used later in the paper were collected. Changes that have been introduced since are then outlined.

The social security system had two tiers. On the first tier, Unemployment Benefit (UB) was received by those who had built up an entitlement to it by making insurance contributions during previous periods of working. UB was paid only for a year, after which time the unemployed person dropped to the second tier of the system, Supplementary Benefit (SB, subsequently Income Support), which did not depend on insurance contributions.

The budget constraint associated with UB is shown in fig. 1. UB was not means-tested except that an addition for a dependant spouse was paid only if she was earning less than the amount of the addition. This meant that there was a region on the household budget constraint where family income was lower if the wife worked than if she did not, between *b* and *c* in fig. 1. In effect, this rule introduced an element of means testing into the scheme, resulting in the normal distinction between Insurance- and Assistance-based programmes being blurred to some extent.

Figures 1 and 2 about here

SB was means-tested, so that earnings of other family members caused a reduction in benefits paid[3] one-for-one with those earnings, beyond a £4 disregard. This meant that the benefit to a wife's working was just £4 unless she was earning more than the family's SB entitlement; the marginal tax rate on her earnings was effectively 100% between the level of the earnings disregard and the amount of benefit entitle-

[3] Ownership of more than £2,000 of financial assets also reduced entitlement to benefits.

ment, between *b* and *c* in fig. 2. The disregard operated over the short range of hours between points *c* and *d*.

It can be seen by comparing figs. 1 and 2 that the range of hours over which there was no gain from working an extra hour was greater for the wife of an SB recipient than for the wife of a UB recipient. It is also clear that the effective *average* tax rate was generally higher for a woman whose husband was on SB.

If the needs of a household receiving UB were judged to be above its resources, including UB, then SB could be received in conjunction with UB. The level of UB was unrelated to the level of previous earnings and the rate of payment was low, so many households received 'top-up' SB. The budget constraint that was relevant to many households whose head qualified for UB when unemployed was, in these cases, that illustrated in fig. 3. Although this figure resembles fig. 2, it is notable that the flat region of the budget constraint, from *b* to *c*, extends over a smaller range of hours in fig. 3 than in fig. 2.[4] Moreover, the absolute level of household income is higher at all hours of work of the wife beyond *b*.

Figure 3 about here

A third benefit that was means-tested was Housing Benefit (HB). If the household qualified for SB, then rent and rates were automatically paid by HB, but if the household did not qualify for SB, a comparison of needs and resources was made that resulted in a payment that was typically less than the amount of the rent, so ineligibility for SB affected household income also through its effect on the basis on which HB was calculated.

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[4] 12 hours compared to 23 hours in the examples shown.

This system was changed in 1996 in a way that extends the means testing of benefits further. UB and SB have been abolished and replaced with contributory Job Seekers Allowance (JSA) and means-tested JSA respectively. These benefits are the same as the benefits they replace except in the following important details:

- The duration for which UB is payable has been reduced from a year to six months, so the higher degree of means testing associated with SB applies to the income of many more unemployed people.
- The dependant's allowance paid with UB has been abolished, resulting in a fall in the amount of UB payable and thus, a higher proportion of households qualifying for top-up SB as well as UB, so that more wives face the budget constraint shown in fig. 3, rather than that shown in fig. 1. Of course, the discontinuity in the budget constraint of fig. 1 is also nullified.
- A 'Back to Work' bonus has been introduced, specifically with the aim of reducing the disincentive to re-enter the labour market of both claimants and their spouses. Whereas previously, for every £1 earned beyond a £5 disregard, SB was reduced by £1, now a credit of 50p is built up for every £1 earned by either a claimant or his spouse in part-time work and, on finding a full-time job, the amount of credit built up is re-paid in a lump sum.

The results of studies that have been conducted to date on the subject have been mixed. Davies et al. (1992) and Elias (1997) both attempt to measure the means-testing effect by estimating the effect of the husband's unemployment lasting for more than twelve months on his wife's labour supply, since UB exhaustion indicates a shift in the means-testing regime. The difficulty with this approach is that, as mentioned above, many households receive SB during the first twelve months, either alone or together with UB, so for many households moving past the twelve month point does not entail being means tested for the first time, a fact which is likely to blur any twelve month effect and make it more difficult to detect. Despite this possible blurring, both papers report that there is a means-testing effect, explaining 8 and 12 points of the difference in participation between the wives of the employed and unemployed in Davies et al. and Elias respectively.

Other studies that have attempted to model the household budget constraint explicitly have found smaller effects. Garcia (1989) reports a small response to increases in SB entitlements, a 10% increase causing a less than 1% decrease in participation. Kell and Wright (1990) report significant negative effects of means-testing, with women married to men entitled to SB 19 points less likely to participate than those married to UB-entitled men, although this may be due to differences in characteristics between SB and UB receivers. Bingley and Walker (1996) also found a small effect, a shift from UB to SB entitlement reducing the probability of participation by about 3.5 points. On the other hand, Pudney and Thomas (1992, 1993) do not find any significant effect of means testing at all, and nor do Giannelli and Micklewright (1995), when using German data.

3. Data

The Living Standards During Unemployment Survey (*LSUS*) surveyed the unemployed and their families directly. The individuals included were randomly selected from those starting to register as unemployed between July 21 and August 20 1983 in Britain, subsequently discarding all those whose unemployment ended within three months.

The structure of the survey is as follows. At the first interview, held about three months into the unemployment spell, questions concerning the date at which the interview was held and the 'key date', one month before the unemployment spell began, were asked. The second interview was held a year after the first, and hence fifteen months after the sampled unemployment spell began and sixteen months after the key date.[5] Thus, all sampled individuals were still unemployed at the three month stage, whereas some had obtained employment again by the time of the second interview. Moreover, because of the length of the survey period, the exhaustion of UB entitlement is also observed. Thus, between principal dates, women may be expected to react to their husband's unemployment, but also to their re-employment and/or the exhaustion of UB. Table 2 summarizes the extent of transitions made by husbands to which their wives may react.

Table 2 about here

At the first interview, detailed information was collected about the situation of the household at that date and at the key date, one month before the unemployment spell began. The data collected included information for both husband and wife on wage and property income, savings and debts, occupation and industry and on labour supply in four discrete hours ranges (full-time work, part-time work of more than ten hours per week, part-time work of less than ten hours per week, and no paid work). Similarly detailed questions were asked at the second interview a year later. Also at the second interview, retrospective information on the week-by-week employment status of both spouses in the previous 52 weeks was gathered.

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[5] Throughout the paper, the key date, first interview and second interview are referred to collectively as the 'principal dates', and where appropriate, the key date is referred to as $t=-1$, the date of the first interview as $t=3$ and the date of the second interview as $t=15$.

In this paper, a sub-sample of the *LSUS* which includes only households headed by men who were married to the same woman throughout the sample period was used, yielding a sample size of 1727 households.

It is one of the major advantages of these data that they comprise a relatively large sample of the population of interest – the unemployed. This allows a focus on the question of how the wives of men who are likely to become unemployed react to their husband's unemployment.

The data show that 466 women (27%) change from one of the four status categories (full-time work; part-time work of more than ten hours per week; part-time work of less than ten hours per week; no paid work) to another between two of the three principal dates. 85 (4.9%) change their status twice; for 45 of these (2.6%) the second change is back to their original status, i.e. they change status between the key date and the first interview, only to make a transition back to their original status by the second interview.

Tables 3 and 4 show the patterns of movement between the key date and the first interview, and between the first interview and the second. In these tabulations, figures on the diagonal (highlighted) indicate individuals who are in the same state at both dates; those to the left of the diagonal are working more at the second date than at the first, while those to the right of the diagonal are working less at the second date than previously.

Tables 3 and 4 about here

The first point that can be made about the information in these tabulations is that the employment rate of these women before their husband's unemployment began was 36%. The rate of employment prevailing among all married women in the UK in 1983 was 57% (General Household Survey, 1983), so the participation of the wives surveyed in *LSUS* is clearly lower than average.

As to the transitions themselves, Table 2 shows that, initially at least, the forces inducing the women concerned to work fewer hours - which may be because of disincentive effects or of a labour market shock affecting both partners - seem to be stronger than the added-worker effects. 135 women (8%) are working fewer hours at $t = 3$ than they were at $t = -1$, the key date, while 58 (3%) are working more hours.

The cross-tabulation of the states occupied at $t = 3$ and $t = 15$ in Table 3 shows a reversal of this pattern, however. More individuals have changed state, as would be expected given the longer time available. But the extent of the transitions towards fewer hours of work is very similar to that between the key date and the first interview, despite there being more time available; a further 122 women (7%) work fewer hours at the second interview than at the first interview, compared to 135 (8%) working fewer hours at the first interview than at the key date. Movement towards working more hours shows a much greater increase, however; at the date of the second interview, 184 (11%) are working more than they were at the first interview, compared to the 58 at the date of the first interview working more than previously. It seems that adjustment towards paid work is slower than from work to non-work. This is reasonable, as it is likely to take more time to find a job than to quit a job.

It is interesting to note that the rate of transitions in the *LSUS* is much higher than for the general population of British women at that time. Luxembourg Employment Study (LES) data show that 7.8% of married women in Britain who were working in 1988 were not in the labour force in 1989. This compares with a rate of exit from the labour force of women in the *LSUS* data of 17.7% between the first and second interviews, which is clearly significantly higher. Even more striking is the fact that between $t = -1$ and $t = 3$, and hence in the space of four months, 17.3% of working women left employment, which rate, if annualized, is equivalent to a rate of exit of 51.8%. It seems that a woman's husband becoming unemployed tends to cause a reconsideration of the labour supply decision that makes it much more likely that a labour market transition will be observed.[6]

A further pattern observable in the data is that there is a distinction between those who are 'stayers' and those who are 'movers' according to job status before the husband's unemployment spell began. Figure 4 shows that a little over three-quarters of those working full-time before a husband's unemployment are in the same state three months after the spell began. Similar figures for stayers in each group apply to those who are working part-time initially. The figure for those not working at first is substantially higher, however. This might be explained by the point that it takes longer to find a job than to quit a job, or even to find another job.

Figure 4 about here

One year later, however, the pattern remains: fifteen months after their husbands' unemployment began, women who were not working before their husbands became unemployed still tend to be stayers to a greater extent than other women – 86% as opposed to 63% of initial full-timers, 56% of part-timers who worked more than ten hours, and just one third of part-timers working less than ten hours per week initially,

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[6] Of course, given that the *LSUS* and LES apply to different years, changes in macro-economic conditions may affect this comparison. The 1989 level of unemployment was low and falling, whereas in 1983 the unemployment rate was high and rising.

even though it might be expected that adjustment delays are less relevant at this stage.[7]

A final point, which is relevant to the estimation of an econometric model, is the lack of transitions between full-time work and working low part-time hours. Other cells of the transitions matrices are also quite sparse, particularly for transitions between the key date and the first interview, such as from high part-time hours to full-time work, and from low part-time hours to both high part-time hours and to no work. Thus, although women working low part-time hours before the husband's sampled unemployment spell began make transitions to a greater extent than any other group, the modelling of these transitions is problematic because of the low absolute number in this group. The implications of small cell sizes for modelling the transitions made by the women surveyed are further discussed in Section 4.

4. The Mover-Stayer Model

The descriptive analysis of the labour market transitions of the wives of the unemployed given above indicates that there is a difference among women according to the state occupied before their husbands' unemployment began, particularly between those who worked before their husbands became unemployed and those who did not. This may be due either to unobserved heterogeneity or to state dependence. 'True' state dependence means that the experience of an event changes preferences, budget constraints or prices so that choices in one period affect choices in future periods, whilst 'spurious' state dependence means that previous experience determines future

[7] At the fifteen month stage many women are facing another situation - being affected by a means test, or husbands having exited unemployment - to which they must adjust.

experience solely because it is a proxy for unobservables which affect choices and which are persistent over time. True state dependence may arise for several reasons, including:

- If human capital depreciates whilst a woman is out of the labour force, so that the quality of women who have been out of the labour force is reduced.
- If employers use current employment as an indicator of the quality of an applicant, in terms of her commitment to the labour force.
- If preferences are endogenous, so that they are formed by habit, as discussed, for example, in Kapteyn and Woittiez (1990).

The fact that the *LSUS* data include information at three points in time can be taken advantage of by modelling the transitions of the wives surveyed. In order to account for any true state dependence, a first-order Markov process can be posited, and the destination states at the first and second interviews modelled conditionally on the labour market states occupied at the origin dates, at $t = -1$ and $t = 3$ respectively. To the extent that the states occupied at the origin dates themselves reflect unobserved heterogeneity, such an approach will also account for the latter to some extent.[8]

In order to account more fully for the evidence of a mover-stayer pattern in the data discussed in Section 2, the Mover-Stayer model (Blumen et al., 1955; Goodman, 1957) is introduced. This model proposes a particular form of extreme heterogeneity in the population that cannot be captured by a Markov matrix, namely that there are some individuals in the population, the stayers, who will never leave the state they oc-

[8] A companion paper models unobserved characteristics explicitly, using a fixed effects model (Doris, 1999). Dynamic fixed effects models cannot be used with explanatory variables (Maddala, 1987), so unobserved heterogeneity must be taken into account in another way in dynamic models.

cupy, so that they have a zero probability of making a transition. The remainder, the movers, make transitions according to a first order Markov chain model.

If S_j is the proportion of the sample who are stayers in state *j* and V_{jkt} is the probability that a mover is in state *k* at time *t* given that she was in state *j* at time $t-1$, then the transition probabilities of an individual who has not been identified as a stayer or a mover are

$$P_{jjt} = S_j + (1-S_j)V_{jjt}$$

and

$$P_{jkt} = (1-S_j)V_{jkt} \tag{1}$$

Goodman proposes a simple non-parametric estimator for the S_j, the proportion of the sample who make no transition throughout the sample period. Generally however, unless the observation period is long, some movers will be mistakenly identified as stayers; hence Goodman describes his estimator, $\hat{S}_j$, as an upper bound for the true S_j, since if any of those who do not move throughout the sample period are in fact movers rather than genuine stayers, then the true S_j are lower. Frydman (1984) confirms that $\hat{S}_j$ is not the Maximum Likelihood Estimator (MLE) of S_j unless *T* is large, and develops the MLE of S_j. The calculation of an alternative S_j based on Frydman's intuition is proposed below.

4.1. Estimation when movers can be perfectly identified

Prior to addressing the issues that arise in using Goodman's estimator of S_j in the estimation of a Mover-Stayer model of transitions, it is useful first to discuss the estimation of the model when information exists that perfectly identifies movers and stayers in the sample. The implications of the possibility that $\hat{S}_j$ is an over-estimate of the true S_j can then be clarified.

Two common methods of estimating Mover-Stayer models are considered here. One approach is based on the Double-Hurdle (D-H) model proposed by Cragg (1971). In D-H models, an individual must pass two hurdles before she is observed making a transition; first, she must be a mover and second, she must wish to make a transition. Modelling behaviour in this way is consistent with the hypothesis that individuals may be divided into movers and stayers, since stayers do not consider making transitions, by definition.

Examples of the application of D-H models are provided by Blundell et al. (1986) in their work on female labour supply, where the first hurdle to be overcome is an un-employment constraint, and by Jones (1989) in his study of cigarette consumption, where the first hurdle is a participation decision. In both of these examples, both hurdles are specified parametrically, but it is also possible to estimate the first hurdle non-parametrically, as in Micklewright et al. (1990), in their investigation of early school leaving, where the first hurdle is calculated using administrative school-leaving rules.

The D-H model that is relevant to the Mover-Stayer framework may be written as follows:

Observed choice: $v_{it} = j$ where $P_{iljt} > P_{ilkt} \; \forall \; k \neq j$

$$P_{ijjt} = S_j + (1 - S_j)V_{ijjt}$$

$$P_{ijkt} = (1 - S_j)V_{ijkt} \tag{2a}$$

Mover hurdle: $w_i = \mathbf{\acute{a}z}_i + u_i$ $\qquad$ i a mover if $w_i > 0$

i a stayer otherwise. (2b)

Choice of state j at t given state k at $t-1$ if i a mover: $V_{ijkt} = F(\boldsymbol{\beta}\mathbf{x}_{it} + e_{it})$ (2c)

where v_{it} is the state occupied by i at time t, $\mathbf{z}_i$ and $\mathbf{x}_{it}$ are vectors of variables and u_i and e_{it} are random error terms.

In the present case, the mover hurdle is not estimated parametrically; rather, estimates of the population S_j such as $\hat{S}_j$ are used. The S_j included as the first hurdle are, therefore, not individual-specific except to the extent that they depend on the state j occupied by the individual at $t = -1$. The likelihood function for the D-H model can therefore be written as:

$$L_i = \prod_j \prod_{v_{it}=v_{it-1}} S_j + (1 - S_j)V_{ijj} \prod_{v_{it} \neq v_{it-1}} (1 - S_j)V_{ijk} \tag{3}$$

In the alternative approach to the estimation of the model, the determinants of the movers' transition matrices are estimated only over those identified as movers. Thus, data on individuals not observed to move throughout the sample period are not used. This is the estimation procedure that is usually understood by the term 'Mover-Stayer Model', following its application in this way by McCall (1971). In the case where there is no error in identifying movers and stayers, estimation in this way yields consistent results.[9]

4.2. Estimation when movers are not perfectly identified

In practice, the S_j are not known and must be estimated; this means that the possibility of error in their estimation arises. A survey over sixteen months, such as the *LSU* survey, would not normally be regarded as having a sufficiently long time-span to identify movers and stayers accurately; $T = 3$ cannot be regarded as 'large'. Admittedly, this problem is mitigated to some extent by the fact that the women in this survey are observed during a period when the household's financial situation is changing in a way that makes transitions more likely. As detailed in Section 3, the

[9] There are other circumstances in which the estimation of McCall's Mover-Stayer model gives consistent results; these are discussed below.

level of transitions in this population of the wives of the unemployed is higher than for all married women. Hence, it is possible to argue that the circumstances under which the *LSUS* was undertaken make the observation of movers making transitions more likely. Nonetheless, it seems likely that some movers are mis-identified as stayers using Goodman's method of calculating S_j, and it is important to consider the consequences of the over-estimation of the S_j for the consistency of the parameter estimates.

In the D-H approach to the estimation of the model, the inconsistent estimation of the first hurdle clearly implies inconsistent estimates of the determinants of the V_{ijkt}, so if the $\hat{S}_j$ are incorrect, estimation of the model using the D-H approach is not appropriate. Moreover, where the $\hat{S}_j$ are correct, it may be argued that while both the McCall and D-H models produce consistent results, the McCall version is superior in terms of efficiency, since it uses extra information that the D-H model does not use, namely the identity of the movers. Although the D-H model uses information on all individuals to estimate the determinants of the movers' transition matrix, the extra individuals it uses in the estimation are irrelevant, since they are, by assumption, stayers.

In order to discuss the implications of the possible over-estimation of the S_j for the consistency of the McCall approach, it is useful to write the model as follows:

$$V_{ijkt} = F(\boldsymbol{\beta}\mathbf{x}_{it} + e_{it})$$

$$I_i = \tilde{\mathbf{a}}\mathbf{q}_i + \varepsilon_i \qquad (4)$$

where I is the propensity of a mover to be identified as a mover; i is identified as a mover if $I > 0$ and as a stayer otherwise. $\mathbf{q}_i$ are variables determining I and ε_i is a random error term.

Recall that the McCall model entails estimation only over those identified as movers, for whom $I > 0$. Thus, the over-estimation of S_j results in the estimation of the determinants of the transitions over a smaller set of individuals than would be the case if the true S_j were known; clearly this results in inefficiency. Moreover, if the error in the identification of movers, ε_i, is correlated with the error in the choice of destination state, *e*, then the problem of sample selection bias also arises. If there are unobservable factors that determine whether a true mover is observed to move or not that also determine an individual's destination state, then the estimates will be biased. This might arise if, for example, within the group of movers, women who have higher labour market motivation are most likely to make a transition quickly, and so to be included in the set of observed movers, and are also most likely to make transitions into destination states entailing higher hours of work. This may be more plausible for women not working initially, and for whom a transition, by definition, entails a move into work.

On the other hand, it is also possible that within the group of movers, who are, by definition, more flexible in their attitude to their working hours than are stayers,[10] those who are most flexible are likely to move sooner than those who are less flexible, and are therefore more likely to be observed as movers. There is no obvious reason why flexibility with regard to hours of work should be associated with a particular destination state. In this case, $\mathrm{cov}(\varepsilon, e) = 0$ and the estimation only over those with $I > 0$ is consistent.

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[10] Such flexibility may derive from a woman having no strong culturally-determined opinion on the 'appropriate' labour market behaviour of a wife.

Although it is not clear whether $\operatorname{cov}(\varepsilon, e) = 0$ or not, this assumption is maintained for the remainder of this paper. The assumption cannot be tested formally, since the equation giving the propensity of a mover to be identified as such is not estimated parametrically. The implication of the independence assumption is that if, as seems likely, the $\hat{S}_j$ over-estimate the true S_j, the estimates of a Mover-Stayer model using the McCall approach are inefficient but unbiased.

Before proceeding further, some practical issues that arise in applying a Mover-Stayer model to the *LSUS* data should be addressed. Firstly, the cell sizes for some transitions are very small, and in some cases non-existent.[11] This problem is addressed by grouping the states at time $t-1$ into two states, working and not working, combining full-time work and both part-time work states into one. Thus the number of individuals over whom estimation is carried out for women working at $t-1$ is large enough that standard errors can be calculated for all variables and destination states.

Moreover, this approach has theoretical validity if it is true that the dependence of the destination state on the initial state arises not because of the number of hours a woman worked in that initial state, but because of the fact that she worked at all at the initial date. This hypothesis is certainly not an unreasonable one; it may be true, for example, that employers regard participation *per se* as an indication of positive unmeasured characteristics and hire from the pool of participants first, or that women get social benefits from working that do not vary with the number of hours worked, and it is this aspect of work which generates a state dependence in their labour supply. The

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[11] When discussing the implications of the small cell sizes for some transitions, it should be mentioned that this feature of the *LSUS* data also makes the estimation of any second order Markov models very difficult.

disadvantage of this approach is that it lessens the extent to which the model can be regarded as one of transitions.

A second modelling issue arises with regard to the time period over which estimation should be carried out. Here, the decision was taken to estimate the transitions between $t = -1$ and $t = 3$ separately from those between $t = 3$ and $t = 15$, rather than pooling the destination states and modelling the destination states conditional on the initial states together. There are two reasons for this. First, the events that occur between the key date and the first interview - the husband becoming unemployed - differ from those that occur between the two interviews - the husband returning to work, or exhausting his Unemployment Benefit (UB) entitlement, as discussed in Section 3 above. These events can be anticipated to varying extents. Thus, the husband's unemployment may well be entirely unexpected, whilst the exhaustion of his UB, once unemployed, is capable of being perfectly anticipated. This means that if there is a delay in implementing decisions once taken, the parameter estimates will depend on the date of the initial date and the destination date.

Secondly, even if this were not the case, and the Markov matrix for movers were expected to be stationary, different amounts of time elapse between the two pairs of dates; four months pass between the key date and the first interview, and twelve months between the two interviews, thus automatically requiring the separate estimation of these transitions.

The estimation of the McCall Mover-Stayer model thus entails the estimation of the following equations:

$$\Pr\{v_{ij3} \mid (v_{i,-1} = \text{FT or PT} > 10 \text{ or PT} < 10, i \notin \hat{S}_j)\} = F(\hat{\mathbf{a}}\mathbf{x}_{ij3}) \qquad (5a)$$

$$\Pr\{v_{ij15} \mid (v_{i,3} = \text{FT or PT} > 10 \text{ or PT} < 10, i \notin \hat{S}_j)\} = F(\hat{\mathbf{a}}\mathbf{x}_{ij15}) \qquad (5b)$$

$$\Pr\{v_{ij3} \mid (v_{i,-1} = None, i \notin \hat{S}_j)\} = F(\mathbf{\hat{a}x}_{ij3}) \tag{5c}$$

$$\Pr\{v_{ij15} \mid (v_{i,3} = None, i \notin \hat{S}_j)\} = F(\mathbf{\hat{a}x}_{ij15}) \tag{5d}$$

Of course, for stayers:

$$\Pr\{v_{ij3} \mid (v_{i-1} = j, i \in \hat{S}_j)\} = 1 \tag{5e}$$

$$\Pr\{v_{ij15} \mid (v_{i3} = j, i \in \hat{S}_j)\} = 1 \tag{5f}$$

where $i \in \hat{S}_j$ indicates that the individual is included in the set of individuals identified as stayers according to Goodman's estimator. To clarify, Equation 5d should be read to mean that the probability of occupying state *j* at $t = 15$ for a woman who was not working at $t = 3$, and given that she has been identified as a mover, is a function of explanatory variables **x** at the values they take at $t = 15$. Note that for a woman who has been identified as a mover, she does not necessarily make a transition between the two dates in question. For example, a woman who moves only between the first and second interviews will register no transition in the model of transitions between the key date and first interview, given by Equations 5a and 5c, but is still included in the estimation sample.

The functional form used for *F* is the logistic one. Since some of the explanatory variables are choice-specific, as described in Section 5 below, a multinomial, conditional logit framework is the appropriate one.

4.3. Improving the efficiency of the estimates

To maximize the efficiency of the estimates obtained using the McCall approach with the *LSUS* data, as much information as possible should be used to identify movers in calculating $\hat{S}_j$. Thus, all transitions, including those among working states as well as those between work and non-work, are counted as valid for the identification of a mover. Moreover, rather than examining the job status of each individual only at the three principal dates to identify movers, the weekly data collected retrospectively for a year at the second interview, are also used. Individuals who are in the same states at the first and second interviews, but who report having made a transition between those two dates, are therefore also included in calculating the $\hat{S}_j$; there are 65 women who fall into this category. Note that, for these women, no transition is made either in the model of transitions between the key date and the first interview, or in that between the first and second interviews.

Nonetheless, it seems likely that, however much information is used in the calculation of $\hat{S}_j$, these estimates may over-state the true S_j, and Frydman (1984) derives the MLE of the S_j. The estimator proposed by Frydman is:

$$\tilde{S}_j = 1 - \frac{n_{j0} - n_j}{n_{j0}(1 - \hat{V}_{jjT})} \tag{6}$$

where n_{j0} is the number of individuals in state *j* at the beginning of the sample period, $t = 0$, n_j is the number of individuals observed in state *j* in all periods, and $\hat{V}_{jjT}$ is the relevant element of the diagonal of the transition matrix according to which a mover moves between $t = 0$ and $t = T$. The quantity ($n_{j0} - n_j$) is the observed number of individuals starting in state *j* and making at least one transition by time *T*, whilst $n_{j0}(1 - \hat{V}_{jjT})$ is the number of individuals expected to make a transition out of state *j* if all n_{j0} individuals are movers. Thus Frydman's estimator can be thought of as the proportion of expected movers observed to stay in one state throughout the sample period, rather than the proportion of the whole sample observed to stay.

Frydman suggests a recursive method for estimating the V_{jjT},[12] but given that data are available in the *LSUS* which might reasonably be expected to explain the pattern of transitions of movers, it seems more appropriate to use predicted probabilities from an estimation over observed movers only to calculate the V_{jjT}. Assuming, as discussed above, that there is no correlation between the error in the identification of movers and the error in the choice of destination state, such an estimation will yield consistent, although not efficient estimates of the effects of variables on the probability of occupying the alternative states if everyone in the sample is a mover. Hence, the procedure used to estimate the $\tilde{S}_j$ is as follows:

1. For each state *j*, the determinants of the probability of occupying that state at $t = 3$ are estimated only over individuals identified as movers according to $\hat{S}_j$, and separately for those working at $t = -1$ and for those not working at that date; this entails estimating Equations 5a and 5c.
2. Using the coefficients obtained, the probability of occupying each state is predicted for all individuals, the state predicted to have the highest probability of being chosen is identified as the predicted state, and those predicted to occupy a different state at $t = 3$ than that observed to have been occupied at $t = -1$ are labelled predicted movers.
3. The same procedure is repeated for predicting movers between $t = 3$ and $t = 15$; Equations 5b and 5d are estimated, again using $\hat{S}_j$.

[12] The method suggested assumes a stationary Markov process, which is unlikely to hold here.

4. The number of individuals predicted to make a transition between either pair of dates is taken as the number of individuals that would move if all individuals moved according to the transition matrix of movers, V_{jkT}.
5. The proportion of those in each initial state who are predicted to move during the sample period and are observed to move is then taken as the proportion of movers in that initial state; $\tilde{S}_j$ is the difference between this quantity and one.

Table 5 gives the elements used in the calculation of both $\hat{S}_j$ and $\tilde{S}_j$, and allows a comparison of the two estimates. The table shows small differences between $\hat{S}_j$ and $\tilde{S}_j$ for those working full-time or high part-time hours before their husbands became unemployed and virtually no difference for initial low-hours part-time workers. However, a notable difference does arise for women not working at $t = -1$. Nonetheless, the proportion of stayers estimated by $\tilde{S}_j$ among the initial non-workers is still very high, at 74%.

Table 5 about here

The incorporation of $\tilde{S}_j$ into a Mover-Stayer framework raises no new issues if estimation is carried out according to the D-H approach detailed in Equation 2. The values of $\tilde{S}_j$ from Table 5 are substituted for $\hat{S}_j$, with consistency of the results depending on the consistency of the $\tilde{S}_j$.

However, a point raised above in comparing the D-H and McCall approaches remains valid; some individuals can be positively identified as movers by the fact that they are observed making transitions, and the use of this information on the identities of some movers improves the efficiency of the estimates.

A Double-Hurdle-based approach to estimation treats any individual who is in the same state at two successive dates in the same way, whether or not she moves at another point during the sample period. It seems preferable to use the fact that, for an individual who is observed to move at some stage, her probability of being a mover is one, and then to use the extra information implied by the calculation of $\tilde{S}_j$ to assign a probability of being a mover to those who are not observed to move.

In order to explain this point more clearly, it is convenient to use a simplified model, entailing a two state world of participation and non-participation. Thus, a transition may be made either from work to non-work or from non-work to work. If the information that some individuals are certainly movers is to be incorporated into the model, sample separation is necessary. For those who are observed to move during the survey period, with $i \notin \hat{S}_j$, the transition probabilities may be specified as follows:

$$P_{jk} = \Pr(i \notin \tilde{S}_j) V_{ijkt} = V_{ijkt} = F(\boldsymbol{\beta} \mathbf{x}_{it})$$

$$P_{jj} = \Pr(i \in \tilde{S}_j) * 1 + \Pr(i \notin \tilde{S}_j) V_{ijjt} = V_{ijjt} = 1 - F(\boldsymbol{\beta} \mathbf{x}_{it}) \qquad (7)$$

These expressions are based on the point that, for an individual who is observed to make a transition, the probability that she is not a stayer, $\Pr(i \notin \tilde{S}_j)$, is one. The contribution of these individuals to the likelihood function is therefore identical to the contribution of a mover to the McCall Mover-Stayer likelihood. Note that the probabilities of making a transition and not making a transition sum to one.

For those who are not observed to move during the survey period, and so with $i \in \hat{S}_j$,

$$P_{jk} = \Pr(i \notin \tilde{S}_j) V_{ijkt} = (1 - \tilde{s}_j) V_{ijkt} = (1 - \tilde{s}_j) F(\boldsymbol{\beta} \mathbf{x}_{it})$$

$$P_{jj} = \Pr(i \in \tilde{S}_j) * 1 + \Pr(i \notin \tilde{S}_j) V_{ijjt} = \tilde{s}_j + (1 - \tilde{s}_j) V_{ijjt}$$

$$= \tilde{s}_j + (1 - \tilde{s}_j)(1 - F(\boldsymbol{\beta} \mathbf{x}_{it})) = 1 - (1 - \tilde{s}_j) F(\boldsymbol{\beta} \mathbf{x}_{it}) \qquad (8)$$

where $\tilde{s}_j$ is the probability of an individual who is not observed to move being a stayer; this must be significantly higher than for the whole sample, since the probability of being a stayer is zero for those observed to move.

The reasoning followed in calculating the $\tilde{s}_j$ for those not observed to move during the sample period is shown below; the detailed calculations are included in Appendix A.

$$\begin{aligned}(1-\tilde{S}_j) &= \Pr(\textit{observed mover is a mover}) * \Pr(\textit{observed to move}) \\ &\quad + \Pr(\textit{observed stayer is a mover}) * \Pr(\textit{observed to stay}) \\ &= 1*(1-\hat{S}_j) + \Pr(\textit{observed stayer is a mover}) * \hat{S}_j\end{aligned}$$

Thus, $$\Pr(\textit{observed stayer is a mover}) = (1-\tilde{s}_j) = \left((1-\tilde{S}_j)-(1-\hat{S}_j)\right)\Big/\hat{S}_j \tag{9}$$

Since this model resembles a mixture of the McCall and D-H approaches to estimating the Mover-Stayer model, I refer to it as the mixed Mover-Stayer model. Equation 10 gives the likelihood function for this model.

$$\begin{aligned}L_i &= \prod_j \prod_{\substack{i\notin\hat{S}_j,\\ v_{it}\neq v_{it-1}}} P_{ijk} \prod_{\substack{i\notin\hat{S}_j,\\ v_{it}=v_{it-1}}} P_{ijj} \prod_{\substack{i\in\hat{S}_j,\\ v_{it}=v_{it-1}}} P_{ijj} \\ &= \prod_j \prod_{\substack{i\notin\hat{S}_j,\\ v_{it}\neq v_{it-1}}} V_{ijk} \prod_{\substack{i\notin\hat{S}_j,\\ v_{it}=v_{it-1}}} V_{ijj} \prod_{\substack{i\in\hat{S}_j,\\ v_{it}=v_{it-1}}} (1-(1-\tilde{s}_j))V_{ijj}\end{aligned} \tag{10}$$

Again, the determinants of the destination states, j, are estimated separately for those working initially and those not working initially, for transitions between $t=-1$ and $t=3$ and for those between $t=3$ and $t=15$.

5. Variable Construction

Based on the premise of utility maximization, Equation 2a may be taken to imply that

$$\Pr[v_{it}=j] = \Pr[U_{itj} > U_{itk}] \quad \forall \quad j \neq k \tag{11}$$

where the possible states are full-time work, high hours part-time work, low hours part-time work and no paid work, these being the hours ranges in which labour supply data were collected.

The wife's utility, U_{itj}, is not observable, but may be specified as a function of observable quantities:

$$U_{itj} = U(y_{itj}, l_{itj}^{w}, l_{it}^{h}; \mathbf{x}_{it}) \tag{12}$$

where U_{itj} is the utility of the wife at time *t* and in labour market state *j*, y_{itj} is total household income at time *t* and in state *j* of the wife, l_{itj}^{w} is the leisure of the wife in state *j*, l_{it}^{h} is the number of hours of leisure of the husband, and $\mathbf{x}_{it}$ is a vector of personal and household demographic characteristics.

The elements of the utility function require some comment. Firstly, it should be noted that the husband's leisure time is not subscipted for the labour market state of the wife, implying an assumption that the husband's labour force status is exogenous to the wife's. This is a strong assumption, although one that is often supported in empirical work (Pencavel, 1986). Two justifications for the assumption are offered. Firstly, the poor state of the labour market at the time of the survey, illustrated by the fact that unemployment in early 1984 was almost 12%, and had been rising since the late 1970's, makes it more likely that the incidence and duration of unemployment was in fact due to pure rationing. And secondly, while it would be interesting to model the labour supply of husbands and wives jointly, and test the assumption, this would be demanding too much of the present data set.

Any effect of means testing on labour market behaviour will come through the effect on the utility of a particular labour market state of income in that state, y_{tj}. The construction of household income used here is based on simulations for different labour market states of the wife.[13] For each household, the first step is the construction of the potential net wage income in each state. A prediction based on OLS regression coefficients was used where no earnings information was available; this wage estimation and other details of the construction of this variable are contained in Appendix B.

The amount of predicted wage income in each of the four alternative hours of work ranges of the wife was then used to simulate benefit entitlement – UB, SB and HB – for both $t = 3$ and $t = 15$. These amounts were then added to husband's wage income and non-labour income to give eight total potential household income variables for each household.

Several previous studies in this area have used similar total household income variables to test for an effect of means testing. However, I would argue that to use such a variable is effectively to assume that means-tested benefit income has the same importance in determining labour supply as own labour income. This may appear to be an uncontroversial assumption at first glance. But if there is incomplete pooling of household income, either in the literal sense, or in the sense that women do not feel the same entitlement to spend income received by their husbands as that they earn themselves, then women's utility may not be affected greatly, or at all, by the income received by their husbands. And evidence does exist that income pooling is an unrealistic assumption (see Pahl, 1989; Lundberg et al., 1997). Therefore, using the elasticity

[13] In the absence of information on hours worked, the assumption is made that full-timers work 37 hours per week, high hours part-timers 20 hours per week and low hours part-timers 7 hours per week. These figures are the mean hours worked in the relevant ranges by a sample of married women from the 1981 Family Expenditure Survey.

of total household income to estimate the means testing effect practically guarantees finding some effect.

For example, a woman's preferences may be such that she is likely to work more hours the higher her market wage, but is indifferent to the level of her husband's benefit income when making her labour supply decision. A decrease in potential full-time household income may be the result of either a decrease in her offered full-time wage or the reduction in her husband's benefit income on exhausting UB entitlement, but only the former can cause her to make a labour market transition. A model that does not distinguish between the sources of household income will, in simulations, predict a reduction in the probability of her working full time when an increase in the degree of means testing is introduced, when in fact only a fall in her offered wage could produce this result.

To attempt to isolate the effect of means testing on a wife's labour supply, it is therefore necessary to allow a distinction to be drawn between the income received by the husband and that received by the wife. Household income is decomposed as:

$$y_{tj} = y_{tj}^{end} + y_t^{ex} \tag{13}$$

where y_{tj} is total household income at time t and in labour market state j of the wife, y_{tj}^{end} is that part of household income which is endogenous to the wife's labour supply, and y_t^{ex} is the household income exogenous to the wife's labour supply. y_{tj}^{end} can then be further divided into the part of endogenous income that the wife receives, $y_{tj}^{end(w)}$, essentially her wage income in state j (plus any unemployment payments to which she is entitled if j is 'none'), and the part that the husband receives, $y_{tj}^{end(h)}$, which amounts to any means-tested benefit income paid to him, including the UB dependant's allowance, SB and HB, where receivable. The advantage of this decomposition of endogenous income is that it allows a focus on means-tested income. If there is complete intra-household income sharing, then $y_{tj}^{end(h)}$ and $y_{tj}^{end(w)}$ should have equal effects on a wife's labour supply, but the possibility that there is not is allowed for.

The income components which are exogenous to the wife's labour supply may also be decomposed further in order to allow a focus on the effects of benefits:

$$y_t^{ex} = y_t^{ex(ben)} + y_t^{ex(nly)} \tag{14}$$

where $y_t^{ex(ben)}$ is exogenous income coming from unemployment payments, which amounts to the part of UB that does not depend on the wife's labour supply and $y_t^{ex(nly)}$ is other exogenous income, which includes the husband's wage income, if any, and other household non-labour income such as interest from savings, child benefit and Family Income Supplement. The components of y_t^{ex} are defined in this way so that $y_t^{ex(nly)}$ is comparable with the definition of the wife's non-labour income that is usually used in studies of female labour supply.

Clearly, however, the issue of whether there is sufficient variation in the data to identify these various income effects arises. Firstly, $y_{tj}^{end(h)}$, the amount of benefit income received by the husband when the wife is in a given state is partly determined by $y_{tj}^{end(w)}$, her earnings in that state. Moreover, among the variables included in $\mathbf{x}_t$ are household composition variables such as number and ages of children, variables that are used in the calculation of benefit entitlements. Furthermore, $y_t^{ex(ben)}$ is positive only if the husband is unemployed, i.e. only if l_t^h is high, and apart from HB entitlement, the same is true for $y_{tj}^{end(h)}$. However, there are sources of exogenous variation in the variables. Firstly, the amount of SB paid for child dependants varies substantially with age, and more frequently than the pre-school versus school-age division of children usually used in labour supply specifiations. Secondly, the husband's labour force status at the second interview is exogenous, albeit by assumption; since employment status determines whether benefit is received, this implies some exogenous variation. Finally, the rules of HB entitlement, with their distinction between those entitled to and not entitled to SB, introduce an important source of exogenous variation.

Regressions were run to test whether $y_{tj}^{end(h)}$ is, in fact, completely determined by other independent variables. The results, not reported here, showed R^2 values in the region of 0.6; this is not a low figure, but does not suggest an unreasonable level of multicollinearity.

6. Results

The results presented in this section are the estimates from the mixed Mover-Stayer models given by Equations 5a-5d, since this is the preferred approach to applying the Mover-Stayer model. Both the McCall model and the D-H model using $\tilde{S}_j$ are reported, [14] for the purposes of comparison, in Appendix C. The model has a conditional logit structure, so choice-specific variables are interpreted as having a direct effect on utility, where significant. Non-choice-specific variables, on the other hand, must be multiplied by dummies for each of the states (see Greene, 1997); the resultant estimates are interpreted as the effect of the variable on the probability of occupying the relevant state. Results for the determinants of the destination states at the first and

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[14] For both the mixed and D-H models, the likelihood functions were programmed in *STATA* and maximized using that package's *ml* maximization routine. The programs are available on request.

second interviews of those working at the key date and first interview respectively are first discussed, and then the same transitions are modelled for those not working at the relevant origin dates.

Before proceeding further, attention should be drawn to the differences in the variables that are included in the specifications. For some variables, these differences arise because of the nature of the variation in the variables. For example, the husband's job status may be included for transitions between $t = 3$ and $t = 15$, since many have re-entered employment by the second interview, whereas at the first interview, all husbands are unemployed – any working are working part-time – so the variable cannot be included for transitions between $t = -1$ and $t = 3$.

Similarly, difficulties may arise in the estimation of the effects of $y_t^{ex(ben)}$ and $y_t^{ex(nly)}$ on certain transitions. In the case of the former, this difficulty comes from the fact that, although at the first interview some individuals' husbands are eligible for UB, the non-variable part of which comprises this variable, while others' are not, by the second interview almost every husband has exhausted his entitlement to UB. The only variation in this variable at $t = 15$ comes from those husbands who have exited their sampled spell and then re-entered unemployment by the second interview, and who are entitled to receive UB, making it difficult to estimate this variable's effect on transitions between $t = 3$ and $t = 15$.

On the other hand, difficulties with the precise estimation of $y_t^{ex(nly)}$ are more likely to occur in estimating transitions between $t = -1$ and $t = 3$, since in many cases this variable is made up almost entirely of the husband's wage, which, because the husbands are unemployed at the first interview, shows little variation at that date.

Thus, a well-determined effect is not expected for this variable at $t = 3$, whereas at $t = 15$, many husbands have returned to work, thus generating the required variation.

The descriptive statistics for the variables used in modelling the labour supply of the wives are shown in Tables A5 and A6 in Appendix C.

6.1. Discussion of results for movers working at t - 1

Income variables

Tables 6 and 7 show the results of modelling the determinants of the destination states at $t = 3$ and $t = 15$ for women working at $t = -1$ and $t = 3$ respectively. The significant positive coefficients on the wage variable, $y_{tj}^{end(w)}$, in both of these models indicate that these women do respond to economic variables in making their labour supply decisions. For transitions both between $t = -1$ and $t = 3$ and between $t = 3$ and $t = 15$, the effect of $y_{tj}^{end(w)}$ is estimated to have a quadratic relationship with utility.

For both sets of results, a £1 increase in the weekly wage in the relevant hours range increases the probability of working in that range by between 0.5 and 1.75 percentage points, while being given £1 not to work increases the probability of being observed not working by around 1 point.[15]

Tables 6 and 7 about here

[15] A £1 increase in the full-time wage is a much lower proportional increase than a £1 rise in the part-time weekly wage, but this because the use of one choice-specific variable for the wage within a conditional logit structure implies that the utility gained from income in a state does not depend on the number of hours worked in earning that income – i.e. the separability of income from leisure in the utility function.

An unsatisfactory aspect of these wage results, however is that the quadratic effect estimated for both these regressions implies a maximum that is within the sample range, at £139 for the destination state at the first interview and at £89 for the state at the second interview. These values are within the observed range for both full-time and high-hours part-time workers, although above the average in each case, implying that beyond a relatively modest weekly income, utility falls with income, a result that is difficult to believe.

In contrast to the wage income variable, $y_{tj}^{end(h)}$, which is the variable of primary interest in these models, is completely insignificant at both the first and second interviews, indicating that, even though the amount of such income received is determined largely by their labour market behaviour, these women do not take it into account when making their labour supply decisions.

There are several reasons why this result might hold. First, there may not be pooling of income in these households, a point which is discussed further below. Secondly, the wife's beliefs as to the likely duration of her husband's unemployment may counteract her evaluation of the effect of means testing on her optimal labour supply decision. However, a dummy variable for whether the husband leaves his sampled unemployment spell by the second interview, which may capture the expected duration of the husband's unemployment, is not significant when included, casting some doubt on the validity of this second explanation.

In both Tables 6 and Table 7, $y_t^{ex(nly)}$, the part of household income that is exogenous to the wife's labour supply, but not received as unemployment payments by the husband, has a negative effect on the labour supply of the wife that is significant in every case except for the probability of choosing high part-time hours at $t = 3$. As pointed out above, a well-determined effect is not expected for this variable at $t = 3$, since most husbands are unemployed and not earning a wage, whereas its significance in the model of Table 7 is not surprising. The other sources of income included in this variable, such as interest receipts, child benefit and FIS, must be driving this result, although these elements would not be expected to change significantly over time, so conditioning on the initial state might be expected to account for the effect of this variable.

$y_t^{ex(ben)}$ is excluded from the model of states at $t = 3$, because of its lack of significance, but is significant at $t = 15$, in contrast to expectations. As noted above, the only variation in this variable at $t = 15$ is from husbands who have exited their sampled unemployment spell, and then re-entered unemployment, but are still entitled to UB. In general, $y_t^{ex(ben)}$ can be expected to have a positive effect on the probability of participation in the labour market to the extent that this variable picks up similarities in characteristics between UB-receiving husbands and their wives, and a negative effect to the extent that the variable is regarded as non-labour income by a wife. The pattern of results here suggests that these effects cancel each other at the first interview, but at the second, conditional on the husband's job status, the variable selects spouses with more strongly positive labour market attributes.

Demographic variables

The age variable estimates from Table 6 indicate that the older a woman is, the more likely she is to be in part-time work at $t = 3$, given that she worked at $t = -1$; the result for the effect on the probability of working full-time is insignificant. For the destination state at $t = 15$, the results show a positive effect of age on the probability of working either full-time or part-time as opposed to not working. The relationship is quadratic, with age reducing the probability of working full-time beyond the age of 40, and beyond 45 and 42 for high and low part-time hours respectively. Overall, the effect of age is to encourage working women to stay in work; perhaps as women get older, habit plays a greater role in the labour supply decisions of women, up to a certain point.

Some of the most striking results given in these models, however, are those for the variables for the presence of children of different ages in the household. Here, variables for both pre-school and school-aged children have significant effects on labour supply at the first interview, but not at the second interview; at $t = 3$, younger children have a negative, but insignificant effect on the probability of working full-time, a completely insignificant effect on the probability of working high part-time hours, and a significant *positive* effect on the probability of working low part-time hours. Older children have no effect on the probability of working full-time or part-time, more than ten hours, but again have a positive effect on the probability of working part-time, less than ten hours per week. At $t = 15$, children have *no* effect on any of the hours choices when included.

The marginal effects of these dummies for the presence of children are large, where positive. For example, the presence of a younger child in the household increases the probability of a woman working part-time, less than ten hours per week at $t = 3$ by nearly 15 points over the probability that she would have of working in this hours range if there were no young child in the household.

The fact that all these women are already working, and thus are likely to have child-minding arrangements already in place when taking the decision modelled would explain insignificant results for the presence of children, but not significant positive effects. Moreover, large positive coefficients for low hours of work also arise for women who do not work initially, a point discussed below. The pattern of the results across the different hours ranges, whereby the effects are increasingly positive as the number of hours worked decreases, suggests that the usual negative effect of children that decreases with the number of hours worked is being counteracted by a positive effect of children on the probability of participation for these women. It seems likely that the positive effect of children on the probability of working is due to an 'income' effect caused by the higher needs of households with children. If, when a husband becomes unemployed, these needs are not matched by the definition of needs used in the calculation of the entitlement to SB, then a woman may be *more* inclined to work if she has children. The unimportance of children to the destination state at $t = 15$ can then be interpreted as the result of the positive and negative effects counteracting each other for all hours ranges.

It seems plausible that for those working initially, having child-care arrangements already established reduces the search costs element of the fixed costs of working implied by children and thus explains why the income effect of children seems to be a stronger effect on labour market behaviour in this model than in the more familiar cross-section models. The discussion of the results for those not working initially is postponed until these results are presented below.

Husband's work status

The final variable that requires comment is the husband's employment status variable, which is included in the specification of the destination state at $t = 15$. The results show that the husband being at work has a positive effect on the probability of the wife working in any of the three hours ranges, although the result is only clearly statistically significant for full-time work, and marginally significant for high part-time hours. The marginal effect of this variable on the likelihood of working full-time is also particularly large, with a 43 point increase in the probability of the average woman being observed in this hours range when this dummy is ‘switched on’. This result may indicate either complementarity of leisure times between husband and wife, or personal characteristics common to both husband and wife that make it more likely that both of them work.

Other variables

Finally, it is worth commenting on the variables that are absent from the specifications shown in Tables 6 and 7. First, the inclusion of many of the variables that may be included to control for heterogeneity was not supported by the data. I refer here to variables such as the number of times the husband had been unemployed in the five years prior to the first interview, or whether the husband exited his sampled unemployment spell by the second interview. This suggests that conditioning on the state occupied by a woman at $t-1$, and on her being a mover, provides adequate control for heterogeneity.

Further, it should be noted that the local rate of unemployment is not included in these specifications because of lack of significance. This is plausible for two reasons: firstly, because women who are already working can choose to remain in the same job,[16] and secondly, because areas of high unemployment tend to have persistently high unemployment, and only changes in the rate of unemployment would be expected to affect the probability of a woman’s participation in the labour market.

[16] It is possible that a higher unemployment rate would increase the probability of continuing to work if it encourages inertia because of fear of being unable to find another job should the household’s situation change again.

6.2. Discussion of results for movers not working at t - 1

In this section, the results of the mixed Mover-Stayer model for those *not* working at each of the two initial dates are reported and discussed. Table 8 gives the estimated results for the destination states chosen at $t = 3$ by women who are movers, but who did not work at $t = -1$, while Table 9 reports the estimated determinants of the labour force status at $t = 15$ of movers who were not working at $t = 3$.

Tables 8 and 9 about here

Income variables

The results shown in Table 8 indicate a strong importance of economic variables for the labour supply decision at $t = 3$ of women who were not working at $t = -1$. Turning first to the results for $y_{tj}^{end(w)}$, the wage variable, the relationship with utility is shown to be quadratic, with a positive effect of wage income on utility, but only up to a weekly income of £107 per week. Beyond this point, the effect is negative, again, well within the sample range of weekly wages. The coefficient size is also notable; it is larger than that found for either of the models reported in the previous section for women working at $t-1$. The marginal effects indicate that a £1 increase in the weekly wage would increase the probability of working of the average woman by between 0.1 and 0.25 percentage points, and, if she received a £1 payment for not working she would be about 2 points more likely to be observed not working.

The most striking result of Table 8, however, is that $y_{tj}^{end(h)}$ has a positive and statistically significant effect on utility, a result not found for women working at $t-1$. As to the size of its effect, it is smaller than that for the wage variable, although the fact that the latter is included as a quadratic makes direct comparison difficult. However, the results indicate that a £16 increase in the means-tested benefit income that a man would receive if his wife worked full-time would be necessary to increase his wife's probability of working in that hours range by 1 percentage point, with a similar rise necessary to increase her probability of working in the low part-time hours range, and a raise of about £8 being sufficient to raise her probability of working part-time more than ten hours per week by 1 point. An increase of £4 in the benefit income which the household would receive if she did not work would increase her probability of not working from 95% to 96%.

It must, of course, be taken into account that many of those not working initially do not react at all to this or any other variable when making their labour supply decisions, by assumption, because they are stayers. Thus, if, for example, the earnings disregard of SB were increased from £4 per week to £8 per week, then amongst movers, the probability of choosing not to work would decrease from 95% to 94%. But since movers comprise just 26% of those not working at the key date according to $\tilde{S}_j$, the effect on participation of the wives of the unemployed would be to increase it by about 0.25%.

For the other income variable that is included, $y_t^{ex(ben)}$, it is found to have a negative effect on both the probability of working full-time and that of working high part-time hours, although the effect for the former hours range is not significant at usual levels of confidence. The negative marginal effects of this variable on the probability of working in these hours ranges are of a similar order to the positive effects of an increase in means-tested benefit income on these probabilities. These women appear to be much more sensitive to unemployment payments, whether endogenous or exogenous to their labour supply, than women who were working before their husbands became unemployed. A possible reason for this is that pooling is more complete in households where a woman does not work outside the home, of necessity. Thus, if her husband becomes unemployed, the unemployment payments which he receives have a greater effect on her utility than if she were working.

Turning to the results for income variables for women who were not working at $t = 3$, the impression gained from Table 8 that women not working initially might be more sensitive to the functioning of the benefit system than their working counterparts is not sustained. The wage variable, $y_{tj}^{end(w)}$, is statistically significant and positive, but smaller than that found for the destination state at $t = 3$ of women who were not working at $t = -1$. Moreover, the means-tested benefit income variable, $y_{tj}^{end(h)}$, is once again insignificant, and $y_{t}^{ex(nly)}$ does not emerge as important either.

Finally, it is useful to point out that when the model of transitions between the key date and the *second* interview is estimated, thereby modelling the choice at $t = 15$ of those who were not working before their husbands' unemployment spells began, $y_{tj}^{end(h)}$ does not emerge as significant. Thus, not only is the significant effect of means-tested benefit income limited to movers who did not work before their husbands' unemployment spells began, it also appears to be a short-term effect.

Demographic variables

I turn now to the results for the variables representing children in these two models. First, no variables for either the presence of or the number of children of different ages in the household were retained in the model of the destination state at $t = 3$ because of their lack of significance. For the model of Table 9, on the other hand, both younger and older children were found to be important to labour supply, with the same pattern as described above for transitions by women who did work at $t - 1$ of increasingly positive coefficients for decreasing hours of work, again suggesting a positive income effect of children on labour supply outweighing the usual negative effects. For women who worked initially, it was suggested that having child-care arrangements already in place might be sufficient to reduce the negative effect of children. For women not working initially, it is not so clear that they would have child-care facilities readily available, but this is more likely to be the case for movers.

In the model of the state occupied at $t = 3$ by women who were not working before their husbands' sampled unemployment spells began, age has a negative effect on the probability of working any positive hours. The older a woman is, the less likely she is to work full-time or high part-time hours at the first interview, given that she is a mover who was not working at the key date; the same is also true for low part-time hours, although this effect is only marginally significant. Taken together, these results mean that an older woman is least likely to enter the labour force immediately after her husband becomes unemployed. For the destination state at the date of the second interview, however, there is a marginally positive effect of age on the probability of working high part-time hours.

Husband's Work Status

One of the more interesting results given in these two tables is that for the work status of the husband. For women not working initially, this effect is positive for all three destination states involving positive hours of work. Unlike the case of initial workers, however, the coefficients are significant for all three working states. In this case, the coefficient is particularly large for its effect on the probability of working high part-time hours. The fact that the results are so much better determined in this case seem to indicate that for women not working initially, the complementarity between their leisure times and their husbands' is stronger than for women working initially. This may be because of the endogeneity of tastes referred to in Section 4, whereby habit may mean that women who work at $t-1$ become accustomed to spending less time with their husbands.

7. Conclusions

In this paper, a mixed Mover-Stayer model was chosen as the appropriate vehicle for controlling for both true state dependence of destination states, and unobserved heterogeneity of the sample. Thus, the labour market states occupied by the wife at the two dates subsequent to the husband becoming unemployed, conditional on her either being a worker or not at the previous date, are modelled for movers only. Stayers have a zero probability of making a transition.

It was estimated that of those not working before their husbands' unemployment began, 74% are stayers, with corresponding figures for the proportion of stayers among those working full-time, high part-time and low part-time hours at the key date of 57%, 51% and 31%.

The results obtained for women working initially who are movers suggest that these women do not take their husband's benefit income into account when deciding on their optimal labour market states. On the other hand, the presence of children causes these women to be more likely to work, due to an income effect of their husbands' unemployment. Complementarity of leisure times also emerges as an important determinant of a woman's labour supply.

For women not working initially, the results are similar, with the exception that these women *are* less likely to work a given number of hours the lower their husbands' means tested benefits when they work that number of hours. However, this effect is a short-term one, determining transitions only in the period immediately after a husband's unemployment begins. Moreover, because it applies only to movers, who are a small proportion of those not working initially, the aggregate effect of the means testing of benefits is small. This means that the increased means testing implied by 1996 reforms that increase the degree of means testing in the benefit system are not predicted to affect the number of women dropping out of the labour market when their husbands become unemployed, but can be expected to reduce further the number of women behaving like the ‘added workers’ of textbook analyses.

Appendix A: Calculation of $\tilde{s}_j$

According to Equation 9,

$$\Pr(\textit{observed stayer is a mover}) = (1 - \tilde{s}_j) = \left((1 - \tilde{S}_j) - (1 - \hat{S}_j)\right) \big/ \hat{S}_j$$

and this is the basis of the calculations shown below.

Stayers in Full-Time Work:

$$\tilde{S}_{FT} = 0.574 \Rightarrow (1 - \tilde{S}_{FT}) = 0.426;\ \hat{S}_{FT} = 0.602 \Rightarrow (1 - \hat{S}_{FT}) = 0.398$$

$$(1 - \tilde{s}_{FT}) = \frac{0.426 - 0.398}{0.602} = 0.047 \Rightarrow \tilde{s}_{FT} = 0.953$$

which means that the probability that a woman who is observed to stay in full-time work throughout the sample period is, in fact, a mover is less than 5%.

Stayers in High Hours Part-Time Work:

$$\tilde{S}_{PT>10} = 0.507 \Rightarrow (1 - \tilde{S}_{PT>10}) = 0.493;\ \hat{S}_{PT>10} = 0.536 \Rightarrow (1 - \hat{S}_{FT}) = 0.464$$

$$(1 - \tilde{s}_{PT>10}) = \frac{0.493 - 0.464}{0.536} = 0.054 \Rightarrow \tilde{s}_{PT>10} = 0.946$$

Stayers in Low Hours Part-Time Work:

$$\tilde{S}_{PT<10} = 0.310 \Rightarrow (1 - \tilde{S}_{PT<10}) = 0.690;\ \tilde{S}_{PT<10} = 0.306 \Rightarrow (1 - \tilde{S}_{PT<10}) = 0.694$$

$$(1 - \tilde{s}_{PT<10}) = 0 \Rightarrow \tilde{s}_{PT<10} = 1$$

Stayers out of Work:

$$\tilde{S}_{NONE} = 0.738 \Rightarrow (1 - \tilde{S}_{NONE}) = 0.262;\ \tilde{S}_{NONE} = 0.825 \Rightarrow (1 - \tilde{S}_{NONE}) = 0.175$$

$$(1 - \tilde{s}_{NONE}) = \frac{0.262 - 0.175}{0.825} = 0.105 \Rightarrow \tilde{s}_{NONE} = 0.895$$

Appendix B: Wage prediction and construction of $y_{itj}^{end(w)}$

Where a woman reports earnings at the first interview, the reported gross figure is divided by the relevant number of hours – 7, 20 or 37, as appropriate – to obtain a gross hourly wage.

Where a woman reports earnings at one of the other principal dates but not at another, the gross wage rate for the missing date is calculated as the reported one appropriately adjusted for wage inflation, using the rate of increase in the within-sample median wage between dates.

Where a woman does not report earnings at any of the principal dates, her wage at the first interview is predicted on the basis of OLS estimates of wage equation coefficients, reported in Table A1. OLS estimation was used because of the lack of a suitable variable in the dataset that would the allow the identification of a model correcting for selection bias. It is notable that education is not included in the estimation, again because of its absence from the dataset. Estimations are carried out and wage rates predicted separately for those whose husbands report a wage and those whose husbands do not.

Table A1 about here

Gross earnings for each labour market state at $t = 3$ are then calculated, and extrapolated to earnings at the second interview, again using within-sample wage inflation. Finally, tax and national insurance rules are used to calculated net earnings in each labour market state for the two dates.

Appendix C: Descriptive statistics and results of McCall and Double-Hurdle Mover-Stayer models

This appendix gives the results of the McCall Mover-Stayer model and the D-H Mover-Stayer model using Frydman's $\tilde{S}_j$; these are the two models discussed in Section 4 as alternatives to the mixed Mover-Stayer model presented in that section. Descriptive statistics for the variables included in that model are also shown.

Tables A2-A7 here

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Tables

Table 1

Employment rates of married women in various countries, percentages.

Country	Employed Husband	Unemployed Husband
Australia (1985)*	62	23
Canada (1987)*	66	46
France (1981)*	55	44
Netherlands (1983)	31	27
Germany (1983)	53	52
Israel (1986)*	49	30
Italy (1986)	37	41
Norway (1979)*	68	43
Switzerland (1982)*	44	26
UK (1979)*	61	47
USA (1986)**	67	59

Notes: * Significant at the 1% level. ** Significant at the 5% level. Source: Giannelli and Micklewright (1995), from Luxembourg Income Study data.

Table 2

Husbands' transitions to which wives may react.

Event	Number	%
Change labour market state: Between key date and first interview	1077	62.4
Between first and second interviews	725	42.0
Stop receiving UB: Total	1108	64.2
Because exit unemployment	586	33.9
Because exhaust entitlement	522	30.0

Table 3

Wives' Transitions between key date and first interview.

Job Status at $t = -1$	Job status at $t = 3$				Total
	Full-Time	Part-Time, > 10 hours	Part-Time, < 10 hours	None	
Full-Time	**227**	17	1	54	299
	(13.5)	(1.0)	(0.1)	(3.2)	(17.8)
Part-Time, > 10 hours	2	**181**	12	42	237
	(0.1)	**(10.8)**	(0.7)	(2.3)	(13.9)
Part-Time, < 10 hours	1	6	**56**	9	72
	(0.1)	(0.4)	**(3.3)**	(0.5)	(4.3)
None	12	24	13	**1023**	1072
	(.7)	(1.4)	(0.8)	**(60.9)**	(63.8)
Total	242	228	82	1128	1680
	(14.4)	(13.6)	(4.9)	(67.1)	(100.0)

Note: Percentage of total sample in brackets.

Table 4

Wives' transitions between first and second interviews.

Job Status at $t = 3$	Job status at $t = 15$				Total
	Full-Time	Part-Time, > 10 hours	Part-Time, < 10 hours	None	
Full-Time	**201**	8	1	37	247
	(11.7)	(0.5)	(0.1)	(2.2)	(14.4)
Part-Time, > 10 hours	24	**156**	14	35	229
	(1.4)	**(9.1)**	(0.8)	(2.0)	(13.4)
Part-Time, < 10 hours	5	17	**34**	27	83
	(0.3)	(1.0)	**(2.0)**	(1.6)	(4.8)
None	38	62	38	**1016**	1154
	(2.2)	(3.6)	(2.2)	**(59.3)**	(67.4)
Total	268	243	87	1115	1713
	(15.6)	(14.2)	(5.1)	(65.1)	(100.0)

Note: Percentage of total sample in brackets.

Table 5

The elements used to calculate $\hat{S}_j$ and $\tilde{S}_j$.

State	n_{j0}	$(n_j)_{ALL}$ *	$(n_{j0} - n_j)_{PRED}$ †	$n_{j0}(1-\hat{V}_{jjT})$	$\hat{S}_j$	$\tilde{S}_j$
Full-Time	299	180	105	265	0.602	0.574
Part-Time, > 10 Hours	237	127	97	207	0.536	0.507
Part-Time, < 10 Hours	72	22	48	71	0.306	0.310
None	1072	884	88	374	0.825	0.738

* Excludes all transitions, whether or not the individual is predicted to move.

† Includes only transitions by those predicted to move.

Table 6

Results of the mixed Mover-Stayer model of destination states at $t = 3$ for women who are movers and were working at $t = -1$. Asymptotic t-statistics in brackets.

Non-Choice-Specific Variables	Full-Time Coefficient (*t-Stat.*)	Full-Time Marginal Effect	Part-Time > 10 Hours Coefficient (*t-Stat.*)	Part-Time > 10 Hours Marginal Effect	Part-Time < 10 Hours Coefficient (*t-Stat.*)	Part-Time < 10 Hours Marginal Effect
$y_t^{ex(nly)}$	-0.0806	-0.0227	-0.0317	0.0029	-0.0878	-0.0053
	(*-2.40*)		(*-1.01*)		(*-2.62*)	
$\left(y_t^{ex(nly)}\right)^2$	0.0012	0.0003	0.0006	-0.0000	0.0012	0.0001
	(*2.21*)		(*1.05*)		(*2.33*)	
Dummy: Children Aged 0-4	-1.1098	-0.2139	0.4587	0.1058	1.2335	0.1482
	(*-1.53*)		(*0.89*)		(*2.16*)	
Dummy: Children Aged > 4	0.0897	-0.0648	0.4808	0.0561	1.0428	0.0738
	(*0.19*)		(*1.25*)		(*2.38*)	
Wife's Age	-0.0178	-0.0131	0.0349	0.0123	0.0450	0.0045
	(*-0.96*)		(*2.04*)		(*2.17*)	
Constant	-2.0239	–	-3.4089	–	-3.3314	–
	(*-2.16*)		(*-4.03*)		(*-3.48*)	

Choice-Specific Variables	Coefficient	*t-Statistic*	Marginal Effects × 10^2 F-T	P-T>10	P-T<10	None
$y_{tj}^{end(w)}$	0.0556	*3.71*	1.3082	1.2414	0.5577	0.7960
$\left(y_{tj}^{end(w)}\right)^2$	-0.0002	*-2.79*	-0.0039	-0.0037	-0.0017	-0.0024
$y_{tj}^{end(h)}$	-0.0041	*-0.31*	-0.0955	-0.0906	-0.0407	-0.0581

Number of Observations: 608 *Log Likelihood:* -350.0

Notes: All money amounts are in pounds. Marginal effects are calculated at the sample probability of occupying the relevant state. Here, $\Pr(FT) = 0.378$, $\Pr(PT > 10) = 0.336$ and $\Pr(PT < 10) = 0.113$.

Table 7

Results of the mixed Mover-Stayer model of destination states at $t = 15$ for women who are movers and were working at $t = 3$. Asymptotic t-statistics in brackets.

Non-Choice-Specific Variables	Full-Time Coefficient (*t-Stat.*)	Full-Time Marginal Effect	Part-Time > 10 Hours Coefficient (*t-Stat.*)	Part-Time > 10 Hours Marginal Effect	Part-Time < 10 Hours Coefficient (*t-Stat.*)	Part-Time < 10 Hours Marginal Effect
$y_t^{ex(nly)}$	-0.0118	-0.0036	-0.0074	-0.0006	-0.0087	-0.0001
	(*-2.74*)		(*-2.07*)		(*-1.63*)	
$y_t^{ex(ben)}$	0.0823	0.0299	0.0255	-0.0031	0.0142	-0.0025
	(*2.34*)		(*0.66*)		(*0.30*)	
Wife's Age	0.4345	0.1108	0.3589	0.0427	0.5524	0.0227
	(*2.86*)		(*2.64*)		(*2.81*)	
(Wife's Age)^2	-0.0054	-0.0015	-0.0040	-0.0004	-0.0066	-0.0003
	(*-2.69*)		(*-2.34*)		(*2.67*)	
Husband at Work	2.8504	0.4363	1.0704	0.0786	0.7277	-0.0788
	(*4.05*)		(*1.89*)		(*1.02*)	
Constant	-12.4273	–	-10.0664	–	-12.7746	–
	(*-4.33*)		(*-3.84*)		(*-3.42*)	

Choice-Specific Variables	Coefficient	*t-Statistic*	Marginal Effects × 10^2 F-T	Marginal Effects × 10^2 P-T>10	Marginal Effects × 10^2 P-T<10	Marginal Effects × 10^2 None
$y_{tj}^{end(w)}$	0.0711	*3.63*	1.7219	1.5579	0.5709	1.0362
$\left(y_{tj}^{end(w)}\right)^2$	-0.0004	*-2.90*	-0.0091	-0.0082	-0.0030	-0.0055
$y_{tj}^{end(h)}$	-0.0044	*-0.35*	-0.1072	-0.0970	-0.0356	-0.0645

Number of Observations: 559 *Log Likelihood:* -274.1

Notes: All money amounts are in pounds. Marginal effects are calculated at the sample probability of occupying the relevant state. Here, $\Pr(FT) = 0.411$, $\Pr(PT > 10) = 0.324$ and $\Pr(PT < 10) = 0.088$.

Table 8

Results of the mixed Mover-Stayer model of destination states at $t=3$ for women who are movers and were <u>not</u> working at $t=-1$. Asymptotic t-statistics in brackets.

Non-Choice-Specific Variables	Full-Time		Part-Time > 10 Hours		Part-Time < 10 Hours	
	Coefficient (*t-Stat.*)	Marginal Effect	Coefficient (*t-Stat.*)	Marginal Effect	Coefficient (*t-Stat.*)	Marginal Effect
$y_t^{ex(ben)}$	-0.0394	-0.0004	-0.0368	-0.0008	0.0126	0.0002
	(*-1.45*)		(*-1.95*)		(*0.46*)	
Wife's Age	-0.1172	-0.0013	-0.0497	-0.0011	-0.0555	-0.0006
	(*-2.66*)		(*-1.96*)		(*-1.67*)	
Constant	-0.9187	–	-1.5968	–	-2.1098	–
	(*-0.59*)		(*-1.55*)		(*-1.79*)	
Choice-Specific Variables	**Coefficient**	***t-Statistic***	**Marginal Effects × 10^2**			
			F-T	P-T>10	P-T<10	None
$y_{tj}^{end(w)}$	0.1071	*3.48*	0.1165	0.2303	0.1269	0.4698
$\left(y_{tj}^{end(w)}\right)^2$	-0.0005	*-2.39*	-0.0006	-0.0011	-0.0006	-0.0022
$y_{tj}^{end(h)}$	0.0556	*2.78*	0.0605	0.1196	0.0659	0.2440

Number of Observations: 1072 *Log Likelihood:* -165.3

Notes: All money amounts are in pounds. Marginal effects are calculated at the sample probability of occupying the relevant state. Here, $\Pr(FT) = 0.011$, $\Pr(PT > 10) = 0.022$ and $\Pr(PT < 10) = 0.012$.

Table 9

Results of the mixed Mover-Stayer model of destination states at $t = 15$ for women who are movers and were not working at $t = 3$. Asymptotic t-statistics in brackets.

Non-Choice-Specific Variables	Full-Time Coefficient (*t-Stat.*)	Full-Time Marginal Effect	Part-Time > 10 Hours Coefficient (*t-Stat.*)	Part-Time > 10 Hours Marginal Effect	Part-Time < 10 Hours Coefficient (*t-Stat.*)	Part-Time < 10 Hours Marginal Effect
Number Children Aged 0-4	-1.5512 (*-3.37*)	-0.0512	-0.3006 (*-0.88*)	-0.0143	0.4884 (*1.65*)	0.0183
Number Children Aged > 4	-0.2541 (*-1.20*)	-0.0098	0.4658 (*2.74*)	0.0247	0.4934 (*2.66*)	0.0157
Wife's Age	-0.0275 (*-1.31*)	-0.0010	0.0385 (*1.71*)	0.0021	0.0095 (*0.37*)	0.0003
Husband at Work	1.7673 (*2.79*)	0.0798	2.9289 (*5.93*)	0.3331	1.9202 (*4.63*)	0.0956
Constant	-1.7675 (*-1.54*)	–	-5.0575 (*4.28*)	–	-3.8271 (*-3.28*)	–
Choice-Specific Variables	**Coefficient**	***t-Statistic***	**Marginal Effects × 10^2: F-T**	**P-T>10**	**P-T<10**	**None**
$y_{tj}^{end(w)}$	0.0184	*2.01*	0.0586	0.0938	0.0586	0.1939
$y_{tj}^{end(n)}$	-0.0063	*-0.48*	-0.0200	-0.0321	-0.0200	-0.0663
No. Observations: 1154				*Log Likelihood:* -320.0		

Notes: All money amounts are in pounds. Marginal effects are calculated at the sample probability of occupying the relevant state. Here, $\Pr(FT) = 0.033$, $\Pr(PT > 10) = 0.054$ and $\Pr(PT < 10) = 0.033$.

Table A1

Results of OLS Wage Estimation

Variable	Husbands Reporting Wages (1)		Husbands Not Reporting Wages (2)	
	Coefficient	*t-Statistic*	Coefficient	*t-Statistic*
Log of Husband's Wage	0.0694	*1.65*	–	–
Age Spline: under 40	0.0060	*1.45*	0.0089	*1.05*
40 to 50 years	-0.0190	*-2.26*	-0.0317	*-1.92*
50 to 60 years	0.0078	*0.46*	0.0441	*1.60*
over 60 years	-0.1889	*-2.24*	–	–
One Child	-0.1409	*-2.57*	–	–
Two or Three Children	-0.2226	*-4.09*	-0.4357	*-4.71*
Four or More Children	-0.2437	*-1.78*	-0.5025	*-2.87*
Husband's Occupation:				
Employer/Manager in Large Establishment	-0.1453	*-1.69*	-0.2243	*-1.26*
Employer/Manager in Small Establishment	-0.1372	*-1.58*	0.4867	*2.65*
Self-Employed Professional	0.6658	*1.32*	0.9557	*2.04*
Personal Services Worker	-0.3561	*-1.81*	–	–
Manual Foreman	-0.2416	*-2.83*	–	–
Skilled Manual Worker	-0.1631	*-2.50*	-0.1106	*-1.32*
Semi-Skilled Manual Worker	-0.1711	*-2.26*	–	–
Unskilled Manual Worker	-0.1873	*-1.58*	–	–
Self-Employed Non-Professional	-0.3996	*-3.47*	–	–
Farmer Employing Others	-0.9486	*-1.88*	–	–
Agricultural Worker	-0.4301	*-2.41*	–	–
Member Armed Forces	-0.2852	*-1.46*	–	–
Husband's Industry: Other Services	0.1589	*2.76*	–	–
Other Manufacturing	-0.1354	*-1.96*	–	–
Metal, Engineering and Vehicles	–	–	-0.1106	*-1.32*
London Resident	0.1697	*2.55*	0.4805	*3.47*
Resident Rest of Sth-East England	0.1813	*3.13*	0.3168	*2.37*
Resident South-West England	-0.2470	*-2.73*	-0.3851	*-1.83*
Resident Wales	–	–	0.1752	*1.44*
Constant	4.9658	*19.47*	5.1511	*20.02*
	No. Obs.: 618	R^2: 0.153	*No. Obs.*: 143	R^2: 0.314

Notes: Dependent variable is log gross hourly wage. Omitted occupational groups in Model 1 are: Employed Professional Worker; Intermediate Non-Manual Worker; Junior Non-Manual Worker; Not Stated. Omitted child variable is 'none'. There were no women aged over 60 among those whose husbands did not report a wage; hence its omission in Model 2.

Table A2

Results of the McCall and Double-Hurdle Mover-Stayer models of destination states at $t = 3$ for women who were working at $t = -1$. Asymptotic t-statistics in brackets.

	McCall Model			**Double-Hurdle Model**		
	Full-Time	Part-Time > 10 Hours	Part-Time < 10 Hours	Full-Time	Part-Time > 10 Hours	Part-Time < 10 Hours
Non-Choice-Specific Variables	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)
$y_t^{ex(nly)}$	-0.0798	-0.1310	-0.0878	-0.0604	-0.0479	-0.0717
	(*-2.40*)	(*-1.00*)	(*-2.64*)	(*-1.36*)	(*-1.33*)	(*-1.74*)
$\left(y_t^{ex(nly)}\right)^2$	0.0012	0.0005	0.0012	0.0006	0.0005	0.0007
	(*2.23*)	(*1.05*)	(*2.35*)	(*1.08*)	(*0.99*)	(*1.29*)
Dummy: Child	-1.0767	0.4493	1.2311	-2.6104	0.4789	1.2041
Aged 0-4	(*-1.49*)	(*0.88*)	(*2.16*)	(*-2.25*)	(*0.65*)	(*1.02*)
Dummy: Child	0.1133	0.4518	1.0395	-1.9705	1.2098	1.6379
Aged > 4	(*0.24*)	(*1.18*)	(*2.38*)	(*-1.67*)	(*2.36*)	(*2.52*)
Wife's Age	-0.0171	0.0339	0.0449	-0.0674	0.0587	0.0813
	(*-0.92*)	(*1.98*)	(*2.17*)	(*-2.19*)	(*2.49*)	(*2.25*)
Constant	-2.0470	-3.3471	-3.3099	-1.7933	-5.8183	-6.2693
	(*-2.19*)	(*-3.96*)	(*-3.46*)	(*-1.35*)	(*-4.77*)	(*-3.56*)
Choice-Specific Variables	Coefficient	(*t-Statistic*)		Coefficient	(*t-Statistic*)	
$y_{tj}^{end(w)}$	0.0542	(*3.61*)		0.1007	(*4.37*)	
$\left(y_{tj}^{end(w)}\right)^2$	-0.0002	(*-2.72*)		-0.0003	(*-2.99*)	
$y_{tj}^{end(n)}$	-0.0043	(*-0.33*)		0.0106	(*0.57*)	
No. Observations	*279*			*608*		
Log Likelihood	*-339.15*			*-441.77*		

Table A3

Results of the McCall and Double-Hurdle Mover-Stayer models of destination states at $t = 15$ for women who were working at $t = 3$. Asymptotic t-statistics in brackets.

Non-Choice-Specific Variables	**McCall Model** Full-Time	**McCall Model** Part-Time > 10 Hours	**McCall Model** Part-Time < 10 Hours	**Double-Hurdle Model** Full-Time	**Double-Hurdle Model** Part-Time > 10 Hours	**Double-Hurdle Model** Part-Time < 10 Hours
	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)
$y_t^{ex(nly)}$	-0.0096	-0.0071	-0.0088	-0.0141	-0.0087	-0.0079
	(*-2.34*)	(*-1.98*)	(*-1.64*)	(*-2.82*)*2*	(*-2.21*)	(*-1.46*)
$y_t^{ex(ben)}$	0.0845	0.0243	0.0015	0.0853	0.0381	0.0172
	(*2.37*)	(*0.63*)	(*0.32*)	(*2.33*)	(*1.02*)	(*0.36*)
Wife's Age	0.4922	0.3318	0.5444	0.3266	0.3751	0.6268
	(*3.03*)	(*2.45*)	(*2.75*)	(*2.07*)	(*2.69*)	(*3.00*)
(Wife's Age)^2	-0.0060	-0.0037	-0.0065	-0.0042	-0.0043	-0.0077
	(*-2.85*)	(*-2.17*)	(*-2.62*)	(*-2.01*)	(*-2.43*)	(*-2.94*)
Husband at Work	2.5346	1.0225	0.7436	2.7817	1.0842	0.4763
	(*3.58*)	(*1.79*)	(*1.04*)	(*3.64*)	(*1.79*)	(*0.66*)
Constant	-13.7186	-9.5546	-12.6677	-9.3135	-9.4664	-13.4077
	(*-4.45*)	(*-3.67*)	(*-3.37*)	(*-3.15*)	(*-3.55*)	(*-3.35*)

Choice-Specific Variables	McCall Model Coefficient	McCall Model (*t*-Statistic)	Double-Hurdle Model Coefficient	Double-Hurdle Model (*t*-Statistic)
$y_{tj}^{end(w)}$	0.0742	(*3.63*)	0.0621	(*3.21*)
$\left(y_{tj}^{end(w)}\right)^2$	-0.0004	(*-3.06*)	-0.0003	(*-2.40*)
$y_{tj}^{end(h)}$	-0.0053	(*-0.41*)	0.0017	(*0.13*)
No. Observations	*225*		*559*	
Log Likelihood	*-255.09*		*-497.05*	

Table A4

Results of the McCall and Double-Hurdle Mover-Stayer models of destination states at $t = 3$ for women who were not working at $t = -1$. Asymptotic t-statistics in brackets.

Non-Choice-Specific Variables	McCall Model			Double-Hurdle Model		
	Full-Time	Part-Time > 10 Hours	Part-Time < 10 Hours	Full-Time	Part-Time > 10 Hours	Part-Time < 10 Hours
	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)	Coefficient (*t-Statistic*)
$y_t^{ex(ben)}$	-0.0424	-0.0406	0.0094	-0.0325	-0.0302	0.0193
	(*-1.55*)	(*-2.11*)	(*0.34*)	(*-1.16*)	(*-1.57*)	(*0.70*)
Wife's Age	-0.1207	-0.0479	-0.0576	-0.1177	-0.0491	-0.0542
	(*-2.60*)	(*-1.75*)	(*-1.62*)	(*-2.71*)	(*-2.03*)	(*-1.71*)
Constant	-0.4187	-1.2794	-1.6413	-0.9434	-1.6139	-2.2471
	(*-0.26*)	(*-1.19*)	(*-1.32*)	(*-0.58*)	(*-1.50*)	(*-1.99*)

Choice-Specific Variables	McCall Coefficient	McCall (*t*-Statistic)	Double-Hurdle Coefficient	Double-Hurdle (*t*-Statistic)
$y_{tj}^{end(w)}$	0.1159	(*3.59*)	0.1017	(*3.01*)
$\left(y_{tj}^{end(w)}\right)^2$	-0.0006	(*-2.51*)	-0.0004	(*-2.13*)
$y_{tj}^{end(h)}$	0.0556	(*2.73*)	0.0615	(*2.64*)
No. Observations	*188*		*1072*	
Log Likelihood	*-144.14*		*-237.24*	

Table A5

Results of the McCall and Double-Hurdle Mover-Stayer models of destination states at $t = 15$ for women who were <u>not</u> working at $t = 3$. Asymptotic t-statistics in brackets.

Non-Choice-Specific Variables	**McCall Model** Full-Time Coefficient (*t-Statistic*)	**McCall Model** Part-Time > 10 Hours Coefficient (*t-Statistic*)	**McCall Model** Part-Time < 10 Hours Coefficient (*t-Statistic*)	**Double-Hurdle Model** Full-Time Coefficient (*t-Statistic*)	**Double-Hurdle Model** Part-Time > 10 Hours Coefficient (*t-Statistic*)	**Double-Hurdle Model** Part-Time < 10 Hours Coefficient (*t-Statistic*)
No. Children Aged 0-4	-1.2383 (*-2.63*)	0.0422 (*0.11*)	0.9274 (*2.60*)	-1.707 (*-3.06*)	-0.5819 (*-1.61*)	0.2054 (*0.68*)
No. Children Aged > 4	-0.1311 (*-0.59*)	0.6091 (*3.34*)	0.6549 (*3.32*)	-0.2609 (*-1.09*)	0.3471 (*1.95*)	0.3533 (*1.95*)
Wife's Age	-0.0236 (*-1.09*)	0.0430 (*1.83*)	0.0113 (*0.40*)	-0.0444 (*-1.80*)	0.0203 (*0.85*)	-0.0108 (*-0.42*)
Husband at Work	1.7530 (*2.74*)	2.8133 (*5.56*)	1.5371 (*3.53*)	1.7070 (*2.42*)	2.8767 (*5.47*)	2.0182 (*4.78*)
Constant	-1.8679 (*-1.60*)	-5.0709 (*-4.13*)	-3.5477 (*-2.81*)	-1.0416 (*-0.80*)	-4.0984 (*-3.28*)	-2.9692 (*-2.58*)

Choice-Specific Variables	McCall Model Coefficient	McCall Model (*t*-Statistic)	Double-Hurdle Model Coefficient	Double-Hurdle Model (*t*-Statistic)
$y_{tj}^{end(w)}$	0.0196	(*2.10*)	0.0105	(*1.07*)
$y_{tj}^{end(n)}$	-0.0161	(*-1.19*)	-0.0026	(*-0.18*)
No. Observations	*246*		*1154*	
Log Likelihood	*-266.24*		*-529.11*	

Table A6

Descriptive statistics for variables used in the mixed Mover-Stayer model, women working at $t-1$

Variable		At $t=3$ for workers at $t=-1$				At $t=15$ for workers at $t=3$			
		Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
$y_{tj}^{end(w)}$	F-T	63.48	34.50	10.9	443.0	70.58	36.07	11.1	382.9
	P-T>10	38.81	19.68	5.91	264.2	42.93	20.23	6.0	228.3
	P-T<10	16.18	8.75	2.1	96.8	17.87	9.27	2.1	84.8
	None	0.59	3.72	0	25.3	0.83	4.74	0	40.9
$y_{tj}^{end(h)}$	F-T	7.94	11.09	0	73.7	5.43	12.09	0	75.6
	P-T>10	16.37	15.10	0	84.2	10.80	17.60	0	86.4
	P-T<10	31.94	18.72	0	100.5	18.73	24.83	0	94.7
	None	41.20	20.15	0	120.6	23.00	28.88	0	97.4
$y_{t}^{ex(ben)}$		19.47	10.39	0	26.5	1.36	5.86	0	27.5
$y_{t}^{ex(nly)}$		11.91	19.76	0	297.0	70.49	64.69	0	488.2
Wife's Age		39.29	10.69	19	65	39.57	10.66	20	65
No. Children Aged 0-4		0.13	0.39	0	2	0.16	0.42	0	2
No. Children Aged > 4		0.73	1.01	0	4	0.68	0.97	0	4
Local Unemployment		13.12	3.11	5.9	19.4	14.47	3.85	5.7	23.5
Husband at Work		0.04	0.21	0	1	0.57	0.50	0	1
No. Observations		*608*				*561*			

Notes: All money variables are measured in pounds.

Table A7

Descriptive statistics for variables used in the mixed Mover-Stayer model, women not working at $t-1$

Variable		At $t=3$ for non-workers at $t=-1$				At $t=15$ for non-workers at $t=3$			
		Mean	Std. Dev.	Min.	Max.	Mean	Std. Dev.	Min.	Max.
$y_{tj}^{end(w)}$	F-T	53.14	15.38	8.9	287.8	54.98	13.30	9.1	175.5
	P-T>10	33.49	8.64	4.8	159.9	34.63	7.80	4.9	99.4
	P-T<10	13.17	4.24	1.7	62.5	13.46	3.98	1.7	42.3
	None	0.86	4.51	0	25.6	0.51	3.74	0	36.2
$y_{tj}^{end(h)}$	F-T	12.38	12.76	0	88.6	12.69	15.03	0	98.4
	P-T>10	22.79	17.07	0	110.0	23.12	21.78	0	127.6
	P-T<10	39.67	19.69	0	132.1	35.88	29.6	0	155.2
	None	46.62	21.02	0	149.0	41.32	33.22	0	172.8
$y_t^{ex(ben)}$		16.91	11.87	0	28.0	1.76	6.63	0	27.8
$y_t^{ex(nly)}$		15.23	18.70	0	355.6	56.50	82.43	0	1350
Wife's Age		34.06	11.32	16	73	35.42	11.49	17	74
No. Children Aged 0-4		0.68	0.81	0	4	0.66	0.83	0	4
No. Children Aged > 4		0.88	1.12	0	8	0.92	1.13	0	8
Local Unemployment		13.38	3.04	5.9	19.4	14.84	3.84	5.7	23.5
Husband at Work		0.04	0.18	0	1	0.32	0.47	0	1
No. Observations		*1072*				*1159*			

Notes: All money variables are measured in pounds.

Figures

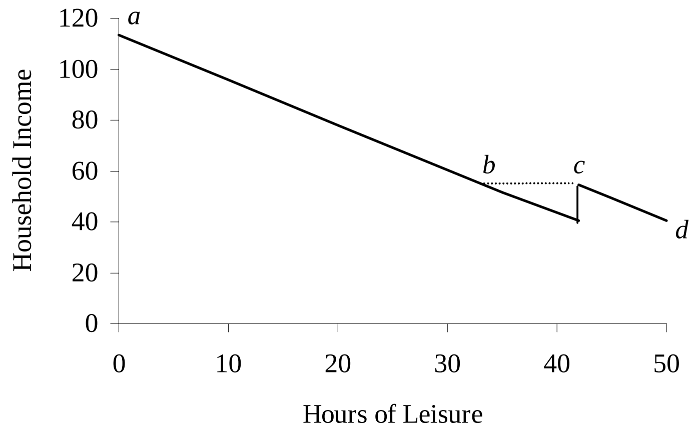

Figure 1. Budget constraint faced by the wife of an unemployed man who receives UB.

Note: The budget constraint is calculated for an hourly wage rate of £1.77, the average net wage in the *LSUS* data used later in the paper, and for a UB entitlement of the husband of £25, plus £15.45 dependant's allowance. These were the prevailing rates in 1983-84. The tax system is ignored.

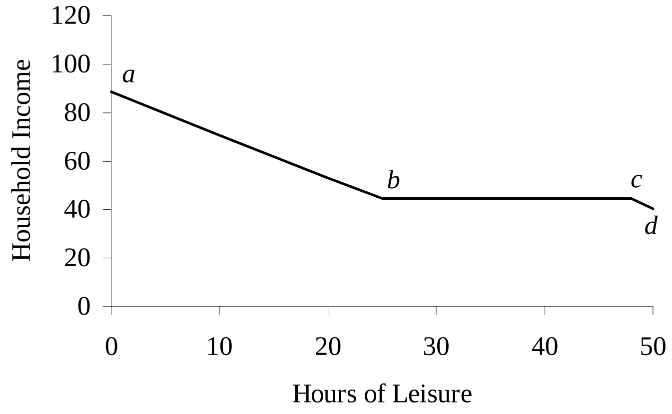

Figure 2. Budget constraint faced by the wife of an unemployed man who receives SB.

Note: The amount of SB entitlement illustrated is the same as for Figure 1 when the wife works zero hours, so the differences between Figure 1 and Figure 2 reflect only the difference in treatment of the wife's income between UB and SB.

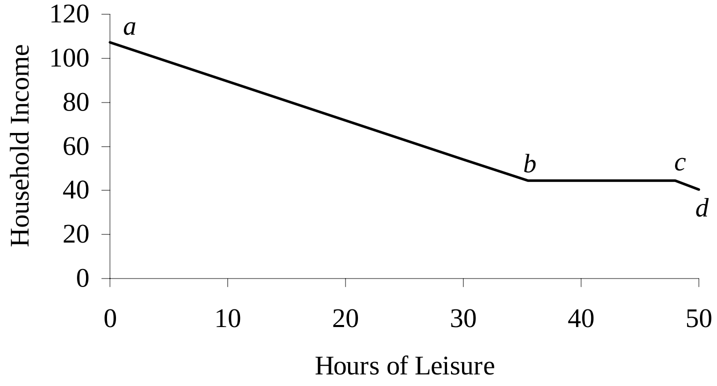

Figure 3. Budget constraint faced by the wife of an unemployed man who receives both UB and SB.

Note: The amount of UB entitlement illustrated is the three-quarter rate of £18.75 plus £11.59 dependant's allowance, with household income topped up to £40.45 by SB. Thus, the total benefit entitlement at zero hours of work of the wife is the same as for Figures. 1 and 2.

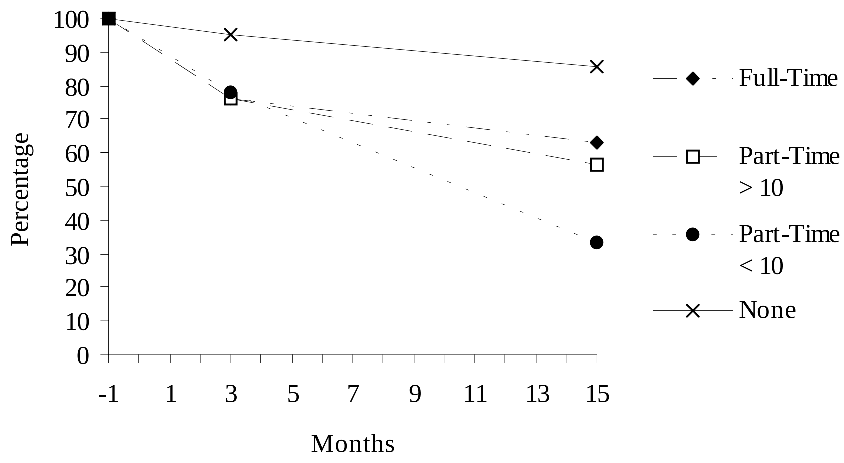

Figure 4. Proportion of those initially in each state who are still in that state at $t = 3$ and $t = 15$.