An Economic Model of Household Income Dynamics, with an Application to Poverty Dynamics among American Women

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Editorial Note

Simon Burgess is a Reader and Carol Propper is a Professor in the Department of Economics, University of Bristol, and both are associates of CASE.

Acknowledgements

Abstract

The rise in inequality and poverty is one of the most important economic and social issues in recent times. But in contrast to the literature on individual earnings inequality, there has been little work modelling (as opposed to documenting) household income dynamics. This is largely because of the difficulties created by the fact that on top of the human capital issues that arise in personal earnings, individuals are continually forming, dissolving and reforming household units. This paper proposes a framework for modelling household income dynamics. it emphasises the role of household formation and dissolution, and labour market participation. It allows standard economic theory to address the issues of household, as distinct from individual, income and poverty dynamics. We illustrate this framework with an application to poverty rates among young women in the US. We use this model to analyse differences in poverty experiences, particularly between black and white women.

Contents

1. Non-Technical Summary

The rise in inequality and poverty is one of the most important economic and social issues in recent times. After declining through the 1960s and 1970s, poverty rates in the US started trending upwards from the end of the 1970s. This renewed interest in distributional issues has been influenced by a dynamic perspective on household income generation. It is now well established that income levels for any one household can fluctuate substantially over time. Indeed, stability is the exception rather than the norm: the Census Bureau reports that nearly 80 percent of the population see their family income to needs ratio change by at least 5 percent in a year, with falls and rise roughly in balance. The probability of larger movements is also high: the Economic Report of the President quotes unpublished work showing the chance of changing income decile to be around 30 percent per year. Similarly high levels of income mobility have been found in other countries. Such income mobility clearly includes movement across the poverty line.

There has been a great deal of work documenting the rise in inequality and poverty (see for example, work by Atkinson, Danziger and Gottschalk, Gottschalk and Moffitt, Gottschalk and Smeeding, and Hills). There has also been work highlighting the importance of dynamics in the income generation process. But we need to go further and explain and understand these processes. In contrast to the work on individual earnings dispersion, there has been little work modelling (as opposed to documenting) household income dynamics. Indeed, Sawhill has noted that economists have no model of household income dynamics or poverty (pp. 1085-6, p. 1113). This view is repeated ten years later by Gottschalk: "the gaps [in models of individual earnings] are small compared to the limited understanding of the processes generating families and family income"; also in Gottschalk and Smeeding, pp. 635, 668 and 676). This is largely because on top of the human capital issues that arise in personal earnings, individuals are continually forming, dissolving and reforming household units. If we follow convention and take the household to be the unit for which poverty is defined, and adopt an income-based definition of poverty an individual is classified as being poor if the income of the household of which she is a member falls below a threshold. Income is assumed to be shared within a household, so to determine whether a household is poor (and so all its members are poor), the household's collective income is compared to its

collective needs. If each household was composed of a fixed set of individuals, analysis of household behaviour and the probability of a given household being poor would be straightforward. The key issues would be the determination of household labour supply and the level of the human capital resources available to the household. To understand this we would need to model dynamic processes such as the labour supply response of one individual to another losing her job, for example. Even where households are stable collections of individuals, individual decisions and events have an impact on the poverty status of all household members. This line of argument might suggest taking the household as the unit of analysis as well as the unit of measurement, and modelling the income of the household unit as a whole, for the life of the household.

There are two problems with this, both of which imply that we need to keep the individual as the unit of analysis. First, we are in the end concerned with the well-being of individuals, and we would therefore need to map back from the household to the individual. Second, particular households actually have short lives on average, too short for this approach to be useful; much of the dynamic 'action' involves individuals transiting between household types. That is to say, typically households are not stable groupings. Young adults leave the parental home, form partnerships, have children, split up and see their own children leave home. These events may occur more than once in an individual's life and in different sequences. The individuals who make the economic decisions on employment and earnings are being continually resorted into different household groups. These household transitions are not exogenous: they are influenced by the behaviour of individuals. Thus an economic model of household income (and so of poverty) is a mix of individual decisions taken in a household context and decisions on household formation. The probability of a single identified individual being poor depends on the income flows into the household in which the individual lives and the household's needs. The aggregate poverty rate for a group of individuals depends on the earnings available to the group, and how the group organises into households. These are the economic processes which constitute the poverty transition process. The central components are labour market factors such as labour supply and earnings generation, and household formation and dissolution processes such as marriage, divorce and fertility. This is the issue we address in this paper. We propose a framework for modelling household income dynamics, and present an empirical implementation relating to poverty dynamics using a panel dataset of young Americans, the National Longitudinal Survey of Youth (NLSY). We do not in this paper attempt to deal with all the econometric prob-

lems involved in modelling household behaviour. Instead we offer a framework for analysing household income and poverty dynamics and embed in that a relatively simple model of behaviour that we feel captures the main factors involved. We estimate the components of this framework using recent models of labour supply, household formation and dissolution and child-bearing.

We illustrate this approach by using these estimates to investigate the dynamics of the very different experiences of poverty among black and white women. We find that differences in behaviour underlying the transition processes make a major contribution to differences in poverty rates. While we show that all transition rates matter, rates of marriage appear to be the single most important factor, as marriage gives access to another income stream. For example, if black women are given the marriage behaviour of white women, their poverty rate is almost halved. Some aspects of an individual's situation early in life affect their likely subsequent poverty status, particularly the level of completed education, but in general transition behaviour is more important. For example, white women who are unmarried mothers at age 18 have a poverty rate three times the white average at age 20, but only fifty percent higher at age 29. The results demonstrate the feasibility of using this approach and that new insights can be derived about the factors lying behind household income changes.

2. Introduction

The rise in inequality and poverty is one of the most important economic and social issues in recent times. After declining through the 1960s and 1970s, poverty rates in the US started trending upwards from the end of the 1970s. Underlying these average poverty rates are important dynamic processes. It is well established that income levels for any one household can fluctuate substantially over time. Indeed, stability is the exception rather than the norm: the Census Bureau reports that nearly 80% of the population see their family income to needs ratio change by at least 5% in a year, with falls and rise roughly in balance[1]. Similarly high levels of income mobility have been found in other countries[2]. Such income mobility clearly includes movement across the poverty line.

How should economists analyse and understand these facts? In contrast to the work on individual earnings dispersion[3], there has been little work modelling (as opposed to documenting) household income dynamics. Indeed, Sawhill ([43]) noted that economists have no model of household income dynamics or poverty (pp. 1085-6, p. 1113). This view is repeated ten years later by Gottschalk ([21], p. 22): "the gaps [in models of individual earnings] are small compared to the limited understanding of the processes generating families and family income"; also in Gottschalk and Smeeding ([23], pp. 635, 668 and 676). This is largely because on top of the human capital issues that arise in personal earnings, individuals are continually forming, dissolving and reforming household units.

This is the issue we address in this paper. We propose a framework for modelling household income dynamics, and present an empirical implementation relating to poverty dynamics using a panel dataset of young Americans, the National Longitudinal Survey of Youth (NLSY). Obviously, we do not in this paper attempt to deal with all the econometric problems involved in modelling household behaviour. Rather we offer a framework for analysing household income and poverty dynamics and embed in that a relatively simple model of behaviour that we feel captures the main factors involved. Further work adopting the approach can build on this model. We then illustrate our approach by using these esti-

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[1]See Masumura [38]. The income/needs ratio is the ratio of annual family income to the appropriate poverty line. The figures refer to the late 1980s and early 1990s. The probability of larger movements is also high. The Economic Report of the President [25] quotes unpublished work of Burkhauser, Holtz-Eakin and Rhody showing the chance of changing income decile to be around 30% per year.

[2]See OECD[42]

[3]See for example Levy and Murnane [32]

mates to investigate the dynamics of the very different experiences of poverty among black and white women.

In the next section we set out the key issues underlying our approach, and review other recent work. Section 3 then sets out the framework linking models of individual decisions to household income dynamics. Section 4 describes a simple behavioural model that fits into this framework. Sections 5 through 7 implement this approach using the NLSY. We describe the data, estimate behavioural equations and use these to produce a behavioural model of poverty. Among other findings, we show the importance of differences in behaviour underlying marriage formation, the persistence of being in a low income state at age 19, the persistent effect of shocks in early adulthood, and the overall importance of the economic behaviour underlying transitions between demographic states. Section 8 concludes.

3. Issues and Literature

A common starting point for the measurement and analysis of poverty is to define poverty in income terms. The level of money income used as the poverty threshold is an administratively chosen amount (for example, the official US poverty line developed in the 1960s, or the European choice of half average earnings). An individual is defined as poor if the income of the household of which she is a member, falls below this threshold $\overline{y}$, where typically $\overline{y}$ depends on household composition. But underlying this single administrative state of having income below $\overline{y}$ are a number of economic processes. An individual may be poor if her income from employment is low, or if another member of her household is unemployed, or if her household is large and household 'needs' are high. A number of points follow from this, which influence how poverty is modelled.

3.1. Issues

If we follow convention and take the household to be the unit for which poverty is defined and adopt an income-based definition of poverty, an individual is classified as being poor if the income of the household of which she is a member falls below a threshold[4]. Income is assumed to be shared within a household, so to determine whether a household is poor (and so all its members are poor), the household's

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[4]Equivalently, if her equivalised income is below some predetermined threshold.

collective income is compared to its collective needs[5]. If each household[6] was composed of a fixed set of individuals, analysis of household behaviour and the probability of a given household being poor would be straightforward. The key issues would be the determination of household labour supply and the level of the human capital resources available to the household. To understand this we would need to model dynamic processes such as the labour supply response of one individual to another losing her job, for example. Even where households are stable collections of individuals, *individual* decisions and events have an impact on the poverty status of *all* household members. This line of argument might suggest taking the household as the unit of analysis as well as the unit of measurement, and modelling the income of the household unit as a whole, for the life of the household.

There are two problems with this, both of which imply that we need to keep the individual as the unit of analysis. First, we are in the end concerned with the well-being of individuals, and we would therefore need to map back from the household to the individual. Second, particular households actually have short lives on average, too short for this approach to be useful; much of the dynamic 'action' involves individuals transiting *between* household types. That is to say, typically households are not stable groupings. Young adults leave the parental home, form partnerships, have children, split up and see their own children leave home. These events may occur more than once in an individual's life and in different sequences. The individuals who make the economic decisions on employment and earnings are being continually resorted into different household groups. These household transitions are not exogenous: they are influenced by the behaviour of individuals. Thus an economic model of household income (and so of poverty) is a mix of individual decisions taken in a household context and decisions on household formation. The probability of a single identified individual being poor depends on the income flows into the household in which the individual lives and the household's needs. The aggregate poverty rate for a group of individuals depends on the earnings available to the group, and how the group organises into households. These are the economic processes which constitute the poverty transition process. The central components are labour market factors such as labour supply and earnings generation, and household formation and dissolution processes such as marriage, divorce and fertility.

Poverty status is a binary indicator, and so might be thought susceptible to

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[5]We therefore ignore the important issue of intra-household allocation of resources.

[6]Including single person households.

dynamic discrete choice modelling of the type surveyed by Eckstein and Wolpin [19]. This approach relies on defining the objective function for an individual, dependent on the discrete state variable, maximising, and characterising the resulting transition probabilities as functions of the covariates. However, from the above it is clear that such an approach does not fit naturally to the case of poverty. Unlike "retirement", "having a child", or "buying a car", being in poverty is not an economic state for which one can straightforwardly compare the utility streams in and out of that state. As just noted, there are certainly economic processes and states underlying the poverty state and these affect utility but, to repeat, the state of being in poverty is an administrative state, which has no impact on utility over and above that of the component processes[7].

Below we propose a model of household income dynamics that will *(i)* focus on the processes and events which underlie income transitions, and *(ii)* incorporate individual behaviour in a household context.

Before presenting details of this model we review the relevant previous literature, and relate it to our approach.

3.2. Literature

The recent upsurge in interest in income inequality[8] has highlighted the importance of dynamics in the income generation process, or, equivalently, the distinction between permanent and transitory inequality. But as noted in the introduction, this literature lacks appropriate models for analysing (as opposed to documenting) household income dynamics. One context in which approaches to such a model have been proposed is in the analysis of poverty dynamics.

The bulk of economics research on poverty has been concerned with defining and quantifying measures of poverty. This literature has tackled a wide range of complex issues. These include welfare based questions such as the appropriate definition of poverty, technical questions on devising measures of poverty which have useful properties, and a large amount of empirical work implementing these measures. Such work is summarised in Seidl [44] and Foster [20] (for measurement and welfare issues), and Sawhill [43] and Danziger and Gottschalk [17] (for US empirical work). Some of the more recent empirical work has documented dynamic

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[7]Unless being poor (as administratively defined) has social stigma attached to it, over and above that simply arising from a relative lack of income. But individuals are typically unaware of whether they are officially classified as poor, as opposed to receiving welfare benefits, say.

[8]See for example, Atkinson [2], Danziger and Gottschalk [17], Gottschalk and Moffitt [22], Gottschalk and Smeeding [23], Hills , and OECD [42].

aspects of poverty, such as duration, incidence and repeat spells (see Duncan, [18], Stevens, [46]). Other work has stressed that such dimensions of poverty (as well as the depth of poverty) should be included in measures of poverty ([29]).

There is a large literature on processes which are clearly related to poverty, such as chronic unemployment, low pay, marriage and divorce, child-bearing at young ages, welfare recipiency, disability and ill-health. As use of panel data becomes routine these models pose dynamic questions. Examples are welfare recidivism, unemployment inflow and duration , duration of marriage, time to first birth and subsequent child spacing. Recent work also allows for inter-relationships between processes. Lillard ([34]) models simultaneous hazard functions for divorce and fertility. But there is no framework to put this work to use in an analysis of poverty.

There are, however, two approaches which are of considerable relevance. The first is a dynamic earnings function approach, first proposed by Lillard and Willis ([35]); the second is a poverty spells, event analysis approach, first undertaken by Bane and Ellwood ([4]), and recently updated by Stevens ([45]).

Lillard and Willis investigate one of the processes which underlie poverty: the earnings of men. They estimate an earnings function for male heads of household using the seven years of the PSID then available. Their estimation allows for the impact of observable characteristics, an unobservable time-invariant individual effect, and a serially correlated random term on log earnings. Adopting half median male earnings as the poverty line, they calculate the probability of being in poverty from the distributions of the observable variables, the individual effect and the random term, and the serial correlation parameter.

The paper provides a framework for linking earnings functions, and therefore human capital theory, to sequences of poverty probabilities, emphasising the impact of persistence (serial correlation) and heterogeneity. However, it appears to be less well suited to an analysis of household income dynamics in general. First, it looks only at changes in male earnings as a source of poverty transitions. This is only one, possibly minor, component of the poverty process. The work of both Bane and Ellwood and Stevens has shown that a major component of poverty dynamics is due to household formation and dissolution. Because of this, female earnings are as important in determining poverty status as male earnings. Second, and more importantly, the Lillard and Willis model is necessarily based on individuals: they compare individuals' earnings to an individual poverty line. But poverty as generally understood is a household characteristic. So a focus on the earnings of one individual in the household excludes from the analysis

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any consideration of household formation decisions, which are crucial to poverty transitions[9].

Bane and Ellwood focus on spells of time in and out of poverty, also using the data in the PSID. They calculate poverty exit rates and the implied distributions of spell lengths, and examine the events coinciding with entry into and exit from poverty. They find that 40% of spell starts are associated with a drop in household head's earnings, and 60% of spell endings are associated with a rise in household head's earnings.

This type of analysis provides a useful characterisation of the nature of poverty, but does not attempt to offer a behavioural model for analysing poverty. The events considered, such as marriage, divorce, child-rearing, and earnings changes, are not exogenous to individuals. They can be thought of as being partly under the influence of the individual and therefore can be modelled in a standard economic choice setting. Granted this endogeneity, it seems inappropriate to focus on the occurrence of the events themselves as the key factors in an analysis of poverty. Also, the events-based approach identifies *one* of the factors associated with a move in or out of poverty, but cannot model the link between different events which may occur at one time. So for example, when a number of events coincide with the poverty transition, the selection of which one to tag is arbitrary. Bane and Ellwood adopt a hierarchical scheme and assume that any household composition change is primary, and assign that as the source of the poverty transition. But it may not be chance that a number of events coincide: this may reflect individuals reacting to or anticipating a shock. And because of this the approach cannot easily be used to trace through the later impact of the shock on poverty transitions. So, for example, it is possible using this approach to note that much poverty is associated with household dissolution and that after a movement into poverty different individuals leave at different rates based on their human capital, but the link between the household dissolution shock and any prior or subsequent employment shocks is not explicitly modelled and so is difficult to explore.

We can briefly summarise these approaches in a formal way and compare them

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[9]The basic framework could in principle be extended to address this issue. First, the model could simply be applied to household income rather than individual earnings and the human capital interpretation dropped. However, it is unlikely that an autoregressive process of the type Lillard and Willis fit to male earnings would fit the large and discontinuous jumps that occur in equivalised household income as a result, say, of divorce, child birth or non-employment. However, if it was possible to identify the different earnings regimes associated with different household types, and use information on that for estimation, then the problem of discontinuity could be overcome. The approach we set out could be viewed in this way.

to our own, set out more fully below. Let π be the probability that an individual is in poverty. We will model that as depending on the state the individual is currently in, denoted d, and a set of characteristics, X. The state is endogenous, determined by the previous state, another set of characteristics Z, and lagged income, y_{t-1}: $\pi_t(X_t, d_t)$, $d_t(d_{t-1}, Z_t, y_{t-1})$. We can contrast this with many standard studies of poverty, which regress π_t on a set of variables, $\pi_t(W_t)$, where W may include a sub-set of (X, Z). Also in this category is the work of Huff Stevens and others estimating models of poverty inflows and outflows (see Huff Stevens[46]), which can be written as $\Delta\pi_t(W_t)$. Such studies provide very useful evidence documenting the characteristics of the poor and the nature of poverty, but do not aim to provide a model for analysing poverty.

We estimate the functions $d_t(.)$ and earnings functions to explore the behaviour underlying household income dynamics. The reduced form of this approach $(\pi_t(X_t, Z_t, d_0, y_0))$ is very similar to standard studies, but the analysis of endogenous changes of state means that poverty dynamics (and household income dynamics in general) can be modelled in a behavioural way. The event analysis approach of Bane and Ellwood can be characterised as looking at data associations of the form $\Delta\pi_t(\Delta d_t)$. This ignores the influence of X, and more importantly ignores the endogeneity of d. Lillard and Willis's model can be written in these terms as $\pi_t(X_t|d = d_1)$, where d_1 denotes the state continuously employed, and (almost) continuously married[10].

In summary, the analysis of Lillard and Willis is undermined as a study of household income dynamics by the omission of household formation. Bane and Ellwood emphasise this but purely from a descriptive point of view. The recognition that such factors are endogenous implies that they be set in a choice model. We develop an economic analysis which includes endogenous household formation decisions, and models income generation. Relative to Lillard and Willis, our approach focuses on households rather than individuals as the unit for poverty measurement, and explicitly addresses the household formation issues that arise from that. We retain the human capital approach to earnings and earnings functions for individual members of a household participating in the labour market.

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[10]Their sample is selected on the basis of reporting some earnings each year, and the sample statistics indicate that in 94% of the (N*T) observations the respondent is married.

4. Framework

We present here a framework for analysing household income dynamics, which we focus around the study of poverty. In the next section we embed in it a model of individual behaviour, but the overall framework is conceptually distinct from a particular model proposed for individual behaviour. We propose a behavioural model in section 4, but different behavioural models could be used.

4.1. Our approach

We define a set of interrelated labour market and household formation and dissolution processes, for example seeking employment, looking for a spouse. Each process has a number of outcomes, for example, being unemployed or employed, being single or married. Since poverty is measured over a fixed period of time, we work in discrete time. At any date t the individual will be in one of the possible outcome states for each process, and be in an overall state defined by the outcomes of the full set of processes. Each overall state is associated with a household income distribution. An individual will be in poverty at t if her realised household income is below the level defined as the poverty level for the household with the composition of her own at t (say $\bar{y}$)[11]. A poverty transition occurs if the individual's household income was below $\bar{y}$ at t, but above $\bar{y}$ at $t+1$, or *vice versa*. Household income transitions are naturally modelled as a mixture model[12], where the weights are the probabilities of moving into each overall state (given the current overall state), and each overall state is characterised by an income distribution. The probabilities of transitions between different household income levels can be calculated, and given a definition of $\bar{y}$, poverty transitions between t and $t + \tau, \tau \geq 1$ can also be derived.

We assume that these transitions are influenced by an individual's behaviour. For example, the individual may put effort into searching for a job, and/or for a partner, and this will affect the probability of transition. The amount of effort the individual puts into each process will be chosen to maximise her present and future expected utility[13]. We present our utility maximising model in section 4;

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[11]The choice of $\bar{y}$ is exogenous to the our modelling approach, but could be defined in several ways

[12]Or equivalently as a switching regression model with endogenous switching (see Maddala[37] pp. 283 - 6).

[13]As discussed above, the model of poverty dynamics is logically distinct from any one particular model of individual behaviour. At this stage, therefore, we omit the details of the utility

here we focus on the framework.

4.2. The processes, the overall state and income in each state

Each individual has a set of characteristics Z, and a current household income level y. We allow Z to be time-varying, though in what follows we omit the time subscript. The components of the framework are as follows.

First, the transition processes. While in principle the individual can make decisions over effort in a number of household and labour market processes, in this exposition we assume she faces only two, a marital state process and a labour market process. Let m denote the marital state process and l denote the labour market process. Each process has two possible outcomes at each date. m_t is the individual's marital status at t and has outcomes $c = couple$ and $s = single$. l_t is the individual's employment outcome at t and has outcomes $w = employed$ and $n = not\ employed$. We also define l'_t as the individual's partner's labour market state, if a partner is present; this is null if $m_t = s$.

Second, the overall state at t is given by a triple of marital and labour market process outcomes and is denoted $\Omega_t = (m_t, l_t, l'_t)$. m_t can be either s or c and l_t and l'_t can be either w or n (l'_t will be null if $m_t = s$), giving six possible combinations of states, any particular one being Ω_{jt}, $j = 1, ..6$.

Third, the determination of earnings. Let the random variable $\tilde{e}_t$ denote an individual's earnings; $\tilde{e}_t'$ denotes the individual's partner's earnings, if present. The individual faces an earnings distribution which depends upon her personal characteristics, Z and her overall state Ω, denoted $f(\tilde{e}_t; Z, \Omega_t)$. The income of an individual not working is denoted b[14]. In each overall state, the individual has a household income. If the individual is in a state in which she is alone, the household is by definition a one person household and individual income is household income; if the individual is in a state in which there is another household member, the other member may also have an income. We write total household income as

$$\tilde{y}_t = I_{lt}\tilde{e}_t + (1 - I_{lt})b + I_{mt}(I_{l't}\tilde{e}_t' + (1 - I_{l't})b') \qquad (4.1)$$

where I_{lt} (respectively I_{mt}) equals one if $l_t = w$ (respectively $m_t = c$). The

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maximisation problem; we return to this below.

[14]This simple formulation avoids the difficulties associated with the complexities of real benefit systems. Clearly, we could allow $b(\Omega)$ with no difficulty. We discuss the way we deal with the US system in the empirical sections below.

distribution of household income in a state is derived from the distribution of earnings $f(\widetilde{e}_t;\ Z, \Omega_t)$, the definition of y_t above and the covariance of $\widetilde{e}_t$ and $\widetilde{e}_t{}'$. We denote this distribution $\phi(\widetilde{y}_t;\ Z, Z', \Omega_t)$, the $\sim$ denoting that y is a random variable (as opposed to the current realised value which we also use below), and Z' denotes the personal characteristics of the partner. This can be compared with the appropriate household poverty line, dependent on household composition $\overline{y}(1 + I_{mt}\omega)$, with $\omega \leq 1$ being the weight on the second adult. This is how the NLSY reports the official US poverty lines and so this is how we proceed in the empirical implementation below[15].

4.3. Transition probabilities

The one period movement between overall states, for example Ω_{kt} to Ω_{jt+1}, is derived from the transition probabilities for each behavioural process. These are denoted λ_{mt} and λ_{lt} (in a non-stationary world, the transition probabilities will differ by t).

We assume these transition probabilities depend on the state of origin and are not exogenous to the individual. Details of the modelling of these are in section 4, but all we assume for this section is that the transition probabilities will in general depend on the current overall state Ω, the current income realisation and the characteristics of the individual Z.

Let λ_{mt}^* and λ_{lt}^* denote the optimised probability of changing m and l state respectively between t and $t+1$. Given these, the probability of changing overall state between t and $t+1$ i.e. moving from Ω_{kt} at t to Ω_{jt+1} at $t+1$ is

$$q_{\Omega_{jt+1}}(y_t, \Omega_t, Z, Z') = q(\lambda_{mt}^*(y_t, \Omega_t, Z), \lambda_{lt}^*(y_t, \Omega_t, Z), \lambda_{lt}'^*(y_t, \Omega_t, Z')) \qquad (4.2)$$

Note that the subscript to q indexes a *specific destination* state in $t+1$, the date of arrival in the destination state, while the Ω_t as an argument of λ denotes dependence of the transition probabilities on the *current (t)* origin state. The functional form of (4.2) is general. Its precise form will depend upon the particular assumptions made about the timing of the outcomes of the two probabilities in the time period between t and $t+1$. We could assume that the transition probability

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[15]Alternatively, we could examine the distribution of per capita equivalised household income, ypc. This is simply total household income divided by weighted household members: $ypc = \frac{\widetilde{e} + I(m=c)\widetilde{e}'}{1 + I(m=c)\omega}$

of one process is independent of the other i.e.

$$q_{\Omega_{jt+1}} = \lambda_{mt}^*(y_t, \Omega_t, Z)\lambda_{lt}^*(y_t, \Omega_t, Z)\lambda_{lt}^{'*}(y_t, \Omega_t, Z') \qquad (4.3)$$

This would amount to an assumption that, conditional on optimised effort, the probability of one event does not affect the other. This would be reasonable if Z and Z' are fully specified. Alternatively, we could assume that one of the two transition probabilities is realised before the other, so that the effort undertaken with respect to the second is conditional on the outcome of the first. So for example, if marital status is determined first, the optimal effort with respect to changing work state will be conditional on an outcome of the transition probability of the marital state. In this case

$$q_{\Omega_{jt+1}} = \lambda_{mt}^*(y, \Omega_t, Z)\lambda_{lt}^*(y, \Omega_t, Z \mid m_{t+1})\lambda_{lt}^{'*}(y, \Omega_t, Z' \mid m_{t+1}) \qquad (4.4)$$

where m_{t+1} is the outcome of the marital process after undertaking effort. Finally, we could allow a model where the two transition processes are simultaneous, and $q_{\Omega_{jt+1}}$ is the joint probability of the outcome of changing different components of Ω_t.

The model outlined here does not require that any particular one of these assumptions holds; each one will raise econometric issues and questions. The key point is that $q_{\Omega t}$ depends on optimal effort with respect to each of the processes. Note also that the q transition probabilities represent movement between combinations of the component states. It is these 'component' transitions that are the true underlying economic processes. This is why we focus on them as the economic decision variables.

4.4. Household income distribution

An individual currently characterised by Ω_t may move into one of 6 possible states next period, Ω_{jt+1}. In each of these states there is a household income distribution; in overall state j it is $\phi(\widetilde{y}_t; Z, \Omega_{jt+1}, Z')$. Given these and the set of transition probabilities, $q_{\Omega_{jt+1}}$, we can derive the distribution of next period's household income:

$$g(\widetilde{y}_{t+1}; y_t, Z, Z', \Omega_t) = \sum_j q_{\Omega_{jt+1}}(y_t, \Omega_t, Z, Z') \, \phi(\widetilde{y}_{t+1}; \Omega_{jt+1}, Z, Z') \qquad (4.5)$$

That is, the income distribution for the individual in the next period is the income distribution in overall state j ($\phi(\widetilde{y}_{t+1}; \Omega_{jt+1}, Z, Z')$) weighted by the probability

of transition to that state $(q_{\Omega_{jt+1}}(y_t, \Omega_t, Z, Z'))$, summed over all states j. This mixture distribution depends on the current overall state, and personal characteristics including current income. $g(\widetilde{y})$ is a legitimate mixture distribution provided the $q_{\Omega t}$ do not depend on the actual realisations of $\phi(.)$. In choosing optimal effort to put into job search or partner search the individual will take expectations over the wage offer or the expected income of a partner, but will not know the realised wage or income at the time she makes her choice of effort. Finally, we need to evaluate the expected income distribution for a single person becoming a couple. That is, some assumption has to be made about the Z' vector of the potential partner. We assume that individuals use an average value of Z' conditional on their own circumstances.

4.5. Poverty transitions

We illustrate this approach by focussing on household income dynamics across the poverty line.

4.5.1. One Period Transitions

From (4.5) we can define the probability of being poor and derive a number of poverty transitions. Let $\bar{y}$ be the poverty threshold for an equivalent adult. If (4.5) is continuous, the probability of the individual being poor is

$$\pi(y_t, \ Z, \ Z', \ \Omega_t) = \int_0^{\bar{y}} g(\widetilde{y}_{t+1}; \ y_t, \ Z, \ Z', \ \Omega_t) \ d\widetilde{y} \tag{4.6}$$

and if (4.5) is discrete the probability is

$$\sum g(\widetilde{y}_{t+1}; \ y_t, \ Z, \ Z', \ \Omega_t) \text{ for all } \widetilde{y}_t \ < \ \bar{y} \tag{4.7}$$

Alternatively we can write (4.6) as:

$$\pi(y_t, \ Z, \ Z', \ \Omega_t) = \sum_j q_{\Omega_{jt+1}}(y_t, \Omega_t, Z, Z') \ \pi_j(\ Z, \ Z') \tag{4.8}$$

where:

$$\pi_j(\ Z, \ Z') = \int_0^{\overline{y}} \phi(\widetilde{y}_{t+1}; \Omega_{jt+1}, \ Z, \ Z')d\widetilde{y} \tag{4.9}$$

For one individual, π is the probability of being poor next period conditional on current income, current state and characteristics. If that person currently has

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an income above the poverty line, this probability is the inflow probability. If their current income is below the poverty line, it is one minus the outflow probability. This is appropriate: an individual is currently either poor or not, so only one transition rate can be defined at any one date.

For groups of individuals, we can define inflow and outflow rates. That is, for a group defined by a common (Z, Z', Ω_t) but varying in income we can integrate over their distribution of current realised income, $\gamma(y)$, to derive poverty inflow and outflow rates[16]. For a group sharing the same (Z, Z', Ω_t), i.e. a set of personal characteristics and a current state, but varying with respect to current income, the inflow rate is:

$$i_t(Z, Z', \Omega_t) = \int_{\underline{y}}^{\infty} \pi(y_t,\ Z,\ Z',\ \Omega_t)\ \gamma(y) dy \tag{4.10}$$

Similarly, the outflow rate is:

$$x_t(Z, Z', \Omega_t) = \int_0^{\overline{y}} [1 - \pi(y_t,\ Z,\ Z',\ \Omega_t)]\ \gamma(y) dy \tag{4.11}$$

For example, the poverty outflow rate among single mothers, or the inflow rate of a particular age group can be derived given the $\pi(y_t, Z, Z', \Omega_t)$ function.

Clearly, given this individual and (Z, Z', Ω_t)-group level information, we can aggregate up to more diverse groupings of people. For example, the poverty flows of people defined by a particular Z set are:

$$x_{Z,t}(Z, Z') = \sum_{\Omega_{jt}} \omega_{jt}\ x_t(Z, Z', \Omega_t) \tag{4.12}$$

$$i_{Z,t}(Z, Z') = \sum_{\Omega_{jt}} \omega_{jt}\ i_t(Z, Z', \Omega_t) \tag{4.13}$$

and the outflow and inflow rates of individuals currently in overall state Ω_t are

$$x_{\Omega t}(\Omega_{jt}) = \int\ x_t(Z, Z', \Omega_t)\ d\Psi(Z, Z') \tag{4.14}$$

$$i_{\Omega t}(\Omega_{jt}) = \int\ i_t(Z, Z', \Omega_t)\ d\Psi(Z, Z') \tag{4.15}$$

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[16]Clearly, in a stationary equilibrium, $g(\widetilde{y})$ and $\gamma(y)$ will be related. But in this paper we are not concerned with the properties of such a stationary equilibrium. Rather, we focus on the one-step poverty transitions (and below τ-step transitions) conditional on current realisations of the stochastic components.

where ω_{jt} is the weight on the j'th component of Ω and $\Psi(Z, Z')$[17] is the joint distribution of Z and Z'. Equations 4.12 and 4.13 address questions such as the level of poverty flows among 25-30 year old female high-school graduates. Equations 4.14 and 4.15 might concern flows among all employed single individuals, for example.

4.5.2. Many-Period Transition Probabilities

We can use this approach to evaluate poverty probabilities and transitions further ahead than one year. The question is: for an individual currently defined by $(y_t,\ Z,\ Z',\ \Omega_t)$, what is the probability that she is in poverty in τ periods time? Define $\pi^\tau(y_t,\ Z,\ Z', \Omega_t)$ as the probability that an individual currently described by the set $(y_t,\ Z,\ Z', \Omega_t)$ is in poverty in τ periods' time. This is given by:

$$\pi^\tau(y_t,\ Z,\ Z',\ \Omega_t) = \sum_j q_{\Omega_{jt+\tau}}(y_t, \Omega_t, Z, Z')\ \pi_{j\tau}(\ Z,\ Z',\ \Omega_t) \qquad (4.16)$$

where $\pi_{j\tau}(\ Z,\ Z',\ \Omega_t) = \int_0^{\overline{y}} \phi(\widetilde{y}_{t+\tau}; \Omega_{jt+\tau},\ Z,\ Z')d\widetilde{y}$ and $\phi(\widetilde{y}_{t+\tau}; \Omega_{jt+\tau},\ Z,\ Z')$ is the distribution of income for the individual in state $\Omega_{jt+\tau}$ in period $t+\tau$. The $q_{\Omega_{jt+\tau}}$ are the τ-step transition probabilities: the probability of ending up in each state j, conditional on an origin state. These result from the product of the one-step transition probabilities τ times. Let $q(\Omega_{1t})$ be the row vector of transition probabilities for an individual currently (t) in overall state 1; i.e.. the probabilities of moving from the state Ω_{1t} to all possible states in the following period. There are j such row vectors. Let

$$Q(t) = \begin{bmatrix} q(\Omega_{1t}) \\ q(\Omega_{2t}) \\ \cdot \\ \cdot \\ q(\Omega_{Jt}) \end{bmatrix} \qquad (4.17)$$

Then

$$q_{\Omega_{jt+\tau}} = q_{\Omega_{jt+1}} \prod_{s=2}^{\tau} Q(t+s) \qquad (4.18)$$

Different transition probabilities at different ages and duration dependence mean that $Q(s) \neq Q(r), r \neq s$. The dependence of q on y, Z and Z' is suppressed in 4.18, but remains.

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[17]These are both empirical distributions of the current realised values.

Along the same lines as the 1-step flow rates, from 4.16 we can compute the τ-step inflow and outflow rates:

$$i_t^\tau(Z, Z', \Omega_t) = \int_{\underline{y}}^{\infty} \pi^\tau(y_t,\ Z,\ Z',\ \Omega_t)\ \gamma(y)dy \tag{4.19}$$

$$x_t^\tau(Z, Z', \Omega_t) = \int_0^{\overline{y}}[1 - \pi^\tau(y_t,\ Z,\ Z',\ \Omega_t)]\ \gamma(y)dy \tag{4.20}$$

Given these τ-period flows, equations analogous to 4.12, 4.13, 4.14 and 4.15 can easily be produced.

4.6. Adding Children

The framework set out above includes two processes; clearly, there is no conceptual problem about adding more. One additional process that is important is fertility. Studies have shown links between poverty and the number and age of children. We do not include this process in the framework as set out above, as adding another process adds no further insight. But fertility can be straightforwardly accommodated. We can expand the state space to include changes in the stock of children, and Z can be updated to include beginning-of-period stock. The definition of equivalised household income would also need to be amended to include the number of weighted children in the denominator.

4.7. Advantages of this Approach

We have set out a framework for modelling household income dynamics. Transition rates between states combine with a distribution of household income in each overall state to define a mixture distribution for income in the following period. From this we can derive household income transition probabilities; we illustrated this with poverty transitions. The key features of this framework are its dynamic approach and the central role played by household formation and dissolution. This appears to be an essential ingredient of an understanding of household income transitions. Furthermore, we have argued that the transition probabilities are endogenous. The framework allows us to incorporate a model of individual behaviour in which individuals make decisions on the basis of utility maximisation to influence these transition rates.

The assumption of endogeneity of transition rates moves attention away from actual *realisations* of events to the underlying causal relationships which determine these realisations. The endogeneity of the transition processes also means

that they must be inter-related: individuals choose the optimal investment in each process, and this will in general depend on the outcome or expected value of the other process[18]. The framework does not require a particular model of individual behaviour.

It is important to allow for the effects of serial correlation (persistence) and heterogeneity on poverty status. Our framework includes a variety of intertemporal linkages which, coupled with the optimal choice of investments, provide a set of mechanisms which allow persistence. The intertemporal linkages are state-dependent transition probabilities, interdependencies between the processes, and possible serial correlation in the earnings distribution[19]. The framework also permits individual heterogeneity in a number of different dimensions: mean earnings, volatility of earnings, work transitions, household transitions, fertility, likely characteristics of a partner, and the key behavioural parameters of these different processes.

The uses and advantages of this framework are as follows. Firstly, and trivially, it presents expressions for the probability of an individual being poor, and for the inflow and outflow rates of groups of individuals. It therefore provides a way of interpreting the dependence of these variables on personal or group characteristics: i.e. as affecting earnings in states or transitions between states. This can be done both for 1 period transitions and τ-period transitions.

Secondly, it can be used to examine the effects of a shock on subsequent poverty status. For example, a single individual loses her job, and this pushes her into poverty. What is the expected 'recovery' time i.e. time to exit poverty? How does that depend on the initial state and the nature of the shock? The framework allows us to distinguish and estimate the likelihood of a number of different paths back to non-poverty. First, the labour market process may switch the individual back to being employed; second, the other process (household formation) may effect a transition, and finally earnings may improve in the current state. The crucial point is that the model endogenises these transitions and so allows us to analyse the individual's best response to the shock and the consequent impact of the optimal investments on transitions. It may be that the optimal response to an adverse realisation of a process is in fact to invest in securing a transition on the

---

[18]Note that the framework outlined in this section could be developed with a q_Ω which is not derived from the underlying marital and labour market transitions λ_m. This would be a reduced form version of the framework outlined here, so there would be a less clear behavioural interpretation of the q_Ω

[19]The last of these was not mentioned in the discussion above, but can be easily introduced in $f(\widetilde{e}; .)$ via a dependence on e_{t-1}.

other process. For example, consider two individuals with the same employment status and same income at time t who have different ability to earn in the future. Let individual A's ability to earn be higher than individual B's. Then the optimal response for A may be to invest in finding another job, while B's optimal response may to invest in finding a partner. The two actions may lead to different time paths to exit poverty. The framework outlined here can help understand and explain these transitions, not simply describe patterns in the data.

Our framework allows us to address both the poverty transition rates of individuals who are in a particular state and of all individuals. From (4.19) and (4.20) it is clear that the transition rates depend on the current overall state: that is, the probability of being poor at $t + \tau$ conditional on being poor today $(1 - x_t^\tau(Z, Z^{'}, \Omega_t))$, depends on the current value of Ω_t. This makes sense: given state dependent transition rates, the current state is a necessary piece of information. Clearly, this allows the persistence of poverty to differ depending on the current state (and of course across different groups defined by Z). Our framework can also address the unconditional question posed by Lillard and Willis by integrating over the distribution of current states or current Z value. So we can use (4.12) and (4.13) to answer questions such as 'What proportion of young white high-school graduates who are poor now will still be poor in τ periods time?' (race and education being components of Z). We can use (4.14) and (4.15) to answer questions such as "What proportion of persons who are currently married and employed will become poor over the next τ periods?' (as marital and work status define the current Ω). As noted, the persistence and incidence of poverty can vary across all these groups. This framework allows us to disentangle why.

It is also useful to drop the focus on states, and to examine instead the underlying behaviour of the individual. The investments to influence the transition rates between different underlying states are the central behavioural variables in the framework. The trade-off between investing in one process or another determines the path that individuals will take into or out of poverty. This suggests that the parameters of the transition rates are a central (empirical) issue for investigation. Armed with estimates of these parameters, a number of empirical exercises are possible. The effects of changing an initial Z on poverty profiles can be computed; standard decompositions of differences in poverty between groups into differences in parameters and variables can be undertaken. Given the likely inter-relationships between the transitions and state-dependency, it is also interesting to isolate the key behavioural parameters; for example, changes in which transition/earnings parameters have the largest impact on simulated poverty pro-

files?

5. Behavioural Model

In this section we sketch a behavioural model. The two components of the approach set out above are the transitions between demographic and labour market states, and the generation of earnings. We begin our analysis once individuals having finished their education, when the human capital decision has been implemented. Under the human capital approach to earnings, once the level of schooling is determined, expected earnings for an individual are largely set by that choice, age and other exogenous factors. Therefore, the decisions agents make concern their investments to change state.

5.1. Optimising Transition Rates

There are a set of transition processes that an individual is subject to. Each of these processes has a number of states. The processes we focus on are marriage/divorce (m), fertility (k) and employment (l). Consequently Ω (the overall state) is defined as being a particular marital state, employment state and the number of children. We assume that the realised outcome of each process is not exogenous to the individual. Moving between the outcomes of each process is partly under the control of the individual, but is also partly stochastic. We think of the individual making investments (of time and/or money), denoted σ, to influence the probability of movement, but cannot force the probability to unity or zero. The amount of this investment or effort she will undertake is derived from a model of utility optimisation. The individual will undertake effort to remain for another period in a given marital or labour market state if the expected benefits from staying in the state are positive. Conversely, if the expected benefit from moving is greater than the expected benefit from staying one more period the individual will undertake effort to move. Note that it is investment, not location itself that is optimised, and so the individual will not necessarily always be in her preferred state.

There may be significant transactions costs in changing state. That is, the current state that the individual occupies may influence the probability of changing state, whatever the level of investment made. For example, it may be harder to move from being single to married, than from married to married. This means that the chance of moving at any particular date depends on previous actual reali-

sations of the process, and not just the desired state. Knowing an agent's location at $t-1$ is informative about the likely location at t, over and above information characterising the individual's optimal location. This is true even if we assume that individuals are completely forward-looking. While agents will have forward looking plans about which states they want to end up in and invest accordingly in an optimal 'pathway', they may still be unlucky on the way and hence the probability of being in a particular state in the next period will still depend on where they are currently.

We can briefly formalise this. Let the probability of transiting from the unmarried state to being married be λ_m. This discussion indicates this will take the form:

$$\lambda_m = \lambda_m(\sigma_m, \Omega, Z)$$

where σ_m is the investment in getting married, Ω is the current overall state and Z is a set of exogenous variables. The inclusion of Z indicates that some exogenous characteristics may also influence transition probabilities (age, for example). Similarly, let λ_k be the probability of adding a child, and let λ_l be the transition rate into employment. We make the following assumptions about the impact of investments, σ_m. First, we assume the individual undertakes separate effort to affect her transitions in the different processes; that is, σ_m only affects λ_m. Second, we assume that effort at t changes the probability of leaving the state at the end of time t, but does not affect transition probabilities from period $t+1$ onwards. However, while effort today does not affect the probability of transition tomorrow, the state the individual is in tomorrow (the beginning of $t+1$) will affect future transitions probabilities.

The individual's utility depends on her state and her consumption; the latter in turn is simply income minus investments[20]:

$$U(y - \sum \sigma, \Omega, Z)$$

Note that the inclusion of Ω means that utility depends on whether the individual is working or not (and so implicitly on the value of leisure), whether the individual is married or not, and the presence of children. Individual income

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[20]We ignore saving and borrowing in this exposition. This will be important for some issues in household income dynamics, but probably not for households in the bottom tail of the income distribution. One thing this means is that we do not allow individuals to borrow to use their wealth to influence their transition probabilities now.

is derived from earnings if the individual is working; the level of earnings is a draw from the earnings distribution introduced above, $f(\widetilde{e}; Z, \Omega)$, realised after the state transition processes[21]. Income if not working is derived from benefit sources, and may depend on family structure ie. on Ω.

5.2. Two Period Example

The main insight from this set-up can be illustrated in a simple two period context. An individual starts from a particular state at time 0, say Ω_{i0}, and she has a given income level, y_0. She then chooses $\sigma_m, \sigma_k,$ and σ_l to maximise:

$$
U(y_0 - \sum \sigma, \Omega_{i0}, Z) + \delta \sum_j q_{\Omega_j 1}(y_0, \sigma_m, \sigma_k, \sigma_l, \Omega_{i0}, Z).EU(y_1, \Omega_{j1}, Z) \qquad (5.1)
$$

where E is the expectations operator and expectations are taken over the earnings distribution, and δ is a discount factor.

The solution to this will be of the form:

$$
\sigma_a^* = \sigma_a(\Omega_{j0}, Z, y_0) \quad a = m, k, l \qquad (5.2)
$$

implying transition rates:

$$
\lambda_a = \lambda_a(\Omega_{j0}, Z, y_0) \quad a = m, k, l \qquad (5.3)
$$

Thus agents' optimal transition investments will depend on their current situation in terms of their state, income and stock of children, and their personal characteristics. These factors are then also the determinants of the transition rates between states.

These general points remain in an infinite horizon model. In this case optimal transition efforts at date t will depend on the anticipated future stream of incomes and utilities in states, and the future probabilities of changing state. But these depend on future Ω, which is endogenous, future Z, and future *parameters* of the $\lambda_m(\sigma_m, \Omega, Z)$ and $f(\widetilde{e}; Z, \Omega)$ functions. The last of these are common parameters

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[21]The setup can be thought of as standard search theory. *Ex ante*, the probability of making a transition depends on the chance of receving an 'offer' times the chance of accepting it. The individual's impact on this process is the choice of search intensity (investment) and reservation level. In reduced form, the individual's situation will simply influence the transition probability.

facing all agents[22], and so will cancel out of empirical work based on different outcomes between agents. Of the variables in Z, some are time-invariant (gender or race); others may vary but can only be predicted on the basis of known current (and historical) values of Z. Thus we will again derive general forms as given in 5.2 and 5.3, though some of the parameters will now have to be interpreted as measuring the present and expected future effect of the variables.

This implies that transitions between outcomes of the processes will depend upon the state of all the processes and exogenous variables. The earnings distribution will depend on the same factors.

5.3. Detailed Specification for Estimation

We use the general framework just described to determine what factors to use in our empirical estimation.

Economic models of marriage and divorce have highlighted that individuals choose between being married or single on the basis of utility in each state. This utility will be a function of the resources available within and outside a match, as well as the non-monetary attributes of the partner. Bargaining models have emphasised that the gain from a match depends on the outside options; search theory as applied to marriage has emphasised the effect of the quality of the searcher on the quality of the final match and the speed of transition into marriage (see Becker[6]; Burdett and Coles[10]). Therefore, in the transition into marriage equation, we take into account age, years of completed education, lagged earnings, lagged employment status, the presence of children, health status, family (parental) income, and variables that proxy a taste for marriage (mother's and father's education, whether the respondent lived with both parents at age 14, and whether the respondent had a religious upbringing). In the divorce equation, we drop parental income and the other background variables, but include marriage duration, a richer specification of children (and interactions between these), and also the partner's earnings, and the generosity of state AFDC payments as a measure of outside income.

There are two distinct literatures modelling fertility (see Montgomery and Trussell [40]). One is based on demography and emphasises the age profile of fertility. The other takes a more explicit economic approach, typically the home

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[22]This has to be true at some level; even if, say, the relationship between marriage probability and age differs between men and women, this parameter can be written as the product of a common parameter and a gender dummy: ie. a common parameter and a z variable.

production approach (see Gronau[26], Becker[5]), and focuses on the time and money inputs into subsequent child care (see Browning[9]). One conclusion from this literature is that the effect of income variables on fertility is not straightforward. Care for children can be provided by the parents or bought in; to the extent that the former is at least partially chosen, the price of parental time is relevant to the fertility decision. Furthermore, if the main provider of parental time is going to be the mother, then it is particularly the value of her time that is relevant: we might expect to see high wage women delaying or foregoing having children. The income effect incorporates both the quantity of children desired, but also what has become known as child 'quality': individuals may choose to have a few children and invest a lot in them. Economic theory suggests that the relationship between fertility and labour supply is a close one, these two decisions being jointly taken in any dynamic model of household production setting. On the other hand, as noted above, an individual's present state may not always reflect her plans and choices, and so there is an argument that labour supply and fertility may have some causal linkages. Separately identifying these links is difficult (see Browning[9], and for a recent attempt Angrist and Evans[1]), but in line with our approach of looking at state transitions, we include the lagged employment state as an explanatory factor in the fertility equation. We also model fertility and participation as joint processes. So in our model, fertility depends on age, the wage rate[23] of the respondent and the wage rate of her partner, the number of children already born to the woman, lagged employment and marital status (including duration of marriage), health status, a measure of local labour market opportunity (the state unemployment rate), measure of the generosity of the state AFDC rate, and a set of background variables reflecting tastes (the number of siblings the respondent has, whether the respondent subscribes to traditional views on gender roles, and whether the respondent had a religious upbringing).

Labour supply is one of the most intensively modelled behaviours in labour economics (for recent surveys see Blundell[8] and Card[13]). The variables influencing the decision to work in the labour market are those affecting the value of home time relative to market time: parent-provided child care, and the market wage. The individual makes her participation decision taking into account the potentially joint decision of her partner, thus her labour supply may depend on

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[23]Since non-working women are at risk of child-birth, and also because of simultaneity issues, we use a fitted wage rate for all women. This derives from a regression of the hourly wage rate on schooling, age, race, local unemployment, selection correction and state and time dummies. This applies to the male wage rate too.

the wage rate of her partner, as well as her own. We take a reduced form approach and use the wage determinants in the participation equation, where wages are a function of age and education of the individual and her spouse, if present. We follow the standard practice in the estimation of participation equations and include the following variables: completed education, age, marital status and the earning capacity of the partner as proxied by their age and completed education, the number of children, local unemployment and AFDC rate, and health status (plus year and state dummies).

For earnings, we adopt the standard human capital approach (Mincer [39], Willis [47]). So earnings are modelled as depending on years of education, age, health status, the local unemployment rate and year and state dummies. Since we are using annual earnings (see below) there will be variation in hours worked amongst those coded as working. Thus we include the partner's fitted wage rate and the lagged number of children. We choose not to condition on a set of variables that others have used in earnings regressions, including job tenure and union status. This is because when we come to model household income dynamics we need to treat included variables as time-invariant, or model them as time-varying. We have also excluded dynamics from the earnings model, not because it is unimportant (see Lillard and Willis[35], Lillard and Weiss[33], and also Atkinson, Bourguignon and Morrisson[3]), but because the emphasis in this paper is on the interplay of demographic change and earnings differences.

6. An Empirical Implementation using the NLSY

In this and the following two sections we report the results of implementing this framework using data from the National Longitudinal Survey of Youth (NLSY). While the approach set out above is a general one, we choose to illustrate it by focussing on the poverty experiences of women. We use the framework to investigate some of the factors underlying the differences in poverty rates between black and white women, going beyond documenting differences in household formation and employment[24].

We begin in this section with a description of the data, poverty rates and their correlates.

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[24]All the empirical work in this project was carried out using Stata 5.

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6.1. NLSY

The NLSY is a panel dataset running from 1979[25], containing data on 12686 people aged 14 - 22 in 1979. One significant feature of the data is the effort put into tracking respondents, and consequently attrition from the sample is minimal: in 1990, 90% were still interviewed. The NLSY consists of three samples: a representative sample of youth (6111 people), a supplemental sample of young Hispanics, blacks and disadvantaged non-Hispanic/non-black (5295), and a military sample representing youth serving in the armed forces in 1978 (1280). The NLSY supplies weights to account for the over-sampling of some groups, and to produce representative group population estimates in tabulations. These weights are time-varying to compensate for differential non-interview[26]. The NLSY provides a great deal of data on family background and the early experiences of respondents, as well as subsequent labour market outcomes and household structure.

Despite the relatively low sample attrition rate, data on income is still missing for some respondents, a common problem in panel data. The income data needed some cleaning, which we carried out largely following the suggestions of Cole and Currie [16]. The income data in the 1979 survey year refer to income earned in the previous calendar year, so our sample of 1979-1992 is reduced to 1979-1991.

6.2. Poverty in the NLSY

Using this data, we find an overall poverty rate of just under 13 percent for the pooled N*T sample; this therefore includes people aged between 14 and 36. But this overall rate masks considerable cross-individual variation. For comparison, Table 1 presents aggregate poverty rates in 1995 from Census reports, and confirms the well-known differences between racial/ethnic groups and family types. Panel B of the Table shows that these features are replicated in the NLSY, and also shows a declining age profile in poverty rates and a sharp educational profile. Panel C of the table reports some results exploiting the panel nature of the NLSY. It shows, that for this age group at least, poverty spells are short on average, though the distribution is very skewed. Two out of five young Americans experienced at least one year in poverty. So 60 percent of the sample are never in poverty. Of

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[25]In this paper we use data through 1992.

[26]This produces small changes for most respondents, but some dramatic variations for some. Examining the time series variation in the weights by individual, the median value of the ratio of the standard deviation over the mean is 5.5%, but the third quartile is 43% and the 90th percentile is 143%.

those who are in poverty most experience just one or at most two years in which they were poor. One half of these years occurred between the ages of 18 and 22, a time at which individuals leave home, go to college, form new households and have children. But for a minority poverty is a frequent and/or long lasting event. Of those who are poor at least once, the average number of years out of the 13 for which we see them for which they are in poverty is 4. Of those who are poor at 18, at least 30 percent will experience another spell in poverty. For those poor once, falling back into poverty once they have got out is not uncommon. Being uneducated, female and black all increase the chances of being poor once, and once poor, of being poor again (further details can be found in Burgess and Propper[12]).

The focus of our approach is to consider movement between states and poverty within states. In Figure 1 we present the raw data on the distribution of black and white women across 16 mutually exclusive states, by age, and poverty rates for the two groups by state and age. The states are defined by the triple: $\{m, k, l\}$: where m is whether in a partnership or not (N or Y in the Figure), k is number of children (0, 1, 2, 3+ in the Figure) and l is whether participating in the labour force or not (N or Y). The Figure shows the complexity of the issue: aggregate poverty changes as people move between 'good' and 'bad' states, and as poverty rates change within states (the latter occurs for two reasons: as things change for fixed individuals in a state and as the composition of individuals in a state changes). The figure reveals some interesting patterns. For example in panel (a), with the exception of the single/no kids/working state (N0Y), the movement in the unmarried states is mostly vertical, whereas the movement in the married states is more horizontal. That is, the probability of being in the unmarried states changes more among black women with age than it does among white women; the opposite is the case in the married states. Similarly in panel (b), some states are always bad for anyone (N3+N); in others, average poverty rates change at different rates for the two groups - for example, the average poverty rate in married/2 kids/not working falls for white women over time, but not for black women.

6.3. Data Selection for Estimation

We make a number of overall data selection decisions, and then construct datasets to estimate the different behavioural relationships. First, here we focus on women (though we have also estimated the behavioural models for men). Second, we restrict our attention to blacks and whites and drop the observations on Hispanics.

Previous work has found considerable differences in marital and fertility behaviour between ethnic and racial groups, and we wanted to allow for that in our estimation by estimating separate response equations for the different groups. In view of this, the sample size for some of the models was insufficient for Hispanic women. Third, we drop observations from the military subsample, and indeed observations from other samples while they were employed in the military. Since we are focussing on individuals who make their own decisions about employment, marriage and fertility, we include individuals in estimation from age 19. This means that we miss various sub-populations such as young teenage mothers (see Lundberg and Plotnick [36]). We also delete observations from our data while individuals are enrolled in college. So individuals in the dataset who finish college contribute to our estimation from age 22 onwards[27].

From this data we create datasets for estimating each process. We use some observations to estimate, say, the earnings function, even though they may have missing values for a variable that therefore excludes them from estimation of the fertility process. For the marriage process, we estimate separately the conditional probability of becoming married (ie. conditional on being single), and the conditional probability of becoming single, which necessitates the construction of two separate datasets containing the 'at-risk' populations for each process.

Overall, our dataset contains 50,681 (N*T) annual observations, 15,087 for black women and 35594 for white women. These derive from 1427 black women and 3320 white women, yielding on average 10.6 and 10.7 years per person respectively. Sample sizes for estimation are given in the relevant tables below.

6.4. Estimation of Behavioural Equations

We first set out an ideal model, and then discuss the econometric issues leading us to the specification we estimate.

6.4.1. A General Model

For these samples we estimate transition equations and an earnings function. The transition equations are: labour market participation (process p), a fertility equation (process b), and two conditional marriage equations (process m). The fertility equation models the probability of a woman giving birth in a particular

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[27]We also drop a few observations with completed years of schooling below 8, and some with implied earnings per hour above \$70 or below \$0.5.

year, and the marriage equations model the chance of becoming married or staying married. The earnings function, assumed to be conditional on the current state Ω, is only observed for those reporting some work during the year.

Denote the outcomes of each of the processes d_{its}, and earnings, e, where the notation is individual (i), calendar time (t), and process (s). We think of individual i at time t as characterised by observable time-invariant features, W_i, unobservable time-invariant features, μ_i, observable time-varying features, X_{it}, and current outcomes of the processes: $d_{i,t-1}, e_{i,t-1}, e_{i,t-1}^{spouse}$, where $d_{i,t-1}$ is the vector $(d_{itm}, d_{itb}, d_{itp})$. Let $Z_{it} = (W_i, X_{it})$.

We set the transition equations up in discrete time because this allows us to discuss correlation amongst the processes in a relatively straightforward way, and some of the data lends itself more naturally to a discrete interpretation. For each process

$$
\begin{aligned}
d_{its} &= 1 \text{ if } d_{its}^* \geq 0 \\
&= 0 \text{ otherwise}
\end{aligned}
$$

and

$$
d_{its}^* = \beta^s Z_{it}^s + \delta^s e_{i,t-1} + \delta'^s e_{i,t-1}^{spouse} + \gamma^s d_{i,t-1} + \mu_i^s + \varepsilon_{it}^s \tag{6.1}
$$

where β^s, δ^s and γ^s are coefficient vectors. The superscript s indicates a potentially different selection of Z variables for each process and a different coefficient vector. Spouse's earnings can only matter for those in partnerships.

Earnings only accrue to the employed, ie. for those with $d_{itp} = 1$. So earnings are determined by:

$$
\begin{aligned}
e_{it} &= \alpha Z_{it}^e + \mu_i^e + \nu_{it} && \text{if } d_{itp} = 1 & (6.2) \\
&= 0 && \text{otherwise} & (6.3)
\end{aligned}
$$

where e_{it} is earnings, Z_{it}^e is a subset of Z variables, μ_i^e is a time-invariant individual effect and ν_{it} is a time-varying error term.

6.4.2. Main Econometric Issues

The main issue is the error correlation structure in a panel context with individual effects. The correlation of the unobservable elements in the transition processes determines whether we can treat the processes as conditionally independent or not.

Recalling that the behavioural model involved the simultaneous determination of investment in these transition processes, we would in general expect the individual effects in all these equations to be correlated amongst themselves[28]. We would also like to allow the idiosyncratic errors to be correlated across processes. Allowing for such a general correlation structure appears to be at or beyond the bounds of current feasible econometric practice. Other issues include the treatment of persistence in the earnings equation, and selection issues in a panel context[29]. Given that econometric innovation is not the main aim of this paper, we have adopted a simpler approach.

The main decision is whether to exploit the panel structure of the dataset or to pool to create an N*T sample. Obviously, there are advantages to panel data, though these are not necessarily overwhelming. The key issue is dealing with different sources of correlation. The model has three dimensions: individual, time, process, and the main potential sources of correlation are *(a)* across time within id and process (ie. the individual effects: the correlation of $(\mu_i^s + \varepsilon_{it}^s)$ and $(\mu_i^s + \varepsilon_{it+\tau}^s)$) and *(b)* across process within id and time (the correlation of $(\mu_i^p + \varepsilon_{it}^p)$ and $(\mu_i^b + \varepsilon_{it+\tau}^b)$). We could ignore *(b)* and estimate fixed effect discrete choice models; or we could ignore *(a)* and estimate multi-variate discrete choice models. Both of these have advantages and disadvantages[30], but the approach we took was to let the data influence the choice.

We tested for correlation among the different transitions processes. Pairwise LM tests suggested that the marriage/divorce process was not very strongly correlated with the participation and fertility processes, conditional on the included variables. However, strong correlation was apparent between the participation (p) and fertility (b) processes. In the setting of a pair of univariate probits, this is correlation between $(\mu_i^p + \varepsilon_{it}^p)$ and $(\mu_i^b + \varepsilon_{it}^b)$, that is, arising either from correla-

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[28]Given that these are fixed effects, the correlation here refers to an *ex post* correlation between the estimated fixed effects, not a parameterised correlation among random effects.

[29]For example, Lillard and Willis [35] included a simple AR process in their panel estimate of earnings, but did not worry about sample selection correction. Chowdhury and Nickell [15] also have serial correlation but do not allow for sample selection. Keane, Moffitt and Runkle [30] do the reverse.

[30]Estimation of logit or probit models on panel data brings a number of benefits, but also brings technical estimation problems. These are discussed in Chamberlain [14], Heckman [27] and Hsiao[28]. The presence of lagged dependent variables is problematic in short panels (Nickell[41]). Estimating a bivariate probit on a pairs of equations is feasible. Such work is discussed in Maddala[37]. Estimation of multivariate models in a panel data context with unobserved individual effects is very rare. Some examples include van den Berg, Lindeboom, Ridder (no date), and Lindeboom and Kerkhofs (1995).

tion of the fixed effects, μ, or from the within-period errors, ε, or both. In an attempt to distinguish between these cases, we ran a number of tests including bivariate probits with and without pseudo-fixed effects[31] and unconditional fixed effect logits, correlating the estimated fixed effects of the two processes. The results of these tend to suggest that the correlation of the individual effects across the two processes did not account for much of the overall correlation between the processes[32]. We therefore chose to estimate a bivariate model for participation and fertility, and separate models for marriage and separation, and we ignore correlation across time, that is, we do not estimate individual fixed effects.

It is clear from the nature of the behavioural model set out above and the empirical structure that the individual's lagged state is potentially important. From a theoretical perspective, the role of the lagged state is clear. Recall that it is investment, not location itself that is optimised, and so the individual will not necessarily always be in her preferred state. So the lagged state matters in a way that it might not if the individual were able to completely determine her location. However, if, empirically, the current state does affect the chance of moving, it may be proxying omitted individual effects, i.e. the individual wanted to be in a particular state because of these unobserved factors, and still does, so the impact of these excluded factors is picked up by the previous choice. On the other hand, if individuals cannot by themselves completely determine their location, just using their characteristics is not an accurate measure of their chance of moving. For example, some individuals may really want to move from single to married, but be unlucky and not do so; if the chance of being married at $t+1$ depends on whether married at t, then lagged marital state is a legitimate explanatory variable. From an empirical perspective, we face the problem of distinguishing state dependence from unobserved heterogeneity.

Turning to the earnings function, the main issue is the link with the transition processes and our desire to estimate coefficients on time-invariant variables. Clearly, an earnings equation is only relevant for states where individuals are working, but working individuals may be in either marital state, and have any number of children. Rather than simply include dummy variables for these states

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[31]That is, time-invariant variables constructed individual-by-individual, summarising their "lifetime" labour supply and fertility histories.

[32]The estimated correlation between the two processes is -0.224 for black women and -0.293 for white. If we include lifetime measures of activity, these only fall to -0.158 and -0.229 respectively. Conversely, if we estimate individual fixed effects separately for the two processes, the correlation between them is 0.102 (black women) and -0.03 (white). Simple cross-tabs of the data back up this view.

we chose to model separate earnings equations for different states. Since we are modelling earnings of people found in particular states, we need to include selection correction terms. While there is work on selection correction in panels (e.g. Keane, Moffitt and Runkle[30]), the added complexity involved here from the multiple selection criteria makes this problematic. We therefore do not include fixed effects in the earnings estimation.

To implement this approach, we use the Lee[31] 2-step model for multiple states. The states we define are **A**: not working (this is the base case for the multinomial logit, no earnings function is estimated); **B**: working, not married, no children; **C**: working, not married, some children; **D**: working, married, no children; **E**: working, married, some children. We first estimate a multinomial logit model for being in these states, and compute the predicted probabilities for observation i deriving from these equations as P_{ij}, $j = \mathbf{B}, \mathbf{C}, \mathbf{D}, \mathbf{E}$:

$$P_{ij} = \frac{\exp(\beta_j' X_i^{all})}{1 + \sum_j \exp(\beta_j' X_i^{all})} \quad , j = \mathbf{B}, \mathbf{C}, \mathbf{D}, \mathbf{E} \tag{6.4}$$

and then incorporate the correction factors[33].

6.4.3. Empirical Definition of the Dependent Variables

We first consider the marriage and divorce processes. The variable we use covers both formal marriage and also cohabitation[34]; 'divorce' includes both formal divorce and separation[35]. The NLSY allows very accurate dating of marriage and divorce, but cohabitation is only reported on an annual basis. For our sample, in 32.9% of the N*T observations for black women the respondent is married, and 56.6% for white women. By the end of the sample, when the women were on average 31, 35.4% of black women and 12.6% of white women had never formed a partnership (marriage or cohabitation); the age profile of marriage rates is shown in Figure 2.

We model conditional marriage rates: that is, the probability of becoming married, and separately the probability of ceasing to be married. The annual probability of becoming married is around 9.9% for black women and 19.6% for

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[33]These are formed as $\lambda_{ij} = f(H_{ij})/F(H_{ij})$, where $f(.)$ and $F(.)$ are respectively the normal density and distribution functions, and $H_{ij} = F^{-1}(P_{ij})$.

[34]There is a specific question on this in the NLSY.

[35]Many individuals separate prior to a divorce.

white women, while the annual probability of remaining married is 84.9% and 87.7% respectively.

For fertility, the process we model is the probability of adding a child to the household. The dependent variable equals 1 if the respondent had a child in that year. The NLSY offers two potential data sources for children: a woman's fertility record including the birth dates of her children, and the household record, counting the respondent's own children in the household. We use the former as it allows more accurate dating of the birth event. These two sources differ somewhat as a person's natural children may no longer live in their household, and there may be children in the household born to other mothers.

Of our sample of 50681 with non-missing household records, 44% of the observations have no children in the household, 24% have 1, 20% have 2, and 12% have 3 or more. By the end of the window of observation, most women have at least one child, 70% of black women and 66% of white women having had at least one birth. The mean of our dependent variable, having a birth in a particular year, is 12.1% for black women and 10.5% for whites, the annual rates by marital status being 9.9% unmarried and 16.5% married for black women, and 3.4% and 16.1% for white women. The age profile of the birth event data are shown in Figure 3 and reveal rather different patterns for the two groups. This is reflected in the mean age at first birth of 22.7 for black women and 24.2 for white women.

Turning to participation, the first issue is the choice of the dependent variable. The NLSY gives data on weeks worked per year, hours worked per year, and whether the respondent worked just before the survey week. Given that we want a single binary variable, we chose one that cut the data in the way most relevant to poverty transitions. In our sample 19% of woman-year observations worked no weeks per year, 41% worked 52 weeks per year and the remainder worked some weeks. Of the women ever having a year with no weeks worked, on average they spent about half their time in that state; similarly, of those ever working all year, the spent about 60% of their time in that state. The state of working some weeks per year (as opposed to all weeks) appears to be a more transient state with a 41% chance of leaving per year. Turning to hours, of those working all year, only 7% worked fewer than 25 hours per week; and only 18% of part-year workers worked less than 25 hours. These numbers, plus the work of Blank [7] showing that part-time work is not usually a 'stepping-stone' state, suggests we should focus more on the weeks worked than the hours worked dimension. Given these facts, we chose to define our participation measure as doing any working at all: the variable is zero if the woman did no paid work in the year, and one otherwise.

Our mean participation rates are 75% of the N*T data for black women and 83% for white women. The age profiles are shown in Figure 4.

Finally the earnings function. We model earnings rather than earnings per hour as the latter would then require the addition of an hours model to an already complicated setup[36]. We model annual earnings from labour market activity, excluding self-employment income. Mean earnings for black and white women are about $9,600 and $11,300 respectively. Some details on the states used for estimation using the Lee methodology are given in Table 2. These figures confirm that all of these states have sufficient observations, and are occupied by a high proportion of the women in the dataset. Each state is visited by at least a quarter of the sample, and none of the states are transient on average: the lowest average occupancy time being 43% of the window length.

Recall that to implement the modelling framework outlined above we need an estimate of the distribution of the household's annual (labour) income in each state. So in the case of a two-earner household, this entails the distribution of the *sum* of the incomes. The choice of dependent variable is not straightforward in this context: the necessity of summing the two random variables essentially forces us to model earnings rather than the more standard log earnings. This assumption may not be too problematic in this context, given that we are interested in the distribution of earnings *surprises* over time for *one individual*. For this question, a normal distribution is not unreasonable. For example, if we simply take earnings and test for normality over time individual-by-individual, this is rejected in 36% of cases. However, if we repeat the test on the residuals from regressing earnings on age and age squared, years of education and its square and a gender dummy, then normality is rejected in only 2% of cases.

Noting that we model the distribution of the *sum* of the incomes in two-earner households, we need to investigate the covariance of earnings shocks for the two. This is potentially important: within-period labour supply adjustment by one partner in response to a shock to the other's income seems plausible. Alternatively, common shocks to the income of both may be important. To address this we estimated the partial correlation over time between income shocks of the two earners. Specifically, we ran a regression of earnings on age and spouse's earnings, absorbing the fixed effects, yielding coefficients of 0.020 for black women and -0.017 for white women[37]. The implied partial correlation coefficients, controlling

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[36]Earnings per hour regressions run on this data replicate standard findings on rates of return to education etc.

[37]We ran the same experiment separately on marriages that had lasted at least five years, and

for age and fixed effects, are 0.0020 and 0.0018 respectively. We therefore feel that this is not a first-order problem.

6.5. Estimation Results: Transition Equations

6.5.1. Marriage

The estimation results are given in Table 3a. We discuss first the process of becoming married. Being employed last period significantly raises the chance of finding a match, as does having children to support. Both of these are significant effects. We also find that a high value of the individual's own earnings raises the chance of becoming married for blacks, though reduces it for whites. High family (parental) income tends to raise the chance of marriage. These findings are generally not out of line with the literature[38] and with our underlying behavioural model. From a poverty dynamics perspective, the connections between marital status, number of children, employment status and earnings means that a shock that affects one of these, say earnings, will have an impact on family formation.

Among married women, the probability of remaining married depends positively on the elapsed duration of marriage, negatively on the woman's own earnings and positively on her partner's earnings. We allow the presence of children to have different effects at different marriage durations. For white women, the net effect is that having children very early in a marriage seems to raise the chance of it terminating, but having children later in a marriage tends to protect it. This is less true for black women, and the presence of children has a net negative effect on the probability of marriage. Lagged employment status is negatively associated with remaining married, in line with other findings in this area.

In both processes, a variety of taste and background variables are significant. One to point out is the relative generosity of AFDC payments at state level. This has a significantly negative effect on the chance of a marriage continuing.

6.5.2. Fertility and Participation

Fertility and participation were estimated as a bivariate probit, though we estimated a range of models including univariate probit, bivariate probit, fixed effect logit and poisson regression on the number of dependent children at any one time,

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on earnings above the mean: the results were 0.021 and -0.022, and 0.013 and -0.021 respectively.

[38]We have investigated the relationship between marital status and earnings in more detail elsewhere (see Burgess et al [11]).

and these all produced the same qualitative results. In that sense the results reported in Table 3b are robust. The main patterns are that fertility as defined here is reduced by a high female wage rate. This is consistent with a modelling approach that treats this as a key price in the provision of child care. Fertility is higher if the respondent is married, and higher within marriage the higher is the partner's wage rate. This can be explained by the income (demand) effect dominating the time price effect if male time is less of an input into childcare. There is little evidence of an age profile, conditional on the wage rate. The woman's previous number of children matters: generally, the presence of a single child raises the chance of having another, whereas three or more reduces it. Finally, lagged employment status is negatively associated with the likelihood of fertility. It could be argued that we should not condition on lagged employment status, as employment is a choice variable affected by the same processes as fertility. However, when we estimate a fixed effect logit model for fertility, lagged employment is significant, suggesting it reflects more than unobserved heterogeneity. Implicitly we assume that some individuals are constrained. Again a number of the background variables have significant effects.

Turning to the jointly modelled participation process, the effects we find are largely standard. The level of education matters strongly and there is a clear concave pattern in age. Bad health and high local unemployment both reduce the likelihood of working. The presence of children in the previous period severely reduces the chance of working: the more children, the lower the chance of working. Lagged marital status appears to have different effects for black and white women: among the former, marriage is associated with a higher probability of participation, among the latter with a lower probability. Variables included to measure the earning capacity of the woman's partner (age and education of spouse) are insignificant for black women and negative for white women.

The estimated correlation of the errors of the two equations is negative. This suggests that any shock making fertility more likely makes participation less likely. This seems to fit well with the idea that child care and paid employment are competing uses for women's time.

6.6. Estimation Results: Earnings Functions

We first estimate a multinomial logit model for occupancy of the set of demographic states defined above, compute the selection correction terms and incorporate these into the four earnings regressions. Clearly, the probabilities of being

found in these states will depend on the same set of variables as those described above explaining transitions into and out of marriage and work, and the probability of adding a child. We use a core subset of the combination of all those variables, denoted X^{all}. The results are in Table 4. The coefficients estimate the impact of a variable on the relative chance of being in a state relative to the base state (not working). The results represent a reduced form combination of the previously estimated individual transition processes; consequently, unlike the individual transition processes, they do not have a clear interpretation.

The selection terms are calculated from 6.4 and are included as additional regressors in the earnings equations. They are identified by variables included in X_i^{all} but excluded from the earnings equations: parental income, parental human capital, family structure at age 14, number of siblings, whether the respondent had a religious upbringing, whether the respondent lived in the South at age 14, duration of marriage, state AFDC payment rate, and whether the respondent has a traditional view of gender roles. While one could argue a case against some of these, others would appear to have a negligible direct impact on earnings.

We argued above that since we are modelling *annual* earnings, we should include the number of children in the states with some children. Although children older than one are pre-determined, new ones are not, so we instrument current children variables with lagged children.

The results are in Table 5. The coefficients generally reproduce standard human capital findings. The implied rate of return on education includes the effect both on earnings per hour and on hours worked. For black women in state B this can be calculated as a difference of $1200 going from 12 to 13 years, on a mean earnings at 12 years of about $10000, a rate of 12%. Unsurprisingly, illness, high local unemployment and the presence of children all reduce earnings. Spouse's (fitted) wage rate is generally positive for married women. This captures both labour supply responses, and given our omission of fixed effects, some assortative mating based on earnings. The selection variable is negative in all cases, and strongly significant in most. The usual concave age profile is missing in some cases: this may be because the selection variable is strongly trended (in age).

Finally, we need to model the earnings of other members of the household. To predict the distribution of earnings of the spouse (if one is present), we estimate an earnings function for all men of the race of the respondent [39]. This gives us coefficients on the variables to calculate the mean, plus an estimate of the

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[39]That is, using the earnings of male respondents in the NLSY, not the spouse's earnings of female respondents, because of the likelihood of measurement error.

variance (see below). Since we do not have data on all the required variables for the spouse, we assign values of the variables for the male spouse as follows. Many characteristics are naturally shared, for example marital status, the number of children, the state of residence, the year. The age and years of education of spouse are reported in the NLSY. Health status of spouse is not reported and we use the mean value of men in the NLSY.

7. Fitting Poverty Probabilities

We are now in a position to estimate poverty rates and poverty dynamics using the approach set out in section 3. In this section we set out the method and evaluate the goodness of fit. We first focus on estimating poverty rates one-step ahead: that is, we take the data on the respondents' current state, Ω_t, current realised income y_t, and other characteristics (Z, Z') and apply 4.8 and 4.9 to calculate the probability for each respondent of being poor one year later. We then take the realised data on (Ω, y, Z, Z') for the next date and repeat the procedure. This produces a time series of poverty probabilities for each respondent. This allows us to evaluate the model as a whole as a predictor of poverty rates and to carry out some experiments. Note that this is not simulation: there is no randomisation or assignment of people to states. We simply calculate the probability that an individual is in poverty next year, based on her chance of entering different states and the distribution of her income in those states. These results provide a general overview of the sources of variations in poverty between black and white women and provide a useful diagnostic for the approach.

7.1. Setting up the Framework

Following the estimation, we define states Ω as married or not (with marriage duration of 1, 2 or 3 or more years), working or not, and having 0, 1, 2, or 3 or more children. An examination of our data on male labour supply suggested that modelling the participation of the spouses of our female respondents was unlikely to be worthwhile, since only a small and special group of men did no paid work during a year.

We use our estimated transition processes to form q_Ω (see 4.2). The marriage and separation probabilities are assumed independent of the fertility/participation pair which have a bivariate normal distribution. The distribution of household income in each end-state, $\phi(\widetilde{y}; Z, Z', \Omega)$, is assumed normal with means derived

from the estimation above. As discussed above, the covariance between shocks to spouse's income and own income is set to zero. The variance is also derived from the estimation procedure. A cross-sectional variance would pick up unmeasured differences between individuals. These are largely irrelevant to the earnings dynamics of one individual over time. We therefore exploit the panel element of our data to calculate the within-variance of the residuals from each earnings regression for each individual. These are averaged by gender/race group and earnings states. In principle, we could use much more finely averaged variances but there did not appear to be large differences in the within-variance between educational groups or coarse age bands. Nor, perhaps surprisingly, does there appear to be a clear relationship between mean fitted income and within-variance: see Figure 5.

A number of further assumptions are required. We assume that upon divorce, the female partner is responsible for the children (ie. they affect *her* earnings and *her* participation, future fertility and future re-marriage probabilities). We assume that the partner's earnings awaiting an unmarried woman becoming married is equal to the mean of that of just-married women with the same characteristics. We ignore income from capital; this will clearly be an issue for some groups and some income levels, but is not a major problem for young poor people. Alimony and child support payments are more likely to matter, particularly given our focus on household formation and destruction. In fact, the NLSY reports very few people receiving alimony payments, no more than 30 cases per year, so we cannot use this data. Child support payments are more common, and average about $1800 among unmarried women receiving them. On average, some 18% (black) and 30% (white) of currently unmarried women with children receive such payments[40]. While we ignore both alimony and child support payments in this paper, these figures suggest that the latter is a worthwhile phenomenon to include in this framework.

The final issue is welfare receipts. For the non-elderly, the main cash benefit[41] is AFDC, available to lone parents with dependent children and low or zero earnings. For all but one year of our sample period (1981 to 1992) the AFDC system has operated as a state-specific guarantee level and a 100% benefit reduction rate on any earnings. This implies that $y = max(e, AFDC)$, where e is earnings, and y is income. Furthermore, if $AFDC < \overline{y}$ (the poverty threshold) for any family type, then

$$pr(poverty) = pr(y < \overline{y}) = pr(e < \overline{y})$$

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[40]These are weighted using the sample weights; unweighted the numbers are 18% and 15%.
[41]And so included in the official poverty measure

That is, in this case, modelling take-up of AFDC or assigning appropriate levels of AFDC to eligible women would make no difference to the poverty probability calculated from our earnings distribution. An examination of the rates of AFDC payment suggest that it is reasonable to assume that AFDC levels are below poverty thresholds[42]. We ignore all in kind transfers that may be made to those with AFDC payments which are lower than the poverty line, as we do not estimate these benefits at all in our model. We also ignore payment of foodstamps and other AFDC-related benefits: thus we are likely to underpredict total income among the very poor.

7.2. Evaluation of the fit of the estimated transitions

As an evaluation of the approach, the simplest exercise is to compare the one-step mean predicted poverty rate for each year for women in both race groups in the NLSY with the actual means. These are given in Figure 6. If we had estimated poverty rates directly using the poverty rate data then the fitted mean would *necessarily* be equal to the actual mean. In our case however, there is no reason for this equality to hold: none of our estimation has actually used the data on poverty status at all. Recognising this, the match between actual and fitted poverty rates is reassuring. The graph shows that we overpredict poverty rates amongst the young. However, at older ages our predicted one-step poverty rates follow actual values quite closely. The overprediction at young ages probably arises because we have not modelled income from adults other than partners, but in the under-25 age group there are a significant minority of individuals who still live in the parental home.

We can compare the actual and fitted poverty probabilities for a variety of sub-groups. This is shown in Table 6a. These tables reflect the general overprediction at young ages apparent in Figure 6. Within this, the degree of over-prediction is consistent across demographic groups for black women, and is higher for married white women, and white women without children.

A harder test is to look at movements in the fitted poverty probability over time, individual-by-individual. Some results are given in Table 6b and Figure 7. The table shows that we generally over-predict poverty inflows among the non-poor, and under-predict outflows among the poor. That is, we do not capture all the heterogeneity between people: while we get the average poverty rate about right for (quite narrowly defined) groups, *within* that group poverty rates are too

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[42]See for example, US Department of Health and Human Services[24]

similar among the members of the group, and we do not get enough of some people being frequently poor and others rarely poor. This is perhaps unsurprising given that we do not use fixed effects estimation. This point is illustrated graphically in Figure 7a.

However, we do manage to do rather more than just predict the average experience for everyone. In Figure 7b we look at poverty individual-by-individual over time. We split people into ten groups defined by the proportion of their time in the observation window spent in poverty. These are marked along the horizontal axis of the figure. We then plot the distribution of the fitted proportion of time spent poor over the window for each of these groups[43]. The figure shows a wide range within each group, but that nevertheless the approach does a reasonable job of separating people likely to spend a long time poor from those likely to be never poor.

We can use this one-step analysis to examine the extent to which differences in poverty between black and white women are the result of differences in the transitions between, or earnings in, the overall states. To answer this we computed poverty rates of black women as before; for white women we used the black women's transition rates but the white women's earnings equations. That is to say, we took the mean of each transition rate for each age-race cell, and applied this mean to both black and white women in the appropriate age group. Note that this means that it is not just the "behaviour" (the coefficients) that are being transferred, but the "environment" too (the variables); we separate these in the next section. The results are given in Figure 8. This indicates that if white women experienced the same one step transition rates as black women, they would on average experience much higher poverty rates. Indeed, from the mid-twenties, the differences in transition rates account for almost all of the gap in poverty rates.

From this we can conclude that a major part of the differences in one-step poverty rates between young black women and young white women is due to differences in the rates at which the two groups move between states. The remainder is due to higher earnings of white women when in these states. The advantage of our approach is that we can now take a further step and look at the source of this difference using the τ-step poverty transitions introduced above.

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[43]This is simply the sum of the fitted per-period probabilities.

8. Results

This section uses the framework to investigate the underlying forces behind poverty dynamics. Specifically, we examine and separate out the effect of endowments which are given for the individual (such as parental income at 18 or education) and the behavioural responses of the rates of marriage, employment, child bearing, and earnings, to these endowments. The analyses we undertake include an examination of the speed with which individuals recover from an exogenous shock, the identification of the transitions which appear to be most closely associated with recovery or with the persistence of poverty, and the identification of the transitions and income differences which account for differences in poverty between groups.

8.1. Model Setup

We define the set of states to differentiate different durations of marriage: 1 year, 2 years, 3 years or more. We thus have 32 states comprising Ω and construct the transition matrix $Q(t)$ from 4.17. We compute $Q(t)$ for each age (t) using the estimated coefficients and the appropriate variables. Some of these are defined by the state of origin (for example "lagged marital status" equals 1 in married origin states) and earnings are set at the mean of the distribution predicted for that origin state. Others are exogenous, including education, family background and state of the labour market variables. This procedure differs from the previous section only in that we compute the transition probabilities out of *each* possible starting state, rather than just the state the respondent actually was in at time t.

An individual is defined by *(i)* a set of background variables, Z, which include parental income, own earnings and wage rate at 19, potential spouse income at 19)[44], *(ii)* a location in a specific origin state at any time (i.e. for each individual one element of $\Omega(t)$ equals 1 at each t), and *(iii)* a set of behavioural equations which model the transitions between states and the income distribution within each of the states. We separately examine the effect of each on poverty probabilities.

For the base calculation we use the race-specific mean actual values for Z at age 18, the actual frequency distribution of individuals over states at age 18 (Ω_0), and the race-specific estimated behavioural coefficients in the transitions and earning equations. The results are given in Table 7. These show the probability

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[44]The other variables in Z are health status, maximum education attained, variables defining houshold type and location at age 14, parental education, religious and other attitudes, state unemployment rate.

of being poor one year ahead, two years ahead and so on up to ten years ahead, for a person with that set of characteristics at age 18, and following that set of behavioural patterns. We do not run the process on beyond age 29 as the behavioural equations were estimated on the age range 18 - 34. The table shows that the fitted values are greater than the actual for both blacks and whites at early ages, but after 23 or so they are very close and mirror the observed fall in poverty rates over this age group. The overprediction at young ages arises for exactly the same reasons as the overprediction in the one-step analyses: we omit sources of income other than the individual's own earnings or those of a partner. It appears that the fitted poverty probabilities in Table 7 are converging to a steady state value, but the transition process is not strictly stationary in the sense that the Q matrix depends on time (age).

The fit is remarkably good: the data is used to set up the initial conditions, but thereafter the model is simply re-applied ten times. To some extent the fact that the model fits so well may be coincidental: a number of simplifying assumptions have been made along the way, and it may be that these more or less cancel out in their effect. Our omission of other sources of income suggests we should overpredict poverty; simply taking the whole of the measured within-variance as the variance of the income shocks is too simple; the normality assumption may be misleading, the omission of fixed effects means we ignore some sources of heterogeniety, and so on. Nevertheless, the similarity between the prediction and the data provides a good base for the experiments reported below.

Poverty rates are a function of transitions between states and the income received in those states. Our framework allows us to separate how the background variables affect the states individuals are predicted to be in from the income they earn in each state. Figure 9 shows the probabilities underlying the base run of being in particular elements of Ω (collapsed into 8 categories for ease of interpretation) at each age for whites and blacks. The results indicate that for both black and white women, there is movement into states characterised by marriage and children over time. But there are differences in the relative chances of occupying these states across the races. Black women are more likely to be single and not in work than white women, and the difference between the races in the proportion who are in this state with at least one child is particularly large. White women are more likely to be married, both with and without children, and less likely to have children outside marriage.

8.2. The Influences on Poverty

We examine the impact of Z (background and environmental factors), Ω_0 (starting state), and transitions and earnings behaviour. We look at the impact within and between black and white women. For each analysis, we present the impact on poverty rates and then exploit the underlying modelling framework to illustrate how differences in household formation and participation rates affect poverty.

8.2.1. Initial Background

Table 8 presents the results of changing initial values of various background variables. The table contains the results only for ages 20, 25 and 29, but the patterns are similar between these years and the information is omitted only for ease of presentation. In columns (1) and (2) we examine the effect of differences in family (parental) income on predicted poverty rates, changing this variable by \$10,000 either side of the mean (which is about one standard deviation). In our estimated model, family income affects the rate at which people become married. The effect on poverty is negligible for whites. For blacks, the impact of changing parental income is larger. Decreasing income by this amount increases the poverty rate from one and a half percentage points at age 20 to six at age 29. This reflects the importance of marriage rates among black women. Columns (3) and (4) examine the effect of not living with both parents at age 14. They show this has little impact for blacks but the effect is larger for whites, raising poverty probability at age 29 by about a quarter.

The variable with the largest effect on poverty rates is education (columns (5) and (6)). Having a college education basically eliminates the chance of poverty, holding all else constant. The probability of being poor at age 29 is reduced from 36.6% to 4.6% for black women and from 8.0% to 1.2% for white women. The results for having completed high school only are similar to the base run, as this is close to the average education of the sample. The final column of table 8 shows the effect of increasing the unemployment rate by 4 percentage points. Unemployment does not vary with time in our model, so this is equivalent to an examination of the impact of entering and working in a labour market at a poor stage of the business cycle relative to entering and working in a good stage of the business cycle. Comparing the final column of Table 8 with the base run shows poverty rates are predicted to be nearly 50% higher for whites and 25% higher for blacks when the unemployment rate is 4 percentage points higher. This is because unemployment not only affects earnings, but also has significant impact

on the transition probabilities of participation and having children.

The pattern of state occupancy is affected by education. Figure 10(a) presents the distribution across the same states for black female high school and college graduates separately. From this it is clear that the impact of higher education is to increase the probability of being married and working with children, to decrease the probability of being married without children, and to decrease the probability of being single, with and without children. The proportion in states with children does not change, but the probability of being married with children increases. Given that both marriage and participation are associated with lower poverty rates, the effect of education on poverty rates is through lower occupancy of states associated with low income. From the estimated transitions equations, the direct impact of education for black women appears to be primarily through participation (see Tables 2 and 5). This then has a strong influence on the marriage probability, reinforcing the direct effect of education.

8.2.2. Initial State

Next we investigate the impact of Ω_0, the starting state at age 19. We compare the results of starting from an unfavourable and a favourable state in Table 9. The unfavourable state is single, not working, one child. Column (1) shows this has a large impact on the likelihood of poverty for young white women at age 20: poverty rates increase from 19% under the base run to 54%. Over time, however, this initial shock is somewhat dissipated, and the poverty rate at 29 is 12% compared to 8% under the base run. The effects for black women are similar: the initial impact is to increase poverty rates, and the effect of the starting state is gradually reduced. Nevertheless, for both races poverty rates from this unfavourable starting state remain above that predicted by the base run. This is not surprising: having children is an irreversible change for women in our model, and this therefore has a permanent effect on the set of possible states the woman can occupy.

Column (2) presents the results of starting in a favourable location at age 19: in work, unmarried and with no children. The initial impact of this is to decrease poverty rates, and although the effect falls off over time, rates at 29 are still lower than under the base run. Again the effects are similar across the two races. The final column of table 9 presents the effect of an unemployment shock at 19[45]. The

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[45]The probability of being in any state in Ω_o in which employment is positive is set equal to 0, and all the other origin state probabilities are adjusted upwards pro rata.

effect is to increase the probability of being poor by around 6 percentage points for each race initially, and that there is a small but lasting effect over the 10 year period. The table indicates that starting states matter and though they become less important over time, there is still an effect on predicted poverty rates 10 year out.

We can go below poverty rates to examine how starting states determine the subsequent distribution of states. Figure 10(b) shows the differences in demographic states underlying this difference in poverty rates for white women. The top panel is for a starting state of single, working and no children; the bottom panel for a starting state of single, not working and one child. Looking first at the top panel, we see that the proportion in states without children falls and the proportion in states with children increases over time. This is not surprising. Comparison of the top and bottom panels indicates that having a child early in life changes the long run distribution over states. An early child means, relative to those who do not have a child early on, a greater probability by age 29 of being in the married, not working and some children state.

8.2.3. The impact of behaviour

The last set of investigations isolates the impact of the behavioural equations that determine the transitions between states and the earnings in these states. For example, we can examine the impact on predicted poverty rates and state occupancy for white women of having the marriage and divorce propensities of black women, holding all other behaviour, starting states and background variables constant. The model allows changes in the estimated transitions in one process to feed through into the other transitions and earnings.

Table 10 presents results of such analyses. Column (1) represents the base run analysis for white women, and column (6) does this for black women. Column (2) attributes white women with all the behavioural equations of black women. Comparison of column(2) with (6) indicates that if white women were subject to the same transition probabilities and earnings functions as black women, their poverty rates would be very similar. In other words, their starting states and background variables appear to have little effect. Columns (3) - (5) report the results of changing just the marriage and divorce probabilities, the participation and fertility propensities (together because these are jointly estimated), and the earnings functions respectively. Column (3) indicates that if white women had the same marriage and divorce propensities as their black counterparts (all other

propensities left unchanged), their rates of poverty would rise by approximately 6 percentage points each year. On the other hand, column (5) shows the impact of changing earnings is to increase poverty rates more initially, but this impact falls over age. So by age 29 the estimated poverty rates under this experiment are lower than those predicted by changing marriage and divorce propensities. Column (4) shows the impact of changing participation and fertility propensities is similar to, but less extreme than, the effect of giving whites blacks' earnings functions. These columns indicates that for whites, starting states are not very important, and that the different transition probabilities have rather different short and longer run effects.

The results for black women indicate some similarities and some differences. Giving black women all the behavioural responses of white women lowers the probability of poverty, though the probability of being poor is still above that of white women at all ages (column (2) compared to column (6)), indicating that starting values continue to have an impact for black women. The effect of changing marriage propensities to those of white women is to decrease rates of poverty at all ages. As for whites, the longer term impact on poverty rates of changing marriage propensities is larger than that of changing either earnings or participation and fertility. However, in contrast to the results of columns (3)-(5), poverty rates of blacks fall by similar amounts if any of the transition probabilities or earnings functions are swapped with those of white women. This is perhaps an indication of the greater importance of starting states and initial background for blacks compared to whites.

Across both races, these analyses indicate that partnership formation and dissolution have the smallest short run and the largest long run effect on poverty probabilities, while earnings have the largest short run effect and the smallest long run effect[46].

Changing the probability of being in one state at any t affects the estimated probabilities of being in any of the other states and earnings at a later date. The changes in poverty rates from the base runs that result from changes in the probability of being married, having children etc, are a combination of changes in the distribution over states and the income in those states. We can examine how changing behaviour affects the distribution over states. Table 11 presents the modal predicted state at ages 20, 25 and 29 which correspond to the simulations in the columns in Table 10. In terms of income, the states of being married and

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[46]Note since we are examinig poverty rates we ignore changes in the level of income above the poverty line that may improve the overall distribution of income.

working are high income states, as in these states individuals are predicted to have income both from their own (female) employment and that of their male partners, who have higher average earnings than women. The last row of the table shows the proportion predicted to be single and not working at age 29, which is a state associated with a very low income and hence a high probability of being poor.

The first column shows that the model under the base run predicts the most common state for white women at age 20 to be single, working with no children, the modal state at age 25 is married and working with some children, and the modal state at age 29 is married, working and some children. The probabilities are predicted to be 44, 30 and 39 percent respectively. The proportion who are predicted age 29 to be single and not working is less than 5 percent.

If white women were to have their own background variables but the behavioural responses of black women the most common states at 20 would be single, working and no children (31%), at 25 would be married, working and some children (18%), and at 29 would be married, working and some children (25%). Compared to the base run, a smaller proportion are predicted to be in a state characterized by higher income (marriage) at both 25 and 29. Additionally, a considerably larger proportion are predicted to be in a low income state (single and not working) at 29. Comparison of columns (2) and (6) indicates that the distribution of white women, if they had all the behavioural responses of black women and their own initial values and starting states, would be close but not identical to that of black women. In fact the distribution of black women in terms of access to income is slightly more favourable. This is reflected in the slightly higher predicted poverty rates in Table 10 of column (2) compared to column (6).

Column (3) shows the impact of changing just the marriage and divorce transitions. Compared to the base run, the proportion not married rises considerably, and in addition, the proportion without children also rises. The net effect is to increase the proportion who are single and childless at age 20 from 44 to 52 percent, to change the modal location at age 25 from being married, working and with children to being single, working and without children, and to reduce the proportion married, working and with children at age 29 from 39 to 29 percent. As the distribution has shifted towards states which are characterised by lower income, so has the predicted poverty rate risen. Note that the predicted fall in the number of children is not because white women have been given the fertility behaviour of black women, but is the result of a lower marriage rate for white women which in turn leads to fewer predicted children using white women's fertility estimates.

Column (4) shows the impact on the distribution across states of giving white

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women the fertility estimates of black women. The predicted proportion who are in high income states actually rises at ages 25 and 29 compared to the base run, but predicted poverty (Table 10) in this state remains higher than under the base run. This is the result of (i) more women who are predicted to be single and not working at age 29 and (ii) a higher predicted number of children which increase poverty. Column (5) shows the effect of giving white women blacks' earnings equations. This has almost no impact on the distribution over states. All the (small) effect on poverty rates comes from the lower predicted own earnings of black women, and this difference is largest at younger ages. The result, as shown in table 10, is that predicted differences in poverty rates between column (5) and the base run in column (1) are highest at young ages.

Columns (6) through (10) carry out the same exercise for black women. Column (6) shows that the distribution of states for black women in terms of income is considerably worse than for white women. In comparison with column (1) far more blacks are predicted to be outside the high income states at ages 20, 25 and 29, and in the lowest income state at age 29. If black women were to have the same behavioural estimates as whites (column (7)) this would shift the distribution towards higher income states.

Column (8) shows that if black women were to have only the marriage and divorce equations of whites, the distribution would shift towards married states, which would have, as table 10 shows, a large negative impact on predicted poverty rates. The change in the distribution from this experiment is greater than for any of the others considered here, and the predicted fall in poverty rates is commensurately the highest. However, predicted black poverty rates do not drop to those of whites at 29, in part because the proportion predicted to be single and without work at 29 is still considerably higher than that of whites.

Column (9) indicates that the effect on the distribution of modal states of giving blacks the fertility equations of whites is small, but the predicted number who are in the worst income state at age 29 does fall. This accounts for the fall in poverty rates relatively to the base run seen in Table 10. Column 10 of table 11 shows that a change only in earnings equations has the same effect for blacks as for whites. The distribution of modal states hardly alters at all, and all the impact on poverty rates comes through the change in earnings. In states in which the probability of poverty is high, whites' earnings are higher than those of blacks at younger ages but little different above 25.

9. Conclusions

This paper proposes a framework for modelling household income dynamics. It emphasises the role of household formation and dissolution, and labour market participation. It allows standard economic theory to address the issues of household, as distinct from individual, income and poverty dynamics. Here we set out a simple behavioural model for the underlying economic processes, but other models can also be used.

We illustrate this framework with an application to poverty rates among young women in the US. We estimate marriage, fertility and participation transition equations, and earnings functions under relatively simple assumptions about the correlations between the different processes. Based on these estimates, our approach produces predicted poverty rates that match the data reasonably well. We use this model to analyse differences in poverty experiences, particularly between black and white women.

The results demonstrate the feasibility of this approach and that new insights can be derived about the factors lying behind household income changes. We find that differences in behaviour underlying the transition processes make a major contribution to differences in poverty rates. While we show that all transition rates matter, rates of marriage appear to be the single most important factor, as marriage gives access to another income stream. Some aspects of an individual's situation early in life affect their likely subsequent poverty status, particularly the level of completed education, but in general transition behaviour is more important.

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Table 1(a): Poverty Rates of Blacks and Whites
US Aggregate Data

Numbers Below Poverty Line in 1995		
	Number (000s)	percent
PERSONS	36,425	13.8
White	24,423	11.2
White: Not of Hispanic Origin	16,267	8.5
Black	9,872	29.3
Asian and Pacific Islander	1,411	14.6
Hispanic Origin	8,574	30.3
FAMILIES	7,532	10.8
White	4,994	8.5
White: Not of Hispanic Origin	3,384	6.4
Black	2,127	26.4
Asian and Pacific Islander	264	12.4
Hispanic Origin	1,695	27.0
FAMILY TYPE		
Married Couple	2982	5.6
White	2443	5.1
Black	314	8.5
Female Householder, no husband present	4057	32.4
White	2200	26.6
Black	1701	45.1

Source: Poverty in the United States, Current Population Reports, Consumer Income P60-194. US Department of Commerce, Bureau of the Census.

Table 1(b) : Poverty Rates of Black and White Women
NLSY Data

	Poverty Rate (%):	
	Black Women	White Women
OVERALL	38.8	10.0
AGE:		
14	44.1	10.8
18	44.3	12.1
22	41.1	12.6
26	37.0	9.5
30	35.5	8.3
34	28.4	9.2
EDUCATION LEVEL[*]:		
High school drop out	77.2	28.0
High school graduate	37.1	10.1
College Graduate	15.4	3.1
MARITAL STATUS[*]:		
Never Married	43.3	11.3
Married	15.1	4.1
Separated/Divorced	52.5	22.0
NUMBER OF CHILDREN[*]:		
0	19.7	5.4
1	33.2	6.2
2	38.1	8.5
3	48.2	14.9
Sample number	1129	2452

Averaged over 1979 - 1992, Weighted
[*] Poverty Rate at age 28

Table 1(c): Poverty Transitions and Durations by Race

Poverty Rate (%):

	Blacks (Men and Women)	Whites (Men and Women)
Number of years in poverty[*]	3.8	1.2
Number of years in poverty of those having some poverty	6.0	3.2
Mean inflow rate (% per year)	11.7	4.8
Mean outflow rate (% per year)	23.4	45.4
Mean duration of first spell (years)	2.46	1.56

[*] Out of a maximum of 13 in the window
Source: NLSY, Burgess and Propper [12]

Table 2: Descriptive Statistics for Earnings States

(a) Black Women					
	Overall		Between		Within
	Freq	%	Freq	%	%
A: Not Working	3521	25.17	747	52.87	64.06
B: Working, Single, No kids	2911	20.81	671	47.49	67.68
C: Working, Single, Some kids	3683	26.33	800	56.62	60.47
D: Working, Married, No kids	964	6.89	340	24.06	46.57
E: Working, Married, Some kids	2909	20.80	646	45.72	58.01
Total	13988	100	3204	226.75	60.85

(b) White Women					
	Overall		Between		Within
	Freq	%	Freq	%	%
A: Not Working	4961	16.51	1324	40.63	54.94
B: Working, Single, No kids	7806	25.97	2016	61.86	62.34
C: Working, Single, Some kids	2243	7.46	792	24.30	43.03
D: Working, Married, No kids	6169	20.52	1892	58.05	49.06
E: Working, Married, Some kids	8878	29.54	1867	57.29	61.27
Total	30057	100	7891	242.13	55.73

Note: Numbers are unweighted, because the use of weights in a between/within context is problematic. Weighted tabulation for the overall N*T cross-section produced very similar numbers.

Table 3a: Marriage and Divorce Transitions

Variables	Probit Estimates of Becoming Married		Probit Estimates of Remaining Married	
	Black	White	Black	White
Earnings(t-1) ($'000)	0.335	-0.608***	-0.410	-0.532*
Family/Spouse Income (t-1) ($'000)	0.018***	0.031**	0.067***	0.050***
Employed(t-1)	0.218***	0.212***	-0.113	-0.118**
Education	0.026*	-0.009	-0.021	0.031***
Ill Health	0.069	0.013	-0.047	-0.050
kids(t-1)=0	-0.059	-0.174***	-	-
kids(t-1)=1	-	-	-0.117	-0.098
kids(t-1)=2	-	-	-0.328*	-0.114
kids(t-1)=3	-	-	-0.300	-0.769
Marriage Duration=2	-	-	0.025	0.194***
Marriage Duration=3	-	-	0.177	0.249***
(MarrDur=2)*(k=1)	-	-	0.178	0.120
(MarrDur=2)*(k=2)	-	-	0.253	0.112
(MarrDur=2)*(k=3)	-	-	0.003	0.728*
(MarrDur=3)*(k=1)	-	-	0.112	0.264**
(MarrDur=3)*(k=2)	-	-	0.205	0.234
(MarrDur=3)*(k=3)	-	-	0.192	0.846**
State AFDC Rate	-	-	-0.061***	-0.025**
Mother's Education	-0.093**	-0.019	-	-
Father's Education	0.062	-0.010	-	-
Both parents at age 14	0.005	0.012	0.094	0.158***
Religious Upbringing	-0.074	-0.006	0.048	0.009
# siblings	-		0.067***	0.008
Age, Age squared	Yes	Yes	Yes	Yes
Constant	-3.899***	-1.858***	-1.442	0.460
LogL	-2025.632	-5043.243	-1058.375	-3182.046
N	6833	9209	3458	15473

Sample for each is 'at risk' group; dependent variable = 1 if transition to other state made
*** p<0.001, **p<0.01, *p<0.05

Table 3b: Participation and Fertility

	Participation			Fertility	
	Bivariate Probit Estimates of Participation and Fertility				
Variables	Black	White	Variables	Black	White
Education	0.264***	0.123***	Own wage	-0.289***	-0.239***
Marital Status (t-1)	0.160***	-0.147***	Spouse's wage	0.093***	0.135***
Age of spouse	0.001	-0.005***	Employed(t-1)	-0.191***	-0.172***
Ed'n of spouse	0.012*	-0.005			
kids(t-1)=1	-0.380***	-0.609***	kids(t-1)=1	0.192***	0.184***
kids(t-1)=2	-0.465***	-0.737***	kids(t-1)=2	0.069	-0.243***
kids(t-1)=3	-0.571***	-0.922***	kids(t-1)=3	-0.020	-0.288***
Ill Health	-0.271***	-0.143***	Ill Health	0.079**	0.077***
State unemp. rate	-0.075***	-0.027***	State unemp. rate	-0.009	-0.002
State AFDC Rate	0.029	-0.045**	State AFDC Rate	0.002	0.028***
			MarrDur=1	0.350***	0.637***
			MarrDur=2	0.241***	0.627***
			MarrDur=3	0.148***	0.664***
Lived in South at age 14	-0.031	-0.048	#Sibs	0.015	0.021***
			Trad. gender roles	-0.019**	0.010*
			Religious Upbringing	-0.088**	-0.032
Age, age squared	Yes	Yes	Age, age squared	Yes	Yes
Year Dummies	Yes	Yes		-	-
State Dummies	Yes	Yes		-	-
Constant	-3.875***	-0.217	Constant	0.149	-1.234
Correlation	-0.206***	-0.279***	Correlation	-0.206***	-0.279***
Log Likelihood	-8818.429	-16322.115		-8818.429	-16322.115
N	10880	22935	N	10880	22935

*** p<0.001, **p<0.01, *p<0.05

Table 4: Multinomial Logit Results for Earnings States Selection

	B: Working, Single, No kids		**C**: Working, Single, Some kids		**D**: Working, Married, No kids		**E**: Working, Married, Some kids	
	Black	White	Black	White	Black	White	Black	White
Age	0.640**	0.972***	-0.475***	0.187	0.849**	0.482***	0.166	0.172
Age Squared	-0.011*	-0.018***	0.008**	-0.004	-0.016**	-0.010***	-0.005	-0.003
Education	0.314***	0.224***	0.267***	0.105***	0.139**	0.068***	0.224***	0.029
MarrDur=1(t-1)	-0.863**	-0.987***	0.128	-0.251	0.232	-0.143	0.462**	0.326***
MarrDur=2(t-1)	-0.032	-1.595***	0.629**	-0.341	0.500	-0.552***	0.672***	0.333***
MarrDur=3(t-1)	0.236	-0.990***	0.343*	-0.372***	0.875***	-0.274**	0.690***	0.300***
Some kids (t-1)	-	-	2.121***	2.486***	-	-	1.300***	1.105***
Employed (t-1)	3.645***	4.410***	3.111***	3.332***	3.546***	3.760***	2.938***	3.169***
Family Income (t-1)	0.001	-0.003	-0.009*	0.000	0.000	0.000	0.000	0.000
Ill health	-0.699***	-0.769***	-0.258***	-0.117	-0.373*	-0.422***	-0.324***	-0.079
State AFDC	0.019	-0.093*	-0.103***	-0.157***	-0.150**	-0.006	-0.149***	-0.021
Age Spouse	-	-	-	-	0.063***	0.056***	0.063***	0.045***
Ed'n Spouse	-	-	-	-	0.180***	0.091***	0.142***	0.070***
State unemp rate	-0.046*	-0.041**	-0.068***	-0.039**	-0.110***	-0.018	-0.092***	-0.017**
In South at 14	0.394**	-0.052	0.241**	-0.157	0.318	0.150	0.027	-0.001
Mother's Ed'n	-0.175	-0.513***	-0.132	-0.094	-0.212	0.029	-0.078	0.073
Father's Ed'n	-0.069	-0.217	0.010	0.016	0.131	0.033	0.043	0.061
Both parents at 14	0.246	0.427***	0.115	0.118	-0.035	-0.024	0.024	0.010
Religious upbr'g	-0.225	-0.006	-0.158	0.148	0.051	0.072	0.086	-0.029
# siblings	-0.132***	-0.082*	-0.065**	-0.073**	-0.102*	-0.096***	-0.011	-0.047***
Trad. gender att's	-0.022	0.005	-0.062**	-0.089***	0.038	-0.062***	-0.095***	-0.055***
Constant	-12.445***	-14.385***	1.620	-5.291*	-16.519***	-9.444***	-8.062**	-6.469***
N	8381	19182	8381	19182	8381	19182	8381	19182

Table 5: Earnings Equations Results

	B: Working, Single, No kids		C: Working, Single, Some kids		D: Working, Married, No kids		E: Working, Married, Some kids	
	Black	White	Black	White	Black	White	Black	White
Age	-0.677	-0.747	0.243	1.535*	1.659	0.232	-0.343	0.986**
Age Squared	0.019	0.021**	0.004	-0.026*	-0.020	0.001	0.012	-0.012
Education	-3.481***	-2.125***	0.814	-0.732	3.071**	-1.621**	-1.896**	0.091
Education squared	0.187***	0.125***	0.014	0.075**	-0.071	0.099***	0.122***	0.027
Spouse's wage	-	-	-	-	-0.154	0.467*	0.847***	0.297
Kids = 2	-	-	-1.371***	-1.255***	-	-	-0.266	-1.902***
Kids = 3	-	-	-2.136***	-2.558***	-	-	-1.806***	-3.625***
Ill health	-1.479***	-1.455***	-1.146***	-0.463	-0.669	-1.430***	-1.669***	-0.974***
State unemp rate	-0.346***	-0.361***	-0.243***	-0.423***	-0.504***	-0.288***	-0.254***	-0.121***
Year dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
State dummies	Yes	Yes	Yes	Yes	Yes	Yes	Yes	Yes
Selection Variable	-4.683***	-4.397***	-2.173***	-1.969***	-1.559	-6.574***	-2.605***	-1.526***
Constant	32.327***	26.013***	-8.270	-11.334	-42.502**	11.307	15.704	-13.395**
R^2	0.415	0.385	0.302	0.200	0.383	0.286	0.295	0.182
N	1380	3841	2238	1339	513	3838	1793	6190

Notes: Spouse's wage is a fitted value

*** $p<0.001$, **$p<0.01$, *$p<0.05$

Table 6: One-Step Fitted and Actual Poverty Rates

(a) By Demographic group

Marital Status (t-1):	Black	White
Single:		
Fitted	0.347	0.153
Actual	0.278	0.095
Married:		
Fitted	0.465	0.532
Actual	0.333	0.222
Children (t-1):	**Black**	**White**
No children:		
Fitted	0.273	0.165
Actual	0.213	0.075
Some children:		
Fitted	0.467	0.352
Actual	0.376	0.300
Total:		
Fitted	0.354	0.193
Actual	0.282	0.108

(b) By Lagged Poverty Status

Poverty Status and age group:	Black	White
Not Poor (t-1)		
19 - 25**:**		
Fitted	0.389	0.229
Actual	0.147	0.065
26 - 30:		
Fitted	0.198	0.105
Actual	0.095	0.053
Poor (t-1)		
19 - 25**:**		
Fitted	0.586	0.316
Actual	0.658	0.395
26 - 30:		
Fitted	0.361	0.202
Actual	0.663	0.496

Table 7: τ-Step Fitted and Actual Poverty Rates

Age	White Women		Black Women	
	Fitted	Actual	Fitted	Actual
20	19.0	12.6	60.5	47.2
21	16.2	11.9	57.4	45.9
22	14.0	10.9	54.5	43.8
23	12.3	10.5	51.7	41.4
24	11.0	9.6	48.9	42.4
25	10.1	8.8	46.2	38.2
26	9.3	9.1	43.6	38.8
27	8.8	8.2	41.1	36.8
28	8.3	8.1	38.7	34.2
29	8.0	7.7	36.6	36.1

Notes: Actual data are weighted means.

Table 8: τ-Step Poverty Rates: The Influence of Background Variables

	Fitted Poverty Rates							
	White Women							
Age	Base	(1)	(2)	(3)	(4)	(5)	(6)	(7)
20	19.02	19.03	19.02	18.59	4.62	20.95	18.35	27.31
25	10.06	10.02	10.10	9.77	1.76	11.52	9.49	14.63
29	8.03	7.99	8.07	7.80	1.21	9.58	7.41	11.19
	Black Women							
Age	Base	(1)	(2)	(3)	(4)	(5)	(6)	(7)
20	60.51	58.69	61.97	55.12	14.04	61.28	59.62	70.51
25	46.22	40.80	51.31	40.65	8.52	47.17	45.11	56.22
29	36.60	30.83	42.46	31.36	4.64	37.71	35.30	46.25

Other columns are as base, except
(1) Family (parental) income + $10000
(2) Family (parental) income - $10000
(3) Years of education = 12
(4) Years of education = 16
(5) Did not live with both parents at age 14
(6) Did live with both parents at age 14
(7) State unemployment rate + 4 percentage points

Table 9: τ-Step Poverty Rates: The Influence of Initial State

	Fitted Poverty Rates							
	White Women				**Black Women**			
Age	Base	(1)	(2)	(3)	Base	(1)	(2)	(3)
20	19.0	53.8	15.4	26.7	60.5	77.0	57.2	67.8
25	10.1	18.0	8.0	13.3	46.2	56.6	39.7	51.4
29	8.0	11.9	6.6	10.1	36.6	44.2	30.8	40.5

Other columns are as base, except
(1) Starting state is {Not Working, Single, 1 child}
(2) Starting state is {Working, Single, no children}
(3) Starting state is base with all weight (proportionately) in {Not Working} states

Table 10: τ-Step Poverty Rates: The Influence of Behaviour

		Fitted Poverty Rates:									
		B = Black values used; W = White values used									
Starting values and starting states		W	W	W	W	W	B	B	B	B	B
Marriage and Divorce Coefficients		W	B	B	W	W	B	W	W	B	B
Fertility and Participation Coefficients		W	B	W	B	W	B	W	B	W	B
Earnings Coefficients		W	B	W	W	B	B	W	B	B	W
Age	20	19.0	59.8	23.1	30.1	32.6	60.5	30.1	51.7	51.9	50.4
	21	16.2	57.0	21.9	26.3	26.2	57.4	24.3	43.7	47.5	48.8
	22	13.9	54.5	20.6	22.8	21.7	54.5	20.2	37.9	43.9	47.1
	23	12.3	52.0	19.4	19.9	18.3	51.7	17.2	33.5	40.6	45.1
	24	11.0	49.5	18.3	17.6	15.7	48.9	15.0	29.9	37.6	43.2
	25	10.1	47.1	17.3	15.8	13.7	46.2	13.4	27.1	34.7	41.3
	26	9.3	44.7	16.4	14.3	12.0	43.6	12.1	24.7	32.1	39.7
	27	8.8	42.5	15.5	13.1	10.7	41.1	11.2	22.7	29.6	38.2
	28	8.4	40.4	14.8	12.3	9.5	38.7	10.5	21.0	27.3	36.9
	29	8.0	38.4	14.3	11.6	8.6	36.6	9.9	19.7	25.2	35.9

Table 11: Modal States

	B = Black values used; W = White values used									
Starting values and starting states	W	W	W	W	W	B	B	B	B	B
Marriage and Divorce Coefficients	W	B	B	W	W	B	W	W	B	B
Fertility and Participation Coefficients	W	B	W	B	W	B	W	B	W	B
Earnings Coefficients	W	B	W	W	B	B	W	B	B	W
Age: 20	swz	swz	swz	swz	swz	swz	swz	swz	swz	swz
	44%	31%	52%	31%	44%	27%	35%	23%	41%	28%
25	mws	mws	swz	mws	mws	sws	mws	mws	sws	sws
	30%	18%	25%	37%	31%	24%	33%	36%	24%	24%
			(mws=20)				*(sws=11)*	*(sws=12)*		
29	mws	mws	mws	mws	mws	mws	mws	mws	mws	mws
	39%	25%	29%	47%	40%	28%	42%	44%	26%	28%
Percentage in states {single, not working}										
29	3.2%	22%	5.5%	5.1%	3.2%	19%	3.8%	8%	8%	19%

Figure 1: Poverty Rates and Frequencies by State

(a) Probabilities of being in states
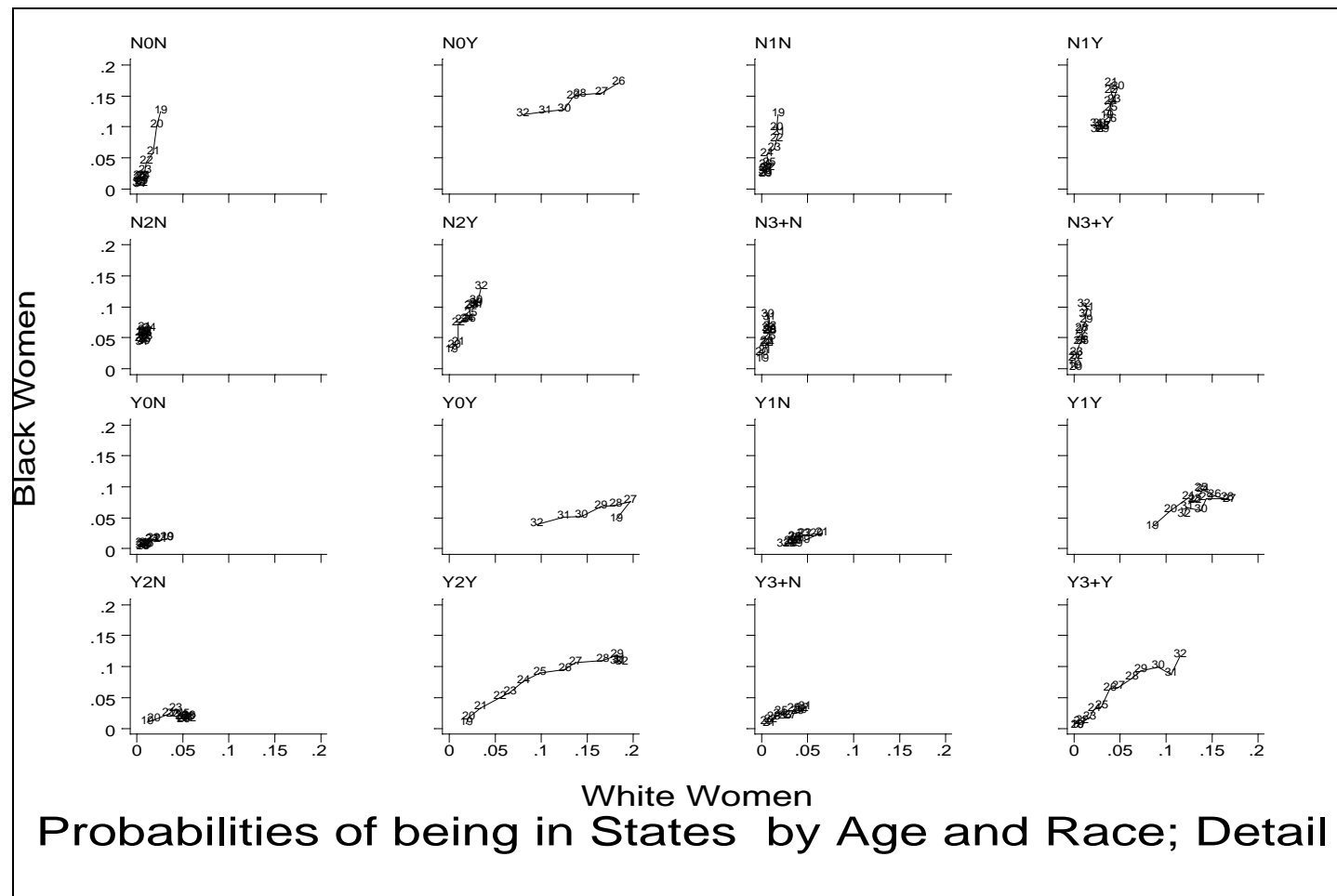
Probabilities of being in States by Age and Race; Detail

Figure 1: Poverty Rates and Frequencies by State
(b) Poverty rates in states
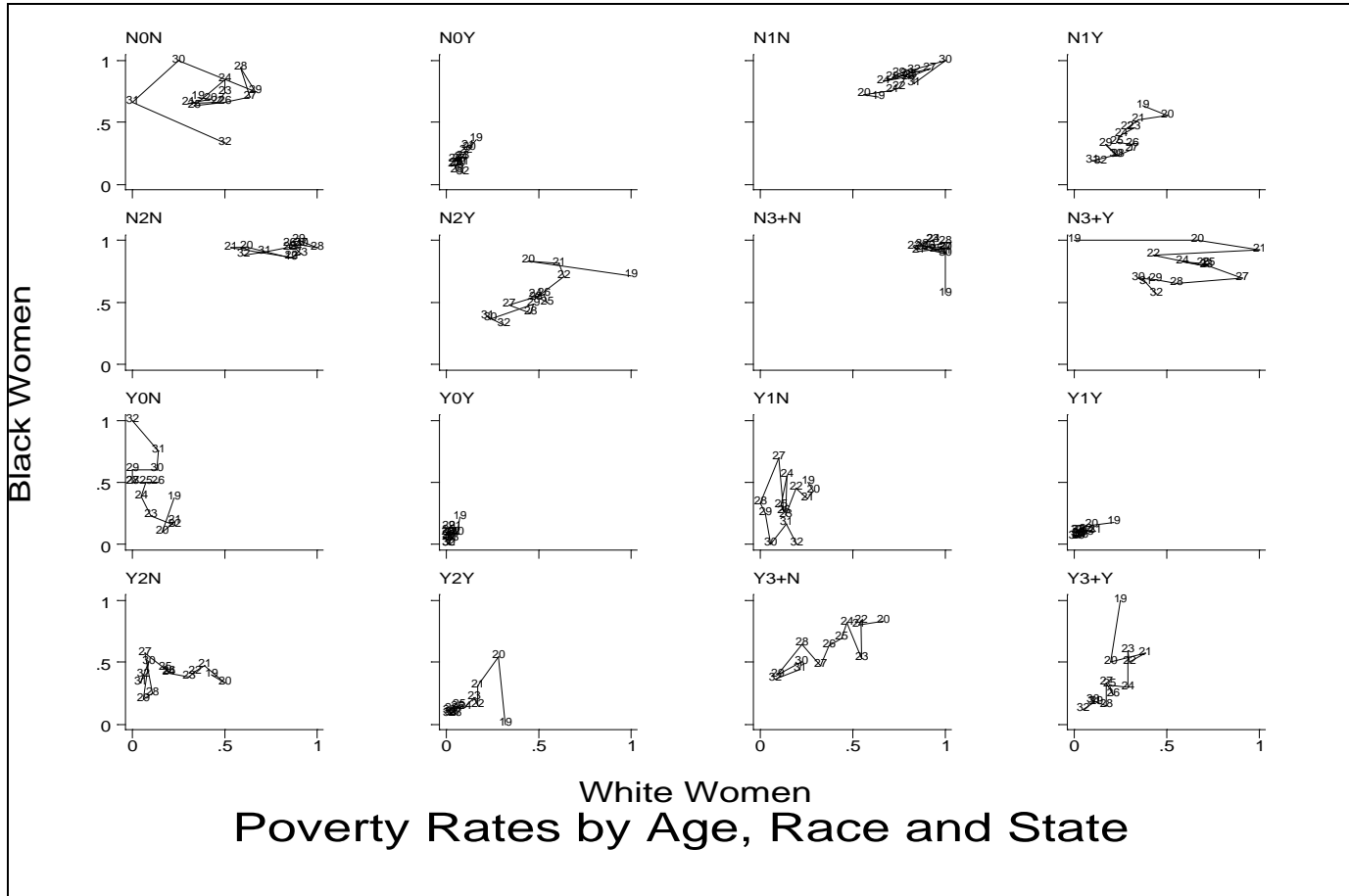
Poverty Rates by Age, Race and State

Figure 2: Marriage Rates by Age and Race
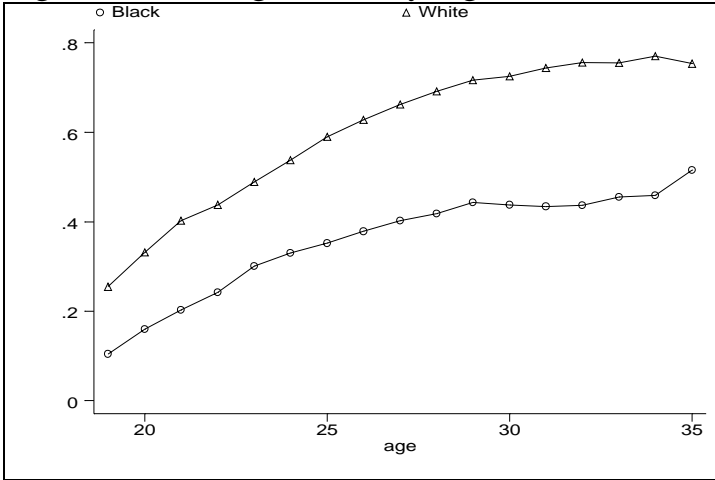
Weighted averages
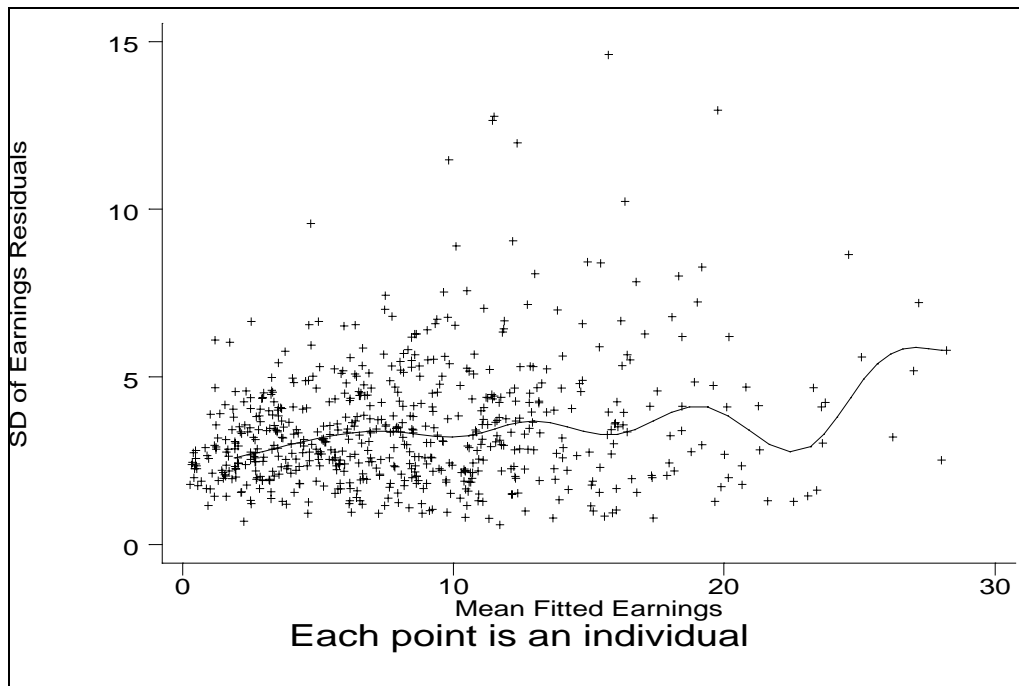
Figure 3: Birth Rates by Age and Race
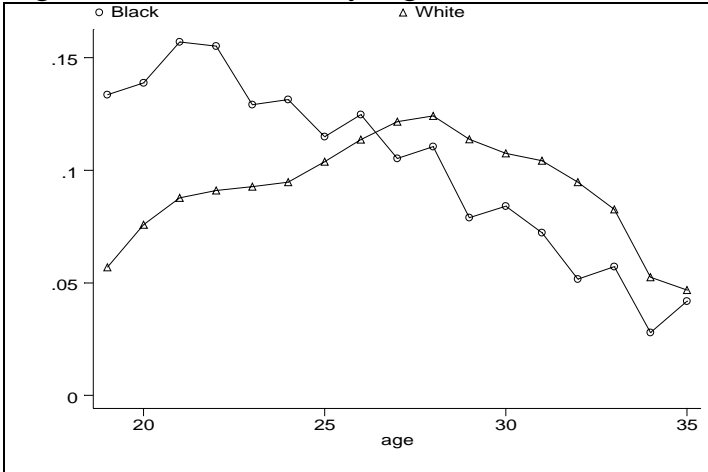
Weighted averages

Figure 4: Participation Rates by Age and Race
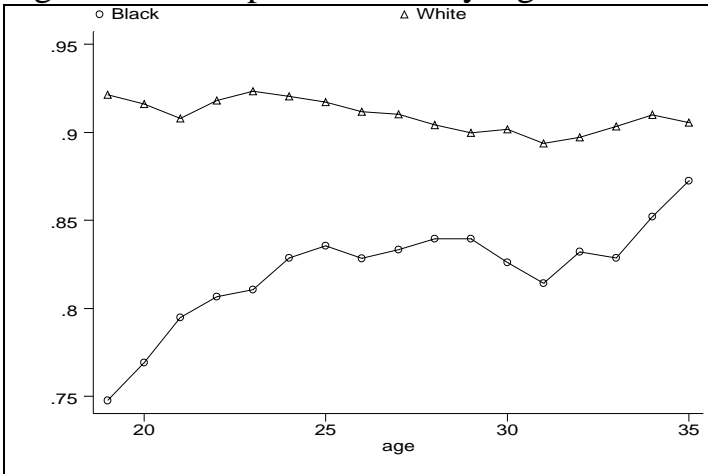
Weighted averages

Figure 5: Mean Fitted Earnings and Standard Deviation of Earnings Residuals

Black Women

White Women
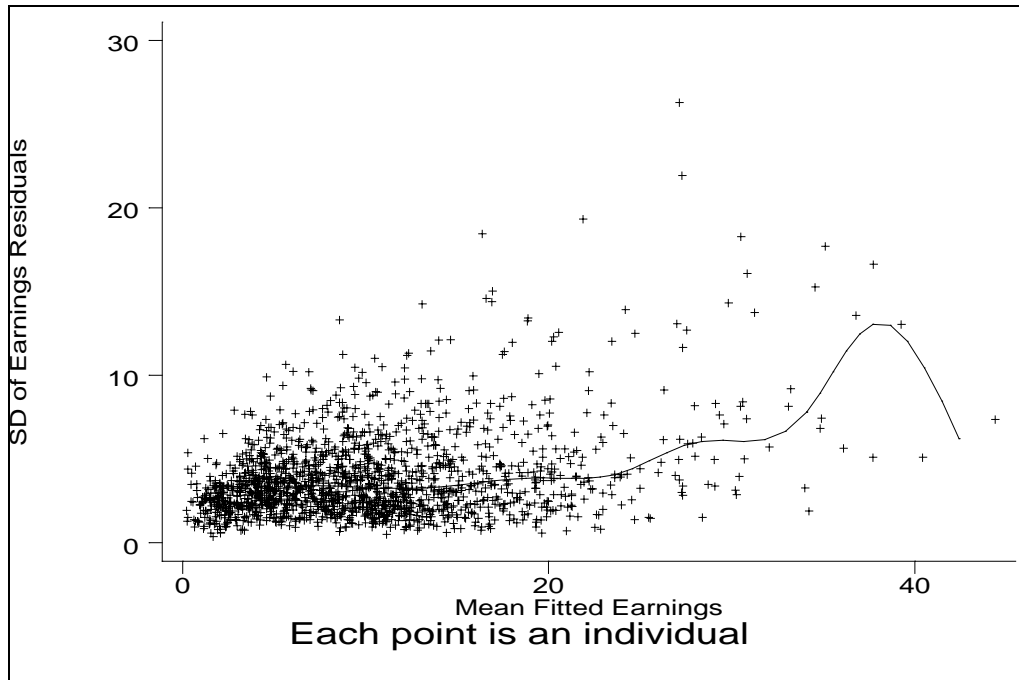
Figure 6: One-Step Actual and Fitted Poverty Rates

○ Fitted Poverty Rate   + Actual Poverty Rate

Black

White

age

Graphs by Race
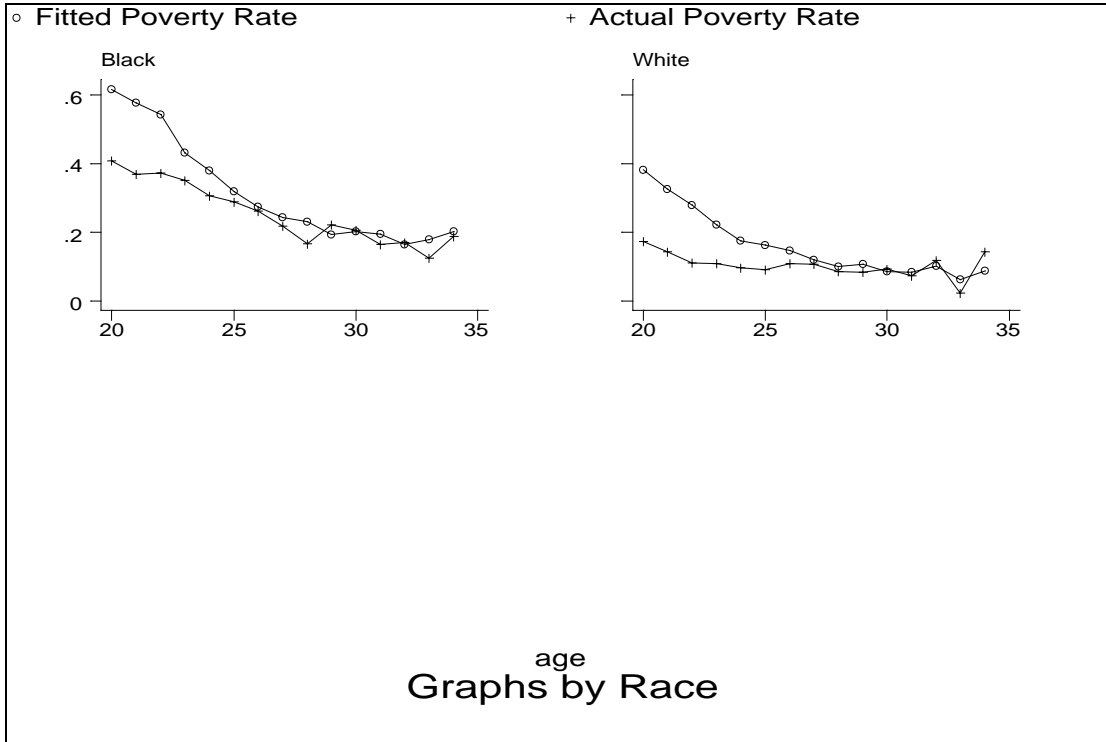
Figure 7: Persistence in Fitted Poverty Status

(a) Poverty Status by Previous Poverty Status
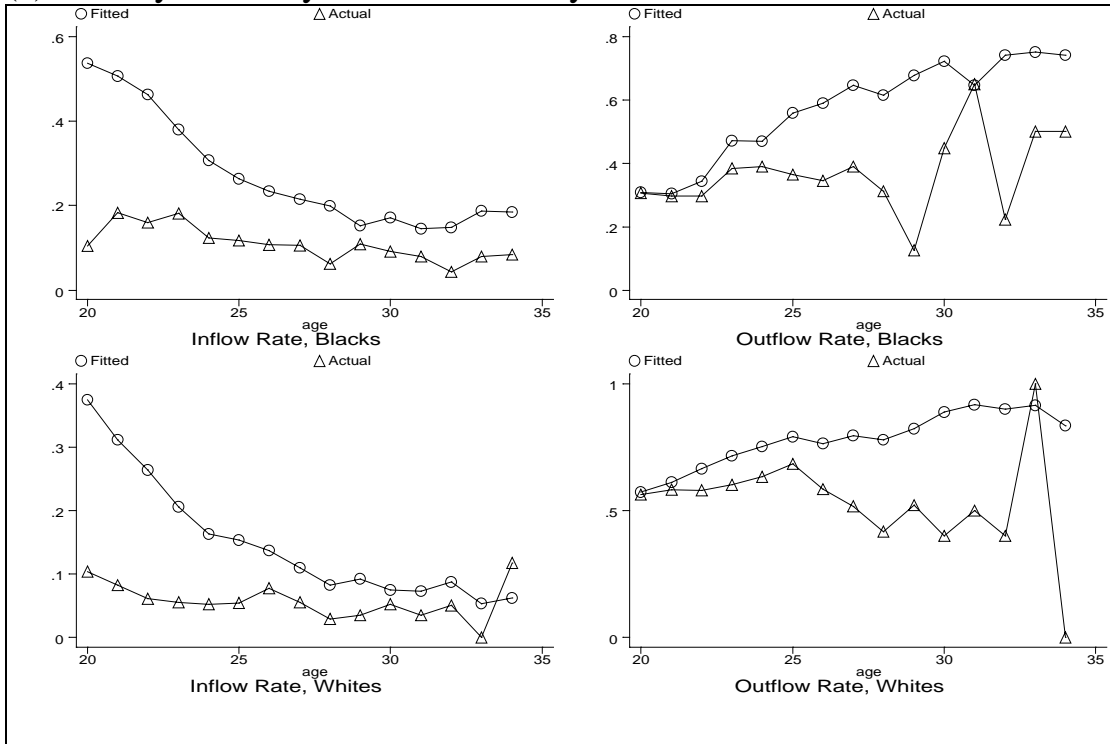
(b) Box-Plot for Fitted 'Lifetime' Proportion of time in Poverty against Actual 'Lifetime' Proportion of time spent poor
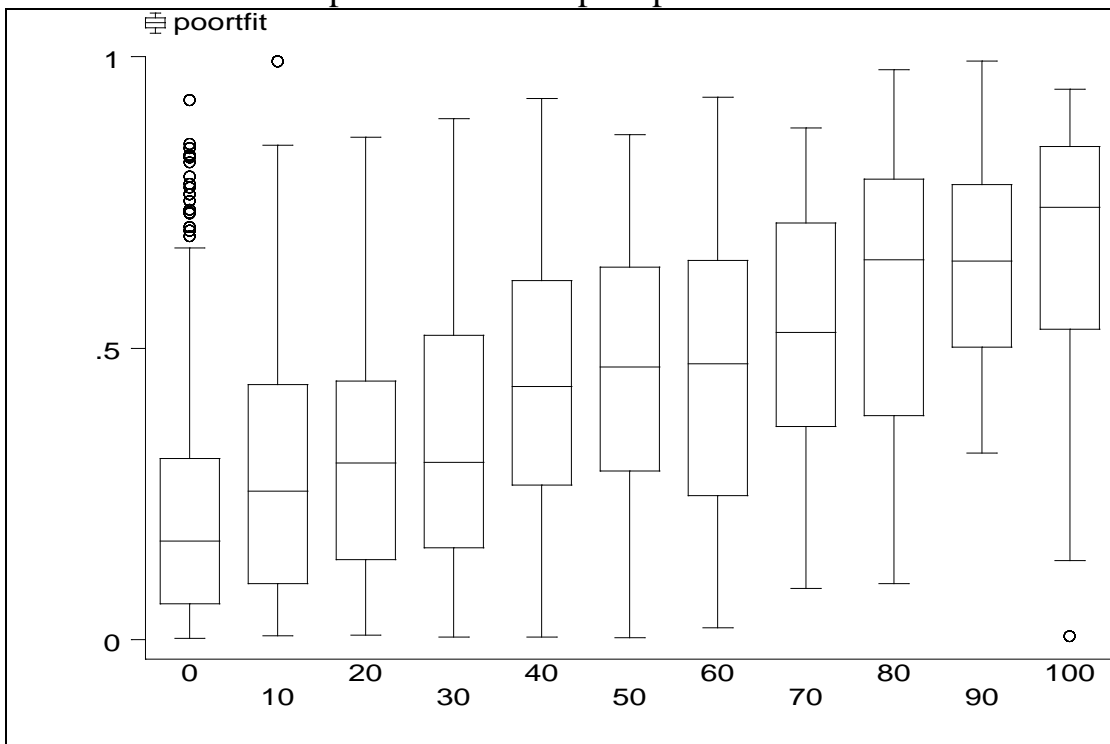
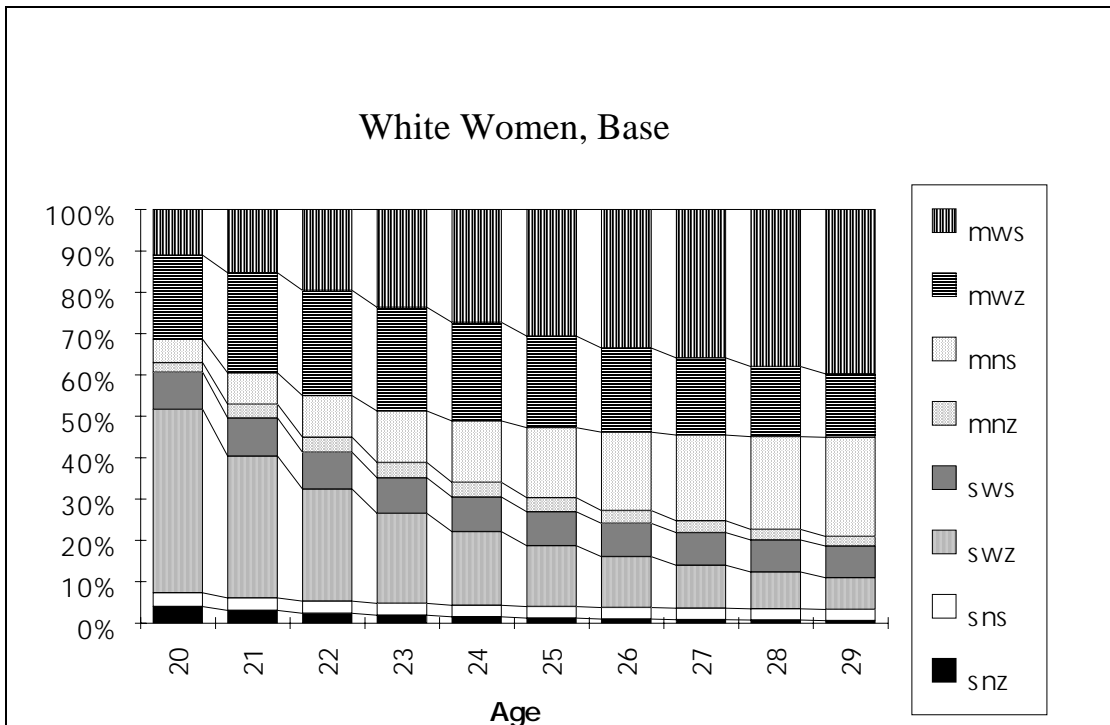Figure 8: Fitted Poverty Rates with Black Transition Rates and White Income Rates

Using all Black Transition Rates
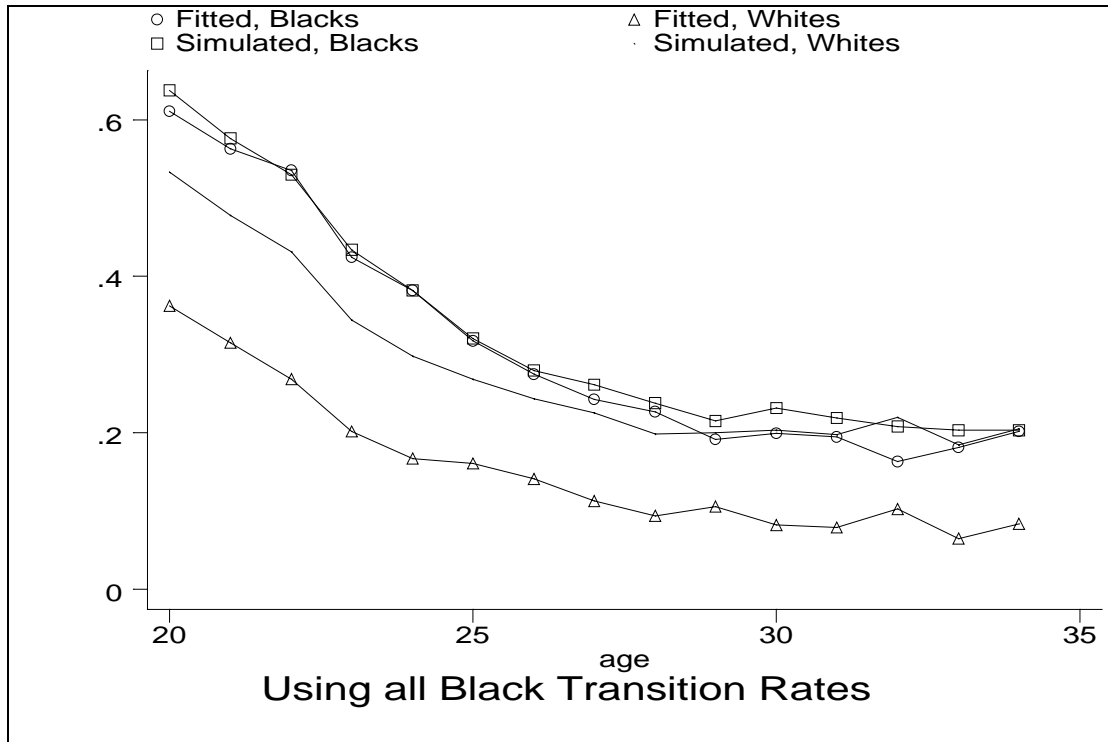
Figure 9: Demographic States: Base Case

Black Women, Base
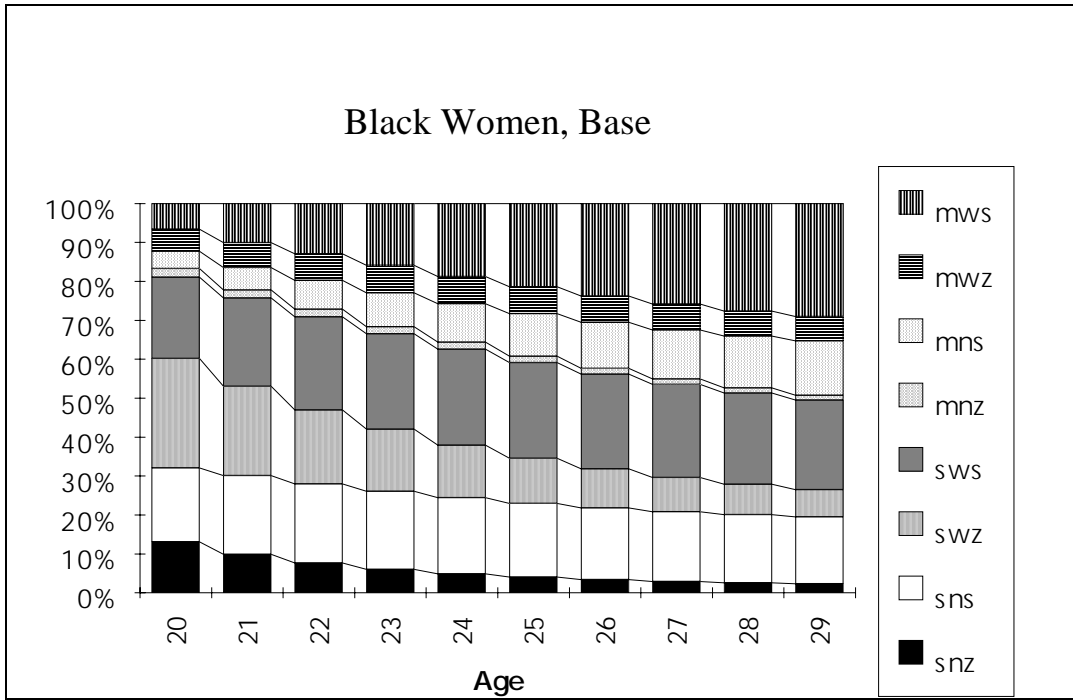
White Women, Base
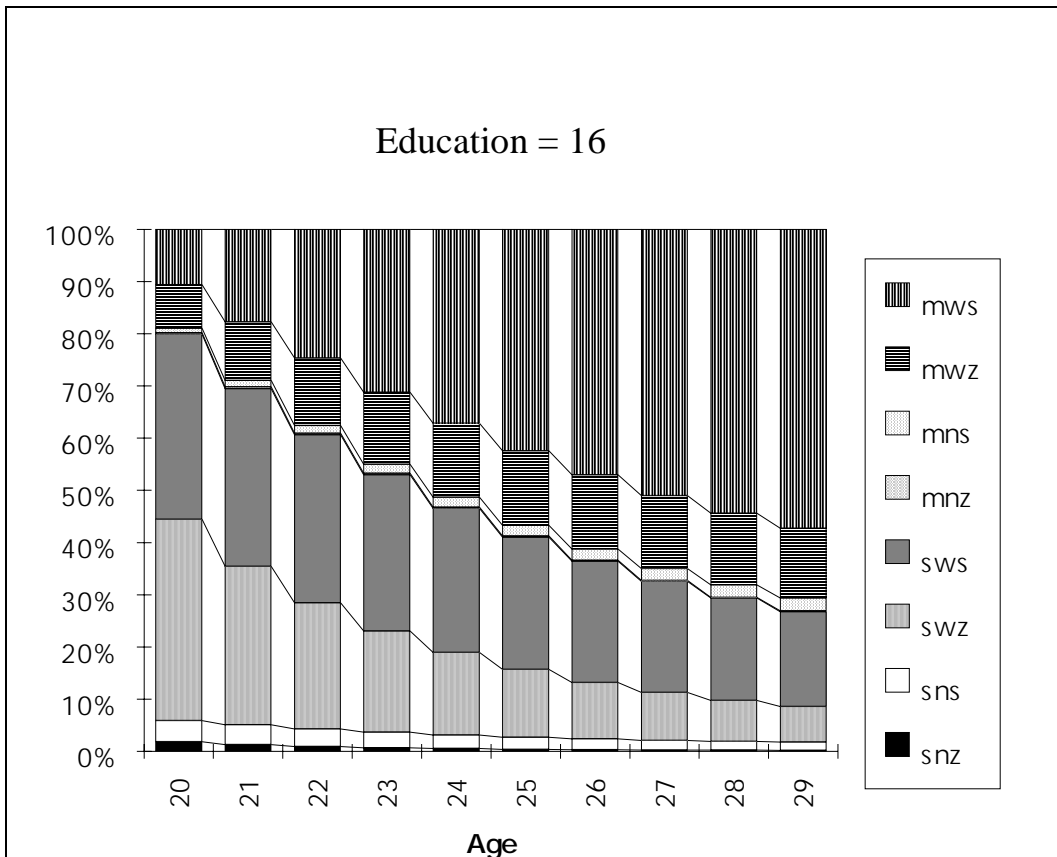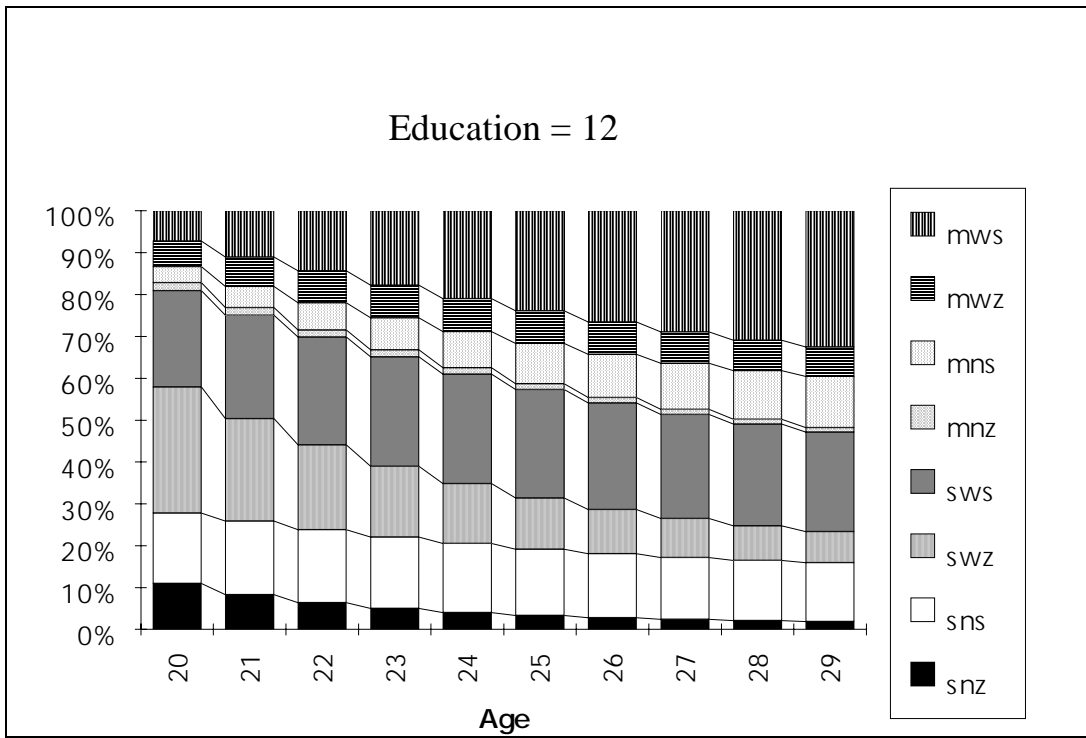
Figure 10a: Different Education Level; Black Women

Education = 12

Education = 16

Fiure 10b: Different Initial State; White Women

Starting State = swz

Starting State = sns