Is the Correlation in Welfare Participation across Generations Spurious?

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Working Paper No. 224
July 1992

July 1992

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Introduction

The recent availability of several longitudinal data sets that cover a sufficient number of years to span two or more generations has made it possible to start exploring a set of intergenerational questions not previously open to empirical analysis. This paper develops methods to analyze the correlation between the welfare participation of mothers and their daughters. However, one might equally well be interested in the correlation between marital states, fertility histories, criminal histories, or religious preferences of parents and their children. What all these topics have in common is that they focus on the correlation in outcomes that can change over a person's life— parents marry and divorce, adults are childless and then have a sequence of births, lawbreakers become law abiding citizens and then revert back to crime, people change religions. Furthermore, any intergenerational correlation in these time varying outcomes can reflect behavioral links between generations or spurious correlation.

This paper attempts to identify the effects of what might be called intergenerational state dependence from the effects of spurious correlation in unobservables shared between parents and children. Intergenerational state dependence is the behavioral effect on the child of the parent's outcomes— for example the effect on the child of the parent receiving AFDC or the parent having been incarcerated during the child's formative years. If there is state dependence then changing the parent's outcome will alter the child's outcome. On the other hand, if the observed intergenerational correlation reflects only correlation in unobservables, then changing the parent's outcome (getting the mother off of public assistance or the parent not to commit a crime) will not affect the child. For example, if children tend to live in neighborhoods that are similar to their parents and if neighborhood characteristics matter, then parents and children will have correlated outcomes even if the parent's actual outcome has no independent impact on the child.[1] In this case altering the parent's outcome will not directly affect the child but changing neighborhood characteristics will affect both parent and child.

[1]In fact, denying assistance may increase the child's probability of receiving assistance if the loss of income to the mother causes her to move to a worse neighborhood.

Well known techniques from event history analysis can be used to describe the correlation between generations in events that change over each person's life. The two event histories are allowed to be correlated by allowing the unobservables in the child's equation to be correlated with the unobservables in the parent's equation. Two computationally feasible techniques are developed for estimating these types of models.

The paper is divided into five sections. The first gives an overview of the issues raised in the literature on intergenerational correlation of welfare participation and discuss weaknesses with previous studies. The next section develops a methodology for estimating the correlation in event histories and for identifying the extent to which that correlation reflects intergenerational state dependence. Sections three and four present the data and results. The paper concludes with a discussion of the implications of the results.

The Intergenerational Welfare Participation Debate

Public and academic attention on the "underclass" has focused both on the traits of persons currently classified as being in the underclass and on the correlation across generations in outcomes associated with being in the underclass. Specifically, considerable attention has been focused on the possibility that receipt of public assistance by one generation may be associated with greater participation of the next generation. The widespread public perception that daughters of mothers who receive AFDC are more likely to receive public assistance themselves fits the view that there may be causal links across generations. The public policy implication of the observed intergenerational correlation, however, depends crucially on the transmission mechanism.

The observed correlation is sometimes assumed to reflect the transmission of preferences from generation to generation— mothers who participate have low aversion to receiving aid and this trait is passed on to their daughters— or to the transmission of constraints— parents who attend schools in poor neighborhoods often end up sending their children to similar schools. Alternatively, there may be a direct affect of growing up in a household that receives aid. Children may learn how to cope with the welfare system by living in a household that participates and, therefore, the child may face lower psychic costs of participating when she grows up.

The source of the correlation in participation is crucial since alternative causal mechanisms have different policy implications. If the correlation in participation reflects the transmission of preferences, then the daughter's outcome will not be changed unless the mother's preferences are changed— mother's who have a high tolerance for having to rely on public assistance may pass this attitude on to their daughters, whether the mother participates or not. Similarly, if the correlation reflects correlated constraints then it is the constraints that need to be changed if policy is to have an effect on the daughter.

Lowering the mother's participation will have an impact on the daughter only if there is true intergenerational state dependence— the experience of growing up in a household that receives aid matters per se. These behavioral effects are consistent with standard job shopping models that predict that the lower cost of obtaining information about welfare if one's mother receives assistance will raise the probability that the child will participate. Viewed in this light, intergenerational correlation in welfare participation is no more surprising than the well documented intergenerational correlation in occupations. Children are more likely to follow in their parents' footsteps because they obtain information at low cost about this option.

There are now several studies of the correlation of welfare experiences between parents and their children (Antel, 1988; An, Haveman and Wolfe, 1992; Duncan, Hill and Hoffman,1988; Gottschalk, 1991; McLanahan, 1988; Rainwater 1987; and Solon, Corcoran, Gordon, and Laren,1987; Tienda,1990). All studies have found statistically significant intergenerational correlations, even after controlling for a large number of covariates. These studies provide useful descriptions of observed correlations but they provide little information on the causal links.

The traditional approach to heterogeneity in the intergenerational literature has been to obtain better measures of observables. For example, tract level data has recently been appended to the Panel Study of Income Dynamics (PSID) to test for neighborhood effects. Since it is unlikely that we will ever be able to control for all the variables affecting the daughter's history, it is necessary to model the unobservables. Antel (1989) is the only study that has taken steps in this direction. By estimating a bivariate probit model for the mother's participation at the beginning of the survey and the daughter's participation at the end of the survey he allows unobservables to be correlated. While an important first step, his approach has disadvantage of using a regression framework to

study what are ultimately two correlated event histories. One important advantage of modeling the full histories is that this opens new avenues for identification.

In the following sections I present two alternative methods for dealing with the unobserved heterogeneity in intergenerational duration data. The approach I take has two advantages. First, it explicitly recognizes that welfare participation varies over time by introducing heterogeneity into the joint estimation of duration models of the mother's and daughter's participation histories. The use of duration models to study intergenerational welfare dynamics is a natural extension of earlier work on welfare duration.[2] Duration models of the daughter's and mother's histories use all available information on mothers and daughters histories, including censored spells[3]. This minimizes the probability of misclassification which is inherent in studies that focus on the mother during a limited number of years at the beginning of the panel and on the daughters during a limited number of years at the end of the panel. This is a major advantage since many welfare spells are short and would be missed by focusing on an unnecessarily short "window" for the mother and for the daughter. Furthermore, the histories do not have to be summarized into a arbitrary summary statistic, as is done in all studies that use a regression framework.[4] The second advantage of the method developed in this paper is that identification is achieved through assumptions about timing rather than through exclusionary restrictions. This is a natural outcome of moving to duration models in order to measure intergenerational correlation of participation.

Methodology

Source of the Problem

Before presenting event history models, I present a simple regression framework which highlights the source of the heterogeneity problem. To clarify issues consider the following structure that describes the time path of a continuous or latent variable Y* for daughters (Y^*_{dt}) and their mothers (Y^*_{mt}):

(1a) $Y^*_{dt} = Z_{dt}\,\beta_d + f(Y^*_{mt_0}, Y^*_{mt_0+1}, \ldots Y^*_{mt}) + \varepsilon_{dt}$

(1b) $Y^*_{mt} = Z_{mt}\,\beta_m + \varepsilon_{mt}$,

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[2] See Blank (1989) for a study of welfare duration that takes explicit account of unobserved heterogeneity.

[3] Using a regression framework to analyze event histories also posses the problem of how to enter time varying covariates. If the variables affecting the daughter's outcome change over time, then the path of these variables may matter. Using event history methods is the natural method of dealing with these problems.

[4] McLanahan(1988) is the only other study that uses duration models. She, however, models only the daughter's history and does not model the unobserved heterogeneity.

where t is the age of the child (for example Y^*_{mt} is the mother's value of Y* when the daughter is t years old) and $f(Y^*_{mt_0}, Y^*_{mt_0+1},\ldots Y^*_{mt})$ is a function that captures the effects of the parents' outcome when the child is between t_0 and t on the child's outcome at age t, Y^*_{dt}. The disturbance terms in the daughters' and mothers' equations contain both a person specific effects and iid disturbances:[5]

(2a) $\varepsilon_{dt}= \delta_d+\varepsilon^*_{dt}$

(2b) $\varepsilon_{mt}= \delta_m+\varepsilon^*_{mt}$,

where the δ's may be correlated but $cov(\varepsilon^*_{dt},\varepsilon^*_{d\tau})= cov(\varepsilon^*_{mt},\varepsilon^*_{m\tau})= 0$ for $t\neq\tau$. The histories of parents and children are correlated if $f(Y^*_{mt_0}, Y^*_{mt_0+1},\ldots Y^*_{mt})$ is non–zero or if δ_d and δ_m are correlated[6]. The former measures true state dependence (childhood experiences matter) while the latter reflects spurious correlation (the child's history is correlated with the parents through unobservables, even if the parent's actual history has no effect.).

If mothers and daughters have correlated unobservables that affect participation, then ignoring this correlation will yield bias estimates. For example, if mothers and daughters either face similar constraints or if tastes are transmitted intergenerationally then $Y^*_{m\tau}$ and ε_{dt} will be correlated through the δ's— unobservable constraints facing the mother (or her tastes) are embedded in δ_m, which is correlated both with the mother's actual participation, $Y^*_{m\tau}$, and with the daughter's unobserved constraints, δ_d, which affects ε_{dt}. If $Y^*_{m\tau}$ and ε_{dt} are correlated, one cannot separate the impact of state dependence (the mother's participation matters per se) from spurious correlation (unobserved factors cause both mother and daughter to be eligible and to participate).

Identification

Two crucial assumptions identify the model in equations 1a and 1b. The first assumption focuses on the timing of the mother's outcomes. When the child is t years old the only outcomes of the mother that causally affect the daughter are outcomes that occurred when

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[5]Parents' unobservables may include the effects of their parents' histories as well as other unobservables.

[6]The correlated two factor model used in the text is equivalent to the following oblique three factor model with factor loadings:

$$\varepsilon_{dt}= \lambda_f+ \delta^*_d+\varepsilon^*_{dt}$$

$$\varepsilon_{mt}= \alpha\lambda_f+ \delta^*_m+\varepsilon^*_{mt}$$

where λ_f is a family specific component and $cov(\delta_d^*,\delta_m^*)=0$

the daughter was t or younger. The assumption that only prior outcomes matter is reflected in the expression $f(Y^*_{mt_0}, Y^*_{mt_0+1},\ldots Y^*_{mt})$, which only includes terms up to t. For example, if the mother participates in a future period as a result of an AFDC rule change, then the mother's participation is assumed not to affect the daughter in a prior period.

The second key identifying assumption is that mothers can affect daughters but that daughters don't affect mothers. This assumption of intergenerational ordering is incorporated in equation 1b, which does not include outcomes of the daughter in the mother's equation.

Both assumptions are, of course, open to question. If the mother's and daughter's participation are sufficiently close in time it is possible that the anticipation of the mother's future outcome has a causal effect on the daughter, thus violating the assumption that only prior outcomes matter. Mothers may also learn about welfare from their daughters, which would violate the intergenerational ordering assumption. While these assumptions impose structure in order to identify the causal mechanism, these timing assumptions are an attractive alternative to the exclusionary restrictions used by Antel (1988).

The assumption that only prior outcomes matter and the assumption that daughters' outcomes don't affect mothers' outcomes are necessary to insure that the correlation between the daughter's outcome and mother's future participation captures only the effects of heterogeneity. Since the correlation between daughter's participation and mother's prior participation includes both this heterogeneity effect and a causal effect, the contrast between the correlations of the daughters outcomes and the mothers future and prior participation identifies the causal mechanism.

To see this a bit more formally consider the following simplified model that maintains the essence of equations (1a) and (1b).

(3a) $Y^*_{dt} = \gamma^* Y^*_{mt-1} + \delta_d + \varepsilon^*_{dt}$

(3b) $Y^*_{m\tau} = \delta_m + \varepsilon^*_{m\tau},$

where Y^*_{dt} and $Y^*_{m\tau}$ are continuous variables so identification does not depend on nonlinearities. The essential elements of the causal links between generations is

simplified by assuming that $f(Y^*_{mt_0}, Y^*_{mt_0+1},....Y^*_{mt})$ equals $\gamma^* Y^*_{mt-1}$— only the mother's outcome in the prior year causally affects the daughter's outcome. All observed covariates have been dropped in order to highlight the fact that exclusionary restrictions are not necessary to identify the intergenerational effects.

The covariance structure of equations 3a and 3b yields

$$(4a) \quad \text{cov}(Y^*_{dt}, Y^*_{mt-1}) = \text{cov}(\delta_d, \delta_m) + \gamma^* \text{ var } (Y^*_{mt-1})$$

$$(4b) \quad \text{cov}(Y^*_{dt}, Y^*_{mt+1} | Y^*_{mt-1}) = \text{cov}(\delta_d, \delta_m)$$

Equation (4a) uses the covariance between mother's prior participation and daughter's current participation to capture the combined causal and spurious effects. Equation (4b) yields the spurious effect from the covariance of the mother's future participation (conditional on her prior participation) with the daughter's current participation.[7]. Equations 4a –4b are sufficient to identify γ^*, the parameter of interest since they can be solved for γ^*:

$$(4c) \quad \gamma^* = \frac{\text{cov}(Y^*_{dt}, Y^*_{mt-1}) - \text{cov}(Y^*_{dt}, Y^*_{mt+1} | Y^*_{mt-1})}{\text{var } (Y_{mt-1})}$$

This simple example shows that the non–linearities and exclusionary restrictions in the model presented below aid in identification but are not crucial since identification is achieved even in the linear model without covariates.

Statistical Model

In this section I present two alternative statistical models that take explicit account of unobservables affecting mothers' and daughters' participation histories. I first present the notation used in modeling the daughter's event history. The two methods of modeling the unobservables are then presented and evaluated.

Daughter's Event History Model

[7]Given the specific model in (3a) and (3b), past values of $\tau \neq t-1$ also yield estimates of the spurious component. This artifact of the specific model being examined disappears when more general forms of $f(Y^*_{mt_0}, Y^*_{mt_0+1},....Y^*_{mt})$ are used in the rest of the paper.

The daughter's childbearing and AFDC participation status in each year determine an indicator variable, $Y_{d,t}$[8]. From the time the daughter is 14 until the year of first birth she can occupy one of three states:

$Y_{d,t} = 0$ daughter is childless at age t

$= 1$ daughter has her first child but does not participate in AFDC at age t .

$= 2$ daughter has her first child, and does participate in AFDC at age t,

After the year of first birth, Y_{dt} can no longer be equal to zero.

The process determining $Y_{d,t}$ is assumed to be governed by the mother's prior welfare history, a vector of observable covariates, $Z_{d,t}$, and a vector of unobservable heterogeneity components governing the probability that the daughter will be in each state. These may be correlated with the mother's unobservable heterogeneity components.

The full specification of the model requires assumptions about the functional form for $f(Y^*_{mt_0}, Y^*_{mt_0+1}, \ldots Y^*_{mt})$, the probability law generating the sequence of states, and the distribution of the heterogeneity components.

Functional Form for Causal Variable

In order to implement the model I must specify a functional form for the f function, which summarizes the effects of the mother's history. Since the mother's participation is a discrete variable, her history from the time the daughter is t_0 to the time the daughter is t can be written as $f(Y_{mt_0}, Y_{mt_0+1}, \ldots Y_{mt})$, where $Y_{mt} = 1$ if $Y^*_{mt} > 0$. The restriction I adopt falls in the class of linear functions

$$f(Y_{mt_0}, Y_{mt_0+1}, \ldots Y_{mt}) = \gamma \underline{Y_t}$$

[8] Gottschalk (1991) further disaggregates non–participants in the NLSY into eligible and ineligible non–participants. He finds that there is still substantial intergenerational correlation, even after controlling for eligibility. When his definition of eligibility was applied in preliminary work for this study (that uses the PSID) the findings were very similar. Since disaggregating nonparticipants by eligibility status adds substantial complexity to the estimation without adding insight, this distinction is not used in this paper.

where $\underline{Y}_t$ is a tx1 vector of Y_{mt}'s and γ is a 1xt vector of coefficients . Without further restrictions this specification allows a free lag structure on the effects of the mother's participation 1,2, ... t years ago. In the empirical work presented in this paper I further impose two different restrictions on the elements of γ. The first requires that each element is equal to $\gamma^*/(t-t_0)$, where the scalar γ^* becomes the single parameter to be estimated. This specification implies that the mother's history can be summarized by the proportion of years she was on AFDC between the time that the daughter was t_0 and t years old.[9] Since the impact of the mother's participation may decay with the passage of time, I also estimate models in which the proportion of time the mother received AFDC in different subperiods are allowed to have different impacts[10].

Probability of Sequence of States

I assume that the probability of being in each state is described by the multinomial logit expression:

$$(5a) \qquad \Pr(Y_{d,t}=0 \mid Z_{d,t}, \underline{Y}_t, \delta_d) = \frac{1}{D}$$

$$(5b) \qquad \Pr(Y_{d,t}=1 \mid Z_{d,t}, \underline{Y}_t, \delta_d) = \frac{\exp(Z_{d,t}\beta_1 + \gamma \underline{Y}_t)}{D}$$

$$(5c) \qquad \Pr(Y_{d,t}=2 \mid Z_{d,t}, \underline{Y}_t, \delta_d) = \frac{\exp(Z_{d,t}\beta_2 + \gamma \underline{Y}_t + \delta_d)}{D}$$

where $D=1+ \exp(Z_{d,t}\beta_1 + \gamma \underline{Y}_t) + \exp(Z_{d,t}\beta_2 + \gamma \underline{Y}_t + \delta_d)$[11]. δ_d is the daughter's heterogeneity parameter whose distribution must be estimated along with the β's and γ.

After the year of first birth the daughter can no longer have $Y_{d,t}$ equal to zero so the number of competing states is reduced from three to two. The probabilities of being in each state are given by:

$$(5d) \qquad \Pr(Y_{d,t^*}=1 \mid Z_{d,t^*}, \underline{Y}_t, \delta_d) = \frac{\exp(Z_{d,t^*}\beta_3 + \gamma \underline{Y}_t)}{D}$$

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[9]Under this structure $\gamma \underline{Y}_t = \gamma^*/(t-t_0)\, \mathbf{I}\, Y^t_m$, where $\mathbf{I}$ is a 1 x t vector of ones. Therefore, under this specification $\gamma \underline{Y}_t = \gamma^* \frac{1}{(t-t_0)} \sum_{\tau=t-t_0}^{t} Y_{m\tau}$

[10]The mother's average participation during the last three years (between years t–2 and t), the previous two years (t–3 and t–4) and all earlier years are allowed to have different coefficients.

[11]The parameterization of δ_d insures that the odds of having $Y_{d,t}=1$ versus $Y_{d,t}=0$ is unaffected by δ_d— this heterogeneity parameter only affects the odds of receiving assistance versus other outcomes.

$$(5e) \qquad \Pr\left(Y_{d,t^*}=2 \mid Z_{d,t^*}, \underline{Y}_t, \delta_d\right) = \frac{\exp(Z_{d,t^*}\beta_4 + \gamma \underline{Y}_t + \delta_d)}{D}$$

where $D=\exp(Z_{d,t^*}\beta_1 + \gamma \underline{Y}_t) + \exp(Z_{d,t^*}\beta_2 + \gamma \underline{Y}_t + \delta_d)$ and t* indicates an observation after the daughter has had her first child.[12]

Modeling Unobservable Heterogeneity

The model described above has simply added an unobservable individual specific effect, δ_d, to the standard multinomial logit model. The key econometric problem arises if δ_d is correlated with the mother's participation.

In order to eliminate the potential bias arising from ignoring this correlation, it is necessary to explicitly model the relationship between δ_d and the mother's outcomes. Two different methods are developed to control for the possibility that the daughter's outcome may be tied to her mother's outcome through δ_d. Each method exploits different information about the mother's welfare history.

Mother's Future Participation

The first method used to correct for the correlation between mothers' and daughters' unobservables uses information on the timing of the mother's and daughter's participation. The procedure is based on concepts developed in Heckman (1978) and in Chamberlain (1980).

Heckman (1978) suggests that the order in which random events occur can be used to separate the effects of unobserved heterogeneity from state dependence. The concept is most clearly seen in his example of drawing balls from two urns. If the urns differ only in the proportion of black balls (the urns are heterogeneous but draws from a single urn are independent) then all sequences are equally likely— an urn with two thirds black balls (B) and one third red balls (R) will be as likely to produce a run of B, B, R as B, R, B. If on the other hand each successive draw depends on prior draws (i.e. there is state dependence) then some runs will be more likely than others. For example, B, B,

[12] β_3 and β_4 are allowed to differ from β_2 and β_3 in order to allow the odds to change after the option of not having a child is eliminated.

R will be more likely than B, R, B if blacks tend to follow blacks. Thus, the proportion of black balls without regard to order will give information on heterogeneity while the order of draws will give information on state dependence.

In terms of intergenerational correlation of welfare participation, if the observed correlation between the participation of the mother and daughter reflects state dependence then the timing of the mother's and daughter's spells should matter— the probability of observing the daughter on welfare in period t should be higher if the mother participated prior to t than if the mother participated after t[13].

For example, consider the probability of a daughter participating in AFDC when she is 18. Compare the probabilities for two observationally identical daughters whose (observationally identical) mothers participate in AFDC only once during their lives but the mothers' timing is different. The first mother participates when her daughter is 16, while the other mother participates when her daughter is 20. If there is state dependence, the former daughter will have a higher probability of receiving aid when she is 18 than the latter daughter, since her mother's participation when she was 16 will have a causal impact. The participation of the second mother (when her daughter is 20) does not have a causal effect on the daughter's outcome when the daughter is 18. If, on the other hand, it is only unobservable heterogeneity that ties the generations then the two daughters will have the same probabilities since the mothers' participation is only indicative of unobservables that are correlated with the daughters' unobservables— the timing of events does not matter. A similar logic underlies Chamberlain's (1980) method of controlling for heterogeneity in panel data by entering future as well as past values of covariates. The future values capture heterogeneity, while the past values capture causal dependence as well as heterogeneity.

This suggests entering a summary measure of time the mother spent on AFDC after the daughter was age t, as well as a summary of time the mother received aid prior to t, in the daughter's equation. In the empirical work presented in this paper I use the average amount of time the mother spent on welfare after the daughter was age t, $\underline{Y}_{t+}$, to capture heterogeneity. In terms of the previous notation:

(6) $\delta_d = \alpha \underline{Y}_{t+}$

[13]These statements are, of course, conditional on other factors, such as age, that also affect the timing of welfare spells.

where α is a coefficient to be estimated.[14]

Mother's Participation Conditional on Her Expected Participation

The second method for separating the impact of unobservables from the impact of state dependence uses information about the difference between the mother's predicted and actual history to make inferences about her unobservable characteristics—a mother with characteristics which would lead one to predict that she would have a high probability of participating who, in fact, does not receive aid, is likely to be someone who has a dislike for aid or little information about the program. If these characteristics of the mother are transmitted to the daughter, then the daughter may be less likely to receive assistance herself, whether the mother participates or not. Likewise, a mother with high expected earnings who works few hours and receives aid is conceptually different from a mother with low expected earnings who is also a recipient— the former reveals low cost of participation which may again be transmitted to her children, thus lowering the daughter's cost of participation.

To make this more concrete consider two mothers. One is an unmarried high school dropout while the other is a married high school graduate. Suppose that they both have identical welfare histories. If the welfare histories of the daughters of these two mothers reflect their mothers' actual participation histories then the two daughters should have similar histories, since the two mothers participation histories are identical. On the other hand, if it is unobservables that matter, then information on these unobservables can be gained from the fact that the unmarried high school dropout had a welfare participation history as low as that of the married high school graduate. Since, in general, unmarried high school dropouts have higher expected participation, this particular high school dropout exhibited a below average propensity to participate. If these unobserved characteristics are passed on to her daughter, then the daughter will also have a below average propensity. In essence, the actual history gives information on state dependence while the difference between the actual and the expected history gives information on heterogeneity.

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[14] $\underline{Y}_{t+}$ is recalculated for every t since the future is always defined in reference to the daughter's current age.

This basic insight can be incorporated into our model by estimating a random effects logit duration model, using a binary mixing distribution.[15] We assume that the unobservables affecting the mother's and daughter's eligibility and participation are random draws from a joint binary distribution. By estimating the two generations' models simultaneously one can control for correlated unobservables as well as observables.

Specifically, the probability that a mother will occupy a given state when her daughter is τ years old, is also modeled as a logistic probability which depends on her unobservable (as well as observable) characteristics. Since the mother has by definition already had her first child by the time she is observed in the panel, she can only occupy two states:

$$(7a) \qquad \Pr\ (Y_{m,\tau}=1 \mid Z_{m,\tau}, \delta_m) = \frac{1}{D^{**}}$$

$$(7b) \qquad \Pr\ (Y_{m,\tau}=2 \mid Z_{m,\tau}, \delta_m) = \frac{\exp(Z_{m,\tau}\,\beta_{3+}\delta_m)}{D^{**}}$$

where $D^{**}=1+ \exp(Z_{m,\tau}\,\beta_3+\delta_m)$.

In order to write the likelihood of the histories of mother daughter pairs it is necessary to specify the probability law generating the unobservables, δ_d and δ_m . I assume that the unobservables each have two points of support— δ_d can take on the values of zero or δ_d^*. Likewise, δ_m can take on the values of zero or δ_m^*. These assumptions define the joint distribution of the mother and daughter's unobservables. The probability of each combination of heterogeneity components is given by:

$$(8a) \qquad \Pr\ (\delta_m = \delta_m^*, \delta_d = \delta_d^*) = \pi_{11}$$

$$(8b) \qquad \Pr\ (\delta_m = \delta_m^*, \delta_d = 0\ ) = \pi_{10}$$

$$(8c) \qquad \Pr\ (\delta_m = 0\ , \delta_d = \delta_d^*\ ) = \pi_{01}$$

$$(8d) \qquad \Pr\ (\delta_m = 0\ , \delta_d = 0\ ) = 1-\pi_{11}-\pi_{10}-\pi_{01}$$

The log likelihood function for the sample of mothers and their daughters can, therefore, be written as a sum of weighted pairs of log–likelihoods for the mothers' and daughters' histories, where the weights are given by the π's. The likelihood function can then be maximized with respect to the β's, δ^*'s, and π's[16].

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[15] Our model expands on Engberg, Gottschalk and Wolf (1989).

[16] The likelihood function is given in the appendix.

Data Definitions

Selection of Data Base

The Panel Study of Income Dynamics (PSID) and the National Longitudinal Survey of Youth (NLSY) are two obvious data sets to consider using in a study of intergenerational welfare dynamics. Both provide nationally representative samples and both include the standard control variables used in this line of research. Furthermore, with the addition of the fertility file in Wave XIX of the PSID, information on childbearing histories of daughters is available in the PSID as well as in the NLSY.

Each data set has advantages in tracing the welfare histories of mothers and daughters. The primary strength of the PSID is that the mothers' histories can be traced over considerably longer periods than in the NLSY. In the NLSY the mother's welfare status can only be observed as long as the child is living in the parental household. The PSID, however, follows the original family members after the daughter splits from the original household. Having a long observation period on the mother is particularly important in studying welfare dynamics since the majority of welfare spells are short and can easily be missed if the mother is observed only over a short period. Furthermore, when controlling for heterogeneity by including the mother's future participation it is essential to be able to follow the mother's history after the daughter leaves home.

The PSID has the additional advantage of including daughters of all ages while the NLSY includes only daughters 14 to 22 at the start of the survey. Therefore, the PSID includes information on the mother's participation in AFDC when the child is younger than 14.

Given these advantages of the PSID, it is the data set used in this study. The PSID, however, has two major disadvantages. First, in order to use the marital and fertility histories it is necessary to limit the sample to individuals who were in the sample in 1985, when the retrospective demographic questions were asked of all individuals. The requirement that the individual not have attrited by 1985 opens the possibility of attrition bias. If attrition is correlated both with the parent's AFDC participation history and the child's AFDC history, then attrition may induce spurious correlation between these outcomes. While this is possible, there is no a priori reason to suspect that such a correlation exits. Furthermore, a recent evaluation of the PSID by Becketti, Gould, Lillard and Welch (1988) concludes that there is little evidence of attrition bias in either unconditional means or in the models they estimate.

The second disadvantage of the PSID is that receipt of AFDC is available for heads and wives in all years of the PSID but not for other family members. However, starting in 1975 the PSID asked each individual in the surveyed household whether he or she received any transfer income and, if so, the type of transfer. Persons are classified as participating in AFDC if they report receiving a transfer and report AFDC or "other welfare" as the type of transfer.[17] Individuals who receive more than one type of transfer can name only one source when asked the type of transfer. They will be misclassified as not receiving AFDC if they name one of their other sources of transfer income.[18]

Data Creation

Marital, fertility and welfare histories are created for all daughters from the time they turn 14 to the end of the survey. A welfare history is created for each daughter by using the AFDC data from the individual file if the daughter is neither the head or wife in a new household. Household information on receipt of AFDC by the head or spouse is used once the daughter splits from the original household and either becomes a head of household or spouse[19].

The identification numbers of the mothers of sample members are used to link daughters with their mothers.[20] The mothers' welfare histories are then created similarly to the daughters' histories. As long as the mother is either the head or the spouse, family information on AFDC is used. Data on transfer income from the individual file is used when the mother is neither the head nor the spouse.

Sample

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[17] A person is coded as receiving AFDC if she reports receiving either AFDC or "other welfare". Staff at the Institute for Social Research suggested including "other welfare" since it is often confused with AFDC by respondents.

[18]This only applies to persons who are not heads or wives since information on AFDC receipt for heads or wives is available in the family record.

[19]Although AFDC receipt is available on the individual file only starting in 1975 AFDC, this does not affect the sample used in the estimated models since our sample of daughters 20 to 23 in 1985 were 10 to 13 in 1975.

[20]Starting in the 1986 Wave of the PSID, the mother's sample number is available in the individual file .

The initial sample includes all daughters who were 18 to 31 by 1985 and could be linked to their mothers. The age restriction is imposed in order to insure that all sample members were of childbearing age and could, therefore, have participated in AFDC during the survey. Table 1 shows how these cuts affected sample size. The initial data set starts with 1216 non–black and 1101 black females who were classified as daughters in at least one year of the survey years and were between the ages of 14 and 50 in 1985. Among non–blacks, 866 daughters were matched with 586 mothers. The comparable figures for blacks is 791 daughters matched with 432 mothers. Restricting the age in 1985 to 18 to 31 reduces the sample by roughly 15 percent. Adding the criterion that the daughters have valid data on year at first birth further reduces the white sample by 1 percent and the black sample by 6 percent.

Results

Tabular Evidence

Tables 2 and 3 present crosstabular evidence of the unconditional relationship between daughters' childbearing and AFDC participation by the end of the survey and their mothers' AFDC participation during the survey period. These data serve as a benchmark for the models in the following section. Table 2 is for all daughters 18 to 31 in 1985, while Table 3 controls for age by limiting the sample to daughters 20 to 23 in 1985. Focusing on these younger daughters, who were 3 to 6 at the start of the survey, also has the advantage of insuring that mothers were observed over the full period when their daughters could have been affected by the mother's outcome.

These tables cross classify daughters' childbearing and AFDC status at the end of the survey according to their parents' AFDC participation during the survey period. Columns 1 and 3 present data for non–black and black daughters respectively whose parents didn't receive AFDC at any point during the survey. Columns 2 and 4 are for daughters whose parents did participate in AFDC during the survey.

Comparing Columns 1 with column 2 and column 3 with column 4 indicates that there is a strong relationship between mothers' and daughters' participation for non–blacks and blacks respectively. The probability of having a child by the end of the survey is substantially higher if the parent participated than if the parent did not participate. For non–blacks the probability that the daughter gave birth increases from .363 (column 1) to .610 (column 2) if the parent participated. For blacks the comparable increase is nearly as

large (from .434 to .646.) Thus, the mother's participation during the survey is correlated with her daughter's probability of having a child by the end of the survey.

The bottom panel focuses on the correlation between daughters' and mothers' participation. The second to last row of Table 2 shows the conditional probability that the daughter received AFDC during the survey, given that she had a child. These summary statistics indicate that there is a strong relationship between the mother's participation and the daughter's conditional probability of receiving aid, given that she had a child . For non–blacks the conditional probability of receiving aid increases from .182 (column 1) to .354 (column 3) if the parent participated in AFDC. For blacks the comparable difference is even larger (.313 versus .752.)

Table 2, therefore, shows strong correlation between parental participation and daughters' childbearing and participation for daughters 18 to 31 in 1985. Table 3 focuses on the narrower age group of daughters (20 to 23 in 1985). While the sample is considerably smaller, the patterns are very similar to those found in Table 2— daughters are substantially more likely to have had a child by the end of the survey if their parents participated and, among those who did have a child, the conditional probability of receiving aid is substantially higher if the parent received AFDC during the survey period.

Tables 2 and 3, therefore, show that welfare participation of parents are positively correlated with daughters' childbearing and participation. In order to try and disentangle whether these correlations reflect correlated unobservables or intergenerational state dependence, I now turn to the estimation of the statistical model presented earlier.

Estimated Models

Mother's Future Participation as Control

The first model uses the mother's future participation to capture the effects of unobservable heterogeneity , as specified in equation (6). The key identifying assumption is that the mother's future participation does not have a causal effect on the daughter's current participation. If this assumption is met, then any correlation between the daughter's outcome in period t and the mother's participation in period $\tau > t$ reflects correlated unobservables and not intergenerational state dependence.

The multinomial logit model for years through the year of first birth (as specified in equations 5a to 5c) is estimated using "stacked" observations on the daughter through the year of her first birth (or until censored). During this period she can be in one of three states: (1) childless, (2) gives birth and doesn't receive AFDC in the year of birth, or (3) gives birth and does receive assistance in that year. The model for subsequent years for daughters who have a child (as specified in equations 5d to 5e) is estimated by using data on the years after the birth of the first child. During this period the daughter can make transitions between participation states but cannot reenter the state of being childless. This reduces the competing states from three to two. Focusing on the period before and after the daughter's first birth allows coefficients to change after the childless state is removed.

The two key variables are the mother's prior participation, $\underline{Y}_t$, and the mother's future participation, $\underline{Y}_{t+}$. The mother's prior participation (when the daughter is t years old) is measured in two different ways. The first specification uses the proportion of years that the mother reported receiving AFDC between the time the daughter was 6 and t years old as a measure of the daughter's exposure to AFDC by the time she is t years old. In the second specification I enter three measures of the mother's average participation: her participation during the most recent three years, the prior two years and all earlier years (back to the time the daughter was six years old.[21]) In both specifications the mother's future participation is the proportion of years the mother participates between the time the daughter is t+1 and 20 years old. Since these averages change as the daughter ages, these are all time varying covariates.

The sample includes daughters 20 to 23 in 1985. These daughter's outcomes are modeled between the ages of 14 and 19. Age 14 is the youngest age at which a daughter could be at risk of giving birth. The upper age of 19 is imposed to insure that at least one year of data on the mother's future participation is available for all observations. Using a narrow age range, focused on the beginning of the daughter's childbearing years, insures that all daughters are observed over similar portions of their lifecycles. Since these daughters were 3 to 6 years old in 1968, we obtain an exhaustive history of their mother's participation history.

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[21]Three time varying variables are created. For example, when the daughter is 17, the three variables are the mother's average participation when the daughter was 15 to 17, 13 to 14, and 6 to 12.

The coefficients on the key variables, mother's prior and future participation, are shown in Tables 4a for non–blacks (columns 1 and 2) and blacks (columns 3 and 4)[22]. The measure of mother's prior participation (when the daughter is t years old) is the average number of years the mother participated between the time the daughter was 6 and t years old. The equations also include a quadratic in the daughter's age, the unemployment rate and the AFDC Need Standard in the daughter's state of residence, and the daughter's marital status in each year. In order to control for observable characteristics of the mother I also include average parental income, mother's age at first birth, mother's marital status at mother's first birth, and whether the mother completed high school.[23] For the years after the daughter's first birth (bottom panel) I also include controls for daughter's age at first birth and the presence of a child 1 to 3 years old. Results are presented with (columns 2 and 4) and without (columns 1 and 3) the mother's future participation as a control for unobservables.

The top panel shows the estimates from the multinomial logit equation estimated through the year of first birth. The bottom panel displays the estimates of the model estimated for the years after the first birth. The latter is shown only for blacks, since the number of non–blacks having a child during the panel was insufficient to yield enough observations on post birth outcomes.

Column 1 shows that the probability that a non–black daughter had a child in year t increases with the proportion of time the mother spent on welfare prior to year t. The probability of a daughter entering either the state of having a child and receiving AFDC or giving birth and not receiving AFDC both increase with mother's prior participation. The elasticities, shown in brackets, indicate that a ten percent increase in the mother's participation increases the probability that the daughter will have a child and receive assistance by 2.3 percent. It, however, only increases the probability of having a child and not receiving assistance in the year of first birth by .8 percent.[24] The finding of statistically significant effects of mother's prior participation, even after controlling for a large number of observable characteristics of the daughter and the mother, confirms the conclusions drawn from the tabular evidence from Tables 2 and 3.

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[22]The coefficients on the other variables are available from the author.

[23] Average parental income is calculated over the years when the daughter is 6 to 20 years old.

[24]The average probability of having a birth and receiving assistance in any one year is .0064 for non–blacks. If the mother increase her participation by ten percent this probability increases by 2.3 percent to .00655. The comparable increase in the probability of having a child and not receiving assistance is from .0242 percent to .0244.

Column 2 shows the effect of adding the mother's future participation as a covariate. The effect of the mother's prior participation on the odds of the daughter having a child and receiving AFDC decreases from 4.49 to 3.16 but remains statistically significant. While the mother's prior participation continues to have an effect, the coefficient on the mother's future participation is both large and significant. This suggests that there is substantial unobserved heterogeneity which is correlated with both the daughter's current outcome and the mother's future outcome for non–blacks.

Black daughters show somewhat different patterns in a number of dimensions. First, column 3 shows that the mother's prior participation decreases the probability that a black daughter will give birth without receiving assistance— the increased proportion of daughters having a child and receiving assistance comes from a reduction both in the proportion of daughters who remain childless and the proportion giving birth but not receiving assistance. Second, the elasticities are substantially larger for blacks than non–blacks. While the elasticity of the proportion of daughters giving birth and receiving aid is .23 for non–blacks it is .68 for blacks. Third, adding the mother's future participation as a control for unobservables has a somewhat smaller effect for blacks than non–blacks. The elasticity on mother's prior participation drops only from .68 to .51 (instead of from .23 to .16) . This suggests that unobserved heterogeneity is less important in explaining the intergenerational correlation in welfare participation among blacks than non–blacks.

Table 4a measures mother's prior participation as the proportion of time the mother received assistance. This implies that the timing of the mother's prior participation does not matter — the mother's participation 10 years earlier has the same effect as her participation in the last two years. Table 4b loosens this assumption by allowing the mother's participation during the most recent tree years, the prior two years and all earlier years to have different impacts.

Table 4b, indicates that it is only the recent exposure to welfare that seems to affect the daughter's behavior. For both blacks and non–blacks it is only the mother's participation during the most recent three years that is statistically significant. However, Table 4b shows the same general patterns as Table 4a. Entering mother's future participation lowers the coefficient on prior participation for both blacks and non–blacks. However, both future and prior participation continue to be significant. Thus, the conclusions based on Table 4a are robust to this change in specification.

Jointly Estimated Duration Models

The second method for controlling for heterogeneity is to explicitly model the unobservables determining the daughter's and mother's event histories and to estimate the parameters of the two event histories simultaneously, as described in equations 5, 7 and 8. Table 5 presents the results. The sample and control variables for the daughters are the same as those used in Tables 4a and 4b. The mother's equation includes a quadratic in age, the state unemployment rate, the state AFDC Need Standard, the mother's age at first birth, her marital status, a dummy variable for graduation from high school, two dummy variables for the presence of a child 1 to 3 and 4 to 6.[25]

The top panel shows the estimated coefficients on mother's prior participation. The lower panel shows the estimates of the two heterogeneity parameters (δ_m* and δ_d*) and the estimates of the three probabilities defined in equation 8.[26] For comparability, Table 5 repeats the estimates for the models without heterogeneity (found in columns 1 and 3 of Table 4a), which is equivalent to setting δ_m* and δ_d* equal to zero. Columns 2 and 4 show the results when the heterogeneity parameters are allowed to take on non–zero values.

The results of this alternative method for controlling for correlated unobservables confirms the earlier results . The effect of mother's prior participation is again reduced after controlling for heterogeneity, but continues to be significant for both blacks and non–blacks. The coefficients on mother's prior participation, however, declines less in Table 5 then in the previous tables. The elasticity of giving birth and participating declines only from .23 to .21 for non–blacks and from .68 to .61 for blacks. 6. The decline reflects the positive correlation between the mother's and daughter's unobservables, as exhibited in the bottom panel. Thus, black daughter's who were more likely to participate (than daughters with similar observable characteristics) had mothers whose conditional participation probabilities were also above average.

Conclusions

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[25]A full set of estimated coefficients for the mother's and daughter's equations are available from the author.

[26]The probabilities are constrained to lie between zero and one by estimating the α's in logit expressions of the form $\pi_{11} = e^{\alpha 1}/[1+e^{\alpha 1}+ e^{\alpha 2}+e^{\alpha 3}]$. The reported probabilities are the π's. The t statistics are for the estimated α's.

This paper has attempted to go beyond the findings of previous studies that show that welfare participation of mothers and daughters are correlated. The question posed is whether this correlation reflects state dependence (the mother's participation affects the daughter) or correlated unobservables (mothers and daughters are affected by unobserved factors that are correlated across generations.) If the correlation reflects correlated unobservable, such as poor opportunities for mothers and daughters or correlated tastes, then reducing the welfare participation of mothers without affecting these factors will have little effect on daughters' outcomes. If the correlation reflects state dependence then changing the mother's outcome will directly affect the daughter's probability of participating.

I have presented two alternative methods that attempt to control for correlated unobservables. While the two differ in their identifying assumptions, they give qualitatively similar results. Correlated unobservables are only part of the story. Even after controlling for unobservables in two very different manners there is still a sizable and statistically significant correlation between mothers' and daughters' welfare participation histories. While more refined methods may further whittle away at the correlation, the current evidence does not allow us to reject the hypotheses that there are causal links across generations.

Care should be taken in drawing policy conclusions from this line of research. At most, this research can test for causal links. It cannot, at this stage, identify the routes by which links are established. For example, it is possible that mothers who participate pass on information to daughters who need public assistance but who would not have participated if they had not had access to this information if their mothers had not participated. In this case the intergenerational links should be viewed as a benefit, not a cost, of the mother receiving assistance. On the other hand, if living in a household that receives assistance lowers the daughter's self esteem or ambition, which leads to welfare dependence, then these are adverse consequences that need to be addressed.

Appendix

This appendix details the likelihood function used to jointly estimate the event histories of mothers and daughters.

Following the notation in the body of the paper, the probabilities of being in each state through the year of first birth are given by the multinomial logit expressions:

$$\Pr\ (Y_{d,t}=0 \mid Z_{d,t}, \underline{Y_t}, \delta_d) = \frac{1}{D}$$

$$\Pr\ (Y_{d,t}=1 \mid Z_{d,t}, \underline{Y_t}, \delta_d) = \frac{\exp(Z_{d,t}\,\beta_1 + \gamma\,\underline{Y_t})}{D}$$

$$\Pr\ (Y_{d,t}=2 \mid Z_{d,t}, \underline{Y_t}, \delta_d) = \frac{\exp(Z_{d,t}\,\beta_2 + \gamma\,\underline{Y_t} + \delta_d)}{D}$$

where $D=1+ \exp(Z_{d,t}\,\beta_1 + \gamma\,\underline{Y_t}) + \exp(Z_{d,t}\,\beta_2 + \gamma\,\underline{Y_t} + \delta_d)$. After the year of first birth the probabilities of being in each possible state (the daughter can no longer be childless) are given by:

$$\Pr\ (Y_{d,t^*}=1 \mid Z_{d,t^*}, \underline{Y_t}, \delta_d) = \frac{\exp(Z_{d,t^*}\,\beta_1 + \gamma\,\underline{Y_t})}{D_a}$$

$$\Pr\ (Y_{d,t^*}=2 \mid Z_{d,t^*}, \underline{Y_t}, \delta_d) = \frac{\exp(Z_{d,t^*}\,\beta_2 + \gamma\,\underline{Y_t} + \delta_d)}{D_a}$$

where $D_a=\exp(Z_{d,t^*}\,\beta_1 + \gamma\,\underline{Y_t}) + \exp(Z_{d,t^*}\,\beta_2 + \gamma\,\underline{Y_t} + \delta_d)$ and t^* indicates an observation after the daughter has had her first child.

Let S_{kt} be an indicator variable signifying the state the person occupies in each period: $S_{kt}=1$ if $Y_{d,t}=k$ or if $Y_{d,t^*}=k$, $S_{kt}=0$ otherwise. The daughter's event history between the ages of T_0 and T_1, conditional on δ_d, is therefore given by:

$$L_d(\delta_d) = \prod_{t=T_0}^{t^*} \left[\frac{1}{D}\right]^{S_{0t}} \left[\frac{\exp(Z_{d,t}\,\beta_1 + \gamma\,\underline{Y_t})}{D}\right]^{S_{1t}} \left[\frac{\exp(Z_{d,t}\,\beta_2 + \gamma\,\underline{Y_t} + \delta_d)}{D}\right]^{S_{2t}}$$
$$\prod_{t=t^*+1}^{T_1} \left[\frac{\exp(Z_{d,t}\,\beta_1 + \gamma\,\underline{Y_t})}{D_a}\right]^{S_{1t}} \left[\frac{\exp(Z_{d,t}\,\beta_2 + \gamma\,\underline{Y_t} + \delta_d)}{D_a}\right]^{S_{2t}},$$

where the daughter is assumed to give birth at age t^*. Likewise, the probability of the mother being in each state is given by:

$$\Pr\ (Y_{m,\tau}=1 \mid Z_{m,\tau}, \delta_m) = \frac{1}{D^{**}}$$

$$\Pr\ (Y_{m,\tau}=2 \mid Z_{m,\tau}, \delta_m) = \frac{\exp(Z_{m,\tau}\,\beta_3 + \delta_m)}{D^{**}}$$

where $D^{**}=1+\exp(Z_{m,\tau}\beta_3+\delta_m)$. Therefore, the likelihood of the mother's event history, conditional on δ_m, is given by:

$$L_m(\delta_m)=\prod_{\tau}\left[\frac{1}{D^{**}}\right]^{S_{1\tau}}\left[\frac{\exp(Z_{m,\tau}\beta_3+\delta_m)}{D^{**}}\right]^{S_{2\tau}}$$

where τ varies across all observations on the mother.

The probabilities of each configuration of unobservables is given by:

$$\Pr(\delta_m=\delta_m^*,\delta_d=\delta_d^*)=\pi_{11}$$
$$\Pr(\delta_m=\delta_m^*,\delta_d=0)=\pi_{10}$$
$$\Pr(\delta_m=0,\delta_d=\delta_d^*)=\pi_{01}$$
$$\Pr(\delta_m=0,\delta_d=0)=1-\pi_{11}-\pi_{10}-\pi_{00}$$

Therefore, the likelihood of the joint histories of mother daughter pairs is given by:

$$L_p=L_d(\delta_d^*)\,L_m(\delta_m^*)\,\pi_{11}+L_d(0)\,L_m(\delta_m^*)\,\pi_{10}+$$
$$L_d(\delta_d^*)\,L_m(0)\,\pi_{01}+L_d(0)\,L_m(0)\,[1-\pi_{11}-\pi_{10}-\pi_{00}]$$

and the likelihood of the sample of all mother daughter pairs is the product of these likelihoods :

$$L=\prod_{p} L_p$$

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Table 1
Sample Size

Cumulative Cuts	Non-Black	Black
Daughters 14-50 in 1985[1]	1216	1101
Matched with Mothers		
Daughters 14-50 in 1985	866	791
(Mothers matched)	(586)	(432)
Daughters 18-31 in 1985	760	635
(Mothers matched)	(523)	(367)
With Valid Year of First Birth	752	596

[1] Persons classified as daughters in at least one year of the panel.

Table 2
Distribution of Daughters at the End of the Survey Period by Parenthood and AFDC Status

Daughters 18-31 in 1985

	Non-Black		Black	
	Parent Didn't Receive AFDC (1)	Parent Received AFDC (2)	Parent Didn't Receive AFDC (3)	Parent Received AFDC (4)
Distribution of Daughters by End of Survey				
Had Child	.363	.610	.434	.646
Didn't Receive AFDC	.297	.349	.298	.160
Received AFDC	.066	.261	.136	.486
Childless	.637	.390	.566	.354
	1.000	1.000	1.000	1.000
Conditional Prob. of Receiving AFDC If Had Child	.182	.354	.313	.752
Number of Daughters	651	101	253	343

Table 3
Distribution of Daughters at the End of the Survey Period by Parenthood and AFDC Status

Daughters 20-23 in 1985

	Non-Black		Black	
	Parent Didn't Receive AFDC (1)	Parent Received AFDC (2)	Parent Didn't Receive AFDC (3)	Parent Received AFDC (4)
Distribution of Daughters by End of Survey				
Had Child	.216	.559	.309	.625.
Didn't Receive AFDC	.170	.206	.204	.146
Received AFDC	.046	.353	.105	.479
Childless	.783	.441	.690	.374
	1.000	1.000	1.000	1.000
Conditional Prob. of Receiving AFDC If Had Child	.213	.631	.340	.766
Number of Daughters	213	42	92	132

Table 4a
Logit Coefficients on Mother's Prior and Future Participation
First Specification[1]

	Non- blacks		Blacks	
	(1)	(2)	(3)	(4)
Through Year of First Birth[2]				
Have Child and Didn't Receive AFDC.				
Mother's Prior Participation	1.51 (1.43) [0.08]	1.77 (1.52) [0.09]	-2.66 (-3.23) [-0.75]	-2.83 (-3.17) [-0.79]
Mother's Future Participation		-76.66 (-0.01) [-3.41]		0.33 (0.46) [0.06]
Have Child and Did Receive AFDC.				
Mother's Prior Participation	4.49 (3.11) [0.23]	3.16 (1.88) [0.16]	2.40 (3.89) [0.68]	1.76 (2.42) [0.51]
Mother's Future Participation		9.72 (2.93) [0.22]		0.92 (1.72) [0.18]
Log likelihood	-140.43	-134.58	-261.74	-260.13
After Year of First Birth[3]				
Did Receive AFDC				
Mother's Prior Participation			3.23 (3.28) [0.50]	2.38 (2.26) [0.37]
Mother's Future Participation				1.36 (1.72) [0.17]
Log likelihood			-54.28	-54.32

[1] t-statistics in parentheses. Elasticities in brackets.

[2] Variables in daughter's equation through year of first birth: Age, age squared, unemployment rate, state need standard, married plus the following mother's characteristics: average parental income during common years (10-24) , mother completed high school, mother's age at first birth, mother's marital status at mother's first birth.

[3] Additional variables in equation: presence of a child 1-3 years old and daughter's age at first birth.

Table 4b
Logit Coefficients on Mother's Prior and Future Participation Second Specification[1]

	Non- blacks		Blacks	
	(1)	(2)	(3)	(4)
Through Year of First Birth[2]				
Have Child and Did not Receive AFDC				
Mother's Prior Participation:				
1. Prior three years	-0.27 (-.17) [-.02]	0.29 (0.17) [0.01]	-2.43 (-2.18) [-0.63]	-2.94 (-2.45) [-0.76]
2. Following two prior years	1.60 (1.40) [0.08]	1.55 (1.36) [0.08]	0.44 (0.45) [0.13]	0.62 (0.45) [0.18]
3. Earlier years	-0.28 (-0.23) [-0.01]	-0.18 (-0.15) [-0.01]	-1.22 (-1.27) [-0.34]	-1.22 (-1.29) [-0.34]
Mother's Future Participation		-76.54 (-0.01) [-1.41]		0.90 (1.17) [0.18]
Have Child and Did Receive AFDC				
Mother's Prior Participation:				
1. Prior three years	6.43 (3.26) [0.36]	4.36 (1.72) [0.24]	2.71 (3.64) [0.70]	2.47 (3.02) [0.65]
2. Following two prior years	-1.44 (-0.51) [-0.07]	-0.73 (-0.26) [-0.04]	-0.83 (-0.90) [-0.24]	-0.84 (-0.90) [-0.24]
3. Earlier years	1.81 (0.73) [0.07]	1.73 (0.68) [0.07]	0.43 (0.53) [0.13]	0.39 (0.47) [0.12]
Mother's Future Participation		8.37 (1.87) [0.07]		0.42 (0.75) [0.08]
Log likelihood	-135.62	-133.07	-255.57	-254.67

[1] t- statistics in parentheses. Elasticities in brackets.
[2] Variables in daughter's equation through year of first birth: Age, age squared, unemployment rate, state need standard, married plus the following mother's characteristics: average parental income during common years (10-24) , mother completed high school, mother's age at first birth, mother's marital status at mother's first birth.

Table 5
Coefficients on Mother's Prior Participation
and Parameters of Mixing Distribution[1]

	Non-blacks		Blacks	
	(1)	(2)	(3)	(4)
Through Year of First Birth[2]				
Have Child and Didn't Receive AFDC				
Mother's Prior Participation	1.51 (1.43) [0.08]	1.46 (1.50) [0.07]	-2.66 (3.23) [-0.75]	-2.33 (2.50) [-.66]
Have Child and Did Receive AFDC.				
Mother's Prior Participation	4.49 (3.11) [0.23]	3.95 (2.73) [.21]	2.40 (3.89) [0.68]	2.16 (3.35) [.61]
After Year of First Birth[3]				
Did Receive AFDC				
Mother's Prior Participation			3.23 (3.28) [0.50]	2.55 (2.58) [0.42]
Parameters of Mixing Distribution				
Heterogeneity Parameters				
δ_d*		1.66 (4.3)		.703 (1.39)
δ_m*		4.27 (14.8)		3.33 (24.6)
Probability Distribution[4]				
$Pr(\delta_m=0, \delta_d=0)$		.853 (6.4)		.638 (2.50)
$Pr(\delta_m=\delta_m^*, \delta_d=0)$		.087 (1.8)		.062 (1.02)
$Pr(\delta_m=0, \delta_d=\delta_d^*)$		.030 (.009)		.012 (1.72)
Log likelihood[5]		-532.1		-1319.8

[1] t statistics in parentheses. Elasticities in brackets.

[2] Variables in daughter's equation through year of first birth: Age, age squared, unemployment rate, state need standard, married plus the following mother's characteristics: average parental income during common years (10-24) , mother completed high school, mother's age at first birth, mother's marital status at mother's first birth.

[3] Additional variables in equation: presence of a child 1-3 years old and daughter's age at first birth.

[4] t statistic on logit coefficients specifying probabilities.

[5] Log likelihood of daughter's and mother's histories. Mother's equation includes the following covariates: age, age squared, , the state unemployment rate, the state AFDC Need Standard, the mother's age at first birth, her marital status, a dummy variable for graduation from high school, two dummy variables for the presence of a child 1 to 3 and 4 to 6.

Table 4b
Logit Coefficients on Mother's Prior and Future Participation
Second Specification[1]
(Continued)

After Year of First Birth[2]				
Did Receive AFDC				
Mother's Prior Participation:				
1. Prior three years			3.22 (3.09) [0.52]	2.85 (2.36) [0.46]
2. Following two prior years			-0.91 (-0.81) [-0.15]	-0.89 (-0.79) [-0.14]
3. Earlier years			1.26 (1.08) [0.19]	1.25 (1.07) [0.19]
Mother's Future Participation				0.54 (0.56) [0.02]
Log likelihood			-50.24	-50.08

[1] t statistics in parentheses. Elasticities in brackets.
[2] Additional variables in equation: presence of a child 1-3 years old and daughter's age at first birth.