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"Estimating Welfare Effects Consistent with Forward-Looking Behavior. Part I: Lessons from a Simulation Exercise"

by

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Estimating Welfare Effects Consistent With Forward-Looking Behavior

Part I.: Lessons From A Simulation Exercise

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I. Introduction

There is an extensive literature in economics that seeks to determine the quantitative impact of welfare benefits on female labor supply and the propensity of women to participate in the welfare system. A growing literature also examines the impact of welfare generosity on fertility and marriage - behaviors that influence welfare eligibility and the level of benefits. Most of the studies adopt a static choice framework, albeit not always explicitly, to motivate their empirical specifications.[1] However, the behaviors that are presumably affected by the welfare system (fertility, marriage, work, school) clearly have both immediate and long-term consequences. If potential welfare recipients are forward-looking, they will consider these long term consequences when making current decisions. In this paper, we investigate the implications of the existence of forward-looking behavior for empirical work that seeks to determine the effect of welfare benefits on behavior.[2] In the companion paper that follows, we estimate the effect of welfare on those decisions adopting an empirical specification that is consistent with forward-looking behavior and interpretable within that framework.

To demonstrate concretely the implications of forward-looking behavior on the estimation of welfare effects, we specify and simulate a simplified dynamic model of contraceptive use and welfare participation. In formulating a specific behavioral model, we provide a rationale for the choice of variables, other than those that characterize the welfare system, to include as "controls" when estimating the effects of welfare benefits. In simulating the model, we illustrate the importance of two additional estimation issues: (i) the appropriate measurement of welfare benefits, and (ii) the source of sample variation used in estimating welfare effects, more specifically, the use of between vs. within-state variation in welfare benefits.

The appropriate choice of control variables in estimating decision rules, and the interpretation given to them, depends on the optimization model. In forward-looking models, current decisions depend on expectations about future preferences and constraints. Thus, variables that help to forecast future preferences or constraints belong in the decision rule, even if they do not affect current preferences or constraints. For example, the prior marital status of a currently unmarried woman may affect the probability of marriage in the future. Some prior decisions may alter current as well as future preferences or constraints. An example of this dependence is the effect of the number of children (prior births) on an unmarried woman's current and future welfare entitlement. As this last case also illustrates, in static models, i.e., models with myopic agents, prior choices may still affect current decisions through their effects on current preferences and constraints. But, interestingly, prior empirical work based on static models have not systematically included lagged choices as controls.[3] Finally, in forward looking models, the estimated effects of lagged choices potentially operate both directly through contemporaneous preferences and constraints and through expectations.

With respect to the measurement of welfare benefits, most researchers have used a measure based on what a "representative" woman would receive (usually a woman who has zero income and either one or two children) as a way to summarize the generosity of the welfare system.[4] However, this "representative" benefit can result from different combinations of a base level guarantee and the marginal benefit for additional children. We show in our simulations that, as one would expect from the theory, the effects of varying these components on fertility and welfare participation can be quite different. The result of using the composite measure is that estimates of welfare effects based on different combinations of states and calendar periods will differ simply because the source of variation of the composites as between the base level guarantee and the marginal benefit for additional children will differ. Thus, to provide estimates that would be invariant to the sample composition would require that the components of the rule are included separately.[5]

A common finding has been that estimates of welfare effects, particularly on demographic outcomes such as marriage and fertility, are quite sensitive in terms of statistical significance and magnitude to whether the specification includes state of residence fixed-effects, i.e., whether or not cross-state variation in benefit levels is exploited. Our simulations demonstrate a possible reason for that sensitivity. If women are forward-looking, the effect of changes in welfare benefits on their behavior depends critically on how they form expectations about future welfare benefits. In particular, changes in benefits can have very different effects depending on whether they are perceived as being permanent or transitory. Estimation strategies that rely on different sources of sample variation in benefits (e.g., variation across states vs. variation within states over time) may result in different estimates simply because they identify responses to benefit changes that may be perceived as having different degrees of permanence.

The most dramatic example of the impact of expectations on the effect of welfare rule changes is with respect to the decision to have a first birth. Since a decision to become pregnant can usually only result in a birth no less than nine months later, an increase in welfare benefits that is perceived as purely transitory, i.e., an increase that is in effect for a period shorter than the time interval to a birth, should not provide any incentive at all to have a first birth.[6] Hence, the effect of an increase in benefits on the propensity to have a first birth will depend almost entirely on the perceived persistence of the increase. This, in turn, will depend both on the process by which benefits evolve and the mechanism by which potential welfare recipients form expectations. Our simulations illustrate this clearly.

It seems likely that differences in benefit levels across states and annual changes in benefit levels within states have different degrees of persistence. In that case, estimates that rely only on within-state variation vs. those that rely also on across-state variation for identification will tend to capture differentially the impact of permanent and transitory benefit changes. For this reason alone, estimates with and without state fixed-effects will differ. For example, suppose that across-state variation is largely permanent while within-state variation is largely transitory. Then, in the case of pregnancies, one might observe a response using cross-section variation and no response using only within-state variation. Indeed, in the absence of income effects, in order to observe a response in pregnancies, the current benefit realization must be perceived as being correlated with future realizations holding fixed the permanent parameters of the benefit rule. The simulations of the model concretely demonstrate these conclusions.

The paper is organized as follows. In section II, we present the model of contraceptive usage and welfare participation that forms the basis for the simulation work. The following section provides details of the solution method Section IV presents results of the simulations that illustrate the three main lessons of the paper for empirical implementation in a non-structural setting. The last section summarizes.

II. An Illustrative Model of Fertility and Welfare Participation:

The model we present in this section serves as the basis for illustrating the issues raised above concerning the interpretation and estimation of welfare effects on behavior. Given that purpose, the model is highly stylized, but could serve as a foundation for a more complete decision model to motivate a structural empirical implementation or, as we do in the companion paper, the non-structural estimation of approximate decision rules.

Choice Set:

We consider a woman who decides at each age a of her lifetime whether or not to contracept, $c_a \in \{0, 1\}$, and whether or not to receive welfare, $f_a \in \{0, 1\}$, given that she meets the eligibility criteria. A woman who chooses to contracept is assumed to avoid a pregnancy, $p_a = 0$, with certainty, while choosing not to contracept is assumed to lead to a pregnancy, $p_a = 1$, with some positive probability that depends on the woman's age. Thus, if q_a is the probability of becoming pregnant at age a,

$$(1) \quad \begin{aligned} q_a &= q(c_a, a) \quad && \text{if } c_a = 0, \\ &= 0 && \text{otherwise}. \end{aligned}$$

We adopt a logit specification for the conception probability, i.e., $q(c_a, a) = [1 + \exp(q_0 + q_1 a)]^{-1}$, which can be thought of as a simplified conception production function. A woman who becomes pregnant at age a has a birth at age a+1.[7] Thus, the stock of children at age a, N_a, evolves according to

$$(2) \quad N_a = N_{a-1} + p_{a-1},$$

where at a=1 (the initial fecund age) the woman has zero children.

Preferences:

The woman receives a utility flow at each age that depends on her stock of children and her consumption, X, assumed to be strongly separable. There is also a psychic cost associated with contraception and a stigma effect of welfare participation. Specifically, contemporaneous utility is given by:

$$(3)\quad U_a(c_a, f_a) = X_a + \gamma_1 N_a - \gamma_2 N_a^2 + (\bar{\gamma}_{30} + \bar{\gamma}_{31} a + \epsilon_a^{c}) c_a + (\bar{\gamma}_4 + \epsilon_a^{f}) f_a .$$

Utility is normalized to dollars of the composite consumption good and is quadratic in the number of children. It is also assumed that the effects of contraception and welfare participation on utility are subject to per-period stochastic shocks ($\epsilon_a^k; k = f, c$) that are serially independent and that the psychic cost of contraception is age-dependent.

Budget Constraint:

We assume that the woman satisfies the following budget constraint each period:

$$(4)\quad X_a = Y_a + f_a B_a ,$$

where Y_a is the woman's earnings at age a and B_a is the amount of welfare benefits the woman is eligible to receive.[8] Earnings are modeled as stochastic and dependent on the number of children (to capture the time cost of children that we do not explicitly model that leads to a reduction in labor supply) and age, namely

$$(5)\quad Y_a = (\alpha_0 + \alpha_1 a - \alpha_1 N_a)\exp(\epsilon_a^y) .$$

As with the preference shocks, the productivity shocks, ϵ_a^y, are also assumed to be serially independent. Welfare benefit eligibility and amount for a woman residing in state s who is age a at calendar time t depends (non-linearly) on the number of children residing with her and on her earnings according to:

$$(6)\quad \begin{aligned} B_t^s(N_{at}, Y_{at}) &= b_{0t}^s + b_{1t}^s N_{at} - b_{2t}^s N_{at}^2 - b_{3t}^s Y_{at} \quad \text{if } B_{at}^s > 0,\ N_{at} > 0, \\ &= 0 \qquad\qquad \text{otherwise.} \end{aligned}$$

In (6), we refer to $b_{0t}^s, b_{1t}^s, b_{2t}^s$ as the guarantee parameters and to b_{3t}^s as the benefit reduction (or tax) rate applying to all residents of state s (at a particular calendar time). We refer to $B_t^s(N_{at}, Y_{at})$ as the benefit rule and to the b's as the benefit rule parameters.

The benefit rule parameters, and thus benefits themselves, are assumed to change over time. Therefore, women, if they are forward-looking, will incorporate into their decision rules their forecasts of the future values of the benefit rule parameters. We consider three alternative processes for the evolution of the benefit rule parameters, each of which is embedded in the following general vector autoregression (VAR):

$$(7)\quad \mathbf{b}_t^s = \lambda^s + \Lambda^s \mathbf{b}_{t-1}^s + \mathbf{u}_t^s$$

where $\mathbf{b}_t^s$ and $\mathbf{b}_{t-1}^s$ are 4×1 column vectors of the benefit rule parameters, λ^s is a 4×1 column vector of regression constants, Λ^s is a 4×4 matrix of autoregressive parameters and $\mathbf{u}_t^s$ is a 4×1 column vector of iid mean zero innovations drawn from a stationary distribution with variance-covariance matrix Ω^s. We call (7) the evolutionary rule (ER) and λ^s, Λ^s, Ω^s the parameters of the ER.

The three evolutionary rules are: (1) Type 1 rule -- the benefit rule parameters are mutually serially independent, i.e., $\Lambda^s = \mathbf{0}$; (2) Type 2 rule -- each benefit rule parameter follows a random walk, i.e., Λ^s is the identity matrix; (3) Type 3 rule -- the benefit rule parameters are mutually serially dependent, i.e., A^s is unrestricted. Evolutionary rules are specific to the woman's state of residence. It is assumed that a woman remains in the same location throughout her life.[9]

The type one ER assumes that all changes in benefit rule parameters are transitory. A deviation from the mean of any parameter in any period provides no information about future deviations. The type two ER assumes that all changes in benefit parameters permanently affect their means. The best predictor of the parameters of the benefit rules that will be in place at t are those in place at t-1. The type three ER combines both permanent and transitory features; parameters in force today have some persistence.

Objective Function:

The woman is assumed to choose the contraception-welfare participation combination that maximizes at each age her expected present discounted value of remaining lifetime utility. The maximized value (the value function) of this present value is given by

$$(8) \quad V_a(S_a) = \max_{\{c_a, f_a\}} E\left[\sum_{\tau=a}^{A} \delta^{\tau-a} U_\tau(c_\tau, f_\tau) | S_a\right],$$

where A is the terminal decision period and where the expectation is taken over the distribution of future preference and earnings shocks and the distribution of the future innovations of the ER.[10] In (8), the state space S_a denotes the relevant factors known at age a that affect current or future utility or that affect the distributions of the future shocks. The state space at age a consists of the following elements: the woman's age, the number of children the woman has had by age a (the number of pregnancies through age a-1), the current preference shocks to contraception and welfare participation, the current earnings shock and the current set of benefit rule parameters (in the year the woman is age a).

Decision Rules:

The solution to the optimization problem is a set of age-specific decision rules that relate the optimal choice at any age, from among the feasible choices, to the elements of the state space at that age. Recasting the problem in a dynamic programming framework, the value function, $V_a(S_a)$, can be written as the maximum over alternative specific value functions, denoted as $V_a^{cf}(S_a)$, i.e., the expected discounted value of the contraception-welfare participation options, that satisfy the Bellman equation, namely

$$
\begin{aligned}
V_a(S_a) &= \max[V_a^{00}(S_a), V_a^{01}(S_a), V_a^{10}(S_a), V_a^{11}(S_a)] \\
(9) \quad V_a^{cf}(S_a) &= U_a^{cf}(S_a) + \delta E(V_{a+1}(S_{a+1}) | c_a, f_a, S_a) \quad \text{for } a < A, \\
&= U_A^{cf}(S_a) \qquad\qquad \text{for } a = A,
\end{aligned}
$$

where we have written the utility function as explicitly depending on the state space. It is understood that a woman can choose to receive welfare only if she is eligible ($B_a > 0$). A woman (permanently) residing in state s chooses the option at each age a with the greatest expected present discounted value of lifetime utility, given: (i) a benefit rule as in (6); (ii) a particular ER with current realizations of the benefit rule parameters (corresponding to the calendar time she is of age a) $b_{a0}, b_{a1}, b_{a2}, b_{a3}$; (3) her current stock of children, N_a; and (4) her shocks to preference and earnings, $\epsilon_a^c, \epsilon_a^f, \epsilon_a^y$.

III. The Solution Method:

The solution of the optimization problem is in general not analytic. In solving the model numerically, one can regard its solution as consisting of the values of $EV_{a+1}(S_{a+1} \mid c_a, f_a, S_a)$ for all c_a, f_a, and S_a. We refer to this function at age a as Emax_a for convenience. The finite horizon as well as the assumption that age matters in the conception and earnings functions implies that the Emax functions depend on age. As seen in (9), treating the Emax functions as known scalars for each value of the state space transforms the dynamic optimization problem into the more familiar static multinomial choice structure.

The solution method proceeds by backwards recursion beginning with the last decision period. There are two computational problems associated with determining the value of the Emax functions at all of the state points: (i) for each period beyond the first we must perform a multiple integration of dimension equal to the number of shocks in the model; and (ii) we must perform that multiple integration at each point of the state space. With respect to the first, there are eight shocks in the model as presented, the two utility function shocks, the income shock, the implicit conception shock if the woman does not contracept and the four benefit rule parameter shocks; thus the integration that needs to be performed is eight dimensional. Clearly, in order to perform that integration, it is necessary to make distributional assumptions. In terms of the state space, in the case of the type 2 and type 3 ER's the previous period's benefit rule parameters must be included in the state space, which, unlike the other state space elements, are continuous. Thus, unless the benefit rule parameters follow a type 1 ER, the state space has an infinite number of elements.[11]

To solve for the Emax functions, we adopt an approximation method (see Keane and Wolpin (1994, 1997)) in which the Emax functions are calculated at a limited set of state points using Monte Carlo integration and their values are used to fit a polynomial approximation in the state variables consisting of linear, quadratic and interaction terms. These polynomial approximations to the Emax functions serve as solutions for the Emax functions used to simulate the model. To reduce the dimension of the Monte Carlo integration and thus save on computation, we do not explicitly integrate over the benefit rule parameters. Instead, the Emax functions are first integrated over the four other shocks and then an expectation is taken over a quadratic approximation in the benefit rule parameters. In addition, because conception is dichotomous, either a woman who did not contracept at age conceives and has a child at age a+1 or does not, the Emax function requires a Monte Carlo integration only over three shocks. We assume that those three shocks are mutually independent and normally distributed.

The approximations to the Emax functions are formed in the following way. Upon performing the integration over the preference, earnings and conception shocks under the assumption that women have perfect foresight about the benefit rule parameters, the Emax function at each age a is assumed to be fully quadratic in: (i) the stock of children at age a, N_a; (ii) an indicator of whether the woman has any children at age a, $I(N_a>0)$; and (iii) the actual benefit parameters at age a, $b_{a0}, b_{a1}, b_{a2}, b_{a3}$.[12] The Emax approximating regression is estimated with these arguments and, then, to accommodate the fact that the benefit parameters are not perfectly foreseen, we take an expectation of this approximation. The final Emax approximation function thus depends on the full variance-covariance matrix of the shocks governing the benefit rule parameter ER's and on the lagged benefit rule parameters in the case of type 2 or 3 ER's.

Given the Emax functions, a sample of women belonging to the same cohort can be simulated drawing a set of preference and earnings shocks at a=1 for each woman and a set of benefit rule parameters that apply to all women residing in the same state, determining each woman's optimal choice, updating the state space which requires drawing from the conception probability function, drawing a new set of shocks and benefit parameters at a=2, etc. Notice that different birth cohorts of women residing in the same state will face different benefit rule parameters, and thus can be expected to make different life cycle choices.

IV. Model Simulations:

To help benchmark the simulations of the model, we use data on welfare benefits, the sum of the benefits from Aid for Dependent Children (AFDC) and Food Stamps (FS), from six states over the period 1967-1990 to estimate the benefit rules. The six states, California (CA), Michigan (MI), New York (NY), North Carolina (NC), Ohio (OH) and Texas (TX), span high and low welfare states. We actually estimated an expanded version of the benefit rule (6) that more accurately represents the AFDC benefit structure. The expanded version allows for child-care subsidies to working mothers, which requires distinguishing between earned and non-earned income in the benefit formula (denoted by Y_a^e and Y_a^n respectively). Specifically, letting h=1 indicate part-time work and h=2 full-time work (and $I(\cdot)$ an indicator function equal to one if the expression inside the parentheses is true) the benefit structure we estimate is given by:

$$
\begin{aligned}
B_t^s(N_{at}, Y_{at}^n, Y_{at}^e) &= b_{0t}^s + b_{1t}^s N_{at} - b_{2t}^s N_{at}^2 - b_{3t}^s Y_{at}^n = B_1 \\
&\qquad\qquad \text{if } B_t^s>0,\ N_{at}>0,\ Y_{at}^e=0 \\
(10)\qquad &= \min(B_1,\ b_{4t}^s + b_{5t}^s N_{at} - b_{3t}^s (Y_{at}^n + Y_{at}^e) + b_{6t}^s I(h_{at}=2)) \\
&\qquad\qquad \text{if } B_t^s>0,\ N_{at}>0,\ Y_{at}^e>0 \\
&= 0 \qquad \text{otherwise}.
\end{aligned}
$$

There are thus seven parameters describing the benefit rule. The benefit rule parameters are estimated separately for each of the six states and for each year using monthly benefit amounts expressed in 1987 New York equivalent dollars, i.e., for each state we obtained an estimate of the benefit rule parameters separately for each year, b^s_{0t}, b^s_{1t}, b^s_{2t}, b^s_{3t}, b^s_{4t}, b^s_{5t}, b^s_{6t}.

Note that (10) (as well as (6)) is a linear in parameters approximation to the actual rule. It is comprised of three line segments: a maximum benefit level that depends on the number of children and the amount of non-earned income (the first line in (10)), a negatively sloped line segment that intersects the horizontal maximum at a positive amount that depends on the number of children and on whether the woman works part- or full-time (the second line in (10)), and the horizontal axis (the third line in (10)) that becomes relevant at a level of income determined by the benefit reduction rate. The approximation given by (10) fits the data quite well, with the R-squared statistics for the first line segment mostly above .98 and for the second, mostly above .95.[13] Given the estimates of the time-series of benefit rule parameters for each state obtained from (10), we then estimated the three ER's.

Table 1 provides summary statistics of the seven parameters by state. Table 2 transforms the benefit parameters into a more convenient set of benefit measures, namely the total monthly income of non-working women (with zero non-earned income) who have either one, two or three children and the total monthly income of women with two children who have part-time earnings of 500 dollars or full-time earnings of 1000 dollars. Referring to table 2, among the six states, NY, CA and MI are considerably more generous than NC, OH and TX. Among the first group Michigan is the most generous, with benefits over the 24 years for a woman with one child averaging 699 (1987 NY) dollars per month, and among the second group Texas is the least generous, with the same average benefits figure only 228 dollars. Benefit reduction rates, net of child-care allowances, are fairly high. For example, a woman who had two children and earned 500 dollars per-month while working part-time would have kept 80 per cent of it if she resided in Texas and between 60 and 70 per cent of it if she resided in any of the other five states.[14] If instead she had earned 1,000 dollars per month working full-time, her retained portion would have been as high as 70 percent in Texas and as low as 51 percent in New York and Michigan.

In implementing the simulation model, which ignores non-earned income and the labor supply decision, only the simpler benefit rule given by (6) is relevant. Looking at table 1, it can be seen that the average amount of the "disregard" for full-time employment is rather small and that the within-state per-child increase in benefits in the two line segments, i.e., the average values of b_{1t} and b_{5t}, do not differ greatly from each other. Although the benefit structure given by (6) is used in the simulations, Tables 1 and 2 are based on (10) in order to provide an exact picture of the over time and cross state variation in the structure of benefits.[15]

The estimated coefficients relevant for the three ER's, based on the values in table 1 of b^s_{t0}, b^s_{t1}, b^s_{t2}, b^s_{t3}, are presented by state in Appendix tables A.1-A.3.[16] For the type 1 ER (table A.1) they correspond to the summary statistics in table 1 (annualized), although table A.1 includes in addition the set of contemporaneous correlations of all paired benefit parameters. These correlations, as seen, are in many instances quite high, i.e., there are strong co-movements of the parameters over time. In the three more generous states, the guarantee parameters tend to move up and down together, but they tend not to be highly correlated with the benefit reduction rate. The correlation pattern appears to be quite different for the less generous states, with guarantee parameters being less highly correlated with each other and more highly correlated with the benefit reduction rate.

For the type 2 ER (table A.2), the random walk case, the constant term provides an estimate of the trend in each benefit parameter over the 24 year period. Evidently, unlike the overall levels, there appears to be more diversity in trends. For example, although the benefit amount provided to a non-working woman with one child fell in all states beginning in the early to mid-1970's, the decline was much steeper in Michigan and New York than in California.[17] Notice that the contemporaneous correlations in this case differ considerably from the first case.

The type 3 ER (table A.3) is the unrestricted VAR representation.[18] The estimates, which show significant own and cross-lag effects, imply that neither of the first two ER's represents the actual process very well.[19] There is no obvious pattern to the contemporaneous correlation structure. An interesting and, as we shall see, important feature of the unrestricted VAR's is that for the three more (less) generous states the coefficient on $b_{1,t-1}$ is always positive (negative) in the $b_{0,t}$ equation, that is, increases in (the linear component of) the per-child benefit is followed by an increase (a decrease) in the base guarantee in the next year.

Table 3 presents simulation results for the three ER's for each of the six states and for two birth cohorts, women whose first decision period is either 1967 or 1971. Each simulation is based on a decision model with 20 periods. We report the total number of periods pregnant and the total number of periods receiving welfare over those 20 periods for each cohort. For the 1967 cohort, those periods span the first available 20 years of benefit parameter realizations (1967-1986) and the second cohort the last 20 years (1971-1990). Women residing in the same state use the same ER specific to that state regardless of their cohort, although the cohorts face a different pattern of age-specific realizations of the benefit parameters.

The parameters of the behavioral components of the model, which are the same for all women in both cohorts and in all residence states, are given in table A.4. The parameter values were chosen to produce high fertility and welfare participation populations given actual benefit rules, which are the most suitable for illustrating our points.[20] They were not chosen to be representative of the behavior in any of the states.

As table 3 illustrates, the model generates quite different behavior across states for all of the ER's. That is, women who are otherwise identical systematically make different fertility and welfare participation decisions because they reside in states which differ in the structure of their welfare programs.[21] More specifically, these simulations of the model show that:

(1) Women facing the welfare programs of states that appear to be more generous in terms of the benefit measures presented in table 2 have more pregnancies and receive welfare over a larger part of their lives–at the extremes, the number of pregnancies in the first 20 periods range from a little over one to over four with the concomitant range for welfare participation periods from slightly over one to as many as fourteen.[22] However, there is not an exact correspondence between welfare generosity, as summarized in table 2, and welfare participation or pregnancies. For example, with the type 3 ER, Ohio women from the 1971 cohort receive welfare more often and have more pregnancies than do NY women from the same cohort even though welfare is considerably less generous in Ohio than in NY.

(2) The ER affects decisions, but there is no strict relationship between the number of pregnancies and the extent of welfare participation and the type of the ER.

(3) If the ER is of type 1, then there are no cohort differences in the number of pregnancies for women residing in the same state, although there will be differences in the level of welfare participation.[23] There are within-state cohort differences for the other ER types in both

pregnancies and welfare participation.

The reason for this last result is important to understand. It is due to the fact that welfare is received only after a child is born. If there is no forecastable component to future benefit rule parameters, then births cannot be timed to coincide with a high benefit and pregnancies will not respond to a randomly high benefit in any given period. If, on the other hand, a randomly high benefit implies that future benefits will be high, it may be optimal for women to attempt to become pregnant in response.[24] Indeed, as seen in table 3, cohort differences in the case of the type 2 and 3 ER's are not necessarily small. However, unlike contraceptive behavior, welfare take-up does respond to a currently high benefit even if it has no implications for future benefits (under the model's assumption that being on welfare in a period has no effect on the future).

Given that we know the behavioral model governing contraception and welfare participation decisions, we can answer hypothetical questions about the impact of changes in welfare benefits on pregnancies and welfare take-up. There are two types of changes in welfare that are of interest, those pertaining to a change in the ER and those pertaining to a change in the actual realizations of the benefit rule parameters for a given ER. Table 4 simulates the effects of permanent changes in two of the guarantee parameters on the average completed (age 20 is the last age in the simulation) number of pregnancies of the 1971 cohort of women residing in each of the six states. For each ER, we simulate the impact of a permanent 1000 dollar increase in welfare benefits that is independent of the number of children, that is, the (unconditional, or long-run) mean of b_0 is increased by that amount as is each of its realizations. Similarly, we also simulate the effect of a 500 dollar increase in the per- child welfare payment, that is, the long-run mean of b_1 is increased by that amount as is each of its realizations. Each of these changes is an alternative way to permanently increase the benefits to an eligible woman with two children by 1000 dollars on average. It is useful to stress that in these simulations the sample draws from the distributions of preference, earnings and pregnancy shocks are the same across states, that is, state differences in behaviors are due solely to differences in welfare programs.

As seen in table 4, the response in contraceptive use to these permanent changes in the guarantee parameters of the welfare program varies considerably among the states and with the ER. Averaging over the states, regardless of which parameter is changed, the type 1 ER seems to generate the largest response and the type 2 ER the smallest. That ordering is universal among the six states with the exception of Texas for which the type 2 ER generates the largest response and New York for which the type 3 ER generates the largest response. Among the states, the responses range from essentially no response to a change in either parameter (Michigan for all ER's) to an increase of almost two pregnancies for a change in the per-child benefit (Ohio for the type 1 ER.).

In almost every case, an increase in the per-child guarantee parameter has a larger effect on the mean number of pregnancies than does the increase in the constant guarantee parameter. The two exceptions are for Texas and Michigan under the type 3 ER. Averaging the effects over the six states, under the type 2 ER the effect of a permanent change in b_1 is three times as large as the effect of a permanent change in b_0, while under the other two evolutionary rules, it is twice as large. Thus the quantitative effect of increasing the level of benefits that would be provided to a woman with two children depends on how the increase is structured, whether as an increase in the per-child guarantee parameter or as an increase in the constant guarantee parameter.

Table 5 presents simulations of the impact on pregnancies of a transitory change in the same two guarantee parameters under the type 3 ER., i.e., a change in the realizations of benefit rule parameters with no change in the ER.[25] We consider two cases, the effect of a change in the realization of the two guarantee parameters at a single age on the rate of pregnancy at that age and the effect of a change in all of the realizations up to a given age on the mean number of pregnancies at that age. This latter effect is directly comparable at age 20 to the permanent effect depicted in table 4.

Perhaps the most striking result is that, unlike a permanent change in benefit parameters, a transitory increase in either of the guarantee parameters does not necessarily lead to an increase in pregnancies. For example, in both California and New York a $1,000 increase in the constant guarantee parameter at a = 1 reduces pregnancies by 2.5 percentage points at that age. However, a $500 increase in the per-child benefit at a = 1 increases the pregnancy rate by almost 19 percentage points in the case of California and by almost 25 points in the case of New York. The situation is, however, qualitatively exactly the reverse for North Carolina and Texas. A $1,000 increase in b_0 at a = 1 increases pregnancies at that age by 7.1 and 5.4 percentage points respectively, but a $500 increase in b_1 reduces the pregnancy rate by 5.9 and .5 percentage points. These results arise because the structure of the state-specific VAR's in table A.3 do not imply that unexpected increases in the benefit guarantee in a period will be followed necessarily by higher benefits in the future.

Table 6 demonstrates these differences in the structure of the VAR's. Specifically, for each state, impulse responses obtained from the type 3 ER's due to separate orthogonal one standard deviation shocks in each of the two parameters are used to calculate the over time effect of a $1000 increase in b_0 and a $500 increase in b_1 on the expected benefit paid to a woman with two children and zero earnings. In the case of California, the $1000 increase in b_0, that initially increases benefits by $1000, is expected to be followed in the next period by only a $453 increase and to actual reductions in benefits by the fourth period subsequent to the increase. Even more extreme, in the case of New York the reduction in benefits is expected to occur in the period directly after the increase, the first period the woman becomes eligible to collect on the additional birth. These anticipated future declines in benefits induce a reduction in the number of pregnancies that was seen in table 5. On the other hand, in North Carolina and in Texas the initial $1000 increase is expected to be followed by even larger benefit increases. Significant increased benefits persist for at least 10 years after the initial shock. On the other hand, in both California and New York, an initial increase in the per-child benefit is followed by significant future increases in benefits that persist, while the same initial increase produces large future declines in benefits in North Carolina and small declines in Texas.

Thus, in the simulations, if women take into account the existing structure of how benefit parameters evolve, estimates of the impact of a transitory increase in welfare generosity on pregnancies may be seemingly perverse, although they do not represent perverse behavior. However, in the current model, this pattern of response will not occur for welfare take-up. Without additional state dependencies that relate current welfare participation or contraception to past welfare participation (for example, if employment opportunities are affected by past welfare participation), transitory increases in welfare generosity will not decrease current welfare participation.

V. Implications for Non-Structural Estimation:

Table 7 illustrates the implications of the simulation results for conventional empirical specifications using the simulated data.[26] We present non-structural estimates, that mimic the kind of analyses found in the literature, of the effect of changes in benefits on the probability of a pregnancy based on a logit specification of the fertility decision rule.[27] Comparing estimates with and without state fixed-effects confirms that our simulation results carry over to the conventional empirical methodology.

The first specification of benefits in the table shows that the effect of increasing the benefit to a non-working woman with two children, a statistic often used in the literature as a summary measure of welfare generosity, is sensitive to the inclusion of state fixed-effects. When data on both of the simulated cohorts are used in the estimation, the benefit effect is reduced by about two-thirds in the fixed-effects specification. Even more striking, for the 1967 cohort, the benefit effect is actually negative in the state fixed-effects specification. As we discussed, this result does not indicate an irrational response, but rather reflects the fact that the response to a transitory increase in benefits depends on the path of future benefits that are anticipated to evolve.

The second specification estimates the separate impact of increasing the benefit guarantee parameter and the per-child benefit parameter, rather than their combination ($b_{0t} + 2b_{1t}$). Again, the results from the simulations carry over to the logit framework As seen, the effect of increasing the per-child benefit parameter is twice as large as the effect of increasing the guarantee parameter using data from both cohorts and without state fixed-effects. Interestingly, when state fixed-effects are included, the impact is eight times as large. Thus, the prediction of how increasing the benefit to a woman with two children would affect pregnancies depends on how the increase is structured. There would be a many times larger impact if the increase came from a change in the per-child benefit parameter than from the guarantee parameter.

VI. Summary:

In this paper we have used simulations of a simple dynamic model of the welfare participation and fertility decisions of women to clarify the mechanisms through which changes in welfare benefits affect behavior. In order to address this issue, we constructed a complete record of the welfare rules of all 50 U.S. states for the period from 1967 through 1990. Although these rules are extremely complex (see, e.g., the appendices in Keane and Moffitt (1998)), we showed that they can be very well approximated by a six parameter piecewise linear function (with number of children and income as arguments) where the parameters differ over states and time. We estimated VARs for the six parameters of each state, and found that the time-series processes generating the (six) parameters differ substantially across states. As a result, we were able to examine for the first time whether transitory realizations of the benefit rule parameters have different effects on behavior than do the underlying permanent across-state differences in generating processes of the welfare-rule parameters (which we refer to as "evolutionary rules" or ERs for short).

Our simulations reveal two important lessons for the specification and interpretation of non-structural estimates of welfare effects. First, the practice of summarizing welfare generosity by a single statistic, such as the benefits available to non-working women with two children, obscures the differential effects of a change in the benefit guarantee that is independent of the number of children vs. a change in the per-child payment. As theory would suggest, and as our simulations showed, increasing the per-child payment has a substantially larger impact on fertility than does increasing the guarantee.

Second, estimates of welfare effects depend critically on whether the benefit variation that is exploited reflects permanent changes in the benefit rules or transitory realizations of the parameters of the benefit rules. Our simulations showed, for example, that a permanent increase in the guarantee would increase fertility, but that a transitory increase could either increase or decrease fertility depending on how future benefits are expected to evolve. This difference may account for the general finding in the non-structural literature that welfare effects are not robust to the inclusion of state fixed-effects, that is, to the use of cross-state or within-state variation in benefits. There is an important difference, however, in the origin of this non-robustness. In the literature, it is attributed to omitted characteristics of individuals across states or to differences in other state policies not included in the analysis. Neither of these explanations is responsible for the results of our simulations.

The ultimate purpose of the simulation exercises is as a guide to the correct specification and interpretation of behavioral decision rules that can be used to determine the magnitude of welfare effects. Consistent with the lessons learned from the simulation exercise, in Part II. we estimate welfare benefit effects on an expanded set of behaviors in a non-structural estimation approach.

Footnotes

1. Moffitt (1983) is an exception in that he explicitly specifies and structurally estimates a static model of labor supply and welfare participation. Keane and Moffitt (1994) extend that framework to a consideration of multiple program participation. Explicit models of demographic behavior are rarer, although Rosenzweig (1995) is an exception. For recent surveys of the literature see Moffitt (1992, 1996).

2. There are a few papers that specify and structurally estimate explicit dynamic models of behavior (Kerttula (1996), Swann (1995)), although there are also econometric exercises that look at over-time changes in behavior using longitudinal data (e.g., Gritz and MaCurdy (1992) look at exits from welfare to work).

3. In the context of static models, to the extent that lagged choice variables are uncorrelated with measures of current welfare benefits, excluding lagged choices from decision rules will not lead to bias in the estimates of welfare effects. However, a correlation will exist, and estimates of welfare effects will be biased, if welfare benefits are serially correlated.

4. The level of benefits to which a woman is entitled essentially depends on three factors, the number of children she has, her labor market earnings and her non-earned income. The mapping of these quantities into benefits differs by state of residence and varies over time within a state.

5. Indeed, most labor supply studies include the benefit reduction rate, i.e., the tax on labor earnings and other income, as a separate determinant. Interestingly, the benefit reduction rate is almost never included in studies of demographic behaviors even though the evidence suggests important labor supply effects of welfare and decisions about labor supply, fertility and marriage are known to be intimately connected.

6. The argument is made for first births because women who already have children would have higher income due to the increase in welfare generosity, which may change their propensity to have an additional birth..

7. We assume for convenience that all pregnancies result in a live birth, i.e., we rule out exogenous miscarriages. Abortion can be viewed as a method of perfect contraception.

8. We do not allow for an explicit goods cost to bearing and rearing children, which can be thought of as being impounded in the utility parameter α_1. Similarly, although contraception is assumed to be purchased at no cost, its market price can be thought of as impounded in the psychic cost.

9. Introducing migration would greatly complicate the decision problem.

10. We are assuming that the woman knows the evolutionary rule that applies to her state. If she does not, and uses an incorrect rule, the benefit parameter realizations would still be drawn from the true ER although her expected present value of lifetime utility would be calculated using the incorrect rule.

11. A similar problem would arise if the utility function or income shocks were serially correlated.

12. Incorporating a dummy variable for whether the woman has a child is necessary to capture the fact that welfare benefit eligibility is conditioned on having a child.

13. These regressions are available on request.

14. Benefit reduction rates for AFDC and for Food Stamps are federally set. The reason they differ among states in the tables in the text is due to our approximation and the fact that AFDC payments terminate at different income levels among the states while food stamp payments are still non-zero and the two programs have different benefit reduction rates. There is thus a kink in

the schedule of total welfare payments with income that our approximation smooths over.

15. We also use (10) as the basis for the estimation presented in the companion paper.

16. These coefficients are based on annualized benefit amounts in order to correspond better to an annual decision period.

17. In Michigan the benefit amount for such a woman fell from about 950 (1987 NY) dollars to only 550 dollars, while in California the fall was from about 700 to 600 dollars.

18. Plots of the impulse response functions indicated that the VAR's are stationary.

19. Both of these nested alternatives are rejected at usual significance levels.

20. The model will tend to generate a declining pattern of pregnancies with age beginning from the first period. To introduce some reason for delay in pregnancies, it was necessary to allow for contraception to have positive utility at the earliest ages. In particular, for the parameters we have chosen, contraception increases utility for the first three periods.

21. The benefit parameter realizations used in the simulation are those that correspond to the actual realizations within the state, regardless of ER.

22. Notice that for the given values of the utility function parameters, the marginal utility of an additional child is negative at one child. Thus, the main reason to have children is to receive welfare, although there is an additional motive to avoid the cost of contraception.

23. Table A.5 presents a more complete picture of the pattern of pregnancies and welfare take-up for the baseline simulation in each state for the 1971 cohort. Note that, because there is no future, the proportion of women with a pregnancy in the last period is the same in all states.

24. Allowing for non-separability of consumption and the stock of children in the utility function, for a monetary cost of contraception or for savings would lead to wealth effects on

fertility for women who already have children.

25. Recall that for the type 1 ER, the pattern of realizations of benefit parameters has no effect on pregnancies because they are unrelated to the level of benefits that the woman can expect to receive after the child is born. In addition, for the type 2 ER, permanent and transitory changes (with the same realizations) have the same impact because any transitory change is expected to persist indefinitely. We therefore do not present these cases in tabular form.

26. The simulated data contain 1000 individuals observed for 20 periods in each of the six states and for each of the two cohorts. There are thus 240,000 person periods in the simulated data set.

27. We defer to Part II. the discussion of the correct specification of decision rules. Note, though, that the additional regressors includes the only other state variables in the model, the age at the pregnancy observation and the number of children ever born up to the observation age.

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Table 1: Summary Statistics of Parameters of Benefit Rules for Selected States: 1967-1990 [a, b]

		Parameters						
		b_0	b_1	b_2	b_3	b_4	b_5	b_6
CA								
	μ	424	175	4.0	0.70	614	172	30.4
	σ	49	27	1.5	0.13	150	22	8.2
	min	327	135	1.3	0.51	451	144	20.1
	max	503	220	6.8	1.00	869	210	43.9
MI								
	μ	512	190	3.1	0.71	663	191	30.3
	σ	108	55	5.1	0.10	223	26	10.1
	min	382	140	-1.9	0.56	396	134	15.0
	max	722	292	13.0	1.00	1078	229	44.1
NY								
	μ	454	161	0.6	0.71	575	177	30.2
	σ	68	44	3.5	0.11	171	34	9.9
	min	389	116	-3.1	0.53	386	138	16.1
	max	622	247	8.3	1.00	832	230	44.1
NC								
	μ	376	113	3.2	0.54	499	108	24.3
	σ	56	24	0.8	0.16	155	18	13.6
	min	297	63	1.4	0.41	299	86	8.5
	max	470	151	4.5	1.00	723	145	44.1

Table 1: Continued

OH							
μ	348	153	3.4	0.62	516	140	26.9
σ	38	36	2.2	0.13	184	24	12.5
min	251	114	0.8	0.48	327	110	11.7
max	404	258	11.3	1.00	726	176	44.2
TX							
μ	228	134	4.9	0.48	400	115	19.8
σ	49	16	2.7	0.17	128	29	13.3
min	145	119	2.2	0.33	237	80	2.0
max	333	170	13.3	1.00	570	183	44.7

a. 1987 NY dollars.

b. based on monthly benefit amounts.

Table 2: Summary Statistics of Total Monthly Income for Alternative Number of Children and Employment Scenarios for Selected State: 1967-1990

		Zero earnings			Part-time earnings of $500/month	Full-time earnings of $1000/month
		one child	two children	three children	two children	two children
CA						
	μ	594	756	911	1108	1320
	σ	69	89	108	211	251
	min	465	597	725	864	1025
	max	718	922	1115	1461	1722
MI						
	μ	699	879	1054	1190	1396
	σ	150	189	219	265	281
	min	532	682	822	867	1059
	max	958	1198	1422	1623	1849
NY						
	μ	614	773	931	1074	1283
	σ	105	140	170	213	253
	min	512	633	755	804	1000
	max	848	1059	1256	1400	1617
NC						
	μ	485	589	686	944	1231
	σ	64	77	92	158	162
	min	406	568	581	765	1000
	max	603	741	870	1201	1471

Table 2: Continued

OH						
	μ	497	640	776	985	1228
	σ	50	74	49	174	176
	min	439	561	676	783	1000
	max	594	782	960	1223	1414
TX						
	μ	362	486	601	890	1190
	σ	55	66	80	129	134
	min	277	384	464	726	1001
	max	462	589	714	1052	1379

Table 3: Simulated Behavioral Outcomes by State for 1971 and 1967 cohorts under Alternative Benefit Parameter Evolutionary Rules

	1971 Cohort						1967 Cohort					
	CA	MI	NY	NC	OH	TX	CA	MI	NY	NC	OH	TX
No. Periods Pregnant [a]												
Evolutionary Rule:												
Type 1	3.23	4.18	3.73	1.50	2.00	1.16	3.23	4.18	3.73	1.50	2.00	1.16
Type 2	4.10	4.26	3.92	3.23	3.61	2.03	3.00	3.74	3.27	2.38	2.65	1.50
Type 3	3.32	4.34	2.81	1.82	3.05	1.61	3.13	4.34	3.01	1.96	2.59	1.69
No. Periods on Welfare [a]												
Evolutionary Rule:												
Type 1	9.66	13.56	10.73	3.14	4.49	1.39	10.03	14.00	11.38	3.45	4.69	1.43
Type 2	12.79	13.88	11.85	9.83	10.24	4.34	8.83	12.38	9.83	6.08	6.39	2.33
Type 3	9.98	14.08	7.91	4.44	8.18	2.26	9.64	14.40	9.08	5.26	6.55	2.91

a. Through age 20

Table 4: Comparison of Effects of Permanent Changes in Guarantee Parameters by Type of Evolutionary Rule: 1971 Cohort

	Type 1		Type 2		Type 3	
	Δb_0= \$1000	Δb_1= \$500	Δb_0= \$1000	Δb_1= \$500	Δb_0= \$1000	Δb_1= \$500
Δ Mean Pregnancies by Age 20						
CA	0.50	1.07	0.08	0.26	0.15	0.98
MI	0.09	0.21	0.03	0.14	0.00	0.00
NY	0.29	0.66	0.13	0.37	0.78	1.37
NC	0.68	1.48	0.21	0.89	0.63	1.45
OH	0.91	1.91	0.27	0.65	0.50	1.16
TX	0.74	1.57	0.91	2.02	0.76	0.39
Average	0.54	1.15	0.27	0.72	0.47	0.89

Table 5: Simulated Effects of Transitory Changes in Guarantee Parameters at Selected Ages by State: 1971 Cohort (Type 3 ER)

	$\Delta b_{0t} = \$1000$							$\Delta b_{0\tau} = \$1000 \ \forall \tau \leq t$					
	Δ Percent Pregnant							Δ Mean Pregnancies					
	CA	MI	NY	NC	OH	TX		CA	MI	NY	NC	OH	TX
Age (t)													
1	-2.5	0.0	-2.5	7.1	7.2	5.4		-0.03	0.0	-0.03	0.07	0.07	0.05
5	-0.8	0.0	-0.2	4.6	2.2	5.2		-0.09	0.0	-0.08	0.28	0.26	0.28
12	-0.1	0.0	-0.1	0.3	0.5	0.7		-0.11	0.0	-0.13	0.41	0.32	0.46
20	0.0	0.0	0.0	0.0	0.0	0.0		-0.11	0.0	-0.14	0.42	0.34	0.47

	$\Delta b_{1t} = \$ 500$							$\Delta b_{1\tau} = \$ 500 \ \forall \tau \leq t$					
	Δ Percent Pregnant							Δ Mean Pregnancies					
	CA	MI	NY	NC	OH	TX		CA	MI	NY	NC	OH	TX
Age (t)													
1	18.9	0.0	24.8	-5.9	5.6	-0.50		0.19	0.0	0.25	-0.06	0.06	-0.005
5	6.6	0.0	11.5	-4.3	3.0	-0.30		0.62	0.0	0.84	-0.29	0.28	-0.04
12	1.1	0.0	1.5	-1.0	0.9	0.0		0.78	0.0	1.17	-0.46	0.38	-0.05
20	0.0	0.0	0.0	0.0	0.0	0.0		0.79	0.0	1.20	-0.47	0.39	-0.06

Table 6: Impulse Responses of Type 3 ER's to Innovations in the Guarantee and Per-Child Benefit Parameters: Effects on Benefits for Women With Two Children and Zero Earnings for Selected States

	CA		NY		NC		TX	
Period	b_0	b_1	b_0	b_1	b_0	b_1	b_0	b_1
1	1000	500	1000	500	1000	500	1000	500
2	453	404	-16	498	1396	0	1148	274
3	237	428	-127	521	1604	-430	1142	139
4	52	526	-147	559	1637	-536	1068	56
5	-72	625	-155	573	1549	-920	955	4
6	-144	688	-163	569	1352	-990	841	-24
7	-175	707	-163	547	1110	-960	727	-36
8	-165	688	-157	517	918	-860	625	-44
9	-155	640	-155	474	593	-710	528	-40
10	-124	582	-143	429	363	-560	443	-8
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
.	.	.	.	.	.	.	.	.
25	-14	82	11	-49	36	-22	33	-4

Table 7: Logit Regression Estimates of the Pregnancy Decision Rule[a,b]

	Both Cohorts	1967 Cohort	1971 Cohort	Both Cohorts	1967 Cohort	1971 Cohort
Specification of Benefit Parameters						
(1) Benefit for Non-Working Women With Two Children	.144[c] (.004)	.142 (.006)	.164 (.005)	.051 (.007)	-.033 (.016)	.095 (.014)
(2) Separate Benefit Parameters						
Guarantee: b_0	.137 (.005)	.156 (.006)	.111 (.006)	.031 (.009)	-.020 (.014)	.051 (.013)
Per-Child: b_1	.271 (.017)	.191 (.025)	.455 (.030)	.103 (.021)	-.144 (.043)	.232 (.031)
State Fixed Effects	No	No	No	Yes	Yes	Yes

a. Additional regressors include age, age squared, children ever born, children ever born squared, children ever born times age.
b. Robust standard errors in parentheses.
c. Coefficients and standard errors times 1000.

Table A.1: Type 1 Evolutionary Rules for Benefit Parameters

	CA				MI				NY			
	b_{0t}	b_{1t}	b_{2t}	b_{3t}	b_{0t}	b_{1t}	b_{2t}	b_{3t}	b_{0t}	b_{1t}	b_{2t}	b_{3t}
Constant	5083	2096	49.5	0.698	6146	2276	36.6	0.709	5449	1926	6.64	0.709
					Contemporaneous Residual Correlations[a]							
b_{0t}	587				1293				813			
b_{1t}	0.705	319			0.786	663			0.851	533		
b_{2t}	0.704	0.890	174		0.660	0.966	61.0		0.748	0.780	40.9	
b_{3t}	0.239	0.405	0.544	0.126	-0.119	0.022	0.003	0.094	0.191	-0.200	-0.121	0.103

	NC				OH				TX			
Constant	4508	1356	38.2	0.542	4173	1834	40.6	0.623	2745	1663	58.6	0.479
					Contemporaneous Residual Correlations[a]							
b_{0t}	673				458				586			
b_{1t}	0.139	283			0.042	429			0.184	187		
b_{2t}	-0.184	0.876	9.74		-0.390	0.914	26.0		-0.563	0.379	32.1	
b_{3t}	-0.480	0.531	0.673	0.107	-0.620	-0.093	0.092	0.104	0.275	-0.399	-0.916	0.099

a. Root mean squared error on diagonals

Table A.2: Type 2 Evolutionary Rules for Benefit Parameters

	CA				MI				NY			
	Db_{0t}[a]	Db_{1t}	Db_{2t}	Db_{3t}	Db_{0t}	Db_{1t}	Db_{2t}	Db_{3t}	Db_{0t}	Db_{1t}	Db_{2t}	Db_{3t}
Constant	-33.7	9.93	1.46	-0.0073	-76.4	0.691	0.378	-0.0107	-7.73	-24.9	0.818	-0.0081
					Contemporaneous Residual Correlations[b]							
b_{0t}	339				625				484			
b_{1t}	0.077	248			0.534	292			0.439	250		
b_{2t}	-0.077	0.948	14.8		0.321	0.904	33.3		0.305	0.949	28.0	
b_{3t}	0.180	-0.106	-0.114	0.099	0.138	0.184	0.263	0.085	-0.232	0.371	0.497	0.094

	NC				OH				TX			
Constant	-55.8	29.5	1.364	-0.0159	-48.4	8.18	1.30	-0.0174	36.5	-14.9	-5.41	0.0159
					Contemporaneous Residual Correlations[b]							
b_{0t}	213				515				459			
b_{1t}	0.451	133			-0.752	332			-0.234	90.8		
b_{2t}	0.080	0.850	7.05		-0.851	0.964	30.0		-0.872	0.347	23.1	
b_{3t}	0.193	-0.115	-0.135	0.066	0.085	0.144	0.089	0.073	-0.569	0.244	0.783	0.056

a. $Db_{jt} = b_{jt} - b_{j\,t-1}$

b. Root mean squared error on diagonals

Table A.3: Type 3 Evolutionary Rules for Benefit Parameters[a]

	CA				MI				NY			
	b_{0t}	b_{1t}	b_{2t}	b_{3t}	b_{0t}	b_{1t}	b_{2t}	b_{3t}	b_{0t}	b_{1t}	b_{2t}	b_{3t}
b_{0t-1}	0.329	0.074	0.0058	$4.21*10^{-5}$	0.693	0.018	-0.002	$-2.67*10^{-5}$	0.084	-0.056	-0.003	$-2.44*10^{-5}$
	(0.087)[b]	(0.120)	(0.0066)	$(4.48*10^{-5})$	(0.227)	(0.094)	(0.010)	$(2.55*10^{-5})$	(0.285)	(0.172)	(0.020)	$(5.93*10^{-5})$
b_{1t-1}	0.108	0.772	0.0048	$-2.35*10^{-4}$	2.23	1.78	0.131	$1.76*10^{-4}$	1.25	1.22	0.024	$-2.87*10^{-5}$
	(0.247)	(0.341)	(0.019)	$(1.27*10^{-4})$	(1.32)	(0.556)	(0.060)	$(1.51*10^{-4})$	(0.363)	(0.219)	(0.026)	$(7.57*10^{-5})$
b_{2t-1}	20.6	-6.67	0.343	0.0042	-21.9	-10.0	-0.491	-0.0016	-0.320	-4.09	0.597	$4.18*10^{-4}$
	(4.57)	(6.31)	(0.346)	(0.0024)	(11.7)	(4.92)	(0.526)	(0.0013)	(3.55)	(2.15)	(0.251)	$(7.41*10^{-4})$
b_{3t-1}	-34.8	-854	-52.7	0.661	-294	-23.1	7.16	0.485	-1247	-339	-56.3	0.402
	(311)	(430)	(23.6)	(0.160)	(1429)	(601)	(64.3)	(0.164)	(1120)	(675)	(79.0)	(0.233)
constant	2222	997	48.7	0.282	-2250	-1494	-235	0.156	3412	97.4	11.7	0.576
	(453)	(626)	(34.3)	(0.233)	(2140)	(899)	(96.4)	(0.245)	(1729)	(1043)	(122)	(0.360)
R^2	0.935	0.588	0.523	0.589	0.825	0.879	0.837	0.352	0.815	0.846	0.660	0.352
	Contemporaneous Residual Correlations[c]											
b_{0t}	162				611				390			
b_{1t}	0.61	224			0.48	257			0.50	235		
b_{2t}	0.43	0.94	12.3		0.16	0.86	27.5		0.35	0.95	27.5	
b_{3t}	0.12	0.01	-0.06	0.084	-0.05	0.15	0.26	0.070	-0.15	0.45	0.55	0.081

Table A.3: Continued

	NC				OH				TX			
	b_{0t}	b_{1t}	b_{2t}	b_{3t}	b_{0t}	b_{1t}	b_{2t}	b_{3t}	b_{0t}	b_{1t}	b_{2t}	b_{3t}
b_{0t-1}	1.16	0.117	$7.57*10^{-4}$	$1.07*10^{-5}$	0.520	0.064	-0.0017	$-4.49*10^{-5}$	0.853	0.149	0.0015	$1.28*10^{-5}$
	(0.065)	(0.044)	(0.003)	$(2.21*10^{-5})$	(0.356)	(0.281)	(0.023)	$(5.81*10^{-5})$	(0.283)	(0.058)	(0.013)	$(3.15*10^{-5})$
b_{1t-1}	-1.12	0.555	0.004	$6.14*10^{-5}$	-0.485	1.52	0.076	$1.92*10^{-4}$	-0.318	0.733	0.0131	$3.50*10^{-5}$
	(0.307)	(0.205)	(0.012)	$(1.04*10^{-4})$	(0.796)	(0.629)	(0.051)	$(1.30*10^{-4})$	(0.624)	(5.72)	(0.029)	$(6.95*10^{-5})$
b_{2t-1}	17.9	1.36	0.312	-0.003	16.9	-14.5	-0.882	-0.0027	4.99	4.81	0.586	$9.40*10^{-4}$
	(9.33)	(6.22)	(0.373)	(0.003)	(14.3)	(11.3)	(0.915)	(0.0023)	(11.5)	(2.37)	(0.533)	(0.128)
b_{3t-1}	-1461	-785	-33.3	0.653	1551	-1091	-87.3	0.566	657	-1097	-23.6	0.370
	(412)	(275)	(16.5)	(0.139)	(854)	(676)	(54.7)	(0.140)	(2937)	(603)	(136)	(0.327)
constant	755	432	35.2	0.033	1272	9.33	-5.00	0.178	394	202	3.23	0.103
	(363)	(242)	(14.5)	(0.123)	(848)	(671)	(54.3)	(0.138)	(952)	(195)	(44.0)	(0.106)
R^2	0.959	0.873	0.605	0.685	0.483	0.653	0.361	0.603	0.564	0.839	0.507	0.718
	Contemporaneous Residual Correlations[c]											
b_{0t}	152				354				40.9			
b_{1t}	0.01	102			-0.57	280			-0.19	84		
b_{2t}	-0.27	0.92	6.09		-0.72	0.95	227		-0.81	0.41	18.9	
b_{3tt}	0.22	-0.08	-0.05	0.052	0.07	0.17	0.11	0.058	-0.44	0.23	0.75	0.046

a. Benefit parameters expressed in annual amounts.

b. Robust standard errors in parentheses.

c. Breush-Pagan test of indepedence rejected at p=.000 for all states. Root mean squared errors on diagonals.

Table A.4: Parameter Values for Simulations

Utility Function				
	$\gamma_1 = 400$	$\gamma_2 = 500$	$\bar{\gamma}_{30} = 1,000$	$\bar{\gamma}_{31} = 300$
	$\gamma_4 = -2,500$	$\sigma_c = 2,828$	$\sigma_f = 894$	
Income Generating Function				
	$\alpha_0 = 10,000$	$\alpha_1 = 200$	$\alpha_2 = -1,250$	$\sigma_y = 0.63$
Pregnancy Probability Function				
	$q_0 = -0.35$	$q_1 = 0.175$		

Table A.5: Simulated Behavioral Outcomes by State at Selected Ages for 1971 Cohort: Type 3 ER

	Percent Pregnant						Percent on Welfare					
Age	CA	MI	NY	NC	OH	TX	CA	MI	NY	NC	OH	TX
1	30.7	51.0	24.9	9.4	25.1	4.8	0	0	0	0	0	0
5	28.1	37.9	19.8	9.4	26.9	8.0	46.4	73.2	41.2	17.0	33.7	5.5
12	11.3	12.3	10.5	10.1	10.7	9.2	50.5	72.3	36.9	23.3	45.1	13.5
20	4.1	4.1	4.1	4.1	4.1	4.1	57.9	76.2	43.0	31.4	56.4	26.1
	Mean No. Periods Pregnant						Mean No. Periods on Welfare					
Age	CA	MI	NY	NC	OH	TX	CA	MI	NY	NC	OH	TX
1	0.307	0.510	0.249	0.094	0.251	0.048	0	0	0	0	0	0
5	1.48	2.26	1.28	0.509	1.32	0.340	1.31	2.41	1.17	0.488	0.831	0.155
12	2.80	3.85	2.31	1.32	2.54	1.11	5.55	8.12	4.66	2.01	4.07	0.871
20	3.32	4.34	2.81	1.82	3.05	1.61	9.98	14.08	7.91	4.44	8.18	2.26
	Percent Ever Pregnant						Percent Ever on Welfare					
Age	CA	MI	NY	NC	OH	TX	CA	MI	NY	NC	OH	TX
1	30.7	51.0	24.9	9.4	25.1	4.8	0	0	0	0	0	0
5	79.1	96.1	69.0	42.3	75.9	28.3	63.5	89.8	57.5	28.5	49.1	11.2
12	93.5	99.8	82.8	73.7	92.1	63.6	90.9	99.0	78.5	59.8	86.7	35.1
20	95.9	99.7	88.3	82.8	95.1	76.0	94.7	99.7	84.4	77.0	93.2	62.1

Table A.6: Simulated Effect of Permanent Changes in Guarantee Parameters for Selected Ages by State: 1971 Cohort (Type 3 ER)[a]

	$\Delta b_0 = \$ 1000$													
	Δ Percent Pregnant							Δ Mean No. Periods Pregnant						
Age	CA	MI	NY	NC	OH	TX	Mean	CA	MI	NY	NC	OH	TX	Mean
1	2.3	0.0	18.9	15.2	14.2	13.4	10.7	0.02	0.0	0.19	0.15	0.14	0.13	0.11
5	1.7	0.0	6.8	4.5	3.1	7.8	4.0	0.09	0.0	0.56	0.48	0.42	0.54	0.35
12	0.2	0.0	0.7	0.2	0.0	1.0	0.5	0.15	0.0	0.76	0.63	0.50	0.76	0.47
20	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.15	0.0	0.78	0.63	0.50	0.76	0.47
	$\Delta b_1 = \$ 500$													
	Δ Percent Pregnant							Δ Mean No. Periods Pregnant						
Age	CA	MI	NY	NC	OH	TX	Mean	CA	MI	NY	NC	OH	TX	Mean
1	19.9	0.0	25.7	24.7	24.4	5.7	16.7	0.20	0.0	0.26	0.25	0.24	0.06	0.17
5	8.5	0.0	14.9	13.6	9.2	4.2	8.4	0.74	0.0	0.90	1.03	0.76	0.25	0.61
12	1.1	0.0	2.1	1.3	1.4	0.8	1.1	0.96	0.0	1.33	1.45	1.12	0.38	0.87
20	0.0	0.0	0.0	0.0	0.0	0.0	0.0	0.98	0.0	1.37	1.48	1.16	0.39	0.89

a. Permanent change in VAR to reflect increase in long-run mean of benefit parameter. Realizations of benefit parameter changed to reflect new long-run mean.