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HOW IMPORTANT IS
WELFARE DEPENDENCE?

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How Important Is Welfare Dependence?

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Abstract

This paper develops a theoretical model of welfare dependence, in which current participation in AFDC induces greater future use of the program. One prediction is duration dependence in welfare spells. This is tested using six years of monthly data on time spent in the AFDC program among female household heads in the control group of the Seattle/Denver Income Maintenance Experiment. A variety of duration dependence models are estimated, investigating the effect of different functional form assumptions, as well as the impact of accounting for time-varying covariates, competing risks, and data heterogeneity in the estimates.

Monthly AFDC participation does not show strong evidence of duration dependence. In fact, during the initial months on the program the probability of leaving the program, conditional on past participation, appears to be flat or increasing. After about eight months the probability of leaving starts to decrease, but it becomes virtually flat after 18 to 24 months. There is some indication that there are two distinct groups that utilize welfare: one group which has a very low probability of leaving welfare and whose rate of exit changes little over time; and a second group which is more affected by time on the program. The propensity of black women to have longer AFDC spells appears to be totally due to their lower probability of leaving AFDC via marriage, rather than any difference in leaving via earnings or other income increases.

Even where duration dependence is present in the data, however, it does not provide adequate evidence for program-induced welfare

dependence. The final part of the paper presents a model of earnings change and AFDC participation which contains no welfare dependence effects. Welfare spells simulated from this model show duration dependence effects which appear quite similar to those observed in the actual data.

1. INTRODUCTION

The Aid to Families with Dependent Children (AFDC) program continues to generate controversy. At the heart of the discussion are questions regarding the effect of this program on the behavior of participants. A well-established literature exists, measuring the short-run impact of the program on labor market behavior and household composition of eligible households;[1] however, in recent years it has been suggested that the more serious effect is a long-run one, typically referred to as "welfare dependence." In this paper, welfare dependence will refer to a situation in which current participation in AFDC increases the probability of future participation. This paper is a study of the extent to which such program induced welfare dependence occurs among AFDC participants.

Using six years of monthly information on female-headed household behavior, the primary result of this study is that current monthly AFDC participation does not appear to be strongly affected by past AFDC usage. First, the statistical evidence for duration dependence in welfare spells is weak. In fact, during the initial months of AFDC, the probability of leaving the program, conditional on past participation, appears constant or increasing. After about eight months the conditional probability of leaving starts to decrease, but it becomes virtually flat after 18 to 24 months. At least part of this decrease is due to a mixing of heterogeneous populations. There is some indication that there are at least two distinct groups that utilize welfare: a group that has a very low probability of leaving welfare and whose rate of exit increases slowly over time; and another group that is more affected by time on the program.

Second, this paper shows that statistical duration dependence is not sufficient proof of welfare dependence. A simple model of income generation, with no program dependence effects, can produce simulated welfare spells which exhibit similar duration dependence to that observed in the actual data.

These results contrast with existing literature on AFDC duration. A number of previous studies have found significant duration dependence, using annual data on AFDC spells. These findings have been interpreted as explicit evidence of welfare dependence.

The next section of this paper describes the existing econometric literature on the dynamics of AFDC participation. The third section presents several theoretical models of welfare dependence. The fourth develops the empirical tools necessary to estimate a time-dependence model of welfare spells. The fifth section presents AFDC duration estimates based on a variety of different functional form assumptions. Models incorporating heterogeneity and competing risks are also discussed. The sixth section presents a simple model of income generation, uses it to create simulated welfare spells from the data, and compares the resulting duration effects with those estimated in the actual data. The last section discusses the relationship between these results and those in the existing literature, and indicates some of the questions that this study leaves unanswered.

Past Research on Welfare Dependence

Most of the literature on AFDC participation focuses on point-in-time decisions within cross-sectional data.[2] It is only in the past few years

that a literature on the dynamics of AFDC usage has emerged. Two early papers, by Hutchens (1981) and Plotnick (1983), estimate transition models of movements in and out of AFDC using relatively simple econometric techniques and ignoring many problems of spell censoring. Bane and Ellwood (1983) provide a more complete descriptive picture of patterns of welfare use, using the Michigan Panel Study of Income Dynamics (PSID) data set over a 12-year period. They do some simple multivariate analysis on spell length using discrete logistic models. Ellwood (1986) has updated these results with 15 years of PSID data, focusing on recidivism and multiple spells. O'Neill, Bassi, and Hannan (1984) provide a comparable analysis to that of Bane and Ellwood, repeating their analysis on the PSID and also using the National Longitudinal Survey (NLS) of Young Women over an 11-year time period. O'Neill, Bassi, and Wolf (1985) present discrete duration dependence models of AFDC spell length from the NLS.

The last four papers all discuss the issue of duration dependence in welfare spells (although it is not the primary focus of the papers by Ellwood and Ellwood and Bane), explicitly assuming that duration dependence implies welfare dependence. Unfortunately, they reach somewhat conflicting conclusions. Bane and Ellwood find significant duration dependence in their data, although Ellwood's more recent work finds somewhat smaller, but still significant, effects. In contrast, O'Neill et al. find virtually no evidence of duration dependence, even when using similar PSID data. Ellwood (1986) criticizes these results, indicating that they are due to a inappropriate definition of AFDC spells.[3]

All of the studies cited above indicate that demographic charac-
teristics have an important influence on spell length, younger black
women with young children being the least likely to leave welfare
quickly. In addition, the determinants of leaving welfare via marriage
are quantitatively different from the determinants of leaving via earn-
ings increases.

This paper extends the analysis of these studies in several ways.
First, the existing literature is entirely empirical and does not attempt
to explicitly define and model welfare dependence. Second, this litera-
ture relies on relatively simple discrete empirical models to estimate
duration effects. The econometric literature provides a variety of more
sophisticated ways of approaching duration dependence issues, emphasizing
the importance of testing distributional assumptions, using continuous
time models, and accounting for heterogeneity in the population.[4]

Third, these studies all rely upon annual data,[5] which provide infor-
mation only on whether a household received any welfare over the year,
with no information about the timing of AFDC receipt. Thus, a household
could receive welfare in January of one year, be off the rolls for 22
months, then receive welfare in December of the following year, and its
experience would be counted as a continuous spell of welfare.[6] The use
of annual data can be expected to produce longer and more continuous
spells on AFDC than occur in reality. A major contribution of this paper
is the use of six years of monthly AFDC data in the investigation of
duration dependence.[7]

Finally, earlier research makes no attempt to relate the empirical
findings on duration dependence to any causal models of income generation

and welfare participation. This paper will simulate a simple model of income change, which indicates that duration dependence (declining hazard rates) may occur even in the absence of AFDC dependence effects.

MODELS OF WELFARE DEPENDENCE

The term "welfare dependence" is frequently used in discussions of the AFDC program in the popular media, but it is rarely defined. The existing academic literature is largely empirical, and has not provided a theoretical model of how welfare participation is affected as time on welfare increases.[8]

The standard model of AFDC participation is based on a utility comparison between the utility obtainable by participating in AFDC (U_w) and utility obtainable by not participating in AFDC (U_n). Let $\Phi = U_w - U_n$. A household chooses to participate if $\Phi > 0$. If household utility is determined by household income and leisure (or hours of work) of the head, then Φ will be a function of the range of variables which affect labor market opportunities and leisure/labor choice. This point-in-time model of the welfare participation decision can become the basis for a dynamic model if it is assumed that a household regularly reassesses its current AFDC status, entering or leaving AFDC if the utility comparison has changed.

There are two ways by which current participation in AFDC can have an impact on future AFDC participation choices. First, current participation may change future values of the labor market and household variables that enter the utility function. Second, participation in AFDC

may enter directly into the utility function, changing the shape or location of the utility curves.

To describe the first effect, there are two sets of variables that welfare usage may affect over time. First, welfare use may change the labor market opportunities available to a household head in the future. The most obvious channel by which this could occur is through reductions in labor market experience. It is well known that welfare participation reduces labor supply. Thus, a woman using AFDC in time period t works H^*_t hours, where $H^*_t < H_t$, the hours she would work in the absence of the AFDC program. If a woman is on welfare from t to t+n, her experience decreases by $\sum_{i=t}^{t+n} (H_i - H^*_i)$ due to welfare participation. Experience may enter the utility function in several ways. It is typically assumed that experience positively affects wage rates, so workers with less experience have poorer wage opportunities. (To the extent that low-skilled women tend to take jobs where past work experience matters little, this effect may not be very large.) It is also possible that experience may influence a woman's knowledge of the labor market and of job availability. There is evidence that one of the strongest effects of job placement and training programs for welfare participants occurs by providing information on where jobs are located (Danziger, 1981).

Second, the use of AFDC may change household composition in a way that makes future welfare use more likely. There is an ongoing controversy over the extent to which welfare usage decreases marriage and divorce rates, and increases family size. The best evidence appears to indicate that AFDC has little impact on number of children, but does have a small positive impact on divorce rates.[9] The effect on marriage rates

has not been well determined, largely because it is very difficult to separate out AFDC effects from other social and cultural changes. Since this issue is not the primary concern of this paper, let me simply say that _if_ participation in AFDC creates marriage disincentives or increases household size, then the program increases the probability of future welfare use by these women.[10] In most states, married couples are ineligible for AFDC or face much stricter eligibility requirements. But even if eligibility were not an issue, single parenthood decreases household income opportunities and thus makes welfare participation a more attractive option. To the extent that AFDC participation encourages the continued maintenance of single-parent households, then AFDC raises the probability that these households will use welfare in the future.

Although AFDC participation may change the labor market and household circumstances of participants and lead to greater future welfare use, this is not the model which many people have in mind when they refer to welfare dependence. An alternative story claims that use of AFDC changes household tastes over time so that people come to rely on and prefer AFDC income to labor market income. This requires a model where AFDC participation changes the labor-leisure choice locus.

There are two ways of conceptualizing this form of welfare dependence. First, one can consider a shift in the location of utility curves over time, and second, one can consider an actual change in the curvature or shape of the utility curves. In these models welfare dependence may occur even when AFDC has no impact on the labor market or demographic variables that enter the utility function.

Shifts in the location of utility curves can be thought of as changes in the magnitude of "stigma effects." Moffitt (1983) has modeled welfare

choice by including an additional term, S, into the utility comparison Φ defined above. S refers to an underlying "distaste" for welfare, which Moffitt calls stigma. Thus, the decision to participate in welfare can be written as $\Phi = U_w - S - U_n$. AFDC is chosen if $\Phi > 0$. To put this into a dynamic context, consider that all terms are time subscripted and assume that S_t is a function of past time spent on welfare, W^*_t, where $W^*_t = \sum_{i=0}^{t} I_i$ and I is an index function equal to 1 when $\Phi_t > 0$ and equal to 0 when $\Phi_t \leq 0$. If $dS_t/dW^*_t < 0$, then exposure to the AFDC program over time decreases an individual's "distaste" for the program, shifting the utility function upward, and raising net utility with welfare relative to the utility available without welfare. This situation is depicted graphically in Figure 1.

The alternative to conceptualizing welfare dependence as a locational change in the utility function is to assume that the curvature of the utility function changes over time. Utility is frequently parameterized as $U(H,Y,X)$, where H is hours of work (negative leisure), Y is income, and X is a set of household characteristics that are assumed to determine the shape of the underlying function. An increasing "reliance on welfare" can be considered equivalent to shifting the utility function in favor of greater leisure and flattening the labor/leisure trade-off. Thus at time period t, the utility available on welfare is $U(H^*_t, Y^*_t, X^*_t, W^*_t)$, where H^*, Y^*, and X^* are the hours of work, income, and household characteristics of a household that participates in welfare in time period t, and W^* is as defined above. Utility of nonparticipants is $U(H_t, Y_t, X_t, W^*_t)$. (Past welfare participation affects the shape of the underlying utility and thus enters all utility functions.) The decision

FIGURE 1

Locational Changes in Utility Curves Due to
Changing Stigma Effects as Time on Welfare
Increases

Income

$U_w - S(W_2^*)$ U_n

$U_w - S(W_1^*)$

$W_2^* > W_1^*$

When past usage is W_1^*, person does
not participate in AFDC.
When past usage is W_2^*, person does
participate in AFDC.

AFDC
Benefit Max.

Hours
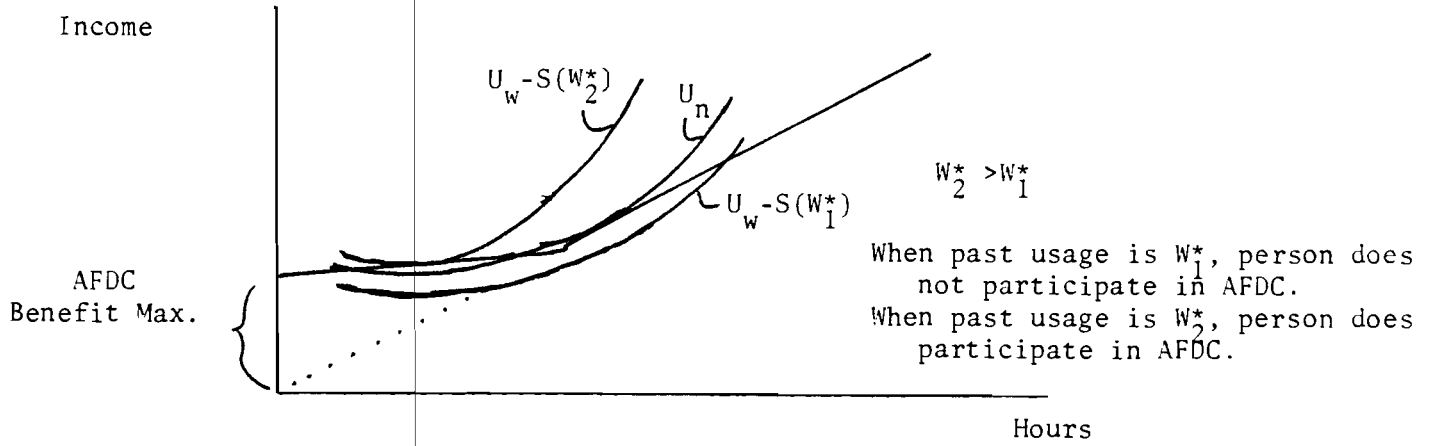
FIGURE 2

Curvature Changes in Utility Curves as
Time on Welfare Increases

Income

$U(W_2^*)$ $U(W_1^*)$

$W_2^* > W_1^*$

AFDC
Benefit Max.
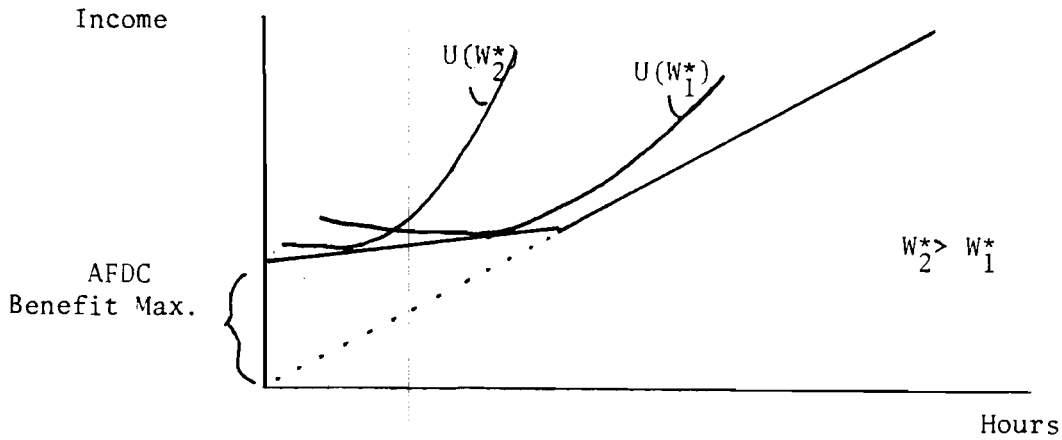
Hours

to participate on welfare is based on the comparison

$$\Phi_t = U(H^*_t, Y^*_t, X^*_t, W^*_t) - U(H_t, Y_t, X_t, W^*_t).$$

If $\Phi_t > 0$, then welfare participation is chosen. The effect of W^* can be characterized as $d(dU/dH)/dW^* < 0$, and $d(dU/dY)/dW^* < 0$, implying that as time on welfare increases, hours of work appear more onerous relative to the additional income that they produce. Figure 2 depicts such a change.

This paper empirically tests the proposition that time spent on welfare increases the probability of continued welfare participation, holding constant all variables which are normally assumed to influence utility choice (including labor market opportunities and household composition). If I find that AFDC usage affects participation probabilities even with these other variables held constant, I can interpret this as evidence supportive of those models in which AFDC usage influences the shape or location of the utility function independent of its effects on other variables. Of course, to the extent that I am not able to control fully for all other variables, I will not be able to distinguish between the above models.

Before turning to an econometric representation of this model of welfare dependence, let me highlight two important issues. First, the sum of previous periods on welfare may not be an accurate representation of how previous welfare usage influences current usage. It may be that only recent AFDC participation affects future welfare use; or that past spells are important but have less impact than current welfare spells. Because of the econometric difficulties of dealing with multiple spells (and because I have fewer data on multiple spells), I will assume that

only the current spell of welfare influences the length of that spell. This issue is discussed further below.

Second, there may be many variables that influence welfare participation behavior which I cannot measure or observe. In this case, evidence that past welfare usage influences current welfare usage may be due to these unmeasured variables, and not due to the impact of AFDC itself. This is the classic problem of population heterogeneity versus program impacts. If all individuals have the same probability of entering welfare initially (perhaps because of random bad luck in the labor market or the marriage market), but if certain individuals are less motivated than others, then the more motivated individuals will be more likely to leave welfare sooner. A measured "duration dependence" effect of AFDC may result simply from the fact that, over time, the group of people who are on the program longer is composed of an increasingly greater percentage of less-motivated individuals. In this situation, concluding that welfare dependence occurs and is induced by the AFDC program is inaccurate. The longer welfare usage is less-motivated individuals is due solely to their own innate characteristics, which were fixed before they entered AFDC. This is a serious problem in virtually all models of duration dependence, and I will use the existing statistical techniques that are designed to uncover the presence of unmeasured heterogeneity. However, at some level, this problem cannot be conclusively resolved and all my results must be interpreted with this in mind.

ECONOMETRICALLY MODELING WELFARE DEPENDENCE

This section provides the econometric background to the empirical results of the next section. The analysis of time-dependent data has become increasingly common in economics. Among the best background papers are Flinn and Heckman (1981) and Heckman and Singer (1984a). Texts, such as that of Kalbfleisch and Prentice (1980), are also available. This section will, therefore, lay out the econometrics of state dependence quite briefly, focusing on the issues of importance in analyzing AFDC participation duration.

Let $F^*(t, X_t)$ represent the cumulative distribution of time spent on welfare, where X_t is a time-dependent vector of household characteristics, labor market opportunities, and parameters of the AFDC program. F^* is the result of a set of participation decisions, Φ_1 through Φ_t, characterized in Section 3, above. $f(t, X_t)$ is the associated density function. Let $F(t, X_t) = 1 - F^*(t, X_t)$ be the survival function, the percentage surviving (still on welfare) at time t. Define the instantaneous rate of leaving welfare at $T = t$, conditional upon participating to time t, as the hazard rate h(t), where

$$(1) \quad h(t, X_t) = \lim_{\delta t \to 0} \frac{P(t \leq T \leq t+\delta t \mid T \geq t, X_t)}{\delta t}$$

$$= f(t, X_t)/(F(t, X_t))$$

$$= -d\log(F(t, X_t))/dt.$$

Integrating, it is clear that

$$(2) \quad F(t,X_t) = \exp(-\int_0^t h(u,X_u)du) \text{ and}$$

$$(3) \quad f(t,X_t) = h(t,X_t)\exp(-\int_0^t h(u,X_u)du).$$

Thus, choosing a hazard function, h, is equivalent to choosing a distribution for t.

Note that time dependence in the exogenous (X) variables makes this integration more complex. However, if time-varying covariates are present, and the researcher replaces them with constant covariates (such as beginning-of-spell values) this can induce significant bias into the results (Flinn and Heckman, 1981). Children's ages and household size will vary over a welfare spell, as do area labor market opportunities, the parameters of the AFDC program, and income sources such as alimony or unemployment compensation.

The models of welfare dependence developed in the previous section imply that the hazard rate--the conditional probability of leaving welfare as time on welfare increases--should decrease over time, ceteris paribus. The absence of such an effect will provide evidence against the existence of program-induced welfare dependence. Given a data set containing information on the length of AFDC spells, the likelihood that any individual is observed to use welfare from time 0 to time t is simply $f(t,X_t)$. If the data are right-censored, i.e., if the individual starts a spell of welfare at time 0 and if at time T, when data collection ends, the individual is still participating in welfare, the probability of that censored event is simply the value of the survival function at T, $F(T,X_T)$. (Left-censored observations are omitted from the sample, as

discussed below.) Thus, the estimated likelihood function for the entire population is

$$(4) \quad \prod_{i=1}^{n_1} f_i \ (t,X_t) \ \prod_{j=1}^{N_2} F_j \ (t,X_t)$$

where there are n_1 completed spells of welfare observed and n_2 right-censored spells.

The choice of the appropriate functional form for the hazard function is a much-debated topic. Most commonly, people choose hazards which integrate into tractable functional forms for the distribution $F(t,X_t)$. Since the results may vary with functional assumptions, I will compare a variety of parametric and nonparametric distributional assumptions for the hazard in the empirical work below.

Population Heterogeneity

The potential for unobserved heterogeneity among the sample population was discussed above. If there are variables that I cannot include in the exogenous vector of characteristics, and which are correlated with AFDC usage, I will derive inappropriate estimates of duration dependence if this heterogeneity is not taken into account. Heckman and Singer (1984a) prove that the presence of population heterogeneity induces a negative bias in the hazard function, potentially producing estimates of a decreasing hazard when the true underlying hazard is flat or increasing. To account for heterogeneity, write the hazard function as $h(t,X_t,\theta)$, where θ represents a set of unobservable variables. The density of the underlying distribution of time spent on welfare is

$$(5) \quad F(t,X_t,\theta) = \int \exp(-\int_0^t h(u,X_u \mid \theta)du) \; g(\theta)d\theta,$$

where $g(\theta)$ is the distribution of the underlying unobservables. Given both a distribution for t and a distribution for θ, one can estimate the density F. However, even more uncertainty exists over the appropriate distributional characterization of θ than exists over the appropriate distribution for t.[11] Most commonly, some form of a mixing distribution is assumed, in which the parameters that characterize the size and shape of the hazard function are allowed to take two or more values, and these values, as well as their associated probabilities, are estimated as part of a maximum likelihood procedure. (See Heckman and Singer, 1984a, 1984b.) I will describe below the exact form of the heterogeneity model estimated in this paper. However, it should be noted that the results will be dependent upon the form of heterogeneity which is assumed.

With respect to the issue of time spent on welfare, the concepts of duration dependence and heterogeneity are rather inextricably linked in the data, and at some level it is not clear that attempting to separate them out makes a great deal of sense. It is quite possible that AFDC usage changes preferences by affecting these unobservable variables (such as motivation). In this case, what we observe as duration dependence in the data may indeed be due to differences in the unobservables—but these unobservables themselves are changed by the AFDC program. Alternatively, since we do not observe all women from their very first spell of welfare, but have a cross-section of women over a given six-year period, it is possible that exposure to AFDC prior to the beginning of the sample is the cause of the existing heterogeneity. In this case also, controlling

for the heterogeneity does not eliminate a "bias" from the true duration effect, but rather eliminates a duration dependence effect that appears to be part of the unobservable only because our observation period for welfare spells is too short. The conclusion is that while the heterogeneity adjustments provide interesting additional information about the duration data, they are difficult to interpret; the duration estimates done in the absence of heterogeneity corrections may be the appropriate results to consider.

Competing Risk Models

Once participating in the AFDC program, a woman can leave by several ways. She can take a job that raises her income above the AFDC eligibility boundary; she can experience an increase in nonlabor income (such as alimony or disability assistance) that puts her above the income eligibility limit; her youngest child can reach age 18, eliminating her AFDC eligibility; or she can marry, also eliminating her AFDC eligibility. It is not clear that these ways of leaving AFDC should all be modeled in a similar manner. The determinants of leaving AFDC via marriage may be quite different from the determinants of leaving by increased earnings. This situation can be handled with a competing risk model, in which there are multiple ways for a welfare spell to terminate, each characterized by a different hazard function. Let $h_1(t, X_t)$ be the hazard function associated with leaving welfare via an earnings increase, and $h_2(t, X_t)$ be the hazard associated with leaving via another route. Then the overall probability that a woman will end a welfare spell at time t, given it has lasted from time 0, is

(6) $h_{cr}(t,X_t) = h_1(t,X_t) + h_2(t,X_t)$.

The survival function in a competing risk model becomes

(7) $F_{cr}(t,X_t) = \exp(-\int_0^t h_{cr}(u,X_u)du)$.

The distribution of a completed spell that ends for reason m (m = 1,2) is

(8) $f_m(t,X_t) = h_m(t,X_t) \exp(-\int_0^t h_m(u,X_u)du)$.

The likelihood function for the sample is

(9) $\prod_{i=1}^{n_1} f_{1i}(t,X_t) \prod_{j=1}^{n_2} f_{2j}(t,X_t) \prod_{k=1}^{n_3} F_{crk}(t,X_t)$,

where n_1 individuals leave welfare via earnings increases, n_2 individuals leave via other changes, and n_3 individuals are censored.

Alternative Distributional Assumptions for the Hazard

As noted above, estimated duration models are often quite sensitive to the functional form assumed for the hazard function. As a result, I will compare estimates based on a variety of different assumptions. This section briefly presents each of the four hazard functions that are used below.

a. _Weibull Distribution._ Because of its mathematical ease, the most commonly used form for $F(t,X_t)$ is a Weibull distribution. In this case the hazard function is[12]

(10) $h(t,X) = p*\exp(X\beta)*(\exp(X\beta)*t)^{p-1}$.

(The constant, β_o, provides a measure of the second Weibull parameter, lambda.) If $p<1$ ($p>1$) the Weibull hazard monotonically decreases

(increases). If p=1 the Weibull collapses to the exponential distribution that is characterized by a constant hazard.

b. **Log-Logistic Distribution**. The log-logistic is computationally convenient and more flexible than the Weibull. Its hazard function is

$$(11) \quad h(t,X) = p*exp(X\beta)*(exp(X\beta)*t)^{p-1}/(1 + (exp(X\beta)*t)^p).$$

If $p > 1$, the log-logistic hazard increases from zero to a maximum at $t = (p-1)^{1/p}/exp(\beta_o)$, and decreases thereafter.

c. **Flinn-Heckman Hazard**. Flinn and Heckman use a form for the hazard function which they derive from a particularly flexible general function. In their data applications, this becomes

$$(12) \quad h(t,X) = exp(\beta_o + \tau_1 t + \tau_2 t^2 + X\beta).$$

Typically used with t and t-squared, this imposes a clear quadratic form on the hazard, although higher powers of t can be included, of course.

d. **Continuous Stepwise Nonparametric Hazard**. To allow the data as far as possible to reveal the underlying hazard without imposition of a functional form, I estimate a simple stepwise hazard, allowing the hazard function to take on a series of constant values as t increases:

$$(13) \quad h(t,X) = c_1 \text{ if } t \leq 2, \qquad h(t,X) = c_6 \text{ if } 19 \leq t \leq 24$$
$$h(t,X) = c_2 \text{ if } 3 \leq t \leq 5, \qquad h(t,X) = c_7 \text{ if } 25 \leq t \leq 36$$
$$h(t,X) = c_3 \text{ if } 6 \leq t \leq 8, \qquad h(t,X) = c_8 \text{ if } 37 \leq t \leq 48$$
$$h(t,X) = c_4 \text{ if } 9 \leq t \leq 12, \qquad h(t,X) = c_9 \text{ if } 49 \leq t.$$
$$h(t,X) = c_5 \text{ if } 13 \leq t \leq 18,$$

where $c_i = \exp(\beta_{oi} + X\beta)$.[13] A larger number of steps were tried, but nine appear to fit the data reasonably well. Increases in the number of steps do not change the estimates of β, and significantly increase the cost of estimation. This stepwise hazard is completely nonparametric, and I will rely on a comparison between it and other hazard models to determine how well the others describe the data.

EMPIRICAL RESULTS OF DURATION MODELS

The data used in this study are those on the control group in the Seattle/Denver Income Maintenance Experiments (SIME/DIME).[14] The SIME/DIME Monthly Composite provides monthly information on income and labor market variables for a six-year period, 1970-1975 in Seattle and 1971-1976 in Denver.[15] From the control group I extract all women who head households containing children under the age of 17 at some point during the six-year period. This is the group of potential AFDC users. There are 1121 such women in the sample. Of this group, 714 receive AFDC income for at least one month over the sample. While I can observe most women for the entire 72 months,[16] few are female household heads with children (i.e., potentially eligible for AFDC) throughout the sample. Changes in marital status and household composition take women out of the eligible category.

While 72 months of data represent a significant length of time over which to observe household behavior, this is still a shorter time period than one would ideally want. Because I have no presample information in the data, any spells that are in progress in the first period are left-censored and are omitted from this analysis.[17] Thus, I am limited to

spells that start within the time period of the sample. The results will necessarily be biased by lack of information on very long spells—they are either both right- and left-censored and do not appear in the data at all, or they are right-censored and provide only limited information for the likelihood function.

This section estimates duration models of AFDC receipt using the first observed spell of welfare for each household starting within the sample period. There are 508 such spells in the data, of which 185 (36 percent) are right-censored. The analysis assumes that only the current spell on welfare affects spell duration. Of course, for households in the midst of multiple spells this may not be a good assumption.[18]

Table 1 provides information on the distribution of these welfare spells. Column 1 looks at the length distribution of the 323 completed spells. Fifteen percent of them end within two months whereas 62 percent end within a year after they start. (The average length is a little over a year.) Column 3 indicates the length of the 185 censored spells. While Table 1 shows evidence of a large number of short spells, no conclusions on spell length can be drawn from it, since both completed and censored spells must be jointly accounted for to adequately estimate expected duration.

One justification given for using annual data to study AFDC dynamics is that women may move in and out of AFDC for one or two months owing to administrative problems, and these should not be counted as real AFDC spell endings. In my data there is little evidence of this. Out of 605 total observed spell ending in the data, in only 20 cases do women return to AFDC after one month. In 16 cases they return after two months, and

Table 1

Spell Distribution in the Monthly SIME/DIME Data

| | Completed First Observed Spells | | Censored First Observed Spells | |
	Number Completed in:	% Completed in:	Number Censored after:	Cumulative % Censored after:
2 months	47	15%	10	5%
6 months	125	39	31	17
12 months	201	62	56	30
24 months	267	83	103	56
36 months	302	93	133	72
48 months	316	98	158	85
60 months	320	99	175	95
72 months	323	100	185	100

Note: Expected length of completed spells is 13.3 months.

in 14 cases they return after three months. In other words, although some women experience only short periods off AFDC, theirs is not a predominant pattern. Furthermore, if one looks at the 50 short spells off AFDC, 29 of them are readily explainable: the household clearly has increased income in these months, either through employment, or because of increases in other income sources. Thus, there is little evidence of "welfare churning" in these data, and little justification for assuming that brief periods off welfare are not real spell endings.[19]

Table 2 looks at the causes behind spell beginnings and endings.[20] Forty percent of the spells begin immediately after a change in marital or household status; only 8 percent begin with the birth of a child. Fifty-two percent begin within a household that was already potentially eligible (i.e., female-headed with children) before AFDC receipt began.

Looking at spell endings, 36 percent of the spells are censored, and I therefore do not know how they end. In 18 percent of the cases women get married and in 7 percent of the cases their children grow past the age of eligibility. Thirty-nine percent of the cases leave AFDC although they remain female-headed households. These recipients either work their way off AFDC or find other sources of income.

Table 3 presents the means of the variables used to estimate AFDC spell duration. Variables that do not vary over a spell are race, education, and age at the beginning of the spell. The remainder of the variables can change as the spell progresses. I report the means for number of children and other income at the beginning of the spell, and the mean unemployment rate and maximum benefit payment over the entire six years. "Other income" refers to non-AFDC, nonlabor market income.

Table 2

Beginning and Ending Reasons for First Observed Spells

	Number	Percent
Beginning Reasons		
Enter AFDC when household composition changes	244	48
Change in marital or household status[a]	205	40
Increase in number of children	39	8
Enter AFDC from previously state of female headship	264	52
Decrease in head's labor market income	138	27
Decrease in other income[b]	60	12
Unable to determine reason	66	13
Total first observed spells	508	100
Ending Reasons		
Censored	185	36
Leave AFDC when household composition changes	127	25
Change in marital status	91	18
Decrease in number of children	36	7
Leave AFDC while still female head	196	39
Increase in head's labor market income	108	21
Increase in other income[b]	51	10
Unable to determine reason	37	7
Total first observed spells	508	100

[a]Includes both divorces or separations and individuals who move out of another household (typically their parents').

[b]Other income includes all household income except labor market income of the head and public assistance.

For these women such income is small (about $28/month), and is mainly
composed of alimony payments and other sources of public income such as
social security or disability payments. Unemployment rates are for the
Seattle and the Denver SMSAs. Benefit maximums are specific to each
household size in Washington or Colorado. These vary annually if state
legislatures readjust the rates, and they vary monthly as they are
affected by inflation. For both states they tend to decrease over time,
as inflation erosions are larger than legislative increases. Inflation
adjustments for Seattle are based on the Seattle SMSA CPI; for Denver,
which lacks its own CPI during these years, they are based on the average
urban CPI for the nation. Table 3 describes a population that is dispro-
portionately nonwhite, poorly educated, and with little outside income
support.

Table 4 presents estimates of the probability of exit from an AFDC
spell, using the four functional forms for the hazard presented above.
Five of the variables in the estimation (children under 6, children under
17, other income, unemployment rate, and benefit maximums) are explicitly
allowed to vary over time.[21]

All functional forms show quite similar coefficient patterns for the
seven exogenous variables.[22] Age and education of the head have signifi-
cant and positive effects (i.e., they increase the probability of leaving
welfare). Race has a significant negative effect (i.e., being black
decreases the probability). The impact of children is negative, but only
the total number of children under 17 shows significance. Other income
significantly increases the probability of leaving welfare, while the
unemployment coefficient is negative but uniformly insignificant. The

Table 3

Means of Variables in SIME/DIME Data: First Observed Spells

	SIME Subsample	DIME Subsample	Total Sample
Variables constant over spell:			
Age at start of spell	29.4	26.3	27.9
Race (1 = nonwhite)	.58	.45	.52
Years of education	11.1	10.8	11.0
Variables that can vary over spell:			
Number of children < age 6[a]	.82	1.00	.91
Total children < age 17[a]	1.98	2.04	2.01
Other income per month[b]	$30.46	$26.99	$28.78
Unemployment rate[c]	9.4%	3.8%	6.6%
Benefit maximum per month[d]	$238	$179	$208
Number of observations	262	246	508

[a]Measured at start of spell.

[b]Includes all household income except labor market income of the head and AFDC. Is adjusted for inflation (1975 dollars) and measured at start of spell.

[c]Mean for sample period. The Unemployment Rate is the reported unemployment in the Seattle and Denver SMSA's, respectively.

[d]Mean for a family of three for the sample period for the states of Washington and Colorado, adjusted for inflation (1975 dollars).

Table 4

Duration Models of First Observed Welfare Spells,
with Time-Varying Covariates
(Number of observations = 508)

Variable	Functional Form			
	Weibull Hazard	Log-Logistic Hazard	Flinn-Heckman Hazard	Nonparametric Stepwise Hazard
Constant	-4.345** (.506)	-4.063** (.576)	-3.719** (.494)	-1[a]
Age	.018** (.007)	.017** (.008)	.016** (.007)	.016** (.007)
Race (1 = nonwhite)	-.257** (.123)	-.259** (.135)	-.213** (.115)	-.213* (.114)
Education	.060* (.033)	.060* (.039)	.055* (.031)	.055* (.031)
Number of children < 6	-.083 (.095)	-.064 (.103)	-.096 (.089)	-.093 (.087)
Total number of children < 17	-.240** (.113)	-.316** (.130)	-.171* (.111)	-.164* (.107)
Other income	.0004** (.0002)	.003** (.001)	.0004** (.0002)	.0003* (.0002)
Unemployment rate	-.003 (.003)	-.005* (.003)	-.002 (.003)	-.002 (.003)
Benefit maximum	.003 (.003)	.006* (.003)	.002 (.003)	.002 (.003)

-Continued-

Table 4 (Continued)

Variable	Functional Form			
	Weibull Hazard	Log-Logistic Hazard	Flinn-Heckman Hazard	Nonparametric Stepwise Hazard
Distributional Parameters				
P	.924** (.042)	1.256** (.057)	-	-
Time	-	-	-.039** (.013)	-
Time squared	-	-	.0004* (.0003)	-
Likelihood value	-1381	-1368	-1372	-1369
Mean of survival function (in months)	21	18	21	22

Note: Standard errors in parentheses.

[a]Stepwise hazard includes 9 time-varying constants as described in text. All are significant at the 2% level.

*Significant at the 10% level.
**Significant at the 2% level.

maximum AFDC benefit payment is generally positive, a counterintuitive result, but the coefficients are insignificant. While other research typically finds that benefit levels are very important in determining welfare participation, much of the power of this variable comes from the large differences in benefit levels across states within a national data sample. I have observations from only two locations, within which the variance in benefit levels over time is relatively small.[23]

The Weibull distribution has a P parameter of .92, very close to one. (Recall that P=1 in a Weibull distribution implies a constant hazard.) Thus, the Weibull indicates only weak duration dependence in the data. A graph of the Weibull hazard function, shown in Figure 3, confirms this.[24] After a small initial fall, the conditional probability of leaving welfare is almost flat. (Note that the hazard rates graphed in Figures 3 through 9 are directly interpretable as the conditional probability of leaving AFDC in a given month, expressed in percentage terms.)

In contrast, the log-logistic distribution has a P of 1.26, which in this distribution indicates a rising hazard (an increasing probability of leaving welfare) for six months, and a falling hazard thereafter. Figure 4 graphs this function. The likelihood value indicates that the log-logistic distribution fits the data much better than the Weibull.

The Flinn-Heckman hazard shows a somewhat different duration pattern: the hazard rate decreases from the first month, but after 45 months it levels off and begins slowly to increase, as Figure 5 shows. This pattern appears largely due to the restrictions of the quadratic form on the time variable. I have experimented with the inclusion of higher orders of the time variable in the model. While third or fourth order terms are
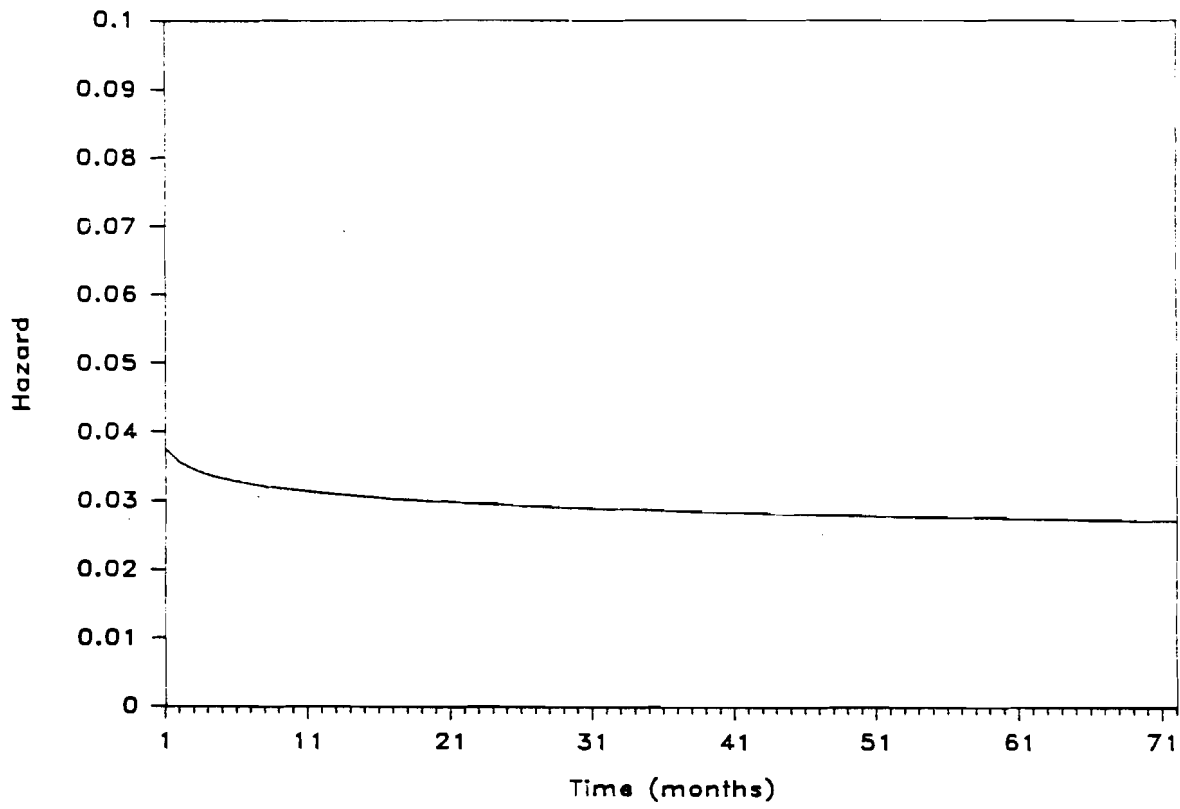
FIGURE 3
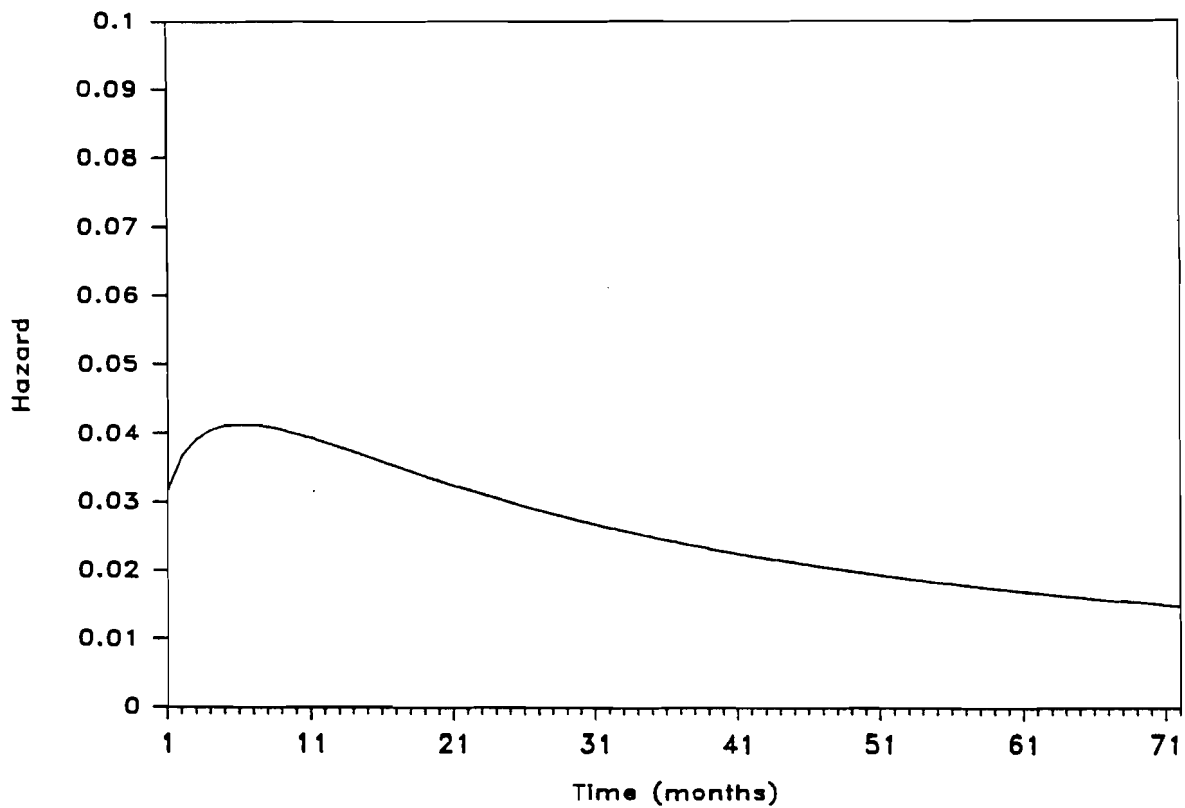# Weibull Hazard Rate

FIGURE 4
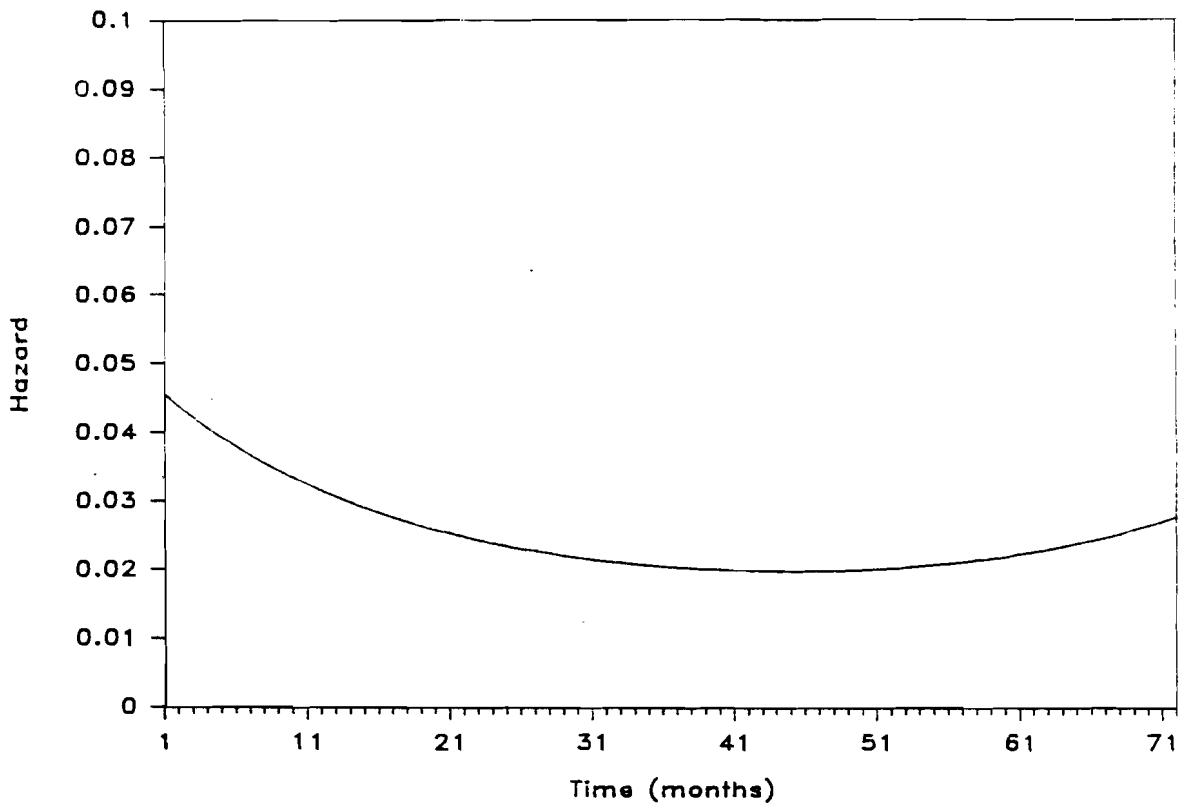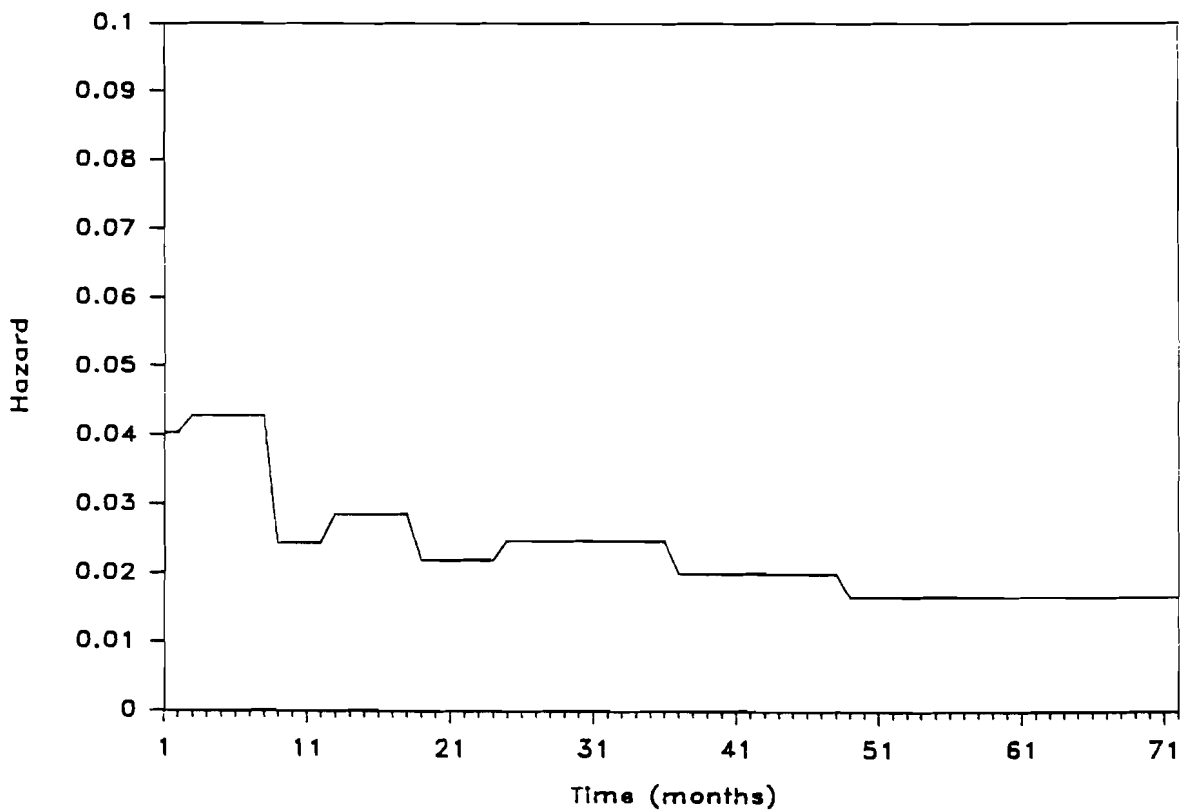# Log—logistic Hazard Rate

FIGURE 5

Flinn—Heckman Hazard Rate

FIGURE 6

Stepwise Hazard Rate

not significant, their inclusion does decrease the magnitude of the
upturn induced in the data by the quadratic time variable.[25] The
Flinn-Heckman distribution is inferior to the log-logistic in overall
fit.

Given the divergence in duration results between the three distribu-
tionally defined hazards, the nonparametric stepwise hazard should pro-
vide useful additional information on the true form of the underlying
data. As described above, this model allows the data to fit its own
hazard function across nine constants. The estimated hazard function
(see Figure 6) appears closest to the log-logistic hazard. The hazard
remains essentially flat for the first eight months, then decreases, but
soon flattens out and is essentially constant after 18 months. The like-
lihood value confirms the similarity between the log-logistic and the
nonparametric estimates.

There are several conclusions from Table 4. First, it is clear that
household characteristics are very important in determining how quickly a
woman will leave welfare. White women who are older when their welfare
spell starts, who have more education, higher alternative sources of
income, fewer children and fewer young children move off welfare faster.
These results are entirely consistent with earlier research. Table 5
uses the coefficients from the nonparametric stepwise distribution in
Table 4 to simulate the effect of changes in race, education, and number
of children on expected spell length and exit probabilities from AFDC.
This table further confirms the importance of household characteristics
on AFDC usage.

Second, functional assumptions are clearly very important and produce
different patterns for the hazard function. Among the parametric

Table 5

Variations in Expected Spell Length and Survival
Probabilities with Household Characteristics[a]

Race 1 = Black	Years of Education	No. Children Under 6	Total No. Children	Expected AFDC Spell Length	Probability of Remaining on AFDC after:		
					2 mo.	6 mo.	2 yrs.
1	11	1	2	36.3 mo.	92.2	77.7	47.7
0	11	1	2	30.0	90.5	73.2	40.1
1	12	1	2	34.7	91.8	76.6	45.8
0	12	1	2	28.3	90.0	71.9	38.1
1	11	0	1	28.6	90.1	72.1	38.4
0	11	0	1	22.7	87.9	66.8	30.7
1	11	2	3	43.4	93.9	82.3	56.5
0	11	2	3	37.6	92.6	78.5	49.3

[a]All calculations are done for a household in Seattle. Age of head is 27 years, with $30/month in other income. Unemployment rates and benefit maximums are set at their mean level in Seattle (9.8% and $238/mo., respectively). Estimates are based on the coefficients of the nonparametric stepwise hazard estimated in Table 4, column 4.

distributions, the log-logistic clearly fits the data best, and produces results very similar to the nonparametric estimates. This makes the log-logistic an appealing functional form, particularly since it is much less computationally expensive than the nonparametric stepwise estimates (which must estimate nine parameters to describe the hazard, rather than just one.)

Third, the hazard rate which best fits the data is one which is flat (or rising) for about the first eight months of welfare use. This falls between nine and eighteen months and then is essentially constant for all longer spells. Recall that a flat or rising hazard contradicts any assumption of welfare dependence. However, a falling hazard for some period of time after the initial months on welfare is consistent with a welfare dependence story, in which several months of participation in AFDC creates reliance on the program.

Adding Heterogeneity to the Model

As noted above, the observed fall in the hazard rates may be due to differences in the unobservable characteristics of households. If one group has a high probability of leaving welfare and a second group has a low probability of leaving, over time those on welfare will be more and more likely to belong to the second group. A single estimated hazard rate will appear to fall over time as the AFDC population mix changes, even if there are no dependence effects for either population. Using the above results, I shall assume that the underlying hazard rate is log-logistic, and characterize population heterogeneity in a nonparametric manner.

Assume that the unobservable is reflected in the constant, so that n

heterogeneous groups will have constants $\theta_1 \ldots \theta_n$. The probability that

an individual is in any group i is π_i, where $\sum_{i=1}^{n} \pi i = 1$. The appropriate

hazard rate for a member of group i is thus

(14) $h(t, X_t, \theta_i) = p \cdot \exp(\theta_i + X_t \beta) \cdot (\exp(\theta_i + X_t \beta) \cdot t)^{p-1}$.

I will estimate a heterogeneity model in which there are three groups,

whose β coefficients are identical, but whose constants vary. The proba-

bility that an individual is in group 1 or 2 will be estimated as π_1 and

π_2. $(\pi_3 = 1 - \pi_1 - \pi_2.)$[26]

Table 6 presents the results for this heterogeneity model. The coef-

ficients on the exogenous variables are quite similar to those presented

in Table 4. However, the allowance for different underlying constants

clearly produces evidence of significant heterogeneity. Individuals are

quite likely to fall into the first group (probability 52 percent) or the

second group (probability 38 percent). There is only a small chance they

will be in the third group (probability 9 percent). The likelihood func-

tion indicates that this model fits the data better than the simple

log-logistic model in Table 4, with no heterogeneity.

Figure 7 graphs the three hazard functions resulting from the esti-

mates in Table 6. (Recall that this graph is constructed for the average

individual. Hazard rates for women with different characteristics would

show similar patterns, but different magnitudes.) If an individual falls

into the first group, she enters AFDC with virtually no probability of

leaving, and has a very slowly increasing hazard which remains low

throughout the 72 months. Clearly this group—a majority of the
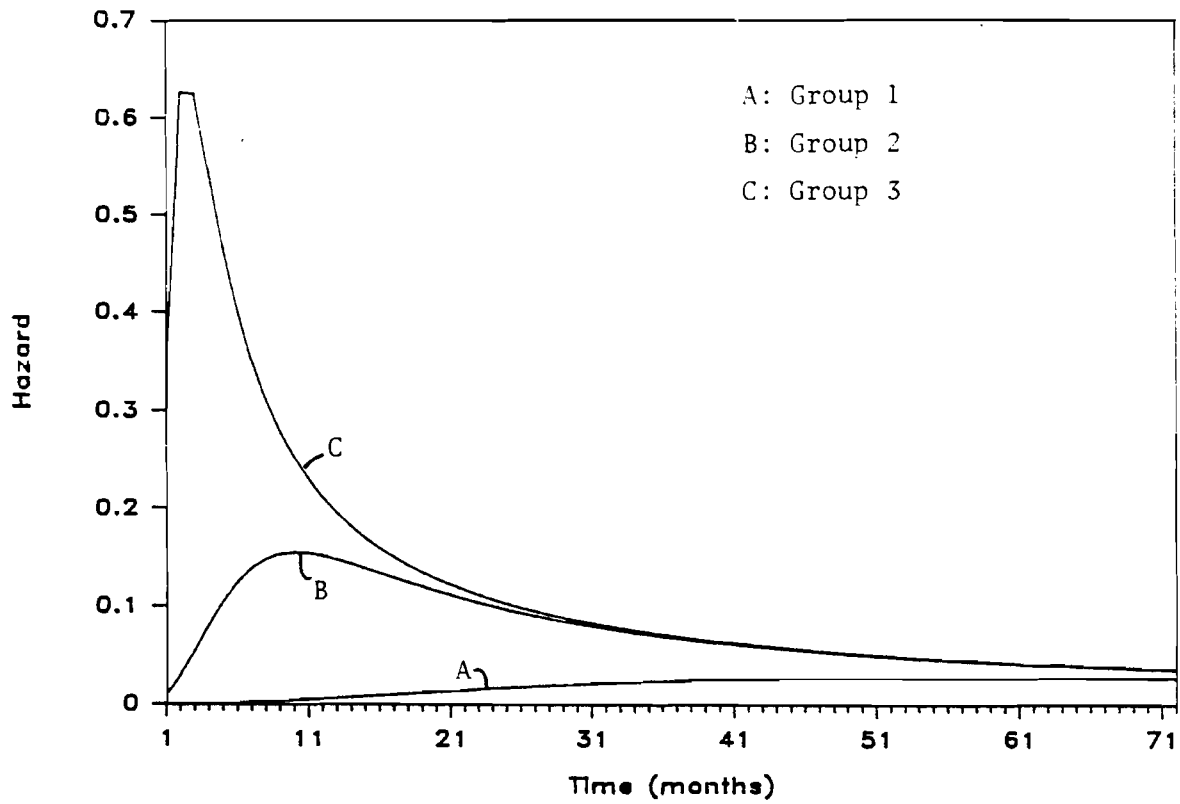
FIGURE 7

Log–logistic Hazard w/ Heterogeneity

A: Group 1
B: Group 2
C: Group 3

Table 6

Duration Model of First Observed Welfare Spells
with Heterogeneity and Time-Varying Covariates
(Number of Observations = 508)

Variable	Shared Coefficients	Group 1	Group 2	Group 3
Constant		-4.812** (.440)	-3.126** (.445)	-1.702** (.459)
Age	.019** (.007)			
Race (1 = nonwhite)	-.199* (.109)			
Education	.069** (.028)			
Number of children < 6	-.078 (.084)			
Total number of children < 17	-.156* (.099)			
Other income	.002** (.001)			
Unemployment rate	-.004* (.002)			
Benefit maximum	.002 (.002)			
P (distributional parameter)	2.571** (.255)			
Probability of being in group		.527** (.038)	.380** (.040)	.093**[a] (.030)
Likelihood value	-1358			
Mean of survivor function (in months)		54	8	1
Goodness-of-fit measure	197			

Note: Standard errors in parentheses.
[a]Calculated from the probabilities for groups 1 and 2.
*Significant at the 10% level.
**Significant at the 2% level.

population—will rely on welfare a long time. However, there is no evi-
dence of duration dependence in these spells; i.e., there is no evidence
that this long-term usage is related to time on the program.

If the individual is part of the second group, she is increasingly
likely to leave AFDC in the first few months (the hazard rises to over 15
percent); but after 10 months over 60 percent of this group is off
welfare and the hazard begins to fall steadily, down to around 5 percent.
The last group, which is least common in the data, leaves AFDC very early
and very fast; their initial probability of leaving is well over 50 per-
cent. Over 90 percent of this group is off welfare within four months.
The hazard falls precipitously at this point, as the few that remain then
leave more slowly. The falling hazard rates in these last two groups may
be interpreted as consistent with the welfare dependence models presented
above. However, the fact that the hazard begins to fall only after the
majority of each group has left welfare creates the suspicion that this
hazard could be created by a model with no welfare dependence effects at
all. Once the majority of a population has crossed an income threshold,
it is statistically quite common (given an underlying distribution in
propensity for income change) for the remainder to cross it more and more
slowly. This possibility will be discussed further below.

The problem with heterogeneity models, of course, is that there is no
way to identify which group an individual belongs to—the distinction is
based on an assumed unobservable variable (all observable variables are
already included in the estimation.) It appears that there is some large
group which enters AFDC with virtually no alternative opportunities, for
whom the possibility of leaving improves slowly over time, but who will

be on welfare a long time. There are other groups who do have ways of escaping AFDC early, but who become less and less likely to leave AFDC as time passes. At least part of the falling hazard estimated in Table 4 is due to the mixing of these different groups, not to program dependence effects. Better understanding of these results will require better data which allow exploration of the nature of that which is currently being termed "unobservable."

A Competing Risk Model

Given the uncertainty of interpretation of the heterogeneity results, an alternative specification is to estimate a competing risk model. In some sense, the competing risk model is a very restricted form of hetero-geneity, in which heterogeneous groups are explicitly identified by the manner in which they leave AFDC. Unfortunately, neither the simple log-logistic model of Table 4 nor the heterogeneity model of Table 6 are nested within the competing risk model, and the likelihood functions will therefore not be directly comparable. As before, I choose to work with a log-logistic specification for the competing risk hazard functions.[27]

Table 7 presents estimates of a three-way competing risk model. The first hazard is estimated for those who leave AFDC when they marry. The second group leaves welfare through an earnings increase, although their potential eligibility continues (i.e., they remain female-headed house-holds with children). The third group also remains female-headed, but leaves via some change other than earnings.[28]

The coefficients on the exogenous variables differ significantly across these three groups. The likelihood of leaving AFDC through marriage is strongly and positively affected by age, and strongly and

Table 7

Duration Models of First Observed Welfare Spells
with Three-Way Competing Risks and Time-Varying Covariates
(Number of Observations = 508)

Variable	Log-Logistic Hazard		
	Spells Ending with Marriage	Spells Ending with Earnings Increase	Spells Ending with Other Changes[a]
Constant	-3.989** (.700)	-7.818** (1.039)	-5.360** (.957)
Age	.029** (.011)	-.003 (.016)	.019 (.016)
Race (1 = nonwhite)	-.738** (.298)	.134 (.269)	-.005 (.027)
Education	.027 (.053)	.243** (.090)	-.017 (.082)
Number of children < 6	-.004 (.014)	-.216 (.193)	-.052 (.226)
Total number of children < 17	-.168 (.153)	-.543* (.417)	-.201 (.613)
Other income	.001 (.002)	.002 (.002)	.005** (.002)
Unemployment rate	-.009** (.004)	-.001 (.007)	-.001 (.009)
Benefit maximum	.001 (.004)	.010 (.008)	.004 (.012)
P (distributional parameter)	1.200** (.087)	1.012** (.078)	.953** (.090)
Likelihood value		-1698	
Mean of survivor function (in months)		20	
Goodness-of-fit measure		226	

Note: Standard errors in parentheses.
[a]Includes increases in nonearned income, children leaving home, and unknown reasons for which a female-headed household leaves the AFDC program.
*Significant at the 10% level.
**Significant at the 2% level.

negatively affected by unemployment and race. This is consistent with other evidence showing that poor black women are less likely to marry. In contrast, the probability of leaving AFDC by earnings increases is primarily affected by educational level and number of children. Being nonwhite has little effect on the probability of this type of spell ending--the negative effects of race in the earlier aggregate models appear to have been solely due to the lower propensity of black women to marry, rather than their lower probability of leaving welfare by other means. Since the third group is a mixture of "other reasons for leaving" it is not surprising that few explanatory variables are significant. Only income other than earnings shows positive effects, indicating that women with high other-income sources while on welfare are more likely to leave through future increases in this income.

The three hazard rates estimated in these competing risk models are graphed in Figure 8 for the mean individual. The hazard rate for the probability of leaving AFDC via marriage is very low and virtually flat. The probability of leaving by changes other than earnings increases or marriage is also low (although higher than marriage), and decreases slightly over time. In contrast, the probability of leaving AFDC via earnings increases is higher, especially in the initial months, and falls steadily, from about 1.8 percent to close to 1 percent. Overall, the competing risk estimation clearly indicates that the process of leaving AFDC through household changes is quite different from leaving via an earnings change, because of both differences in the coefficients and differences in the shape of the duration parameters. Note that the hazard rates are additive in the competing risk model (each individual is "at

FIGURE 8

3-Way Competing Risk Hazards

A: Marriage
B: Earnings Change
C: Other Change
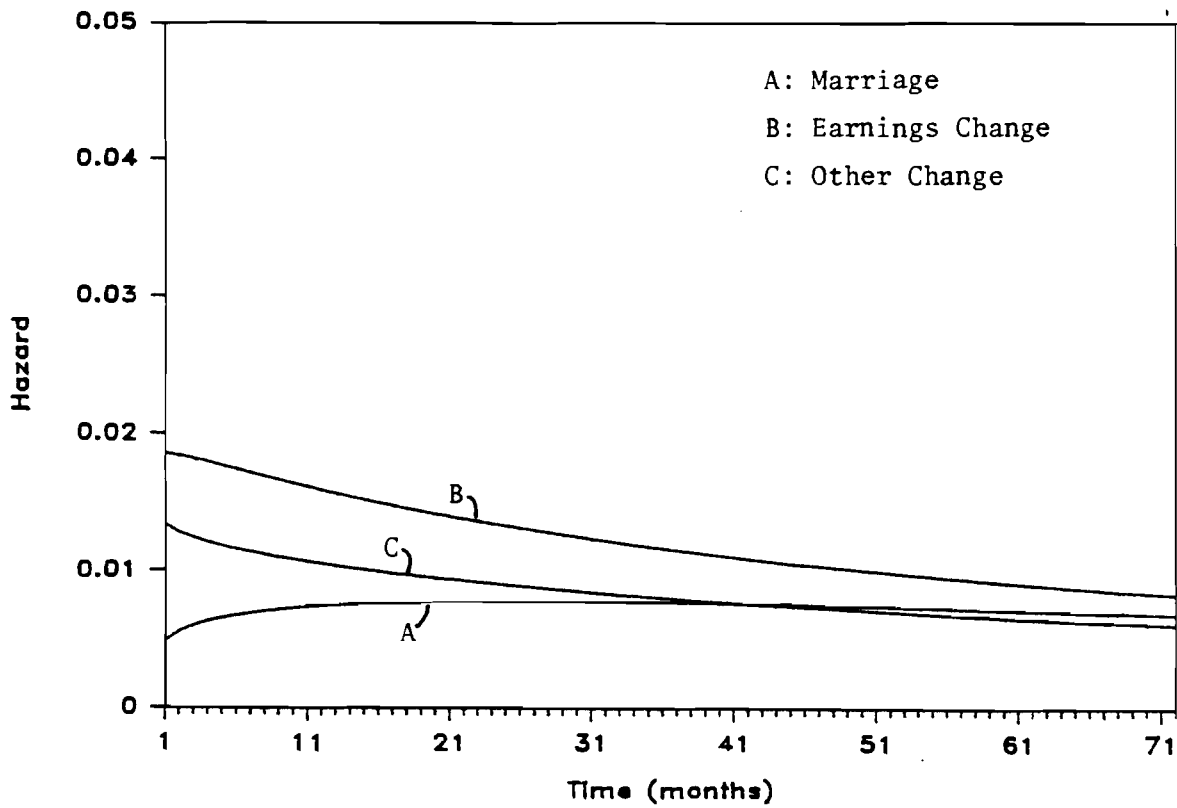
risk" of each of the categories), which means that the magnitude of each hazard rate will necessarily be lower on average than those estimated in previous models.

The hazard rate that is of most interest in the competing risk model is that for leaving welfare via earnings increases.[29] While the hazard rates in earlier models showed some increases in the early months on AFDC, the competing risk hazard for earnings change clearly has no such property. The hazard decreases steadily over time, although the rate of decrease is very small. The lack of an initial "rising period" in the competing risk earnings hazard seems puzzling in relation to the earlier estimates. However, there are reasons to believe that the competing risk estimates are somewhat less reliable. First, each hazard rate in the competing risk model is estimated with many fewer data (limited to those who leave via that category). This means that the earnings hazard is determined primarily by those 108 spells that end with earnings increases; this is probably an insufficient number to adequately deter- mine the shape of a 72-period hazard rate.[30] Since the hazard rates in Tables 4 and 6 were estimated from a much larger set of data, they should be more reliable.

Second, one can calculate a goodness-of-fit measure to compare the estimates in Tables 6 and 7 (given at the bottom of these tables). This is based on a Pearson chi-squared statistic, comparing the actual versus the predicted number of people who either complete a spell of a given length, or are censored after a given period of time (144 potential categories.) The heterogeneity model has a distinctly lower goodness-of- fit number, indicating that the predicted fit from this model is closer to the pattern of the actual data.[31]

Several conclusions result from the estimates in Tables 6 and 7. First, there is evidence that some significant degree of heterogeneity exists in the data. This is one reason for falling hazard rates in the aggregate data. Second, for a significant number of people (group one in the heterogeneity estimates, and those at risk of marriage or other changes in the competing risk model) there is no evidence of time-dependent effects in their propensity to leave AFDC. For these AFDC participants, the data do not support a model of welfare dependence. Third, for other groups, the conditional probability of leaving AFDC does vary over time. It may be flat or rising in the early months on the program, but in all models there is some significant portion of time over which the hazard rate falls for some AFDC participants. For these groups, this falling hazard is consistent with a welfare dependence story. Finally, the parameter estimates from the competing risk model indicate that race is an important variable in explaining welfare usage because it is correlated with different marriage probabilities, not because of its effect on other variables.

A SIMULATED MODEL OF AFDC PARTICIPATION WITHOUT DEPENDENCE

We started this paper by asserting that a declining hazard was consistent with a model of duration dependence. Had we found no evidence of declining hazards, that would have been a strong argument against welfare dependence as we have defined it. However, we have found evidence that hazard rates for leaving AFDC do decline, although not over all spell lengths and not for all individuals. The next step is to ask whether this is sufficient evidence to conclude that some degree of welfare

dependence exists. I will investigate this question by building a model of income change which is unaffected by participation in AFDC. I can simulate expected income over time for each of my AFDC households from the SIME/DIME data. The AFDC participation decision will be based on a simple comparison of whether simulated income is above or below the break-even point.[32] This will produce a set of simulated welfare spells. To do so requires moving from the purely data-descriptive techniques of hazard rates to an explicit model of income dynamics. If the hazard rates that describe the data in the above models can be duplicated in the simulated data without assuming any time-dependence effects of welfare participation, then those declining hazards are not sufficient proof of welfare dependence.[33]

Assume that earned income moves over time according to the autocorrelated model:

(15) Y_t = Yperm + e_t, where e_t = αe_{t-1} + v_t.

Y_t is earned income in period t; Yperm is long-run expected permanent earned income; and v_t is a normally distributed random error term with mean zero. In this model, earnings diverge from their long-run level as random shocks occur and slowly die out over time. Given a starting value, e_1, an estimate of Yperm, and estimates of α and σ_v, the standard error of v, I can generate a stream of income expectations for a household. If the starting point for the model is the first month of AFDC participation, the expected income for a household in each succeeding period can be generated and compared with the AFDC cutoff point for that household. When expected income crosses the cutoff point, the household

is assumed to leave AFDC. This creates a sample of simulated AFDC spells; the estimated hazard from these simulated spells can be compared with the hazard estimated from the actual data. Note that these simulated spells have no welfare dependence effects; the generated stream of household earnings is unaffected by AFDC participation.[34]

The Appendix contains a description of how the starting values for this simulation are produced and describes the simulation more fully. Briefly, I use estimates for α and σ_v derived from a very similar data set. Yperm is calculated for each household, using coefficients estimated from the monthly earnings of a sample of female-headed households in the SIME/DIME who do not participate in welfare. (Yperm is determined by the typical set of household characteristics which enter most human capital wage equations.) Households are assigned their actual observed earned income in the first month on AFDC (Y_1). Income in the second period is calculated using equation (15), where $e_1 = Y_1 - Yperm$. A random number generator which selected from a normal distribution with variance σ_v was used to generate values for the random income shock, v, in each period.

For much of my sample, this model implies that an AFDC spell starts with a large negative "shock" to income. (Many women have zero earnings during their first month on AFDC, so $Y_1 - Yperm = -Yperm$.) Over time, the earnings stream should converge back towards Yperm. An AFDC spell ends when estimated income exceeds the estimated break-even point for a household. Spells are censored if they are still in progress when the SIME/DIME sample period is over. (Each spell is assumed to start at its actual calendar time.)

The spells generated by this simulation are summarized in Table 8, which can be compared to the actual data in Table 1. Table 8 shows that 188 spells were censored—very close to the 185 censored spells in the actual data. The expected length of a completed spell is somewhat longer in the simulated data (20 months) than in the actual data (13 months).

This simulated spell data is used to estimate a log-logistic model of AFDC duration, identical to that presented in column 2 of Table 4. The results of this estimation are in Appendix Table A. Given the nature of the simulation, it is not surprising that most exogenous variables have insignificant coefficients. Figure 9 provides a graph of the resulting hazard function. For comparison, Figure 9 also graphs the earnings hazard from the competing risk model and the hazard function from the simple log-logistic model in Table 4.

The hazard function resulting from these simulated welfare spells is very revealing. The hazard has a somewhat similar shape to that estimated by the log-logistic model in Table 4, although it starts at a lower point and rises more slowly. It rises for 24 months, then falls steadily throughout the rest of the period.[35] The reason behind this decline is clear; a significant number of AFDC participants cross the income threshold out of AFDC in the initial months, but over time, those who are left cross at a decreasing rate. Those whose permanent income is close to (or below) the break-even point, or those who receive further negative income shocks, remain on AFDC longer. Over the range in which it decreases, the rate of decrease is very similar to the decrease observed in the earnings hazard from the competing risk model; the two lines essentially parallel each other at different magnitudes.
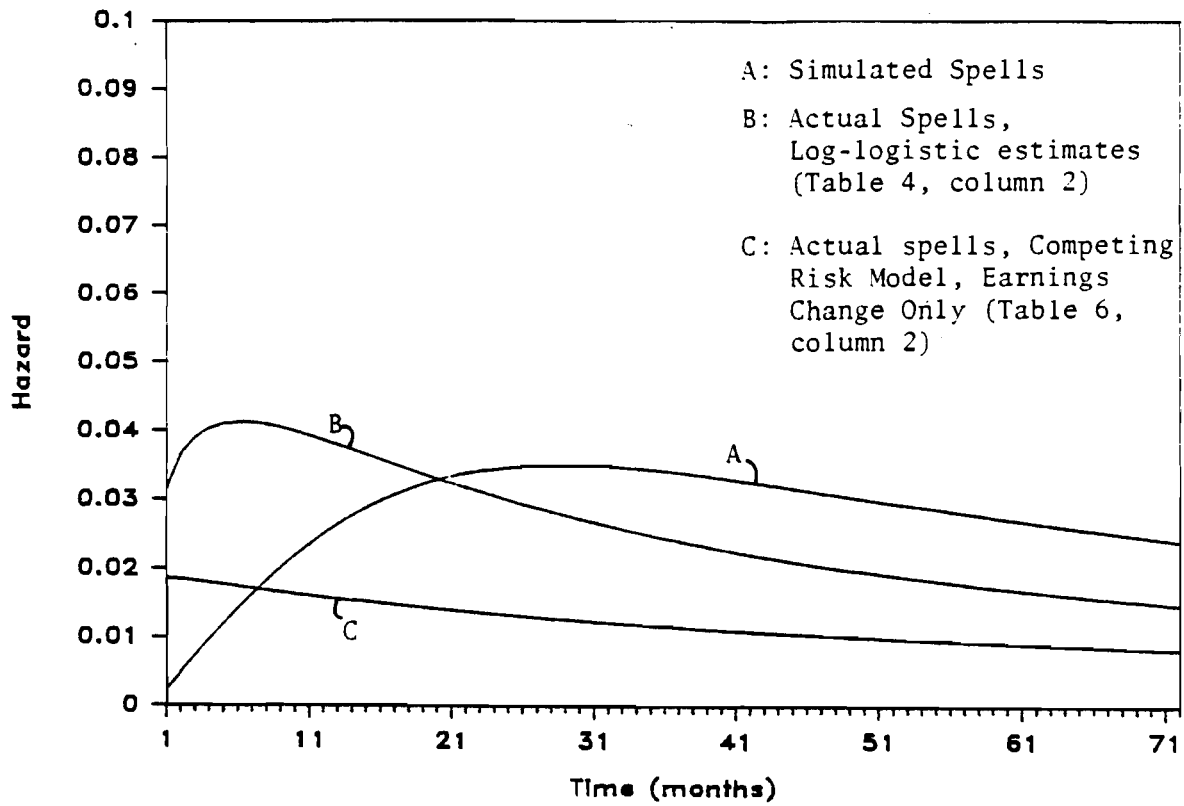
Table 8

Spell Distribution of Simulated Spells

Time	Completed Spells		Censored Spells	
	Number Completed in:	Cumulative % Completed in:	Number Censored after:	Cumulative % Censored after:
2 months	28	9%	6	3%
6 months	53	17	22	12
12 months	109	34	44	23
24 months	227	71	82	44
48 months	305	95	146	78
72 months	320	100	188	100

Note: Expected length of completed spells is 19.6 months.

FIGURE 9

Simulated Hazard Rate vs. Actual

A: Simulated Spells

B: Actual Spells,
   Log-logistic estimates
   (Table 4, column 2)

C: Actual spells, Competing
   Risk Model, Earnings
   Change Only (Table 6,
   column 2)

The primary conclusion from this simulation is that a declining hazard has no necessary relationship to welfare dependence. Indeed, a very simple model of income change with no AFDC dependence effects can produce a declining hazard that is somewhat similar to those hazards estimated from models using actual data. This simulation casts doubt on whether the fact that hazard rates do decline for some participants over certain spell lengths provides any evidence of welfare dependence. It also calls into question previous studies of welfare dependence which take declining hazards to be proof that welfare dependence exists.

FINAL COMMENTS

A few comments need to be made on the interpretation of these results and their relationship to previous work on welfare dependence. In comparison to Bane and Ellwood, I find shorter spells of welfare use[36] and less evidence of duration dependence. Many of the estimated hazard rates in this paper show either no evidence of duration dependence, or show only a very moderate decrease over time. In large part, this is probably due to the use of monthly data versus annual data, which smooths together multiple spells of welfare. In addition, these differences must also be due to the shorter time period of my data and the focus on single spells of welfare. If Ellwood is correct in finding greater duration dependence over a longer time period, then results from multispell models should show more evidence of duration dependence.

The simulation results in this paper indicate the danger of drawing causal inferences from purely data-descriptive techniques. Even the

presence of significant duration dependence in welfare spells may not reflect any program-induced effects. This highlights the need to build and test explicit causal models of welfare participation in future research.

It is important to note that one should not interpret the results in this paper as indicating that few women stay on welfare a long time. In fact, the heterogeneity estimates indicate that the probability of leaving AFDC is very low for more than half of the sample; these women will clearly rely on welfare as a long-term source of income support. The primary point of this paper is that these long spells are neither created nor lengthened by the use of AFDC itself. The results of this paper indicate that the welfare population is exceptionally diverse (a conclusion also emphasized by Ellwood): some women within it leave welfare quickly, while others have few nonwelfare opportunities. Further evidence of the fact that some women have few options outside welfare comes from the calculation of permanent income which I made for every household in order to complete the simulation in the previous section. For almost one-third of the households, estimated permanent income levels were below AFDC break-even levels.

Finally, this study also emphasizes the close links between AFDC usage and household composition change--particularly marriage and remarriage rates. This issue deserves a great deal more research attention than it has received. Until we have better models of household formation and change, we will be unable to estimate better causal models of AFDC recipiency.

Notes

[1]See, for example, Moffitt (1983), Ellwood and Bane (1984), Blank (1985).

[2]See Moffitt (1983) or Blank (1985). Plant (1984) looks primarily at single participation decisions, but has some multiperiod analysis.

[3]When Ellwood redoes his analysis using O'Neill et al.'s (1984) definitions for AFDC spells, he eliminates most (but not all) of the differences in results.

[4]The use of discrete duration models may be particularly questionable when the welfare spell is based on annual data, a clear aggregation.

[5]One exception is a study by Feaster, Gottschalk, and Jakubson (1985), which uses monthly informaiton on AFDC recipients in Wisconsin to investigate the impact of the 1981 legislative changes on length of AFDC spells.

[6]Bane and Ellwood (1983) and Ellwood (1986) test the effect of not counting years when the amount of welfare received is very small, and find little change in their results.

[7]Of course, it would be preferable to have monthly data available for as long a period of time as the annual panel studies. My data will provide less information on multiple spells and on long spells, but it should provide more precise information on AFDC usage within the six-year period that it covers. The prospect is bleak for obtaining a longer sample of monthly data than the 72 months available here. The newly developed Survey of Income and Program Participation (SIPP) panel follows household for 36 months before rotating them out of the sample.

[8]An exception is Gottschalk (1986), who investigates the impact of tax and transfer levels on welfare duration in a dynamic model.

[9]The most complete study of this issue is Ellwood and Bane (1984). For a discussion of earlier literature, see Bishop (1980) and MacDonald and Sawhill (1978).

[10]Note that this paper only deals with a situation where actual time spent on AFDC affects these variables. An alternative model might assume that it is the potential availability of AFDC which affects marriage propensities. This requires a different set of empirical tests and is not addressed in this paper.

[11]In particular, one cannot produce nonparametric estimates of both $g(\theta)$ and $f(t)$; at least one of the distributions has to take an explicit assumed form. Heckman and Singer suggest letting the unobservable take a nonparametric form. This is the approach used in this paper. However, Trussell and Richards (1985) indicate that this is just as subject to distributional biases as when the distribution of t is estimated nonparametrically.

[12]For the remainder of this section, I drop the time subscripts on the X vector for notational simplicity.

[13]This is the equivalent of estimating a set of exponential distributions (in which the hazard is constant) over different values of t. One could also arrive at this model by replacing the continuous time variables in (12) with dummies for different values of t.

[14]SIME/DIME was not a random sample of the population, but had an upper-income cutoff point at about median income. This will exclude all women who were in a high-income household at the start of the sample.

Since I am interested only in AFDC spells, to the extent that few women move from high-income households onto AFDC, this will not greatly affect my results. SIME/DIME also excluded those for whom labor market participation was not possible (such as the disabled).

[15]While my data covers a more limited time period than that used by other studies referenced above (which have annual data through the early 1980s), this should not create a serious problem of comparison. Moffitt (1986) finds evidence of a structural shift in AFDC participation between 1967-1973, but little evidence of any shift after that time period.

[16]There are some who leave the sample early, including migrants. In this study moving from the control group into the experimental group is also considered equivalent to leaving the sample.

[17]While there are techniques to adjust for left-censored data, they are cumbersome and often arbitrary.

[18]While I observe some multiple spells in my data, I choose not to work with them. First, they are highly selected, since the sample length permits only short-duration, closely spaced multiple spells to appear. Because I have no information outside of the six-year sample period, I have no basis on which to treat the observed multiple-spell participants differently from other participants, whose earlier or later spells may be censored or outside the sample. Second, the appropriate model for multiple spells requires a model of time both on and off AFDC (so that the probability of reentering AFDC for a new spell can be estimated). This is more than a simple two-state model, since time off AFDC may include marriage, higher earnings, periods without children, etc. Given the complexity of this task, together with the data problems, this paper is limited to an analysis of single spells.

[19]I have eliminated the remaining 21 inexplicable short spells off welfare by recoding the data to show a continuous spell. (The results are unaffected by this recoding.)

[20]The data in Table 2 were derived by looking at various causal variables for six months before a spell began and six months after it ended. Changes in marital or household status or in number of children were coded first. In the remaining data, if both labor market and other income changed, coding was determined on the basis of which involved the larger dollar change.

[21]When these five variables are set at their beginning-of-spell values and no time variance is allowed, quite different coefficients are estimated, both in value and significance. Likelihood values are significantly lower without time-varying exogenous variables.

[22]The coefficient values across columns in Table 4 are similar, but since each column is based on a different functional form, they are not directly comparable. However, elasticity estimates for the variables also show very similar patterns across all functional forms. This is not surprising, as the exogenous variables enter each distribution in a similar manner, through the term $\exp(\beta X)$.

[23]This variable also appears to act partially as a proxy for differences between the two locations. If a dummy variable is included for location in Seattle, its coefficient is insignificant, but the coefficient on benefit maximums becomes even smaller.

[24]Figures 3 through 9 graph the hazard rates for a black woman in Seattle of mean age (27), mean other income ($28/month), with 11 years of education and two children, one age 3 and the other age 7. Unemployment

and benefit maximums are also set equal to their mean levels, so the graphs indicate expected hazard rates for the mean individual, holding all exogenous variables constant.

[25]The lack of many spells longer than 45 months means that this long-term upturn in the hazard is very imprecisely estimated.

[26]Increasing the number of groups results in convergence problems. Using only two groups, I have tested for heterogeneity in the shape parameters (the p's) and in the β's. There is no evidence of heterogeneity in the β's. One can estimate a two-group model in which both the constants and the p's vary (this model will not converge for three groups.) However, the resulting two hazard rates look very much like those presented here: one is virtually flat and very low, and the other peaks sharply at a high level and then falls rapidly. Probability weights are evenly spread between the two groups. This estimate is not presented since it does not provide a great deal of additional information to the three-group model with varying constants shown here.

[27]Since there is no heterogeneity in this model, one could use a nonparametric procedure. However, the number of simultaneously estimated parameters in the competing risk model is large, and adding multiple shape parameters for each hazard would require unacceptably large amounts of computer time and money.

[28]This includes those whose income rises because of increases in nonearned income, those whose children leave home, and those whose reasons for leaving are unknown.

[29]The virtual flatness of the hazards for exiting AFDC through marriage or other changes indicates that there is no issue of time dependence in these types of exits.

[30]I have attempted to estimate a competing risk model, with heterogeneity in the probability of leaving via earnings increases. This model has serious instability problems, largely related to the very few observations from which it is trying to estimate heterogeneity effects within the earnings hazard.

[31]This measure is $\sum$ (Actual$_i$ - Predicted$_i$)^2/Predicted$_i$, i = 1,144. Note that while this measure is indicative of the comparative fit of both models, it is not a reliable statistic since its distribution is unknown. It does not provide a X^2 statistic since it does not account for the fact that the predicted model is based on estimated parameters. Unfortunately, with the censoring in the data, individuals each have a different number of periods during which they are "at risk." Goodness-of-fit statistics which correct for this problem (see Heckman, 1983) all require symmetrical data, in which each individual can potentially fall into every cell.

[32]This is similar to the model of AFDC participation that is presented in Ashenfelter (1983) and tested empirically with annual data in Plant (1984). It is also similar to the model of income change developed in Lillard and Willis (1978).

[33]Ideally, one would like to be able to directly translate a causal model of income generation into an estimable hazard model. This is typically not possible. Most dynamic models of income change require a set of flexible correlations between time periods. There are no easily estimated functional forms which allow for intercorrelations between more than 2 or 3 time periods.

[34]This model allows women to leave AFDC only through earnings increases. I have not allowed for the probability of leaving through marriage or other changes, largely because there is no obvious way of jointly modeling marriage, divorce, fertility, and income changes. My primary interest will thus be in comparing the shape of the generated hazard, not its magnitude.

[35]One reason for the longer rising hazard in the simulated data is that the simulation does not allow large and sudden jumps in income, as often happens when a woman finds a job. In the actual data, many of the early leavers seem to experience such jumps in the first few periods on welfare.

[36]Ellwood and Bane calculate a mean expected spell length of 5.2 years. Ellwood, using somewhat revised data, calculates a mean length of 4.4 years. My mean length (Table 5) is 3.1 years.

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Appendix

A SIMULATION MODEL OF INCOME CHANGE AND AFDC PARTICIPATION

The model of income generation is a simple autocorrelated procedure,

(A1) $\quad Y_t = Y_{perm} + e_t$, where $e_t = \alpha e_{t-1} + v_t$.

Simulated income for each household is generated starting with the first

period when they enter AFDC. In this first period their earned income is

set at its actual value (Y_1).

Yperm for each household is estimated by using those households in

June of 1973 (the mid-point of the sample) who were female-headed but did

not receive AFDC. Earned income among this sample was estimated with a

maximum likelihood equation in which the probability of labor market par-

ticipation and monthly earnings were estimated simultaneously. The coef-

ficients from this estimation were used to calculate expected earnings

among each AFDC household (conditional upon participation) as an estimate

of Yperm. (These estimates were adjusted for price changes between June

1973 and the months when the household was on AFDC.)

Estimates of α, the autocorrelation coefficient, and σ_v, the

standard error of the random term v, were taken from Ashenfelter and Card

(1985), who have a very similar sample of earners. Their research esti-

mates the structure of earnings from a national sample of low-income

women between the years 1970 and 1975 who then participated in the CETA

program in 1976. Their data was annual. Their estimated autocorrelation

coefficient is .791, which translates into a monthly coefficient of .98.

They find that 71.5 percent of the variation in income over time was due

to random variation. Calculating 71.5 percent of the variance in income

among my sample over time, I arrive at an estimate for σ_v of 89.65. (This is in dollars per month.)

In order to set the income-generation process running, I need an estimate of e_1, the "shock" to income occurring in the first period when these women enter welfare. I assume that this is equal to Y_1-Yperm, the difference between actual and predicted earnings in this first period.

With these parameters, earned income in the second period on welfare becomes

(A2) Y_2 = Yperm + e_2, where $e_2 = \alpha e_1 + v_2$.

v_2 is generated from a number generator which selects from a normal distribution, based on a zero mean and a standard error of 89.65.

In a similar fashion, I can generate earnings expectations from period 2 into the future.

Total income in each period is simply

(A3) $Ytot_t$ = Y_t + $Yoth_t$ + $Benefit_t$,

where Y_t is the earnings generated by the above model in period t, $Yoth_t$ is the observed other income of the household (provided in the data), and $Benefit_t$ is calculated according to the formula

(A4) $Benefit_t$ = $BenMx_t - t_p(Y_t - 30 + Yoth_t)$.

BenMx is the benefit maximum for the household's size and location. T_p is the participant tax rate, calculated according to the formula used in Blank (1985). The 30 represents the $30 set-aside in effect during this time period for AFDC participants. By definition, as a household nears the break-even level, Benefit approaches zero.

The AFDC break-even point occurs where Benefit=0. It is assumed that each household is on AFDC as long as $t_p(Y_t - 30 + Yoth_t)$ is less than $BenMx_t$. In the time period when this is no longer true, the household is assumed to leave AFDC, ending its welfare spell. Spells are assumed to begin in their actual calendar time, thus any household which has not left AFDC by the end of the SIME/DIME sample period is counted as censored.

Table 8 in the text presents a summary of the AFDC spells generated by this model. These spells are used to estimate a standard log-logistic model of welfare duration. The results of this estimation are presented in Appendix Table A. Few of the exogenous variables are significant, not surprisingly, since they have only indirect effects on spell length (through their effect on the estimate of Yperm, and on the estimate of $Benefit_t$).

Table A

Duration Model of Simulated Welfare Spells
(Number of observations = 508)

Variable	Log-Logistic Hazard
Constant	-2.915**
	(.461)
Age	.009*
	(.006)
Race (1 = Nonwhite)	.058
	(.095)
Education	.038
	(.032)
Number of Children < 6	.012
	(.085)
Total Number of Children	-.102
	(.113)
Other Income	.004**
	(.001)
Unemployment Rate	.003
	(.003)
Benefit Maximum	-.005**
	(.002)
P (Distributional Parameter)	1.999
	(.993)
Likelihood Value	-1340
Mean of Survivor Function (in Months)	28

*Significant at the 10% level.
**Significant at the 2% level.
Standard errors in parentheses.