A NON-EXPERIMENTAL ANALYSIS OF "TRUE" STATE DEPENDENCE IN MONTHLY WELFARE PARTICIPATION SEQUENCES

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1. INTRODUCTION

The substantial serial persistence exhibited in welfare participation over time is a well-documented empirical fact (e.g., Bane and Ellwood 1983). There are two potential explanations for this dependence in discrete outcomes that have been emphasized in the statistical literature (Heckman 1981a and c). On one hand, persistence may be the result of "true" or "structural" state dependence in which current participation directly affects the preferences or opportunities of individuals and, therefore, an individual's propensity to participate in the future. On the other hand, persistence can also result from permanent unobserved heterogeneity across individuals, in that individuals have different underyling propensities to experience an outcome in all periods. In this case, current participation does not structurally affect the future propensity to participate, but rather this source of serial correlation can be viewed as "spurious".

The debate over the impact of welfare programs hinges crucially on the ability to credibly estimate the degree of true state dependence. If welfare has "narcotic" incentive effects, then changing welfare program parameters, such as benefits levels, can reduce the average length of welfare spells. If most participation is due to permanent characteristics, then changing the nature of welfare programs will have little real effect. In addition, accounting for true lag adjustment in participation is necessary for obtaining consistent estimates of the long-run impact of changing welfare benefits. Finally, since the outcomes examined are discrete, the existence of true state dependence suggests that small shocks to the process underlying the participation decision could have discontinuous, lasting effects.

This study attempts to differentiate state dependence from spurious serial correlation in nonlinear outcomes. The ideal analysis of the relationship between current and past participation would involve a controlled experiment in which the researcher randomly assigns program participation across individuals and then observes differences in participation sequences in subsequent periods. Due to the lack of experimental data with a rich time-series, this study examines "semi-parametric" non-experimental methods in which the longitudinal structure of the data is used to control for confounding biases. The approaches used non-parametrically adjust for permanent heterogeneity bias.

The key advantage of this study is that it analyzes unique and reliable administrative data from California that contain many families (over 60,000) observed over a long period (4 years) at frequent intervals (monthly). This rich data allows us to precisely test for the presence of duration dependence in binary welfare participation sequences using relatively unrestricted models. Specifically, we examine rarely used dynamic "fixed effects" conditional logit models (Cox 1958 and Chamberlain 1985), which do not require specification of the distributions of either the unobserved heterogeneity or the initial conditions. The analysis leverages the multiple spells that each case experiences to obtain estimates of the duration dependence that are independent of the mixing distribution of the unobservables. Consequently, these methods are less parametric than the ubiquitous single-spell duration models often used to address this question. Another attractive feature of these models is that the "counterfactual" groups of families that are used to identify true path dependence are transparent.

In the conditional logit model that absorbs individual-specific first-order Markov chains, the hypothesis of no second-order state dependence is easily rejected in our data. This suggests that past welfare participation predicts future participation given the present state and unrestricted heterogeneity, and provides evidence that duration dependence exists at the individual level. The estimates of the duration dependence vary slightly by the characteristics of the case, and aggregating the monthly data to the quarterly and semi-annual levels leads to severe attenuation in the estimated path dependence. The patterns in our administrative data strongly suggest that welfare durations cannot be represented by a mixture of exponential distributions.

2. CONDITIONAL LOGIT MODELS

2.1 Background on Welfare Dependence

In the econometrics literature, it is well-established that identification of binary response panel data models that allow for both unobserved heterogeneity and state dependence is very tenuous, especially for the typical case of a data set with many individuals but a small number of time periods. A fundamental issue that arises is accounting for the effects of both the heterogeneity and the unobserved initial conditions of the dynamic process on the estimated parameters (Heckman 1981b).

An example of a dynamic panel data model of welfare participation that allows for unobserved heterogeneity and first-order state dependence is:

$$y_{it} = 1(\, y_{it}^* > 0) = 1(\gamma y_{it-1} + \alpha_i + u_{it} > 0);$$
$$i=1,\ldots,N;\ t=1,\ldots,T,$$

where y_{it} is the welfare participation outcome for individual i in period t, $1(\bullet)$ is an indicator function equal to one if the enclosed statement is true and zero otherwise, y_{it}^* is the latent process that guides the participation decision, α_i is an unobserved individual-specific effect, and u_{it} is the transitory error which is assumed to be i.i.d. over time. In our context, γ is the parameter of interest since it represents true state dependence in participation (i.e., the "welfare trap"). A positive γ implies that participation in the previous period causes a greater likelihood of participation in the current period. The term α_i, on the other hand, is the source of spurious serial correlation attributable to permanent unobserved differences across individuals in earnings potential and tastes for leisure. It allows for the possibility that different individuals have permanently different propensities to be on welfare in all periods.

Few studies have tried to account for the contribution of unobserved heterogeneity to the serial persistence in welfare participation. Blank (1989) and Sandefur and Cook (1997) estimate single-spell duration models in which the unobserved heterogeneity distribution is restricted to be a discrete random variable. Plant (1984), on the other hand, estimates a three-period panel data probit model of participation that assumes that the heterogeneity is normally distributed. All three studies conclude that much of the observed serial dependence in welfare participation is attributable to individual heterogeneity and not state dependence. However, their estimates are very imprecise due to the small samples (fewer than 1,000 welfare recipients) used in the analyses. Fortin and Lacroix (1997) estimate a proportional hazard model that specifies the heterogeneity to be a multiplicative factor in the hazard. Their estimates converge for only one of the many demographic groups examined. Other examples of studies that have examined welfare spell lengths are Gritz and MaCurdy (1992), Hoynes and MaCurdy (1994), and Gottschalk and Moffitt (1994).

2.2 Conditional Logit Analysis of Binary Sequences

In the absence of a controlled experiment, non-experimental econometric methods are the only alternative for estimating the amount of path dependence in welfare participation. We examine "fixed-effects" conditional logit models in which no assumptions are required on the mixing distribution of the unobserved individual effects. Instead, certain restrictions on the distribution of the transitory errors imply that the unobservables can be "absorbed" with the proper conditioning statement in the likelihood analysis. We illustrate this for the cases in which the individual is observed for at least 4 and 6 periods, respectively. With access to additional time periods, one can match on richer participation sequences when estimating duration dependence. The conditional logit model crystallizes the "treatment" and "control" groups that are used to identify the effect of the past on the present (and future).

If individuals are observed for at least four periods, then it is possible to identify the logit binary response model that allows for both unobserved heterogeneity and first-order state dependence. Cox (1958) shows that if the transitory errors have an i.i.d. logistic distribution, then there exists a set of sufficient statistics that absorb both the individual effects and initial conditions when conditioned on. The model is:

$$P(y_{it} = 1|\alpha_i,\, y_{i1},\ldots,y_{it-1}) = \frac{\exp(\gamma y_{it-1} + \alpha_i)}{1+\exp(\gamma y_{it-1} + \alpha_i)}.$$

The set of sufficient statistics is $B \equiv \{y_{i1},\, y_{iT},\, s\}$, where $s = \sum_{t=1}^{T} y_{it}$ is the sufficiency class. Then we have the following conditional probability:

$$\text{(1)} \qquad P(y_{i1},\ldots,y_{iT}|B) = \frac{\exp\left(\gamma \sum_{t=2}^{T} y_{it} y_{it-1}\right)}{\sum_{d\in B} \exp\left(\gamma \sum_{t=2}^{T} d_t d_{t-1}\right)},$$

where the relationship between the initial observation and the unobserved heterogeneity is left unspecified. Consistent identification of γ is based on the fact that this conditional probability does not depend on the incidental parameters, α_i. In addition, conditioning on y_{i1} and y_{iT} addresses both the problems of initial conditions (left censoring) and right censoring, respectively.

Under the null of no first-order state dependence, the model suggests that individuals within the same sufficiency class and with the same realizations in the first and final periods are "exchangeable" and, therefore, provide a valid counterfactual for what would have occurred in the absence of state dependence. Within a particular conditioning group B, sequences in which individuals participate in adjacent periods should be no more prevalent than sequences that have less "clumping" of participation, if there is no state dependence. Systematic deviations from this in a sample of welfare cases provide evidence of state dependence. When T=4, the following pairs of sequences give conditional probabilities that depend on

γ; (1100 vs. 1010) and (0011 vs. 0101). The only difference between the sequences is the "path" taken in the two intervening periods that connect the same initial and final points. Differences in the observed probabilities of these binary sequences lead to inferences on the amount of path dependence in the process. Estimates of γ are based on maximizing the sample log-likelihood analog of (1).

Chamberlain (1985) notes that tests for the presence of first-order state dependence in binary sequences, even those which condition out individual heterogeneity, may not be strict tests of true duration dependence. Specifically, the interpretation of measured serial correlation at the individual level depends on the interval between periods of observation. As the interval goes to zero (e.g., continuous time), the probability that a person who participated last period will participate this period goes to one. Consequently, a more substantive test of duration dependence in binary sequences may be to see whether an individual's past can predict the future <u>conditional on the current state</u>. Deviations from a first-order Markov property would provide evidence of duration dependence at the individual level that is insensitive to the sampling frame. This framework provides a non-parametric test of the hypothesis that the welfare spells can be represented by a mixture of exponential distributions (Heckman, Robb, and Walker 1990). Residual serial dependence that remains after allowing for an "infinite" mixture leads to a rejection of the hypothesis.

Under the assumption of i.i.d. logistic errors, Chamberlain (1985) derives a conditional logit estimator for second-order state dependence that allows each individual to have individual-specific first-order Markov chains. If individuals are observed for at least six periods, then there exist sufficient statistics for two sets of individual-specific incidental parameters and for the initial conditions. The model is:

$$P(y_{it} = 1|\alpha_i, y_{i1},\ldots,y_{it-1}) = \frac{\exp(\alpha_i + \gamma_{1i}y_{it-1} + \gamma_2 y_{it-2})}{1+\exp(\alpha_i + \gamma_{1i}y_{it-1} + \gamma_2 y_{it-2})}.$$

Sufficient statistics for the incidentals (α_i and γ_{1i}) and initial conditions are $B \equiv \{y_{i1}, y_{i2}, y_{iT-1}, y_{iT}, s, s_{11}\}$, where $s_{11} = \sum_{t=2}^{T} y_{it}y_{it-1}$ is the total number of times individuals participate in adjacent periods. It follows that:

$$\text{(2)} \qquad P(y_{i1},\ldots,y_{iT}|B) = \frac{\exp\left(\gamma_2 \sum_{t=3}^{T} y_{it}y_{it-2}\right)}{\sum_{d\in B}\exp\left(\gamma_2 \sum_{t=3}^{T} d_t d_{t-2}\right)}.$$

This conditional probability does not depend on the incidental parameters.

Under the null of no second-order state dependence, the model suggests that sequences within the same conditioning group B should be equally likely to occur. The existence of duration dependence implies that individuals within the same conditioning group should be more likely to experience sequences in which they participate in every other period than sequences in which they do not. When T=6, the following pairs of sequences give conditional probabilities that provide information on γ_2; (101000 vs. 100100), (000101 vs. 001001), (010111 vs. 011011), and (111010 vs. 110110). To the extent that the first sequence in each pair occurs more often in the data, the observed relative probabilities suggest the existence of path dependence in the process.

There are two important points about equation (2). First, the conditional logit estimator identifies the duration dependence by comparing groups of individuals with similar sequences. As more time periods are observed, one can be more "judicious" about which comparisons will identify the structural state dependence due to the additional information that can be conditioned on. Matching individuals within a conditioning group, the analysis attempts to determine which path/sequence is more likely to occur.

Second, it is clear that the estimated path dependence is identified from multiple spells on and off welfare for a given individual. For example, in the 6-period case, only individuals with two spells on welfare and two spells off welfare provide information on second-order state dependence. In popularly used single-spell duration models, identification of duration dependence relies heavily on moment or tail conditions on the heterogeneity mixing distribution (Elbers and Ridder 1982, Heckman and Singer 1984 and 1985, Honoré 1990, Ridder 1990, Horowitz 1999). Heckman (1991) concludes that these identifying assumptions are not verifiable and often drive the results. Honoré (1993) shows that access to multiple spells facilitates the identification of duration dependence without any assumptions on the mixing distribution. However, he does not derive an estimator. The conditional logit fixed-effects approach makes no restrictions on the form of the heterogeneity, while incorporating multiple spells in an intuitive and simple manner.

Before proceeding, we note two caveats with our analysis. First, the above logit models do not allow for time-varying "exogenous" covariates. Honoré and Kyriazidou (1997) derive a consistent conditional logit estimator of a model that allows for first-order state dependence and exogenous covariates. However, when Chay and Hyslop (1998) apply this estimator to survey data on welfare participation, they find little evidence that allowing for covariates (children and marital status) affects the estimated state dependence. In addition, we find below that an important time-varying covariate in our context, number of children in the case under 6 years of age, is changing very similarly in the comparison groups used to identify second-order state dependence. Finally, note that equation (2) implies that the analysis will only be confounded by omitted variables that exhibit very frequent changes.

Another caveat is that equations (1) and (2) rely on the assumption that the transitory errors have a logistic distribution function. Although not providing direct evidence, we found that random effects probit models that allow for serially correlated errors (Gourieroux and Monfort 1993, Hyslop 1998) and instrumental variables linear probability models (Anderson and Hsiao 1981, Arellano and Bond 1991) generated similar estimates of the first-order state dependence.

3. DESCRIPTION OF ADMINISTRATIVE DATA

A great deal of information is absorbed in equation (2) to "non-parametrically" condition out the unobservable incidental parameters. Consequently, these models may not have much power in detecting state dependence in the small samples generally used in the literature. A large and rich administrative data set, on the other hand, could allow for a meaningful empirical implementation of these unrestricted tests for path dependence.

This study uses the *Longitudinal Database of Cases* (LDB), which is administrative panel data providing information on monthly welfare participation for 10 percent of all Medicaid (or Medi-Cal) cases in California from 1987-1995 (UCData 1995). The data file is constructed from a 10 percent sample of all Medicaid recipients in January 1987 and 10 percent samples of all "new" cases that start in each year from 1987 on. A new case corresponds to a person who has not received Medi-Cal since January 1987. The data, which are based on administrative records, contain monthly recipiency information from the time the case is first observed through the end of 1995. Each case is followed as it moves into and out of welfare recipiency. The data also contain case characteristics such as age and race/ethnicity of the parent(s) and the number and ages of the children in the case.

Our analysis focuses on individuals in the 1988-1991 cohorts of the LDB who receive AFDC, where the cohort is defined by the year in which the AFDC case entered the sample. Consequently, all of the cases in our sample are observed for at least 48 months. We do not use the cases in the 1987 cohort because the vast majority of their welfare spells are left censored. We construct a balanced panel that follows 62,040 cases for the first 48 months after their initial entry onto AFDC. For computational reasons, our analysis of monthly welfare participation sequences focuses on recipiency status in the first 32 months. To examine the sensitivity of the estimates of duration dependence to time aggregation, we also pool the 48 months of participation data into 16 quarterly and 8 semi-annual periods, respectively. Here, a case is recorded as being on AFDC if it participated in any month during the quarter or 6-month period.

This data set is uniquely suited for our analysis for several reasons. First and foremost, the size of our sample is unprecedented, in terms of the number of cases and the length and frequency of observation. The richness of the data allows for a precise and powerful implementation of the semi-parametric tests for the presence of true welfare dependence described above. Second, since the data are based on administrative records, the welfare spells are measured more reliably than those from survey data. In particular, there is strong evidence of recall error in retrospective surveys that leads to severe "seaming" in the constructed welfare spells (Marquis and Moore 1990). Thirdly, California contains about 15 percent of the nation's AFDC caseload, more than twice the size of the next largest state (U.S. House of Representatives, 1994).

In addition, since the initial period of observation coincides with the actual start of each spell in our sample, the analysis circumvents the problem of initial conditions and left censoring (Heckman and Singer 1985). Finally, the receipt of AFDC benefits requires satisfying California's eligibility criteria on a <u>monthly</u> basis. Although it is not clear that each family makes their participation decisions from month-to-month, the periodicity of our data does have some natural significance. As a result, examining the above discrete time models with monthly participation data may not be a bad approximation to the agent's decision process relative to continuous time duration models (Heckman and Singer 1985).

4. EMPIRICAL RESULTS

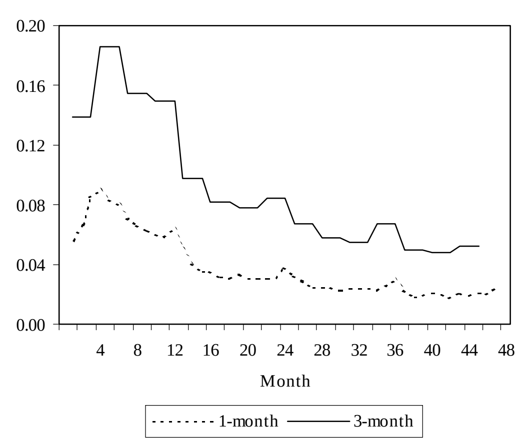

Figure 1: Kaplan-Meier Monthly and Quarterly Empirical Hazards

Figure 1 presents the empirical welfare hazard functions derived from the non-parametric Kaplan-Meier estimator applied to the pooled welfare spells constructed from both the monthly and quarterly participation sequences. As has been documented in other data sets, the estimated probability of leaving AFDC is declining in the length of the welfare spell for both types of spells. Although there is some evidence of seaming in the LDB data (i.e., a disproportionate number of spells end in December and begin in January), it does not account for the strong secular declines in the monthly hazard rates. However, changes in the composition of the cases could also explain the declining hazards, and this figure may mask these potential heterogeneity biases.

Table 1 provides a first pass at examining first-order state dependence in the 32-month participation sequences, purged of fixed sources of bias. In the Cox (1958) conditional logit model, the sufficiency class, s=

Table 1. Actual and Expected Number of Observations by Conditioning Group and S11
Under Null Hypothesis of No 1st Order State Dependence
32-Period Monthly Sequences

Tabulations for 10 Largest Conditioning Groups

Conditioning Group: Sufficiency Class	*Conditioning Group: P_1,P_{32}*	*S11*	*Actual N*	*Exp. N*
32	(1,1)	31	13355	13355
3	(1,0)	0	7	2734
		1	103	405
		2	3036	7
4	(1,0)	0	4	2197
		1	9	791
		2	194	61
		3	2842	1
5	(1,0)	0	0	1500
		1	1	1044
		2	17	196
		3	272	10
		4	2460	0
6	(1,0)	0	0	964
		1	0	1148
		2	3	417
		3	29	54
		4	341	2
		5	2213	0
2	(1,0)	0	78	2186
		1	2183	75
7	(1,0)	0	0	501
		1	0	948
		2	1	593
		3	4	151
		4	31	15
		5	369	1
		6	1803	0
8	(1,0)	0	0	240
		1	0	690
		2	0	690
		3	1	303
		4	5	61
		5	49	5
		6	380	0
		7	1554	0
31	(1,1)	29	1967	1967
9	(1,0)	0	0	98
		1	0	420
		2	0	643
		3	0	454
		4	4	158
		5	7	30
		6	63	2
		7	375	0
		8	1352	0

NOTE: The sample consists of monthly welfare participation over a 32-month period for 62,034 families. Actual N is the number of cases within a conditioning class (defined by sufficiency class, 1st and 32nd period participation), and S11 group ($\Sigma y_t y_{t-1}$). Exp. N is the expected number of cases under the null hypothesis of no first order state dependence (the product of the total number of observations within the conditioning group times the conditional probability (under the null) that this value of S11 should occur).

$\sum_{t=1}^{T} y_{it}$, and the realizations in the first and final periods (P_1,P_{32}) are sufficient statistics for the unobserved heterogeneity. If there is no state dependence conditional on the incidental parameters, one may observe different numbers of cases across "conditioning groups" (defined by s, P_1, and P_{32}), but would also see approximately the same number of cases in each sequence within a group. In the presence of first-order state dependence, one should observe more cases in sequences with consecutive 1's within a conditioning class.

Table 1 presents the frequencies of cases in the sequences of the 10 largest conditioning classes, which contain about 57% of all cases. Since there are 2^{31}=2.1 billion potential sequences a case can experience, we choose just these sequences for simplicity. The sequences are sorted by conditioning group and S11 (third column), which is the total number of times that an individual has two consecutive periods of participation ($\sum_{t=2}^{T} y_{it} y_{it-1}$). The final two columns provide the actual frequency of cases in each sequence and the "expected frequency", which is the number of observations that would be expected in the sequence under the null hypothesis of no first-order state dependence (γ=0). This is calculated by determining the total number of possible sequences within the group defined by sufficiency class, P_1, and P_{32}. The probability of each sequence occurring is then equal to 1/NP, where NP is the total number of possible sequences. These probabilities are aggregated up into groups for each value of S11. The expected frequency is equal to the S11 group probability multiplied by the total number of observations within the entire conditioning class.

The data rejects the null of no state dependence if there are more cases than expected in sequences with higher numbers of S11 and less cases than expected in sequences with lower numbers of S11, within a given class. Disregarding the two classes with only 1 value of S11, the patterns in the table clearly reject the null of no first-order state dependence. In addition, the actual and expected frequencies in all of the informative classes imply extremely large odds ratios for the relative likelihood that the sequence that exhibits greater state dependence will occur.

Next, we examine Chamberlain's (1985) conditional logit model testing for the presence of second-order state dependence conditional on individual-specific first-order Markov chains. As discussed above, controlling for sufficiency class, S11, and the first and last two periods of participation (P_1, P_2, P_{31}, P_{32}) absorbs a person-specific intercept, the initial conditions, and individual-specific first-order state dependence in the logit framework. We define S12 to be the number of times an individual participates in every other period during the 32 months ($\sum_{t=3}^{T} y_{it} y_{it-2}$). In the absence of second-order duration dependence conditional on the incidentals, one should observe approximately equal numbers of cases in sequences with different values of S12 that are in the same conditioning group.

Table 2 presents the actual and expected frequencies, under the null of no second-order dependence (γ_2=0), in the sequences of the 10 largest conditioning classes that provide identifying information. The sequences are sorted by the conditioning group and S12 values. The expected frequencies are calculated in a manner analogous to the procedure used for Table 1. For each sequence, the final two columns of the table show the average number of kids under 6 years of age in a case and the average change in the number of under-6 kids from the first to final periods. These provide a gauge of whether this important time-varying observable variable changed similarly over the period for the comparison groups used to test for the presence of duration dependence.

In the table, the data support the presence of second-order dependence, if, within a class, sequences with higher (lower) values of S12 have more (less) cases than expected. The patterns in the table seem to reject the hypothesis that the data can be represented by a mixture of exponential distributions. For all 10 classes, it is true that sequences with greater second-order dependence occur more often than expected. The evidence systematically supports the existence of duration dependence in welfare participation. In addition, the similarity in the averages of the covariates for cases in different sequences within the same groups, suggests that the results are probably not picking up spurious correlations.

Finally, Table 3 presents various estimates of the first- and second-order state dependence in monthly, quarterly, and semi-annual participation sequences, both for the whole sample of cases and for specific sub-groups of cases. The results come from maximum likelihood estimation of the logit models implied by equations (1) and (2). The likelihood that cases will experience sequences with greater state dependence can be calculated directly from the estimated state dependence coefficients. This probability is presented in brackets in the Table.

First, notice that for the overall sample, there is a substantial amount of first- and second-order dependence in monthly participation sequences, with estimated coefficients (5.84 and 0.648) that are highly significant. However, as one aggregates the periodicity of the data to the quarterly and semi-annual levels, the

Table 2. Actual and Expected Number of Observations by Conditioning Group and S12
Under Null Hypothesis of No 2^{nd} Order State Dependence
32-Period Monthly Sequences

Tabulations for 10 Largest Informative Conditioning Groups

Conditioning Group Suff. Class	$P_1,P_2,P_{31}P_{32}$	S11	S12	Actual N	Exp. N	Average Number of Kids<6	Change in Number of Kids<6
11	(1,1,0,0)	9	7	157	296	0.742 (.05)	0.197 (.05)
			8	181	54	0.689 (.05)	0.260 (.04)
			9	14	2	0.864 (.25)	-0.071 (.20)
8	(1,1,0,0)	6	4	219	278	0.562 (.04)	0.055 (.04)
			5	119	69	0.658 (.06)	0.160 (.05)
			6	12	3	1.156 (.44)	-0.083 (.15)
9	(1,1,0,0)	7	5	229	275	0.749 (.04)	0.140 (.04)
			6	102	60	0.537 (.06)	0.186 (.06)
			7	6	2	0.944 (.52)	0.167 (.17)
10	(1,1,0,0)	8	6	223	269	0.716 (.04)	0.126 (.04)
			7	93	53	0.694 (.07)	0.172 (.05)
			8	8	2	0.900 (.34)	0.000 (.19)
7	(1,1,0,0)	5	3	198	246	0.623 (.04)	0.071 (.04)
			4	111	73	0.395 (.05)	0.144 (.05)
			5	12	3	0.381 (.14)	0.251 (.13)
6	(1,1,0,0)	4	2	183	213	0.680 (.05)	0.158 (.05)
			3	88	80	0.631 (.07)	0.125 (.06)
			4	25	3	0.533 (.11)	0.120 (.07)
12	(1,1,0,0)	10	8	200	228	0.781 (.05)	0.135 (.05)
			9	61	39	0.687 (.05)	0.098 (.07)
			10	7	1	0.667 (.27)	0.143 (.26)
14	(1,1,0,0)	12	10	168	207	0.689 (.05)	0.196 (.05)
			11	68	33	0.700 (.07)	0.088 (.08)
			12	5	1	1.129 (.39)	0.200 (.20)
15	(1,1,0,0)	13	11	161	199	0.748 (.05)	0.323 (.07)
			12	68	31	0.624 (.07)	0.132 (.08)
			13	2	1	0.267 (.38)	0.500 (.71)
17	(1,1,0,0)	15	13	160	189	0.715 (.06)	0.050 (.06)
			14	57	29	0.808 (.09)	0.123 (.09)
			15	2	1	2.118 (1.8)	0.500 (.71)

NOTE: See NOTE to Table 1. Actual N is the number of cases within a conditioning class (sufficiency class, 1^{st}, 2^{nd} , 31^{st} and 32^{nd} period participation, S11), and S12 group ($\Sigma y_t y_{t-2}$). Exp. N is the expected number of cases under the null hypothesis of no second order state (the product of the total actual number of observations within the conditioning group times the conditional probability (under the null) that this value of S12 should occur). The average number of kids<6 is estimated over months in receipt of welfare; the change in the number of kids<6 is measured between the first and last months of welfare receipt (standard errors are in parentheses).

estimates of the path dependence become severely attenuated. This attenuation is particularly noticeable in the estimates of second-order state dependence, where semi-annual data lead to imprecisely estimated negative duration dependence.

Another noteworthy point is that the estimates of first-order state dependence are extremely large, not quite as sensitive to time aggregation, and vary only slightly across the stratified groups. In addition, estimates of the second-order dependence based on the monthly data are very precise for all of the groups examined. While they do reveal some heterogeneity in the amount of duration dependence across groups, the biggest source of sensitivity comes from time aggregation of the data. All of these results were previously unknown, and highlight how access to rich, administrative data facilitates the estimation of these semi-parametric conditional logit models.

Table 3. Fixed-Effects Estimates of 1st and 2nd Order State Dependence in Welfare Participation Sequences Based on Conditional Logit Models

	1st-Order State Dependence Estimates			*2nd-Order State Dependence Estimates*		
Sample of Cases Used	*8 Semi-Annual*	*16 Quarters*	*32 Months*	*8 Semi-Annual*	*16 Quarters*	*32 Months*
All Cases {62,040}	3.85 (.019)	4.77 (.013)	5.84 (.011)	-0.053 (.031)	0.149 (.022)	0.648 (.017)
	[0.979]	[0.992]	[0.997]	[0.487]	[0.537]	[0.657]
Black {10,551}		4.80 (.033)	5.76 (.028)		0.256 (.058)	0.820 (.041)
		[0.992]	[0.997]		[0.564]	[0.694]
Hispanic {16,066}		4.59 (.025)	5.67 (.022)		0.138 (.042)	0.555 (.034)
		[0.990]	[0.997]		[0.534]	[0.635]
White {24,769}		4.70 (.020)	5.79 (.017)		0.103 (.033)	0.594 (.028)
		[0.991]	[0.997]		[0.526]	[0.644]
15-19 Years Old {5,696}		4.40 (.044)	5.27 (.037)		0.118 (.067)	0.602 (.054)
		[0.988]	[0.995]		[0.529]	[0.646]
20-24 Years Old {9,690}		4.62 (.032)	5.64 (.028)		0.110 (.047)	0.695 (.041)
		[0.990]	[0.996]		[0.527]	[0.667]
25-30 Years Old {10,199}		4.72 (.031)	5.83 (.028)		0.067 (.048)	0.640 (.044)
		[0.991]	[0.997]		[0.517]	[0.655]
31-37 Years Old {8,972}		4.77 (.033)	5.92 (.029)		-0.032 (.044)	0.560 (.049)
		[0.992]	[0.997]		[0.492]	[0.636]
38-64 Years Old {6,710}		5.12 (.045)	6.16 (.037)		0.187 (.073)	0.705 (.061)
		[0.994]	[0.998]		[0.547]	[0.669]
0 Kids Under 6 {31,631}		4.84 (.019)	5.88 (.016)		0.170 (.032)	0.703 (.025)
		[0.992]	[0.997]		[0.542]	[0.669]
1 Kid Under 6 {23,721}		4.71 (.021)	5.81 (.019)		0.116 (.035)	0.594 (.029)
		[0.991]	[0.997]		[0.529]	[0.644]
2+ Kids Under 6 {6,688}		4.67 (.039)	5.82 (.034)		0.179 (.062)	0.573 (.057)
		[0.991]	[0.997]		[0.545]	[0.639]
One-Parent FG {50,615}		4.80 (.015)	5.86 (.013)		0.160 (.025)	0.687 (.020)
		[0.992]	[0.997]		[0.540]	[0.665]
Two-Parent UP {11,425}		4.64 (.031)	5.78 (.027)		0.102 (.049)	0.468 (.045)
		[0.990]	[0.997]		[0.525]	[0.615]
1988 Cohort {16,732}		4.65 (.024)	5.75 (.022)		0.067 (.046)	0.632 (.033)
		[0.991]	[0.997]		[0.517]	[0.653]
1989 Cohort {15,544}		4.70 (.026)	5.88 (.023)		0.094 (.041)	0.616 (.037)
		[0.991]	[0.997]		[0.523]	[0.649]
1990 Cohort {15,463}		4.79 (.027)	5.84 (.023)		0.230 (.044)	0.606 (.037)
		[0.992]	[0.997]		[0.557]	[0.647]
1991 Cohort {14,301}		4.99 (.030)	5.92 (.024)		0.245 (.051)	0.747 (.038)
		[0.993]	[0.997]		[0.561]	[0.679]
1st-Quarter Entry {25,869}		4.84 (.021)	5.83 (.017)		0.263 (.035)	0.751 (.027)
		[0.992]	[0.997]		[0.565]	[0.679]
2nd-Quarter Entry {12,465}		4.70 (.029)	5.82 (.026)		0.083 (.063)	0.615 (.041)
		[0.991]	[0.997]		[0.521]	[0.649]
3rd-Quarter Entry {13,872}		4.76 (.028)	5.89 (.025)		0.091 (.042)	0.524 (.040)
		[0.992]	[0.997]		[0.523]	[0.628]
4th-Quarter Entry {9,834}		4.70 (.033)	5.85 (.030)		0.042 (.036)	0.554 (.047)
		[0.991]	[0.997]		[0.510]	[0.635]

NOTE: Sample sizes are in {braces}; standard errors are in (parentheses); and probabilities are in [brackets]. The probabilities correspond to the fraction of cases with sequences that exhibit more state dependence as implied by the estimates: $p=\exp(\gamma)/[1+\exp(\gamma)]$. The estimates of the standard errors are based on the Huber formula for a robust estimator of the variance-covariance matrix.

5. CONCLUSION

The non-experimental analysis of the monthly binary sequences leads to several findings. Although not necessarily an appropriate test for duration dependence, the estimated first-order state dependence in monthly welfare participation, purged of individual effects, is substantial. In the conditional logit model that absorbs individual-specific first-order Markov chains, the hypothesis of no second-order state dependence is also easily rejected. This stricter test suggests that past welfare participation predicts future participation given the present state and unrestricted heterogeneity, and provides substantive evidence of the existence of duration dependence at the individual level. The estimates of the duration dependence vary slightly by the characteristics of the case. More importantly, aggregating the monthly data to the quarterly and semi-annual levels leads to severe attenuation in the estimated path dependence. Using fixed-effects models to test for duration dependence would not be fruitful for the much smaller survey data sets typically examined in the literature. The patterns in our administrative data strongly suggest that welfare durations cannot be represented by a mixture of exponential distributions.

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