CENTER FOR LABOR ECONOMICS
UNIVERSITY OF CALIFORNIA BERKELEY
WORKING PAPER NO. 47

Estimating the Dynamic Treatment Effects of an Earnings Subsidy For Welfare-Leavers

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March 2002

Abstract

In the Self Sufficiency Program (SSP) welfare demonstration, members of a randomly assigned treatment group could receive a generous earnings subsidy for full time work. The subsidy was available for up to three years, but only to those who initiated payments within a year of random assignment. We use logistic regression models with state dependence and unobserved heterogeneity to measure the effects of the subsidy program on welfare transitions. Because of the eligibility rules, members of the treatment group who qualified for the subsidy were a selective subset of the experimental population, confounding the measurement of SSP's treatment effects in the post-eligibility period. Moreover, the eligibility process had a direct effect on welfare participation, since those who received SSP payments become ineligible for welfare. We incorporate these features by modeling the endogeneity of eligibility status and estimating separate treatment effects for the pre-eligibility period, the post-eligibility period, and a transitional period. Our estimates suggest that SSP had both a short-run effect, associated with the establishment of eligibility, and a longer-run effect on welfare entry and exit rates, with a bigger long-run impact on exit flows.

*We are grateful to Ken Chay and Charles Michalopoulos for helpful discussions, and to SDRC for making available the data for this project. All findings and conclusions in this paper are solely the responsibility of the authors, and do not represent the opinions or conclusions of SDRC, MDRC or the sponsors of the Self Sufficiency Project.

Welfare policy makers have become increasingly interested in understanding the dynamic behavior underlying observed patterns of welfare participation. Part of this interest reflects a concern over the distribution of welfare use: depending on the incidence rate of new spells and the exit rate from existing spells, a given rate of welfare participation may be more or less concentrated among a small fraction of long term recipients.[1] Part also reflects a belief that policy interventions lead to behavioral changes in transition rates that only gradually affect the welfare caseload. Nevertheless, the estimation of policy effects on transition rates is difficult because the set of individuals who are on or off welfare at any time is highly selective. As emphasized by Ham and Lalonde (1996), even with a randomly-assigned policy intervention the estimation of dynamic impacts requires a complete specification of the process that leads to the observed welfare histories of different individuals.

In this paper we develop and evaluate a series of models that describe the behavioral impacts of a high-powered earnings subsidy offered to Canadian welfare recipients in the Self Sufficiency Project (SSP). SSP is an experimental welfare reform that supplements the earnings of welfare recipients who enter full time work. The subsidy is available for up to three years, *but only* to those who fulfil the eligibility conditions and begin receiving payments within a year of being offered the program. These features create three distinct incentive regimes. Prior to establishing eligibility, those who are offered the subsidy have an incentive to look for a full time job (or combination of jobs) that will satisfy the eligibility rules. For those who achieve eligibility there is an immediate "mechanical" effect on welfare participation, since the program rules disqualify supplement takers from welfare eligibility. Thereafter, eligible treatment group members can return to welfare at any time. The availability of the subsidy alters the tradeoff between work and welfare, however, potentially lowering welfare entry rates and raising exit rates throughout the post-eligibility period.

The SSP demonstration was conducted as a randomized experiment. One half of a group of

[1]See for example, Bane and Ellwood (1986), Blank (1989), and Gritz and MaCurdy (1992).

long-term welfare recipients in two Canadian provinces (British Columbia and New Brunswick) was randomly assigned to a treatment group, and offered the supplement, while the other half remained in the regular welfare system. Simple comparisons of the program group and the control group show that the supplement offer reduces welfare participation and increases employment and earnings.[2] Moreover, the time path of the program impacts roughly parallels the changing nature of the SSP incentives. In the first 15 months of the demonstration the welfare participation rate of the program group fell relative to the control group. In later months the participation rate of the program group stabilized while the controls gradually caught up, leading to an erosion of the program impact.

We use logistic regression models that include state dependence and unobserved heterogeneity to model the probability of welfare participation and measure the effects of the SSP subsidy on transition rates in the pre- and post-eligibility periods. A key issue is the selective nature of the subset of the program group that actually qualifies for a subsidy. We model the probability of achieving SSP eligibility in successive months as a function of the permanent individual component of the welfare participation model, and potentially of recent welfare outcomes. Our findings suggest that the selection effect is important: individuals with a higher probability of being on welfare in any period are less likely to achieve eligibility, and tend to achieve it later. As a result, differences between the observed transition rates of the SSP-eligible subgroup and those of the control group in the post-eligibility period significantly over-state the true causal effect of the supplement offer. We also find that monthly welfare participation exhibits second order state dependence – a finding that accords with other research using high frequency administrative data (e.g., Chay, Hoynes and Hyslop, 2001). Models with second order state dependence and a simple specification of individual heterogeneity provide a reasonably successful description of the welfare histories of the treatment and control groups in the SSP experiment.

[2]In the 5th quarter after random assignment 70.2 percent of the program group were still on welfare, compared with 83 percent of the control group. See Lin et al. (1998), Table 3.6.

In the next section of the paper we provide an overview of SSP and the experimental sample. We also briefly summarize SSP's effects on welfare participation rates and the labor market outcomes of the experimental group relative to the controls. We then present a series of models fit to the monthly welfare outcomes of the control group, and compare different specifications in terms of goodness-of-fit to the observed welfare histories. Next, we discuss the determination of SSP eligibility among members of the treatment group and the institutional link between SSP and welfare eligibility. We then present an empirical model that includes both the controls and the experimental group, and discuss the estimation problems caused by the endogeneity of eligibility status. Finally, we present estimation results for several versions of this model, and compare goodness-of-fit measures for the welfare histories of the program and control groups.

II. The SSP Demonstration

a. Income Assistance Programs and the SSP Experiment

The Self Sufficiency Project was designed to test of the effect of enhanced work incentives on the behavior of long-term welfare recipients in Canada.[3] Under the regular welfare system available to low income families, known as Income Assistance (IA), recipients who work have their welfare payments reduced by the full amount of their earnings beyond a modest set-aside amount.[4] The implicit 100 percent tax rate on earnings, coupled with the availability of other benefits for IA recipients (e.g., free dental services and free prescription drugs) reduce the incentives for people who have entered IA to work more than a few hours per week. Many observers have argued that these features lead to long-term

[3]SSP was conceived and funded by Human Resources and Development Canada. See Lin et al (1998) for a comprehensive description of the program and results from the first 18 months of the experiment.

[4]The IA program is operated at the provincial level, but all the provincial programs share several important features, including a dollar-for-dollar benefit reduction rate. See Human Resources and Development Canada (1993) for a detailed inventory and description of income support programs in Canada.

welfare dependency, as recipients gradually become detached from the regular labor market and more reliant on income assistance.

Under SSP, an individual who finds a full time job (or combination of jobs) receives a supplement equal to one-half of the difference between his or her actual earnings and a target level set well above the level of IA benefits available to most families. SSP raises the payoff to work relative to welfare, presumably leading some people to leave IA who otherwise would not. The incentive effects for those who would have left welfare on their own (i.e., in the absence of the program) are not as clearcut. For those who would have been off IA and working part-time, SSP provides a strong incentive to raise hours. For those who would have been off IA and working full time, however, there is a negative work incentive, since SSP raises income and lowers the marginal wage rate (see Blank, Card, and Robins, 2000). Unlike a more conventional negative income tax, the full time eligibility rule limits any potential responses to this disincentive effect.

Table 1 summarizes the main features of the SSP experiment, including the eligibility requirements and supplement formula. The experiment was conducted in lower mainland British Columbia (in and around Vancouver) and in southern New Brunswick, with random assignment between late 1992 and early 1995. Some 5,600 single parents were enrolled in the experiment and followed for a period of 5 years after random assignment, with surveys at the baseline (just prior to random assignment) and at 18, 36, and 54 months after random assignment.

Relative to other financial incentive reforms, such as those tested under the waiver programs in the U.S. in the early 1990s, SSP is very generous (see Blank, Card, and Robins, 2000). For example, a single mother in New Brunswick with one child was eligible for a maximum monthly IA grant of $712 in 1994. Her gross income if she were to leave IA and take a full time job at the minimum wage would be $867 per month -- a net gain of only $155 per month, or about $1 per hour of work. Under SSP, however, she would receive a monthly supplement payment of $817, raising the relative gain for work to

$972 per month, or about $6.50 per hour. The gain is smaller when taxes and transfers are taken into account, but is still relatively large (see Lin et al, 1998, Table G.1).

A key feature of SSP is time-limited eligibility. Individuals who initiated supplement payments within 12 months of random assignment could receive SSP payments for up to three years in any month that they were working full time. SSP recipients could not simultaneously receive conventional welfare payments, but they could return to IA at any time without losing their future eligibility. Those who failed to initiate an SSP payment within a year of random assignment lost all future eligibility.[5] The time limit creates a strong incentive to find a full time job within a year of random assignment. For a single mother with one child in New Brunswick, for example, total SSP payments could be as high as $29,000 – a very large sum for many of the people in the program.

b. The Experimental Sample and Program Impacts

The experimental population for the SSP demonstration consisted of single parents over 18 years of age who were currently in the IA system and had received welfare payments in at least 11 of the previous 12 months.[6] These requirements meant that nearly everyone had been on IA continuously in the year prior to random assignment. A very small number left IA between the time of their initial selection into the experimental sample and the completion of their assignment into either the treatment or control groups. To simplify our empirical models, however, we restrict attention to the 5,617 people who

[5]As we explain below, because of administrative and other delays the time limit is actually more like 14 months.

[6]No further limitations were placed on the sample. Thus, the experimental sample is in principle representative of the population of IA recipients who had been receiving welfare for a year or more in the two provinces. Roughly 90 percent of people who were contacted to participate in the experiment signed an informed consent decree and participated in the baseline survey, and were randomly assigned (Lin et. al, 1998, p.8).

were on IA in the two months prior to random assignment.[7]

Table 2 provides an overview of the characteristics of the SSP sample. The first two columns report the means for the control and program groups of the experiment, while the third and fourth columns show the means for program group members who were were either successful or unsuccessful in establishing eligibility. The experimental sample is about 95 percent single mothers, with a mean age of 32 and an average of 1.5 children per family. About 14 percent of the sample are immigrants -- nearly all in the Vancouver area. Sample members exhibit many of the characteristics that are usually associated with low income and high welfare participation, including a low rate of high school graduation (45 percent versus roughly 70 percent in the adult population of Canada), and a high probability of being raised by a single parent. Despite their disadvantaged background, nearly all sample members have participated in the labor market at some time in the past, with an average of 7.3 years of experience. In the three years prior to random assignment sample members spent an average of about 30 months on IA. Forty percent had been on IA continuously over the entire three years.

SSP has significant impacts on welfare participation and labor market outcomes. Figure 1a shows the average IA participation rates of the treatment and control groups in the 12 months before and 36 months after random assignment, while the entries in the lower panel of Table 2 give IA participation rates at six month intervals in the post-assignment period. In the year before random assignment the IA participation rates of both the treatment and control groups were over 99 percent.[8] In the period after random assignment the two groups diverged, with a faster decline in IA participation for the program

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[7]A total of 40 program group members and 27 treatment group members are excluded by this requirement. The difference in probabilities between the groups has a p-value of 10 percent. Since people did not know there program status (treatment or control) until after random assignment, we believe that the difference is accidental.

[8]Our sample requires that IA participation is 100 percent in the two months prior to assignment. Without this restriction, the IA rates are very similar to those shown in Figure 1a, with average rates of 99.4 percent in the two months before assignment.

group in the first 16 months, and subsequent catch-up by the control group. The program impacts are also plotted in Figure 1a, and show a peak difference of −15 percentage points in month 15, falling to −7 percentage points in month 36.

Similar patterns are also evident in the labor market outcomes of the treatment and control groups. For example, Figure 1b plots the full time employment rates of the two groups. Prior to random assignment, 5-6 percent of the SSP population were working full time. After random assignment, the full time employment rate of the program group rose rapidly, reaching about 28 percent by month 13 and holding roughly constant thereafter. By comparison the full time employment rate of the controls shows a slower but steadier upward trend. As a result, the estimated impact of SSP on the full time employment rate peaked at about 15 percentage points in month 13, and declined to about 9 percentage points by month 33.[9]

SSP impacts on many other outcomes over the first three years of the experiment are documented in Lin et al (1998) and Michalopoulos et al (2000). The impact on overall employment (including full time or part time work) is similar to the effect shown in Figure 1b, although a little smaller, reflecting a 2-3 percentage point shift from part-time to full-time work among the program group. The higher rate of employment for program group members is mainly attributable to the entry of lower-wage workers who would not have been working in the absence of SSP (see Card, Michalopoulos and Robins, 2001). Indeed, a comparison of wage distributions shows that nearly all the added workers in the program group earned hourly wages within $2 of the minimum wage (Lin et al, 1998, Table 3.3; Michalopoulos et al, 2000, Table 2.2). Monthly earnings profiles show the same pattern as the employment profiles, with a rapid rise for the program group relative to the controls in the first 15 moths of the experiment (peak

[9]Employment outcomes in the pre-assignment period were collected in the baseline survey, while those in the first 18 months were collected in the 18 month survey and those in months 18-36 were collected in the 36 month survey. This introduces some seam bias in the employment outcomes between the months just before and after assignment that is evident in Figure 1b. Moreover, about 8 percent of the sample did not participate in the 18 month survey, and 13 percent did not participate in the 36 month survey.

impact = $125 per month), and a gradual decline later months 16-36 as the control group caught up.

Some further insight into the SSP impacts is gained by comparing IA transition rates among the program and control groups. Figure 2a shows monthly IA exit rates (i.e., the fraction of those who were on IA in the previous month who are off IA in the current month), while Figure 2b shows IA entry rates (i.e., the fraction of those who were off IA in the previous month who are on IA in the current month). For reference, Table 3 reports the average monthly transition rates in earlier and later months of the experiment. Because of the selective nature of the "risk sets" (the group who are either on or off welfare at a point in time) differences in the IA entry and exit rates between the program and control group do not necessarily reveal the causal effect of the program Nevertheless, it is interesting to note that the exit rates of the program group are 1-2 percentage points higher than those of the controls in the first year and a half after random assignment, but only about 0.5 percentage points in later months. Similarly, the IA entry rates of the program group are lower in the first year and a half (particularly in the interval from 5 to 14 months after assignment) but not much different in later months.

c. The SSP-Eligible and Ineligible Program Subgroups

The time limit on SSP eligibility creates two subgroups within the program group: those who achieved eligibility and those who did not. Comparisons of the two right-hand columns of Table 2 show that individuals who achieved eligibility are slightly younger, more likely to have a high school degree, and more likely to be working just prior to assignment. On the other hand, their family composition and marriage histories are similar to those of the ineligible group. Reflecting the SSP rules, which require individuals to leave IA once they start receiving SSP payments, the subsidy-eligible group exhibit a very rapid fall-off in IA participation in the first 18 months after random assignment. After that point their IA participation rate stabilizes at about 28 percent. By comparison, the IA participation rate of the SSP-ineligible group remains relatively high, falling only to 75 percent by the end of the 3-year period, compared to 65 percent for the controls. The higher IA participation rate of the ineligible program group than the control group presumably reflects the selective nature of the eligibility process, since SSP should not have affected the behavior of those who were ineligible for supplement payments, at least in the later months of the experiment.[10]

The welfare transition rates of the eligible and ineligible program groups are also dramatically different. As shown in the two right hand columns of Table 3, the SSP-eligible group exhibits relatively high IA exit rates and low IA entry rates, both in the first 18 months after assignment and in the later period. Given the selective nature of the SSP-eligible subgroup, however, it is difficult to infer much about the causal effect of SSP from comparisons of their transition rates to those of the control group or the SSP-ineligible group.

III. Models of IA Participation for the Controls

a. Basic Models

Before developing models to analyze the effects of SSP on IA transition rates, we first consider some models of welfare participation in the absence of the program. Let y_{it} represent an indicator that equals 1 if person i is recorded as receiving IA in period t, where t runs from 1 (the first month after random assignment) to 36, and let $x_{i1}, \ldots x_{i36}$ represent a sequence of observed covariates for individual i. We consider models for the welfare outcomes of the control group within the following class:

(1) $$P(y_{i1}, \ldots y_{i36} \mid x_{i1}, \ldots x_{i36}) = \int P(y_{i1}, \ldots y_{i36} \mid \alpha_i, x_{i1}, \ldots x_{i36})\, \phi(\alpha_i \mid \sigma_\alpha)\, d\alpha$$

with

$$P(y_{i1}, \ldots y_{i36} \mid \alpha_i, x_{i1}, \ldots x_{i36}) = \prod_t L(\alpha_i + x_{it}\beta + \gamma_1 y_{it-1} + \gamma_2 y_{it-2} + \gamma_3 y_{it-1}\, y_{it-2}),$$

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[10]Members of the ineligible program group may have altered their behavior in the early stage of the experiment in an effort to become eligible, and ended up with different labor market or IA outcomes in the last months of the eligibility period than they would have had in the absence of the program. Presumably most of this effect would “wear off” by the third year of the experiment.

where L( ) represents the logistic distribution function and $\phi(\cdot \mid \sigma_\alpha)$ is the normal density with mean 0 and standard deviation σ_α. Equation (1) specifies a logistic regression model with second order state dependence and a normally distributed individual heterogeneity component α_i. A limitation of this model is the assumption of independence between monthly IA outcomes, conditional on α_i and two lags of previous welfare outcomes. Chay and Hyslop (2001) compare the goodness of fit of various dynamic welfare participation models using high-frequency welfare participation data from the Survey of Income and Program Participation, and conclude that models in the class of (1) fit about as well as more computationally demanding multi-variate probit models that allow for serial correlation in the transitory error component of welfare participation. In view of this, and the goodness of fit results reported below, we limit our attention to this group of models.

Table 4 presents estimation results for four alternative specifications of equation (1), fit to data for the control group of the SSP experiment. Note that since everyone in our sample was on income assistance in the two months prior to random assignment (i.e., in periods 0 and -1), all the observations have the same initial conditions, allowing us to simplify the empirical model. The models are estimated by maximum likelihood, using the method of Gaussian quadrature to approximate the integral in (1).[11] The specifications in columns 1 and 2 assume that IA participation exhibits only first order state dependence, while the models in columns 3 and 4 allow for second order dependence.

The model in column 1 includes a cubic function of time as the only explanatory variables, while the model in column 2 adds 18 individual covariates, all measured just before random assignment.[12]

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[11]As noted by Butler and Moffitt (1982), the likelihood for models in the class of equation (1) has the form $\int g(x) \exp(-x^2)\, dx$, which can be approximated by the sum: $\sum_i w_i\, g(x_i)$, where g is evaluated at a fixed set of N points (x_i), and the sum is formed with a fixed set of weights (w_i). We use N=10 points: see Abramowitz and Stegum (1965, p. 924).

[12]These are taken from the baseline survey, and include controls for location, labor force status, education, work experience, previous welfare participation, number and age of children, and attitudes toward work.

Comparing the two specifications, it is clear that observed characteristics explain some of the individual heterogeneity in welfare participation. Excluding thecovariates the estimated standard deviation of the individual effect (σ_α) is about 14 percent larger than when they are added. Moreover, the likelihood ratio statistic for the 18 added covariates is 409.4, far above any conventional critical value. On the other hand, the inclusion of the covariates has no effect on the estimated state dependence parameter. In addition, the predicted fractions of individuals on IA in each month from 1 to 36 are nearly identical under the two models. To save computational burden we therefore decided to ignore covariates other than the time trends in the remainder of our analysis, and let the individual effects α_i absorb all permanent differences in welfare participation across the sample members.

The model in column 3 of Table 4 expands the specification in column 1 by including IA participation 2 months earlier, and the interaction of the first and second lags of IA status. These variables leads to a significant improvement in the log likelihood and a substantial reduction in the estimate of σ_α. Finally, in column 4, we report a generalized second order model that allows the state dependence parameters to vary linearly with the individual random effect (i.e., $\gamma_k = \gamma_{k0} + \gamma_{k1}\,\alpha_i$, for k=1,2,3). Two of the three interaction terms are significant at conventional levels, and their addition leads to some improvement in the likelihood of the model (the chi-squared statistic for the three interaction terms is 10.4, which is significant at the 1.5 percent level), although overall the gain is modest.

How well do models like those in Table 4 explain observed patterns of welfare dependence? At the level of explaining *average* IA participation rates, the answer is very good. The predicted fraction of individuals on IA in each month from any of the models is very close to the actual fraction. This is not too surprising, given that we have included a third order polynomial trend function, and given the relatively smooth decline in average IA rates in the control group. A more difficult challenge is to predict the distribution of welfare histories among the control group.[13] To evaluate the models along this dimension, we decided to compare the predicted and actual fractions of the control group that fall into a set of mutually exclusive cells defined by the total number of months on IA in the three years after random assignment, and the total number of transitions on or off welfare. The cells used in our comparison, and the actual and predicted fractions of the control group in each cell, are shown in Table 5. We selected the cells to so that there are reasonable numbers of observations in each cell: thus, we group welfare histories with 1, 2, or 3 or more transitions, and those with 0, 1-3, 4-6, ... months on IA. In total, we classify the very large number (2^{38}) of possible IA histories into 38 cells.

Panel A of Table 5 shows the actual distribution of the control group across the possible welfare histories. An important feature of the data is the relatively large fraction of the control group (1,230÷ 2,786=44.2 percent) who are on IA continuously in the three years after random assignment. The high fraction of continuous participants is strong evidence of heterogeneity in welfare participation. In a homogeneous sample with the same *average* IA participation rate in each month as the SSP control group, the expected fraction of continuous participants is under 0.1 percent.[14] The control group also includes a relatively high fraction (9 percent) who leave IA for one or two months, then return and remain on welfare for the rest of the sample period.

Panel B of Table 5 shows the predicted cell fractions arising from the first order model in column 1 of Table 4. This model gives a reasonable prediction for the number of controls who never leave welfare (1228.8 predicted versus 1230 actual) but under-predicts the fraction with 1 transition and over- predicts the fractions with 3 or more transitions. A simple chi-squared statistic summarizing the

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[13]The idea of comparing predicted and actual frequencies from multinomial probability models is discussed in Moore (1977), and is used in Card and Sullivan (1988) and Chay and Hyslop (2001). We construct predicted cell fractions by simulating each model with 100 replications per sample member.

[14]With a homogeneous sample the expected fraction of people on IA continuously is $\prod_t P(t)$, where P(t) is the IA participation rate in month t. The product of the P(t)'s for the control group sample is 0.00014.

deviations between the fitted and actual cell fractions (shown in the last row of Table 4) is 240.48, substantially above the critical value for chi-squared variate with 37 degrees of freedom.[15] By comparison, the predicted cell fractions from the second order model (in Panel C of Table 5) are much closer to the actual fractions, and the overall goodness of fit statistic is much lower (68.02), although still above a conventional critical value. Interestingly, the expanded model in column 4 of Table 4 that allows for interactions between the random effect and the state dependence parameters provides a roughly similar overall fit.

Based on the evidence in Table 5, we conclude that a second order model with normally distributed heterogeneity provides a relatively good fit to the observed distribution of welfare histories of the SSP control group. Although the model under-predicts certain welfare histories (e.g., those with only 1 or 2 transitions in the first three years of the SSP experiment) it provides reasonably good predictions of the marginal distribution of total months on IA (see the right-hand columns in Table 5). We therefore use this simple specification as the basis for our models for the program group.

IV. Models for the Program Group

a. SSP Eligibility

SSP eligibility was granted to program group members who started working at a full time job or combination of jobs within12 months of random assignment. Those who did so became eligible for up to three years of supplement payments in any month that they were working full time. SSP rules required supplement takers to leave IA.[16] This was accomplished by having SSP staff notify the appropriate

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[15]The statistic is $\sum_c (N_c - PN_c)^2/PN_c$, where N_c is the number in cell c and PN_c is the predicted number in cell c. We have not adjusted the goodness of fit statistic for the fact that the model parameters are estimated. Moore (1977) presents an appropriate adjustment.

[16]Technically, the combination of minimum full time earnings and SSP payments was above the level of IA benefits for all but a handful of sample members with very large families in British Columbia, so this

Income Assistance office that an individual was about to begin receiving SSP. In most cases, notification occurred within a month of SSP eligibility. Assuming a 1 or 2 month delay in the IA system, newly eligible program group members would be required to leave welfare within 2 or 3 months of establishing eligibility.

These rules create a direct mechanical connection between the initiation of SSP eligibility and subsequent IA participation. Anyone who was on IA at the time of their eligibility determination was required to leave the welfare system within a month or two. Once a program group member achieved eligibility, however, she could stop working and return to IA at any time without jeopardizing future eligibility. The nature of the rules suggests that the behavioral impacts of the SSP program can be separated into three regimes: the pre-eligibility period (up to the date of eligibility or the close of the eligibility window); a transitional period immediately following eligibility in which individuals are forced to leave IA; and a post-eligibility period.

b. Measuring the Timing of SSP Eligibility

The actual date of SSP eligibility is not recorded in the administrative files that are available to us. Thus, we have to estimate the eligibility date from other information, including the timing of SSP payments and survey data on labor market outcomes during the experiment. To aid in developing a plausible estimation procedure we conducted an "event study" of IA participation and full time employment around the first month of SSP receipt for the eligible subset of the program group. The results are shown in Figure 3. The rate of full time employment rises prior to the date of the first SSP check, reaching a maximum of just under 80 percent in the month before the check. Assuming that people in the program group became eligible in their first month of full time employment, this pattern

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rule amounts to a requirement that SSP payments are treated as income by the IA system.

suggests about a 1 month lag between eligibility and the dating of the supplement check.[17] By comparison, the IA participation rate reaches a minimum 2 months *after* the date of the first SSP check, or about 3 months after SSP eligibility. This is consistent with operational data suggesting a maximum 3 month delay between SSP eligibility and the posting of SSP income in the IA administrative system.

A similar pattern emerges in Figure 4, where we show IA participation rates, full time employment rates, and SSP recipiency rates for the program and control groups around the time of the first month of full time employment. Among program group members, the move to full time employment is followed by a rapid rise in SSP recipiency and gradual drop in IA. For the control group the general pattern is similar, although the drop in IA participation is smaller in magnitude, as might be expected given the absence of the supplement. The first transition to full time employment also generates a more persistent rise in full time rates for the program group than the controls, consistent with the incentive effects of the supplement.

A simple characterization of the data in Figures 3 and 4 is that the initiation of full time employment by program group members precedes the first SSP check by 1 or 2 months, and precedes the exit from IA by 3-4 months. Based on these patterns, we set the date of SSP eligibility equal to the earliest of three dates: (1) the first month of full time employment; (2) the first month of SSP receipt, minus 1 month for the delay in processing; (3) 14 months after random assignment.[18] Using this measure, about 18 percent of the eligible program group became eligible in the first month after random assignment, about 9 percent became eligible in each of the second and third months, and roughly 6

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[17]SSP recipients were required to mail their pay stubs to an administrative office to verify their employment. Delays in mailing and processing would be expected to generate at least a month delay between the actual commencement of full time work and the issuance of the first SSP check.

[18]We use 14 months, rather than 12 or 13, to reflect the possibilities of measurement error and delays in processing, and the fact that some discretion was allowed in the determination of eligibility for people who started a full time job near the end of the eligibility window.

percent became eligible in each of the next 10 months. Just under 3 percent became eligible in the last possible month (month 14).

The link between SSP eligibility and subsequent IA participation is illustrated in Figure 5, where we show IA participation rates for eligible program group members in the five months before and after our estimated eligibility date. The average fraction on IA falls very slightly in the month just before eligibility (from around 95 percent to 91 percent), falls a little more in the eligibility month itself (to 85 percent), and then drops steadily over the next 3 months, eventually stabilizing at 26 percent. Consistent with administrative information suggesting a 1-3 month lag between the initiation of SSP and the loss of IA eligibility, Figure 5 suggests that the "mechanical" effect of SSP eligibility on IA participation is concentrated in the interval from 1 to 3 months after eligibility. Another interesting feature of Figure 5 is that the rate of IA participation never falls to 0 after the start of eligibility, although nearly everyone in the eligible program group is off IA for at least one month. This reflects the fact that a significant fraction of newly eligible individuals return to IA after only a month or two.

c. Modeling SSP's Incentive Effects

We now turn to a specification of the incentive effects of SSP on the program group. Let D_i represent an indicator for members of the program group, and let E_{it} represent an indicator for the event that individual i in the program group is eligible for SSP as of the start of period t (i.e., $E_{it}=1$ if the individual became eligible in period $t-1$ or earlier). Note that the sequence of indicators $\{E_{it}\}$ makes at most a single transition from 0 to 1. If people who are less likely to remain on welfare are more likely to achieve SSP eligibility, or tend to achieve it earlier, then eligibility status at period t cannot be considered "exogenous" in a model like (1), and must be treated as a jointly endogenous variable along with IA participation. Consequently, we assume that IA participation and eligibility are related to a single normally-distributed heterogeneity component:

(2) $P(y_{i1}, \ldots y_{i36}, E_{i1},\ldots E_{i36} \mid x_{i1}, \ldots x_{i36}, D_i=1)$

$$= \int P(y_{i1}, \ldots y_{i36}, E_{i1},\ldots E_{i36} \mid \alpha_i, x_{i1}, \ldots x_{i36})\, \phi(\alpha_i \mid \sigma_\alpha)\, d\alpha .$$

Using the fact that treatment status is randomly assigned, we also assume that the distribution of unobserved heterogeneity effects α_i is *the same* in the program group as in the control group of the SSP experiment.

Conditional on α_i, the covariates x_i, and lagged values of IA participation and eligibility status, we assume that (E_{it}, y_{it}) are determined recursively: E_{it} is determined first, then the probability of welfare participation is determined conditional on E_{it}.[19] This leads to:

(3) $P(y_{i1}, \ldots y_{i36}, E_{i1},\ldots E_{i36} \mid \alpha_i, x_{i1}, \ldots x_{i36})$

$$= \prod_t P(y_{it}, E_{it} \mid y_{it-1}, y_{it-2}, E_{it-1}, E_{it-2}, \ldots, x_{it}, \alpha_i)$$

$$= \prod_t P(E_{it} \mid y_{it-1}, y_{it-2}, E_{it-1}, E_{it-2}, \ldots, x_{it}, \alpha_i) \times P(y_{it} \mid y_{it-1}, y_{it-2}, E_{it}, E_{it-1}, \ldots, x_{it}, \alpha_i) .$$

We assume that the probability of IA participation follows a similar specification as for the control group, with the addition of a "treatment effect" $\tau(\cdot)$ that depends on eligibility status and lagged IA status:

(4) $P(y_{it} \mid y_{it-1}, y_{it-2}, E_{it}, E_{it-1},\ldots, x_{it}, \alpha_i)$

$$= L(\alpha_i + x_{it}\beta + \gamma_1 y_{it-1} + \gamma_2 y_{it-2} + \gamma_3 y_{it-1}\, y_{it-2} + \tau(t, E_{it}, E_{it-3}, y_{it-1})) ,$$

where L( ) represents the logistic distribution function, and

$$\begin{aligned}\tau(t, E_{it}, E_{it-3}, y_{it-1}) = {} & (1-E_{it}) \times 1(t \le 14) \times \{\theta_0\, 1(y_{it-1}=0) + \theta_1\, 1(y_{it-1}=1)\} \\ & + E_{it} \times (1 - E_{it-3}) \times \{\psi_0\, 1(y_{it-1}=0) + \psi_1\, 1(y_{it-1}=1)\} \\ & + E_{it-3} \times \{\lambda_0\, 1(y_{it-1}=0) + \lambda_1\, 1(y_{it-1}=1)\} .\end{aligned}$$

Note that we have divided the treatment effects into 3 regimes: a "pre-eligibility" period that includes all months in which $E_{it}=0$ (up to the close of the 14 month eligibility window); a "transitional" period for

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[19]Since E_{it} is eligibility status at the start of the month, and eligibility does not depend on leaving IA, we believe this is reasonable.

eligible program group members starting with the first month of eligibility and running for the next three months (identified by the conditions E_{it}=1 and E_{it-3}=0), and a "post-eligibility" period for eligible program group members that starts four months after eligibility (identified by E_{it-3}=1). In each regime, we include separate treatment effects for the probability of IA participation, conditional on being on or off IA in the previous period. Thus, the parameters θ_0, ψ_0, and λ_0 measure SSP's incentive effects on the IA entry rate in the three regimes, while the parameters θ_1, ψ_1, and λ_1 measure the effects on IA exit rates.

Given the "once for all" nature of the eligibility process, a natural model for E_{it} is a hazard model for the probability of achieving eligibility in period t, conditional on not achieving it earlier. Specifically, we assume that the hazard of eligibility depends on the individual heterogeneity effect α_i and on lagged realizations of IA:

$$
\begin{aligned}
(5)\qquad & P(E_{it} \mid y_{it-1}, y_{it-2}, E_{it-1}, x_{it}, \alpha_i) \\
& = \Phi[\, d(t) - \eta y_{it-1} - k\alpha_i \,] \quad \text{if } E_{it-1} = 0 \;\&\; t \le 14 , \\
& = 1 \quad \text{if } E_{it-1} = 1 , \\
& = 0 \quad \text{if } E_{it-1} = 0 \;\&\; t > 14 ,
\end{aligned}
$$

where Φ is the standard normal distribution function, and d(t) is a smooth function of time. Reflecting the time-limited eligibility rules for SSP, the hazard of eligibility falls to 0 after month 14.

Assuming that people with a lower propensity to stay on welfare have a higher probability of achieving eligibility in any period (conditional on not yet being eligible) the coefficient k in equation (5) will be positive. The sign of the coefficient η is less clear. To the extent that exits from welfare anticipate a move to full time employment, the coefficient η of lagged IA status will be negative.[20] On

[20]Given income assistance and SSP rules, one would not necessarily expect people to leave IA *before* they had a full time job in hand. Indeed, as show in Figure 5, most people who became eligible for SSP remained on IA until after their eligibility was established.

the other hand, not all the people who leave IA do so because of a change in labor market status. Some leave because of a change in family composition (e.g., marriage/co-habitation or the departure of a dependent child). Such "non-economic" welfare leavers may be less likely to find a full time job in the near future than those who remain on welfare. In this case, the coefficient η could be positive, reflecting the heterogeneity of reasons for leaving welfare, rather than a causal effect of IA participation on the future likelihood of starting full time work.

d. Estimates for the Program and Control Groups

Table 6 presents estimates of a series of specifications based on equations (1)-(5). All the models allow for second order state dependence and include a cubic function of time (measured in months) in the IA participation model. As a starting point, the specification in column (1) ignores any potential correlation between SSP eligibility and the unobserved individual effect α_i, and treats E_{it} as an exogenous covariate. The other models in Table 6 treat E_{it} as endogenous. In the specification in column (2), the function d(t) in the eligibility hazard includes a constant (d_0) and a linear trend (d_1). In columns (3)-(6), d(t) is expanded to include an inverse function of time: $d(t) = d_0 + d_1 t + d_2(1/t)$. Following the specification of equation (4), the transitional period after initial SSP eligibility is assumed to last for three months for all the models except the one in column (5), where it is extended to four months. The models in columns 2-5 set the coefficient η to 0 in the eligibility hazard, ignoring any potential effect of lagged IA participation on the likelihood of eligibility, whereas the model in column 6 allows for such an effect. Finally, the specification in column (4) allows the post-eligibility treatment effects to depend linearly on the individual heterogeneity effects: $\lambda_k(\alpha_i) = \lambda_{k0} + \lambda_{k1}\,\alpha_i$ for k=0,1.

All six models in Table 6 yield estimates of the state dependence and heterogeneity parameters that are similar to the estimates for the control group alone presented in column 3 of Table 4. The signs of the treatment effect estimates are also similar across specifications, with large negative estimates of the SSP eligibility effect in the transitional period, and smaller but highly significant negative treatment effects in the post-eligibility period. Compared to the selection-adjusted models in columns 2-6, the specification in column (1) yields larger estimated treatment effects, particularly for the post-eligibility period. Such a pattern would be expected if those who are more likely to remain on welfare are less likely to become eligible. In the more complex models, some of the differential in IA transition rates between the eligible and ineligible program subgroups is attributed to the selectivity of eligibility status, whereas in the model in column (1) all of the difference is assigned to a causal effect of SSP. Consistent with this, the estimates of the parameter k from the eligibility hazard are positive and highly significant for all the specifications.

Figure 6 shows the implied distributions of the individual effects among the eligible and eligible program group, based on the model in column 2 of Table 6.[21] Relative to the overall distribution of α's (which is normal with mean 0 and standard deviation 1.33), the distribution among the eligible program group is shifted to the left (with median 0.90), whereas the distribution among the ineligible group is shifted to the right (with median 0.36). While there is some overlap between the distributions of the eligible and ineligible groups, the model suggests a high degree of selectivity in eligibility status.

The bottom two rows of Table 6 report goodness of fit statistics that summarize the ability of the different models to predict the fractions of the program and control groups in each of the 38 cells described in Table 5. The model in column (1) provides a noticeably worse fit than the other models. The five selection-adjusted models have roughly similar goodness of fit statistics. None of these models provides as good a fit for the controls as the specification in column (3) of Table 4, although the difference is modest. Figure 7 shows predicted and actual IA participation rates for the program and control groups in the three years after random assignment, based on the model in column 2 of Table 6.

[21]These estimated distributions were obtained by simulating the eligibility model with 50,000 replications.

Overall, the predictions are fairly accurate, although the model has some difficulty in the period immediately after the close of the eligibility window (months 13-20), systematically over-predicting welfare participation in the program group and under-predicting the controls.[22] These difficulties are highlighted Figure 8, which shows predicted and actual IA participation rates among the eligible and ineligible program groups. The predictions for the ineligible group are quite accurate (root mean squared error of 0.008), while those for the eligible group are less so (root mean squared error 0.03), particularly in months 13-18. Evidently, the model has trouble reproducing the “dip” in welfare participation just after the close of the eligibility window. A closer look at the data for this period suggests that a relatively high fraction of those who achieved SSP eligibility near the end of eligibility window only managed to stay off IA for a few months. Some of the “late qualifiers” apparently made an exceptional effort to find a full time job and achieve eligibility, but subsequently found that full time work was not sustainable. This kind of behavior is not well-captured by our simple model.

Table 7 shows the actual and predicted fractions of the control and program groups in each of the 38 “welfare history” cells, using the specification from column (2) of Table 6. Panel a of the table shows the results for the control group. Overall, the predictions are quite similar to those in panel c of Table 5, based on a second order model fit to the controls alone. This similarity is reassuring, since if specification is correct, it should yield estimates for the parameters of the welfare participation process that are very close to the estimates we obtained using only the data for the controls, and similar predictions as such as model.[23] Panel b shows the results for the program group. Relative to the controls, a smaller fraction of the program group are on IA continuously (36.2 percent versus 44.2

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[22]The root mean squared prediction errors are 0.006 in each case. The model explains 99.6 percent of the variance of the time path in IA participation for the controls, and 99.7 percent for the program group.

[23]Formally, the difference in the estimates of the subset of parameters that are shared between the program and control groups from the pooled sample and from the controls alone can be viewed as a Hausman test. If these parameters are similar the predictions should be similar.

percent) and a larger fraction spend less than 10 months on IA (17.3 percent versus 10.3 percent). Comparisons between the actual and predicted distributions suggest that the model provides a reasonable fit for the program group, although (as with the control group) the fraction with only a single welfare transition is under-predicted

Relative to the basic selection-adjusted model in column (2), the extended models in columns (3), (4) and (6) generate higher values for the log-likelihood, but provide similar fits to the welfare histories. For example, the estimate of the parameter d_2 (the coefficient of (1/t)) in column (3) is highly significant, but its addition to the model has little impact on the other parameters or on the goodness of fit. Similarly, the addition of the interaction terms in the post-eligibility treatment effect to the specification in column (4) leads to a modest increase in the log likelihood, but little change in the other parameters, or in the ability of the model to predict the distribution of the control and program groups across the welfare history cells. The specification in column (5) extends the transitional period after SSP eligibility by an extra month. This change has little effect on the parameter estimates relative to the parallel model in column (3), although it leads to a slight improvement in the goodness of fit.

Finally, the model in column (6) adds lagged IA status to the eligibility hazard. The estimate of the parameter η is -0.41, implying that people who were on IA in the previous period have a *higher* likelihood of achieving eligibility than those who were not, controlling for the value of the individual effect α_i and the fact that they had not yet established eligibility. We suspect that this pattern is driven by the behavior of people who leave IA for non-earnings-related reasons – for example, because of a change in family circumstances. Those who exit welfare because they move in with a new spouse/boyfriend, or because their children leave home, may be may be less likely to start full time work in the near future than those who remain on welfare. Such an explanation underscores a limitation of our analysis, which makes no distinction between welfare transitions that occur for job-related versus other reasons.[24] In any case, adding the effect of past IA to the eligibility hazard leads to slightly smaller estimates of the effect of SSP on post-eligibility transitions, but has small impacts on the other parameters.

e. How Did SSP Affect IA Participation?

By simulating the models in Table 6 with the various treatment effects turned on or off it is possible to gain some insights into the behavioral responses of the program group, and the reasons for the "hump shaped" pattern of SSP impacts on IA participation in Figure 1. A decomposition of the impacts is presented in Figure 9, using the estimates for the simplest selection-adjusted model in column 2. The starting point for this decomposition is the observation that the pre-eligibility effects of SSP are small and statistically insignificant. Since our model assumes that members of ineligible program group are only affected by SSP in the pre-eligibility period, this implies that nearly all the impact of SSP can be attributed to its effect on the eligible program group. As a benchmark, we therefore begin by plotting the predicted welfare participation path of the eligible program group in the absence of SSP. Next, we plot the path of the eligible program group, taking account of the pre-eligibility treatment effects (which are very small) and the transitional treatment effects (which are larger). This path represents the expected welfare trajectory under the assumption that the *only* effect of SSP was to induce people to enter full time work and leave IA before the close of the eligibility window. Predicted welfare participation under this scenario trends downward until month 15, at which point the transitional phase is completed for nearly everyone in the eligible program group. Thereafter, as the transitional effects gradually "wear off", the predicted fraction on IA trends toward the fraction that would be expected in the absence of any treatment effects.

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[24]Blank (1989) estimates a competing risks model for welfare exits that compares exits that occur for earnings-related and other reasons.

SSP's impacts in the later months of the experiment arise from a combination of the "initial conditions" generated by the transitional phase, and the post-eligibility treatment effects on IA exit and entry rates (λ_1 and λ_0, respectively). The third line in Figure 9 represents the predicted IA participation rate, taking account of the pre-eligibility and transitional effects, and the post-eligibility effect on IA exits, but ignoring any post-eligibility effect on IA entry rates. Finally, the fourth line represents the predicted IA path, including all pre-eligibility, transitional, and post-eligibility treatment effects. Comparisons of the three predicted paths suggest that in the later months of the experiment (months 30-36), the overall treatment effect on IA participation of the eligible control group was comprised of a small lingering effect of the transitional phase (9% of the total effect), a modest post-eligibility effect on the IA entry rate (28% of the total), and a larger post-eligibility effect on the IA exit rate (63% of the total effect).

We have conducted simulations of the other selection-adjusted models in Table 6 and decomposed the predicted treatment effects from these models using the same approach as in Figure 9. The results are fairly similar across specifications. According to the models, the time profile of the SSP impact on IA participation represents a combination of a "once for all" eligibility effect, and a longer run effect on welfare entry and exit rates that is potentially attributable to the enhanced tradeoff between work and welfare. The eligibility effects reach a peak impact of about -20 percentage points between 8 and 14 months after random assignment, and decline after that point. By three years after random assignment, the eligibility effects are largely dissipated, accounting for 15 percent or less of the total impact on welfare participation. The longer-run effects reach an impact of about -20 percentage points by two years after random assignment, and are fairly stable thereafter, with 1/4 to 1/3 of the total due to lower welfare entry rates, and 2/3 to 3/4 due to accelerated welfare leaving.

V. Summary and Conclusions

The results of our analysis suggest that the monthly welfare outcomes of long-term welfare recipients are well described by a class of dynamic binary response models that incorporate state dependence and permanent individual heterogeneity. These models, coupled with a relatively simple model of the eligibility process for people who were offered the SSP earnings supplement, provide several insights into the behavioral responses generated by the program. Most importantly, the time-varying impact of SSP arises from two forces: a once-for-all eligibility effect that accelerates the pace of welfare exits relative to the control group; and a longer-term post-eligibility effect on welfare transition rates. Although the welfare exits attributable to the eligibility effect occurred early in the SSP demonstration, their impact persisted longer because of the high degree of state dependence in welfare participation. The post-eligibility effects, by comparison, grew in magnitude over the duration of the experiment. Thirty months after random assignment, the post-eligibility effect on welfare *exit* rates had lowered welfare participation of the eligible program group by about 15 percentage points, while the parallel effect on welfare *entry* rates had lowered participation by an additional 5 percentage points. The combination of the initial eligibility effects and the cumulating post-eligibility effects offers a simple explanation for the "hump shaped" time path of SSP's impacts on IA participation.

The conclusion that SSP led to a rise in welfare leaving rates for those who were eligible for the earnings supplement is consistent with standard models of dynamic labor market behavior (e.g. Mortensen, 1986). In particular, an earnings supplement would be expected to increase the intensity of job search and raise the job acceptance rate, speeding the transition from welfare to work. The effect on welfare entry rates is also consistent with conventional theories. For example, individuals who are eligible for supplement payments may have faster job-to-job transition rates, reducing the probability of having to re-enter welfare when a job ends. Similarly, they may be able to adapt to family problems (such as a disruption in child care) without having to leave an existing job. An important task for future research is to develop a more complete understanding of the mechanisms underlying the longer-run post-eligibility effects of the SSP subsidy. This in turn could shed light on the question of whether the post-eligibility impacts would persist beyond the end of the three-year eligibility period for SSP supplement payments.

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Table 1: Key Features of the SSP Recipient Demonstration

A. Program Eligibility

· single parents who have received Income Assistance (IA) for at least 12 months

· sample members drawn from IA registers in lower mainland British Columbia (including Vancouver) and southern New Brunswick (including Saint John, Moncton, and Fredrickton)

· sample members randomly assigned between November 1992 and February 1995

· 2,858 single parents assigned to program group; 2,826 assigned to control group

B. Program Features

· supplement payments are available to program group members who work at least 30 hours per week (over a four-week or monthly accounting period)

· supplement recipients must earn at least the minimum wage ($5.00 per hour in New Brunswick in 1993; $6.00 per hour in British Columbia in 1993)

· supplement recipients cannot receive IA

· supplement payment is one-half of the difference between actual earnings and an earnings benchmark, set at $2,500 per month in New Brunswick and $3,083 per month in British Columbia in 1993, and adjusted for inflation in subsequent years

· supplement payment is not affected by unearned income, or income of spouse/partner

· supplement payments are treated as regular income for income tax purposes

· supplement payments are available for up to 36 months from time of first payment. Supplement is only available to program group members who successfully initiate their first supplement payment within one year of random assignment

· program group members can return to IA at any time. Supplement payments are re-established if an eligible program group member leaves IA and meets the full-time hours requirement

· employers are not informed of SSP status. Program group members apply for supplement payments by mailing in copies of pay stubs (which show weekly hours)

Table 2: Characteristics of SSP Control and Experimental Groups

	Controls	Programs	Program Group by SSP-Eligibility: Eligible	Program Group by SSP-Eligibility: Ineligible
Percent in BC	52.6	53.2	50.9	54.4
Percent Male	4.7	5.2	4.6	5.5
Mean Age	31.9	31.9	31.1	32.4
Percent Age 25 or Less	17.8	17.1	18.5	16.3
Percent Never Married	48.1	48.3	48.0	48.5
Mean Number of Kids < 6	0.7	0.7	0.7	0.7
Mean Number of Kids 6-15	0.8	0.8	0.8	0.8
Percent Immigrant	13.8	13.3	12.2	13.9
Percent Raised in Two-Parent Family	59.7	59.4	62.1	58.1
Percent High School Grad	44.6	45.7	56.9	39.9
Mean Years Work Exp.	7.4	7.3	8.6	6.7
Percent Working at Baseline	19.0	18.2	31.5	11.4
IA History in 3 Years Prior to Baseline:				
Mean Months on IA	29.6	30.1	29.2	30.6
On IA Continuously	41.5	43.8	36.3	47.7
IA Status After Baseline:				
Month 6	90.7	83.1	62.8	93.5
Month 12	83.7	72.4	39.1	89.4
Month 18	77.9	65.9	27.2	85.6
Month 24	73.0	63.3	26.5	82.1
Month 32	68.0	60.5	27.0	77.7
Month 36	65.3	58.8	27.6	74.8
Number Observations	2,786	2,831	957	1,874

Table 3: IA Participation and Transition Rates of Program and Control Groups in Months 1-16 and 17-36

	Controls	Programs	Program Group by SSP-Eligibility: Eligible	Program Group by SSP-Eligibility: Ineligible
Months 1-16				
On IA	87.91	79.66	55.37	92.06
	(0.15)	(0.19)	(0.40)	(0.16)
IA Exit Rate	2.54	4.13	11.36	1.74
	(0.08)	(0.10)	(0.33)	(0.08)
IA Entry Rate	9.19	7.11	5.31	12.22
	(0.42)	(0.28)	(0.29)	(0.70)
Months 17-36				
On IA	71.44	62.38	26.63	80.63
	(0.19)	(0.20)	(0.32)	(0.20)
IA Exit Rate	3.06	3.46	9.13	2.52
	(0.09)	(0.10)	(0.40)	(0.09)
IA Entry Rate	5.38	4.78	3.49	7.36
	(0.18)	(0.15)	(0.15)	(0.31)

Notes: Estimated standard errors in parentheses. These are calculated without accounting for multiple observations per person.

Table 4: Estimated Dynamic IA Participation Models for Controls Only

	First Order Models		Second Order Models	
	(1)	(2)	(3)	(4)
Coefficient of:				
y(t-1)	4.89 (0.05)	4.90 (0.05)	4.93 (0.11)	4.69 (0.16)
y(t-2)	--	--	1.68 (0.07)	1.63 (0.10)
y(t-1)×y(t-2)	--	--	-0.97 (0.12)	-0.63 (0.17)
y(t-1)×a(i)	--	--	--	-0.28 (0.13)
y(t-2)×a(i)	--	--	--	-0.14 (0.08)
y(t-1)×y(t-2)×a(i)	--	--	--	0.43 -0.15
Individual Covariates	none	18	none	none
Standard Deviation of Random Effect (σ_a)	1.84 (0.05)	1.62 (0.05)	1.50 (0.06)	1.48 (0.11)
Log Likelihood	-14,272.8	-14,068.1	-14,002.9	-13,997.7
Goodness of Fit	240.48	–	68.02	64.08

Notes: Approximate standard in parentheses. See text for model specifications. Models estimated by maximum likelihood, using Gaussian quadrature with 10 points.

Table 5: Summary of IA Participation Sequences – Controls

Total Months on IA:	Number of Transitions 0	1	2	3+	Total
A: Actual IA Participation					
0	0	14	0	0	14
1-3	0	61	3	6	70
4-6	0	76	2	17	95
7-9	0	66	3	40	109
10-12	0	54	8	36	98
13-15	0	48	10	29	87
16-18	0	48	11	35	94
19-21	0	46	9	45	100
22-24	0	41	14	48	103
25-27	0	52	25	56	133
28-30	0	44	31	52	127
31-33	0	53	53	68	174
34-35	0	49	260	43	352
36	1230	0	0	0	1230
Total	1230	652	429	475	2786
B: Predicted – 1st Order Model (Table 4, Column 1)					
0	0	26.2	0.0	0.0	26.2
1-3	0	62.4	0.6	16.5	79.5
4-6	0	51.0	1.2	29.7	82.0
7-9	0	45.6	2.2	41.1	88.9
10-12	0	40.7	3.1	46.0	89.7
13-15	0	35.8	5.3	52.2	93.2
16-18	0	33.2	7.1	55.7	96.0
19-21	0	31.3	10.4	57.9	99.6
22-24	0	30.8	16.1	62.7	109.5
25-27	0	33.2	26.3	66.9	126.3
28-30	0	38.1	48.9	67.6	154.6
31-33	0	51.3	112.7	64.8	228.8
34-35	0	50.7	218.2	14.0	282.9
36	1228.8	0	0	0	1228.7
Total	1228.8	530.1	452.0	575.2	2786.0
C: Predicted – 2nd Order Model (Table 4, Column 3)					
0	0	24.3	0	0	24.3
1-3	0	67.8	0.9	15.2	83.9
4-6	0	56.9	1.9	26.3	85.1
7-9	0	52.2	3.2	33.2	88.6
10-12	0	47.1	4.5	39.8	91.4
13-15	0	43.0	6.5	43.7	93.2
16-18	0	40.3	8.5	47.6	96.4
19-21	0	38.2	12.3	49.2	99.7
22-24	0	37.9	17.6	50.9	106.4
25-27	0	37.4	25.1	56.0	118.4
28-30	0	41.2	39.6	56.0	136.8
31-33	0	47.2	66.8	63.7	177.6
34-35	0	44.5	291.5	45.1	381.1
36	1203.2	0	0	0	1203.2
Total	1203.2	577.9	478.2	526.7	2786.0

Notes: Number of transitions is the number of changes in IA participation from month just before random assignment to month 36.

Table 6: Estimated Dynamic Participation Models for Control and Program Groups

	(1)	(2)	(3)	(4)	(5)	(6)
State Dependence Parameters						
γ_1	5.16	5.14	5.13	5.11	5.14	5.13
	(0.08)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
γ_2	1.60	1.60	1.59	1.57	1.58	1.59
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
γ_{12}	-1.04	-1.05	-1.05	-1.01	-1.08	-1.05
	(0.08)	(0.07)	(0.08)	(0.08)	(0.07)	(0.08)
Selection Parameters						
d_0	-	-1.90	-2.20	-2.17	-2.20	-2.74
		(0.04)	(0.06)	(0.06)	(0.06)	(0.10)
d_1	-	-0.10	0.17	0.19	0.18	0.33
		(0.04)	(0.06)	(0.06)	(0.06)	(0.06)
d_2	-	-	0.53	0.54	0.53	0.57
			(0.08)	(0.08)	(0.08)	(0.08)
k	-	0.31	0.28	0.29	0.27	0.38
		(0.03)	(0.02)	(0.02)	(0.02)	(0.03)
η	-	-	-	-	-	-0.41
						(0.06)
Treatment Parameters						
Pre-Eligibility Period						
θ_1	0.11	-0.01	0.10	0.12	0.08	0.08
	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)	(0.06)
θ_0	0.26	0.03	0.15	0.13	0.12	0.13
	(0.10)	(0.10)	(0.09)	(0.09)	(0.09)	(0.09)
Transitional Period						
ψ_1	-3.48	-2.75	-2.78	-2.77	-2.74	-2.58
	(0.08)	(0.09)	(0.09)	(0.09)	(0.09)	(0.09)
ψ_0	-2.19	-1.44	-1.50	-1.50	-1.48	-1.40
	(0.15)	(0.14)	(0.15)	(0.15)	(0.13)	(0.15)
Post-Eligibility Period						
λ_1	-2.09	-1.19	-1.25	-1.32	-1.22	-1.03
	(0.07)	(0.08)	(0.08)	(0.08)	(0.08)	(0.08)
λ_0	-1.38	-0.56	-0.65	-0.57	-0.65	-0.40
	(0.07)	(0.08)	(0.08)	(0.11)	(0.08)	(0.08)
λ_1 × random effect	-	-	-	-0.13	-	
				(0.08)		
λ_0 × random effect	-	-	-	0.24	-	
				(0.09)		
Heterogeneity Parameter						
σ_α	1.25	1.33	1.33	1.32	1.35	1.37
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
–Log Likelihood	29,667	33,889	33,863	33,856	33,849	33,839
Goodness-of-Fit						
Controls	121.6	77.3	89.7	86.9	83.4	76.9
Programs	120.9	99.9	101.9	78.8	92.9	110.8

Notes: Approximate standard errors in parentheses. See text and notes to Table 4.

Table 7a: Summary of Monthly IA Sequences – Control Group

Total Months On IA:	Number of Transitions 0	1	2	3+	Total
A: Actual					
0	0	14	0	0	14
1-3	0	61	3	6	70
4-6	0	76	2	17	95
7-9	0	66	3	40	109
10-12	0	54	8	36	98
13-15	0	48	10	29	87
16-18	0	48	11	35	94
19-21	0	46	9	45	100
22-24	0	41	14	48	103
25-27	0	52	25	56	133
28-30	0	44	31	52	127
31-33	0	53	53	68	174
34-35	0	49	260	43	352
36	1230	0	0	0	1230
Total	1230	652	429	475	2786
B: Predicted – 2nd Order Model with Selection (Table 6, Column 2)					
0	0	20.5	0	0	20.5
1-3	0	58.9	1.0	12.7	76.6
4-6	0	56.9	2.6	24.1	83.4
7-9	0	52.2	4.2	32.0	88.4
10-12	0	46.9	6.3	38.9	92.0
13-15	0	44.4	8.9	43.8	97.1
16-18	0	40.6	11.3	48.2	100.2
19-21	0	39.4	15.6	50.0	105.0
22-24	0	37.0	21.9	53.1	112.0
25-27	0	37.5	31.9	55.8	125.2
28-30	0	40.3	48.7	59.2	148.2
31-33	0	47.0	79.2	65.2	191.4
34-35	0	45.8	296.8	42.1	384.7
36	1165.2	0	0	0	1165.2
Total	1165.2	567.3	528.4	525.1	2786

Notes: See notes to Table 5.

Table 7b: Summary of Monthly IA Sequences – Program Group

Total Months On IA:	Number of Transitions 0	1	2	3+	Total
A: Actual					
0	0	20	0	0	20
1-3	0	132	2	17	151
4-6	0	136	3	37	176
7-9	0	94	7	43	144
10-12	0	81	12	61	154
13-15	0	71	15	53	139
16-18	0	38	21	66	125
19-21	0	23	8	67	98
22-24	0	23	19	57	99
25-27	0	25	24	66	115
28-30	0	27	25	64	116
31-33	0	34	61	80	175
34-35	0	38	212	44	294
36	1025	0	0	0	1025
Total	1025	742	409	655	2831
B: Predicted – 2nd Order Model with Selection (Table 6, Column 2)					
0	0	24.3	0	0	24.3
1-3	0	128.9	1.5	26.5	156.8
4-6	0	104.6	3.4	56.4	164.4
7-9	0	79.8	5.5	66.0	151.3
10-12	0	62.4	7.5	68.6	138.5
13-15	0	46.8	8.6	66.6	122.1
16-18	0	28.2	12.0	61.5	101.6
19-21	0	26.6	14.0	58.8	99.3
22-24	0	25.1	19.0	56.9	101.0
25-27	0	27.6	27.2	59.5	114.3
28-30	0	29.8	41.2	59.7	130.7
31-33	0	36.2	69.3	64.4	169.9
34-35	0	35.9	265.4	40.7	342.0
36	1014.8	0	0	0	1014.8
Total	1014.8	656.3	474.3	685.6	2831

Notes: See notes to Table 5.

Figure 1a: Monthly IA Participation Rates

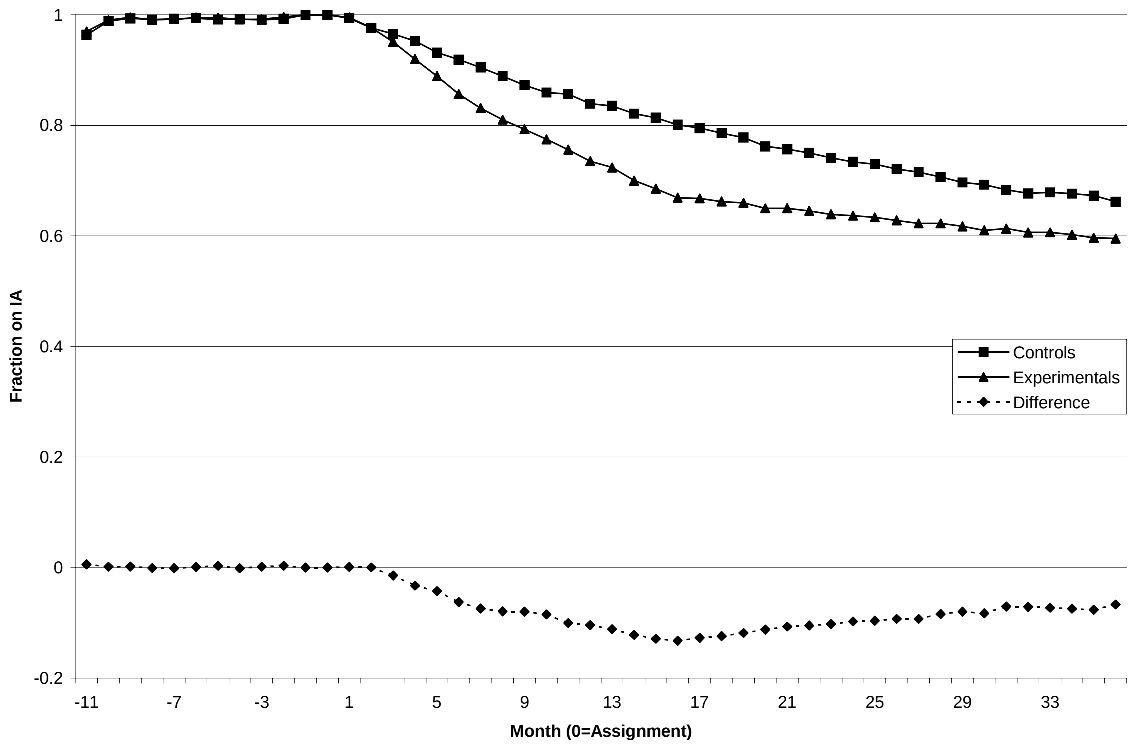

Figure 1b: Monthly Full-time Employment Rates

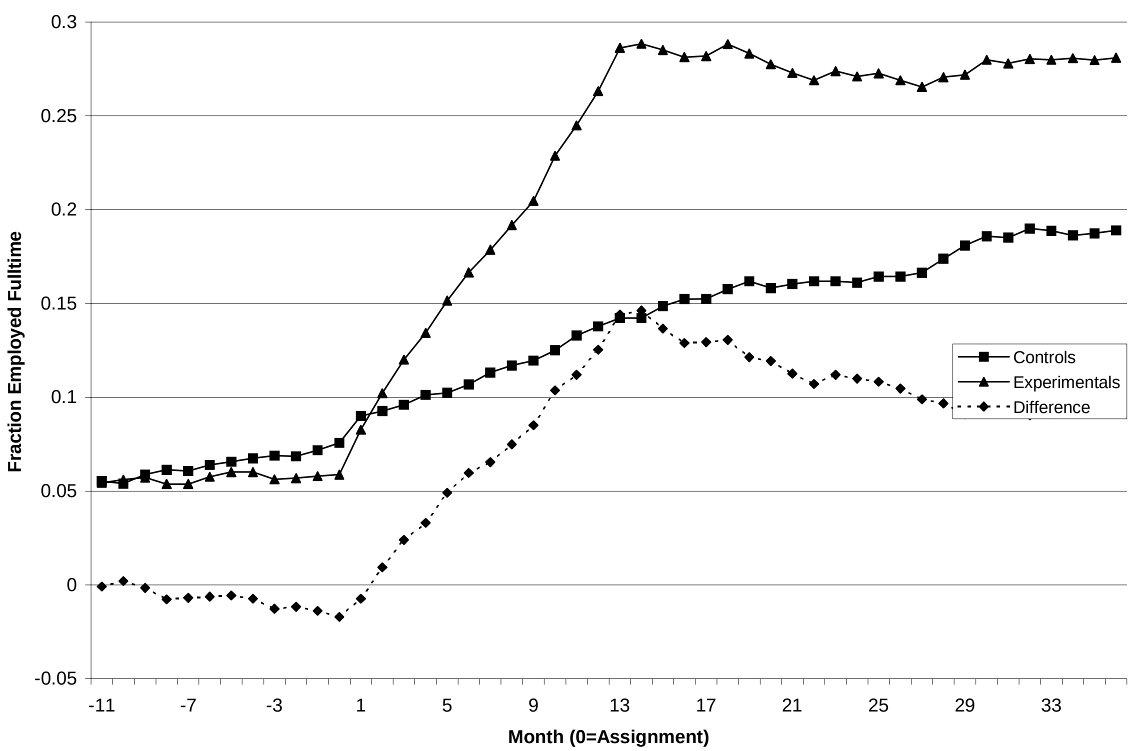

Figure 2a: Monthly Exit Rate from Income Assistance

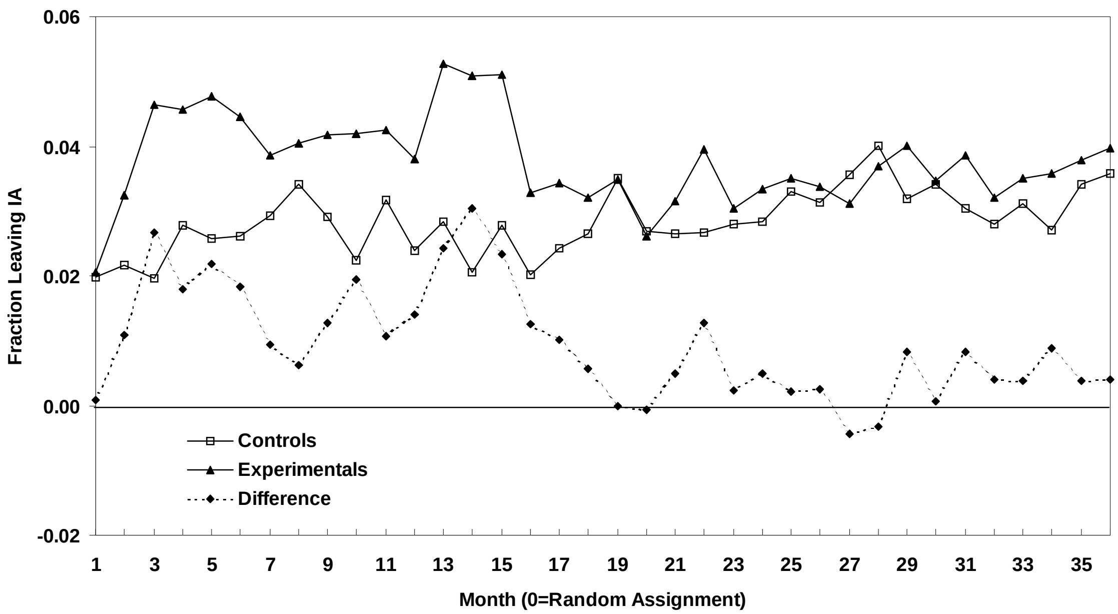

Figure 2b: Monthly Entry Rate into Income Assistance

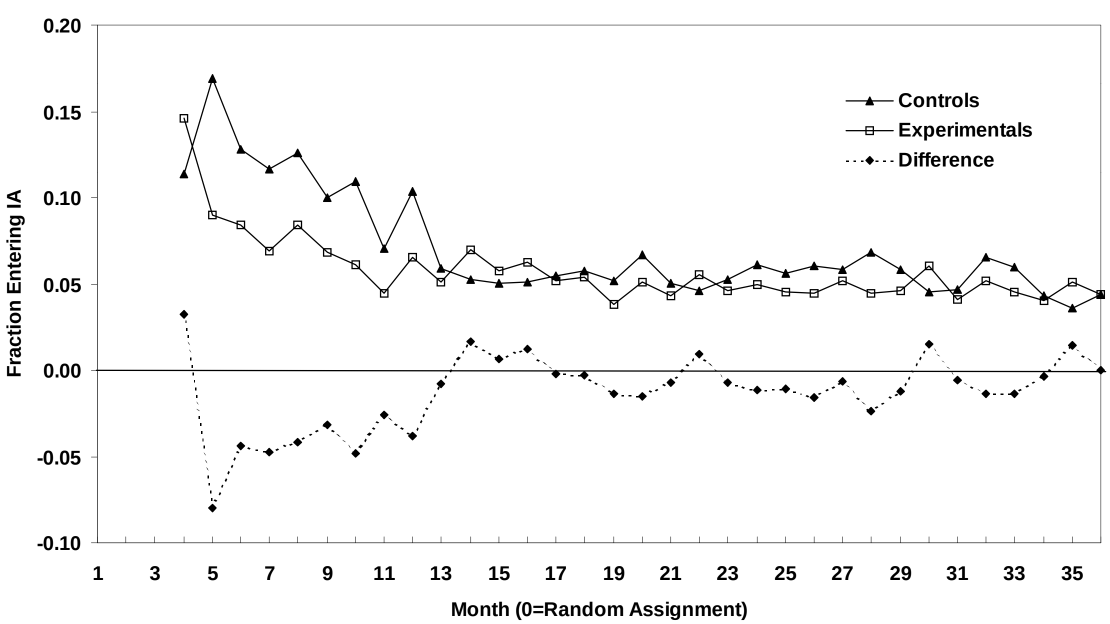

Figure 3: IA Participation and SSP Receipt in Months Surrounding First Month of Supplement Receipt for SSP-Eligible Program Group

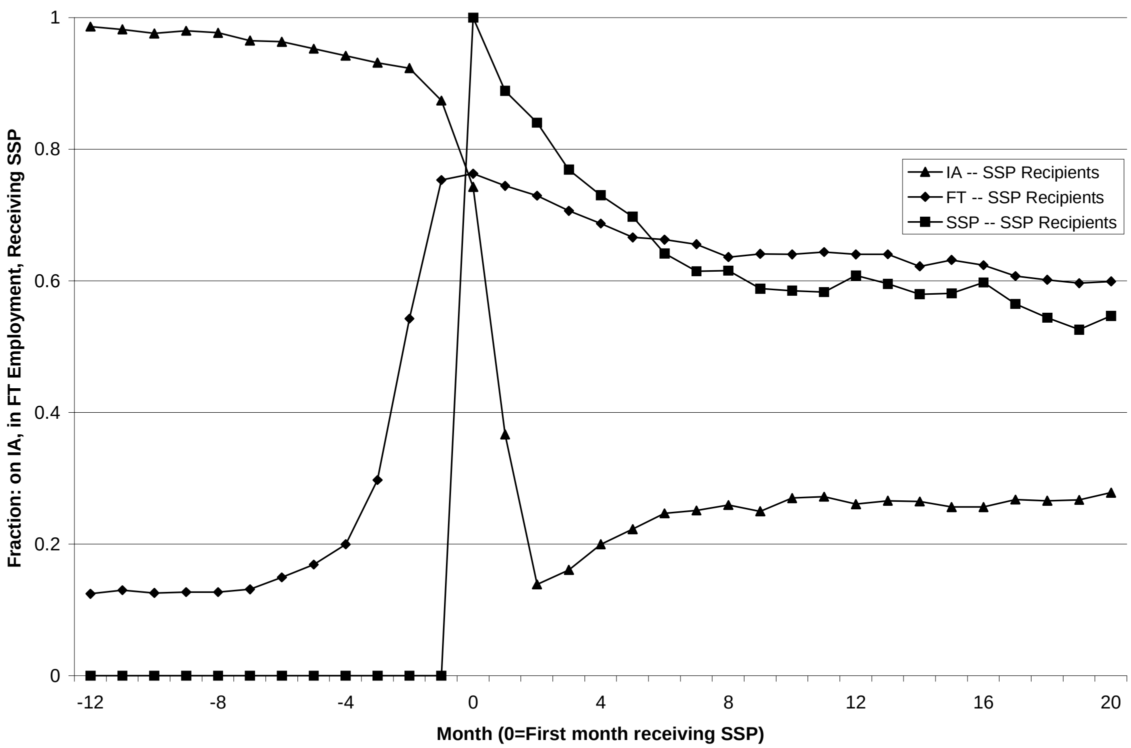

Figure 4: IA Participation, SSP Receipt, and Full Time Employment Rates for SSP Program and Control Groups Around First Month of Full Time Employment

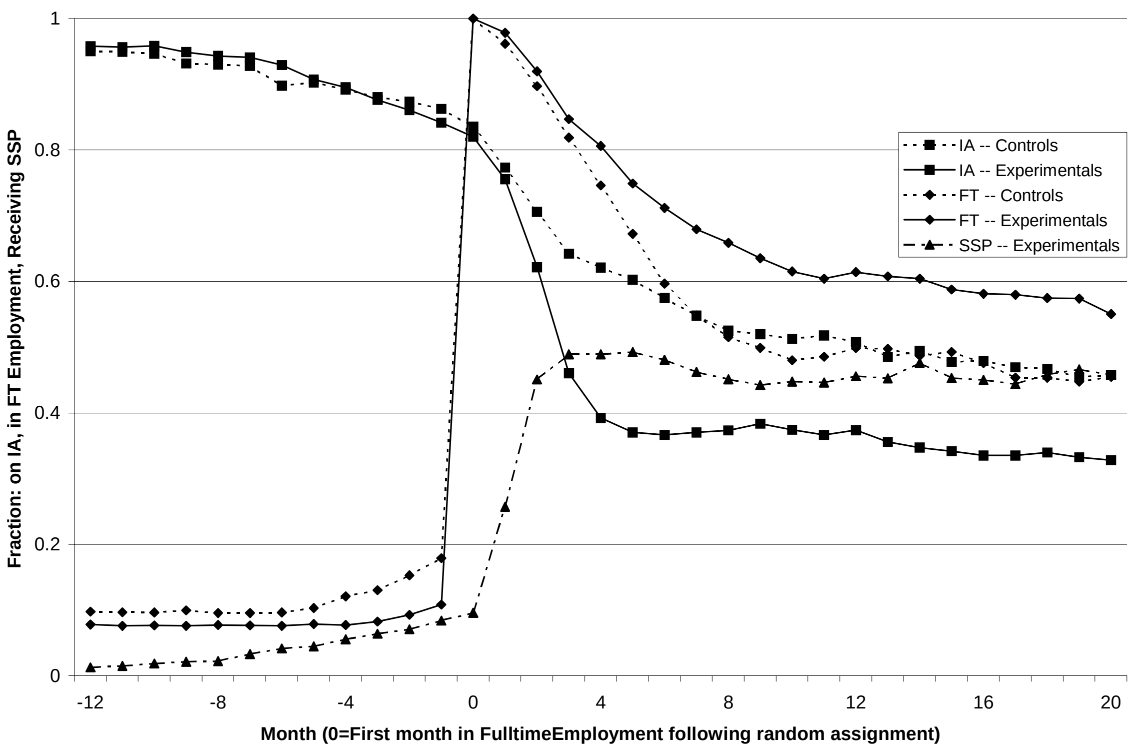

Figure 5: IA Participation of Eligible Program Group Around SSP Eligibility Date

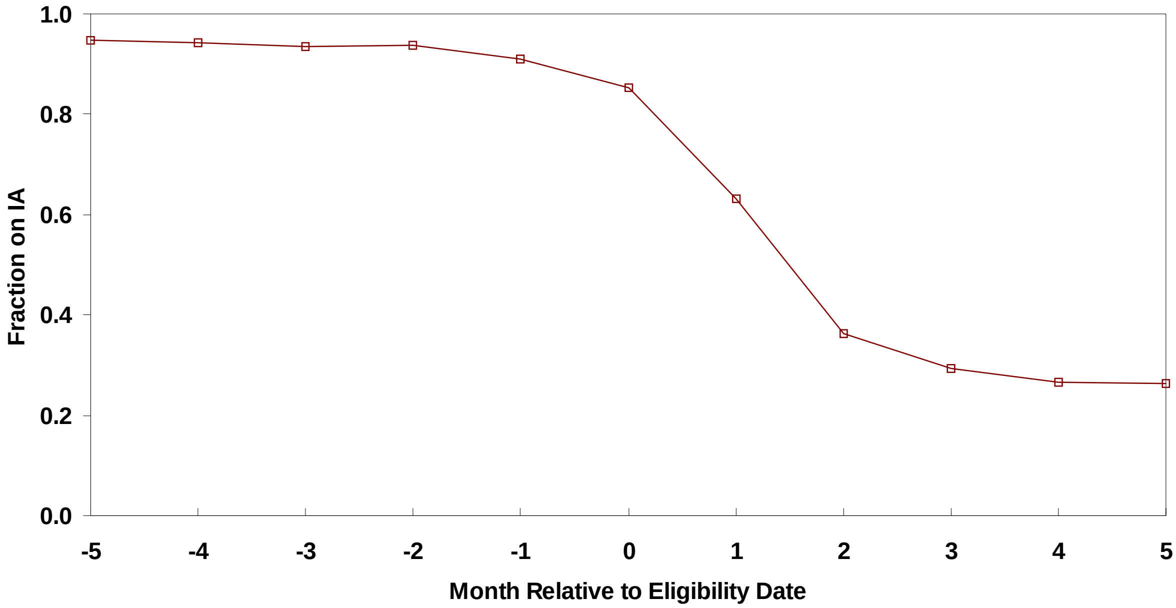

Figure 6: Distribution of Random Effects: Eligible, Ineligible, and Overall Groups

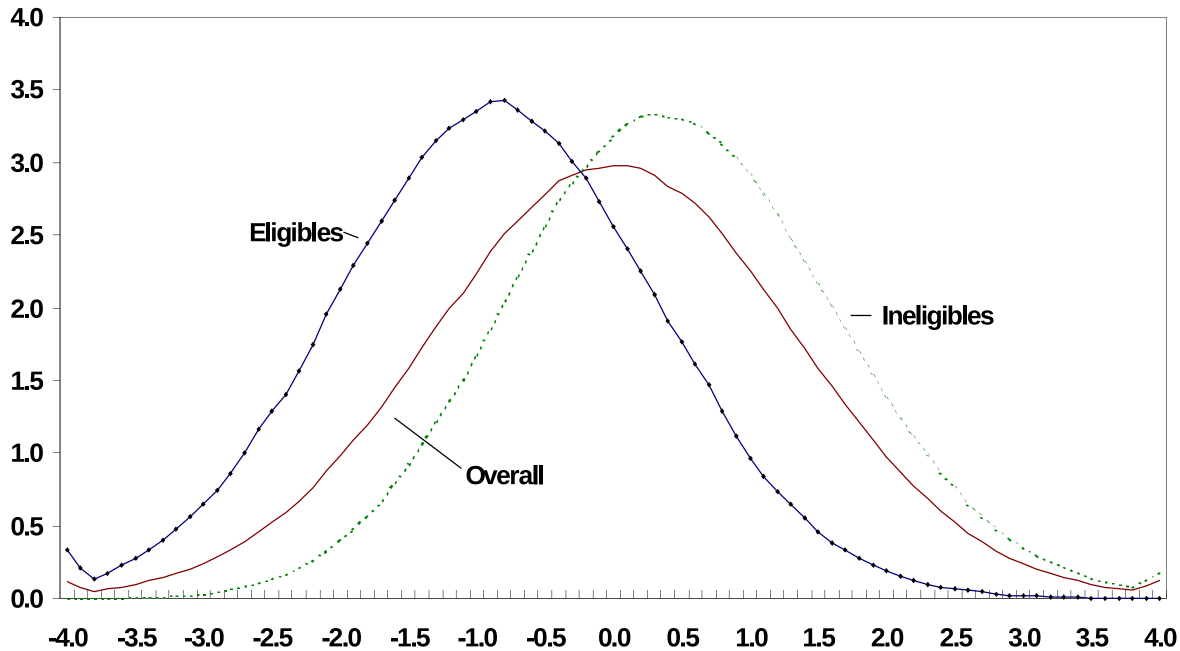

Figure 7: Actual and Predicted IA Rates for Control and Program Groups

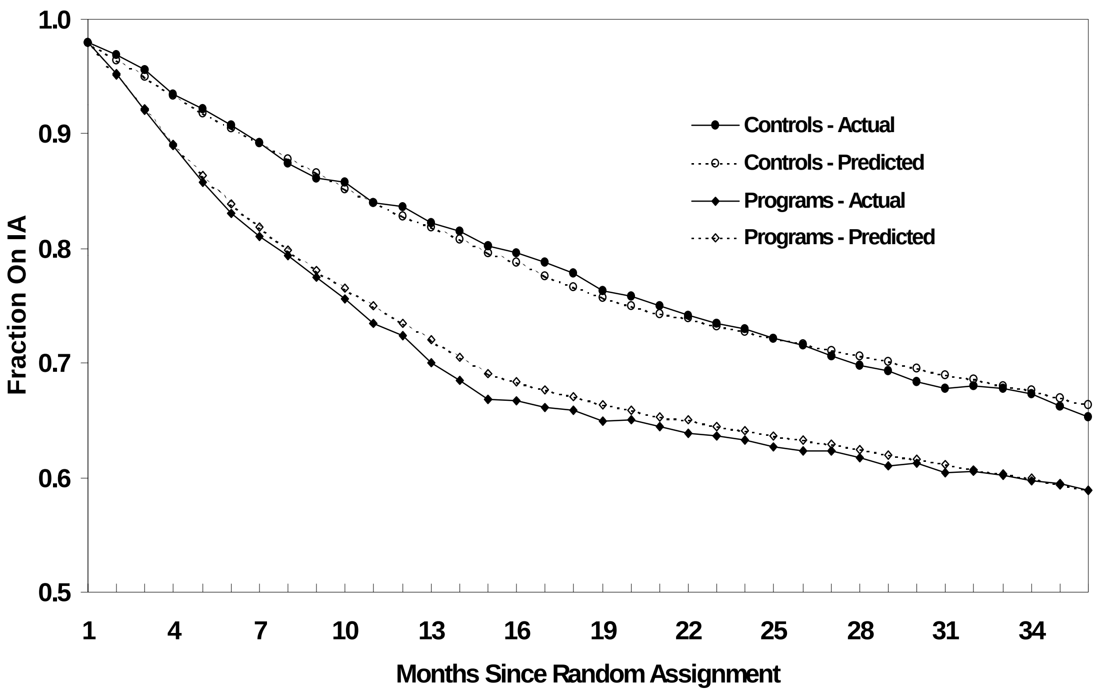

Figure 8: Actual and Predicted IA Rates for Eligible and Ineligible Program Groups

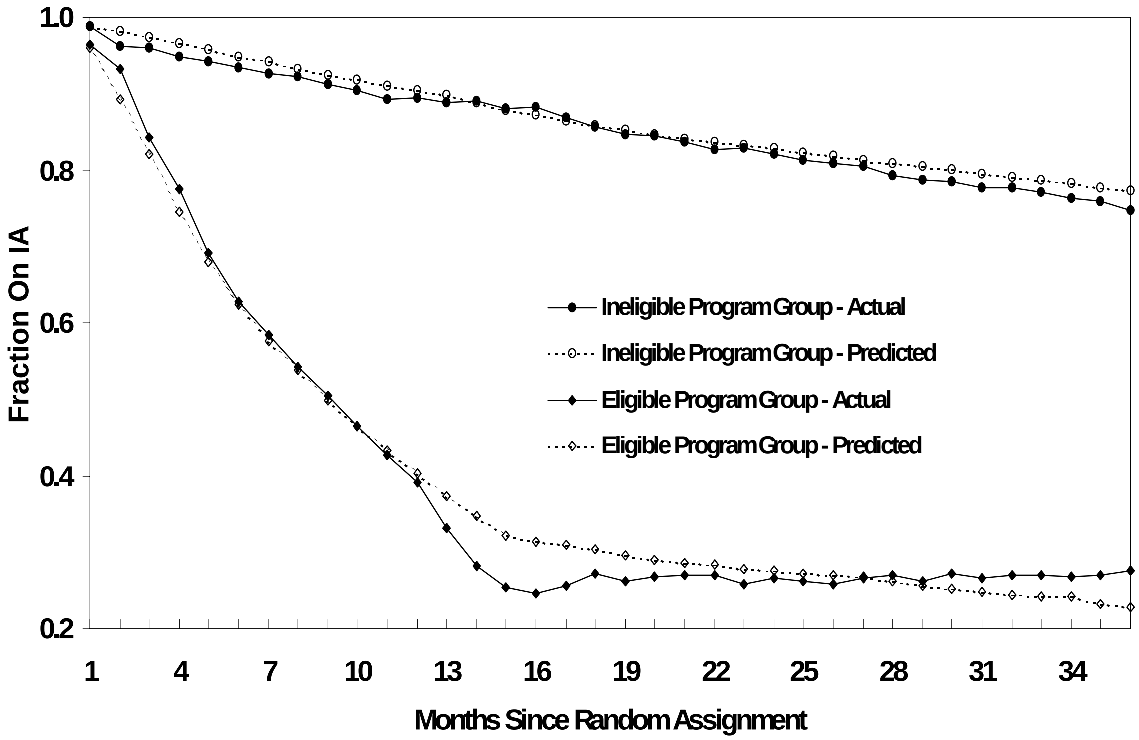

Figure 9: Decomposition of Predicted IA Rates for Eligible Program Group