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Abstract

In the Self Sufficiency Program (SSP) welfare demonstration, members of a randomly assigned treatment group could receive an earnings subsidy for full time work. The subsidy was available for three years, but only to people who began working full time within 12 months of random assignment. Because of the limited eligibility window, SSP generated both a one-time "entitlement incentive" to find a job within a year of random assignment, and a longer term incentive to choose work over welfare once eligibility was achieved. We develop an econometric model that allows us to distinguish between these two effects, and assess the long-run impact of SSP on welfare participation. Our estimated models suggest that about one-half of the peak impact of SSP was attributable to the entitlement incentive. Despite the extra work effort engendered by the program's incentives, SSP had no long run impact on wages, and little or no long run effect on welfare participation.

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Over the past decade several countries have introduced major reforms to their income support programs. A common theme in many of these reforms is the enhancement of financial incentives for work (see, e.g., Blundell and Hoynes, 2001, and Blank, Card, and Robins, 2000). Traditional means-tested welfare systems create high implicit tax rates on recipients, reducing the incentives for work beyond a few hours per week. Many analysts have argued that the absence of work incentives creates a "welfare trap". Once in the system, recipients become increasingly detached from the labor market, and the subsequent erosion of skills and work habits makes it less likely they can leave in the future.[1]

In the early 1990s the government of Canada funded an innovative social experiment – the Self Sufficiency Project or SSP – to test the effects of a high-powered earnings subsidy for long-term welfare recipients. SSP typically *doubled* the earnings of its low-wage participants. Unlike the U.S. Earned Income Tax Credit program or the broader wage subsidies advocated by Phelps (1994), SSP was a time-limited subsidy for full time work. SSP payments were available for three years, but *only* to those who began working full time within a year of selection into the program. Once eligible, individuals could move back and forth between welfare and work, receiving subsidy payments whenever they were working full time. At the end of their eligibility period, participants returned to the regular welfare environment.

SSP was conducted as a randomized experiment. One half of a group of long-term welfare recipients in two Canadian provinces was offered the supplement, while the other half remained in the regular welfare system. Data were collected over the next four to six years, permitting an analysis of both the immediate impacts of the subsidy, and longer term effects after supplement payments ended. Simple comparisons between the treatment and control groups show that SSP had significant impacts on welfare participation and work, raising the full time employment rate and lowering welfare participation

[1]See Blank (1997, pp. 151-156) for a brief overview. The idea that welfare participation creates a dependency trap is a very old one. For example, Hexter (1917) analyzed the duration of relief spells at a private charity and found that people on relief longer had a lower likelihood of leaving. High implicit tax rates also create incentives to participate in the underground sector: see Fortin, Fechette, and Lemieux (1994).

by 15 percentage points in the second year of the experiment. In later years, however, differences between the treatment and control groups faded. By the fourth year after random assignment the experimental impacts had fallen by 50 percent or more, and at 69 months the difference in welfare participation rates between the groups was negligible.

In this paper we develop a dynamic econometric model to describe the effects of SSP on welfare participation. A key feature of our model is the incorporation of two distinct incentive effects created by the eligibility rules of SSP. A simple behavioral model suggests that SSP generated both a one-time "entitlement incentive" to find a full time job within a year of random assignment, and an ongoing incentive to choose work over welfare once eligibility was achieved. Our statistical model allows us to distinguish between these two effects, and assess the long-run impact of SSP on welfare participation. Separating the two incentive effects not only provides a better description of the time-varying impact of SSP, but also permits a generalization of SSP's findings to other contexts.

Ham and Lalonde (1996) show that, even with a randomly assigned intervention, the estimation of dynamic impacts requires a full specification of the process generating individuals' welfare histories. We use logistic regression models with state dependence and unobserved heterogeneity to model welfare participation and the effects of SSP on movements into and out of welfare. We allow separate behavioral effects on welfare participation in the period surrounding the establishment of eligibility, and in subsequent months when people could move between welfare and work without affecting eligibility. Recognizing the possibility that individuals who became eligible for SSP were non-randomly selected from the treatment group, we model SSP eligibility and the probability of welfare participation jointly. Our estimates confirm that eligibility status is highly selective: those with a higher probability of being on welfare were less likely to establish eligibility for SSP, and tended to achieve it later. As a result, differences between the observed transition rates of the SSP-eligible subgroup and the control group overstate the causal effect of the supplement. The results suggest that about one-half of the peak impact of SSP was attributable to the "entitlement incentive" created by the time-limit on eligibility. We also find that the extra jobs taken by program group members who would not have worked in the absence of SSP paid relatively low wages – consistent with simple optimizing models of welfare participation. Despite the extra work effort engendered by the program's incentives, SSP had no significant long-run impact on wages, and little or no long run effect on welfare participation.

I. The SSP Demonstration - Description and Expected Impacts

a. Income Assistance Programs and the SSP Experiment

Under the regular welfare system available to low income families in Canada, 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.[2] The implicit 100 percent tax rate on earnings, coupled with the availability of other benefits (e.g., free dental services) limit the incentives for people who have entered IA to work more than a few hours per week. Rising caseloads in the 1980s led to concern over the costs of the Canadian welfare system and the increasing dependency of low-income families. Against this background the Self Sufficiency Project was conceived as a test of a generous earnings subsidy for long term welfare recipients.[3] To encourage a break from program dependency, SSP was only available to full time workers who left welfare, and subsidy payments were limited to a maximum of three years.

Table 1 summarizes the main features of the program, including the eligibility requirements and the subsidy formula. The SSP payment formula is equivalent to a negative income tax with a 50 percent

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[2]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 in the early 1990s.

[3]See Lin et al (1998) for a comprehensive description of the program and results from the first 18 months of the experiment, Michalopoulos et al (2000) for a summary of results in the first 36 months, and Michalopoulos et al (2002) for the final report on the experiment.

tax rate, a "guarantee level" somewhat above average IA benefits (but independent of family size) and a full-time hours requirement.[4] The experiment was conducted in areas around Vancouver, British Columbia and southern New Brunswick, with random assignment between late 1992 and early 1995. Some 5,600 single parents were enrolled in the experiment and followed over the next four and one-half years, with surveys just prior to random assignment and 18, 36, and 54 months after. In addition, administrative data on welfare participation are available for 69 months following random assignment.

Relative to other experimental welfare reforms, such as those tested under the waiver programs in the United States in the early 1990s, SSP is very generous (see Blank, Card, and Robins, 2000). For example, under the regular welfare system a single mother in New Brunswick with one child was eligible for a maximum IA grant of $712 per month in 1994. If she were to leave welfare and take a full time job at the minimum wage her gross income would be $867 per month -- a net gain of $155 per month, or only about $1 per hour of work. Under SSP, however, she would receive an $817 subsidy, raising the relative payoff for work versus welfare to $972 per month, or $6.50 per hour. The financial 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 a supplement payment within 12 months of random assignment could receive SSP payments over the next three years in any month they were working full time. Those who failed to initiate a SSP payment within a year of random assignment lost all future eligibility. As a consequence, members of the program group had a strong incentive to find a full time job within the first year of the program. For a single mother with one child in New Brunswick, for example, SSP eligibility created an entitlement of up to $29,412 ($817 per month × 36 months). Once eligibility was established, members of the program group faced a stronger work incentive than members of the control group, but future eligibility was independent of the decision to

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[4]In a conventional negative income tax with constant tax rate t and guaranteed (or minimum) income G, an individual with earnings y receives a subsidy of $G - ty$. This is equivalent to an earnings supplement equal to t times the difference between actual earnings and the "breakeven" level $B = G/t$.

work or participate in welfare in any given month. The restricted eligibility window makes it hard to generalize the results from SSP to other settings, since part of the behavioral response to the program was arguably attributable to the "one-time" incentive to achieve eligibility. One of our key goals of our econometric model is to disentangle the short term entitlement incentive of the program from the longer term effect among those who achieved eligibility.

b. Behavioral Responses to SSP

What are the expected impacts of SSP on welfare participation? To answer this question, and to provide a guide for our empirical model, this section outlines a simple dynamic model of work and welfare participation.[5] The model is based on a standard search-theoretic framework (e.g., Mortensen, 1977, 1986). In particular, we posit a discrete-time search model in which a single parent has two options: full time employment or welfare participation. Welfare pays a monthly benefit \$b and yields a flow payoff of b. Full time employment at a monthly wage of \$w yields a flow payoff of $w-c$, where c reflects the cost of work (including child care costs, work expenses, and the value of foregone leisure). Individuals maximize expected future income using a monthly discount rate of r. To keep the model as simple as possible, we assume that each month an individual receives a single job offer with probability λ, and that the arrival rate of offers is the same for workers and nonworker. Wage offers are drawn from a distribution with density f(w) and cumulative distribution F(w). Finally, we assume a constant rate of job destruction δ, which applies to new as well as existing jobs.

Under these assumptions, optimal behavior in the absence of a wage subsidy program is characterized by a stationary value function U(w) that gives the discounted expected value associated with a job paying wage w, and a value V^0 of non-work (or welfare participation). People who are employed at a wage w accept any offer paying more than w. People who are on welfare follow a

[5]A more complete description of the model is presented in the Appendix.

reservation wage strategy and accept any job paying more than R, the (fixed) reservation wage satisfying $U(R)=V^0$. Under the assumptions of the model it is readily shown that the optimal reservation wage is R=b+c.[6]

This model predicts that welfare transitions in the absence of SSP are determined by a combination of the arrival rate of job offers, the rate of job destruction, the level of welfare benefits, the distribution of wages, and the pecuniary and non pecuniary costs of work. Specifically, the exit rate from welfare is $\lambda(1-\delta)\times(1-F(b+c))$, while the entry rate into welfare is δ. Individual heterogeneity in welfare exits arises from variation in λ, δ, c, and in the location of the wage offer distribution relative to the welfare benefit level. Individual differences in welfare entry rates arise from heterogeneity in δ.

If a time-limited earnings subsidy similar to SSP is made available at time 0 the decision problem becomes non stationary and it is necessary to consider three separate value functions: $V_i(t)$, the value of not working in month t, conditional on not yet having established eligibility; $U_e(w,d)$, the value of a job paying a wage w conditional on SSP-eligibility with d months of elapsed eligibility; and $V_e(d)$, the value of not working conditional on eligibility and d months of elapsed eligibility. The rules of SSP provide a link between these functions and the value function in the absence of the program. In particular, $V_i(t)=V^0$ for $t\geq 13$, since those who fail to find full time work within 12 months of being offered the subsidy lose all future eligibility. In addition, $U_e(w,d) = U(w)$ for all d>36, since subsidy payments are only available for three years. Similarly, $V_e(d) = V^0$ for all $d\geq 36$. A revealed preference argument establishes that $U_e(w,d) > U(w)$ for all w and any $d\leq 36$, since the subsidy paid to a worker earning a wage w, s(w), is strictly positive. By the same token $V_i(t)$ is decreasing in t, since the passage of time leaves less time to establish eligibility. Finally, since SSP ends after 3 years, $U_e(w,d)$ and $V_e(d)$ are both decreasing in months of elapsed eligibility.

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[6]If on-the-job and off-the-job search are equally productive, there is no reason to turn down a job yielding flow value (w-c) greater than the flow value of welfare (b). Hence the reservation wage is the income equivalent of welfare, b+c.

As is the case in the absence of the subsidy, people who are working and eligible for the supplement accept any job offer that pays more than their current wage, while those who are on welfare with d months of elapsed eligibility follow a reservation wage strategy with a reservation wage $R_e(d)$, with $V_e(d) = U_e(R_e(d), d)$. Assuming that people can quit jobs that are no longer acceptable once their SSP eligibility ends, it is straightforward to show that the optimal reservation wage for an SSP-eligible nonworker equates the net income from a reservation-wage job to the flow value of welfare, b+c. Since b and c are fixed, R_e is independent of d and is defined by the equality $R_e+s(R_e) = b+c$.[7]

Individuals who are still on welfare in month t and not yet SSP-eligible have a reservation wage R(t) satisfying the condition $V_i(t) = U_e(R(t), 1)$. From this equality, and the fact that $V_i(t)$ is decreasing in t, it follows that the reservation wage R(t) is decreasing in t. The reservation wage in the last month of potential eligibility, R(12), satisfies $V_i(12) = U_e(R(12), 1)$. Since $V_i(12) = V^0 < V_e(1)$ (i.e., people would strictly prefer to be on welfare but eligible for SSP than to be on welfare in the absence of SSP), and $V_e(1) = U_e(R_e, 1)$, it follows that $U_e(R(12), 1) < U_e(R_e,1)$. Using the fact that $U_e(w,d)$ is increasing in w, this inequality implies that $R(12) < R_e$: i.e., the reservation wage just before the close of the eligibility window is <u>strictly less than</u> the reservation wage once eligibility is established.

The effects of SSP on the welfare/work decision are summarized by the difference between the reservation wage profiles of a representative welfare recipient in the presence or absence of SSP. The upper panel of Figure 1 shows the sequence of reservation wages for a person who is offered SSP but fails to establish eligibility, along with the (constant) reservation wage R=b+c in the absence of the program. During the 12-month window that individuals have to establish eligibility the reservation wage is below R and declining. Thereafter, those who failed to find a job revert to the reservation wage in the absence of the program. The lower panel of Figure 1 shows the sequence of reservation wages for a

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[7]Since $s(w)\geq 0$ the reservation wage for SSP-eligibles is below the reservation wage in the absence of the program -- i.e., $R_e = b+c-s(R_e) \leq b+c = R$.

person who is offered SSP and establishes eligibility in month $t_e \leq 12$. Prior to t_e the reservation wage is declining. From month t_e to month t_e+36 (i.e., in the period that subsidy payments are available) the reservation wage satisfies the condition $R_e = b+c-s(R_e)$. After eligibility ends (in month t_e+36) the reservation wage reverts to b+c.

The path of the optimal reservation wage illustrates the three different incentive regimes experienced by the treatment group of the SSP experiment. During the pre-eligibility period (up to 12 months after random assignment or the establishment of eligibility), members of the treatment group have a low and declining reservation wage, leading to a faster rate of transition from welfare to work than would be expected for the control group. Members of the treatment group who achieve eligibility adopt a somewhat higher reservation wage, but still lower than they would in the absence of the program, implying that they are more likely to leave welfare and re-enter work than otherwise similar members of the control group. Once subsidy eligibility ends (or starting in month 12 for those who never attain eligibility), the reservation wage returns to its level in the absence of the program and the behavioral effects of SSP disappear. The jump in the reservation wage at t_e implies that some people who accepted low-paying jobs to gain eligibility would be expected to quit and return to welfare almost immediately. Similarly, at the close of eligibility, people who were holding jobs paying less than the reservation wage in the absence of SSP would be expected to quit and re-enter welfare.

While this stylized model provides a guide to the potential effects of SSP, it is obviously oversimplified. For example, the model assumes that the pecuniary and non pecuniary costs of work are constant. More realistically, the costs of work can change over time (e.g., if a child becomes sick), leading people to revise their reservation wages and quit some jobs that were previously acceptable. A generous earnings subsidy widens the range of cost fluctuations that can be tolerated at any wage, leading to a reduction in the flow from work back to welfare. Another limitation of the model is the assumption that people either work full time or receive welfare. In fact some people leave welfare *without* entering full time work, introducing slippage between the event of first exiting welfare and the event of first entering full time work. In our empirical model, we therefore have to distinguish between leaving welfare and becoming SSP-eligible. Finally, the model ignores human capital accumulation or habit persistence effects that might cause SSP to have long-term effects. For example, if wages rise with accumulated work experience, the subsidy would be expected to lead to faster average wage growth for program group members than controls. Alternatively, if the cost of work, c, is reduced by previous work experience (as in a simple habit persistence model), the program would lead to lower reservation wages for the program group than the controls, even after the end of subsidy payments. Our empirical analysis will therefore address the possibility of persistent effects of SSP.

II. The Experimental Sample and Overview of the Program Impacts

a. The SSP Sample

The SSP experimental sample was drawn from the pool of welfare recipients in selected areas of New Brunswick and British Columbia who were single parents, more than 18 years of age, and had received IA payments in at least 11 of the previous 12 months.[8] These requirements meant that nearly everyone in the experiment had been on IA continuously in the year prior to random assignment. A small number left IA between the time of their initial selection into the experiment and their assignment to treatment or control status. To simplify our empirical models, however, we restrict attention to the 5,617 people who were on IA in the two months prior to random assignment.[9] We are able to follow the

[8]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 completed the baseline survey, and were then randomly assigned (Lin et. al, 1998, p.8).

[9]This restriction eliminates any “initial conditions” problems. 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

welfare outcomes of the sample for 69 months following random assignment – 18 months after the last SSP recipient stopped receiving subsidy payments.

Table 2 provides an overview of the characteristics of the SSP sample. The first two columns show the means for the control and program groups of the experiment, while the third and fourth columns distinguish between individuals in the program group who were either successful or unsuccessful in establishing eligibility. Note that because of the random assignment of treatment status the "pre assignment" characteristics in columns 1 and 2 are very similar. The sample is about 95 percent single mothers, with a mean age of 32 and an average of 1.5 children. About 14 percent are immigrants -- nearly all in British Columbia. Sample members have many characteristics that are associated with low economic status, including a low rate of high school graduation (45 percent versus roughly 70 percent in the adult population of Canada), and a relatively high probability of being raised by a single parent. Nevertheless, nearly everyone had worked at some time in the past, and average work experience is relatively high (7.3 years). In the three years prior to random assignment sample members spent an average of about 30 months on IA. Forty percent had been on welfare continuously.

Despite their previous welfare history, sample members began leaving welfare immediately after random assignment. Figure 2a shows average IA participation rates of the program and control groups in the first 69 months after random assignment, while the lower panel of Table 2 reports the fractions on welfare at various points in the post assignment period.[10] In the 15 months after random assignment the IA participation rate of the program group fell more rapidly than that of the control group, while in subsequent months the controls caught up. The program impacts (i.e., the differences in IA participation

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control) until after random assignment, we believe that the difference is accidental.

[10]The IA data are taken from administrative records for the two provinces where the SSP sample was drawn. Some individuals may have left their original province and entered welfare in another province – such behavior would not be captured by the available measures. As noted in the text, our sample is restricted to individuals who were on IA in the two months prior to assignment. Without this restriction, the IA rates are very similar to those shown in Figure 2a, but about one-half of a percentage point lower.

between the program and control groups) are also plotted in Figure 2a, and show a peak difference of −15 percentage points in month 15, falling to −7 percentage points in month 36, and gradually converging to 0 by month 69.

A similar pattern is evident in the employment and earnings of the treatment and control groups, although these outcomes are only available for the first 53 months after random assignment, and are missing for about 18 percent of individuals who could not be contacted or refused to answer the 54-month survey.[11] For example, Figure 2b plots the full time employment rates of the two groups. 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 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 36, and to only 2 percentage points by month 53. SSP's effects on average earnings (not shown here) parallel the impacts on full time employment, with a peak impact of about \$130 per month in months 12-15, falling to about \$60 per month by three years after random assignment, and to less than \$20 per month by month 53.

Consistent with the implications of the search model presented above, comparisons of hourly wages between members of the program and control group suggest that the increased employment rate of the program group coincided with a drop in their reservation wage rates. Figure 3 plots average hourly wages for workers in the two groups, along with mean wages for a series of subsamples of the program group formed by eliminating enough of the lowest-wage workers in each month to give the same fraction

[11]Labor market data were collected in the 18 month, 36 month, and 54 month surveys. The distribution of response patterns to the three surveys for the program and control groups is fairly similar (chi-squared statistic = 11.4 with 7 degrees of freedom, p-value=0.12). However, a slightly larger fraction of the experimental group have labor market data for the 53rd month – 83.0 percent versus 80.5 for the controls.

of workers in as in the control group.[12] In the first 19 months of the experiment, average wages of the control group rose by about $1 per hour while average wages of the program group were constant. Mean wages for the "trimmed" subsamples track the control group very closely, however, implying that the apparent stagnation of the program group's relative wages can be attributed to the labor market entry of relatively low wage workers who would not have worked in the absence of SSP. In later months, the mean wages of the program group gradually caught up with those of the controls as the employment gap between the groups declined. In the last four months for which data are available (months 50-53), when the employment rates of the two groups had nearly equalized, the wage gap had closed to 20 cents per hour or less.[13] This convergence suggests that the enhanced work effort of the program group over the experimental period had little lasting effect on their wages. The absence of an effect is not too surprising, since the rate of wage growth for low-education female workers is modest (1-3 percent per year, based on cross-sectional estimates for a typical SSP sample member) and the experiment only raised the relative experience of the program group by about one-third of a year.[14]

An initial indication of SSP's impacts on welfare flows is presented in Figures 4a and 4b, which show monthly exit and entry rates into Income Assistance. Because of the selective nature of the risk sets for these conditional probabilities, differences in the entry and exit rates between the program and

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[12]This idea is suggested by the approach of Lee (2002) to bounding treatment effects with differential attrition. The subsample in a given month was constructed as follows: First, we calculated the fraction of control group members in each of the two provinces that was working in the month. Then, we sorted the province-specific samples of workers in the program group by ascending wages, and eliminated the lowest wage workers until the fraction of the program group remaining was equal to the employment rate of the control group. Then we pooled the two provincial subsamples. We conducted the trimming by province because wage rates are about 20 percent lower in New Brunswick, and the treatment effects of SSP on employment are not exactly equal in the two provinces.

[13]The difference is 0.22 in month 50 (standard error 0.23); 0.21 in month 51 (0.23), 0.18 in month 52 ((0.23) and 0.12 in month 53 (0.23).

[14]From random assignment to month 53, the program group had on average 3.3 extra months with positive hours than the control group (with a standard error of 0.5 months). The relative gain in months of full-time equivalent experience is 3.8 months (with a standard error of 0.5 months).

control group do not necessarily reveal the causal effect of the program. Nevertheless, it is interesting that the exit rate of the program group was 1-2 percentage points above the rate for the controls in the first 15 months of the experiment, then about half a point higher over the period from 15-48 months after random assignment (while program group members could receive SSP payments), and about equal to the rate for the controls in the period after the end of SSP-eligibility. These patterns are roughly consistent with the implications of the simple model presented above. Conversely, the program group's welfare entry rates were 2-4 percentage points below those of the controls in the first 15 months after random assignment, about half a point lower in the period from 18 to 48 months after random assignment, and similar later on. Welfare entry rates of the program group also surpassed those of the controls in the period from 15 to 18 months after random assignment, perhaps reflecting the decision of some program group members to take a job near the end of the eligibility window and then quit.

b. The SSP-Eligible and Ineligible Program Subgroups

The time limit for SSP eligibility split the program group into two subgroups: those who achieved eligibility and those who did not. Comparisons of columns 3 and 4 of Table 2 show that the eligible subgroup was younger, better-educated, and more likely to be working just prior to random assignment. Reflecting SSP rules, which required people to leave IA once they started to receive SSP payments, the eligible group experienced a rapid fall off in IA participation in the first 18 months after random assignment. Thereafter, their IA participation rate was fairly steady, ending up at about 25 percent in month 69. In contrast, the IA participation rate of the ineligible group remained relatively high, ending at 55 percent in month 69. The 30 point gap between the eligible and ineligible groups in month 69 illustrates the selective nature of the eligibility process. *Overall* there was no program impact on IA participation in month 69. Assuming that impacts on the eligible and ineligible subgroups were both zero by the end of the experiment, the gap in their IA participation rates is purely a reflection of the correlation between eligibility status and long-run welfare propensities.[15]

The welfare transition rates of the eligible and ineligible program subgroups are also dramatically different. 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 later months. Given the selective nature this group, however, it is difficult to infer much about the causal effect of SSP from such simple comparisons. Rather, we use parametric models that explicitly incorporate the selective eligibility process.

III. Models of IA Participation for the Controls

a. Basic Models

Before developing models that incorporate the effects of SSP we consider models of welfare participation in the absence of the program. Let y_{it} represent an indicator that equals 1 if person i receives IA in month t (t runs from 1, the first month after random assignment, to T=69), and let x_{i1}, ..., x_{iT} represent a sequence of observed covariates for individual i. We consider models for the welfare outcomes of the control group in the following class:

$$(1) \quad P(y_{i1}, ... y_{iT} \mid x_{i1}, ... x_{iT}) = \int \{ \prod_t L(\alpha_i + x_{it}\beta + \gamma_1 y_{it-1} + \gamma_2 y_{it-2} + \gamma_3 y_{it-1}\, y_{it-2}) \} \; \phi(\alpha_i \mid \sigma_\alpha)\, d\alpha ,$$

$$\text{with} \quad y_{i0} = y_{i\,-1} = 1 ,$$

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.[16] Equation (1) describes a logistic regression model with second order state dependence and a normally distributed heterogeneity component α_i. This specification is fairly restrictive, in that it imposes independence between monthly welfare outcomes, conditional on α_i, x_{it} and

[15]It is possible that SSP had offsetting long run impacts on the eligible and ineligible groups. Based on the nature of the program, however, we believe this is extremely unlikely.

[16]Note that, as everyone in our sample was receiving IA in the two months prior to random assignment (periods 0 and −1), we do not have to model the distribution of initial conditions.

two lags of previous participation. Chay and Hyslop (2001) compare the goodness of fit of various dynamic welfare participation models using high-frequency 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 component of welfare participation. In view of these findings we limit our attention to this class of models.

Table 3 presents estimation results for four alternative versions of equation (1), fit to data for the SSP control group. The models are estimated by maximum likelihood, using the method of Gaussian quadrature to approximate the integral in equation (1).[17] The specifications in columns 1 and 2 assume that IA participation exhibits homogeneous first order state dependence; the model in column 3 allows for homogeneous second order state dependence; and the model in column 4 allows for the state dependence effects to vary with the unobserved heterogeneity.

The model in column 1 includes a fourth order polynomial in time as the only explanatory variable, while column 2 adds 18 individual covariates, all measured before random assignment.[18] The likelihood ratio statistic for the added variables is highly significant. On the other hand, their inclusion has little effect on the estimated state dependence parameter. Moreover, the values of the covariate index ($x_i\beta$) are approximately normally distributed, and the sum of the individual effects and the covariate index from the model in column 2 has virtually the same standard deviation as the individual effects from the model in column 1.[19] To save computational burden we therefore decided to drop the covariates and

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[17]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).

[18]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.

[19]The index $x_i\beta$ has a standard deviation of 0.74. Thus the standard deviation of ($\alpha_i + x_i\beta$) is 1.64, about the same as the standard deviation of α_i alone in the model that excludes the covariates. A Kolmogorov-

allow the random effects to absorb all permanent differences in welfare participation.

The model in column 3 of Table 3 expands the specification in column 1 by including welfare participation 2 months earlier and the interaction of the first and second lags of IA status. These additional terms are highly significant. Their pattern implies that people who have been on welfare for two months are more likely to remain than those who have been on for only a month (controlling for α_i). 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). This specification relaxes the "linear in log odds" assumption of the logistic functional form and permits the degree of state dependence to vary by whether individuals have a higher or lower long-run propensity to participate in welfare. The interaction terms are statistically significant and their addition leads to a noticeable improvement in the likelihood of the model. The sign pattern of the interactions implies that the state dependence effects are larger for those who are less likely to be on welfare in the long run.

How well do models like those in Table 3 explain observed patterns of welfare dependence? As a description of average IA participation, the answer is very good. The time path of welfare participation predicted by any of the models is fairly close to the actual path. This is not too surprising, however, given that the models include a fourth order polynomial trend, and that the control group's welfare profile is fairly smooth. A more difficult challenge is to predict the distribution of welfare histories among the control group.[20] To evaluate the models on this dimension we decided to compare the predicted and actual fractions of the control group in a set of mutually exclusive cells defined by the total months on IA since random assignment, the number of welfare transitions, and whether the number of transitions is odd (in which case the individual ends up off IA) or even (in which case she ends up on IA). The cells used

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Smirnov test for the normality of the fitted index has a probability value of 15 percent.

[20]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 10 replications per sample member.

in our comparisons, together with actual and predicted numbers of observations from the SSP control group in each cell, are shown in Table 4. We selected the cells to yield reasonable cell sizes: thus, we grouped welfare histories with 0-2, 3-8, 9-14, ... total months on IA, with separate cells for 68 or 69 months on IA. Overall, we collapsed the 2^{69} possible welfare histories into 50 cells.

Panel A of Table 4 shows the actual distribution of the control group across the cells. An important feature of the data is the mass of people (604 = 21.7 percent of the group) who were on IA continuously. The large fraction of continuous participants is strong evidence of either heterogeneity and/or state dependence in welfare participation: in a *homogeneous* sample with the same monthly participation rates as the SSP control group, the expected number of continuous participants is virtually 0.[21] The control group also includes a relatively large number of people who left welfare for one month and then returned (these are the 189 = 6.8 percent of the sample with 68 months on IA and 2 transitions). Anecdotal evidence suggests that many of these one-month gaps represent administrative breaks in participation, rather than true behavior. For example, a divorced mother who receives a large check for past-due child support may have her IA payments suspended for one month.[22] In light of this, it is not too surprising that our models have some difficulty predicting the number of cases with exactly one month off IA.

For each of the models in Table 3 we constructed a chi-squared statistic based on the deviation between the predicted and actual number of observations in each cell.[23] These goodness of fit statistics

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[21]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.

[22]The possibility of such administrative breaks in IA participation is the reason that the SSP sample was drawn from people who had been on welfare for 11 or more months in the previous year.

[23]We constructed the standard Pearson statistic: $\sum_j (O_j - E_j)^2 / E_j$, where O_j is the number of observed cases in cell j=1..J and E_j is the expected number. Since the expected number is based on a model fit to the same data, the statistic does not necessarily have a chi-squared distribution with J-1 = 49 degrees of freedom. We interpret the goodness of fit statistics as informal summary measures of fit.

are reported in the bottom row of Table 3. None of the models does a particularly good job of predicting the welfare histories of the control group, although the specification in column 4 clearly provides the best fit. Panel B of Table 4 shows the predicted distribution of the control group generated by this model. The model gives reasonable predictions for the distribution of total months on IA, with the exception of the last three groups (63-67 months on IA, 68 months on IA, and 69 months on IA). Compared to the actual data, the model over predicts the fraction with 63-67 months on IA and under predicts the fractions with 68 or 69 months. Despite these problems, we decided to use the second order model with interactions between the state dependence coefficients and the random effects as the basis of our models for the program group.

IV. Models for the Program Group

SSP differs from many other experimental programs in that treatment group members were not automatically eligible for the financial treatment. Instead, supplement eligibility was limited to program group members who started working at a full time job or combination of jobs within 12 months of random assignment. The time limit on eligibility created two conceptually distinct “treatment effects”: a one-time incentive to move quickly off welfare; and a continuing incentive for those who established eligibility to work rather than return to welfare. As emphasized in our theoretical model, the timing of eligibility is critical in distinguishing between these effects. Before presenting our empirical model, we discuss the measurement of the eligibility date, and the programmatic link between SSP eligibility and subsequent welfare behavior.

a. The Timing of SSP Eligibility

The actual date of SSP eligibility is not recorded in the available data files. Instead we have to estimate it from administrative data on the timing of SSP payments and survey information on employment outcomes. To aid in developing a plausible estimation procedure we conducted an "event study" around the first month of SSP receipt for the eligible subset of the program group. Figure 5 shows monthly IA participation rates, full time employment rates, and the fraction of people receiving SSP payments before and after the month that is recorded as the date of the first SSP check (month "0" on the graph). Following the jump associated with the first check, the rate of SSP recipiency falls off, gradually drifting down to about 60 percent. The rate of full time employment rises prior to the date of the first SSP check, reaching a maximum of about 80 percent in the month before the check. Assuming that people in the program group became eligible once they started working full time, there appears to be about a 1 month delay between eligibility and the dating of the supplement check.[24]

The IA participation rates in Figure 5 suggest that welfare-leaving is related to SSP initiation, although with a significant lag: The fraction on IA is fairly stable until one month before the first SSP check, drops a little in the month of the first check, and then falls rapidly in the next two months. This pattern is consistent with SSP and IA program rules. SSP required supplement takers to leave IA, creating a direct mechanical connection between the initiation of SSP eligibility and subsequent IA participation.[25] However, IA eligibility is based on retrospective income flows, so one would expect a 1-2 month delay between the start of SSP recipiency and the end of IA payments.

A simple characterization of the data in Figure 5 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 2-3 months. We therefore 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

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[24]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.

[25]This was implemented by having SSP staff notify the appropriate Income Assistance office that an individual was about to begin receiving subsidy payments.

processing; (3) 14 months after random assignment.[26] About 18 percent of the program group became eligible in the first month after random assignment, 9 percent became eligible in each of the second and third months, and roughly 6 percent became eligible in each of the next 10 months. Just under 3 percent became eligible in the last possible month (month 14). Recognizing the delay between the start of a full time job that establishes SSP eligibility and leaving IA, we then add 2 months to these dates for our analysis of welfare dynamics: the adjusted eligibility dates range from 3 to 16 months after random assignment.

The strong but imperfect link between welfare behavior and the onset of SSP eligibility is illustrated in Figure 6, where we plot IA participation rates for eligible program group members in the five months before and after our (adjusted) eligibility date. The fraction on IA is more than 90 percent until one month before the estimated eligibility date, then drops steadily over the next three months, eventually stabilizing at 25 percent. As we would expect, the “mechanical” effect of SSP eligibility on IA participation is concentrated in the interval from 0 to 2 months after our estimated eligibility date. It is important to point out, however, that over one-third of the SSP-eligible group first left IA some time before the estimated eligibility date. Many of these early leavers returned to welfare within a month or two, explaining the stability of average IA participation prior to the eligibility date in Figure 5. Another 16 percent of eligible program group members were late leavers, first exiting from welfare more than 2 months after the estimated eligibility date.[27]

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[26]We use 14 months, rather than 12 or 13, to reflect the possibilities of measurement error and delays in processing. Only 9 observations (out of 957) had their eligibility date set without reference to either the first SSP check date or the first month of full time work.

[27]Indeed, about 3 percent of the SSP-eligible population are recorded as being on IA continuously for the first 24 months after random assignment.

b. Modeling SSP's Incentive Effects

We now turn to a specification of the incentive effects of SSP on the program group on welfare dynamics. Our approach is to treat the date of SSP eligibility as jointly determined with welfare participation, and to specify the behavioral effects of SSP on welfare dynamics conditional on the date of eligibility (t^e_i). In particular, we distinguish between four phases: the pre-eligibility period, ending at t^e_i-1 after random assignment for those who establish eligibility in month t^e_i, and at 16 months for those who do not achieve eligibility; the transitional period lasting for the 3-month period from t^e_i to t^e_i+2 when the program rules required leaving welfare; the eligibility period lasting from t^e_i+3 to t^e_i+36; and the post-eligibility period when supplement payments were no longer available, beginning at t^e_i+37 for those who became eligible for SSP, and at month 17 for those who did not achieve eligibility.[28]

To proceed, let E_{it} represent an indicator for the event that individual i is eligible for SSP as of the start of month t. Note that the sequence $\{E_{it}\}$ makes at most a single transition from 0 to 1, and that this occurs in the eligibility month t^e_i (i.e., $t^e_i = \min_t \{E_{it}=1\}$). For the SSP program group we assume that IA participation and the sequence of eligibility indicators are related to a single normally-distributed heterogeneity component:

$$(2) \quad P(y_{i1}, \ldots y_{iT,} \; E_{i1},\ldots E_{iT} \mid x_{i1}, \ldots x_{iT})$$

$$= \int \{ \textstyle\prod_t P(y_{it}, E_{it} \mid y_{it-1}, y_{it-2}, \ldots \; E_{it-1}, E_{it-2}, \ldots, x_{it}, \alpha_i) \} \; \phi(\alpha_i \mid \sigma_\alpha) \, d\alpha \, .$$

Using the fact that treatment status is randomly assigned, we also assume that the distribution of unobserved heterogeneity effects α_i is the same for the program and the control groups.

Conditional on α_i and the covariates x_{it} we assume that E_{it} is determined independently of current or lagged IA status, while y_{it} depends on current eligibility, how long an individual has been eligible, and

[28]It is possible that SSP had a "permanent" effect on those who became eligible, although the evidence in Figure 2a suggests that did not occur. In this case, we have to distinguish between the post-eligibility periods of those who received and did not receive supplement payments.

on 2 lags of previous IA status.[29] Specifically, we assume:

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

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

We further assume that IA participation of the program group follows the same model as the control group, with the addition of a treatment effect that depends which of the four phases the individual is currently occupying. Specifically, we assume that

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

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

where L( ) represents the logistic distribution function, and $\tau(t, E_{it}, t^e_i, y_{it-1})$ is the behavioral impact of SSP. As a baseline specification, we begin with the assumption that the effects of SSP are confined to the transitional period and the eligibility period, and allow separate treatment effects depending on whether the individual was on or off IA in the previous period:

$$\begin{aligned}\tau(t, E_{it}, t^e_i, y_{it-1}) \quad = \quad & E_{it} \times 1(\ t^e_i \le t \le t^e_i+2\ )\ \{\ \psi_0\, 1(y_{it-1}=0)\ +\ \psi_1\, 1(y_{it-1}=1)\ \} \\ & +\ E_{it} \times 1(\ t^e_i+3 \le t \le t^e_i+35\ )\ \{\ \lambda_0\, 1(y_{it-1}=0)\ +\ \lambda_1\, 1(y_{it-1}=1)\ \}\ .\end{aligned}$$

In this simplified case, ψ_0 and ψ_1 measure the effects of SSP eligibility during the transitional period on individuals who were off or on IA in the previous month, respectively, while λ_0 and λ_1 measure the corresponding incentive effects during the eligibility period. We experiment below with specifications that allow treatment effects in the pre and post eligibility periods.

Given the single-transition nature of the eligibility process, a natural model for E_{it} is a hazard model for the event of achieving eligibility in month t, conditional on not achieving it earlier. We assume that the hazard of eligibility depends on the individual heterogeneity effect α_i and on the month:

[29] The assumption that eligibility is independent of previous IA outcomes is clearly an over-simplification. In fact, people who remained on IA were slightly more likely to become eligible than those who did not.

$$(5) \qquad P(E_{it} \mid E_{it-1}, E_{it-2}, ..., x_{it}, \alpha_i)$$

$$= \Phi[\, d(t) - k\alpha_i \,] \quad \text{if } E_{it-1} = 0 \;\;\&\;\; 1 \le t \le 16 \,,$$

$$= 1 \quad \text{if } E_{it-1} = 1 \,,$$

$$= 0 \quad \text{if } E_{it-1} = 0 \;\;\&\;\; t > 16 \,,$$

where Φ is the standard normal distribution function and d(t) is a smooth function of time. If k=0 then eligibility is independent of the unobserved determinants of welfare participation and the treatment effect $\tau(\cdot)$ can be treated as exogenous in equation (4). More realistically, however, k is positive since people with a higher propensity to stay on welfare have a lower probability of achieving eligibility in any period.

c. Estimates for the Program and Control Groups

Table 5 presents a series of estimates based on equations (1)-(5). All the specifications allow for second order state dependence, with interactions between the state dependence effects and the random effects, and include a fourth order trend in the IA participation model. The specification in column (1) ignores any correlation between SSP eligibility and the unobserved individual effect α_i, and treats E_{it} as an exogenous covariate. The other specifications include an eligibility model based on equation (5), with a trend function $d(t) = d_0 + d_1(t\text{-}1) + d_2/t$.[30] In addition, the specifications in columns (1) and (2) assume that the treatment effects are constant across individuals, while the specifications in columns (3)-(5) allow the transitional and eligibility period treatment effects to vary linearly with the random effects. Finally, the models in columns (4) and (5) allow for individual heterogeneity in the trend in IA participation by including interactions of α_i with a quadratic in months since random assignment.

All the models in Table 5 yield estimates of the state dependence and heterogeneity parameters that are similar to the estimates obtained for the control group alone. The estimated treatment effects are

[30]The 1/t term is included to capture the fact that the hazard of eligibility falls from 18 percent in month 1 to around 8 percent by months 4-10.

roughly similar across specifications, with large negative estimates of the SSP eligibility effect in the transitional period, and smaller but significantly negative treatment effects in the eligibility period. Closer inspection of the treatment effects in columns (1) and (2), however, shows that the implied eligibility-period effects are about 30 percent larger when eligibility is treated is exogenous (column 1) than when it is modeled as endogenous (column 2). This is the pattern that would be expected if people with a lower probability of IA participation are more likely to become SSP-eligible. In the selection-corrected model, some of the differential in eligibility period 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 interpretation, the estimates of the parameter k from the eligibility model are positive and highly significant for all the specifications. The implied distributions of the individual effects among the eligible and ineligible program groups are quite distinct. For example, simulations from the model in column (2) of Table 5 show that the median of the α_i's for the eligible program group is -0.98, while the median for the ineligible group is 0.36. (Recall that the mean and median of the α_i's is 0 for the overall population).

The bottom rows of Table 5 report goodness of fit statistics for the control and program groups, based on the same set of 50 cells used in Table 4. The specification in column (1) clearly provides a better fit than the specification in column (2). Indeed, the specification in column (1) yields a substantially better fit for the controls than the (analogous) model in column (4) of Table 3. Although the eligibility model in column (2) is flexible enough to provide a reasonable fit to the distribution of months to eligibility, the overall goodness of fit to the welfare histories is worse when this distribution is treated is endogenous than when it is treated as exogenous.

The model in column 3 generalizes the specification in column 2 by allowing the SSP treatment effects to vary with the random effects. The interaction term is especially large for the transitional period effect on IA exits, and implies that SSP eligibility raised the log-odds of leaving welfare more for people with higher values of the individual effect α_i (i.e., those who were less likely to leave in the absence of the program). As a result, the predicted probabilities of leaving IA in the period just after the establishment of eligibility are roughly the same for people with different values of the α_i's. Since most people who became eligible for SSP were off IA for at least a month in the transitional period, the generalized model gives a better description than the model that assumes a homogeneous effect on the log odds. Consistent with this observation, the goodness of fit statistics for the model in column 3 are somewhat better than those of the simpler specification in column 2.

The specification in column 4 introduces an additional degree of flexibility by including interactions of α_i with a quadratic in months since random assignment. We developed this model out of concern that imposing a homogeneous trend might inadvertently bias our estimates of the treatment effects, since the eligible program group has a non-random distribution of α_i's. As with the other interaction terms, the trend interactions are statistically significant, although their introduction has little effect on the size of the estimated treatment effects. They also have an ambiguous effect on the goodness-of-fit statistics, leading to an improvement for the control group but a worse fit for the program group. Panel C of Table 4 shows this model's predictions for distribution of welfare histories of the control group, while Table 6 shows the actual and predicted welfare histories for the program group. The model fits the controls a little better than the specification in column 4 of Table 3, although it still under predicts the fraction of both experimental groups who stayed on welfare continuously, and also the fraction who was off IA for exactly one month.

The specifications in columns 1-4 of Table 5 all ignore any effects of the offer of SSP on welfare behavior prior to the eligibility date. As a check, the final specification in column 5 of Table 5 allows *pre-eligibility* treatment effects on the welfare entry and exit rates of the treatment group (including both SSP-eligibles and ineligibles). The interpretation of these estimated effects is potentially confounded by measurement problems and by other misspecification issues. For example, if our estimated eligibility dates are too late (relative to the true dates) people will appear to leave IA before they become eligible for supplement payments, leading to negative pre-eligibility effects.

The estimated pre-eligibility treatment effects are relatively small but, contrary to our initial expectations, the “effect” on IA exits is positive and statistically significant. Rather than a true causal effect, we believe that this positive estimate is driven by the behavior of the (relatively small) group of welfare recipients who left IA for reasons such as marriage or a change in family structure. Typically, these individuals did not become SSP-eligible, inducing a spurious positive correlation between IA participation and subsequent eligibility that generates an apparent positive effect of future eligibility on welfare participation.

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 4 of Table 5. Overall, the predictions are fairly accurate, although the model slightly over predicts welfare participation of the program group in the period immediately after the close of the eligibility window (months 13-15), and also over predicts IA participation of the controls in months 40-48. The model explains 99.9 percent of the variance in average monthly IA participation of both the program and control groups, with root mean squared prediction errors of 0.3 and 0.5 percent, respectively. It is also notable that the prediction errors in the last year of the followup period are relatively small.[31] By month 54, everyone in the program group who was SSP-eligible had come to the end of the three-year eligibility period. Thus, from month 54 onward, the predicted behavior of the program group is based on the assumption that SSP has no long run impact. The model does a good job of tracking the average monthly IA participation rate of the program group in this period, suggesting that this assumption is valid.

Further insight into the accuracy of the model is provided in Figure 8, which shows predicted and

[31]The root mean squared prediction errors in months 51-69 are 0.34 percent for the controls and 0.27 percent for the program group.

actual welfare participation rates for the eligible and ineligible program groups. The predictions for the ineligible group are relatively accurate (root mean squared error of 1.0 percent), while those for the eligible group are a little less so (root mean squared error 2.2 percent), particularly in months 13-18. Evidently, the model has difficulty 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 the eligibility window returned to IA within a few months. Such behavior is actually potentially consistent with our theoretical model, which predicts that some people will take a relatively unattractive job to gain eligibility, and then quit immediately. Our simple empirical model, however, does not allow different welfare entry rates at the beginning of the eligibility period than later on.

Another problem for the model is the trend in welfare participation of the eligible program group 18-36 months after random assignment. During this period the actual participation rate of the eligible group is very stable at between 27 and 28 percent, whereas the model predicts a decline in participation, particularly after month 24. The predicted downward trend is a result of the behavior of the controls and the ineligible program group, which both show steady declines in IA participation in months 18-36. Even allowing for heterogeneity in the trend for different values of the random effect, the best fitting model cannot explain the absence of a parallel trend for the eligible program group.

Finally, it is interesting to examine the fit of the model in months 54-69, when the treatment effects are all assumed to be zero. In this interval, the fit to the two program subgroups is relatively good, suggesting that the data are consistent with the conclusion of no long run effect on welfare participation. To probe this further, we fit a model that allowed a fraction θ of the two eligibility period treatment effects to persist after the expiration of SSP. In a specification parallel to the one in column 4 of Table 5, the estimate of θ is 0.43 (with a standard error 0.05), suggesting that an important fraction of the treatment effect persisted. Simulations of this model, however, show that it under predicts the IA participation of the eligible program subgroup in months 65-69. Based on this poor fit, and the evidence in Figure 2a of convergence in welfare participation, we believe that models that set the post expiration effects to zero provide a more robust description of the data.

d. Decomposing SSP's Effects

By simulating the models in Table 5 with the various treatment effects turned on or off it is possible to gain some additional insights into the behavioral responses of the program group, and in particular into the "hump shaped" pattern of SSP impacts on IA participation rates shown in Figure 2a. Figure 9 uses the model in column 4 of Table 5 to decompose the predicted monthly welfare participation rates of the eligible program group into selection effects, transitional-period effects, and eligibility-period effects, while Figure 10 shows the predicted and actual SSP impacts on IA participation, with a decomposition of the predicted impacts into transitional and eligibility period effects.

Beginning with Figure 9, the upper solid line shows the predicted welfare participation rate of the control group, and the dotted line shows the predicted welfare participation rate of the eligible program group in the absence of SSP. The divergence from the solid line reflects the selective nature of the eligible program group. For example, in month 36 the model predicts a 46 percent IA participation rate for the eligible program group in the absence of any treatment effects, versus a 66 percent rate for the control group (or equivalently, for the overall program group with no treatment effects).

Next, we plot the path of the eligible program group, taking account only of the transitional-period treatment effects. These represent the impact of the program group's effort to achieve SSP eligibility, and peak at (or just after) the close of the eligibility window. Because of the high degree of state dependence in IA participation, the effect of this transitional-eligibility effort persists for almost two more years. Finally, the fourth line in Figure 9 (with solid squares) represents the predicted IA participation rate, taking account of both the transitional and eligibility period effects of SSP on IA behavior. Comparisons of the various paths show that in the early months of the experiment (months 6-18) most of the overall treatment effect for the eligible program group derived from the transitional-effects. Over the period from the 18th to 36th month this effect gradually dissipated and the eligibility-period effects dominated. Starting in month 36 and continuing through month 50 members of the eligible program group gradually exhausted their three years of supplement eligibility, and the treatment effect faded out. Finally, after month 50 all treatment effects ended, and the eligible program group gradually returned to their path in the absence of any treatment. Although not shown in Figure 9, we have also decomposed the eligibility-period effects on IA participation into a component due to faster IA exits, and a component due to slower IA entry. Roughly three quarters of the overall eligibility period effect is attributable to faster welfare exit rates, while one-quarter is attributable to reduced welfare entry rates.

We have conducted simulations of the other models in Table 5 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 on the eligible program group represents the combination of a one-time entitlement effect and a longer run effect on welfare entry and exit rates that ended once individuals' SSP eligibility expired. The entitlement effect reached a peak of about −20 percentage points at 15 months after random assignment, accounting for 55 percent of the overall impact on the eligible program group at that point. By three years after random assignment, the entitlement effect had faded, accounting for 15 percent or less of the total impact on welfare participation. The impact of the longer-run effects associated with the eligibility-period treatment parameters peaks at about −20 percentage points by two years after random assignment, and is fairly stable over the next year, before dissipating as people come to the end of their three-year eligibility window.

Figure 10 presents a decomposition of SSP's predicted impacts on the overall behavior of the program group relative to the control group, along with a comparison of the predicted and actual differences in IA participation of the two groups (using the model in column 4 of Table 5). The distinctive "V-shaped" profile of the predicted impacts is attributed to the combination of the two SSP incentive effects. Overall, the predicted and actual impacts are fairly close, although as noted earlier our model has some difficulty reproducing the peak impact of SSP in months 12-15, and the negative trend in impacts between months 24 and 36. The pattern of predicted and actual treatment effects in months 54-69 is also worth emphasizing. In the first half of this interval our model tends to under predict SSP's impact on IA participation of the program group relative to the controls, while by month 64 the predictions are very close. On average in the post eligibility period, then, the predicted treatment effects are slightly too small. This explains why a specification that allows a post eligibility treatment effect shows some evidence of persistence.

V. Conclusions

The results of our analysis suggest that the monthly welfare outcomes of long-term welfare recipients in the SSP experiment are reasonably well described by a class of dynamic binary response models that incorporate state dependence and permanent individual heterogeneity. Such 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 important, SSP generated two behavioral effects: a one-time transitional effect that accelerated the pace of welfare exits relative to the control group; and a longer-term effect on welfare transition rates that persisted while SSP payments were available. These responses are roughly consistent with a simple theoretical model of dynamic labor market behavior, which predicts that people who are offered SSP will adopt a declining reservation wage over the period they have to find a full time job and establish eligibility, and a higher (but still relatively low) reservation wage during the subsequent period that supplement payments are available. Moreover, as predicted by such a model, the higher rate of employment of the program group can be attributed to people accepting relatively low wage jobs.

A second important finding is that the behavioral effects of SSP substantially faded once the subsidy was no longer available. Despite the additional work and reduced welfare participation by the program group during the period when subsidy payments were available, the average wages of the program group were no higher than those of the control group 53 months after random assignment, and the welfare participation rate of the program group had converged back to that of the control group by the end of our 69-month observation window. Thus, the SSP demonstration provides little support for the idea that welfare dependency can be permanently reduced by offering a time-limited work incentive to long-term welfare recipients.

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Appendix: A Simple Model of Work and Welfare Participation

a. Model in the Absence of SSP

We consider a discrete time search model with time measured in months. Individuals are risk neutral and discount the future at the monthly interest rate r. Net income if on welfare is b. Net income if working at the wage w is $w-c$. Each month, an individual receives a single job offer with probability λ, drawn from a distribution with density f(w) and cumulative density F(w), with $\ell \le w \le m$. The job destruction rate is δ. Optimal behavior is characterized by a value function U(w), representing the value of holding a job that pays w, and by a value V^0 of unemployment. To derive U(w), note that for an individual who is currently holding a job with wage w, expected value next month is:

$$\lambda(1-F(w))\{ (1-\delta) E[U(\omega) \mid \omega>w] + \delta V^0 \} + (1 - \lambda(1-F(w)) \{ (1-\delta)U(w) + \delta V^0 \} .$$

The first term in this expression represents the outcome if an offer is obtained (which occurs with probability λ) and it pays more than the current wage (which occurs with probability $1-F(w)$). In this case, with probability $(1-\delta)$ the job survives to the end of the month, and with probability δ it ends right away. The second term represents the outcome if no acceptable offer is obtained, in which case with probability $1-\delta$ the existing job survives and with probability δ it ends. With some re-arrangement, this expression becomes

$$\delta V^0 + (1-\delta)U(w) + \lambda (1-\delta) \int_w^m (U(\omega) - U(w)) f(\omega) d\omega .$$

Thus,

$$U(w) = (w-c)/(1+r) + 1/(1+r) \{ \delta V^0 + (1-\delta)U(w) + \lambda (1-\delta) \int_w^m (U(\omega) - U(w)) f(\omega) d\omega \} ,$$

or

$$\text{(A1)} \quad U(w) = (w-c)/(r+\delta) + \delta/(r+\delta)V^0 + \lambda(1-\delta)/(r+\delta) \int_w^m (U(\omega) - U(w)) f(\omega) d\omega .$$

To derive the value of unemployment, note that if an individual is currently unemployed, and will accept a job paying at least R, then (using the same arguments as above) expected value next month is:

$$\lambda(1-F(R))\{ (1-\delta) E[U(\omega) \mid \omega>R] + \delta V^0 \} + (1 - \lambda(1-F(R)) V^0 .$$

This can be re-written as

$$V^0 + \lambda(1-\delta) \int_R^m (U(\omega) - V^0) f(\omega) d\omega .$$

Thus,

$$V^0 = b/(1+r) + 1/(1+r) \{ V^0 + \lambda(1-\delta) \int_R^m (U(\omega) - V^0) f(\omega) d\omega \} ,$$

or

(A2) $V^0 = b/r + \lambda(1-\delta)/r \int_R^m \{ U(\omega) - V^0 \} f(\omega)\, d\omega$.
Standard arguments imply that the optimal reservation wage R has the property that $U(R)=V^0$. With this substitution, a comparison of A1 and A2 reveals that R=b+c.

b. Model with SSP

In the presence of SSP there are three value functions: $V_i(t)$, the value of welfare participation if not yet SSP-eligible, t months after assignment; $U_e(w,d)$, the value of a job paying a wage w if SSP-eligible with d months of elapsed eligibility; and $V_e(d)$, the value of not working if SSP-eligible with d months of elapsed eligibility. From revealed preference arguments we have the following inequalities:

$$V_i(t) \geq V_i(t+1) \geq V^0 \text{ , with } V_i(13) = V^0 \text{ ,}$$

$$U_e(w, d) \geq U_e(w, d+1) \geq U(w), \text{ with } U_e(w, 37) = U(w) \text{ ,}$$

$$V_e(d) \geq V_e(d+1) \geq V_0, \text{ with } V_e(36) = V^0 \text{ .}$$

Following the same line of argument as used in the derivation of U(w), the value for a job paying wage w after d months of elapsed eligibility is:

(A3) $$U_e(w,d) = (w-c+s(w))/(1+r) + (1-\delta)/(1+r) \max \{ U_e(w,d+1) , V_e(d+1) \} + \delta/(1+r)\, V_e(d+1) + \lambda(1-\delta)/(1+r) \int_w^m \{ U_e(\omega,d+1) - U_e(w,d+1) \} f(\omega)\, d\omega \text{ ,}$$

where s(w) is the SSP subsidy for a worker with wage w, and allowance has been made for the fact that in a nonstationary environment, an individual may take a job in month d that she will quit in month d+1. Similarly, the value of nonemployment while still SSP eligible is

(A4) $$V_e(d) = b/(1+r) + 1/(1+r)\, V_e(d+1) + \lambda(1-\delta)/(1+r) \int_{Re(d)}^m \{ U_e(\omega,d+1) - V_e(d+1) \} f(\omega)\, d\omega \text{ ,}$$

where $R_e(d)$ is the reservation wage for an SSP-eligible person with d months of elapsed eligibility, and the value of nonemployment for those who are not yet eligible for SSP is

(A5) $$V_i(t) = b/(1+r) + 1/(1+r)\, V_i(t+1) + \lambda(1-\delta)/(1+r) \int_{Ri(t)}^m \{ U_e(\omega,1) - V_i(t+1) \} f(\omega)\, d\omega \text{ ,}$$

where $R_i(t)$ is the reservation wage in month t for people who are offered SSP but not yet eligible.

The optimal reservation wage for an SSP-eligible person satisfies the equality $U_e(R_e(d), d) = V_e(d)$. Substituting this into (A3) and (A4) and working backward from month d=36 (i.e., the last month of SSP eligibility) it is readily shown that $R_e(d) = R_e$, where $R_e+s(R_e) = b+c$.

Table 1: Key Features of the SSP Recipient Demonstration

A. Program Eligibility

· Eligibility limited to 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), with random assignment between November 1992 and February 1995.

· 2,858 single parents assigned to the program group, 2,826 assigned to the 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 equals 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 payments are unaffected by unearned income or the earnings of a spouse/partner, and are treated as regular income for income tax purposes.

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

· Once eligible, program group members can return to IA at any time. Supplement payments are re-established if an eligible person begins working full time again.

· Employers are not informed of SSP status. Program group members apply for supplement payments by mailing in copies of pay stubs.

Table 2: Characteristics of SSP Control and Experimental Groups

	Controls	Programs	Program Group by SSP-Eligibility	
			Eligible	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	90.8	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 36	65.4	58.8	27.6	74.8
Month 48	56.7	53.5	29.3	65.9
Month 60	50.6	48.4	28.5	58.5
Month 69	45.0	45.0	25.4	55.0
Number Observations	2,786	2,831	957	1,874

Note: Sample includes individuals in SSP treatment and control groups who were on IA in the two months prior to random assignment. Eligible program group members are those who ever received an SSP supplement payment.

Table 3: Estimated Dynamic IA Participation Models for Controls Only

	First Order Models		Second Order Models	
	(1)	(2)	(3)	(4)
Coefficient of:				
y(t-1)	5.22 (0.03)	5.21 (0.03)	5.19 (0.07)	4.74 (0.06)
y(t-2)	--	--	2.19 (0.05)	2.04 (0.05)
y(t-1)×y(t-2)	--	--	-1.39 (0.08)	-0.87 (0.05)
y(t-1)×α(i)	--	--	--	-0.73 (0.06)
y(t-2)×α(i)	--	--	--	-0.26 (0.04)
y(t-1)×y(t-2)×α(i)	--	--	--	0.81 (0.08)
Individual Covariates	none	18	none	none
Standard Deviation of Random Effect (σ_α)	1.64 (0.03)	1.47 (0.04)	1.32 (0.03)	1.57 (0.06)
Log Likelihood	-28,227.6	-27,971.2	-27,225.6	-27,202.6
Goodness of Fit	752.6	--	670.0	469.2

Notes: Approximate standard in parentheses. See text for model specifications. All models include fourth order trend (not shown). Models are estimated by maximum likelihood, using Gaussian quadrature with 10 points.

Table 4: Summary of IA Participation Sequences – Controls

Months On IA	Number of Transitions: 0	1	2	3 + Sum Odd	4 + Sum Even	Total
A. Actual Distribution						
0-2	0	38	0	3	0	41
3-8	0	125	2	40	0	167
9-14	0	87	5	52	3	147
15-20	0	72	2	64	6	144
21-26	0	66	5	72	7	150
27-32	0	70	3	83	13	169
33-38	0	59	7	90	18	174
39-44	0	58	8	87	29	182
45-50	0	55	18	83	29	185
51-56	0	41	10	82	33	166
57-62	0	40	30	77	53	200
63-67	0	37	67	40	113	257
68	0	11	189	0	0	200
69	604	0	0	0	0	604
Total	604	759	346	773	304	2786
B. Predicted by Model in Column 4 of Table 3						
0-2	0	70.5	0.3	2.8	0	73.6
3-8	0	123.0	2.6	41.2	0.2	167.0
9-14	0	87.8	3.7	69.9	1.0	162.4
15-20	0	62.9	3.8	83.6	3.4	153.7
21-26	0	54.5	5.9	89.7	8.2	158.3
27-32	0	40.7	8.3	85.2	11.4	145.6
33-38	0	41.9	9.6	96.0	16.3	163.8
39-44	0	38.9	15.2	91.7	23.7	169.5
45-50	0	36.4	20.2	88.3	35.7	180.6
51-56	0	45.9	41.1	80.4	46.0	213.4
57-62	0	46.5	73.8	58.1	60.4	238.8
63-67	0	59.6	181.5	25.3	47.5	313.9
68	0	12.6	86.0	0	0	98.6
69	546.8	0	0	0	0	546.8
Total	546.8	721.2	452.0	812.2	253.8	2786.0
C. Predicted by Model in Column 4 of Table 5						
0-2	0	54.5	0.2	1.7	0	56.4
3-8	0	120.9	2.1	34.0	0.2	157.2
9-14	0	107.0	3.4	65.4	1.0	176.8
15-20	0	77.4	4.2	83.3	3.3	168.2
21-26	0	64.9	5.4	89.5	8.2	168.0
27-32	0	44.8	6.1	88.3	10.7	149.9
33-38	0	40.7	7.1	94.3	17.3	159.4
39-44	0	35.2	11.0	95.5	23.2	164.9
45-50	0	32.2	13.5	88.2	35.8	169.7
51-56	0	37.2	29.8	83.4	48.9	199.3
57-62	0	40.4	60.3	64.2	74.9	239.8
63-67	0	52.5	188.3	30.2	75.9	346.9
68	0	12.6	110.3	0	0	122.9
69	506.6	0	0	0	0	506.6
Total	490.0	720.3	441.7	818.0	299.4	2786.0

Note: Entries represent actual and predicted numbers of observations with number of months on IA (in 69 month period after random assignment) given in row heading and number of IA transitions given in column heading.

Table 5: Estimated Dynamic Participation Models for Control and Program Groups

	(1)	(2)	(3)	(4)	(5)
<u>State Dependence Parameters</u>					
y(t-1)	4.78	4.72	4.68	4.69	4.69
	(0.04)	(0.04)	(0.04)	(0.04)	(0.04)
y(t-2)	1.90	1.86	1.84	1.84	1.85
	(0.03)	(0.03)	(0.03)	(0.03)	(0.03)
y(t-1)×y(t-2)	-0.87	-0.80	-0.79	-0.82	-0.85
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
y(t-1)×α(i)	-0.74	-0.90	-0.77	-1.11	-1.14
	(0.04)	(0.04)	(0.04)	(0.07)	(0.08)
y(t-2)×α(i)	-0.40	-0.35	-0.33	-0.40	-0.43
	(0.03)	(0.03)	(0.03)	(0.04)	(0.03)
y(t-1)×y(t-2)×α(i)	0.76	0.79	0.74	1.09	1.15
	(0.05)	(0.05)	(0.04)	(0.08)	(0.09)
<u>Treatment Parameters</u>					
Transitional Period					
ψ_1 (exit)	-3.02	-2.76	-3.26	-3.10	-3.04
	(0.06)	(0.06)	(0.07)	(0.07)	(0.07)
ψ_0 (entry)	-1.92	-1.63	-1.84	-1.75	-1.71
	(0.13)	(0.13)	(0.14)	(0.14)	(0.14)
$\psi_1 \times \alpha_i$	--	--	-0.53	-0.61	-0.64
			(0.06)	(0.07)	(0.07)
$\psi_0 \times \alpha_i$	--	--	-0.27	-0.22	-0.19
			(0.09)	(0.15)	(0.15)
Eligibility Period					
λ_1 (exit)	-1.35	-1.10	-1.08	-1.11	-1.09
	(0.04)	(0.05)	(0.04)	(0.04)	(0.04)
λ_0 (entry)	-0.86	-0.51	-0.69	-0.72	-0.71
	(0.05)	(0.05)	(0.05)	(0.05)	(0.05)
$\lambda_1 \times \alpha_i$	--	--	-0.03	-0.07	-0.09
			(0.04)	(0.06)	(0.07)
$\lambda_0 \times \alpha_i$	--	--	-0.26	-0.35	-0.36
			(0.04)	(0.07)	(0.07)

Note: table continues.

Table 5 Continued.

	(1)	(2)	(3)	(4)	(5)
Treatment Parameters (continued)					
Pre-Eligibility Period					
θ_1 (exit)	--	--	--	--	0.25
					(0.05)
θ_0 (entry)	--	--	--	--	-0.13
					(0.08)
Selection Parameters					
d_0 (constant)	--	-2.23	-2.23	-2.22	-2.22
		(0.06)	(0.06)	(0.06)	(0.06)
d_1 (linear trend)	--	0.19	0.18	0.18	0.18
		(0.04)	(0.06)	(0.06)	(0.06)
d_2 (1/t)	--	0.55	0.55	0.55	0.55
		(0.08)	(0.08)	(0.08)	(0.08)
k (loading on α(i))	--	0.21	0.19	0.29	0.30
		(0.01)	(0.02)	(0.02)	(0.02)
Interaction of Random Effects and Trends					
Linear trend×α(i) (÷10)	--	--	--	0.30	0.32
				(0.04)	(0.05)
Quadratic trend×α(i) (÷1000)	--	--	--	-0.33	-0.35
				(0.06)	(0.06)
Heterogeneity Parameter					
σ_α	1.75	1.76	1.86	1.18	1.13
	(0.04)	(0.04)	(0.04)	(0.06)	(0.06)
Log Likelihood	-57,018	-61,116	-61,032	-60,960	-60,945
Goodness-of-Fit					
Controls	277.1	360.0	325.4	314.8	333.1
Programs	194.1	314.5	303.2	329.4	351.4

Notes: Approximate standard errors in parentheses. See text and notes to Table 3. All models include fourth order trend (not shown).

Table 6: Summary of IA Participation Sequences – Program Group

Months On IA	Number of Transitions: 0	1	2	3 + Sum Odd	4 + Sum Even	Total
A. Actual Distribution						
0-2	0	85	0	9	0	94
3-8	0	198	3	58	1	260
9-14	0	120	4	104	2	230
15-20	0	48	3	103	14	168
21-26	0	33	4	83	21	141
27-32	0	39	5	78	25	147
33-38	0	38	7	86	26	157
39-44	0	49	5	77	25	156
45-50	0	39	18	65	37	159
51-56	0	41	17	58	62	178
57-62	0	31	37	56	90	214
63-67	0	26	72	24	141	263
68	0	9	172	0	0	181
69	483	0	0	0	0	483
Total	483	756	347	801	444	2831
B. Predicted by Model in Column 4 of Table 5						
0-2	0	83.5	0.3	2.8	0	86.6
3-8	0	185.2	3.8	73.9	1.1	264.0
9-14	0	123.8	5.6	122.5	4.7	256.6
15-20	0	54.1	6.4	121.2	12.8	194.5
21-26	0	34.2	6.3	94.3	14.6	149.4
27-32	0	25.9	7.1	93.9	19.3	146.2
33-38	0	24.9	8.8	88.4	27.3	149.4
39-44	0	20.5	10.8	79.6	35.6	146.7
45-50	0	25.2	15.3	73.3	47.1	160.9
51-56	0	26.6	25.6	70.6	62.0	184.8
57-62	0	30.4	57.8	52.9	84.6	225.7
63-67	0	38.9	176.8	26.8	73.4	315.9
68	0	8.6	93.1	0	0	101.7
69	448.6	0	0	0	0	448.6
Total	448.6	681.8	417.7	900.4	382.5	2831.0

See notes to Table 4.

Figure 1: Theoretical Profiles of Reservation Wages for Current Welfare Recipients

a. Reservation Wage of Ineligible Program Group Member

b. Reservation Wage of Eligible Program Group Member

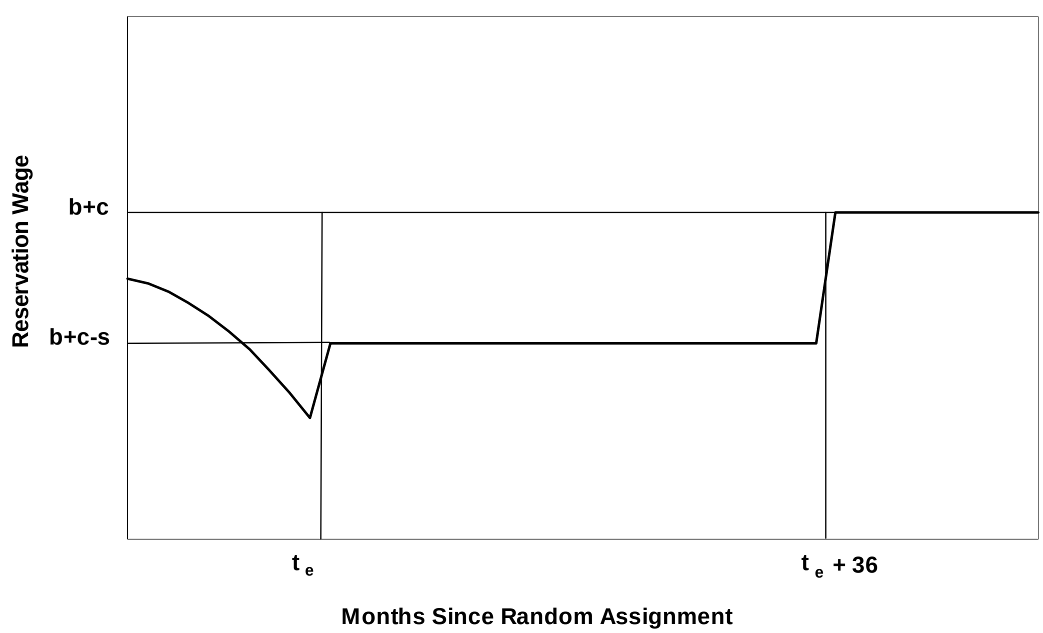

Figure 2a: Monthly Income Assistance Participation Rates

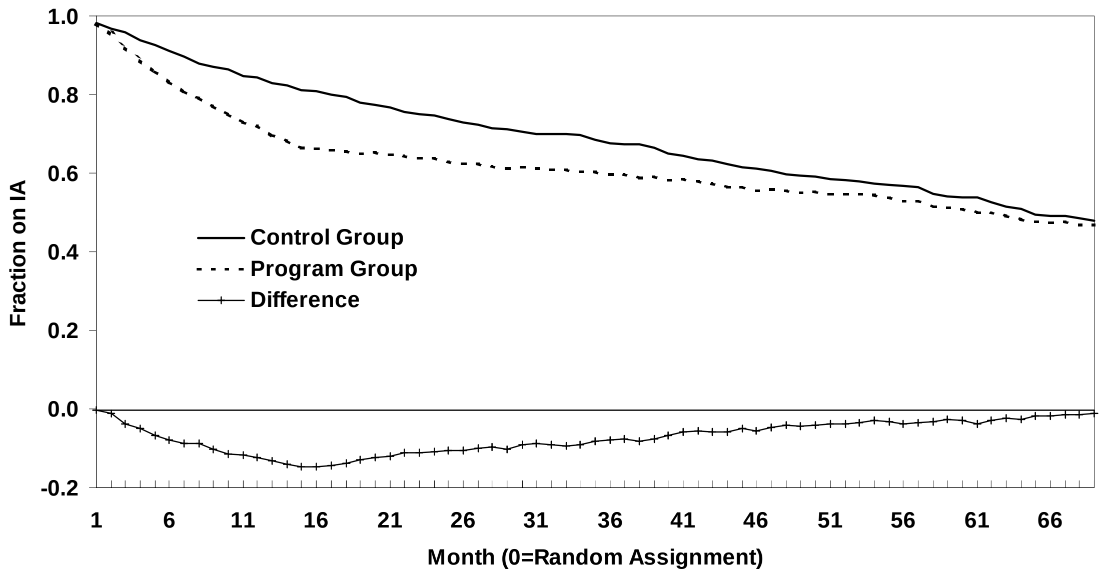

Figure 2b: Monthly Full Time Employment Rate

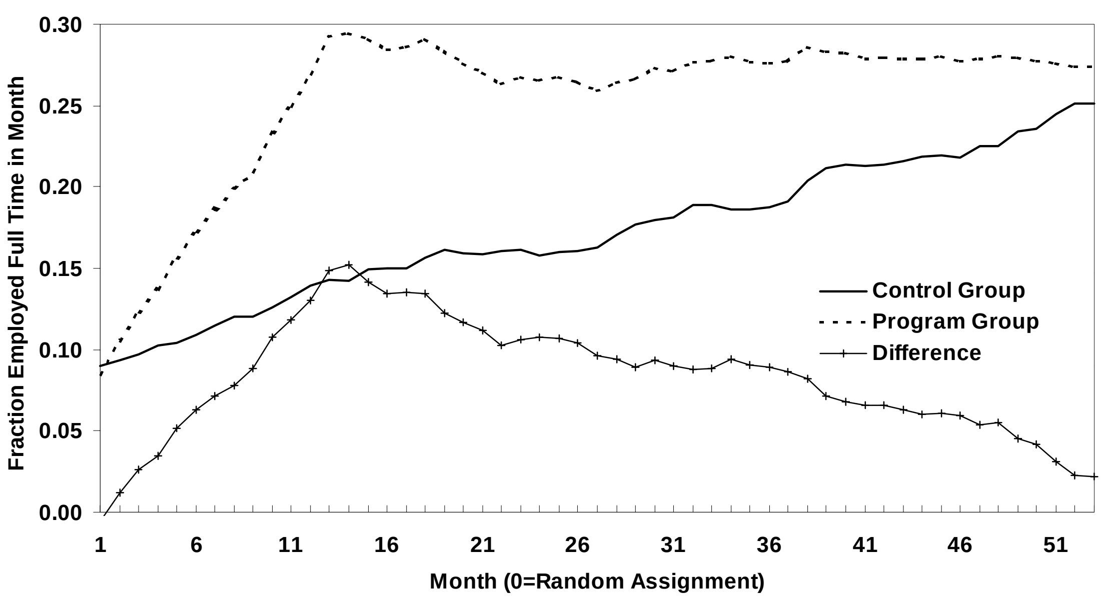

Figure 3: Mean Wages of Control and Program Groups

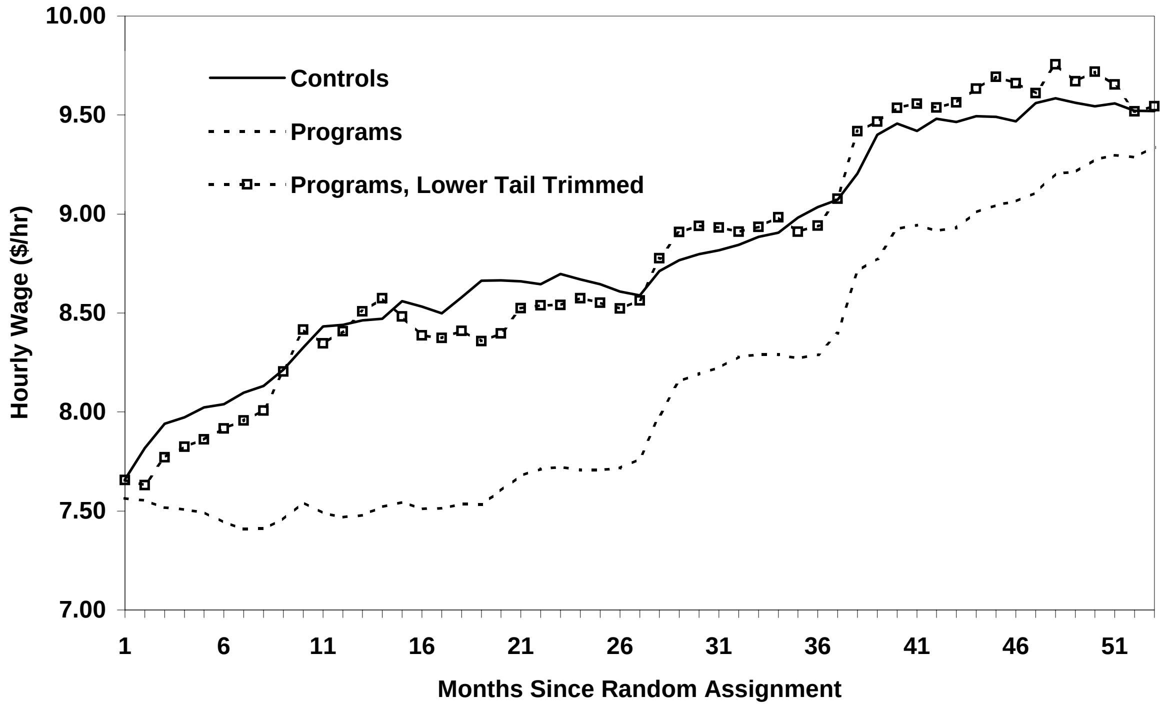

Figure 4a: Exit Rates from Income Assistance

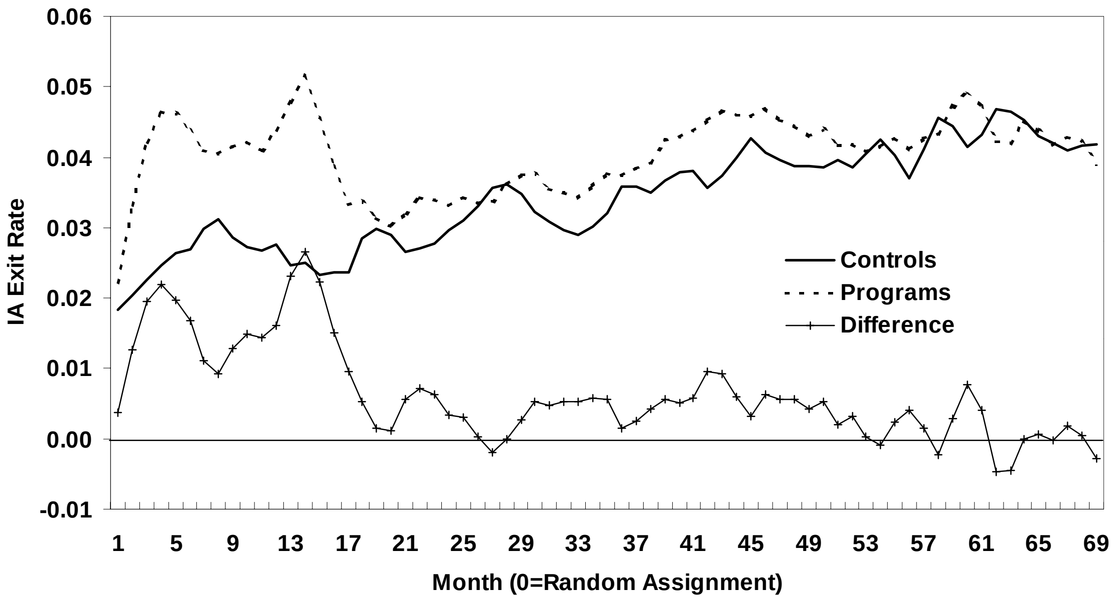

Figure 4b: Entry Rates into Income Assistance

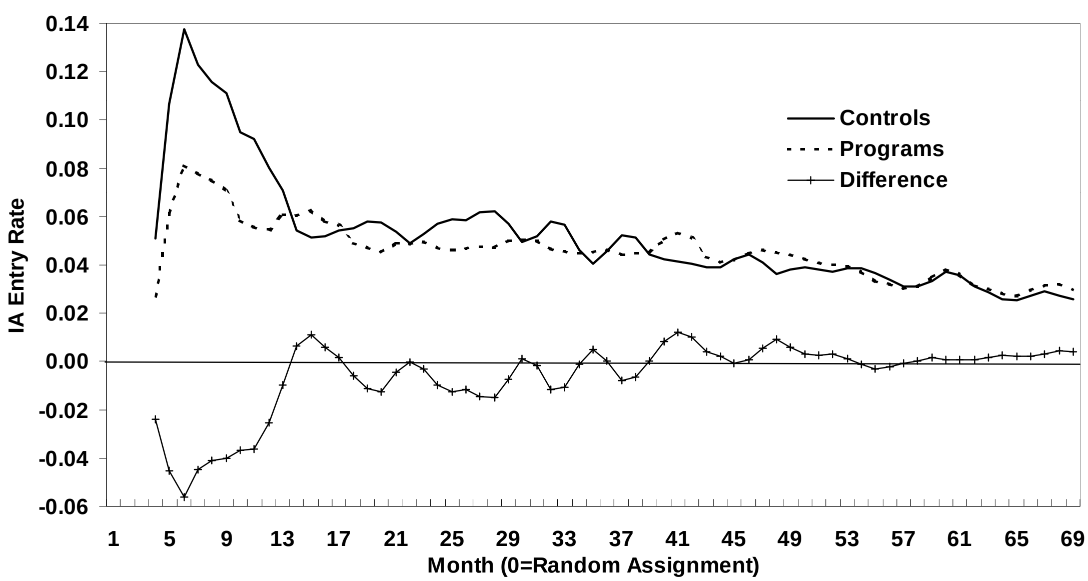

Figure 5: Program Participation and Full Time Work Around First Month of SSP Receipt

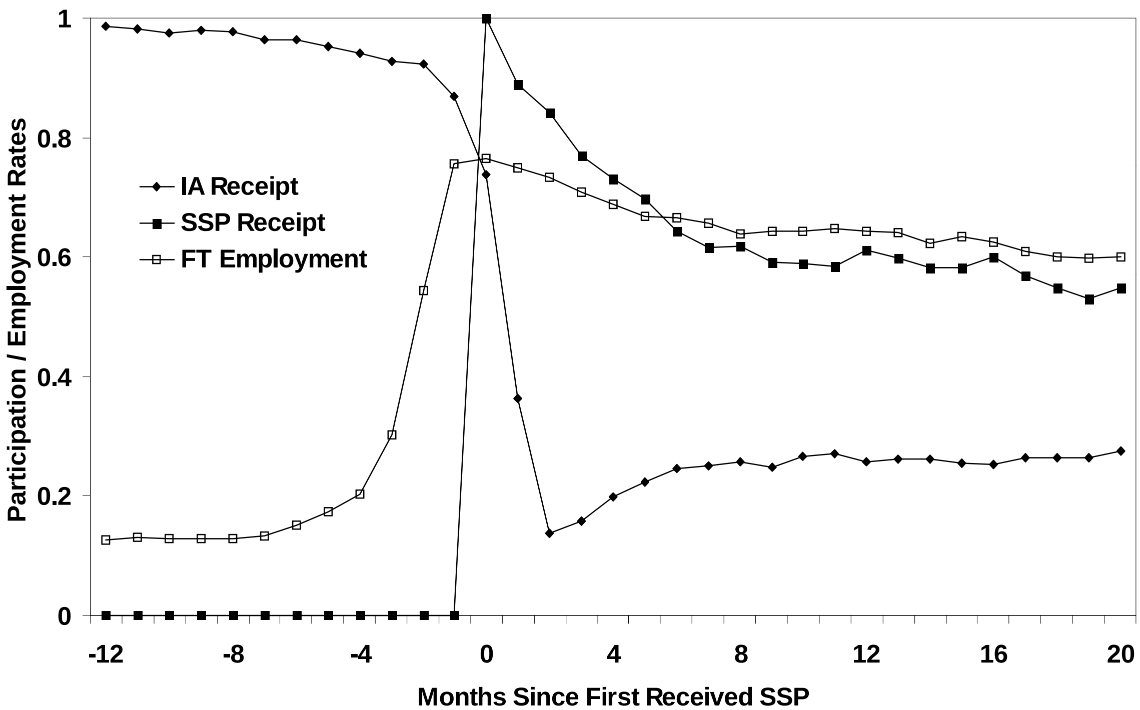

Figure 6: IA Participation of Eligible Program Group Around SSP Eligibility Date

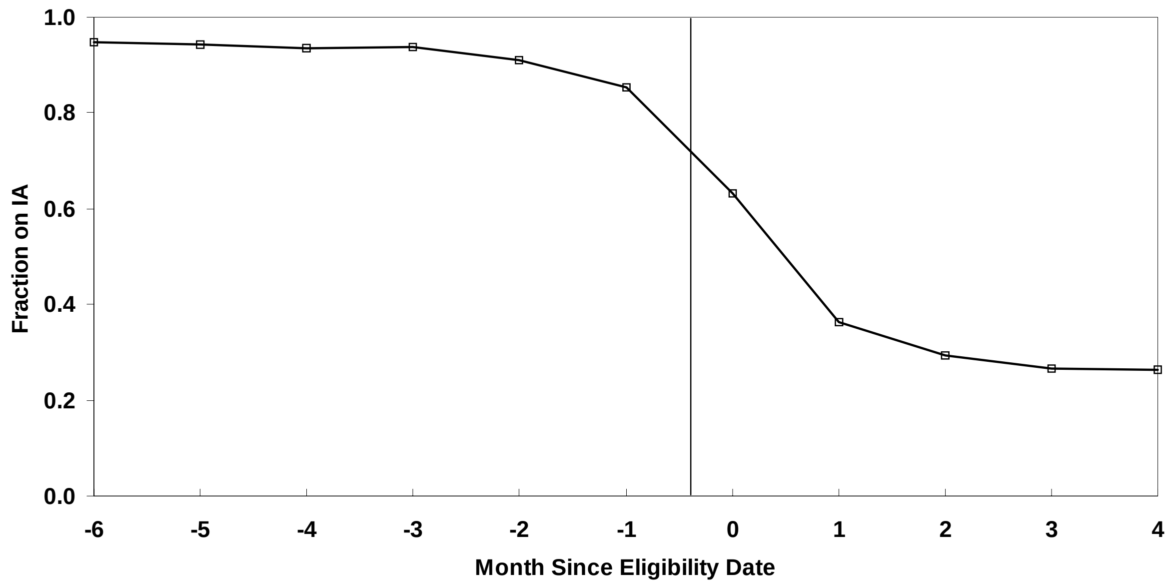

Figure 7: Actual and Predicted IA Rates for Control and Program Groups

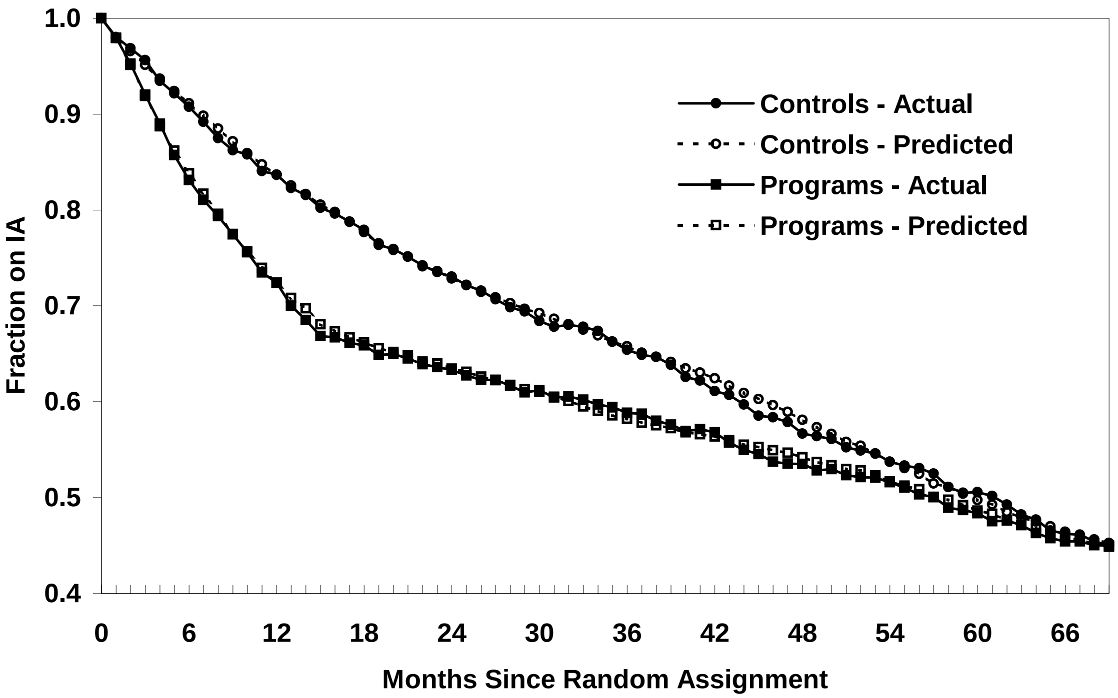

Figure 8: Actual and Predicted IA Rates, Eligible and Ineligible Program Groups

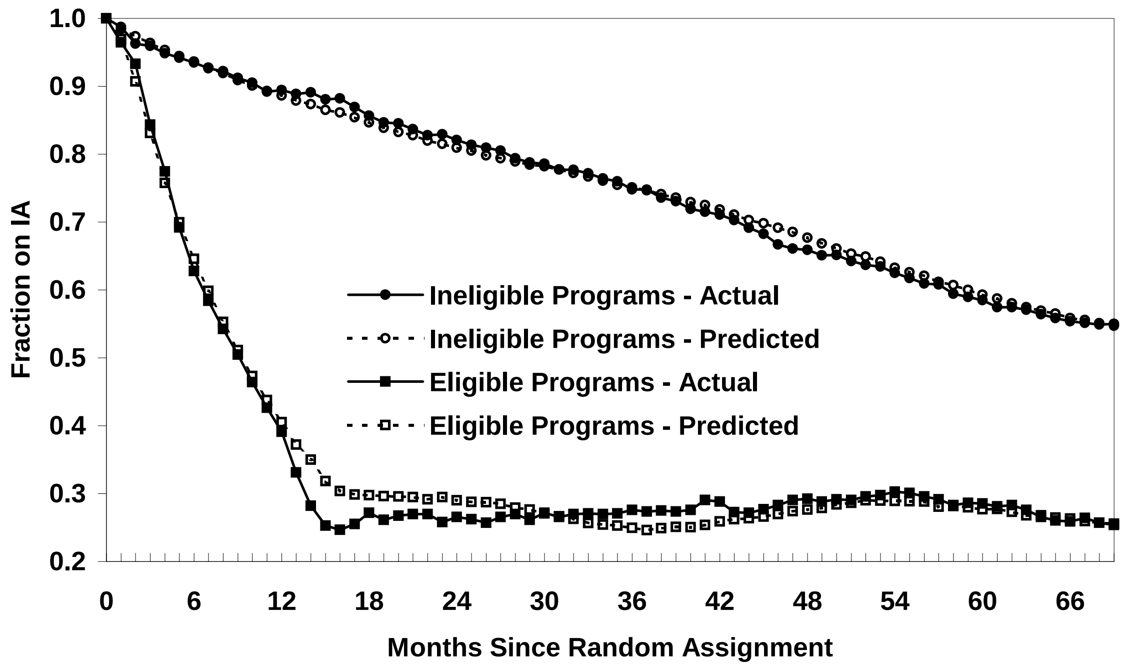

Figure 9: Decomposition of Predicted IA Rates for Eligible Control Group

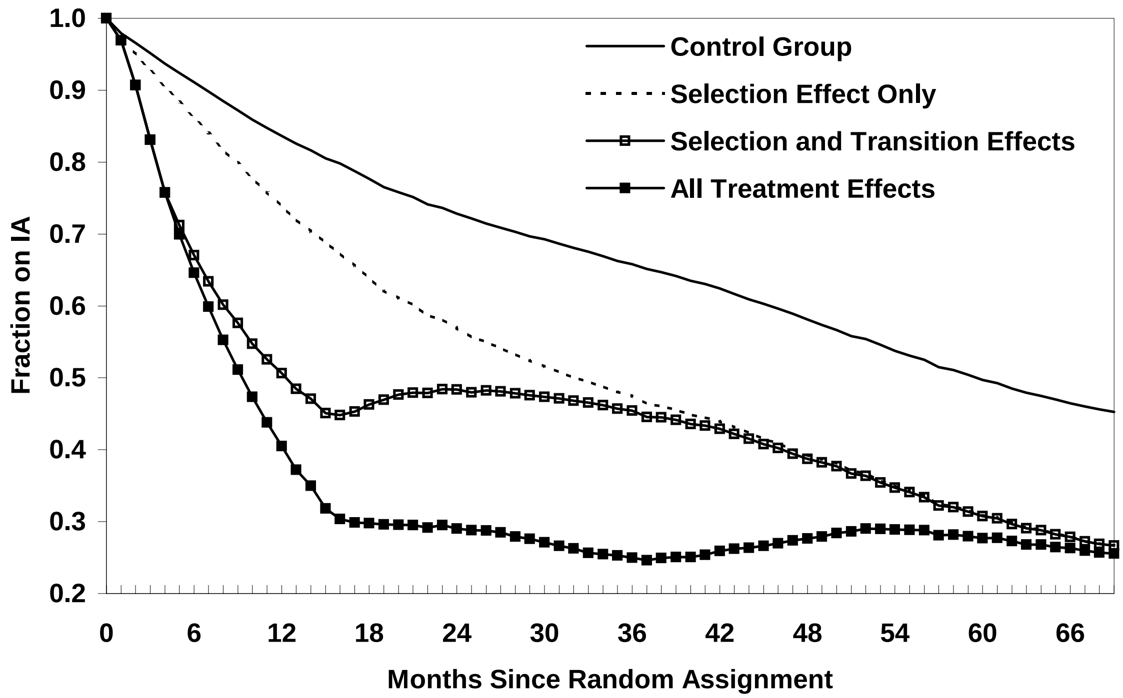

Figure 10: Actual and Predicted Treatment Effects: Programs - Controls