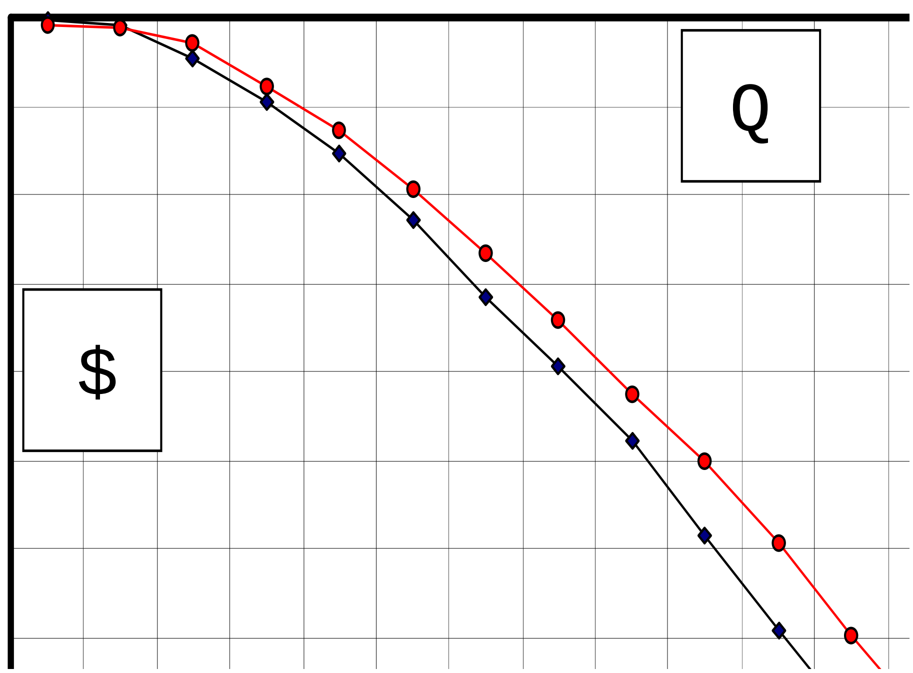
The Effect of Child Support and Self-Sufficiency Programs on Reducing Direct Support Public Costs



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The Effect of Child Support and Self-Sufficiency Programs on Reducing Direct Support Public Costs

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Abstract

There has been growing interest in determining direct and indirect cost returns from public investments in social programs. Child support enforcement (CSE) programs have been unique in generating direct returns through collections income; in fact, collections income has far exceeded program costs. But with recent changes CSE direct returns are expected to decrease. The work in this paper focuses on indirect returns, known as cost avoidance, attributable to CSE programs. While the work is restricted to CSE cost avoidance in Washington State, much of the methodology developed in this work would be applicable in other states with computer information systems. The findings reported could also serve as a basis of comparison with other states and nationally.

We examine the effects of CSE collections on custodial parent welfare use in a longitudinal study with two cohorts: 93Q4 Cohort - all adults who used welfare (AFDC) in Washington State in 4th quarter 1993, with 13 quarters of follow-up; and, 95Q4 Cohort - all adults who used welfare (AFDC) in Washington State in 4th quarter 1995, with 5 quarters of follow-up.

The effects of CSE collections were isolated from other factors which influence patterns of welfare use by controlling for client characteristics, history, and location; and also controlling for clients accessing State programs which promote self-sufficiency. At this point only the Job Opportunity and Basic Skills (JOBS) program could be included. While the JOBS program is no longer in existence in Washington, and may not have been implemented in all states, the work presented here does demonstrate a methodology for analysis of multiple program impacts and cost effects. When a group of clients may receive services from several programs it could be important to determine the effects of each program, and, if there is cost avoidance, what part of the total is attributable to each program.

We report that, other things being equal, substantial cost savings from reduced welfare use are associated with good CSE collections (defined as monthly order amount more than $0 and total arrears less than twice the monthly order amount, with all information taken from the quarter of cohort selection). With the 93Q4 cohort this is $5.5 million (13 Quarter cumulative) cost savings for 6,287 custodial parents with good CSE collections. But the bulk of savings is delayed in time. Slightly less than half is recovered in the last four quarters of follow-up. With the 95Q4 cohort cost avoidance associated with CSE collections is $1.0 million (5 Quarter cumulative) for 6,319 custodial parents with good CSE collections. Very strong cost trends are associated with good CSE collections, and could be expected to continue beyond the observation period.

We also report a beneficial interaction between CSE collections and JOBS. When custodial parents in the 95Q4 Cohort have both good CSE collections and affiliation with JOBS there is a 20% cost savings bonus.

From analyses of length of stay in the various states of welfare and work we suggest that good CSE collections, other things being equal, are likely to have an effect on public costs only after custodial parents have left welfare, by extending the length of time off welfare. The results show that good CSE collections are associated with lower intrinsic rates of recidivism regardless of work status, but there is little or no effect on intrinsic welfare exit rates, or on the rates of finding or losing work.

With JOBS the results show an association only with an increased intrinsic rate of finding work while on welfare. JOBS entrants were not markedly different than other welfare clients in their intrinsic welfare exit rates or recidivism rates. However, JOBS does show an association with increased overall welfare exit rates because those working while on welfare have faster welfare exit rates. Thus these two programs could be expected to work well together, with JOBS helping clients leave welfare and good CSE collections helping them stay off welfare. The positive interaction seen with the 95Q4 cohort is evidence that the programs were mutually beneficial. Understanding the differences in results with the two cohorts will require further study.

The results with JOBS suggest that welfare-using non-custodial parents (NCPs) who had accessed JOBS may be more likely to have left welfare for employment, and thus be more likely to have CSE cases with good collections. Preliminary results are reported indicating that this is true. This provides documentation that efforts to help NCPs move towards self-sufficiency may result in reduced welfare use for both the NCP and the custodial parent.

Other results, not directly related to cost avoidance, provide support for the work emphasis of welfare reform. For those working while on welfare the expected time on welfare is about four times less than for those on welfare without work. Considering only welfare exits to employment, for those working while on welfare the expected time on welfare is about one hundred times less than for those on welfare without work.

The work and results reported in this paper suggest that investments to improve CSE collections will pay off both directly, through collections income, and indirectly, through reduced costs of welfare use.

INTRODUCTION

The need to understand and quantify the social benefits of child support enforcement (CSE), beyond simply support dollars collected, is highlighted by the changing policies surrounding public support of needy families. With the Personal Responsibility and Work Opportunity Reconciliation Act many aspects of public support of families have changed, or will change. One change has been in the distribution of collected child support for custodial parents on welfare. The funding of child support efforts by direct collections will be reduced, and it is essential to ask if public investment in child support efforts is returned by reduced public expense in other areas, or by increased revenues in other areas.

This paper focuses on AFDC use by custodial parents, and the impact of child support collections on AFDC use. Other areas of direct support public cost, such as Medicaid and Food Stamps, are not considered at this time but will be included in future work. Under AFDC a custodial parent on welfare assigned rights to child support payments to the State, as a direct offset to payments received through AFDC. After leaving AFDC rights to current support payments reverted to the custodial parent; distribution of payments on arrears was controlled by a complex set of regulations.

It is well known that CSE collections have far exceeded the cost of the program. Data from *OCSE Annual Reports to Congress* (*Ref. 1*) show that in Washington State for FY93-FY96 total collections varied between 3.35 to 3.53 times program costs. There is a small body of research (*Ref. 2*) that suggests that child support collections produce indirect cost savings in public assistance. Our work demonstrates a new methodology for estimating and understanding indirect cost offsets in AFDC attributable to CSE efforts.

Very little child support is collected without CSE effort. Data from *OCSE Annual Reports to Congress* (*Ref. 1*) show that in Washington State for FY93-FY96 total voluntary payments varied between 0.22% to 0.54% of total collections. This is in agreement with our preliminary work for the cohorts of this study. There was a very low probability of good CSE collections (defined in the next section) without indications of CSE effort.

The first section, Outcomes and Costs, reports a net impact analysis. Basically this method asks - all other things being equal, what is the effect of CSE collections? We use this method to estimate actual cost savings from reduced AFDC use for two cohorts of AFDC adults.

The second section, Spells Analysis, reports a survival analysis, where we analyze the length of stay, and rates of leaving, various states of welfare and work. By considering client movements on and off welfare (again, all other things being equal) we are able to propose a very feasible mechanism for the bulk of cost savings attributable to CSE. This mechanism is simply that if child support payments are likely to flow to the custodial parent, after the parent leaves AFDC, the custodial parent is less likely to return to welfare regardless of work status.

Of course, we cannot control for “all other things,” because we do not have information on all factors which may influence welfare use. But, while there may remain some hidden bias, we do control for many factors which do influence welfare use, and the models developed have strong predictive power. Questions of selection bias are partly resolved by the results from survival analysis. Those with good CSE collections (defined in the next section) are not markedly different from those with poor CSE collections in their intrinsic rates of leaving welfare, or in their intrinsic rates of finding or losing work.

The results obtained and presented here form a basis for an analysis of the impact of welfare reform. The same methodology applied to TANF cohorts would allow us to compare AFDC and TANF at the level of detail demonstrated by this paper. Preliminary results with a TANF cohort do show that good CSE collections are associated with extended time off welfare. At present, however, the follow-up information available on even the earliest TANF cohort is barely sufficient for a meaningful comparison.

OUTCOMES AND COSTS

This work follows the welfare use of two cohorts: all adults (N=116,377) who used AFDC in 4th quarter of 1993 (93Q4), and all adults (N=111,007) who used AFDC in 4th quarter of 1995 (95Q4). Welfare use history was obtained from two years prior to the cohort selection quarter through 97Q1. New welfare regulations began to be implemented in Washington State in 97Q3, and by limiting data to 97Q1 or earlier we hope to avoid the impact of the TANF program in the present study. Other work in progress focuses on TANF.

Earnings history for the cohorts was obtained for the same time period. CSE data corresponding to the cohort selection quarter was obtained for both cohorts. Data from the Jobs Opportunity and Basic Skills (JOBS) program for the period 1993-1996 was obtained for both cohorts. Details of data sources, treatments, and analytical procedures can be found in Appendix 2.

The analyses presented in this section are at the individual level and on a quarterly basis. Discussion will focus on results with the 93Q4 cohort, where there is greater certainty because the follow-up period is longer, and because results are less complex.

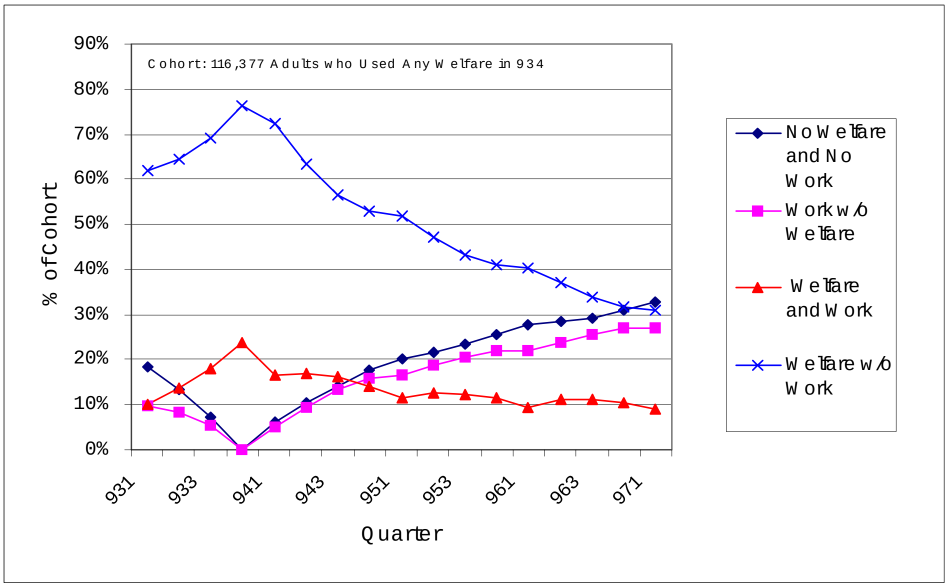
Four-State Model

Figure 1: Four State Model

		Welfare	
		Yes	No
Work	Yes	Welfare and Work *Assume welfare cost @ $250/Mo*	Work w/o Welfare
	No	Welfare w/o Work *Assume welfare cost @ $500/Mo*	No Welfare, and no Work

Outcomes in follow-up quarters were based on a simple four-state model of work and welfare, shown in Figure 1. Individuals with any reported earnings in the quarter occupy the upper half of the square. Individuals with any welfare use in the quarter occupy the left half of the square. Assumed welfare costs per adult are shown in the left half of Figure 1. A rounded value of average payments was used for the cost of “Welfare w/o Work.” The cost for “Welfare and Work” was estimated from average earnings while on welfare and the income disregard in effect at that time. The percentage of the 93Q4 cohort in each state for each quarter is shown in Figure 2. The 95Q4 cohort shows a similar pattern, but with only 5 quarters of follow-up.

Figure 2: Unadjusted Outcomes Progression



An outcome model is developed for each state of the four state system. Using the four-state approach allows for more specific results since the models for each state are significantly different. The four-state outcome models based on the 93Q4 cohort, even without the program factors discussed below, are in fact able to make up to 80% accurate predictions of outcomes for the 95Q4 cohort.

Logistic modeling is used to fit the observed outcomes to a dependence on explanatory variables. All explanatory variables are based on data in, or prior to, the selection quarter. Once this dependence is known the model is determined, and controlled outcomes can be found based on chosen values of explanatory variables. This will enable an estimation of the impact of any single explanatory variable while all other explanatory variables are held constant. The explanatory variables of interest in this work relate to Child Support Enforcement (CSE) collections, and this approach will allow us to begin isolating the impact of CSE collections on custodial parent welfare use in these two cohorts.

Program Categories

The status of CSE collections is represented by the three categories shown in Figure 3 (see Appendix 2 for further discussion). But it is also important to consider other programs which may be accessed by CSE clients, and which may also

Figure 3: Program Categories

CSE Payment (data from cohort selection quarter)

Good Collections (CG) - monthly order amount (moa) greater than $0.00 and total arrears less than twice moa.

Poor Collections (CP) - in CSE, but not in Good Collections

No CSE (CN) - no match in CSE data

JOBS

JOBS Yes (JY) - earliest JOBS entry prior to selection quarter

JOBS No (JN) - no match in JOBS data or later entry

influence use of welfare. We include the JOBS program because other work *(Ref. 3)* has shown an association with reduced welfare use; and, there is a significant tendency for those with better CSE collections to have participated in JOBS (see Figure 3 and Table 1), leading to a bias if JOBS were not included. All JOBS entrants in the cohort are flagged if they entered JOBS before the selection quarter. The combined program factors (0/1 indicators) for CSE and JOBS are given in Figure 4. In most cases the outcome for the “Not in CSE” (CN) and “Poor CSE Col-

Table 1:Clients with Good CSE Collections Are More Likely to be in JOBS

Significant at the 0.001 Level

Percentage of CSE Category in JOBS			
	CN	CP	CG
93Q4	24.1%	28.4%	32.2%
95Q4	32.7%	35.1%	38.4%

Figure 4: Program Indicator Variables

		CSE		
		No	Poor	Good
JOBS	No	CNJN	CPJN	CGJN
	Yes	CNJY	CPJY	CGJY

lections" (CP) categories were only slightly different and our discussion will be limited to the four program indicators "Poor CSE Collections without JOBS" (CPJN), "Good CSE Collections without JOBS" (CGJN), "Poor CSE Collections with JOBS" (CPJY), and "Good CSE Collections with JOBS" (CGJY). Other explanatory variables include client characteristics, history, and location, and are detailed in Appendix 2.

Controlled Outcomes

With the best fit models and the average values for non-program explanatory variables, we can determine controlled outcomes for average welfare clients in each program category. Figure 5 gives the reference controlled outcomes, and

Figure 5: Adjusted Outcomes Progression for Average Welfare Clients with No CSE and No JOBS

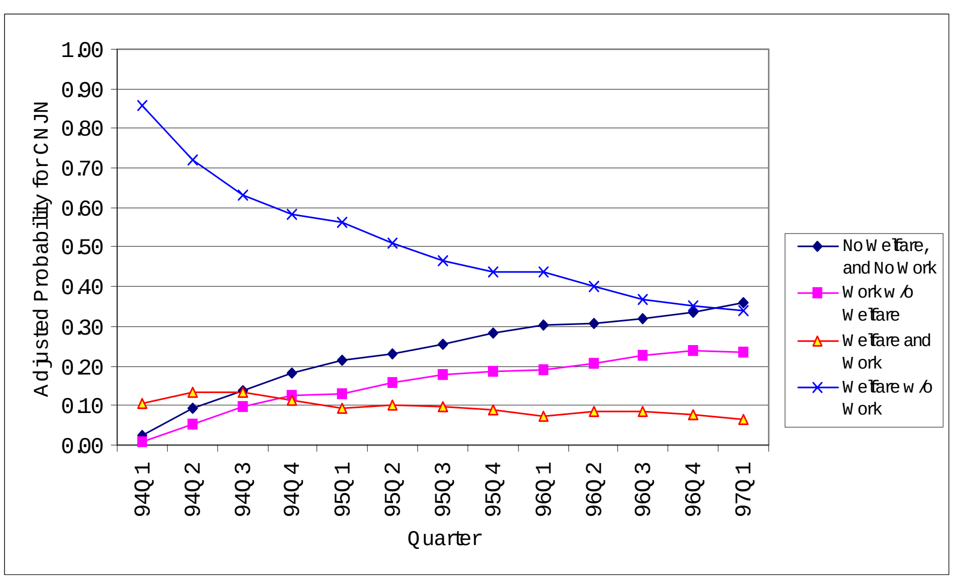


Figure 6: Adjusted Outcomes; Impact of Good CSE Collections for Average Welfare Clients with No JOBS

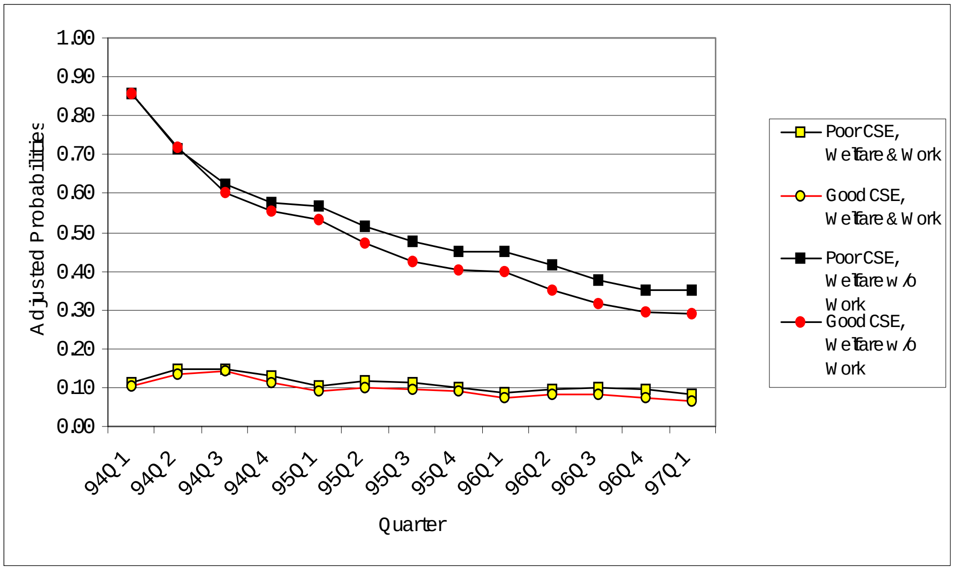
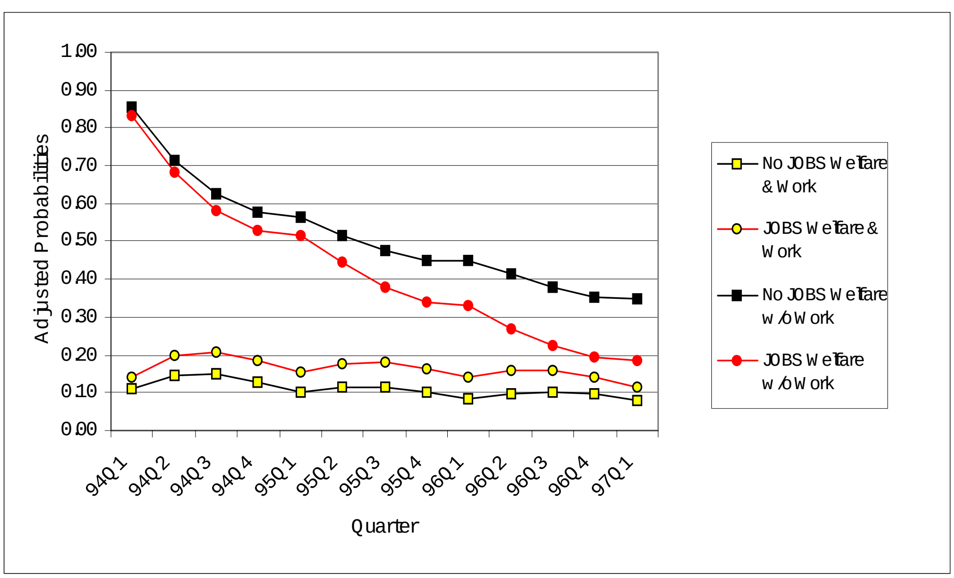


Figure 6 shows the impact on welfare use associated with good CSE collections for those who were not JOBS entrants. There is a very small decrease in the percentage in the state "Welfare and Work," but a substantial decrease in percentage in "Welfare w/o Work." See Appendix 2 for a statistical verification of this impact of good CSE collections.

The impact associated with the JOBS program (see Figure 7) shows a substantial increase in the percentage in the state "Welfare and Work," and a large decrease

Figure 7: Adjusted Outcomes; Impact of JOBS for Average Welfare Clients with Poor CSE Collections



in the percentage in the state "Welfare w/o Work."

<u>Comparison of Program Costs</u>

We will first discuss a comparison of costs across program categories, and then

Figure 8: Program Comparison Cumulative Cost Avoidance Associated with Good CSE Collections; 93Q4 Cohort

The cost of CGJN minus the cost of CPJN and the cost of CGJY minus the cost of CPJY (reported in $ per client)

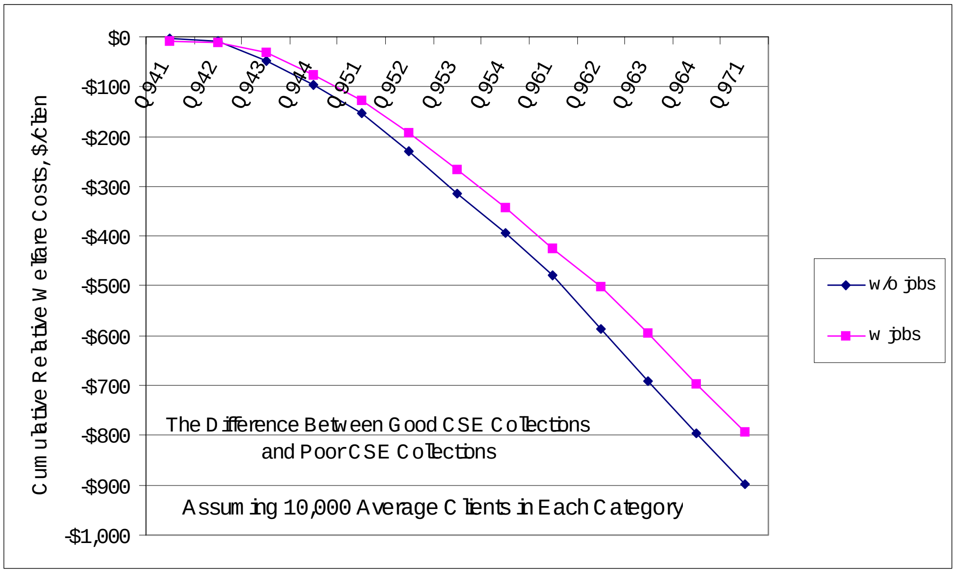


Figure 9: Program Comparison Cumulative Cost Avoidance Associated with JOBS; 93Q4 Cohort

The cost of CGJY minus the cost of CGJN and the cost of CPJY minus the cost of CPJN (reported in $ per client)

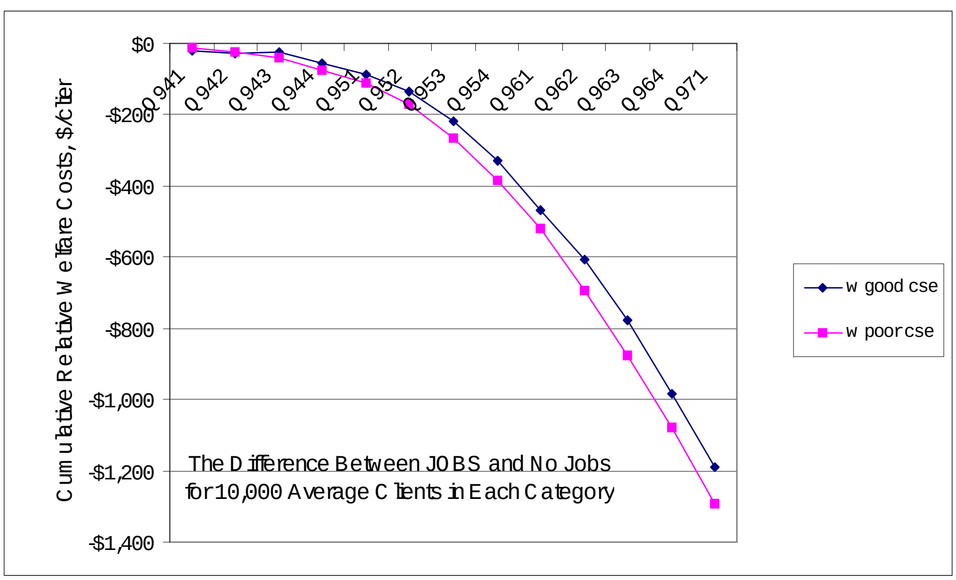


Figure 10: Program Comparison Cumulative Cost Avoidance Associated with Good CSE Collections; 95Q4 Cohort

The cost of CGJN minus the cost of CPJN and the cost of CGJY minus the cost of CPJY (reported in $ per client)

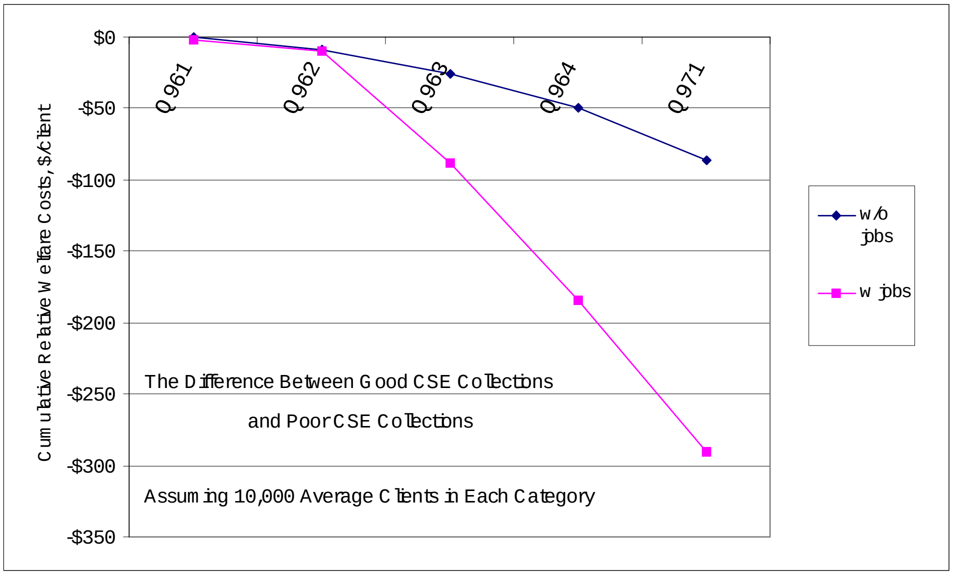
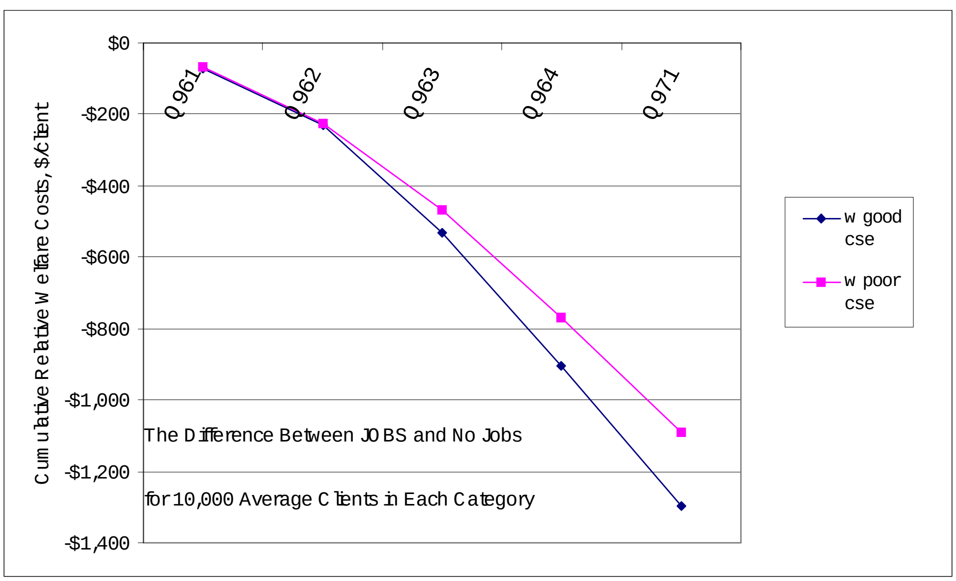


Figure 11: Program Comparison Cumulative Cost Avoidance Associated with JOBS; 95Q4 Cohort

The cost of CGJY minus the cost of CGJN and the cost of CPJY minus the cost of CPJN (reported in $ per client)



develop an estimation of actual cost offsets for the two cohorts. In order to compare the program categories, we assume 10,000 average welfare clients in each category and determine cost estimates for each program category based on the controlled outcome percentages (as in Figures 6 & 7) and the cost values shown in Figure 1. The cost differences can then be obtained by simple subtraction. Figures 8 - 11 show the cost offsets associated with good CSE collections and with JOBS. The difference in the two lines in Figures 8 and 10 represents the effect of JOBS on the cost offset due to good CSE collections. Program interaction effects will be specifically discussed in the next subsection below.

For the 93Q4 cohort there is a substantial cumulative reduction in welfare costs associated with good CSE collections (Figure 8). While the saving per individual is $800 - $900, there is a strong trend established where from the 5th follow-up quarter to the 13th, savings increase approximately six-fold. 46% - 47% of the total cumulative cost avoidance is recovered in the last four quarters.

The JOBS program shows a somewhat larger cost reduction for the 93Q4 cohort (Figure 9). The trend is substantially stronger, with an approximate twelve-fold increase from the 5th follow-up quarter to the 13th.

Figure 10 shows the reduction in welfare costs associated with good CSE collections for the 95Q4 cohort. The most striking feature is the large increase in cost reduction when good CSE collections are combined with JOBS.

Figure 11 shows the reduction in welfare costs associated with JOBS for the 95Q4 cohort. The magnitude of cumulative cost effects associated with the JOBS program in the 5 quarters following 95Q4 are approximately the same as the 13 quarters of cumulative cost effects following 93Q4.

Comparing cumulative cost reductions at the 5th quarter in both cohorts in Table 2 shows a somewhat reduced cost avoidance of CSE alone in the 95Q4 cohort, but large increases in cost avoidance associated with JOBS. In the 5 quarters following 4th quarter 1995 the JOBS program appears to have been very effective in reducing welfare use. This may be related to expanding work opportunities in Washington State in that time period, so that welfare recipients were able to take advantage of JOBS training. Further work may be able to control for changing economic conditions (see Appendix 1, Cohort Overlap). While it would be useful to control for economic conditions, it is unlikely to be critical since we are look-

Table 2: Comparing Cumulative Cost Offsets at the 5th Quarter

Program Comparison - 10,000 Average Welfare Clients in Each Category

5th Quarter Cumulative Relative Welfare Costs in dollars per client				
	good CSE - poor CSE		in JOBS - no JOBS	
	w/o JOBS	w JOBS	w good CSE	w poor CSE
93Q4	-$153	-$129	-$88	-$112
95Q4	-$86	-$291	-$1,296	-$1,091

ing at differences, and all cohort members were experiencing the same general economic conditions. Economic conditions do vary by location, but we explicitly control for location.

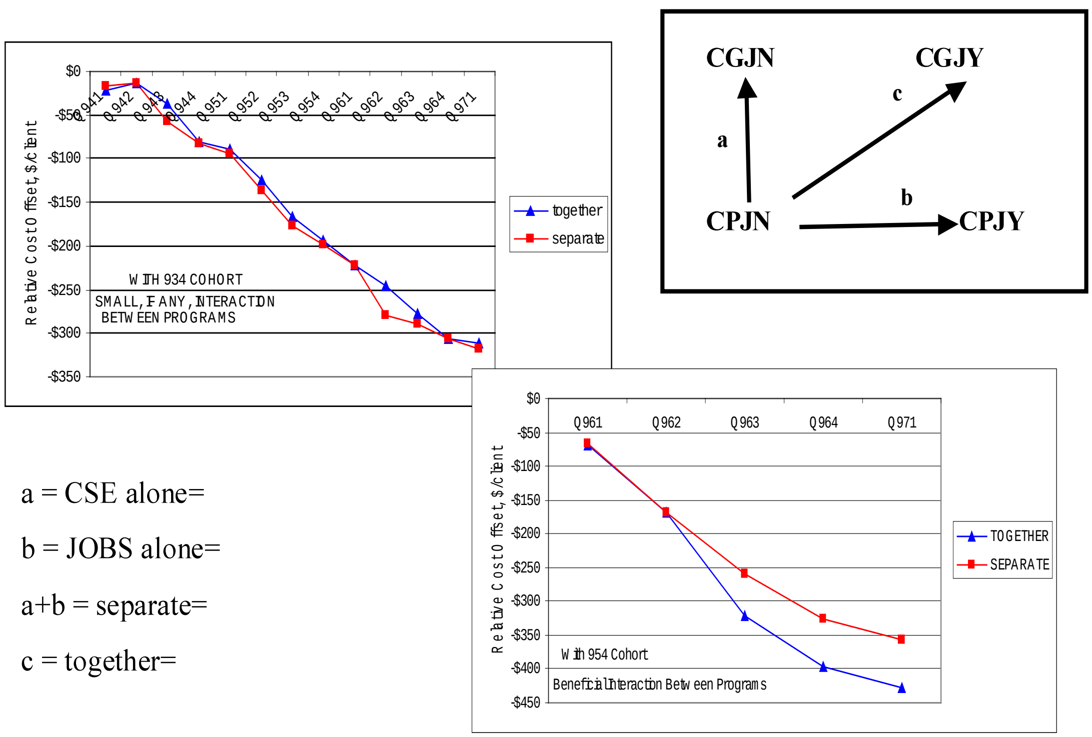
Program Interactions

In considering interactions between CSE and JOBS, it is useful to look at the cost

Figure 12: Interaction Between CSE and JOBS

Program Comparison - 10,000 Average Welfare Clients in Each Category

Quarterly costs, not cumulative



reductions of each alone, and at the cost reductions of the two together. Figure 12 shows how this is done and presents the cost reduction in each quarter (not cumulative).

We see that in the 93Q4 cohort the differences are quite small, and there is no clear trend established. The 95Q4 cohort shows a trend of differences increasing over time. The differences suggest that the cumulative cost reduction for the two programs applied together is about 20% greater than the sum of cost reductions for the separate programs – essentially a 20% bonus with no additional investment!

Understanding this interaction will require further work. Could there be selection bias, or could joint programs provide multiple supports when there are multiple barriers to success? Why is the effect not seen with the 93Q4 cohort? Perhaps some answers could be obtained from further comparisons of the two cohorts, or studies of other cohorts and other program interactions.

Actual Costs

To generate estimates of actual cost offsets we use the actual numbers of individuals in each program category. To estimate costs for CSE impact we generated reference outcomes using the average values for non-program explanatory variables for the individuals in each program category.

Table 3 shows that, isolated as much as possible from other effects, the investments of resources which led to good CSE collections for 6,287 custodial parents in 93Q4 generated a cost avoidance return of $5.5M in reduced custodial parent welfare use over the period 94Q1 to 97Q1 (about $900 per client). The investments which led to good CSE collections for 6,319 custodial parents in 95Q4 generated a cost avoidance return of $1.0M over the period 96Q1 to 97Q1 (about $200 per client). With the strong trends demonstrated above, it could be expected that these returns would keep growing in the time following 97Q1.

Table 3: Estimating Actual Cost Avoidance Associated with Good CSE Collections

		AFDC Costs; CSE w/o JOBS			
	Number	CPJN	CGJN	Diff.	% Diff.
93Q4*	4,261	$48.9M	$45.1M	-$3.8M	-7.80%
95Q4**	3,893	$22.3M	$22.0M	-$0.3M	-1.30%
		AFDC Costs; CSE w JOBS			
	Number	CPJY	CGJY	Diff.	% Diff.
93Q4*	2,026	$21.2M	$19.5M	-$1.7M	-8.00%
95Q4**	2,426	$10.9M	$10.2M	-$0.7M	-6.40%
		AFDC Costs; Totals			
	Number	CP	CG	Diff.	% Diff.
93Q4*	6,287	$70.1M	$64.6M	-$5.5M	-7.85%
95Q4**	6,319	$33.2M	$32.2M	-$1.0M	-3.00%
*13Q Cum. Costs; **5Q Cum. Costs					

There is significant overlap in the two cohorts. This can be seen in Figure 2 where about 50% of the 93Q4 cohort are still on welfare in 95Q4, and would be included in the 95Q4 cohort. Thus the cost offsets for the two cohorts cannot be simply added. We will discuss this overlap further in Appendix 1.

We consider the collections level in a particular quarter as an indicator of eventual cost avoidance. Those with good collections in a particular quarter are probably more likely to also have good collections in preceeding and following quarters. We show in Appendix 1 that for custodial parents in both cohorts 59.2% of those in CGJY in 93Q4 are in CGJY in 95Q4. Additional data could provide a better answer to the question of persistence of good collections, but it would still be difficult to associate cost avoidance to CSE collections in a particular time frame. This is especially true because of the delayed nature of cost avoidance, which is further delineated in the next section. For this reason we feel that the popular indicator - return per dollar collected - could be very misleading.

SPELLS ANALYSIS

In the Outcomes and Costs Section, results were based on adjusted levels in each state of the four-state model in each follow-up quarter. In this section we will use survival analysis to investigate the flow of clients between states and the expected length of residence in each state. The level in a particular state in the four-state model is the sum result of three types of exit events and three types of entry events. With survival analysis we can isolate each of these events.

We use the same data as in the Outcomes and Costs Section with analyses at the individual level, but on a monthly basis, unless otherwise indicated. Details of analytical procedures can be found in Appendix 2.

Figure 13: Quarter to Quarter State Changes

Work \ Welfare	Yes	No
Yes	~ 50% Stay *Unstable*	~ 85% Stay *Stable*
No	~ 85 % Stay *Stable*	~ 85 % Stay *Stable*

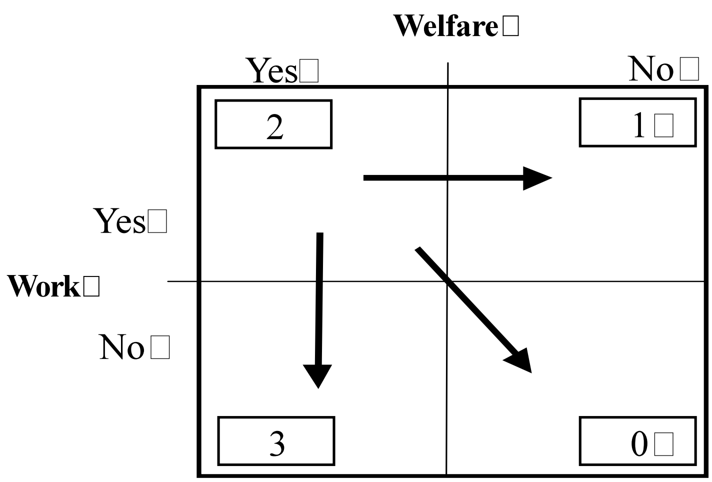
The simplest view of dynamics is to look at quarter to quarter changes of state by individuals. A clear pattern emerges, demonstrated in Figure 13, with three states of the four state model being rather stable - about 80 - 90% of individuals in these states in any particular quarter remain in that state in the next quarter. The state "Welfare and Work," which showed the smallest changes in level throughout the follow-up period (see Figure 2) , however, has the largest quarter to quarter movement with only about 50% remaining in the next quarter.

The probability of movement between states, however, also depends on how long an individual has resided in that state, usually with lower probability of movement with increasing spell duration. Our ultimate aim is to obtain an understanding of the processes underlying the cost avoidance impacts of CSE collections and affiliation with JOBS. For this, it is necessary to use the more sophisticated techniques of survival analysis.

Four-State Survival Model

Consideration of a four state survival model will provide us with more detail of state dynamics, and lead to a better understanding of the basis of cost offsets. For each state in the four state model there are three movement options as represented by Figure 14. Figure 14 also introduces numerical symbols for each state, so that transitions can be more easily represented. For example, shown on Figure 14 are transitions *2 → 1*, *2 → 0*, and *2 → 3*. These are considered as competing risks, because once individuals have exited by a particular pathway, they are no longer at risk of experiencing the other movement options. The techniques of survival analysis allow us to isolate competing risks and to obtain controlled survival times as if each pathway were the only movement option.

Figure 14: Competing Risk Survival Analysis



For the 93Q4 cohort there are only three substantial effects seen. The 95Q4 cohort also shows these main effects, but the results are more complex due to interactions between CSE and JOBS. We ignore diagonal movements (0 ↔ 2 and 1 ↔ 3) in the four state model for the moment. We show below that these movements rarely occur in the time frame of our data (observation by quarter for working status and observation by month for welfare status).

Figures 15 and 16 show that reduced recidivism is associated with good CSE collections regardless of work status. When a custodial parent has good collections, as defined in this paper, CSE payments have been flowing into that parent's case account and arrears are small. Thus it may be expected that support payments are more likely to accrue to the custodial parent after leaving welfare. That income could then be expected to help the custodial parent to stay off welfare.

Figure 15: Four-State Survival Times; Spells in State 1 ⟶ State 2

Adjusted - spells for average welfare clients

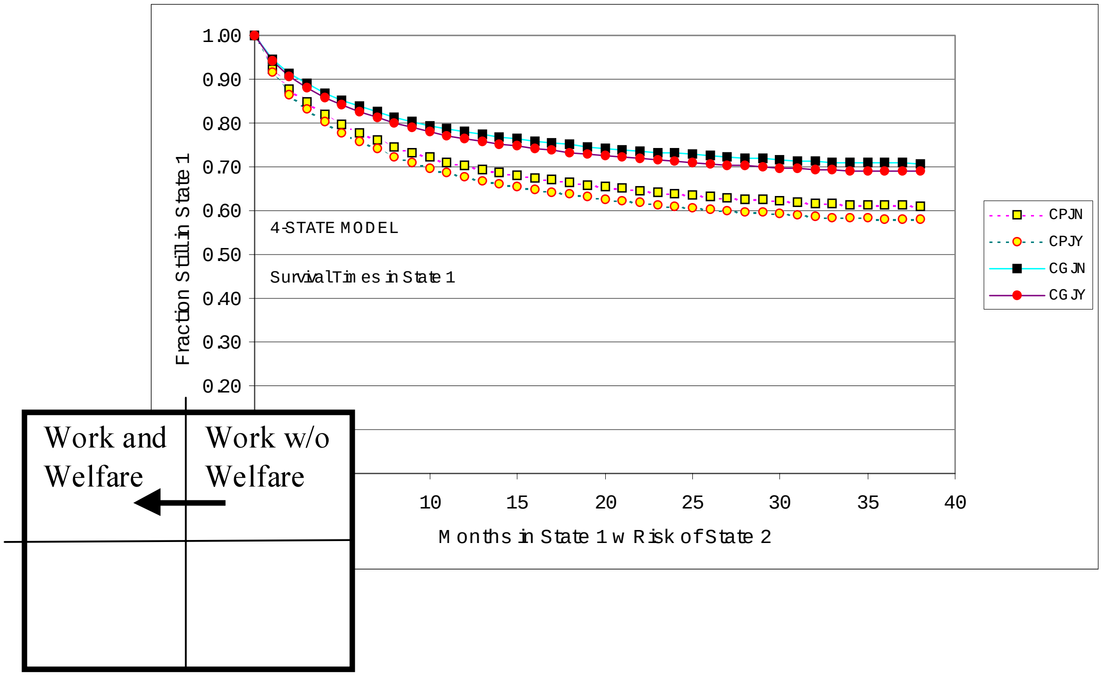


Figure 16: Four-State Survival Times; Spells in State 0 ⟶ State 3

Adjusted - spells for average welfare clients

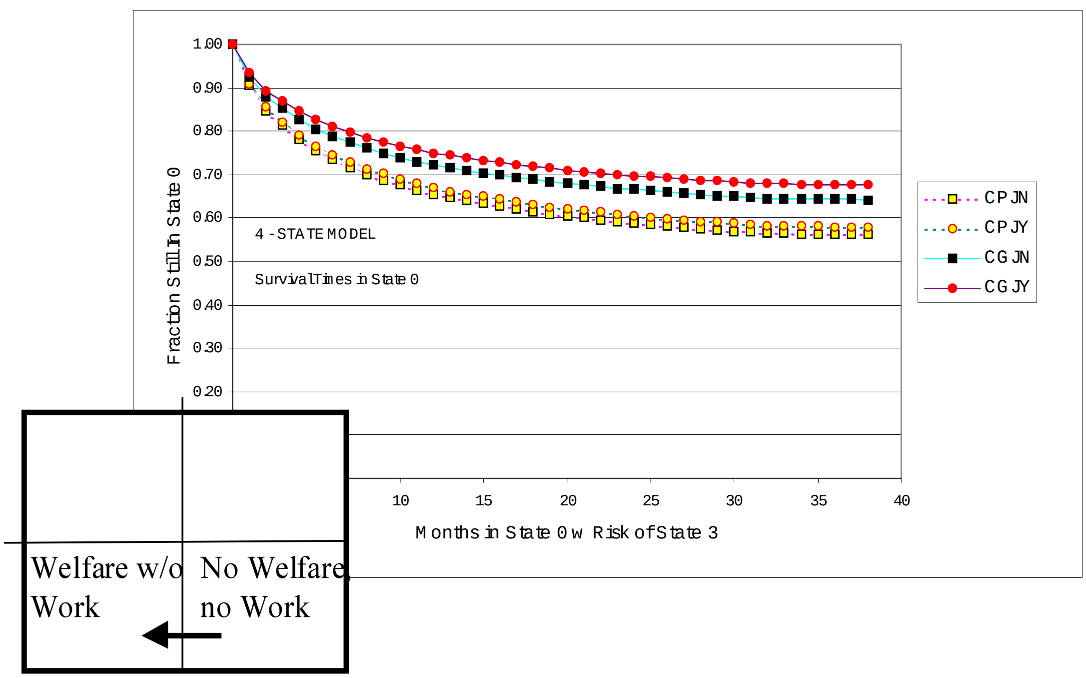
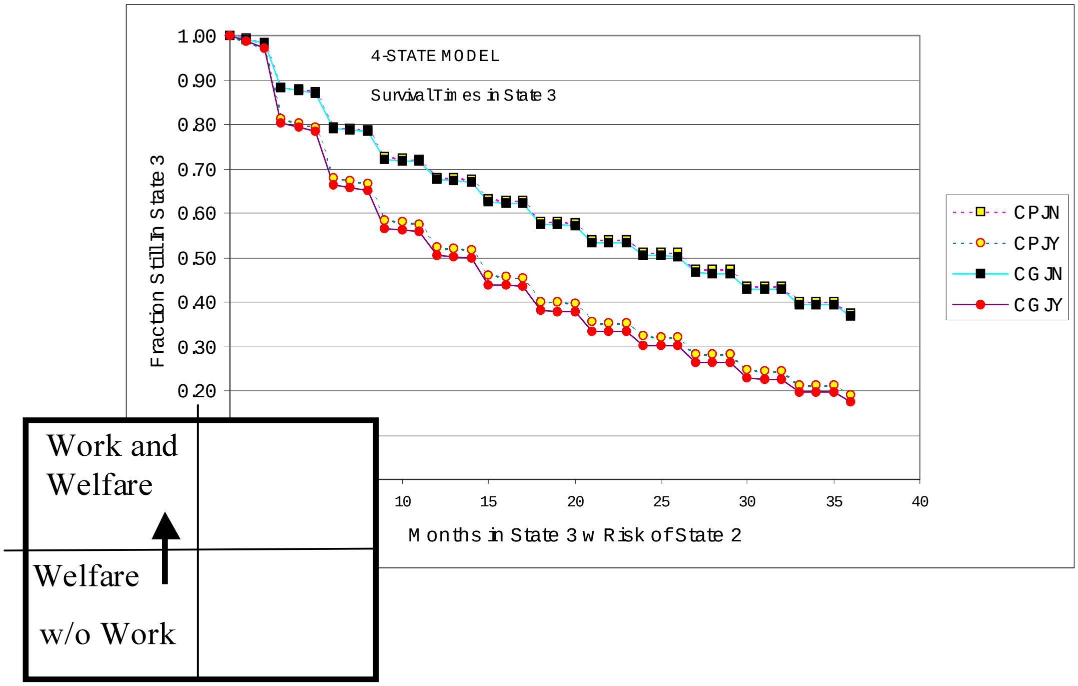


Figure 17 shows the main effect associated with the JOBS program in the four state model: increased movement from “Welfare w/o Work” to “Work and Wel-

Figure 17: Four-State Survival Times; Spells in State 3 → State 2
Adjusted - spells for average welfare clients



fare" (median times of 14 months vs. 26 months); see also Figure 7. In the 93Q4 cohort there is no large effect on welfare exits rates from either state, but individuals in the state "Work and Welfare" are much more likely to exit welfare quickly, and exit welfare to employment, than those in "Welfare w/o Work" (see discussion below). Thus the JOBS program seems to have achieved increased welfare exit rates by moving individuals into the more favorable state of "Work and Welfare." The overall impact of the JOBS program, then, would have been moving individuals from the state "Welfare w/o Work" to the state "Work w/o Welfare" (see discussion below) via the state "Welfare and Work."

Hazard Rate and Expected Duration

While the median times are useful measures of the tendency for movement, in many cases we cannot obtain median times because survivals do not fall to 50% before observation ends. A more generally useful measure, known as the hazard or risk function, can be obtained from our data for all transition pathways. The hazard is an intrinsic rate – the number of events (transitions) expected per individual in the time unit being considered (the month in our study). The inverse of the hazard gives us the expected time between events, or the expected duration in the state being considered, assuming the event being considered is the only risk. While the hazard is not a probability, when its value is less than 1.00 it can be expressed as a percentage and interpreted as the percentage of individuals in the state at the beginning of the month who are expected to experience the particular event by the end of the month. The problem with using the hazard is that it is not necessarily constant with time – in this study it is generally decreasing with time. But by determining the hazard at a particular month, we obtain a measure that is useful for all transitions and across studies. We only report results with the 93Q4 cohort; our analysis with the 95Q4 cohort is not yet completed.

Using the approach detailed in Appendix 2 we are able to estimate the hazard rates for all transitions and for all program categories. By their magnitudes and error limits the hazards at 9 months fall into four groups, as indicated in Table 4. The Risk Ratios given in Table 5 are the ratios of the hazard rate to the reference hazard rate. The analytical survival procedure yields hazards which may be time dependent, but ratios between hazards will not be time dependent. The error in the Risk Ratio is generally lower than 5%, averaging about 3%. The marked Risk Ratios in Table 4 are those we consider strongly significant. A Risk Ratio outside the interval ~0.8 – ~1.25 is above the 95% confidence limit for a real difference in hazard values, assuming a 5% error. Because the diagonal transitions are much slower than competing transitions, certain assumptions of the survival procedure are likely to be violated and lower confidence is necessary for the diagonal events (marked with an open symbol).

Table 4: Controlled Reference Hazard Rates for Average Welfare Clients

in order of increasing rate

Transition	Hazard Rate @ 9 Mo	Expected Mean Stay
Fast Transitions		
2 to 1	0.11 /Mo	9 Mo
2 to 3	0.08	12.5 Mo
1 to 0	0.04	25 Mo
Medium Transitions		
3 to 0		
3 to 2	all	all
0 to 1	0.02 - 0.03	~ 40 Mo
0 to 3	/Mo	
1 to 2		
Slow Transitions		
	all	all
2 to 0	0.003 -	~ 300 Mo
1 to 3	0.004/Mo	
Very Slow Transitions		
	all	all
3 to 1	~0.001	~ 1000 Mo
0 to 2	/Mo	

Table 5: Relative Controlled Hazard Rates for Average Welfare Clients

Risk Ratios		
Relative to CPJN		
Transition	CPJY	CGJN
0 to 1	1.138	1.149
0 to 2	° 1.404	° 0.730
0 to 3	0.946	• 0.769
1 to 0	0.812	0.944
1 to 2	1.103	• 0.701
1 to 3	1.008	° 0.791
2 to 0	1.000	1.000
2 to 1	1.140	1.119
2 to 3	0.838	0.905
3 to 0	1.000	1.000
3 to 1	° 1.368	1.000
3 to 2	• 1.686	1.020

Table 6 then shows the strongest and most certain effects associated with the program indicators. An extension of the time off welfare is the most certain effect strongly associated with increasing the level of CSE collections. The mean expected time off welfare extends from 43 months to 56 months for those without work, and from 50 months to 71 months for those with work. Work status has little or no effect on the impact associated with the level of CSE collections, however. In Table 5 there is not a significant difference between the risk ratios 0.769 and 0.701. The most certain effect strongly associated with the JOBS program is a decrease in the time required to find work while on welfare. The mean expected time on welfare without work is reduced from 35 months to 20 months.

The hazard rates shown in Table 4 offer strong support for the work emphasis of welfare reform. The hazard rates for welfare exit from State 2, “Welfare and Work” are about four times larger than hazard rates for welfare exit from State 3. Hazard rates for welfare exits to employment are about one hundred times faster from State 2, compared with State 3.

The hazard results also give us a perspective on possible selection bias in identifying those with good CSE collections. Those with good collections do not differ

Table 6: Strongest Hazard Impacts Associated with Program Indicators

Associated with CSE Level				
	CPJN		CGJN	
Transition	Hazard Rate @ 9 Mo	Expected Mean Stay	Hazard Rate @ 9 Mo	Expected Mean Stay
0 to 3	0.023 per Mo	43 Mo	0.018	56 Mo
1 to 2	0.020	50	0.014	71
Associated with JOBS				
	CPJN		CPJY	
3 to 2	0.029	35	0.049	20

markedly from those with poor collections in their hazards for exiting welfare via events 2 → 1 or 3 → 0; in their hazards for finding work via events 0 → 1 or 3 → 2; or in their hazards for losing work via events 1 → 0 or 2 → 3. There is also a question of selection bias in including the JOBS program. The hazard results indicate that JOBS entrants are not markedly different from other welfare clients in their hazards for exiting welfare via events 2 → 1 or 3 → 0, or in their hazards for recidivism via events 0 → 3 or 1 → 2. The main effect associated with the JOBS program is an increased hazard for employment while on welfare. This, in fact, does lead to an increased overall rate of welfare exits, because, as seen in Figure 7, a higher proportion of JOBS entrants reside in State 2 while on welfare.

Delayed Cost Returns

For both programs the time factor is very important in considering cost avoidance. It appears that we cannot expect good CSE collections to have a large impact on reducing costs until custodial parents have left welfare. And that takes some time. With the 93Q4 cohort 46% - 47% of the total cumulative cost avoidance is recovered during the 10th to 13th quarters after 93Q4. The JOBS program appears not to have moved custodial parents directly off welfare, but to have moved them into a situation with partial cost offset, from which they were more likely to exit welfare. Thus delayed cost returns could also be expected from JOBS.

Appendix 1

Preliminary Progress on New Work

COHORT OVERLAP

From Figure 2 in the Outcomes and Costs Section it can be seen that a large fraction of the 93Q4 cohort are still on welfare in 95Q4, and thus will also be included in the 95Q4 cohort. There are 60,784 individuals who are in both cohorts. 38,877 of these had a CSE case in 93Q4, while 40,761 had a CSE case in 95Q4. However, in the cohort overlap there was movement both into CSE by about 3,900 custodial parents and out of CSE by about 2,000 custodial parents (see Table 7). All individuals flagged in JOBS in 93Q4 would also be flagged in JOBS in 95Q4, since the criterion is entry prior to the selection quarter. But about 8400 individuals in the overlap entered JOBS in the two years between the cohort

Table 7: Changes in CSE Case Status in Cohort Overlap

	CSE95Q4		
	0	1	
CSE93Q4			
0	18,018	3,889	21,907
1	2,005	36,872	38,877
	20,023	40,761	

Table 8: Changes in JOBS Status in Cohort Overlap

	JOBS95Q4		
	0	1	
JOBS93Q4			
0	35,858	8,419	44,277
1	0	16,507	16,507
	35,858	24,926	

selection quarters (see Table 8).

We show below the details of shifts between program categories for those in the cohort overlap. The general picture demonstrated in Table 9 is a movement towards program categories associated with greater likelihood of reducing welfare use. In the cohort overlap the size of the CGJY group increases by 67% in two years.

In Table 10 below we show how each program group redistributed in the two years between 93Q4 and 95Q4. The values given are percentages of the 93Q4 program category which were found in the 95Q4 program category. Thus 65% of the 16,376 who were in the 93Q4 CNJN program category were also in CNJN in 95Q4, while about 16% were in CNJY and about 14% were in CPJN. While the overall movement appears to be towards more favorable program combinations, we note that there is also movement in the opposite direction. Of those with

Table 9: Changes in Program Categories in Cohort Overlap

	93Q4	95Q4	% CHANGE
CNJN	16,376	11,984	-26.80%
CNJY	5,531	8,039	45.30%
CPJN	25,727	21,707	-15.60%
CPJY	9,994	15,245	52.50%
CGJN	2,174	2,167	-0.30%
CGJY	982	1,642	67.20%

Good CSE Collections in 93Q4, over 35% were found in Poor CSE Collections in 95Q4 (36.5% of CGJN and 37.8% of CGJY). This, of course, would tend to diminish the apparent program impacts discussed in the main sections of this paper; the program groupings would be becoming more alike. This could suggest that the cost avoidance estimates presented are a lower limit; but additional data and a more sophisticated analysis - program categories as time-dependent explanatory variables - would be needed to understand the movement between program categories with time and its effects on the cost avoidance estimates presented in the main sections. This type of analysis would also allow us to include other time varying factors such as economic indicators.

Table 10: Redistribution of Program Categories in Cohort Overlap

	93Q4					
	CNJN	CNJY	CPJN	CPJY	CGJN	CGJY
95Q4						
CNJN	65.40%	0.00%	4.70%	0.00%	2.80%	0.00%
CNJY	15.80%	85.10%	1.00%	4.40%	0.60%	3.10%
CPJN	13.50%	0.00%	72.70%	0.00%	36.50%	0.00%
CPJY	4.10%	14.00%	16.40%	90.20%	8.50%	37.80%
CGJN	0.80%	0.00%	4.20%	0.00%	43.70%	0.00%
CGJY	0.30%	0.80%	1.00%	5.40%	7.90%	59.20%

NON-CUSTODIAL PARENT

In the Outcomes and Costs and Spells Analysis sections we have presented strong evidence that affiliation with the JOBS program reduced welfare use, mostly by helping individuals move from the state "Welfare w/o Work" to the state "Work w/o Welfare." It would certainly be expected that non-custodial parents (NCPs) in "Work w/o Welfare" are more likely to pay child support than parents in "Welfare w/o Work." This could be an important policy issue, because if this speculation is valid it would mean that there could be a double return from a focus on getting NCPs off welfare and working. Not only will NCP welfare use be reduced, but custodial parent welfare use could also be reduced.

The data used in the main body of this paper was not adequate to address this question. We linked custodial parent Social Security Number (SSN) from our 95Q4 analytical data file back into CSE data to obtain corresponding 95Q4 NCP SSN. Matching against welfare records, 44,122 NCPs were selected who had adult welfare use with beginning date within five years prior to 95Q4. CSE case data for 95Q4 indicated that 2,343 of these (5.3%) had Good CSE Collections. Note that in both cohorts in the main study 9.0% of custodial parents matched in CSE data had good CSE collections (see Appendix 2). Of the 44,122 NCPs there were 5,603 who entered JOBS prior to 93Q4, and 10,088 who entered JOBS prior to 95Q4.

Logistic regressions using good CSE collections as the dependent variable, and client demographic and location factors and JOBS as explanatory variables gave the results shown in Table 11.

There is a tendency for custodial parents to have Good CSE Collections in 95Q4 if the NCP had entered JOBS prior to 93Q4, but the tendency disappears for JOBS entry prior to 95Q4. This would be expected because of timing factors discussed in the Spells Analysis Section. It can take many quarters for the NCP welfare exit to occur, and by including NCPs who entered JOBS between 93Q4 and 95Q4, we would expect the effect of JOBS to be diminished.

This issue is worth a more rigorous and through study.

Table 11: Relative Odds for Good CSE Collections

	NCP entry prior to 934	NCP entry prior to 954
	sig.@ 0.01 level	diff. not sig.
NCP No JOBS	1.0	
NCP In JOBS	1.2	

Appendix 2

Technical Details

Data Sources and Preparation

State administrative databases were the only sources used in all analyses. The Office of Financial Management (OFM) Eligibility File provided information on monthly welfare use from 1986 to the 1st Quarter of 1997. This file was also used to obtain client demographic data - gender, age, race, primary language, number in family, disability status, and location. Quarterly earnings records from two years prior to the selection Quarter to the 1st Quarter of 1997 for selected individuals were obtained from the Employment Security Department (ESD) Wage Tax File. Data on JOBS from State Fiscal Year 1993 to State Fiscal Year 1996 was obtained from the JOBS Automated System (JAS) jointly administered by ESD and the Department of Social and Health Services (DSHS). Child support enforcement data for custodial parents for the selection Quarter was obtained from historical extracts of the Support Enforcement Management System (SEMS) of DSHS, Division of Child Support (DCS). Social Security Numbers (SSN) were used for matching across data files.

Welfare use history was converted to adult use only, with only three possibilities in each month - no use, 1-parent case, or 2-parent case. For the 3 months of the selection quarter these three possibilities were maintained, otherwise monthly welfare history was collapsed into use, or no use, of welfare. Individuals were classified as using welfare in a quarter if any monthly use occurred in that quarter. Cohorts were selected as adults who used welfare in the selection Quarter. Prior welfare history for selected adults was obtained as the sum of months welfare used in the two years prior to the selection quarter.

Quarterly work history for selected individuals was obtained by classifying individuals as working in the Quarter when there were any reported earnings, otherwise individuals were classified as not working in the Quarter. Previous earnings history was obtained as the average Quarterly reported earnings in the two years prior to the selection Quarter.

Using the four-state model shown in Figure 1, Outcomes and Costs, state residence in each quarter, or in each month, was then obtained using the welfare status and work status for each individual.

JOBS data was used to extract dates of entry into the JOBS program for each matched individual. Where there was more than one date of entry for an individual, only the earliest date of entry was kept. Individuals were classified as in JOBS when the date of entry occurred prior to the cohort selection Quarter. 26.9% of the 93Q4 cohort were in JOBS and 34.4% of the 95Q4 cohort were in JOBS.

Custodial parent monthly order amount (MOA) and total arrears (TARRS) were extracted from CSE data. When a custodial parent appeared on more than one case, both MOA and TARRS were summed for all cases. When a cohort SSN was found in custodial parent CSE data, the individual was classified as in CSE; and classified with Good Collections when MOA was greater than $0.00 and TARRS was less than twice MOA. An individual in CSE, but not meeting the criteria for Good Collections, was classified with Poor Collections. With the 95Q4 cohort other definitions of good collections were tested at the beginning of this work, with similar impacts of CSE collections on outcomes in 96Q3. Our definition aims at regularity of payment and does not directly consider the amount of payment. Other work in progress does indicate that larger CSE collections in the selection quarter are associated with larger subsequent cost avoidance.

For both cohorts about 60% were in CSE and 9.0% of those in CSE had Good Collections. Program indicator variables were obtained from CSE status and JOBS status as indicated in Figure 4, Outcomes and Costs. Details of classification and CSE information are shown in Tables 12 and 13. These Tables show that while a MOA of $0 restricts many custodial parents to the Poor Collections category,

Tables 12 and 13: Program Classification of Cohorts and CSE Details

93Q4 Cohort							
	All Clients			Clients with MOA > 0			
	Number	Avg MOA	Avg TARRS	Number	Percent	Avg MOA	Avg TARRS
CGJY	2,026	$241	$116	2,026	100%	$241	$116
CPJY	18,068	$179	$6,575	12,165	67%	$266	$9,297
CGJN	4,261	$241	$115	4,261	100%	$241	$115
CPJN	45,578	$159	$6,585	25,796	57%	$282	$10,865
CNJY	11,184	n/a	n/a	n/a	n/a	n/a	n/a
CNJN	35,260	n/a	n/a	n/a	n/a	n/a	n/a
Total	116,377						

95Q4 Cohort							
	All Clients			Clients with MOA > 0			
	Number	Avg MOA	Avg TARRS	Number	Percent	Avg MOA	Avg TARRS
CGJY	2,426	$239	$105	2,426	100%	$239	$105
CPJY	22,455	$192	$8,061	15,879	71%	$271	$10,740
CGJN	3,893	$245	$122	3,893	100%	$245	$122
CPJN	41,459	$169	$7,336	24,847	60%	$282	$11,439
CNJY	13,316	n/a	n/a	n/a	n/a	n/a	n/a
CNJN	27,458	n/a	n/a	n/a	n/a	n/a	n/a
Total	111,007						

more than half the poor CSE custodial parents in both cohorts do have a MOA greater than $0, and are restricted to Poor Collections by very large arrears (average total arrears up to 40 times average MOA).

A list of explanatory variables, where most demographic data were converted to dichotomous indicator variables, used in both logistic and survival analytical procedures is given below in Table 14. All explanatory variables are based on information in, or prior to, the selection quarter. Table 15 gives the mean values for explanatory variables for both cohorts. For dichotomous variables the mean

Table 14: Explanatory Variables in Logistic and Survival Analysis Procedures

Variable	Type	Explanation
GEN	Dichotomous	Gender; =1 if male, otherwise = 0
BLACK	"	Race; =1 if Black
API	"	Race; =1 if Asian/Pacific Islander
HISP	"	Race; =1 if Hispanic
NAT	"	Race; =1 if Native American
REFUG	"	Race; =1 if Refugee
UNKRACE	"	Race; =1 if unknown
ASIAN	"	Primary Language
SPANISH	"	Primary Language
SEASIAN	"	Primary Language; Southeast Asian
OTHEU	"	Primary Language; other European (not English)
RUSUKR	"	Primary Language; Russian/Ukrainian
OTHLANG	"	Primary Language; other
DISABLD	"	Disability field is not null
PREVSTAT	"	Status in present quarter; working while on welfare=1
YOUNG	"	Age is less than 25
OLD	"	Age is greater than 50
EAST	"	Location is in Eastern State labor market
WEST	"	Location is in Non-Urban Western State labor market
NUMFAM	Continuous	Number in family
PREEARN	"	Average Quarterly Earnings ($) in previous two years
PREWELF	"	Number of months of welfare use in previous two years
EEE	Dichotomous	Monthly pattern of Welfare use in selection qtr; 3 Mos of E (2 parent program)
OCC	"	1 Mo of no welfare followed by 2 Mos of C (1 parent program)
COO	"	Self explanatory from above
CCO	"	Self explanatory from above
OOC	"	Self explanatory from above
OOE	"	Self explanatory from above
OEE	"	Self explanatory from above
EOO	"	Self explanatory from above
EEO	"	Self explanatory from above
COC	"	Self explanatory from above
CEE	"	Self explanatory from above
CCE	"	Self explanatory from above
ECC	"	Self explanatory from above
EEC	"	Self explanatory from above
EOE	"	Self explanatory from above
OCO	"	Self explanatory from above
OEO	"	Self explanatory from above
CEO	"	Self explanatory from above
COE	"	Self explanatory from above
ECO	"	Self explanatory from above
CEC	"	Self explanatory from above
OCE	"	Self explanatory from above
EOC	"	Self explanatory from above
ECE	"	Self explanatory from above
OEC	"	Self explanatory from above

Table 15: Mean Values for Explanatory Variables

Variable	MEAN 93Q4	MEAN 95Q4
GEN	0.211	0.208
BLACK	0.089	0.093
API	0.042	0.049
HISP	0.035	0.023
NAT	0.040	0.037
REFUG	0.015	0.007
UNKRACE	0.055	0.073
ASIAN	0.001	0.001
SPANISH	0.021	0.022
SEASIAN	0.032	0.038
OTHEU	0.003	0.005
RUSUKR	0.018	0.026
OTHLANG	0.003	0.003
DISABLD	0.046	0.033
PREVSTAT	0.238	0.253
YOUNG	0.285	0.259
OLD	0.018	0.021
EAST	0.271	0.269
WEST	0.203	0.216
NUMFAM	2.9	2.9
PREEARN	$386	$429
PREWELF	15.0	15.3
EEE	0.212	0.196
OCC	0.030	0.033
COO	0.030	0.035
CCO	0.029	0.031
OOC	0.028	0.029
OOE	0.021	0.021
OEE	0.020	0.019
EOO	0.018	0.018
EEO	0.016	0.016
COC	0.004	0.004
CEE	0.003	0.003
CCE	0.003	0.002
ECC	0.003	0.003
EEC	0.002	0.003
EOE	0.002	0.002
OCO	0.002	0.002
OEO	0.002	0.001
CEO	0.0003	0.0003
COE	0.0003	0.0003
ECO	0.0002	0.0003
CEC	0.0001	0.0002
OCE	0.0001	0.0001
EOC	0.0001	0.0002
ECE	0.0001	0.0001
OEC	0.00005	0.0001

value is also the fraction of clients in that category; for example the mean value of the variable GEN tells us that the fraction of males in the 93Q4 cohort is 0.211 or 21.1%.

Methods

<u>*Net Impact Analysis*</u>

Logistic regression is used to fit the quarterly state residence in follow up quar-

Figure 18: Logistic Equations Relating Probability to Explanatory Variables

Creating Model with Logistic Regression

$$P_{s,q} = 1/(1+e^{-Y_{s,q}}$$

$\boldsymbol{P_{s,q}}$ is the probability of state ***s*** in Quarter ***q***

$$Y_{s,q} = \sum_{i=0}^{M} \beta_{s,q,i} \; x_i$$

x_i is the ***i*** th explanatory variable

$\beta_{s,q,i}$ is the state ***s***, quarter ***q*** coefficient for the ***i*** th variable

Figure 19: Determining the Logistic Model

Creating Model with Logistic Regression

$P_{s,q}$ is fit to the outcomes, $O_{s,q}$ for each individual

Where $\sum_{s} O_{s,q} = 1$

The model is defined by the set of coefficients,

$$\beta_{s,q,i}$$

which produce the best fit

ters to explanatory variables. This is a series of logit models with dichotomous dependent variables. Figures 18 and 19 show the basic form of logistic regression, and Figure 20 identifies the explanatory variables. Once the model is determined variables x_0 to x_{47} can be held constant while different values of pro-

Figure 20: Explanatory Variables in Logistic and Survival Analysis Procedures

Explanatory Variables=

$\mathbf{x_0}$	= 1, intercept=
$\mathbf{x_1 - x_{18}}$	0/1 indicators for demogr. characteristics=
$\mathbf{x_{19}}$	number in family=
$\mathbf{x_{20}}$	0/1 indic. for working in selection quarter=
$\mathbf{x_{21}}$	avg qtrly earning in prior two years=
$\mathbf{x_{22}}$	months on welfare in prior two years=
$\mathbf{x_{23} - x_{47}}$	0/1 indic. welfare pattern in selec. qtr=
$\mathbf{x_{48} - x_{52}}$	0/1 program indic.=

Figure 21: Applying the Logistic Model

Applying the Model=

$$\overline{Y}_{s,q\ CNJN} = \sum_{i=0}^{47} \beta_{s,q,i}\ \overline{x}_i$$

The $\overline{x}_i$ are the mean values of the explanatory variables

$$\overline{Y}_{s,q\ CNJY} = \overline{Y}_{s,q\ CNJN} + \beta_{s,q,48}\quad 1=$$

etc., then probability sum set to 1 for each q=

$$\sum_s \overline{P}_{s,q\ PGM} \doteq 1$$

gram indicator variables x_{48} to x_{52} can be substituted to obtain controlled program impacts (see Figure 21). In most of the work presented variables x_0 to x_{47} were set to the average values for the cohort.

Figure 22 gives an example of the output from the *SAS* logistic procedure, for the “Welfare w/o Work” state in the 13th follow-up quarter for the 93Q4 cohort.

While the CNJN program category was used as reference in work presented in Outcome and Costs, in this example the CPJN category was reference. This is done to verify the statistical validity of the critical feature of Figure 6 in Outcome and Costs. The validity of cost avoidance estimates rely on the validity of the difference between the "Poor CSE, Welfare w/o Work" line and the "Good CSE, Welfare w/o Work" line in Figure 6. The *SAS* output in Figure 22 tells us that the coefficient for CGJN is significant at the 0.0001 level and that the odds of being

Figure 22: Example of SAS Logistic Output

Variable	Parameter Estimate	Pr > Chi-Square	Odds Ratio
INTERCPT	-1.2221	0.0001	.
GEN	-0.3790	0.0001	0.685
BLACK	0.1356	0.0001	1.145
API	-0.1331	0.0013	0.875
HISP	-2.6937	0.0001	0.068
NAT	0.1379	0.0001	1.148
REFUG	-3.6247	0.0001	0.027
UNKRACE	0.7711	0.0001	2.162
SPANISH	0.4714	0.0001	1.602
SEASIAN	1.1326	0.0001	3.104
OTHEU	0.4362	0.0008	1.547
RUSUKR	0.4120	0.0001	1.510
OTHLANG	0.9902	0.0001	2.692
DISABLD	-0.7419	0.0001	0.476
PREVSTAT	-0.5196	0.0001	0.595
YOUNG	0.2460	0.0001	1.279
OLD	-0.1813	0.0012	0.834
EAST	0.2507	0.0001	1.285
WEST	0.2521	0.0001	1.287
NUMFAM	0.1429	0.0001	1.154
PREEARN	-0.0002	0.0001	1.000
PREWELF	0.0289	0.0001	1.029
EEE	-0.4159	0.0001	0.660
OCC	-0.2022	0.0001	0.817
COO	-0.9247	0.0001	0.397
CCO	-0.8087	0.0001	0.445
OOC	-0.2642	0.0001	0.768
OOE	-0.6793	0.0001	0.507
OEE	-0.6481	0.0001	0.523
EOO	-1.1429	0.0001	0.319
EEO	-0.8599	0.0001	0.423
CEE	-0.2675	0.0277	0.765
EOE	-0.4860	0.0055	0.615
OCO	-1.0382	0.0001	0.354
OEO	-1.1701	0.0001	0.310
CEO	-1.2217	0.0136	0.295
CNJN	-0.0427	0.0255	0.958
CNJY	-0.7769	0.0001	0.460
CPJY	-0.8047	0.0001	0.447
CGJN	-0.2443	0.0001	0.783
CGJY	-1.1932	0.0001	0.303

in "welfare w/o work" for those in CGJN are about 78% of the odds of being in "welfare w/o work" for those individuals in the reference group (CPJN).

Figure 23 shows how costs are estimated for program comparisons. For actual

Figure 23: Cost Avoidance Calculations

Generating Program Comparison Cost Estimates

For comparison assume 10,000 average welfare clients in each program

Number in state ***s***, quarter ***q*** for each program, ***PGM:***

$$\overline{N}_{s,q}(PGM) = 10{,}000 \quad \overline{P}_{s,q}(PGM)$$

Cost in quarter ***q*** for each program, ***PGM:***

$$\overline{C}_q(PGM) = \$500 \ 3 \ \overline{N}_{3,q}(PGM) + \$250 \ 3 \ \overline{N}_{2,q}(PGM)$$

CSE cost avoidance in quarter ***q*** :

$$\overline{C}_q(CGJN) - \overline{C}_q(CPJN) \quad or \quad \overline{C}_q(CGJY) - \overline{C}_q(CPJY)$$

cost estimates, the actual number of individuals in the program category are used. Base probabilities were recalculated for CSE cost estimates using average values for variables x_0 to x_{47} for the actual individuals in the program categories.

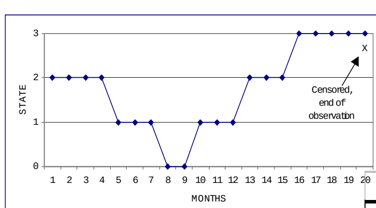
Survival Analysis

For survival analysis we used a monthly basis since welfare status was known at this level. With this basis, work status was constant for the three months of a quarter. For survival analysis, the first step is converting state residence to spells

Figure 24: Converting to Spells

(example; not real data)

Survival Analysis: Spells, Durations, & Events



Spell	Duration	Event
2	4mo	1
1	3	0
0	2	1
1	3	2
2	3	3
3	5	X

in a particular state. Figure 24 shows an example of how this is done. In the example the duration of the last spell, in state 3, is only known to be 5 months *or longer*, since the event terminating this state was not observed. Note that the month in a spell does not refer to a particular point in time; in the example the 1st month of the first instance of spell 1 is the 5th month of observation, while in the second instance of spell 1 the 1st month is the 10th month of observation. The fact that individuals may have multiple spells in a particular state can produce a bias towards apparently smaller coefficients and apparently higher significance. A simple test suggested by Allison (*Ref. 4*), the square root of the ratio of number of individuals to number of spells, indicates that corrections to significance would be small and would not alter the significance of differences discussed in the paper. Corrections to coefficients are harder to obtain, and were not attempted.

The survival analysis procedure (Cox regression, *SAS* procedure PHREG) fits the duration of spells for the cohort to a probability based on explanatory variables as indicated in Figures 25 and 26. As with the logistic procedure controlled program impact survival functions can be obtained by holding variables x_0 to x_{47} constant while different values of program indicator variables x_{48} to x_{52} are substituted. For survival curves presented in the Spells Analysis section 95% confi-

Figure 25: Equations Relating Survival to Explanatory Variables

Survival Analysis: Creating Model

Survival Function: fraction surviving @ time ***t:***

$$S_t = \exp\left\{ -\sum_{u=0}^{t} h\ u\ \Delta u \right\}$$

Hazard Function: risk @ time ***u:***

$$h\ u\ = \exp\left\{ \alpha\ u\ + \sum_i \beta x_i \right\}$$

β s are adjusted for best fit

Figure 26: Fitting the Survival Model

0 oGeOnJ of (Yents

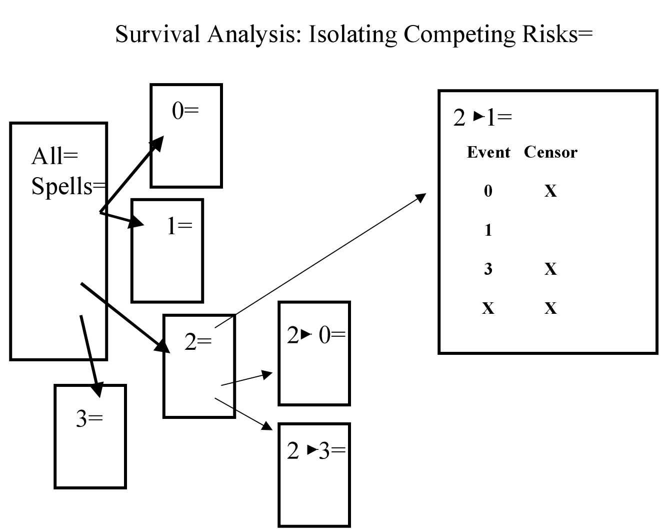
Non-Censored (vents at tiP e ☺ are P oGeOGEy the SroEaEiOty of an eYent occurrinJ in a sP aOtiP e interYaOarounG ☺

Censored (vents at tiP e ☺ are P oGeOGEy the SroEaEiOty of an eYent occurrinJ at a tiP e ☺or Jreater than ☺

dence limits are approximately represented by the size of the markers on the curves.

Figure 27 shows the procedure for analyzing competing risks. All events, other than the one of interest, are treated as censored events.

Figure 27: Treating Competing Risks



The hazard rate is the negative of the derivative of ln*S* – the slope of a plot of ln*S* vs *t*. None of the twelve unique transitions in this system gave a linear plot; in all cases the hazard appears to be time-dependent. Most plots of ln*S* vs *t* showed a slope smoothly decreasing with time, a situation that can be approximated by a Gompertz hazard function:

$$h = \kappa e^{pt}$$

$$\ln S = \ln \frac{N}{N_0} = \frac{\kappa}{p}\ 1 - e^{pt}\ \ = a\ 1 - e^{bt}$$

The *SAS* NLIN procedure for a non-linear least squares regression was used to obtain the Gompertz parameters. In most cases the log survival curves could be fit very well with a sum of two Gompertz functions; in a few cases a sum of three Gompertz functions were needed. However, our objective is to use the parameters of the Gompertz function to calculate the hazard rate at a particular point in time, and for this only one Gompertz function is justified. As the number of parameters in the fit increases, the parameter errors also increase, leading to a larger error in the hazard rate. In no case was a multiple Gompertz fit hazard rate significantly different than the hazard rate calculated with a single Gompertz.

Using this approach we are able to determine magnitudes of the hazard rates for all transitions and for all program categories. The ratios of the hazards for program categories obtained in this way are very close to those obtained directly from PHREG output. But it is better, in terms of confidence limits, to use the Gompertz fit procedure described above to obtain the magnitude of the reference hazard, and then use the risk ratios output from PHREG to estimate the full set of hazard rates. By determining the hazard at a standard point in time (we have chosen 9 months) we can compare rates across all transitions and across studies.

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2. *Luttrell, Public Policy Analysis and Management Conference, 1996; Hu, Dept. Economics, UCLA 1995; Meyer, Demography, 30, 45-62, 1993; Wheaton & Sorensen, Georgetown Public Policy Review, 4, 23-37, 1998.*

3. *Formoso, 1997, Washington Employment Security Department internal report.*

4. *P. D. Allison, Event History and Survival Analysis-Course Notes, 1997, pg 79.*