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Net Impact Estimates of the Workforce Development System in Washington State

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Abstract

This study estimates the net impacts and private and social benefits and costs of nine workforce development programs administered in Washington State. Five of the programs serve job-ready adults: Community and Technical College Job Training, Private Career Schools, Apprenticeships, Job Training and Partnership Act (JTPA) Title III programs, and Community and Technical College Worker Retraining. Two of the programs serve adults with employment barriers: Community and Technical College Adult Basic Skills Education and JTPA Title II-A programs. The other two programs serve youth: JTPA Title II-C programs and Secondary Career Technical Education.

The net impact analyses were conducted using a nonexperimental methodology. Individuals who encountered the workforce development programs were statistically matched to individuals who did not. Administrative data with information from the universe of program participants and Employment Service registrants (who served as the comparison group pool) supported the analyses. These data included over 10 years of pre-program and outcome information including demographics, employment and earnings information from the Unemployment Insurance wage record system, and transfer income information such as Food Stamp and Temporary Assistance for Needy Families (TANF) recipiency and benefits.

A variety of estimation techniques were used to calculate net impacts including comparison of means, regression-adjusted comparison of means, and difference-in-difference comparison of means. We estimated *short-run* net impacts that examined outcomes for individuals who exited from the education or training programs (or from the employment service) in the fiscal year 1999/2000 and *longer-run* impacts for individuals who exited in the fiscal year 1997/98. Short-run employment impacts are positive for seven of the nine programs and negative for the other two. Short-run earnings impacts are insignificant for four of the programs, negative for two, and positive for the remaining three. The longer-run impacts are more sanguine. Employment impacts are positive for all nine programs, and earnings are positive for seven and insignificantly different from zero for the other two. The benefit-cost analyses show that all of the programs have discounted future benefits that far exceed the costs for participants, and that society also receives a positive return on investment.

The Washington State Workforce Training and Education Coordinating Board (WTECB) has a commitment to accountability and data-driven performance monitoring and management. Biennial evaluations provide the public a substantial amount of data about the extent to which participants in the state workforce development system 1) achieve workplace competencies, 2) find employment, 3) achieve family-wage levels of earned income, 4) are productive, 5) move out of poverty, and 6) are satisfied with program services and outcomes. The performance data for these outcomes come from administrative data or surveys of program participants (or employers of participants).

The WTECB has a seventh evaluative outcome—return on investment—that is most appropriately calculated by using data from nonparticipants as well as participants. The data burden is greatly expanded compared to what is required for the other six criteria, and so the strategy that the state has followed has been to examine this outcome every four years. The most recent study was done in 1997. This paper provides updated net impact estimates of the Washington State employment preparation and training system and its economic value to the state.

WHY ARE NET IMPACT AND COST–BENEFIT ANALYSES USEFUL?

Washington's legislative mandate to calculate net impacts of its workforce development programs and their costs and benefits is rare among states. Why has the state insisted on these analyses? It recognizes that investment in workforce development requires considerable public resources, and for that reason alone the WTECB needs to be accountable to the public for achieving results. But it is important to dissect carefully the results that are achieved in order to assure the public that its resources are being wisely invested.

Individuals who participate in training or educational programs may experience successful outcomes such as the six outcomes listed above. However, it is not always clear that individuals' positive outcomes were the direct result of the programs. There could have been other factors, such as an improving economy, that caused positive results. In social science evaluation, this is called the *attribution question*. Can participants' successes be truly *attributed* to participation in the program, or might some other factor coincidental to the program have played a role?

A net impact analysis must be conducted to answer the attribution question. This analysis attempts to answer the question of what would have happened to participants *if there were no program* and individuals were left to their next best alternatives. To find the answer, we construct a comparison group of individuals who are very similar to the participants in each of the programs but who did not receive training or enroll in education. We observe both the participants and comparison group members over time. We then attribute to the program any differences in outcomes that we observe for program participants to those of comparison group members.

The net impacts of workforce development programs are likely to be positive for participants; the programs are delivering valuable skills to individuals who will use those skills in the labor market. However, accountability generally needs to go beyond positive net impacts. Of interest to the public is whether the net impacts (outcomes for program participants minus outcomes for similar individuals comprising a comparison group) aggregated over all participants will have exceeded the costs of the program. Thus, to get a full picture of the return on investment, it is necessary to compare the programs' net benefits to their costs.

PROGRAMS, OUTCOMES, AND TIME PERIODS BEING ANALYZED

The paper describes analyses (net impact and benefit–cost) of nine programs. Five of the programs serve job-ready adults: Community and Technical College Job Training, Private Career Schools, Apprenticeships, Job Training and Partnership Act (JTPA) Title III programs, and Community and Technical College Worker Retraining. Two of the programs serve adults with employment barriers: Community and Technical College Adult Basic Skills Education and JTPA Title II-A programs. The other two programs serve youth: JTPA Title II-C programs and Secondary Career and Technical Education.

For the participants in each of these programs, we estimated the net impacts of participation on the following outcomes:

- employment rates
- hourly wages
- hours worked per quarter
- quarterly earnings
- receipt of Unemployment Insurance (UI) benefits
- receipt of Temporary Assistance for Needy Families (TANF) benefits
- receipt of Food Stamps
- receipt of Medicaid benefits.

The first four outcomes are derived from the quarterly wage record data generated from the UI system and thus are measured over a calendar quarter.[1] Quarterly earnings and hours worked per quarter come directly from employer wage record reports filed with quarterly UI tax payments. Prior to receiving the data, the state preparation of the data included adding together the information from multiple employers for those individuals who had more than a single employer in a quarter. Through interstate agreements, Washington had gathered quarterly wage record data from

[1]The appendix provides details about data editing that was performed on the wage record data.

surrounding states (Alaska, Idaho, Oregon, and California) and from the federal payroll. The data from the other jurisdictions contributed to quarterly earnings but did not have hours information. We defined employment as having at least $100 in earnings in a quarter. Hourly wages are defined as total quarterly wages divided by hours worked in the quarter.

Unemployment Insurance benefits were gathered from the Washington UI system. Unemployment Insurance receipt in a quarter is defined as having nonzero benefits in the calendar quarter. The last three outcomes—TANF benefits, Food Stamp benefits, and Medicaid benefits—were gathered from the Washington State Department of Human Services. For TANF and Food Stamps, data on benefit levels and receipt were used. The levels were measured as quarterly benefits received by the assistance unit that included the individual who participated in the education or training program, and receipt was defined as having nonzero benefits in the quarter. The Medicaid data were limited to enrollment during the quarter; no attempt was made to assign a dollar value or to calculate total assistance unit medical usage in a quarter.

METHODS

There is contentiousness in program evaluation about the appropriate methodology for estimating net impacts–experimentation or nonexperimentation. Most evaluators probably would agree that the best way to estimate net impacts is to conduct a random assignment experiment. If it were feasible to do so, an experiment could sort individuals who apply and are eligible for services randomly into two groups—those who are allowed to receive services and those who are not. As long as assignment into treatment or control is random, then the evaluator can have high levels of statistical confidence that the program was responsible for any differences in outcomes.[2]

The issue is moot in the present context, however, because the programs being evaluated were essentially entitlements for which anyone in the state could participate. Experiments were not feasible; thus, this study relied on a nonexperimental methodology. Individuals who encountered the workforce development programs were compared to individuals who did not, and members of the latter group were not randomly chosen. In other words, there were systematic (nonrandom) differences between the participants and the individuals to whom they were compared. Thus, the statistical estimators used to calculate the net impacts require strong assumptions and/or multivariate conditionality to control for those differences.

Four Approaches to Estimating Net Impacts

In this study, we used four general approaches to calculate net impacts. Let T_i (for treatment) denote the administrative data from individuals who exited from the ith program, and let C_i (for comparison group) denote a data set that provides information about individuals who did not participate in the ith program. We will assume that the latter is a subset[3] of U (for universe).

We will denote the outcome(s) of interest as Y_i, and we will denote by X_i the data about individuals, the services they may have received, the economic conditions in their regions of residence, and other variables that we have observed and that are believed to affect the outcome(s). Note that we typically have a substantial time series of outcome data. Further note that the X_i

[2]Even with an experiment, there may be implementation problems or behavioral responses that threaten its external validity. For example, problems such as crossover, differential attrition, or Hawthorne effects may arise.

[3]C_i need not be a proper subset of U; they may be identical.

variables may be time-varying or time-invariant, but that we typically only observe them for one period (during program participation).

The first net impact estimator that we calculated is the simple (unconditional) difference in postprogram outcome means. Average quarterly earnings is one of the outcome variables of interest. Then the net impact of program *I* per participant could be estimated as follows:

$$(1) \qquad Y_i = \sum_j \frac{ET_j}{nT_i} - \sum_k \frac{EC_k}{nC_i},$$

where ET_j = the average quarterly earnings (adjusted to constant \$) over some particular period of time for the *j*th individual after exiting program[4] *i*,

EC_j = the average quarterly earnings (adjusted to constant \$) over the same period of time for the *k*th individual in the comparison group, and

nT_i, nC_i = the number of individuals in T_i and C_i, respectively.

Accepting this as a reasonable estimate of the net impact of the program requires rather strict (unreasonable) assumptions. For (1) to hold, either enrollment into the program is totally random, or the outcome is independent of characteristics that are systematically different between the treatment and comparison group.

The second approach effectively recognizes the systematic differences between the treatment group and the comparison group, and estimates regression-adjusted differences in means. Assuming that the relationship between the outcome variable and covariates is identical for the comparison group and for the treatment group suggests that the net impact can be estimated as in (2).

$$(2) \qquad Y_i = E\left(E_{tj} \middle| X_j; j \in T_i\right) - E\left(E_{ck} \middle| X_k; k \in C_i\right)$$

[4]"After exiting the program" is discussed below.

Econometrically, we assume that the conditional dependence may be parametrically estimated through a linear regression as in the following:

(3) $E_{ji} \quad = \quad a + B'X_j + cT_i + e_j$,

where E_{ji} = ET_j, if $j \in T_i$; EC_j, if $j \in C_i$,

X_j = vector of variables describing individual j that are thought to be correlated to the outcome E_{ji} ,

T_i = 1 for individuals in the participant sample and 0 for individuals in the comparison sample, and

e_j = error term, usually assumed to have a mean of 0 and standard deviation of 1.

The parameter estimate c would be the net impact of participation in the program.

Because we had rich data on the outcome variables before and after program participation, it was possible to use a difference-in-differences approach as our third method for estimating the net program impact. This approach effectively allowed the use of preprogram levels of the outcome variable(s) to control for the net impact effect. This third approach for net impact estimation is represented in (4):

(4) $$Y_i \quad = \quad \sum_j \frac{ET_j - ETBASE_j}{nT_i} - \sum_k \frac{EC_k - ECBASE_k}{nC_i},$$

where $EBASE_{j,k}$ = the average quarterly earnings (adjusted to constant \$) of the jth, kth individuals for a period of time (one or more quarters) that predates participation in the program of the individuals in T_i .

It is easily seen that the net program impact from (4) will be identical to that from (1) if the individuals in T_i and C_i have the same average level of base earnings.

The assumptions that must hold for the net impact estimate derived from (4) to be reasonable again include an assumption that the outcomes are independent of the observed characteristics in the treatment and comparison groups (or that the groups are statistically independent of each other). To control for observed differences between the two groups, our fourth approach was to regression-adjust the difference-in-differences. In other words, the net impact estimator becomes the difference-in-differences in conditional means as in (5).

$$(5) \qquad Y_i = E\left[\left(ET_j - EBASE_j\right)\middle| X_j;\, j \in T_i\right] - E\left[\left(EC_k - EBASE_k\right)\middle| X_k;\, k \in C_i\right].$$

As with the net impacts estimated from outcome levels, we can econometrically estimate the regression-adjusted difference-in-differences impact by assuming that the conditional dependence may be parametrically modeled through a linear regression as in the following:

$$(6) \qquad E_{ji} - EBASE_{ji} = a + B'X_j + cT_i + e_j \quad .$$

The parameter estimate *c* would be the net impact of participation in the program.

Choice of Outcome and Base Periods

Net impacts were calculated for each program using two different fiscal years. *Short-run* net impacts were calculated by specifying the treatment group as all individuals who exited from a program in fiscal 1999–2000. *Longer-run* net impacts were calculated by using individuals who exited in fiscal 1997–1998 as the treatment group. The comparison groups were drawn from administrative data for individuals who last received services from the Employment Service during those two fiscal years. (In other words, the counterfactual situation for the net impact analysis was that without the state's workforce development system, the next best alternative for participants would have been the Employment Service.)

We used two different approaches for identifying the specific time periods of measuring outcomes. The first approach was 3 quarters after exiting from the program, and the second was the quarterly average during quarters 8–11 after exiting from the program. The most recent quarter that we had data from was quarter 1 of 2001, so we were only able to use the first approach for the 1999–2000 program exiters. For difference-in-differences estimators, we specified the preprogram base period to be the average of quarters 3–6 prior to registration.

Construction of the Comparison Group

The basic problem that had to be solved was how to choose the appropriate observations from the data sets[5] that were used to extract the comparison samples for each of the programs being examined. The source of data that was used to construct the comparison group for most of the programs was the labor exchange registrant data system (JOBNET). The question to answer was which observations in the labor exchange registrant system (or high school follow-up survey) were most comparable to exiters from each of the programs.

The general situation was that we had one set of administrative data from individuals who exited from an education or training program in a year and an entirely different set of administrative data from other individuals who may or may not be reasonable matches for the program exiters.[6] The solution we employed was to let C_i be comprised of the observations where the individuals were

[5]There actually were two data sets—the Employment Service (ES) registrant data and general track students from administrative data supplied by high schools. The latter were used for secondary vocational-technical education.

[6]The fact that the treatment and potential comparison samples come from different administrative data eliminates some possible comparison samples. For instance, in many net impact evaluations of training programs, the comparison group that is used is comprised of program applicants who do not enroll and do not participate in the program. Such comparison samples may have an advantage over the proposed situation because the comparison group would clearly have known about the programs and would have been motivated to apply for services.

most "like" the individuals comprising T_i. Fortunately, there was substantial overlap in the variables that were in most of the data sets, such as age, race/ethnicity, education at program entry, disability status, English as a Second Language (ESL) status, gender, region of state, veteran status, prior employment and earnings history, and prior Welfare/UI/Food Stamp receipt.

With a substantial number of common variables in each data set, we could have constructed the comparison group members with a "nearest neighbor" algorithm. This type of algorithm minimizes a distance metric between observations in T_i and U. If we let X represent the vector of variables that are common to both T_i and U, and let X_j, X_k be the values of X taken on by the jth observation in T_i and kth observation in U, then C_i will be comprised of the observations in U that minimize the distance metric $\left|\left(X_j - X_k\right)\right|$.[7]

In work concerning the evaluation of training programs, Ashenfelter (1978) demonstrated that preprogram earnings usually decrease prior to enrollment in a program. This implies that a potential problem with the "nearest neighbor" approach is that individuals whose earnings have "dipped" might be matched with individuals whose earnings have not. Thus, even though earnings *levels* would be close, the individuals would not make good comparison group matches.

In response to this concern, evaluators have used a propensity score approach to estimate the likelihood of being eligible to participate in the training (Dehejia and Wahba, 1999). Essentially, the observations in T_i and U are pooled, and the probability of being in T_i is estimated. The predicted probability is called a propensity score, and treatment observations are matched to observations in the comparison sample with the closest propensity scores. The selection of

[7]The literature usually suggests that the distance metric be a weighted least-squares distance; $\left(X_j - X_k\right)' \sum^{-1}\left(X_j - X_k\right)$, where $\sum^{-1}$ is the inverse of the covariance matrix of X in the comparison sample. This is called the Mahalanobis metric. If we assume that the X_j are uncorrelated, then this metric simply becomes least-squared error.

comparison sample observations can be done with or without replacement. We relied on the propensity score matching (with replacement) approach in this study.

In other words, we estimated the following model using logit:

$$(7) \quad T_{ij} = 1 \text{ if } p_j^* > 0$$

$$= 0 \text{ otherwise,}$$

$$\text{Where } p_j^* = \beta X_j + e_j \quad ,$$

X_j = jth observation's values for the vector of common variables in T_i and U, and

e_j = error term distributed as standard logistic.

The propensity score is the predicted probability of being in T_i using the estimates from (7).

The underlying theory for this approach is that the treatment group is systematically different from the overall pool being used for selecting comparison group members, i.e. U, in observable variables, but the systematic differences are not perfect. That is, if the model estimated in (7) does not fit well, then there is essentially little difference between the treatment group and the comparison pool observations in observable characteristics, and the comparison group could be chosen randomly. On the other hand, if there is some characteristic that perfectly discriminates between treatment and comparison pool, then the approach will not work because there is no statistical support in the comparison pool for the treatment observations.

An individual was considered to be a member of a treatment group if he or she exited from a program during either of the two fiscal years analyzed. An individual was considered to be a member of the comparison group pool if they exited (last received services) from the Employment Service during either of those years. Note that because administrative data were used, sometimes the concept of exiting from a program was ambiguous and arbitrary, especially for individuals who exited before completing. For the education or training programs that resulted in a certificate or credential for individuals who successfully complete all of the requirements, the individual's exit date was clearly when they earned the credential. However, individuals who stopped attending a program were unlikely to report their intention to program administrators, and so there is a lag in the data that reflects how long it takes for the program's administrative information system to "catch" the exit. Some programs use the rule that no contact over a 12-month period means that the individual exited the program; some programs use a 6-month rule. All in all, we note that the exit date may be subject to measurement error, which therefore implies that length of time receiving treatment and initial outcome periods after treatment are somewhat subject to error.

SUMMARY OF RESULTS

Table 1 provides the short-run net impacts of the nine programs on employment and earnings. The elements reported in the table show the increase (or decrease) in employment, defined as having at least $100 in earnings in the third quarter after exiting from the program, and the increase (or decrease) in quarterly earnings, on average, for that quarter. Note that these results include all participants—those individuals who completed their training and those who left without completing. Separate results for these two groups were estimated.

The employment impacts are in percentage point terms and are all statistically significant. Two of the programs have negative short-run employment programs, whereas all of the others are positive. The employment rate of the comparison group is on the order of 60 to 70 percent, so these impacts range from about 3 to 12 percent. The short-run earnings impacts are not as sanguine.[8] With the exception of community college job preparation, apprenticeship, and high school career technical education, the short-run earnings impacts are negative or not statistically significantly different from zero.

Table 2 illustrates the longer-run payoff to education and training. All of the employment impacts are positive, and for the three JTPA programs and adult basic education at community colleges, the longer-run employment impacts are much larger than the short-run impacts. The earnings picture is also far better in the longer run. Two of the programs, JTPA II-C for disadvantaged youth and adult basic education, have earning impacts that are essentially 0, but all other programs show sizeable earnings impacts that, in percentage terms, are on the order of 20 percent.

Table 3 summarizes the benefit–cost estimates. The table presents these on a per participant basis, and it shows the benefits and costs to the participant and to the public. For participants, the benefits include net earnings changes (earnings plus fringe benefits minus taxes) and transfer income changes (UI benefits plus TANF plus Food Stamps plus Medicaid). These changes may be positive, indicating that the additional earnings and transfer income accrue to the participant, or they may be negative if earnings and/or transfers are projected to decrease. For the public, benefits include taxes paid plus reductions in transfer payments. Again, these may be positive (taxes are received and transfers are reduced) or negative. For participants, the costs are foregone earnings during the period of training and tuition/fees (for community college enrollment). For the public, costs represent the budgetary expenditures necessary to provide the training/education services. Whereas

[8]The earnings estimates were derived from regression-adjusted levels models for youth and dislocated worker programs and regression-adjusted difference-in-differences models for adult programs.

it is a theoretical possibility for foregone earnings to be negative, practically all of the costs are positive. All of the benefits are discounted back to 2001 at a rate of 3.0 percent.

The table shows the per participant benefits and costs that accrue over the first 10 quarters after exiting from the program and over the expected working lifetime of the participant. From the participant's perspective, about half of the programs have discounted benefits that exceed costs over the 10-quarter time frame, while the other programs have costs that exceed benefits over the short-term period. However, all of the programs have discounted benefits that significantly exceed costs over the participant's working lifetime. From the public's perspective, all of the programs have benefits that exceed costs in the long run, but only JTPA II-A and secondary vocational education have public benefits that exceed the public costs in the first 2.5 years.

Table 1

Short-Run[a] Net Impacts of Washington's Education and Training System, by Program

Program	Net employment impact (in percentage points)	Net quarterly earnings impacts (2001, $)
JTPA II-A	3.6	$105**
JTPA II-C	–4.0	$86**
JTPA III	2.2	–$397
Comm. college ABE	–5.2	–$613
Comm. college job prep	7.6	$1,470
Comm. college worker retraining	8.0	$147**
Private career schools	2.6	$10**
Apprenticeships	5.4	$2,030
High school career technical ed.	5.5	$112

[a]Defined as three quarters after exit.
**Not statistically significant at the 0.10 level.

Table 2

Longer-Run[a] Net Impacts of Washington's Education and Training System, by Program

Program	Net employment impact (in percentage points)	Net quarterly earnings impacts (2001, $)
JTPA II-A	7.4	$543
JTPA II-C	5.3	–$72**
JTPA III	7.3	$466
Comm. college ABE	1.6	–$43**
Comm. college job prep	7.0	$1,185
Comm. college worker retraining	6.3	$423
Apprenticeships	5.3	$1,908
High school career technical ed.	5.7	$451

[a]Defined as average over quarters 8–11 after exit.
**Not statistically significant at the 0.10 level.

Table 3

Discounted Benefits and Costs of Washington's Education and Training System, by Program

	First 2.5 years		Lifetime	
Program	Participant	Public	Participant	Public
JTPA II-A	Bene. = $200 Costs = $360	Bene. = $4,348 Costs = $3,384	Bene. = $52,428 Costs = $ 360	Bene. = $21,450 Costs = $ 3,384
JTPA II-C	Bene. = –$2,500 Costs = $ 343	Bene. = $1,865 Costs = $2,325	Bene. = $29,819 Costs = $ 343	Bene. = $ 6,793 Costs = $ 2,325
JTPA III	Bene. = $ 4,240 Costs = $12,175	Bene. = $ 960 Costs = $2,575	Bene. = $68,485 Costs = $12,175	Bene. = $21,867 Costs = $ 2,575
Comm. college ABE	Bene. = $2,818 Costs = $ 278	Bene.= –$2,026 Costs = $ 983	Bene. = $5,911 Costs = $ 278	Bene. = $405 Costs = $983
Comm. college job prep	Bene. = $4,179 Costs = $4,493	Bene. = $1,885 Costs = $6,916	Bene. = $117,849 Costs = $ 4,493	Bene. = $34,891 Costs = $ 6,916
Comm. college worker retraining	Bene. = $ 1,941 Costs = $16,630	Bene. = $1,385 Costs = $4,692	Bene. = $59,300 Costs = $16,630	Bene. = $20,222 Costs = $ 4,692
High school career technical ed.	Bene. = $ 2,747 Costs = $ 0	Bene. = $ 902 Costs = $ 870	Bene. = $60,050 Costs = $ 0	Bene. = $11,186 Costs = $ 870

NOTE: Benefits for a participant include discounted values of earnings and fringe benefits less taxes plus income transfers (TANF, Food Stamps, Medicaid, UI benefits); for the public, benefits include tax receipts minus transfer payments. Costs include program costs (public and participant, if tuition/fees) and foregone earnings (participant).

Appendix: Longitudinal Data File Editing

1. **Multiple participant records for an education or training program**. The state supplied us with individual-level data for each of the nine programs. In some of the program files, we found a few duplicate records, despite the fact that the file specifications indicated that each individual would have a single record. For example, in JTPA Title III, there were multiple records because there were multiple funding streams—special state grants in addition to the general title funding. In all cases where there were multiple records, we used the record with the latest exit date.

2. **Missing or "out of bounds" quarterly hours data in earnings records**. Records that had missing hours, zero hours (despite having reported earnings), and hours greater than 990 in the employment records had hours imputed. The imputation was done in three steps. The first step was to impute the hours using reported (nonimputed) information from adjacent quarters. The same rule was applied as was used by the state contractor, which was basically an interpolation of data from the adjacent records. For records that still have missing or zero hours, the next step in the algorithm was to assign the median working hours by the individual's industry and earnings class. If the industry was not available, the last step was to assign the population median working hours by earnings class. When hours exceeded 990, they were truncated to 990. Table A1 shows the percentage of records for which hours were imputed. With only a little variation across programs, the state had imputed data on about 3 percent of the records; we imputed data for about 5 percent of the records, which means that about 92 percent of the records did not have imputed hours.

3. **Comparison group records that have received prior intervention.** The state made the decision that the analyses were to reflect the impact and economic benefit of the entire system of education and training programs in the state. So, comparison group records were deleted for individuals who had been served by any of the education or training programs (except for secondary vocational/technical education) in recent years.

Table A1

Percentage of Records with Imputed Hours

Program	1997/1998	1999/2000
JTPA II-A	7.3	7.4
JTPA II-C	7.9	8.3
JTPA III	6.5	7.0
Community college ABE	5.9	6.7
Community college job prep	7.5	7.4
Community college worker retraining	8.0	7.4
Private career schools	—	7.8
Apprenticeships	7.4	7.1
High school career technical ed.	5.1	2.7
Job net	7.7	7.5

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