Assessing Active Labour-Market Programs: How Effective Is Ontario Works?

By Jason Adams, Ken Chow, and David Rosé

Appendix: Model and Methodology

Individual recipients can have multiple assistance spells if they leave the program and then re-enrol in OW at a later date. We form a cross-sectional dataset for each assistance spell by pooling each recipient's demographic and program characteristics associated with that spell. If the variable can change during the assistance spell – for example, age or education level – we use the value in the first period (month) of the spell. The initial employment assistance program assignment is the item of interest in the analysis because any later program assignment during a recipient's spell is likely dependent on that first assignment (see discussion in Sianesi 2004).

Consider an individual i in the Ontario Works program who is enrolled in employment assistance program j, where $j \in$ "{SJS,TP,SJSTP,PS}" (representing the categories of employment assistance programs outlined above, and SJSTP represents a recipient assigned to both SJS and TP). The outcome variable for person i is y_i. We study three outcomes: benefit-spell duration and the one-year and two-year rates of return to social assistance after leaving. Outcome y_i is related to initial program assignment j in the following regression model:

$$y_i = \beta_0 + \sum_{j \in J} \beta_j Prog_{ij} + X_i \gamma + \varepsilon_i$$

where $Prog_{ij}$ is a dummy variable that equals 1 if person i is enrolled in program j, X_i is a vector of control variables, and ε_i the error term.

Because we are interested in the causal impact of the assistance program on the individual's outcome – that is, the β_j coefficients – we must address the correlation between the outcome variable and factors such as local labour-market conditions and the individual's characteristics that are likely to be correlated with the outcomes of interest. The first step we take to control for confounding factors is to include a rich set of demographic and economic variables in the regression. For demographic controls, we include age, gender, highest education level achieved, number of children and dependent adults in the household, immigrant status, local unemployment rate, whether English or French is the preferred language, whether individuals live in an urban or rural area, and the median financial assistance level for similar recipients as a proxy for the generosity of the system. We also include skills (languages spoken, certificates achieved, licences held, etc.), occupational classification of the last job held by the recipient, and quarterly fixed effects as well as EI economic region geographic fixed effects interacted with the year to control for exogenous economic and temporal factors that are likely to influence the outcome variables.

Despite the comprehensive set of controls, there could still be unobservable characteristics, such as ability, that correlate with both the outcome variables and the program in which OW beneficiaries are assigned. As an illustration of the problem, suppose the omitted variable is some immeasurable ability positively related to finding employment, A_i. It is reasonable to assume that $E(y_i A_i) < 0$ (i.e., there is a negative relationship

Table A1: Program Effects on Spell Duration and Return Rate (OLS estimates)			
Reference Program: Independent Job Search	Spell Duration (months)	Return Rate (percentage points)	
		One year	Two Year
Structured Job Search	0.003	-0.7*	-0.9*
Training Programs	2.302*	-0.9*	-1.3*
Structured Job Search and a Training Program	1.426*	-1.0*	-1.4*
Placement Services	1.652*	-0.2	-0.4
Number of Observations	547,424	547,424	547,424

Note: Program effects marked with an asterisk are statistically significant at the 0.05 level. These results are biased and inconsistent because they do not address the endogeneity issue with program assignment. They can, however, be compared to the results attained from two-stage least squares estimation to highlight the difference made by instrumenting for program assignment.

between ability and the outcome variables)[a] could be possible if outcome y_i is spell duration – that a higher-ability individual spends less time on social assistance. Moreover, a higher-ability individual is also more likely to be assigned to independent job search instead of being enrolled in one of the five more intensive employment assistance programs. Thus, we would expect that an individual who is enrolled in structured job search has lower ability on average than someone enrolled in independent job search, and, therefore, we should expect a longer social assistance spell for someone in structured job search than in independent job search. Then, an ordinary least squares (OLS) regression that does not control for this unobserved ability would understate the effectiveness of structured job search (measured by $\hat{\beta}_{SJS}$) because the pool of individuals in this program has lower ability on average than the baseline group (Table A1 provides OLS estimates).

To address this endogeneity issue, we employ an instrumental variables (IV) approach. To instrument for each $Prog_{ij}$, the program participation dummy variable, we use Z_{ij}, the share of other recipients assigned to the same OW office as person i in the same year who get assigned to that program (program j).[b] It is given by the following equation:

$$Z_{ij} = \frac{1}{n_i - 1} \sum_{k \neq i}^{n_i - 1} Prog_{kj}$$

a It could be the case that educational attainment is also correlated with unobserved ability. However, regressions run with and without education as a control variable show that its inclusion does not have a large impact on our results. This finding suggests that the instrument is orthogonal to education/unobserved ability and should assuage this concern about the identification strategy used.

b To get a mapping of six-digit postal codes to assigned Ontario Works offices, we used the Ontario Ministry of Community and Social Services online Social Assistance Office Finder.

where n_i is total number of people assigned to the same office in the same year as individual i and is indexed by k, and $Prog_{kj}$ equals 1 if individual k is assigned to program j.

Intuitively, the propensity of a social assistance office to assign other people, k where $k \neq i$, to the program j should be uncorrelated with person i's unobserved characteristics (e.g., ability) and should affect only person i's employment outcome through its effect on program assignment. Similar instruments have been used in the literature previously – for example, Doyle, Jr. (2007) and Dean et al. (2015, 2016).

The validity of this instrument must satisfy the "first stage" and the exclusion restriction (Angrist and Pischke 2008). For the "first stage" assumption, there is a strong correlation between these instruments and their respective $Prog_{ij}$ variable. There is also variation in the instrument across offices in our data. Next, although we can never be certain of the strength of the exclusion restriction assumption, there are several arguments for its validity. First, the OW office for all participants is determined by their residential location, and they cannot choose which office they are assigned to (there are some exceptions, and in these cases the OW offices have been grouped together), meaning that the office that an individual interacts with is exogenous.[c] Second, to counter concerns that the variation in job availability where the programs are effective may jointly affect the outcome and the program choices of the caseworkers at the office, we have included the local unemployment rates for recipients' areas of residence as well as geographic/annual interaction fixed effects as control variables.

c In practice, postal codes for the most part map to a single Ontario Works office. In cases where residents of a postal code could be assigned to one of multiple offices, those offices are aggregated together for the sake of the instrumental variable calculations.