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Estimating the effects related to the timing of participation in employment assistance services using rich administrative data[1]

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Abstract

This study assessed whether starting participation in Employment Assistance Services (EAS) earlier after initiating an Employment Insurance (EI) claim leads to better impacts for unemployed individuals than participating later during the EI benefit period. As in Sianesi (2004) and Hujer and Thomsen (2010), the analysis relied on a stratified propensity score matching approach conditional on the discretized duration of unemployment until the program starts. The results showed that individuals who participated in EAS within the first four weeks after initiating an EI claim had the best impacts on earnings and incidence of employment while also experiencing reduced use of EI starting the second year post-program.

Key Words: Administrative data, Dynamic treatment assignment, Method of matching, Program evaluation, Treatment effects.

1. Introduction

Employment Assistance Services (EAS) are offered to unemployed individuals to help them return to work. According to recent evaluation work conducted by Employment and Social Development Canada (ESDC) on EAS delivered under the Labour Market Development Agreements (LMDAs), these services achieved their objectives of helping active Employment Insurance (EI) claimants to return to employment by increasing the incidence of employment and decreasing the use of EI. Active EI claimants are individuals who were actively on EI at the time of receiving EAS. Evaluations also showed that EAS participation led to short-term decreases in earnings. However, EAS does not focus on human capital development and is not necessarily expected to improve the employment earnings of participants.

Until recently, little was known about whether those services are provided at the right time to foster quicker return to work. The study discussed in this paper attempted to provide some answers to this policy question by examining the extent to which the labour market impacts from EAS participation under the LMDAs vary according to the timing of participation during an EI claim. It used a propensity score matching approach to compare the labour market impacts from participating in EAS at different times during and EI claim (e.g., during the first month after starting a claim relative to participating at a later time or to not participating at all). It focused on active EI claimants who started their EAS participation between April 1, 2002 and March 31, 2005. It examined impacts on earnings, employment and use of EI over the participation period (one year) and five consecutive post-participation years that occurred between 2002 and 2011. It also examined whether staring EAS earlier during an EI claim leads to quitting EI earlier. This was used as a proxy for measuring return to work.

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2. Background on EAS and the LMDAs

EAS is one tool among a broader suite of active labour market measures that aims to ease the transition from unemployment to employment. EAS generally comprise low intensity/short-term assistance such as counselling, help with job search or short workshops (e.g., First Aid). These services are implemented under a number of employment programs funded by the Government of Canada. One of them is the LMDAs between Canada and each of the 13 provincial/territorial governments. These agreements were introduced starting 1996 under Part II of the *EI Act.* Under the LMDAs, Canada transfers $1.95B to provinces/territories for the design and delivery of Employment Benefits and Support Measures mainly offered to unemployed EI eligible individuals[4]. EAS represented approximately 86% of new LMDA interventions delivered in 2012-2013 and 33% of LMDA funding directed to Employment Benefits and Support Measures across Canada.

3. Methodology

3.1 Evaluation Approach: Model for Dynamic Treatment Evaluation

We considered the treatment in a discrete time setting in which participation in EAS could start at any time during an EI benefit period. The average treatment effect on the treated was identified under the unconfoundedness and no-anticipation assumptions (Sianesi, 2004). We estimated the effect of EAS separately for different cohorts of participants which were defined based on the number of weeks that elapsed between the start of the EI benefit period and the start of the treatment. In order to draw conclusions about the effects related to the timing of the participation, we compared how impacts from participation varied across the cohorts of participants.

The dynamic nature of the treatment introduced several methodological challenges, which affected the selection of a comparison group. The main issue was that individuals who did not participate in EAS at a particular point in time might become participants later on. As a result, the binary Conditional Independence Assumption used in a static treatment setup (i.e., binary treatment case where the treatment is only observed once during the observation period) was no longer valid (Sianesi, 2004; Fredriksson and Johansson, 2008; and Crépon et al. 2009).

Following Sianesi (2004, 2008) and Hujer and Thomsen (2010), we analyzed the effects of participation for active EI claimants who had only one instance of EAS participation during the 3-year reference period (2002-2005).[5] We distinguished between treatment starting during the first, second and third month of the unemployment spell (cohort U1, U2 and U3 respectively) and treatment starting during the second, third and fourth quarters of the EI benefit period (cohort U6, U9 and U12, respectively). Participants selected for each cohort excluded individuals who started EAS during the time period assigned to the cohort but stopped claiming EI during the same period of time.

To formalise the evaluation approach in the dynamic setting, we followed the same approach as used by Sianesi (2004, 2008) and, Hujer and Thomsen (2010) and implemented the following notations:

- U = {1, 2, …, U_{max}} defined discrete points of elapsed time within the EI benefit period since its commencement (i.e., Benefit Period Commencement). $U_{max} = 12$ (i.e.; month as unit until $U = 3$ and quarter as unit for $U = 6,\ U = 9$ and $U = 12$)
- *u* denoted the point in time within the EI benefit period during which the EAS participation starts, and D_u the binary treatment indicator specific to the discrete time point u.
- D_u = 1 if the individual started EAS at time *u*, and D_u = 0 if he/she did not (i.e., is waiting).
- $Y^1_{t,u}$ and $Y^0_{t,u}$ denoted potential labor market status for active EI claimants at time *t* if joining EAS program in time *u* and if not joining any at least until time *u*, respectively.

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[4] All active labour market measures funded under the LMDAs are offered to active and former EI claimants except EAS which is also offered to unemployed individuals not eligible for EI.

[5] Individuals with multiple treatments (multiple instances of participation) were excluded; see Lechner and Miquel (2001), and Lechner (2004) for the matching estimation of dynamic and multiple treatment models.

- For each u, interest lied in the time series of average impact at time t, for those joining EAS at time u compared to remaining on EI for a longer time. This was:

$$\Delta_{t,u}^{ATT} = E\left(Y_{t,u}^{1} - Y_{t,u}^{0} \mid D_u = 1, D_1 = \dots D_{u-1} = 0\right)$$

$$= E\left(Y_{t,u}^{1} \mid D_u = 1, D_1 = \dots D_{u-1} = 0\right) - E\left(Y_{t,u}^{0} \mid D_u = 1, D_1 = \dots D_{u-1} = 0\right) \quad \dots\dots (1)$$

As in the static approach, the first term was actually observed in the outcome data for participants. The second term represented the counterfactual and was not observable in the actual data. However, it may be estimated by invoking an adjusted version of the Conditional Independence Assumption (as in the case of binary treatments). Under the Dynamic Conditional Independence Assumption for the average treatment effect on the treated, the hypothetical outcome at time *t* after not participating up to time *u* is independent of program participation at time *u*, conditional on a set of observed characteristics X_u or, equivalently, the propensity score $p(X_u)$ measured at time *u:*

$$Y_{t,u}^{0} \coprod D_u \mid p(X_u), D_1 = \dots D_{u-1} = 0.$$

Since the parameter of interest is the average effect only, all that is required for the average treatment effect on the treated in the dynamic setting is the weaker version of this assumption, namely the Dynamic Conditional Mean Independence Assumption for the average treatment effect on the treated:

$$E\left(Y_{t,u}^{0} \mid p(X_u), D_u = 1, D_1 = \dots D_{u-1} = 0\right) \quad \dots\dots (2)$$
$$= E\left(Y_{t,u}^{0} \mid p(X_u), D_1 = \dots D_u = 0\right)$$

As identified in the existing literature (see for instance Heckman et al., 1998), matching methods, in our case, are based on the identifying Dynamic Conditional Mean Independence Assumption in equation (2) which assumes selection on observables only. The Dynamic Conditional Mean Independence Assumption states that active claimants who participated and those who did not participate were comparable in their non-participation outcomes at time t conditional on $p(X_u)$, conditional on being unemployed up to time $u-1$, and conditional on not participating before u.

The Dynamic Conditional Mean Independence Assumption required detailed knowledge of the factors that drove participation in EAS, as well as the access to suitable data to capture participation determinants that were likely to affect outcomes.

The matching approach used in this study was chosen in light of the richness of the administrative data available. These data captured a large number of characteristics reflecting the individual's socio-demographic characteristics (e.g. age, gender, marital status, disability, etc.), location, qualifications (e.g. occupational group, skill levels related to last job before opening their EI claim and industry codes) and labour market history (e.g. use of EI benefits and weeks, employment/self-employment earnings, use of Social Assistance and incidence of employment in the five years preceding participation).

In summary, given the detailed and comprehensive large administrative panel data used in the propensity score model, the analysis was able to consider most factors characterising the individual's labour market situation in the years preceding the treatment. For this reason, we could argue that the Dynamic Conditional Mean Independence Assumption held and we could use the matching estimator in the dynamic setting to evaluate the employment effects of EAS for each cohort of participants.

Since the Dynamic Conditional Mean Independence Assumption was considered to hold, the parameters of interest were estimated using propensity score matching combined with Difference-in-Differences (Heckman et al., 1997; Heckman and Smith, 1999; Gerfin and Lechner, 2002; Caliendo and Kopeinig, 2008) in the following way:

(a) By definition, the outcome observed at time *t* among participants who joined at time *u* were denoted as $E\left(Y_{t,u}^{1} \mid p(X_u), D_u = 1, D_1 = \dots D_{u-1} = 0\right)$;

(b) As demonstrated in (2) above, under the Dynamic Conditional Mean Independence Assumption, the expected hypothetical or "counterfactual" outcome at time *t* among this same cohort of participants was equal to the average mean outcome, also at time *t*, among non-participants who:
   (i) did not join treatment up to and including time segment *u* during their EI spell, and
   (ii) had similar observable characteristics as measured by their propensity score index $p(X_u)$
   These are denoted as $E\left(Y_{t,u}^{0} \mid p(X_u), D_1 = \ldots D_u = 0\right)$;
(c) The effect of the treatment on the treated, which represented the difference in the expected values of the outcome under actual versus counterfactual conditions for the treated individuals, was defined as:

$$\Delta_{t,u}^{ATT} = E\left(Y_{t,u}^{1} \mid p(X_u), D_u = 1, D_1 = \ldots D_{u-1} = 0\right) - E\left(Y_{t,u}^{0} \mid p(X_u), D_1 = \ldots D_u = 0\right)$$

The second expression represented the required counterfactual based on the Dynamic Conditional Mean Independence Assumption which was the average of the observed outcomes of the cohort D_u = 0 (non-treated) conditional on the distribution of X being the same as in the D_u = 1 cohort (treated). In analogy to the average treatment effect on the treated in the static setting, the second term approximates participant's outcome at *t* of joining a program (EAS) in *u* by the outcome of the comparable non-participants in *u*.

3.2 Data and Samples Selection

The empirical analysis is based on longitudinal rich administrative data extracted from the EI part I (i.e., EI claim) and part II (LMDA participant data) data files that have been merged with Canada Revenue Agency taxation files. The files included records from 1996 to 2011. The data used for policy, analysis, research and evaluation are governed by stringent rules and processes put in place at the departmental level to maintain privacy and confidentiality. In particular, the information used for evaluation is subject to a process that masks personal identifying information (e.g., Social Insurance Numbers, names or addresses) before it is analyzed. This process is done to prevent the identification of individuals when undertaking policy, analysis, research and evaluation.

The original participants' sample contained 100% of all EI active claimants who joined EAS between April 2002 and March 2005. Random samples of 50% of participants were used for cohorts U1 to U6 (mainly for for computer capacity considerations) and 100% for U9 and U12. The non-participants' sample was drawn from a random sample of all active EI claimants who were eligible to participate but did not started an EBSM between April 2002 and March 2005. Table 1on the following page shows the comparison group selection process for each cohort and indicates the number of participants and comparison cases for each cohort.

As mentioned previously, the participants and the comparison groups were selected dynamically. During each time period (cohort), participants consisted of active claimants who participated in EAS for the first time in that particular time period and did not participated again in EAS or any other EBSM during a 3-year window. The comparison group in (cohort) were the active claimants who were eligible to participate in EAS at that time but neither did not join a program nor left unemployment (i.e., remained on EI) up to that specific time period. In addition, for each cohort, we excluded comparison cases who ended their EI benefits in the previous time period observed.

3.3 Robustness check

In order to check the sensitivity and robustness of the results, in addition to Kernel Matching, we have used two alternative matching estimators (Inverse Probability Weighting and Nearest Neighbor). The estimated treatment effect were generally not sensitive to the choice of the matching estimator (here, we used Kernel Matching (baseline), compared to Inverse Probability Weighting and Nearest Neighbor estimates).

As in Busso et al (2008), we have implemented the Inverse Probability Weighting estimator for the average treatment effect on the treated by normalizing the weights of the members of the comparison groups to sum up to one. Since the distribution of scores seemed to have sufficient overlap, we did not use any trimming rule.

Table 1
Number of participants and comparison cases in each cohort

Cohorts (start of EAS after start of an EI claim)	**Individuals selected**	**n=**
U1 (in 1st month)	Participants	78,708
	Comparison cases in U1	2,983,255
	Ended EI before U1	N/A
U2 (in 2nd month)	Participants	62,336
	Comparison group in U2	2,910,600
	Ended EI before U2 (excluded from comparisons group in U2)	10,612
U3 (in 3rd month)	Participants	48,648
	Comparison group in U3	2,812,597
	Ended EI before U3 (excluded from comparisons group in U3)	60,545
U6 (in 2nd quarter)	Participants	77,027
	Comparison group in U6	2,623,813
	Ended EI before U6 (excluded from comparisons group in U6)	173,355
U9 (in 3rd quarter)	Participants	38,495
	Comparison group in U9	2,176,372
	Ended EI before U9 (excluded from comparisons group in U9)	593,667
U12 (in 4th quarter)	Participants	24,456
	Comparison group in U12	1,603,554
	Ended EI before U12 (excluded from comparisons group in U12)	1,152,830

4. Results

As shown in Table 2, of all the cohorts examined, individuals who started their participation within four weeks following the start of their EI benefit period (U1) had the larger post-program impacts on their earnings and incidence of employment. They had a total increase of $10,192 in their earnings over the five post-program years, which was accompanied by increases in their incidence of employment ranging between 0.9 to 2.6 percentage points per year.

Participants who started in the second and third months of their EI claim (U2 and U3) also had increases in earnings totalling $3,888 and $2,543 respectively over the post-program period. The increases in earnings for participants who started in the second month were accompanied by statistically non-significant impacts on incidence of employment. Participants who started in the third month had decreases in their incidence of employment after participation. The participants who started their EAS participation later during their EI benefit period (U4, U5 and U6) generally had decreases in both their employment earnings and their incidence of employment following participation.

Participants in all cohorts generally had decreases in the amounts of EI benefits collected in the five years following participation. However, the decreases were larger for the later cohorts compared to the earlier cohorts. Participants who started in the first month had a $503 decrease in the amount of EI benefits collected during the total post-program period while those who started in the fourth quarter had a $3,143 decrease. However, the post-program decreases experienced by participants in later cohorts could be due to the exhaustion of their EI benefits during or immediately after participation. As such, they may have not been able to continue claiming EI if they could not find employment right after participation.

The study also examined the effects on the return to employment. Those impacts were measured by calculating the difference between the number of EI weeks unused by participants and the number of EI weeks unused by the comparison group. The number of EI weeks unused represents the difference between the total number of weeks of EI entitlement and the number of weeks during which the individual received EI benefits. This is used as a proxy for measuring the return to employment since an EI claimant who stopped claiming EI before the end of his/her entitlement most likely do it because he/she found employment.

Of all the cohorts examined, only participants who started in the first month of their EI benefit period (U1) returned to employment more quickly than the comparison group. Specifically, they returned to employment 3 weeks earlier than the comparison group. Participants in all other cohorts returned to employment 0.5 to 3.5 weeks later than the comparison group.

Table 2
Incremental Impacts by Cohort

	n=[1]	In-program	Post-program period					
			1 year	2 years	3 years	4 years	5 years	Total
Employment Earnings ($)								
U1	*39,354*	-505***	258***	1,708***	2,343***	2,804***	3,080***	10,192***
U2	*31,168*	-2,046***	-765***	444***	1,123***	1,511***	1,574***	3,888***
U3	*48,648*	-3,109***	-839***	124	783***	1,179***	1,296***	2,543***
U6	*38,513*	-4,566***	-1,106***	-240**	327***	603***	775***	358
U9	*38,495*	-6,680***	-1,139***	-703***	-178	151	114	-1,754***
U12	*24,456*	-6,814***	-545***	-696***	-253	-11	287	-1,218
Incidence of Employment (percentage points)								
U1	*39,354*	2.6***	2.1***	1.6***	1.6***	0.9***	0.3	N/A
U2	*31,168*	1.4***	0.4*	0.3	0.2	-0.3	-0.8***	N/A
U3	*48,648*	0.2	-0.6***	-0.6***	-0.4**	-0.6***	-1.0***	N/A
U6	*38,513*	-1.2***	-0.5**	-0.6**	-0.4	-0.5**	-0.7***	N/A
U9	*38,495*	-4.1***	-0.5**	-0.7***	-0.6**	-0.7***	-1.0***	N/A
U12	*24,456*	-5.8***	-0.4	-1.1	-0.5	-0.8	-0.2	N/A
EI Benefits ($)								
U1	*39,354*	298***	5	-209***	-137***	-84***	-80***	-503***
U2	*31,168*	1,174***	-31***	-214***	-195***	-157***	-65***	-663***
U3	*48,648*	1,470***	-385***	-270***	-229***	-198***	-146***	-1,228***
U6	*38,513*	1,809***	-687***	-333***	-196***	-138***	-94***	-1,449***
U9	*38,495*	1,823***	-1,502***	-453***	-364***	-240***	-164***	-2,723***
U12	*24,456*	1,498***	-1,911***	-442***	-355***	-266***	-167***	-3,143***

** Significant at 10%; ** significant at 5%; *** significant at 1%*
[1]n= refers to the number of participants. It corresponds to a 50% random sample for cohorts U1 to U6 and 100% for U9 and U12.

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