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Estimating the Impact of Active Labour Market Programs using Administrative Data and Matching Methods[1]

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Abstract

In this paper, we discuss the impacts of Employment Benefit and Support Measures delivered in Canada under the Labour Market Development Agreements. We use linked rich longitudinal administrative data covering all LMDA participants from 2002 to 2005. We Apply propensity score matching as in Blundell et al. (2002), Gerfin and Lechner (2002), and Sianesi (2004), and produced the national incremental impact estimates using difference-in-differences and Kernel Matching estimator (Heckman and Smith, 1999). The findings suggest that, both Employment Assistance Services and employment benefit such as Skills Development and Targeted Wage Subsidies had positive effects on earnings and employment.

Key Words: propensity score matching, EBSM, active labour market program evaluation, employment, earnings

1. Introduction

This study applies matching methods using a panel of administrative data to undertake an analysis of the impact of Employment Benefit and Support Measures (EBSM) delivered in Canada under the Labour Market Development Agreements (LMDAs). The EBSMs examined include Employment Assistance Services (EAS), Skills Development (SD) and Targeted Wage Subsidies (TWS). Based on rich administrative data covering all participants who started participation between April 2002 and March 2005, the study analyses the impacts of active labour market programs on the employability and employment earnings of the participating individuals in the short and medium term (up to five years) following their participation. This is the first time that such an analysis has been conducted at the national level in Canada.

A useful guide is provided by Card, Kluve & Weber's 2010 meta-analysis of recent microeconometric evaluations of active labour market policies from 97 separate studies on the program impacts in European, Nordic and Anglo countries (Card et al., 2010). It is important to note that services available in Canada under the EBSM programs resemble the offerings of the other OECD countries. In order to limit the analysis and discussion, this paper focuses on these three EBSM interventions:

- EAS provides a variety of support services to help unemployed persons who require assistance to enter or return to the labour force. Services offered range from job search assistance for job-ready clients to the development of in-depth return-to-work action plans for clients facing multiple employment barriers.

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[1] The views expressed in research papers are those of the authors and do not necessarily reflect the opinions of Employment and Social Development Canada (ESDC) or of the federal government. This paper is based on methodologies and analyses developed in the context of LMDA evaluations. In developing these methodologies, evaluators at ESDC benefited from advice and peer reviews from various academic experts. As well, in 2014, the evaluators held an internal expert panel to critically review and discuss the evaluation methodologies. In particular, we would like to thank Professors Walter Nicholson, Jeff Smith, Guy Lacroix and David Gray for providing advice on these evaluation studies.

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- SD helps individuals obtain employment skills ranging from basic to advanced levels. It provides direct assistance to individuals for training and, where applicable, contributions to provinces and territories or to provincially/territorially funded training institutions to cover costs not included in tuition fees.
- TWS encourages employers to hire unemployed individuals by providing financial assistance which covers a portion of the new hires' wages as well as some employment-related costs.

The vast majority of the literature has focused on formal training programs; and a comprehensive summary is provided by Heckman, LaLonde, and Smith (1999). This paper builds on the past literature by weaving theoretical, methodological and empirical discussions to examine the impacts and effectiveness of active labour market interventions in Canada.

An important contribution of this analysis is the use of a rich informative panel data which links all administrative information from Employment Insurance (EI) and the Canada Revenue Agency. The analysis covers active claimants from all 13 provinces and territories who started their participation in EAS, SD and TWS between April 1, 2002, and March 31, 2005. The assessment of EAS and SD impacts is limited to a random sample of 10% and 50%, respectively, of active claimants due to the very large number of individuals participating in these interventions and for computer capacity considerations (38,564 for EAS, 64,283 participants for SD and 18,767 for TWS). The comparison group consists of active EI claimants[4] who were eligible for participation in that period but did not participate. We estimate the effects separately for EAS, SD and TWS. The final selected comparison groups consisted of 263,176 comparison cases for EAS, 274,062 for SD and 146,284 for TWS. The key labour market outcome indicators for this analysis are the average incidence of employment (i.e., the average annual probability of having employment earnings), the average earnings from employment and the amount of EI benefits collected. All indicators are measured on a yearly basis.

2. Data

The incremental impact analysis is carried out using linked administrative panel data from the EI databank (EI part I data on EI claim and EI part II data on EBSM participation) and the Canada Revenue Agency taxation files. The data available for the study cover large random samples, and up to 100% in some cases, of EBSM participants across Canada, 20% of EI benefit recipients with no EBSM participation in the three territories and the Atlantic Provinces, and 10% of EI benefit recipients with no EBSM participation in the remaining provinces from 1990 to 2011. In this regard, it is noted that 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 study examines incremental impacts for participants who started an EBSM between 2002 and 2005 and follows them over up to six consecutive years occurring between 2002 and 2011. The choice of the reference period is influenced by the desire to measure program impacts over at least five years following the end of participation.[5] The most recent year for which we have Canada Revenue Agency data is 2011. As a result, the analysis focuses on action plan equivalents [6] that started between April 1, 2002 and March 31, 2005. The action plan equivalent is the unit of analysis used in the study. It regroups all EBSMs given to an individual within no more than six months of each other. The goal of the action plan equivalent is to capture the continuum of employment programs and services provided to EBSM participants. Since action plan equivalents contain more than one intervention, for reporting purpose, the observed effect is assigned to the longest intervention included in an action plan equivalent unless this action plan equivalent is composed only of EAS.

Overall, the overwhelming majority participants included in the study have completed their action plan equivalents in the 2003-2006 period.

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[4]Active EI claimant" means an individual who is actively on Employment Insurance at the time of participation.
[5]Impacts are measured over up to 7 years after the participation start year.

3. Evaluation Approach and Methodology

The study examines the impacts of Employment Benefits such as EAS, SD and TWS by comparing individuals who received these interventions to those who did not participate.

The matching methods combined with difference-in-differences are used to determine the impacts. The basic idea of these methods is that based on the observed characteristics, two groups with the same probability of participation will show up in the participant and non-participant samples in equal proportions. Thus, they can be combined for purposes of outcome comparison (before and after participation). The main advantage of these methods is that matching does not require any functional form assumptions for the outcome equation (that is, it is non-parametric) and are therefore not susceptible to misspecification bias along that dimension.

This study adopted the standard Rubin Framework known as the potential outcome approach or the Neyman-Roy-Rubin model (Neyman, 1935; Roy 1951; Rubin 1974). The matching method used is Propensity Score Matching (Rosenbaum and Rubin (1983)). Propensity Score Matching is defined as the probability of treatment assignment conditional on observed baseline covariates and usually referred to as the Conditional Independence Assumption (Rosenbaum and Rubin, 1983; Dehejia and Wahba, 2002; Heckman et al., 1998; Caliendo and Kopeinig, 2008; Galdo, Smith and Black, 2007; Smith and Todd, 2005; Imbens, 2004; Caliendo et al., 2005).

The data used for the analysis cover a large number of characteristics reflecting the individual's labour market experience including the socio-demographic characteristics of participant and comparison cases (e.g. age, gender, marital status, disability), their economic region and province, their qualifications (e.g. occupational group, skill levels related to last job before opening their EI claim, industry codes) as well as their labour market history (e.g. use of EI benefits and weeks, employment/self-employment earnings, use of Social Assistance, incidence of employment in the five years preceding participation).

The richness of the available administrative data allow for the inclusion of the most relevant variables influencing the decision to participate in EBSMs and the labour market outcomes in the propensity-score model. The use of standard personal characteristics, pre-treatment outcomes, transitions between different labour market states, regional information and labour market history is very important for decreasing the likelihood of biased estimator of the true treatment effect.

An assessment of the Conditional Independence Assumption demonstrates that the analysis considers most, if not all, factors that determine participation and labour market outcomes. In this context, it is assumed that the Conditional Independence Assumption is satisfied and the matching estimator can be used with confidence to estimate the incremental effects of EBSMs on the selected outcome indicators. The common support results show clearly the large overlap between participants and comparison group in each EBSM type.

To fully illustrate the quality of the matching, we present in Table 1, the summary results of covariate balancing tests before and after matching in each program by using standardized mean difference between participants and non-participants (DiPrete and Gang. 2004). The estimates show that the average value for standardized differences before matching for SD is about 8.3. After matching, this value is reduced to 0.9. It is clear that the reduction of differences in the distribution of the covariates between the treatment and comparison groups is very substantial and that the propensity score matching was able to achieve balance on the covariates. The details on the list of covariates used in the propensity score model and balancing scores can be released upon request.

Table 1
Mean Standardized Bias and Pseudo R^2 - Balancing test summary results

EBSMs	Participants		Comp Group		Pseudo R2		Mean Bias		Common Support[1]
	Before	After	Before	After	Before	After	Before	After	
Employment Assistance Services (EAS)	37382	37364	146284	146284	0.193	0.003	8.6	1	18
Skills Development (SD)	63481	63450	274062	274062	0.178	0.002	8.3	0.9	31
Targeted Wage Subsidies (TWS)	18767	18762	263176	263176	0.197	0.015	8.4	1.9	5

Note:- The calculations are performed using PSMATCH2 package by Leuven and Sianesi (2003) and PSTEST and PSGRAPH
- The number of observations for participants in EAS and SD correspond respectively to the random sample of 10% and 50% among participants in the originals files. For TWS, all the participants' population is used. For comparison group, 5 % random sample is used for EAS and SD and 10% random sample is used for TWS.

The incremental impact estimates are produced using the difference-in-differences and Kernel Matching, and other two methods for robustness purposes. In this analysis, the pre/post outcome differential is calculated in both groups by looking at the value of the outcome of interest in a specific post-participation period, and subtracting the value of the same outcome of interest in a corresponding pre-program period called the base period. The validity of the difference-in-differences depends on the stability of the bias between participants and non-participants in the pre-program period. This implies that a sufficiently long pre-program period is required to properly control for the similarity between participants and non-participants, and to identify and deal with the Ashenfelter dip[7]. The current study uses a period of five years to observe pre-program behaviour.

Rigorous sensitivity analysis testing is also carried out by applying Nearest Neighbor and Inverse Probability Weighting matching estimators. This reveals that the estimated effects are not sensitive to different matching estimators. In addition, to check for hidden bias caused by unobservable characteristics, we tests for the robustness of our results and models using the so-called Rosenbaum bounds (see Rosenbaum 2002, 2005, 2010).[8] Note that this test does not determine if the results are biased or if there are any omitted variables in the propensity score model, but rather measures the sensitivity of the estimates on the deterioration of the model. The Rosenbaum results, available on demand, are mixed but do not change the impacts and directions.

The main limitation of this study is the possibility of pre-existing but unobserved differences between the participants and comparison cases that were not measured in the matching process. These could have had an influence on the outcomes. For example, factors such as ability, health, education and motivation to seek employment were not directly measured except to the extent they were captured in prior income and labour market attachment patterns. Complete data exists with respect to occupations, skills level related to last occupation, EI and earnings patterns in the five years before participation. This information is used with confidence as a proxy for the pre-existing differences between

[7] Ashenfelter, O. (1978), "Estimating the Effect of Training Programs on Earnings", Review of Economics and Statistics, 60, 47–57. Ashenfelter found that among participants a period of transitory labour market instability (referred to as the "Ashenfelter dip") often precedes program participation. Since the same instability does not affect non-participants, it is important to identify if such a transitory period exists, and avoid it when choosing an appropriate pre-program base period. A sufficiently long pre-program period is required to properly control for the similarity between participants and non-participants, and to identify and deal with the Ashenfelter phenomenon.

[8] The sensitivity analysis is carried out applying ***rbound*** and ***mhbounds*** stata command provided by Diprete and Gangl, 2004, and Becker and Caliendo, 2007, respectively. The rbound is performed on continuous outcomes variables and is based on the Wilcoxon sign rank test and Hodges-Lehmann point estimate for sign rank test, while ***mhbounds*** focuses on the case of binary outcomes variables and is based on Mantel and Haenszel (MH, 1959) test statistic.

participants and non-participants. In this context, it is impossible to conclusively state that the incremental impacts were not influenced by the pre-existing differences between the participants and the comparison groups.

4. Results

As previously discussed, the main goal of this paper is to estimate the effects of three active labour market programs (EAS, SD and TWS) on earnings and the probability of employment for participants. The overall effect of the program in raising employment and earnings among the participants is positive and highly significant.

Table 2 below presents the estimated treatment effects of the different programs until five years after start. The estimates are also produced for more homogenous subsamples by age group.

Table 2
Incremental Impact Analysis for Active Claimants

Incremental Impacts for Active Claimants									
Indicators	In-program period		Post-program period						Total in- and post-program
	Program start year	Additional program year	1st year	2nd year	3rd year	4th year	5th year	Total post-program	
Employment Assistance Services (EAS) (n=38,564)									
Employment earnings ($)	-2,913***		-1,097***	-279***	347*	645***	742***	358	-2,555***
Incidence of employment (percentage points)	-0.5***		0.6*	0.8***	1.7***	1.8***	1.7***	N/A	N/A
EI benefits ($)	697***		-451***	-312***	-251***	-222***	-136***	-1,375***	-677***
Skills Development (SD) (n=64,283)									
Employment earnings ($)	-4,747***	-4,211***	204***	2,052***	3,077***	3,761***	4,059***	13,156***	4,197***
Incidence of employment (percentage points)	-4.5***	-4.7***	2.4***	3.7***	4***	4.2***	4.4**	N/A	N/A
EI benefits ($)	1,847***	222***	-470***	-218***	-128***	-89***	-69***	-976***	1,093***
Targeted Wage Subsidies (TWS) (n=18,767)									
Employment earnings ($)	-1,404***	752***	661***	971***	1,747***	1,815***	1,930***	7,125***	6,473***
Incidence of employment (percentage points)	4.4***	7.2***	5.0***	4.9***	5.1***	5.0***	5.1***	N/A	N/A
EI benefits ($)	100***	-208***	-2	52	39	104***	146***	339***	231

Significance level *** 1%; ** 5%; * 10%

The incremental impact analysis shows the positive effects of EAS, SD and TWS and for active claimants. The participants had gains in employment earnings, in incidence of employment, and reduction in EI benefits collected after their participation. The most pronounced effects are identified for SD participants. During the five years following participation, the annual employment earnings of active claimants were $204 to $4,059 higher than if they had not participated in SD. Additionally, earnings gains were accompanied by gains in incidence of employment ranging between 2.4 percentage points during the first year to 4.4 in the fifth year post-program. Similarly, active claimants had incremental gains in earnings and incidence of employment after participating in TWS.

EAS participants had increases in incidence of employment and decreases in EI use in all years after participation which suggest that they returned to employment after participation. EAS participants had 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.

5. Conclusion

The aim of this paper is to evaluate the short- and medium-term effects of active labour market programs delivered under the LMDAs in Canada using non-parametric methods. This is the first paper to analyze these programs for the most recent period and to estimate medium-run effects at the national Canadian level. The paper uses rich administrative dataset and found positive impact for the three programs after participation.

SD is effective at increasing the employment earnings and incidence of employment for active claimants. Importantly, for active claimants, participation in SD led to the largest incremental gains in employment earnings among all EBSMs. It is also remarkable that the incremental impacts on earnings grew continuously over the five years that followed the end of participation. The same trend is found for the TWS program, which is shown to be effective at increasing the employment earnings and incidence of employment. Among all EBSMs, participation in TWS leads to the largest increases in incidence of employment for active claimants. EAS achieved their objectives of helping participants to return to employment by increasing the incidence of employment and decreasing the use of EI.

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