The Distributional Impacts of Active Labor Market Programs for Indigenous Populations

By Donna Feir and Kelly Foley and Maggie E.C. Jones*

Indigenous peoples around the world have higher unemployment rates, lower labor force participation rates, and lower average wages than the non-Indigenous populations in their countries. Programs that aim to improve labor market outcomes among Indigenous peoples also exist in many countries (United Nations, 2009); yet, there is little quantitative evidence about their effectiveness. There are comprehensive reviews of active labor market program evaluations in the non-Indigenous context (LaLonde, 1995; Greenberg, Michalopoulos and Robins, 2003; Card, Kluve and Weber, 2010, 2018), but there are reasons to believe the general lessons from that literature may not apply. This paper evaluates the Aboriginal Skills and Employment Training Strategy (ASETS), a Canadian program that provided federal funding to Indigenous organizations that delivered a range of active labor market programs for Indigenous peoples.

We use administrative data covering the universe of ASETS program participants to evaluate how participation in different types of interventions affects earnings. We compare the outcomes of participants in high-intensity programs to those in low-intensity programs, with "intensity" being differentiated primarily along the dimension of program duration. We find that, on average, men and women who participate in high-intensity programs have higher earnings two-years post participation than those in low-intensity programs.

Since prior evaluations of welfare reform have demonstrated that there is considerable heterogeneity in effects along the distribution of income and earnings (Bitler, Gelbach and Hoynes, 2006, 2017), we estimate both average impacts and quantile treatment effects (QTE). In our data, QTEs of high- relative to low-intensity program participation increase across the earnings distribution for both men and women.

Existing work on welfare reform has attributed distributional impacts to labor-supply incentives that vary along the distribution of earnings. In the context of active labor market programs, such heterogeneity might occur for both supply- and demand-side reasons. For example, participants at the top of the earnings distributions might be working in industries where the returns to skills investment are higher. Whether the effects of high-intensity interventions vary across the earnings distribution can reveal whether this form of programming (relative to low-intensity) might reduce inequality both within Indigenous populations and between Indigenous and non-Indigenous populations.

There are at least two reasons why it is necessary to study the impacts of active labor market programs for Indigenous populations. First, despite the extensive literature evaluating active labor market programs, the lessons from these studies may not carry over to the Indigenous context.

* Feir: University of Victoria, 3800 Finnerty Road Victoria BC, dfeir@uvic.ca. Foley: University of Saskatchewan, 9 Campus Dr, Saskatoon, SK, kelly.foley@usask.ca. Jones: University of Victoria, 3800 Finnerty Road Victoria BC, maggie.ec.jones@gmail.com. The University of Victoria is located on the territory of the Lkwungen (Songhees), Wyomilth (Esquimalt), and WS'ANEC' (Saanich) peoples. The University of Saskatchewan is located on Treaty Six Territory and the Homeland of the Métis. We thank seminar participants at the IESG seminar, CPEG annual meeting, UBC, SWORDC, and the University of Regina for useful feedback on this work and Kate Fairley for excellent research assistance. This research is funded by the Government of Canada. The paper is part of a research project undertaken in collaboration with the Social Research and Demonstration Corporation (SRDC). The opinions and interpretations in this publication are those of the authors and do not necessarily reflect those of the Government of Canada or SRDC.

Across the world Indigenous people have been relocated to regions that are often economically and geographically isolated, such as reservations or reserves. Whether active labor market programs are effective in these locations is not clear because of potential demand-side labor market issues. Indigenous people are often subject to different tax and transfer programs and government services than the non-Indigenous people within the countries they reside, and this may also impact the effectiveness of supply-side interventions. Finally, participation in traditional activities within Indigenous communities may influence the relevance of labor market programs.

Second, federal labor market programming for Indigenous people delivered by Indigenous service organizations is not unique to Canada. The United States Department of Labor funds tribal service delivery organizations that administer employment training programs specifically for Native Americans (U.S. Department of Labor, 2020). Federally supported labor market programs for Indigenous people, which leverage local service providers, are also present in Australia. With over 370 million Indigenous people worldwide, many of whom face similar economic challenges (United Nations, 2009), understanding the impacts of these sorts of programs is of global importance.

Aside from a recent evaluation from Employment and Skills Development Canada (ESDC) that found program effects were largest among participants who were concurrently receiving Employment Insurance (EI) benefits (Employment and Social Development Canada, 2020), relatively little is known about the impacts of ASETS programs. Based on the Office of the Auditor General of Canada (2018) report and spending from Minister of Indigenous and Northern Affairs (2016), we estimate that funding for ASETS in 2015-2016 was roughly four percent of total federal spending on Indigenous programs. ASETS operated between 2010 and 2018 and provided funding by the Government of Canada to Indigenous service delivery organizations. These organizations designed and delivered job training services to Indigenous people in their communities, with the goal of increasing Indigenous participation in the Canadian labour market. The federal funding of ASETS did not preclude Indigenous people from accessing other programs provided through the provinces and territories. In 2019, ASETS was replaced by the Indigenous Skills and Employment Training program, which is still ongoing.

I. Data and Definition of Comparison Groups

We use the Labour Market Program Data Platform (LMPDP), a large data repository created by ESDC. The LMPDP integrates data from five administrative sources using a unique person identifier: Employment Benefit and Support Measures, which are details on labor market program participation, Employment Insurance (EI) records, Records of Employment (ROE), T4 Supplementary records, and T1 Tax Return records.[1]

Individuals appear in the LMPDP if they have ever received EI benefits or participated in any labor market program, or both. Because participation in ASETS was not conditional on EI receipt, and roughly half of all ASETS participants had never received EI, we do not observe a non-participating counterfactual group for all ASETS participants. Instead, following Andersson et al. (2016), within the group of ASETS participants, we estimate the effect on earnings of participating in high- or low-intensity interventions.

High-intensity interventions promoted skills development or created employment incentives, with job creation partnerships or wage subsidies. In contrast, low-intensity interventions include only employment assistance services or job counselling, which provided support for employment search.[2]

[1]Employers must file a Record of Employment each time an EI insured employee stops working. The T4 is the tax form completed by an employer to record earnings and deductions, and a T1 is the tax return completed by individuals. In general, filing a T1 is not required of individuals who do not owe additional taxes.

[2]ASETS also included school-work-experience and self-employment programs, but we exclude these partic-

Using language common in program evaluation, high-intensity participants form our "treatment" group, while those in low-intensity interventions form the "control" group. One of the distinguishing characteristics of high-intensity interventions is that they were longer in duration than low-intensity ones; median durations were 82 and 7 days, respectively. Since some interventions might be more effective than others, grouping the high-intensity interventions together estimates a weighted average of the effects across the different types and combinations of high- relative to low-intensity interventions.

Because we condition on ASETS participation, and evaluate the impact of different types of interventions, selection *into* ASETS is not a potential source of bias. Instead, selection into high-intensity interventions, conditional on ASETS participation, is the primary threat to identification that we discuss below.

Our sample includes those aged 18 to 60, who first entered ASETS between 2010 and 2014. Because our panel ends in 2016, we estimate the impact of high- relative to low-intensity participation on earnings two years post-participation. Although this time horizon may not be long enough to capture the full effects of high-intensity participation, it does allow us to include several cohorts in our sample. Post-participation earnings are measured by aggregating gross earnings across all of an individual's T4 records in the second post-participation year, and are zero for those with no T4 records.

Following Lechner and Wunsch (2013), we construct a number of variables to include as controls in our empirical specifications. These include standard demographic characteristics, like age, number of children, disability status, Indigenous population group, marital status, program-entry year, and employment information for the pre-intervention period, such as indicators for individuals' past employment and earnings history. To approximate local labor market characteristics, we also use the complete count of all clients on the LMPDP to construct average earnings and unemployment at the Forward Sortation Area (FSA)-year level.[3] A detailed description of all the variables and their construction is included in the online appendix.

ipants because we expect that these interventions had different intended outcomes. For more details on how high- and low-intensity participation is defined, see the online appendix.

II. Methods and Identification

We estimate the average treatment effects (ATE) and quantile treatment effects (QTE) of high- relative to low-intensity participation. We estimate ATEs using a doubly-robust inverse propensity score weighting and regression adjustment estimator and QTEs using the estimator for unconditional quantile treatment effects proposed by Firpo (2007). These methods will identify average and quantile treatment effects under the assumption of strong ignorability, which requires potential outcomes to be independent of treatment, conditional on a set of covariates, and that the comparison groups have a common support. QTEs also require uniqueness of quantiles for identification.

In the online appendix, we plot propensity-score distributions for both groups to show evidence in support of the common support assumption. We assess the plausibility of unconfoundedness at any given quantile through a falsification exercise in which our dependent variable is the outcome one period before the program start year, conditional on lags from prior periods 2-5, the cumulative of lags 5-10, as well as other controls that are time invariant from the point of view of two years prior to participation. Since the outcomes in period $t-1$ precede participation, and therefore should not be affected by it, large and statistically significant coefficient estimates would be evidence against the unconfoundedness assumption. Figure 1 presents the results of this exercise. The horizontal axis indicates percentiles and the vertical axis displays QTEs in $1,000s.

[3] The Forward Sortation Area is the first three digits of the postal code, and is the smallest level of geography that is included in the data.

Nearly all estimates are statistically indistinguishable from zero. Together with the distributions of propensity scores, this provides evidence in favor of strong ignorability.

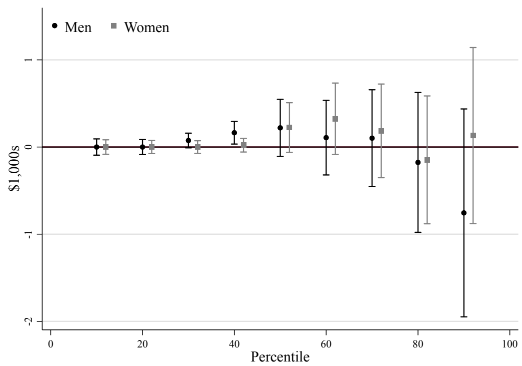

Figure 1. : QTEs on Pre-Participation Earnings

III. Results and Discussion

Table 1 displays our main results, where the first two columns are for men and the second two for women. In the first and third columns, we present the estimated treatment effect, and, for context, in the second and fourth columns we report the level of earnings two-years post-participation for the low-intensity group, in $1,000s. Our estimates of the average treatment effect, which are reported in the first row, suggest that the earnings-returns to high-intensity participation are substantial for both men and women. On average, women in the high-intensity group earned $1,181 more than their low-intensity counterparts, which represents a difference of 9.3%. The estimated average treatment effect is smaller among men, both in level ($759), and proportionately (4.6%).

In the remaining rows of Table 1, we report the Quantile Treatment Effects for each decile. There is no effect on earnings in the bottom two deciles where participants in both groups have no earnings. This is primarily because, as we show in Feir, Foley and Jones (2021), there is very little effect on the extensive employment margin. The quantile treatment effects are increasing monotonically for the most part. For men, the effect sizes are fairly constant across the middle of the distribution but then increase sharply in the top three deciles. The estimated difference in earnings at the 90th percentile between men in the high- and low-intensity groups is $2,221. For women, the earnings-returns to high intensity participation are larger in the center of the distribution and increase more gradually, such that at the top of the earnings distribution the quantile treatment effects are similar in size for men and women.

Table 1—: Earnings QTEs Two Years Post

	Men		Women	
	Estimate	**Level**	**Estimate**	**Level**
Average Treatment Effects				
ATE	0.7585	16.3359	1.1812	12.6358
	(0.2186)		(0.1761)	
Quantile Treatment Effects				
10^{th} Percentile	0.0000	0.0000	0.0000	0.0000
	(0.0673)		(0.0635)	
20^{th} Percentile	0.0000	0.0000	0.0000	0.0000
	(0.0628)		(0.0581)	
30^{th} Percentile	0.4355	0.6315	0.2936	0.0000
	(0.0659)		(0.0567)	
40^{th} Percentile	0.6802	3.5231	0.9507	1.6330
	(0.1781)		(0.0809)	
50^{th} Percentile	0.5340	8.0089	1.2845	5.3956
	(0.2438)		(0.2359)	
60^{th} Percentile	0.5168	13.5213	1.5152	10.2418
	(0.2927)		(0.2993)	
70^{th} Percentile	0.8334	20.2695	1.6605	16.6238
	(0.3605)		(0.3564)	
80^{th} Percentile	1.1145	29.4752	1.5769	24.6168
	(0.4474)		(0.4033)	
90^{th} Percentile	2.2205	44.8339	2.0012	35.7626
	(0.6619)		(0.4961)	
Sample Size	63,766	63,766	54,631	54,631

Note: The dependent variable is earnings 2 years post–participation and is reported in $1,000s. All dollars are real 2010 Canadian dollars. Standard errors in parentheses clustered by Forward Sortation Area. Quantile treatment effects are estimated using the procedure described in Firpo (2007). Columns titled Level present the level of the quantile in the control group.

This pattern of effects provides some insight on whether different types of interventions can reduce disparities in earnings. Within the Indigenous population, high-intensity programs might reduce gender gaps in earnings, but only in the middle of the distribution. Overall, because the effects are largest at top deciles, earnings inequality could increase within the population of ASETS participants. This is potentially significant because ASETS participants account for roughly 10% of the Indigenous population. Relative to low-intensity interventions, participation in high-intensity interventions is associated with meaningfully higher earnings. Since even the earnings at the top decile in our sample are below the median for the whole Canadian population (excluding those with zero earnings), high-intensity ASETS interventions may support closing the non-Indigenous-Indigenous earnings gap.

REFERENCES

Andersson, Fredrik, Harry J. Holzer, Julia I. Lane, David Rosenblum, and Jeffrey Andrew Smith. 2016. "Does Federally-Funded Job Training Work? Non-experimental Estimates of WIA Training Impacts Using Longitudinal Data on Workers and Firms." CESifo Group Munich CESifo Working Paper Series 6071.

Bitler, Marianne P, Jonah B Gelbach, and Hilary W Hoynes. 2006. "What mean impacts miss: Distributional effects of welfare reform experiments." *American Economic Review*, 96(4): 988–1012.

Bitler, Marianne P, Jonah B Gelbach, and Hilary W Hoynes. 2017. "Can variation in subgroups' average treatment effects explain treatment effect heterogeneity? Evidence from a social experiment." *Review of Economics and Statistics*, 99(4): 683–697.

Card, David, Jochen Kluve, and Andrea Weber. 2010. "Active labour market policy evaluations: A meta analysis." *The Economic Journal*, 120(548): F452–F477.

Card, David, Jochen Kluve, and Andrea Weber. 2018. "What works? A meta analysis of recent active labor market program evaluations." *Journal of the European Economic Association*, 16(3): 894–931.

Employment and Social Development Canada. 2020. "Evaluation of the Aboriginal Skills And Employment Training Strategy and the Skills And Partnership Fund." Her Majesty the Queen in Right of Canada.

Feir, Donna, Kelly Foley, and Maggie E.C. Jones. 2021. "Heterogeneous Returns to Active Labour Market Programming for Indigenous Populations." University of Victoria Working paper.

Firpo, Sergio. 2007. "Efficient Semiparametric Estimation of Quantile Treatment Effects." *Econometrica*, 75(1): 259–276.

Greenberg, David H., Charles Michalopoulos, and Philip K. Robins. 2003. "A Meta-Analysis of Government-Sponsored Training Programs." *Industrial and Labor Relations Review*, 57(1): 31–53.

LaLonde, Robert J. 1995. "The Promise of Public Sector-Sponsored Training Programs." *The Journal of Economic Perspectives*, 9(2): 149–168.

Lechner, Michael, and Conny Wunsch. 2013. "Sensitivity of Matching-Based Program Evaluations to the Availability of Control Variables." *Labour Economics*, 21(April): 111–121.

Minister of Indigenous and Northern Affairs. 2016. "Indigenous and Northern Affairs Canada 2015–16 Departmental Performance Report."

Office of the Auditor General of Canada. 2018. "Employment Training for Indigenous People—Employment and Social Development Canada." Ottawa, Ontario:Office of the Auditor General of Canada.

United Nations. 2009. *State of the world's indigenous peoples.* Vol. 9, Publications Permanent Forum on Indigenous Issues (United Nations) and United Nations. Statistical Division.

U.S. Department of Labor. 2020. "Employment and Training Administration, Indian and Native American Programs."