Propensity Score Matching for Program Evaluation
Accelerated Growth Service Program

Quantitative Impact Assessment Workshop

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February 9, 2026

Outline

- Overview of Propensity Score Matching
- Accelerated Growth Service Program
- Leveraging B-LFE and BIGS for impact analysis

What is Propensity Score Matching?

A method developed by Rosenbaum and Rubin (1983)

Designed for use in observational studies

Applied when random assignment is not feasible

- Policy and program evaluations
- Economic impact analysis
- Health, labour, education, and social science research
- Settings where randomized controlled trials are impractical

Reduces or eliminates sample selection bias in making comparisons across groups (e.g. treatment/control) on ***observable*** characteristics

Propensity Score Matching | Methodology

Suppose we have a treatment group and a control group

Treatment status D is a binary variable:

$$\begin{aligned} D &= 1 : \text{treated observations} \\ D &= 0 : \text{control observations} \end{aligned}$$

What is the Propensity Score?

The propensity score is the predicted probability of receiving treatment, conditional on observed pre-treatment covariates x

$$p(x) = prob(D = 1|x) = E(D|x)$$

Estimating the Propensity Score

Estimated using a probit/logit model

D is the dependent variable

x are the covariates that affect both treatment assignment and the outcome

Step 1: Obtain the predicted probability of treatment (the propensity score) for each observation

Step 2: Choose a matching method

Common matching approaches

- Nearest Neighbor Matching
- Kernel Matching
- Caliper (Radius) Matching
- Stratification Matching
- Mahalanobis Distance Matching
- Genetic Matching

Matching method | Nearest Neighbour

For each treated observation i, select a control observation j that has the closest x

$$min\|p_i - p_j\|$$

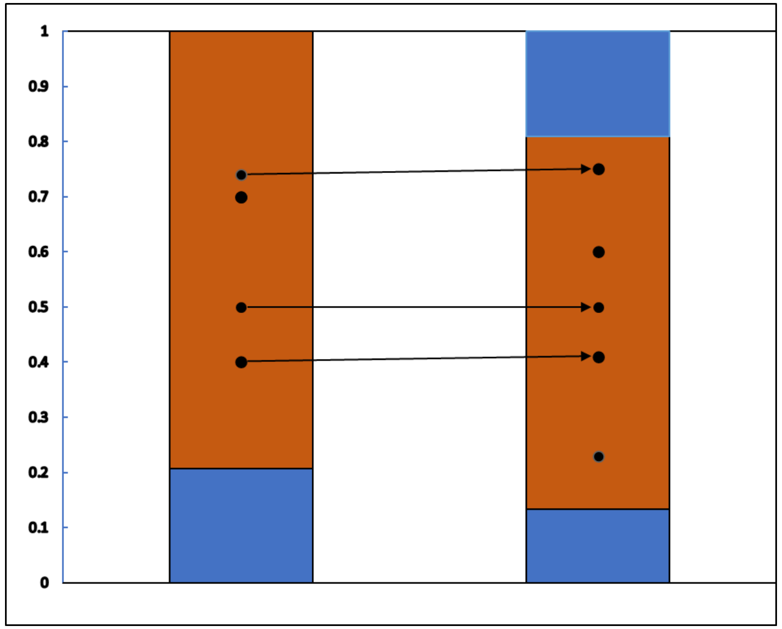
Matching with or without replacement

Without replacement

- Each control observation is used at most once as a match for a treated observation

With replacement

- Control observation may be matched to multiple treated observations



Matching is restricted to observations within the common support range of propensity scores

Matching method | Kernel matching

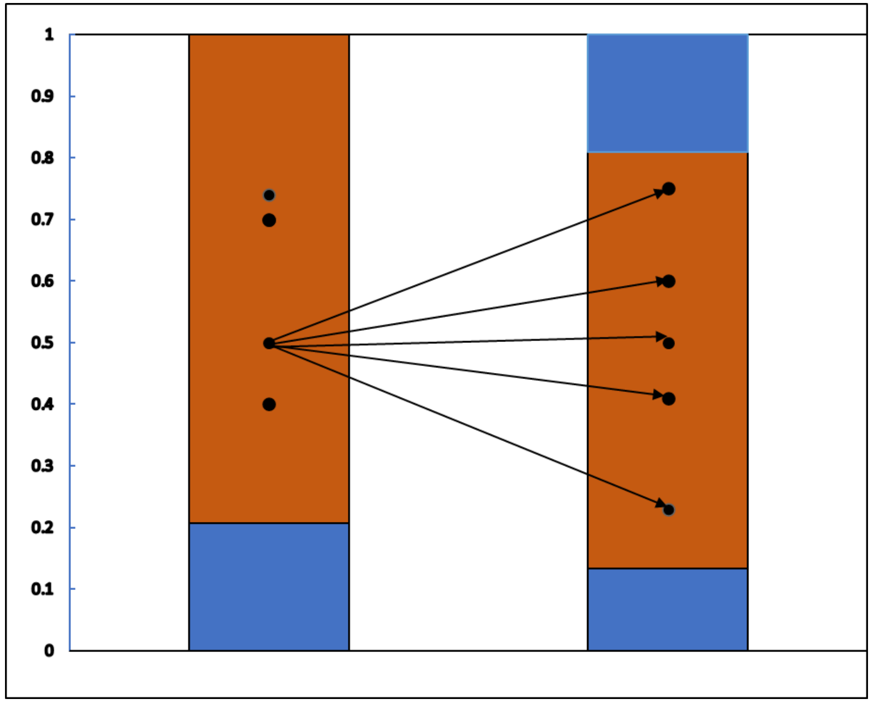
Each treated observation i is matched with multiple control observations

Control observations are weighted inversely to the distance between treated and control observations

$$W_{(i,j)} = \frac{k\left(\frac{p_j - p_i}{h}\right)}{\sum_{j=1}^{n_0} k\left(\frac{p_j - p_i}{h}\right)}$$

Bandwidth parameter

h is the bandwidth parameter



Compare the outcomes | Average Treatment Effect on the Treated (ATET)

$ATET$ measures the difference between the outcomes of treated and the outcomes of the treated observations if they had not been treated

$$ATET = E(y_1|x, D = 1) - E(y_0|x, D = 1)$$

$\boldsymbol{E(y_0|x, D = 1)}$ is a *counterfactual* (not directly observable) and needs to be estimated

$$ATET = E(y_1|p(x,), D = 1) - E(y_0|p(x), D = 0)$$

After matching on propensity scores and checking for balancing condition, outcomes of treated and control groups are compared

A difference-in-differences model is applied when panel data on outcomes are available (Wooldridge, 2010)

$$ATET = E(y_{1a} - y_{1b}|x, D = 1) - E(y_{0a} - y_{0b}|x, D = 1)$$

Application of Propensity Score Matching | Accelerated Growth Service Program (AGS)

Catalogue no. 18-001-X
ISBN 978-0-660-71604-6

Reports on Special Business Projects

Assessing the economic impact of Accelerated Growth Service program participants, 2017 to 2019

by Mahamat Hamit-Haggar

Release date: October 7, 2024

Commissioned evaluation of AGS advisory services

Objective: Assess whether AGS support leads to measurable business outcomes

- Financial performance
- Export activity
- Business resilience

Data provided:

1000 businesses receiving AGS support

Reference period from 2017 to 2023

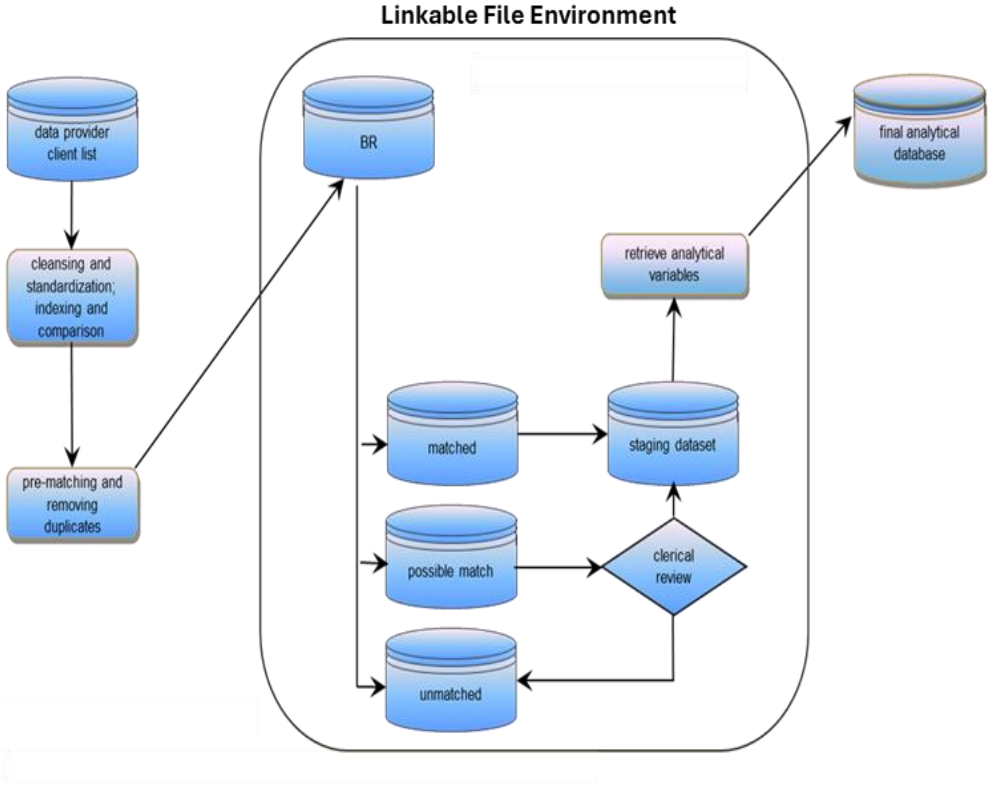
Matching AGS clients to Statistics Canada Business Register

Match rate: 99%

Linkages to Business Linkable File Environment (B-LFE)

Statistics Canada Business Register	2014 to 2023
Payroll Deduction Accounts (PD7) File	2014 to 2023
General Index of Financial Information (GIFI)	2014 to 2023
Research and Development in Canadian Industry (RDCI)	2014 to 2021
Exporter Register (XPTR)	2014 to 2023

Matched businesses to GIFI database	**99%**
Matched businesses to the PD7	**90%**



Source: Adapted from Christen et al. (2012)

Analytical approach

1. Run a probit model to obtain the predicted probability of being treated, based on a set of pre-treatment covariates
2. Examine region of common support
3. Apply nearest neighbour matching
4. Assess covariates balance in the matched sample
5. Estimate treatment effects

Software and tools

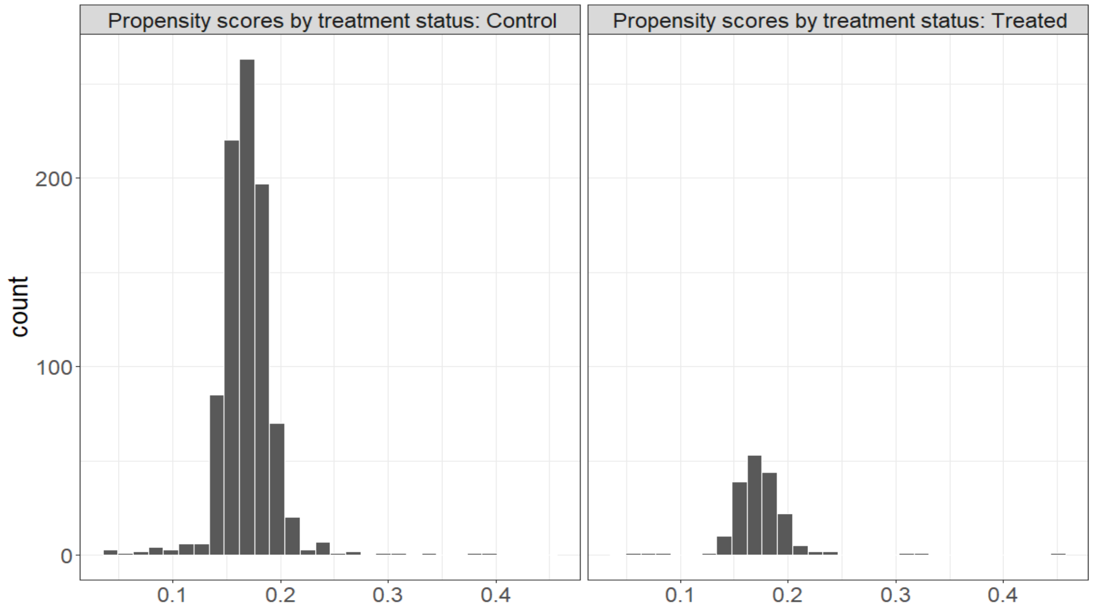
Propensity score matching is performed using **R package MatchIt** (Stuart et al, 2011)

Empirical results | Propensity score distribution (2018 cohort)

Propensity score distribution of businesses receiving AGS services overlap with those of potential comparison group

This overlap indicates presence of a **common support region**

Identifies pairs of observations with similar propensity scores



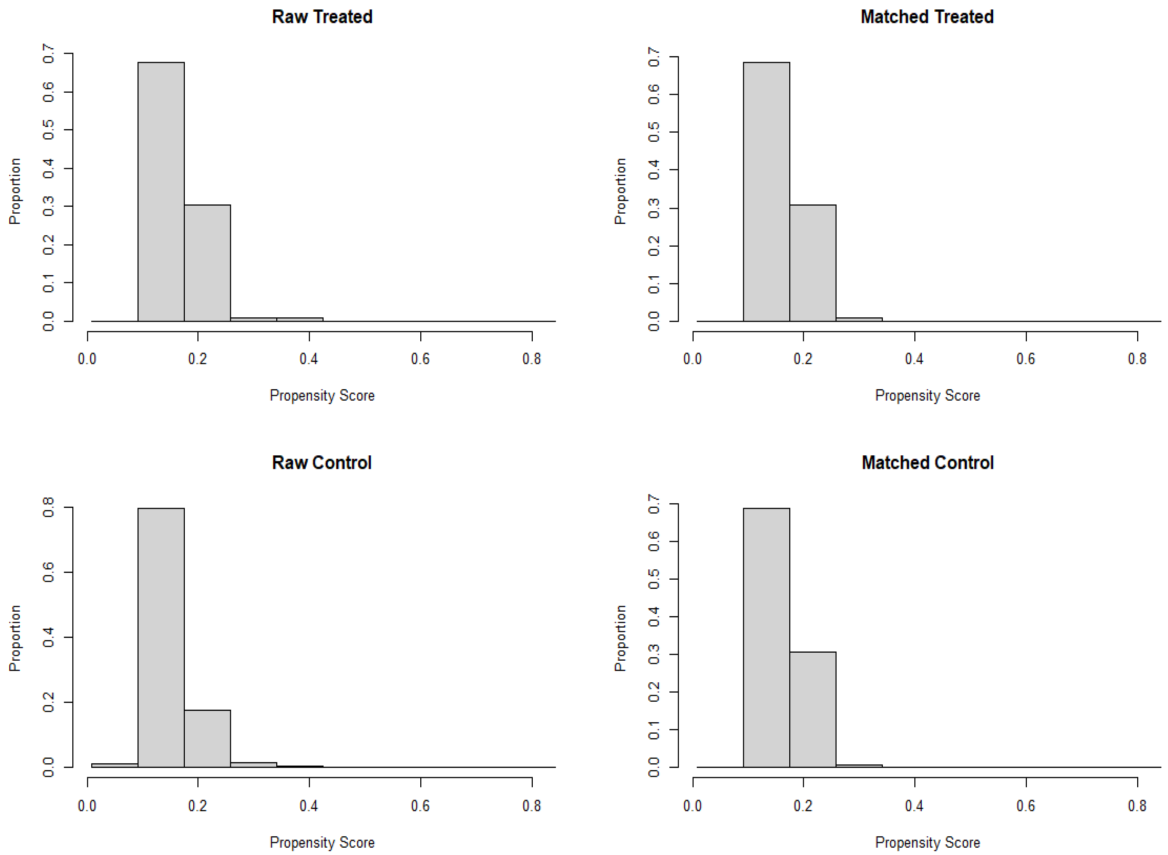
Empirical results | Propensity score distribution after matching (2018 cohort)

Nearest neighbour matching with a caliper is applied

Each AGS client is matched to a single non-beneficiary with the most similar propensity score

This approach combines two matching approaches (Cochran & Rubin, 1973):

1. Nearest neighbour matching
2. Caliper (radius) matching



Empirical results | Covariate balance after matching (2018 cohort)

Summary of balance (Cohort of 2018)

	Summary of Balance for All Data			Summary of Balance for Matched		
	Means Treated	Means Control	Std. Mean Diff.	Means Treated	Means Control	Std. Mean Diff.
Distance	0.1750	0.1644	0.1748	0.1692	0.1692	0.0003
Revenue	0.3312	0.2715	0.1064	0.3439	0.3504	-0.0116
Employment	0.2638	0.2011	0.0939	0.2942	0.2589	0.0529
Profits	0.1091	0.3893	-0.1384	0.3139	0.2768	0.0183
R&D expenditures	0.7809	0.8586	-0.0121	0.8667	0.6756	0.0296
Exports/Revenue	0.0233	0.0194	0.0166	0.0176	0.0196	-0.0085
Sample Sizes						
All	155	778	...	...	...	...
Matched	...	...	...	153	153	...
Unmatched	2	625	...	...	...	...

... not applicable
Source: Author' computation

Results indicate that a satisfactory level of covariate balance has been achieved

Standardized mean differences for covariates fall below the recommended threshold of **0.1** (Stuart et al. 2013)

Standardized mean differences above 0.1 would lead to biased effects

Empirical results | Treatment effects (2018 cohort)

Treatment effects (Cohort of 2018 premium)

	Average treatment effect	t-statistic
Revenue		
1 Year growth	3.3590	2.9350
3 Year growth	5.2700	2.8560
Employment		
1 Year growth	1.2380	1.6400
3 Year growth	2.1990	2.3130
Profits		
1 Year growth	-0.3260	1.6380
3 Year growth	0.9580	2.0400
Exports/Revenue		
1 Year growth	-0.3330	0.0330
3 Year growth	2.2680	1.0560
R&D Expenditures		
1 Year growth	5.7290	2.0900
3 Year growth	12.1110	3.7660

Source: Author' computation

Revenue growth among AGS clients was **3.35% higher after one year** and **up to 5.27% after three years** relative to matched comparison businesses

Employment growth was **1.23% higher after one year** and **2.19% higher after three years** for AGS clients

R&D expenditure increased among AGS clients compared to non-beneficiaries

Empirical results | Main take-aways

AGS-supported businesses are more likely to innovate

AGS clients perform better than comparable non-beneficiaries across most performance metrics

AGS clients exhibit greater market resilience than non-beneficiaries (results not shown)

Leveraging B-LFE and BIGS for Impact Analysis

Context

In 2017, the federal budget launched a whole-of-government review of programs supporting businesses

In 2022, $5.9 billion in funding delivered to over 39,000 businesses through 172 federal programs
(e.g., National Research Council' Industrial Research Assistance Program (National); Atlantic Canada Opportunities Agency Business Development Program (Regional)

Challenge

Businesses often benefit from multiple programs, making it difficult to assess which interventions are most effective and efficient

Limited evidence exists on the effectiveness of public support when businesses access different programs

Does the mix of national and regional programs help businesses become more competitive, innovative and productive?

Leveraging B-LFE and BIGS for Impact Analysis

Objective

Empirically distinguish and simultaneously analyze the effects of national and regional programs on innovation in Canadian small and medium-sized enterprises

Methodology

Leverage the B-LFE and BIGS databases to construct the analysis

Apply propensity score matching in a multi-treatment setting
(Gerfin and Lechner 2002, Czarnitzki and Lopes-Bento, 2014 and Guerzoni and Raiteri, 2015)

Relevance

Evaluating the policy mix of public support informs how well programs achieve intended policy goals

Results help guide future policy and funding decisions for business support

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