Matching Strategies

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I. Motivation

- **Utility in Non-Randomized Contexts:**
  - Ideal for studies utilizing observational data (e.g., surveys, financial records) where randomization isn't feasible.
- **Constructing Comparable Groups:**
  - Matches treatment groups with statistically comparable control groups, mimicking randomization in experimental settings.
- **Diverse Applications:**
  - Widely used to compare entities like exporting vs. non-exporting firms, subsidized vs. unsubsidized organizations, or strategic alliances vs. independent operations.
  - Applicable at individual, firm, and country levels.

II. Basic example: Treatment group

ID	Subsidized	Employees	Industry	R&D workers	New Patents
a	1	200	Pharma	22%	3
b	1	400	Pharma	35%	5
c	1	800	Software	16%	2
d	1	500	Software	25%	3
Mean		475		24.5%	3.25
Mean Pharma			50%		
Mean Software			50%		

II. Basic example: Control group

ID	Subsidized	Employees	Industry	R&D workers	New Patents
e	0	100	Agriculture	2%	2
f	0	40	Pharma	20%	1
g	0	180	Pharma	25%	2
h	0	400	Pharma	32%	1
i	0	820	Software	27%	3
j	0	450	Software	15%	2
k	0	22000	Food Processing	3%	12
Mean		3427		17.7%	3.3
Mean Pharma			43%		
Mean Software			29%		

II. Basic example: Matched Control group (e, f, k out)

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ID	Subsidized	Employees	Industry	R&D workers	New Patents
g	0	180	Pharma	25%	2
h	0	400	Pharma	32%	1
i	0	820	Software	27%	3
j	0	450	Software	15%	2
Mean		463		24.8%	2.0
Mean Pharma			50%		
Mean Software			50%		

III. (a) Weighted vs Unweighted (1 of 2)

1:1 Matching Without Replacement (Unweighted):

Description: Matches each treatment unit with the closest control unit that has not been previously matched.

Advantages: Simple interpretation and easy implementation. Reduces selection bias by creating directly comparable pairs.

Limitations: Excludes some observations, potentially reducing sample size and power. Sensitive to the order of matching; may not capture all nuanced differences in treatment/control characteristics.

Kernel Matching (Weighted):

Description: Assigns weights to control units based on their distance to each treatment unit, using a kernel function.

Advantages: Utilizes all available data, increasing efficiency and precision. Smooths over small differences across units, providing a more comprehensive comparison.

Limitations: More complex to implement and interpret due to weight calculations. Sensitive to kernel choice and bandwidth selection.

III. (a) Weighted vs Unweighted (2 of 2)

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Use Case Considerations:

1:1 Without Replacement: Best for smaller samples where robustness and simplicity are desired.

Kernel: Ideal for larger datasets where maximizing information from control units is crucial.

Implementation in Stata (psmatch2):

1:1 Without Replacement Example: *psmatch2 treatment, out(outcome) neighbor(1) noreplacement*

Kernel Matching Example: *psmatch2 treatment, out(outcome) method(kernel)*

Conclusion:

Choose based on study goals, sample size, and the importance of including more data vs. having a straightforward analysis.

III. (b) Propensity Score vs Strata (1 of 2)

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Propensity Score Kernel Matching:

Description: Assigns weights to control units based on the distance between their propensity scores and those of treatment units, utilizing a kernel function.

Advantages: Flexibility in capturing the entire distribution of covariates across treated and control groups. Retains practically all observations, maximizing dataset usage and analytical power. Very good with continuous variables (sales).

Limitations: Requires careful bandwidth and kernel function selection. Complex interpretation due to reliance on weighted averages.

Coarsened Exact Matching (CEM):

Description: Segment the data into strata based on coarsened values of covariates, ensuring exact matches within each stratum.

Advantages: Simple and intuitive; facilitates balance checks and diagnostics. Reduces model dependence and improves estimation precision by exact matching within coarsened strata. Very good with qualitative data (industry).

Limitations: Potentially discards a significant number of units, reducing sample size. It does not work with continuous variables.

III. (b) Propensity Score vs Strata (2 of 2)

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Use Case Considerations:

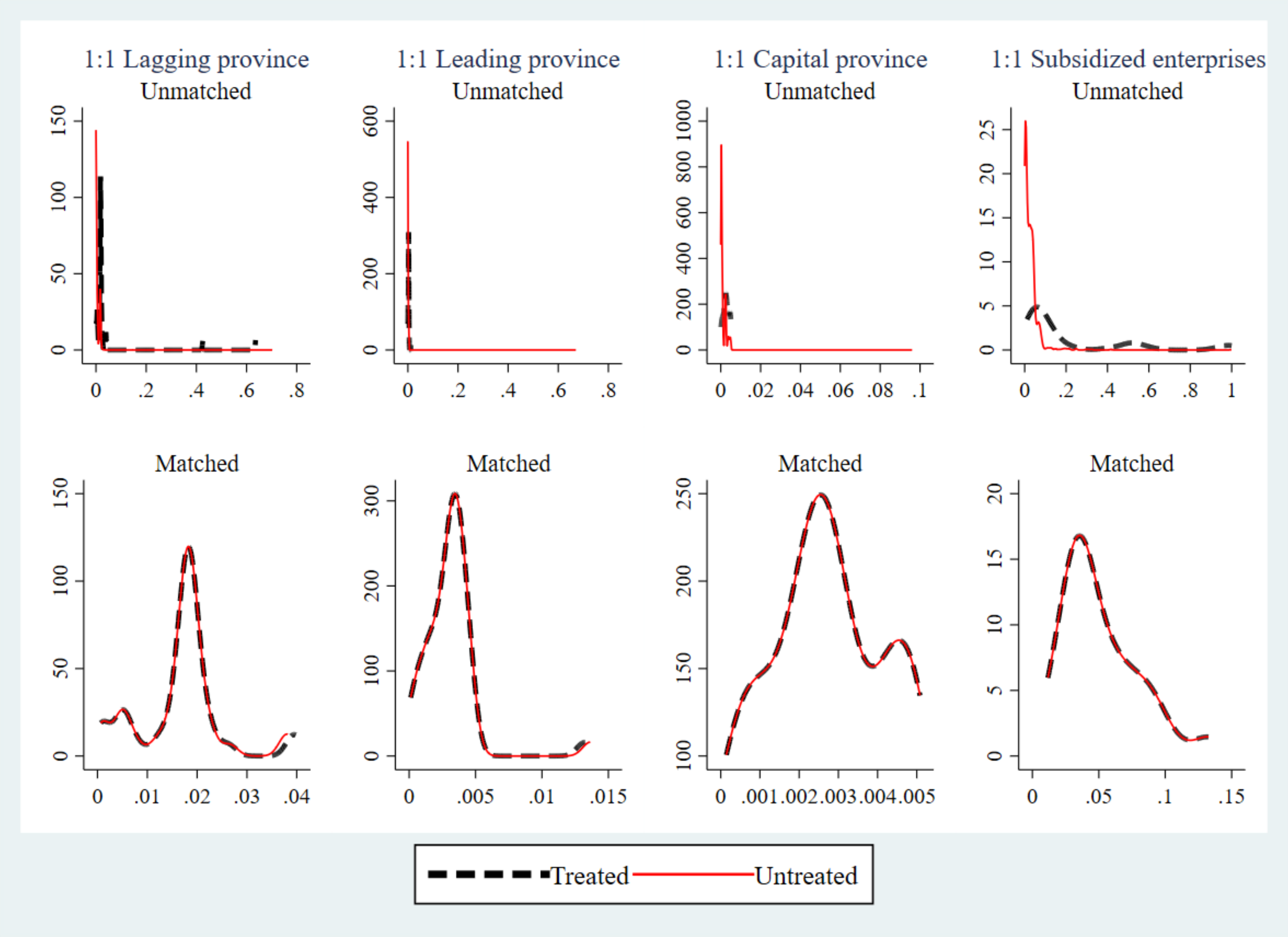
- **CEM (Coarsened Exact Matching):** Best for smaller samples where balance is a priority. It works very well when covariates are dummy or categorical.
- **Kernel Matching:** More suitable for larger datasets, as it utilizes weighted averages from multiple control units, improving efficiency while preserving more information. Works well with covariates as continuous.

Implementation in Stata: *psmatch2* for Kernel and *cem* for CEM

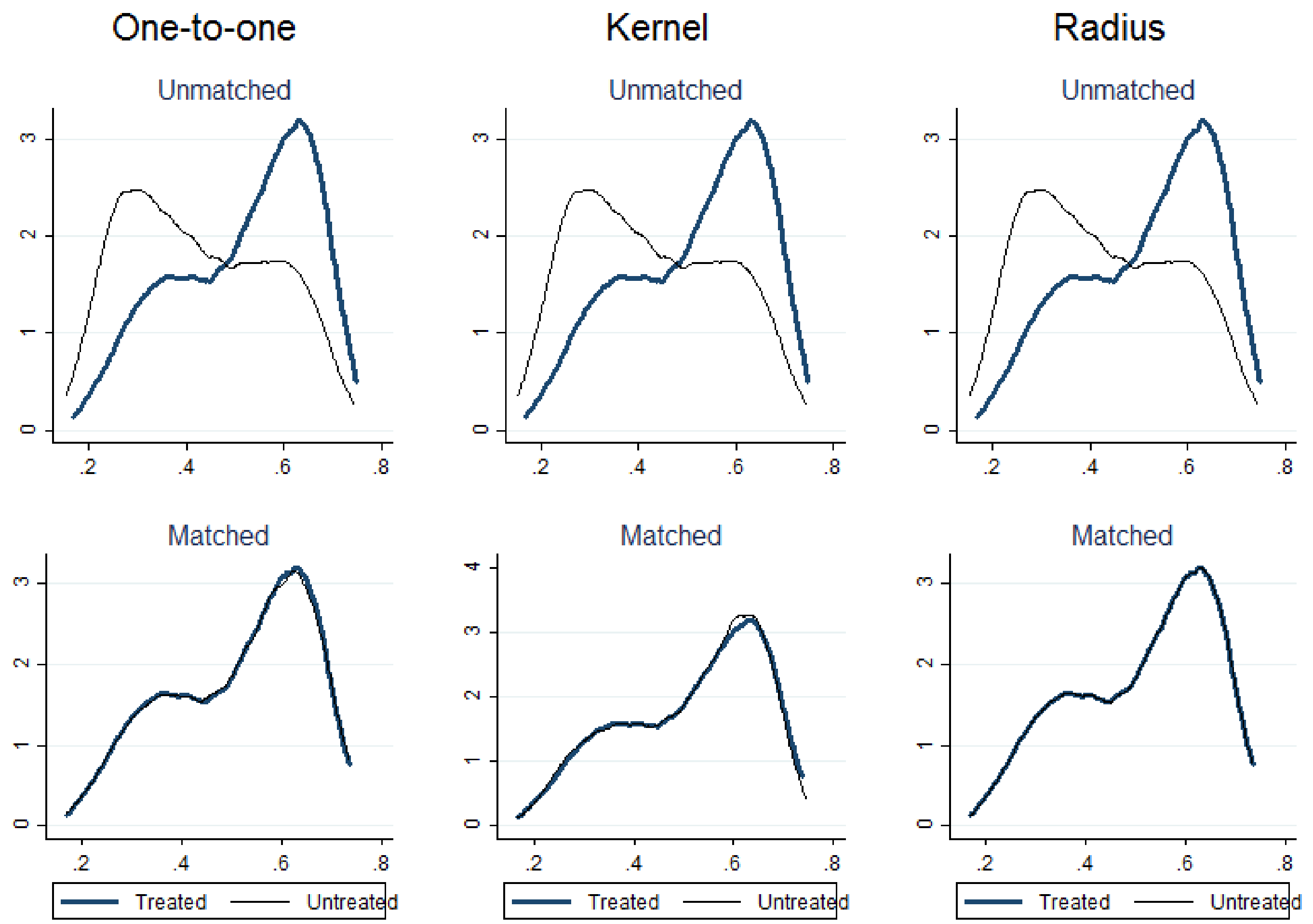
CEM Example:

cem   Industry1 Industry2 Employees(10 50 250), treatment(treatment)

IV. (a) Reduction Bias: Density Plot



IV. (a) Reduction Bias: Density Plot



IV. (a) Reduction Bias: Density Plot – Stata code

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// Unmatched plot

```
tw (kdensity `outcome_var' if `treatment_var'==1, kernel(`kernel_type') lcolor(black) clpattern(dash) lwidth(thick)) ///
  (kdensity `outcome_var' if `treatment_var'==0, kernel(`kernel_type') lcolor(red) lwidth(medium)), ///
  title("`title_main'") subtitle("Unmatched") ytitle("") xtitle("") ///
  legend(on order(1 "Treated" 2 "Untreated") colgap(zero) keygap(zero) size(small)) ///
  graphregion(color(white) lcolor(black)) plotregion(fcolor(white)) ///
  plotregion(style(none)) ylab(, nogrid)
graph save output_prefix1.gph, replace
```

// Matched plot

```
tw (kdensity `outcome_var' if `treatment_var'==1 & `match_var'==1, kernel(`kernel_type') lcolor(black) clpattern(dash) lwidth(thick)) ///
  (kdensity `outcome_var' if `treatment_var'==0 & `match_var'==1, kernel(`kernel_type') lcolor(red) lwidth(medium)), ///
  title("") subtitle("Matched") ytitle("") xtitle("") ///
  legend(on order(1 "Treated" 2 "Untreated") colgap(zero) keygap(zero) size(small)) ///
  graphregion(color(white) lcolor(black)) plotregion(fcolor(white)) ///
  plotregion(style(none)) ylab(, nogrid)
graph save output_prefix2.gph, replace
```

Graph Combine output_prefix1.gph output_prefix2.gph

IV. (b) Reduction Bias: Table

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	Before Matching		Nearest Three Neighbors with Replacement			Nearest Five Neighbors with Replacement		
Variables	Difference in means (before)	T-test (before)	Difference in means (after)	T-test (after)	Bias reduction (%)	Difference in means (after)	T-test (after)	Bias reduction (%)
Population	1.870	37.92***	0.038	0.52	98.0	0.032	0.44	98.3
Income	11.171	13.19***	1.614	1.24	85.6	1.077	0.82	90.4
Broadband Providers	2.801	15.86***	0.2519	0.83	91.0	0.151	−0.50	94.6
Population per Household	0.101	10.02***	−0.0376	−2.30**	137.4	−0.033	−2.00**	132.4
Ln(MSW per Capita) Lag1	0.24625	10.93***	0.06204	2.65**	74.8	0.05921	2.50**	76.0
Ln(MSW per Capita) Lag2	0.24796	10.72***	0.05505	2.33**	77.8	0.05643	2.32**	77.3
Ln(MSW per Capita) Trend	−0.53928	−0.15	0.0354	0.02	106.6	−0.75219	−0.37	-39.5

Dhanorkar, S. (2019). Environmental benefits of internet-enabled C2C closed-loop supply chains: A quasi-experimental study of Craigslist. *Management Science*, *65*(2), 660-680.

IV. (b) Reduction Bias: Table – Stata code

psmatch2 treatment, out(outcome) neighbor(1) noreplacement

pstest, both

IV. (c) Reduction Bias: Logit

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- **Methodological Approach:**
  - Utilizes logistic regression models applied before and after matching.
- **Dependent and Independent Variables:**
  - Dependent Variable: Treatment variable.
  - Independent Variables: All variables used in the matching process.
- **Objective:**
  - Pre-Matching:
    - Independent variables should be highly significant.
    - Model exhibits high explanatory power.
  - Post-Matching:
    - Independent variables should become statistically insignificant.
    - Model's explanatory power significantly reduces.=

- **Purpose:**
  - Validate the matching process's effectiveness in covariate balancing.
  - Simulate a randomized experimental design.
  - Diminish selection bias for more robust causal inference.

V. My experience with matching strategy

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1. Unweighted manual
    a) Technovation (2014)
2. Unweighted psmatch2
    a) Regional Studies (2014)
    b) International Business Review (2020)
3. Weighted vs Unweighted Psmatch2
    a) Journal of Business Research (2021)
4. Rounds of unweighted Psmatch2 e.g.,
    a) 2:1 with a single sample (Journal of International Business Studies, 2022)
    b) 4:1 with 4 comparison groups (Research Policy I, under review)
5. Weighted vs Unweighted & Weighted vs Strata Psmatch2 and CEM
    a) Long Range Planning (2023)
    b) Research policy II (under review)
6. Unweighted Psmatch2
    a) Small Business Economics (2025)
    b) Journal of International Business Studies (Under review)

Policy related papers

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Technovation (2014) → Spin-off vs non-academic start-ups. Manual Matching at the outset (foundation). Corroborated using Logit before and after matching. Companies followed over time using SABI data.

Key result: Spin-offs are less productive at the outset, but achieve higher productivity growth rates. 3 years after foundation they reach similar levels, and after that they are more productive.

Regional Studies (2014) → Cluster vs Non-cluster firms. *Psmatch2* 1:1 matching. Two data points (2002 and 2008) – matching done in 2002. Corroborated using Logit before and after matching.

Key result: The results provide some weak evidence for the existence of additionality associated with the policy.

Exporting related papers

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Journal of Business Research (2021): Servitized vs non-servitized firms on exports. German cross-section data. *Psmatch2* 1:1, Kernel and Radius. Graphical validation.

Key result: Firms that are servitized have 7-9% higher export intensity that firms that do not servitize.

Journal of International Business Studies (2022): Self-selection and learning by exporting simultaneously tested using a Heckman approach. Matching for the home market economic development (HIC, UMIC, LMIC, LIC). 1:1 and 2:1. No further validation of the matching (only in-text description).

Key result: Self-selection is more prominent in HIC and Learning by exporting is more prominent in HIC.

Alliances related research (1 of 2)

Long Range Planning (2023): The effect of pre-acquisition alliances on post-acquisition performance. Data from SDC platinum (combining alliances database with acquisitions database). Weighted and unweighted, and also CEM vs psmatch2; Kernel vs 1:1 vs CEM.

> *Key result*: Courtship effect exists, but is stronger in domestic settings, and the effect decreases with cultural distance.

Alliances related research (2 of 2)

	(1)	(2)	(3)	(4)
	Full sample	One-to-One	Kernel	CEM
PSA	5.1205**	3.6374***	5.4072***	5.6167***
	(2.0043)	(1.3621)	(2.0234)	(1.8043)
	0.0109	0.0080	0.0077	0.0020
PSA*Cultural distance	-1.3708**	-1.5660***	-1.6150**	-1.7705***
	(0.6340)	(0.5678)	(0.6395)	(0.6442)
	0.0310	0.0062	0.0118	0.0063

VI. Other Considerations

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a) **Caliper:** In 1:1 matching (also weighted Radius matching), it determines the distance in propensity score that defines a matched observation—the smaller the distance, the more restrictive the matching. The appropriate caliper size depends on the distribution of propensity scores; a value of 0.1 may be restrictive in some cases and too lenient in others.

b) **Common support**: Discard treated observations whose propensity score is higher than the maximum or less than the minimum propensity score of untreated firms.

c) **Average Treatment Effect:** Quantifies the mean difference in outcomes between individuals who receive a treatment and those who do not, reflecting the treatment's overall impact across a population.

VI. Other Considerations

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d) **Use of lags:** When panel data is available, it is recommended to do the matching in one year and the outcome in the following year.

e) **Induced vs Counterfactual**: It helps differentiating the change in outcome that has been produced by the treatment, and the part that would have been achieved anyway.

   i. This method normally requires more than two year lags – one for the treatment, and another for assessing the induced effect (e.g., digital -> export - > productivity).

   ii. Notice that Panel Data is not very friendly with matching, so one strategy is to do repeated 3-year matching cross sections (with 2-year lags) if the panel is of 4 years or more.

f) **Continuous treatment:** In some instances, it is relevant to consider a continuous treatment, in this case a dose response approach is appropriate, which is based on the generalized propensity scores. The treatment effect focuses on the change in the treatment variable (invest £1,000 more).

References
(not including the under review papers)

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Thank you!

Questions?