Advanced Quantitative Research Methodology, Lecture Notes: Coarsened Exact Matching[1]

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References

- Stefano M. Iacus, Gary King, and Giuseppe Porro, "Causal Inference Without Balance Checking: Coarsened Exact Matching," 2010.

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- Largest class of matching methods (EPBR, e.g., propensity scores, Mahalanobis distance): requires normal data (or DMPES); all X's must have same effect on Y; Y must be a linear function of X; aims only for expected (not in-sample) imbalance; $\rightsquigarrow$ in practice, we're lucky if mean imbalance is reduced
- Not well designed for observational data:
  - Least important (variance): matched n chosen ex ante
  - Most important (bias): imbalance reduction checked ex post
- Hard to use: Improving balance on 1 variable can reduce it on others
  - Best practice: choose n-match-check, tweak-match-check, tweak-match-check, tweak-match-check, $\cdots$
  - Actual practice: choose n, match, publish, STOP. (Is balance even improved?)

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If $\boldsymbol{\epsilon}$ is reduced, $\boldsymbol{\gamma}(\boldsymbol{\epsilon})$ decreases & $\gamma(\epsilon)$ is unchanged

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	CEM	pscore	Mahalanobis	Genetic
% Common Units	96.5	70.2	80.9	80.0

Other CEM properties we prove

- Automatically eliminates extrapolation region (no separate step)
- Bounds model dependence
- Bounds causal effect estimation error
- Meets the congruence principle
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Imbalance Measures

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Variable-by-Variable Difference in Global Means

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Local Imbalance by Variable (given strata fixed by matching method)

$$I_2^{(j)} = \frac{1}{S}\sum_{s=1}^{S}\left|\bar{X}_{m_T^s}^{(j)} - \bar{X}_{m_C^s}^{(j)}\right|, \quad j = 1, \dots, k$$

CEM in Practice: EPBR-Compliant Data

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Difference in means (I_1):

	X_1	X_2	X_3	X_4	X_5	Seconds

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Difference in means (l_1):

	X_1	X_2	X_3	X_4	X_5	Seconds
initial	1.00	1.00	1.00	1.00	1.00	

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	X_1	X_2	X_3	X_4	X_5	Seconds
initial	1.00	1.00	1.00	1.00	1.00	
MAH	.20	.20	.20	.20	.20	.28

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Local (I_2) and multivariate $\mathcal{L}_1$ imbalance:

	X_1	X_2	X_3	X_4	X_5	$\mathcal{L}_1$

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	X_1	X_2	X_3	X_4	X_5	$\mathcal{L}_1$
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PSC	2.38	1.25	.74	1.25	.74	1.18

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$\rightsquigarrow$ CEM dominates EPBR-methods in EPBR Data

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Monte Carlo: Exact replication of Diamond and Sekhon (2005), using data from Dehejia and Wahba (1999). CEM coarsening automated.

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initial	-423.7	1566.5	1622.6	.00	1.28

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PSC	260.5	1025.8	1058.4	.02	1.23
GEN	78.3	499.5	505.6	27.38	1.12

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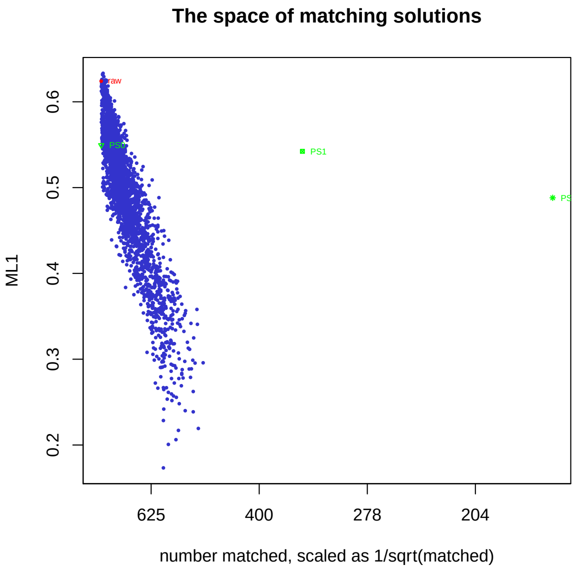
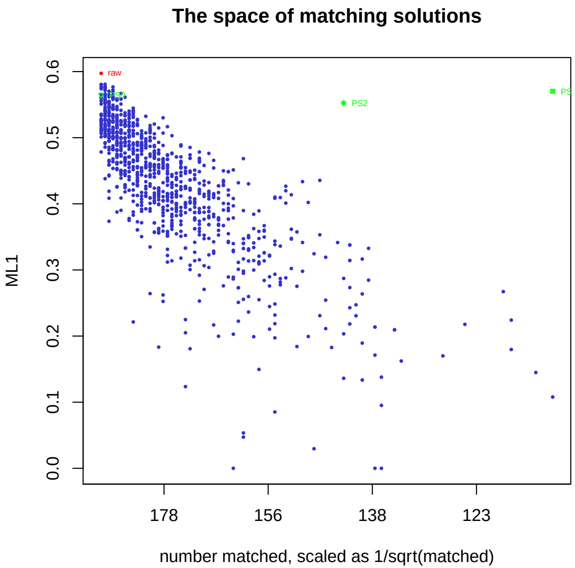
$\rightsquigarrow$ CEM works well in non-EPBR data too

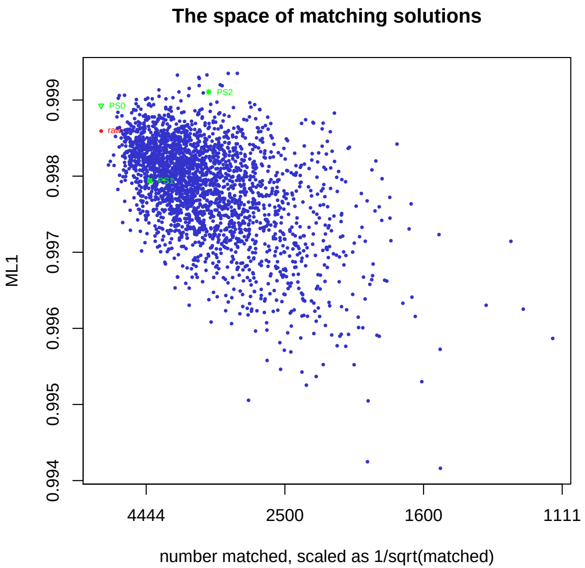
Bias v Efficiency in Matching Methods: I



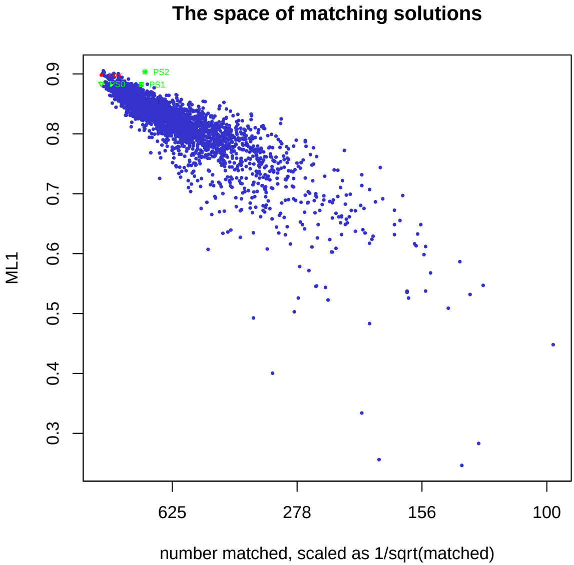
Bias v Efficiency in Matching Methods: II



Bias v Efficiency in Matching Methods: III



Bias v Efficiency in Matching Methods: IV



CEM Extensions I

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- CEM and Multiple Imputation for Missing Data

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  1. put missing observation in stratum where plurality of imputations fall

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- Detecting Extreme Counterfactuals

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   - don't possess most other CEM properties
   - but inherent CEM properties if applied within CEM strata
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   - requires correct specification or balance can drop (the usual specification tests are irrelevant; must check balance)
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   - may be good for applications with many covariates we know little about (so we're willing to take balance on any subset)
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7. $\rightsquigarrow$ & whatever else you all come up with

For papers, software (for R and Stata), tutorials, etc.

http://GKing.Harvard.edu/cem