Coarsened Exact Matching

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Talk at Washington University, St. Louis, 1/22/2010

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

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

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⇝ CEM works well in non-EPBR data too

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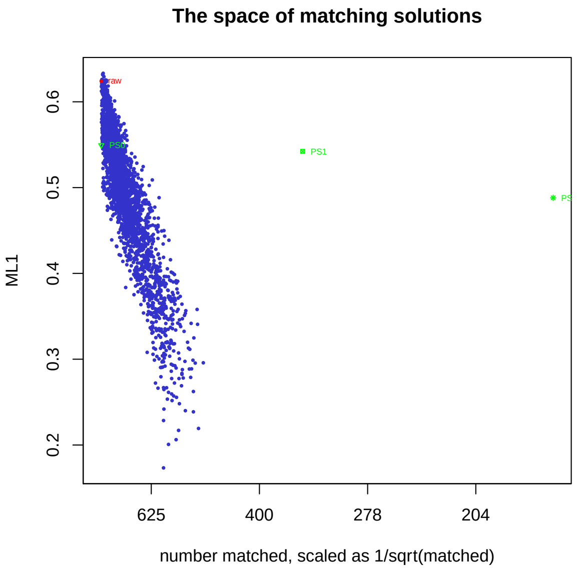
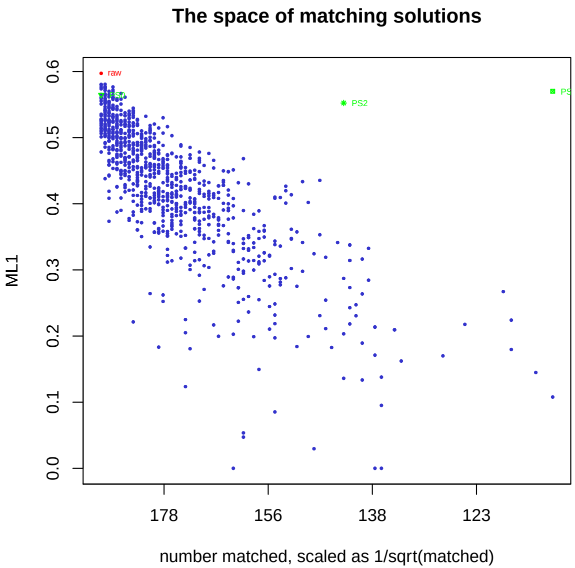
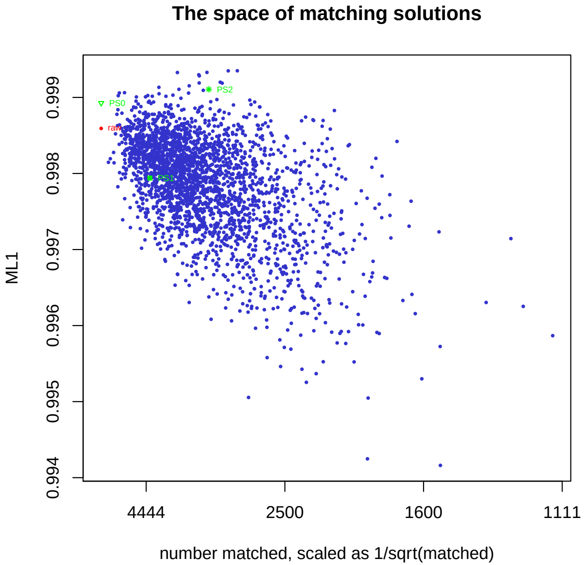


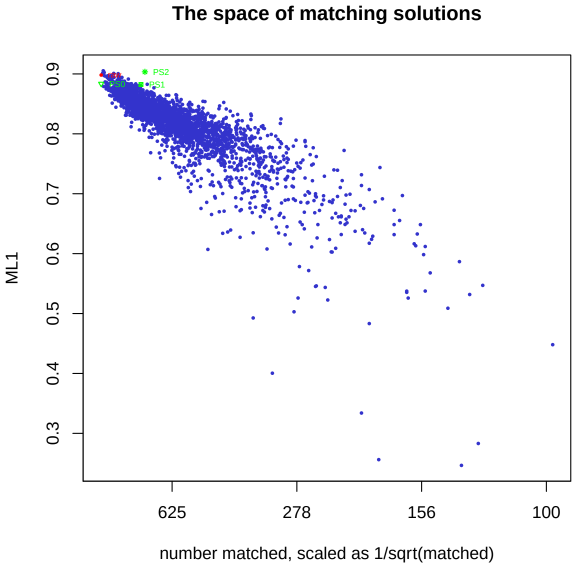
Bias v Efficiency in Matching Methods: II



Bias v Efficiency in Matching Methods: III



Bias v Efficiency in Matching Methods: IV



CEM Extensions I

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7. $\rightsquigarrow$ & whatever else you all come up with

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

http://GKing.Harvard.edu/cem