

The Essential Role of Pair Matching in Cluster-Randomized Experiments, with Application to the Mexican Universal Health Insurance Evaluation

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January 18, 2008

The paper is available at <http://imai.princeton.edu>

Cluster-Randomized Experiments (CREs)

- Problem of many **field experiments**:
 - unit of randomization = clusters of individuals
 - unit of interest = individuals
- Public health & medicine: CREs have “risen **exponentially** since 1997” (Campbell, 2004)
- Cluster randomization → loss of efficiency & specialized methods
- **Matched-Pair Designs (MPDs)** to improve efficiency:
 - 1 Pair clusters based on the similarity of background characteristics
 - 2 Within each pair, randomly assign one cluster to the treatment group and the other to the control group

Methodological Recommendations Against MPDs

- “Analytical limitations” of MPDs (Klar and Donner, 1997):
 - 1 restriction of prediction models to cluster-level baseline risk factors
 - 2 inability to test for homogeneity of causal effects across clusters
 - 3 difficulties in estimating the intracluster correlation coefficient
- In 10 or fewer pairs, MPDs can lose power (Martin *et al.* 1993)
- Echoed by other researchers and clinical standard organizations
- But, we show **these claims are all unfounded.**

- No formal definition of causal effects to be estimated
- No formal evaluation of the existing estimators for MPDs

Contributions of Our Paper

- **Conclusion: pair-matching should be used whenever feasible**
 - MPDs improve bias, efficiency, and power
 - Not pairing = throwing away one's data!
- Show that “analytical limitations” do not exist or are irrelevant
- Show that power calculations rely on unrealistic assumptions
- Existing estimator is based on a highly restrictive model
- Formally define causal quantities of interest
- Propose new simple design-based estimators and s.e.'s
- Offer power and sample size calculations
- Extend the estimator to CREs with unit-level noncompliance
- Clarify the assumptions about interference

Motivating Example: Seguro Popular de Salud (SPS)

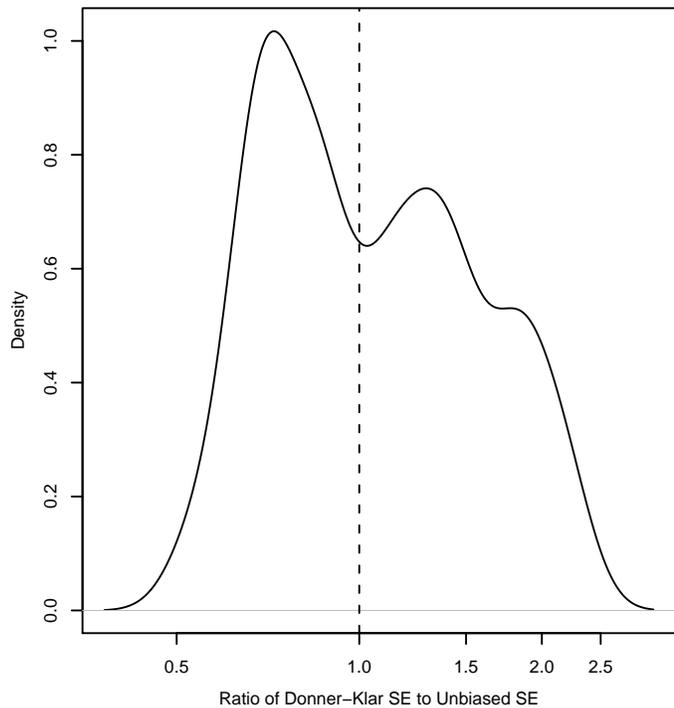
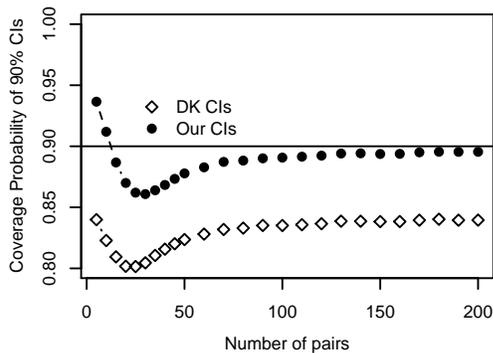
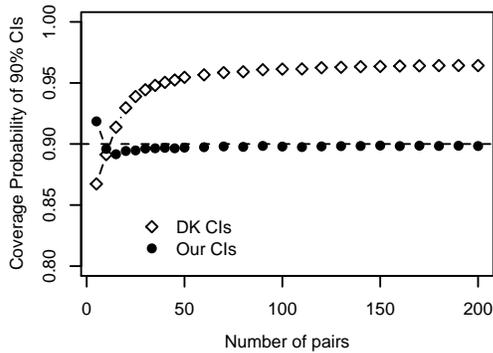
- Evaluation of the Mexican universal health insurance program
- Aim: “provide social protection in health to the **50 million** uninsured Mexicans” (Frenk *et al.*, 2003)
- A key goal: reduce out-of-pocket health expenditures
- Sounds obvious but not easy to achieve in developing countries
- Individuals must affiliate in order to receive SPS services
- 12,824 “health clusters”
- 100 clusters nonrandomly chosen for randomized evaluation
- Pairing based on population, socio-demographics, poverty, education, health infrastructure etc. (King *et al.*, 2007)
- “Treatment clusters”: **encouragement** for people to affiliate
- Data: aggregate characteristics, surveys of 32,000 individuals

Design-based Analysis of CREs under MPDs

- Existing **Model-based** approach: assume DGP for observed data
- The Donner-Klar estimator assumes the homogeneity across clusters: **no point of matching** to begin with!
- Our **Design-based** approach avoids modeling assumptions (Neyman, 1923)
- Randomness comes from:
 - 1 **randomization** of treatment assignment
 - 2 **random sampling** of clusters and units within clusters
- Conditions for unbiasedness:
 - 1 Exact match on sample cluster sizes
 - 2 Exact match on within-cluster ATEs
- Match on **cluster sizes** and **important covariates**.

Bias and Inefficiency of Existing Approach

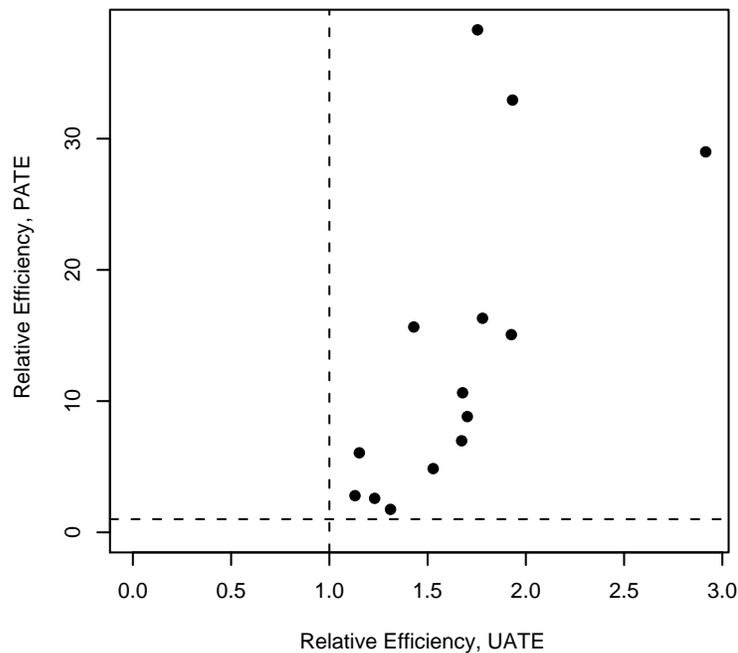
- Simulation: ours (bias=0, RMSE=6), DK (bias=21, RMSE=22)



Efficiency Comparison

Relative Efficiency of MPDs

- UATE: MPDs are between 1.1 and 2.9 times more efficient
- PATE: MPDs are between 1.8 and 38.3 times more efficient!



Initial Empirical Analysis of SPS Data

- Average causal effects of SPS on the prob. of a household suffering from **catastrophic health expenditures**
- More than 30% of annual post-subsistence income (10% of all households)
- Its reduction is a major aim of SPS

	SATE	CATE	UATE	PATE
ITT	-.014 ($\leq .007$)	-.023 ($\leq .015$)	-.014 (.007)	-.023 (.015)
CACE	-.038 ($\leq .018$)	-.064 ($\leq .024$)	-.038 (.018)	-.064 (.024)