A "Politically Robust" Experimental Design for Public Policy Evaluation, with Application to the Mexican Universal Health Insurance Program

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Joint work with Emmanuela Gakidou, Nirmala Ravishankar, Ryan T. Moore, Jason Lakin, Manett Vargas, Martha María Téllez-Rojo, Juan Eugenio Hernández Ávila, Mauricio Hernández Ávila, Héctor Hernández Llamas

Project References

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- A 'Politically Robust' Experimental Design for Public Policy Evaluation, with Application to the Mexican Universal Health Insurance Program Gary King, Emmanuela Gakidou, Nirmala Ravishankar, Ryan T. Moore, Jason Lakin, Manett Vargas, Martha María Téllez-Rojo, Juan Eugenio Hernández Ávila, Mauricio Hernández Ávila, Héctor Hernández Llamas. Forthcoming, JPAM.

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- The Essential Role of Pair Matching in Cluster-Randomized Experiments, with Application to the Mexican Universal Health Insurance Evaluation Kosuke Imai, Gary King, and Clayton Nall.

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- The Essential Role of Pair Matching in Cluster-Randomized Experiments, with Application to the Mexican Universal Health Insurance Evaluation Kosuke Imai, Gary King, and Clayton Nall.

- Public Policy for the Poor? A Randomized Evaluation of the Mexican Universal Health Insurance Program Gary King, Emmanuela Gakidou, Kosuke Imai, Jason Lakin, Ryan T. Moore, Nirmala Ravishankar, Manett Vargas, Martha María Téllez-Rojo, Juan Eugenio Hernández Ávila, Mauricio Hernández Ávila, Héctor Hernández Llamas.

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  - includes key fail-safe components

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- First cohort: 148 "health clusters," 1,380 localities, approximately 118,569 households, and about 534,457 individuals.

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- We were able to randomize at the "health cluster" level, the health clinic and catchment area around it — except in areas favored by politicians or presently infeasible to offer services

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  - Smaller standard errors: up to 6 times smaller

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8. Repeat surveys in 10 months and subsequently to see effects

Remaining in study: 148 clusters in 7 states

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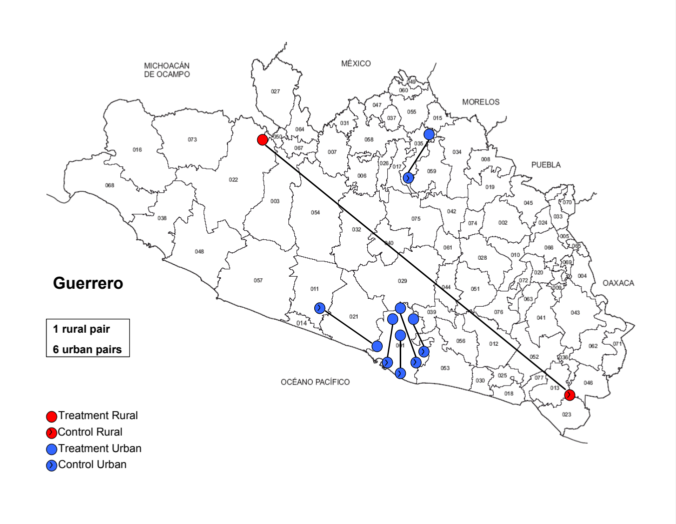
All experiments should use matched pairs when feasible

Matched Pairs, Guerrero

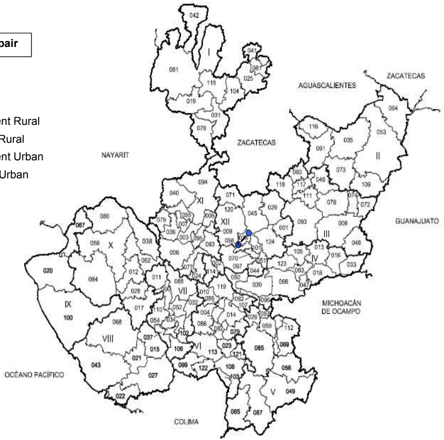


Matched Pairs, Jalisco

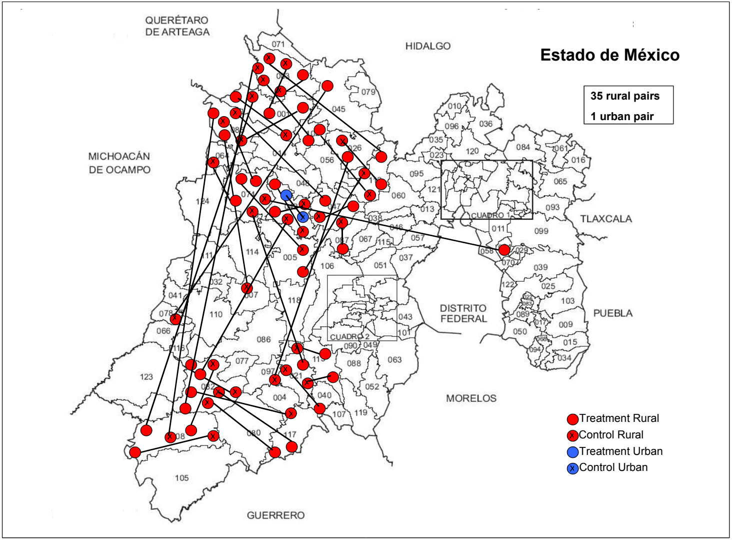
Jalisco

1 urban pair

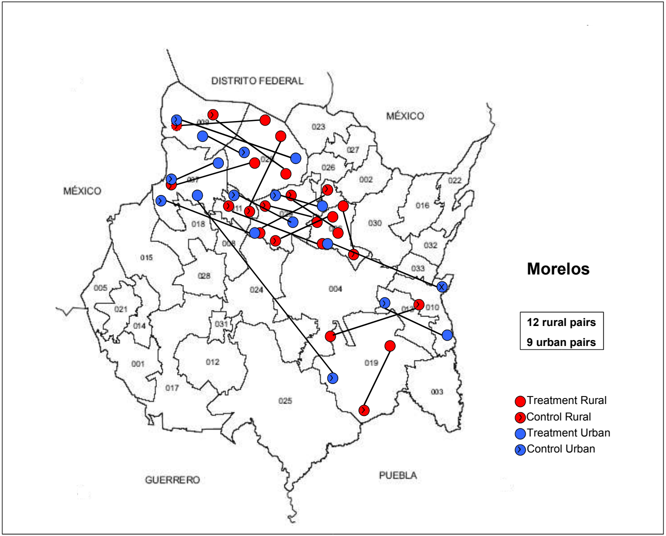
Treatment Rural
Control Rural
Treatment Urban
Control Urban



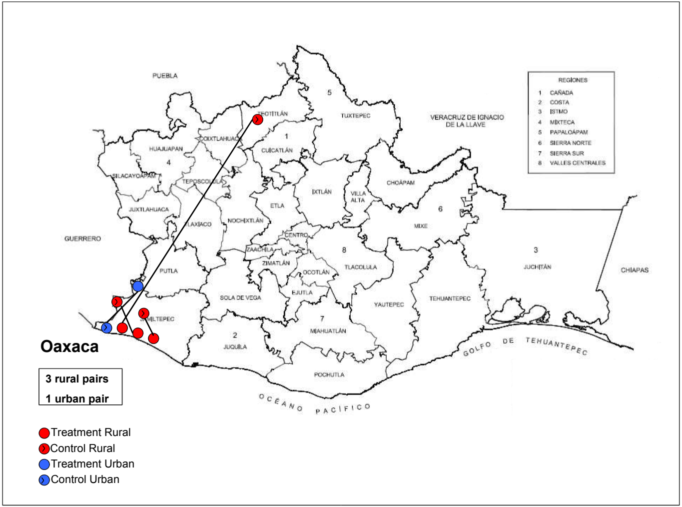
Matched Pairs, Estado de México



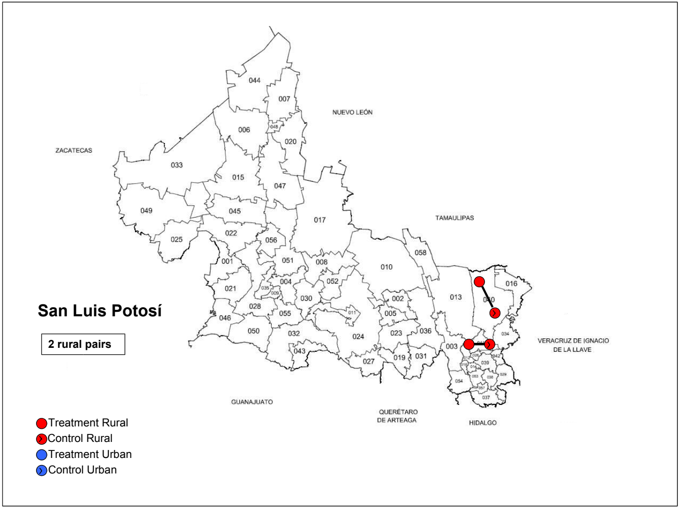
Matched Pairs, Morelos



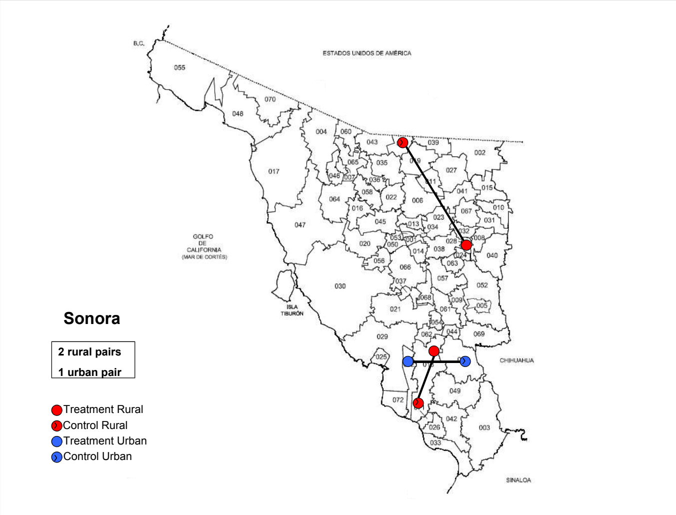
Matched Pairs, Oaxaca



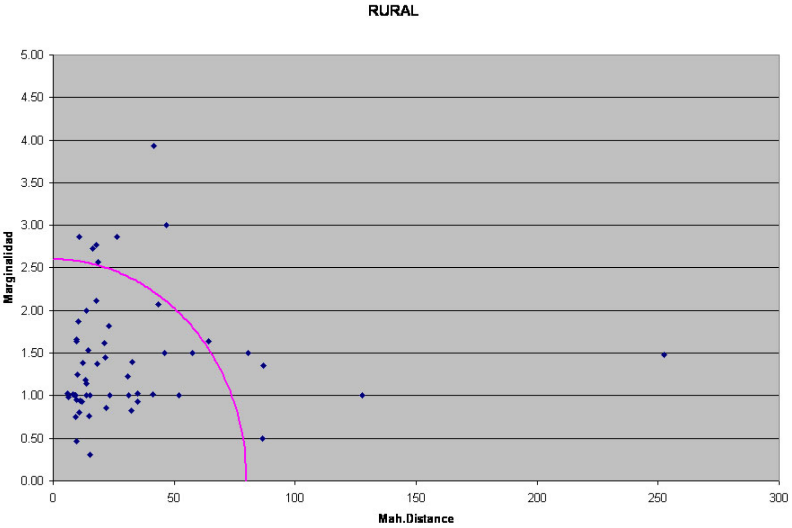
Matched Pairs, San Luis Potosí



Matched Pairs, Sonora



Choosing Pairs for the Survey



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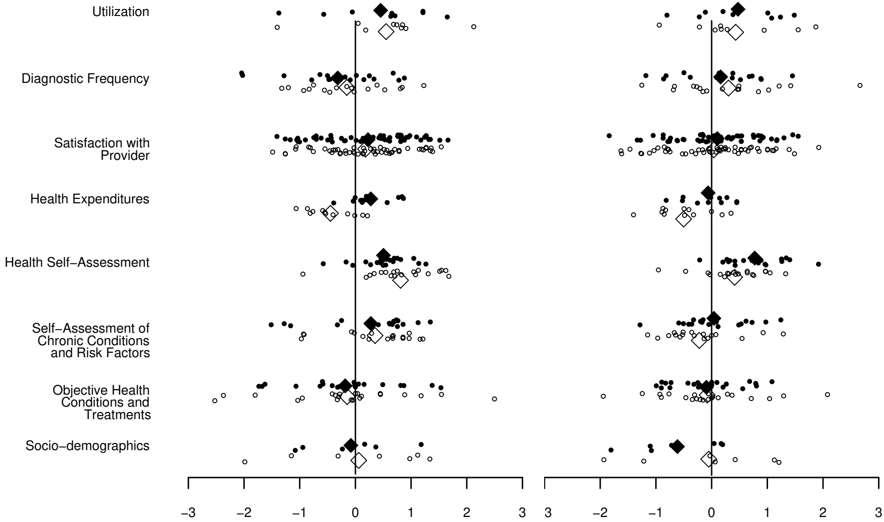
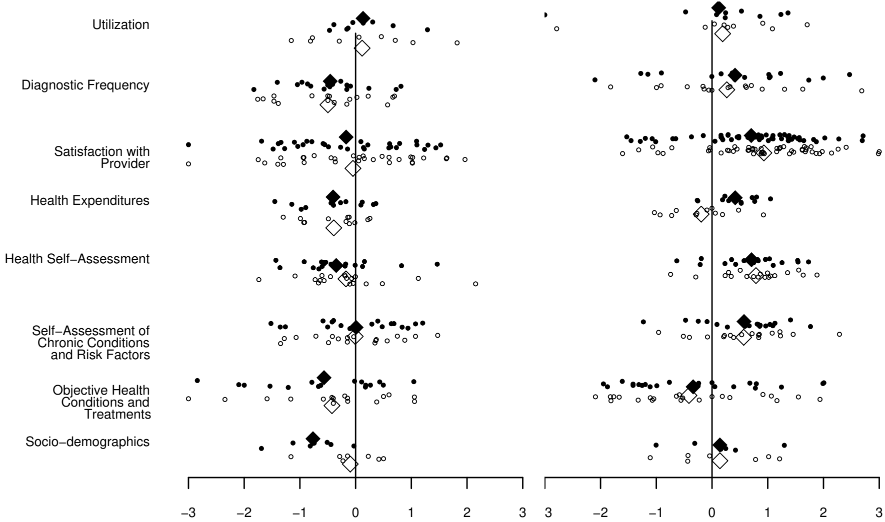
2. If we lose pairs, we check for selection bias by rerunning this check

ITT on Outcome Measures at Baseline, for all families (left) and poor families, in Oportunidades (right)



ITT on Outcome Measures at Baseline, for wealthy families (left) and middle income families (right)



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- Imai-King-Nall: prove above results and offer simple estimators for MPDs making minimal assumptions for both intent to treat and complier average treatment effects

For more information

http://GKing.Harvard.edu

Effect of SP Rollout at Baseline: 1 of many

(Expected effects at 10 months: small, medium, large)

Dependent Variable [mean; SD]

Skilled birth attendance [0.9; 0.13]
Cholesterol cov. [0.07; 0.08]
Diarrhea children [0.86; 0.12]
Resp Infection children [0.64; 0.2]
Cervical exam [0.22; 0.11]
Papsmear [0.29; 0.12]
Flu vaccine [0.19; 0.1]
Diabetes [0.46; 0.18]
Hypertension cov. [0.33; 0.11]
Antenatal care [0.51; 0.22]
Mammography [0.05; 0.04]
Glasses [0.13; 0.07]