

10 Experiments in Public Policy and What We Can Learn From Them

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- ▶ **Senior Social Scientist**
(The Lab @ DC)
- ▶ **Fellow in Methodology (US Office of
Evaluation Sciences: “OES”)**

Why this talk, here?

Waseda University Mission

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“Waseda University pledges to contribute to the progress of the times by establishing **a path for the practical use of scholarship** as well as pursuing theoretical research for its own sake.”



Goals

- ▶ Inspire your thinking about what *could* be an experiment (our best hope for causal inference)

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- ▶ Introduce you to some results from experiments in the field
- ▶ Draw out lessons for applied and community-based research

Ten Randomized Experiments in Public Policy

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1. Seguro Popular
2. 911 Nurse Triage Line
3. Welfare Recertification, TANF
4. Retirement Savings, 457b
5. Police Body-Worn Cameras
6. Flexible, Shallow Rent Housing Subsidy
7. Police training, Nat Museum of African-American History and Culture
8. Warning Taxpayers about Preparers
9. Opioid Buyback
10. Fire Inspectors Risk-Score Lists

Seguro Popular

- ▶ *Partner*: Mexican federal government and health bureaucracy
- ▶ *Intervention*: Randomize federal health infrastructure spending, household insurance to Mexican households
- ▶ *Finding*: Reduced catastrophic health expenditures for households
- ▶ *A Lesson*: Applied work can inspire new methodological research

(King et al. 2007, 2009)

Nurse Triage Line

- ▶ *Partner*: DC Fire and Emergency Management Services
- ▶ *Intervention*: Randomize whether 911 emergency callers talk to a nurse
- ▶ *Finding*: Reduced ambulance dispatches, transports; increased primary care visits
- ▶ *A Lesson*: Advocates matter. Even when it seems impossible, there may be a way. Effects can be huge.

(Wilson et al. 2024)

Welfare Recertification, TANF

- ▶ *Partner*: DC Human Services
- ▶ *Intervention*: Randomized whether households due to recertify received a behaviorally-informed reminder letter
- ▶ *Finding*: Improved recertification rates, especially when we indicate flexibility
- ▶ *A Lesson*: We can build *capacity* in partners

(Moore et al. 2022)

Retirement Savings of Public Employees

- ▶ *Partner:* DC Human Resources
- ▶ *Intervention:* Randomized email with simplified decisions and present-framing future gains
- ▶ *Finding:* Improved contributions for those *already* contributing, but 0 new contributors
- ▶ *A Lesson:* Human behavior is sticky!

Policy Body-worn Cameras

- ▶ *Partner:* DC Metro Police Department
- ▶ *Intervention:* Randomized whether police officers wore body-cameras
- ▶ *Finding:* No detectable effects on police use of force, citizen complaints, police activity
- ▶ *A Lesson:* Null effects can happen for many reasons, are important to share, and do not doom a program

(Yokum, Ravishankar, and Coppock 2019)

DC Flex: Flexible, shallow subsidy

- ▶ *Partner:* DC Housing and Homelessness agencies
- ▶ *Intervention:* Flexible, shallow rent subsidy
- ▶ *Finding:* Null effects on homelessness, but decreased use of other services (first year)
- ▶ *A Lesson:* Giving needy control can simplify administration without adverse outcomes

(Avila et al. 2023)

Police Training at Nat'l Museum of African-American History and Culture

- ▶ *Partner:* MPD, Nat Museum of African-American History and Culture
- ▶ *Intervention:* Randomized training of police officers on history of race and policing
- ▶ *Finding:* (Stay tuned!)
- ▶ *A Lesson:* Experiments can be imperfect, and approximate observational studies

Warning Taxpayers about Preparers

- ▶ *Partner:* US Tax Service (IRS)
- ▶ *Intervention:* Letters to taxpayers with info about their tax preparers
- ▶ *Finding:* Changed taxpayer filing behavior
- ▶ *A Lesson:* Well-designed experiments can measure interference/spillovers

Opioid Buyback

- ▶ *Partner:* Veterans Affairs Hospital
- ▶ *Intervention:* Reminder card mailed one week after surgery
- ▶ *Finding:* Improved rates of return by 30% (7pp)
- ▶ *A Lesson:* Connect at a reasonable, appropriate moment

Fire Inspector Risk-Score Lists

- ▶ *Partner:* DC Fire Inspectors
- ▶ *Intervention:* Randomize whether inspectors receive lists of buildings that come from *high risk scores* or *all risk scores*
- ▶ *Finding:* (Stay tuned!)
- ▶ *A Lesson:* We can combine data science predictive modeling and field experiments fruitfully; models should be validated in the field.

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▶ Ride Along

- ▶ Understand how implementers view data
- ▶ Gain technical knowledge of context, processes (EMS, pothole team, fire inspectors, ...)
- ▶ Fastest way to learn: watch the experts

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 - ▶ Avoid harm, gain consent
 - ▶ We are constantly “experimenting”
 - ▶ Resources are limited
 - ▶ Agents really do want to learn

Thank you
for an extraordinary week.
Stay in touch!

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