

Experimental Design as Market Design

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Golden Age of Randomized Experiments

Randomized Controlled Trials (RCT) or A/B tests
=Gold standard of evidence-based decision-making in

1. Medicine



2. Social Policy



3. Web



- Stake is often high & sometimes life-or-death (especially in 1 & 2; e.g. cancer & malaria treatment, basic income)
- # of subjects is large (especially in 1 & 3)

My agenda: **Propose randomized experiment that respects subject welfare**

Preview

I propose an experimental design that at once satisfies

- ① randomly assigning treatment &
generating at least as much causal info as usual RCT
- ② as much as possible, assigning treatment to subjects with
 - better predicted treatment effects or
 - stronger preferences for the treatment



Usual designs fail to satisfy (2)

Setting

i_1, \dots, i_n : Experimental subjects

t_0, t_1, \dots, t_m : Treatments

$c_t \in \mathbb{N}$: Treatment t 's capacity (with $\sum_t c_t \geq n$)

w_{it} : Subject i 's willingness to pay for treatment t with

$$w_{it} \geq w_{it'} \Leftrightarrow i \text{ weakly prefers } t \text{ over } t'$$

e_{ti} : t 's predicted treatment effect for subject i with

$$e_{ti} \geq e_{ti'} \Leftrightarrow t \text{ is predicted weakly more effective for } i \text{ than for } i'$$

t_0 : Placebo or control with normalization $e_{t_0 i} = w_{it_0} = 0$ for all i

Detail

Proposal

Definition (Experiment-as-Market a.k.a. EXaM)

- ① In computer, distribute common artificial budget b to every subject
- ② Find “price-discriminated market equilibrium”
i.e., feasible treatment assignment prob.s $(p_{it}^*)_{i,t}$ & prices $(\pi_{te}^*)_{t,e}$ with
 - Utility maximization s.t. budget constraint: For all i ,
$$(p_{it}^*)_t \in \operatorname{argmax}_{\text{feasible } (p_{it})_t} \sum_t p_{it} w_{it} \text{ s.t. } \sum_t p_{it} \pi_{te}^* \leq b$$

(Ties are broken by uniformly mixing cheapest (p_{it}) 's)
 - Effectiveness-discriminated treatment pricing: $\forall t \exists \alpha_t < 0 \ \& \ \beta_t \ \forall e$,
$$\pi_{te}^* = \alpha_t e + \beta_t$$
 - Meeting capacity constraint: $\sum_i p_{it}^* \leq c_t$ for all t
- ③ Draw final treatment assignment from $(p_{it}^*)_{i,t}$.

Getting to the Goals

Proposition (Randomized Controlled Welfare Property)

Experiment-as-Market always exists & satisfies:

- ① randomly assigning treatments,
i.e., $p_{it}^* = p_{i't}^*$ for all t, i, i' with $(w_{it}, e_{ti})_t = (w_{i't}, e_{ti'})_t$
generating at least as much causal info as usual RCT,
i.e., any thing identified by vanilla RCT is also identified by EXaM
- ② as much as possible, assigning treatment to subjects with
 - better predicted treatment effects or
 - stronger preferences for the treatmenti.e., \nexists assignment prob.s (p_{it}) with
 - $\sum_t p_{it} e_{ti} \geq \sum_t p_{it}^* e_{ti}$ (expected predicted effect) &
 - $\sum_t p_{it} w_{it} \geq \sum_t p_{it}^* w_{it}$ (expected willingness to pay)for all i with at least one strict inequality

Comparison with Existing Designs

Proposition

None of following designs has Randomized Controlled Welfare Property.

- Vanilla RCT

Designs respecting preferences:

- “Consent Trial” (Zelen 79, Angrist-Imbens 91, many medical RCT)
- “Selective Trial” (Chassang-Miquel-Snowberg 12)
- “Thompson Sampling” (Thompson 33, many web A/B tests)

Designs respecting predicted treatment effects:

- “Play-the-Winner Trial” (Wei-Durham 78, many medical RCT)
- “Adaptive Biased Coin Design” (Eisele 94, many medical RCT)
- “Empirical Welfare Maximization” (Manski 05, B-Dupas 12)

From Identification to Analyzing Data from EXaM

Recall EXaM makes treatments conditionally randomly assigned

Suggested Analysis Procedure

For simplicity assume only 1 treatment t_1 & control t_0 .

- 1 Identify t_1 's average effect conditional on $x_i \equiv (w_{it}, e_{ti})_t$ by

$$\underbrace{E(Y_i | i \text{ assigned } t_1, x_i)}_{\text{Observable}} - \underbrace{E(Y_i | i \text{ assigned } t_0, x_i)}_{\text{Observable}} \equiv (CATE)$$

- 2 Integrate (\$) to get treatment effects of interest
e.g. Average Treatment Effect = $\int (CATE) dF((x_i))$

Application in Progress



Setting:

Anti-malarial bed net pricing RCT in Kenya
(Cohen-Dupas 10)

Embedding this setting into my theory:

t_1 & t_0 : Free anti-malarial bed net & control

w_{it_1} : Subject i 's willingness to pay for bed net

→ Estimate it using C-D's randomization of bed net prices

$e_{t_1 i}$: Bed net's predicted treatment effect for subject i

→ Proxy it by i 's pre-RCT hemoglobin level (indicator of malaria)

Plan: Implement & compare Experiment-as-Market vs existing designs

Future Directions

Further econometric comparison of EAaM vs existing designs by...

- Identification (Blackwell-informativeness or identifiable parameters)?
- Estimation (Power or mean squared error)?

Extensions to...

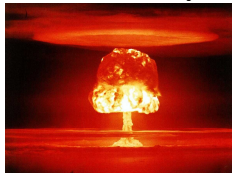
- Dynamic (sequential) design?
- Uncertain & multi-dimensional predicted effects e_{ti} ?
- Endogenous sample size n ?

Using my framework to analyze other key aspects of RCT?

(e.g. pre-analysis plan, re-randomization, external validity, attrition)

Stepping Back: The Science Unto Death

Science not only saves us but also kills us:



Atomic bomb



Biological weapon

Randomized experiment

Y Combinator announces basic income pilot experiment in Oakland

Posted May 31, 2016 by [Kate Conger](#) (@kateconger)



Experiment-as-Market is step toward “best” allocation of lives & deaths created by randomization-driven science