Adaptive experimentation for social scientists

Jae Yeon Kim

Most of the stuff here is based on the following resources:

1. 10 Things to Know About Adaptive Experimental Design by Donald Green: https://egap.org/resource/10-things-to-know-about-adaptive-experimental-design/

2. Adaptive experiments for policy research by Maximiilian Kasy and Anja Sautmann: https://voxdev.org/topic/methods-measurement/adaptive-experiments-policy-research

3. Adaptive Experimental Design: Prospects and Applications in Political Science by Offer-Westort, Coppock, and Green: https://ajps.org/2021/02/08/adaptive-experimental-design-prospects-and-applications-in-political-science/

4. Adaptive & Iterative Experimentation by Susan Athey and her team (this is a series of projects and papers): https://www.gsb.stanford.edu/faculty-

I'm still learning about this field, and there's a lot to learn. I am looking forward to learning from you as well.

What is adaptive exprimentation?

Static design: every aspect of an experimental design (e.g., treatment characteristics, sample size) is fixed in advance. It's recommended to pre-register these things before running an experiment to avoid p-hacking.

Adaptive design: some aspects of an experimental design will change in the process of experimentation based on the relationship between the experimental design and outcomes. (The idea is pretty old ... see Thompson (1933) and Wei (1978))

Pros and Cons

Pros: a principled way of optimizing an experimental design by allocating resources (survey respondents) efficiently across treatment arms (one instance of adaptive design).

This benefit is huge if you have (1) competing interventionist and (2) care about increasing the probability of succeeding an experiment.

Pros and Cons

Cons: "no guarantee that adaptive design outperforms static design in terms of speed or accuracy" (Green's point). What if all treatment arms are equally effective? What about the random variations in the searching process?

For these reasons, adaptive design needs "multiple periods of treatment and outcome assessment."

So, if you have N = 1,000, divide them in 10 periods (100 for each).

TL;DR:

1. Experimentation is precise but the learning cost is high ... Adaptive design is one way to solve this problem.
2. However, this design is likely to work if you have sequential observations in an experimental setting.
3. Recent approaches try to make this limitation as less restricting and also introduce

Adaptation

How does it work?

1. Algorithms: Based on algorithms that balance between exploration and exploitation. The most popular one is Thompson sampling (Thompson 1933). For a more recent approach, see Kasy and Sautmann (2020) (putting more emphasis on exploration) and Offer-westort, Coppock, and Green (2021) (allocating respondents to the best arm as well as control)

2. Bias correction: Adaptiation can increase bias in the treatment estimation. So, "applying inverse probability weights for each period" might be useful to correct this problem (Gerber and Green 2012).

These two elements should be included in a pre-analysis plan.

Figure 2 Share of successful calls in each treatment arm

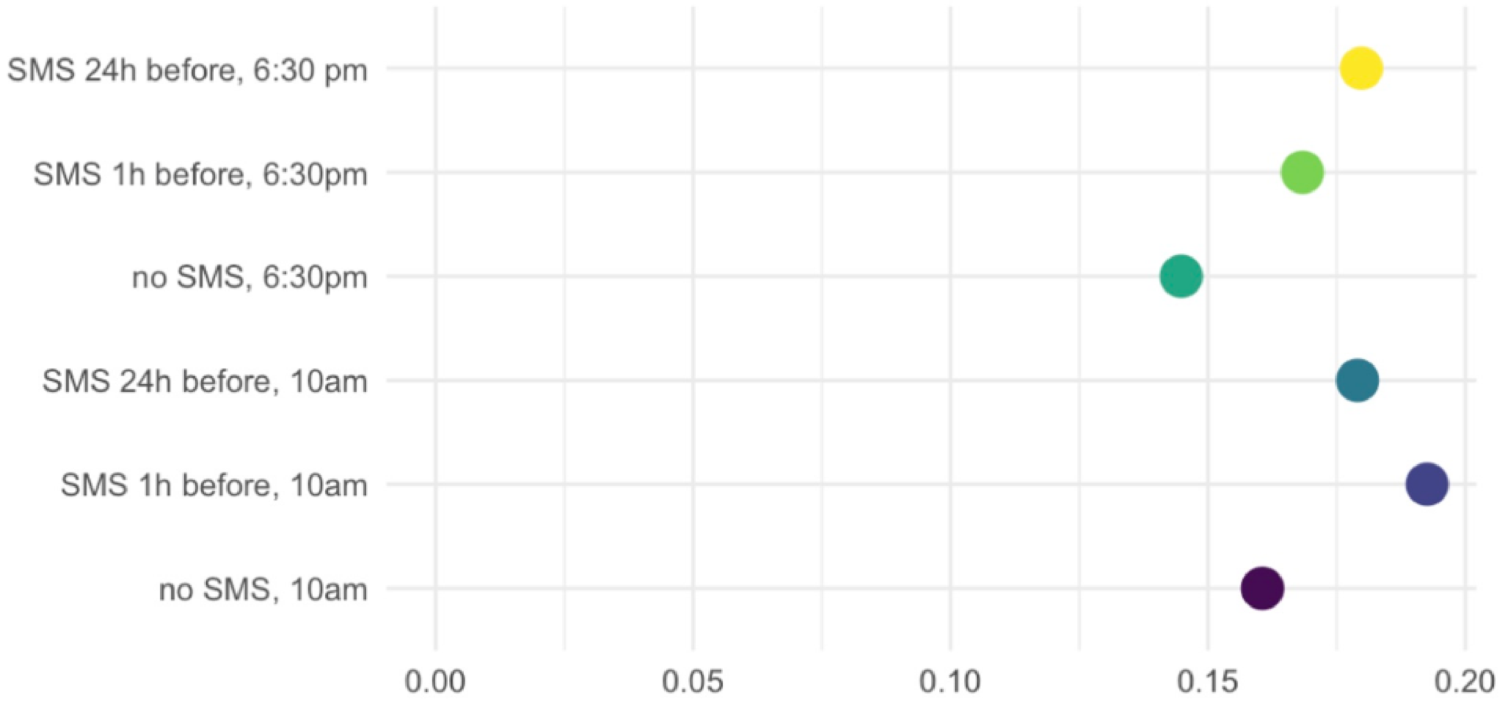


Figure 3 Assignment shares over time

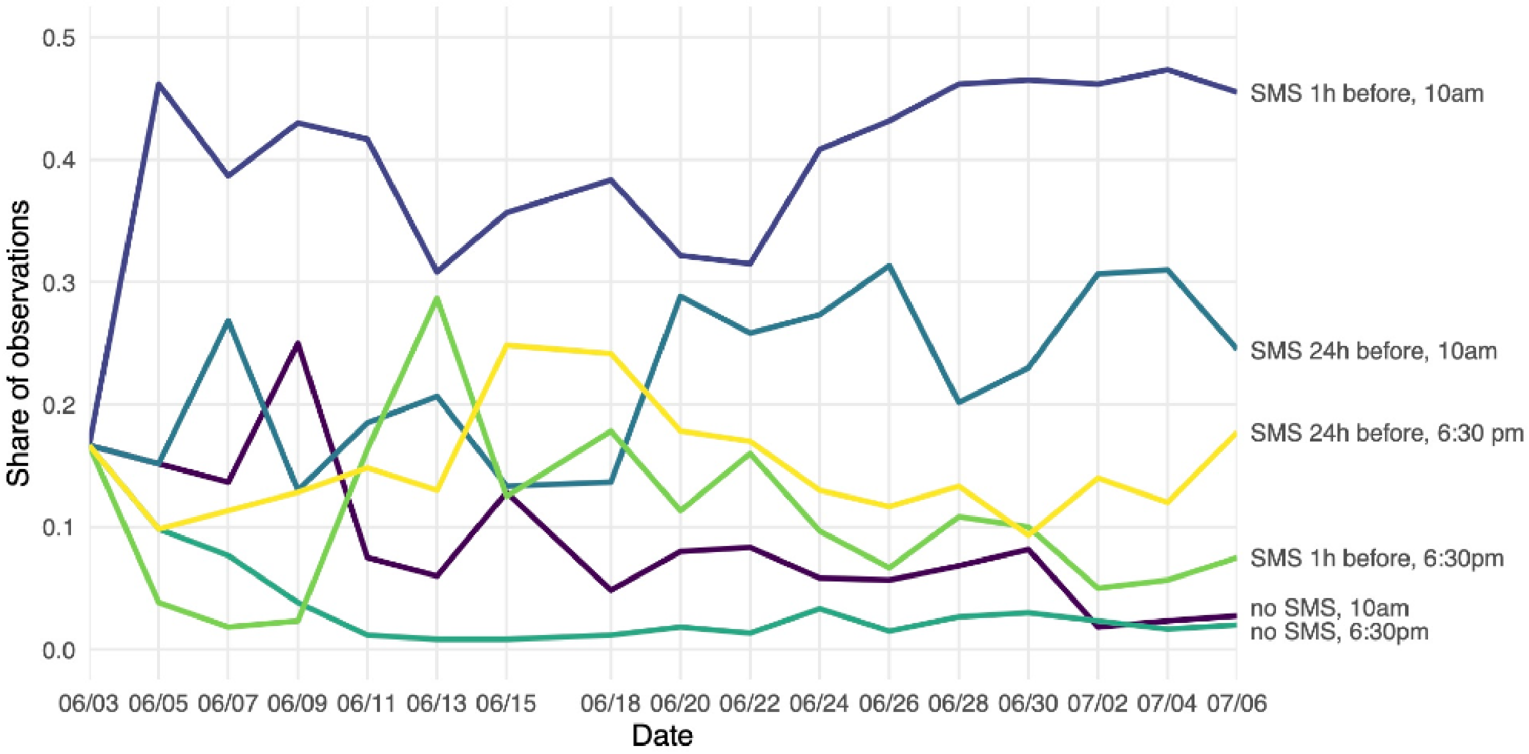


Figure 4 Aggregate number of observations (phone numbers) assigned to each treatment arm at the end of the experiment

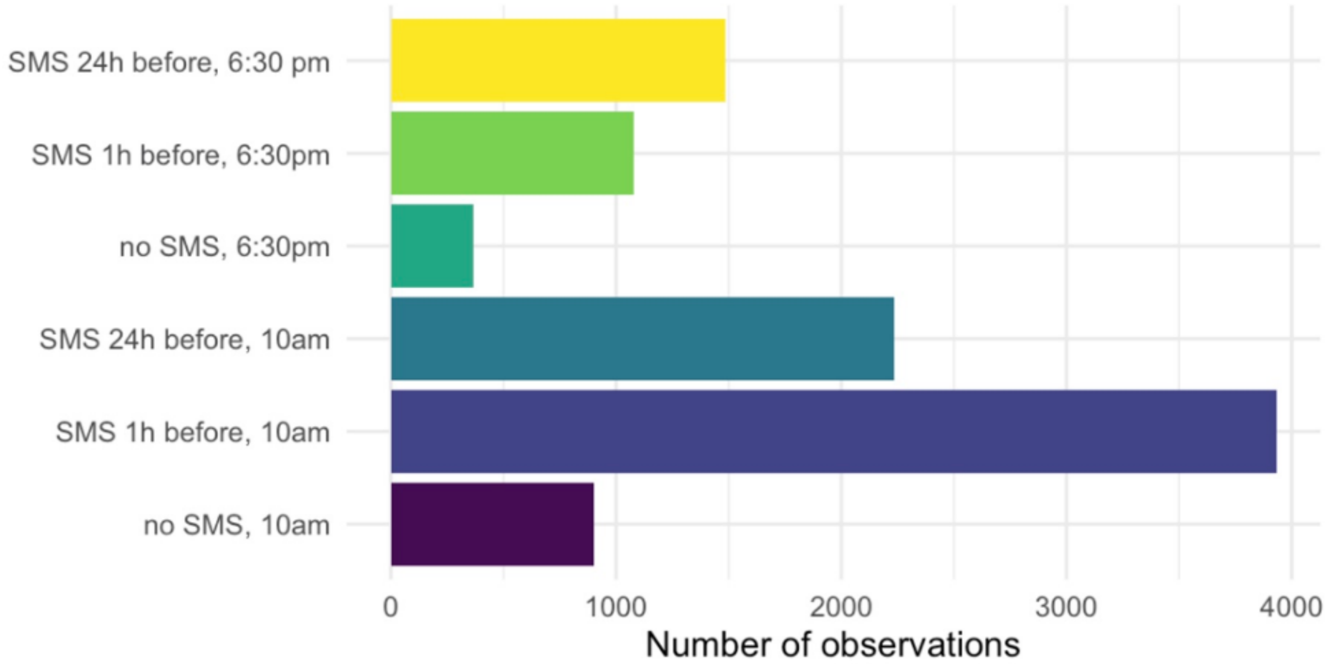
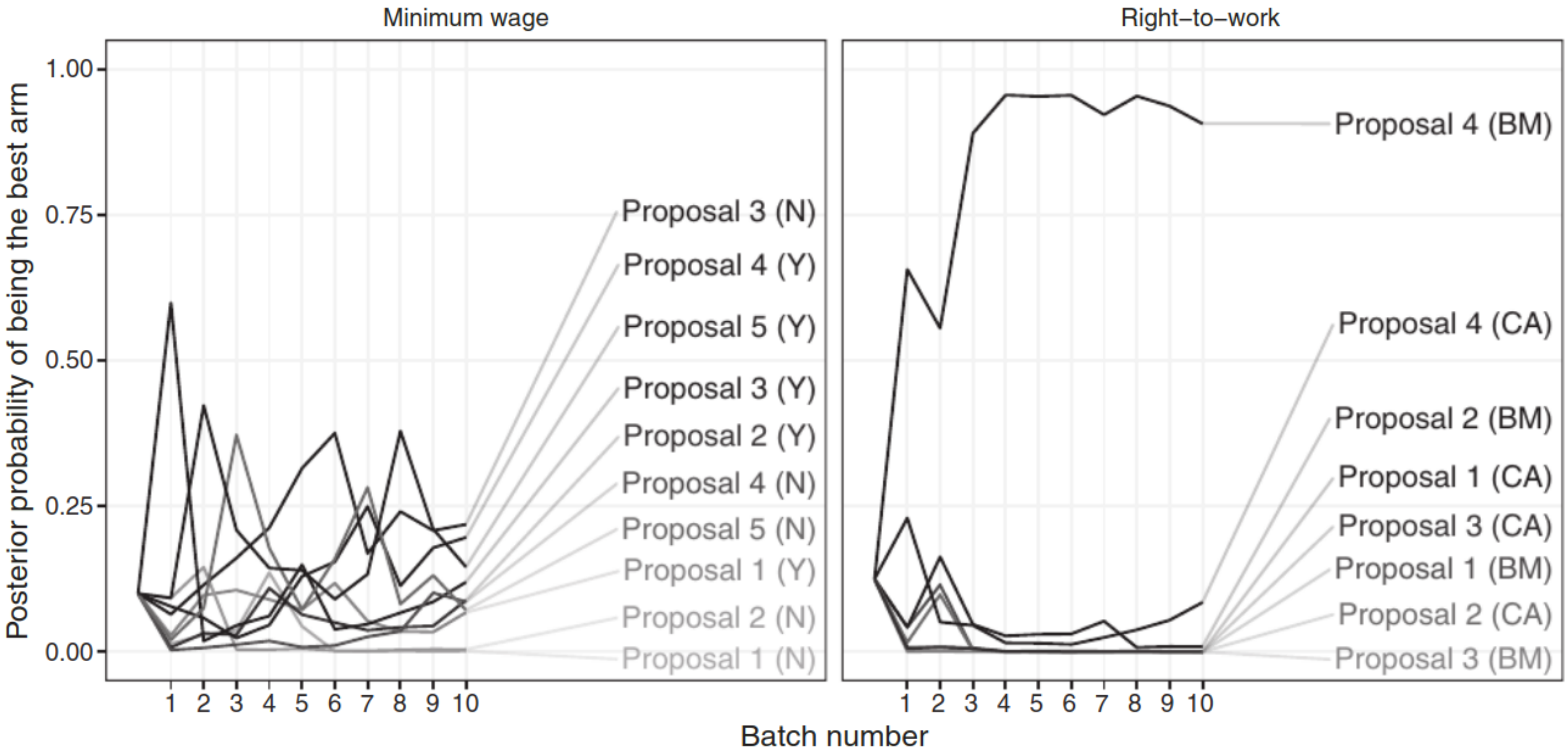
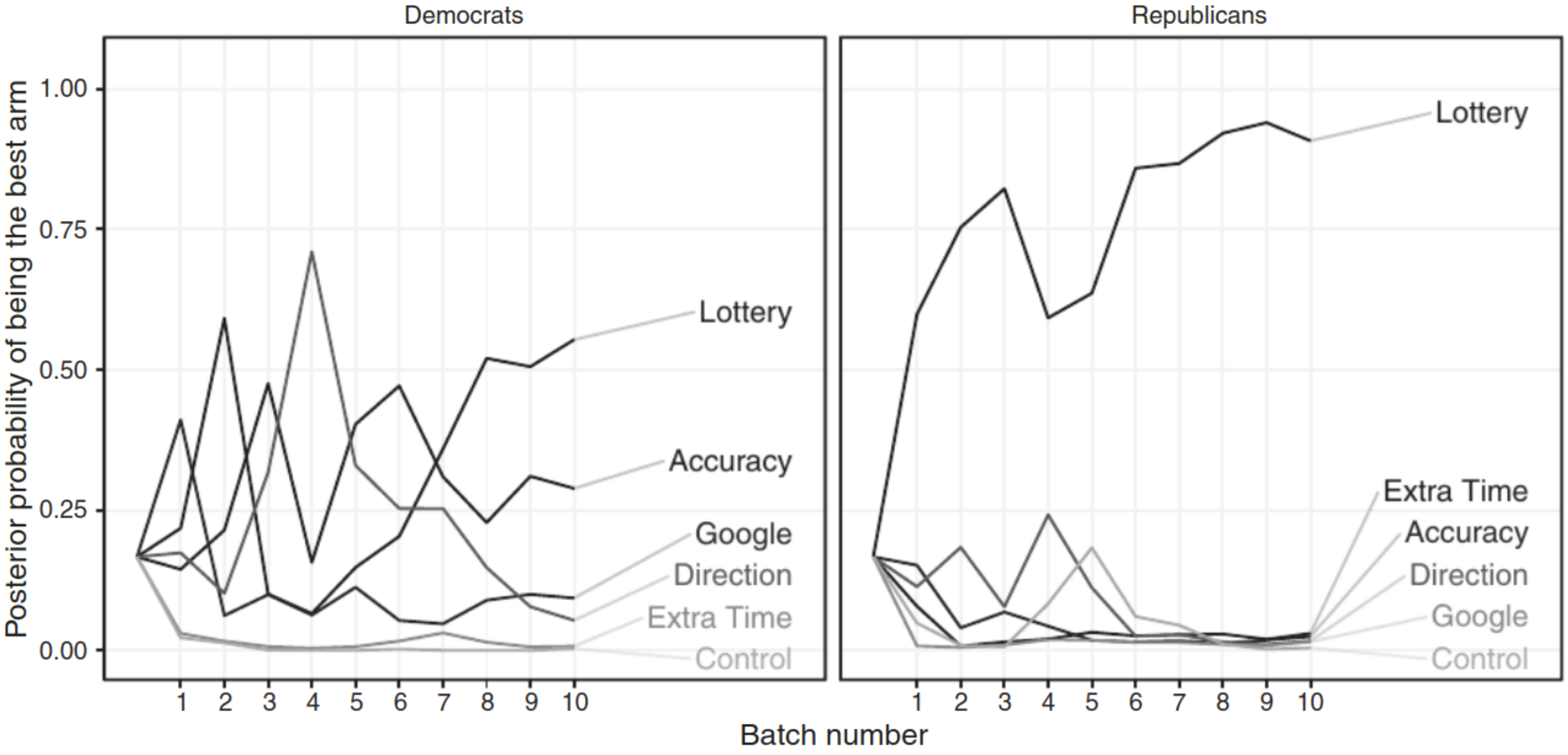


FIGURE 3 Study 1, Over Time Posterior Probabilities



Note: "Y" versions of the minimum wage proposals include the current minimum wage and "N" versions do not. 'CA' versions of the right-to-work proposals are described as 'constitutional amendments' and 'BM' ('ballot measure') versions are not.

FIGURE 5 Study 2, Overtime Posterior Probabilities



Applications

A very popular method in the industry (e.g., website and mobile optimization)

Gaining popularity in biomedical research: see Chow and Chang (2008) for a review on adaptive experimentation in clinical trials: https://ojrd.biomedcentral.com/articles/10.1186/1750-1172-3-11

Not much so in social science research. But there are individuals and groups already leading the way in econ, political science, etc .

Tools

README.md

Ax

pypi v0.1.20 | python 3 | wheel yes | Build and Test Workflow passing | codecov 94% | license MIT

Ax is an accessible, general-purpose platform for understanding, managing, deploying, and automating adaptive experiments.

Adaptive experimentation is the machine-learning guided process of iteratively exploring a (possibly infinite) parameter space in order to identify optimal configurations in a resource-efficient manner. Ax currently supports Bayesian optimization and bandit optimization as exploration strategies. Bayesian optimization in Ax is powered by BoTorch, a modern library for Bayesian optimization research built on PyTorch.

For full documentation and tutorials, see the Ax website