Assignment #5
MACS 30000, Dr. Evans
Due Monday, Nov. 12 at 11:30am
Haowen Shang

1. **Experiments on Amazon Mechanical Turk**

(a) I am interested in "Investment experiment (~10 mins $$ BONUS UP TO 75 CENTS)". This experiment is created by Fynn Gerken.

(b) The flat-rate reward of this experiment is $0.5 and the bonus is up to $0.75. The total reward is up to $1.25.
The reward is 50 cents for every participant. If participants choose to answer the 3 comprehension questions, they will earn 25 cents bonus for each correct answer.

(c) There are four qualifications required for this experiment.
First, the participant should be located in US. Second, the participant's HIT approval rate (%) should be greater than 95. Third, the participant's previous participation has not been granted. Fourth, the participant needs to do an investment test with 3 questions to make sure his investment experience is 100.

(d) This job takes 10 minutes. The implied hourly rate is $3 per hour for participants who just participate without answering comprehension questions, and up to $7.5 per hour for who answer the comprehension questions correctly.

(e) This job expires on 11/30/2018 (in 21 days from 11/09/2018).

(f) This project would cost the HIT experiment creator $ 1,250,000 at most if 1 million people participated in the task.

Reference:

Amazon Mechanical Turk website:
https://worker.mturk.com/?filters%5Bsearch_term%5D=experiment&page_size=20&page_number=1&sort=num_hits_desc&filters%5Bmin_reward%5D=0.01

2. Costa and Kahn (2013)

In the paper "*Energy Conservation Nudges and Environmentalist Ideology: Evidence from a Randomized Residential Electricity Field Experiment*", the authors try to answer the question: "How do political ideology and environmentalism influence household's response to energy conservation "nudge" of providing a home electricity report?" (Costa & Kahn, 2013, p.680).

In order to answer this question, the authors merged 4 data sources to create a data set. The data sources are "residential billing data from January 2007 to October 2009", "treatment and control data", "individual voter registration and marketing data for March 2009", and "an ancillary data set" (Costa & Kahn, 2013, p.685-686).
Firstly, the residential billing data (provided by an electric utility company) has the households' information on "kilowatt hours purchased per billing cycle", "the length of the billing cycle (measured in days)", "whether the house uses electric heat", "whether the household is enrolled in the electric utility's program to purchase energy from renewable sources" and "the mean temperature in that billing cycle" (Costa & Kahn, 2013, p.685). Secondly, the treatment and control data contains information on "when the household began to receive the HERs", "square footage of the house", "whether the home heats with electricity or natural gas", and "the age of the house" (Costa & Kahn, 2013, p.685). Thirdly, the individual voter registration and marketing data (purchased from www.aristotle.com) contains the information on "party affiliation", "whether the individual donates to environmental organizations", and "by the census block group, the share of registered voters who were liberal (Democrat, Green, or Peace and Freedom) in 2000 and the share of the college-educated in the block group" (Costa & Kahn, 2013, p.685). Last, the ancillary data set comes from a survey that the electric utility company in 2009 conducted. In this survey, 1,375 households were asked questions about the HER report they received, so this data set contains the information about the households' attitudes of the HER (Costa & Kahn, 2013, p.686).

The authors used a randomized HER experiment. The treatment in this experiment is sending households a Home Energy Report. The control group has around 49,000 households who have never received a HER, while the treatment group has around 35,000 households who received the report on a quarterly or monthly basis (Costa & Kahn, 2013, p.683). "The HER experiment selected households from 85 census tracts with a high density of single-family homes" (Costa & Kahn, 2013, p.683). There are some requirements for treatment and control households: "they had to have a current account with the electric utility that had been active for at least one year, could not be living in apartment buildings, and had to be living in a house with square footage between 250 and 99,998 square feet" (Costa & Kahn, 2013, p.683). The households in treatment or control group were randomly chosen from groups of contiguous census blocks (Costa & Kahn, 2013, p.683). "A "block batch" of five contiguous census blocks was randomly assigned to the treatment group and then a contiguous census block batch was assigned to the control group" (Costa & Kahn, 2013, p.683). Both treatment and control groups roughly have 35,000 households in this process and the 14,000 households in the remaining census blocks were added into the control group (Costa & Kahn, 2013, p.683).

Schultz et al. (2007) used within-subjects design to explore "how normative information may differentially affect an important social behavior depending on whether the message recipients' behavior is above or below the norm" (Schultz, Nolan, Cialdini, Goldstein, and Griskevicius, 2007, p.430). In order to control for participant heterogeneity, they divided households into two categories: those with energy consumption above average for the community and those with energy consumption below average for the community. In Costa and Kahn's study, they used mixed design of experimental research. Beyond the previous work of Schultz et al. (2007), the extra layer of participant heterogeneity they controlled for is the household environmental ideology. The ideology was measured by "the customer's political party of registration, household donations to environmental organizations, household participation in renewable energy programs, and the characteristics of the local residential communities where the households live" (Costa & Kahn, 2013, p.681).

Costa and Kahn find that compared with political conservatives, "liberal households are less likely to drop out of the experiment and more likely to report that they like receiving the report" (Costa & Kahn, 2013, p.698). And liberal households' response to reduce much more electricity consumption than conservatives (Costa & Kahn, 2013, p.698). Also, "environmental nudges are most effective in relatively liberal communities" (Costa & Kahn, 2013, p.698).

Reference:

Costa, Dora L. and Matthew E. Kahn, "Energy Conservation Nudges and Environmentalist Ideology: Evidence from a Randomized Residential Electricity Field Experiment," Journal of the European Economic Association, June 2013, 11 (3), 680–702.

P. Wesley Schultz, Jessica M. Nolan, Robert B. Cialdini, Noah J. Goldstein, and Vladas Griskevicius, "The Constructive, Destructive, and Re- constructive Power of Social Norms," Psychological Science, 2007, 18 (5), 429–434.

3. Analytical exercise

(a) In this experiment, we want to estimate the effect of receiving text message reminders on vaccination uptake. The treatment is text message reminders. The treatment group is patients who receive text message reminders while the control group is patients without receiving text message reminders. We want our estimation to be valid, so we need to reduce spillovers and hidden treatment effects. If there are few unobserved factors, the treatment from one person doesn't spill over onto another person and nothing other than the treatment that causes people in the treatment and control conditions to be treated differently (Salganik, 2018, p.207), we can focus our resources on a small number of clinics with lower cost. Otherwise, if there are many unobserved factors between clinics, and there are spillovers and hidden treatment effect, then we need spread our resources more widely to balance on unobserved factors, reduce standard error of average treatment effect and reduce spillovers and hidden treatment effects. For example, if patients from the same clinic will communicate with each other and affect each other on their vaccination decisions(spillovers) and the reputation and location of clinics also influence patient's decisions on vaccination (hidden treatment effect), then we need to choose more clinics to balance on these unobserved factors.

(b) "It is hard to detect a relative small effect in noisy outcome data. But if you difference-out this naturally occurring variability, then there is much less variability, and that makes it easier to detect a small effect." (Salganik, 2018, p.209). In order to detect a smaller effect, we need to reduce variability. In other words, we need the standard error of average treatment effect to be smaller when we want to detect a smaller effect. The first factor to determine the smallest effect size is the number of subjects, because larger sample size leads to higher precision level and smaller standard error of average treatment effect and then smaller effect can be detected. The more subjects we have, the smaller effect we can detect. The experiment design is also a factor to determine the smallest effect size. When using the mixed design with difference-in-means estimator, smaller effect can be detected than using the between subjects design with difference-in-means estimator. "A difference-in-differences estimator, which is typically used in a mixed design, can lead to smaller variance than a difference-in-means estimator, which is typically used in a between-subjects design." (Salganik, 2018, p.208). If we use the between-subjects design, we will use difference-of-means estimator to estimate the average treatment effect. Then the allocation of participants is another factor to determine the smallest effect size, because if we use the optimal allocation of participants to make sure the costs of treatment and control in the standard error are the same, then the smallest effect size will be detected. In conclusion, the number of subjects, the experiment design and the allocation of participants will determine the smallest effect size we can detect with our budget.

Reference:

Salganik, Matthew J., Bit by Bit: Social Research in the Digital Age, Princeton University Press, 2018.