Experiment-as-Market: 
Incorporating Welfare into Randomized Controlled Trials*

Yusuke Narita†

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Abstract

Randomized Controlled Trials (RCTs) enroll hundreds of millions of subjects and involve many human lives. To improve subjects’ welfare, I propose a design of RCTs that I call Experiment-as-Market (EXAM). EXAM produces a Pareto efficient allocation of treatment assignment probabilities, is asymptotically incentive compatible for preference elicitation, and unbiasedly estimates any causal effect estimable with standard RCTs. I quantify these properties by applying EXAM to a water cleaning experiment in Kenya (Kremer et al. 2011). In this empirical setting, compared to standard RCTs, EXAM substantially improves subjects’ predicted well-being while reaching similar treatment effect estimates with similar precision.

Keywords: Clinical Trial, Social Experiment, A/B Test, Market Design, Competitive Equilibrium from Equal Income, Pareto Efficiency, Causal Inference, Development Economics

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†Yale University, Department of Economics and Cowles Foundation. Email: yusuke.narita@yale.edu
URL: www.yusuke-narita.com Address: 37 Hillhouse Avenue, New Haven, CT 06511

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1 Introduction

Today is the golden age of Randomized Controlled Trials (RCTs). RCTs started as safety and efficacy tests of farming and medical treatments, but have grown to become the society-wide standard of evidence. RCTs are widespread in business and politics, as well as public policy, the social sciences, and engineering.

RCTs are high-stakes. Firstly, a large number of individuals participate in RCTs. I find that over 360 million patients and 22 million individuals participated in registered clinical trials and social RCTs, respectively, during 2007-17. Second, many RCTs randomize high-stakes and even life-or-death treatments. For instance, in a glioblastoma therapy trial, the five-year death rate of glioblastoma patients is 97% in the control group but only 88% in the treatment group (Stupp et al. 2009). In expectation, therefore, the lives of up to 9% of the study’s 573 participants depend on who receives treatments. Social RCTs also randomize critical treatments such as basic income\(^1\), high-wage job offers (Dal Bó et al. 2013), and HIV testing (Angelucci and Bennett 2017). This high-stakes nature even prompted some RCT participants to sue their experimenters.\(^2\)

RCTs thus determine the fate of numerous people, giving rise to a long-standing dilemma:

> How can a physician committed to doing what he thinks is best for each patient tell a woman with breast cancer that he is choosing her treatment by something like a coin toss? How can he give up the option to make changes in treatment according to the patient’s responses? (“Patients’ Preferences in Randomized Clinical Trials” by physician Marcia Angell)

Similar concerns motivated pioneering experimental designs to incorporate participant preferences as a welfare measure into treatment assignment probabilities (Zelen 1979; Angrist and Imbens 1991; Chassang et al. 2012). Other prior designs respect another welfare measure, i.e., predicted treatment effects (Zelen 1969; Wei and Durham 1978).

This paper develops an experimental design that optimally incorporates both of the two welfare criteria (preferences and predicted effects), thus further alleviating the concern with RCTs. This experimental design not only improves participant welfare, but also always unbiasedly and often precisely estimates treatment effects.

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I start by defining experimental designs as procedures that determine each subject’s treatment assignment probabilities based on data about two measures of welfare: (a) the predicted treatment effect of each treatment on each subject and (b) each subject’s willingness-to-pay (WTP) for each treatment. These complementary welfare measures are allowed to be heterogeneous and correlated with each other. In practice, the experimenter may estimate them from prior experimental or observational data, or ask subjects to self-report them, especially WTP.

I propose an experimental design that I call Experiment-as-Market (EXAM). I choose this name because EXAM is an experimental design based on an imaginary centralized market, inspired by the idea of competitive market equilibrium from equal incomes (Friedman, 1962; Varian, 1974; Hylland and Zeckhauser, 1979; Budish et al., 2013; He et al., 2017; Mollner and Weyl, 2018). EXAM uses this artificial market to Pareto optimally incorporate both predicted effects and WTP.

Specifically, EXAM randomly assigns treatments to subjects via the following hypothetical market created in the experimenter’s computer. EXAM first endows each subject with a common artificial budget and lets her use the budget to purchase the most preferred (highest WTP) bundle of treatment assignment probabilities given their prices. The prices are personalized so that each treatment is cheaper for subjects with better predicted effects of the treatment. EXAM computes its treatment assignment probabilities as what subjects demand at market clearing prices, where subjects’ aggregate demand for each treatment is balanced with its supply or capacity (assumed to be exogenously given). EXAM finally requires every subject to be assigned to every treatment with a positive probability.3

This virtual-market construction gives EXAM nice welfare and incentive properties. EXAM has a Pareto optimality property, in that no other design makes every subject better-off in terms of expected predicted effects of and WTP for assigned treatment. EXAM also allows the experimenter to elicit WTP in an asymptotically incentive compatible way. That is, when the experimenter asks subjects to self-report their WTP to be used by EXAM, every subject’s optimal choice is to report her true WTP, at least for large experiments.4

Importantly, EXAM also allows the experimenter to unbiasedly estimate the same treatment effects as standard RCTs do (in a finite sample and for a wide class of treatment effect parameters). To see this, note that in the end, EXAM is an experiment stratified on

3 EXAM is executable even without WTP and predicted effects (when WTP and predicted effects are unknown or irrelevant to the experimenter). When the experimenter uses neither WTP nor predicted effects, EXAM reduces to the standard RCT. EXAM therefore nests the standard RCT.

4 I have to be satisfied with asymptotic incentive compatibility since exact incentive compatibility is known to be incompatible with Pareto efficiency. The incentive analysis owes much to studies on the incentive compatibility of competitive equilibria and experimental designs (Jackson, 1992; Chassang et al., 2012; Azevedo and Budish, 2017; He et al., 2017).
observable predicted effects and WTP, in which the experimenter observes each subject’s assignment probabilities (propensity scores). As a result, EXAM’s treatment assignment is random (independent from potential outcomes) conditional on the observables. As in causal inference with stratified experiments and selection-on-observables (Imbens and Rubin 2015), the conditionally independent treatment assignment allows the experimenter to unbiasedly estimate the average treatment effects conditional on observables. By integrating such conditional effects, EXAM can unbiasedly estimate the (unconditional) average treatment effect and other effects. This informational virtue materializes regardless of whether the experimenter correctly predicts treatment effects and WTP.

I also characterize the statistical efficiency in EXAM’s average treatment effect estimation. EXAM’s standard error is potentially smaller than that of RCTs, but in general, the standard error comparison of EXAM and a typical RCT is ambiguous. This motivates an empirical comparison of the two designs, which also allows me to verify and quantify the other welfare, incentive, and unbiasedness properties.

I apply EXAM to data from a water cleaning experiment in Kenya (Kremer et al., 2011). Compared to RCTs, EXAM turns out to substantially improve participating households’ predicted welfare. Here, welfare is measured by predicted effects of clean water on child diarrhea and revealed WTP for water cleaning. EXAM is also found to almost always incentivize subjects to report their true WTP. Finally, EXAM’s data produces treatment effect estimates and standard errors similar to those from RCTs. EXAM therefore produces information that is as valuable for the outside society as that from RCTs.

Taken together, EXAM sheds light on a way economic thinking can “facilitate the advancement and use of complex adaptive (...) and other novel clinical trial designs,” a performance goal by the US Food and Drug Administration (FDA) for 2018-2022. Experimental design is a potentially life-saving application of economic market design (Roth, 2015). More concretely, my analysis shows how best to use predicted treatment effects for experimental design. The use of predicted effects for new experiments is established in medicine (Food and Drug Administration 2010) and business (White 2012), and emerging in the social sciences (Hahn et al., 2011) as important interventions such as deworming and conditional cash transfers ask for repeated evaluations. EXAM combines the predicted-effects consideration

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5 This experimental value of EXAM and competitive equilibrium from equal incomes echoes Abduladiroglu et al. (2017) and Narita (2016), who highlight the informational values of a different sort of mechanism design (centralized school choice with lotteries).

6 Along the way, I develop a computer program to implement EXAM with little computational cost. A single execution of EXAM on data with 1540 subjects and 2 treatments takes only 6 minutes on average with a standard personal computer.

with another idea of respecting subjects’ WTP for treatments.

After a review of related experimental designs, Section 2 outlines my motivation by providing facts about the impact of RCTs on participant welfare. Section 3 develops the EXAM experimental design, and Section 4 shows its welfare and incentive properties. Section 5 studies the experimental information embedded in EXAM and explains how to use data from EXAM for causal inference. An empirical application is in Section 6. Finally, Section 7 summarizes my findings, discusses their limitations, and outlines future directions. Proofs are in Appendix A.2.

1.1 Comparison with Existing Designs

Classical Experimental Design

The traditional experimental design literature (Cox and Cochran (1992), Athey and Imbens (2017) Section 7) is as old as the very concept of RCTs. This literature focuses on how to design experiments for maximizing information measured by the power of testing the null hypothesis of no treatment effect and other measures. This focus on information continues in much of the modern literature on sequential and adaptive experimental designs (Hahn et al., 2011). My interest lies more in subject welfare.

Preference- and Response-adaptive Designs

With its interest in subject well-being measured by WTP and predicted effects, EXAM is closer to younger and smaller strands of the literature on preference- and response-adaptive experimental designs. Preference-adaptive designs reflect subject preferences in treatment assignment probabilities. For example, Randomized Consent or Preference Trials (originally proposed by Zelen (1979) and further advocated by Angrist and Imbens (1991)) randomize subjects into two groups. In one group, subjects are allowed to choose the treatment or the control based on their preferences. All subjects in the other group are assigned to the control.

Selective Trials by Chassang et al. (2012) are more general preference-adaptive designs where the treatment assignment probability is increasing in the WTP for the treatment. Chassang et al. show their Selective Trials can be implemented as dominant-strategy mechanisms and are Blackwell more informative than RCTs in the limit. See also Björklund (1988) for a related experimental design proposal. Other examples of preference-adaptive designs are development economics RCTs that elicit and use subject preferences for treatment (Ashraf et al., 2006; Cohen and Dupas 2010; Ashraf et al., 2010; Devoto et al., 2012; Dupas 2014; Berry et al., 2018).
In complementary response-adaptive designs (reviewed by Hu and Rosenberger (2006) and Food and Drug Administration (2010)), the experimenter incorporates predicted treatment effects into treatment assignment probabilities. For example, Play-the-Winner Rules (Zelen, 1969; Wei and Durham, 1978) more likely assign a treatment to patients predicted to have better treatment effects.\footnote{The treatment assignment literature in econometrics (Manski, 2008) and medicine (Chakraborty and Moodie, 2013) attempts a related but distinct task of using experimental data to optimally assign treatment to maximize welfare alone. See also related biostatistics developments on optimal dynamic treatment regimes by Murphy (2003) and Robins et al. (2008) among others.}

Building upon these prior ideas, EXAM integrates preference- and response-adaptive designs into a single design. EXAM is formally shown to strike an optimal balance between WTP and predicted effects without compromising incentive compatibility and experimental information. EXAM thereby extends existing preference- and response-adaptive designs: If the experimenter shuts down WTP consideration by assuming constant WTP, EXAM simplifies to a Play-the-Winner Rule. Similarly, EXAM reduces to a Consent or Selective Trial if the experimenter ignores predicted effects.

**Multi-Armed Bandit Algorithms**

EXAM shares much of its spirit with Multi-Armed Bandit (MAB) algorithms in computer science, machine learning, and statistics (Bubeck and Cesa-Bianchi, 2012): Both MAB and EXAM strike a balance between exploration (gaining information) and exploitation (improving subject or experimenter welfare). MAB algorithms are popular in the web industry, especially for online ads, news, and recommendations (White, 2012). There are many differences between MAB and EXAM. For example, MAB mostly ignores incentive issues. In contrast, EXAM is formally and empirically shown to be nearly incentive compatible. EXAM may also be easier to implement than MAB since the implementation of MAB often requires a system for frequently observing outcome data and updating treatment assignment.

**Clinical Trial Practices and Regulations**

Finally, clinical trial practitioners and regulators have long recognized ethical concerns with RCTs, as highlighted in Marcia Angell’s quote in the introduction. Their concerns manifested in regulations and practices that safeguard patients from excessive experimentation. Primary examples include the following: informed consent, a “stopping rule” that requires a sequential clinical trial to terminate if it becomes clear that its treatment is sufficiently better or worse than the control (Friedman et al. (1998) chapters 2 and 16), and a “randomized phase-in” design that assigns everybody to the treatment with randomized timing (Duflo et al.
EXAM complements these existing practices and specify treatment assignment probabilities conditional on deciding to conduct a trial at a point in time and having subjects agreeing to participate in the trial.

2 Why Subject Welfare?

My goal is to design an experiment with an emphasis on subject welfare. Why should I study subject well-being? This section provides normative and practical reasons. Here I focus on the internal welfare of experimental subjects, leaving the external welfare of the outside population to Sections 5 and 6.

Normative Considerations

First, RCTs involve a large number of subjects. To demonstrate it, I assembled data on clinical trials registered in the WHO International Clinical Trials Registry Platform (ICTRP)\(^9\). ICTRP is the largest international clinical trial registry and subsumes domestic platforms like ClinicalTrials.gov for the US\(^10\). Table 1 Panel a shows that the sum of sample sizes of registered trials is over 360 million for 2007-2017. As for social and economic RCTs, I scraped the American Economic Association’s registry to find the sum of sample sizes of registered RCTs amounts to above 22 million for the last decade (Table 1 Panel b)\(^11\).

For such a large subject population, RCTs frequently randomize high-stakes treatment. The high-stakes and occasionally life-threatening nature of many RCTs is highlighted by examples in Table 2. In the first clinical trial (row i in Panel a), for example, a cholesterol-lowering drug treatment was found to lower the 5-year death rate of heart disease patients by about 30% relative to the baseline death rate in the control group. Other clinical trials in Table 2 Panel a also report significant impacts on survival and other crucial outcomes\(^12\). As exemplified in Table 2 Panel b, social and economic RCTs also randomize treatment such as

\(^11\) More detailed statistics are in Appendix Tables A.1-A.6. It is important to note that the figures in Table 1 are likely to underestimate the total scale of the RCT landscape. Many countries (such as Australia and Japan) do not legally require clinical trials to register (as of January 2019). Even when trials are required to register, the expected fine for failing to do so is often negligible compared to the total trial cost; see Stat News’ article, “Failure to report: A STAT investigation of clinical trials reporting,” at https://www.statnews.com/2015/12/13/clinical-trials-investigation/ retrieved in January 2019. As a consequence of these regulatory loopholes, there is likely a “dark pool” of clinical trials never reflected in any public database like ICTRP (Goldacre 2014). Consistent with this hypothesis, as legal and institutional pressures for trial registration mount, the annual numbers of registered trials and subjects are rapidly growing (about 14 million in 2007 vs. 72 million in 2016 for the number of subjects; see Appendix Figure A.1). This means that these figures will likely be larger in the next decade.

\(^12\) The medical ethics literature reviews other examples (Shamoo and Resnik 2009 chapters 12 and 13).
cash transfers, health insurance, HIV testing, and police patrol, as well as other numerous interventions related to childhood development, education, labor, and public finance \cite{Fryer2017, Rothstein2017}. These treatments are often found to have profound treatment effects.

Practical Considerations

Practical considerations also motivate a care for subject welfare. The successful implementation of any RCT depends on subject choices, including whether subjects participate in the RCT, whether subjects take up and use the assigned treatment, and whether subjects stay in contact in a follow-up period. The RCT produces useful information only if participants are active in each step. This prerequisite is hard to achieve, however. RCTs often suffer from subject indifference or fear in the form of non-participation, non-compliance, and dropouts before, during, and after experiments \cite{Friedman1998, Duflo2007, Glennerster2017}.

A welfare-conscious experimental design could alleviate non-participation, non-compliance, and dropouts. Indeed, \cite{King2005} provide a clinical trial meta-analysis suggesting that incorporating subject preferences makes subject recruitment easier. In a range of econometric and theoretical models, welfare-enhancing treatment assignment is predicted to facilitate compliance with treatment assignment \cite{Bjorklund1987, Heckman2005, Chan2006}. \cite{Chan2006} use AIDS trial data to find that subjects experiencing better treatment effects are less likely to drop out.\footnote{In an effort to maximize the treatment take-up rate and minimize attrition, many field experiments start with an expression-of-interest survey before randomization and recruit only survey respondents who express strong interest. This recruitment practice causes external validity concerns. These concerns may also be alleviated by replacing the experimenter’s discretionary selective recruitment with an experimental design respecting subject welfare in a rule-based way. See also \cite{Hull2018} and references therein for other survey designs and analysis methods to deal with attrition.}

Finally, ethical experimental designs would ease collaboration with partner governments and companies that may have an ethical and reputational concern with involvement in RCTs \cite{Glennerster2017}.

3 Experiment-as-Market (EXAM)

3.1 Framework

The normative and practical importance of subject well-being prompts me to design an experiment that balances subject welfare with experimental information. An experimental...
design problem consists of:

- Experimental subjects $i_1, ..., i_n$.
- Experimental treatments $t_0, t_1, ..., t_m$ where $t_0$ is a placebo or control.
- Each subject $i$’s preference or WTP $w_{it} \in \mathbb{R}$ for treatment $t$ where $w_{it} \geq w_{it'}$ means subject $i$ weakly prefers treatment $t$ over $t'$. Let $w_i \equiv (w_{it})_t$.
- Each treatment $t$’s predicted treatment effect $e_{ti} \in \mathbb{R}$ for subject $i$ where $e_{ti} \geq e_{t'i}$ means treatment $t$ is predicted to have a weakly better effect than $t'$ for subject $i$. When multiple outcomes matter, $e_{ti}$ can be set to the predicted effect on a known function of these outcomes. Let $e_i \equiv (e_{ti})_t$.

I assume $e_{ti}$ and $w_{it}$ to be deterministic for simplicity. I normalize $e_{ti}$ and $w_{it}$ by assuming $e_{t_0i} = w_{i0} = 0$ for every subject $i$. $e_{ti}$ and $w_{it}$ are therefore the predicted effect of $t$ and WTP for $t$, respectively, relative to the control $t_0$. This normalization is without loss of generality because only differences in WTP and predicted effects matter for subject welfare from treatments $t_0, ..., t_m$. Every experimental design discussed below produces the same assignment probabilities with and without the normalization.

I use $e_{ti}$ and $w_{it}$ as complementary welfare measures, one outcome- or treatment-effect-based and one WTP-based. Each has an established role in economic welfare analysis, especially because WTP is sometimes found to be weakly or even negatively correlated with treatment effects (Walters, 2018). The medical literature more frequently studies treatment effects but also acknowledges that patients often have heterogeneous preferences for treatments (even conditional on treatment effects). This is especially the case for psychologically sensitive treatments like abortion methods (Henshaw et al., 1993) and depression treatments (Chilvers et al., 2001). In response to these findings, a US-government-endorsed movement tries to bridge the gap between evidence-based medicine and patient-preference-centered medicine (Food and Drug Administration, 2016). According to advocates, “patient-centered care (...) promotes respect and patient autonomy; it is considered an end in itself, not merely a means to achieve other health outcomes” (Epstein and Peters, 2009). My welfare criterion echoes this trend and accommodates both outcome- and preference-based approaches.

Predicted effects and WTP may also be freely heterogeneous and correlated. This is an important generality since evidence of correlation between treatment effects and WTP is ample both in the social sciences and medicine (Preference Collaborative Review Group).

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14 Here I assume WTP and predicted effects are fixed and with cardinal meaning. See Appendices A.1.3 and A.1.4 for discussions about what to do when WTP and predicted effects are uncertain or ordinal.
To be consistent with the evidence, the above setup allows arbitrary correlation between predicted effects and WTP.

### 3.1.1 Where Do WTP and Predicted Effects Come From?

It is best to estimate predicted effects $e_{ti}$ from prior experimental or observational data. In particular, the experimenter could use prior data to estimate heterogeneous treatment effects conditional (stratified) on observable subject characteristics, and apply the estimates to each subject $i$’s characteristics, producing predicted effects $e_{ti}$. The most reliable data source is a prior RCT of the same treatment. Subjects in the prior RCT can be different from those in the new experiment to be designed. Such sequential RCTs with the same treatment are common in medicine ([Friedman et al., 1998](https://www.ncbi.nlm.nih.gov/pubmed/9809499)) and business ([Siroker and Koomen, 2013](https://doi.org/10.1037/0022-3514.75.6.1081)), and are growing in the social sciences (e.g., many RCTs for deworming). I illustrate the use of prior RCT data in my empirical application.

For WTP $w_{it}$, there are a couple of possible sources. The experimenter may ask each subject $i$ to self-report WTP $w_i$ in an incentive compatible way, as proposed by [Zelen (1979)](https://www.jstor.org/stable/23375144) and [Chassang et al. (2012)](https://doi.org/10.1007/s10680-012-9359-3). Alternatively, the experimenter may estimate WTP with prior data on subjects’ treatment choices and their observable characteristics. Such data allows the experimenter to estimate heterogeneous revealed WTP conditional on subject characteristics. The WTP estimates then provide the experimenter with a prediction for each subject $i$’s WTP given $i$’s characteristics. I conduct such demand estimation with a discrete choice model in my empirical application in Section 6.

### 3.2 Experimental Designs

Taking any experimental design problem as given, an *experimental design* specifies treatment assignment probabilities ($p_{it}$) where $p_{it}$ is the probability that subject $i$ is assigned to treatment $t$ under the experimental design. The benchmark design is the standard Randomized Controlled Trial, formalized as follows.

**Definition 1 (Randomized Controlled Trial a.k.a. RCT).** Randomized Controlled Trial is an experimental design that assigns each subject $i$ to each treatment $t$ with the impersonal treatment assignment probability $p^{RCT}_t$ that is assumed to be written as $p^{RCT}_t = c_t/n$ for some natural number $c_t < n$.

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15 This self-reporting method raises the question of incentive compatibility. I study incentive compatibility theoretically in Section 4.2 and empirically in Section 6.3.

16 Similar demand elicitation or estimation but for different purposes can be found in [Ashraf et al. (2006)](https://www.jstor.org/stable/41341485); [Cohen and Dupas (2010)](https://doi.org/10.1093/restud/rdq055); [Ashraf et al. (2010)](https://doi.org/10.1016/j.jebo.2008.07.009); [Kremer et al. (2011)](https://doi.org/10.1017/S0020243611000302); [Devoto et al. (2012)](https://doi.org/10.1017/S002024361200045X); [Dupas (2014)](https://doi.org/10.1007/s10680-014-9267-0); [Berry et al. (2018)](https://doi.org/10.1017/S002024361800065X).
The vast majority of clinical trials use RCT or similarly impersonalized randomization, an empirical fact shown in Appendix A.3.2 and Appendix Table A.6. I call $c_t$ pseudo capacity or supply, and require experimental designs to satisfy the pseudo capacity constraint that $\sum_i p_{it} \leq c_t$ for every treatment $t = t_1, ..., t_m$. This pseudo capacity constraint is important when treatment is expensive or hard to make and deliver.

I investigate welfare-enhancement with a design that I call Experiment-as-Market or EXAM in short.

**Definition 2** *(Experiment-as-Market a.k.a. EXAM)*. In the experimenter’s computer, distribute any common artificial budget $b > 0$ to every subject. Any $b$ is without loss of generality in that any $b$ results in the same assignment probabilities. Find any price-discriminated competitive market equilibrium, i.e., any treatment assignment probabilities $(p_{it}^*)$ and their prices $\pi_{te}$ with the following properties:

- Effectiveness-discriminated treatment pricing: There exist $\alpha < 0$ and $\beta_t \in \mathbb{R}$ for each treatment $t$ such that the price of a unit of assignment probability to $t$ for subjects with $e_{ti} = e \in \mathbb{R}$ is

$$\pi_{te} = \alpha e + \beta_t.$$

- Subject utility maximization: For each subject $i$,

$$(p_{it}^*)_t \in \arg\max_{p_i \in P} \sum_t p_{it} w_{it} \text{ s.t. } \sum_t p_{it} \pi_{tei} \leq b,$$

where $p_i \equiv (p_{it})_t$ and $P \equiv \{p_i \in \mathbb{R}^{m+1} | \sum_{t=t_0}^{t_m} p_{it} = 1 \text{ and } |p_{it}| \leq p\}$ where $p$ is a large enough number. $\pi_{tei}$ is the price of a unit of the assignment probability to treatment $t$ for subject $i$. EXAM breaks ties or indifferences so that every subject $i$’s $p_{it}^*$ solves the above problem with the minimum expenditure $\sum_t p_{it} \pi_{tei}$ while $(p_{it}^*)_t = (p_{jt}^*)_t$ for any subjects $i$ and $j$ with $w_i = w_j$ and $e_i = e_j$.

- Meeting capacity constraints: $\sum_i p_{it}^* \leq c_t$ for every treatment $t = t_1, ..., t_m$ and $\sum_i p_{it}^* < c_t$ only if $\pi_{tei} \leq 0$ for every $i$.

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17 A significant fraction of the real-world experiments are stratified. If the benchmark is an experiment stratified on some variables, I would implement EXAM conditional on the stratifying variables, i.e., for each subpopulation of subjects sharing the same stratifying variables. The subsequent comparison between RCT and EXAM holds conditional on the stratifying variables.

18 There may be multiple equilibria. I fix any equilibrium selection method.

19 The latter part is necessary to make sure that EXAM wastes treatment $t$ only when there is no enough demand for $t$ even with a nonpositive price.
Let \( \epsilon \) be a non-negative number such that the experimenter would like the assignment probabilities to be always within \([\epsilon, 1-\epsilon]\). Take any \( \epsilon \in [0, \bar{\epsilon}] \) as given, where \( \bar{\epsilon} \equiv \min_t p^{RCT}_t \) is the largest possible value of \( \epsilon \).

I define EXAM’s treatment assignment probabilities as

\[
p^*_it(\epsilon) \equiv (1-q)p^*it + q p^{RCT}_t,
\]

where \( q \equiv \inf\{q' \in [0, 1]| (1-q')p^*it + q' p^{RCT}_t \in [\epsilon, 1-\epsilon] \text{ for all } i \text{ and } t\} \).

I name this experimental design Experiment-as-Market (EXAM) because EXAM randomly assigns treatments to subjects via a synthetic centralized market. \( p^*_it(\epsilon) \) in Step 1 can be seen as a generalization or variation of the classic idea of competitive market equilibrium from equal incomes (Friedman, 1962; Varian, 1974; Hylland and Zeckhauser, 1979; Budish et al., 2013; He et al., 2017; Mollner and Weyl, 2018).

More specifically, in Step 1 of Definition 2, EXAM endows each subject with a common imaginary budget. This budget has nothing to do with economic conditions subjects face in the real world. EXAM then lets each subject use the budget to purchase one of the most preferred bundles of treatment assignment probabilities, taking their prices as given. The prices are personalized so that each treatment is cheaper for subjects predicted to benefit more from the treatment. EXAM computes its treatment assignment probabilities as the resulting personalized-price competitive market equilibrium. EXAM finally requires each subject to get each treatment with a probability strictly between 0 and 1, as done in Step 2. This requirement is important for EXAM to produce non-degenerate random assignments and unbiasedly estimate causal treatment effects; some foundations for this desire for non-degenerate randomization can be found in Proposition 1 below, Blackwell and Girshick (1954) section 8.7, Imbens and Rubin (2015) chapter 3, and Banerjee et al. (2017).

To sum up, the steps for implementing EXAM are as follows.

20 Why is \( \bar{\epsilon} \) the largest possible value of \( \epsilon \)? Suppose \( \epsilon > \bar{\epsilon} \equiv \min_t p^{RCT}_t \). For any \( t \in \arg \min_t p^{RCT}_t \), whenever \( p^*_it \leq p^{RCT}_t \), I have

\[
(1-q')p^*_it + q' p^{RCT}_t \not\in [\epsilon, 1-\epsilon]
\]

for any \( q' \in [0, 1] \). On the other hand, if \( \epsilon \leq \bar{\epsilon} \), then \( q' = 1 \) guarantees that \( (1-q)p^*_it + q' p^{RCT}_t = p^{RCT}_t \in [\epsilon, 1-\epsilon] \) for all \( i \) and \( t \). Thus \( \epsilon \) must be between 0 and \( \bar{\epsilon} \).

21 The first step of Definition 2 raises two questions, whether such an equilibrium exists and how to find such an equilibrium. After positively solving the first existence question in Proposition 2 below, I develop and implement a script to find an equilibrium in the empirical application in Section 6. See Budish et al. (2016) for a related algorithmic development on a different problem (MBA course allocation).

22 See Kasy (2016) for an argument against randomization. Definitions 1 and 2 leave unspecified how to draw a final treatment assignment from \( p^{RCT}_t \) and \( p^*_it(\epsilon) \), respectively. For the moment, my analysis applies to any method to draw a treatment assignment. I impose more structures in Section 5 and implement an algorithm to draw an assignment in the empirical application in Section 6. For EXAM, it is known to be always possible to draw a treatment assignment in a way consistent with \( p^*_it(\epsilon) \) (Budish et al. (2013)’s Theorem 1, the generalized Birkhoff-von Neumann Theorem).
(1) Obtain predicted effects $e_{ti}$ if possible and relevant, as described in Section 3.1.1.

(2) Obtain WTP $w_{it}$ if possible and relevant, as described in Section 3.1.1.

(3) Apply Definition 2 of EXAM to the data from steps 1 and 2, producing assignment probabilities $p^*_{it}(\epsilon)$.

EXAM is an enrichment of RCT using simple randomization. To see this, note that EXAM allows the experimenter to turn off welfare considerations. For instance, if the experimenter does not know or care about predicted effects, she would let $e_{ti} = e_{tj}$ for all subjects $i$ and $j$ and treatment $t$. Similarly, let $w_{it} = w_{jt} > 0$ if WTP is unknown or irrelevant; I make the common WTP positive for a minor technical reason.23 For example, the experimenter may want to exclude WTP when there is a concern that revealed or self-reported WTP may be distorted by ignorance, information frictions, or liquidity constraints. The following fact shows that EXAM is equivalent to RCT when the experimenter ignores both WTP and predicted effects.

**Proposition 1** (EXAM nests RCT). Suppose that WTP and predicted effects are unknown or irrelevant so that $w_{it} = w_{jt} > 0$ and $e_{ti} = e_{tj}$ for all subjects $i$ and $j$ and treatment $t$. Then EXAM reduces to RCT using simple randomization, i.e., for every $\epsilon \in [0, \bar{\epsilon}]$, subject $i$, and treatment $t$, I have

$$p^*_{it}(\epsilon) = p^R_{tRCT}.$$

EXAM also extends other more sophisticated designs, such as the Play-the-Winner Rule (Wei and Durham, 1978), Consent Trials (Zelen, 1979; Angrist and Imbens, 1991), and Selective Trials (Chassang et al., 2012). These designs emerge if EXAM ignores either WTP or predicted effects, but not both, as explained in Section 1.1.

4 Welfare and Incentive

4.1 Welfare

As opposed to the special case in Proposition 1, the experimenter is often concerned about WTP and predicted effects (as in studies reviewed in Section 2). In such cases, EXAM differs from RCT and is welfare-optimal in the following sense.

**Proposition 2** (Existence and Welfare). There exists $p^*_{it}$ that satisfies the conditions in Definition 3. For any such $p^*_{it}$ and any $\epsilon \in [0, \bar{\epsilon}]$, the resulting EXAM assignment probability

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23 I need to make every subject prefer each treatment over the control.
\( p_{it}^*(\epsilon) \) satisfies the following property: There is no other experimental design \((p_{it}) \in P^n\) with \( p_{it} \in [\epsilon, 1 - \epsilon] \) for all subject \( i \) and treatment \( t \), \( \sum_i p_{it} \leq c_t \) for all \( t = t_1, ..., t_m \), and the following better welfare property:

\[
\sum_t p_{iti} w_{it} \geq \sum_t p_{iti}^*(\epsilon) w_{it} \quad \text{and} \quad \sum_t p_{iti} e_{ti} \geq \sum_t p_{iti}^*(\epsilon) e_{ti}
\]

for all \( i \) with at least one strict inequality.

Proposition 2 says that no other experimental design ex ante Pareto dominates EXAM in terms of the expected WTP for and predicted effect of assigned treatment (while satisfying the random assignment and capacity constraints). This ex ante Pareto optimality is known to imply ex post Pareto optimality and “ordinal” ex ante optimality (Bogomolnaia and Moulin 2001). In contrast, RCT fails to satisfy the welfare property as it ignores WTP and predicted effects. I empirically quantify the welfare gap between RCTs and EXAM in Section 6.3.

4.2 Incentive

Proposition 2 takes WTP \( w_{it} \) as given and assumes that it represents true WTP. In practice, the experimenter often needs to elicit the WTP information \( w_{it} \) from subjects, raising an incentive compatibility concern. This section shows EXAM allows the experimenter to extract WTP in an almost incentive compatible way. My analysis of incentive compatibility builds upon the literature on incentive compatibility of competitive equilibria and experimental designs (Jackson 1992; Chassang et al. 2012; Azevedo and Budish 2017; He et al. 2017).

Unfortunately, it is known that no experimental design satisfies the welfare property in Proposition 2 and exact incentive compatibility for general problems (Hylland and Zeckhauser 1979). This compels me to investigate approximate incentive compatibility in large experimental design problems. Only for this section, consider a sequence of experimental design problems \((i_1, ..., i_n, t, t_1, ..., t_m, (c_i^n))_{n \in \mathbb{N}}\) indexed by the number of subjects, \( n \). Let \( \epsilon^n \in [0, \bar{\epsilon}^n] \) (where \( \bar{\epsilon}^n \) is \( \bar{\epsilon} \) for the \( n \)-th problem) be the value of the bound parameter \( \epsilon \) the experimenter picks for the \( n \)-th problem in the sequence. The set of treatments \( t, t_1, ..., t_m \)

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24 Proposition 2 implies that EXAM is ex ante Pareto optimal for expected WTP alone if the experimenter shuts down predicted effects by assuming \( e_{ti} = e_{tj} \) for all subjects \( i \) and \( j \) and treatment \( t \). Similarly, EXAM satisfies Pareto optimality for expected predicted effects alone when EXAM ignores WTP.

25 Ex post optimality means that no other \((p_{it})\) has the following property: \( w_{it} \geq w_{it}^* \) and \( e_{ti} \geq e_{t^*i} \) always hold for all \( i \) with at least one strict inequality, where \( t_i \) and \( t^*_i \) are treatments ex post assigned to \( i \) under the alternative design \((p_{it})\) and EXAM, respectively. Ordinal ex ante optimality is a stronger property that there is no other \((p_{it})\) such that for all affine transformations \( f \) and \( g \), \( \sum_t p_{it} f(w_{it}) \geq \sum_t p_{iti}^*(\epsilon) f(w_{it}) \) and \( \sum_t p_{it} g(e_{ti}) \geq \sum_t p_{iti}^*(\epsilon) g(e_{ti}) \) for all \( i \) with at least one strict inequality.
is fixed, but everything else may change as \( n \) increases. This modeling with a fixed number of treatments and an increasing number of subjects is consistent with real-world experiments with only a few treatments but with hundreds of subjects or more.

To investigate the incentive structure in EXAM, imagine that subjects report their WTP to EXAM. EXAM then uses the reported WTP to compute treatment assignment probabilities. For the \( n \)-th problem in the sequence, let \( p_i^n(w_i, e_i, w_{-i}, e_{-i}; e^n) \) be EXAM’s treatment assignment probability vector for subject \( i \) when subjects report WTP \((w_i, w_{-i})\) and predicted effects \((e_i, e_{-i})\) are realized from \( n - 1 \) iid draws from the distribution \( F \in \Delta(W \times E) \), where \( \Delta(W \times E) \) is the set of full-support distributions over the WTP space \( W \) and the predicted effect space \( E \). Only for this section, I restrict WTP and predicted effects to belong to finite sets \( W \) and \( E \), respectively, in any problem along the sequence. It is possible to eliminate this simplifying assumption by using an alternative proof technique like He et al. (2017)’s. This concept allows me to state an asymptotic incentive compatibility property.

**Proposition 3** (Incentive). EXAM with WTP reporting is asymptotically incentive compatible, i.e., for any sequence of experimental design problems with any \( e^n \) in \([0, e^n]\), any \( F \in \Delta(W \times E) \), any \( \delta > 0 \), there exists \( n_0 \) such that, for any \( n \geq n_0 \), any subject \( i \), any predicted effect \( e_i \), any true and manipulated WTP values \( w_i \) and \( w_i' \), I have

\[
\sum_t p_{it}^n(w_i, e_i, F; e^n) \times w_{it} \geq \sum_t p_{it}^n(w_i', e_i, F; e^n) \times w_{it} - \delta.
\]

Proposition 3 says that EXAM approximately incentivizes every subject to report her true WTP, at least for large enough experimental design problems. The experimenter using EXAM can therefore ask subjects to report their true WTP without any deception. As additional support for incentive compatibility, Section 6.3 shows that EXAM is close to incentive compatible in my empirical application only with a finite number of subjects. This suggests asymptotic Proposition 3 is relevant even for real-scale problems.

For intuition, first consider a case with only one treatment \( t_1 \) that subject \( i \) prefers over the control \( t_0 \). Why is there no incentive for subject \( i \) to misreport a larger WTP for \( t_1 \)? As long as subject \( i \) prefers \( t_1 \) over \( t_0 \), subject \( i \) spends her entire budget \( b \) into
purchasing \( t_1 \) and gets an assignment probability of \( b/\pi_{t_1} \). Misreporting a larger WTP would not affect this assignment probability, confirming the incentive compatibility. More generally, exact incentive compatibility may break down in small problems; see Hylland and Zeckhauser (1979) for such an example. Nevertheless, EXAM is always asymptotically incentive compatible since there is no incentive to misreport when the prices are exogenously fixed, which is approximately true when the number of subjects is large.

5 Information

Despite the welfare merit, EXAM also lets the experimenter estimate treatment effects as unbiasedly and precisely as they would do in RCTs. To spell it out, I switch back to any given finite problem and discuss not only bias but also variance in treatment effect estimation. The finite-sample econometric comparison of EXAM and RCT requires me to specify how each design draws a treatment assignment from its assignment probabilities. For simplicity, only the main text assumes that \( p_t n_p \) is an integer for every \( t \) and \( p_t \) where \( n_p \equiv \sum_{i=1}^{n} 1\{p^*_i(\epsilon) = p\} \) is the number of subjects with assignment probability vector \( p \) and \( p_t \) is the \( t \)-th element of \( p \). Appendix [A.1.1] generalizes the definition and argument below to a general setting where \( p_t n_p \) is any real number. Consider the following method of drawing a deterministic treatment assignment.

**Definition 2** (EXAM Continued). Starting from the end of Definition 2 in Section 3.2, draw a treatment assignment from \( p^*_i(\epsilon) \) as follows. For each assignment probability vector \( p \),

- Uniformly randomly pick \( p_{t_0} n_p \) subjects from \( \{i|p^*_i(\epsilon) = p\} \) and assign them to \( t_0 \).

For each subsequent step \( k = 1, \ldots, m \),

- Step \( k \): From the remaining \( n_p - \sum_{t=t_0}^{t_{k-1}} p_t n_p \) subjects in \( \{i|p^*_i(\epsilon) = p\} \), uniformly randomly pick \( p_{t_k} n_p \) subjects and assign them to \( t_k \).

I assume that an RCT would draw a deterministic treatment assignment by a specialization of the above method assuming every subject \( i \) to have \( p^*_i(\epsilon) = p^{RCT}_t \).

Suppose the experimenter is interested in the causal effect of each treatment on an outcome \( Y_i \). Following the standard potential outcome framework for causal inference (Imbens and Rubin 2015), let \( Y_i(t) \) denote subject \( i \)'s potential outcome that would be observed if subject \( i \) receives treatment \( t \). Let \( D_{it} \) be the binary indicator that subject \( i \) is ex post assigned to treatment \( t \). The observed outcome is written as \( Y_i = \sum_t D_{it} Y_i(t) \). While \( Y_i(t) \) is assumed to be fixed, \( D_{it} \) and \( Y_i \) are random variables, the distributions of which depend
on the experimenter’s choice of an experimental design. Let \( Y \equiv (Y_i) \), \( D_i \equiv (D_{it})_t \), and \( D \equiv (D_t) \).

The experimenter would like to learn any parameter of interest \( \theta \) of the distribution of potential outcomes \( Y_i(t) \)'s, many of which are unobservable. Formally, \( \theta \) is any mapping \( \theta : \mathbb{R}^{n \times (m+1)} \rightarrow \mathbb{R} \) that maps each possible value of \((Y_i(t))\) into the corresponding value of the parameter. For example, \( \theta \) may be the average treatment effect (ATE) of treatment \( t \) over control \( t_0 \), \( \sum_{i=1}^{n} (Y_i(t) - Y_i(t_0)) \). The experimenter estimates \( \theta \) with an estimator \( \hat{\theta}(Y, D) \), a function only of observed outcomes and treatment assignments. Given any experimental design \((p_{it})\), I say an estimator \( \hat{\theta}(Y, D) \) is simple if \( \hat{\theta}(Y, D) \) can be written as

\[
\hat{\theta}(Y, D) = \sum_i f(Y_i, D_i, p_i) + \sum_t \sum_p \sum_{p'} g_{tpp'}((N_{pt}) \hat{\mu}_p(t) \hat{\mu}_{p'}(t))
\]

for some function \( f \), \( \hat{\mu}_p(t) \equiv \frac{\sum_{i:p_i=p} D_{it} Y_i}{\sum_{i=1}^{n} 1\{p_i = p\}} \), and weights \( g_{tpp'} \), which may depend on \( N_{pt} \equiv \sum_{i:p_i=p} D_{it} \) but not on individual \( D_{it} \)'s \( ^{26} \). I say parameter \( \theta \) is unbiasedly estimable with experimental design \( p \equiv (p_{it}) \) and a simple estimator if there exists a simple estimator \( \hat{\theta}(Y, D) \) such that

\[
E(\hat{\theta}(Y, D) | (p_{it})) = \theta,
\]

where \( E(\cdot | (p_{it})) \) is expectation with respect to the distribution of \( D_{it} \) induced by experimental design \((p_{it})\) \( ^{27} \).

EXAM turns out to be as informative as RCT in terms of the set of parameters unbiasedly estimable with each experimental design and a simple estimator. Throughout this section, assume \( p_t n_t > 1 \) for all \( t \) and \( p \) for which at least one subject \( i \) has \( p_t^*(\epsilon) = p \).

**Proposition 4** (Unbiased Estimability). If parameter \( \theta \) is unbiasedly estimable with RCT \( p_t^{RCT} \) and a simple estimator, then \( \theta \) is also unbiasedly estimable with EXAM \( p_t^*(\epsilon) \) with any \( \epsilon > 0 \) and a simple estimator.\( ^{28} \)

Many key parameters, such as the average treatment effect, the treatment effect on the treated, and the mean and variance of potential outcomes are known to be unbiasedly es-

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\(^{26}\) More formally, \( f : \mathbb{R} \times D \times P \rightarrow \mathbb{R} \) where \( D \equiv \{d \in \{0,1\}^{m+1} | \sum d_i = 1 \} \) and \( P \equiv \{p_i | i = i_1, ..., i_n \} \). \( g_{tpp'} : N^{(m+1)} \rightarrow \mathbb{R} \) for each \( t, p, \) and \( p' \). I allow \( f \) and \( g_{tpp'} \) to use known elements of the experimental design problem such as capacities \( c_i \) and treatment assignment probabilities \( p_{it} \). I do not allow \( \hat{\theta}(Y, D) \) to use unknown elements, especially potential outcomes.

\(^{27}\) I use this finite-sample framework throughout this section. The appendix provides an alternative large-sample setting.

\(^{28}\) On the other hand, EXAM and RCT are not comparable in terms of Blackwell’s order \( ^{\text{[Blackwell and Girshick 1954]}} \) in my finite sample framework. This contrasts to the large sample analysis by \( ^{\text{[Chassang et al. 2012]}} \), where they compare their Selective Trial and RCT in terms of Blackwell’s order.
timable with RCT and a simple estimator (see Appendix A.2). Proposition 4 implies that these parameters are also unbiasedly estimable with EXAM.

**Corollary 1.** The average treatment effect, the treatment effect on the treated, and the mean and variance of potential outcomes are unbiasedly estimable with EXAM.

### 5.1 Unbiased ATE Estimation with EXAM Data

I use the average treatment effect (ATE) to illustrate the intuition for and implementation of Proposition 4 and Corollary 1. Why is ATE unbiasedly estimable with EXAM? EXAM makes all subjects share the same budget constraint. As a result, if subjects share the same predicted effects and WTP, these subjects solve the same utility maximization problem and purchase the same vector of treatment assignment probabilities. EXAM therefore produces treatment assignment that is independent from (unconfounded by) potential outcomes conditional on predicted effects and WTP, which are observable to the experimenter:

\[(Y_i(t))_t \perp D_i|(e_{it}, w_{it})_t.\]  

(1)

With this conditional independence, EXAM fits into causal inference with stratified experiments, selection-on-observables, and the propensity score, i.e., treatment assignment probabilities conditional on observables (see Imbens and Rubin (2015) for an overview). In particular, conditional independence (1) implies that the same conditional independence holds conditional on the propensity score (Imbens and Rubin (2015) section 12.3), which EXAM computes as \(p^*_{it}(\epsilon) \equiv (p^*_{it}(\epsilon))_t\) and again known to the econometrician:

\[(Y_i(t))_t \perp D_i|p^*_{it}(\epsilon).\]  

(2)

This conditionally independent treatment assignment allows the experimenter to unbiasedly estimate the conditional average treatment effects of each \(t\) over \(t_0\) conditional on observable propensity scores \(p^*_{it}(\epsilon)\),

\[\frac{\sum_{i=1}^{n} 1\{p^*_{i}(\epsilon) = p\}(Y_i(t) - Y_i(t_0))}{\sum_{i=1}^{n} 1\{p^*_{i}(\epsilon) = p\}},\]

which I denote by \(CATE_{pt}\) and is defined for each \(p\) such that at least one subject \(i\) has \(p^*_{it}(\epsilon) = p\). These conditional-on-the-propensity-score effects are a version of Marginal Treatment Effects.

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29 I define the treatment effect on the treated for experimental design \((p_{it})\) as \(E(\sum_{i=1}^{n}(Y_i(t) - Y_i(t_0))D_{it})/(p_{it})\) while the mean of potential outcomes as \(1/n \sum_{i=1}^{n} Y_i(t)\). I define the variance of potential outcomes as \(1/n \sum_{i=1}^{n} (Y_i(t) - 1/n \sum_{j=1}^{n} Y_j(t))^2\) or \(1/n - 1 \sum_{i=1}^{n} (Y_i(t) - 1/n \sum_{j=1}^{n} Y_j(t))^2\), both of which are unbiasedly estimable with RCT and a simple estimator.
Effects (Björklund and Moffitt [1987] Heckman and Vytlacil [2005]). Marginal Treatment Effects are therefore estimable with EXAM’s data.30

By summing up such marginal or conditional effects, the experimenter can also back out the (unconditional) ATE, the single most important causal object identified and estimated by RCT. That is, with weights \( \delta_p \equiv n_p/n \), I use \( CATE_{pt} \)’s to get ATE as follows:

\[
\sum_p \delta_p CATE_{pt} = ATE_t.
\]

Importantly, the key conditional independence properties (1) and (2) hold regardless of whether \( e_{ti} \) and \( w_{it} \) coincide with the true treatment effects and WTP. In this sense, like RCT, EXAM’s informational virtue is robust to any of the experimenter’s potential misspecifications about predicted effects and WTP.

The above estimability argument motivates a strategy to estimate ATE with EXAM’s data. As a warm-up, focus on \( \{i|p^*_i(\epsilon) = p\} \), the subpopulation of subjects with propensity vector \( p \), and consider this regression on the subpopulation:

\[
Y_i = \alpha_p + \sum_{t=t_1}^{t_m} \beta_{pt} D_{it} + \epsilon_i.
\]

By the conditional independence property (2), OLS estimate \( \hat{\beta}_{pt} \) from this regression is unbiased for \( CATE_{pt} \) for each treatment \( t \neq t_0 \). I then aggregate the resulting estimates \( \hat{\beta}_{pt} \)’s into \( \sum_p \delta_p \hat{\beta}_{pt} \), which I denote by \( \hat{\beta}^*_t \). This \( \hat{\beta}^*_t \) is a multinomial propensity score weighting estimator that unbiasedly estimates the average treatment effect with its variance in an analytical form.

**Proposition 5 (Bias and Variance).** Suppose that the data-generating experimental design is EXAM \( p^*(\epsilon) \equiv (p^*_i(\epsilon))_{it} \) with any given \( \epsilon > 0 \). \( \hat{\beta}^*_t \) is an unbiased estimator of the average

30 To see this, as in Heckman and Vytlacil [2005], focus on an experimental design problem with only one treatment \( t_1 \) compared to the control \( t_0 \). Given EXAM’s assignment probability \( p^*_t(\epsilon) \), let \( R_i \sim U[0,1] \) with \( R_i \perp (Y_i(t_0), Y_i(t_1)) \), \( Z_i = 1 - R_i \), and \( V_i = 1 - p^*_i(\epsilon) \). Write the treatment assignment as

\[
D_{it} = 1\{R_i \leq p^*_t(\epsilon)\} = 1\{1 - R_i \geq 1 - p^*_t(\epsilon)\} = 1\{Z_i \geq V_i\}.
\]

Note that \( E(1\{Z_i \geq V_i\}) = p^*_t(\epsilon) \) as desired. This model is a special case of Heckman-Vytlacil’s model with local instrumental variable \( Z_i \), because \( Z_i \) is independent of \( (Y_i(t_0), Y_i(t_1), V_i) \) by construction while \( V_i \) can be correlated with \( (Y_i(t_0), Y_i(t_1)) \). As a result, Heckman and Vytlacil [2005]’s method allows the experimenter to identify Marginal Treatment Effects with EXAM’s data. Chassang et al. [2012] provide a similar discussion about their Selective Trial idea. See also Kowalski [2016]; Mogstad and Torgovitsky [2018] for recent developments in the marginal treatment effect method.

31 On the other hand, the welfare optimality in Proposition 2 is welfare-relevant only if the experimenter predicts treatment effects and WTP well.
treatment effect. In particular,

\[ E(\hat{\beta}_t^* | p^*(\epsilon)) = ATE_t \text{ and } \text{Var}(\hat{\beta}_t^* | p^*(\epsilon)) = \sum_p \delta_p^2 \left( \frac{S_{pt}^2}{p_t n_p} + \frac{S_{pt0}^2}{p_{t0} n_p} - \frac{S_{ptt0}^2}{n_p} \right), \]

where \( \bar{Y}_p(t) \equiv \frac{\sum_{i: p_i^*(\epsilon) = p} Y_i(t)}{n_p} \) is the mean of \( Y_i(t) \) in the subpopulation with propensity \( p \),

\[ S_{pt}^2 \equiv \frac{\sum_{i: p_i^*(\epsilon) = p} (Y_i(t) - \bar{Y}_p(t))^2}{n_p - 1} \]

is the variance of \( Y_i(t) \) in the subpopulation, and

\[ S_{ptt0}^2 \equiv \frac{\sum_{i: p_i^*(\epsilon) = p} (Y_i(t) - Y_i(t') - (\bar{Y}_p(t) - \bar{Y}_p(t')))^2}{n_p - 1} \]

is the variance of \( Y_i(t) - Y_i(t') \) in the subpopulation.

Though this variance expression is not identified in general, it provides guidance on when the variance is likely to be large or small. In practice, statistical inference may be based on randomization or large-sample inference.

Alternatively, empirical researchers may prefer a single regression controlling for propensity vectors:

\[ Y_i = a + \sum_{t=t_1}^{t_m} b_tD_{it} + \sum_{t=t_1}^{t_m} c_{it}p_i^*(\epsilon) + e_i, \quad (3) \]

producing an alternative estimator \( \hat{\beta}_t^* \). As verified in the appendix, \( \hat{\beta}_t^* \) is an unbiased estimator of a differently weighted treatment effect:

\[ E(\hat{\beta}_t^* | p^*(\epsilon)) = \frac{\sum_p \lambda_{pt} CATE_{pt}}{\sum_p \lambda_{pt}} \text{ with weights } \lambda_{pt} \equiv \delta_{pt}(1 - p_t). \quad (4) \]

Estimators like \( \hat{\beta}_t^* \) and \( \hat{\beta}_t^* \) allow the experimenter to unbiasedly estimate key causal effects with EXAM.

5.2 Power Comparison of EXAM and RCT

Does EXAM compete with RCT in terms of statistical efficiency in ATE estimation? With RCT’s data, the most standard estimator of ATE of treatment \( t \) over control \( t_0 \) is the difference in the average outcome between subjects assigned to treatment \( t \) and those assigned to control \( t_0 \):

\[ \hat{\beta}_t^{RCT} \equiv \frac{\sum_i D_{it} Y_i - \sum_i D_{ito} Y_i}{\sum_i D_{it} - \sum_i D_{ito}}. \]

This \( \hat{\beta}_t^{RCT} \) is a special case of \( \hat{\beta}_t^* \) when \( p_i^*(\epsilon) = p_i^{RCT} \). By Proposition 5, therefore, \( \hat{\beta}_t^{RCT} \) is unbiased for ATE with the following variance, confirming a classic result about RCT.
Corollary 2 (Imbens and Rubin (2015)’s Theorem 6.2).

\[ E(\hat{\beta}_t^{RCT}|p^{RCT}) = ATE_t \text{ and } V(\hat{\beta}_t^{RCT}|p^{RCT}) = \frac{S_t^2}{c_t} + \frac{S_{t0}^2}{c_{t0}} - \frac{S_{tt0}^2}{n}, \]

where \( S_t^2 = \frac{1}{n-1} \sum_i (Y_i(t) - \bar{Y}(t))^2 \) and \( S_{tt0}^2 = \frac{1}{n-1} \sum_i (Y_i(t) - Y_i(t') - (\bar{Y}(t) - \bar{Y}(t')))^2 \).

Proposition [5] and Corollary 2 imply that EXAM may produce more precise ATE estimates \( (V(\hat{\beta}_t^*|p^*(\epsilon)) < V(\hat{\beta}_t^{RCT}|p^{RCT})) \). Such a situation occurs if potential outcomes are well correlated (positively or negatively) with EXAM’s treatment assignment probabilities, as illustrated by the following example.

**Example 1.** Suppose there is only one treatment \( t_1 \), \( n = 40 \), and \( c_{t0} = c_{t1} = 20 \). Every subject has \( Y_i(t_0) = 1 \). The subjects are divided into four groups \( A, B, C, \) and \( D \) of the same size \( (10) \) based on their potential outcomes \( Y_i(t_1) \). Let \( Y_i(t_1) = 1, 2, 3, \) and \( 4 \) for anybody in group \( A, B, C, \) and \( D \), respectively. Assume the experimenter imperfectly predicts treatment effects: \( e_{t1i} = 0 \) for every \( i \) in group \( A \) or \( B \) while \( e_{t1i} = 2 \) for group \( C \) or \( D \). Let \( w_{t1i} > 0 \) for all subjects. EXAM with \( \epsilon < .2 \) gives the following treatment assignment probabilities

\[ p_{t1i}^*(\epsilon) = 0.2 \text{ for every } i \text{ in groups } A \text{ and } B \text{ while } p_{t1i}^*(\epsilon) = 0.8 \text{ for groups } C \text{ and } D. \]

Under \( RCT, p_{t1}^{RCT} = p_{t0}^{RCT} = 20/40 = 0.5 \) for all subjects. Applying Proposition [5] and Corollary 2 to this example, I have

\[ V(\hat{\beta}_t^*|p^*(\epsilon)) = 0.013... < 0.032... = V(\hat{\beta}_t^{RCT}|p^{RCT}). \]

This example makes clear that information production in EXAM is not a diluted version of that in RCT. EXAM’s ATE estimation is not only unbiased but also potentially more precise than RCT’s; this is true even if the experimenter’s prediction of treatment effects is imperfect. Appendix A.1.2 provides further support for this point by showing it remains true in an asymptotic framework.

In general, however, the precision comparison of EXAM and RCT is ambiguous. There are other examples with \( V(\hat{\beta}_t^{RCT}|p^{RCT}) < V(\hat{\beta}_t^*|p^*(\epsilon)) \); one such example with a binary treatment \( t_1 \) vs. \( t_0 \) is where \( p_{t0}^{RCT} = p_{t1}^{RCT} = 0.5 \) for every \( i \), \( p^*(\epsilon) \neq p^{RCT} \), and there is no correlation between potential outcomes and \( p^*(\epsilon) \). This ambiguity is common in precision comparisons of experimental designs. This motivates me to empirically compare EXAM and RCT’s estimation precision. The empirical application also allows me to verify and quantify the welfare, incentive, and unbiasedness properties of EXAM.

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32 EXAM outputs these treatment assignment probabilities if I set \( \alpha = -\frac{15b}{8} \), \( \beta_{t1} = 5b \), and \( \beta_{t0} = 0 \) given any budget \( b \).
6 Empirical Application

6.1 Overview

My empirical test bed for EXAM is an application to a spring protection experiment in Kenya. Waterborne diseases, especially diarrhea, remain the second leading cause of death among children, comprising about 17% of child deaths under age five (about 1.5 million deaths each year). The only quantitative United Nations Millennium Development Goal is in terms of “the proportion of the population without sustainable access to safe drinking water and basic sanitation,” such as protected springs. Yet there is controversy about the health impacts of spring protection. Experts argue that improving source water quality may only have limited effects, since, for example, water is likely recontaminated in transport and storage. These arguments were made in the absence of any randomized experiment.

This controversy motivated Kremer et al. (2011) to analyze randomized spring protection conducted by an NGO (International Children Support) in Kenya in the mid 2000s. This experiment randomly selected springs to receive protection from the universe of 200 unprotected springs. The experimenter selected and followed a representative sample of about 1500 households that regularly used some of the 200 springs before the experiment; these households are experimental subjects. Kremer et al. (2011) found that spring protection substantially improves source water quality and is moderately effective at improving household water quality after some recontamination. Diarrhea among children in treatment households fell by about a quarter of the baseline level. I call this real experiment “Kremer et al. (2011)’s experiment” and distinguish it from EXAM and RCT as formal concepts in my model.

Kremer et al. (2011)’s experiment provides an ideal setup for empirically evaluating EXAM. Their experiment is about a high-stakes treatment and produces rich data that allows me to measure not only treatment effects but also subjects’ WTP for the treatment. I consolidate Kremer et al. (2011)’s experimental data and my methodological framework to empirically evaluate EXAM. Applying the language and notation of my model, experimental subjects are households in Kremer et al. (2011)’s sample. The protection of the spring each household uses at baseline is a single treatment $t_1$ while no protection is the control $t_0$.

---


34 See [http://www.un.org/millenniumgoals/](http://www.un.org/millenniumgoals/), retrieved in January 2019. Spring protection encases the source of a natural spring in concrete, allowing water to flow from a pipe rather than seeping from the ground. In this way, the water source is protected from human or animal waste.

35 Alternatively, it’s possible to interpret springs as the subjects in my model. The resulting analysis produces similar results (available upon request).
household $i$’s WTP for better water access $t_1$ is denoted by $w_{it_1}$, which I estimate below. I also estimate the heterogeneous treatment effect $e_{t_1i}$ of spring protection $t_1$ on household $i$’s child diarrhea outcome. Using this embedding, I implement EXAM and compare it with RCT to see which is a better design of a hypothetical future experiment on the spring protection treatment.

### 6.2 Treatment Effects and WTP

#### Treatment Effects

For executing EXAM, I need to measure $w_{it_1}$ and $e_{t_1i}$ and substitute them into EXAM. I estimate heterogeneous treatment effects $e_{t_1i}$ of access to better water in a similar way as Kremer et al. (2011). This treatment effect estimation exploits additional details of Kremer et al. (2011)’s experiment. The experimenter NGO aspired to eventually protect all the 200 springs but planned for the protection intervention to be phased in over four years due to financial and administrative constraints. In each round, a subset of springs were randomly picked to be protected. Figure I in Kremer et al. (2011) details the timeline of the experiment. This experimental scheme legitimizes the following OLS regression at the (child $i$, spring $j$, survey round $t$)-level:

$$Y_{ijt} = (\phi_1 + \phi_2 X_i)T_{jt} + \alpha_i + \alpha_t + u_{ij} + \epsilon_{ijt}, \quad (5)$$

where $Y_{ijt}$ is the binary outcome indicating that child $i$ in a household drawing water from spring $j$ at baseline has diarrhea in survey round $t$. $X_i$ contains covariates of child $i$’s household (baseline latrine or sanitation density, diarrhea prevention knowledge score, mother’s years of education). Every covariate is normalized to be mean zero so that the coefficient $\phi_1$ can be interpreted as the average treatment effect. $T_{jt}$ is the binary treatment indicating that spring $j$ is treated in survey round $t$. $\alpha_i$, $\alpha_t$, and $u_{ij}$ are fixed effects. The treatment effect is $\phi_1 + \phi_2 X_i$ and is heterogeneous across subjects with different covariates $X_i$.

Estimates from the OLS regression (5) are in Table 3. The average treatment effect is about 4.5% absolute reduction or about 25% relative reduction in the diarrhea outcome $Y_{ijt}$. Households with higher scores in diarrhea prevention knowledge or mother’s education level tend to have better treatment effects, although the relatively large standard errors argue for caution in interpretation. This heterogeneity may be present because such households are more likely to prefer and use protected springs, as suggested by a revealed preference analysis below.

I then use the OLS estimates to predict the treatment effect for each household $i$ with

Electronic copy available at: https://ssrn.com/abstract=3094905
\( \hat{e}_{ti} \equiv \hat{\phi}_1 + \hat{\phi}_2 X_i \), where \( \hat{\phi}_1 \) and \( \hat{\phi}_2 \) are OLS estimates of \( \phi_1 \) and \( \phi_2 \), respectively. Kremer et al. (2011)’s experiment randomized \( T_{jt} \) and gives its coefficient estimate \( \hat{e}_{ti} \) an interpretation as a causal effect. Estimated treatment effects \( \hat{e}_{ti} \) exhibit significant heterogeneity, as illustrated in Figure 1 Panel a.

**WTP**

I estimate heterogeneous WTP \( w_{it} \) for the treatment as follows. In the experimental target area, each household draws water from a water source the household chooses among multiple sources in the neighborhood. This fact motivates a discrete choice model of households’ water source choices, in which households trade off water quality against other source characteristics such as proximity. This model produces revealed preference estimates of household WTP for the spring protection treatment as a spring characteristic, which is identified by exogenous variation in the treatment generated by Kremer et al. (2011)’s experiment.

Specifically, I use a mixed or random-coefficient logit model (Train (2003), chapter 6):

\[
U_{ijt} = (\beta_i + \gamma_1 X_i)T_{jt} - c_i D_{ij} + \delta_j + \epsilon_{ijt},
\]  

where \( U_{ijt} \) is household \( i \)'s utility from source \( j \) in survey round \( t \), and \( D_{ij} \) is household \( i \)'s roundtrip distance to spring \( j \) (measured in terms of minutes of walking time). \( \beta_i \) and \( c_i \) are random preference coefficients assumed to be distributed according to normal and triangular distributions, respectively, with unknown parameters to be estimated. I restrict the triangular distribution of \( c_i \) to have the same mean and standard deviation, making sure every household prefers proximity. \( \delta_j \)'s are spring-type fixed effects in the spirit of Berry et al. (1995). \( \delta_j \)'s attempt to capture the average preference for potentially unobserved spring type characteristics other than treatment \( T_{jt} \) and distance \( D_{ij} \). \( \epsilon_{ijt} \) is logit utility shocks iid according to the type I extreme value distribution with usual variance normalization to \( \pi^2/6 \). I estimate the model with data on households’ spring choices (in the final survey round after random spring protection) and a standard maximum simulated likelihood method (Train (2003), chapter 10), which I detail in Appendix A.3.3.

The mixed logit preference estimates are in Table 4. Households have significant distaste for distance and significant preferences for protected treatment springs (other characteristics being equal). Not surprisingly, households with better diarrhea prevention knowledge scores or higher education levels of mothers tend to have stronger revealed preferences for the spring protection treatment. This heterogeneity is expected if such households are more conscious of water quality.\(^{36}\)

---

\(^{36}\) Tables 3 and 4 show slight differences from Kremer et al.’s estimates. It is because I include the same...
I then exploit the mixed logit estimates to estimate household \( i \)'s WTP for treatment \( t_1 \) as
\[
\hat{w}_{it1} = \hat{\beta}_i + \hat{\gamma}_1 X_i,
\]
where \( \hat{\beta}_i \) and \( \hat{\gamma}_1 \) are mixed logit estimates of \( \beta_i \) and \( \gamma_1 \), respectively. I bootstrap the random coefficient \( \hat{\beta}_i \) from its estimated distribution. The identification of \( \hat{w}_{it1} \) is helped by Kremer et al. (2011)'s experimental variation in protection treatment \( T_{jt} \) since otherwise \( T_{jt} \) is likely correlated with unobserved spring characteristics \( \epsilon_{ijt} \), making it impossible to identify the WTP for spring protection alone.

Since \( \hat{w}_{it1} \) is in an elusive utility unit, I convert it into a more easily interpreted measure in terms of time cost of water collection. To do that, I first compute \( \hat{w}_{it1}/\hat{c}_i \), where \( \hat{c}_i \) is the mixed logit estimate of \( c_i \) (the distaste coefficient on distance). Again, I bootstrap the random coefficient \( \hat{c}_i \) from its estimated distribution. I then multiply it by each household's self-reported time cost of traveling for a unit of distance. This procedure gives me a time cost measure of WTP for the treatment, \( \hat{w}_{it1} \). This \( \hat{w}_{it1} \) is measured by workdays utility-equivalent to \( \hat{w}_{it1} \).

The estimated WTP \( \hat{w}_{it1} \) is displayed in Figure 1 Panel b, showing the histogram of simulated values of \( \hat{w}_{it1} \). The median WTP is about 25 workday-equivalent. While both WTP \( \hat{w}_{it1} \) and treatment effects \( \hat{e}_{t1i} \) show sizable heterogeneity, there turns out to be only limited correlation between the two. This fact can be seen in the joint density plot in Figure 1 Panel c, where there is a positive correlation between WTP \( \hat{w}_{it1} \) and treatment effects \( \hat{e}_{t1i} \), but the magnitude of the correlation is small (\( R^2 \) is lower than 0.12 when I regress one on the other). This demonstrates that WTP \( \hat{w}_{it1} \) and treatment effects \( \hat{e}_{t1i} \) contain different types of information about subject welfare, suggesting the importance of respecting both WTP and predicted effects separately. This is what EXAM attempts to do, as I explain next.

6.3 EXAM vs RCT

Now imagine somebody is planning a new experiment for further investigating the same spring protection treatment. What experimental design should she use? Specifically, which is better between RCT and EXAM? A full-fledged comparison of experimental designs requires a meta-experiment that randomly assigns different designs to many experimental studies. To circumvent the difficulties of such a meta-experiment, I resort to an alternative approach exploiting the above WTP and treatment effect estimates.

My approach is to use the estimated WTP \( \hat{w}_{it1} \) and predicted effects \( \hat{e}_{t1i} \) to simulate EXAM and compare EXAM with RCT in terms of welfare, information, and incentive properties. Throughout the comparison, I fix the set of subjects and treatments as in Kremer et al. (2011)'s experiment. That is, there are 1540 households as subjects to be assigned set of a small number of covariate interactions both in the OLS and mixed logit models while Kremer et al. include different sets of covariate interactions and other controls in their models.
either to the single water source protection treatment $t_1$ or the control $t_0$. Set the treatment capacity $c_{t_1}$ to be the number of households assigned to the treatment $t_1$ in Kremer et al.’s experiment (by the end of their survey period). I set the bound parameter $\epsilon$ to be 0.2; I investigate how the results change under another value of $\epsilon$ at the end. I fix predicted effects $e_{t,i}$ to their point estimate $\hat{e}_{t,i}$.

I simulate WTP with parametric bootstrap from the estimated distribution of $\hat{w}_{it_1}$, i.e., the estimated mixed logit model (6) (conditional on each household’s fixed characteristics $X_i$). In this WTP simulation, I require all families with the same characteristics $X_i$ to share the same WTP. After simulating $\hat{w}_{it_1}$, I compute treatment assignment probabilities $p_{it_1}^*(\epsilon)$ by running EXAM on the bootstrapped data along with other fixed parameters such as the treatment capacity. The algorithm I use for executing EXAM is described in Appendix A.3.4.

The simulation process for RCT is analogous except that the treatment assignment probability is fixed at $p_{it_1}^{RCT} \equiv c_{t_1}/n = .43$. Note that this RCT is a hypothetical experimental design in line with my Definition 1 and different from Kremer et al. (2011)’s experiment involving additional real-world complications.

Welfare

I start with evaluating EXAM’s welfare performance. Use EXAM’s treatment assignment probabilities $p_{it_1}^*(\epsilon)$ to calculate two welfare measures for each household $i$:

$$w_i^* = \sum_t p_{it_1}^*(\epsilon)w_{it} \quad \text{and} \quad e_i^* = \sum_t p_{it_1}^*(\epsilon)e_{ti}.$$  

$w_i^*$ and $e_i^*$ are empirical analogues of the two welfare measures in my theoretical welfare analysis (Proposition 2).

I find that EXAM improves on RCT in terms of the welfare measures $w_i^*$ and $e_i^*$, a result reported in Figure 2. The figure draws the distribution of $w_i^*$ and $e_i^*$ over households and 1000 bootstrap samples. Among other things, the mean of average WTP $w_i^*$ for assigned treatments is about 89% or 9.4 workday-equivalent utilities higher under EXAM than it is under RCT. Another interpretation of this WTP improvement is about 37% of the average WTP for the treatment. Similarly, EXAM improves the mean of $e_i^*$ by about 0.8% absolute reduction or 42% reduction relative to RCT’s level. This predicted effect benefit amounts to

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37 To make treatment assignment probabilities take a modest number of values, I coarsen the values of WTP and predicted effects. Specifically, for each simulation and each of WTP and predicted effects, I first group its values into four quartiles and then replace each household’s value by the median value within the quantile group to which the household belongs.
about 17% of the average treatment effect of the spring protection found by Kremer et al. (2011) and Table 3.

Information

Data from EXAM also allows me to obtain more or less the same conclusion about treatment effects as RCT. To see this, I augment the above counterfactual simulation with average treatment effect estimation as follows: I first simulate $w_{it1}$ and run EXAM to get treatment assignment probabilities $p^{*}_{it}(\epsilon)$. I use $p^{*}_{it}(\epsilon)$ to draw a final deterministic treatment assignment, denoted by a binary indicator $D_i$ indicating $i$ is ex post assigned to $t_1$. I then simulate counterfactual or predicted outcome $Y_i$ under $D_i$ by simulating the OLS model I estimate in the last section:

$$Y_i \equiv (\hat{\phi}_1 + \hat{\phi}_2 X_i)D_i + \hat{\alpha}_i + \text{(average of } \hat{\alpha}_t \text{ across all } t) + \text{(average of } \hat{u}_{ij} \text{ across all } j),$$

where objects with a hat mean estimates of the corresponding parameters in regression (5). I take the average of $\hat{\alpha}_t$’s and $\hat{u}_{ij}$’s to adapt regression (5) at the $(i, j, t)$-level to my counterfactual simulation setting at the household-$i$-level. Note that the above expression is the definition of $Y_i$, not a regression. Finally, I use the above simulated $Y_i$ and $D_i$ to estimate treatment effects with $\hat{b}^*$ from this OLS regression:

$$Y_i = a + bD_i + cp^{*}_{it1}(\epsilon) + e_i,$$

where I control for propensity score $p^{*}_{it1}(\epsilon)$ to make treatment assignment $D_i$ random. This regression is a stripped-down version of the regression strategy (3) in Section 5. I also implement the other propensity-score-weighting estimator $\hat{\beta}^*$, again following the description in Section 5. The procedure for RCT is analogous except that the treatment assignment probability is fixed at $p^{RCT}_{it}$.

Program evaluation with EXAM turns out to be as unbiased and precise as that with RCT. Figure 3 plots the distribution of the resulting treatment effect estimates $\hat{b}^*$ and $\hat{\beta}^*$ over 1000 simulations. In line with Propositions 4 and 5, the means of $\hat{b}^*$ and $\hat{\beta}^*$ for EXAM are indistinguishable from those under RCT. Both experimental designs successfully recover Kremer et al. (2011)’s average treatment effect estimate (4.5% reduction in diarrhea; recall column 1 in Table 3).

Perhaps more importantly, the distributions of $\hat{b}^*$ and $\hat{\beta}^*$ for EXAM have similar standard deviations as those for RCT. This means that the two experimental designs produce similar exact, finite-sample standard errors in their estimates $\hat{b}^*$ and $\hat{\beta}^*$. Variations of this
observation are in Figure 4, which shows the distribution of $p$ values for the estimates $\hat{b}^*$. The four panels use $p$ values based on exact, non-robust, robust, and Abadie et al. (2017)’s finite population causal standard errors, respectively, where the exact standard error means the standard deviation in the distribution of $\hat{b}^*$ in Figure 3. RCT produces slightly smaller $p$ values than EXAM, but the median $p$ value is about 0.03 for RCT and about 0.04 for EXAM. Both EXAM and RCT therefore detect a significant average treatment effect for a majority of cases. Overall, EXAM appears to succeed in its informational mission of eliminating selection bias and recovering ATE precisely enough.

**Incentive**

EXAM’s WTP benefits can be regarded as welfare-relevant only if EXAM provides subjects with incentives to reveal their true WTP. I conclude my empirical analysis with an investigation of the incentive compatibility of EXAM. I repeat the following procedure many times: As before, I simulate $w_{it1}$ and run EXAM to get treatment assignment probabilities $p_{it}^*(\epsilon)$. I then randomly pick one subject $j$ as a WTP manipulator and one potential WTP manipulation $w_{jt1}'$ by $j$. I choose the manipulator $j$ uniformly randomly among all subjects. The manipulation $w_{jt1}'$ is either from $N(w_{jt1}, 100), N(w_{jt1}, 1000), U(w_{jt1}, w_{jt1} + 100)$, or $U(w_{jt1} - 100, w_{jt1})$ where $w_{jt1}$ is $j$’s true WTP. These computational scenarios cover different types of misreporting, that is, both over-reporting and under-reporting with different magnitudes. I run EXAM on the simulated data but with the WTP manipulation $w_{jt1}'$ to get treatment assignment probabilities $p_{it}^*(\epsilon)$. I finally compute the true WTP gain from the manipulation $w_{jt1}'$:

$$\Delta w \equiv \sum_t p_{it}^*(\epsilon)w_{jt} - \sum_t p_{it}^*(\epsilon)w_{jt}.$$ 

EXAM is found to give subjects little incentive for WTP misreporting, empirically verifying Proposition 3. Figure 5 shows this by drawing the distribution of $\Delta w$ over 1000 simulations and households. Across all scenarios, the WTP gain $\Delta w$ from misreporting is mostly negative and well below zero on average.

Ideally, I would like to compute the gains from the optimal (as opposed to random) WTP manipulations. The optimal WTP manipulations are hard to find, however, since equilibrium prices endogenously respond to WTP manipulations in a complex, unknown manner. As a feasible exercise, Table 5 shows that even the most profitable manipulations in Figure 5 lead to normalized gains $\Delta w/w_{it1}$ smaller than 0.021. This result suggests that there are unlikely to be manipulations that produce large gains.

Overall, in this empirical setting, EXAM provides subjects with stronger average incentives for truthful WTP reporting than RCT does (because subjects in RCT are indifferent
among all possible WTP reports). EXAM may therefore be better at eliciting reliable WTP data.

**Role of Design Parameters**

Finally, I analyze how the results depend on the choice of design parameters, especially $\epsilon$, which governs how close EXAM must be to RCT. With a smaller value of $\epsilon = 0.1$, the same set of results as in Figures 2-5 and Table 5 are reported in Appendix Figures A.2-A.5 and Table A.8. The results stay qualitatively the same between the two analyses. This confirms the above baseline empirical analysis is robust.

Yet there is a key quantitative difference: Appendix Figure A.2 with $\epsilon = 0.1$ finds better welfare performance of EXAM compared to Figure 2 with $\epsilon = 0.2$. On the other hand, Appendix Figure A.4 and Figure 4 suggest EXAM’s statistical efficiency deteriorates as $\epsilon$ drops from 0.2 to 0.1. This tradeoff is intuitive as smaller values of $\epsilon$ allow EXAM’s assignment probabilities to get away from RCT’s and focus more on welfare enhancement. This welfare enhancement may come at the cost of diluted information. The parameter $\epsilon$ thus embodies the welfare vs information tradeoff among different versions of EXAM. This observation raises an intriguing yet challenging methodological question of how to optimally specify $\epsilon$. I leave this direction for future research.

**7 Takeaway and Future Directions**

Motivated by the high-stakes nature of many RCTs, I propose a data-driven, stratified experiment dubbed Experiment-as-Market (EXAM). EXAM is a solution to a hybrid experimental-design-as-market-design problem of maximizing participants’ welfare subject to the constraint that the experimenter must produce as much information and incentives as in RCTs (Propositions 2-5). These properties are then verified and quantified in an empirical application where I simulate my design on a water source protection experiment. Taken together, the body of evidence suggests that EXAM improves subject well-being with little information and incentive costs. The demonstrated benefits are conservative in that they do not incorporate potential additional benefits from EXAM for improving recruitment, compliance with assigned treatment, and attrition (recall the discussion in Section 2).

This paper takes a step toward introducing welfare and ethics into experimental design. This opens the door to several open questions. In ongoing work, I am implementing EXAM in the field. This implementation raises practical questions, such as how to design an easy-to-use interface through which EXAM interacts with subjects, as well as a fast and scalable algorithm to implement EXAM, and how best to obtain predicted effects and WTP.
The empirical and computational analysis in Section 6 is an effort to tackle these practical challenges.

Econometrically and theoretically, this paper’s analysis is simplistic in many respects, asking for a variety of extensions. Key extensions include introducing a decision-theoretic framework with an explicit social welfare function for the experimenter; analyzing EXAM in an instrumental variable setting where subjects may not comply with treatment assignment; analyzing experimental designs with endogenous subject participation and dropout; introducing monetary compensation and other contracts like informed consent; analyzing EXAM’s dynamic or sequential properties; optimally choosing sample size and treatment definitions (in addition to designing treatment assignment probabilities given the sample size and treatment definition); considering information frictions and psychological elements in patient preferences; and analyzing games among experimenters with experimental design as an action or strategy. I leave these challenging directions for future research.
References


Goldacre, Ben, Bad Pharma: How Drug Companies Mislead Doctors and Harm Patients, Macmillan, 2014.


Zelen, Marvin, “Play the Winner Rule and the Controlled Clinical Trial,” *Journal of the American Statistical Association*, 1969, 64 (325), 131–146.

### Table 1: Magnitude of the RCT Landscape

(a) Registered Medical Clinical Trials & Sample Sizes

| Total Number of Clinical Trials Registered | Sample Period 2007-2017 May | 296,597 |
| Sum of Sample Sizes                       |                           | 367,902,580 |

(b) Registered Social and Economic Experiments & Sample Sizes

| Total Number of Economic RCTs Registered  | Sample Period 2007-2017 May | 1055 |
| Sum of Sample Sizes                      |                           | 22,190,304 |

Notes: Panel a provides summary statistics of clinical trials registered in the WHO International Clinical Trials Registry Platform (ICTRP, [http://www.who.int/ictrp/en/](http://www.who.int/ictrp/en/) retrieved in January 2019). The sample consists of clinical trials registered there between January 1st 2007 to May 30th 2017. I exclude trials with registered sample size larger than five millions. Panel b provides summary statistics of economic RCTs registered in the American Economic Association RCT Registry ([https://www.socialscienceregistry.org](https://www.socialscienceregistry.org) retrieved in January 2019). The sample consists of RCTs registered there between January 1st 2007 to May 30th 2017 and where the unit of outcome measurement is an individual or a household. I focus on RCTs with individual or household subjects in order to make it possible to sum up sample sizes. See Section 2 for discussions about this exhibit and Appendix A.3.1 for the detailed computational procedure. Additional results are in Appendix Figure A.1 and Tables A.1-A.6.
Table 2: A Selection of High-stakes Randomized Controlled Trials

(a) Medical Clinical Trials

<table>
<thead>
<tr>
<th>Treatment Outcome</th>
<th>Treatment Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>i Cholesterol Lowering Drug</td>
<td>Mortality (in 5 Years)</td>
</tr>
<tr>
<td>ii Medication to Reduce Interocular Pressure</td>
<td>Visual Field Abnormality (in 6 Years)</td>
</tr>
<tr>
<td>iii HIV Prevention Drug</td>
<td>HIV Infection Rate (in 1 Year)</td>
</tr>
<tr>
<td>iv Antiretroviral Therapy</td>
<td>HIV Transmission Rate (in 1.7 Years)</td>
</tr>
<tr>
<td>v Hormone Therapy</td>
<td>Coronary Heart Disease (in 5 Years)</td>
</tr>
</tbody>
</table>

(b) Social and Economic Experiments

<table>
<thead>
<tr>
<th>Treatment Outcome</th>
<th>Treatment Effect</th>
</tr>
</thead>
<tbody>
<tr>
<td>I Unconditional Cash Transfers</td>
<td>Consumption (9 Months Later)</td>
</tr>
<tr>
<td>II Police Patrol</td>
<td>Crime Calls</td>
</tr>
<tr>
<td>III HIV Testing</td>
<td>Fertility (in 2-3 Years)</td>
</tr>
<tr>
<td>IV Health Insurance (Medicaid)</td>
<td>Depression Rate (in 2 Years)</td>
</tr>
<tr>
<td>V High Wage Job Offer</td>
<td>Offer Acceptance Rate</td>
</tr>
</tbody>
</table>

Notes: This table lists examples illustrating the high-stakes nature of certain RCTs. Following the convention in the medical literature, treatment effects are measured relative to the average outcome in the control group, which I normalize to 100%. Every treatment effect is statistically significant at the 5% or lower level. The control is a placebo or the absence of any treatment unless otherwise noted below. See the following references for the details of each RCT:

Panel a Study i: Scandinavian Simvastatin Survival Study Group and Others (1994)
Panel a Study ii: Kass et al. (2002)
Panel a Study iii: Grant et al. (2010)
Panel a Study iv: Cohen et al. (2011)
Panel a Study v: Writing Group for the Women’s Health Initiative Investigators and Others (2002)
Panel b Study I: Haushofer and Shapiro (2016)
Panel b Study II: Sherman and Weisburd (1995)
Panel b Study III: Angelucci and Bennett (2017)
Panel b Study IV: Bai et al. (2013)
Panel b Study V: Dal Bó et al. (2013), where the control is a lower wage job offer.

See Section 2 for discussions about this table. Appendix Table A.7 provides further details.
Table 3: OLS Regression Estimates of Heterogeneous Treatment Effects

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
<th>(5)</th>
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</thead>
<tbody>
<tr>
<td>Treatment</td>
<td>-0.045***</td>
<td>-0.045***</td>
<td>-0.046***</td>
<td>-0.044***</td>
<td>-0.045***</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.012)</td>
<td>(0.012)</td>
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</tr>
<tr>
<td>Treatment * latrine density</td>
<td>-0.061</td>
<td></td>
<td>-0.046</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.069)</td>
<td></td>
<td>(0.068)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment * diarrhea prevention</td>
<td></td>
<td>-0.012***</td>
<td></td>
<td>-0.010**</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td>(0.004)</td>
<td></td>
<td>(0.004)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment * mother’s education</td>
<td></td>
<td></td>
<td>-0.007**</td>
<td></td>
<td>-0.006*</td>
<td></td>
</tr>
<tr>
<td></td>
<td></td>
<td></td>
<td>(0.003)</td>
<td></td>
<td>(0.003)</td>
<td></td>
</tr>
<tr>
<td>Observations</td>
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<td>6,750</td>
<td>6,750</td>
<td>6,742</td>
<td>6,742</td>
<td></td>
</tr>
<tr>
<td>Mean of dependent variable in comparison group</td>
<td>0.193</td>
<td>0.193</td>
<td>0.193</td>
<td>0.193</td>
<td>0.193</td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table shows OLS regression estimates of heterogeneous treatment effects of spring protection. Data from all four survey rounds (2004, 2005, 2006, 2007), sample restricted to children under age three at baseline (in 2004) and children born since 2004 in sample households. Diarrhea defined as three or more “looser than normal” stools within 24 hours at any time in the past week. Different columns differ in the set of baseline household characteristics interacted with the treatment indicator. Every household characteristic is normalized to be mean zero so that the coefficient on the treatment indicator can be interpreted as the average treatment effect. The gender-age controls include linear and quadratic current age (by month), and these terms interacted with a gender indicator. I use specifications without additional controls. Stars *, **, and *** mean significance at 90%, 95%, and 99%, respectively, based on Huber-White robust standard errors clustered at the spring level. See Section 6.2 for the model description and discussions about this table.
Table 4: Maximum Simulated Likelihood Estimates of Mixed Logit Model of Spring Choice

<table>
<thead>
<tr>
<th></th>
<th>(1)</th>
<th>(2)</th>
<th>(3)</th>
<th>(4)</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>(Main)</td>
<td>(Main)</td>
<td>(Main)</td>
<td>(Main)</td>
</tr>
<tr>
<td>Spring protection treatment indicator (Normal)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>2.205***</td>
<td>3.163***</td>
<td>2.999***</td>
<td>3.516***</td>
</tr>
<tr>
<td></td>
<td>(0.213)</td>
<td>(0.235)</td>
<td>(0.288)</td>
<td>(0.308)</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>5.426***</td>
<td>5.702***</td>
<td>5.557***</td>
<td>5.741***</td>
</tr>
<tr>
<td></td>
<td>(0.298)</td>
<td>(0.291)</td>
<td>(0.405)</td>
<td>(0.305)</td>
</tr>
<tr>
<td>Treatment * latrine density</td>
<td>7.533***</td>
<td></td>
<td>2.751**</td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.939)</td>
<td></td>
<td>(1.178)</td>
<td></td>
</tr>
<tr>
<td>Treatment * diarrhea prevention</td>
<td>1.080***</td>
<td>0.565***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.104)</td>
<td>(0.095)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Treatment * mother’s education</td>
<td>0.650***</td>
<td>0.609***</td>
<td></td>
<td></td>
</tr>
<tr>
<td></td>
<td>(0.066)</td>
<td>(0.069)</td>
<td></td>
<td></td>
</tr>
<tr>
<td>Distance to source, minutes walk (Restricted triangular)</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>Mean</td>
<td>0.222***</td>
<td>0.220***</td>
<td>0.220***</td>
<td>0.221***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Standard Deviation</td>
<td>0.222***</td>
<td>0.220***</td>
<td>0.220***</td>
<td>0.221***</td>
</tr>
<tr>
<td></td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
<td>(0.010)</td>
</tr>
<tr>
<td>Source type: borehole/piped</td>
<td>-1.079***</td>
<td>-1.047***</td>
<td>-1.055***</td>
<td>-1.054***</td>
</tr>
<tr>
<td></td>
<td>(0.135)</td>
<td>(0.136)</td>
<td>(0.139)</td>
<td>(0.133)</td>
</tr>
<tr>
<td>Source type: well</td>
<td>-1.924***</td>
<td>-1.954***</td>
<td>-1.943***</td>
<td>-1.944***</td>
</tr>
<tr>
<td></td>
<td>(0.137)</td>
<td>(0.131)</td>
<td>(0.134)</td>
<td>(0.131)</td>
</tr>
<tr>
<td>Source type: stream/river</td>
<td>-1.422***</td>
<td>-1.387***</td>
<td>-1.443***</td>
<td>-1.393***</td>
</tr>
<tr>
<td></td>
<td>(0.144)</td>
<td>(0.141)</td>
<td>(0.148)</td>
<td>(0.143)</td>
</tr>
<tr>
<td>Source type: lake/pond</td>
<td>-0.312</td>
<td>-0.313</td>
<td>-0.333</td>
<td>-0.299</td>
</tr>
<tr>
<td></td>
<td>(0.269)</td>
<td>(0.273)</td>
<td>(0.274)</td>
<td>(0.406)</td>
</tr>
<tr>
<td>Number of observations</td>
<td>53,427</td>
<td>53,427</td>
<td>53,427</td>
<td>53,427</td>
</tr>
</tbody>
</table>

Notes: This table shows mixed logit estimates used for estimating heterogeneous WTP for the treatment. Each observation is a unique water collection trip recorded in the final round of household surveys (2007). The omitted water source category is non-program springs outside the target area of the experiment. Different columns differ in the set of baseline household characteristics interacted with the treatment indicator. The indicator for the spring that each household used at baseline is in the models, but its coefficient estimate is not shown in the table. Standard errors are based on the information matrix with the Hessian being estimated by the outer product of the gradient of the simulated likelihood at the estimated parameter value. Stars *, **, and *** mean significance at 90%, 95%, and 99%, respectively. See Section 6.2 for the model description and discussions about this table. See Appendix A.3.3 for the estimation procedure to produce these estimates.
Figure 1: Treatment Effects and WTP for the Treatment

(a) Heterogeneity in Treatment Effects $\hat{e}_{t_{1i}}$

(b) Heterogeneity in WTP $\hat{w}_{it_{1}}$

(c) Correlation between Treatment Effects & WTP

Notes: This figure shows the pattern of heterogeneity in estimated WTP $\hat{w}_{it_{1}}$ and predicted treatment effects $\hat{e}_{t_{1i}}$. Panel a is about the predicted treatment effects $\hat{e}_{t_{1i}}$ measured in percentage point reduction in the incidence of child diarrhea in the past week, while Panel b is about WTP for the spring protection treatment $\hat{w}_{it_{1}}$, measured by time cost of water collection in the unit of workdays. Both predicted effects $\hat{e}_{t_{1i}}$ and WTP $\hat{w}_{it_{1}}$ are based on the main statistical specifications including all of the interactions between the treatment indicator and household characteristics (baseline latrine density, diarrhea prevention knowledge score, and mother’s years of education). Panel c demonstrates the correlation between WTP $\hat{w}_{it_{1}}$ and predicted treatment effects $\hat{e}_{t_{1i}}$. For the sake of visibility, I focus on the three standard deviations around the mean. See Section 6.2 for discussions about this figure. See Appendix A.3.3 for the detailed computational procedure.
Figure 2: EXAM vs RCT: Welfare

(a) Average WTP for Assigned Treatments $w^*_i$

[Diagram showing cumulative distribution functions for WTP measured by time cost of water collection (Unit: Workdays), with Kolmogorov-Smirnov test: $D = 0.246$, p-value = 0.]

(b) Average Predicted Effects of Assigned Treatments $e^*_i$

[Diagram showing cumulative distribution functions for predicted effects measured by % reduction in child diarrhea, with Kolmogorov-Smirnov test: $D = 0.425$, p-value = 0.]

Notes: To compare EXAM and RCT’s welfare performance, this figure shows the distribution of average subject welfare over 1000 bootstrap simulations under each experimental design. Panel a measures welfare with respect to average WTP $w^*_i$ for assigned treatments while Panel b with respect to average predicted effects $e^*_i$ of assigned treatments. A dotted line indicates the distribution of each welfare measure for RCT while a solid line indicates that for EXAM. Each vertical line represents mean. Kolmogorov-Smirnov tests find the EXAM and RCT distributions to be significantly different both for $w^*_i$ and $e^*_i$. Both predicted effects $\hat{e}_{it}$ and WTP $\hat{w}_{it}$ are based on the main statistical specifications including all of the interactions between the treatment indicator and household characteristics (baseline latrine density, diarrhea prevention knowledge score, and mother’s years of education). See Section 6.3 for discussions about this figure.
Figure 3: EXAM vs RCT: Average Treatment Effect Estimates

(a) Distribution of Treatment Effect Estimates $\hat{b}^*$

(b) Distribution of Average Treatment Effect Estimates $\hat{\beta}^*$

Notes: This figure compares EXAM and RCT’s causal inference performance by showing the distribution of average treatment effect estimates under each experimental design. Grey bins indicate average treatment effect estimates for RCT while transparent bins with black outlines indicate those for EXAM. The solid vertical line indicates the mean for EXAM while the dashed vertical line indicates that for RCT. See Section 6.3 for discussions about this figure.
Figure 4: EXAM vs RCT: $p$ Values for $\hat{b}^*$

(a) Exact, Finite Sample $p$ Values
(b) Non-robust $p$ Values
(c) Robust $p$ Values
(d) Abadie et al. (2017)'s $p$ Values

Notes: This figure compares EXAM and RCT's causal inference performance by showing the distribution of $p$ values accompanying treatment effect estimates $\hat{b}^*$ under each experimental design. The $p$ values are based on exact, non-robust, robust, or Abadie et al. (2017)’s finite population causal standard errors. Grey bins indicate $p$ values for RCT while transparent bins with black outlines indicate those for EXAM. The solid vertical line indicates median for EXAM while the dashed vertical line indicates that for RCT. See Section 6.3 for discussions about this figure.
Figure 5: EXAM vs RCT: Incentive

(a) WTP manipulation \(\sim\) true WTP + \(N(0, 100)\)  (b) WTP manipulation \(\sim\) true WTP + \(N(0, 1000)\)

(c) WTP manipulation \(\sim\) true WTP + \(U(0, 100)\)  (d) WTP manipulation \(\sim\) true WTP + \(U(-100, 0)\)

Notes: This figure shows the histogram of true WTP gains from potential WTP misreporting to EXAM, quantifying the incentive compatibility of EXAM. Different panels use different ways of drawing WTP manipulations indicated by the panel titles. Each solid vertical line represents the mean WTP gain from potential WTP misreporting to EXAM. The dash vertical line is for RCT, where the true WTP gain from any WTP misreport is zero. See Section 6.3 for discussions about this figure.
Table 5: EXAM vs RCT: Incentive Details

<table>
<thead>
<tr>
<th>Figure 5 Panel a</th>
<th>Manipulation  $\sim N(0, 100)$</th>
<th>$\Delta w/w_{it1}$ True WTP Gains from Misreporting Relative to True WTP for Treatment $t_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>95 Percentile</td>
<td>0.00%</td>
<td>0.00%</td>
</tr>
<tr>
<td>96 Percentile</td>
<td>0.10%</td>
<td>0.34%</td>
</tr>
<tr>
<td>97 Percentile</td>
<td>0.63%</td>
<td>1.55%</td>
</tr>
<tr>
<td>98 Percentile</td>
<td>1.55%</td>
<td>1.82%</td>
</tr>
<tr>
<td>99 Percentile</td>
<td>1.55%</td>
<td>1.82%</td>
</tr>
<tr>
<td>Max</td>
<td>1.55%</td>
<td>1.82%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Figure 5 Panel b</th>
<th>Manipulation  $\sim N(0, 1000)$</th>
<th>$\Delta w/w_{it1}$ True WTP Gains from Misreporting Relative to True WTP for Treatment $t_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>95 Percentile</td>
<td>0.92%</td>
<td>1.12%</td>
</tr>
<tr>
<td>96 Percentile</td>
<td>1.32%</td>
<td>1.42%</td>
</tr>
<tr>
<td>97 Percentile</td>
<td>1.55%</td>
<td>1.82%</td>
</tr>
<tr>
<td>98 Percentile</td>
<td>1.55%</td>
<td>1.82%</td>
</tr>
<tr>
<td>99 Percentile</td>
<td>1.55%</td>
<td>1.82%</td>
</tr>
<tr>
<td>Max</td>
<td>1.82%</td>
<td>1.82%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Figure 5 Panel c</th>
<th>Manipulation  $\sim U(0, 100)$</th>
<th>$\Delta w/w_{it1}$ True WTP Gains from Misreporting Relative to True WTP for Treatment $t_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>95 Percentile</td>
<td>0.69%</td>
<td>0.89%</td>
</tr>
<tr>
<td>96 Percentile</td>
<td>1.20%</td>
<td>1.41%</td>
</tr>
<tr>
<td>97 Percentile</td>
<td>1.54%</td>
<td>2.04%</td>
</tr>
<tr>
<td>98 Percentile</td>
<td>1.54%</td>
<td>2.04%</td>
</tr>
<tr>
<td>99 Percentile</td>
<td>1.54%</td>
<td>2.04%</td>
</tr>
<tr>
<td>Max</td>
<td>2.04%</td>
<td>2.04%</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>Figure 5 Panel d</th>
<th>Manipulation  $\sim U(-100, 0)$</th>
<th>$\Delta w/w_{it1}$ True WTP Gains from Misreporting Relative to True WTP for Treatment $t_1$</th>
</tr>
</thead>
<tbody>
<tr>
<td>95 Percentile</td>
<td>0.76%</td>
<td>0.98%</td>
</tr>
<tr>
<td>96 Percentile</td>
<td>1.24%</td>
<td>1.46%</td>
</tr>
<tr>
<td>97 Percentile</td>
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<tr>
<td>98 Percentile</td>
<td>1.64%</td>
<td>1.87%</td>
</tr>
<tr>
<td>99 Percentile</td>
<td>1.64%</td>
<td>1.87%</td>
</tr>
<tr>
<td>Max</td>
<td>1.87%</td>
<td>1.87%</td>
</tr>
</tbody>
</table>

Notes: This table provides additional details about Figure 5. In particular, for each scenario in Figure 5, this table shows the most profitable true WTP gains from potential WTP misreporting to EXAM, quantifying the incentive compatibility of EXAM. See Section 6.3 for discussions about this table.
A Appendix (For Online Publication)

A.1 Methodological Details

Throughout Appendix A.1, I impose the simplifying assumption that \( \sum_i p^*_i(\epsilon) \in \mathbb{Z} \) for every \( t \). It is possible to dispense with this assumption with additional notational burden.

A.1.1 Propositions 4 and 5: Generalizations

This section extends Proposition 5 to a general case where \( p_t n_p \) (the expected number of subjects with propensity vector \( p \) and assigned to treatment \( t \) under EXAM) may not be an integer. Let \( N_{pt} \equiv \sum_i 1\{p^*_i(\epsilon) = p\}D_{it} \) be a random variable that stands for the number of subjects with propensity vector \( p \) and assigned to treatment \( t \). Denote the realization of \( N_{pt} \) by \( n_{pt} \equiv \sum_i 1\{p^*_i(\epsilon) = p\}d_{it} \) where \( d_{it} \) is the realization of \( D_{it} \). Let \( n_{pt} \) be the greatest integer less than or equal to \( p_t n_p \). With this regularity condition, I extend Definition 2 as follows to use EXAM to draw a deterministic treatment assignment and the associated \( n_{pt} \)'s.

Definition 2 (EXAM Continued; Generalization). Starting from the end of Definition 2 in Section 3.2, draw a treatment assignment from \( p^*_i(\epsilon) \) as follows. First apply Budish et al. (2013)'s algorithm (in their Appendix B) to draw \( (n_{pt}) \in \mathbb{N} \) that satisfy the following properties (I detail their algorithm and its use below):

- \( n_{pt} = p_t n_p \) for all \( p \) and \( t \) such that \( p_t n_p \in \mathbb{N} \).
- \( n_{pt} \in \{n_{pt}, n_{pt} + 1\} \) for all \( p \) and \( t \) such that \( p_t n_p \notin \mathbb{N} \).
- \( \sum_t n_{pt} = n_p \) for all \( p \).
- \( \sum_p n_{pt} = \sum_i p^*_i(\epsilon) \) for all \( t \).
- \( E(n_{pt}) = p_t n_p \) for all \( p \) and \( t \).

Given the drawn values of \( (n_{pt}) \), for each propensity vector \( p \),

- I uniformly randomly pick \( n_{pt_0} \) subjects from \( \{i|p^*_i(\epsilon) = p\} \) and assign them to \( t_0 \).

For each subsequent step \( k = 1, \ldots, m \),

- Step \( k \): From the remaining \( n_p - \sum_{t=t_0}^{t_{k-1}} n_{pt} \) subjects, I uniformly randomly pick \( n_{pt_k} \) subjects and assign them to \( t_k \).
When \(p_t n_p\) is an integer for all \(p\) and \(t\), \(n_{pt} = p_t n_p\) always holds for all \(p\) and \(t\) so that this generalized definition reduces to Definition 2 in Section 5. With this extended Definition 2, Proposition 4 holds as it is in the main text. I obtain the following characterization of the variance of ATE estimator \(\hat{\beta}_t^*\), which nests Proposition 5 in Section 5.

**Proposition 5 (Generalization).** Suppose that the data-generating process is EXAM \(p^*(\epsilon) \equiv (p^*_t(\epsilon))_{it}\) with any given \(\epsilon > 0\). \(\hat{\beta}_t^*\) is an unbiased estimator of the average treatment effect with the following variance.

\[
V(\hat{\beta}_t^* | p^*(\epsilon)) = \sum_p \delta_p^2 \left\{ \sum_{t' \in \{t_0, t\}} \left[ \frac{S_{pt'}^2}{n_{pt'}} (1 - p_t n_p + n_{pt'}) + \left( \frac{S_{pt'}^2}{n_{pt'}} + 1 \right)(p_t n_p - n_{pt'}) \right] - \frac{S_{ptt_0}^2}{n_p} \right\},
\]

where recall that \(\delta_p \equiv n_p/n\), \(\bar{Y}_p(t) \equiv \frac{\sum_{i:p_t^*(\epsilon) = p} Y_i(t)}{n_p}\) is the mean of \(Y_i(t)\) in the subpopulation with propensity \(p\), \(S_{pt'}^2 \equiv \frac{\sum_{i:p_t^*(\epsilon) = p} (Y_i(t) - \bar{Y}_p(t))^2}{n_p - 1}\) is the variance of \(Y_i(t)\) in the subpopulation, and \(S_{ptt_0}^2 \equiv \frac{\sum_{i:p_t^*(\epsilon) = p} (Y_i(t) - Y_i(t') - (\bar{Y}_p(t) - \bar{Y}_p(t')))^2}{n_p - 1}\) is the variance of \(Y_i(t) - Y_i(t')\) in the subpopulation.

**Using Budish et al. (2013)’s Algorithm**

In the above generalized Definition 2, I use Budish et al. (2013)’s algorithm to draw \((n_{pt})\). To do so, I embed my setting into their notation as follows: \(N \equiv \{ p \in [0, 1]^{n+1} \mid \text{there exists some subject } i \text{ such that } p_t^*(\epsilon) = p \}\) is the set of “agents” in their terminology. Let \(O \equiv \{t_0, t_1, ..., t_m\}\) be the set of “objects.” \(\mathcal{H} \equiv \{\mathcal{H}_1, \mathcal{H}_2\}\) is a “constraint structure” where \(\mathcal{H}_1 \equiv \mathcal{H}_0 \cup \mathcal{H}_1', \mathcal{H}_0 \equiv \{\{ (p, t) \}_p \in N, t \in O \}, \mathcal{H}_1 \equiv \{ (p, t) | t \in O \}_p \in N, \) and \(\mathcal{H}_2 \equiv \{ (p, t) | p \in N \}_t \in O\). Upper and lower constraints are as follows.

- \(\bar{q}_s = 1\) and \(\underline{q}_s = 0\) if \(s \in \mathcal{H}_0\).
- \(\bar{q}_s = \underline{q}_s = n_p - \sum_t n_{pt}\) if \(s \in \mathcal{H}_1'\).
- \(\bar{q}_s = \underline{q}_s = \sum_i p_t^*(\epsilon) - \sum_p n_{pt}\) if \(s \in \mathcal{H}_2\).

Budish et al. (2013) show that applying their algorithm to this problem produces \((x_{pt})\) such that \(n_p = n_{pt} + x_{pt}\) satisfies the properties in Definition 2. For completeness, I define their algorithm; see their Appendix B for more details. I first construct a network flow as follows. Let \(\Omega \equiv \{\{(p, t)\}_p \in N, t \in O\}\) and \(X = (x_{\omega})_{\omega \in \Omega}\). The set of vertices is composed of the
source \( s \) and the sink \( s' \), two vertices \( v_\omega \) and \( v_{\omega'} \) for each element \( \omega \in \Omega \), and \( v_S \) for each \( S \in \mathcal{H} \setminus [(\bigcup_{\omega \in \Omega} \{\omega\}) \cup (N \times O)] \). I place (directed) edges according to the following rule.

- For each \( \omega \in \Omega \), an edge \( e = (v_\omega, v_{\omega'}) \) is placed from \( v_\omega \) to \( v_{\omega'} \).
- For each \( k = 1, 2 \), an edge \( e = (v_S, v_{S'}) \) is placed from \( S \) to \( S' \neq S \) where \( S, S' \in \mathcal{H}_k \), if \( S' \subset S \) and there is no \( S'' \in \mathcal{H}_k \) where \( S' \subset S'' \subset S \).
- An edge \( e = (s, v_S) \) is placed from the source \( s \) to \( v_S \) if \( S \in \mathcal{H}_1 \) and there is no \( S' \in \mathcal{H}_1 \) where \( S \subset S' \).
- An edge \( e = (v_S, s') \) is placed from \( v_S \) to the sink \( s' \) if \( S \in \mathcal{H}_2 \) and there is no \( S' \in \mathcal{H}_2 \) where \( S \subset S' \).

I associate flow with each edge as follows. For each edge \( e = (v_\omega, v_{\omega'}) \), I associate flow \( x_e = x_\omega \). For each \( e \) that is not of the form \( (v_\omega, v_{\omega'}) \) for some \( \omega \in \Omega \), the flow \( x_e \) is (uniquely) set to satisfy the flow conservation, that is, for each vertex \( v \) different from \( s \) and \( s' \), the sum of flows into \( v \) is equal to the sum of flows from \( v \). I use this network flow to define the following algorithm.

**Definition 3** [Budish et al. (2013)’s Algorithm]. If \( \deg[X(\mathcal{H})] \equiv |\{S \in \mathcal{H} | x_s \in \mathbb{Z}\}| = |\mathcal{H}| \), then stop the algorithm. Otherwise, move on to the following steps:

1. **Cycle-Finding Procedure**
   
   (a) **Step 0**: Since \( \deg[X(\mathcal{H})] < |\mathcal{H}| \) by assumption, there exists an edge \( e_1 = (v_1, v'_1) \) such that its associated flow \( x_{e_1} \) is fractional. Define an edge \( f_1 = (v_1, v'_1) \) from \( v_1 \) to \( v'_1 \).
   
   (b) **Step \( t = 1, \ldots \)**: Consider the vertex \( v'_t \) that is the destination of edge \( f_t \).
      
      i) If \( v'_t \) is the origin of some edge \( f'_t \in \{f_1, \ldots, f_{t-1}\} \), then stop. The procedure has formed a cycle \( (f'_t, f'_{t+1}, \ldots, f_t) \) composed of edges in \( \{f_1, \ldots, f_t\} \). Proceed to **Termination-Cycle Procedure** below.
      
      ii) Otherwise, since the flow associated with \( f_t \) is fractional by construction and the flow conservation holds at \( v'_t \), there exists an edge \( e_{t+1} = (u_{t+1}, u'_{t+1}) \neq e_t \) with fractional flow such that \( v'_t \) is either its origin or destination. Draw an edge \( f_{t+1} \) by \( f_{t+1} = e_{t+1} \) if \( v'_t \) is the origin of \( e_{t+1} \) and \( f_{t+1} = (u'_{t+1}, u_{t+1}) \) otherwise. Denote \( f_{t+1} = (v_{t+1}, v'_{t+1}) \).

2. **Termination-Cycle Procedure**
(a) Construct a set of flows associated with edges \((x^1_e)\) which is the same as \((x_e)\), except for flows \((x_{e,t})\), that is, flows associated with edges that are involved in the cycle from the last step. For each edge \(e_r\) such that \(f_r = e_r\), set \(x^1_{e_r} = x_{e_r} + \alpha\), and each edge \(e_r\) such that \(f_r \neq e_r\), set \(x^1_{e_r} = x_{e_r} - \alpha\), where \(\alpha > 0\) is the largest real number such that the induced expected assignment \(X^1 = (x^1_\omega)_{\omega \in \Omega}\) still satisfies all constraints in \(\mathcal{H}\). By construction, \(x^1_S = x_S\) if \(x_S\) is an integer, and there is at least one constraint set \(S \in \mathcal{H}\) such that \(x^1_S\) is an integer while \(x_S\) is not. Thus \(\text{deg}[X^1(\mathcal{H})] > \text{deg}[X(\mathcal{H})]\).

(b) Construct a set of flows associated with edges \((x^2_e)\) which is the same as \((x_e)\), except for flows \((x_{e,t})\), that is, flows associated with edges that are involved in the cycle from the last step. For each edge \(e_r\) such that \(f_r = e_r\), set \(x^2_{e_r} = x_{e_r} - \beta\), and each edge \(e_r\) such that \(f_r \neq e_r\), set \(x^2_{e_r} = x_{e_r} + \beta\), where \(\beta > 0\) is the largest real number such that the induced expected assignment \(X^2 = (x^2_\omega)_{\omega \in \Omega}\) still satisfies all constraints in \(\mathcal{H}\). By construction, \(x^2_S = x_S\) if \(x_S\) is an integer, and there is at least one constraint set \(S \in \mathcal{H}\) such that \(x^2_S\) is an integer while \(x_S\) is not. Thus \(\text{deg}[X^2(\mathcal{H})] > \text{deg}[X(\mathcal{H})]\).

(c) Set \(\gamma\) by \(\gamma \alpha + (1 - \gamma)(-\beta) = 0\), i.e., \(\gamma = \frac{\beta}{\alpha + \beta}\).

(d) Decompose \(X\) into \(X = \gamma X^1 + (1 - \gamma)X^2\).

Note that \(\text{deg}[X^k(\mathcal{H})] > \text{deg}[X(\mathcal{H})]\) for both \(k = 1, 2\), implying that repeating the above algorithm transforms the original \(X\) into a distribution over deterministic \((x_{pt})\)'s where every \(x_{pt}\) is an integer. The induced distribution can then be used to draw deterministic \((x_{pt})\) consistent with \(X\). [Budish et al. (2013)]'s Theorem 1 and Appendix B show that the resulting \((x_{pt})\) has the property that \(n_{pt} = n_{pt} + x_{pt}\) satisfies the conditions in Definition 2.

### A.1.2 Asymptotic Power Comparison of EXAM and RCT

Section 5 illustrates that EXAM’s ATE estimation is potentially more precise than RCT’s in a finite sample. This appendix shows the same point in an asymptotic framework.

#### Sequence of Experimental Design Problems

Following [Abadie et al. (2017)], I consider a sequence of finite populations of potential subjects indexed by population size \(N\). For each population \(N\), I randomly sample subjects who participate in the experiment. Let \(R_{N,i}\) denote the indicator of subject \(i\) being sampled from population \(N\), i.e., \(R_{N,i} = 1\) if \(i\) is sampled and \(R_{N,i} = 0\) otherwise. Denote the number
of subjects by \( n = \sum_{i=1}^{N} R_{N,i} \). Given each finite population \( N \), I consider a sequence of experimental design problems, each of which consists of

- A set of \( n \) experimental subjects \( \{i|R_{N,i} = 1\} \).
- Experimental treatments \( t_0, t_1, \ldots, t_m \).
- Each treatment \( t' \)'s pseudo capacity \( c_{N,t} \in \mathbb{N} \) with \( \sum_{t=0}^{m} c_{N,t} = n \).
- Each subject \( i \)'s WTP \( w_{N,it} \) for each \( i \in \{j|R_{N,j} = 1\} \).
- Each treatment \( t' \)'s predicted treatment effect \( e_{N,ti} \) for each \( i \in \{j|R_{N,j} = 1\} \).

Among these components, experimental treatments are nonrandom and do not depend on \( N \) or \( n \). The other elements are random because \( R_{N,i} \) is random. I allow \( c_{N,t} \) to be random even conditional on \( \{i|R_{N,i} = 1\} \).

I study a sequence of experimental designs \( p_N = (p_{N,it})_{i|R_{N,i}=1,t=t_0,\ldots,t_m} \) along with the sequence of experimental design problems. \( p_N \) is random because some of the components of an experimental design problem is random. For each sampled experimental design problem and each \( i \in \{j|R_{N,j} = 1\} \), I use \( D_{N,it} = 1 \) to indicate that subject \( i \) is assigned to treatment \( t \), and \( D_{N,it} = 0 \) to indicate that subject \( i \) is assigned to any other treatment or control. The distribution of \( (D_{N,it}) \) depends on the algorithm to draw deterministic treatment assignments. Let \( Y_{N,i}(t) \) be the fixed potential outcome of subject \( i \) that would be observed if \( i \) is sampled from population \( N \) and assigned to treatment \( t \). The observed outcome of subject \( i \) in the sample is \( Y_{N,i} = \sum_{t=t_0}^{m} D_{N,it} Y_{N,i}(t) \). I observe \( (Y_{N,i}, D_{N,it}, w_{N,it}, e_{N,it}) \) for each subject \( i \) in the sample.

**Sequence of Parameters and Estimators**

I consider a sequence of two parameters as estimands, the population average treatment effect and the sample average treatment effect, defined as follows:

\[
\beta^\text{pop}_{N,t} = \frac{1}{N} \sum_{i=1}^{N} (Y_{N,i}(t) - Y_{N,i}(t_0)) \quad \text{and} \quad \beta^\text{sample}_{N,t} = \frac{1}{n} \sum_{i=1}^{n} R_{N,i}(Y_{N,i}(t) - Y_{N,i}(t_0)).
\]

Let \( \beta^\text{pop}_N = (\beta^\text{pop}_{N,t_1}, \ldots, \beta^\text{pop}_{N,t_m})' \) and \( \beta^\text{sample}_N = (\beta^\text{sample}_{N,t_1}, \ldots, \beta^\text{sample}_{N,t_m})' \). Note that \( \beta^\text{pop}_N \) is nonrandom while \( \beta^\text{sample}_N \) is random due to the random sampling of a subject sample. I put the following assumption.
Assumption 1. There exist $G$ sequences of nonempty subpopulations, $\{P_{N,1}\}, ..., \{P_{N,G}\}$, such that for all $N$, (i) $P_{N,1}, ..., P_{N,G}$ form a partition of population $N$, (ii) for all $i, j \in P_{N,g}$, I have $(w_{N,it}, e_{N,it})_t = (w_{N,jt}, e_{N,jt})_t$, and (iii) if $(w_{N,it}, e_{N,it})_t = (w_{N,jt}, e_{N,jt})_t$ for some $i \in P_{N,g}$ and $j \in P_{N,g'}$, then $g = g'$.

Denote the size of $P_{N,1}, ..., P_{N,G}$ by $N_1, ..., N_G$, respectively. Let $n_{g} = \sum_{i \in P_{N,g}} R_{N,i}$ be the number of subjects sampled from subpopulation $P_{N,g}$. Now consider two parameters defined on subpopulation $P_{N,g}$:

\[
\beta_{N,gt}^{\text{pop}} = \frac{1}{N_g} \sum_{i \in P_{N,g}} (Y_{N,i}(t) - Y_{N,i}(t_0)) \quad \text{and} \quad \beta_{N,gt}^{\text{sample}} = \frac{1}{n_g} \sum_{i \in P_{N,g}} R_{N,i} (Y_{N,i}(t) - Y_{N,i}(t_0)).
\]

Let $\beta_{N,g}^{\text{pop}} = (\beta_{N,gt_1}^{\text{pop}}, ..., \beta_{N,gt_m}^{\text{pop}})'$ and $\beta_{N,g}^{\text{sample}} = (\beta_{N,gt_1}^{\text{sample}}, ..., \beta_{N,gt_m}^{\text{sample}})'$. The population average treatment effect $\beta_{N,t}^{\text{pop}}$ and the sample average treatment effect $\beta_{N,t}^{\text{sample}}$ can be written as the weighted average of $\beta_{N,gt}^{\text{pop}}$ and $\beta_{N,gt}^{\text{sample}}$, respectively:

\[
\beta_{N,t}^{\text{pop}} = \sum_{g=1}^{G} \frac{N_g}{N} \beta_{N,gt}^{\text{pop}} \quad \text{and} \quad \beta_{N,t}^{\text{sample}} = \sum_{g=1}^{G} \frac{n_g}{n} \beta_{N,gt}^{\text{sample}}.
\]

As in Section 5, I estimate both $\beta_{N,t}^{\text{pop}}$ and $\beta_{N,t}^{\text{sample}}$ with

\[
\hat{\beta}_{N,t}^* = \sum_{g=1}^{G} \frac{n_g}{n} \hat{\beta}_{N,gt}^*;
\]

where

\[
\hat{\beta}_{N,gt}^* = \frac{\sum_{i \in P_{N,g}} R_{N,i} D_{N,it} Y_{N,i}}{\sum_{i \in P_{N,g}} R_{N,i} D_{N,it}} - \frac{\sum_{i \in P_{N,g}} R_{N,i} D_{N,it_0} Y_{N,i}}{\sum_{i \in P_{N,g}} R_{N,i} D_{N,it_0}}.
\]

I assume that if two subjects are in different subpopulations, EXAM gives them different assignment probabilities and puts them in different subsamples. Let $\hat{\beta}_{N,g}^* = (\hat{\beta}_{N,gt_1}^*, ..., \hat{\beta}_{N,gt_m}^*)'$. 

Asymptotic Distribution of $\hat{\beta}_{N,t}^*$

To derive the asymptotic distribution of $\hat{\beta}_{N,t}^*$, I need a series of regularity conditions. I first assume that each subject is sampled independently with the same sampling probability, and the expected sample size of each subsample goes to infinity as $N$ goes to infinity. Let $\delta_{N,g} = N_g/N$. 

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Assumption 2. (i) There is a sequence of sampling probabilities, \( \rho_N \), such that for all \( r \in \{0, 1\}^N \),
\[
\Pr(R_N = r) = \frac{\sum_{i=1}^{N} r_i (1 - \rho_N)^{N-\sum_{i=1}^{N} r_i}}{\rho_N^r (1 - \rho_N)^{N-r}}.
\]
(ii) For all \( g \), \( N_g \rho_N \to \infty \), \( \rho_N \to \rho \in [0, 1] \) and \( \delta_{N,g} \to \delta_g \in [0, 1] \) as \( N \to \infty \).

I apply EXAM to each realized experimental design problem to obtain treatment assignment probabilities. Denote the assignment probabilities by \( p_N^* (\epsilon) \). I impose the following restriction on the distribution of capacities conditional on sample. Below expectations are taken over \( R_N \equiv (R_{N,1}, ..., R_{N,N})', \), \( (c_{N,t}) \) and \( (D_{N,it}) \).

Assumption 3. For all \( g \), there is a sequence of constant vectors of size \( m + 1 \), \( q_{N,g} \), such that \( E[p_{N,it}^*(\epsilon)|R_N = r] = q_{N,g,t} \) for all \( t \), \( r \in \{0, 1\}^N \), and all \( i \in P_{N,g} \cap \{ j | r_j = 1 \} \).

For each subject \( i \in P_{N,g} \cap \{ k | R_N = 0 \} \), define \( p_{N,it}^*(\epsilon) \) as \( p_{N,it}^*(\epsilon) = p_{N,jt}^*(\epsilon) \) for an arbitrary \( j \in P_{N,g} \cap \{ k | R_k = 1 \} \). I also define random variable \( D_{N,it} \) with \( i \in \{ k | R_k = 0 \} \) such that the following assumption is true and treatment assignments are independent across subjects given assignment probabilities \( p_N^*(\epsilon) \).

Assumption 4. \( (D_{N,it})_{t=0,...,t_m} \) and \( (D_{N,jt})_{t=0,...,t_m} \) are independent for any \( i \neq j \) conditional on \( R_N = r \).

I put a few additional regularity conditions.

Assumption 5. For all \( g \), there exists some \( \delta > 0 \) such that the sequence \( \frac{1}{N_g} \sum_{i \in P_{N,g}} E[|Y_{N,i}|^{4+\delta}] \) is bounded.

Now let \( X_{N,it} = D_{N,it} - E[D_{N,it}], \) \( D_{N,i} = (D_{N,i,t_1}, ..., D_{N,i,t_m})', \) \( X_{N,i} = (X_{N,i,t_1}, ..., X_{N,i,t_m})' \), and for each \( g \),
\[
\Omega_{N,g} = \frac{1}{N_g} \sum_{i \in P_{N,g}} E \left[ \begin{pmatrix} Y_{N,i} \\ X_{N,i} \\ 1 \end{pmatrix} \begin{pmatrix} Y_{N,i} \\ X_{N,i} \\ 1 \end{pmatrix}' \right].
\]

Assumption 6. For all \( g \), \( \Omega_{N,g} \to \Omega_g \), where the limit is full rank.

Let \( \beta_{N,it} = Y_{N,i}(t) - Y_{N,i}(t_0) \) and \( \beta_{N,i} = (\beta_{N,i,t_1}, ..., \beta_{N,i,t_m})' \). For all \( g \) and all \( i \in P_{N,g} \), let
\[
\epsilon_{N,i} = \sum_{t=t_0}^{t_m} D_{N,it} (Y_{N,i}(t) - \frac{1}{N_g} \sum_{i \in P_{N,g}} Y_{N,i}(t)).
\]

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Let $\Delta^{\text{cond}}_g = \lim_{N \to \infty} \frac{1}{N_g} \sum_{i \in P_{N,g}} \text{Var}(X_{N,i} \epsilon_{N,i})$ and $\Delta^{\text{ehw}}_g = \lim_{N \to \infty} \frac{1}{N_g} \sum_{i \in P_{N,g}} E(X_{N,i} \epsilon_{N,i}^2 X'_{N,i}).$

Assumption 7. For all $g$, $\Delta^{\text{cond}}_g$ and $\Delta^{\text{ehw}}_g$ exist and are positive definite.

Assumption 8. For all $g$, $\sqrt{n}(n_g - N_g) \beta^{\text{pop}}_{N,g} \xrightarrow{p} 0$ as $N \to \infty$.

Proposition 6 (Asymptotic Distribution of $\hat{\beta}^*_{N,t}$). Suppose Assumptions 1, 2, 3, 4, 5, 6 and 7 hold. Let $H_g = \lim_{N \to \infty} \frac{1}{N_g} \sum_{i \in P_{N,g}} E(X_{N,i} X'_{N,i}).$ Then,

$$
\sqrt{n}(\hat{\beta}^{\star}_{N,t_j} - \beta^{\text{sample}}_{N,t_j}) \xrightarrow{d} \mathcal{N}(0, V_{1, jj}),
$$

where $V_{1, jj}$ is the $j$-th diagonal element of $V_1^* \equiv \sum_{g=1}^G \delta_g H^{-1}_g (\rho \Delta^{\text{cond}}_g + (1 - \rho) \Delta^{\text{ehw}}_g) H^{-1}_g$.

$$
\sqrt{n}(\hat{\beta}^{\star}_{N,t_j} - \beta^{\text{sample}}_{N,t_j}) \xrightarrow{d} \mathcal{N}(0, V_{2, jj}),
$$

where $V_{2, jj}$ is the $j$-th diagonal element of $V_2^* \equiv \sum_{g=1}^G \delta_g H^{-1}_g \Delta^{\text{cond}}_g H^{-1}_g$.

Asymptotic Efficiency Comparison of EXAM and RCT

How does EXAM compare to RCT in terms of asymptotic standard errors? With RCT, the estimator for $\beta^{\text{pop}}_{N,t}$ and $\beta^{\text{sample}}_{N,t}$ is

$$
\hat{\beta}^{\text{RCT}}_{N,t} = \frac{\sum_{i : R_{N,t} = 1} D_{N,i,t} Y_{N,i}}{\sum_{i : R_{N,t} = 1} D_{N,i,t}} - \frac{\sum_{i : R_{N,t} = 1} D_{N,i,t} Y_{N,i}}{\sum_{i : R_{N,t} = 1} D_{N,i,t}}.
$$

$\hat{\beta}^{\text{RCT}}_{N,t}$ is a special case of $\hat{\beta}^{\star}_{N,t}$ when $w_{N,i,t} = w_{N,j,t} > 0$ and $e_{N,t} = c_{N,t}$ for all $i, j$ and $t$ (recall Proposition 1). For this RCT special case, Assumption 2 holds with $G = 1$ and $P_{N,1}$ being the set of all subjects. Assumption 8 also holds since $\sqrt{n}(n_g - N_g) \beta^{\text{pop}}_{N,g} = 0$ for all $g$ and $N$. Let $\epsilon_{N,i} = D'_{N,i}(\beta_{N,i} - \beta^{\text{pop}}_{N}) + Y_{N,i}(0) - \frac{1}{N} \sum_{i=1}^N Y_{N,i}(0)$, $\Delta^{\text{cond}} = \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^N \text{Var}(X_{N,i} \epsilon_{N,i})$ and $\Delta^{\text{ehw}} = \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^N E(X_{N,i} \epsilon_{N,i}^2 X'_{N,i}).$ Proposition 6 therefore implies the following result.

Corollary 3 (Asymptotic Distribution of $\hat{\beta}^{\text{RCT}}_{N,t}$). Suppose Assumptions 2, 3, 4, 5, 6 and 7 hold with $G = 1$ and $p^{*}_{N,i,t}(\epsilon) = c_{N,i}/N$ for all $i, t$, and $N$. Let $H = \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^N E(X_{N,i} X'_{N,i})$.

$$
\sqrt{n}(\hat{\beta}^{\text{RCT}}_{N,t_j} - \beta^{\text{pop}}_{N,t_j}) \xrightarrow{d} \mathcal{N}(0, V^{\text{RCT}}_{1, jj}),
$$

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where \( V_{1,jj}^{RCT} \) is the \( j \)-th diagonal element of \( V_1^{RCT} \equiv H^{-1}(\rho \Delta^\text{cond} + (1-\rho)\Delta^\text{ehw})H^{-1} \).

\[
\sqrt{n}(\hat{\beta}_N^{RCT} - \beta_{N,tj}^\text{sample}) \xrightarrow{d} \mathcal{N}(0, V_{2,jj}^{RCT}),
\]

where \( V_{2,jj}^{RCT} \) is the \( j \)-th diagonal element of \( V_2^{RCT} \equiv H^{-1} \Delta^\text{cond} H^{-1} \).

To compare EXAM and RCT by their asymptotic variances, consider a simple situation where there is only one treatment. For EXAM, let

\[
q_{g,t} = \lim_{N \to \infty} q_{N,g,t}, S^2_{gt} = \lim_{N \to \infty} \frac{\sum_{i \in P_{N,g}} (Y_{N,i}(t) - \bar{Y}_{N,g}(t))^2}{N_g}
\]

and

\[
S^2_{gtv} = \lim_{N \to \infty} \frac{\sum_{i \in P_{N,g}} (Y_{N,i}(t) - Y_{N,i}(t') - (\bar{Y}_{N,g}(t) - \bar{Y}_{N,g}(t')))^2}{N_g},
\]

where \( \bar{Y}_{N,g}(t) = \frac{\sum_{i \in P_{N,g}} Y_{N,i}(t)}{N_g} \). For RCT, let

\[
q_t = \lim_{N \to \infty} q_{N,t}, S^2_t = \lim_{N \to \infty} \frac{\sum_{i=1}^N (Y_{N,i}(t) - \bar{Y}_N(t))^2}{N}
\]

and

\[
S^2_{tv} = \lim_{N \to \infty} \frac{\sum_{i=1}^N (Y_{N,i}(t) - Y_{N,i}(t') - (\bar{Y}_N(t) - \bar{Y}_N(t')))^2}{N},
\]

where \( q_{N,t} = E[c_{N,t}/n] \) and \( \bar{Y}_N(t) = \frac{\sum_{i=1}^N Y_{N,i}(t)}{N} \). I assume these limits exist.

**Assumption 9.** For all \( g \), \( q_{g,t}, S^2_{gt}, S^2_{gtv} \) and \( S^2_{gtv} \) exist with \( q_{g,t} \in (0, 1) \).

**Assumption 10.** \( q_t, S^2_t, S^2_t \) and \( S^2_{tv} \) exist with \( q_t \in (0, 1) \).

**Corollary 4** (Binary Treatment Case). Suppose there is only one treatment \( t_1 \) to be compared to the control \( t_0 \). For EXAM, under Assumptions \( 2, 3, 4, 5, 6, 7, 8 \) and \( 9 \)

\[
\sqrt{n}(\hat{\beta}_N^{*}\pi_{t} - \beta_{N,t1}^{\text{pop}}) \xrightarrow{d} \mathcal{N}(0, \sum_{g=1}^G \delta_g(S^2_{gt1} + \frac{S^2_{g,t1}}{1 - q_{g,t1}} - \rho S^2_{gt1,t0})).
\]

(7)

\[
\sqrt{n}(\hat{\beta}_N^{*}\pi_{t} - \beta_{N,t1}^{\text{sample}}) \xrightarrow{d} \mathcal{N}(0, \sum_{g=1}^G \delta_g(S^2_{gt1} + \frac{S^2_{g,t1}}{1 - q_{g,t1}} - S^2_{g,t1,t0})).
\]

(8)

For RCT, suppose Assumptions \( 2, 3, 4, 5, 6, 7, 8 \) and \( 10 \) hold with \( G = 1 \) and \( \pi_{N,t}(\epsilon) = c_{N,t}/N \) for all \( i \) and \( t \). Then,

\[
\sqrt{n}(\hat{\beta}_N^{RCT} - \beta_{N,t1}^{\text{pop}}) \xrightarrow{d} \mathcal{N}(0, \frac{S^2_t}{q_{t1}} + \frac{S^2_t}{1 - q_{t1}} - \rho S^2_{t1,t0}).
\]

(9)
\[
\sqrt{n}(\hat{\beta}_{N,t_1}^{RCT} - \hat{\beta}_{N,t_1}^{sample}) \xrightarrow{d} \mathcal{N}(0, \frac{S^2_{t_1}}{q_{t_1}} + \frac{S^2_{t_0}}{1 - q_{t_1}} - S^2_{t_1,t_0}).
\] (10)

The asymptotic variance comparison of RCT and EXAM depends on the limiting distribution of potential outcomes and treatment assignment probabilities. As is the case with other stratified experiments, EXAM may produce more precise ATE estimates than RCT if potential outcomes are well correlated with EXAM’s treatment assignment probabilities. The following example illustrates this possibility, providing an asymptotic analogue of Example [1]

**Example 2.** Suppose there is only one treatment \(t_1\), and \(\rho_N = 1\) for all \(N\) so that \(n = N\) with probability one. Every subject has \(Y_{N,i}(t_0) = 0\) for all \(N\). The subjects in every population are divided into four groups \(A, B, C\) and \(D\) based on their potential outcomes \(Y_{N,i}(t_1)\). Let \(Y_{N,i}(t_1) = 1, 2, 3,\) and \(4\) for anybody in group \(A, B, C\) and \(D\), respectively. Denote the number of subjects in group \(A, B, C\) and \(D\) by \(N_A, N_B, N_C\) and \(N_D\), respectively. The sequences of pseudo capacities and the size of groups \(A, B, C\) and \(D\) are as follows:

- If \(N = 4k\) for some \(k \in \mathbb{N}\), \(c_{N,t_0} = c_{N,t_1} = 2k\) and \(N_A = N_B = N_C = N_D = k\).
- If \(N = 4k + 1\) for some \(k \in \mathbb{N}\), \(c_{N,t_0} = 2k\), \(c_{N,t_1} = 2k + 1\), \(N_A = k + 1\) and \(N_B = N_C = N_D = k\).
- If \(N = 4k + 2\) for some \(k \in \mathbb{N}\), \(c_{N,t_0} = 2k + 1\), \(c_{N,t_1} = 2k + 1\), \(N_A = N_B = k + 1\) and \(N_C = N_D = k\).
- If \(N = 4k + 3\) for some \(k \in \mathbb{N}\), \(c_{N,t_0} = 2k + 1\), \(c_{N,t_1} = 2k + 2\), \(N_A = N_B = N_C = k + 1\) and \(N_D = k\).

Assume the experimenter imperfectly predicts treatment effects: \(e_{N,t_1,i} = 0\) for every \(i\) in group \(A\) or \(B\) while \(e_{N,t_1,i} = 2\) for every \(i\) in group \(C\) or \(D\). Let \(w_{N,i,t_1} = 1\) for every \(i\) in group \(A\) or \(B\) and \(w_{N,i,t_1} = 2\) for every \(i\) in group \(C\) or \(D\). There are two subpopulations, \(P_{N,1}\) and \(P_{N,2}\), such that \(i \in P_{N,1}\) for every \(i\) in group \(A\) or \(B\) and \(i \in P_{N,2}\) for every \(i\) in group \(C\) or \(D\). For every \(N\), EXAM with \(\epsilon < .2\) gives the following treatment assignment probabilities\(^{38}\): \(p_{N,i,t_1}(\epsilon) = 0.2\) for every \(i \in P_{N,1}\) while \(p_{N,i,t_1}(\epsilon) = 0.8\) for every \(i \in P_{N,2}\). Under RCT, \(p_{N,i,t_1}^{RCT} = c_{N,t_1}/N = q_{N,t_1}\). Note that \(\delta_{N,1} = N_1/N = (N_A + N_B)/N \rightarrow 0.5\), \(\delta_{N,2} = N_2/N = (N_C + N_D)/N \rightarrow 0.5\), \(q_{N,1,t_1} \rightarrow 0.2\), \(q_{N,2,t_1} \rightarrow 0.8\) and \(q_{N,t_1} \rightarrow 0.5\) as \(N \rightarrow \infty\).

\(^{38}\) EXAM outputs these treatment probabilities if I set \(\alpha = -\frac{15b}{8}\), \(\beta_{t_1} = 5b\), and \(\beta_{t_0} = 0\) given any budget \(b\). Note that the capacity constraint holds, i.e., \(\sum_{i=1}^N p_{N,i,t_1} \leq c_{N,t_1}\).
Applying Corollary 4 to this example, I have
\[
aVar(\hat{\beta}_{N,t}^*) = \frac{0.53125}{N} < \frac{1.25}{N} = aVar(\hat{\beta}_{N,t}^{RCT}),
\]
where \(aVar\) is the asymptotic variance relative either \(\beta_{N,t}^{pop}\) or \(\beta_{N,t}^{sample}\), both of which produce the same asymptotic variance by \(\rho = 1\). The above inequality means that EXAM’s ATE estimation may be asymptotically more precise than RCT’s even if the experimenter imperfectly predicts potential outcomes.

A.1.3 Uncertainty in Predicted Effects and Preferences

Unlike the baseline setting in the main body, the experimenter’s information about preferences and predicted effects may be uncertain and probabilistic. What experimental design should the experimenter use with uncertain preferences and predicted effects? An uncertain experimental design problem consists of experimental subjects, treatments, pseudo capacities, and the following objects.

- Each subject \(i\)’s preference or WTP \(\tilde{w}_{it}\) for treatment \(t\) where \(\tilde{w}_{it}\) is a random variable.
- Each treatment \(t\)’s predicted treatment effect \(\tilde{e}_{ti}\) for subject \(i\) where \(\tilde{e}_{ti}\) is a random variable.

\(\tilde{w}_{it}\) and \(\tilde{e}_{ti}\) are the experimenter’s statistical perceptions about WTP and predicted treatment effect, respectively. Denote \(w_{it} \equiv E(\tilde{w}_{it})\) and \(e_{ti} \equiv E(\tilde{e}_{ti})\) where each expectation is with respect to the distribution of \(\tilde{w}_{it}\) and \(\tilde{e}_{ti}\), respectively.

When I apply EXAM to \((w_{it}, e_{ti})\), the resulting EXAM nests RCT, is efficient with respect to \((w_{it}, e_{ti})\), is approximately incentive compatible, and is as informative as RCT in the same senses as in Propositions 1-5.

A.1.4 Ordinal Predicted Effects and Preferences

The experimenter’s information about preferences and predicted effects may be ordinal. What experimental design should the experimenter use with ordinal preferences and predicted effects? An ordinal experimental design problem consists of experimental subjects, treatments, pseudo capacities, and the following objects.

- Each subject \(i\)’s ordinal preference \(\succsim_i\) for treatment \(t\) where \(t \succsim_i t'\) means subject \(i\) weakly prefers treatment \(t\) over \(t'\). \(\succsim_i\) may involve ties and indifferences.
• Each treatment \( t \)'s ordinal predicted treatment effect \( \preceq_t \) for subject \( i \) where \( i \preceq_t i' \) means treatment \( t \) is predicted weakly more effective for subject \( i \) than for subject \( i' \). Again, \( \preceq_t \) may involve ties and indifferences.

I consider the following adaptation of EXAM to this ordinal experimental design problem.

**Definition 4 (Ordinal EXAM).** (1) Create any cardinal WTP \( w_{it}' \) of each subject \( i \) for each treatment \( t \) so that \( w_{it}' > w_{it}'' \) if and only if \( t \succ_i t' \).

(2) Create any cardinal predicted effect of each treatment \( t \) for each subject \( i \) so that \( e_{ti}' > e_{ti}'' \) if and only if \( i \succ_t i' \).

(3) Run EXAM (as defined in Definition 2) on \( (w_{it}', e_{ti}') \) to get treatment assignment probabilities \( p_{it}^{*o}(\epsilon) \)

Ordinal EXAM nests RCT, is approximately incentive compatible, and is as informative as RCT in the same senses as in Propositions 1, 3, and 4, respectively. For approximate incentive compatibility, I modify the setting so that subjects report ordinal preferences \( \preceq \) instead of cardinal WTP \( w_{it}' \). Moreover, ordinal EXAM has the following nice welfare property with respect to ordinal preferences and predicted effects.

**Proposition 7.** \( p_{it}^{*o}(\epsilon) \) is ordinally efficient in the following sense. There is no other experimental design \( (p_{it}) \) with \( p_{it} \in [\epsilon, 1 - \epsilon] \) for all subject \( i \) and treatment \( t \), \( \sum_i p_{it} \leq c_t \) for all \( t = t_1, ..., t_m \), and with the following better welfare property: For all cardinal WTP \( w_{it} \) consistent with ordinal \( \preceq \) and all cardinal predicted effects \( e_{ti} \) consistent with ordinal \( \preceq_t \), I have

\[
\sum_t p_{it}w_{it} \geq \sum_t p_{it}^{*o}(\epsilon)w_{it} \quad \text{and} \quad \sum_t p_{it}e_{ti} \geq \sum_t p_{it}^{*o}(\epsilon)e_{ti}
\]

for all \( i \) with at least one strict inequality.

**A.2 Proofs**

**Proof of Proposition 1**

Suppose to the contrary that there exist some \( \epsilon \in [0, \bar{\epsilon}] \), \( i \), and \( t \) such that \( p_{it}^{*o}(\epsilon) \neq p_{it}^{RCT} \). Since \( e_{ti} = e_{tj} \) for all subjects \( i \) and \( j \) and treatment \( t \), I have \( \pi_{teti} \equiv \alpha e_{ti} + \beta_t = \alpha e_{tj} + \beta_t \equiv \pi_{tetj} \) for all subjects \( i \) and \( j \) and treatment \( t \). Combined with \( w_{it} = w_{jt} \) for all subjects \( i \) and \( j \) and treatment \( t \), this implies that any subjects \( i \) and \( j \) face the same utility maximization problem:
arg max_{p_i \in P}(\sum_t p_{it}w_{it} \text{ s.t. } \sum_t p_{it}\pi_{te_i} \leq b) = \arg max_{p_{ij} \in P}(\sum_t p_{jt}w_{jt} \text{ s.t. } \sum_t p_{jt}\pi_{tej} \leq b).

This implies \(p^*_j(\epsilon) = p^*_l(\epsilon) \neq p^*_t^{RCT} = c_t/n\) by the requirement in Definition 2 that \((p^*_i)_i = (p^*_j)_j\) for any \(i\) and \(j\) with \(w_i = w_j\) and \(e_i = e_j\).

If \(p^*_j(t)(\epsilon) = p^*_l(t)(\epsilon) > c_t/n\) for some \(t \neq t_0\), then \(\sum_{j=1}^n p^*_j(\epsilon) = n p^*_l(\epsilon) > nc_t/n = c_t\), which implies \(\sum_{j=1}^n p^*_j > c_t\) (since \(\sum_{j=1}^n p^*_l^{RCT} = c_t\)). This contradicts the capacity constraint in the definition of \(p^*_l\). If \(p^*_j(t)(\epsilon) = p^*_l(t)(\epsilon) < c_t/n\), then there is another treatment \(t' \neq t\) for which \(p^*_j(t')(\epsilon) = p^*_l(t')(\epsilon) > c_t/n\) for any subject \(j\). This implies that \(\sum_{j=1}^n p^*_j(t')(\epsilon) = np^*_l(t')(\epsilon) > nc_{t'}/n = c_{t'}\), again contradicting the capacity constraint if \(t' \neq t_0\).

The only remaining possibility is \(p^*_j(t_0)(\epsilon) = p^*_l(t_0)(\epsilon) > c_{t_0}/n \geq \epsilon > 0\). This implies \(p^*_j(\epsilon) = p^*_l(\epsilon) < c_t/n \leq 1 - \epsilon\) for some \(t \neq t_0\) and so \(p^*_j = p^*_l < c_t/n\) (since \(p^*_l^{RCT} = c_t/n\) for any \(i\)). But this is a contradiction since \(j\) can increase the value of her objective function \(\sum_t p_{jt}w_{jt}\) by changing \(p^*_j(t_0)\) to \(p^*_j(t_0) - \delta\) and \(p^*_j(t_0) + \delta\), respectively, for small enough \(\delta > 0\), since \(w_{jt} = w_{j0} = 0\). Such \(p^*_j(t_0) - \delta\) and \(p^*_j(t_0) + \delta\) satisfy the budget constraint since \(\pi_{tej} \leq 0\) for every \(i\) and so

\[
\sum_{t' \neq t_0,t} p^*_{jt'}\pi_{te_{t'j}} + (p^*_j(t_0) - \delta)\pi_{t_0e_{t0j}} + (p^*_j(t_0) + \delta)\pi_{te_{tj}} \leq \sum_{t'} p^*_{jt'}\pi_{te_{t'j}} \leq b.
\]

Therefore, it cannot be the case that \(p^*_j(t_0)(\epsilon) = p^*_l(t_0)(\epsilon) > c_{t_0}/n\). Thus, for every \(\epsilon \in [0,\tilde{\epsilon}]\), \(i\), and \(t\), it must be the case that \(p^*_l(\epsilon) = p^*_t^{RCT}\).

**Proof of Proposition 2**

**EXAM always exists:** It is enough to find \((p^*_i)\) that satisfies the conditions in Step (1) of Definition 2.

**Lemma 1.** There exists \((p^*_i)\) that satisfies a weaker version of Definition 2 that is the same as Definition 2 except that EXAM breaks ties or indifference so that every subject \(i\)'s \(p_i\) solves the utility maximization problem with the minimum expenditure \(\sum_t p_{it}\pi_{te_i}\) (but it is not necessarily the case \((p^*_i)_i = (p^*_j)_j\) for any \(i\) and \(j\) with \(w_i = w_j\) and \(e_i = e_j\)).

**Proof of Lemma 1.** Fix \(\alpha\) at any negative constant \(\alpha^* < 0\). Fix \(\beta_{t_0} = 0\). Define a space of possible values of \(\beta \equiv (\beta_i)_i\) by \(B \equiv \beta_{t_0} \times [0, nb - \alpha^*\bar{e}1\{\bar{e} > 0\}]^m\) where \(\bar{e} = \max\{e_{t_i}\}\). For any given \(\gamma \geq 0\), define the demand correspondence for each subject \(i\) by \(p^*_i(\beta, \gamma) \equiv \arg\max_{p_i \in P}\sum_t (p_{it}w_{it} - \gamma p_i(\alpha^*e_{ti} + \beta_i))\) s.t. \(\sum_t p_{it}(\alpha^*e_{ti} + \beta_i) \leq b\). Define the excess demand correspondence \(z_\gamma(\cdot) : B \to \mathbb{R}^{m+1}\) by

\[
z_\gamma(\beta) = \{\sum_i p_i - c | p_i \in p^*_i(\beta, \gamma) \text{ for every } i\} \equiv \sum_i p^*_i(\beta, \gamma) - c
\]

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where \(c \equiv (c_t)\). This correspondence \(z_\gamma(\cdot)\) is upper hemicontinuous in \(\beta\) and convex-valued because it is a linear finite sum of \(p^*_t(\beta, \gamma)\)'s, which are upper hemicontinuous and convex-valued as shown below.

**Step 1.** For every subject \(i\) and \(\gamma \geq 0\), her demand correspondence \(p^*_t(\beta, \gamma)\) is nonempty, convex-valued, and upper hemicontinuous in \(\beta\).

**Proof of Step 1** \(\Box\) \(p^*_t(\beta, \gamma)\) is convex-valued since for any \(p_i, p'_i \in p^*_t(\beta, \gamma) \subset P\) and \(\delta \in [0, 1]\), it holds that \(p_{\delta, i} = \delta p_i + (1 - \delta)p'_i\) is in \(p^*_t(\beta, \gamma)\) because the objective \(\sum_t p_{\delta, it}w_{it} - \gamma p_{\delta, it}(\alpha^* e_{ti} + \beta_i) = \sum_t (w_{it} - \gamma(\alpha^* e_{ti} + \beta_i))p_{\delta, it}\) is linear and \(p_{\delta, i}\) satisfies the budget constraint because \(\sum_t p_{\delta, it}(\alpha^* e_{ti} + \beta_i) = \delta \sum_t p_{it}(\alpha^* e_{ti} + \beta_i) + (1 - \delta) \sum_t p'_t(\alpha^* e_{ti} + \beta_i) \leq \delta b + (1 - \delta)b = b\). \(p^*_t(\beta, \gamma)\) is non-empty and upper-hemicontinuous by the maximum theorem. To see this, note that (1) the utility function is linear and (2) the correspondence from \(\beta\) to the choice set \(\{p_i \in P | \sum_t p_{it}(\alpha^* e_{ti} + \beta_i) \leq b\}\) is both upper-hemicontinuous and lower-hemicontinuous as well as compact-valued and nonempty ((\(p_{it}\)) \(t=t_1, \ldots, t_m = (1, 0, \ldots, 0\) is for free and always in the choice set). Thus the maximum theorem implies that \(p^*_t(\beta, \gamma)\) is non-empty and upper-hemicontinuous, completing the proof of Step 1. \(\Box\)

Let \(\bar{c} \equiv \max c_t\) and \(\tilde{B} \equiv 0 \times [-\bar{c}, n(b + \bar{c}) - \alpha^* \bar{e}1\{\bar{e} > 0\}]^m\). Define a truncation function \(f : \tilde{B} \to B\) by \(f(\beta) \equiv 0 \times (\max\{0, \min\{\beta_t, nb - \alpha^* \bar{e}1\{\bar{e} > 0\}\}\}) t=t_1, \ldots, t_m\). Define correspondence \(g_\gamma : \tilde{B} \to B\) by \(g_\gamma(\beta) \equiv f(\beta) + z_\gamma(f(\beta))\).

**Step 2.** For all \(\gamma \geq 0\), \(g_\gamma\) has a fixed point \(\beta^*_\gamma \in g_\gamma(\beta^*_\gamma)\).

**Proof of Step 2**. \(z_\gamma(f(\beta))\) is upper hemicontinuous and convex-valued as a function of \(\beta \in \tilde{B}\) because \(f(\cdot)\) is continuous and \(z_\gamma(\cdot)\) is an upper hemicontinuous and convex-valued correspondence, as explained above. This implies that \(g_\gamma(\beta)\) is upper hemicontinuous and convex-valued as well. The range of \(g_\gamma(\beta)\) lies in \(\tilde{B}\), i.e., \(g_\gamma : \tilde{B} \to \tilde{B}\). It is because

- \(f(\beta) \equiv 0 \times (\max\{0, \min\{\beta_t, nb - \alpha^* \bar{e}1\{\bar{e} > 0\}\}\}) t=t_1, \ldots, t_m \in [0, nb - \alpha^* \bar{e}1\{\bar{e} > 0\}]^{m+1}\), which is by \(nb - \alpha^* \bar{e}1\{\bar{e} > 0\} \geq 0\) (recall \(\alpha^* < 0\)).
- \(\bar{c} \equiv \max c_t \geq 1\).
- \(z_\gamma(f(\beta)) \in [-\bar{c}, n]^{m+1}\) because, for any \(\beta \in \tilde{B}\) and \(t\), the excess demand \(z_{t, \gamma}(\beta)\) is at least \(-\bar{c}\) (since the supply of any treatment \(t\) is \(c_t \leq \bar{c}\) by definition) and at most \(n\) (since there are \(n\) subjects and the demand for any treatment \(t\) by any subject \(i\) is at most 1).
Finally, $\tilde{B}$ is nonempty by $-\bar{c} < 0 < n(b + \bar{c}) \leq n(b + \bar{c}) - \alpha^* \bar{e} \{\bar{e} > 0\}$. $g_\gamma(\beta) \equiv f(\beta) + z_\gamma(f(\beta))$ is therefore an upper hemicontinuous, nonempty, and convex-valued correspondence defined on the non-empty, compact, and convex set $\tilde{B}$. By Kakutani’s fixed point theorem, there exists a fixed point $\beta_\gamma^* \in g_\gamma(\beta_\gamma^*)$, proving Step 2.

**Step 3.** For any sequence of $\gamma_n > 0$ with $\lim_{n \to \infty} \gamma_n = 0$, consider the associated sequence of fixed points $\beta_\gamma^{n*} \in g_{\gamma_n}(\beta_\gamma^{n*})$. There exists a subsequence of $(\beta_\gamma^{n*})$ that converges to some $\beta^*$. Any such limit $\beta^*$ is a fixed point of $g_0$ in the sense that $\beta^* \in g_0(\beta^*)$.

**Proof of Step 3.** The space of possible values of $\beta_\gamma^{n*}$ is $B \equiv \beta_{t_0} \times [0, nb - \alpha^* \bar{e} \{\bar{e} > 0\}]^m$, which is compact. The Bolzano-Weierstrass Theorem therefore implies the existence of a convergent subsequence of $(\beta_\gamma^{n*})$.

The last part follows from $\beta^* \in \lim_{n \to \infty} g_{\gamma_n}(\beta^*) \subset g_0(\beta^*)$, which I show below, where $\lim_{n \to \infty} g_{\gamma_n}(\beta^*)$ is the set-theoretic limit define by $\{\beta|\lim_{n \to \infty} 1\{\beta \in g_{\gamma_n}(\beta^*)\} = 1\}$. This set-theoretic limit exists by the following reason: Since $\beta^* \in B$ and $f(\beta^*) = \beta^*$, I have

$$g_{\gamma_n}(\beta^*) \equiv f(\beta^*) + z_{\gamma_n}(f(\beta^*)) = \beta^* + z_{\gamma_n}(\beta^*) = \beta^* + \sum_i p_i^*(\beta^*, \gamma_n) - c.$$ 

For proving the existence of $\lim_{n \to \infty} g_{\gamma_n}(\beta^*)$, it is enough to show $\lim_{n \to \infty} p^*(\beta^*, \gamma_n)$ exists. To show it, note that if $p^1 \in p^*(\beta^*, \gamma_j)$ and $p^1 \notin p^*(\beta^*, \gamma_k)$ for $\gamma_j > \gamma_k > 0$, then for all $\gamma_l$ with $\gamma_k > \gamma_l > 0$, I have

$$p^1 \notin p^*(\beta^*, \gamma_l),$$

which is true by the following reason: $p^1 \in p^*(\beta^*, \gamma_j)$ and $p^1 \notin p^*(\beta^*, \gamma_k)$ imply there exists some $p^2$ satisfying the budget constraint and such that

$$\sum_t p^2_{it} w_{it} - \gamma_k p^2_{it}(\alpha^* e_{ti} + \beta_t) > \sum_t p^1_{it} w_{it} - \gamma_k p^1_{it}(\alpha^* e_{ti} + \beta_t)$$

while

$$\sum_t p^2_{it} w_{it} - \gamma_j p^2_{it}(\alpha^* e_{ti} + \beta_t) \leq \sum_t p^1_{it} w_{it} - \gamma_j p^1_{it}(\alpha^* e_{ti} + \beta_t).$$

Taking the difference between the last two equations results in

$$\sum_t p^2_{it}(\alpha^* e_{ti} + \beta_t) > \sum_t p^1_{it}(\alpha^* e_{ti} + \beta_t).$$

Plugging this inequality back into an earlier expression, I get $\sum_t p^2_{it} w_{it} > \sum_t p^1_{it} w_{it}$. Therefore, $p^1 \notin p^*(\beta^*, \gamma_l)$. Note also that for any small $\epsilon > 0$ there exists infinitely many $n$ such that $\gamma_n < \epsilon$ and finitely many $m$ such that $\gamma_m > \epsilon$. By a result from measure theory (Billingsley).
Therefore, \( \lim \inf_{n \to \infty} p^*(\beta^*, \gamma_n) = \lim \sup_{n \to \infty} p^*(\beta^*, \gamma_n) \) and the set-theoretic limit \( \lim_{n \to \infty} p^*(\beta^*, \gamma_n) \) exists, implying by the above argument that \( \lim_{n \to \infty} g_{\gamma_n}(\beta^*) \) also exists.

It only remains to prove \( \lim_{n \to \infty} g_{\gamma_n}(\beta) \subset g_0(\beta) \) for all \( \beta \in \tilde{\beta} \). Suppose to the contrary there exist some \( b \) and \( \beta \) such that \( b \notin \lim_{n \to \infty} g_{\gamma_n}(\beta) \) but \( b \notin g_0(\beta) \). Thus \( b \in \lim_{n \to \infty} \arg \max_{p \in P} \left( \sum_t p_{it} w_{it} - \gamma_n p_{it}(\alpha^* e_{ti} + \beta_i) \right) \) s.t. \( \sum_t p_{it}(\alpha^* e_{ti} + \beta_i) \leq b \) but there exists some \( b^* \) satisfying the budget constraint such that \( \sum_t b^*_{it} w_{it} > \sum_t b_{it} w_{it} \). This implies \( \lim_{n \to \infty} \sum_t b^*_{it} w_{it} - \gamma_n b^*_{it}(\alpha^* e_{ti} + \beta_i) > \lim_{n \to \infty} \sum_t b_{it} w_{it} - \gamma_n b_{it}(\alpha^* e_{ti} + \beta_i) \) since \( \gamma_n \to 0 \). This is a contradiction to the assumption \( b \in \lim_{n \to \infty} g_{\gamma_n}(\beta) \). It is thus true that \( \beta^* \in \lim_{n \to \infty} g_{\gamma_n}(\beta^*) \subset g_0(\beta^*) \), implying \( \beta^* \in g_0(\beta^*) \), \( \square \).

**Step 4.** For the fixed point \( \beta^* = \lim_{\gamma_n \to 0} \beta_{\gamma_n}^* \) of \( g(\cdot) \), the associated equilibrium treatment assignment probability \( (\pi_{te} \equiv \alpha^* e + f_t(\beta^*))_t \), where \( f_t(\beta^*) \) is the \( t \)-th element of \( f(\beta^*) \), satisfies the conditions in Lemma 1.

**Proof of Step 4** By the definition of a fixed point and correspondence \( g(\cdot) \), there exists \( z^* \equiv (z_t^*) \in z(f(\beta^*)) \) such that \( \beta_t^* = f_t(\beta^*) + z_t^* \) for all \( t \). Fix any such \( z^* \) and the associated \( \beta^* \). It is enough to show that the associated equilibrium treatment assignment probability vector \( (p_{it}^*) \) with \( \arg \max_{p \in P} \left( \sum_t p_{it} w_{it} \right) \) s.t. \( \sum_t p_{it}(\alpha^* e_{ti} + f_t(\beta^*)) \leq b \) satisfies the capacity constraint for every treatment \( t = t_1, \ldots, t_m \). For each treatment \( t \), there are three cases to consider:

**Case 1:** \( \beta_t^* < 0 \). Then \( f_t(\beta^*) \equiv \max\{0, \min\{\beta_t^*, nb - \alpha^* \bar{e}1\{\bar{e} > 0\}\}\} = 0 \) and hence \( \beta_t^* = f_t(\beta^*) + z_t^* \) implies \( \beta_t^* = z_t^* \equiv \sum_t p_{it} - c_t < 0 \), implying \( \sum_t p_{it}^* < c_t \), i.e., the capacity constraint holds.

**Case 2:** \( \beta_t^* \in [0, nb - \alpha^* \bar{e}1\{\bar{e} > 0\}] \). By the definition of \( f \), I have \( f_t(\beta^*) = \beta_t^* \). Then \( \beta_t^* = f_t(\beta^*) + z_t^* \) implies \( z_t^* = 0 \), i.e., the capacity constraint holds with equality.

**Case 3:** \( \beta_t^* > nb - \alpha^* \bar{e}1\{\bar{e} > 0\} \). Then \( f_t(\beta^*) = nb - \alpha^* \bar{e}1\{\bar{e} > 0\} \) and hence \( \beta_t^* = f_t(\beta^*) + z_t^* \) implies that \( z_t^* = \beta_t^* - nb + \alpha^* \bar{e}1\{\bar{e} > 0\} > 0 \), i.e., treatment \( t \) is in excess demand at price \( \pi_{te} \equiv \alpha^* e + f_t(\beta^*) \). However, for any possible predicted effect level \( e \leq \bar{e} \), I have

\[
\pi_{te} \equiv \alpha^* e + f_t(\beta^*) = \alpha^* e + nb - \alpha^* \bar{e}1\{\bar{e} > 0\} = \begin{cases} nb + \alpha^*(\bar{e} - \bar{e}) & \text{if } \bar{e} > 0 \\ nb + \alpha^* e & \text{otherwise,} \end{cases}
\]

where the last inequality is by \( \alpha^* < 0 \) and \( e \leq \bar{e} \leq 0 \). Therefore, for each subject \( i \), \( p_{it}^* \leq b/\pi_{tei} \leq 1/n \). This implies that \( \sum_i p_{it}^* \leq 1 \leq c_t \), a contradiction.
Finally, the construction of $\beta^*$ as $\beta^* = \lim_{\gamma_n \to 0} \beta^*_\gamma$ guarantees that every subject $i$’s $p_i$ solves the utility maximization problem with the minimum expenditure $\sum_t p_{it} \pi_{tei}$. This completes the proof of Step 4 and Lemma 1.

I use Lemma 1 to show there exists $(p^*_{it})$ that satisfies the conditions in Definition 2. Let $(p^*_{it})$ be the assignment probability profile found in Lemma 1. Define $I(w, e) \equiv \{i \in \{i_1, ..., i_n\} | w_i = w, e_i = e\}$ be the set of subjects whose WTP and predicted effect vectors are $w$ and $e$, respectively. For each $w, e$, and $i \in I(w, e)$, let

$$p^*_{i} \equiv \frac{\sum_{i \in I(w, e)} p^*_{it}}{|I(w, e)|}.$$ 

$p^*_{i}$ solves the utility maximization problem in Step (1) of Definition 2 with the minimum expenditure since $\sum_t p^*_{it} w_{it} = \sum_t p^*_{it} e_{it}$ and $\sum_t p^*_{it} \pi_{tei} = \sum_t p^*_{it} \pi_{tei} \leq b$. The above construction guarantees that $p^*_{i} = p^*_j$ for any $i$ and $j$ with $w_i = w_j$ and $e_i = e_j$. $p^*$ also satisfies the capacity constraints by $\sum_i p^*_{i} = \sum_i p^*_i \leq c_t$ for all $t$, where the last inequality is by Lemma 1. $p^*_{i}$ thus satisfies the conditions in Definition 2.

EXAM is ex ante Pareto efficient subject to the randomization and capacity constraint: Suppose to the contrary that there exists $\epsilon \in [0, \bar{\epsilon})$ such that $p^*_{it}(\epsilon)$ is ex ante Pareto dominated by another feasible treatment assignment probabilities $(p^*_{it}(\epsilon))_{i, t} \in P^n$ with $p_{it}(\epsilon) \in [\epsilon, 1 - \epsilon]$ for all $i$ and $t$ and $\sum_i p_{it} \leq c_t$ for all $t = t_1, ..., t_m$, i.e.,

- $\sum_t p_{it}(\epsilon) e_{ti} \geq \sum_t p^*_t(\epsilon) e_{ti}$ for all $i$ and
- $\sum_t p_{it}(\epsilon) w_{it} \geq \sum_t p^*_t(\epsilon) w_{it}$ for all $i$

with at least one strict inequality. Let me use $p_{it}(\epsilon)$ to define the following treatment assignment probabilities:

$$p_{it} \equiv [p_{it}(\epsilon) - q p^*_t RCT]/(1 - q),$$

where $q \equiv \inf\{q' \in [0, 1] | (1 - q') p^*_t + q' p^*_t RCT \in [\epsilon, 1 - \epsilon] \text{ for all } i \text{ and } t\}$ is the mixing weight used for defining and computing $p^*_t(\epsilon)$ in Definition 2. In other words, $p_{it}$ are the treatment assignment probabilities such that the following holds:

$$p_{it}(\epsilon) = (1 - q)p_{it} + q p^*_t RCT.$$
Since both $p_{it}(\epsilon)$ and $p_{it}^{RCT}$ are in convex set $P^n$, $p_{it}$ is also in $P^n$ (note that $\sum_t p_{it} = \sum_t [p_{it}(\epsilon) - q p_{it}^{RCT}] / (1 - q) = (1 - q) / (1 - q) = 1$ for every $i$). For each $i$, I have

$$\sum_t p_{it}(\epsilon)e_{ti} \geq \sum_t p_{it}^*(\epsilon)e_{ti} \iff \sum_t ((1 - q)p_{it} + qp_{it}^{RCT})e_{ti} \geq \sum_t ((1 - q)p_{it}^* + qp_{it}^{RCT})e_{ti}$$

$$\iff \sum_t (1 - q)p_{it}e_{ti} \geq \sum_t (1 - q)p_{it}^*e_{ti}$$

$$\iff \sum_t p_{it}e_{ti} \geq \sum_t p_{it}^*e_{ti}.$$  

Similarly, for each $i$, I have

$$\sum_t p_{it}(\epsilon)w_{it} \geq \sum_t p_{it}^*(\epsilon)w_{it} \iff \sum_t ((1 - q)p_{it} + qp_{it}^{RCT})w_{it} \geq \sum_t ((1 - q)p_{it}^* + qp_{it}^{RCT})w_{it}$$

$$\iff \sum_t (1 - q)p_{it}w_{it} \geq \sum_t (1 - q)p_{it}^*w_{it}$$

$$\iff \sum_t p_{it}w_{it} \geq \sum_t p_{it}^*w_{it}.$$  

Therefore, the assumption that $p_{it}(\epsilon)$ ex ante Pareto dominates $p_{it}^*(\epsilon)$ implies that $p_{it}$ ex ante Pareto dominates $p_{it}^*$, i.e.,

- $\sum_t p_{it}e_{ti} \geq \sum_t p_{it}^*e_{ti}$ for all $i$ and
- $\sum_t p_{it}w_{it} \geq \sum_t p_{it}^*w_{it}$ for all $i$

with at least one strict inequality. There are two cases to consider.

**Case 1:** $\sum_t p_{it}e_{ti} > \sum_t p_{it}^*e_{ti}$ for some $\bar{i}$. This implies

$$\sum_t \sum_i p_{it}e_{ti} > \sum_t \sum_i p_{it}^*e_{ti} \iff \sum_t \sum_i p_{it}(\pi_{te_{ti}} - \beta_{ti}) / \alpha > \sum_t \sum_i p_{it}^*(\pi_{te_{ti}} - \beta_{ti}) / \alpha$$

(by the definition of $\pi_{te} \equiv \alpha e + \beta_{ti}$ with $\alpha \neq 0$)

$$\iff \sum_t \sum_i p_{it}\pi_{te_{ti}} / \alpha > \sum_t \sum_i p_{it}^*\pi_{te_{ti}} / \alpha$$

(since $\sum_i p_{it} = \sum_i p_{it}^* = c_t$)

$$\iff \sum_t \sum_i p_{it}\pi_{te_{ti}} < \sum_t \sum_i p_{it}^*\pi_{te_{ti}}.$$  

(since $\alpha < 0$ by Definition 2)
I thus have
\[
\sum_{t} \sum_{i} p_{it} \pi_{tei} < \sum_{t} \sum_{i} p_{it}^* \pi_{tei}.
\] (11)

However, it has also to be the case that \( \sum_{t} p_{it} \pi_{tei} \geq \sum_{t} p_{it}^* \pi_{tei} \) for any \( i \) since (a) \( \sum_{t} p_{it} w_{it} \geq \sum_{t} p_{it}^* w_{it} \) by assumption and (b) \( p_{it}^* \) is (a mixture of) the cheapest among all feasible assignment probability vectors that \( i \) most prefers under prices \((\pi_{te})_{t,e}\) and budget \( b \). Thus \( \sum_{t} \sum_{i} p_{it} \pi_{tei} \geq \sum_{t} \sum_{i} p_{it}^* \pi_{tei} \), a contradiction to inequality (11).

**Case 2:** \( \sum_{t} p_{it} w_{it} > \sum_{t} p_{it}^* w_{it} \) for some \( \tilde{i} \). Since \( \tilde{i} \) most prefers \((p_{it}^*)_{t}\) among all assignment probability vectors in \( P^n \) that satisfies the budget constraint under prices \((\pi_{te})_{t,e}\), the strictly more preferred treatment assignment probability vector \((p_{it})_{t}\) must violate the budget constraint, i.e., \( \sum_{t} p_{it} \pi_{tei} > b \geq \sum_{t} p_{it}^* \pi_{tei} \), where the second weak inequality comes from the assumption that \((p_{it}^*)_{t}\) satisfies the budget constraint under prices \((\pi_{te})\). Moreover, for any other subject \( i \neq \tilde{i} \), \( \sum_{t} p_{it} \pi_{tei} \geq \sum_{t} p_{it}^* \pi_{tei} \) since \((p_{it}^*)_{t}\) is (a mixture of) the cheapest among all assignment probability vectors in \( P \) that \( i \) most prefers under prices \((\pi_{te})_{t,e}\) and budget \( b \). I thus have
\[
\sum_{t} p_{it} \pi_{tei} + \sum_{t \neq \tilde{i}} \sum_{t} p_{it}^* \pi_{tei} > \sum_{t} p_{it}^* \pi_{tei} + \sum_{t \neq \tilde{i}} \sum_{t} p_{it} \pi_{tei} \Leftrightarrow \sum_{t} \sum_{i} p_{it} \pi_{tei} > \sum_{i} \sum_{t} p_{it}^* \pi_{tei}.
\]

However, by the logic described in Case 1, the assumption \( \sum_{t} p_{it} e_{ti} \geq \sum_{t} p_{it}^* e_{ti} \) for all \( i \) implies that \( \sum_{i} \sum_{t} p_{it} \pi_{tei} \leq \sum_{i} \sum_{t} p_{it}^* \pi_{tei} \), a contradiction.

Therefore, \( p_{it}^*(\epsilon) \) with any \( \epsilon \in [0, \bar{\epsilon}] \) is never ex ante Pareto dominated by another treatment assignment probabilities \((p_{it}(\epsilon))_{i,t} \in P^n \) with \( p_{it}(\epsilon) \in [\epsilon, 1 - \epsilon] \) for all \( i \) and \( t \).

**Proof of Proposition 3**

The proof uses intermediate observations.

**Lemma 2.** EXAM is “envy-free,” i.e., for any experimental design problem, any \( \epsilon \in [0, \bar{\epsilon}] \), any subjects \( i \) and \( j \) with \( e_{ti} = e_{tj} \) for all \( t \),
\[
\sum_{t} p_{it}^*(\epsilon) w_{it} \geq \sum_{t} p_{jt}^*(\epsilon) w_{jt}.
\]

**Proof of Lemma 2.** In Definition 2 all subjects have the same budget and any subjects \( i \) and \( j \) with \( e_{ti} = e_{tj} \) face the same price \( \pi_{te} \) of treatment \( t \). For any subjects \( i \) and \( j \) with \( e_{ti} = e_{tj} \) for all \( t \), therefore, \((p_{jt}^*)_{t}\) satisfies \( i \)'s budget constraint and \( \sum_{t} p_{it}^* w_{it} \geq \sum_{t} p_{jt}^* w_{jt} \).
This implies the desired conclusion since

\[
\sum_{t} p_{it} w_{it} \geq \sum_{t} p_{jt} w_{it} \iff (1 - q) \sum_{t} p_{it} w_{it} + q \sum_{t} p_{RCT}^{\ast} w_{it} \geq (1 - q) \sum_{t} p_{jt} w_{it} + q \sum_{t} p_{RCT}^{\ast} w_{it}
\]

\[
\iff \sum_{t} p_{it}^{\ast} (\epsilon) w_{it} \geq \sum_{t} p_{jt}^{\ast} (\epsilon) w_{it},
\]

where the first equivalence is by \( p_{RCT}^{\ast} = p_{RCT}^{\ast} \equiv c_i/n \).

**Lemma 3.** \( \text{EXAM with WTP reporting is "semi-anonymous."} \) That is, for any sequence of experimental design problems, any \( n \) with any \( \epsilon^n \in [0, \epsilon^n] \), any subjects \( i \) and \( j \) with \( e_{ti} = e_{tj} \) for all \( t \), let \( (w_i, w_j, w_{-\{i,j\}}) \) be a permutation of \( (w_j, w_i, w_{-\{i,j\}}) \) obtained by permuting \( i \) and \( j \)'s WTP reports \( w_i \) and \( w_j \). Semi-anonymity means that

\[
p_i^{\ast n}(w_i, w_j, w_{-\{i,j\}}; \epsilon^n) = p_j^{\ast n}(w_j, w_i, w_{-\{i,j\}}; \epsilon^n),
\]

\[
p_j^{\ast n}(w_i, w_j, w_{-\{i,j\}}; \epsilon^n) = p_i^{\ast n}(w_j, w_i, w_{-\{i,j\}}; \epsilon^n), \text{ and}
\]

\[
p_k^{\ast n}(w_i, w_j, w_{-\{i,j\}}; \epsilon^n) = p_k^{\ast n}(w_j, w_i, w_{-\{i,j\}}; \epsilon^n), \text{ for all } k \neq i, j.
\]

**Proof of Lemma 3.** In Definition 2 of EXAM, all subjects have the same budget and any subjects \( i \) and \( j \) with \( e_{ti} = e_{tj} \) face the same price \( \pi_{te} \) of treatment \( t \). For any subjects \( i \) and \( j \) with \( e_{ti} = e_{tj} \) for all \( t \), therefore, given any \( w_{-\{i,j\}} \), subject \( i \) with WTP report \( w_j \) solves the same constrained utility maximization problem as subject \( j \) with WTP report \( w_j \) does. Therefore, \( p_i^{\ast n}(w_i, w_j, w_{-\{i,j\}}; 0) = p_j^{\ast n}(w_j, w_i, w_{-\{i,j\}}; 0) \) and \( p_j^{\ast n}(w_i, w_j, w_{-\{i,j\}}; 0) = p_i^{\ast n}(w_j, w_i, w_{-\{i,j\}}; 0) \). This implies semi-anonymity since

\[
p_i^{\ast n}(w_i, w_j, w_{-\{i,j\}}; \epsilon^n) \equiv (1 - q^n) p_i^{\ast n}(w_i, w_j, w_{-\{i,j\}}; 0) + q^n p_i^{RCT n} = (1 - q^n) p_j^{\ast n}(w_j, w_i, w_{-\{i,j\}}; 0) + q^n p_j^{RCT n} \equiv p_j^{\ast n}(w_j, w_i, w_{-\{i,j\}}; \epsilon^n),
\]

where \( q^n \) is the mixing probability \( q \) for the \( n \)-th problem in the sequence of experimental design problems while \( p_i^{RCT n} = p_j^{RCT n} \equiv c_i^n/n \). The last line follows from the fact that the switch of \( w_i \) and \( w_j \) have no effect on the utility maximization problem for any other \( k \neq i, j \).

**Lemmas 2 and 3** imply Proposition 3 by using Theorem 1 of Azevedo and Budish (2017) (precisely, a generalization of their Theorem 1 in their Supplementary Appendix B).
A Statistical Lemma and Its Proof

**Lemma 4.** Assume a sample of \( m \) subjects is uniformly randomly drawn (i.e., every combination of \( m \) subjects occurs with equal probability) from the fixed finite population of \( n \) subjects with a fixed vector of a variable \((X_1, \ldots, X_n)\). Denote the random sample by \( I \). Let \( \mu = \frac{1}{n} \sum_{i=1}^{n} X_i \), \( \sigma^2 = \frac{1}{n-1} \sum_{i=1}^{n} (X_i - \mu)^2 \), \( \hat{\mu} = \frac{1}{m} \sum_{i \in I} X_i \) and \( \hat{\sigma}^2 = \frac{1}{m-1} \sum_{i \in I} (X_i - \hat{\mu})^2 \). Then,

\[
V(\hat{\mu}) = \frac{n - m}{nm} \sigma^2 \quad \text{and} \quad E(\hat{\sigma}^2) = \sigma^2.
\]

**Proof of Lemma 4.** Let \( W_i = 1 \{i \in I\} \) so that \( \hat{\mu} = \frac{1}{m} \sum_{i=1}^{n} X_i W_i \) and \( \hat{\sigma}^2 = \frac{1}{m-1} \sum_{i=1}^{n} (X_i - \hat{\mu})^2 W_i \). Then \( E(W_i) = E(W_i^2) = \frac{m}{n} \) for all \( i \), implying \( V(W_i) = \frac{m}{n} - \left( \frac{m}{n} \right)^2 = \frac{m(n-m)}{n^2} \) for all \( i \). Since \( E(W_i W_j) = \frac{m(m-1)}{n(n-1)} \) for any \( i \neq j \), it is the case that for any \( i \neq j \),

\[
Cov(W_i, W_j) = E[(W_i - \frac{m}{n})(W_j - \frac{m}{n})] = E(W_i W_j) - \frac{m}{n} E(W_j) - \frac{m}{n} E(W_i) + \left( \frac{m}{n} \right)^2 = \frac{m(m-1)}{n(n-1)} - \left( \frac{m}{n} \right)^2 = -\frac{m(n-m)}{n^2(n-1)}.
\]

It follows that

\[
V(\hat{\mu}) = \frac{1}{m^2} V(\sum_{i=1}^{n} X_i W_i)
= \frac{1}{m^2} \left( \sum_{i=1}^{n} X_i^2 V(W_i) + \sum_{i=1}^{n} \sum_{j \neq i} X_i X_j Cov(W_i, W_j) \right)
= \frac{1}{m^2} \left( \frac{m(n-m)}{n^2} \sum_{i=1}^{n} X_i^2 - \frac{m(n-m)}{n^2(n-1)} \sum_{i=1}^{n} \sum_{j \neq i} X_i X_j \right)
= \frac{n - m}{n^2m} \left( \sum_{i=1}^{n} X_i^2 - \frac{1}{n-1} \sum_{i=1}^{n} \sum_{j \neq i} X_i X_j \right)
= \frac{n - m}{n^2m} \left( \sum_{i=1}^{n} X_i^2 - \frac{1}{n-1} \sum_{i=1}^{n} \sum_{j=1}^{n} X_i X_j + \frac{1}{n-1} \sum_{i=1}^{n} X_i^2 \right)
= \frac{n - m}{n^2m} \left( \frac{n}{n-1} \sum_{i=1}^{n} X_i^2 - \frac{1}{n-1} \sum_{i=1}^{n} \sum_{j=1}^{n} X_i X_j \right).
\]
\[
= \frac{n - m}{nm(n - 1)} \left( \sum_{i=1}^{n} X_i^2 - \frac{1}{n} \sum_{i=1}^{n} \sum_{j=1}^{n} X_i X_j \right)
\]
\[
= \frac{n - m}{nm(n - 1)} \left( \sum_{i=1}^{n} X_i^2 - \frac{2}{n} \sum_{i=1}^{n} X_i \sum_{j=1}^{n} X_j + \frac{1}{n} (\sum_{i=1}^{n} X_i)^2 \right)
\]
\[
= \frac{n - m}{nm(n - 1)} \sum_{i=1}^{n} (X_i^2 - \frac{2}{n} X_i \sum_{j=1}^{n} X_j + \frac{1}{n^2} (\sum_{j=1}^{n} X_j)^2)
\]
\[
= \frac{n - m}{nm(n - 1)} \sum_{i=1}^{n} X_i - \frac{1}{n} \sum_{j=1}^{n} X_j^2
\]
\[
= \frac{n - m}{nm} \sigma^2.
\]

For the other part,
\[
E(\hat{\sigma}^2) = \frac{1}{m - 1} E\left( \sum_{i=1}^{n} (X_i - \hat{\mu})^2 W_i \right)
\]
\[
= \frac{1}{m - 1} E\left( \sum_{i=1}^{n} (X_i^2 W_i - 2X_i W_i \hat{\mu} + \hat{\mu}^2 W_i) \right)
\]
\[
= \frac{1}{m - 1} E\left( \sum_{i=1}^{n} X_i^2 W_i - 2m \hat{\mu}^2 + m \hat{\mu}^2 \right)
\]
\[
= \frac{1}{m - 1} E\left( \sum_{i=1}^{n} X_i^2 W_i - m \hat{\mu}^2 \right)
\]
\[
= \frac{1}{m - 1} \left( \frac{m}{n} \sum_{i=1}^{n} X_i^2 - m(V(\hat{\mu}) + [E(\hat{\mu})]^2) \right)
\]
\[
= \frac{1}{m - 1} \left( \frac{m}{n} \sum_{i=1}^{n} X_i^2 - \frac{n - m}{n} \sigma^2 - m \mu^2 \right)
\]
\[
= \frac{1}{m - 1} \left( \frac{m(n - 1)}{n} \sigma^2 - \frac{n - m}{n} \sigma^2 \right)
\]
\[
= \sigma^2,
\]

where the third last equality is by \( E(\hat{\mu}) = \mu \) while the second last equality is by the definition of \( \sigma^2 \). \( \square \)

**Proof of Proposition 4**

The proof uses the following lemma.

**Lemma 5.** There exists estimator \( \hat{\theta}_{EXAM,t} \) such that \( E(\hat{\theta}_{EXAM,t} | p^*(\epsilon)) = E(\hat{\mu}_{RCT}(t)^2 | p^{RCT}) \)

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where \( \hat{\mu}_{RCT}(t) \equiv \frac{\sum_i D_{it} Y_i}{c_t} \) with \( D_{it} \) being the treatment assignment indicator under \( RCT \).

Proof of Lemma 3. Let \( \mu_t \equiv \frac{1}{n} \sum_{i=1}^n Y_i(t) \) and \( S_t^2 \equiv \frac{1}{n - 1} \sum_{i=1}^n (Y_i(t) - \mu_t)^2 \). I have

\[
E(\hat{\mu}_{RCT}(t)^2|p^{RCT}) = Var(\hat{\mu}_{RCT}(t)|p^{RCT}) + E(\hat{\mu}_{RCT}(t)|p^{RCT})^2
= \frac{n - c_t}{nc_t} S_t^2 + \mu_t^2
\]

\[= \frac{n - c_t}{nc_t} \frac{1}{n - 1} \left( \sum_{i=1}^n Y_i(t)^2 - n \mu_t^2 \right) + \mu_t^2 \]

\[= \frac{n - c_t}{(n - 1)c_t} \frac{1}{n} \sum_{i=1}^n Y_i(t)^2 + \frac{n(c_t - 1)}{(n - 1)c_t} \mu_t^2, \quad (13)
\]

where the second equality holds by the first part of Lemma 4 and the fact that \( E(\hat{\mu}_{RCT}(t)|p^{RCT}) = \mu_t \).

Below I construct unbiased estimators with EXAM's data for each term in the right-hand side of equation (13), that is, \( \frac{1}{n} \sum_{i=1}^n Y_i(t)^2 \) and \( \mu_t^2 \). I then combine these estimators into developing an unbiased estimator for \( E(\hat{\mu}_{RCT}(t)^2|p^{RCT}) \) (which I interpret as a parameter) with EXAM. Under EXAM \( p^*(\epsilon) \), \( \hat{\theta}_t = \frac{1}{n} \sum_{i} \frac{1}{p_t} \sum_{i: p_i^*(\epsilon) = p} Y_i^2 D_{it} \) unbiasedly estimates \( \frac{1}{n} \sum_{i=1}^n Y_i(t)^2 \) because

\[
E(\hat{\theta}_t|p^*(\epsilon)) = \frac{1}{n} \sum_{i} \frac{1}{p_t} \sum_{i: p_i^*(\epsilon) = p} Y_i(t)^2 E(D_{it}|p^*(\epsilon))
= \frac{1}{n} \sum_{i} \frac{1}{p_t} \sum_{i: p_i^*(\epsilon) = p} Y_i(t)^2 p_t
= \frac{1}{n} \sum_{i} \sum_{i: p_i^*(\epsilon) = p} Y_i(t)^2
= \frac{1}{n} \sum_{i=1}^n Y_i(t)^2.
\]

Next I obtain an unbiased estimator for \( \mu_t^2 \) under EXAM \( p^*(\epsilon) \). Recall \( n_p \equiv \sum_{i=1}^n 1\{p_i^*(\epsilon) = p\} \) is the number of subjects with assignment probability vector \( p \) and \( N_{pt} \equiv \sum_{i: p_i^*(\epsilon) = p} D_{it} \) is a random variable that stands for the number of subjects with assignment probability vector \( p \) and assigned to treatment \( t \). Let \( \mu_{pt} \equiv \frac{1}{n_p} \sum_{i: p_i^*(\epsilon) = p} Y_i(t) \), \( \hat{\mu}_{EXAM,pt} \equiv \frac{1}{p_t n_p} \sum_{i: p_i^*(\epsilon) = p} Y_i D_{it} \) and \( \hat{\mu}_{EXAM,t} \equiv \sum_p \frac{n_p p_t n_p}{n} \hat{\mu}_{EXAM,pt} \). Note that \( \mu_t = \sum_p \frac{n_p}{n} \mu_{pt} \). By Definition 2 (3), conditional on \( (N_{pt}) \), every deterministic treatment assignment consistent with \( (N_{pt}) \) happens
with equal probability. This implies that

\[ E(D_{it} | (N_{pt}) = (n_{pt}), p^*_t(\epsilon) = p) = \frac{n_{pt}}{n_p}. \]

In addition, conditional on \((N_{pt}) = (n_{pt}),\) the set \(\{ i : p^*_t(\epsilon) = p, D_{it} = 1 \}\) can be regarded as a random sample of \(n_{pt}\) subjects from the subpopulation of \(n_p\) subjects with propensity vector \(p.\) Applying the first part of Lemma 4 I have

\[ Var(\frac{1}{N_{pt}} \sum_{i:p^*_t(\epsilon) = p} Y_i D_{it} | (N_{pt}) = (n_{pt}), p^*(\epsilon)) = \frac{n_p - n_{pt}}{n_p n_{pt} S^2_{pt}}, \]

where \(S^2_{pt} = \frac{1}{n_p - 1} \sum_{i:p^*_t(\epsilon) = p}(Y_i(t) - \mu_{pt})^2.\) It follows from the above expressions that

\[ E(\tilde{\mu}_{EXAM,pt} | (N_{pt}) = (n_{pt}), p^*(\epsilon)) = \frac{1}{p_t n_p} \sum_{i:p^*_t(\epsilon) = p} Y_i E(D_{it} | (N_{pt}) = (n_{pt}), p^*(\epsilon)) \]

\[ = \frac{1}{p_t n_p} \sum_{i:p^*_t(\epsilon) = p} Y_i \frac{n_{pt}}{n_p} \mu_{pt}, \tag{14} \]

and

\[ Var(\tilde{\mu}_{EXAM,pt} | (N_{pt}) = (n_{pt}), p^*(\epsilon)) = \left( \frac{n_{pt}}{p_t n_p} \right)^2 Var(\frac{1}{N_{pt}} \sum_{i:p^*_t(\epsilon) = p} Y_i D_{it} | (N_{pt}) = (n_{pt}), p^*(\epsilon)) \]

\[ = \left( \frac{n_{pt}}{p_t n_p} \right)^2 \frac{n_p - n_{pt}}{n_p n_{pt} S^2_{pt}}. \tag{15} \]

Definition 2 (3) also implies that treatment assignments are independent across subpopulations with different propensities conditional on \((N_{pt}).\) Hence, \(\tilde{\mu}_{EXAM,pt}\) is independent across \(p\) conditional on \((N_{pt}).\) I have

\[ E(\tilde{\mu}^2_{EXAM,t} | (N_{pt}), p^*(\epsilon)) = E(\sum_n \frac{n_p p_t n_p}{n} \tilde{\mu}_{EXAM,pt}^2 | (N_{pt}) = (n_{pt}), p^*(\epsilon)) \]

\[ = \sum_p \sum_{p' \neq p} \frac{n_p p_t n_p}{n^2} E(\tilde{\mu}_{EXAM,pt} | (N_{pt}), p^*(\epsilon)) p_t' n_p' \frac{p_t n_p}{n_{pt}} E(\tilde{\mu}_{EXAM,p't} | (N_{pt}), p^*(\epsilon)) \]

\[ + \sum_p \frac{n^2_p}{n^2} \left( \frac{p_t n_p}{n_{pt}} \right)^2 E(\tilde{\mu}^2_{EXAM,pt} | (N_{pt}) = (n_{pt}), p^*(\epsilon)) \]

\[ = \sum_p \sum_{p' \neq p} \frac{n_p n_p'}{n^2} \mu_{pt} \mu_{p't} + \sum_p \frac{n^2_p}{n^2} \left( \frac{p_t n_p}{n_{pt}} \right)^2 (Var(\tilde{\mu}_{EXAM,pt} | (N_{pt}) = (n_{pt}), p^*(\epsilon)) \]

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+ E(\hat{\mu}_{EXAM,pt}|(N_{pt}) = (n_{pt}), p^*(\epsilon))^2)

= \sum_p \sum_{p' \neq p} \frac{n_p n_{p'}}{n^2} \mu_{pt}\mu_{pt'} + \sum_p \frac{n_p^2}{n^2} \left( \frac{p_{tn_{pt}}}{n_{pt}} \right)^2 \left\{ \left( \frac{n_{pt}}{n_{pt}} \right)^2 n_p - n_{pt} S^2_{pt} + \left( \frac{n_{pt}}{n_{pt}} \right)^2 \mu_{pt}^2 \right\}

= \sum_p \sum_{p' \neq p} \frac{n_p n_{p'}}{n^2} \mu_{pt}\mu_{pt'} + \sum_p \frac{n_p^2}{n^2} \left( n_p - n_{pt} \right) \frac{S^2_{pt}}{n_{pt}} + \mu_{pt}^2

= \left( \sum_p \frac{n_p}{n} \mu_{pt} \right)^2 + \sum_p \frac{n_p^2}{n^2} \left( n_p - n_{pt} \right) S^2_{pt}

= \mu_t^2 + \sum_p \frac{n_p^2}{n^2} \frac{n_p - n_{pt}}{n_{pt}} S^2_{pt},

where I use the independence of \( \hat{\mu}_{EXAM,pt} \) across \( p \) conditional on \( (N_{pt}) \) for the second equality, equation (14) for the third and the fourth equalities and equation (15) for the fourth equality. By the law of iterated expectations,

\[
E(\hat{\mu}_{EXAM,t}^2|p^*(\epsilon)) = E(E(\hat{\mu}_{EXAM,t}^2|(N_{pt}), p^*(\epsilon))|p^*(\epsilon))
\]

= \mu_t^2 + \sum_p \frac{n_p^2}{n^2} \left( E\left( \frac{1}{N_{pt}} | p^*(\epsilon) \right) - \frac{1}{n_p} \right) S^2_{pt}

= \mu_t^2 + \sum_p \frac{n_p^2}{n^2} \left( \frac{1}{n_{pt}} (1 - pt n_p + n_{pt}) + \frac{1}{n_{pt} + 1} (pt n_p - n_{pt}) - \frac{1}{n_p} \right) S^2_{pt}

= \mu_t^2 + \sum_p \frac{n_p^2}{n^2} \left( \frac{1 - pt n_p + 2n_{pt}}{n_{pt} (n_{pt} + 1)} - \frac{1}{n_p} \right) S^2_{pt}, \quad (16)

where the third equality holds because Definition 2(3) implies

\[
Pr(N_{pt} = n_{pt}|p^*(\epsilon)) = \begin{cases} 
1 - pt n_p + n_{pt} & \text{if } n_{pt} = n_{pt} \\
pt n_p - n_{pt} & \text{if } n_{pt} = n_{pt} + 1 \\
0 & \text{otherwise}
\end{cases}
\]

Now consider an unbiased estimator for \( S^2_{pt} \). Let \( \hat{S}_{pt}^2 = \frac{1}{pt n_p - 1} \sum_i: p_i^*(\epsilon) = p \left( Y_i - \frac{p_{tn_{pt}}}{n_{pt}} \hat{\mu}_{EXAM,pt} \right)^2 D_{it} \).

This \( \hat{S}_{pt}^2 \) is unbiased for \( S^2_{pt} \), because

\[
E(\hat{S}_{pt}^2|p^*(\epsilon)) = E(E(\hat{S}_{pt}^2|(N_{pt}), p^*(\epsilon))|p^*(\epsilon))
\]

= \left[ \frac{N_{pt} - 1}{pt n_p - 1} \right] E\left\{ \frac{1}{N_{pt} - 1} \sum_i: p_i^*(\epsilon) = p \left( Y_i - \frac{1}{N_{pt}} \sum_j: p_j^*(\epsilon) = p Y_j D_{jt} \right)^2 D_{it} | (N_{pt}), p^*(\epsilon) \right\}|p^*(\epsilon)]

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\[ E\left( \frac{N_{pt}}{p_t n_p} - 1 \right) S^2_{pt} | p^*(\epsilon) \]
\[ = E \left( p_t n_p - 1 \right) S^2_{pt} \]
\[ = S^2_{pt}, \]
where the first equality holds by the law of expected iterations, I use the second part of Lemma 4 for the third equality and the fact that \( E(N_{pt} | p^*(\epsilon)) = p_t n_p \) for the fourth equality. Combining this with equation (16), I obtain an unbiased estimator for \( \mu_2^2 \)
\[ \hat{\theta}^2_{t} = \hat{\mu}^2_{EXAM,t} - \sum_{t\in p} \frac{n_p^2}{n^2} \frac{1 - p_t n_p + 2 q_{pt}}{n_p(n_p + 1)} - \frac{1}{n_p} S^2_{pt}. \]
By equation (13), the following is an unbiased estimator for \( E(\hat{\mu}^2_{RCT}(t) | p_{RCT}) \):
\[ \hat{\theta}^2_{EXAM,t} = \frac{n - c_t}{(n - 1)c_t} \hat{\theta}_{1t} + \frac{n(c_t - 1)}{(n - 1)c_t} \hat{\theta}_{2t}. \]

Let \( D_i \) be the set of all feasible deterministic treatment assignments for subject \( i \), i.e.,
\[ D_i \equiv \{ d_i \equiv (d_{it}) \in \{0, 1\}^{m+1} \mid \sum_t d_{it} = 1 \}. \]
Let \( D^{'E X A M}_i \) and \( D^{'R C T}_i \) be the sets of deterministic treatment assignments that happen with a positive probability under EXAM and RCT, respectively. That is, \( D^{'E X A M}_i \equiv \{ d_i \in D_i \mid Pr(d_i | p^*(\epsilon)) > 0 \} \) and \( D^{'R C T}_i \equiv \{ d_i \in D_i \mid Pr(d_i | p_{RCT}) > 0 \} \), where \( Pr(d_i | p_{it}) \) is the probability that \( d_i \) occurs under experimental design \( (p_{it}) \). With Definition 2, \( D_{it} = 1 \) holds with a positive probability for every \( t \) and \( i \) both under EXAM and RCT, implying
\[ D^{'R C T}_i = D^{'E X A M}_i = D_i. \] (17)
With the support equivalence property (17), I am ready to show the proposition. Recall that given any experimental design \( (p_{it}) \), I say an estimator \( \hat{\theta}(Y, D) \) is simple if \( \hat{\theta}(Y, D) \) can be written as
\[ \hat{\theta}(Y, D) = \sum_i f(Y_i, D_i, p_i) + \sum_t \sum_p \sum_{p'} g_{tpp'} \hat{\mu}_p(t) \hat{\mu}_{p'}(t) \]
for some function \( f \), weights \( g_{tpp'} \)'s, and \( \hat{\mu}_p(t) = \frac{\sum_{i:p_i=p} D_{it} Y_i}{p_t \sum_{i=1}^m 1(p_i = p)} \). Suppose that parameter \( \theta \) is unbiasedly estimable with RCT \( p^{RCT} \) and a simple estimator \( \hat{\theta}^{RCT}(Y, D) = \)
\[ \sum_i f(Y_i, D_i, p_i^{RCT}) + \sum_t g_t \mu_{RCT}^2(t) = \frac{E(\hat{\theta}^{RCT}(Y, D)|p^{RCT})}{E(\hat{\theta}^{RCT}(Y, D)|p^{RCT})} = \theta. \]  

Note that \( g_t \) is constant since for RCT, the only potential randomness in \( g_t \) comes from \( (\sum D_t)_t \), which is the same as the constant pseudo-capacity vector \( (c_t)_t \). Now consider another estimator for EXAM:

\[ \hat{\theta}^{EXAM}(Y, D) = \sum_i \frac{\Pr(D_i|p^{RCT})}{\Pr(D_i|p^*(\epsilon))} f(Y_i, D_i, p_i^{RCT}) + \sum_t g_t \hat{\theta}_{EXAM,t}. \]

With the knowledge of the original estimator \( \theta^{RCT}(Y, D) \), it is possible to compute \( \hat{\theta}^{EXAM}(Y, D) \) since \( \Pr(D_i|p^{RCT}) \) and \( \Pr(D_i|p^*(\epsilon)) \) are known to the experimenter. This \( \hat{\theta}^{EXAM}(Y, D) \) is unbiased for \( \theta \) under EXAM:

\[
\begin{align*}
E(\hat{\theta}^{EXAM}(Y, D)|p^*(\epsilon)) &= E(\sum_i \frac{\Pr(D_i|p^{RCT})}{\Pr(D_i|p^*(\epsilon))} f(Y_i, D_i, p_i^{RCT}) + \sum_t g_t \hat{\theta}_{EXAM,t}|p^*(\epsilon)) \\
&= \sum_i \Pr(d_i|p^*(\epsilon)) \frac{\Pr(d_i|p^{RCT})}{\Pr(d_i|p^*(\epsilon))} f(Y_i(d_i), d_i, p_i^{RCT}) + \sum_t g_t E(\hat{\mu}_{RCT}^2(t)|p^{RCT}) \\
&= E(\hat{\theta}^{RCT}(Y, D)|p^{RCT}) = \theta,
\end{align*}
\]

where \( Y_i(d_i) = \sum_t d_t Y_i(t) \) is the value of observed outcome \( Y_i \) when \( D_i = d_i \), the second equality is by Lemma 5, the third equality is by the support equivalence property (17), and the last equality is by the unbiasedness assumption (18). This means that \( \hat{\theta}^{EXAM}(Y, D) \) is an unbiased estimator for \( \theta \) under EXAM \( p^*(\epsilon) \). To complete the proof of Proposition 4, it only remains to show \( \hat{\theta}^{EXAM}(Y, D) \) is a simple estimator under EXAM.

**Lemma 6.** \( \hat{\theta}^{EXAM}(Y, D) \) is a simple estimator under EXAM \( p^*(\epsilon) \).

**Proof of Lemma 6.** First note that

\[
\hat{S}^2_{pt} = \frac{1}{p_t N_p - 1} \left( \sum_{i|p_i^*(\epsilon)=p} Y_i^2 D_{it} - 2 \sum_{i|p_i^*(\epsilon)=p} Y_i D_{it} \frac{p_t n_p}{N_p} \hat{\mu}_{EXAM,pt} + \sum_{i|p_i^*(\epsilon)=p} \left( \frac{p_t n_p}{N_p} \right)^2 \hat{\mu}_{EXAM,pt}^2 D_{it} \right)
\]
\[
\frac{1}{p_t n_p - 1} \sum_{i:p^*_t(i) = p} Y^2_i D_{it} - \frac{(p_t n_p)^2}{N_{pt}} \hat{\mu}^2_{EXAM,pt}.
\]

I therefore have

\[
\hat{\theta}_{EXAM,t} \\
\equiv \frac{n - c_t}{(n - 1)c_t} \hat{\theta}_{1t} + \frac{n(c_t - 1)}{(n - 1)c_t} \hat{\theta}_{2t}
\]

\[
= \frac{n - c_t}{(n - 1)c_t} \frac{1}{n} \sum_{p_t} \sum_{i:p^*_t(i) = p} \frac{1}{p_t} Y^2_i D_{it} + \frac{n(c_t - 1)}{(n - 1)c_t} \left( \hat{\mu}^2_{EXAM,t} - \sum_p \frac{n^2_p}{n^2} \left( \frac{1 - p_t n_p + 2 n_{pt}}{n_{pt}(n_{pt} + 1)} - \frac{1}{n_p} \right) \hat{\mu}^2_{EXAM,pt} \right)
\]

\[
= \sum_p \sum_{i:p^*_t(i) = p} \frac{n - c_t}{(n - 1)c_t} \frac{1}{n} Y^2_i D_{it} + \frac{n(c_t - 1)}{(n - 1)c_t} \left\{ \left( \sum_p \frac{n_p}{n} \frac{p_t n_p + 2 n_{pt}}{n_{pt}(n_{pt} + 1)} - \frac{1}{n_p} \right) \hat{\mu}^2_{EXAM,pt} \right\}
\]

\[
= \sum_p \sum_{i:p^*_t(i) = p} \left\{ \frac{n - c_t}{(n - 1)c_t} \frac{n_p n_p'}{n^2} \frac{p_t n_p p_t n_{p'}'}{n_{p'}(n_{p'} + 1)} \hat{\mu}^2_{EXAM,pt} \right\}
\]

\[
\sum_p \sum_{i:p^*_t(i) = p} \left( (c_t - 1) n_p^2 p_t n_p p_t' \hat{\mu}^2_{EXAM,pt} \right)
\]

\[
= \sum_i a_{1p^*t} Y^2_i D_{it} + \sum_p \sum_{p' \neq p} \left\{ \frac{(c_t - 1) n_p^2 p_t n_{p'}}{n_{p'}(n_{p'} + 1)} - \frac{1}{n_p} \right\} \hat{\mu}^2_{EXAM,pt}
\]

where \( n_{pt} \) is the greatest integer less than or equal to \( p_t n_p \) and

\[
a_{1p^*} = \frac{n - c_t}{(n - 1)c_t n_p} - \frac{(c_t - 1) n_p^2}{(n - 1) c_t n_p (p_t n_p - 1)} \left( \frac{1 - p_t n_p + 2 n_{pt}}{n_{pt}(n_{pt} + 1)} - \frac{1}{n_p} \right)
\]

\[
a_{2pp'} = \begin{cases} 
\left( \frac{(c_t - 1) n_p^2 p_t n_{p'}'}{(n - 1) c_t n_{pt} n_{p'}'} \right) & \text{if } p \neq p' \\
\left( \frac{(c_t - 1) n_p^2}{(n - 1) c_t n_{pt}} \frac{1}{n_{pt}} + \left( \frac{1 - p_t n_p + 2 n_{pt}}{n_{pt}(n_{pt} + 1)} - \frac{1}{n_p} \right) \frac{1}{p_t n_p - 1} \right) & \text{if } p = p'.
\end{cases}
\]

It follows that
For RCT, let \( \theta \) be unbiasedly estimable with RCT and a simple estimator. Consider two possible definitions of the variance of potential outcomes:

\[
\hat{\theta}^{\text{EXAM}}(Y, D) = \sum_i \frac{\Pr(D_i | p^{RCT})}{\Pr(D_i | p^*(\epsilon))} f(Y_i, D_i, p_i^{RCT}) + \sum_t g_t \hat{\theta}_{\text{EXAM}, t}
\]

\[
= \sum_i \frac{\Pr(D_i | p^{RCT})}{\Pr(D_i | p^*(\epsilon))} f(Y_i, D_i, p_i^{RCT}) + \sum_t g_t \sum_p \sum_p' \epsilon \mu_{\text{EXAM}, p, p'} \mu_{\text{EXAM}, p'}
\]

\[
= \sum_i f^*(Y_i, D_i, p_i) + \sum_t \sum_p \sum_p' g_{tpp'} \epsilon \mu_{\text{EXAM}, p, p'} \mu_{\text{EXAM}, p'}
\]

where \( f^*(Y_i, D_i, p_i) = \frac{\Pr(D_i | p^{RCT})}{\Pr(D_i | p^*(\epsilon))} f(Y_i, D_i, p_i^{RCT}) + \sum_t g_t a_{1p_t} Y_i^2 D_i t \) and \( g_{tpp'} = g_t a_{2pp'} \).

Therefore, \( \hat{\theta}^{\text{EXAM}}(Y, D) \) is a simple estimator under EXAM \( p^*(\epsilon) \).

**Proof of Corollary 1**

The mean of potential outcomes for treatment \( t \) is unbiasedly estimable with RCT and a simple estimator by the following reason. Let \( \hat{\theta}(Y, D) = \sum_{i=1}^n \frac{D_i Y_i}{c_t} \). \( \hat{\theta}(Y, D) \) is a simple unbiased estimator by \( E(\hat{\theta}(Y, D)|p^{RCT}) = \sum_{i=1}^n \frac{p^{RCT}_t Y_i(t)}{c_t} = \frac{1}{n} \sum_{i=1}^n Y_i(t) \).

ATE of treatment \( t \) over control \( t_0 \) is also unbiasedly estimable with RCT and a simple estimator. To see this, let \( \hat{\theta}(Y, D) = \sum_{i=1}^n \frac{(D_i - D_{t_0}) Y_i}{c_t} \). This is a simple estimator, and it follows from the above argument for the mean potential outcome that \( E(\hat{\theta}(Y, D)|p^{RCT}) = \frac{1}{n} \sum_{i=1}^n Y_i(t) - \frac{1}{n} \sum_{i=1}^n Y_i(t_0) \).

The variance of potential outcomes for treatment \( t \) is unbiasedly estimable with RCT and a simple estimator. Consider two possible definitions of the variance of potential outcomes:

\[
S_t^2 = \frac{1}{n-1} \sum_{i=1}^n (Y_i(t) - \frac{1}{n} \sum_{j=1}^n Y_j(t))^2 \text{ and } \Sigma_t^2 = \frac{1}{n} \sum_{i=1}^n (Y_i(t) - \frac{1}{n} \sum_{j=1}^n Y_j(t))^2.
\]

To see that \( S_t^2 \) is unbiasedly estimable with RCT and a simple estimator, let \( \hat{\theta}_1(Y, D) = \frac{1}{c_t - 1} \sum_{i=1}^n D_i (Y_i - \hat{\mu}_R(t))^2 \), where \( \hat{\mu}(t) = \frac{1}{c_t} \sum_{i=1}^n D_i Y_i \). Since I can write \( \hat{\theta}_1(Y, D) \) as

\[
\hat{\theta}_1(Y, D) = \sum_{i=1}^n \frac{D_i Y_i^2}{c_t - 1} - \frac{c_t}{c_t - 1} \hat{\mu}^2(t),
\]

this is a simple estimator with

\[
f(Y_i, D_i, p_i) = \frac{D_i Y_i^2}{c_t - 1}, g_t = -\frac{c_t}{c_t - 1} \text{ and } g_{t'} = 0 \text{ for all } t' \neq t.
\]

For RCT, \( \{i : D_i = 1\} \) can be seen as a random sample of \( c_t \) subjects from the population of \( n \) subjects. Using Lemma 4 I obtain \( E(\hat{\theta}_1(Y, D)|p^{RCT}) = S_t^2 \).

To see that \( \Sigma_t^2 \) is also unbiasedly estimable with RCT and a simple estimator, let \( \hat{\theta}_2(Y, D) = \frac{n-1}{n} \hat{\theta}_1(Y, D) \). Since I can write \( \hat{\theta}_2(Y, D) \) as \( \hat{\theta}_2(Y, D) = \sum_{i=1}^n \frac{n-1}{n} \frac{D_i Y_i^2}{c_t - 1} - \frac{c_t}{c_t - 1} \hat{\mu}^2(t) \), this is a simple estimator with

\[
f(Y_i, D_i, p_i) = \frac{n-1}{n} \frac{D_i Y_i^2}{c_t - 1}, g_t = -\frac{c_t}{c_t - 1} \text{ and } g_{t'} = 0 \text{ for all } t' \neq t.
\]
\[
\frac{n - 1}{n} \frac{c_t}{c_t - 1} \hat{\mu}^2(t), \text{ this is a simple estimator with }
\]

\[
f(Y_i, D_i, p_i) = \frac{n - 1}{n} D_{it} Y_i^2 - \frac{n - 1}{n} \frac{c_t}{c_t - 1} \text{ and } g' = 0 \text{ for all } t' \neq t.
\]

It follows that \( E(\hat{\theta}_2(Y, D)|p^{RCT}) = \frac{n - 1}{n} E(\hat{\theta}_1(Y, D)|p^{RCT}) = \frac{n - 1}{n} S_t^2 = \sum_t^2 \).

Finally, I consider the unbiased estimability of the average treatment effect on the treated (ATT) with RCT and EXAM. I first define ATT of \( t \) over \( t_0 \) conditional on the treatment assignment being \( d \) as

\[
\text{ATT}(t|d) \equiv \frac{\sum_{i=1}^n (Y_i(t) - Y_i(t_0))}{\sum_{i=1}^n D_{it}}.
\]

I define ATT of \( t \) over \( t_0 \) for experimental design \((p_{it})\) as

\[
\text{ATT}(t|(p_{it})) \equiv E(\text{ATT}(t|D)|(p_{it})) = E\left(\frac{\sum_{i=1}^n (Y_i(t) - Y_i(t_0))}{\sum_{i=1}^n D_{it}} |(p_{it})\right).
\]

For RCT,

\[
\text{ATT}(t|p^{RCT}) = \frac{1}{c_t} \sum_{i=1}^n (Y_i(t) - Y_i(t_0)) p^{RCT}_{it} = \frac{1}{n} \sum_{i=1}^n (Y_i(t) - Y_i(t_0)) = \text{ATE}.
\]

Since ATE is unbiasedly estimable with RCT and a simple estimator, ATT is also unbiasedly estimable with RCT. For EXAM,

\[
\text{ATT}(t|p^*(\epsilon)) = \frac{1}{\sum_i p^*_t(\epsilon)} \sum_{i=1}^n (Y_i(t) - Y_i(t_0)) p^*_t(\epsilon)
\]

\[
= \frac{1}{\sum_i p^*_t(\epsilon)} \sum_p \sum_{i:p^*_t(\epsilon)=p} (Y_i(t) - Y_i(t_0)) p_t
\]

\[
= \sum_p \frac{p_t n_p}{\sum_i p^*_t(\epsilon)} \frac{1}{n_p} \sum_{i:p^*_t(\epsilon)=p} (Y_i(t) - Y_i(t_0))
\]

\[
= \sum_p \frac{p_t n_p}{\sum_i p^*_t(\epsilon)} \text{ CATE}_{pt}.
\]

Since \( \frac{p_t n_p}{\sum_i p^*_t(\epsilon)} \) is known to the experimenter and \( \text{CATE}_{pt} \) is unbiasedly estimable with EXAM and \( \hat{\beta}_{pt} \), ATT is unbiasedly estimable with EXAM and \( \sum_p \frac{p_t n_p}{\sum_i p^*_t(\epsilon)} \hat{\beta}_{pt} \).
Proof of Proposition 5

I define $N_{pt} \equiv \sum_i 1\{p^*_i(\epsilon) = p\}D_{it}$ as a random variable that stands for the number of subjects with propensity vector $p$ and assigned to treatment $t$. Denote the realization of $N_{pt}$ by $n_{pt} \equiv \sum_i 1\{p^*_i(\epsilon) = p\}d_{it}$. Recall that $n_{pt}$ is defined as the greatest integer less than or equal to $ptn_p$ (the expected number of subjects with propensity vector $p$ and assigned to treatment $t$). Define $\mathcal{N}$ as the set of all $(n_{pt})$ that satisfy the following:

- $n_{pt} = n_{pt}$ for all $p$ and $t$ such that $ptn_p \in \mathbb{N}$.
- $n_{pt} \in \{n_{pt}, n_{pt} + 1\}$ for all $p$ and $t$ such that $ptn_p \notin \mathbb{N}$.
- $\sum_t n_{pt} = n_p$ for all $p$.
- $\sum_p n_{pt} = \sum_i p^*_i(\epsilon)$ for all $t$.

I also define $D(n_{pt})$ as the set of deterministic treatment assignments where the realization of $(N_{pt})$ is $(n_{pt})$:

$$D(n_{pt}) \equiv \{d \in \{0, 1\}^{n \times (m+1)} | \sum_t d_{it} = 1 \text{ for every } i \text{ and } \sum_i 1\{p^*_i(\epsilon) = p\}d_{it} = n_{pt} \text{ for every } p \text{ and } t\}.$$ 

The method of drawing deterministic treatment assignments in Definition 2 in Section 5 and Appendix A.1.1 satisfies the following properties.

**Lemma 7** (Small Support). The support of $(N_{pt})$ is included by $\mathcal{N}$.

**Lemma 8** (Conditional Uniformity). Conditional on any $(n_{pt})$ in the support of $(N_{pt})$, every deterministic treatment assignment consistent with $(n_{pt})$ happens with equal probability:

$$Pr(D = d|(N_{pt}) = (n_{pt}), p^*(\epsilon)) = \begin{cases} |D(n_{pt})|^{-1} & \text{if } d \in D(n_{pt}) \\ 0 & \text{otherwise.} \end{cases}$$

To show the mean part of Proposition 5, note that by Lemma 8, every feasible treatment assignment occurs equally likely conditional on $(N_{pt})$ so that for every $p$, $t$ and $i$ with $p^*_i(\epsilon) = p$,

$$E(D_{it}|(N_{pt}) = (n_{pt}), p^*_i(\epsilon) = p) = \frac{n_{pt}}{n_p}$$  \hspace{1cm} (19)

I therefore have

$$E(\hat{\beta}^*_i|(N_{pt}) = (n_{pt}), p^*_i(\epsilon) = p)$$
\[
E(\sum_p \delta_p \beta_{pt})(N_{pt}) = (n_{pt}), p^*_i(\epsilon) = p
\]
\[
= \sum_p \delta_p E(\beta_{pt})(N_{pt}) = (n_{pt}), p^*_i(\epsilon) = p
\]
\[
= \sum_p \delta_p E[\sum_i 1\{p^*_i(\epsilon) = p\}\left(\frac{D_{it}Y_i(t)}{N_{pt}} - \frac{D_{ito}Y_i(t_0)}{N_{pto}}\right)|((N_{pt}) = (n_{pt}), p^*_i(\epsilon) = p]
\]
\[
= \sum_p \delta_p \sum_i 1\{p^*_i(\epsilon) = p\}\left(\frac{E(D_{it}|(N_{pt}) = (n_{pt}), p^*_i(\epsilon) = p)Y_i(t) - E(D_{ito}|(N_{pt}) = (n_{pt}), p^*_i(\epsilon) = p)Y_i(t_0)}{n_{pto}}\right)
\]
\[
= \sum_p \delta_p \frac{1}{n_p} \sum_i 1\{p^*_i(\epsilon) = p\}(Y_i(t) - Y_i(t_0))
\]
\[
= \sum_p \delta_p CAT E_{pt},
\]
where I use equation (19) for the fifth equality. By the law of iterated expectation, I conclude

\[
E(\hat{\beta}^*_i|p^*(\epsilon)) = E[E(\hat{\beta}^*_i|(N_{pt}) = (n_{pt}), p^*(\epsilon)|p^*(\epsilon)]
\]
\[
= E[\sum_p \delta_p CAT E_{pt}|p^*(\epsilon)]
\]
\[
= \sum_p \delta_p CAT E_{pt}.
\]

For the variance part of Proposition 5, I prove the general version given in Appendix A.1.1. For notational simplicity, I make conditioning on \( p^*(\epsilon) \) implicit. By the law of total variance, \( V(\hat{\beta}^*_i) \) can be written as:

\[
V(\hat{\beta}^*_i) = E(V(\hat{\beta}^*_i|(N_{pt})) + V(E(\hat{\beta}^*_i|(N_{pt}))).
\]

As I show above, \( E(\hat{\beta}^*_i|(N_{pt})) = \sum_p \delta_p CAT E_{pt} \), implying \( V(E(\hat{\beta}^*_i|(N_{pt}))) = 0 \). Thus

\[
V(\hat{\beta}^*_i) = E(V(\hat{\beta}^*_i|(N_{pt}))).
\]

To show that \( E(V(\hat{\beta}^*_i|(N_{pt}))) \) is equal to the expression in Proposition 5, I introduce a lemma.

**Lemma 9.** For all \((n_{pt})\) in the support of \((N_{pt})\),

\[
V(\hat{\beta}^*_i|(N_{pt}) = (n_{pt})) = \sum_p \delta_p^2 \left(\frac{S^2_{pt}}{n_{pt}} + \frac{S^2_{pt0}}{n_{pto}} - \frac{S^2_{ptt0}}{n_p}\right).
\]
Proof of Lemma. By Lemma 8, treatment assignments are independent across subpopulations with different propensities conditional on \((N_{pt})\). \(\hat{\beta}_{pt}\) is therefore independent across \(p\) conditional on \((N_{pt})\). Hence,

\[
V(\hat{\beta}_t | (N_{pt}) = (n_{pt})) = V(\sum_p \delta_p \hat{\beta}_{pt} | (N_{pt}) = (n_{pt})) = \sum_p \delta_p^2 V(\hat{\beta}_{pt} | (N_{pt}) = (n_{pt})).
\]

It is therefore enough to show that

\[
V(\hat{\beta}_{pt} | (N_{pt}) = (n_{pt})) = \frac{S_{pt}^2}{n_{pt}} + \frac{S_{pt0}^2}{n_{pt0}} - \frac{S_{ptt0}^2}{n_p}.
\]

For notational simplicity, I make conditioning on \((N_{pt}) = (n_{pt})\) implicit. Let \(I^{ptt0}\) be a random set of subjects with propensity vector \(p\) and assigned to either treatment \(t\) or \(t_0\), i.e.,

\[
I^{ptt0} \equiv \{ i \mid p_t^*(\epsilon) = p \text{ and } D_{it} + D_{it_0} = 1 \}.
\]

\(I^{ptt0}\) takes on \(\binom{n_p}{n_{pt} + n_{pt0}}\) values equally likely, a consequence of Lemma 8. By the law of total variance, \(V(\hat{\beta}_{pt})\) can be written as:

\[
V(\hat{\beta}_{pt}) = E(V(\hat{\beta}_{pt} | I^{ptt0})) + V(E(\hat{\beta}_{pt} | I^{ptt0})).
\]

(21)

Conditional on \(I^{ptt0} = I\), the randomness in \(\hat{\beta}_{pt}\) comes from the randomness in choosing \(n_{pt}\) subjects assigned to treatment \(t\) and \(n_{pt0}\) subjects assigned to treatment \(t_0\) from the set \(I\) of \(n_{pt} + n_{pt0}\) subjects. Every combination occurs with equal probability, so the standard results of binary-treatment RCT (Theorems 6.1 and 6.2 in Imbens and Rubin (2015) apply:

\[
E(\hat{\beta}_{pt} | I^{ptt0} = I) = \frac{1}{n_{pt} + n_{pt0}} \sum_{i \in I} (Y_i(t) - Y_i(t_0)),
\]

\[
V(\hat{\beta}_{pt} | I^{ptt0} = I) = \frac{S_{pt}^2}{n_{pt}} + \frac{S_{pt0}^2}{n_{pt0}} - \frac{S_{ptt0}^2}{n_{pt} + n_{pt0}},
\]

where \(S_{pt}^2, S_{pt0}^2\) and \(S_{ptt0}^2\) are the variances of \(Y_i(t)\), \(Y_i(t_0)\) and \(Y_i(t) - Y_i(t_0)\), respectively, conditional on the set of subjects \(I\). Regarding \(n_p, n_{pt} + n_{pt0}\), and \(Y_i(t) - Y_i(t_0)\) as performing the roles of \(n, m,\) and \(X_i\) in Lemma 4 respectively, I use Lemma 4 to get

\[
V(E(\hat{\beta}_{pt} | I^{ptt0} = I)) = V(\frac{1}{n_{pt} + n_{pt0}} \sum_{i \in I} (Y_i(t) - Y_i(t_0))) = \frac{n_p - n_{pt} - n_{pt0}}{n_p(n_{pt} + n_{pt0})} S_{ptt0}^2,
\]

\[
E(V(\hat{\beta}_{pt} | I^{ptt0} = I)) = \frac{E(S_{pt}^2)}{n_{pt}} + \frac{E(S_{pt0}^2)}{n_{pt0}} - \frac{E(S_{ptt0}^2)}{n_{pt} + n_{pt0}} = \frac{S_{pt}^2}{n_{pt}} + \frac{S_{pt0}^2}{n_{pt0}} - \frac{S_{ptt0}^2}{n_{pt} + n_{pt0}},
\]

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where the last equality is by the second part of Lemma 4. Combining these with equation (21), I have
\[ V(\hat{\beta}_{pt}) = \frac{S^2_{pt}}{n_{pt}} + \frac{S^2_{pt0}}{n_{pt0}} - \frac{S^2_{pt0}}{n_p}. \]

By Lemma 7, \( N_{pt} \) can take on either \( n_{pt} \) or \( n_{pt} + 1 \). Since \( N_{pt} \) has expectation \( p_t n_p \), the marginal distribution for each \( N_{pt} \) must be
\[
\Pr(N_{pt} = n_{pt}) = \begin{cases} 
1 - p_t n_p + n_{pt} & \text{if } n_{pt} = n_{pt} \\
p_t n_p - n_{pt} & \text{if } n_{pt} = n_{pt} + 1 \\
0 & \text{otherwise.} 
\end{cases} \tag{22}
\]

Using equation (20), Lemma 9, and equation (22), I have
\[
V(\hat{\beta}_t^*) = E\left\{ \sum_p \delta_p^2 \left( \frac{S^2_{pt}}{N_{pt}} + \frac{S^2_{pt0}}{N_{pt0}} - \frac{S^2_{pt0}}{n_p} \right) \right\} \\
= \sum_p \delta_p^2 \left\{ \sum_{t' \in \{t, t'\}} E\left( \frac{S^2_{pt'}}{N_{pt'}} \right) - \frac{S^2_{pt0}}{n_p} \right\} \\
= \sum_p \delta_p^2 \left\{ \sum_{t' \in \{t, t'\}} \left[ \left( \frac{S^2_{pt'}}{N_{pt'}} \right) \left( 1 - p_t n_p + n_{pt'} \right) + \left( \frac{S^2_{pt'}}{n_{pt'} + 1} \right) \left( p_t n_p - n_{pt'} \right) \right] - \frac{S^2_{pt0}}{n_p} \right\}.
\]

**Proof of Equation (4)**

I prove equation (4) with two lemmas below.

**Lemma 10.** \( E(\hat{B}_t|p^*(\epsilon)) = \sum_p \lambda_{pt} \text{CATE}_{pt} \) for all \( t \) where \( \hat{B}_t \) is the OLS estimate of \( B_t \) in this regression:
\[
Y_i = \sum_{t=t_1}^{t_m} B_t D_{it} + \sum_p C_p 1\{p_i^*(\epsilon) = p\} + E_i. \tag{23}
\]

**Proof of Lemma 10.** I reparametrize the regression as follows with \((B_t, D_p)\), where \( D_p \equiv C_p + \sum_{t=t_1}^{t_m} B_t p_t \).
\[
Y_i = \sum_{t=t_1}^{t_m} B_t (D_{it} - p_{it}^*(\epsilon)) + \sum_p D_p 1\{p_i^*(\epsilon) = p\} + E_i. \tag{24}
\]

This reparametrization does not change \( \hat{B}_t \). Note also that \( Y_i \) can be written as follows.
\[ Y_i = \sum_p 1\{p_i^*(\epsilon) = p\} Y_p(0) + \sum_p \sum_{t=t}^{t_m} 1\{p_i^*(\epsilon) = p\} CATE_{pt} D_{it} + \mu_i, \]

where \( Y_p(0) \equiv \sum_i 1\{p_i^*(\epsilon) = p\} Y_i(0) \) and \( \sum_i 1\{p_i^*(\epsilon) = p\} \mu_i = 0 \) for every \( p \). Therefore, the OLS estimates \((\hat{B}_t, \hat{D}_p)\) of \((B_t, D_p)\) in regression [24] can be written as follows.

\[
(\hat{B}_t, \hat{D}_p) = \arg \min_{(B_t, D_p)} \sum_i \left\{ \sum_p 1\{p_i^*(\epsilon) = p\} Y_p(0) + \sum_p \sum_{t=t}^{t_m} 1\{p_i^*(\epsilon) = p\} CATE_{pt} D_{it} \right. \\
- \sum_{t=t}^{t_m} B_t(D_{it} - p_{it}^*(\epsilon)) \left. \right\}^2 \\
= \arg \min_{(B_t, D_p)} \sum_i \left\{ \sum_p 1\{p_i^*(\epsilon) = p\} (Y_p(0) - D_p + \sum_{t=t}^{t_m} CATE_{pt} D_{it}) - \sum_{t=t}^{t_m} B_t(D_{it} - p_{it}^*(\epsilon)) \right\}^2 \\
= \arg \min_{(B_t, D_p)} \sum_i \left\{ \sum_p 1\{p_i^*(\epsilon) = p\} (Y_p(0) - D_p + \sum_{t=t}^{t_m} CATE_{pt} D_{it}) \right. \\
- 2 \sum_p 1\{p_i^*(\epsilon) = p\} (Y_p(0) - D_p + \sum_{t=t}^{t_m} CATE_{pt} D_{it}) \sum_{t=t}^{t_m} B_t(D_{it} - p_{it}^*(\epsilon)) \\
+ \left\{ \sum_{t=t}^{t_m} B_t(D_{it} - p_{it}^*(\epsilon)) \right\}^2 \right\}^2 \\
= \arg \min_{(B_t, D_p)} \sum_i \left\{ \sum_p 1\{p_i^*(\epsilon) = p\} (Y_p(0) - D_p + \sum_{t=t}^{t_m} CATE_{pt} D_{it}) \right. \\
- 2 \sum_p 1\{p_i^*(\epsilon) = p\} \sum_{t=t}^{t_m} CATE_{pt} D_{it} \sum_{t=t}^{t_m} B_t(D_{it} - p_{it}^*(\epsilon)) + \left\{ \sum_{t=t}^{t_m} B_t(D_{it} - p_{it}^*(\epsilon)) \right\}^2 \right\}^2 \]

because \( \sum_i (D_{it} - p_{it}^*(\epsilon)) = 0 \). Minimizing this over \( B_t \) leads to

\[
\hat{B}_t = \frac{\sum_i \sum_p 1\{p_i^*(\epsilon) = p\} CATE_{pt} D_{it} (D_{it} - p_{it}^*(\epsilon))}{\sum_i (D_{it} - p_{it}^*(\epsilon))^2}. 
\]

Because \( P(D_{it} = 1) = \frac{\sum_p \sum_i 1\{p_i^*(\epsilon) = p\} p_{it}^*(\epsilon)}{n} \) and

\[
P(p_{it}^*(\epsilon) = p|D_{it} = 1) = \frac{\sum_i 1\{p_i^*(\epsilon) = p\} p_{it}^*(\epsilon)}{\sum_q \sum_i 1\{(p_i^*(\epsilon) = q) p_{it}^*(\epsilon)\},}
\]

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Electronic copy available at: https://ssrn.com/abstract=3094905
it follows that the numerator is equal to \( \sum_p p_t(1 - p_t)\delta_p CAT E_{pt} \) and that the denominator is equal to \( \sum_p p_t(1 - p_t)\delta_p \). This implies that \( E(\hat{B}_t|p^*(\epsilon)) = \sum_p \lambda_{pt} CAT E_{pt} \).

Lemma 11. \( \hat{B}_t = \hat{b}_t^* \) for any \( t \) and any realization of treatment assignment \( D_{it} \).

Proof of Lemma 11. By the Frisch-Waugh-Lovell theorem, the OLS estimates of (23) can be obtained by regressing each of \( Y_t \) and \( D_{it} \) on the fully-saturated propensity score controls and then using the residuals from these regressions as the dependent and independent variables for a bivariate regression that omits the propensity score controls. Consider the auxiliary regressions that produce these residualized variables: they have \( D_{it} \) on the left hand side, with a saturated control for \( p_{it}^*(\epsilon) \) on the right. By the law of iterated expectations, the conditional expectation function associated with this auxiliary regression is

\[ E[D_{it}|p_{it}^*(\epsilon)] = p_{it}^*(\epsilon). \]

In other words, the conditional expectation function \( E[D_{it}|p_{it}^*(\epsilon)] \) is linear in regressors \( p_{it}^*(\epsilon) \), so it and the associated auxiliary regression function coincide (note that I use a saturated model for \( p_{it}^*(\epsilon) \)). Therefore, regression (3), which additively separably and linearly controls for \( p_{it}^*(\epsilon) \)'s, produces the same estimate as regression (23).

Proof of Proposition 6

The proof uses the following lemma.

Lemma 12. Suppose Assumptions 1, 2, 3, 4, 5, 6, and 7 hold. For all \( g \), as \( N \to \infty \),

\[ \sqrt{n_g}(\hat{\beta}_{N,g} - \beta_{N,g}^{\text{pop}}) \xrightarrow{d} \mathcal{N}(0, H_g^{-1}(\rho \Delta_{g}^{\text{cond}} + (1 - \rho)\Delta_{g}^{\text{ehw}})H_g^{-1}). \]
\[ \sqrt{n_g}(\hat{\beta}_{N,g} - \beta_{N,g}^{\text{sample}}) \xrightarrow{d} \mathcal{N}(0, H_g^{-1}\Delta_{g}^{\text{cond}}H_g^{-1}). \]

Proof of Lemma 12. This result is a consequence of Theorem 3 of Abadie et al. (2017). To verify their assumptions hold, fix any \( g \), and regard subpopulation \( P_{N,g} \) as the entire population. Note that \( N_g \to \infty \) as \( N \to \infty \) by Assumption 2 (ii). \( D_{N,i} \) and 1 in my notation correspond to \( U_{N,i} \) and \( Z_{N,i} \) in Abadie et al. (2017). Their Assumption 3 holds by the following reason: For all \( g \) and \( i \in P_{N,g}, \)

\[ \Pr((D_{N,it})_{t=t_0,\ldots,t_m} = d_i|R_N = r) = E[\Pr((D_{N,it})_{t=t_0,\ldots,t_m} = d_i|R_N = r, (c_{N,t}))|R_N = r] \]
\[ = E[\sum_{t=t_0}^{t_m} p_{N,it}^*(\epsilon)1\{d_{it} = 1\}|R_N = r] \]
\[
= \sum_{t=t_0}^{t_m} q_{N,g,t}1\{d_{it} = 1\},
\]

where the third equality holds by my Assumption 3. Then, \(Pr((D_{N,it})_{t=t_0,...,t_m} = d_i) = E[Pr((D_{N,it})_{t=t_0,...,t_m} = d_i | R_N = r)] = Pr((D_{N,it})_{t=t_0,...,t_m} = d_i | R_N = r)\). Under my Assumption 4,

\[
Pr((D_{N,it}) = (d_i) | R_N = r) = \prod_{i=1}^{N} Pr((D_{N,it})_{t=t_0,...,t_m} = d_i | R_N = r) = \prod_{i=1}^{N} \Pr((D_{N,it})_{t=t_0,...,t_m} = d_i),
\]

and

\[
Pr((D_{N,it}) = (d_i)) = E[Pr((D_{N,it}) = (d_i) | R_N = r)] = \prod_{i=1}^{N} \Pr((D_{N,it})_{t=t_0,...,t_m} = d_i).
\]

Therefore, \((D_{N,1,t})_{t=t_0,...,t_m}, ...,(D_{N,N,t})_{t=t_0,...,t_m}\) are jointly independent from each other, and independent of \(R_N\). Assumption 3 in Abadie et al. (2017) therefore holds. Since \(E[D_{N,i}] = (q_{N,g,t_1}, ..., q_{N,g,t_m})'\) for \(i \in P_{N,g}\), Assumption 7 in Abadie et al. (2017) holds. Note that

\[
Y_{N,i} = \sum_{t=t_0}^{t_m} D_{N,it}Y_{N,i}(t) = \sum_{t=t_1}^{t_m} D_{N,it}(Y_{N,i}(t) - Y_{N,i}(t_0)) + \sum_{t=t_0}^{t_m} D_{N,it}Y_{N,i}(t_0) = D_{N,i}'\beta_{N,i} + Y_{N,i}(t_0),
\]

implying Assumption 8 in Abadie et al. (2017) holds. I next show that my \(\beta_{N,g}^{pop}\) and \(\beta_{N,g}^{sample}\) are equal to their \(\theta_{N,c}^{causal}\) and \(\theta_{N,c}^{causal,sample}\), respectively. To make it explicit that \(\theta_{N,c}^{causal}\) and \(\theta_{N,c}^{causal,sample}\) vary across \(g\) in our setting, denote them by \(\theta_{N,g,c}^{causal}\) and \(\theta_{N,g,c}^{causal,sample}\). Since \(E[X_{N,i}] = 0\) and \(E[X_{N,i}X_{N,i}']\) is constant across \(i \in P_{N,g}\),

\[
\theta_{N,g,c}^{causal} = (\frac{1}{N_g} \sum_{i \in P_{N,g}} E[X_{N,i}X_{N,i}'])^{-1} \frac{1}{N_g} \sum_{i \in P_{N,g}} E[X_{N,i}Y_{N,i}]
\]

\[
= (E[X_{N,1}X_{N,1}'])^{-1} \frac{1}{N_g} \sum_{i \in P_{N,g}} E[X_{N,i}(D_{N,i}'\beta_{N,i} + Y_{N,i}(t_0))]
\]

\[
= (E[X_{N,1}X_{N,1}'])^{-1} \frac{1}{N_g} \sum_{i \in P_{N,g}} E[X_{N,i}((X_{N,i} + E[D_{N,i}])'\beta_{N,i} + Y_{N,i}(t_0))]
\]

\[
= (E[X_{N,1}X_{N,1}'])^{-1} E[X_{N,1}X_{N,1}'] \frac{1}{N_g} \sum_{i \in P_{N,g}} \beta_{N,i}
\]

\[
= \beta_{N,g}^{pop}.
\]
and

\[
\theta_{N,g}^{\text{causal, sample}} = \left( \frac{1}{n_g} \sum_{i \in P_{N,g}} R_{N,i}E[X_{N,i}X'_{N,i}] \right)^{-1} \frac{1}{n_g} \sum_{i \in P_{N,g}} R_{N,i}E[X_{N,i}Y_{N,i}]
\]

\[
= (E[X_{N,1}X'_{N,1}])^{-1} \frac{1}{n_g} \sum_{i \in P_{N,g}} R_{N,i}E[X_{N,i}(\{X_{N,i} + E[D_{N,i}]\}^\prime \beta_{N,i} + Y_{N,i}(t_0))]
\]

\[
= (E[X_{N,1}X'_{N,1}])^{-1} E[X_{N,1}X'_{N,1}] \frac{1}{n_g} \sum_{i \in P_{N,g}} R_{N,i} \beta_{N,i}
\]

\[
= \beta_{N,g}^{\text{sample}}.
\]

Note that \( \gamma_{N,g}^{\text{causal}} \) in Abadie et al. (2017)'s notation is

\[
\gamma_{N,g}^{\text{causal}} = \frac{1}{N_g} \sum_{i \in P_{N,g}} E[Y_{N,i}] = \frac{1}{N_g} \sum_{i \in P_{N,g}} E[D'_{N,i} \beta_{N,i} + Y_{N,i}(t_0)] = E[D'_{N,1}] \beta_{N,g}^{\text{pop}} + \frac{1}{N_g} \sum_{i \in P_{N,g}} Y_{N,i}(t_0).
\]

For \( i \in P_{N,g} \),

\[
\epsilon_{N,i} = D'_{N,i}(\beta_{N,i} - \beta_{N,g}^{\text{pop}}) + Y_{N,i}(t_0) - \frac{1}{N_g} \sum_{i \in P_{N,g}} Y_{N,i}(t_0)
\]

\[
= \sum_{t=t_1}^{t_m} D_{N,it}(Y_{N,i}(t) - Y_{N,i}(t_0)) - D'_{N,i} \theta_{N,g}^{\text{causal}} + Y_{N,i}(t_0) - \frac{1}{N_g} \sum_{i \in P_{N,g}} Y_{N,i}(t_0)
\]

\[
= Y_{N,i} - D'_{N,i} \theta_{N,g}^{\text{causal}} - \frac{1}{N_g} \sum_{i \in P_{N,g}} Y_{N,i}(t_0)
\]

\[
= Y_{N,i} - X'_{N,g} \theta_{N,g}^{\text{causal}} - E[D'_{N,1}] \beta_{N,g}^{\text{pop}} - \frac{1}{N_g} \sum_{i \in P_{N,g}} Y_{N,i}(t_0)
\]

\[
= Y_{N,i} - X'_{N,g} \theta_{N,g}^{\text{causal}} - \gamma_{N,g}^{\text{causal}},
\]

where the last equality is by \( \gamma_{N,g}^{\text{causal}} = E[D'_{N,1}] \beta_{N,g}^{\text{pop}} + \frac{1}{N_g} \sum_{i \in P_{N,g}} Y_{N,i}(t_0) \) shown above. It only remains to check Abadie et al. (2017)'s Assumption 5 holds. Since \( \|X_{N,i}\| \leq \sum_{t=t_1}^{t_m} |X_{N,it}| \leq \sum_{t=t_1}^{t_m} (|D_{N,it}| + |p_{N,it}(\epsilon)|) \leq 2 \) with probability one for all \( i \), \( \frac{1}{N_g} \sum_{i \in P_{N,g}} E[\|X_{N,i}\|^{4+\delta}] \leq \frac{1}{N_g} \sum_{i \in P_{N,g}} 1 = 1 \) for all \( N \) and for any \( \delta > 0 \). Hence, the sequences \( \frac{1}{N_g} \sum_{i \in P_{N,g}} E[\|X_{N,i}\|^{4+\delta}] \), and \( \frac{1}{N_g} \sum_{i \in P_{N,g}} E[\|Y_{N,i}\|^{4+\delta}] \) are uniformly bounded under my Assumption 5. Applying Abadie et al. (2017)'s Theorem 3 gives me Lemma 12. \( \square \)

\( \hat{\beta}_{N,g}^{*} \) is independent across \( g \) since each subject is sampled independently, and \( (D_{N,1t})_{t=t_0, \ldots, t_m} \)
\( (D_{N,t})_{t=t_0,\ldots,t_m} \) are jointly independent from each other and independent of \( R_N \) (a consequence of my Assumption 4). Notice that 
\[
E[n/N] = E[\sum_{i=1}^{N} R_{N,i}] / N = \rho_N \quad \text{and} \quad Var(n/N) = Var(\sum_{i=1}^{N} R_{N,i}) / N^2 = \rho_N(1 - \rho_N) / N \to 0.
\]
Thus, \( n/N \xrightarrow{p} \rho_N \). Similarly, \( n_g/N_g \xrightarrow{p} \rho_N \).

The continuous mapping theorem implies \( \sqrt{n_g/n} \xrightarrow{d} \sqrt{\delta_g} \) and \( \sqrt{n_g/n} \xrightarrow{p} \sqrt{\delta_g} \). I have

\[
\sqrt{n}(\hat{\beta}_N - \beta_{pop}^N) = \sqrt{n} \sum_{g=1}^{G} \frac{n_g}{n} (\hat{\beta}_{N,g} - \beta_{pop}^{N,g}) + \frac{G}{n} \beta_{pop}^{N,g} \quad \text{where the last convergence is by } \sqrt{n_g/n} \xrightarrow{p} \sqrt{\delta_g}, \text{ Lemma } \ref{lemma} \text{ and Assumption } \ref{assumption}. \]

Similarly,

\[
\sqrt{n}(\hat{\beta}_N - \beta_{sample}^N) = \sqrt{n} \sum_{g=1}^{G} \frac{n_g}{n} (\hat{\beta}_{N,g} - \beta_{sample}^{N,g}) \quad \text{where the last convergence is by } \sqrt{n_g/n} \xrightarrow{p} \sqrt{\delta_g} \text{ and Lemma } \ref{lemma}. \]

**Proof of Corollary 4**

Note that

\[
\epsilon_{N,i} = D_{N,i,t_1}(Y_{N,i}(t_1) - \bar{Y}_N(t_1)) + (1 - D_{N,i,t_1})(Y_{N,i}(t_0) - \bar{Y}_N(t_0)).
\]

I have

\[
E[X_{N,i} \epsilon_{N,i}] = \Pr(D_{N,i} = 1)(1 - q_{N,t_1})(Y_{N,i}(t_1) - \bar{Y}_N(t_1)) + \Pr(D_{N,i} = 0)(-q_{N,t_1})(Y_{N,i}(t_0) - \bar{Y}_N(t_0))
\]
Electronic copy available at: https://ssrn.com/abstract=3094905

\[ E[X_{N,i}^2] = \Pr(D_{N,i} = 1)(1 - q_{N,t1})^2(Y_{N,i}(t_1) - \bar{Y}_N(t_1))^2 + \Pr(D_{N,i} = 0)(-q_{N,t1})^2(Y_{N,i}(t_0) - \bar{Y}_N(t_0))^2. \]

and

\[ E[X_{N,i}^2] = \Pr(D_{N,i} = 1)(1 - q_{N,t1})^2(Y_{N,i}(t_1) - \bar{Y}_N(t_1))^2 + (1 - q_{N,t1})q_{N,t1}(Y_{N,i}(t_0) - \bar{Y}_N(t_0))^2. \]

I therefore get

\[ \Delta^{ehw} = \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} E[X_{N,i}^2] = q_{t1}(1 - q_{t1})^2S_{t1}^2 + (1 - q_{t1})q_{t1}^2S_{t0}^2 \]

and

\[ \Delta^{cond} = \Delta^{ehw} - \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} E[X_{N,i}^2] = \Delta^{ehw} - q_{t1}(1 - q_{t1})^2S_{t1t0}. \]

I also have

\[ E[X_{N,i}^2] = \Pr(D_{N,i} = 1)(1 - q_{N,t1})^2 + \Pr(D_{N,i} = 0)(-q_{N,t1})^2 \]

leading to

\[ H = \lim_{N \to \infty} \frac{1}{N} \sum_{i=1}^{N} E[X_{N,i}^2] = q_{t1}(1 - q_{t1}). \]

(7) and (8) follow from substituting the above observations into Proposition 6. Analogously, (9) and (10) follow from Corollary 3.

**Proof of Proposition 7**

By Proposition 2 there is no other experimental design \((p_{it})\) with \(p_{it} \in [\epsilon, 1 - \epsilon]\) for all subject \(i\) and treatment \(t\) and such that

\[ \sum_t p_{it}w_{it} \geq \sum_t p_{it}^o(\epsilon)w_{it} \]

for all \(i\) with at least one strict inequality. \(w'_{it}\) and \(e'_{ti}\) are consistent with ordinal \(\succsim_i\) and \(\succsim_t\), respectively. Therefore, there is no other experimental design \((p_{it})\) such that for all cardinal WTP \(w_{it}\) consistent with ordinal \(\succsim_i\) and all cardinal predicted effects \(e_{ti}\) consistent with ordinal \(\succsim_t\), I have

\[ \sum_t p_{it}w_{it} \geq \sum_t p_{it}^o(\epsilon)w_{it} \]

for all \(i\) and \(\sum_t p_{it}e_{ti} \geq \sum_t p_{it}^o(\epsilon)e_{ti}\) for all \(i\) with at least one strict inequality.

**A.3 Empirical Details**

**A.3.1 Why Subject Welfare? Data**

Table A.1 Panel a, Appendix Figure A.1 Panel a, and Appendix Tables A.1-A.3 are based on data I assemble from the WHO International Clinical Trials Registry Platform (ICTRP) at http://www.who.int/ictrp/en/, retrieved in January 2019. I first use the “date of registration” variable to define the year associated with each trial. Starting from the universe of trials registered between January 1st 2007 to May 31st 2017, I exclude outlier trials with registered sample size greater than 5 millions. Some trials come with sample size classified as
“Not Specified.” I set their sample size as zero. This makes my total sample size calculation conservative. For a trial that does not have a well-defined trial phase, I classify its trial phase as “Not Specified.” Finally, for each trial, I define its “Geographical Region” according to which country runs the registry including that trial. Many registries like ClinicalTrial.gov recruit subjects in multiple countries under the same trial ID, making it challenging to pin down the physical location of each trial.

Table 1 Panel b, Appendix Figure A.1 Panel b, and Appendix Tables A.4 and A.5 are based on data I assemble from the American Economic Association’s registry (AEA registry) for randomized controlled trials at https://www.socialscienceregistry.org, retrieved on May 27th, 2017. From the AEA registry, I obtain information about each experiment such as the sample size, the year when the experiment was conducted, the country where the experiment was conducted, registered keywords, and the randomization unit. When some information is missing, I manually enter it by referring to accompanying documents such as experimental design descriptions and abstracts. I classify an item as “Not specified” when I cannot specify it even after the manual procedure. When the sample size of an experiment is unspecified, I set the sample size as zero. This makes my total sample size calculation conservative. I use the “starting date of experiment” to define the year associated with each trial. Finally, for each trial, I define its “Geographical Region” according to the country in which the experiment was conducted. I include all registered experiments conducted during 2007-2017 period.

A.3.2 Do Clinical Trials Use Simple Randomization?

Do clinical trials randomize treatment as in Definition 1 of RCT? I provide an answer to this question using the Clinical Trial Registry India (CTRI). To my knowledge, CTRI is the only major clinical trial registry that provides data about randomization methods in clinical trials. I assembled data about individual clinical trials including the date the trial was conducted and the method used to randomize subjects into control or treatment groups. The data includes trials spanning from October 9th, 2007 to October 9, 2017. I removed trials with sample size 0 and trials that have been classified as “NA” for randomization method. According to the CTRI description manual, the relevant variable (“method of generating random sequence”) takes some of the following categories:

- **Computer generated randomization:** A machine randomly assigns the subject or subject group to a study or treatment group.

- **Permuted block randomization (fixed):** Participants are randomly allocated in a way that maintains a covariate balance across treatment groups. Allocation occurs by
assigning a specified number of participants to a block that has a specified number of
treatment assignments. In this case, the block size is fixed.

- **Permuted block randomization (variable):** Same method as permuted block random-
  ization (fixed), but with varying block sizes.

- **Random number table:** Each subject or subject group is assigned a number, and a random number table determines if the subject is assigned to a control or treatment group.

- **Coin toss, lottery, toss of dice, shuffling cards etc.:** Based on a coin toss, the subject, or subject group is placed in either a control or treatment group.

- **Stratified randomization:** In order to control for covariates (patient characteristics which might affect the outcomes), a stratum is generated for each combination of covariates, and subjects are assigned to the appropriate strata of covariates. After all subjects are assigned to strata, simple randomization is performed within each stratum to assign subjects to a treatment or control group.

- **Stratified block randomization:** Same method as stratified randomization, but once patients are assigned to their strata, permuted block randomization is performed within each stratum.

- **Adaptive randomization:** Adaptive randomization, like stratified randomization, takes covariates into account. In the “minimization method,” for example, a new patient is sequentially assigned to the group with the fewest number of existing patients with the same covariates, making covariates balanced across groups.

- **Other:** 179 trials listed “Other” as the method of randomization.

The popularity of each randomization method is described in Appendix Table A.6. The table shows that 85% of all trials use one of the impersonal simple randomization methods that do not take patient covariate or past data into account. This suggests that Definition 1 of RCT is a reasonable approximation to most clinical trials.

### A.3.3 Treatment Effects and Preferences: Details

#### Sample Restriction in Treatment Effect Estimation (Table 3)

For the OLS regressions in Table 3, I impose the same sample restriction as Kremer et al. and exclude the following children: children not at Intent-to-Treat springs, i.e., springs found to
be nonviable after treatment random assignment, children in households that receive water
guards in 2007, children not in representative households (defined as households that are
named at least twice by all users of a given spring when survey enumerators ask spring
users at a spring to name households that also use the same spring), children above age 3 at
baseline and children above age 3 when they join the sample in later rounds, children whose
anthropometric (weight, height, BMI) and age data are flagged as having serious error, and
children in households with missing data on whether they use the identified spring exclusively
or use multiple springs.

Estimation of the Mixed Logit WTP Model (Table 4)

With the random utility function (6), choice likelihoods take the following form (Train (2003),
chapter 6):

$$P(o_{ijt} = 1|\theta, \gamma_1, \delta_j) = \frac{\exp \left( (\beta_i + \gamma_1 X_i) T_{jt} - c_i D_{ij} + \delta_j \right)}{\sum_{h \in H} \exp \left( (\beta_i + \gamma_1 X_i) T_{ht} - c_i D_{ih} + \delta_h \right)} f(\beta_i, c_i|\theta) d(\beta_i, c_i)$$

where $o_{ijt} \in \{0, 1\}$ is the indicator that household $i$ chooses source $j$ in trip $t$ among alterna-
tives $h \in H$ and $f(\beta_i, c_i|\theta)$ is the mixing distribution parametrized by $\theta$. $f(\beta_i, c_i|\theta)$ is taken
to be the normal distribution with unknown mean and variance for the spring protection
treatment coefficient $\beta_i$ and the triangular distribution (restricted to be nonnegative) for the
distance coefficient $c_i$. I use the quasi Newton method to maximize a simulation approxima-
tion of the joint likelihood $\sum_{ijt} P(o_{ijt} = 1|\theta, \gamma_1, \delta_j)$ with respect to $\theta, \gamma_1,$ and $\delta_j$, producing
maximum simulated likelihood estimates $\hat{\theta}, \hat{\gamma}_1,$ and $\hat{\delta}_j$. I compute standard errors using the
information matrix with the Hessian being estimated by the outer product of the gradient
of the simulated likelihood at the estimated parameter value.

Simulation of WTP (Figure 1 Panel b and Subsequent Figures)

I create simulated WTP data for Figure 1 Panel b and subsequent figures with parametric
bootstrap below.

(1) Simulate a value of the distance coefficient $c \sim \text{Triangular}(\hat{\theta}^D)$ for each household
group sharing the same characteristics where $\hat{\theta}^D$ is the point estimate of the parameter
of the distance coefficient distribution, i.e., the estimated mean and standard deviation.
To correct for potential measurement error in distance, follow Kremer et al. (2011)’s
method and multiply the distance coefficient by $-1/0.38$, where 0.38 is the correlation
across survey rounds in the reported walking distance to the reference spring and is
taken to be the size of measurement error from recall error. See Kremer et al. (2011)’s Section IV.B for details.

(2) Draw a value of the treatment coefficient $w \sim N(\hat{\mu}, \hat{\sigma})$ for each household group sharing the same characteristics where $\hat{\mu}$ and $\hat{\sigma}$ are the point estimates of mean $\mu$ and standard deviation $\sigma$ of the treatment coefficient distribution.

(3) Compute the ratio $w/c$ as WTP for the treatment in terms of minutes of walking time. Follow Kremer et al. (2011)’s method to get WTP in terms of the number of workdays taken to walk to the spring in a year. Specifically, multiply the ratio by $(32 \times 52)/(60 \times 8)$ where $32 \times 52$ is the average number of water trips taken by a household per year and $60 \times 8$ is the number of minutes per workday. See Kremer et al. (2011)’s Section IV.B for details.

A.3.4 EXAM vs RCT: Algorithm Details

In this section, I describe the details of the algorithm I use for computing EXAM’s treatment assignment probabilities $p^*_it(\epsilon)$ in my empirical application in Section 6.3. I first define sub-routines and then call them together at the end to perform the main computation. Though simple, this algorithm works well in my application: The market clearing error, defined as $\sqrt{\sum_t(\sum_i p^*_it - c_t)^2 / \sum_t c_t}$, is smaller than 0.005 in all simulation runs.
Algorithm 1 Experimental as Market (EXAM)

Input: \( n \) the number of subjects, \( m \) the number of treatments, \((c_t) \in \mathbb{N}\) treatment \( t \)'s pseudo capacity with \( \sum_t c_t = n \), \((w_{it})\) subject \( i \)'s WTP for treatment \( t \), \((e_{iti})\) treatment \( t \)'s predicted treatment effect for subject \( i \), \( b \) the budget constraint

Output: \((p^t_{it})\) treatment \( t \)'s assignment probability for subject \( i \), \((\alpha^*, \beta_t^*)\) parameters determining treatment \( t \)'s equilibrium price of the form \( \pi^*_te = \alpha^*e + \beta_t^* \), \(\text{error}_{\text{min}}\) minimized market clearing error relative the total capacity of treatments

1: function \text{INITIAL ALPHA}( )
2: \( \alpha \leftarrow \text{generate random number } \sim \text{Uniform}(-b, 0) \) \sloppy \triangleright \text{set the value of } \alpha
3: return \( \alpha \)

4: function \text{INIT BETA}( )
5: \( \beta_{t_0} \leftarrow 0 \)
6: for each \( t = t_1, \ldots, t_m \) do
7: \( \beta_t \leftarrow \text{generate random number } \sim \text{Uniform}(-b, b) \) \sloppy \triangleright \text{set the initial value of } \beta_t
8: return \( (\beta_t) \) \sloppy \triangleright \text{return an } m\text{-dimensional vector}

9: function \text{PRICE}(\alpha, (\beta_t))
10: for each \( i, t = t_1, \ldots, t_m \) do
11: \( \pi_{te_{ti}} = \alpha e_{ti} + \beta_t \) \sloppy \triangleright \text{return the } n \times m \text{ price matrix}
12: return \( (\pi_{te_{ti}}) \)

13: function \text{DEMAND}(\!(\pi_{te_{ti}})\!)
14: for each \( i \) do \sloppy \triangleright \text{perform utility maximization for each subject } i
15: \( (p_{it})_t \leftarrow \text{arg max}_{(p_{it})_t} \sum_t w_{it}p_{it} \text{ s.t. } \sum_t \pi_{te_{ti}}p_{it} \leq b \)
16: return \( (p_{it}) \) \sloppy \triangleright \text{return the } n \times m \text{ demand matrix}

17: function \text{EXCESS DEMAND}(\!(p_{it})\!)
18: for each \( t = t_1, \ldots, t_m \) do
19: \( d_t \leftarrow \sum_i p_{it} - c_t \) \sloppy \triangleright \text{return the } m\text{-dimensional excess demand vector}
20: return \( (d_t) \)

21: function \text{CLEARING ERROR}(\!(d_t)\!)
22: if \( d_t < 0 \) for all \( t \) then
23: return 0
24: else
25: error \( \leftarrow \sqrt{\sum d_t^2 / \sum c_t} \) \sloppy \triangleright \text{return the market clearing error}
26: return error

Electronic copy available at: https://ssrn.com/abstract=3094905
27: \[ \delta_\beta \leftarrow b/50 \] \hspace{1cm} \triangleright \text{scaling factor for } \beta_t \text{'s to set new prices}

28: \textbf{function} \ BetaNew((\beta_t, d_t)) \hspace{1cm} \triangleright \text{recalibrate } \beta_t \text{'s to set new prices}
29: \hspace{1cm} \text{for each } t = t_1, \ldots, t_m \text{ do}
30: \hspace{2cm} \beta_t^{new} \leftarrow \beta_t + d_t \delta_\beta
31: \hspace{1cm} \text{return} \ (\beta_t^{new})

32: \textbf{function} \ ClearMarket( \ ) \hspace{1cm} \triangleright \text{the main function}
33: \hspace{1cm} \alpha \leftarrow \text{INITIAL\textsc{alpha}}( \ )
34: \hspace{1cm} (\beta_t) \leftarrow \text{INIT\textsc{beta}}( \ )
35: \hspace{1cm} (\pi_{te_t}) \leftarrow \text{Price}(\alpha, (\beta_t))
36: \hspace{1cm} (p_{it}) \leftarrow \text{DEMAND}((\pi_{te_t}))
37: \hspace{1cm} (d_t) \leftarrow \text{EXCESS\textsc{demand}}((p_{it}))
38: \hspace{1cm} \text{error} \leftarrow \text{CLEARING\textsc{error}}((d_t))
39: \hspace{1cm} \text{error}_{\text{min}} \leftarrow \text{error} \hspace{1cm} \triangleright \text{initialize the minimum of clearing error}
40: \hspace{1cm} \text{ClearingThreshold} \leftarrow 0.01 \hspace{1cm} \triangleright \text{threshold for the market clearing error}
41: \hspace{1cm} \text{IterationThreshold} \leftarrow 10 \hspace{1cm} \triangleright \text{threshold for iteration times}
42: \hspace{1cm} \text{iterations} \leftarrow 0 \hspace{1cm} \triangleright \text{initialize iteration time count}
43: \hspace{1cm} \textbf{while} \ True \hspace{1cm} \textbf{do}
44: \hspace{2cm} \textbf{if} \ \text{iterations} > \text{IterationThreshold} \hspace{1cm} \triangleright \text{start new equilibrium research}
45: \hspace{3cm} \alpha \leftarrow \text{INITIAL\textsc{alpha}}( \ )
46: \hspace{3cm} (\beta_t) \leftarrow \text{INIT\textsc{beta}}( \ )
47: \hspace{3cm} \text{iterations} \leftarrow 0
48: \hspace{2cm} \textbf{else}
49: \hspace{3cm} (\beta_t) \leftarrow \text{BetaNew}((\beta_t), (d_t))
50: \hspace{3cm} (\pi_{te_t}) \leftarrow \text{Price}(\alpha, (\beta_t))
51: \hspace{3cm} (p_{it}) \leftarrow \text{DEMAND}((\pi_{te_t}))
52: \hspace{3cm} (d_t) \leftarrow \text{EXCESS\textsc{demand}}((p_{it}))
53: \hspace{3cm} \text{error} \leftarrow \text{CLEARING\textsc{error}}((d_t))
54: \hspace{2cm} \textbf{if} \ \text{error} < \text{error}_{\text{min}} \hspace{1cm} \triangleright \text{the new prices reduce the error}
55: \hspace{3cm} \text{error}_{\text{min}} \leftarrow \text{error}
56: \hspace{3cm} \alpha^* \leftarrow \alpha
57: \hspace{3cm} (\beta_t^*) \leftarrow (\beta_t)
58: \hspace{3cm} (p_{it}^*) \leftarrow (p_{it})
59: \hspace{2cm} \textbf{if} \ \text{error}_{\text{min}} < \text{ClearingThreshold} \hspace{1cm} \textbf{break}
60: \hspace{3cm} \text{iterations += 1}
61: \hspace{2cm} \textbf{return} \ ((p_{it}^*), \alpha^*, (\beta_t^*), \text{error}_{\text{min}}) \hspace{1cm} \triangleright \text{return the outputs}
A.3.5 Additional Tables and Figures

Figure A.1: Magnitude of Parts of the RCT Landscape: Details

(a) Registered Medical Clinical Trials & Sample Sizes: Time Evolution

![Graph showing the number of clinical trials registered and the sum of sample sizes over time.](image1)

(b) Registered Social & Economic RCTs & Sample Sizes: Time Evolution

![Graph showing the number of economic RCTs registered and the sum of sample sizes over time.](image2)

Notes: Panel a provides summary statistics of clinical trials registered in the WHO International Clinical Trials Registry Platform (ICTRP, [http://www.who.int/ictrp/en/](http://www.who.int/ictrp/en/), retrieved in January 2019). The sample consists of clinical trials registered there between January 1st 2007 to May 30th 2017. I exclude trials with registered sample size larger than five millions. Panel b provides summary statistics of economic RCTs registered in the American Economic Association RCT Registry ([https://www.socialscienceregistry.org](https://www.socialscienceregistry.org), retrieved in January 2019). The sample consists of RCTs registered there between January 1st 2007 to May 30th 2017 and where the unit of outcome measurement is an individual or a household. I focus on RCTs with individual or household subjects in order to make it possible to sum up sample sizes. See Section 2 for discussions about this exhibit and Appendix A.3.1 for the detailed computational procedure.
Table A.1: Magnitude of a Part of the Clinical Trial Industry: Details 1

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<tr>
<td># of Clinical Trials Registered</td>
<td>16,502</td>
<td>23,349</td>
<td>24,468</td>
<td>26,803</td>
<td>25,415</td>
<td>26,794</td>
<td>29,406</td>
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<td>34,854</td>
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<tr>
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Notes: This table extends Table 1 Panel a and details its figures with different sample definitions. This table provides summary statistics of clinical trials registered in the WHO International Clinical Trials Registry Platform (ICTRP, [http://www.who.int/ictrp/en/](http://www.who.int/ictrp/en/), retrieved in January 2019). The sample consists of clinical trials registered there between January 1st, 2007 to May 30th, 2017. Different panels use different sample definitions. See Section 2 for discussions about this exhibit and Appendix A.3.1 for the data processing procedure.
Table A.2: Magnitude of a Part of the Clinical Trial Industry: Details 2

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<tr>
<td>I</td>
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<tr>
<td>I and II</td>
</tr>
<tr>
<td>II</td>
</tr>
<tr>
<td>II and III</td>
</tr>
<tr>
<td>III</td>
</tr>
<tr>
<td>III and IV</td>
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<tr>
<td>IV</td>
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</table>

<table>
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<tr>
<th>Per-trial Sample Size</th>
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<tr>
<td>10 - 99</td>
</tr>
<tr>
<td>100 - 999</td>
</tr>
<tr>
<td>1000 - 9999</td>
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<tr>
<td>10000 - 99999</td>
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<th>Geographical Region</th>
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<td>Asia</td>
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<tr>
<td>Europe</td>
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<tr>
<td>Oceania</td>
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<tr>
<td>Latin America</td>
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<table>
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<td>CHIC TR</td>
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<td>RBR</td>
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<td>S LCTR</td>
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Notes: This table extends Table 1 Panel a and details the number of registered clinical trials across categories. This table provides summary statistics of clinical trials registered in the WHO International Clinical Trials Registry Platform (ICTRP, http://www.who.int/ictrp/en/ retrieved in January 2019). The sample consists of clinical trials registered there between January 1st, 2007 to May 30th, 2017. I exclude trials with registered sample size larger than five millions. See Section 2 for discussions about this exhibit and Appendix A.3.1 for the data processing procedure.
### Table A.3: Magnitude of a Part of the Clinical Trial Industry: Details 3

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### Per-Trial Sample Size

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<th>100-999</th>
<th>1000-9999</th>
<th>10000 or more</th>
<th>Total</th>
</tr>
</thead>
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<td>4,695</td>
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### Registry Name

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<td>11,051,412</td>
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**Notes:** This table extends Table 1 and details trial sample sizes across categories. This table provides summary statistics of clinical trials registered in the WHO International Clinical Trials Registry Platform (ICTRP, [http://www.who.int/ictrp/en/](http://www.who.int/ictrp/en/), retrieved in January 2019). The sample consists of clinical trials registered there between January 1st, 2007 to May 30th, 2017. I exclude trials with registered sample size larger than five millions. See Section 2 for discussions about this exhibit and Appendix A.3.1 for the data processing procedure.
Table A.4: Magnitude of a Part of Economic RCTs: Details 1

| Notes | This table extends Table Panel b and details the number of registered economic RCTs and sample sizes across categories. This table provides summary statistics of economic RCTs registered in the American Economic Association RCT Registry (https://www.socialscienceregistry.org, retrieved in January 2019). The sample consists of RCTs registered there between January 1st 2007 to May 30th 2017 and where the unit of outcome measurement is an individual or a household. “Randomization Unit” is the unit of treatment assignment, which may be different from the unit of outcome measurement. A single RCT may have multiple “Keywords.” See Section for discussions about this exhibit and Appendix A.3.1 for the data processing procedure. |
Table A.5: Magnitude of a Part of Economic RCTs: Details 2

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<td>8</td>
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</tr>
</tbody>
</table>

Notes: This table complements Table Panel b and details the number of registered economic RCTs and sample sizes across categories, focusing on trials where the unit of outcome measurement is not an individual or a household. This table provides summary statistics of economic RCTs registered in the American Economic Association RCT Registry (https://www.socialscienceregistry.org, retrieved in January 2019). The sample consists of RCTs registered there between January 1st 2007 to May 30th 2017. “Randomization Unit” is the unit of treatment assignment, which may be different from the unit of outcome measurement. A single RCT may have multiple “Keywords.” See Section 2 for discussions about this exhibit and Appendix A.3.1 for the data processing procedure.
Table A.6: Do Clinical Trials Use Simple Randomization?

<table>
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<th>Frequency of Randomization Methods in Clinical Trial Registry India (CTRI)</th>
<th>%</th>
<th>Subgroup %</th>
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<td><strong>Simple Randomization</strong></td>
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<td></td>
</tr>
<tr>
<td>Computer generated randomization</td>
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</tr>
<tr>
<td>Permutted block randomization, fixed</td>
<td>5%</td>
<td></td>
</tr>
<tr>
<td>Random number table</td>
<td>6%</td>
<td>85%</td>
</tr>
<tr>
<td>Coin toss</td>
<td>8%</td>
<td></td>
</tr>
<tr>
<td>Permutted block randomization, variable</td>
<td>2%</td>
<td></td>
</tr>
<tr>
<td><strong>Adaptive or Stratified Randomization</strong></td>
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<td></td>
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<tr>
<td>Stratified block randomization</td>
<td>5%</td>
<td></td>
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<tr>
<td>Stratified randomization</td>
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<td>9%</td>
</tr>
<tr>
<td>Adaptive randomization</td>
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<tr>
<td>Other</td>
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<td>6%</td>
</tr>
<tr>
<td><strong>Total interventional trials</strong></td>
<td>5733</td>
<td></td>
</tr>
</tbody>
</table>

**Notes:** This table shows summary statistics of the popularity of different randomization methods in clinical trials, based on the Clinical Trial Registry India (CTRI). The data includes trials spanning from October 9th, 2007 to October 9, 2017. I removed trials with sample size 0 and trials that have been classified as “NA” for randomization method. See Appendix [A.3.2](#) for discussions about this table.
Table A.7: A Selection of High-stakes RCTs (Continued from Table 2)

(a) Medical Clinical Trials

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<th>Subjects</th>
<th>Sample Size</th>
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<tbody>
<tr>
<td>i</td>
<td>Coronary Heart Disease Patients</td>
</tr>
<tr>
<td>ii</td>
<td>Patients with Elevated Intraocular Pressure</td>
</tr>
<tr>
<td>iii</td>
<td>HIV Negative Gay Men and Transgender Women</td>
</tr>
<tr>
<td>iv</td>
<td>Serodiscordant Couples</td>
</tr>
<tr>
<td>v</td>
<td>Postmenopausal Women</td>
</tr>
</tbody>
</table>

(b) Social and Economic Experiments

<table>
<thead>
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<th>Subjects</th>
<th>Sample Size</th>
</tr>
</thead>
<tbody>
<tr>
<td>I</td>
<td>Poor Households in Kenya</td>
</tr>
<tr>
<td>II</td>
<td>Crime Hot Spots in Minneapolis</td>
</tr>
<tr>
<td>III</td>
<td>Unmarried Women in Malawi</td>
</tr>
<tr>
<td>IV</td>
<td>Uninsured Individuals in Oregon</td>
</tr>
<tr>
<td>V</td>
<td>Public Sector Job Applicants in Mexico</td>
</tr>
</tbody>
</table>

Notes: This is a continuation of Table 2. This table lists examples illustrating the high-stakes nature of certain RCTs. See the following references for the details of each RCT:

Panel a Study i: Scandinavian Simvastatin Survival Study Group and Others (1994)
Panel a Study ii: Kass et al. (2002)
Panel a Study iii: Grant et al. (2010)
Panel a Study iv: Cohen et al. (2011)
Panel a Study v: Writing Group for the Women’s Health Initiative Investigators and Others (2002)
Panel b Study I: Haushofer and Shapiro (2016)
Panel b Study II: Sherman and Weisburd (1995)
Panel b Study III: Angelucci and Bennett (2017)
Panel b Study IV: Baicker et al. (2013)
Panel b Study V: Dal Bó et al. (2013), where the control is a lower wage job offer.

See Section 2 for discussions about this table.
Figure A.2: EXAM vs RCT: Welfare (Robustness Check with $\epsilon = 0.1$)

(a) Average WTP for Assigned Treatments $w^*_i$

(b) Avg Predicted Effects of Assigned Treatments $e^*_i$

Notes: This figure reports the same results as Figure 2 except that this figure sets $\epsilon$ to 0.1. To compare EXAM and RCT’s welfare performance, this figure shows the distribution of average subject welfare over 1000 bootstrap simulations under each experimental design. Panel a measures welfare with respect to average WTP $w^*_i$ for assigned treatments while Panel b with respect to average predicted effects $e^*_i$ of assigned treatments. A dotted line indicates the distribution of each welfare measure for RCT while a solid line indicates that for EXAM. Each vertical line represents mean. Kolmogorov-Smirnov tests find the EXAM and RCT distributions to be significantly different both for $w^*_i$ and $e^*_i$. Both predicted effects $e_{it}$ and WTP $w_{it}$ are based on the main statistical specifications including all of the interactions between the treatment indicator and household characteristics (baseline latrine density, diarrhea prevention knowledge score, and mother’s years of education). See Section 6.3 for discussions about this figure.
Figure A.3: EXAM vs RCT: ATE Estimates (Robustness Check with $\epsilon = 0.1$)

(a) Distribution of Average Treatment Effect Estimates $\hat{\beta}^*$

(b) Distribution of Average Treatment Effect Estimates $\hat{\beta}^*$

Notes: This figure reports the same results as Figure 3 except that this figure sets $\epsilon$ to 0.1. This figure compares EXAM and RCT’s causal inference performance by showing the distribution of average treatment effect estimates under each experimental design. Grey bins indicate average treatment effect estimates for RCT while transparent bins with black outlines indicate those for EXAM. The solid vertical line indicates mean for EXAM while the dashed vertical line indicates that for RCT. See Section 6.3 for discussions about this figure.
Figure A.4: EXAM vs RCT: \( p \) Values (Robustness Check with \( \epsilon = 0.1 \))

(a) \( p \) Values for \( \hat{b}^* \) (Exact, Finite Sample)  
(b) \( p \) Values for \( \hat{b}^* \) (Non-robust)  
(c) \( p \) Values for \( \hat{b}^* \) (Robust)  
(d) \( p \) Values for \( \hat{b}^* \) (Abadie et al., 2017)

Notes: This figure reports the same results as Figure 4 except that this figure sets \( \epsilon \) to 0.1. This figure compares EXAM and RCT’s causal inference performance by showing the distribution of \( p \) values accompanying average treatment effect estimates \( \hat{b}^* \) under each experimental design. The \( p \) values are based on exact, non-robust, robust, or Abadie et al. (2017)’s standard errors. Grey bins indicate \( p \) values for RCT while transparent bins with black outlines indicate those for EXAM. The solid vertical line indicates median for EXAM while the dashed vertical line indicates that for RCT. See Section 6.3 for discussions about this figure.
Figure A.5: EXAM vs RCT: Incentive (Robustness Check with $\epsilon = 0.1$)

(a) WTP manipulation $\sim$ true WTP$+N(0,100)$  
(b) WTP manipulation $\sim$ true WTP$+N(0,1000)$

(c) WTP manipulation $\sim$ true WTP$+U(0,100)$  
(d) WTP manipulation $\sim$ true WTP$+U(-100,0)$

Notes: This figure reports the same results as Figure 5 except that this figure sets $\epsilon$ to 0.1. This figure shows the histogram of true WTP gains from potential WTP misreporting to EXAM, quantifying the incentive compatibility of EXAM. Different panels use different ways of drawing WTP manipulations indicated by the panel titles. Each solid vertical line represents the mean WTP gain from potential WTP misreporting to EXAM. The dash vertical line is for RCT, where the true WTP gain from any WTP misreport is zero. See Section 6.3 for discussions about this figure.
Table A.8: EXAM vs RCT: Incentive Details

<table>
<thead>
<tr>
<th>Figure A.5</th>
<th>Panel a</th>
<th>95 Percentile</th>
<th>96 Percentile</th>
<th>97 Percentile</th>
<th>98 Percentile</th>
<th>99 Percentile</th>
<th>Max</th>
</tr>
</thead>
<tbody>
<tr>
<td>( \epsilon = 0.1 ) &amp; manipulation ( \sim N(0, 100) )</td>
<td>1.37%</td>
<td>1.47%</td>
<td>1.53%</td>
<td>1.64%</td>
<td>1.76%</td>
<td>2.32%</td>
<td></td>
</tr>
<tr>
<td>Figure A.5</td>
<td>Panel b</td>
<td>1.08%</td>
<td>1.18%</td>
<td>1.32%</td>
<td>1.52%</td>
<td>1.76%</td>
<td>2.38%</td>
</tr>
<tr>
<td>( \epsilon = 0.1 ) &amp; manipulation ( \sim N(0, 1000) )</td>
<td>1.21%</td>
<td>1.33%</td>
<td>1.39%</td>
<td>1.54%</td>
<td>1.64%</td>
<td>2.06%</td>
<td></td>
</tr>
<tr>
<td>Figure A.5</td>
<td>Panel c</td>
<td>1.11%</td>
<td>1.24%</td>
<td>1.40%</td>
<td>1.52%</td>
<td>1.64%</td>
<td>1.93%</td>
</tr>
<tr>
<td>( \epsilon = 0.1 ) &amp; manipulation ( \sim U(-100, 0) )</td>
<td>1.11%</td>
<td>1.24%</td>
<td>1.40%</td>
<td>1.52%</td>
<td>1.64%</td>
<td>1.93%</td>
<td></td>
</tr>
</tbody>
</table>

Notes: This table provides additional details about Figure A.5. In particular, for each scenario in Figure A.5, this table shows the most profitable true WTP gains from potential WTP misreporting to EXAM, quantifying the incentive compatibility of EXAM. See Section 6.3 for discussions about this table.