

Finely Stratified Rerandomization Designs

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Abstract

We study estimation and inference on causal parameters under finely stratified rerandomization designs, which use baseline covariates to match units into groups (e.g. matched pairs), then rerandomize within-group treatment assignments until a balance criterion is satisfied. We show that finely stratified rerandomization does partially linear regression adjustment “by design,” providing nonparametric control over the covariates used for stratification, and linear control over the rerandomization covariates. We also introduce novel rerandomization criteria, allowing for nonlinear imbalance metrics and proposing a minimax scheme that optimizes the balance criterion using pilot data or prior information provided by the researcher. While the asymptotic distribution of generalized method of moments (GMM) estimators under stratified rerandomization is generically non-Gaussian, we show how to restore asymptotic normality using optimal ex-post linear adjustment. This allows us to provide simple asymptotically exact inference methods for superpopulation parameters, as well as efficient conservative inference methods for finite population parameters.

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1 Introduction

Stratified randomization is commonly used to increase statistical precision in experimental research.¹ Recent theoretical work (e.g. [Bai et al. \(2021\)](#)) has shown that fine stratification, which randomizes within small groups of units tightly matched on baseline covariate information, makes unadjusted estimators like difference of means semiparametrically efficient.² In finite samples, however, the performance of such designs can deteriorate rapidly with the dimension of the stratification variables due to a curse of dimensionality in matching.³ This motivates the search for alternative designs that insist upon nonparametric balance for a few important covariates, but only attempt to balance linear functions of the remaining variables. In this paper, we propose finely stratified rerandomization designs, which first tightly match the units into groups using a small set of important covariates, then rerandomize within groups until a balance criterion on the remaining covariates is satisfied.

Our first contribution is to derive the asymptotic distribution of generalized method of moments (GMM) estimators under stratified rerandomization, allowing estimation and inference on generic causal parameters defined by moment equalities. We consider both superpopulation and finite population parameters, the latter of which may be more appropriate for experiments run in a convenience sample ([Abadie et al. \(2014\)](#)). As in previous work on rerandomization (e.g. [Li et al. \(2018\)](#)), the asymptotic distribution of GMM estimators is an independent sum of a normal and a truncated normal term. Modulo this residual truncated term, we show that the asymptotic variance of unadjusted estimation under stratified rerandomization is the same as that of semiparametrically adjusted GMM (e.g. [Graham \(2011\)](#)) under an iid design. Intuitively, stratified rerandomization implements partially linear regression adjustment “by design.”

Our second contribution is to introduce several novel forms of rerandomization based on nonlinear balance criteria. For example, we allow acceptance or rejection based on the difference of covariate density estimates within each treatment arm, attempting to balance nonlinear features of the covariate distribution. Similarly, we propose a design that rerandomizes until a nonlinear estimate of the propensity score is approximately constant, effectively forcing the covariates to have no predictive power for treatment assignments. In both cases, these nonlinear rerandomization schemes are asymptotically equivalent to standard rerandomization based on a difference of covariate means, but with an implicit choice of covariates and acceptance region, which we characterize.

Our third contribution is to study optimization of the balance criterion itself. We

¹For example, [Cytrynbaum \(2023\)](#) reports a survey of 50 experimental papers in the AER and AEJ from 2018-2023, where 57% used some form of stratified randomization.

²See [Cytrynbaum \(2024\)](#), [Armstrong \(2022\)](#), and [Bai et al. \(2024\)](#) for more detailed discussion.

³Under regularity conditions, the convergence rate of finite sample variance to asymptotic variance is $O(n^{-2/(d+1)})$ for dimension d covariates, see [Cytrynbaum \(2024\)](#).

suggest a novel minimax approach that allows the researcher to specify prior information about the relationship between covariates and outcomes, then rerandomizes until the worst case correlation consistent with this prior information is small. If the prior information set contains the truth, this design provides strong control over the variance of the truncated normal term in the asymptotic distribution. Building on this, we show that if the prior information set is a confidence region estimated from pilot data, then this minimax design bounds the truncated normal variance with high probability.

Our fourth contribution is to provide simple t-statistic based inference methods for general causal parameters under stratified rerandomization designs. To do this, we first characterize and provide a feasible implementation of the optimal ex-post linear adjustment for GMM estimation under stratified rerandomization.⁴ Crucially, optimal ex-post adjustment makes the asymptotic distribution insensitive to the rerandomization acceptance criterion, removing the truncated normal term from the limiting distribution and restoring asymptotic normality. For superpopulation parameters, our inference methods are asymptotically exact. For finite population parameters, our methods are asymptotically conservative, but still exploit the efficiency gains from both stratified rerandomization and ex-post optimal adjustment.

1.1 Related Literature

This paper builds on the literature on fine stratification in econometrics as well as the literature on rerandomization in statistics. Stratified randomization has a long history in statistics, see [Cochran \(1977\)](#) for a survey. Recent work on fine stratification in econometrics includes [Bai et al. \(2021\)](#), [Bai \(2022\)](#), [Cytrynbaum \(2024\)](#), [Armstrong \(2022\)](#), and [Bai et al. \(2024\)](#). Some important theoretical contributions to the literature on rerandomization include [Morgan and Rubin \(2012\)](#) and [Li et al. \(2018\)](#), [Wang et al. \(2021\)](#), and [Wang and Li \(2022\)](#). We build on both of these literatures, studying the consequence of rerandomizing treatments within data-adaptive fine strata. We show that finely stratified rerandomization does semiparametric (partially linear) regression adjustment “by design,” providing nonparametric control over a few important variables and linear control over the rest.

For our main asymptotic theory (Section 3), the most closely related previous work is [Wang et al. \(2021\)](#) and [Bai et al. \(2024\)](#). [Wang et al. \(2021\)](#) study estimation of the sample average treatment effect (SATE) under stratified rerandomization, with quadratic imbalance metrics based on the Mahalanobis norm. We study rerandomization within data-adaptive fine strata, providing asymptotic theory for generic superpopulation and finite population causal parameters defined by moment equalities. We also allow for essen-

⁴This extends recent work on optimal adjustment under pure stratified randomization for ATE estimation, e.g. see [Cytrynbaum \(2023\)](#), [Bai et al. \(2023\)](#), or [Liu and Yang \(2020\)](#).

tially arbitrary rerandomization acceptance criteria, not necessarily based on quadratic forms. [Bai et al. \(2024\)](#) study estimation of superpopulation parameters defined by moment equalities under pure stratified randomization. We extend these results to stratified rerandomization as well as generic finite population parameters, providing “SATE-like” versions of the parameters in [Bai et al. \(2024\)](#).⁵ In concurrent work, [Wang and Li \(2024\)](#) study GMM estimation of univariate superpopulation parameters under stratified rerandomization with fixed, discrete strata. We study significantly more general forms of stratification and rerandomization criteria than considered in their work, allowing for both finite and superpopulation parameters of arbitrary fixed dimension.

For nonlinear rerandomization (Section 4), the closest related results are [Ding and Zhao \(2024\)](#) and [Li et al. \(2021\)](#). [Ding and Zhao \(2024\)](#) rerandomize based on the p-value of a logistic regression coefficient, while we rerandomize until a general smooth propensity estimate is close to constant. To the best of our knowledge, we present the first asymptotic theory for rerandomization based on the difference of nonlinear (e.g. density) estimates. For acceptance region optimization (Section 5), the closest related results are [Schindl and Branson \(2024\)](#), who study the optimal choice of norm for quadratic rerandomization, while [Liu et al. \(2023\)](#) chooses a specific quadratic rerandomization using a Bayesian criterion, in both cases for rerandomization without stratification. We provide a novel minimax approach that accepts or rejects based on the value of a convex penalty function, tailored to prior information provided by the researcher. Our work on optimal adjustment (Section 6) extends recent work on adjustment for stratified designs, e.g. [Liu and Yang \(2020\)](#), [Cytrynbaum \(2023\)](#), [Bai et al. \(2023\)](#), to stratified rerandomization and GMM parameters. Finally our inference methods (Section 7) build on previous work by [Abadie and Imbens \(2008\)](#), [Bai et al. \(2021\)](#), and [Cytrynbaum \(2024\)](#). To the best of our knowledge we provide the first asymptotically exact inference for causal GMM parameters under stratified rerandomization, as well as conservative inference for their finite population analogues.

2 Framework and Designs

Consider data $W_i = (R_i, S_i(1), S_i(0))$ with $(W_i)_{i=1}^n \stackrel{\text{iid}}{\sim} F$. The $S_i(d) \in \mathbb{R}^{d_s}$ denote potential outcome vectors for a binary treatment $d \in \{0, 1\}$, while R_i denote other pre-treatment variables, such as covariates. For treatment assignments $D_i \in \{0, 1\}$, the realized outcome $S_i = S_i(D_i) = D_i S_i(1) + (1 - D_i) S_i(0)$. In what follows, for any array $(a_i)_{i=1}^n$ we denote $E_n[a_i] = n^{-1} \sum_{i=1}^n a_i$, with $\bar{a}_1 = E_n[a_i D_i] / E_n[D_i]$ and $\bar{a}_0 = E_n[a_i (1 - D_i)] / E_n[(1 - D_i)]$. Next, we define stratified rerandomization designs.

⁵These parameters can be seen as causal versions of the conditional estimand defined in [Abadie et al. \(2014\)](#).

Definition 2.1 (Stratified Rerandomization). Let treatment proportions $p = l/k$ and suppose that n is divisible by k for notational simplicity.

- (1) (Stratification). Partition the experimental units into n/k disjoint groups g with $\{1, \dots, n\} = \bigcup_g g$ disjointly and $|g| = k$. Let $\psi = \psi(R)$ with $\psi \in \mathbb{R}^{d_\psi}$ denote a vector of stratification variables, which may be continuous or discrete. Suppose the groups satisfy the homogeneity condition⁶

$$\frac{1}{n} \sum_g \sum_{i,j \in g} |\psi_i - \psi_j|_2^2 = o_p(1). \quad (2.1)$$

Require that the groups only depend on the stratification variables $\psi_{1:n}$ and data-independent randomness π_n , so that $g = g(\psi_{1:n}, \pi_n)$ for each g .

- (2) (Randomization). Independently for each $|g| = k$, draw treatment variables $(D_i)_{i \in g}$ by setting $D_i = 1$ for exactly l out of k units, uniformly at random.
- (3) (Check Balance). For rerandomization covariates $h = h(R)$, consider an imbalance metric $\mathcal{I}_n = \sqrt{n}(\bar{h}_1 - \bar{h}_0) + o_p(1)$.⁷ For an acceptance region $A \subseteq \mathbb{R}^{d_h}$, check if the balance criterion $\mathcal{I}_n \in A$ is satisfied. If so, accept $D_{1:n}$. If not, repeat from the beginning of (2).

Intuitively, steps (1) and (2) describe a data-adaptive “matched k-tuples” design, while step (2) rerandomizes within k-tuples until the balance criterion is satisfied. Equation 2.1 is a tight-matching condition, requiring that the groups are clustered locally in ψ space. Cytrynbaum (2024) provides algorithms to match units into groups that satisfy this condition for any fixed k .

Example 2.2 (Matched Pairs Rerandomization). For $k = 2$, the optimal matched pairs in Equation 2.1 can be found by Derigs (1988) algorithm. Suppose we have done so, and consider rerandomizing until the imbalance criterion $n(\bar{X}_1 - \bar{X}_0)' \Sigma_n (\bar{X}_1 - \bar{X}_0) \leq \epsilon^2$ is satisfied for positive-definite $\Sigma_n \xrightarrow{p} \Sigma$.⁸ Let $\mathcal{I}_n \equiv \Sigma_n^{1/2} \sqrt{n}(\bar{X}_1 - \bar{X}_0) = \sqrt{n}(\bar{h}_1 - \bar{h}_0) + o_p(1)$ for modified covariates $h = \Sigma^{1/2} X$. Then this quadratic criterion is equivalent to $\mathcal{I}_n \in A$ for acceptance region $A = \{x : |x|_2 \leq \epsilon\}$. We study the efficiency consequences of different covariates and acceptance regions in detail in Sections 3 and 5 below.

Example 2.3 (Stratification). Stratification without rerandomization can be obtained by setting $A = \mathbb{R}^{d_h}$ in Definition 2.1. Treatment effect estimation under such designs was studied in Bai (2022), Cytrynbaum (2024), and Bai et al. (2024). Definition 2.1 allows for

⁶The matching condition in Equation 2.1 was introduced by Bai et al. (2021) for matched pairs randomization ($k = 2$). See Bai (2022) and Cytrynbaum (2024) for generalizations.

⁷In particular, we require $\mathcal{I}_n = \sqrt{n}(\bar{h}_1 - \bar{h}_0) + o_p(1)$ under “pure” stratified randomization, the design in steps (1) and (2) only, studied e.g. in Cytrynbaum (2024). We give several examples below.

⁸Several recent papers in the statistics literature have considered such criteria. See e.g. Morgan and Rubin (2012), Li et al. (2018), Wang et al. (2021) among others.

fine stratification (also known as matched k-tuples), with the number of data-dependent groups $g = g(\psi_{1:n}, \pi_n)$ growing with n . It also allows for coarse stratification with fixed strata $s \in \{1, \dots, m\}$ and fixed m , as in [Bugni et al. \(2018\)](#), which can be obtained in this framework by setting $\psi = s$ and matching units into groups at random within the strata $\{i : s_i = k\}$.

Example 2.4 (Complete Randomization). For $p = l/k$, we say that $D_{1:n}$ are completely randomized with probability p if $P(D_{1:n} = d_{1:n}) = 1/\binom{n}{np}$ for all $d_{1:n}$ with $\sum_i d_i = np$.⁹ If so, we denote $D_{1:n} \sim \text{CR}(p)$. [Cytrynbaum \(2024\)](#) shows that $\text{CR}(p)$ randomization can be obtained by setting $\psi = 1$ and $A = \mathbb{R}^{d_h}$ in Definition 2.1, matching units into groups at random.

Causal Estimands. Next, we introduce a generic family of causal estimands defined by moment equalities. Let $g(D, R, S, \theta) \in \mathbb{R}^{d_g}$ be a score function for generalized method of moments (GMM) estimation. Recall $W = (R, S(1), S(0))$ and define the projection $\phi(W, \theta) = E[g(D, R, S, \theta)|W]$, so that $E[\phi(W, \theta)] = 0 \iff E[g(D, R, S, \theta)] = 0$.

Definition 2.5 (Causal Estimands). The *superpopulation* estimand θ_0 is the unique solution to $E[\phi(W, \theta)] = 0$. The *finite population* estimand θ_n is the unique solution to $E_n[\phi(W_i, \theta)] = 0$.

In what follows, we study GMM estimation of both θ_0 and θ_n under stratified rerandomization designs, showing an asymptotic equivalence between stratified rerandomization and partially linear covariate adjustment. In particular, this framework allows us to introduce several useful finite population estimands θ_n that do not appear to have been considered previously in the literature. Note that GMM estimation of θ_0 under pure stratification was studied in [Bai et al. \(2024\)](#) for the exactly identified case. Our finite population parameter θ_n can be viewed as a causal version of the finite population estimand defined in [Abadie et al. \(2014\)](#).¹⁰

Example 2.6 (ATE). Define the Horvitz-Thompson weights $H = \frac{D-p}{p-p^2}$ and let $g(D, Y, \theta) = HY - \theta$, so that $\phi(W, \theta) = E[HY|W] - \theta = Y(1) - Y(0) - \theta$. Then $\theta_0 = E[Y(1) - Y(0)] = \text{ATE}$, the average treatment effect, and $\theta_n = E_n[Y_i(1) - Y_i(0)] = \text{SATE}$, the sample average treatment effect.

For a more interesting example, consider the best parametric predictor of treatment effect heterogeneity in experiments with noncompliance.

Example 2.7 (LATE Heterogeneity). Let $D(z)$ be potential treatments for a binary instrument $z \in \{0, 1\}$. Let $Y(d)$ be the potential outcomes, with realized outcome $Y =$

⁹For notational simplicity, we may assume that $n = lk$ for some $l \in \mathbb{N}$.

¹⁰See also the related finite population estimands studied under iid sampling and assignment in [Xu \(2021\)](#) and [Takehi and Otsu \(2024\)](#).

$Y(D(Z))$. Suppose $D(1) \geq D(0)$, and define compliance indicator $C = \mathbb{1}(D(1) > D(0))$, assuming $E[C] > 0$. Imbens and Angrist (1994) define the local average treatment effect $\text{LATE} = E[Y(1) - Y(0)|C = 1]$. Let $H = (Z - p)/(p - p^2)$ and consider the score function $g(Z, D, Y, X, \theta) = (HY - HD \cdot f(X, \theta))\nabla_{\theta} f(X, \theta)$. Using standard LATE manipulations,

$$\phi(W, \theta) = E[g(Z, D, Y, X, \theta)|W] = C \cdot (Y(1) - Y(0) - f(X, \theta))\nabla_{\theta} f(X, \theta).$$

This is the first order condition of a treatment effect prediction problem in the complier population. In particular, for $\tau \equiv Y(1) - Y(0)$, the parameter θ_0 is the best parametric predictor of treatment effects for compliers:

$$\theta_0 = \underset{\theta}{\operatorname{argmin}} E[(\tau - f(X, \theta))^2 | C = 1].$$

For example, if Y is binary then $Y(1) - Y(0) \in \{-1, 0, 1\}$, so a scaled link function model $f(X, \theta) = 2L(X'\theta) - 1$ may be appropriate. We can easily estimate marginal effects by adding $m(X_i, \theta, \beta) = \beta - (\partial/\partial\theta')f(X_i, \theta)$ to the score function.

Example 2.8 (Finite Population Heterogeneity). Continuing Example 2.7, note that for $\tau_i = Y_i(1) - Y_i(0)$ the corresponding finite population parameter is

$$\theta_n = \underset{\theta}{\operatorname{argmin}} E_n[(\tau_i - f(X_i, \theta))^2 | C_i = 1]. \quad (2.2)$$

We can view θ_n as a ‘‘SATE-like’’ version of θ_0 , the best parametric predictor of treatment effects in the *within-sample* complier population. θ_n may be a more appropriate target for experiments run in a convenience sample. If $f(X, \theta) = X'\theta$ linear, then $\theta_n = \underset{\theta}{\operatorname{argmin}} E_n[(\tau_i - X_i'\theta)^2 | C_i = 1]$ is the within-sample best linear predictor. In the case of perfect compliance $C_i = 1$ for all i , this is $\theta_n = \underset{\theta}{\operatorname{argmin}} E_n[(\tau_i - X_i'\theta)^2]$, a finite-sample version of the best linear predictor of the conditional average treatment effect (CATE). The case $X = 1$ recovers $\theta_n = E_n[Y_i(1) - Y_i(0) | C_i = 1]$, the finite-population LATE, studied e.g. in Ren (2023). Our inference methods in Section 7 produce tighter confidence intervals for these finite population parameters than θ_0 , since we only need to account for the uncertainty due to random assignment, with no sampling uncertainty.

GMM Estimation. Let positive-definite weighting matrix $M_n \in \mathbb{R}^{d_g \times d_g}$ with $M_n \xrightarrow{p} M \succ 0$. For sample moment $\widehat{g}(\theta) \equiv E_n[g(D_i, R_i, S_i, \theta)]$, the GMM estimator¹¹ is

$$\widehat{\theta} = \underset{\theta \in \Theta}{\operatorname{argmin}} \widehat{g}(\theta)' M_n' \widehat{g}(\theta). \quad (2.3)$$

In the exactly identified case, $\widehat{\theta}$ solves $\widehat{g}(\widehat{\theta}) = 0$. In the next section, we study generalized

¹¹In our examples, we will mainly be concerned with the exactly identified case. However, the theory for the over identified case is almost identical, so we include this as well.

method of moments (GMM) estimation of the causal parameters θ_0 and θ_n under stratified rerandomization.

3 Asymptotics for GMM Estimation

In this section, we characterize the asymptotic distribution of the GMM estimator $\hat{\theta}$ under stratified rerandomization designs, as in Definition 2.1. We show that the variance under stratified rerandomization is proportional to the residuals of a partially linear regression model, up to a rerandomization imbalance term. In this sense, stratified rerandomization does partially linear regression adjustment “by design.” First, we state some technical regularity conditions that are needed for the following results.

Assumption 3.1 (Acceptance Region). *Suppose $A \in \mathbb{R}^{d_h}$ has non-empty interior and $\text{Leb}(\partial A) = 0$,¹² and require $E[\text{Var}(h|\psi)] \succ 0$ and $E[|\psi|_2^2 + |h|_2^2] < \infty$.*

Next we state the technical conditions needed for GMM estimation. Define the matrix $G = E[(\partial/\partial\theta')\phi(W, \theta)]|_{\theta=\theta_0} \in \mathbb{R}^{d_g \times d_\theta}$ and let $g_d(W, \theta) = g(d, R, S(d), \theta)$ for $d \in \{0, 1\}$. Recall that $|B|_F^2 = \sum_{ij} B_{ij}^2$ for any matrix B .

Assumption 3.2 (GMM). *The following conditions hold for $d \in \{0, 1\}$:*

- (a) *We have $E[g_d(W, \theta_0)^2] < \infty$ and $E[\sup_{\theta \in \Theta} |g_d(W, \theta)|_2] < \infty$. Also $\theta \rightarrow g_d(W, \theta)$ is continuous almost surely, and Θ is compact with θ_0 in the interior.*
- (b) *The matrix G is full rank, and $g_0(\theta) = 0$ iff $\theta = \theta_0$.*
- (c) *There exists a neighborhood $\theta_0 \in U \subseteq \Theta$ such that $G_d(W, \theta) \equiv \partial/\partial\theta' g_d(W, \theta)$ exists and is continuous. Also $E[\sup_{\theta \in U} |\partial/\partial\theta' g_d(W, \theta)|_F] < \infty$.*

Compactness could likely be relaxed using concavity assumptions or a VC class condition, but we do not pursue this here. In what follows it will be conceptually useful to reparameterize the score function.

Orthogonal Expansion. Recall $\phi(W, \theta) = E[g(D, R, S, \theta)|W]$ for $W = (R, S(1), S(0))$. Define the assignment influence component $\delta(W, \theta) \equiv \text{Var}(D)(g_1(W, \theta) - g_0(W, \theta))$. For the Horvitz-Thompson weights $H = (D - p)/(p - p^2)$, a simple calculation shows that we can expand

$$g(D, R, S, \theta) = \phi(W, \theta) + H\delta(W, \theta). \quad (3.1)$$

Our work below shows that $\delta(W, \theta)$ parameterizes estimator variance due to assignment, while $\phi(W, \theta)$ parameterizes variance due to random sampling. In what follows, we work directly with this expansion.

¹²Note that ∂A denotes the boundary of A , the limit points of both A and A^c .

Example 3.3 (SATE). Continuing Example 2.6 above, let $\bar{Y} = (1 - p)Y(1) + pY(0)$, a convex combination that summarizes each unit’s potential outcome level. Then for the score $g(D, Y, \theta) = HY - \theta$, we have $\delta(W, \theta) = \bar{Y}$ and

$$E_n[H_i \delta(W_i)] = \bar{\delta}_1 - \bar{\delta}_0 = \frac{\text{Cov}_n(D_i, \bar{Y}_i)}{\text{Var}_n(D_i)}.$$

Intuitively, $E_n[H_i \delta(W_i)]$ from Equation 3.1 isolates the estimator variance due to chance correlations between the assignments D_i and outcome levels \bar{Y}_i . By contrast, $\phi(W, \theta) = Y(1) - Y(0) - \theta$ does not depend on assignments D_i , and $\text{Var}(\phi(W, \theta)) = \text{Var}(Y(1) - Y(0))$ isolates the estimator variance due to random sampling of treatment effects.

3.1 Finite Population Estimand

Our first theorem studies GMM estimation of the finite population estimand θ_n solving $E_n[\phi(W_i, \theta_n)] = 0$. We study the superpopulation estimand θ_0 in Corollary 3.8 below. To state the theorem, define the GMM linearization matrix $\Pi = -(G'MG)^{-1}G'M \in \mathbb{R}^{d_\theta \times d_g}$ and denote $v_D = \text{Var}(D) = p - p^2$.

Theorem 3.4 (GMM). *Suppose $D_{1:n}$ as in Definition 2.1. Require Assumption 3.1, 3.2. Then $\sqrt{n}(\hat{\theta} - \theta_n) | W_{1:n} \Rightarrow \mathcal{N}(0, V_\delta) + R_A$, independent RV’s with*

$$V_\delta = v_D^{-1} E[\text{Var}(\Pi \delta(W, \theta_0) - \Gamma'_0 h | \psi)] = \min_{\Gamma \in \mathbb{R}^{d_h \times d_\theta}} v_D^{-1} E[\text{Var}(\Pi \delta(W, \theta_0) - \Gamma' h | \psi)].$$

The residual term $R_A \sim \Gamma'_0 Z_h | Z_h \in A$ for $Z_h \sim \mathcal{N}(0, v_D^{-1} E[\text{Var}(h | \psi)])$.

Note that variance matrix $V_\delta \in \mathbb{R}^{d_\theta \times d_\theta}$ and the minimum is interpreted in the positive semidefinite¹³ sense. Theorem 3.4 shows that $\sqrt{n}(\hat{\theta} - \theta_n)$ is asymptotically distributed as an independent sum of a normal $\mathcal{N}(0, V_\delta)$ and truncated normal R_A . The normal term $\mathcal{N}(0, V_\delta)$ only depends on the “treatment assignment” component of the influence function, $\Pi \delta(W, \theta_0)$. The variance is attenuated nonparametrically by the stratification variables ψ and linearly by rerandomization covariates h . The truncated normal term

$$R_A \sim \Gamma'_0 Z_h | Z_h \in A, \quad Z_h \sim \mathcal{N}(0, v_D^{-1} E[\text{Var}(h | \psi)]).$$

Intuitively, this term arises from leftover covariate imbalances due to slackness in the rerandomization acceptance criterion, $\sqrt{n}(\bar{h}_1 - \bar{h}_0) \in A$. We refer to R_A as the *rerandomization imbalance*. If the acceptance region A is symmetric about zero, i.e. $a \in A$ iff $-a \in A$, then $E[R_A] = 0$, so the asymptotic distribution is centered at 0. In principle, in large samples this term could be made negligible relative to $\mathcal{N}(0, V_\delta)$ by choosing a small

¹³In particular, we say $V_\delta = \min_\Gamma V(\Gamma)$ if $V_\delta \preceq V(\Gamma)$ for all $\Gamma \in \mathbb{R}^{d_h \times d_\theta}$.

enough acceptance region A . For example, if $A = B(0, \epsilon)$ then $R_{B(0, \epsilon)} \sim \{\Gamma'_0 Z_h \mid |Z_h|_2 \leq \epsilon\} \xrightarrow{p} 0$ as $\epsilon \rightarrow 0$. However, in finite samples and for small enough ϵ , this may be computationally infeasible. We study a minimax style criterion that uses prior information or pilot data to choose an efficient acceptance region in Section 5 below.

To isolate the precision gains due to rerandomization, the following corollary specializes Theorem 3.4 to the case of stratification without rerandomization, as well as complete randomization, as defined in Examples 2.3 and 2.4.

Corollary 3.5 (Pure Stratification). *Suppose $D_{1:n}$ as in Definition 2.1 with $A = \mathbb{R}^{d_h}$. Require Assumption 3.1. Then $\sqrt{n}(\hat{\theta} - \theta_n) \mid W_{1:n} \Rightarrow \mathcal{N}(0, V)$ with $V = v_D^{-1} E[\text{Var}(\Pi\delta(W, \theta_0) \mid \psi)]$. In particular, if $D_{1:n} \sim \text{CR}(p)$ then $V = v_D^{-1} \text{Var}(\Pi\delta(W, \theta_0))$.*

Remark 3.6 (Efficiency Gain). Corollary 3.5 highlights how fine stratification reduces the variance of GMM estimation to $V = v_D^{-1} E[\text{Var}(\Pi\delta(W, \theta_0) \mid \psi)] \leq v_D^{-1} \text{Var}(\delta(W, \theta_0))$, a nonparametric improvement. Rerandomization as in Definition 2.1 provides a further linear variance reduction to $V_\delta = \min_{\Gamma \in \mathbb{R}^{d_h \times d_\theta}} E[\text{Var}(\Pi\delta(W, \theta_0) - \Gamma'h \mid \psi)]$, up to the residual imbalance term R_A .

Remark 3.7 (Design-Based Asymptotics). Our results above show that $\sqrt{n}(\hat{\theta} - \theta_n) \mid W_{1:n} \Rightarrow \mathcal{N}(0, V_\delta) + R_A$, conditional¹⁴ on $W_{1:n} = (R_i, S_i(1), S_i(0))_{i=1}^n$. This result is “design-based” in the sense that the variance in the limiting distribution arises solely due to randomness of the treatment assignments $D_{1:n}$. However, we impose structure on the sequence of populations $W_{1:n}$ ex-ante, assuming each population is drawn from a fixed measure, $W_i \sim F$. This allows us to provide intuitive, closed form variance expressions and connect our results with the literature on GMM and partially linear adjustment. By contrast, the finite populations model often used in the statistics literature (e.g. Li et al. (2018)) begins with an arbitrary sequence of finite populations, imposing the minimal structure needed for certain moments to converge ex-post. It may be possible to extend our results to this setting, but we leave this to future work.

3.2 Superpopulation Estimand

The next result extends Theorem 3.4 to the superpopulation estimand θ_0 , which uniquely solves $E[\phi(W, \theta_0)] = 0$.

Corollary 3.8 (Superpopulation Estimand). *Suppose $D_{1:n}$ is as in Definition 2.1. Require Assumption 3.1, 3.2.*

- (a) *We have $\sqrt{n}(\hat{\theta} - \theta_0) \Rightarrow \mathcal{N}(0, V_\phi) + \mathcal{N}(0, V_\delta) + R_A$, independent RV's with $V_\phi = \text{Var}(\Pi\phi(W, \theta_0))$ and V_δ, R_A exactly as in Theorem 3.4.*

¹⁴See Proposition 8.11 in the appendix for a formal statement.

(b) (*Pure Stratification*). If $A = \mathbb{R}^{d_h}$, this is $\sqrt{n}(\hat{\theta} - \theta_0) \Rightarrow \mathcal{N}(0, V)$ with

$$V = \text{Var}(\Pi\phi(W, \theta_0)) + v_D^{-1} E[\text{Var}(\Pi\delta(W, \theta_0)|\psi)].$$

Comparing Corollary 3.8 with the results above, we see that targeting θ_0 instead of θ_n adds an extra independent Gaussian term $\mathcal{N}(0, V_\phi)$ to the asymptotic distribution. Intuitively, V_ϕ arises due to iid random sampling of $\Pi\phi(W, \theta_0)$. Notice that stratification and rerandomization only affect the assignment influence function component $\Pi\delta(W, \theta_0)$, while the sampling influence component $\Pi\phi(W, \theta_0)$ is irreducible. For pure stratification, Bai et al. (2024) were the first to derive an analogue of part (b) of Corollary 3.8 in the exactly identified case, under different GMM regularity conditions than we use here.

Example 3.9 (SATE). Continuing Example 2.6, we had $\phi(W, \theta) = Y(1) - Y(0) - \theta$, so $G = 1$ and $\Pi = 1$. As above, $\delta(W, \theta) = (1 - p)Y(1) + pY(0) \equiv \bar{Y}$. The GMM estimator $\hat{\theta} = \bar{Y}_1 - \bar{Y}_0$ is just difference of means. Then by Theorem 3.4 and Corollary 3.8, we have $\sqrt{n}(\hat{\theta} - \text{SATE})|W_{1:n} \Rightarrow \mathcal{N}(0, V_\delta) + R_A$ and $\sqrt{n}(\hat{\theta} - \text{ATE}) \Rightarrow \mathcal{N}(0, V_\phi + V_\delta) + R_A$ with

$$V_\phi = \text{Var}(Y(1) - Y(0)) \quad V_\delta = \min_{\gamma \in \mathbb{R}^{d_h}} v_D^{-1} E[\text{Var}(\bar{Y} - \gamma' h | \psi)]. \quad (3.2)$$

The term V_ϕ , which only appears when estimating the superpopulation estimand θ_0 , reflects sampling variance due to treatment effect heterogeneity. The term V_δ is the variance due to random assignment, caused by random in-sample correlations between treatments D and outcome levels \bar{Y} . Covariate-adaptive randomization and adjustment can be used to reduce V_δ , while V_ϕ is an irreducible sampling variance.

Remark 3.10. Wang et al. (2021) study SATE estimation under stratified rerandomization in the sequence of finite populations framework. Relative to Wang et al. (2021), by imposing the tight-matching condition 2.1 we are able to derive a simple closed form for the asymptotic variance in terms of the measure $W \sim F$, showing an equivalence with partially linear regression adjustment.

Example 3.11 (Treatment Effect Heterogeneity). Continuing Example 2.7, consider the case with perfect compliance $D = Z$ and $f(X, \theta) = X'\theta$. Then we can use the slightly modified score $g(D, X, Y, \theta) = (HY - X'\theta)X$. For $\tau = Y(1) - Y(0)$, the parameters

$$\theta_n = \underset{\theta}{\operatorname{argmin}} E_n[(\tau_i - X_i'\theta)^2], \quad \theta_0 = \underset{\theta}{\operatorname{argmin}} E[(\tau - X'\theta)^2].$$

We have $\phi(W, \theta_0) = (\tau - X'\theta_0)X$, where $e = \tau - X'\theta_0$ are treatment effect prediction errors. For $\delta(W, \theta_0) = \bar{Y}X$ and $\Pi = E[XX']^{-1}$, the variance matrices above are

$$V_\phi = E[XX']^{-1} E[e^2 XX'] E[XX']^{-1} \quad V_\delta = \min_{\Gamma \in \mathbb{R}^{d_h \times d_x}} v_D^{-1} E[\text{Var}(\bar{Y}\Pi X - \Gamma'h | \psi)].$$

The expression for V_δ shows that if we want to precisely estimate treatment effect heterogeneity, it is important to balance not only the variables that predict outcome levels \bar{Y} , but also their interactions with the heterogeneity variable.

3.3 Equivalence with Partially Linear Adjustment

Example 3.9 showed that, up to the rerandomization imbalance R_A , the unadjusted estimator $\hat{\theta} = \bar{Y}_1 - \bar{Y}_0$ has asymptotic variance given by the residuals of a partially linear regression of \bar{Y} on ψ and h :

$$V_\delta = \min_{\gamma \in \mathbb{R}^{d_h}} v_D^{-1} E[\text{Var}(\bar{Y} - \gamma' h | \psi)] = \min_{\substack{\gamma \in \mathbb{R}^{d_h} \\ t \in L_2(\psi)}} v_D^{-1} \text{Var}(\bar{Y} - \gamma' h - t(\psi)). \quad (3.3)$$

More generally, Theorem 3.4 shows that under stratified rerandomization designs, the usual GMM estimator $\hat{\theta}$ behaves like semiparametrically adjusted GMM. Formally, let $\mathcal{L}(\psi) = L_2^{d_\theta}(\psi)$ be the d_θ -fold Cartesian product of $L_2(\psi)$. Then V_δ in Theorem 3.4 is the variance of the residuals of the influence function $\Pi\delta(W, \theta_0)$ in a partially linear regression on ψ and h :

$$V_\delta = \min_{\substack{\Gamma \in \mathbb{R}^{d_h \times d_\theta} \\ t \in \mathcal{L}(\psi)}} v_D^{-1} \text{Var}(\Pi\delta(W, \theta_0) - \Gamma' h - t(\psi)). \quad (3.4)$$

Intuitively, stratified rerandomization does partially linear regression adjustment “by design,” providing nonparametric control over ψ and linear control over h . For a more explicit equivalence statement, define $m(\psi, h) = \Gamma'_0 h + t_0(\psi)$ to be the partially linear function achieving the optimum in Equation 3.4. Define the oracle semiparametrically adjusted GMM estimator

$$\hat{\theta}^* = \hat{\theta} - E_n[H_i m(\psi_i, h_i)]. \quad (3.5)$$

For example, for the SATE estimation problem one can show that $\hat{\theta}^*$ is just an oracle version of the usual augmented inverse propensity weighting (AIPW) estimator (Robins and Rotnitzky (1995)), with partially linear regression models in each arm.¹⁵

Theorem 3.12 (Partially Linear Adjustment). *Suppose that $D_{1:n} \sim \text{CR}(p)$. The oracle partially linearly adjusted GMM estimator $\sqrt{n}(\hat{\theta}^* - \theta_n) | W_{1:n} \Rightarrow \mathcal{N}(0, V_\delta)$, with variance V_δ as defined in Theorem 3.4.*

Without stratification or rerandomization, we require ex-post semiparametric adjustment to achieve V_δ . Under stratified rerandomization, however, the simple GMM estimator $\hat{\theta}$ automatically achieves V_δ , up to the imbalance term R_A .

¹⁵Feasible partially linear adjustment in an iid mean estimation problem with missing data was studied in Wang et al. (2004). See also the related semiparametric adjustment for GMM parameters in Graham (2011).

4 Nonlinear Rerandomization

In this section, we study various nonlinear rerandomization criteria, showing that in many cases they are asymptotically equivalent to linear rerandomization as in Definition 2.1, with an implicit choice of rerandomization covariates and acceptance region. This shows that our asymptotics and inference methods apply to a broad class of asymptotically linear rerandomization schemes.

4.1 GMM Rerandomization

First, we generalize the imbalance metric \mathcal{I}_n introduced in Definition 2.1, allowing rejection of a treatment allocation $D_{1:n}$ based on potentially nonlinear features of the in-sample distribution of treatments and covariates $(D_i, X_i)_{i=1}^n$. To define the nonlinear imbalance metric, let $m(X_i, \beta)$ be a score function and define the within-arm GMM estimators $\hat{\beta}_1$ and $\hat{\beta}_0$ by

$$\hat{\beta}_1 \in \operatorname{argmin}_{\beta \in \mathbb{R}^{d_\beta}} |E_n[D_i m(X_i, \beta)]|_2^2, \quad \hat{\beta}_0 \in \operatorname{argmin}_{\beta \in \mathbb{R}^{d_\beta}} |E_n[(1 - D_i)m(X_i, \beta)]|_2^2. \quad (4.1)$$

Definition 4.1 (GMM Rerandomization). Define $\mathcal{I}_n^m = \sqrt{n}(\hat{\beta}_1 - \hat{\beta}_0)$ as above, where $m(X, \beta)$ is a score satisfying Assumption 3.2. Suppose $d_\beta = d_m$ (exact identification) and let A a symmetric acceptance region. Do the following: (1) form strata as in Definition 2.1. (2) Draw $D_{1:n}$ by stratified randomization. (3) If imbalance $\mathcal{I}_n^m = \sqrt{n}(\hat{\beta}_1 - \hat{\beta}_0) \in A$, accept. Otherwise, repeat from (2).

Observe that if $m(X_i, \beta) = X_i - \beta$, then $\hat{\beta}_d = \bar{X}_d$ and $\mathcal{I}_n^m = \mathcal{I}_n$, so linear rerandomization is a special case. Intuitively, the generalization \mathcal{I}_n^m allows us to randomize until possibly nonlinear features of the covariates are balanced between the treatment and control groups.

Example 4.2 (Density Rerandomization). Let $f(X, \beta)$ be a parametric density model for the covariates X , which may be misspecified. Consider forming likelihood estimators $\hat{\beta}_1 \in \operatorname{argmax}_\beta E_n[D_i \log f(X_i, \beta)]$ and $\hat{\beta}_0 \in \operatorname{argmax}_\beta E_n[(1 - D_i) \log f(X_i, \beta)]$, then rerandomizing until the imbalance measure $\sqrt{n}|\hat{\beta}_1 - \hat{\beta}_0|_2 \leq \epsilon$. Under suitable regularity conditions, $\hat{\beta}_d$ are GMM estimators as in Equation 4.1 with score function $m(X_i, \beta) = \nabla_\beta f(X_i, \beta)$, so this procedure is a GMM rerandomization with acceptance region $A = \{x : |x|_2 \leq \epsilon\}$.

Let β^* be the unique solution to $E[m(X, \beta^*)] = 0$ and define $G_m = E[(\partial/\partial\beta')m(X_i, \beta^*)]$. Our next result shows that GMM rerandomization with acceptance criterion $\mathcal{I}_n^m \in A$ is equivalent to linear rerandomization (Definition 2.1) with an implicit choice of rerandomization covariates $h_i = m(X_i, \beta^*)$ and linearly transformed acceptance region.

Theorem 4.3 (GMM Rerandomization). *Suppose $D_{1:n}$ is as in Definition 4.1 and Assumption 3.2 holds. Then $\sqrt{n}(\hat{\theta} - \theta_n)|W_{1:n} \Rightarrow \mathcal{N}(0, V_\delta) + R$, independent RV's with*

$$V_\delta = \min_{\eta \in \mathbb{R}^{d_\beta \times d_\theta}} v_D^{-1} E[\text{Var}(\Pi\delta(W, \theta_0) - \eta' m(X_i, \beta^*)|\psi)].$$

The residual $R \sim \eta'_0 Z_m \mid Z_m \in G_m A$ for $Z_m \sim \mathcal{N}(0, v_D^{-1} E[\text{Var}(m(X_i, \beta^)|\psi)])$.*

Theorem 4.3 shows that by rerandomizing until $\sqrt{n}(\hat{\beta}_1 - \hat{\beta}_0) \in A$, we implicitly balance the influence function for the difference of GMM estimators in Equation 4.1, which depends both on $m(X_i, \beta^*)$ and the Jacobian matrix G_m .

This suggests an equivalent, but computationally simpler design with only one round of nonlinear estimation. In particular, let $\hat{\beta} \in \text{argmin}_{\beta \in \mathbb{R}^{d_\beta}} |E_n[m(X_i, \beta)]|_2^2$ and set rerandomization covariates $\hat{h}_i = m(X_i, \hat{\beta})$, rerandomizing until $\sqrt{n}E_n[H_i \hat{h}_i] \in G_m A$. This design is asymptotically equivalent to Definition 4.1, as shown in the next result.

Corollary 4.4. *Suppose Assumption 3.1, 3.2 hold and let score $m(X, \beta)$ as in Definition 4.1. Let $D_{1:n}$ be rerandomized as in Definition 2.1 with $\hat{h}_i = m(X_i, \hat{\beta})$ and acceptance region $G_m A$. Then $\sqrt{n}(\hat{\theta} - \theta_n)|W_{1:n} \Rightarrow \mathcal{N}(0, V_\delta) + R$, with both variables identical to those in Theorem 4.3.*

Corollary 4.4 shows that we can achieve the same effect as Definition 4.1 with a computationally simpler linear rerandomization that balances the estimated covariate $\hat{h}_i = m(X_i, \hat{\beta})$. Next, we introduce a propensity score based approach that also attempts to balance nonlinear covariate features.

4.2 Propensity Rerandomization

To motivate a propensity based rerandomization procedure, note that under stratified randomization we have $E[D_i|W] = p$ for all units. In finite samples, however, the *realized propensity* $\hat{p}(S) = E_n[D_i|X_i \in S]$ may be significantly different from p in certain regions $S \subseteq \mathbb{R}^{d_X}$ of the covariate space. This implies that covariates are predictive of treatment assignments post-randomization, a form of “in-sample confounding.” To enforce balance, we could, for instance, reject allocations where $|\hat{p}(S) - p| > \epsilon$ for some collection of sets S . To make this idea tractable without fully discretizing, consider a parametric propensity model $p(X, \beta) = L(X'\beta)$ and define the MLE estimator

$$\hat{\beta} \in \text{argmax}_{\beta \in \mathbb{R}^{d_\beta}} E_n[D_i \log L(X'_i \beta) + (1 - D_i) \log(1 - L(X'_i \beta))]. \quad (4.2)$$

We can measure the average gap between the estimated and true propensity score using the imbalance metric

$$\mathcal{J}_n = nE_n[(p - L(X'_i \hat{\beta}))^2]. \quad (4.3)$$

Intuitively, if \mathcal{J}_n is large, then the covariates X have power to predict treatment status in some parts of the covariate space. To avoid this, we propose rerandomizing until the imbalance metric \mathcal{J}_n is below a threshold:

Definition 4.5 (Propensity Rerandomization). Do the following: (1) form strata as in Definition 2.1. (2) Draw $D_{1:n}$ and estimate the propensity model in Equation 4.2. (3) If imbalance $\mathcal{J}_n \leq \epsilon$, accept. Otherwise, repeat from (2).

Before we state the main result, we require some regularity conditions

Assumption 4.6. *Impose the following conditions.*

- (a) Let L be twice differentiable, with $|L'|_\infty, |L''|_\infty < \infty$. For each $p \in (0, 1)$, there is a unique c with $L(c) = p$. Also, $|L'(c)| > 0$.
- (b) The score $m(D_i, X_i, \beta) = D_i \frac{L'(X_i' \beta) X_i}{L(X_i' \beta)} - (1 - D_i) \frac{L'(X_i' \beta) X_i}{1 - L(X_i' \beta)}$ satisfies condition 3.2. The solution to Equation 4.2 exists and is unique.
- (c) Covariates $X = (1, h)$ for $E[|h|_2^2] < \infty$. Also, $E[\text{Var}(h|\psi)]$, $E[XX']$ are full rank.

Condition (a) is satisfied by the logit and probit link functions. Our next result shows that propensity rerandomization as in Definition 4.5 is equivalent to a simpler linear rerandomization design, with an implicit choice of ellipsoidal acceptance region.

Theorem 4.7 (Propensity Rerandomization). *Suppose $D_{1:n}$ is as in Definition 4.5. Require Assumptions 3.2, 4.6. Then $\sqrt{n}(\hat{\theta} - \theta_n) | W_{1:n} \Rightarrow \mathcal{N}(0, V_\delta) + R$.*

$$V_\delta = \min_{\Gamma \in \mathbb{R}^{d_h \times d_\theta}} v_D^{-1} E[\text{Var}(\Pi \delta(W, \theta_0) - \Gamma' h | \psi)].$$

The residual $R \sim \Gamma_0' Z_h | Z_h' \text{Var}(h)^{-1} Z_h \leq \epsilon$ for $Z_h \sim \mathcal{N}(0, v_D^{-1} E[\text{Var}(h|\psi)])$ and Γ_0 optimal in the equation above.

Theorem 4.7 shows that for any sufficiently regular link function, propensity rerandomization is asymptotically equivalent to the simpler quadratic rerandomization design in Example 2.2, with acceptance criterion $n(\bar{h}_1 - \bar{h}_0)' \text{Var}_n(h_i)^{-1} (\bar{h}_1 - \bar{h}_0) \leq \epsilon$. Equivalently, propensity rerandomization behaves like linear rerandomization with $\mathcal{I}_n = \sqrt{n}(\bar{h}_1 - \bar{h}_0)$ and ellipsoidal acceptance region $A = \text{Var}(h)^{1/2} B(0, \epsilon)$.¹⁶

Implicit Acceptance Regions. Both nonlinear designs in this section turned out to be equivalent to the standard rerandomization scheme in Definition 2.1, with a specific, implicit choice of rerandomization moments and acceptance region. However, note that the moments and acceptance region chosen by these procedures are entirely determined by the marginal covariate distribution. This implicit choice is not likely to be optimal,

¹⁶A related result was found by Ding and Zhao (2024), who study rerandomizing until the p-value of a logistic regression coefficient is above a threshold.

since the residual term $R_A \sim \Gamma'_0 Z_h | Z_h \in A$ depends not only on the covariates $Z_h \sim \mathcal{N}(0, v_D^{-1} E[\text{Var}(h|\psi)])$, but also on the partially linear coefficient Γ_0 . This coefficient is determined by the *joint* distribution of the assignment influence function $\Pi\delta(W, \theta_0)$ and covariates (ψ, h) . In the next section, we show how to use prior information about this joint distribution to optimize the acceptance region and bound the variance of R_A .

5 Optimizing Acceptance Regions

In this section, we study efficient choice of the rerandomization acceptance region $A \subseteq \mathbb{R}^{d_h}$. For simplicity and intuition, we first restrict to the case of estimating $\theta_n = \text{SATE}$, generalizing in what follows.

Imbalance Decomposition. The difference of means estimator $\hat{\theta} = E_n[Y_i(1) - Y_i(0)] + E_n[H_i \bar{Y}_i] = \theta_n + E_n[H_i \bar{Y}_i]$ for $H_i = (D_i - p)/(p - p^2)$. Intuitively, the scaled errors $\sqrt{n}(\hat{\theta} - \theta_n) = \sqrt{n}E_n[H_i \bar{Y}_i]$ are driven by imbalances in the outcome levels \bar{Y} between treatment arms. The previous section showed that if covariates h are predictive of \bar{Y} , we can reduce these imbalances by rerandomizing until $\sqrt{n}E_n[H_i h_i] = \sqrt{n}(\bar{h}_1 - \bar{h}_0) \in A$. To study the role of the acceptance region A , let (γ_0, t_0) be solutions to the partially linear prediction problem in Equation 3.3 and consider the expansion¹⁷

$$\bar{Y} = \gamma'_0 h + t_0(\psi) + e, \quad E[e|\psi] = 0, \quad E[eh] = 0.$$

We use this to decompose the imbalance in outcome levels \bar{Y} into imbalances in the covariates ψ and h and residuals e . In particular, we can now write the imbalance decomposition

$$E_n[H_i \bar{Y}_i] = E_n[H_i t_0(\psi_i)] + \gamma'_0 E_n[H_i h_i] + E_n[H_i e_i] \equiv I_1 + I_2 + I_3.$$

The analysis in Section 3 showed that for *any* acceptance region $A \subseteq \mathbb{R}^{d_h}$:

- (1) The ψ imbalance component $I_1 = \sqrt{n}E_n[H_i t_0(\psi_i)] \xrightarrow{p} 0$ due to stratification.
- (2) The components $I_2 + I_3 = \gamma'_0 \sqrt{n}E_n[H_i h_i] + \sqrt{n}E_n[H_i e_i] \Rightarrow R_A + v_D^{-1/2} \mathcal{N}(0, \text{Var}(e))$ are asymptotically independent, with $\text{Var}(e)$ not depending on A .

In particular, it suffices to choose A to minimize the component $I_2 = \gamma'_0 \sqrt{n}E_n[H_i h_i]$. This suggests an oracle acceptance criterion, rerandomizing until $|\gamma'_0 \sqrt{n}E_n[H_i h_i]| \leq \epsilon$, with acceptance region $A = \{a : |\gamma'_0 a| \leq \epsilon\}$. However, this acceptance region is infeasible since γ_0 is unknown at design-time. Instead, we take a minimax approach, allowing the researcher to incorporate prior information about γ_0 .

¹⁷This is without loss of generality. Note that we do not impose well-specification $E[e|\psi, h] = 0$.

5.1 Minimax Rerandomization

Suppose that we know $\gamma_0 \in B$ for some prior information set $B \subseteq \mathbb{R}^{d_h}$. Fix $\epsilon > 0$ and consider a “minimax” style acceptance criterion, rerandomizing the treatments $D_{1,n}$ until

$$\sup_{\gamma \in B} |\gamma' \sqrt{n} E_n[H_i h_i]| \leq \epsilon. \quad (5.1)$$

Note that the function $f_B(x) = \sup_{\gamma \in B} |\gamma' x|$ is convex, so we can also interpret this as a convex imbalance penalty, rerandomizing until $f_B(\mathcal{I}_n) \leq \epsilon$ for imbalance metric $\mathcal{I}_n = \sqrt{n} E_n[H_i h_i]$, generalizing the quadratic penalty in Example 2.2. Our first result shows that this minimax design is of the form studied in the Section 3, characterizing the acceptance region induced by this convex penalty.

Theorem 5.1. *The following hold:*

- (a) (Rerandomization). *The acceptance criterion $\sup_{\gamma \in B} |\gamma' \sqrt{n} E_n[H_i h_i]| \leq \epsilon \iff \sqrt{n} E_n[H_i h_i] \in A$ for $A = \epsilon B^\circ$ with $B^\circ = \{a : \sup_{\gamma \in B} |\gamma' a| \leq 1\} \subseteq \mathbb{R}^{d_h}$.¹⁸*
- (b) (Acceptance Region). *$A = \epsilon B^\circ$ is symmetric and convex. If B is bounded, then A is closed and has non-empty interior. If B is open, then A is bounded.*
- (c) (Well-specification). *If $\gamma_0 \in B$, then $\text{Var}(R_A) \leq \epsilon^2$.*

Part (a) of Theorem 5.1 shows that the rerandomization criterion is of the form studied in Definition 2.1, with acceptance region $A = \epsilon B^\circ$. Part (b) shows that A is always symmetric and convex. In particular, the asymptotic distribution of $\hat{\theta}$ is centered at zero. The set B° is known as the absolute polar of B , e.g. see Aliprantis and Border (2006). Part (c) of the theorem shows that if the prior information set B contains the true coefficient γ_0 , then $\text{Var}(R_A) \leq \epsilon^2$. Then by independence, the asymptotic variance is within ϵ^2 of the optimal partially linear variance. If $\gamma_0 \notin B$ (misspecification), then possibly $\text{Var}(R_A) > \epsilon^2$. However, note that misspecification does not affect our inference methods, which allow for general acceptance regions A .

Remark 5.2 (Acceptance Probability). Note that the asymptotic acceptance probability $a(\epsilon) = P(Z_h \in \epsilon B^\circ)$ has $a(\epsilon) \rightarrow 0$ as $\epsilon \rightarrow 0$ and is monotonically increasing. For B bounded, the theorem shows that B° has non-empty interior. In this case, as $\epsilon \rightarrow \infty$ we have $\epsilon B^\circ \uparrow \mathbb{R}^{d_h}$ so $a(\epsilon) \rightarrow 1$. This shows that, at least in large samples, we can choose ϵ to achieve any desired acceptance probability $P(Z_h \in A) \in (0, 1)$. Under well-specification, any such choice of ϵ comes with a variance guarantee provided by the theorem.

¹⁸Note that for a set $S \subseteq \mathbb{R}^d$, we have $\epsilon S = \{\epsilon s : s \in S\}$.

5.2 Specifying Prior Information

Without pilot data, we are left to introspection to choose the prior information set B . Recall that γ_0 is the coefficient from the partially linear projection $\bar{Y} = \gamma'_0 h + t_0(\psi) + e$. Intuitively, γ_0 parameterizes how much we expect the average outcome level to change given a unit change in h , holding ψ fixed. If the partially linear model happens to be well-specified, then $\gamma_0 = \nabla_b E[\bar{Y} | \psi, h = b]$. If $t_0(\psi) = t'\psi$ happens to be linear, then $\bar{Y} = c + \gamma'_0 h + t'\psi + e$ and γ_0 is just an OLS coefficient. The following examples provide some reasonable prior information specifications and their associated acceptance regions. These examples rely on a general characterization of acceptance regions in Lemma 5.5 below.

Example 5.3 (Rectangle). One natural way to specify prior information is to assume $\gamma_{0j} \in [l_j, u_j]$ for each $1 \leq j \leq d_h$, equivalent to setting $B = \prod_{j=1}^{d_h} [l_j, u_j]$. This allows sign constraints, e.g. $0 \leq \gamma_{0j} \leq m$ for some j and $-m \leq \gamma_{0j} \leq 0$ for others. Lemma 5.5 below shows that if $B = \prod_{j=1}^{d_h} [l_j, u_j]$, then $A = \epsilon B^\circ = \{a : |a'l + a'u| + \sum_j |a_j|u_j - |a_j|l_j \leq 2\epsilon\}$, where $l = (l_j)_j$ and $u = (u_j)_j$. An example is shown in Figure 1. Note that the acceptance region A is conservative in directions aligned with the prior information set $B = [1, 2] \times [1, 3/2]$, guarding against covariate imbalances that are aligned with adverse coefficient values $\gamma_0 \in B$. A is more lenient in directions approximately orthogonal to B .

Example 5.4 (Ellipse). Another natural specification is to guess $\gamma_0 \approx \bar{\gamma}$, setting $B = \bar{\gamma} + B_2(0, m)$, for an uncertainty parameter m . By the characterization in Lemma 5.5 below, $A = \epsilon B^\circ = \{a : |a'\bar{\gamma}| + m|a|_2 \leq \epsilon\}$. More generally, if $B = \bar{\gamma} + \Sigma B_2(0, 1)$ for a positive-definite matrix Σ , the lemma shows that $A = \epsilon B^\circ = \{a : |a'\bar{\gamma}| + |\Sigma a|_2 \leq \epsilon\}$. One natural application of this specification is when B is a Wald confidence region constructed using pilot data, as discussed below. An example is shown in Figure 1.

More generally, the following lemma provides a useful characterization of the acceptance region $A = \epsilon B^\circ$ from Theorem 5.1 for a large family of prior information set specifications. To state the lemma, recall that $|x|_p = (\sum_j |x_j|^p)^{1/p}$ for $p \in [1, \infty)$ and $|x|_\infty = \max_j |x_j|$. For $p \in [1, \infty]$, denote $B_p(0, 1) = \{a : |a|_p \leq 1\}$.

Lemma 5.5 (Acceptance Regions). *For $p \in [1, \infty]$, let $1/p + 1/q = 1$, setting $q = 1$ if $p = \infty$ and vice-versa. Suppose $B = x + \Sigma B_p(0, 1)$, for $x \in \mathbb{R}^{d_h}$ and Σ invertible. Then $A = \epsilon B^\circ = \{a : |a'x| + |\Sigma'a|_q \leq \epsilon\}$.*

5.3 Using Pilot Data

Next, we discuss an alternative strategy that uses pilot data to specify the set B . Suppose we have access to $\mathcal{D}_{pilot} \perp\!\!\!\perp (W_{1:n}, D_{1:n})$ of size m . Suppose $\sqrt{m}(\hat{\gamma}_{pilot} - \gamma_0) \approx \mathcal{N}(0, \hat{\Sigma}_{pilot})$ for some estimator $\hat{\gamma}_{pilot}$, discussed below. Consider forming the Wald region $\hat{B}_{pilot} = \{\gamma :$

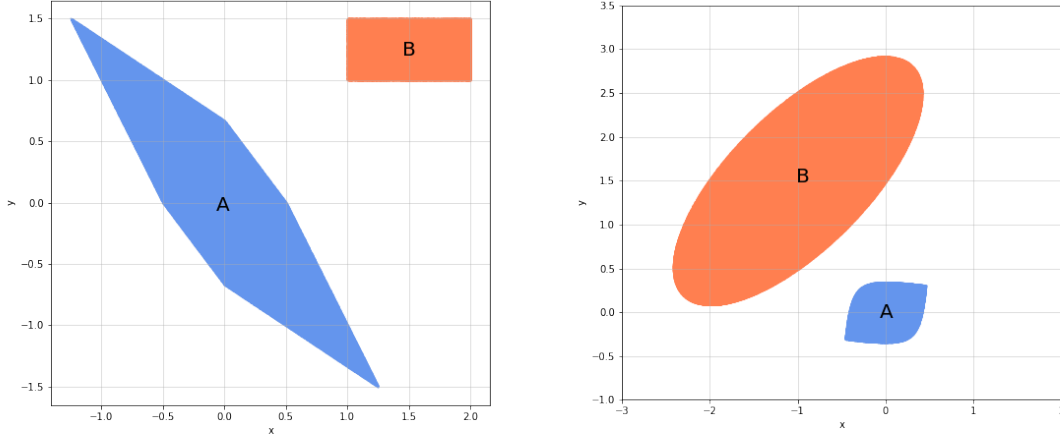


Figure 1: Prior information B and $A = \epsilon B^\circ$ for Examples 5.3 and 5.4.

$m(\hat{\gamma}_{pilot} - \gamma)' \hat{\Sigma}_{pilot}^{-1} (\hat{\gamma}_{pilot} - \gamma) \leq c_\alpha\}$ using critical value $P(\chi_{d_h}^2 \leq c_\alpha) = 1 - \alpha$ for $\alpha \in (0, 1)$. Equivalently, one can write the Wald region as

$$\hat{B}_{pilot} = \hat{\gamma} + c_\alpha^{1/2} m^{-1/2} \cdot \hat{\Sigma}_{pilot}^{1/2} B_2(0, 1). \quad (5.2)$$

Using \hat{B}_{pilot} as a prior information set, by Example 5.4 we have acceptance region

$$\hat{A}_{pilot} = \epsilon \hat{B}_{pilot}^\circ = \{a : |a' \hat{\gamma}_{pilot}| + m^{-1/2} c_\alpha^{1/2} |\hat{\Sigma}_{pilot}^{1/2} a|_2 \leq \epsilon\}. \quad (5.3)$$

Note that the acceptance region \hat{A}_{pilot} grows with the pilot size m . This reflects smaller uncertainty about the true parameter γ_0 , and thus less adversarial worst case imbalance $\sup_{\gamma \in \hat{B}_{pilot}} |\gamma' E_n[H_i h_i]|$. Conversely, \hat{A}_{pilot} shrinks as the confidence parameter α and the scale of the variance estimate $\hat{\Sigma}_{pilot}$ increases, reflecting greater uncertainty and a more conservative approach to covariate balances. Our next result shows that rerandomization with acceptance region \hat{A}_{pilot} controls the variance of the imbalance $R_A = \gamma_0' Z | Z \in \hat{A}_{pilot}$ with high probability marginally over the realizations of the pilot data. The result is an immediate consequence of Theorem 3.4 and Theorem 5.1.

Corollary 5.6 (Pilot Data). *Suppose $P(\gamma_0 \in \hat{B}_{pilot}) \geq 1 - \alpha$, for $\mathcal{D}_{pilot} \perp\!\!\!\perp (W_{1:n}, D_{1:n})$. Let $D_{1:n}$ as in Definition 2.1 with $A = \hat{A}_{pilot} = \epsilon \hat{B}_{pilot}^\circ$, then if Assumptions 3.1, 3.2 hold, then $\sqrt{n}(\hat{\theta} - \theta_n) | \mathcal{D}_{pilot} \Rightarrow v_D^{-1} \mathcal{N}(0, \text{Var}(e)) + R_A$ and $\text{Var}(R_A | \mathcal{D}_{pilot}) \leq \epsilon^2$ with probability $\geq 1 - \alpha$.*

Formally, the pilot estimate of γ_0 and Wald region could be constructed as in Robinson (1988). In practice, a simple approach suggested by the theory is to let $\hat{\gamma}_{pilot}, \hat{\Sigma}_{pilot}$ be point and variance estimators from the regression $Y_T \sim 1 + h + \psi$, for the “tyranny of

the minority” (Lin (2013)) outcomes $Y_T = (1 - p)DY/p + p(1 - D)Y/(1 - p)$, noting that $E[Y_T|W] = (1 - p)Y(1) + pY(0) = \bar{Y}$.

General Parameters. For completeness, we extend the preceding work to general parameters θ_n as in Definition 2.5. Let $\Pi\delta(W, \theta_0)$ be the assignment influence function. As in Equation 3.4, consider the partially linear decomposition

$$\Pi\delta(W, \theta_0) = \Gamma'_0 h + t_0(\psi) + e, \quad E[e|\psi] = 0, \quad E[eh] = 0.$$

Note that $e \in \mathbb{R}^{d_\theta}$ and $E[e|\psi] = 0$ is interpreted componentwise. Consider prior information sets B_j for each Γ_0^j with $1 \leq j \leq d_\theta$, where $\Gamma_0^j \in \mathbb{R}^{d_h}$ is the j th column of Γ_0 . The final result of this section bounds the asymptotic imbalance term R_A if all these prior information sets are well specified.

Theorem 5.7. *Let $D_{1:n}$ as in Definition 2.1 with $A = \cap_{j=1}^{d_\theta} \epsilon B_j^\circ$. Then $\sqrt{n}(\hat{\theta} - \theta_n)|W_{1:n} \Rightarrow \mathcal{N}(0, V_\delta) + R_A$, as defined in Theorem 3.4. If $\Gamma_0^j \in B_j \forall j$, then $\max_{j=1}^{d_\theta} \text{Var}((R_A)_{jj}) \leq \epsilon^2$.*

Note that by construction the conservative acceptance region $A = \cap_{j=1}^{d_\theta} \epsilon B_j^\circ$ is symmetric and convex.

6 Linear Adjustment

In this section, we study optimal linearly adjusted GMM estimation under stratified rerandomization. We show that this can be used to completely remove the impact of the acceptance region and imbalance term R_A to first order, restoring asymptotic normality. This allows for standard t-statistic and Wald-test based inference on the parameters θ_n and θ_0 , provided in Section 7 below. Let w denote the covariates used for ex-post adjustment and suppose $E[|w|_2^2] < \infty$.

Definition 6.1 (Adjusted GMM). Suppose that $\hat{\alpha} \xrightarrow{P} \alpha \in \mathbb{R}^{d_w \times d_g}$. Define the linearly adjusted GMM estimator $\hat{\theta}_{adj} = \hat{\theta} - E_n[H_i \hat{\alpha}' w_i]$. We refer to $\hat{\alpha}$ as the *adjustment coefficient matrix*.

First, we extend Corollary 3.5 to provide asymptotics for the adjusted GMM estimator under pure stratification ($A = \mathbb{R}^{d_h}$).

Proposition 6.2 (Linear Adjustment). *Suppose $D_{1:n}$ as in Definition 2.1 with $A = \mathbb{R}^{d_h}$. Require Assumption 3.2. Then we have $\sqrt{n}(\hat{\theta}_{adj} - \theta_n)|W_{1:n} \Rightarrow \mathcal{N}(0, V(\alpha))$ with $V(\alpha) = v_D^{-1} E[\text{Var}(\Pi\delta(W, \theta_0) - \alpha' w | \psi)]$ and $\sqrt{n}(\hat{\theta}_{adj} - \theta_0) \Rightarrow \mathcal{N}(0, V_\phi + V(\alpha))$.*

A version of this result was given in Cytrynbaum (2023) for the special case $\theta_0 = \text{ATE}$. Motivated by Proposition 6.2, we define the optimal linear adjustment coefficient as the minimizer of the asymptotic variance $V(\alpha)$, in the positive semidefinite sense.

Optimal Adjustment Coefficient. Define the coefficient

$$\alpha_0 \in \underset{\alpha \in \mathbb{R}^{d_w \times d_g}}{\operatorname{argmin}} E[\operatorname{Var}(\Pi\delta(W, \theta_0) - \alpha'w|\psi)]. \quad (6.1)$$

Note that if $w = h$ then $\alpha_0 = \Gamma_0$, as in Theorem 3.4. If $E[\operatorname{Var}(w|\psi)] \succ 0$, then the unique minimizer of Equation 6.1 is the partially linear regression coefficient $\alpha_0 = E[\operatorname{Var}(w|\psi)]^{-1}E[\operatorname{Cov}(w, \Pi\delta(W, \theta_0)|\psi)]$. The main result of this section shows that adjustment by a consistent estimate of α_0 restores asymptotic normality.

Theorem 6.3 (Adjusted GMM). *Suppose $D_{1:n}$ is as in Definition 2.1. Require Assumption 3.1, 3.2. Let $h \subseteq w$ and suppose $\hat{\alpha} \xrightarrow{p} \alpha_0$. Then $\sqrt{n}(\hat{\theta}_{adj} - \theta_n)|W_{1:n} \Rightarrow \mathcal{N}(0, V_\delta^a)$ and $\sqrt{n}(\hat{\theta}_{adj} - \theta_0) \Rightarrow N(0, V_\phi + V_\delta^a)$.*

$$V_\phi = \operatorname{Var}(\Pi\phi(W, \theta_0)) \quad V_\delta^a = \min_{\alpha \in \mathbb{R}^{d_w \times d_g}} v_D^{-1} E[\operatorname{Var}(\Pi\delta(W, \theta_0) - \alpha'w|\psi)].$$

Two-step Adjustment. For nonlinear models, the coefficient α_0 may depend on the unknown parameter θ_0 . This suggests a two-step adjustment strategy, where we

- (1) Use the unadjusted GMM estimator $\hat{\theta}$ to consistently estimate $\hat{\alpha} \xrightarrow{p} \alpha_0$.
- (2) Report the adjusted estimator $\hat{\theta}_{adj} = \hat{\theta} - E_n[H_i \hat{\alpha}' w_i]$.

Similarly to two-step efficient GMM, this process could be iterated until convergence to improve finite sample properties. One feasible estimator of the optimal coefficient α_0 is given in the following theorem. To state the result, define the within-group partialled covariates $\check{w}_i = w_i - \sum_{j \in g(i)} w_j$, where group $g(i)$ contains unit i in Definition 2.1. Let $\hat{\Pi} \xrightarrow{p} \Pi$ consistently estimate the linearization matrix and denote the score evaluation $\hat{g}_i \equiv g(D_i, X_i, S_i, \hat{\theta})$.

Theorem 6.4 (Feasible Adjustment). *Suppose $D_{1:n}$ is as in Definition 2.1. Require Assumption 3.1, 3.2. Assume that $E[\operatorname{Var}(w|\psi)] \succ 0$. Define $\hat{\alpha} = v_D E_n[\check{w}_i \check{w}_i']^{-1} E_n[H_i \check{w}_i \hat{g}_i'] \hat{\Pi}'$. Then $\hat{\alpha} = \alpha_0 + o_p(1)$.*

Remark 6.5 (One Step Adjustment). In many cases, the optimal coefficient α_0 may not depend on θ_0 at all, allowing optimal adjustment to be done in one step. For instance, whenever $\delta(W, \theta) = u(\psi, \theta) + v(W)$ for some functions u, v , then α_0 does not depend on θ_0 . This happens in Example 3.9, where we have $\delta(W, \theta) = (1 - p)Y(1) + pY(0) = \bar{Y}$. The optimal adjustment coefficient is given by $\alpha_0 = E[\operatorname{Var}(w|\psi)]^{-1}E[\operatorname{Cov}(w, \bar{Y}|\psi)]$.

Theorem 6.3 that ex-post linear adjustment can be used to remove the non-Gaussian component of the asymptotic distribution that arises due to rerandomization. In the next section, we exploit this result to provide standard t-statistic based confidence intervals for θ_n and θ_0 .

7 Inference

In this section, we provide novel methods for inference on general causal parameters under stratified rerandomization designs. We make crucial use of asymptotic normality of the optimally adjusted estimator $\hat{\theta}_{adj}$, shown in Theorem 6.3. For the superpopulation parameter θ_0 , we provide asymptotically exact inference methods. The asymptotic variance for estimating the finite population parameter θ_n is generally not identified. In this case, we provide conservative variance estimation that still reflects the precision gains due to stratification and rerandomization.

7.1 Asymptotically Exact Inference

To define our variance estimator, we begin with some definitions. Let \mathcal{G}_n denote the set of groups constructed in Definition 2.1. For each $g \in \mathcal{G}_n$ define the centroid $\bar{\psi}_g = |g|^{-1} \sum_{i \in g} \psi_i$. Let $\nu : \mathcal{G}_n \rightarrow \mathcal{G}_n$ be a bijective matching between groups satisfying $\nu(g) \neq g$, $\nu^2 = \text{Id}$, and the homogeneity condition

$$\frac{1}{n} \sum_{g \in \mathcal{G}_n} |\bar{\psi}_g - \bar{\psi}_{\nu(g)}|_2^2 = o_p(1). \quad (7.1)$$

In practice, ν is obtained by simply matching the group centroids $\bar{\psi}_g$ into pairs using the Derigs (1988) non-bipartite matching algorithm. Let $\mathcal{G}_n^\nu = \{g \cup \nu(g) : g \in \mathcal{G}_n\}$ be the unions of paired groups formed by this matching. Denote $a(g) = \sum_{i \in g} D_i$ and $k(g) = |g|$. Define the adjusted moment $\hat{m}_i \equiv \hat{\Pi} \hat{g}_i - H_i \hat{\alpha}' w_i$, where $\hat{g}_i \equiv g(D_i, X_i, Y_i, \hat{\theta}_{adj})$. Suppose that $\hat{\Pi} \xrightarrow{p} \Pi$ and $\hat{\alpha} \xrightarrow{p} \alpha_0$ for the optimal adjustment coefficient in Equation 6.1. For instance, we can use the consistent estimator provided by Theorem 6.4. Finally, define the variance estimator components

$$\begin{aligned} \hat{v}_1 &= n^{-1} \sum_{g \in \mathcal{G}_n^\nu} \frac{1}{a(g) - 1} \sum_{i \neq j \in g} \hat{m}_i \hat{m}_j' D_i D_j / p \\ \hat{v}_0 &= n^{-1} \sum_{g \in \mathcal{G}_n^\nu} \frac{1}{(k - a)(g) - 1} \sum_{i \neq j \in g} \hat{m}_i \hat{m}_j' (1 - D_i)(1 - D_j) / (1 - p) \\ \hat{v}_{10} &= n^{-1} \sum_{g \in \mathcal{G}_n} \frac{k}{a(k - a)}(g) \sum_{i, j \in g} \hat{m}_i \hat{m}_j' D_i (1 - D_j). \end{aligned}$$

Using these terms, construct the variance estimator

$$\hat{V} = \text{Var}_n(\hat{m}_i) - v_D(\hat{v}_1 + \hat{v}_0 - \hat{v}_{10} - \hat{v}_{10}'). \quad (7.2)$$

We require a slight strengthening of our GMM assumptions 3.2.

Assumption 7.1. *There exists $\theta_0 \in U \subseteq \Theta$ open s.t. $E[\sup_{\theta \in U} |\partial/\partial\theta' g_d(W, \theta)|_F^2] < \infty$.*

Under this condition, we can state our first inference result, showing consistent estimation of the asymptotic variance matrix in Theorem 6.3.

Theorem 7.2 (Inference). *Suppose $D_{1:n}$ is as in Definition 2.1, and impose Assumptions 3.1, 3.2, 7.1. Then $\widehat{V} \xrightarrow{P} V_\phi + V_\delta^a$.*

By Theorem 6.3, $\sqrt{n}(\widehat{\theta}_{adj} - \theta_0) \Rightarrow N(0, V_\phi + V_\delta^a)$. Then the variance estimation result above allows for joint inference on θ_0 using e.g. standard Wald-test or t-statistic based confidence regions.

7.2 Inference on the Finite Population Parameter

In this section, we provide asymptotically conservative inference on linear contrasts of the finite population parameter $c'\theta_n$.

As noted above, the asymptotic variance V_δ^a in Theorem 6.3 for estimating the finite population parameter θ_n is generically not identified. This happens because it depends on terms of the form $\text{Var}(\delta|\psi) \propto \text{Var}(g_1|\psi) + \text{Var}(g_0|\psi) - 2\text{Cov}(g_1, g_0|\psi)$, with $g_d = g(d, X, S(d), \theta_0)$. However, $S(1)$ and $S(0)$ are never simultaneously observed (Neyman (1990)), so $\text{Cov}(g_1, g_0|\psi)$ is generically not identified. We work with linear contrasts $c'\theta_n$ since this allows us to tighten our upper bounds on the (non-identified) variance. To do so, let $\widehat{u}_1 = E_n[\frac{D_i}{p}\widehat{m}_i\widehat{m}_i'] - \widehat{v}_1$ and $\widehat{u}_0 = E_n[\frac{1-D_i}{1-p}\widehat{m}_i\widehat{m}_i'] - \widehat{v}_0$ using the estimator components above and consider the variance estimator

$$\widehat{V}_\delta(c) = v_D([c'\widehat{u}_1c]^{1/2} + [c'\widehat{u}_0c]^{1/2})^2. \quad (7.3)$$

By Theorem 6.3, we have $\sqrt{n}(c'\widehat{\theta}_{adj} - c'\theta_n)|W_{1:n} \Rightarrow \mathcal{N}(0, c'V_\delta^a c)$. Our next result shows how to consistently estimate an upper bound on this asymptotic variance.

Theorem 7.3 (Inference). *Suppose $D_{1:n}$ as in Definition 2.1 and impose Assumptions 3.1, 3.2, 7.1. Then $\widehat{V}_\delta(c) \xrightarrow{P} \bar{V}_\delta(c) \geq c'V_\delta^a c$.*

The variance upper bound $\bar{V}_\delta(c) \geq c'(V_\phi + V_\delta^a)c$, so the confidence intervals derived from this approach are always weakly shorter than those using the variance estimator in Equation 7.2. See Section 8.6 in the appendix for an explicit comparison. The upper bound $\bar{V}_\delta(c)$ incorporates the efficiency gains from stratification, rerandomization, and adjustment. However, this upper bound is generally not sharp (Aronow et al. (2014)). We leave sharp upper bounds on the asymptotic variance matrix V_δ^a to future work.

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8 Proofs

8.1 Rerandomization Asymptotics

Before studying rerandomization, we first establish a CLT for pure stratified designs, conditional on the data $W_{1:n}$.

Theorem 8.1 (CLT). *Suppose $E[|\delta(W)|_2^2] < \infty$. Define $\mathcal{F}_n = \sigma(W_{1:n}, \pi_n)$. Let $D_{1:n}$ as in part (1) of Definition 2.1. Then $X_n \equiv \sqrt{n}E_n[H_i\delta(W_i)]$ has $X_n|\mathcal{F}_n \Rightarrow \mathcal{N}(0, V)$. In particular, for each $t \in \mathbb{R}^{d_\delta}$ we have $E[e^{it'X_n}|\mathcal{F}_n] = \phi(t) + o_p(1)$ with $\phi(t) = e^{-t'Vt/2}$ and $V = v_D^{-1}E[\text{Var}(\delta|\psi)]$.*

Proof. First consider the case $d_g = 1$. Define $u_i = \delta_i - E[\delta_i|\psi_i]$. By Lemma A.3 in Cytrynbaum (2024), since $E[\delta_i^2] < \infty$ we have $\sqrt{n}E_n[(D_i - p)E[\delta_i|\psi_i]] = o_p(1)$. Then it suffices to study $\sqrt{n}E_n[(D_i - p)u_i]$. To do so, we will use a martingale difference sequence (MDS) CLT. Fix an ordering $l = 1, \dots, n/k$ of $g(l) \in \mathcal{G}_n$, noting that $|\mathcal{G}_n| \leq n/k$. Define $D_{g(l)} = (D_i)_{i \in g(l)}$. Define $\mathcal{H}_{0,n} = \mathcal{F}_n$ and $\mathcal{H}_{j,n} = \sigma(\mathcal{F}_n, D_{g(l)}, l \in [j])$ for $j \geq 1$. Define $D_{l,n} = n^{-1/2} \sum_{i \in g(l)} (D_i - p)u_i$ and $S_{j,n} = \sum_{i=1}^j D_{i,n}$.

(1) We claim that $(S_{j,n}, \mathcal{H}_{j,n})_{j \geq 1}$ is an MDS. Adaptation is clear from our definitions.

$$\begin{aligned} E[(D_i - p)\mathbf{1}(i \in g(j))|\mathcal{H}_{j-1,n}] &= E[(D_i - p)\mathbf{1}(i \in g(j))|\mathcal{F}_n, (D_{g(l)})_{l=1}^{j-1}] \\ &= E[(D_i - p)\mathbf{1}(i \in g(j))|\mathcal{F}_n] = E[(D_i - p)|\mathcal{F}_n]\mathbf{1}(i \in g(j)) = 0. \end{aligned}$$

The second equality since $D_{g(j)} \perp\!\!\!\perp (D_{g(l)})_{l \neq j}|\mathcal{F}_n$. Then we compute $E[Z_{j,n}|\mathcal{H}_{j-1,n}] = n^{-1/2} \sum_{i \in g(l)} u_i E[(D_i - p)|\mathcal{H}_{j-1,n}] = 0$. This shows the MDS property.

(2). Next, we compute the variance process. By the same argument in (1), we have

$$\sigma_n^2 \equiv \sum_{j=1}^{n/k} E[Z_{j,n}^2|\mathcal{H}_{j-1,n}] = n^{-1} \sum_{j=1}^{n/k} \left(\sum_{s \neq t \in g(j)} u_s u_t \text{Cov}(D_s, D_t|\mathcal{F}_n) + \sum_{i \in g(j)} u_i^2 \text{Var}(D_i|\mathcal{F}_n) \right)$$

By Lemma C.10 of Cytrynbaum (2024), we have $\text{Cov}(D_s, D_t|\mathcal{F}_n)\mathbf{1}(s, t \in g(l)) = -a(k - a)/k^2(k - 1) \equiv c$ and $\text{Var}(D_i|\mathcal{F}_n) = p - p^2$. Then we may expand σ_n^2 as

$$cn^{-1} \sum_{j=1}^{n/k} \sum_{s \neq t \in g(j)} u_s u_t + (p - p^2)E_n[u_i^2] \equiv cn^{-1} \sum_{j=1}^{n/k} v_j + (p - p^2)E_n[u_i^2] \equiv T_{n1} + T_{n2}.$$

First consider T_{n1} . Our plan is to apply the WLLN in Lemma C.7 of Cytrynbaum (2024) to show $T_{n1} = o_p(1)$. Define $\mathcal{F}_n^\psi = \sigma(\psi_{1:n}, \pi_n)$ so that $\mathcal{G}_n \in \mathcal{F}_n^\psi$. For $s \neq t$ we have $E[u_s u_t|\psi_{1:n}, \pi_n] = E[u_s E[u_t|\psi_{1:n}, u_s, \pi_n]|\psi_{1:n}, \pi_n] = E[u_s E[u_t|\psi_t]|\psi_{1:n}, \pi_n] = 0$. The second equality follows by applying $(A, B) \perp\!\!\!\perp C \implies A \perp\!\!\!\perp C|B$ with $A = u_t$, $B = \psi_t$ and $C = (\psi_{-t}, u_s, \pi_n)$. Then $E[v_j|\mathcal{F}_n^\psi] = 0$ for $j \in [n/k]$. Next, observe that for

any positive constants $(a_k)_{k=1}^m$ we have $\sum_k a_k \mathbf{1}(\sum_k a_k > c) \leq m \sum_k a_k \mathbf{1}(a_k > c/m)$ and $ab \mathbf{1}(ab > c) \leq a^2 \mathbf{1}(a^2 > c) + b^2 \mathbf{1}(b^2 > c)$. Then for $c_n \rightarrow \infty$ with $c_n = o(\sqrt{n})$ we have

$$\begin{aligned} |v_j| \mathbf{1}(|v_j| > c_n) &\leq \sum_{s \neq t \in g(j)} |u_s u_t| \mathbf{1} \left(\sum_{s \neq t \in g(j)} |u_s u_t| > c_n \right) \\ &\leq k^2 \sum_{s \neq t \in g(j)} |u_s u_t| \mathbf{1}(|u_s u_t| > c_n/k^2) \leq 2k^3 \sum_{s \in g(j)} u_s^2 \mathbf{1}(u_s^2 > c_n/k^2). \end{aligned}$$

Then we have

$$n^{-1} E \left[\sum_{j=1}^{n/k} E[|v_j| \mathbf{1}(|v_j| > c_n) | \mathcal{F}_n^\psi] \right] \leq 2k^3 E_n [E[u_i^2 \mathbf{1}(u_i^2 > c_n/k^2) | \psi_{1:n}, \pi_n]] \equiv A_n.$$

Then $E[A_n] = 2k^3 E[E_n[E[u_i^2 \mathbf{1}(u_i^2 > c_n/k^2) | \psi_i]]] = 2k^3 E[u_i^2 \mathbf{1}(u_i^2 > c_n/k^2)] \rightarrow 0$ as $n \rightarrow \infty$. The first equality is by the conditional independence argument above, the second equality is tower law, and the limit by dominated convergence since $E[u_i^2] \leq E[\delta_i^2] < \infty$ by the contraction property of conditional expectation. Then $A_n = o_p(1)$ by Markov inequality. The conclusion $cn^{-1} \sum_{j=1}^{n/k} v_j = o_p(1)$ now follows by Lemma C.7 of [Cytrynbaum \(2024\)](#). For T_{n2} , we have $E_n[u_i^2] \xrightarrow{p} E[u_i^2] = E[\text{Var}(\delta | \psi)]$ by vanilla WLLN. Then we have shown $\sigma_n^2 \xrightarrow{p} (p - p^2) E[\text{Var}(\delta | \psi)]$.

(3) Finally, we show the Lindberg condition $\sum_{j=1}^{n/k} E[Z_{j,n}^2 \mathbf{1}(|Z_{j,n}| > \epsilon) | \mathcal{H}_{0,n}] = o_p(1)$.

$$\begin{aligned} Z_{j,n}^2 \mathbf{1}(|Z_{j,n}| > \epsilon) &= Z_{j,n}^2 \mathbf{1}(Z_{j,n}^2 > \epsilon^2) \leq n^{-1} \sum_{s,t \in g(j)} |u_s u_t| \mathbf{1} \left(n^{-1} \sum_{s,t \in g(j)} |u_s u_t| > \epsilon^2 \right) \\ &\leq k^2 n^{-1} \sum_{s,t \in g(j)} |u_s u_t| \mathbf{1}(|u_s u_t| > n\epsilon^2/k^2) \leq k^3 n^{-1} \sum_{s \in g(j)} u_s^2 \mathbf{1}(u_s^2 > n\epsilon^2/k^2). \end{aligned}$$

Then using the inequality above we compute

$$\begin{aligned} E \left[\sum_{j=1}^{n/k} E[Z_{j,n}^2 \mathbf{1}(|Z_{j,n}| > \epsilon) | \mathcal{H}_{0,n}] \right] &\leq k^3 E \left[n^{-1} \sum_{j=1}^{n/k} \sum_{s \in g(j)} E[u_s^2 \mathbf{1}(u_s^2 > n\epsilon^2/k^2) | \mathcal{F}_n^\psi] \right] \\ &= k^3 E [E_n [E[u_i^2 \mathbf{1}(u_i^2 > n\epsilon^2/k^2) | \psi_i]]] = k^3 E [u_i^2 \mathbf{1}(u_i^2 > n\epsilon^2/k^2)] = o(1). \end{aligned}$$

The first equality by the conditional independence argument above. The second equality by dominated convergence. Then $\sum_{j=1}^{n/k} E[Z_{j,n}^2 \mathbf{1}(|Z_{j,n}| > \epsilon) | \mathcal{H}_{0,n}] = o_p(1)$ by Markov. This finishes the proof of the Lindberg condition. Since $\mathcal{H}_{0,n} = \mathcal{F}_n$, by Theorem C.4 in [Cytrynbaum \(2024\)](#), we have shown that $E[e^{it\sqrt{n}E_n[(D_i - p)\delta_i]} | \mathcal{F}_n] = \phi(t) + o_p(1)$ for $\phi(t) = e^{-t^2 V/2}$ with $V = (p - p^2) E[\text{Var}(\delta | \psi)]$.

Finally, consider $\dim(\delta) \geq 1$. Fix $t \in \mathbb{R}^{d_g}$ and let $\bar{\delta}(W_i) = t' \delta(W_i) \in \mathbb{R}$. Then we

have $X_n(t) \equiv X'_n t = E_n[(D_i - p)\delta(W_i)]'t = E_n[(D_i - p)\delta(W_i)'t] = E_n[(D_i - p)\bar{\delta}(W_i)]$. By the previous result $E[e^{iX_n(t)}|\mathcal{F}_n] \xrightarrow{p} e^{-v(t)/2}$ with variance $v(t) = E[\text{Var}(\bar{\delta}|\psi)] = E[\text{Var}(t'\delta|\psi)] = t'E[\text{Var}(\delta|\psi)]t = t'Vt$. Then we have shown $E[e^{it'X_n}|\mathcal{F}_n] = e^{-t'Vt/2} + o_p(1)$ as claimed. \square

Next, we provide asymptotic theory for stratified rerandomization. The following definition generalizes Definition 2.1 in Section 1.

Definition 8.2 (Rerandomization). Consider the following:

- (a) Suppose $\mathcal{I}_n = \sqrt{n}\hat{\Delta}_h + o_p(1)$ for $\hat{\Delta}_h = E_n[H_i h_i]$. Let $\tau_n = \tau + o_p(1)$ for $\tau \in \mathbb{R}^{d_\tau}$ and define sample and population acceptance regions $T_n = \{x : a(x, \tau_n) \leq 0\}$ and $T = \{x : a(x, \tau) \leq 0\}$ for $a(z, y)$ a measurable function.
- (b) (Assumptions). Assume $P(a(Z_h, \tau) = 0) = 0$ for $Z_h \sim \mathcal{N}(0, E[\text{Var}(h|\psi)])$. Require $P(Z_h \in T) > 0$. Suppose $E[|\delta|_2^2 + |\phi|_2^2 + |h|_2^2] < \infty$.
- (c) (Rerandomization). Let $\mathcal{F}_n = \sigma(W_{1:n}, \pi_n)$, where $\pi_n \perp\!\!\!\perp W_{1:n}$ and define the rerandomization measure $Q(B|\mathcal{F}_n) = P(B|\mathcal{F}_n, \mathcal{I}_n \in T_n)$ and $Q(B) = E[Q(B|\mathcal{F}_n)]$ for any event B .

Lemma 8.3. Let Definition 8.2 hold. Let $\hat{\Delta}_\delta = E_n[H_i \delta_i]$ and $\rho = (\delta, h)$. Fix $t \in \mathbb{R}^{d_\delta}$. Let $(Z_\delta, Z_h) \sim \mathcal{N}(0, \Sigma)$ for $\Sigma = v_D^{-1}E[\text{Var}(\rho|\psi)]$. Then

$$E \left[e^{it'\sqrt{n}\hat{\Delta}_\delta} \mathbf{1}(\mathcal{I}_n \in T_n) | \mathcal{F}_n \right] = E \left[e^{it'Z_\delta} \mathbf{1}(Z_h \in T) \right] + o_p(1).$$

Proof. (1). Define $B_n = (\sqrt{n}\hat{\Delta}_\delta, \mathcal{I}_n, \tau_n)$. Fix $t = (t_1, t_2, t_3) \in \mathbb{R}^{d_g + d_h + d_\tau}$ and consider the characteristic function

$$\begin{aligned} \phi_{B_n}(t) &= E[e^{it'_1 \sqrt{n}\hat{\Delta}_\delta + it'_2 \mathcal{I}_n + it'_3 \tau_n} | \mathcal{F}_n] = e^{it'_3 \tau} E[e^{it'_1 \sqrt{n}\hat{\Delta}_\delta + it'_2 \mathcal{I}_n} | \mathcal{F}_n] + o_p(1) \\ &= e^{it'_3 \tau} E[e^{it'_1 \sqrt{n}\hat{\Delta}_\delta + it'_2 \sqrt{n}\hat{\Delta}_h} | \mathcal{F}_n] + o_p(1) = e^{it'_3 \tau} e^{-t'\Sigma t/2} + o_p(1) = \phi_B(t) + o_p(1). \end{aligned}$$

For the second equality, note that $e^{it'_3 \tau_n} \xrightarrow{p} e^{it'_3 \tau}$ by continuous mapping. Then $R_n = e^{it'_1 \sqrt{n}\hat{\Delta}_\delta + it'_2 \sqrt{n}\hat{\Delta}_h} (e^{it'_3 \tau_n} - e^{it'_3 \tau}) = o_p(1)$. Clearly $|R_n| \leq 2$, so $E[|R_n||\mathcal{F}_n] = o_p(1)$ by Lemma 8.14. The third equality is identical, noting that $e^{it'_2 \mathcal{I}_n} \xrightarrow{p} e^{it'_2 \sqrt{n}\hat{\Delta}_h}$ again by continuous mapping. The fourth equality is Theorem 8.1 applied to $\sqrt{n}E_n[H_i \rho_i]$. The final expression is the characteristic function of $B = (Z_\delta, Z_h, \tau)$ with $(Z_\delta, Z_h) \sim \mathcal{N}(0, \Sigma)$. Then we have shown that $B_n|\mathcal{F}_n \Rightarrow B$ in the sense of Proposition 8.11. Fix $t \in \mathbb{R}$ and define $G(z_1, z_2, x) = e^{it'z_1} \mathbf{1}(a(z_2, x) \leq 0)$ and note that

$$G(B_n) = e^{it'\sqrt{n}\hat{\Delta}_\delta} \mathbf{1}(a(\mathcal{I}_n, \tau_n) \leq 0) = e^{it'\sqrt{n}\hat{\Delta}_\delta} \mathbf{1}(\mathcal{I}_n \in T_n).$$

Define $E_G = \{w : G(\cdot)$ not continuous at $w\}$. By Proposition 8.11, if $P(B \in E_G) = 0$

then $E[G(B_n)|\mathcal{F}_n] = E[G(B)] + o_p(1) = E[G(Z_\delta, Z_h, \tau)] + o_p(1)$, which is the required claim.

To finish the proof, we show that $P(B \in E_G) = 0$. Write $G(z_1, z_2, x) = f(z_1)g(z_2, x)$ for $f(z_1) = e^{it'z_1}$ and $g(z_2, x) = \mathbb{1}(a(z_2, x) \leq 0)$ and define discontinuity point sets E_f and E_g as for E_G above. By continuity of multiplication for bounded functions, if $z_1 \in E_f^c$ and $(z_2, x) \in E_g^c$ then $(z_1, z_2, x) \in E_G^c$. By contrapositive,

$$E_G \subseteq (E_f \times \mathbb{R}^{d_h+d_\tau}) \cup (\mathbb{R} \times E_g).$$

Clearly $E_f = \emptyset$, so $P(B \in E_G) = P((Z_h, \tau) \in E_g)$. Let $E_g^1 = \{z_h : (z_h, \tau) \in E_g\}$. We have $(Z_h, \tau) \in \mathbb{R}^{d_h} \times \{\tau\}$. Then $P((Z_h, \tau) \in E_g) = P(Z_h \in E_g^1)$. Since $z_h \rightarrow a(z_h, \tau)$ is continuous, $\{z_h : a(z_h, \tau) > 0\}$ is open. Let $z_h \in \{z_h : a(z_h, \tau) > 0\}$. Then for small enough r , if $z' \in B(z_h, r)$ then $a(z', \tau) > 0$ and $g(z', \tau) = 0$, so $g(z', \tau) - g(z_h, \tau) = 0$, so z_h is a continuity point. A similar argument applied to $z_h \in \{z_h : a(z_h, \tau) < 0\}$ shows that the discontinuity points $E_g^1 \subseteq \{z_h : a(z_h, \tau) = 0\}$. \square

Theorem 8.4 (Asymptotic Distribution). *Let Definition 8.2 hold. Suppose that $(Z_\delta, Z_h) \sim v_D^{-1}E[\text{Var}((\delta, h)|\psi)]$. The following hold*

(a) *We have $\sqrt{n}E_n[H_i\delta(W_i)]|\mathcal{F}_n \Rightarrow Z_\delta|Z_h \in T = \mathcal{N}(0, V_\delta) + R$, independent RV's s.t.*

$$V_\delta = v_D^{-1}E[\text{Var}(\delta(W) - \Gamma'_0 h|\psi)] = \min_{\Gamma \in \mathbb{R}^{d_h \times d_\theta}} v_D^{-1}E[\text{Var}(\delta(W) - \Gamma' h|\psi)].$$

The residual term $R \sim \Gamma'_0 Z_h | Z_h \in T$.

(b) *Let $X_n = E_n[\phi(W_i)] + E_n[H_i\delta(W_i)]$. Then we have*

$$\sqrt{n}(X_n - E[\phi(W)]) \Rightarrow Z_\phi + Z_\delta|Z_h \in T = \mathcal{N}(0, V_\phi) + \mathcal{N}(0, V_\delta) + R.$$

The RV's are independent with $V_\phi = \text{Var}(\phi(W))$.

Proof. First, we prove (a). Let $\hat{\Delta}_\delta = E_n[H_i\delta(W_i)]$. Let $t \in \mathbb{R}^{d_\delta}$. By definition of Q

$$E_Q \left[e^{it' \sqrt{n} \hat{\Delta}_\delta} | \mathcal{F}_n \right] = E \left[e^{it' \sqrt{n} \hat{\Delta}_\delta} | \mathcal{I}_n \in T_n, \mathcal{F}_n \right] = \frac{E \left[e^{it' \sqrt{n} \hat{\Delta}_\delta} \mathbb{1}(\mathcal{I}_n \in T_n) | \mathcal{F}_n \right]}{P(\mathcal{I}_n \in T_n | \mathcal{F}_n)} \equiv \frac{a_n}{b_n}.$$

Define $a_\infty = E \left[e^{it' Z_\delta} \mathbb{1}(Z_h \in T) \right]$ and $b_\infty = P(Z_h \in T)$. By Lemma 8.3, $a_n \xrightarrow{p} a_\infty$ and $b_n \xrightarrow{p} b_\infty$, with $b_\infty > 0$ by assumption in Definition 8.2. Then we have $b_n^{-1} = O_p(1)$. Then $|a_n/b_n - a_\infty/b_\infty|$ may be expanded as $\left| \frac{a_n b_\infty - a_\infty b_n}{b_n b_\infty} \right| = O_p(1) |(a_n - a_\infty)b_\infty + a_\infty(b_\infty - b_n)| \lesssim_P |a_n - a_\infty| + |b_\infty - b_n| = o_p(1)$. The final equality by Lemma 8.3. Then we have shown

$$E_Q \left[e^{it' A_n} | \mathcal{F}_n \right] = \frac{a_\infty}{b_\infty} + o_p(1) = \frac{E \left[e^{it' Z_\delta} \mathbb{1}(Z_h \in T) \right]}{P(Z_h \in T)} = E[e^{it' Z_\delta} | Z_h \in T] + o_p(1).$$

This proves the first statement. Next, we characterize the law of $Z_\delta | Z_h \in T$. Define $\phi(t) \equiv E[e^{it'Z_\delta} | Z_h \in T]$. Let $\Gamma_0 \in \mathbb{R}^{d_h \times d_g}$ satisfy the normal equations $E[\text{Var}(h|\psi)]\Gamma_0 = E[\text{Cov}(h, \delta|\psi)]$. Such a Γ_0 exists and satisfies the stated inequality by Lemma 8.12. Letting $\tilde{Z}_\delta = Z_\delta - \Gamma'_0 Z_h$, by Lemma 8.12 $\tilde{Z}_\delta \perp\!\!\!\perp Z_h$ and \tilde{Z}_δ is Gaussian. Then $\tilde{Z}_\delta \perp\!\!\!\perp (Z_h, \mathbf{1}(Z_h \in T))$. Recall that $A \perp\!\!\!\perp (S, T) \implies A \perp\!\!\!\perp S | T$. Using this fact, we have $\tilde{Z}_\delta \perp\!\!\!\perp Z_h | Z_h \in T$. Then for any $t \in \mathbb{R}^{d_g}$

$$\begin{aligned}\phi(t) &= E[e^{it'Z_\delta} | Z_h \in T] = E[e^{it'\tilde{Z}_\delta} e^{it'\Gamma'_0 Z_h} | Z_h \in T] \\ &= E[e^{it'\tilde{Z}_\delta} | Z_h \in T] E[e^{it'\Gamma'_0 Z_h} | Z_h \in T] = E[e^{it'\tilde{Z}_\delta}] E[e^{it'\Gamma'_0 Z_h} | Z_h \in T].\end{aligned}$$

By Proposition 8.11, we have shown $Z_\delta | Z_h \in T \stackrel{d}{=} \tilde{Z}_\delta + [\Gamma'_0 Z_h | Z_h \in T]$, where the RHS is a sum of independent random variables with the given distributions. Clearly $E[\tilde{Z}_\delta] = 0$ and $\text{Var}(\tilde{Z}_\delta) = v_D^{-1} E[\text{Var}(\delta - \Gamma'_0 h | \psi)]$. This finishes the proof of (a).

Next we prove (b). We may expand $\sqrt{n}(X_n - E[\phi(W)]) = \sqrt{n}(E_n[\phi(W_i)] - E[\phi(W)]) + \sqrt{n}\hat{\Delta}_\delta \equiv A_n + B_n$. We have $A_n \Rightarrow \mathcal{N}(0, V_\phi)$ with $V_\phi = \text{Var}(\phi(W))$ by vanilla CLT. Then let $t \in \mathbb{R}^{d_\delta}$ and calculate

$$E_Q[e^{it'X_n}] = E_Q[e^{it'A_n} E_Q[e^{it'B_n} | \mathcal{F}_n]] = \phi(t) E_Q[e^{it'A_n}] + o(1) = \phi(t) e^{-t'V_\phi t/2} + o(1).$$

The first equality since $A_n \in \mathcal{F}_n$. The second equality since

$$\left| E_Q[e^{it'A_n} (E_Q[e^{it'B_n} | \mathcal{F}_n] - \phi(t))] \right| \leq E_Q[|E_Q[e^{it'B_n} | \mathcal{F}_n] - \phi(t)|] = o(1).$$

To see this, note that the integrand is $o_p(1)$ by our work above. It is also bounded so it converges to zero in $L_1(Q)$ by Lemma 8.14. The final equality since $A_n \in \mathcal{F}_n = \sigma(W_{1:n}, \pi_n)$ and the marginal distribution of $(W_{1:n}, \pi_n)$ is identical under P and Q by definition. Then $E_Q[e^{it'A_n}] = E_P[e^{it'A_n}] = e^{-t'V_\phi t/2} + o(1)$ by vanilla CLT. Then we have shown

$$E_Q[e^{it'X_n}] = e^{-t'(V_\phi + V_\delta)t/2} E[e^{it'\Gamma'_0 Z_h} | Z_h \in B] + o(1).$$

This finishes the proof of (b). \square

Lemma 8.5 (Linearization). *Suppose Definition 8.2 and Assumption 3.2 hold. Let $\Pi = -(G'MG)^{-1}G'M$. Then $\sqrt{n}(\hat{\theta} - \theta_n) = \sqrt{n}E_n[H_i\Pi\delta(W_i, \theta_0)] + o_p(1)$ and $\sqrt{n}(\hat{\theta} - \theta_0) = \sqrt{n}E_n[\Pi\phi(W_i, \theta_0) + H_i\Pi\delta(W_i, \theta_0)] + o_p(1)$.*

See Section 8.2 below for the proof of this lemma.

Proof of Theorem 3.4. We claim that the conditions of Definition 8.2 hold. This will allow us to apply our general rerandomization asymptotics in Theorem 8.4 and linearization in Lemma 8.5. To check part (a), define $a(x, y) = a(x) = d(x, A) - d(x, A^c)$, where $d(x, A) = \inf_{s \in \mathbb{R}^{d_h}} |x - s|_2$. It's well known that $x \rightarrow d(x, S)$ is continuous for any set S , so

a is continuous. The sample and population regions $T_n = T = \{x : a(x) \leq 0\}$. If $a(x) \leq 0$ then $d(x, A) = 0$, so $x \in A \cup \partial A \subseteq A$ by closedness. If $a(x) > 0$ then $x \notin A$. This shows $T_n = A$, so $\{\mathcal{I}_n \in T_n\} = \{\mathcal{I}_n \in A\}$. Then our criterion is of the form in Definition 8.2. For part (b), $P(a(Z_h) = 0) = P(Z_h \in \partial A) = 0$ since $\text{Leb}(\partial A) = 0$ and by absolute continuity of Z_h relative to Lebesgue measure Leb . We also have $P(Z_h \in T) = P(Z_h \in A) > 0$ since Z_h is full measure by $E[\text{Var}(h|\psi)] \succ 0$ and since A has non-empty interior.

This proves the claim. Then by Lemma 8.5, $\sqrt{n}(\hat{\theta} - \theta_n) = \sqrt{n}E_n[H_i \Pi \delta(W_i, \theta_0)] + o_p(1)$. The result now follows immediately by Slutsky and Theorem 8.4(a), letting $\delta \rightarrow \Pi \delta$. Likewise, Corollary 3.8 follows from Theorem 8.4(b), letting $\phi \rightarrow \Pi \phi$. \square

Proof of Corollary 3.5. By Theorem 3.4, since $A = \mathbb{R}^{d_h}$ we have $\sqrt{n}(\hat{\theta} - \theta_n)|_{W_{1:n}} \Rightarrow \mathcal{N}(0, V_\delta) + R$, independent RV's with $V_\delta = v_D^{-1}E[\text{Var}(\Pi \delta(W, \theta_0) - \Gamma'_0 h|\psi)]$ and $R \sim \Gamma'_0 Z_h$ for $Z_h \sim \mathcal{N}(0, v_D^{-1}E[\text{Var}(h|\psi)])$. Then $\mathcal{N}(0, V_\delta) + R \sim \mathcal{N}(0, V)$ with $V = V_\delta + \text{Var}(\Gamma'_0 Z_h) = v_D^{-1}E[\text{Var}(\Pi \delta(W, \theta_0) - \Gamma'_0 h + \Gamma'_0 h|\psi)] - 2v_D^{-1}E[\text{Cov}(\Pi \delta(W, \theta_0) - \Gamma'_0 h, \Gamma'_0 h|\psi)] = v_D^{-1}E[\text{Var}(\Pi \delta(W, \theta_0)|\psi)]$. The covariance term is zero by Lemma 8.12. The second statement follows by setting $\psi = 1$. \square

8.2 GMM Linearization

This section collects proofs needed for the key linearization result in Lemma 8.5. First, define the following curves and objective functions

$$\begin{aligned} g_0(\theta) &= E[\phi(W_i, \theta)], \quad g_n(\theta) = E_n[\phi(W_i, \theta)], \quad \hat{g}(\theta) = E_n[\phi(W_i, \theta)] + E_n[H_i \delta(W_i, \theta)]. \\ H_0(\theta) &= g_0(\theta)' M' g_0(\theta), \quad H_n(\theta) = g_n(\theta)' M' g_n(\theta), \quad \hat{H}(\theta) = \hat{g}(\theta)' M'_n \hat{g}(\theta) \end{aligned}$$

Define $\hat{G}(\theta) = (\partial/\partial\theta')\hat{g}(\theta)$ and $G_n(\theta) = (\partial/\partial\theta')g_n(\theta)$ and $G_0(\theta) = (\partial/\partial\theta')g_0(\theta)$. Define $G = G_0(\theta_0)$. For each $d \in \{0, 1\}$, define $g_d(W, \theta) = g(d, X, S(d), \theta)$.

Lemma 8.6. *Require Assumption 3.2. Then we have*

- (a) (ULLN). $\|\hat{g} - g_0\|_{\infty, \Theta} = o_p(1)$, $\|g_n - g_0\|_{\infty, \Theta} = o_p(1)$, and $g_0(\theta)$ is continuous. This implies objectives $|H_n - H_0|_{\infty, \Theta} = o_p(1)$ and $|\hat{H} - H_0|_{\infty, \Theta} = o_p(1)$.
- (b) (Consistency). We have $\hat{\theta} - \theta_0 = o_p(1)$ and $\theta_n - \theta_0 = o_p(1)$.
- (c) There is an open ball $U \subseteq \Theta$ with $\theta_0 \in U$ and $\|\hat{G}_n - G_0\|_{\infty, U} = o_p(1)$ and $\|G_n - G_0\|_{\infty, U} = o_p(1)$. Also, $G_0(\theta)$ is continuous on U for $G_0(\theta) = \partial/\partial\theta' E[\phi(W, \theta)]$.

Proof. Consider (a). First we show $\|\hat{g} - g_0\|_{\infty, \Theta} = o_p(1)$. It suffices to prove the statement componentwise. Then without loss assume $d_g = 1$ and fix $\epsilon > 0$. Note also that ϕ, δ are linear combinations of g_d for $d \in \{0, 1\}$, so ϕ and δ inherit the properties in Assumption 3.2. We have $(p - p^2)(\hat{g} - g_n)(\theta) = E_n[(D_i - p)\delta(W_i, \theta)] \equiv E_n[v_i(\theta)]$. For each $\theta \in K$

define $U_{\theta m} = B(\theta, m^{-1})$ and $\bar{v}_{\theta m}(D_i, W_i) = \sup_{\bar{\theta} \in U_{\theta m}} v_i(\bar{\theta})$. Then $\bar{v}_{\theta m}(D_i, W_i)$ may be expanded

$$\begin{aligned} \sup_{\bar{\theta} \in U_{\theta m}} (D_i - p)\delta(W_i, \bar{\theta}) &= (1 - p)D_i \sup_{\bar{\theta} \in U_{\theta m}} \delta(W_i, \bar{\theta}) + p(1 - D_i) \sup_{\bar{\theta} \in U_{\theta m}} -\delta(W_i, \bar{\theta}) \\ &= (p - p^2) \left(\sup_{\bar{\theta} \in U_{\theta m}} \delta(W_i, \bar{\theta}) + \sup_{\bar{\theta} \in U_{\theta m}} -\delta(W_i, \bar{\theta}) \right) \\ &\quad + (D_i - p) \left((1 - p) \sup_{\bar{\theta} \in U_{\theta m}} \delta(W_i, \bar{\theta}) + p \inf_{\bar{\theta} \in U_{\theta m}} \delta(W_i, \bar{\theta}) \right) \equiv f_{\theta m}(W_i) + (D_i - p)r_{\theta m}(W_i). \end{aligned}$$

In particular, $E[\bar{v}_{\theta m}(X_i)] = E[f_{\theta m}(W_i)]$. Note both expectations exist by the envelope condition in Assumption 3.2. By continuity at θ , $f_{\theta m}(W_i) \rightarrow (p - p^2)(\delta(W_i, \theta) - \delta(W_i, \theta)) = 0$ as $m \rightarrow \infty$. Also $|f_{\theta m}(W_i)| \lesssim \sup_{\bar{\theta} \in U_{\theta m}} |\delta(W_i, \bar{\theta})| \leq \sup_{\theta \in \Theta} |\delta(W_i, \theta)|$. Then by our envelope assumption $\sup_m f_{\theta m}(W_i) \in L_1(P)$, so $\lim_m E[\bar{v}_{\theta m}(D_i, W_i)] = \lim_m E[f_{\theta m}(W_i)] = 0$ by dominated convergence. For each θ , let $m(\theta)$ s.t. $E[f_{\theta m(\theta)}(W_i)] \leq \epsilon$. Then $\{U_{\theta m(\theta)} : \theta \in \Theta\}$ is an open cover of Θ , so by compactness it admits a finite subcover $\{U_{\theta_l, m(\theta_l)}\}_{l=1}^{L(\epsilon)} \equiv \{U_l\}_{l=1}^{L(\epsilon)}$. Next, for each (θ, m) we claim $E_n[\bar{v}_{\theta m}(D_i, W_i)] = E[f_{\theta m}(W_i)] + o_p(1)$. We have $E_n[f_{\theta m}(W_i)] = E[f_{\theta m}(W_i)] + o_p(1)$ by WLLN since $E[f_{\theta m}(W_i)] < \infty$ as just shown. Similarly, we have

$$|r_{\theta m}(W_i)| = |(1 - p) \sup_{\bar{\theta} \in U_{\theta m}} \delta(W_i, \bar{\theta}) + p \inf_{\bar{\theta} \in U_{\theta m}} \delta(W_i, \bar{\theta})| \leq \sup_{\bar{\theta} \in U_{\theta m}} |\delta(W_i, \bar{\theta})| \in L_1(P).$$

Then $E_n[(D_i - p)r_{\theta m}(W_i)] = o_p(1)$ by Lemma A.2 in [Cytrynbaum \(2024\)](#). This proves the claim. Define $f_l(W)$ and $r_l(W)$ to be the functions above evaluated at $(\theta_l, m(\theta_l))$. Putting this all together, we have

$$\begin{aligned} \sup_{\theta \in K} E_n[v_i(\theta)] &\leq \max_{l=1}^{L(\epsilon)} \sup_{\theta \in U_l} E_n[v_i(\theta)] \leq \max_{l=1}^{L(\epsilon)} E_n[v_{\theta_l m(\theta_l)}(D_i, W_i)] \\ &= \max_{l=1}^{L(\epsilon)} (E[f_{\theta_l m(\theta_l)}(W_i)] + T_{nl}) \leq \epsilon + \max_{l=1}^{L(\epsilon)} T_{nl} = \epsilon + o_p(1). \end{aligned}$$

By symmetry, we also have $\sup_{\theta \in K} -E_n[v_i(\theta)] \leq \epsilon + o_p(1)$. Then $\sup_{\theta \in K} |E_n[v_i(\theta)]| \leq 2\epsilon + o_p(1)$. Since $\epsilon > 0$ was arbitrary, this finishes the proof of (1).

Next we show $\|g_n - g_0\|_{\infty, \Theta} = o_p(1)$. We have $(g_n - g_0)(\theta) = E_n[\phi(W_i, \theta)] - E[\phi(W, \theta)]$. Under our assumptions, $|E_n[\phi(W_i, \theta)] - E[\phi(W, \theta)]|_{\infty, \Theta} = o_p(1)$ and $g_0(\theta) = E[\phi(W, \theta)]$ is continuous by Lemma 2.4 of [Newey and McFadden \(1994\)](#). This proves the second claim.

For the statement about objective functions, observe that

$$\begin{aligned}
|\widehat{H}(\theta) - H_n(\theta)| &= |\widehat{g}(\theta)' M_n \widehat{g}(\theta) - g_n(\theta)' M g_n(\theta)| \leq |(\widehat{g} - g_n)(\theta)' M_n \widehat{g}(\theta)| \\
&+ |g_n(\theta)' (M_n - M) \widehat{g}(\theta)| + |g_n(\theta)' M (\widehat{g} - g_n)(\theta)| \leq |\widehat{g} - g_n|_2(\theta) \|M_n\|_2 |\widehat{g}(\theta)|_2 \\
&+ |g_n(\theta)|_2 \|M_n - M\|_2 |\widehat{g}(\theta)|_2 + |g_n(\theta)|_2 \|M\|_2 |\widehat{g} - g_n|_2(\theta) \lesssim |\widehat{g} - g_n|_{\infty, \Theta} \|M_n\|_2 |\widehat{g}|_{\infty, \Theta} \\
&+ |g_n|_{\infty, \Theta} \|M_n - M\|_2 |\widehat{g}|_{\infty, \Theta} + |g_n|_{\infty, \Theta} \|M\|_2 |\widehat{g} - g_n|_{\infty, \Theta}.
\end{aligned}$$

The first inequality by telescoping, then Cauchy-Schwarz, then using equivalence of finite-dimensional vector space norms and $\sup_{\theta} a(\theta)b(\theta) \leq \sup_{\theta} a(\theta) \sup_{\theta} b(\theta)$ for positive a, b . We have $|g_n|_{\infty, \Theta}, |\widehat{g}|_{\infty, \Theta} = o_p(1) + |g_0|_{\infty, \Theta} = O_p(1)$ since $|g_0|_{\infty, \Theta} \leq E[\sup_{\theta \in \Theta} \phi(W, \theta)] < \infty$. Also $\|M_n\|_2 = O_p(1)$ and $\|M_n - M\|_2 = o_p(1)$ by continuous mapping. Taking $\sup_{\theta \in \Theta}$ on both sides gives the result. The proof that $|H_n - H_0|_{\infty, K} = o_p(1)$ is identical. By triangle inequality, this proves the claim.

For (2), since $g_0(\theta_0) = 0$ uniquely and $\text{rank}(M) = d_g$, then $H_0(\theta)$ is uniquely minimized at θ_0 . Then $\theta_n \xrightarrow{p} \theta_0$ and $\widehat{\theta} \xrightarrow{p} \theta_0$ by extremum consistency (e.g. Theorem 2.1 in [Newey and McFadden \(1994\)](#)), so $\widehat{\theta} \xrightarrow{p} \theta_n$.

Finally consider (3). Let $U_1 \subseteq \tilde{U}$ an open set $\theta_0 \in U_1$ such that the closed $1/m'$ enlargement $\tilde{U}_1^{1/m'} \subseteq \tilde{U}$ for some $m' \geq 1$. Set $\tilde{\Theta} = \tilde{U}_1^{1/m'}$, which is compact. As in the proof of (1), let $U_{\theta m} = B(\theta, m^{-1})$ for $m \geq m'$. The conclusion now follows from the exact argument in (1), applied to the alternate moment functions $\tilde{g}_z(W_i, \theta) \equiv \partial/\partial\theta' g_z(W_i, \theta)$. In particular, uniform convergence holds on any open set $U \subseteq \tilde{\Theta} \subseteq \tilde{U}$. The final statement about $G_0(\theta)$ follows by dominated convergence. \square

Proof of Lemma 8.5. Since $\widehat{\theta} = \text{argmin}_{\theta \in \Theta} \widehat{H}(\theta)$, so $\nabla_{\theta} \widehat{H}(\widehat{\theta}) = 0 \iff \widehat{G}(\widehat{\theta})' M_n \widehat{g}(\widehat{\theta}) = 0$. By differentiability in Assumption 3.2 and applying Taylor's Theorem componentwise, for each $k \in [d_g]$ and some $\tilde{\theta}_k \in [\theta_0, \widehat{\theta}]$ we have

$$\widehat{g}(\widehat{\theta}) = \widehat{g}(\theta_0) + \frac{\partial \widehat{g}_k}{\partial \theta'}(\tilde{\theta}_k)_{k=1}^{d_g} (\widehat{\theta} - \theta_0).$$

Then we may expand

$$\begin{aligned}
0 &= \widehat{G}(\widehat{\theta})' M_n [\widehat{g}(\theta_0) + \frac{\partial \widehat{g}_k}{\partial \theta'}(\tilde{\theta}_k)_{k=1}^{d_g} (\widehat{\theta} - \theta_0)] \\
\widehat{\theta} - \theta_0 &= -(\widehat{G}(\widehat{\theta})' M_n \frac{\partial \widehat{g}_k}{\partial \theta'}(\tilde{\theta}_k)_{k=1}^{d_g})^{-1} \widehat{G}(\widehat{\theta})' M_n \widehat{g}(\theta_0).
\end{aligned}$$

On the event $S_n = \{\widehat{\theta} \in U\}$, $\tilde{\theta}_k \in U$ for each k . Then $\mathbf{1}(S_n) |\frac{\partial \widehat{g}_k}{\partial \theta'}(\tilde{\theta}_k)_{k=1}^{d_g} - \frac{\partial g_{0k}}{\partial \theta'}(\tilde{\theta}_k)_{k=1}^{d_g}|_F^2 \leq \sum_{k=1}^{d_g} \sup_{\theta \in U} |\frac{\partial \widehat{g}_k}{\partial \theta'}(\theta) - \frac{\partial g_{0k}}{\partial \theta'}(\theta)|_2^2 \leq d_g \sup_{\theta \in U} |\widehat{G}(\theta) - G_0(\theta)|_F^2 = o_p(1)$ by Lemma 8.6. Similarly, $\mathbf{1}(S_n) |\widehat{G}(\widehat{\theta}) - G_0(\widehat{\theta})|_F^2 \leq \sup_{\theta \in U} |\widehat{G}(\theta) - G_0(\theta)|_F^2 = o_p(1)$. Moreover, since $\widehat{\theta} \xrightarrow{p} \theta_0$ and $\tilde{\theta}_k \in [\theta_0, \widehat{\theta}] \forall k$, we have $\mathbf{1}(S_n) |G_0(\widehat{\theta}) - G_0(\theta_0)|_F^2 = o_p(1)$ and $\mathbf{1}(S_n) |\frac{\partial g_{0k}}{\partial \theta'}(\tilde{\theta}_k)_{k=1}^{d_g} - G_0(\theta_0)|_F^2 = o_p(1)$, using continuous mapping and continuity of $\theta \rightarrow G_0(\theta)$ on U , shown in Lemma 8.6.

Since $P(S_n) \rightarrow 1$, we have shown $|\widehat{G}(\widehat{\theta}) - G(\theta_0)|_F^2 = o_p(1)$ and $|\frac{\partial \widehat{g}_k}{\partial \theta'}(\tilde{\theta}_k)_{k=1}^{d_g} - G(\theta_0)|_F^2 = o_p(1)$. Since $\widehat{g}(\theta_0) = O_p(n^{-1/2})$ by Theorem 8.1, by the work above and continuous mapping theorem we have

$$\begin{aligned}\sqrt{n}(\widehat{\theta} - \theta_0) &= -(\widehat{G}(\widehat{\theta})' M_n \frac{\partial \widehat{g}_k}{\partial \theta'}(\tilde{\theta}_k)_{k=1}^{d_g})^{-1} \widehat{G}(\widehat{\theta})' M_n \sqrt{n} \widehat{g}(\theta_0) \\ &= -(G' M G)^{-1} G' M \sqrt{n} \widehat{g}(\theta_0) + o_p(1) = \Pi \sqrt{n} \widehat{g}(\theta_0) + o_p(1).\end{aligned}$$

The proof of the second claim is identical, using $|\theta_n - \theta_0|_2 = o_p(1)$ and $\sup_{\theta \in U} |G_n(\theta) - G_0(\theta)|_F^2 = o_p(1)$ by Lemma 8.6. This shows linearization in P -measure. The statement in Q -measure follows from Lemma 8.16 and our assumptions in Definition 2.1. \square

Lemma 8.7 (Linearization Matrix Estimation). $\widehat{G}_n(\widehat{\theta}) \xrightarrow{p} G_0(\theta_0) = G$. Let $E_n = \{\widehat{G}_n(\widehat{\theta})' M_n \widehat{G}_n(\widehat{\theta}) \succ 0\}$. Then $\widehat{\Pi} = -\mathbb{1}(E_n)(\widehat{G}_n(\widehat{\theta})' M_n \widehat{G}_n(\widehat{\theta}))^{-1} \widehat{G}_n(\widehat{\theta})' M_n \xrightarrow{p} \Pi$.

Proof. Let U be the neighborhood of θ_0 from Lemma 8.6 and set $S_n = \{\widehat{\theta} \in U\}$. Then we have $\mathbb{1}(S_n)|\widehat{G}_n(\widehat{\theta}) - G_0(\theta_0)| \leq \mathbb{1}(S_n)|\widehat{G}_n(\widehat{\theta}) - G_0(\widehat{\theta})| + \mathbb{1}(S_n)|G_0(\widehat{\theta}) - G_0(\theta_0)| \leq \mathbb{1}(S_n)|\widehat{G}_n - G_0|_{\infty, U} + |G_0(\widehat{\theta}) - G_0(\theta_0)| = o_p(1)$. The final equality is by Lemma 8.6 and continuous mapping, since G_0 is continuous at θ_0 . By assumption, $\text{rank}(M) = d_g$ and $\text{rank}(G) = d_\theta \leq d_g$. Then $\text{rank}(G' M G) = d_\theta$, so $\mathbb{1}(E_n)(\widehat{G}_n(\widehat{\theta})' M_n \widehat{G}_n(\widehat{\theta}))^{-1} - \mathbb{1}(E_n)(G' M G)^{-1} \xrightarrow{p} 0$ and $\mathbb{1}(E_n)(\widehat{\Pi} - \Pi) \xrightarrow{p} 0$ by continuous mapping. Finally, by continuous mapping $\lambda_{\min}(\widehat{G}_n(\widehat{\theta})' M_n \widehat{G}_n(\widehat{\theta})) \xrightarrow{p} \lambda_{\min}(G' M G) > 0$, so $\mathbb{1}(E_n) \xrightarrow{p} 1$. The statement now follows from Lemma 8.16. \square

8.3 Nonlinear Rerandomization

Proof of Theorem 4.3. We first prove a slightly more general result, allowing for over-identified GMM estimation with positive definite weighting matrix $\Delta_n \xrightarrow{p} \Delta$. For $|x|_{2,A}^2 = x' A x$, define

$$\widehat{\beta}_d \in \underset{\beta \in \mathbb{R}^{d_\beta}}{\text{argmin}} |E_n[\mathbb{1}(D_i = d)m(X_i, \beta)]|_{2, \Delta_n}^2.$$

Define $g^1(D, X, \beta) = Dm(X, \beta)$ and $g^0(D, X, \beta) = (1 - D)m(X, \beta)$. Under the expansion in Equation 3.1, we have $\phi^1(X, \beta) = pg^1(1, X, \beta) = pm(X, \beta)$ and $\delta^1(X, \beta) = v_D g^1(1, X, \beta) = v_D m(X, \beta)$. Similarly, $\phi^0(X, \beta) = (1 - p)g^0(0, X, \beta) = (1 - p)m(X, \beta)$ and $\delta^0(X, \beta) = -v_D g^0(0, X, \beta) = -v_D m(X, \beta)$. Note that $E[g^1(D, X, \beta)] = pE[m(X, \beta)]$ and $E[g^0(D, X, \beta)] = (1 - p)E[m(X, \beta)]$, so the GMM parameters $\beta_1 = \beta_0 = \beta^*$, where β^* uniquely solves $E[m(X, \beta^*)] = 0$. Let $G_m = E[(\partial/\partial \beta')m(X, \beta^*)]$, which is full rank by assumption. Then $G^1 = E[(\partial/\partial \beta')g^1(D, X, \beta^*)] = pE[(\partial/\partial \beta')m(X, \beta^*)] = pG_m$ and $\Pi^1 = -((G^1)' \Delta G^1)^{-1} (G^1)' \Delta = -p^{-1} (G_m' \Delta G_m)^{-1} G_m' \Delta \equiv p^{-1} \Pi_m$. By symmetry, we have

$\Pi^0 = (1 - p)^{-1}\Pi_m$. Observe that

$$\begin{aligned} (\Pi^1\phi^1 - \Pi^0\phi^0)(X, \beta) &= p^{-1}\Pi_m p m(X, \beta) - (1 - p)^{-1}\Pi_m(1 - p)m(X, \beta) = 0, \\ (\Pi^1\delta^1 - \Pi^0\delta^0)(X, \beta) &= p^{-1}\Pi_m v_D m(X, \beta) - (1 - p)^{-1}\Pi_m v_D(-m(X, \beta)) \\ &= (1 - p)\Pi_m m(X, \beta) + p\Pi_m m(X, \beta) = \Pi_m m(X, \beta). \end{aligned}$$

Then applying Lemma 8.5 to GMM estimation using g^1 and g^0 , we have

$$\begin{aligned} \sqrt{n}(\hat{\beta}_1 - \hat{\beta}_0) &= \sqrt{n}(\hat{\beta}_1 - \beta^* - (\hat{\beta}_0 - \beta^*)) = \sqrt{n}\Pi^1 E_n[\phi^1(X_i, \beta^*) + H_i\delta^1(X_i, \beta^*)] \\ &\quad - \sqrt{n}\Pi^0 E_n[\phi^0(X_i, \beta^*) + H_i\delta^0(X_i, \beta^*)] + o_p(1) = \sqrt{n}\Pi_m E_n[H_i m(X, \beta^*)] + o_p(1). \end{aligned}$$

Then Definition 4.1 is an example of Definition 2.1 with $\mathcal{I}_n = \sqrt{n}E_n[H_i h_i] + o_p(1)$ for $h_i = \Pi_m m(X_i, \beta^*)$. Then Theorem 3.4 holds with $h_i = \Pi_m m(X_i, \beta^*)$. Consider the exactly identified case, so $\Pi_m = -G_m^{-1}$ and $h_i = -G_m^{-1}m(X_i, \beta^*)$. Then by Theorem 3.4, $\sqrt{n}(\hat{\theta} - \theta_n)|W_{1:n} \Rightarrow \mathcal{N}(0, V_\delta) + R_A$. Denote $\Pi\delta = \Pi\delta(W, \theta_0)$ and $m = m(X, \beta^*)$. Then the rerandomization coefficient Γ_0 is

$$\begin{aligned} \Gamma_0 &= E[\text{Var}(h|\psi)]^{-1} E[\text{Cov}(h, \Pi\delta|\psi)] = -E[\text{Var}(G_m^{-1}m|\psi)]^{-1} E[\text{Cov}(G_m^{-1}m, \Pi\delta|\psi)] \\ &= -E[G_m^{-1} \text{Var}(m|\psi)(G_m^{-1})']^{-1} E[G_m^{-1} \text{Cov}(m, \Pi\delta|\psi)] = -G'_m E[\text{Var}(m|\psi)]^{-1} E[\text{Cov}(m, \Pi\delta|\psi)]. \end{aligned}$$

Then $V_\delta = v_D^{-1} E[\text{Var}(\Pi\delta - \Gamma'_0(-G_m^{-1}m)|\psi)] = v_D^{-1} E[\text{Var}(\Pi\delta - \eta'_0 m|\psi)]$, where

$$\eta_0 = \underset{\eta \in \mathbb{R}^{d_\beta \times d_\theta}}{\text{argmin}} v_D^{-1} E[\text{Var}(\Pi\delta - \eta' m|\psi)].$$

From above, we have $\Gamma_0 = -G'_m \eta_0$. Then the residual term

$$\begin{aligned} R_A &\sim \Gamma'_0 Z_h \mid Z_h \in A \sim -\eta'_0 G_m Z_h \mid Z_h \in A \sim -\eta'_0 G_m Z_h \mid (-G_m^{-1})(-G_m)Z_h \in A \\ &\sim \eta'_0 Z_m \mid -G_m^{-1}Z_m \in A \sim \eta'_0 Z_m \mid Z_m \in -G_m A. \end{aligned}$$

The variable $Z_h \sim \mathcal{N}(0, v_D^{-1} E[\text{Var}(h|\psi)])$, so $Z_m = G_m Z_h \sim \mathcal{N}(0, v_D^{-1} G_m E[\text{Var}(h|\psi)] G'_m) \sim \mathcal{N}(0, v_D^{-1} E[\text{Var}(G_m h|\psi)]) \sim \mathcal{N}(0, v_D^{-1} E[\text{Var}(m|\psi)])$ since $G_m h = G_m G_m^{-1} m = m(X, \beta^*)$. Summarizing, we have shown $V_\delta = v_D^{-1} E[\text{Var}(\Pi\delta - \eta'_0 m|\psi)]$ and $R_A \sim \eta'_0 Z_m \mid Z_m \in G_m A$ for $Z_m \sim \mathcal{N}(0, v_D^{-1} E[\text{Var}(m|\psi)])$.

For the corollary, consider letting $\hat{\beta} \in \underset{\beta \in \mathbb{R}^{d_\beta}}{\text{argmin}} \|E_n[m(X_i, \beta)]\|_{2, \Delta_n}^2$. Relative to the expansion in Equation 3.1, $\delta_m(X_i, \beta) = 0$ and $\phi_m(X_i, \beta) = m(X_i, \beta)$, with linearization matrix Π_m as above. Then by Lemma 8.5 $\sqrt{n}(\hat{\beta} - \beta^*) = \Pi_m E_n[m(X_i, \beta^*)] + o_p(1) = O_p(1)$. Consider setting $h_i = m(X_i, \hat{\beta})$. By the mean value theorem, $m(X_i, \hat{\beta}) - m(X_i, \beta^*) =$

$\frac{\partial m(X_i, \tilde{\beta}_i)}{\partial \beta}(\hat{\beta} - \beta^*)$, where the $\tilde{\beta}_i \in [\beta^*, \hat{\beta}]$ may change by row. Then we have

$$\sqrt{n}E_n[H_i m(X_i, \hat{\beta})] - \sqrt{n}E_n[H_i m(X_i, \beta^*)] = E_n[H_i(\partial/\partial \beta)m(X_i, \tilde{\beta}_i)]\sqrt{n}(\hat{\beta} - \beta^*).$$

We claim that $E_n[H_i m(X_i, \tilde{\beta}_i)] = o_p(1)$. Define $v_{ijk} = (m(X_i, \tilde{\beta}_i))_{jk}$. Clearly $v_{ijk} \in \mathcal{F}_n = \sigma(W_{1:n}, \pi_n)$ and $E[v_{ijk}|\mathcal{F}_n] = 0$. Also note $|v_{ijk}| = |(m(X_i, \tilde{\beta}_i))_{jk}| \leq \sup_{\beta \in U} |m(X_i, \beta)|_F \in L_1$ for some open set U by Assumption 3.2. Then $f_n(W) = (m(X, \tilde{\beta}_i))_{jk}$, where $\tilde{\beta}_i = \tilde{\beta}_{in}$ implicitly, is uniformly integrable. Then Lemma A.2 of [Cytrynbaum \(2024\)](#) implies $E_n[H_i v_{ijk}] = o_p(1)$. This proves the claim, showing that $\mathcal{I}_n = \sqrt{n}E_n[H_i m(X_i, \hat{\beta})] = \sqrt{n}E_n[H_i m(X_i, \beta^*)] + o_p(1)$. The result now follows from Theorem 3.4. \square

Assume $E[|X|^2] < \infty$ and $|L'|_\infty, |L''|_\infty < \infty$ continuous and limits to pm infinity, and $X = (1, h)$

Proof of Theorem 4.7. By assumption, $\hat{\beta}$ is a GMM estimator for $m(D_i, X_i, \beta) = D_i \frac{L'(X'_i \beta) X_i}{L(X'_i \beta)} - (1-D_i) \frac{L'(X'_i \beta) X_i}{1-L(X'_i \beta)}$. Let c s.t. $L(c) = p$. Then $\beta^* = (c, 0)$ has $E[m(D, X, \beta^*)] = E[H_i L'(c) X_i] = 0$. Relative to the decomposition in Equation 3.1, we have $\phi(X, \beta) = p \frac{L'(X'_i \beta) X_i}{L(X'_i \beta)} - (1-p) \frac{L'(X'_i \beta) X_i}{1-L(X'_i \beta)}$ and $\delta(X, \beta) = v_D(\frac{L'(X'_i \beta) X_i}{L(X'_i \beta)} + \frac{L'(X'_i \beta) X_i}{1-L(X'_i \beta)})$. Since $L(X'_i \beta^*) = L(c) = p$, apparently we have $\phi(X, \beta^*) = 0$ and $\delta(X, \beta^*) = L'(c) X_i$. A calculation shows that $G_m = E[\frac{\partial}{\partial \beta'} \phi(X, \beta^*)] = -L'(c)^2 E[X_i X'_i]$, so $\Pi_m = -G_m^{-1} = \frac{1}{L'(c)^2} E[X_i X'_i]^{-1}$. By Lemma 8.5, we have shown

$$\begin{aligned} \sqrt{n}(\hat{\beta} - \beta^*) &= \sqrt{n} \Pi_m E_n[\phi(X_i, \beta^*) + H_i \delta(X_i, \beta^*)] + o_p(1) \\ &= \frac{\sqrt{n}}{L'(c)} E[X_i X'_i]^{-1} E_n[H_i X_i] + o_p(1). \end{aligned}$$

Consider rerandomizing until $\mathcal{J}_n = nE_n[(p - L(X'_i \hat{\beta}))^2] \leq \epsilon^2$. Then for β^* s.t. $L(x' \beta^*) = p$, the above quantity is $nE_n[(L(X'_i \hat{\beta}) - L(X'_i \beta^*))^2]$. By Taylor's Theorem, $L(X'_i \hat{\beta}) - L(X'_i \beta^*) = L'(\xi_i)(X'_i \hat{\beta} - X'_i \beta^*) = L'(\xi_i) X'_i (\hat{\beta} - \beta^*)$ for some $\xi_i \in [X'_i \beta^*, X'_i \hat{\beta}]$. Then we have

$$\mathcal{J}_n = n(\hat{\beta} - \beta^*)' E_n[X_i X'_i L'(\xi_i)^2] (\hat{\beta} - \beta^*).$$

Claim that $E_n[X_i X'_i L'(\xi_i)^2] = E_n[X_i X'_i L'(X'_i \beta^*)^2] + o_p(1)$. If so, then $E_n[X_i X'_i L'(\xi_i)^2] = L'(c)^2 E_n[X_i X'_i] + o_p(1) = L'(c)^2 E[X_i X'_i] + o_p(1)$. To see this, note that $|L'(X'_i \beta^*)^2 - L'(\xi_i)^2| = |L'(X'_i \beta^*) - L'(\xi_i)| |L'(X'_i \beta^*) + L'(\xi_i)| \leq 2|L'|_\infty |L''|_\infty |X'_i \beta^* - \xi_i|_2 \lesssim |X'_i \beta^* - X'_i \hat{\beta}|_2 \leq |X_i|_2 |\beta^* - \hat{\beta}|_2$. Then we have

$$\begin{aligned} |E_n[X_i X'_i L'(\xi_i)^2] - E_n[X_i X'_i L'(X'_i \beta^*)^2]|_2 &\leq E_n[|X_i|_2^2 |L'(X'_i \beta^*)^2 - L'(\xi_i)^2|] \\ &\lesssim E_n[|X_i|_2^3] |\beta^* - \hat{\beta}|_2 = o_p(1) \end{aligned}$$

The last equality if $E_n[|X_i|_2^3] = o_p(n^{1/2})$. Note that $E_n[|X_i|_2^3] \leq E_n[|X_i|_2^2] \max_{i=1}^n |X_i|_2 =$

$O_p(1)o_p(n^{1/2})$ since $E[|X_i|_2^2] < \infty$ by assumption, using Lemma C.8 of [Cytrynbaum \(2024\)](#). Then using the claim, $\sqrt{n}(\hat{\beta} - \beta^*) = O_p(1)$, and the linear expansion of $\sqrt{n}(\hat{\beta} - \beta^*)$ above, we have shown $\mathcal{J}_n = L'(c)^2 n(\hat{\beta} - \beta^*)' E[X_i X_i'] (\hat{\beta} - \beta^*) + o_p(1)$, which is

$$\begin{aligned} &= L'(c)^2 (L'(c)^{-1} E[X_i X_i']^{-1} \sqrt{n} E_n[H_i X_i])' E[X_i X_i'] (L'(c)^{-1} E[X_i X_i']^{-1} \sqrt{n} E_n[H_i X_i]) + o_p(1) \\ &= \sqrt{n} E_n[H_i X_i]' E[X_i X_i']^{-1} \sqrt{n} E_n[H_i X_i] + o_p(1). \end{aligned}$$

Note $E_n[H_i] = O_p(n^{-1})$ by stratification. Since $X = (1, h)$, $\sqrt{n} E_n[H_i X_i]' = (0, \sqrt{n} E_n[H_i h_i]') + O_p(n^{-1/2})$. Also, by block inversion $(E[X_i X_i']^{-1})_{hh} = \text{Var}(h_i)^{-1}$. For some $\xi_n = o_p(1)$

$$\begin{aligned} \mathcal{J}_n &= (0, \sqrt{n} E_n[H_i h_i]') E[X_i X_i']^{-1} (0, \sqrt{n} E_n[H_i h_i]')' + o_p(1) \\ &= \sqrt{n} E_n[H_i h_i]' (E[X_i X_i']^{-1})_{hh} \sqrt{n} E_n[H_i h_i] + o_p(1) \\ &= \sqrt{n} E_n[H_i h_i]' \text{Var}(h_i)^{-1} \sqrt{n} E_n[H_i h_i] + \xi_n. \end{aligned}$$

Define the function $a(x, y) = x' \text{Var}(h)^{-1} x + y - \epsilon$. Then $\mathcal{J}_n \leq \epsilon \iff a(\mathcal{I}_n, \xi_n) \leq 0$ for $\mathcal{I}_n = \sqrt{n} E_n[H_i h_i]$ and $\xi_n \xrightarrow{p} 0$. Clearly, $x \rightarrow a(x, 0)$ is continuous. Also note $E[|h|_2^2] < \infty$ by assumption. Finally, for $Z_h \sim \mathcal{N}(0, E[\text{Var}(h|\psi)])$, have $P(a(Z_h, 0) = 0) = P(Z_h' \text{Var}(h)^{-1} Z_h = \epsilon^2) = 0$ since $E[\text{Var}(h|\psi)]$ is full rank. Then this rerandomization satisfies all the conditions in Definition 8.2. By Lemma 8.5, the GMM estimator $\sqrt{n}(\hat{\theta} - \theta_0) = \sqrt{n} E_n[H_i \Pi \delta(W_i, \theta_0)] + o_p(1)$ under this rerandomization. By Theorem 8.4, have $\sqrt{n} E_n[H_i \Pi \delta(W_i)] | \mathcal{F}_n \Rightarrow \mathcal{N}(0, V_\delta) + R$ with $R \sim \Gamma'_0 Z_h | Z_h \in T \sim \Gamma'_0 Z_h | Z_h' \text{Var}(h)^{-1} Z_h \leq \epsilon$ for acceptance region $T = \{x : a(x, 0) \leq 0\} = \{x : x' \text{Var}(h)^{-1} x \leq \epsilon\}$ and

$$V_\delta = \min_{\Gamma \in \mathbb{R}^{d_h \times d_\theta}} v_D^{-1} E[\text{Var}(\Pi \delta(W) - \Gamma' h | \psi)].$$

This finishes the proof. \square

8.4 Covariate Adjustment

Proof of Theorem 3.12. By Lemma 8.5, $\sqrt{n}(\hat{\theta}^* - \theta_n)$ may be expanded as

$$\begin{aligned} \sqrt{n}(\hat{\theta} - \theta_n - E_n[H_i m(\psi_i, h_i)]) &= \sqrt{n} E_n[H_i (\Pi \delta(W_i, \theta_0) - m(\psi_i, h_i))] + o_p(1) \\ &\equiv \sqrt{n} E_n[H_i \beta(W_i, \theta_0)] + o_p(1). \end{aligned}$$

By Theorem 8.4, $\sqrt{n} E_n[H_i \beta(W_i, \theta_0)] | \mathcal{F}_n \Rightarrow \mathcal{N}(0, V)$ with $V = v_D^{-1} \text{Var}(\beta(W, \theta_0))$. Since $\beta(W, \theta_0) = \Pi \delta(W, \theta_0) - \Gamma'_0 h - t_0(\psi)$ for (Γ_0, t_0) solving Equation 3.4, this completes the proof. \square

Proof of Proposition 6.2. Since $\hat{\theta}_{adj} = \hat{\theta} - E_n[H_i \hat{\alpha}' w_i]$ for $\hat{\alpha} \xrightarrow{p} \alpha$ and $E_n[H_i w_i] = O_p(n^{-1/2})$ by Theorem 8.1, then $\hat{\theta}_{adj} = \hat{\theta} - E_n[H_i \alpha' w_i] + o_p(n^{-1/2}) = E_n[H_i (\Pi \delta(W_i, \theta_0) - \alpha' w_i)] +$

$o_p(n^{-1/2})$, the final equality by Lemma 8.5. The first statement now follows from Slutsky and Theorem 8.1. The second statement follows by the same argument used in the proof of Corollary 3.8. \square

Proof of Theorem 6.3. By the same argument in the proof of Proposition 6.2, we have $\widehat{\theta}_{adj} = E_n[H_i(\Pi\delta(W_i, \theta_0) - \alpha'_0 w_i)] + o_p(n^{-1/2})$. Then by Theorem 8.4, $\sqrt{n}(\widehat{\theta}_{adj} - \theta_n) | \mathcal{F}_n \Rightarrow \mathcal{N}(0, V) + R$, independent with

$$V = v_D^{-1} E[\text{Var}(\Pi\delta(W) - \alpha'_0 w - \beta'_0 h | \psi)] = \min_{\beta \in \mathbb{R}^{d_h \times d_\theta}} v_D^{-1} E[\text{Var}(\Pi\delta(W) - \alpha'_0 w - \beta' h | \psi)].$$

The residual term $R \sim \beta'_0 Z_h | Z_h \in A$. Then it suffices to show that $\beta_0 = 0$. Define $\delta_{\Pi\alpha} = \Pi\delta(W, \theta_0) - \alpha'_0 w$. By Lemma 8.12, it further suffices to show $\beta_0 = 0$ solves $E[\text{Var}(h | \psi)]\beta_0 = E[\text{Cov}(h, \delta_{\Pi\alpha} | \psi)]$, i.e. that $E[\text{Cov}(h, \delta_{\Pi\alpha} | \psi)] = 0$. To do so, note that $E[\text{Cov}(h, \delta_{\Pi\alpha} | \psi)] = E[\text{Cov}(h, (\Pi\delta - \alpha'_0 w) | \psi)] = E[\text{Cov}(h, \Pi\delta | \psi)] - E[\text{Cov}(h, w | \psi)]\alpha_0$. By assumption, $E[\text{Var}(w | \psi)]\alpha_0 = E[\text{Cov}(w, \Pi\delta | \psi)]$. Since $h \subseteq w$, we have

$$\begin{aligned} E[\text{Cov}(h, w | \psi)]\alpha_0 &= (E[\text{Var}(w | \psi)])_{hw}\alpha_0 = (E[\text{Var}(w | \psi)]\alpha_0)_{h\theta} \\ &= (E[\text{Cov}(w, \Pi\delta | \psi)])_{h\theta} = E[\text{Cov}(h, \Pi\delta | \psi)] \end{aligned}$$

This shows that $[\text{Cov}(h, \delta_{\Pi\alpha} | \psi)] = 0$, so $\beta_0 = 0$ is a solution, proving the claim. This finishes the proof of the statement for θ_n . The result for θ_0 follows trivially, as in Corollary 3.8. \square

Proof of Theorem 6.4. By Lemma 8.8, $E_n[\ddot{w}_i \ddot{w}'_i] = k^{-1}(k-1)E[\text{Var}(w | \psi)] + o_p(1)$. Then if $E[\text{Var}(w | \psi)] \succ 0$, we have $E_n[\ddot{w}_i \ddot{w}'_i]^{-1} \xrightarrow{p} k(k-1)^{-1}E[\text{Var}(w | \psi)]^{-1}$ by continuous mapping. We have $\widehat{\Pi} \xrightarrow{p} \Pi$ by assumption. Then it suffices to show $E_n[\ddot{w}_i(D_i - p)\widehat{g}'_i] = k^{-1}(k-1)E[\text{Cov}(w, \delta | \psi)] + o_p(1)$. First, claim $E_n[\ddot{w}_i(D_i - p)\widehat{g}'_i] = E_n[\ddot{w}_i(D_i - p)g'_i(\theta_0)] + o_p(1)$, for $g_i(\theta) \equiv g(D_i, X_i, S_i, \theta)$. By Taylor's theorem, $|g_i(\widehat{\theta}) - g_i(\theta_0)|_2 \leq |\frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i)|_2 |\widehat{\theta} - \theta_0|_2$, where $\tilde{\theta}_i$ may change by row. Then $|E_n[\ddot{w}_i(D_i - p)(g_i(\widehat{\theta}) - g_i(\theta_0))']|_2 \leq E_n[|\ddot{w}_i|_2 |g_i(\widehat{\theta}) - g_i(\theta_0)|_2] \leq |\widehat{\theta} - \theta_0|_2 E_n[|\ddot{w}_i|_2 |\frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i)|_2] \leq |\widehat{\theta} - \theta_0|_2 (E_n[|\ddot{w}_i|_2^2] + E_n[|\frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i)|_2^2])$ by Young's inequality. We showed $E_n[|\frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i)|_2^2] = O_p(1)$ in the proof of Lemma 8.10. Similarly, $E_n[|\ddot{w}_i|_2^2] \leq E_n[|w_i|_2^2] = O_p(1)$ by the bound in Lemma 8.8. Since $|\widehat{\theta} - \theta_0|_2 = o_p(1)$ by Theorem 3.4, this proves the claim.

Next, claim $E_n[\ddot{w}_i(D_i - p)g'_i(\theta_0)] = E_n[\ddot{w}_i\delta(W_i, \theta_0)'] + o_p(1)$. By definition, we have $E_n[\ddot{w}_i(D_i - p)g'_i(\theta_0)] = E_n[\ddot{w}_i(D_i - p)\phi(W_i, \theta_0)'] + \text{Var}(D)^{-1}E_n[(D_i - p)^2 \ddot{w}_i\delta(W_i, \theta_0)'] \equiv A_n + B_n$. Expanding $(D_i - p)^2$, $B_n = \text{Var}(D)^{-1}E_n[(\text{Var}(D) + (D_i - p)(1 - 2p))\ddot{w}_i\delta(W_i, \theta_0)'] = E_n[\ddot{w}_i\delta(W_i, \theta_0)'] + \frac{1-2p}{\text{Var}(D)}E_n[(D_i - p)\ddot{w}_i\delta(W_i, \theta_0)']$. Since $\phi = pg_1 + (1-p)g_0$ and $\delta = \text{Var}(D)(g_1 - g_0)$, apparently it suffices to show $E_n[(D_i - p)\ddot{w}_i g_d(W_i, \theta_0)'] = o_p(1)$ for each $d = 0, 1$. Since $E[|g_d(W_i, \theta_0)|_2^2] < \infty$, this follows from Lemma 8.8. Finally, $E_n[\ddot{w}_i\delta(W_i, \theta_0)'] = k^{-1}(k-1)E[\text{Cov}(w_i, \delta(W_i, \theta_0) | \psi_i)] + o_p(1)$ since $E[|w|_2^2 + |g_d|_2^2] < \infty$

and by applying Lemma 8.8 componentwise. This finishes the proof. \square

Lemma 8.8. *Suppose $E[w_i^2 + v_i^2] < \infty$ with $w_i, v_i \in \sigma(W_i)$. Then $E_n[(D_i - p)\check{w}_i\check{v}_i] = o_p(1)$ and $E_n[(D_i - p)\check{w}_i v_i] = o_p(1)$. Also $E_n[\check{w}_i\check{v}_i] = \frac{k-1}{k}E[\text{Cov}(w, v|\psi)] + o_p(1)$.*

Proof. First, note $|g|^{-1} \sum_{i \in g} \check{w}_i^2 = |g|^{-1} \sum_{i \in g} (w_i - |g|^{-1} \sum_{j \in g} w_j)^2 = \text{Var}_g(w_i) \leq E_g[w_i^2] = |g|^{-1} \sum_{i \in g} w_i^2$. Then in particular $\sum_{i \in g} \check{w}_i^2 \leq \sum_{i \in g} w_i^2$ and $E_n[\check{w}_i^2] \leq E_n[w_i^2]$. Write $E_n[(D_i - p)\check{w}_i\check{v}_i] = n^{-1} \sum_g u_g$ for $u_g = \sum_{i \in g} (D_i - p)\check{w}_i\check{v}_i$. Let $\mathcal{F}_n = \sigma(W_{1:n}, \pi_n)$. Then $\mathcal{G}_n \in \mathcal{F}_n$, $E[u_g|\mathcal{F}_n] = 0$ and $u_g \perp\!\!\!\perp u_{g'}|\mathcal{F}_n$ for $g \neq g'$ by Lemma C.10 and Lemma C.9 of Cytrynbaum (2024). By Lemma C.7 of Cytrynbaum (2024), it suffices to show $n^{-1} \sum_g E[|u_g| \mathbf{1}(|u_g| > c_n) | \mathcal{F}_n] = o_p(1)$ for some $c_n = o(\sqrt{n})$ with $c_n \rightarrow \infty$. Note that $|u_g| \leq \sum_{i \in g} |\check{w}_i\check{v}_i| \leq \sum_{i \in g} \check{w}_i^2 + \sum_{i \in g} \check{v}_i^2 \leq \sum_{i \in g} w_i^2 + \sum_{i \in g} v_i^2$ by Young's inequality and the bound above. Note that for any positive constants $(a_k)_{k=1}^m$ we have $\sum_k a_k \mathbf{1}(\sum_k a_k > c) \leq m \sum_k a_k \mathbf{1}(a_k > c/m)$. Applying this fact and the upper bounds gives

$$\begin{aligned} n^{-1} \sum_g E[|u_g| \mathbf{1}(|u_g| > c_n) | \mathcal{F}_n] &\leq n^{-1} \sum_g E \left[\sum_{i \in g} (w_i^2 + v_i^2) \mathbf{1}(\sum_{i \in g} (w_i^2 + v_i^2) > c_n) | \mathcal{F}_n \right] \\ &\leq 2kn^{-1} \sum_g \sum_{i \in g} w_i^2 \mathbf{1}(w_i^2 > c_n/2k) + 2kn^{-1} \sum_g \sum_{i \in g} v_i^2 \mathbf{1}(v_i^2 > c_n/2k) \end{aligned}$$

The final quantity is $2kE_n[w_i^2 \mathbf{1}(w_i^2 > c_n/2k)] + 2kE_n[v_i^2 \mathbf{1}(v_i^2 > c_n/2k)] = o_p(1)$. This follows by Markov inequality since $E[E_n[w_i^2 \mathbf{1}(w_i^2 > c_n/2k)]] = E[w_i^2 \mathbf{1}(w_i^2 > c_n/2k)] \rightarrow 0$ for any $c_n \rightarrow \infty$ by dominated convergence. This proves the first statement, and the second statement follows by setting $\check{v}_i \rightarrow v_i$ above. For the final statement, calculate

$$\sum_{i \in g} \check{w}_i\check{v}_i = \sum_{i \in g} (w_i - k^{-1} \sum_{j \in g} w_j)(v_i - k^{-1} \sum_{j \in g} v_j) = k^{-1}(k-1) \sum_{i \in g} w_i v_i - k^{-1} \sum_{i \neq j \in g} v_i w_j$$

Clearly $n^{-1}k^{-1}(k-1) \sum_g \sum_{i \in g} w_i v_i = k^{-1}(k-1)E_n[w_i v_i] = k^{-1}(k-1)E[w_i v_i] + o_p(1)$. Then it suffices to show $(kn)^{-1} \sum_g \sum_{i \neq j \in g} v_i w_j = k^{-1}(k-1)E[E[w_i|\psi_i]E[v_i|\psi_i]] + o_p(1)$. If so, $E_n[\check{w}_i\check{v}_i] = k^{-1}(k-1)(E[w_i v_i] - E[E[w_i|\psi_i]E[v_i|\psi_i]]) + o_p(1) = k^{-1}(k-1)E[\text{Cov}(w_i, v_i|\psi_i)] + o_p(1)$ as claimed. The analysis of the term \hat{v}_{10} in Lemma A.6 of Cytrynbaum (2024) shows

$$\begin{aligned} n^{-1} \sum_g \sum_{i \neq j \in g} v_i w_j &= n^{-1} \sum_g \sum_{i \neq j \in g} E[v_i|\psi_i]E[w_j|\psi_j] + o_p(1) \\ &= (k-1)E_n[E[v_i|\psi_i]E[w_i|\psi_i]] + o_p(1) = (k-1)E[E[v_i|\psi_i]E[w_i|\psi_i]] + o_p(1). \end{aligned}$$

By above work, this finishes our proof of the claim. \square

8.5 Acceptance Region Optimization

Proof of Theorem 5.1. First we prove part (a). Define the function $f(a) = \sup_{b \in B} |b'a|$. As the sup of linear functions, f is convex (e.g. Rockafellar (1996)). Then the sublevel

set $A \equiv \{a : f(a) \leq 1\}$ is convex. Note that $f(a) = f(-a)$, so A is symmetric. For the main statement of the theorem, let $a_n = \sqrt{n}E_n[H_i h_i]$. Clearly, f is positive homogeneous, i.e. $f(\lambda a) = \lambda f(a)$ for $\lambda \geq 0$. Then note that the LHS event occurs iff $f(a_n) \leq \epsilon \iff f(a_n/\epsilon) \leq 1 \iff a_n/\epsilon \in A \iff a_n \in \epsilon \cdot A$. This proves the main statement.

Next, we prove (b). Symmetry and convexity were already shown. Suppose B is bounded. Then by Cauchy-Schwarz $f(a) \leq |a|_2 \sup_{b \in B} |b|_2 < \infty$ for any $a \in \mathbb{R}^{d_h}$. Then f is a proper function, so f is continuous by Corollary 10.1.1. of [Rockafellar \(1996\)](#). Then $A = f^{-1}([0, 1])$ is closed. Moreover, the open set $f^{-1}((1/3, 2/3)) \subseteq f^{-1}([0, 1]) = A$, so A has non-empty interior. Suppose that B is open. Then B contains an open ball $B(x, \delta)$ for some $x \in \mathbb{R}^{d_h}$ and $\delta > 0$. Fix $a \in \mathbb{R}^{d_h}$ and define $b(a) = x + \text{sgn}(a'x) \frac{\delta}{2|a|} a$. By assumption, $b(a) \in B$. Then $f(a) = \sup_{b \in B} |b'a| \geq |b(a)'a| = |a'x + \text{sgn}(a'x)(\delta/2)|a|| = |a'x| + (\delta/2)|a| \geq (\delta/2)|a|$. Then $f(a) = \sup_{b \in B} |a'b| \geq (\delta/2)|a|$, so $A \subseteq B(0, 2/\delta)$.

Finally, we prove (c). Note that $R_A = \gamma'_0 Z |Z \in \epsilon B^\circ$. By symmetry of ϵB° , we have $E[Z | Z \in \epsilon B^\circ] = 0$. Denote $W = Z/\epsilon$. Then we calculate

$$\begin{aligned} \text{Var}(R_A | Z \in \epsilon B^\circ) &= E[(\gamma'_0 Z)^2 | Z \in \epsilon B^\circ] \leq E[\sup_{\gamma \in B} |\gamma' Z|^2 | Z \in \epsilon B^\circ] \\ &= \epsilon^2 E[\sup_{\gamma \in B} |\gamma' W|^2 | W \in B^\circ] \leq \epsilon^2 \cdot 1 = \epsilon^2. \end{aligned}$$

The first inequality is by well-specification. The final inequality follows since $W \in B^\circ = \{a : \sup_{b \in B} |b'a| \leq 1\}$. This finishes the proof. \square

Proof of Lemma 5.5. For $B = x + \Sigma B_p$ we compute the upper bound.

$$\begin{aligned} \sup_{b \in B} |a'b| &= \sup_{u \in \Sigma B_p} |a'x + a'u| \leq |a'x| + \sup_{u \in \Sigma B_p} |a'\Sigma^{-1}u| \\ &= |a'x| + \sup_{v \in B_p} |(\Sigma'a)'v| = |a'x| + |\Sigma'a|_q. \end{aligned}$$

Before proceeding, we claim that for any $z \in \mathbb{R}^{d_h}$, we have $\max_{v \in B_p} v'z = \max_{v \in B_p} |v'z|$. Clearly $\max_{v \in B_p} v'z \leq \max_{v \in B_p} |v'z|$. Since B_p is compact and $v \rightarrow v'z$ continuous, $v^* \in \arg\max_{v \in B_p} |v'z|$ exists. Then $\max_{v \in B_p} |v'z| = |z'v^*| = z'v^* \text{sgn}(z'v^*) = z'w$ for $w = v^* \text{sgn}(z'v^*) \in B_p$ since $v^* \in B_p$. Then $\max_{v \in B_p} |v'z| = z'w \leq \max_{w \in B_p} z'w$. This proves the claim. Next, define $b(a) = x + \text{sgn}(a'x)\Sigma v(a)$ with $v(a) \in \arg\max_{v \in B_p} v'\Sigma'a$, which exists by compactness and continuity. Note $b(a) \in B$ by construction. We may calculate $|a'b(a)| = |a'x + \text{sgn}(a'x)a'\Sigma v(a)|$. By the claim, $a'\Sigma v(a) \geq 0$. Then by matching signs, $|a'x + \text{sgn}(a'x)a'\Sigma v(a)| = |a'x| + |\text{sgn}(a'x)a'\Sigma v(a)| = |a'x| + |a'\Sigma v(a)|$. By the claim again, this is $|a'x| + a'\Sigma v(a) = |a'x| + \max_{v \in B_p} a'\Sigma v = |a'x| + |\Sigma'a|_q$. Combining with the upper bound above, we have shown that $\sup_{b \in B} |a'b| = |a'x| + |\Sigma'a|_q$. \square

8.6 Inference

Proof of Theorem 7.2. Define $m_i = \Pi g_i(\theta_0) - H_i \alpha'_0 w_i$, the population version of \widehat{m}_i . Also define $m_{1i} = \Pi g_{1i}(\theta_0) - \alpha'_0 w_i/p$ and $m_{0i} = \Pi g_{0i}(\theta_0) + \alpha'_0 w_i/(1-p)$. We may expand

$$\begin{aligned}\phi_b &\equiv pm_{1i} + (1-p)m_{0i} = pg_{1i} + (1-p)g_{0i} = \Pi\phi(W, \theta_0), \\ \delta_b &\equiv v_D(m_{1i} - m_{0i}) = \Pi\delta(W, \theta_0) - \alpha'_0 w_i.\end{aligned}$$

By Theorem 6.3, we need to estimate $V = \text{Var}(\phi_b) + v_D^{-1}E[\text{Var}(\delta_b|\psi)] = \text{Var}(\phi_b) + v_D^{-1}E[\delta_b\delta'_b] - v_D^{-1}E[E[\delta_b|\psi]E[\delta_b|\psi]'] \equiv V_1 - V_2$. We expand $V_1 = \text{Var}(\phi_b) + v_D^{-1}E[\delta_b\delta'_b]$ as

$$\begin{aligned}V_1 &= \text{Var}(pm_{1i} + (1-p)m_{0i}) + v_DE[(m_{1i} - m_{0i})(m_{1i} - m_{0i})'] \\ &= E[(pm_{1i} + (1-p)m_{0i})(pm_{1i} + (1-p)m_{0i})'] + v_DE[(m_{1i} - m_{0i})(m_{1i} - m_{0i})'] \\ &= (p^2 + v_D)E[m_{1i}m'_{1i}] + ((1-p)^2 + v_D)E[m_{0i}m'_{0i}] \\ &= pE[m_{1i}m'_{1i}] + (1-p)E[m_{0i}m'_{0i}] = \text{Var}_n(\widehat{m}_i) + o_p(1).\end{aligned}$$

The second equality since $E[\phi_b] = 0$, and the final equality by Lemma 8.9. By Lemma 8.10, we also have

$$\begin{aligned}V_2 &= v_D^{-1}E[E[\delta_b|\psi]E[\delta_b|\psi]'] = v_D(E[E[m_{1i}|\psi]E[m_{1i}|\psi]'] + E[E[m_{0i}|\psi]E[m_{0i}|\psi]']) \\ &\quad - v_D(E[E[m_{1i}|\psi]E[m_{0i}|\psi]'] + E[E[m_{0i}|\psi]E[m_{1i}|\psi]']) \\ &= v_D(\widehat{v}_1 + \widehat{v}_0 - \widehat{v}_{10} - \widehat{v}'_{10}) + o_p(1).\end{aligned}$$

This finishes the proof. □

Proof of Theorem 7.3. With notation as in the proof of Theorem 7.2, by Theorem 6.3, $c'(\widehat{\theta} - \theta_0) \Rightarrow \mathcal{N}(0, V_\delta(c))$ with variance $V_\delta(c) = v_D^{-1}c'E[\text{Var}(\delta_b|\psi)]c$ for $\delta_b = v_D(m_{1i} - m_{0i})$. Then $V_\delta(c) = v_Dc'E[\text{Var}(m_{1i} - m_{0i}|\psi)]c$ may be expanded as

$$v_D \cdot c'(E[\text{Var}(m_{1i}|\psi)] + E[\text{Var}(m_{0i}|\psi)] - 2E[\text{Cov}(m_{1i}, m_{0i}|\psi)])c.$$

Note that by Cauchy-Schwarz and Jensen we have the bound

$$\begin{aligned}&-2c'E[\text{Cov}(m_{1i}, m_{0i}|\psi)]c \leq 2|E[\text{Cov}(c'm_{1i}, c'm_{0i}|\psi)]| \\ &\leq 2E[\text{Var}(c'm_{1i}|\psi)^{1/2} \text{Var}(c'm_{0i}|\psi)^{1/2}] \leq 2(E[\text{Var}(c'm_{1i}|\psi)]E[\text{Var}(c'm_{0i}|\psi)])^{1/2} \\ &= 2(c'E[\text{Var}(m_{1i}|\psi)]c \cdot c'E[\text{Var}(m_{0i}|\psi)]c)^{1/2}.\end{aligned}$$

Then we bound

$$V_\delta(c) \leq \bar{V}_\delta(c) \equiv v_D[(c'E[\text{Var}(m_{1i}|\psi)]c)^{1/2} + (c'E[\text{Var}(m_{0i}|\psi)]c)^{1/2}]^2.$$

Note $E[\text{Var}(m_{1i}|\psi)] = E[m_{1i}m'_{1i}] - E[E[m_{1i}|\psi_i]E[m_{1i}|\psi_i]'] = E_n[\frac{D_i}{p}\hat{m}_i\hat{m}'_i] - \hat{v}_1 + o_p(1)$ by Lemma 8.9 and Lemma 8.10. Similarly, $E[\text{Var}(m_{0i}|\psi)] = E_n[\frac{1-D_i}{1-p}\hat{m}_i\hat{m}'_i] - \hat{v}_0 + o_p(1)$. Then for $\hat{u}_1 = E_n[\frac{D_i}{p}\hat{m}_i\hat{m}'_i] - \hat{v}_1$ and $\hat{u}_0 = E_n[\frac{1-D_i}{1-p}\hat{m}_i\hat{m}'_i] - \hat{v}_0$ by continuous mapping

$$\hat{V}_\delta(c) = v_D([c'\hat{u}_1c]^{1/2} + [c'\hat{u}_0c]^{1/2})^2 \xrightarrow{p} \bar{V}_\delta(c) \geq V_\delta(c).$$

This finishes the proof. \square

Comparison of Variances. The superpopulation variance is

$$\begin{aligned} V(c) &= \text{Var}(c'\phi_b) + v_D \cdot (E[\text{Var}(c'm_{1i}|\psi)] + E[\text{Var}(c'm_{0i}|\psi)] - 2E[\text{Cov}(c'm_{1i}, c'm_{0i}|\psi)]) \\ &= p^2 \text{Var}(c'm_{1i}) + (1-p)^2 \text{Var}(c'm_{0i}) + v_D \cdot (E[\text{Var}(c'm_{1i}|\psi)] + E[\text{Var}(c'm_{0i}|\psi)]). \end{aligned}$$

Then the variance gap $V(c) - V_\delta(c)$ is

$$\begin{aligned} &p^2 \text{Var}(c'm_{1i}) + (1-p)^2 \text{Var}(c'm_{0i}) - 2v_D(E[\text{Var}(m_{1i}|\psi)] \cdot E[\text{Var}(m_{0i}|\psi)])^{1/2} \\ &= p^2 \text{Var}(E[c'm_{1i}|\psi_i]) + (1-p)^2 \text{Var}(E[c'm_{0i}|\psi_i]) \\ &\quad + (pE[\text{Var}(c'm_{1i}|\psi)]^{1/2} - (1-p)E[\text{Var}(c'm_{0i}|\psi)]^{1/2})^2 \geq 0. \end{aligned}$$

Lemma 8.9. *The following hold:*

- (a) $E_n[\frac{D_i}{p}\hat{m}_i\hat{m}'_i] = E[m_{1i}m'_{1i}] + o_p(1)$ and $E_n[\frac{1-D_i}{1-p}\hat{m}_i\hat{m}'_i] = E[m_{0i}m'_{0i}] + o_p(1)$.
- (b) $\text{Var}_n(\hat{m}_i) = pE[m_{1i}m'_{1i}] + (1-p)E[m_{0i}m'_{0i}] + o_p(1)$.

Proof. For (a), consider the first statement. We may expand this as

$$E_n[(D_i/p)\hat{m}_i\hat{m}'_i] = E_n[(D_i/p)\hat{m}_i(\hat{m}_i - m_i)'] + E_n[(D_i/p)(\hat{m}_i - m_i)m'_i] + E_n[(D_i/p)m_im'_i].$$

For $g_i = g_i(\theta_0)$, we have $|\hat{m}_i - m_i|_2 = |\hat{\Pi}\hat{g}_i - \Pi g_i - H_i(\hat{\alpha} - \alpha)'w_i|_2 \lesssim |\hat{\Pi} - \Pi|_2|\hat{g}_i|_2 + |\Pi|_2|\hat{g}_i - g_i|_2 + |\hat{\alpha} - \alpha_0|_2|w_i|_2$. Then the first term above has

$$\begin{aligned} |E_n[(D_i/p)\hat{m}_i(\hat{m}_i - m_i)']| &\leq |\hat{\Pi} - \Pi|_2 E_n[|\hat{m}_i|_2|\hat{g}_i|_2] + |\Pi|_2 E_n[|\hat{m}_i|_2|\hat{g}_i - g_i|_2] \\ &\quad + |\hat{\alpha} - \alpha_0|_2 E_n[|\hat{m}_i|_2|w_i|_2]. \end{aligned}$$

We claim this term is $o_p(1)$. Note that $|\hat{\Pi} - \Pi|_2 = o_p(1)$ and $|\hat{\alpha} - \alpha_0|_2 = o_p(1)$ by assumption. Then applying Cauchy-Schwarz, it suffices to show $E_n[|\hat{m}_i|_2^2 + |\hat{g}_i|_2^2 + |w_i|_2^2] = O_p(1)$ and $E_n[|\hat{g}_i - g_i|_2^2] = o_p(1)$. First, note $E_n[|w_i|_2^2] = O_p(1)$ since $E[|w|_2^2] < \infty$. Next, note $E_n[|\hat{m}_i|_2^2] = E_n[|\hat{\Pi}\hat{g}_i - H_i\hat{\alpha}'w_i|_2^2] \leq 2E_n[|\hat{\Pi}\hat{g}_i|_2^2] + 2E_n[|\hat{\alpha}'w_i|_2^2] \leq 2|\hat{\Pi}|_2^2 E_n[|\hat{g}_i|_2^2] + 2|\hat{\alpha}|_2^2 E_n[|w_i|_2^2]$, so clearly it suffices to show $E_n[|\hat{g}_i|_2^2] = O_p(1)$ to handle this term.

We start by showing that $E_n[|\hat{g}_i - g_i|_2^2] = o_p(1)$. By the mean value theorem $g_i(\hat{\theta}) - g_i(\theta_0) = \frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i)(\hat{\theta} - \theta_0)$, where $\tilde{\theta}_i \in [\theta_0, \hat{\theta}]$ may change by row. Then we have $E_n[|g_i(\hat{\theta}) - g_i(\theta_0)|_2^2] = E_n[\frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i)(\hat{\theta} - \theta_0)(\hat{\theta} - \theta_0)'] = E_n[|\frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i)|_2^2]E_n[|\hat{\theta} - \theta_0|_2^2] = o_p(1)$.

$g_i(\theta_0)|_2^2] \leq |\hat{\theta} - \theta_0|_2^2 E_n[|\frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i)|_2^2]$, so it suffices to show $E_n[|\frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i)|_2^2] = O_p(1)$. Since $g_i(\theta) = D_i g_{1i}(\theta) + (1 - D_i) g_{0i}(\theta)$ for all θ , $|\frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i)|_2^2 \leq 2|\frac{\partial g_{1i}}{\partial \theta'}(\tilde{\theta}_i)|_2^2 + 2|\frac{\partial g_{0i}}{\partial \theta'}(\tilde{\theta}_i)|_2^2$. Define the event $S_n = \{\hat{\theta} \in U\}$. Then on S_n we have

$$\begin{aligned} |\frac{\partial g_{1i}}{\partial \theta'}(\tilde{\theta}_i)|_2^2 + |\frac{\partial g_{0i}}{\partial \theta'}(\tilde{\theta}_i)|_2^2 &\leq |\frac{\partial g_{1i}}{\partial \theta'}(\tilde{\theta}_i)|_F^2 + |\frac{\partial g_{0i}}{\partial \theta'}(\tilde{\theta}_i)|_F^2 = \sum_{d=0,1} \sum_{k=1}^{d_g} |\nabla g_{di}^k(\tilde{\theta}_{ik})|_2^2 \\ &\leq \sum_{d=0,1} \sum_{k=1}^{d_g} \sup_{\theta \in U} |\nabla g_{di}^k(\theta)|_2^2 \equiv \bar{U}_i. \end{aligned}$$

Then $E_n[|\frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i)|_2^2] \mathbb{1}(S_n) \leq E_n[\bar{U}_i] \mathbb{1}(S_n) = O_p(1)$ since $E[\sup_{\theta \in U} |\nabla g_{di}^k(\theta)|_2^2] < \infty$ by assumption. Then $E_n[|\frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i)|_2^2] = O_p(1)$ since $P(S_n^c) \rightarrow 0$. This finishes the proof of $E_n[|\hat{g}_i - g_i|_2^2] = o_p(1)$. Finally, the claim $E_n[|\hat{g}_i|_2^2] = O_p(1)$ is clear since $E_n[|\hat{g}_i|_2^2] \leq 2E_n[|\hat{g}_i - g_i|_2^2] + 2E_n[|g_i|_2^2] = o_p(1) + O_p(1)$ by the preceding claim.

Then we have shown $|E_n[(D_i/p)\hat{m}_i(\hat{m}_i - m_i)']| = o_p(1)$ and $E_n[(D_i/p)(\hat{m}_i - m_i)m_i'] = o_p(1)$ by an identical argument. This shows that $E_n[(D_i/p)\hat{m}_i\hat{m}_i'] = E_n[(D_i/p)m_i m_i'] + o_p(1)$. Next, we have $E_n[(D_i/p)m_i m_i'] = E_n[(D_i/p)m_{1i} m_{1i}'] = E_n[m_{1i} m_{1i}'] + o_p(1) = E[m_{1i} m_{1i}'] + o_p(1)$. The first equality is by definition of m_i, m_{1i} . The second equality by Lemma A.2 of [Cytrynbaum \(2024\)](#) and the third equality by vanilla WLLN, using $E[|m_i|_2^2] < \infty$. This finishes our proof of the first statement of (a), and the second statement follows by symmetry.

For (b), note $E_n[\hat{m}_i \hat{m}_i'] = pE_n[\frac{D_i}{p} \hat{m}_i \hat{m}_i'] + (1-p)E_n[\frac{1-D_i}{1-p} \hat{m}_i \hat{m}_i'] = pE[\frac{D_i}{p} m_{1i} m_{1i}'] + (1-p)E[m_{0i} m_{0i}'] + o_p(1)$ by part (a) of the lemma. Moreover, $E_n[\hat{m}_i] = E_n[\hat{\Pi} \hat{g}_i - H_i \hat{\alpha}' w_i] = \hat{\Pi} E_n[\hat{g}_i] + o_p(1)$. Note that $E_n[\hat{g}_i] = \hat{g}(\hat{\theta})$ and $\hat{g}(\hat{\theta}) - \hat{g}(\theta_0) = g_0(\hat{\theta}) - g_0(\theta_0) + o_p(1) = o_p(1)$. The first equality since $|\hat{g} - g_0|_{\Theta, \infty} = o_p(1)$ and the second by continuous mapping, using Lemma 8.6. Then $\text{Var}_n(\hat{m}_i) = pE[m_{1i}(\theta_0)m_{1i}(\theta_0)'] + (1-p)E[m_{0i}(\theta_0)m_{0i}(\theta_0)'] + o_p(1)$, finishing the proof. \square

Lemma 8.10. *In the statement of Theorem 7.2, $\hat{v}_{10} \xrightarrow{P} E[E[m_{1i}(\theta_0)|\psi]E[m_{0i}(\theta_0)|\psi]']$ and $\hat{v}_1 \xrightarrow{P} E[E[m_{1i}(\theta_0)|\psi]E[m_{1i}(\theta_0)|\psi]']$, and $\hat{v}_0 \xrightarrow{P} E[E[m_{0i}(\theta_0)|\psi]E[m_{0i}(\theta_0)|\psi]']$.*

Proof. Let \hat{v}_1^o denote the oracle version of \hat{v}_1 , substituting $m_i = \Pi g_i(\theta_0) - H_i \alpha'_0 w_i$ for \hat{m}_i , and similarly for $\hat{v}_0^o, \hat{v}_{10}^o$. In Lemma A.6 of [Cytrynbaum \(2024\)](#), set $A_i = m_{1i}$ and $B_i = m_{1i}$. Applying the lemma componentwise, $\hat{v}_1^o \xrightarrow{P} E[E[m_{1i}(\theta_0)|\psi]E[m_{1i}(\theta_0)|\psi]']$, $\hat{v}_0^o \xrightarrow{P} E[E[m_{0i}(\theta_0)|\psi]E[m_{0i}(\theta_0)|\psi]']$, and $\hat{v}_{10}^o \xrightarrow{P} E[E[m_{1i}(\theta_0)|\psi]E[m_{0i}(\theta_0)|\psi]']$. Then it suffices to show that $\hat{v}_1 - \hat{v}_1^o = o_p(1)$, $\hat{v}_0 - \hat{v}_0^o = o_p(1)$, and $\hat{v}_{10} - \hat{v}_{10}^o = o_p(1)$. For the first statement, expand

$$\hat{v}_1 - \hat{v}_1^o = (np)^{-1} \sum_{g \in \mathcal{G}_n^V} \frac{1}{a(g) - 1} \sum_{i \neq j \in g} D_i D_j (\hat{m}_i \hat{m}_j' - m_i m_j')$$

Expand $\widehat{m}_i \widehat{m}'_j - m_i m'_j = \widehat{m}_i (\widehat{m}'_j - m'_j) + (\widehat{m}_i - m_i) m'_j \equiv A_{ij} + B_{ij}$. Using triangle inequality, $a(g) - 1 \geq 1$ and $p > 0$, we calculate $\widehat{v}_1^o - \widehat{v}_1 \lesssim n^{-1} \sum_{g \in \mathcal{G}_n^\nu} \sum_{i,j \in g} |A_{ij}|_2 + |B_{ij}|_2 \equiv A_n + B_n$. First consider B_n . Using that $|xy'|_2 \leq |x|_2 |y|_2$, we have

$$\begin{aligned} |B_{ij}|_2 &\leq |\widehat{m}_i - m_i|_2 |m_j|_2 = |\widehat{\Pi} \widehat{g}_i - \Pi g_i - H_i(\widehat{\alpha} - \alpha)' w_i|_2 |m_j|_2 \\ &\leq |\widehat{\Pi} - \Pi|_2 |\widehat{g}_i|_2 |m_j|_2 + |\Pi|_2 |\widehat{g}_i - g_i|_2 |m_j|_2 + |\widehat{\alpha} - \alpha|_2 |w_i|_2 |m_j|_2. \end{aligned}$$

Then $B_n = n^{-1} \sum_{g \in \mathcal{G}_n^\nu} \sum_{i,j \in g} |\widehat{\Pi} - \Pi|_2 |\widehat{g}_i|_2 |m_j|_2 + |\Pi|_2 |\widehat{g}_i - g_i|_2 |m_j|_2 + |\widehat{\alpha} - \alpha|_2 |w_i|_2 |m_j|_2 \equiv B_{n1} + B_{n2} + B_{n3}$. Consider B_{n1} . This is

$$\begin{aligned} B_{n1} &= |\widehat{\Pi} - \Pi|_2 \cdot n^{-1} \sum_{g \in \mathcal{G}_n^\nu} \sum_{i,j \in g} |\widehat{g}_i|_2 |m_j|_2 \leq |\widehat{\Pi} - \Pi|_2 \cdot (2n)^{-1} \sum_{g \in \mathcal{G}_n^\nu} \sum_{i,j \in g} |\widehat{g}_i|_2^2 + |m_j|_2^2 \\ &\leq |\widehat{\Pi} - \Pi|_2 \cdot (2n)^{-1} \sum_{g \in \mathcal{G}_n^\nu} |g| \sum_{i \in g} |\widehat{g}_i|_2^2 + |m_i|_2^2 \lesssim |\widehat{\Pi} - \Pi|_2 E_n[|\widehat{g}_i|_2^2 + |m_i|_2^2]. \end{aligned}$$

By an identical argument $B_{n3} \lesssim |\widehat{\alpha} - \alpha|_2 E_n[|w_i|_2^2 + |m_i|_2^2]$. Then to show $B_{n1} + B_{n3} = o_p(1)$, suffices to show $E_n[|w_i|_2^2 + |m_i|_2^2 + |\widehat{g}_i|_2^2] = O_p(1)$. That $E_n[|w_i|_2^2 + |\widehat{g}_i|_2^2] = O_p(1)$ was shown in the proof of Lemma 8.9. Note $E_n[|m_i|_2^2] = E_n[|\Pi g_i - H_i \alpha'_0 w_i|_2^2] \leq 2E_n[|\Pi g_i|_2^2] + 2E_n[|\alpha'_0 w_i|_2^2] \leq 2|\Pi|_2^2 E_n[|g_i|_2^2] + 2|\alpha_0|_2^2 E_n[|w_i|_2^2] = O_p(1)$ since $E[|g_i|_2^2] < \infty$ by assumption. Then $B_{n1} + B_{n3} = o_p(1)$. Finally, consider B_{n2} . By the mean value theorem $g_i(\widehat{\theta}) - g_i(\theta_0) = \frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i)(\widehat{\theta} - \theta_0)$, where $\tilde{\theta}_i \in [\theta_0, \widehat{\theta}]$ may change by row. Then we have

$$\begin{aligned} B_{n2} &= n^{-1} \sum_{g \in \mathcal{G}_n^\nu} \sum_{i,j \in g} |\Pi|_2 |\widehat{g}_i - g_i|_2 |m_j|_2 \leq |\widehat{\theta} - \theta_0|_2 |\Pi|_2 \cdot n^{-1} \sum_{g \in \mathcal{G}_n^\nu} \sum_{i,j \in g} \left| \frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i) \right|_2 |m_j|_2 \\ &\lesssim |\widehat{\theta} - \theta_0|_2 |\Pi|_2 E_n \left[\left| \frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i) \right|_2^2 + |m_i|_2^2 \right] = o_p(1). \end{aligned}$$

The final equality follows since $E_n \left[\left| \frac{\partial g_i}{\partial \theta'}(\tilde{\theta}_i) \right|_2^2 \right] = O_p(1)$, as shown in the proof of Lemma 8.9. Then we have shown $B_n = o_p(1)$, and $A_n = o_p(1)$ is identical. This completes the proof that $\widehat{v}_1 - \widehat{v}_1^o = o_p(1)$, and the proof of $\widehat{v}_0 - \widehat{v}_0^o = o_p(1)$, and $\widehat{v}_{10} - \widehat{v}_{10}^o = o_p(1)$ are identical. \square

8.7 Lemmas

Proposition 8.11 (Lévy). *Consider probability spaces $(\Omega_n, \mathcal{G}_n, P_n)$ and σ -algebras $\mathcal{F}_n \subseteq \mathcal{G}_n$. We say $A_n \in \mathbb{R}^d$ has $A_n | \mathcal{F}_n \Rightarrow A$ if $\phi_n(t) \equiv E[e^{it' A_n} | \mathcal{F}_n] = E[e^{it' A} | \mathcal{F}_n] + o_p(1)$ for each $t \in \mathbb{R}^d$. If $g : \mathbb{R}^d \rightarrow \mathbb{C}$ is bounded, measurable, and $P(A \in \{a : g(\cdot) \text{ discontinuous at } a\}) = 0$ then we have*

$$E[g(A_n) | \mathcal{F}_n] = E[g(A)] + o_p(1). \quad (8.1)$$

See [Cytrynbaum \(2021\)](#) for the proof.

Lemma 8.12. *The following statements hold*

- (a) There exists $\Gamma_0 \in \mathbb{R}^{d_h \times d_\delta}$ solving $E[\text{Var}(h|\psi)]\Gamma_0 = E[\text{Cov}(h, \delta|\psi)]$. For any solution, we have $E[\text{Var}(\delta - \Gamma'_0 h|\psi)] \preceq E[\text{Var}(\delta - \Gamma' h|\psi)]$ for all $\Gamma \in \mathbb{R}^{d_h \times d_\delta}$.
- (b) Let $Z = (Z_\delta, Z_h)$ a random variable with $\text{Var}(Z) = E[\text{Var}((\delta, h)|\psi)] \equiv \Sigma$ and define $\tilde{Z}_\delta = Z_\delta - \Gamma'_0 Z_h$. Then $\text{Cov}(\tilde{Z}_\delta, Z_h) = 0$. In particular, if (Z_δ, Z_h) are jointly Gaussian, then \tilde{Z}_δ is Gaussian with $\tilde{Z}_\delta \perp\!\!\!\perp Z_h$.

Proof. In the notation of (b), it suffices to show $\Sigma_{hh}\Gamma_0 = \Sigma_{h\delta}$. If $\text{rank}(\Sigma_{hh}) = 0$ then $Z_h = c_h$ a.s. for constant c_h and $\Sigma_{h\delta} = \text{Cov}(Z_h, Z_\delta) = 0$. Then any $\Gamma \in \mathbb{R}^{d_h \times d_\delta}$ is a solution. Then suppose $\text{rank}(\Sigma_{hh}) = r \geq 1$. Let $\Sigma_{hh} = U\Lambda U'$ be the compact SVD with $U \in \mathbb{R}^{d_h \times r}$ and $\text{rank}(\Lambda) = r$, and $U'U = I_r$. We claim $Z_h = UU'Z_h$ a.s. Calculate $\text{Var}((UU' - I)Z_h) = (UU' - I)U\Lambda U'(UU' - I) = 0$. Note that $\Sigma_{hh}\Gamma = \Sigma_{h\delta} \iff \text{Var}(Z_h)\Gamma = \text{Cov}(Z_h, Z_\delta) \iff \text{Var}(UU'Z_h)\Gamma = \text{Cov}(UU'Z_h, Z_\delta) \iff U[\text{Var}(U'Z_h)U'\Gamma - \text{Cov}(U'Z_h, Z_\delta)] = 0$. Define $\bar{Z}_h = U'Z_h$ and note $\text{Var}(\bar{Z}_h) = U'U\Lambda U'U = \Lambda \succ 0$. Then let $\bar{\Gamma} = \text{Var}(\bar{Z}_h)^{-1} \text{Cov}(\bar{Z}_h, \delta)$ so that $\text{Var}(\bar{Z}_h)\bar{\Gamma} - \text{Cov}(\bar{Z}_h, Z_\delta) = 0$. Then it suffices to find Γ such that $U'\Gamma = \bar{\Gamma}$. Since $U' : \mathbb{R}^{d_h} \rightarrow \mathbb{R}^r$ is onto, there exists Γ^k with $U'\Gamma^k = \bar{\Gamma}^k$. Then let $\Gamma_0^k \in [\Gamma^k + \ker(U')]$ and set $\Gamma_0 = (\Gamma_0^k : k = 1, \dots, d_\delta)$, so that $U'\Gamma_0 = \bar{\Gamma}$. Then $\Sigma_{hh}\Gamma_0 = \Sigma_{h\delta}$ by work above. For the optimality statement, calculate

$$\begin{aligned} E[\text{Var}(\delta - \Gamma' h|\psi)] &= \Sigma_{\delta\delta} - \Sigma_{\delta h}\Gamma - \Gamma'\Sigma_{h\delta} + \Gamma'\Sigma_{hh}\Gamma = \Sigma_{\delta\delta} - \Sigma_{\delta h}(\Gamma - \Gamma_0 + \Gamma_0) \\ &\quad - (\Gamma - \Gamma_0 + \Gamma_0)'\Sigma_{h\delta} + \Gamma'\Sigma_{hh}\Gamma = \Sigma_{\delta\delta} - 2\Gamma_0'\Sigma_{hh}\Gamma_0 - (\Gamma - \Gamma_0)'\Sigma_{h\delta} - \Sigma_{\delta h}(\Gamma - \Gamma_0) \\ &\quad + \Gamma'\Sigma_{hh}\Gamma \propto -(\Gamma - \Gamma_0)'\Sigma_{hh}\Gamma_0 - \Gamma_0'\Sigma_{hh}(\Gamma - \Gamma_0) + \Gamma'\Sigma_{hh}\Gamma = -(\Gamma - \Gamma_0)'\Sigma_{hh}\Gamma_0 \\ &\quad - \Gamma_0'\Sigma_{hh}(\Gamma - \Gamma_0) + \Gamma'\Sigma_{hh}\Gamma + (\Gamma - \Gamma_0 + \Gamma_0)'\Sigma_{hh}(\Gamma - \Gamma_0 + \Gamma_0) \\ &= \Gamma_0'\Sigma_{hh}\Gamma_0 + (\Gamma - \Gamma_0)'\Sigma_{hh}(\Gamma - \Gamma_0). \end{aligned}$$

Then $E[\text{Var}(\delta - \Gamma' h|\psi)] - E[\text{Var}(\delta - \Gamma'_0 h|\psi)] = (\Gamma - \Gamma_0)'\Sigma_{hh}(\Gamma - \Gamma_0)$ and for any $a \in \mathbb{R}^{d_\delta}$ we have $a'(\Gamma - \Gamma_0)'\Sigma_{hh}(\Gamma - \Gamma_0)a \geq 0$ since $\Sigma_{hh} \succeq 0$. This proves the claim. Finally, we have $\text{Cov}(\tilde{Z}_\delta, Z_h) = \text{Cov}(Z_\delta - \Gamma'_0 Z_h, Z_h) = \Sigma_{\delta h} - \Gamma'_0 \Sigma_{hh} = 0$. The final statement follows from well-known facts about the normal distribution. \square

Lemma 8.13 (SVD). Suppose $\Sigma \in \mathbb{R}^{m \times m}$ is symmetric PSD with $\text{rank}(\Sigma) = r$. Then $\Sigma = U\Lambda U'$ for $U \in \mathbb{R}^{m \times r}$ with $U'U = I_r$ and Λ diagonal.

Proof. Since Σ is symmetric PSD, there exists $B'B = \Sigma$ for $\text{rank}(B) = r$. Let VAU' be the compact SVD of B , with A diagonal. Then $\Sigma = B'B = UA^2U' \equiv U\Lambda U'$ with $U'U = I_r$. \square

Lemma 8.14. Consider probability spaces $(\Omega_n, \mathcal{G}_n, P_n)$ and σ -algebras $\mathcal{F}_n \subseteq \mathcal{G}_n$. Suppose $0 \leq A_n \leq B < \infty$ and $A_n = o_p(1)$. Then $E[A_n|\mathcal{F}_n] = o_p(1)$.

Proof. For any $\epsilon > 0$, note that $E[A_n|\mathcal{F}_n] = E[A_n \mathbf{1}(A_n \leq \epsilon)|\mathcal{F}_n] + E[A_n \mathbf{1}(A_n > \epsilon)|\mathcal{F}_n] \leq \epsilon + BP(A_n > \epsilon|\mathcal{F}_n)$. We have $E[P(A_n > \epsilon|\mathcal{F}_n)] = P(A_n > \epsilon) = o(1)$ by tower law and

assumption. Then $P(A_n > \epsilon | \mathcal{F}_n) = o_p(1)$ by Markov inequality. Then we have shown $E[A_n | \mathcal{F}_n] \leq \epsilon + T_n(\epsilon)$ with $T_n(\epsilon) = o_p(1)$. Fix $\delta > 0$ and let $\epsilon = \delta/2$. Then $P(E[A_n | \mathcal{F}_n] > \delta) \leq P(\delta/2 + T_n(\delta/2) > \delta) = P(T_n(\delta/2) > \delta/2) = o(1)$ since $T_n(\delta/2) = o_p(1)$. Since δ was arbitrary, we have shown that $E[A_n | \mathcal{F}_n] = o_p(1)$. \square

Lemma 8.15. $A_n = O_p(1) \iff A_n = o_p(c_n)$ for every sequence $c_n \rightarrow \infty$.

Proof. It suffices to consider $A_n \geq 0$. The forward direction is clear. For the backward direction, suppose for contradiction that there exists $\epsilon > 0$ such that $\sup_{n \geq 1} P(A_n > M) > \epsilon$ for all M . Then find n_k such that $P(A_{n_k} > k) > \epsilon$ for each $k \geq 1$. We claim $n_k \rightarrow \infty$. Suppose not and $\liminf_k n_k \leq N < \infty$. Then let $k(j) \rightarrow \infty$ such that $n_{k(j)} \leq N$ for all j . Choose $M' < \infty$ such that $P(A_n > M') < \epsilon$ for all $n = 1, \dots, N$. Then for $k(j) > M'$ we have $P(A_{n_{k(j)}} > k(j)) \leq P(A_{n_{k(j)}} > M') < \epsilon$, which is a contradiction. Then apparently $\lim_k n_k = +\infty$. Define $Z_j = \{i : i \geq j\}$. Regard the sequence n_k as map $n : \mathbb{N} \rightarrow \mathbb{N}$. For $m \in \text{Image}(n)$, define $n^\dagger(m) = \min n^{-1}(m)$. It's easy to see that $n^\dagger(m_k) \rightarrow \infty$ for $\{m_k\}_k \subseteq \text{Image}(n)$ with $m_k \rightarrow \infty$. Then write

$$\sup_{k \geq j} P(A_{n_k} > k) = \sup_{m \in n(Z_j)} \sup_{a \in n^{-1}(m)} P(A_m > a) \leq \sup_{m \in n(Z_j)} P(A_m > n^\dagger(m))$$

Note $A_{m_k}/n^\dagger(m_k) = o_p(1)$ by assumption for any $\{m_k\}_k \subseteq \text{Image}(n)$ with $m_k \rightarrow \infty$. Then we have

$$\limsup_k P(A_{n_k} > k) = \limsup_j \sup_{k \geq j} P(A_{n_k} > k) = \lim_j \sup_{m \in n(Z_j)} P(A_m > n^\dagger(m)) = o(1).$$

This is a contradiction, which completes the proof. \square

Lemma 8.16 (Dominance). *Let $(G_n)_{n \geq 1}$ and $(B_n)_{n \geq 1}$ events and random variables. Suppose that the rerandomization measure Q is as in Definition 8.2.*

- (a) *If an event $G_n \in \mathcal{F}_n$ then $P(G_n) = Q(G_n)$. In particular, if a random variable $B_n \in \mathcal{F}_n$ then $B_n = o_p(1)/O_p(1) \iff B_n = o_q(1)/O_q(1)$.*
- (b) *If $P(G_n) = o(1)$ then $Q(G_n) = o(1)$. In particular, if $B_n = o_p(1)/O_p(1)$ then $B_n = o_q(1)/O_q(1)$.*

Proof. The first set of statements since $Q = P$ on \mathcal{F}_n by definition. Let $c = P(Z_h \in T)$, with $c > 0$ by assumption. Define $S_n = \{P(\mathcal{I}_n \in T_n | \mathcal{F}_n) \geq c/2\}$. Then by lemma 8.3, $P(\mathcal{I}_n \in T_n | \mathcal{F}_n) \xrightarrow{P} P(Z_h \in T) = c$, so $P(S_n) \rightarrow 1$. We have the upper bound

$$\begin{aligned} \mathbb{1}(S_n)Q(G_n | \mathcal{F}_n) &= \mathbb{1}(S_n)P(G_n | \mathcal{I}_n \in T_n, \mathcal{F}_n) = \mathbb{1}(S_n) \frac{P(G_n, \mathcal{I}_n \in T_n | \mathcal{F}_n)}{P(\mathcal{I}_n \in T_n | \mathcal{F}_n)} \\ &\leq (c/2)^{-1} \mathbb{1}(S_n)P(G_n, \mathcal{I}_n \in T_n | \mathcal{F}_n) \leq (c/2)^{-1} P(G_n | \mathcal{F}_n). \end{aligned}$$

The first equality by definition of Q . The first inequality by the definition of S_n . The final inequality by additivity of measures. Then for $r_n \equiv (1 - \mathbb{1}(S_n))Q(G_n|\mathcal{F}_n)$, we have $Q(G_n|\mathcal{F}_n) = \mathbb{1}(S_n)Q(G_n|\mathcal{F}_n) + r_n$. Note that $|r_n| \leq 1$ and $r_n \xrightarrow{p} 0$, so $E_Q[r_n] = o(1)$ by modes of convergence. Then expand $Q(G_n)$ as

$$\begin{aligned} E_Q[Q(G_n|\mathcal{F}_n)] &= E_Q[\mathbb{1}(S_n)Q(G_n|\mathcal{F}_n)] + E_Q[r_n] \leq (c/2)^{-1}E_Q[P(G_n|\mathcal{F}_n)] + o(1) \\ &= (c/2)^{-1}E_P[P(G_n|\mathcal{F}_n)] + o(1) = (c/2)^{-1}P(G_n) + o(1). \end{aligned}$$

The second equality follows from part (a), and the final equality by tower law. The $o_p(1)$ results follow by setting $G_n = \{B_n > \epsilon\}$. The $O_p(1)$ results follow by the $o_p(1)$ statement and Lemma 8.15. \square