

# Multiple Treatment Effects Regression

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The package `multte` implements contamination bias diagnostics for regressions with multiple treatments developed in Goldsmith-Pinkham et al. [2024]. This vignette illustrates the methods using data from Fryer and Levitt [2013].

First, we fit a regression of test scores on a race dummy (treatment of interest) and a few controls, weighting using sampling weights:

```
library("multte")
## Regression of IQ at 24 months on race indicators
## and baseline controls
r1 <- stats::lm(std_iq_24 ~ race + factor(age_24) + female +
  SES_quintile, weight = W2C0, data = fl)
## Compute alternatives estimates free of
## contamination bias
m1 <- multte(r1, "race", cluster = NULL)
print(m1, digits = 3)
#> Estimates on full sample:
#>
#>      PL      OWN      ATE      EW      CW
#> Black  -0.2574 -0.2482 -0.2655 -0.2550 -0.2604
#> SE      0.0281  0.0291  0.0298  0.0289  0.0292
#> Hispanic -0.2931 -0.2829 -0.2992 -0.2862 -0.2944
#> SE      0.0260  0.0267  0.0299  0.0268  0.0279
#> Asian   -0.2621 -0.2609 -0.2599 -0.2611 -0.2694
#> SE      0.0343  0.0343  0.0418  0.0343  0.0475
#> Other   -0.1563 -0.1448 -0.1503 -0.1447 -0.1522
#> SE      0.0369  0.0370  0.0359  0.0368  0.0370
```

```

#>
#> P-values for null hypothesis of no propensity score variation:
#> Wald test: 0, LM test: 0
#>
#> SD(estimated propensity score), maximum over treatment arms:
#> Full sample: 0.196
#> Warning in max(x$pscore_sd_o): no non-missing arguments to max; returning -Inf
#> , Overlap sample: -Inf

```

The package reports five different estimators:

1. PL: The uninteracted regression estimator based on the partially linear (PL) model.
2. OWN: The own-treatment effect component of the contamination bias decomposition. If OWN is close to PL, as above, this indicates negligible contamination bias.
3. ATE: The unweighted average treatment effect, implemented using regression that interacts the treatment dummies with the controls.
4. EW: Weighted ATE estimator based on easiest-to-estimate weighting (EW) scheme, implemented by running one-treatment-at-a-time regressions.
5. CW: Weighted ATE estimator using easiest-to-estimate common weighting (CW) scheme from Corollary 2 in Goldsmith-Pinkham et al. [2024], implemented using weighted regression.

Precise definitions of these estimators are given in the Methods section below.

In this example, the propensity score varies significantly with covariates, as indicated by the p-values of the Wald and LM tests.

Including many controls may result in overlap failure, as the next example demonstrates:

```

r2 <- stats::lm(std_iq_24 ~ race + factor(age_24) + female +
  SES_quintile + factor(siblings) + family_structure,
  weight = W2C0, data = fl)
m2 <- multte(r2, treatment = "race")
#> For variable factor(siblings) the following levels fail overlap:
#> 6
#> Dropping observations with these levels
print(m2, digits = 3)
#> Estimates on full sample:
#>
#>      PL      OWN      ATE      EW      CW
#> Black  -0.2438 -0.2043 -0.2482 -0.2180 -0.2408
#> SE      0.0308  0.0332  0.0355  0.0328  0.0389
#> Hispanic -0.2928 -0.2801 -0.2878 -0.2850 -0.2964
#> SE      0.0259  0.0267  0.0300  0.0267  0.0299
#> Asian   -0.2739 -0.2836 -0.2742 -0.2839 -0.2916
#> SE      0.0342  0.0343  0.0420  0.0343  0.0459
#> Other   -0.1520 -0.1277      NA  -0.1295 -0.1459
#> SE      0.0369  0.0374      NA  0.0371  0.0385
#>
#> Estimates on overlap sample:
#>
#>      PL      OWN      ATE      EW      CW
#> Black  -0.2444 -0.2049 -0.2505 -0.2191 -0.2426

```

```
#> SE      0.0309  0.0334  0.0357  0.0329  0.0388
#> Hispanic -0.2915 -0.2791 -0.2871 -0.2839 -0.2974
#> SE      0.0259  0.0267  0.0300  0.0267  0.0299
#> Asian    -0.2766 -0.2863 -0.2769 -0.2865 -0.2924
#> SE      0.0344  0.0345  0.0421  0.0345  0.0459
#> Other    -0.1522 -0.1280 -0.1397 -0.1298 -0.1465
#> SE      0.0369  0.0374  0.0362  0.0371  0.0385
#>
#> P-values for null hypothesis of no propensity score variation:
#> Wald test: 0, LM test: 0
#>
#> SD(estimated propensity score), maximum over treatment arms:
#> Full sample: 0.211, Overlap sample: 0.21
```

The issue is that no observations with 6 siblings have race equal to other:

```
table(fl$race[fl$siblings == 6])
#>
#>      White      Black Hispanic      Asian      Other
#>        18         10         12         5         0
```

Thus, the ATE estimator comparing other to white is not identified. The package drops observations with 6 siblings from the sample to form an “overlap sample” (see Methods section below for precise construction of this sample), where the all estimators are identified.

For a researcher who wants to check whether there is a significant difference between the PL estimator and the other estimators, the data frame `cb_f` reports the difference between the estimates in the full sample, along with the corresponding standard error. The data frame `cb_o` reports the differences and standard errors for the overlap sample:

```
print(m2$cb_f, digits = 3)
#>      PL      OWN      ATE      EW      CW
#> Black  NA -0.03947  0.004397 -0.02573 -0.00292
#> pop_se NA  0.01204  0.017297  0.01027  0.02078
#> Hispanic NA -0.01269 -0.004962 -0.00783  0.00362
#> pop_se NA  0.00571  0.013143  0.00497  0.01274
#> Asian  NA  0.00975  0.000265  0.01001  0.01769
#> pop_se NA  0.00487  0.024595  0.00480  0.02847
#> Other  NA -0.02430      NA -0.02246 -0.00605
#> pop_se NA  0.00738      NA  0.00684  0.01334
print(m2$cb_o, digits = 3)
#>      PL      OWN      ATE      EW      CW
#> Black  NA -0.03951  0.006062 -0.02537 -0.00185
#> pop_se NA  0.01203  0.017395  0.01026  0.02060
#> Hispanic NA -0.01246 -0.004473 -0.00759  0.00589
#> pop_se NA  0.00569  0.013110  0.00494  0.01252
#> Asian  NA  0.00963  0.000209  0.00984  0.01578
#> pop_se NA  0.00488  0.024687  0.00481  0.02840
#> Other  NA -0.02423 -0.012490 -0.02240 -0.00573
```

```
#> pop_se    NA    0.00738    0.010968    0.00683    0.01326
```

We see statistically significant difference between the OWN and PL estimate (i.e. significant contamination bias) for all races, both in the full sample and in the overlap sample.

## Standard errors

The package also computes “oracle” standard errors, in addition to the usual standard errors reported above. These can be accessed in the data frame `est_f` (or `est_o` for the overlap sample results)

```
print(m1$est_f, digits = 3)
#>
#>      PL      OWN      ATE      EW      CW
#> Black   -0.2574 -0.2482 -0.2655 -0.2550 -0.2604
#> pop_se   0.0281  0.0291  0.0298  0.0289  0.0292
#> oracle_se    NA      NA  0.0298  0.0288  0.0290
#> Hispanic -0.2931 -0.2829 -0.2992 -0.2862 -0.2944
#> pop_se   0.0260  0.0267  0.0299  0.0268  0.0279
#> oracle_se    NA      NA  0.0299  0.0268  0.0278
#> Asian   -0.2621 -0.2609 -0.2599 -0.2611 -0.2694
#> pop_se   0.0343  0.0343  0.0418  0.0343  0.0475
#> oracle_se    NA      NA  0.0418  0.0344  0.0465
#> Other   -0.1563 -0.1448 -0.1503 -0.1447 -0.1522
#> pop_se   0.0369  0.0370  0.0359  0.0368  0.0370
#> oracle_se    NA      NA  0.0359  0.0360  0.0366
```

These oracle standard errors (`oracle_se`) don’t account for estimation error in the propensity score, in contrast to the default standard errors (`pop_se`), see Methods section below.

Specifying the `cluster` argument allows for computation of clustered standard errors:

```
## cluster in interviewer ID
m1alt <- multte(r1, "race", cluster = factor(factor(f1$interviewer_ID_24)))
print(m1alt, digits = 3)
#> Estimates on full sample:
#>
#>      PL      OWN      ATE      EW      CW
#> Black   -0.2574 -0.2482 -0.2655 -0.2550 -0.2604
#> SE       0.0412  0.0425  0.0410  0.0422  0.0420
#> Hispanic -0.2931 -0.2829 -0.2992 -0.2862 -0.2944
#> SE       0.0441  0.0454  0.0495  0.0457  0.0474
#> Asian   -0.2621 -0.2609 -0.2599 -0.2611 -0.2694
#> SE       0.0521  0.0523  0.0619  0.0523  0.0675
#> Other   -0.1563 -0.1448 -0.1503 -0.1447 -0.1522
#> SE       0.0404  0.0416  0.0410  0.0414  0.0428
#>
#> P-values for null hypothesis of no propensity score variation:
#> Wald test: 0, LM test: 0
#>
#> SD(estimated propensity score), maximum over treatment arms:
```

```
#> Full sample: 0.196
#> Warning in max(x$pscore_sd_o): no non-missing arguments to max; returning -Inf
#> , Overlap sample: -Inf
```

## Methods

This section describes the implementation of the bias decomposition formula and the implementation of alternative estimators. Relative to Goldsmith-Pinkham et al. [2024], we generalize the setup to allow for sampling weights  $\omega_i^2$  (setting the sampling weights to one recovers unweighted formulas). We also explicitly deal with overlap issues.

We are interested in the effect of treatment  $D_i \in \{0, 1, \dots, K\}$  on an outcome  $Y_i$ . Let  $X_i = \mathbf{I}\{D_i = 1, \dots, D_i = K\}$  denote a vector of treatment indicators, let  $X_{i0} = \mathbf{I}\{D_i = 0\}$ , and let  $Z_i = (1, W_i')'$  denote a vector of controls, including an intercept. We focus on the case where the controls enter linearly, so that control functions take the form  $\mathcal{G} = \{z' \gamma : \gamma \in \mathbb{R}^{1+\dim(W_i)}\}$ .

We assume that  $\mu_k(W_i) := E[Y_i(k) \mid W_i] \in \mathcal{G}$ , so that we may write  $\mu_k(W_i) = W_i' \alpha_k$  for some vectors  $\alpha_k$ ,  $k = 0, \dots, K$ . The average treatment effect (ATE) conditional on  $W_i$  is then given by  $\tau(W_i) = Z_i'(\alpha_k - \alpha_0)$ , and  $\alpha_k$  correspond to the coefficients in the interacted regression

$$Y_i = \sum_{k=0}^K X_{ik} Z_i' \alpha_k + \dot{U}_i, \quad (1)$$

with  $\dot{U}_i$  conditionally mean zero. The uninteracted partially linear (PL) estimator is given by estimating

$$Y_i = \sum_{k=1}^K X_{ik} \beta + Z_i' \phi + U_i, \quad (2)$$

by weighted least squares (WLS), yielding  $\hat{\beta} = (\sum_i \omega_i^2 \dot{X}_i \dot{X}_i')^{-1} \sum_i \omega_i^2 \dot{X}_i Y_i$ , where  $\dot{X}$  is the sample residual from WLS regression of  $X_i$  onto  $Z_i$ . By Proposition 1 in Goldsmith-Pinkham et al. [2024], the population analog of  $\hat{\beta}$ ,  $\beta$ , has the decomposition

$$\beta = E[\text{diag}(\Lambda_i) \tau(W_i)] + E[\Lambda_i - \text{diag}(\Lambda_i) \tau(W_i)],$$

where  $\Lambda_i = E[\dot{X}_i \dot{X}_i']^{-1} E[\dot{X}_i X_i \mid W_i]$ , and  $\dot{X}_i$  is the population analog of  $\dot{X}_i$ , the population residual from regressing  $X_i$  onto  $W_i$ . Let  $\hat{\alpha}_k$  denote the WLS estimates based on (1). By construction, the sample residuals from estimating (1) and  $Z_i$  are both orthogonal to  $\dot{X}_i$ . As a result, we obtain the exact decomposition

$$\begin{aligned} \hat{\beta} &= E_n[\dot{X}_i \dot{X}_i']^{-1} E_n[\dot{X}_i Y_i] = \\ &= E_n[\text{diag}(\hat{\Lambda}_i) \hat{\Gamma}' Z_i] + E_n[(\hat{\Lambda}_i - \text{diag}(\hat{\Lambda}_i)) \hat{\Gamma}' Z_i] =: \hat{\beta}^{\text{Own}} + \hat{\beta}^{\text{CB}}, \end{aligned} \quad (3)$$

where  $\hat{\Gamma}$  is a matrix with columns  $\hat{\gamma}_k = \hat{\alpha}_k - \hat{\alpha}_0$ ,  $\hat{\Lambda}_i = E_n[\dot{X}_i \dot{X}_i']^{-1} \dot{X}_i X_i'$ , and  $E_n[A_i] = \sum_i \omega_i^2 A_i / \sum_i \omega_i^2$  denotes the weighted sample mean.

To compute this decomposition, we don't need to explicitly compute  $\hat{\Lambda}_i$ . Instead, we use the identity

$$\hat{\beta}_k^{\text{Own}} = e_k' E_n[\dot{X}_i \dot{X}_i']^{-1} E_n[\dot{X}_i X_{ik} Z_i' \hat{\gamma}_k] = \hat{\delta}_{kk}' \hat{\gamma}_k,$$

where  $\hat{\delta}_{kk}$  is a WLS estimator of the system of regressions

$$Z_i X_{ik} = \delta_{kk} X_{ik} + \sum_{\ell \neq k} \delta_{k\ell} X_{i\ell} + \Delta_{Z,k} Z_i + \zeta_{ik}. \quad (4)$$

Note this decomposition and associated standard errors, in the next subsection, are purely regression-based, so they remain valid even if  $X_i$  is not a set of binary indicators. Likewise, misspecification of the interacted regression only affects the interpretation of the decomposition; if  $\mu_k$  is not linear, the decomposition will not consistently estimate the contamination bias.

The own treatment weights in this decomposition sum to one, and the contamination weights sum to zero, since  $E_n[\hat{\Lambda}_i] = I_k$ , mimicking the population decomposition. If the propensity score doesn't satisfy  $p_k \in \mathcal{G}$ , the implied estimate of  $\Lambda(w)$ ,

$$\hat{\Lambda}(w) = \frac{1}{n} \sum_{i=1}^n I\{W_i = w\} \hat{\Lambda}_i$$

may not be positive definite; in particular, the diagonal elements may not all be positive, in line with Proposition 1 in Goldsmith-Pinkham et al. [2024].

In addition to this decomposition, the package also computes the following alternative estimators:

1. The unweighted ATE estimator,  $\hat{\beta}_k^{\text{ATE}} = E_n[W_i]' \hat{\gamma}_k$
2. The one-treatment-at-a time estimator  $\hat{\beta}_k^{\text{EW}}$  that fits (2) using only observations with  $D_i \in \{0, k\}$ . In other words, it estimates the regression

$$Y_i = \check{\phi}_k + X_{ik} \check{\beta}_k + W_i' \check{\phi}_k + \check{U}_{ik}, \quad (5)$$

among observations with  $D_i \in \{0, k\}$ . This estimator weights the treatment effects using the variance-minimizing weighting scheme given in Corollary 1 in Goldsmith-Pinkham et al. [2024]. Consequently, we refer to as the efficiently weighted ATE estimator.

3. The common weights estimator  $\hat{\beta}^{\text{CW}}$ , given by the WLS regression of  $Y_i$  onto  $X_i$ , weighting each observation by

$$\frac{\omega_i^2 \pi_{D_i} (1 - \pi_{D_i})}{\hat{p}_{D_i}(W_i) \sum_{k=0}^K \hat{p}_k(W_i)^{-1}},$$

where, by default, the probabilities  $\pi_k$  correspond to the marginal probability  $E_n[X_{ik}]$  in the dataset. The propensity scores  $\hat{p}_k(W_i)$  are based on fitting a multinomial logit model for the treatments. This estimator estimates a weighted ATE with weights  $\lambda^{\text{CW}}(W_i) = \left( \sum_{k=0}^K \frac{\pi_k(1-\pi_k)}{\hat{p}_k(W_i)} \right)^{-1}$ . By Corollary 2 in Goldsmith-Pinkham et al. [2024], this weighting scheme minimizes the average variance, under homoskedasticity, across all treatment comparisons—comparisons of outcomes under treatment  $k$  vs treatment  $\ell$ , if we draw the treatments  $k$  and  $\ell$  independently from the marginal treatment distribution  $(\pi_0, \dots, \pi_K)$ . Option `cw_uniform=TRUE` in the `multe` function sets these probabilities to  $1/K$ ; setting the option to its default, `FALSE`, sets them to  $(E_n[X_{i0}], \dots, E_n[X_{iK}])$ .

## Standard errors

To compute cluster-robust standard errors for an asymptotically linear estimator with influence function  $\psi_i$ , we use the formula

$$\widehat{\text{se}}(\psi)^2 = \frac{G}{G-1} \sum_g \left( \sum_{i=g} \psi_i \right) \left( \sum_{i=g} \psi_i \right)'.$$

Here  $G_i$  denotes cluster membership, as specified by the `multe` argument `cluster`, and  $G$  the number of clusters. Specifying `cluster=NULL` assumes independent data, setting each observation to be in its own cluster ( $G_i = i$  and  $G = N$ ), so the reported standard errors are robust to heteroskedasticity, but not clustering.

We now describe the form of the influence function for the estimators above. For a generic WLS regression of  $A$  onto  $B$ , let  $(Q_1, Q_2) \begin{pmatrix} R & S \\ 0 & 0 \end{pmatrix} \Pi'$  denote the QR decomposition of  $\text{diag}(\omega_i)B$ . If  $B$  has rank  $r$ , then  $R$  has dimension  $r \times r$ ,  $Q$  has dimension  $N \times r$ , where  $r$  is the rank of the regressor matrix, and  $\Pi$  is a permutation matrix. The WLS estimator is then given by  $b = \Pi \begin{pmatrix} R^{-1}Q_1' \text{diag}(\omega_i)A \\ \text{NA} \end{pmatrix}$ . Denoting the regression residual by  $\hat{\epsilon}_i$ , the influence function is thus given by

$$\psi_i(b) = \Pi \begin{pmatrix} R^{-1}Q_1'\omega_i\hat{\epsilon}_i \\ \text{NA} \end{pmatrix}. \quad (6)$$

See the internal function `multe:::reg_if` for implementation. The influence function for the inner product of linear estimators  $a$  and  $b$ , is by the delta method given by

$$\psi_i(a'b) = a'\psi_i(b) + b'\psi_i(a),$$

while for scalars  $s_1, s_2$ ,  $\psi(s_1a + s_2b) = s_1\psi(a) + s_2\psi(b)$ .

We use (6) to compute  $\psi(\hat{\alpha}_k)$ , as well as

$$\begin{aligned} \psi_i(\bar{Z}) &= \frac{\omega_i^2(Z_i - \bar{Z})}{\sum_i \omega_i^2} \\ \psi_i(\hat{\delta}_{kk}) &= \frac{\omega_i^2 \hat{\zeta}_{ik} \ddot{X}_{ik}}{\sum_i \omega_i^2 \ddot{X}_{ik}^2}, \end{aligned}$$

where  $\hat{\zeta}_{ik}$  is the WLS residual based on (4), and  $\ddot{X}_{ik}$  is the residual from regressing  $X_{ik}$  onto  $X_{i,-k}$  and  $Z_i$ . It then follows from (6) and the influence function formulas above, that

$$\begin{aligned} \psi_i(\hat{\beta}_k^{\text{Own}}) &= \hat{\delta}_{kk}'\psi_i(\hat{\gamma}_k) + \hat{\gamma}_k'\psi_i(\hat{\delta}_{kk}) \\ \psi_i(\hat{\beta}) &= \left( \sum_i \omega_i^2 \ddot{X}_i \ddot{X}_i' \right)^{-1} \omega_i^2 \ddot{X}_i \hat{U}_i \\ \psi_i(\hat{\beta}_k^{\text{EW}}) &= \frac{\mathbf{I}\{D_i \in \{0, k\}\} \omega_i^2 \hat{X}_{ik} \hat{U}_{ik}}{\sum_i \mathbf{I}\{D_i \in \{0, k\}\} \omega_i^2 \hat{X}_{ik}^2} \\ \psi_i(\hat{\beta}_k^{\text{ATE}}) &= \bar{Z}'\psi_i(\hat{\alpha}_k - \hat{\alpha}_0) + \psi_i(\bar{Z})(\hat{\alpha}_k - \hat{\alpha}_0). \end{aligned}$$

where  $\hat{X}_{ik}$  is the residual from regressing  $X_{ik}$  onto  $Z$  in the subset with  $D_i \in \{0, k\}$ , and  $\hat{U}_{ik}$  the residual from regressing  $Y_i$  onto  $X_{ik}$  and  $Z_i$  in this subsample.

When the treatment is binary and overlap holds, the formula for  $\psi_i(\hat{\beta}_k^{\text{ATE}})$  is similar to that discussed on page 29 in Imbens and Wooldridge [2009], except we don't assume that the regression error  $V_i$  in (1) is conditionally mean zero, so that the standard error is robust to misspecification.

Derivations in the last section show that the influence function for the common weights estimator is given by  $\hat{\psi}_i(\hat{\beta}_k^{\text{CW}}) = \hat{\psi}_i(\hat{\alpha}_k^{\text{CW}} - \hat{\alpha}_k^{\text{CW}})$ , where

$$\hat{\psi}_i(\hat{\alpha}_k^{\text{CW}}) = \frac{1}{\sum_i \lambda^{\text{CW}}(W_i)} \left( \frac{\lambda^{\text{CW}}(W_i) X_{ik}}{\pi_k(W_i; \hat{\theta})} (Y_i - \hat{\alpha}_k^{\text{CW}}) + a_i(\hat{\theta}) \right). \quad (7)$$

with the formula for  $a_i$  given in (12) below,  $\theta$  corresponds to the parameters in the multinomial logit model,  $\pi_k(W_i; \hat{\theta})$  to the fitted probabilities in this model, and  $\hat{a}_k^{\text{CW}}$  is the estimate based on (11) below.

### Oracle standard errors

The package also reports “oracle” standard errors, which interprets the alternative estimators as estimates of the contrasts

$$\beta_{\lambda,k} = \frac{\sum_{i=1}^N \lambda(W_i)(\mu_k(W_i) - \mu_0(W_i))}{\sum_{i=1}^N \lambda(W_i)},$$

with  $\lambda(W_i) = 1$  for the unweighted ATE,  $\lambda(W_i) = \lambda^{\text{CW}}(W_i)$  for the common weights estimator and  $\lambda(W_i) = \frac{p_k(W_i)p_0(W_i)}{p_k(W_i)+p_0(W_i)}$  for the efficiently weighted ATE estimator. In contrast, the standard errors in the previous subsection set the estimands to be the population counterparts to these weighted averages, replacing the sums in the above display with population expectations. In addition, the oracle standard errors don’t account for estimation error in the propensity score  $p(W_i)$ .

For the unweighted ATE, the oracle standard error is based on the influence function  $\tilde{\psi}_i(\hat{\beta}_k^{\text{ATE}}) = \bar{Z}'\psi_i(\hat{a}_k - \hat{a}_0)$ . From the derivation in the last section, it follows that the oracle standard error for  $\hat{\beta}_k^{\text{EW}}$  is given by

$$\psi_i(\hat{\beta}_k^{\text{EW}}) = \frac{\mathbf{I}\{D_i \in \{0, k\}\} \omega_i^2 \hat{X}_{ik} \hat{U}_i}{\sum_i \mathbf{I}\{D_i \in \{0, k\}\} \omega_i^2 \hat{X}_{ik}^2}, \quad (8)$$

where  $\hat{U}_i$  is the interacted regression residual based on (1).

Finally, the oracle standard errors for  $\hat{\beta}_k^{\text{CW}}$  are based on the influence function  $\tilde{\psi}_i(\hat{\beta}_k^{\text{CW}}) = \tilde{\psi}_i(\hat{a}_k^{\text{CW}}) - \tilde{\psi}_i(\hat{a}_0^{\text{CW}})$ , where

$$\tilde{\psi}_i(\hat{a}_k^{\text{CW}}) = \frac{\omega_i^2 \lambda^{\text{CW}}(W_i; \hat{\theta})}{\sum_i \omega_i^2 \lambda^{\text{CW}}(W_i; \hat{\theta})} \frac{X_{ik}}{\pi_k(W_i; \hat{\theta})} \hat{U}_i. \quad (9)$$

### Overlap sample

The package applies the above formulas to the full sample. In cases with poor overlap, this may not yield well-defined estimates or bias decomposition for all treatments. For components of the decomposition and alternative estimators that are not identified, the package returns NA. In such cases, the package also returns results for a trimmed “overlap sample”, where the decomposition and alternative estimators are all identified. The overlap sample is constructed as follows:

1. Find a factor variable among the controls with the greatest number of levels. If there are no factor variables, skip this step. If for some levels of this variable, we don’t see observations that take on one or more of the  $K + 1$  possible treatments, drop observations with these levels.
2. For the remaining controls, if a control doesn’t display any variation in the subset of the data with treatment  $k = 0, \dots, K$ , drop the control.

### Wald and LM tests

We now give the form of the Wald and LM tests for variation in the propensity score. First, we give a general derivation of these tests in a likelihood context when the Hessian may be reduced rank. We then specialize the formulas to the case where the likelihood corresponds to the that for the multinomial logit model.



Consider a log-likelihood  $\ell_n(\theta)$  for a  $p$ -dimensional parameter  $\theta$ , with score function  $S$  that's approximately normal with covariance matrix  $\Omega$ , and Hessian  $H$ . We're interested in testing the hypothesis that last  $r$  elements of  $\theta$  are zero,  $H_0: \theta_2 = 0$ . We assume that the submatrix  $H_{11}$  of the Hessian corresponding to the restricted model is full rank, but the full matrices  $\Omega$  or  $H$  may not be invertible.

The score evaluated at the unrestricted estimator  $\hat{\theta}$  satisfies

$$0 = \begin{pmatrix} S_1(\hat{\theta}_1, \hat{\theta}_2) \\ S_2(\hat{\theta}_1, \hat{\theta}_2) \end{pmatrix} = \begin{pmatrix} S_1(\theta_1, 0) \\ S_2(\theta_1, 0) \end{pmatrix} + \begin{pmatrix} H_{11}(\hat{\theta}_1 - \theta_1) + H_{12}\hat{\theta}_2 \\ H_{21}(\hat{\theta}_1 - \theta_1) + H_{22}\hat{\theta}_2 \end{pmatrix}$$

ignoring in the notation that the Hessian evaluated needs to be evaluated at intermediate values. Rearranging,

$$\begin{pmatrix} \hat{\theta}_1 - \theta_1 \\ (H_{22} - H_{21}H_{11}^{-1}H_{12})\hat{\theta}_2 \end{pmatrix} = \begin{pmatrix} -H_{11}^{-1}S_1(\theta_1, 0) - H_{11}^{-1}H_{12}\hat{\theta}_2 \\ H_{21}H_{11}^{-1}S_1(\theta_1, 0) - S_2(\theta_1, 0) \end{pmatrix}$$

This yields the Wald statistic

$$W = \hat{\theta}_2'(H_{22} - H_{21}H_{11}^{-1}H_{12})' \text{var}(S_2(\theta_1, 0) - H_{21}H_{11}^{-1}S_1(\theta_1, 0))^+ (H_{22} - H_{21}H_{11}^{-1}H_{12})\hat{\theta}_2,$$

where  $A^+$  denotes a generalized inverse. By Lemma 9.7 in Newey and McFadden [1994], the statistic has an asymptotic  $\chi^2$  distribution with degrees of freedom equal to the rank of the variance.

The score evaluated at the restricted estimator  $\bar{\theta}_1$  satisfies

$$\begin{pmatrix} 0 \\ S_2(\bar{\theta}_1, 0) \end{pmatrix} = \begin{pmatrix} S_1(\theta_1, 0) \\ S_2(\theta_1, 0) \end{pmatrix} + \begin{pmatrix} H_{11}(\bar{\theta}_1 - \theta_1) \\ H_{21}(\bar{\theta}_1 - \theta_1) \end{pmatrix},$$

which implies  $\bar{\theta}_1 - \theta_1 = -H_{11}^{-1}S_1(\theta_1, 0)$ , and hence

$$S_2(\bar{\theta}_1, 0) = S_2(\theta_1, 0) - H_{21}H_{11}^{-1}S_1(\theta_1, 0).$$

Thus the statistic

$$LM = S_2(\bar{\theta}_1, 0)' \text{var}(S_2(\theta_1, 0) - H_{21}H_{11}^{-1}S_1(\theta_1, 0))^+ S_2(\bar{\theta}_1, 0)$$

will again have a  $\chi^2$  distribution.

To apply these formulas in the context of a multinomial logit model, we use the score and the Hessian

$$S(\theta) = \sum_i \omega_i^2 (X_i - \pi(Z_i; \theta)) \otimes Z_i, \quad H(\theta) = - \sum_i \omega_i^2 (\text{diag}(\pi(Z_i; \theta)) - \pi(Z_i; \theta)\pi(Z_i; \theta)') \otimes Z_i Z_i'$$

## Derivations

We first derive (7). Observe first that the common weights estimator is identical to the two-step GMM estimator that in the first step, fits a multinomial logit model

$$P(D_i = k \mid W_i) = \frac{e^{Z_i' \theta_k}}{\sum_{k'=0}^K e^{Z_i' \theta_{k'}}} =: \pi_k(W_i, \theta), \quad (10)$$

with the normalization  $\theta_0 = 0$ . In the second step, we use the moment condition

$$E \left[ \frac{\lambda^{\text{CW}}(W_i; \theta) X_{ik}}{\pi_k(W_i; \theta)} (Y_i - \alpha_k^{\text{CW}}) \right] = 0. \quad (11)$$

to obtain estimates  $\hat{\alpha}_k^{\text{CW}}$ , and set  $\hat{\beta}_k^{\text{CW}} = \hat{\alpha}_k^{\text{CW}} - \hat{\alpha}_0^{\text{CW}}$ .

Let

$$\zeta_k(W_i; \hat{\theta}) = \frac{\lambda^{\text{CW}}(W_i; \hat{\theta})}{\pi_k(W_i; \hat{\theta})} = \frac{e^{-Z_i' \hat{\theta}_k}}{\sum_{j=0}^K \pi_j (1 - \pi_j) e^{-Z_i' \hat{\theta}_j}}$$

By equation (6.6) in Newey and McFadden [1994], the influence function of this two-step estimator is given by

$$\psi_i(\hat{\alpha}_k^{\text{CW}}) = \frac{1}{E[\lambda^{\text{CW}}(W_i)]} \left( \frac{\lambda^{\text{CW}}(W_i) X_{ik}}{\pi_k(W_i)} (Y_i - \alpha_k^{\text{CW}}) + M_k(\theta) \psi_i(\theta) \right),$$

where  $\psi_i(\theta)$  is the influence function of the multinomial logit estimator  $\hat{\theta}$ , and  $M_k(\theta)$  is the derivative of (11) wrt  $\theta$ .

Since  $\partial \zeta_k(W_i; \theta) / \partial \theta_j = Z_i \zeta_k(W_i; \theta) [\pi_j (1 - \pi_j) \zeta_k(W_i; \theta) - \mathbf{I}\{k = j > 0\}]$ , it follows that

$$M_k(\theta) = E[(\eta - e_k) \otimes Z_i \cdot \zeta_k X_{ik} (Y_i - \alpha_{\lambda^{\text{C}},k})], \quad \eta = (\pi_j (1 - \pi_j) \zeta_j, \dots, \pi_K (1 - \pi_K) \zeta_K)'$$

Since the multinomial logit log-likelihood is given by  $\ell_i = \sum_{k=0}^K X_k \log(\pi_k) = \sum_{k=0}^K X_k Z_i' \theta_k - \log(\sum_{k=0}^K e^{Z_i' \theta_k})$ , the score and the Hessian are

$$S_i(\theta) = (X_i - \pi(W_i; \theta)) \otimes Z_i, \quad H(\theta) = -E_n[(\text{diag}(\pi(W_i)) - \pi(W_i) \pi(W_i)') \otimes Z_i Z_i'],$$

Since  $\psi_i(\theta) = -H(\theta)^{-1} S_i(\theta)$ , this yields

$$a_i(\theta) = \hat{M}_k(\hat{\theta}) \hat{H}(\hat{\theta})^{-1} S_i(\theta), \quad S_i(\theta) = (X_i - \pi(W_i; \theta)) \otimes Z_i, \quad (12)$$

with  $\hat{M}_k(\theta) = (\sum_i (\zeta - e_k) \otimes Z_i \cdot \zeta_k X_{ik} (Y_i - \alpha_{\lambda^{\text{C}},k}))$ , and  $\hat{H}(\theta) = \sum_i (\text{diag}(\pi(W_i)) - \pi(W_i) \pi(W_i)') \otimes Z_i Z_i'$ . When  $\pi_k = 1/(K+1)$  this formula reduces to that in Theorem 1 in Li and Li [2019].

Next, we show (8). Note that it follows from Proposition 2 in Goldsmith-Pinkham et al. [2024] that the efficient influence function is given by

$$\begin{aligned} \psi_i(\alpha_{\lambda^{\text{C}},k0}) &= \frac{\lambda(W_i)}{E[\lambda(W_i)]} \left( \frac{X_{ik}}{p_k(W_i)} (Y_i - \mu_k(W_i)) - \frac{X_{i0}}{p_0(W_i)} (Y_i - \mu_0(W_i)) \right) \\ &= \frac{X_{ik} + X_{i0}}{E[\lambda(W_i)]} (X_{ik} - r_k) V_i = \frac{(X_{ik} + X_{i0})(X_{ik} - r_k) V_i}{E[(X_{ik} + X_{i0})(X_{ik} - r_k)^2]}, \end{aligned}$$

where  $r_k = r_k(W_i) = E[X_{ik} \mid W_i, X_{ik} + X_{i0} = 1]$ . The result then follows since  $\hat{X}_{ik}$  is an estimator of  $X_{ik} - r_k(W_i)$ .

Finally, we show (9). The derivative of the moment condition (11) with respect to  $\pi_k = p_k$  (assuming correct specification of the propensity score) is given by

$$-E \left[ \lambda \frac{X_{ik}}{p_k^2(W_i)} (\mu_k - \alpha_k^{\text{CW}}) \dot{p}_k(W_i) \right],$$

where we write  $\lambda$  for  $\lambda^{\text{CW}}(W_i)$ . Since  $p_k$  is a projection, by Proposition 4 in Newey [1994], the influence function for  $\hat{\alpha}_k^{\text{CW}}$  is given by

$$\begin{aligned} \frac{1}{E[\lambda]} \left( \lambda \frac{X_{ik}}{p_k(W_i)} (Y_i - \alpha_k^{\text{CW}}) - \frac{\lambda}{p_k(W_i)} (\mu_k(W_i) - \alpha_k^{\text{CW}}) (X_{ik} - p_k(W_i)) \right) \\ = \frac{1}{E[\lambda]} \left( \lambda \frac{X_{ik}}{p_k(W_i)} (Y_i - \mu_k(W_i)) + \lambda (\mu_k(W_i) - \alpha_k^{\text{CW}}) \right). \end{aligned}$$

Next, as noted in Abadie et al. [2014], we can view  $\tilde{\alpha}_k^{\text{CW}} = \sum_i \lambda \mu_k(W_i) / \sum_i \lambda$  as an estimator of  $\alpha_k^{\text{CW}}$  based on the moment condition  $E[\lambda(\mu_k(W_i) - \alpha_k^{\text{CW}})] = 0$ , which by standard arguments has influence function given by  $\frac{\lambda}{E[\lambda]}(\mu_k(W_i) - \alpha_k^{\text{CW}})$ . Since  $\hat{\alpha}_k^{\text{CW}} - \alpha_k^{\text{CW}} = (\hat{\alpha}_k^{\text{CW}} - \alpha_k^{\text{CW}}) - (\alpha_k^{\text{CW}} - \tilde{\alpha}_k^{\text{CW}})$ , we subtract this influence function from the preceding display to obtain (9).

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