

Replication of Empirical Results in ‘Finite-Sample Optimal Estimation and Inference on Average Treatment Effects Under Unconfoundedness’

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1 Empirical application: NSW

We use a solution path with 3000 steps. At the last step the value of δ is given by 668.48739.

Table 2:

	Opt: RMSE	Opt: FLCI	Matching: RMSE	Matching: FLCI
M			1.00	18.00
δ	1.82	3.30		
Estimate	0.96	0.94	1.39	1.26
Max. Bias	1.64	1.78	1.48	2.21
SE	1.01	0.94	1.09	0.89
cv	3.26	3.55	3.01	4.13
CI lo	-2.33	-2.38	-1.88	-2.41
CI hi	4.26	4.27	4.66	4.93
SE (PATE)	1.06	1.00	1.14	0.94
CI lo (PATE)	-2.75	-2.80	-2.32	-2.78
CI hi (PATE)	4.67	4.69	5.11	5.30
Lindeberg wgt	0.07	0.06	0.19	0.06
Rel. efficiency	101.15		90.41	91.36

Efficiency of FLCI in baseline specification (Section 2.5)

```
ATEHonest::ATTEffBounds(op, C = 1, sigma2 = mean(sigma2))
## $onesided
## [1] 0.977761
##
## $twosided
## [1] 0.970476
```

Optimal estimator and CIs as a function of C . Solid lines mark the CATT CI, while dotted lines mark the PATT CI.

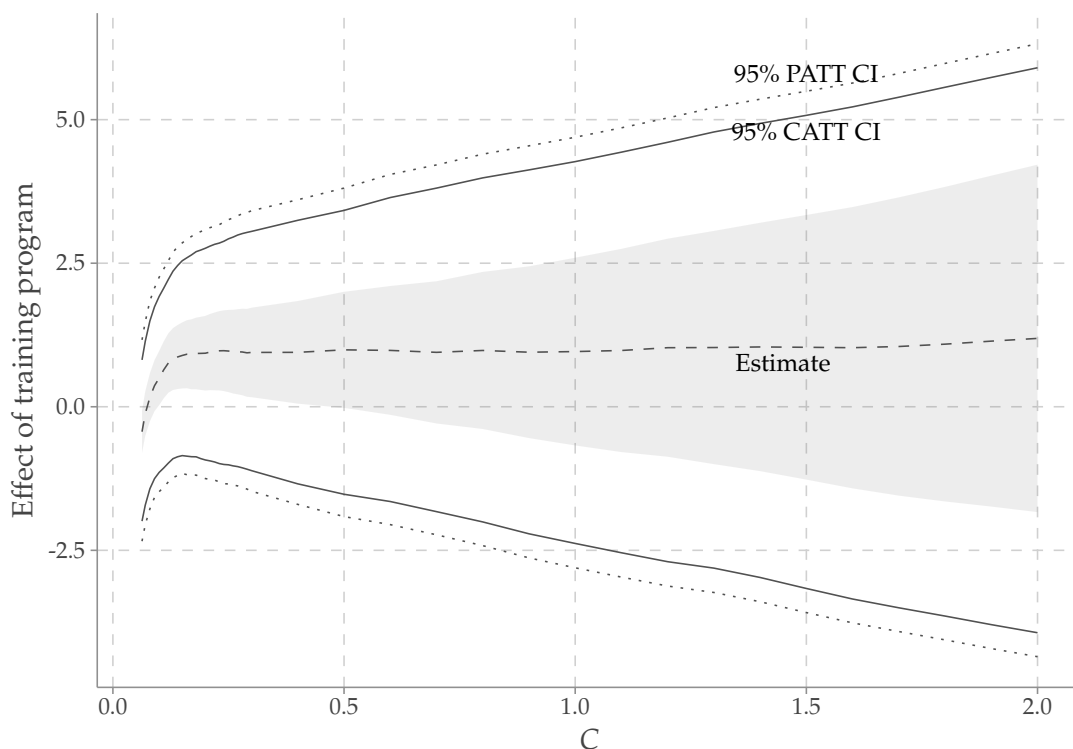


Figure 1: Reproduction of Figure 1 in the paper. Robust SE.

Range of length penalty of PATT relative to CATT in the four columns of Table 2: 1.102, 1.135

Range of point estimate for reasonable C :

```
range(oe$rmse$att[oe$rmse$C > 0.2 & oe$rmse$C < 2])
## [1] 0.939249 1.142967
```

1.1 Matching efficiency

Efficiency at $C = 1$:

C	type	eff
1	RMSE	90.4132
1	FLCI	85.9666

Minimum C such that efficiency is at least 95%:

C	type	eff
1.5	RMSE	95.6341
2.8	FLCI	95.0211

1.2 Lindeberg weights

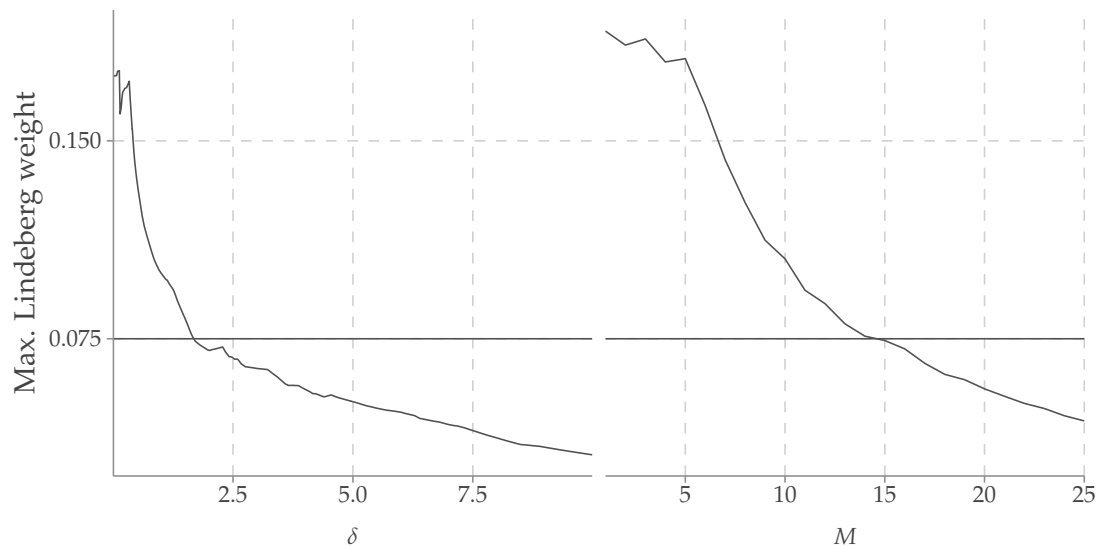


Figure 2: Lindeberg weights for optimal and matching estimator.

For optimal estimator, we need δ to be at least 1.686452. For matching estimator, we need at least 15 matches to be below the 0.075 cutoff.

1.3 Experimental data

```
Xe <- as.matrix(ATEHonest::NSWexper[, 2:10])
de <- ATEHonest::NSWexper$treated
ye <- ATEHonest::NSWexper$re78
s2 <- ATEHonest::nnvar(ATEHonest::distMat(Xe, chol(solve(cov(Xe))),
  method = "euclidean"), de, ye, J = 2)
```

Difference in means estimate:

```
RCTvariance(ye, de, s2, ATEHonest::distMat(Xe, Amain, method = "manhattan",
  de))
##      att  maxbias Cond rob  Cond hom CATT rob  CATT hom PATE HC2 PATE EHW
## 1.794342 1.737712 0.611274 0.578961 0.641517 0.610806 0.670997 0.669315
## PATE hom
## 0.632853
```

1.4 Alternative choice of distance (Supplement)

Now consider the norm in Abadie and Imbens (2011), with $p = 2$, and C described in the text. Optimal FLCI:

```
oe2 <- ATEHonest::ATTOptEstimate(y = y, d = d, D0 = D2, C = 1/sqrt(2 *
  0.07^2), sigma2 = sigma2, opt.criterion = "FLCI")
## Increasing length of solution path to 100
```

```

oe2
##
##
## |      | Estimate| Max. bias|      SE|CI      |      delta|
## |-----|-----:|-----:|-----:|-----:|
## |CATT | 1.72259| 6.25009| 0.842248|(-5.91288, 9.35805) | 3.28971|
## |PATT | 1.72259|      | 0.913810|(-6.31854, 9.76371) |      |
oe2$e["rhl"]
##      rhl
## 7.63546

```

Now consider a matching estimator that matches on this norm:

```

mp2 <- ATEHonest::ATTMatchPath(y, d, D2, M = 1)
## Now calculate worst-case bias under D0
mp2$ep$maxbias <- ATEHonest::ATTbias(mp2$K[, d == 0], D0)
mp2$D0 <- D0
me2 <- ATEHonest::ATTMatchEstimate(mp2, sigma2 = sigma2, C = 1)
me2$e[c("hl", "rhl")]
##      hl      rhl
## 5.38073 3.37502

meff2 <- MatchEfficiency(oe, mp2, mean(sigma2), mineff = 95)
knitr::kable(meff2$effC1, digits = 4, row.names = FALSE)

```

C	type	eff
1	RMSE	77.8138
1	FLCI	74.9252

```

## Efficiency loss relative to using correct norm
meff$effC1$eff - meff2$effC1$eff
## [1] 12.5994 11.0414
## Maximum efficiency
max(meff2$d[meff2$d$type == "RMSE", "eff"])
## [1] 80.1513

```

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