DML Applications

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- **Experimental design**: treatment is random, so the propensity score is known and outcome model can *afford* to be misspecified.

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- DML has the disadvantage of assumptions on the outcome model and the propensity score model.
- Experimental design: treatment is random, so the propensity score is known and outcome model can *afford* to be misspecified.
- Observational design: both the outcome and propensity score must be correctly specified, because rate of convergence is slow.

Causal Model Choice

Partially Linear Regression

- Continuous treatment
- No heterogeneous treatment effects
- No functional form assumption for controls
- Command: DoubleMLPLR

Interactive Regression Model

- Dichotomous treatment
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- **Clustered Data:** DML assumes i.i.d.; assign whole clusters to folds and use cluster-robust SEs (Command: DoubleMLClusterData).

Experimental design

Platas and Raffler (2021): Closing the Gap

Experiment on the effects of providing information in dominant party regimes.

- Information asymmetry in dominant party regimes (in favor of the regime).
- Can provision of information about all parties (especially opposition ones), reduce the asymmetry in terms of voter knowledge, opposition likability or vote intentions.
- 11 constituencies in Uganda. Within each constituency randomly assign some villages to a screening of parliamentary candidate debates.
    - Constituency Fixed Effects
    - Cluster SE at village level

Replicating original results

Main relationship:

- Vote intention $\sim$ Received Informational Treatment (0/1)
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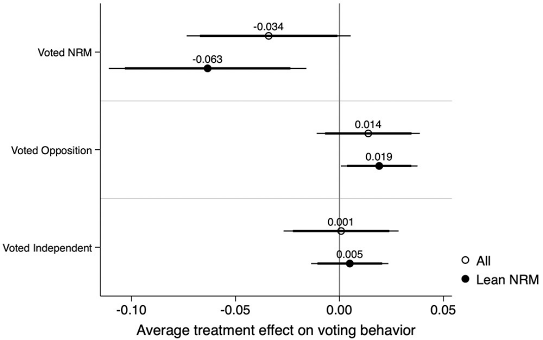
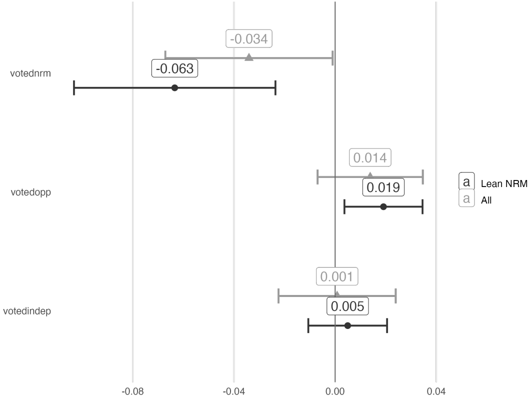
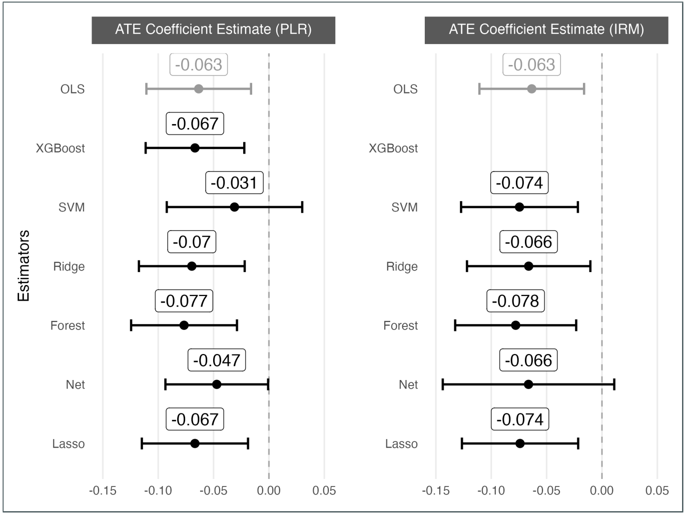


(a) Original



(b) Replication

DML application for experiment



Robustness and Application Notes

- The result we replicated have a binary treatment and outcome. The classification versions of the machine learning models will likely perform better here.

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- For the DoubleMLIRM function, treatment is assumed to be binary, so the learner used to model the propensity score HAS to be a classification learner, not a regression one (e.g. use *classif.cv_glmnet* instead of *regr.cv_glmnet*).

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- Just make a mental note that such differences in data type matter for exploring pairs of learners when using IRM vs. PLR.

Observational design

Brierley and Nathan (2022)

Motivating the Machine: Which Brokers do Parties Pay?

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- Survey of 1,000 party brokers in Ghana.
- Condition on observables.

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Table 5. Major Patronage Payments Immediately after the Election

	(1)
NPP pres. vote swing at polling station 2012–16	.702** (.321)
NPP pres. vote swing at polling station 2012–16 (raw votes)	
Campaign activity in 2016 (,9)	.007 (.005)

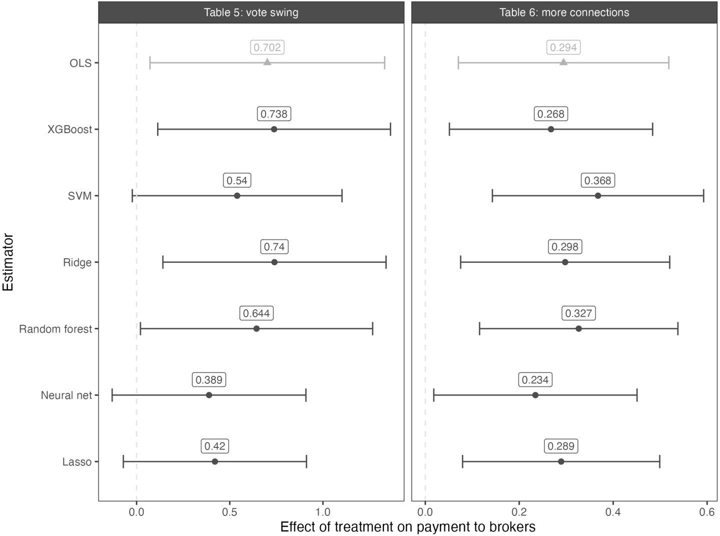
Table 6. Predictors of Major Patronage in the Nonelectoral P

	(1)
Connections Up (wave 1)	.294** (.114)
Connections Up, politicians (wave 1)	
Connections Up, bureaucrats (wave 1)	
Connections Up, constituency executives (wave 1)	

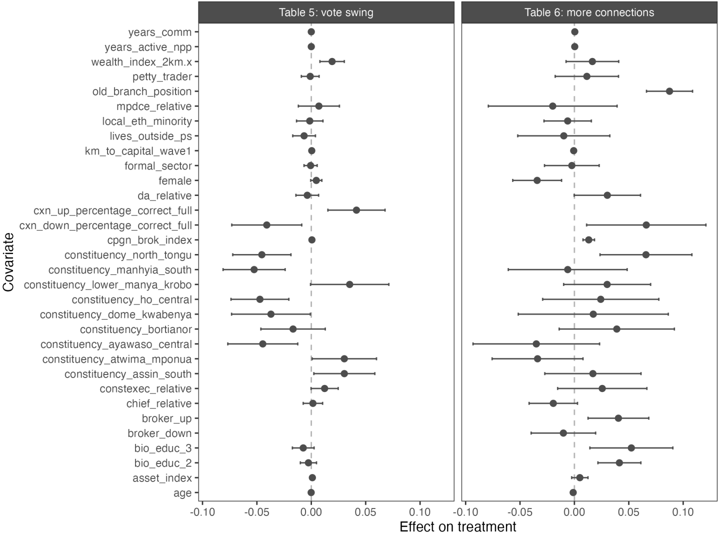
```
> etable(model_replication_t5, model_replication_t6)
                                  model_replicatio..5 model_replicatio..6
Dependent Var.:                          big_pat_immed       big_pat_after2

Constant                           -0.1439 (0.0907)  0.4557*** (0.1059)
npp12to16_ps_swing.NEW             0.7017* (0.3213)   -0.0481 (0.3241)
cpgn_brok_index                     0.0071 (0.0054)    0.0110 (0.0081)
cxn_up_percentage_correct_full      0.1042 (0.0953)   0.2944* (0.1143)
cxn_down_percentage_correct_full   0.1680* (0.0779)   -0.1010 (0.0869)
age                                 0.0011 (0.0012)  -0.0038* (0.0017)
female                              0.0494 (0.0311)  0.2702*** (0.0417)
chief_relative                     0.0598. (0.0324)    0.0244 (0.0344)
constexec_relative                 0.1299. (0.0709)    0.0691 (0.0580)
da_relative                       -0.0593. (0.0334)    0.0033 (0.0476)
mpdce_relative                     -0.0508 (0.0464)   -0.0918 (0.0739)
local_eth_minority                  0.0036 (0.0276)   -0.0393 (0.0347)
lives_outside_ps                   -0.0131 (0.0415)    0.0164 (0.0620)
petty_trader                        0.0093 (0.0377)    0.0439 (0.0541)
formal_sector                       0.0212 (0.0284)  -0.0686. (0.0394)
asset_index                        0.0162. (0.0082)  -0.0200. (0.0109)
years_active_npp                    0.0010 (0.0021)   -0.0029 (0.0020)
years_comm                          0.0010 (0.0008)   0.0022. (0.0013)
km_to_capital_wave1                 3.65e-5 (0.0023)  -0.0010 (0.0023)
wealth_index_2km.x                 -0.0347 (0.0342)   -0.0171 (0.0337)
bio_educ_2                         -0.0004 (0.0227)    0.0039 (0.0348)
bio_educ_3                          0.0379 (0.0491)    0.0306 (0.0617)
```

DML application for observational study

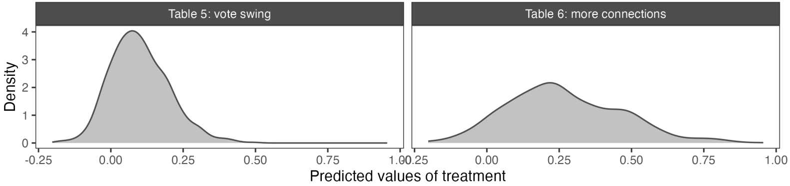
Five-fold cross-fitting and 20 repetitions



Balance of covariates



General propensity approach



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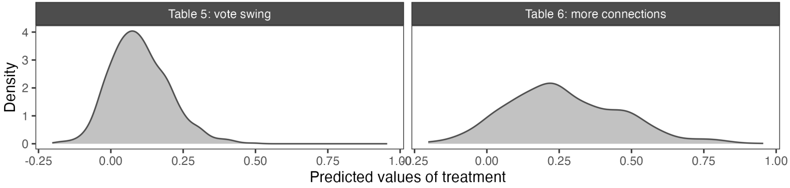

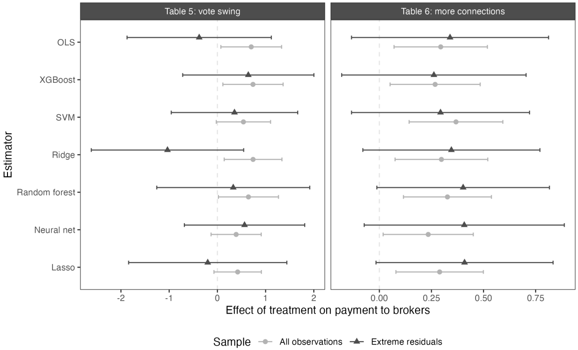

Conclusions

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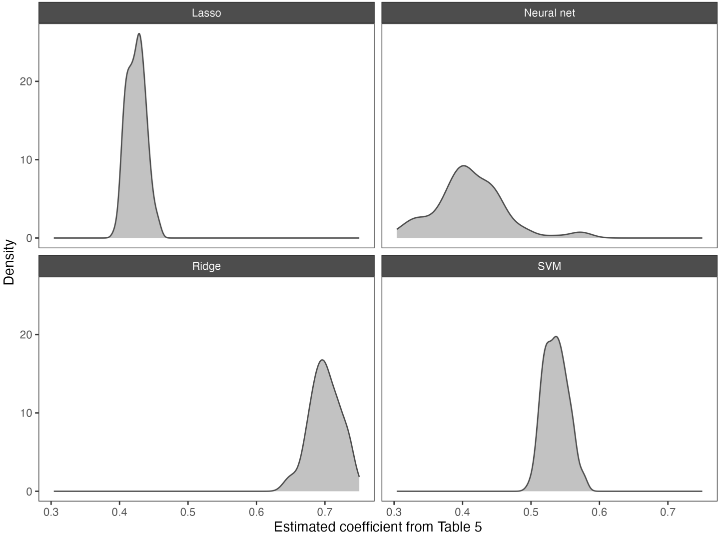
- **Random assignment** ensures the propensity score model is correct, eliminating possibility of bias.
- **Binary vs. continuous** treatments rely on different estimators (AIPW vs. PLR).
- Standard DML assumes **i.i.d.**; clustering requires adjustments.

Appendix

Repeating estimation 100 times (Brierley and Nathan, 2022)



DML with continuous treatment and i.i.d. SEs

R Code

```r
data_dml <- data |>
  # turn into data.table
  as.data.table() |>
  # create the DML data object
  DoubleMLData$new(y_col = outcome,
                   d_cols = treatment,
                   x_cols = c(covariates, dummies))
# define learner as random forest
learner <- lrn("regr.ranger")
# obtain two clones of the learner
ml_l_sim <- learner$clone()
ml_m_sim <- learner$clone()
dml_object <- data_dml |>
  # specify the learners
  DoubleMLPLR$new(ml_l = ml_l_sim, ml_m = ml_m_sim,
                  # use 5-fold cross-fitting and 20 rounds
                  n_folds=5, n_rep=20)
# fit the model
dml_object$fit()
# extract the coefficients and standard errors
coefficients <- tibble(estimate = dml_object$coef, se = dml_object$se)
```

DML with continuous treatment and clustering

R Code

```r
data_dml <- data |>
  # turn into data.table
  as.data.table() |>
  # create the DML data object (note the change in function)
  DoubleMLClusterData$new(y_col = outcome,
                          d_cols = treatment,
                          x_cols = c(covariates, dummies),
                          # key change
                          cluster_cols = clusters)
# define learner as random forest
learner <- lrn("regr.ranger")
# obtain two clones of the learner
ml_l_sim <- learner$clone()
ml_m_sim <- learner$clone()
dml_object <- data_dml |>
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# fit the model
dml_object$fit()
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DML Interactive Regression Model and Clustering

R Code

```
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  # create the DML data object (note the change in function)
  DoubleMLClusterData$new(y_col = outcome,
                          d_cols = treatment,
                          x_cols = c(covariates, dummies),
                          # key change
                          cluster_cols = clusters)
# define learner as random forest
learner <- lrn("classif.ranger")
# obtain two clones of the learner
ml_g = learner$clone() # outcome model
ml_m = learner$clone() # treatment model-must be classification learner
dml_object <- data_dml |>
  # specify the learners
  DoubleMLIRM$new(dml_cl_obj, ml_g, ml_m, n_folds=5)

# fit the model
dml_object$fit()
# extract the coefficients and standard errors
coefficients <- tibble(estimate = dml_object$coef, se = dml_object$se)
```