Replication: Gendered Citation...

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```
df_articles %>%
  group_by(newjnlid, authorteam) %>%
  summarise(N = n()) %>%
  mutate(Percent = 100 * N / sum(N)) %>%
  flextable()
```

newjnlid	authorteam	N	Percent
APSR	Male only	324	69.8275862
APSR	Female only	67	14.4396552
APSR	Mixed	73	15.7327586
Politics & Gender	Male only	27	7.9178886
Politics & Gender	Female only	266	78.0058651
Politics & Gender	Mixed	47	13.7829912
Politics & Gender		1	0.2932551
Political Analysis	Male only	220	74.5762712
Political Analysis	Female only	8	2.7118644
Political Analysis	Mixed	67	22.7118644
Econometri	icMale only	465	76.9867550
Econometri	icæemale only	25	4.1390728
Econometri	icMixed	114	18.8741722
Soc. Methods & Res.	Male only	153	65.1063830
Soc. Methods & Res.	Female only	19	8.0851064

newjnlid	authorteam	N	Percent
Soc. Methods & Res.	Mixed	63	26.8085106

```
df %>%
  filter(refauthcomplete == 1 & !is.na(refteam)) %>%
  group_by(newjnlid, refteam) %>%
  summarise(N = n()) %>%
  mutate(Percent = 100 * N / sum (N)) %>%
  flextable()
```

newjnlid	refteam	N	Percent
APSR	Male	11,617	74.239519
APSR	Female	2,203	14.078476
APSR	Mixed	1,828	11.682004
Politics & Gender	Male	1,649	27.977604
Politics & Gender	Female	3,405	57.770614
Politics & Gender	Mixed	840	14.251781
Political Analysis	Male	4,650	78.933967
Political Analysis	Female	322	5.465965
Political Analysis	Mixed	919	15.600068
Econometr	ic M ale	9,226	84.883614
Econometr	ic E emale	475	4.370227
Econometr	icMixed	1,168	10.746159
Soc. Methods & Res.	Male	2,937	72.464841
Soc. Methods & Res.	Female	347	8.561559
Soc. Methods & Res.	Mixed	769	18.973600

```
logit_fun <- function(y, X, theta){
   if(!is.null(ncol(X))){</pre>
```

```
beta <- theta[1:ncol(X)]</pre>
      mu <- X %*% beta
    } else {
      beta <- theta[1]</pre>
      mu <- X * beta
    }
    p <-1 / (1 + exp(-mu))
    logll \leftarrow sum(y * log(p) + (1 - y) * log(1 - p))
    return(log11)
 }
logistic_per_journal <- function(journal, vcovcoef = FALSE){</pre>
 require(tidyverse)
 require(MASS)
 require(rms)
 require(optimx)
  if(journal != "Pooled"){
    df_anal <- df %>%
      filter(newjnlid %in% journal & refauthcomplete == 1) %>%
      dplyr::select(newjnlid, authorteam, reffemonly, newartid) %>%
      na.omit() %>%
      mutate(Female = ifelse(authorteam == "Female", 1, 0),
             Mixed = ifelse(authorteam == "Mixed", 1, 0)) %>%
      dplyr::select(-authorteam)
      y <- df_anal$reffemonly
 X \leftarrow cbind(1,
             df_anal$Female,
             df_anal$Mixed)
    # start values
  startvals <- rep(0, ncol(X))</pre>
  # optimize
  res <- optim(
```

```
par = startvals,
    fn = logit_fun,
    y = y,
    X = X
    control = list(fnscale = -1),
    hessian = TRUE,
    method = "BFGS"
startvals2 <- c(0, 0) # Why three this time?
restricted <- optim(</pre>
  startvals2,
 logit_fun,
 y = y,
 X = X[, 1],
  # restricted model
  control = list(fnscale = -1),
 method = "BFGS"
  coef <- res$par</pre>
  # vcov <- solve(-res$hessian)</pre>
  # se <- sqrt(diag(vcov))
  # Unfortunately, I am not yet able to compute robust standard errors
  # clustered at article level by hand. But I am on it.
  fit=lrm(data = df_anal, reffemonly ~ Female + Mixed, x=T, y=T)
  vcov <- vcov(robcov(lrm(data = df_anal, reffemonly ~ Female + Mixed, x=T, y=T),</pre>
               cluster = df_anal$newartid)
  se <- sqrt(diag(vcov))</pre>
  ##robust standard error
 } else {
    df_anal <- df %>%
      filter(refauthcomplete == 1) %>%
      dplyr::select(newjnlid, authorteam, reffemonly, newartid) %>%
      na.omit() %>%
      mutate(Female = ifelse(authorteam == "Female", 1, 0),
             Mixed = ifelse(authorteam == "Mixed", 1, 0),
             APSR = ifelse(newjnlid == "APSR", 1, 0),
             PG = ifelse(newjnlid == "Politics & Gender", 1, 0),
             PA = ifelse(newjnlid == "Political Analysis", 1, 0),
             Econ. = ifelse(newjnlid == "Econometrica", 1, 0),
             SMR = ifelse(newjnlid == "Soc. Methods & Res.", 1, 0)) %>%
      dplyr::select(-authorteam)
      y <- df_anal$reffemonly
  X \leftarrow cbind(1,
             df_anal$Female,
```

```
df_anal$Mixed,
             df_anal$PG,
             df_anal$PA,
             df_anal$Econ.,
             df_anal$SMR)
    # start values
  startvals <- rep(0, ncol(X))</pre>
  # optimize
  res <- optim(</pre>
    par = startvals,
   fn = logit_fun,
    y = y,
    X = X,
    control = list(fnscale = -1),
   hessian = TRUE,
    method = "BFGS"
  )
startvals2 <- c(0, 0) # Why three this time?
restricted <- optim(</pre>
  startvals2,
 logit_fun,
  y = y,
  X = X[, 1],
  \# restricted model
  control = list(fnscale = -1),
  method = "BFGS"
)
  coef <- res$par</pre>
  # vcov <- solve(-res$hessian)</pre>
  # se <- sqrt(diag(vcov))
  # Unfortunately, I am not yet able to compute robust standard errors
  # clustered at article level by hand. But I am on it.
  vcov <- vcov(robcov(lrm(data = df_anal, reffemonly ~ Female + Mixed + PG + PA + Econ. + SMR, x=T, y=T
               cluster = df_anal$newartid))
  se <- sqrt(diag(vcov))</pre>
  ##robust standard error
  Names = c("Intercept", "Female", "Mixed", "P&G", "PA", "Econ", "SMR", "Pseudo R2", "NullLL", "LL", "
  if(journal == "Pooled"){
    ModelTable <- data.frame(Name = c(pasteO(round(coef, 2), " (", round(se, 2), ")"),</pre>
                                                round( 1- (restricted$value / res$value), 4),
                                                round(restricted$value, 0),
```

```
round(res$value,0),
                                                length(unique(df_anal$newartid)),
                                                 nrow(df_anal))
                              )
  } else {
    ModelTable <- data.frame(Name = c(pasteO(round(coef, 2), " (", round(se, 2), ")"),</pre>
                                                rep("", 4),
                                                round( 1- (restricted$value / res$value), 4),
                                                round(restricted$value, 0),
                                                round(res$value,0),
                                                length(unique(df_anal$newartid)),
                                                nrow(df_anal)))
  }
  rownames(ModelTable) <- Names</pre>
  colnames(ModelTable) <- journal</pre>
  if(vcovcoef == FALSE){
     return(ModelTable)
  } else {
    return(list(coef = coef,
                vcov = vcov))
  }
}
models <- do.call("cbind", lapply(unique(df$newjnlid), logistic_per_journal) )</pre>
pooled <- logistic_per_journal("Pooled")</pre>
flextable(cbind.data.frame(models, pooled) %>% rownames_to_column(" "))
```

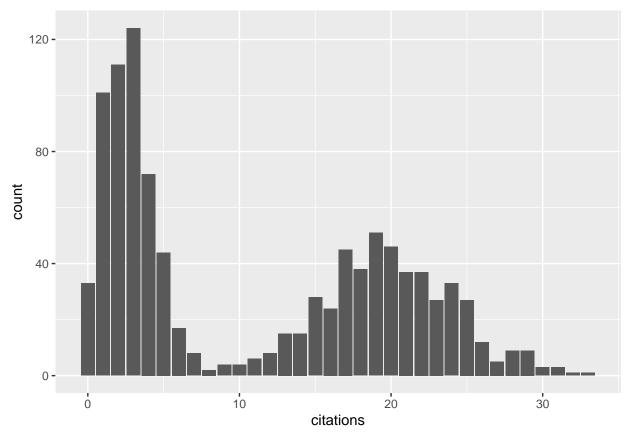
	APSR	Politics & Gender	Political Analysis	Econometri	cSoc. Methods & Res.	Pooled
Intercept	-2.07 (0.05)	-0.01 (0.11)	-2.84 (0.09)	-3.18 (0.06)	-2.46 (0.1)	-2.02 (0.05)
Female	0.99 (0.16)	0.53 (0.12)	0.42 (0.38)	1.14 (0.22)	0.76 (0.28)	0.86(0.1)
Mixed	0.21 (0.13)	-0.15 (0.16)	-0.08 (0.16)	0.07 (0.14)	0.06 (0.18)	0.11 (0.08)
P&G						1.73(0.1)
PA						-0.89 (0.09)
Econ						-1.14 (0.07)
SMR						-0.47(0.1)
Pseudo R2	-0.026	-0.0165	-7e-04	-0.0106	-0.0078	-0.2796
NullLL	-6359	-4007	-1249	-1951	-1185	-18566

	APSR	Politics & Gender	Political Analysis	Econometr	ic S oc. Methods & Res.	Pooled
LL	-6198	-3942	-1248	-1931	-1175	-14509
Clusters	464	332	295	604	232	1927
Observation	nsl 5648	5883	5891	10869	4053	42344

```
models_coef <- lapply(unique(df$newjnlid), logistic_per_journal, vcovcoef = TRUE)</pre>
nsim <- 1000
coef <- models_coef[[1]]$coef</pre>
vcov <- models_coef[[1]]$vcov</pre>
scenarios \leftarrow-data.frame \leftarrow- c(1,0,0)
scenario_female <- c(1,1,0)</pre>
scenario_mixed \leftarrow c(1,0,1)
sim_fun <- function(coef, vcov, nsim, scenarios){</pre>
  S <- mvrnorm(n = nsim, mu = coef, Sigma = vcov)
  scenarios_df <- data.frame()</pre>
  for( scenario in scenarios){
    mu <- S %*% scenario_male</pre>
    p <-1 / (1 + exp(-mu))
    df <- data.frame(ev = mean(p),</pre>
                        lwr = quantile(p, 0.025),
                        upr = quantile(p, 0.975),
                        )
    scenarios_df <- rbind(scenarios_df, df)</pre>
  }
  plot <- ggplot(data =df,</pre>
                   x)
```

A different approach: counts of citations

```
n \leftarrow 1000
female \leftarrow sample(size = n, x = c(0,1), replace = TRUE)
```



```
df %>%
  group_by(female) %>%
  summarise(mean = mean(citations))
```

```
pois_ll <- function(y, X, theta){</pre>
  beta <- theta[1:ncol(X)]</pre>
  #beta <- c(beta0, beta1)
  #y = df$citations
  \#X = cbind(rep(1, nrow(df)), df\$female)
  # logl = sum(Y* (beta %*% t(X)) - exp(beta %*% t(X)))
  logll <- -sum(exp(beta %*% t(X))) + sum(y * (beta%*% t(X))) - sum(log(factorial(y)))</pre>
  #ll \leftarrow prod((exp(-exp(beta %*% t(X))) * exp(beta %*% t(X)) ^ y) / (factorial(y)))
  return(log11)
}
stval \leftarrow c(0, 0)
res <-
  optim(
   stval,
    pois_ll,
   y = df$citations,
   X = cbind(rep(1, nrow(df)), df$female),
    control = list(fnscale = -1), # this is important
    hessian = TRUE,
    method = "BFGS"
    # and tell optimx to maximize rather than to minimize.
coef <- res$par</pre>
varcov <- solve(-res$hessian)</pre>
## simulate the data
scenario \leftarrow c(0,1)
nsim <- 1000
S <- mvrnorm(nsim, coef, solve(-res$hessian))</pre>
sim_pois <- function(scenario, nsim, S){</pre>
  scenarios <- c(1, scenario)</pre>
  mu <- S %*% scenarios
  # response function
  lambda <- exp(mu)</pre>
  pois <- rpois(nsim, lambda)</pre>
```

