PrEP Meta-Analysis

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Contents

1 Setup & Helper Funcs

```
#loading relevant libraries
library(metafor)
library(tidyverse)
```

2 Analysis

2.1 Internalized Homonegativity (IH)

2.1.1 Effect Sizes

```
ih_effect_nonlor_df <- data.frame(
    ogunbajo_2019_A = c("Ogunbajo et al.","2019 A",2019,"Nigeria",251,
                        -0.01151454784,0.02497515401,0.884,2176.002772,"81.10%"),
    zhang_liu_2022 = c("Zhang & Liu",2022,2019.5,"United States",
                       318,0.08427930442,0.02385766616,0.360,58021.4005,"81.80%")
)

rownames(ih_effect_nonlor_df) <- c("Authors","Year","Median Study Year",
                                   "Countries","Sample Size","Effect Size",
                                   "Effect Size Variance",
                                   "Homophobic Climate Index (HCI)",
                                   "GDP per Capita","Percent Willing")
tih_effect_nonlor_df <- as.data.frame(t(ih_effect_nonlor_df))
tih_effect_nonlor_df <- tih_effect_nonlor_df %>%
     mutate_at(c(3,5,6,7,8,9), as.numeric)

ih_effect_lor_df <- data.frame(
  stephenson_2021_A = c("Stephenson et al.","2021 A",2017.5,"United States",
                        0.003847459834, 0.01173335055,764,0.360,58021.4005,
```

```r
                        "42.30%"),
  stephenson_2021_B = c("Stephenson et al.","2021 B",2016.5,
                        "South Africa & Namibia",
                        -0.02888987146,0.03335482513,254,
                        0.5155433071,5166.291339,"15.90%"),
  coulaud_2018 = c("Coulaud et al.",2018,2015,
                   "Mali, Côte d'Ivoire, Burkina Faso, Togo",
                   -0.08081082927,0.2393594359,564,
                   0.7703829787,1044.771277,"87.00%"),
  belludi_2021 = c("Belludi et al.",2021,2016.5,
                   "India",-0.05025167927,0.3335200256,
                   8621,0.663,1732.554242,"67.60%"),
  storholm_2019 = c("Storholm et al.",2019,2016.5,
                    "United States",0.03650708414,0.03404751029,
                    226,0.360,58021.4005,"55.50%"),
  ogunbajo_2019_B = c("Ogunbajo et al.","2019 B",2014,"Kenya",
                      -0.14202375, 0.17723625,352,0.834,1525.235192,"44.90%"),
  ayala_2013 = c("Ayala et al.",2020,2017,"Multinational",
                 0.1452,0.1852040816,3748,0.5150502972,14522.89101,"80.80%"),
  driver_2020 = c("Driver et al.",2020,2017,"China",0.2478,
                  0.1652,123,0.680,8094.363367,"67.80%")
)

rownames(ih_effect_lor_df) <- c("Authors","Year","Median Study Year",
                                "Countries","Log Odds","Log Odds SE",
                                "Sample Size","Homophobic Climate Index (HCI)",
                                "GDP per Capita","Percent Willing")
tih_effect_lor_df <- as.data.frame(t(ih_effect_lor_df))
tih_effect_lor_df <- tih_effect_lor_df %>%
     mutate_at(c(3,5,6,7,8,9), as.numeric)

esize <- rep(0,8)
esize_var <- rep(0,8)

for (i in c(1:8)){
  e_result <- escalc("OR",
                     yi=tih_effect_lor_df[i,5],
                     sei=tih_effect_lor_df[i,6],
                     ni=tih_effect_lor_df[i,7])
  esize[i] <- e_result$yi
  esize_var[i] <- e_result$vi
  i <- i + 1
}

tih_effect_lor_df$`Effect Size` <- esize
tih_effect_lor_df$`Effect Size Variance` <- esize_var



tih_effect_total <- rbind(tih_effect_lor_df %>%
                            select(-c(`Log Odds`,`Log Odds SE`)),
                          tih_effect_nonlor_df)
tih_effect_total <- tih_effect_total %>%
```

```
  arrange(`Year`) %>% arrange(Authors)
tih_effect_total$`Standardized GDP per Capita` <-
  (tih_effect_total$`GDP per Capita`-mean(tih_effect_total$`GDP per Capita`))/(sd(tih_effect_total$`GDP

knitr::kable(tih_effect_total %>%
               select(Authors,Year,Countries,`Sample Size`,
                      `Percent Willing`,`Effect Size`,
                      `Effect Size Variance`,`Median Study Year`,
                      `Standardized GDP per Capita`,`Homophobic Climate Index (HCI)`),
             digits = 3, row.names=FALSE)
```

Authors	Year	Countries	Sample Size	Percent Willing	Effect Size	Effect Size Variance	Median Study Year	Standardized GDP per Capita	Homophobic Climate Index (HCI)
Ayala et al.	2020	Multinational	3748	80.80%	0.145	0.034	2017.0	-0.243	0.515
Belludi et al.	2021	India	8621	67.60%	-0.050	0.111	2016.5	-0.735	0.663
Coulaud et al.	2018	Mali, Côte d'Ivoire, Burkina Faso, Togo	564	87.00%	-0.081	0.057	2015.0	-0.762	0.770
Driver et al.	2020	China	123	67.80%	0.248	0.027	2017.0	-0.490	0.680
Ogunbajo et al.	2019 A	Nigeria	251	81.10%	-0.012	0.025	2019.0	-0.718	0.884
Ogunbajo et al.	2019 B	Kenya	352	44.90%	-0.142	0.031	2014.0	-0.743	0.834
Stephenson et al.	2021 A	United States	764	42.30%	0.004	0.000	2017.5	1.432	0.360
Stephenson et al.	2021 B	South Africa & Namibia	254	15.90%	-0.029	0.001	2016.5	-0.603	0.516
Storholm et al.	2019	United States	226	55.50%	0.037	0.001	2016.5	1.432	0.360
Zhang & Liu	2022	United States	318	81.80%	0.084	0.024	2019.5	1.432	0.360

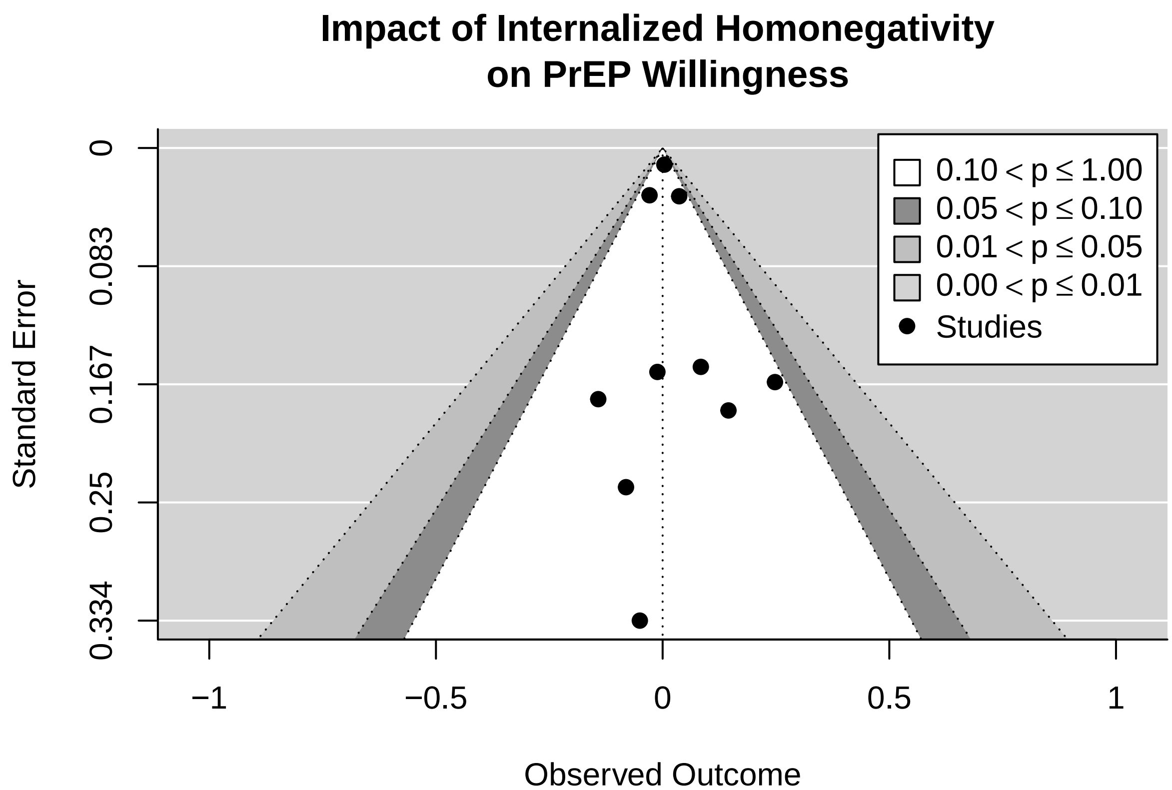
2.1.2 Random Effects Models

```
res_ih <- rma(yi=`Effect Size`, vi=`Effect Size Variance`,
              data=tih_effect_total)
(res_ih)
```

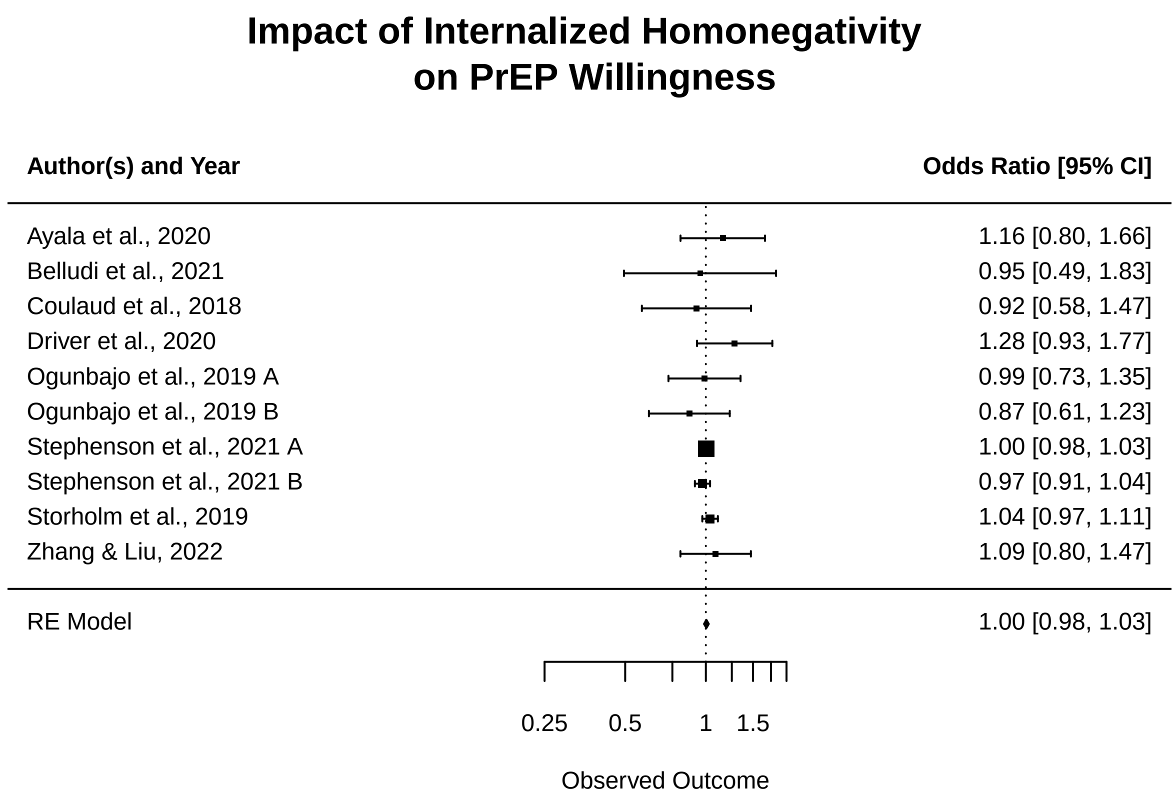
```
##
## Random-Effects Model (k = 10; tau^2 estimator: REML)
##
## tau^2 (estimated amount of total heterogeneity): 0 (SE = 0.0006)
## tau (square root of estimated tau^2 value):      0
## I^2 (total heterogeneity / total variability):   0.00%
## H^2 (total variability / sampling variability):  1.00
##
```

```
## Test for Heterogeneity:
## Q(df = 9) = 5.7492, p-val = 0.7647
##
## Model Results:
##
## estimate      se    zval    pval    ci.lb   ci.ub
##   0.0047  0.0104  0.4525  0.6509  -0.0157  0.0251
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

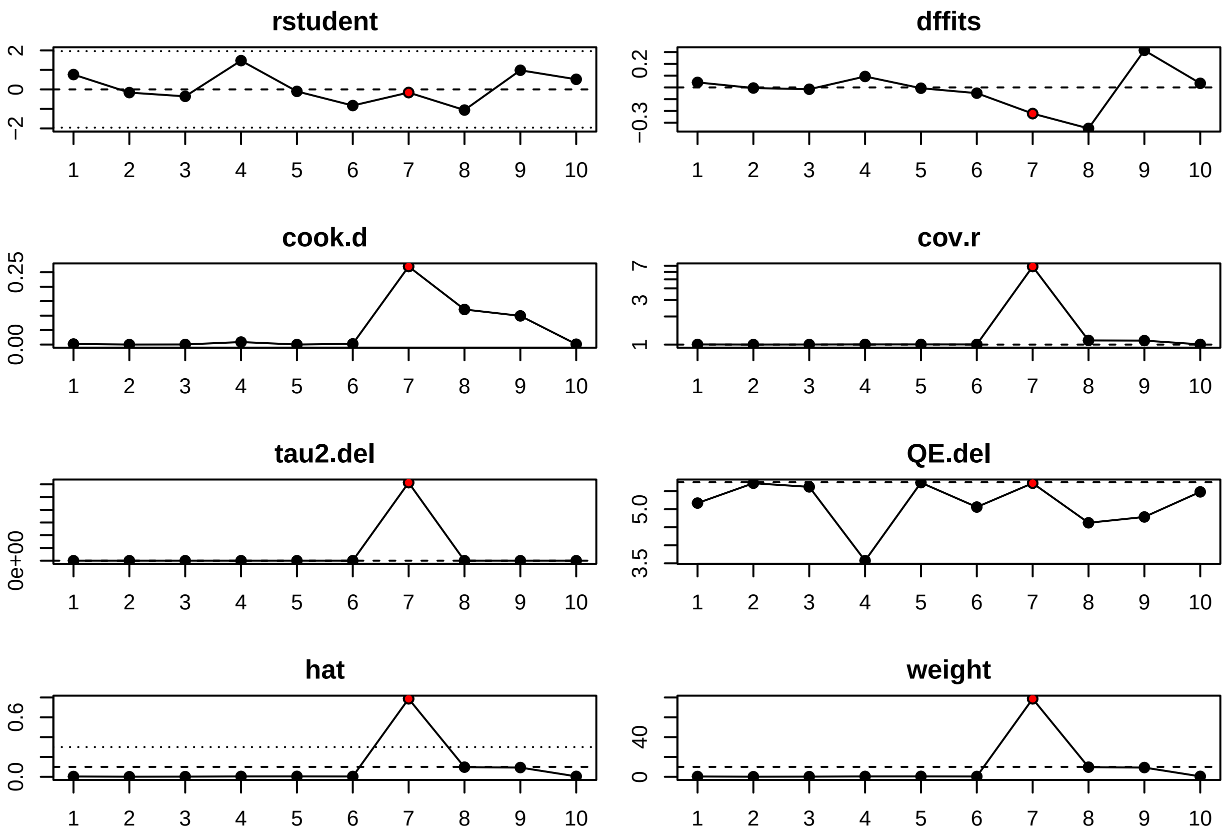
```
funnel(res_ih, level=c(90, 95, 99),
       shade=c("white", "gray55", "gray75"), refline=0, legend=TRUE,
        main = "Impact of Internalized Homonegativity \n on PrEP Willingness")
```




```
forest(res_ih,
       slab = paste(tih_effect_total$Authors,tih_effect_total$`Year`,
                    sep = ", "),
       main = "Impact of Internalized Homonegativity \n on PrEP Willingness",
                 xlim = c(-6, 4),
       at = log(c(0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2)),
       atransf = exp,cex = 0.75)
op <- par(cex = 0.75, font = 2)
text(-6, 12, "Author(s) and Year", pos = 4)
text(4, 12, "Odds Ratio [95% CI]", pos = 2)
```



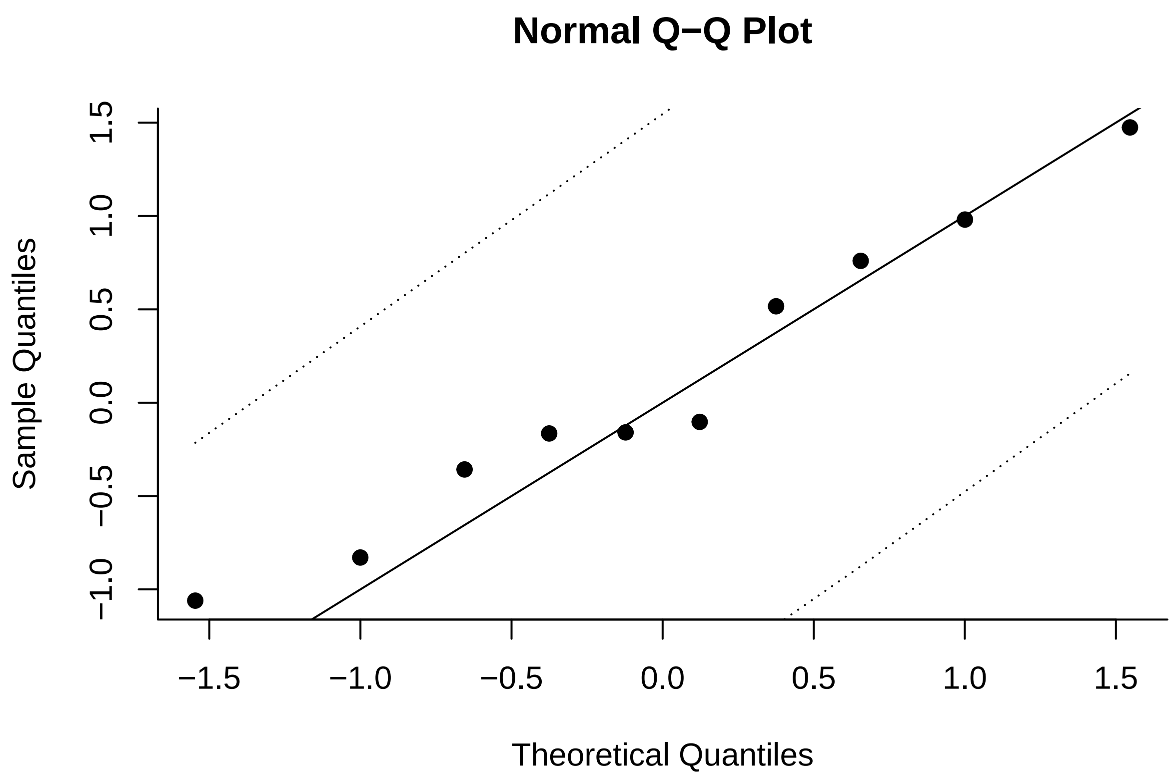

```
par(op)

res_ih_inf.ME <- influence(res_ih)
plot(res_ih_inf.ME)
```




```
knitr::kable(fitstats(res_ih),digits = 3)
```

	REML
logLik:	8.125
deviance:	-16.249
AIC:	-12.249
BIC:	-11.855
AICc:	-10.249

```
qqnorm(res_ih)
```




```r
rma(yi=`Effect Size`, vi=`Effect Size Variance`,
    data=tih_effect_total[-c(7,8),])
```

```
##
## Random-Effects Model (k = 8; tau^2 estimator: REML)
##
## tau^2 (estimated amount of total heterogeneity): 0 (SE = 0.0068)
## tau (square root of estimated tau^2 value):      0
## I^2 (total heterogeneity / total variability):   0.00%
## H^2 (total variability / sampling variability):  1.00
##
## Test for Heterogeneity:
## Q(df = 7) = 3.4851, p-val = 0.8368
##
## Model Results:
##
## estimate      se    zval    pval    ci.lb   ci.ub
##   0.0388  0.0306  1.2693  0.2043  -0.0211  0.0988
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

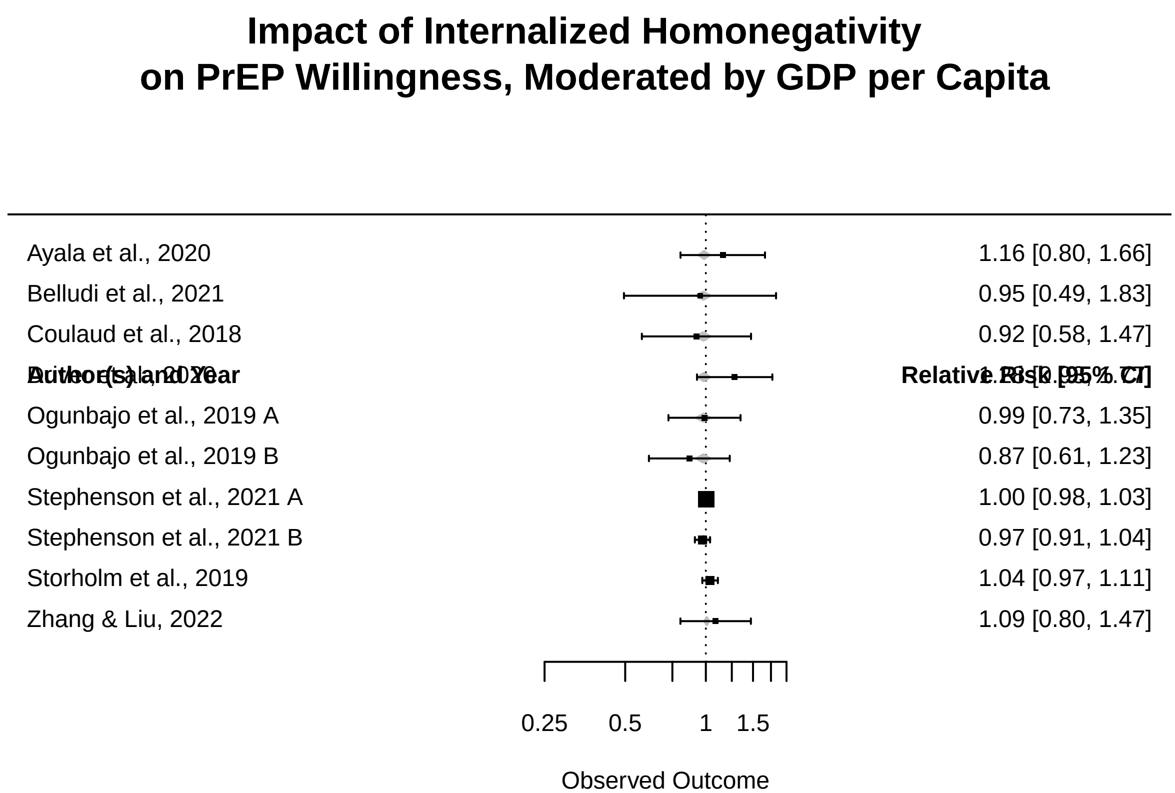
2.1.3 Mixed Effects Models

```r
reg_ih_gdp <- rma(yi = `Effect Size`,
              vi = `Effect Size Variance`,
              data = tih_effect_total,
              mods = ~ `Standardized GDP per Capita`,
              method = "REML")
```

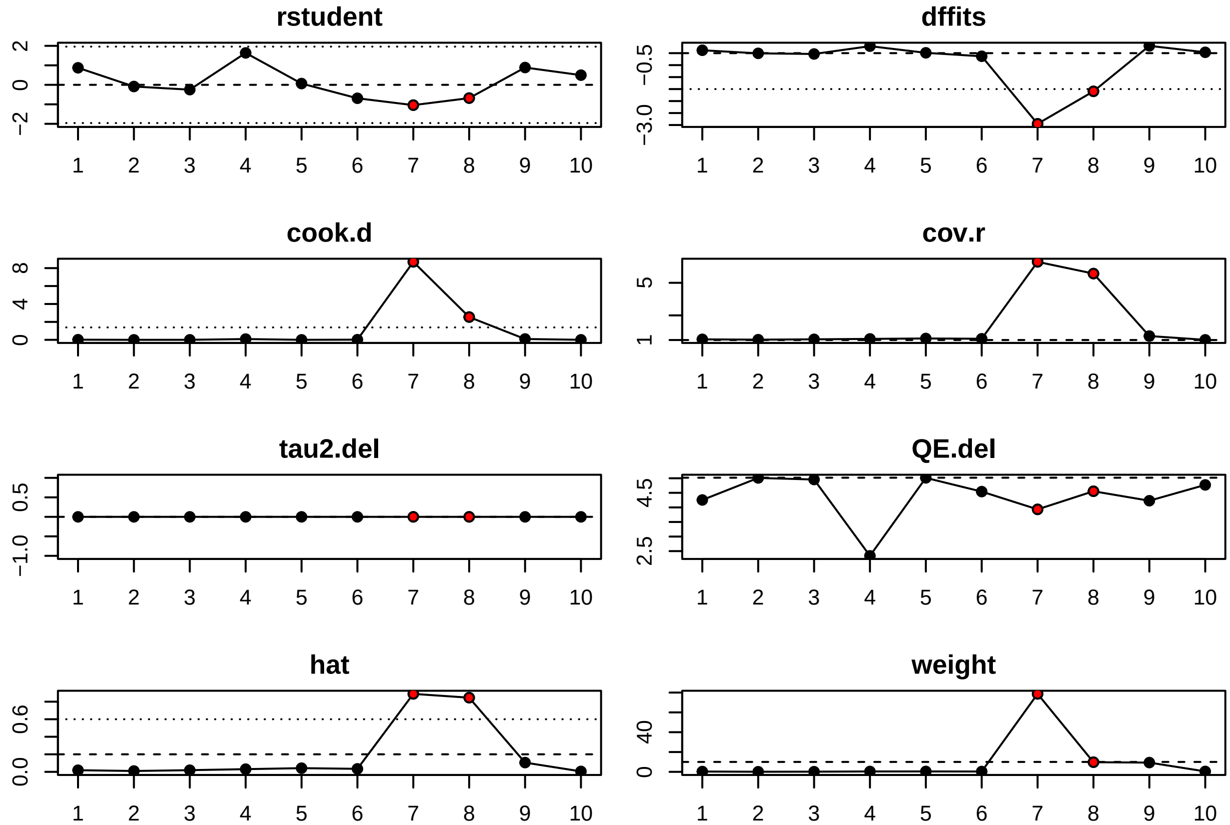
```r
reg_ih_gdp
```

```
##
## Mixed-Effects Model (k = 10; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):     0 (SE = 0.0009)
## tau (square root of estimated tau^2 value):             0
## I^2 (residual heterogeneity / unaccounted variability): 0.00%
## H^2 (unaccounted variability / sampling variability):   1.00
## R^2 (amount of heterogeneity accounted for):            0.00%
##
## Test for Residual Heterogeneity:
## QE(df = 8) = 5.0177, p-val = 0.7557
##
## Test of Moderators (coefficient 2):
## QM(df = 1) = 0.7315, p-val = 0.3924
##
## Model Results:
##
##                                estimate      se     zval    pval    ci.lb
## intrcpt                         -0.0117  0.0218  -0.5361  0.5919  -0.0545
## `Standardized GDP per Capita`    0.0137  0.0160   0.8553  0.3924  -0.0177
##                                 ci.ub
## intrcpt                        0.0311
## `Standardized GDP per Capita`  0.0451
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

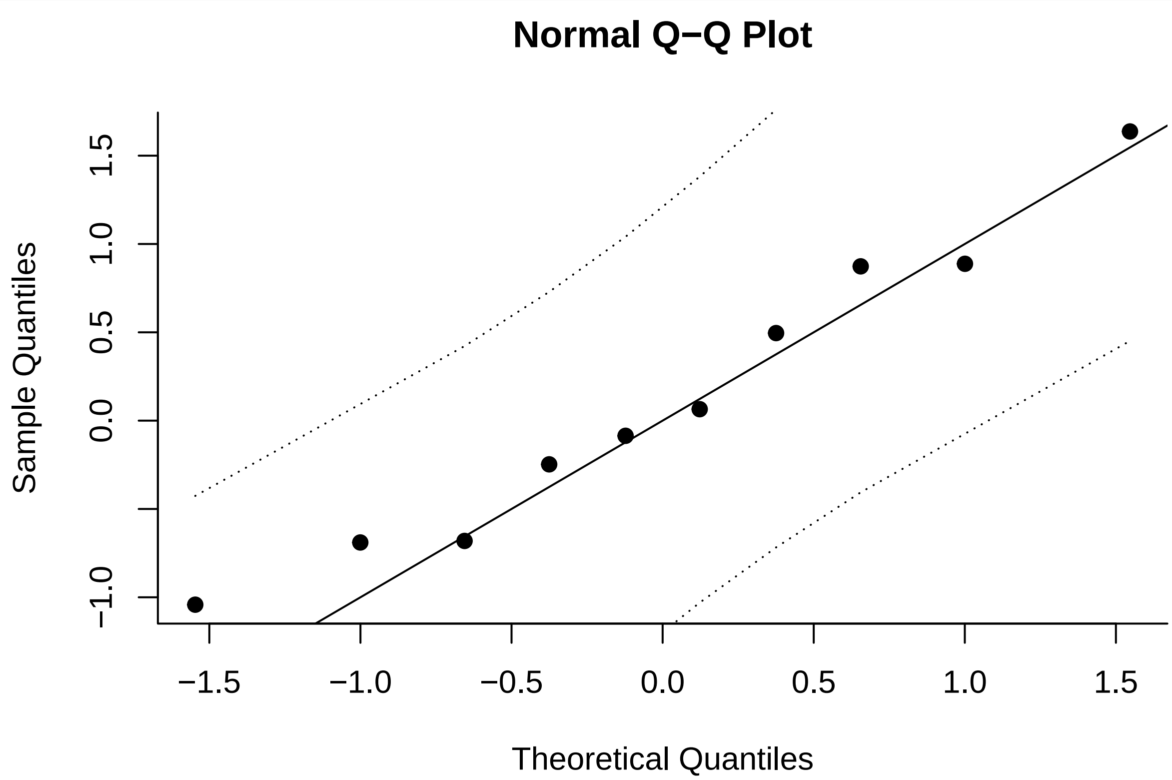
```r
forest(reg_ih_gdp, slab = paste(tih_effect_total$Authors,
                                tih_effect_total$`Year`, sep = ", "),
       main = "Impact of Internalized Homonegativity \n on PrEP Willingness, Moderated by GDP per Capita
                 xlim = c(-6, 4),
       at = log(c(0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2)), atransf = exp,
                 cex = 0.75)
op <- par(cex = 0.75, font = 2)
text(-6, 7, "Author(s) and Year", pos = 4)
text(4, 7, "Relative Risk [95% CI]", pos = 2)
```




```
par(op)

reg_ih_gdp_inf.ME <- influence(reg_ih_gdp)
plot(reg_ih_gdp_inf.ME)
```




```
qqnorm(reg_ih_gdp)
```



```r
reg_ih_mod.RE.ML <- rma(yi=`Effect Size`,
                        vi=`Effect Size Variance`,
                        data=tih_effect_total,
                        method="ML")
reg_ih_gdp_mod.ME.ML <- rma(yi = `Effect Size`,
              vi = `Effect Size Variance`,
              data = tih_effect_total,
              mods = ~ `Standardized GDP per Capita`,
              method = "ML")
reg_ih_year_mod.ME.ML <- rma(yi = `Effect Size`,
              vi = `Effect Size Variance`,
              data = tih_effect_total,
              mods = ~ `Median Study Year`,
              method = "ML")
reg_ih_year_gdp_mod.ME.ML <- rma(yi = `Effect Size`,
              vi = `Effect Size Variance`,
              data = tih_effect_total,
              mods = ~ `Median Study Year` + `Standardized GDP per Capita`,
              method = "ML")
reg_ih_hci_mod.ME.ML <- rma(yi = `Effect Size`,
              vi = `Effect Size Variance`,
              data = tih_effect_total,
              mods = ~ `Homophobic Climate Index (HCI)`,
              method = "ML")

knitr::kable(cbind(fitstats(reg_ih_mod.RE.ML),
                   fitstats(reg_ih_gdp_mod.ME.ML),
                   fitstats(reg_ih_year_mod.ME.ML),
                   fitstats(reg_ih_hci_mod.ME.ML),
                   fitstats(reg_ih_year_gdp_mod.ME.ML)),
             digits = 3, col.names=c("Random Effects",
                                     "Mixed Effects (GDP)",
                                     "Mixed Effects (Year)",
                                     "Mixed Effects (HCI)",
                                     "Mixed Effects (Year + GDP)"))
```

	Random Effects	Mixed Effects (GDP)	Mixed Effects (Year)	Mixed Effects (HCI)	Mixed Effects (Year + GDP)
logLik:	10.620	10.985	10.736	10.854	10.986
deviance:	5.749	5.018	5.517	5.280	5.017
AIC:	-17.239	-15.971	-15.472	-15.709	-13.971
BIC:	-16.634	-15.063	-14.564	-14.801	-12.761
AICc:	-15.525	-11.971	-11.472	-11.709	-5.971

2.2 PrEP Stigma

2.2.1 Effect Sizes

```r
prep_effect_lor_df <- data.frame(
    ogunbajo_2019_A = c("Ogunbajo et al","2019 A",2019,"United States",
                        251, -0.01151454784,0.02497515401,0.360,58021.4005,
                        "81.10%"),
```

```r
    zhang_liu_2022 = c("Zhang & Liu",2022,2019.5,"United States",
                       318,0.08427930442,0.02385766616,0.360,58021.4005,
                       "81.80%"),

    holloway_2017 = c("Holloway et al.",2017,2015,"United States",
                      270, 0.04736105393, 0.1131649572,0.360,58021.4005,
                      "55.30%"),
    bil_2015 = c("Bil et al.",2015,2012.5,"Netherlands",
                 270,-0.4519422329,0.1326387181,0.131,46039.10593,
                 "55.70%"),
    eaton_2017 = c("Eaton et al.",2017,2015,"United States",
                   264,-0.265498889,0.08096737091   ,0.360,58021.4005,"43.56%"),
    sun_2021 = c("Sun et al.",2021,2018,"China",
                 612,-0.1550296911,0.08983203858    ,0.680,8094.363367,
                 "35.00%"),
    golub_2013 = c("Golub et al.",2013,2012,"United States",
                   184,0.0268129064,0.1553931795,0.360,58021.4005,"55.40%"),
    wang_2020_A = c("Wang et al.",2020,2018,"China",
                  70,-1.039618429,0.2748798736,0.680,8094.363367,"67.10%"),
    wang_2020_B = c("Wang et al.",2018,2017,"China",
                    403,-0.7292862272,1.120395591,0.680,8094.363367,"52.90%"),
    draper_2017 = c("Draper et al.",2017,2014,"Myanmar",
                    432,-0.1242306796,0.1277911559,0.797,1136.610665,
                    "62.20%"),
    ayala_2013 = c("Ayala et al.",2013,2012,"Multinational",
                   3748,0.25802,0.07448,0.5150502972,14522.89101,
                   "80.80%"),
    ahouda_2020 = c("Ahouda et al.",2020,2018,"Benin",
                    400,-0.545902591,0.289633366,0.781,1087.287331,
                    "35.70%"),
    uthappa_2017 = c("Uthappa et al.",2017,2015,"India",
                     271,-1.325519023,0.6786891292,0.663,1732.554242,
                     "99.00%"),
    moskowitz_2020 = c("Moskowitz et al.",2020,2019, "United States",
                       491,-0.08713050078,0.0374747664,0.360,58021.4005,
                       "67.80%"),
    wetmoreland_2021 = c("Westmoreland et al.",2021,2017.5,"United States",
                         5817,-0.03901322528,0.02095646939,0.360,58021.4005,
                         "53.30%"),
    driver_2020 = c("Driver et al.",2020,2017,"United States",
                    123,-0.122,0.061,0.360,58021.4005,"67.80%"),
    zhou_2012 = c("Zhou et al.",2012,2009.5,"China",
                  265,-0.67140204,0.1222885987,0.680,8094.363367,
                  "67.80%")
)

rownames(prep_effect_lor_df) <- c("Authors","Year",
                                  "Median Study Year","Countries",
                                  "Sample Size","Effect Size",
                                  "Effect Size Variance",
                                  "Homophobic Climate Index (HCI)",
                                  "GDP per Capita",
                                  "Percent Willing")
```

```
tprep_effect_lor_df <- as.data.frame(t(prep_effect_lor_df))
tprep_effect_lor_df <- tprep_effect_lor_df %>%
     mutate_at(c(3,5,6,7,8,9), as.numeric)

prep_esize <- rep(0,17)
prep_esize_var <- rep(0,17)

for (i in c(1:17)){
  prep_e_result <- escalc("OR",
                   yi=tprep_effect_lor_df[i,6],
                   sei=tprep_effect_lor_df[i,7],
                   ni=tprep_effect_lor_df[i,5])
  prep_esize[i] <- prep_e_result$yi
  prep_esize_var[i] <- prep_e_result$vi
  i <- i + 1
}

tprep_effect_lor_df$`Effect Size` <- prep_esize
tprep_effect_lor_df$`Effect Size Variance` <- prep_esize_var
tprep_effect_lor_df$`Standardized GDP per Capita` <-
  (tprep_effect_lor_df$`GDP per Capita`-mean(tprep_effect_lor_df$`GDP per Capita`))/(sd(tprep_effect_lo

tprep_effect_lor_df <- tprep_effect_lor_df %>% arrange(Authors)

knitr::kable(tprep_effect_lor_df %>%
               select(Authors,Year,Countries,`Sample Size`,
                      `Percent Willing`,`Effect Size`,
                      `Effect Size Variance`,`Median Study Year`,
                      `Standardized GDP per Capita`,`Homophobic Climate Index (HCI)`),
             digits = 3, row.names=FALSE)
```

Authors	Year	Countries	Sample Size	Percent Willing	Effect Size	Effect Size Variance	Median Study Year	Standardized GDP per Capita	Homophobic Climate Index (HCI)
Ahouda et al.	2020	Benin	400	35.70%	-0.546	0.084	2018.0	-1.217	0.781
Ayala et al.	2013	Multinational	3748	80.80%	0.258	0.006	2012.0	-0.704	0.515
Bil et al.	2015	Netherlands	270	55.70%	-0.452	0.018	2012.5	0.497	0.131
Draper et al.	2017	Myanmar	432	62.20%	-0.124	0.016	2014.0	-1.215	0.797
Driver et al.	2020	United States	123	67.80%	-0.122	0.004	2017.0	0.954	0.360
Eaton et al.	2017	United States	264	43.56%	-0.265	0.007	2015.0	0.954	0.360
Golub et al.	2013	United States	184	55.40%	0.027	0.024	2012.0	0.954	0.360
Holloway et al.	2017	United States	270	55.30%	0.047	0.013	2015.0	0.954	0.360
Moskowitz et al.	2020	United States	491	67.80%	-0.087	0.001	2019.0	0.954	0.360

Authors	Year	Countries	Sample Size	Percent Willing	Effect Size	Effect Size Variance	Median Study Year	Standardized GDP per Capita	Homophobic Climate Index (HCI)
Ogunbajo et al	2019 A	United States	251	81.10%	-0.012	0.001	2019.0	0.954	0.360
Sun et al.	2021	China	612	35.00%	-0.155	0.008	2018.0	-0.949	0.680
Uthappa et al.	2017	India	271	99.00%	-1.326	0.461	2015.0	-1.192	0.663
Wang et al.	2020	China	70	67.10%	-1.040	0.076	2018.0	-0.949	0.680
Wang et al.	2018	China	403	52.90%	-0.729	1.255	2017.0	-0.949	0.680
Westmoreland et al.	2021	United States	5817	53.30%	-0.039	0.000	2017.5	0.954	0.360
Zhang & Liu	2022	United States	318	81.80%	0.084	0.001	2019.5	0.954	0.360
Zhou et al.	2012	China	265	67.80%	-0.671	0.015	2009.5	-0.949	0.680

2.2.2 Random Effects Models

```
res_prep <- rma(`Effect Size`, `Effect Size Variance`,
                data=tprep_effect_lor_df)
res_prep
```

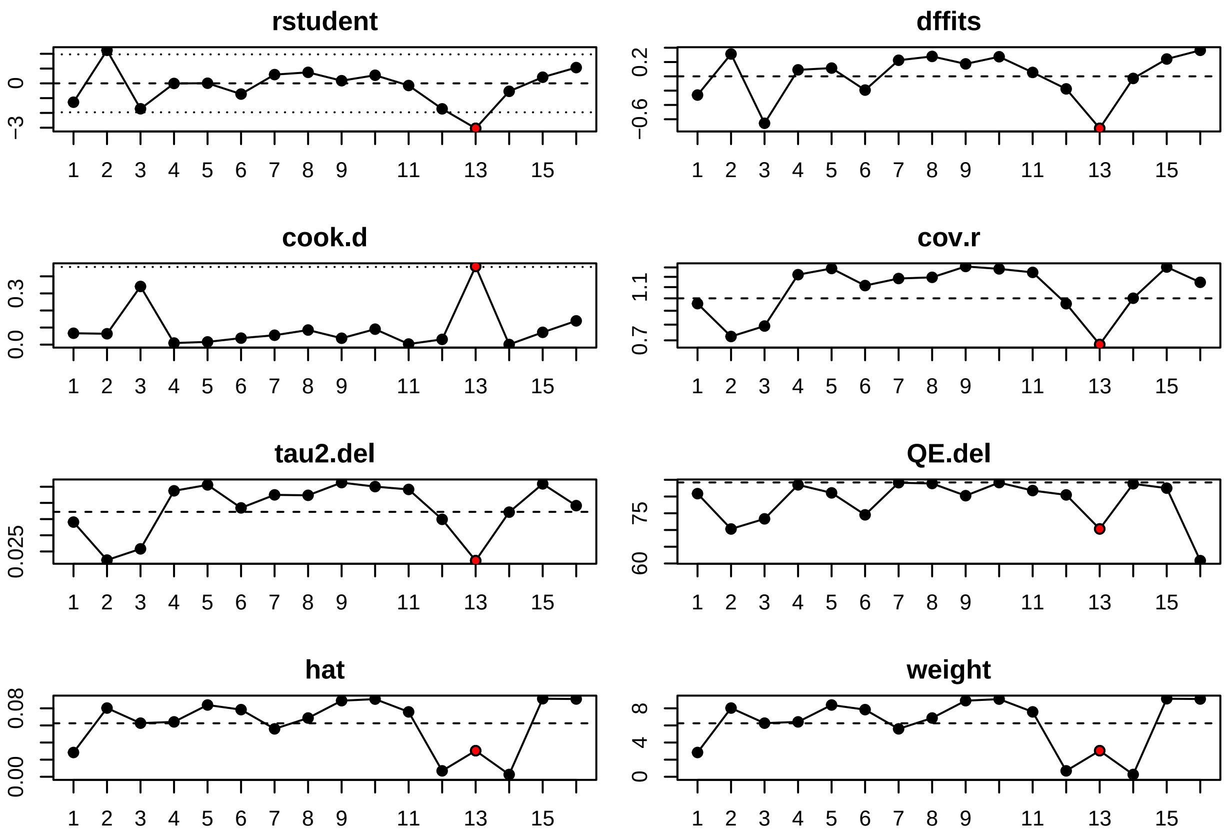
```
##
## Random-Effects Model (k = 17; tau^2 estimator: REML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0638 (SE = 0.0285)
## tau (square root of estimated tau^2 value):      0.2526
## I^2 (total heterogeneity / total variability):   95.89%
## H^2 (total variability / sampling variability):  24.35
##
## Test for Heterogeneity:
## Q(df = 16) = 112.6462, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb    ci.ub
##  -0.1707  0.0711  -2.4010  0.0164  -0.3101  -0.0314  *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```
rma(`Effect Size`, `Effect Size Variance`,
    data=tprep_effect_lor_df[-17,])
```

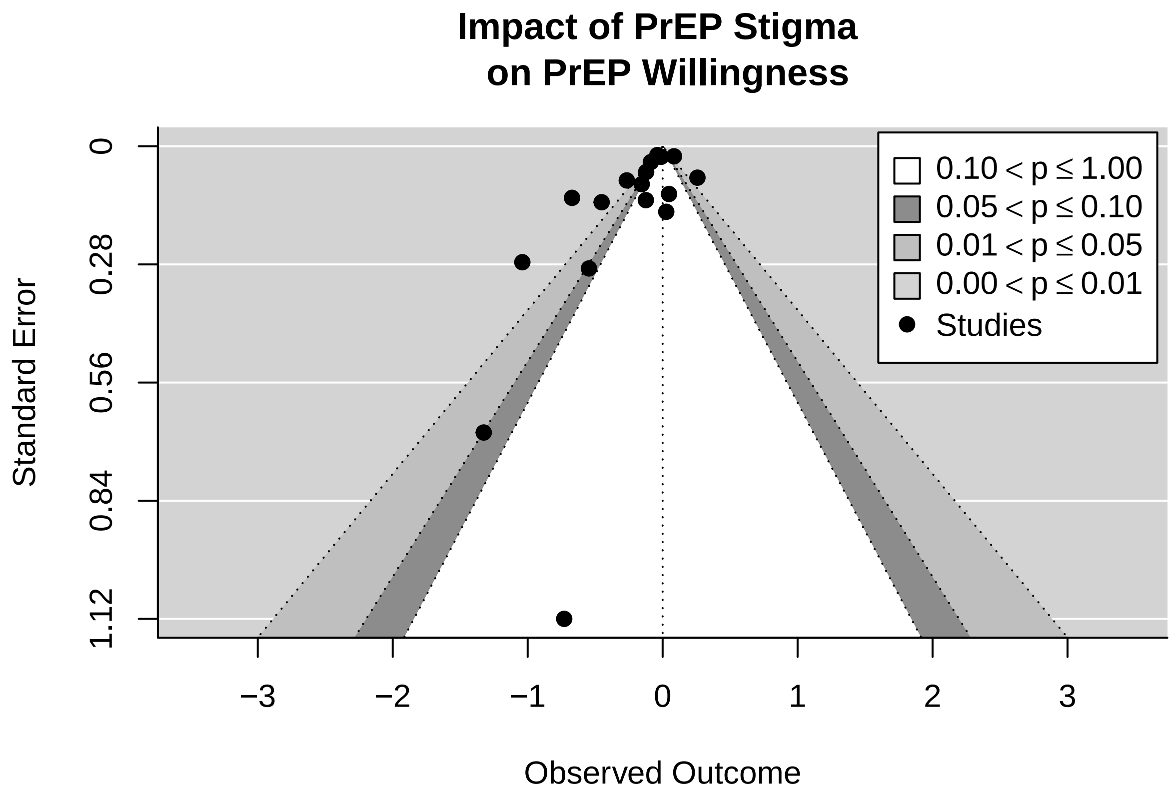
```
##
## Random-Effects Model (k = 16; tau^2 estimator: REML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0372 (SE = 0.0184)
## tau (square root of estimated tau^2 value):      0.1930
## I^2 (total heterogeneity / total variability):   93.48%
```

```
## H^2 (total variability / sampling variability):  15.33
##
## Test for Heterogeneity:
## Q(df = 15) = 84.2055, p-val < .0001
##
## Model Results:
##
## estimate      se     zval    pval    ci.lb    ci.ub
##  -0.1166  0.0586  -1.9886  0.0467  -0.2314  -0.0017  *
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

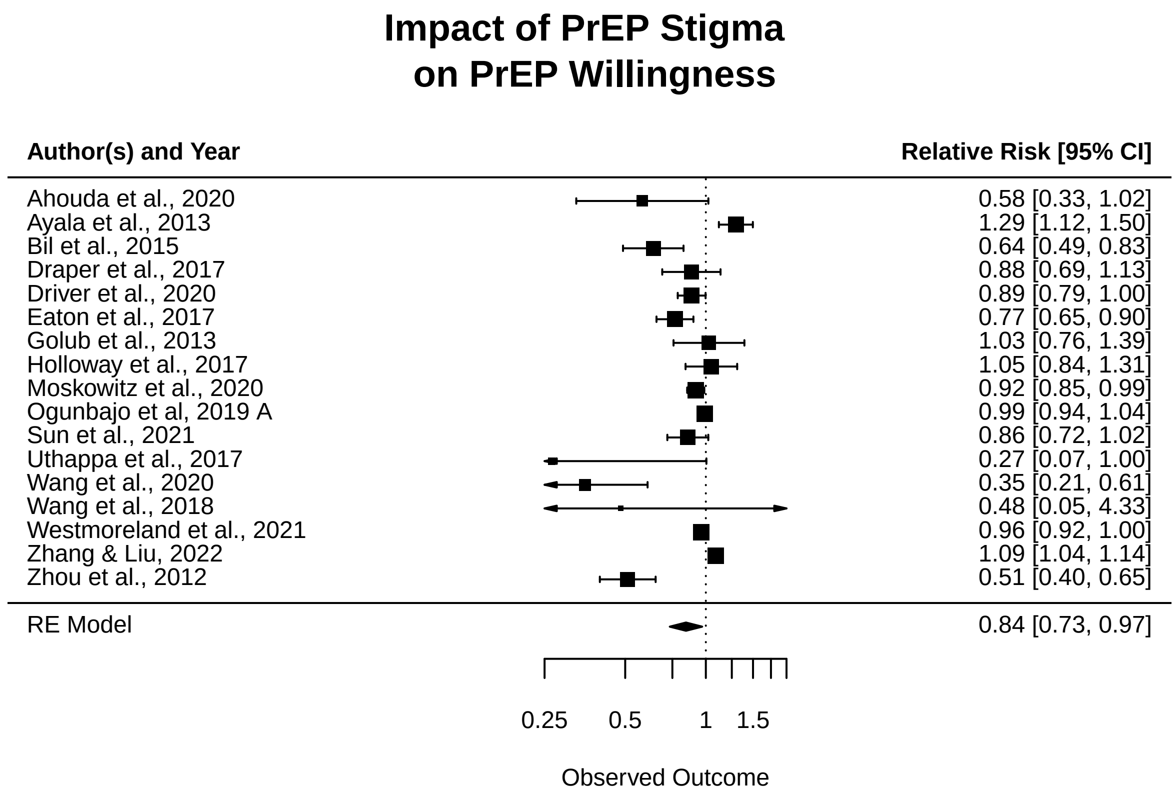
```
plot(influence(rma(`Effect Size`, `Effect Size Variance`,
                   data=tprep_effect_lor_df[-17,])))
```



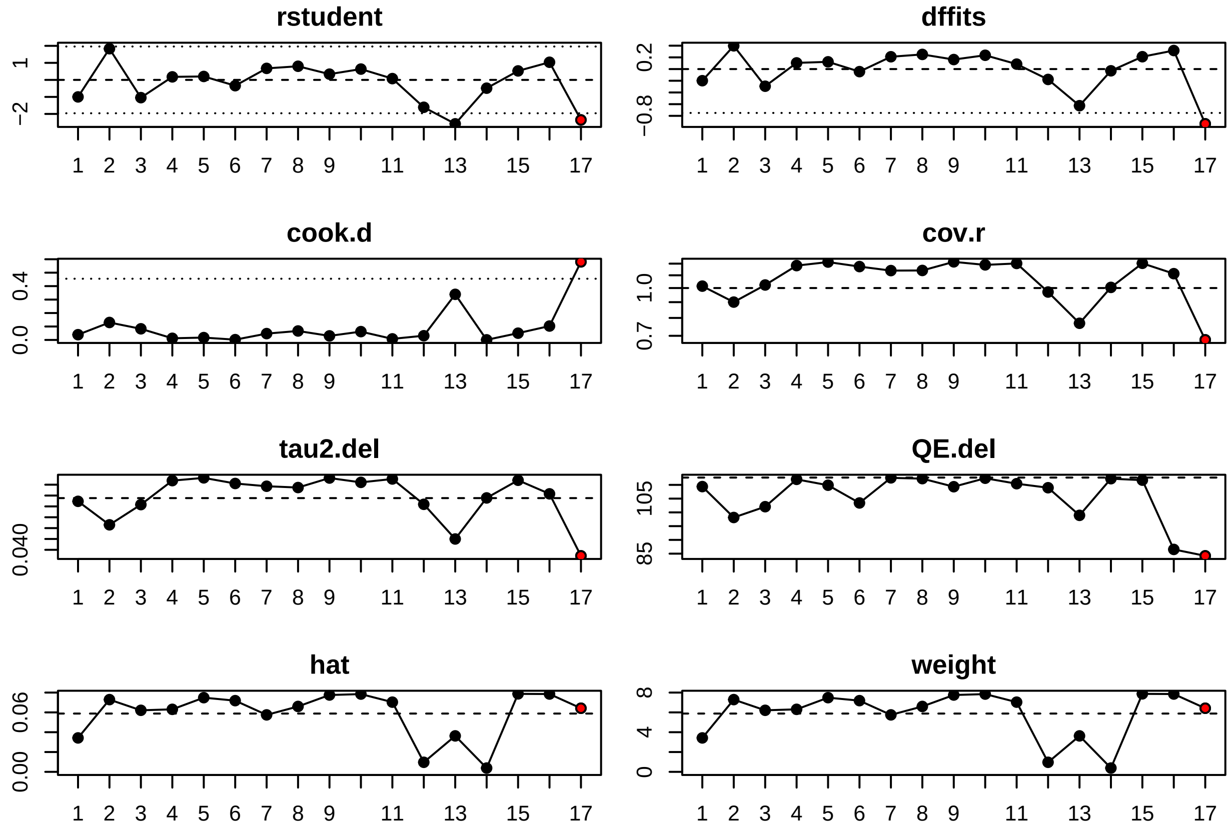

```
funnel(res_prep, level=c(90, 95, 99),
       shade=c("white", "gray55", "gray75"), refline=0, legend=TRUE,
        main = "Impact of PrEP Stigma \n on PrEP Willingness")
```




```
forest(res_prep, slab = paste(tprep_effect_lor_df$Authors,
                              tprep_effect_lor_df$`Year`, sep = ", "),
       main = "Impact of PrEP Stigma \n on PrEP Willingness",
                 xlim = c(-6, 4),
       at = log(c(0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2)), atransf = exp,
                 cex = 0.75)
op <- par(cex = 0.75, font = 2)
text(-6, 19, "Author(s) and Year", pos = 4)
text(4, 19, "Relative Risk [95% CI]", pos = 2)
```



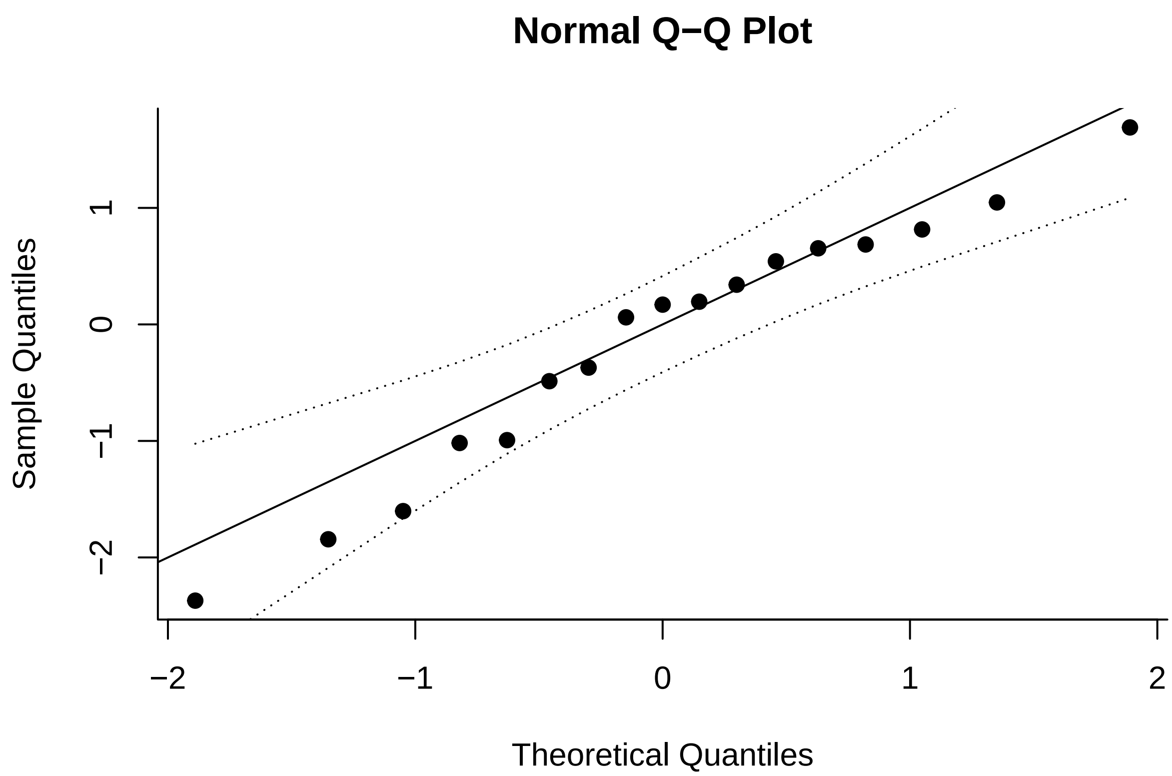

```
par(op)

res_prep_inf.ME <- influence(res_prep)
plot(res_prep_inf.ME)
```




```
fitstats(res_prep)
```

```
##                 REML
## logLik:    -6.208241
## deviance: 12.416483
## AIC:      16.416483
## BIC:      17.961660
## AICc:     17.339560
```

```
qqnorm(res_prep)
```



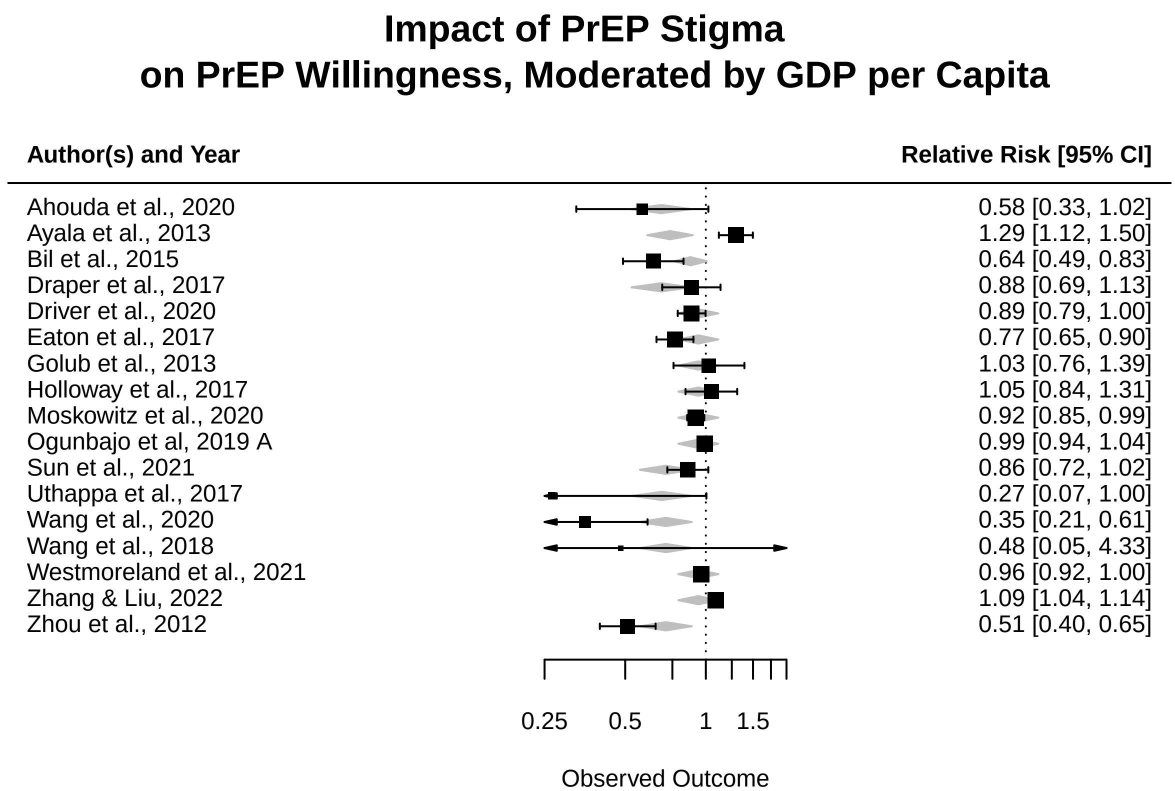
2.2.3 Mixed Effects Models

```
reg_prep_gdp <- rma(yi = `Effect Size`,
               vi = `Effect Size Variance`,
               data = tprep_effect_lor_df,
               mods = ~ `Standardized GDP per Capita`,
               method = "REML")

reg_prep_gdp
```

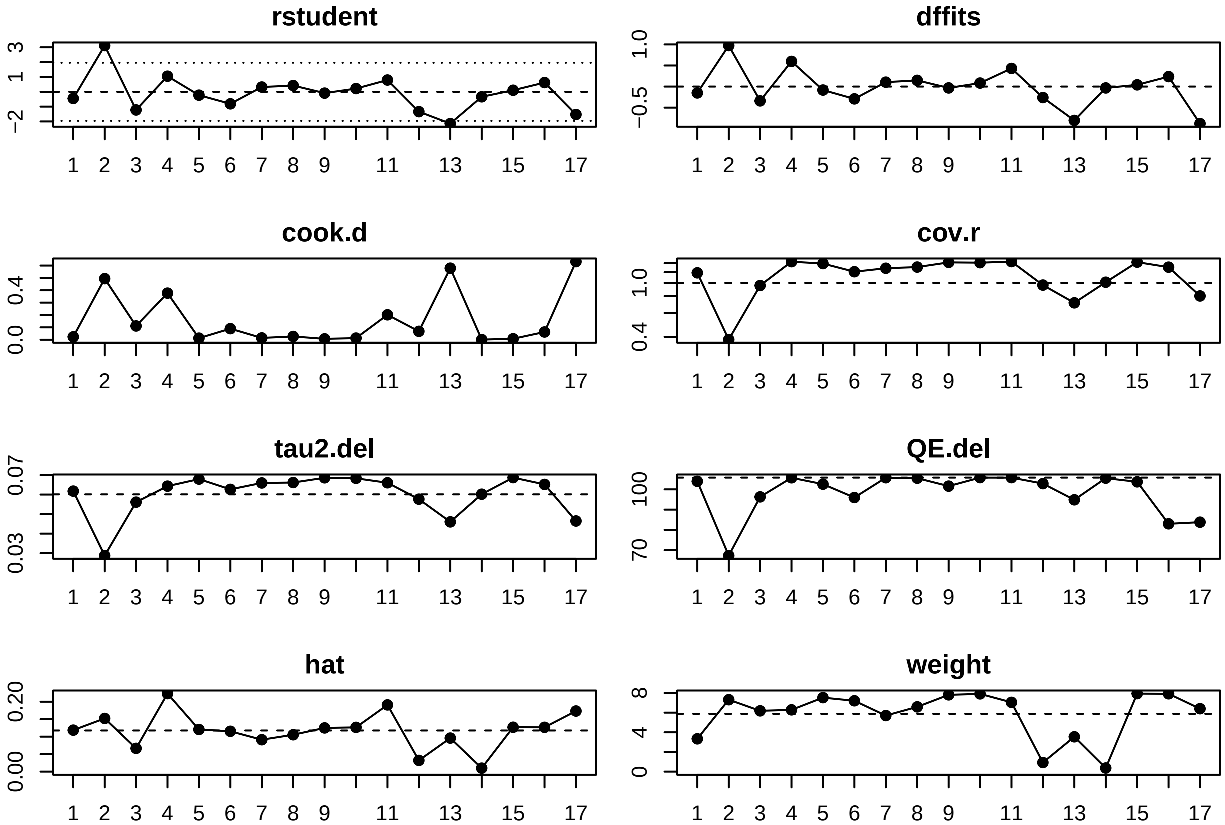
```
##
## Mixed-Effects Model (k = 17; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):     0.0601 (SE = 0.0281)
## tau (square root of estimated tau^2 value):             0.2452
## I^2 (residual heterogeneity / unaccounted variability): 95.76%
## H^2 (unaccounted variability / sampling variability):   23.60
## R^2 (amount of heterogeneity accounted for):            5.83%
##
## Test for Residual Heterogeneity:
## QE(df = 15) = 105.8130, p-val < .0001
##
## Test of Moderators (coefficient 2):
## QM(df = 1) = 3.7369, p-val = 0.0532
##
## Model Results:
##
##                                  estimate      se     zval    pval    ci.lb
## intrcpt                           -0.2044  0.0718  -2.8489  0.0044  -0.3451
```

```
## `Standardized GDP per Capita`    0.1465  0.0758   1.9331  0.0532  -0.0020
##                                   ci.ub
## intrcpt                         -0.0638  **
## `Standardized GDP per Capita`   0.2951   .
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

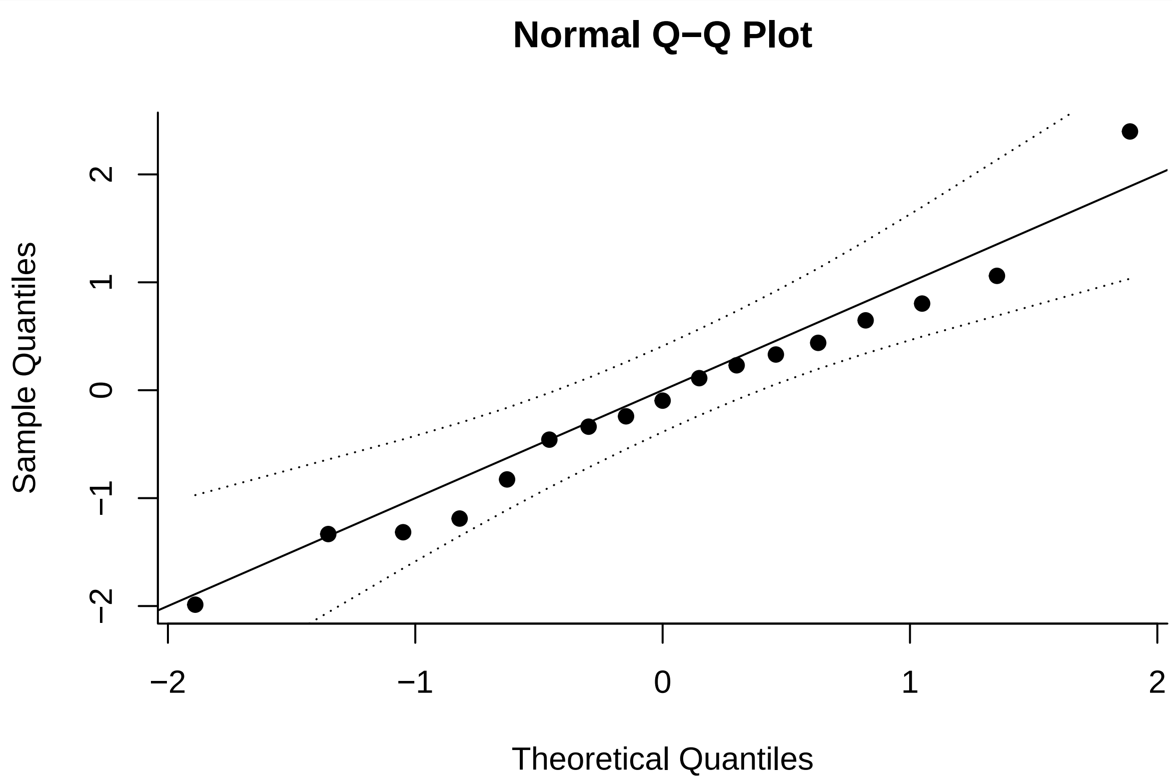
```r
forest(reg_prep_gdp, slab = paste(tprep_effect_lor_df$Authors,
                                  tprep_effect_lor_df$`Year`, sep = ", "),
       main = "Impact of PrEP Stigma \n on PrEP Willingness, Moderated by GDP per Capita",
                xlim = c(-6, 4), at = log(c(0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2)),
       atransf = exp,cex = 0.75)
op <- par(cex = 0.75, font = 2)
text(-6, 19, "Author(s) and Year", pos = 4)
text(4, 19, "Relative Risk [95% CI]", pos = 2)
```




```r
par(op)

reg_prep_gdp_inf.ME <- influence(reg_prep_gdp)
plot(reg_prep_gdp_inf.ME)
```




```
qqnorm(reg_prep_gdp)
```



```r
reg_prep_mod.RE.ML <- rma(yi=`Effect Size`,
                        vi=`Effect Size Variance`,
                        data=tprep_effect_lor_df,
                        method="ML")
reg_prep_hci_mod.ME.ML <- rma(yi = `Effect Size`,
              vi = `Effect Size Variance`,
              data = tprep_effect_lor_df,
              mods = ~  `Homophobic Climate Index (HCI)`,
              method = "ML")
reg_prep_gdp_mod.ME.ML <- rma(yi = `Effect Size`,
              vi = `Effect Size Variance`,
              data = tprep_effect_lor_df,
              mods = ~  `Standardized GDP per Capita`,
              method = "ML")
reg_prep_year_mod.ME.ML <- rma(yi = `Effect Size`,
              vi = `Effect Size Variance`,
              data = tprep_effect_lor_df,
              mods = ~  `Median Study Year`,
              method = "ML")
reg_prep_gdp_hci_mod.ME.ML <- rma(yi = `Effect Size`,
              vi = `Effect Size Variance`,
              data = tprep_effect_lor_df,
              mods = ~  `Standardized GDP per Capita` +
                `Homophobic Climate Index (HCI)`,
              method = "ML")
reg_prep_gdp_yr_mod.ME.ML <- rma(yi = `Effect Size`,
              vi = `Effect Size Variance`,
              data = tprep_effect_lor_df,
              mods = ~  `Standardized GDP per Capita` +
                `Median Study Year`,
              method = "ML")

knitr::kable(cbind(fitstats(reg_prep_mod.RE.ML),
                   fitstats(reg_prep_gdp_mod.ME.ML),
                   fitstats(reg_prep_year_mod.ME.ML),
                   fitstats(reg_prep_hci_mod.ME.ML),
                   fitstats(reg_prep_gdp_yr_mod.ME.ML)),
             digits = 3, col.names=c("Random Effects",
                                     "Mixed Effects (GDP)",
                                     "Mixed Effects (Year)",
                                     "Mixed Effects (HCI)",
                                     "Mixed Effects (Year + GDP)"))
```

	Random Effects	Mixed Effects (GDP)	Mixed Effects (Year)	Mixed Effects (HCI)	Mixed Effects (Year + GDP)
logLik:	-5.875	-3.925	-5.543	-4.668	-3.915
deviance:	56.339	52.440	55.674	53.925	52.420
AIC:	15.750	13.851	17.085	15.336	15.831
BIC:	17.417	16.351	19.585	17.836	19.163
AICc:	16.607	15.697	18.931	17.182	19.164

2.3 HIV Stigma

2.3.1 Effect Sizes

```
hiv_effect_df <- data.frame(
    zhang_liu_2022 = c("Zhang & Liu",2022,2019.5,"United States",
                       315,0.4596033465,0.2507835062,0.360,58021.4005,
                       "81.80%"),
    meyers_2018 = c("Meyers et al.",2018,2013.5,"China",
                    200,0.2282825605,0.1473118038,0.680,8094.363367,
                    "51.50%"),
    chaung_2018 = c("Chuang et al.",2018,2014,"Taiwan",
                    176,0.5799862723,0.215992354,0.580,23071,"35.00%"),
    wheelock_2013 = c("Wheelock et al.",2013,2011,"Thailand",
                      260,0.5003416684,0.2077108941,0.533,5993.305516,
                      "88.40%"),
    fallon_2015 = c("Fallon et al.",2015,2014,"United States",
                    398,0.2297640034,0.1135258395,0.360,58021.4005,"48.00%")
)

rownames(hiv_effect_df) <- c("Authors","Year",
                             "Median Study Year","Countries",
                             "Sample Size","LOR","LOR SE",
                             "Homophobic Climate Index (HCI)",
                             "GDP per Capita","Percent Willing")
thiv_effect_df <- as.data.frame(t(hiv_effect_df))
thiv_effect_df <- thiv_effect_df %>%
     mutate_at(c(2,3,5,6,7,8,9), as.numeric)

hiv_esize <- rep(0,5)
hiv_esize_var <- rep(0,5)

for (i in c(1:5)){
  hiv_e_result <- escalc("OR",
                      yi=thiv_effect_df[i,6],
                      sei=thiv_effect_df[i,7],
                      ni=thiv_effect_df[i,5])
  hiv_esize[i] <- hiv_e_result$yi
  hiv_esize_var[i] <- hiv_e_result$vi
  i <- i + 1
}

thiv_effect_df$`Standardized GDP per Capita` <-
  (thiv_effect_df$`GDP per Capita`-mean(thiv_effect_df$`GDP per Capita`))/(sd(thiv_effect_df$`GDP per Ca
thiv_effect_df$`Effect Size` <- hiv_esize
thiv_effect_df$`Effect Size Variance` <- hiv_esize_var


thiv_effect_df <- thiv_effect_df %>% arrange(Authors) %>%
  select(-c("LOR","LOR SE"))

knitr::kable(thiv_effect_df %>%
               select(Authors,Year,Countries,`Sample Size`,
                      `Percent Willing`,`Effect Size`,
                      `Effect Size Variance`,`Median Study Year`,
                      `Standardized GDP per Capita`,`Homophobic Climate Index (HCI)`),
```

```
            digits = 3, row.names=FALSE)
```

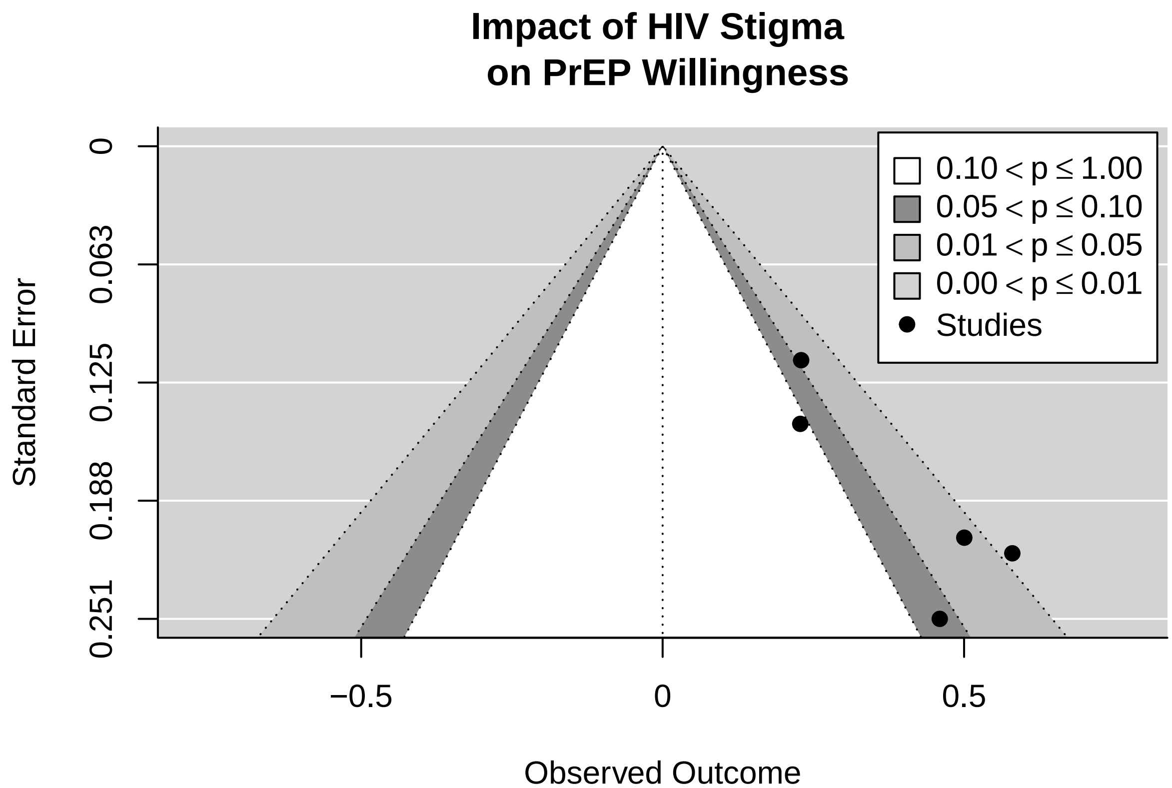
Authors	Year	Countries	Sample Size	Percent Willing	Effect Size	Effect Size Variance	Median Study Year	Standardized GDP per Capita	Homophobic Climate Index (HCI)
Chuang et al.	2018	Taiwan	176	35.00%	0.580	0.047	2014.0	-0.293	0.580
Fallon et al.	2015	United States	398	48.00%	0.230	0.013	2014.0	1.059	0.360
Meyers et al.	2018	China	200	51.50%	0.228	0.022	2013.5	-0.872	0.680
Wheelock et al.	2013	Thailand	260	88.40%	0.500	0.043	2011.0	-0.954	0.533
Zhang & Liu	2022	United States	315	81.80%	0.460	0.063	2019.5	1.059	0.360

2.3.2 Random Effects Models

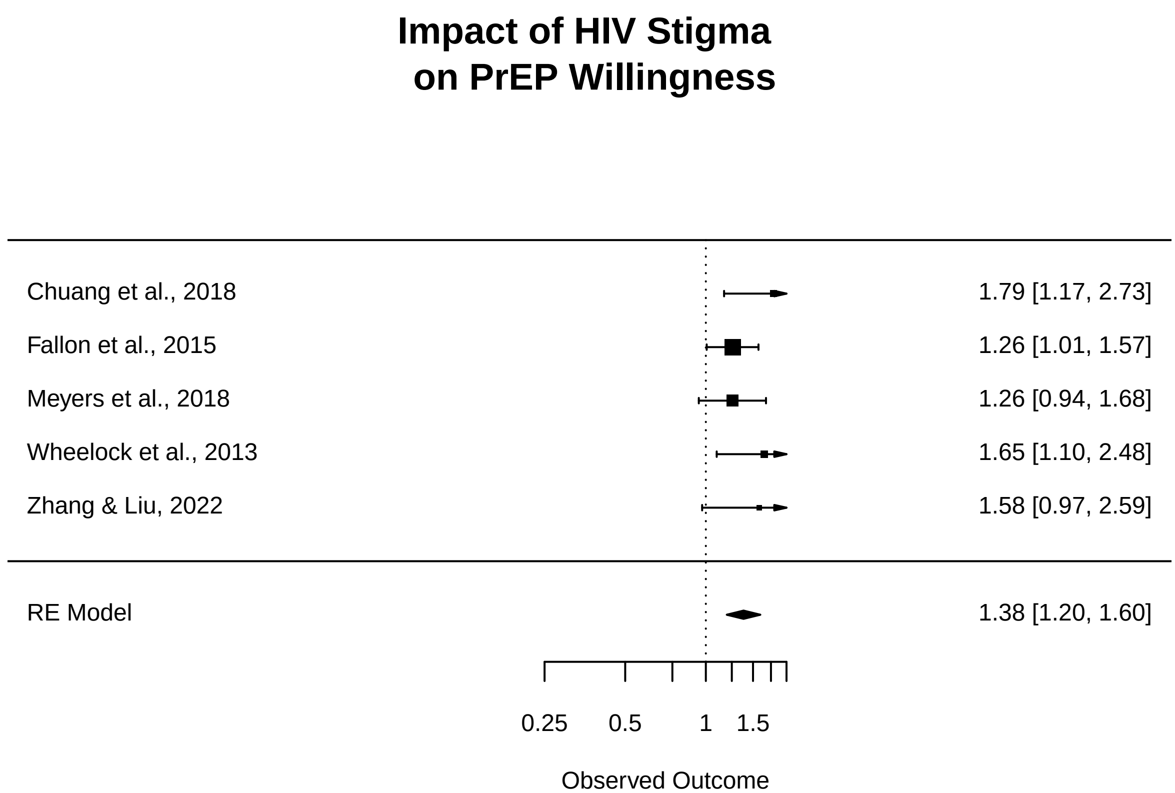
```
res_hiv <- rma(`Effect Size`, `Effect Size Variance`,
               data=thiv_effect_df, method="REML")
res_hiv
```

```
##
## Random-Effects Model (k = 5; tau^2 estimator: REML)
##
## tau^2 (estimated amount of total heterogeneity): 0 (SE = 0.0189)
## tau (square root of estimated tau^2 value):      0
## I^2 (total heterogeneity / total variability):   0.00%
## H^2 (total variability / sampling variability):  1.00
##
## Test for Heterogeneity:
## Q(df = 4) = 3.5290, p-val = 0.4735
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.3240  0.0737  4.3977  <.0001  0.1796  0.4685  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

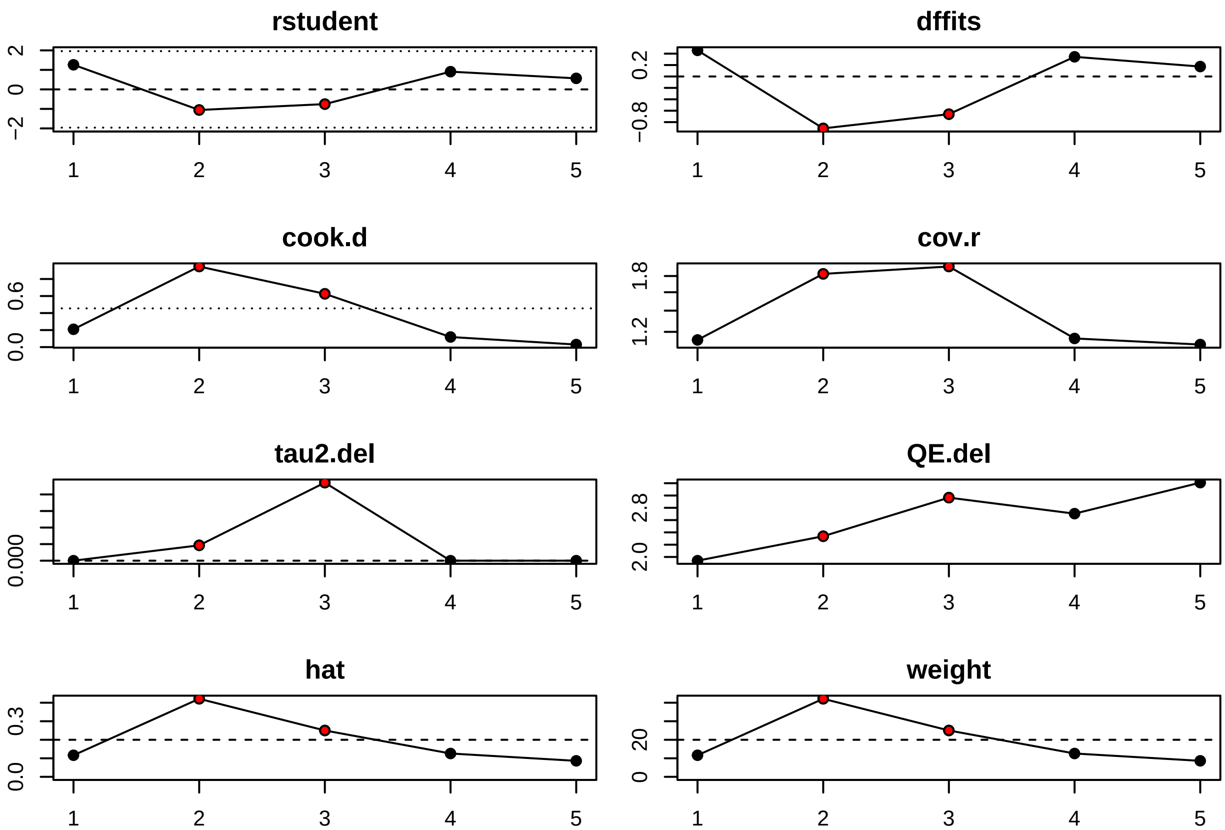
```
funnel(res_hiv, level=c(90, 95, 99), shade=c("white", "gray55", "gray75"),
       refline=0, legend=TRUE,
        main = "Impact of HIV Stigma \n on PrEP Willingness")
```




```
forest(res_hiv, slab = paste(thiv_effect_df$Authors,
                             thiv_effect_df$`Year`, sep = ", "),
       main = "Impact of HIV Stigma \n on PrEP Willingness",
                 xlim = c(-6, 4),
       at = log(c(0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2)), atransf = exp,
                 cex = 0.75)
op <- par(cex = 0.75, font = 2)
text(-6, 19, "Author(s) and Year", pos = 4)
text(4, 19, "Relative Risk [95% CI]", pos = 2)
```



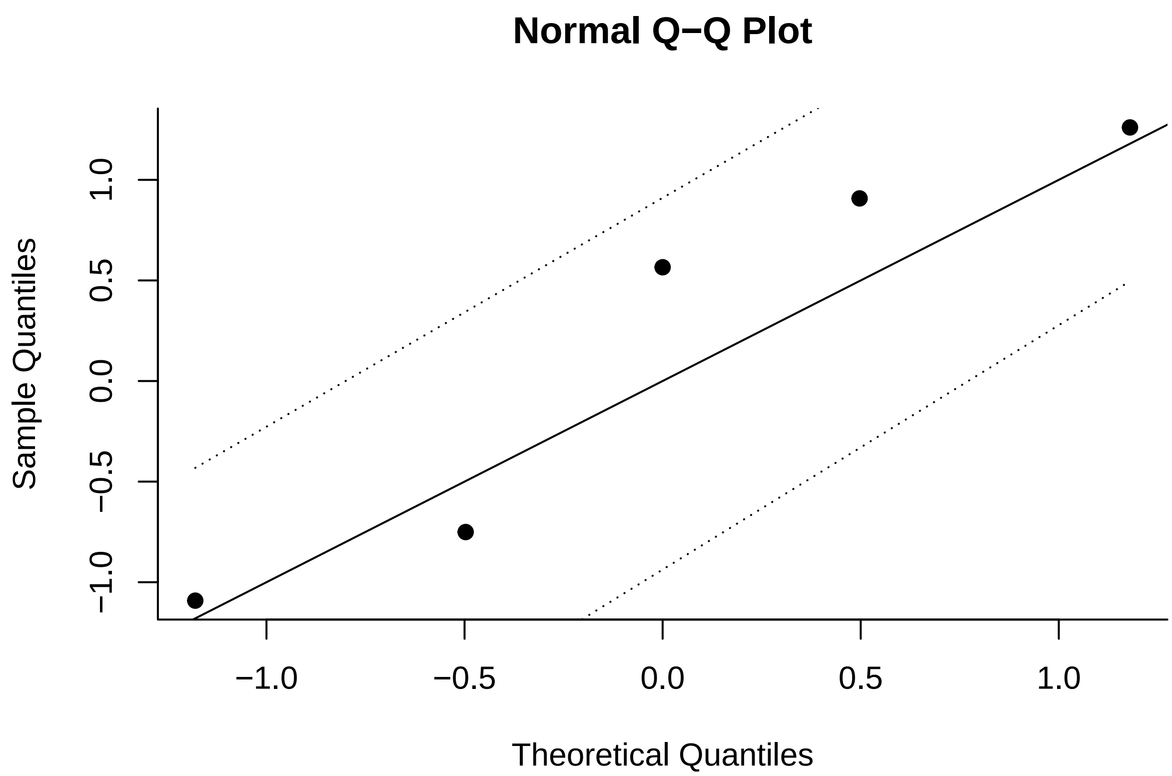

```
par(op)

res_hiv_inf.ME <- influence(res_hiv)
plot(res_hiv_inf.ME)
```




```
fitstats(res_hiv)
```

```
##                  REML
## logLik:     1.3347175
## deviance: -2.6694349
## AIC:        1.3305651
## BIC:        0.1031538
## AICc:      13.3305651
```

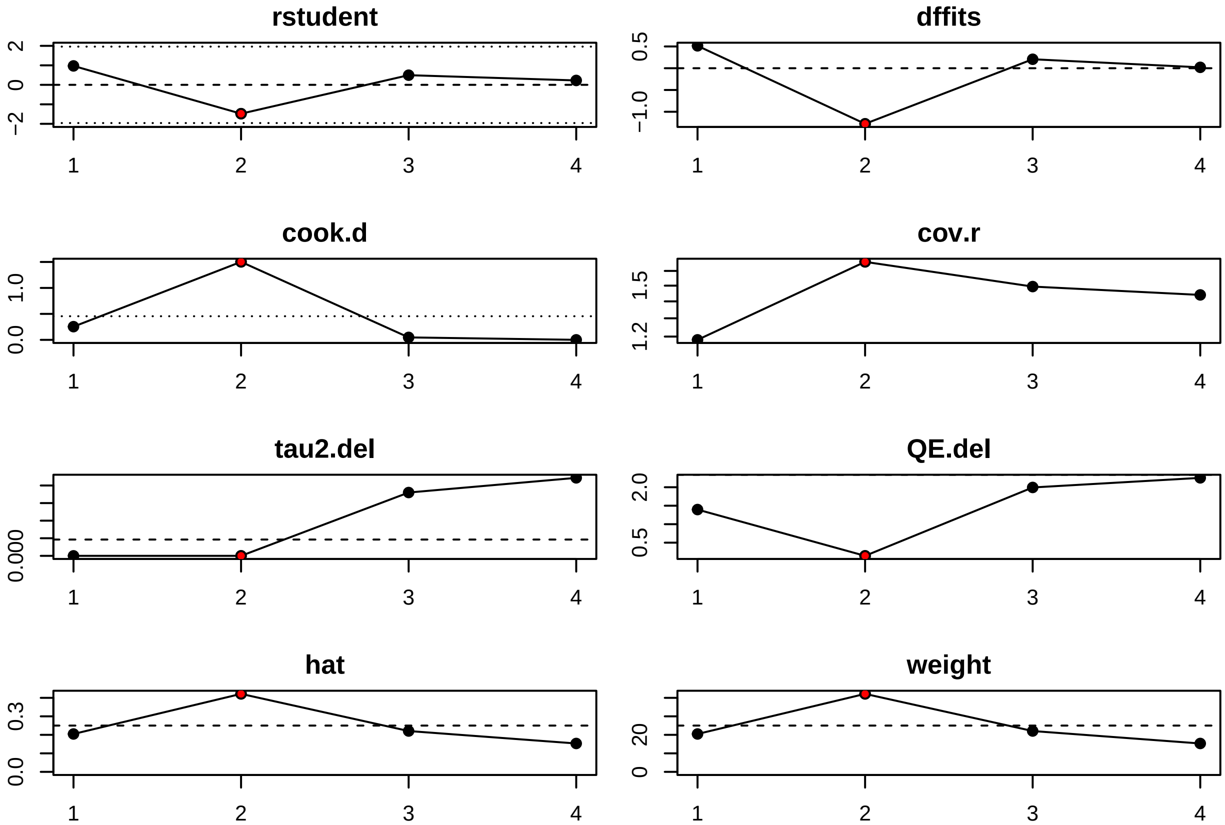
```
qqnorm(res_hiv)
```




```r
rma(`Effect Size`, `Effect Size Variance`,
    data=thiv_effect_df[-2,], method="REML")
```

```
##
## Random-Effects Model (k = 4; tau^2 estimator: REML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0019 (SE = 0.0330)
## tau (square root of estimated tau^2 value):      0.0430
## I^2 (total heterogeneity / total variability):   4.42%
## H^2 (total variability / sampling variability):  1.05
##
## Test for Heterogeneity:
## Q(df = 3) = 2.3373, p-val = 0.5054
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.3957  0.0996  3.9721  <.0001  0.2005  0.5910  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

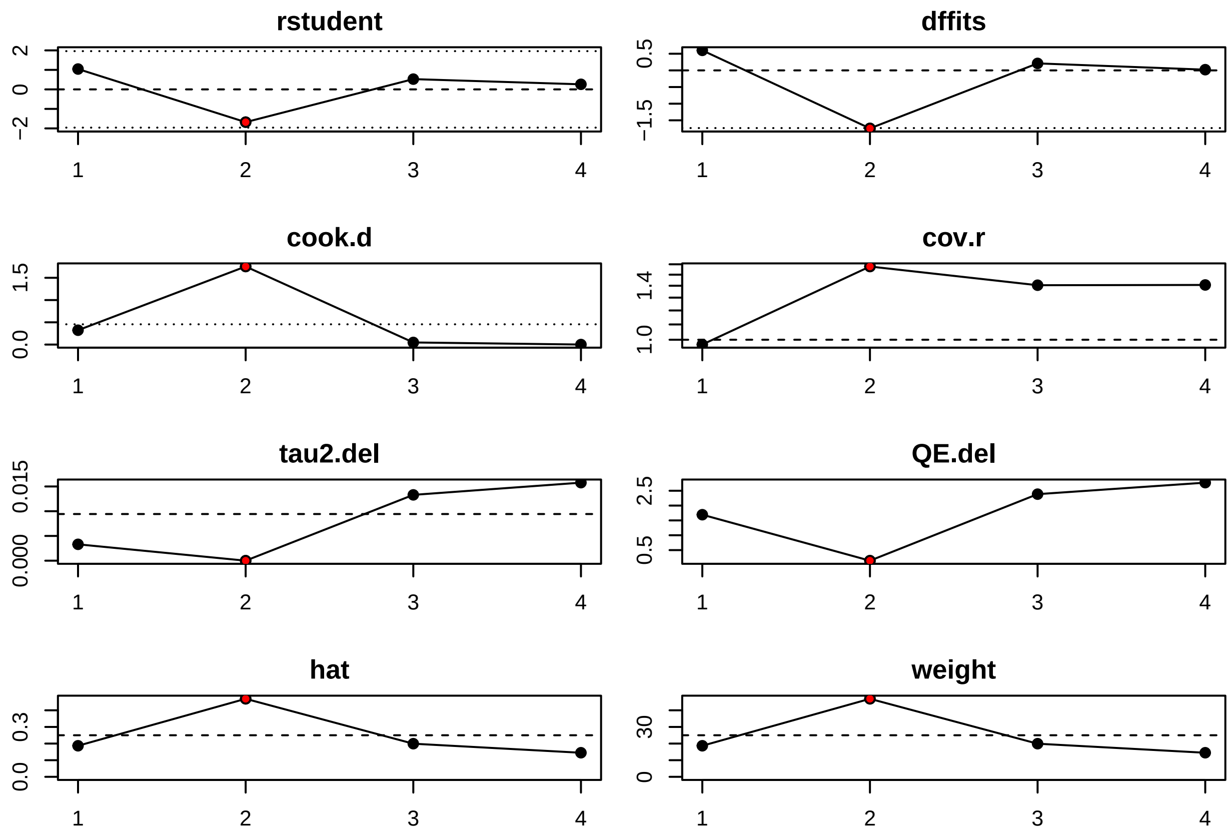
```r
plot(influence(rma(`Effect Size`, `Effect Size Variance`,
                   data=thiv_effect_df[-2,], method="REML")))
```




```
rma(`Effect Size`, `Effect Size Variance`,
    data=thiv_effect_df[-3,], method="REML")
```

```
##
## Random-Effects Model (k = 4; tau^2 estimator: REML)
##
## tau^2 (estimated amount of total heterogeneity): 0.0094 (SE = 0.0355)
## tau (square root of estimated tau^2 value):      0.0971
## I^2 (total heterogeneity / total variability):   21.17%
## H^2 (total variability / sampling variability):  1.27
##
## Test for Heterogeneity:
## Q(df = 3) = 2.9654, p-val = 0.3970
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.3823  0.1023  3.7363  0.0002  0.1818  0.5829  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

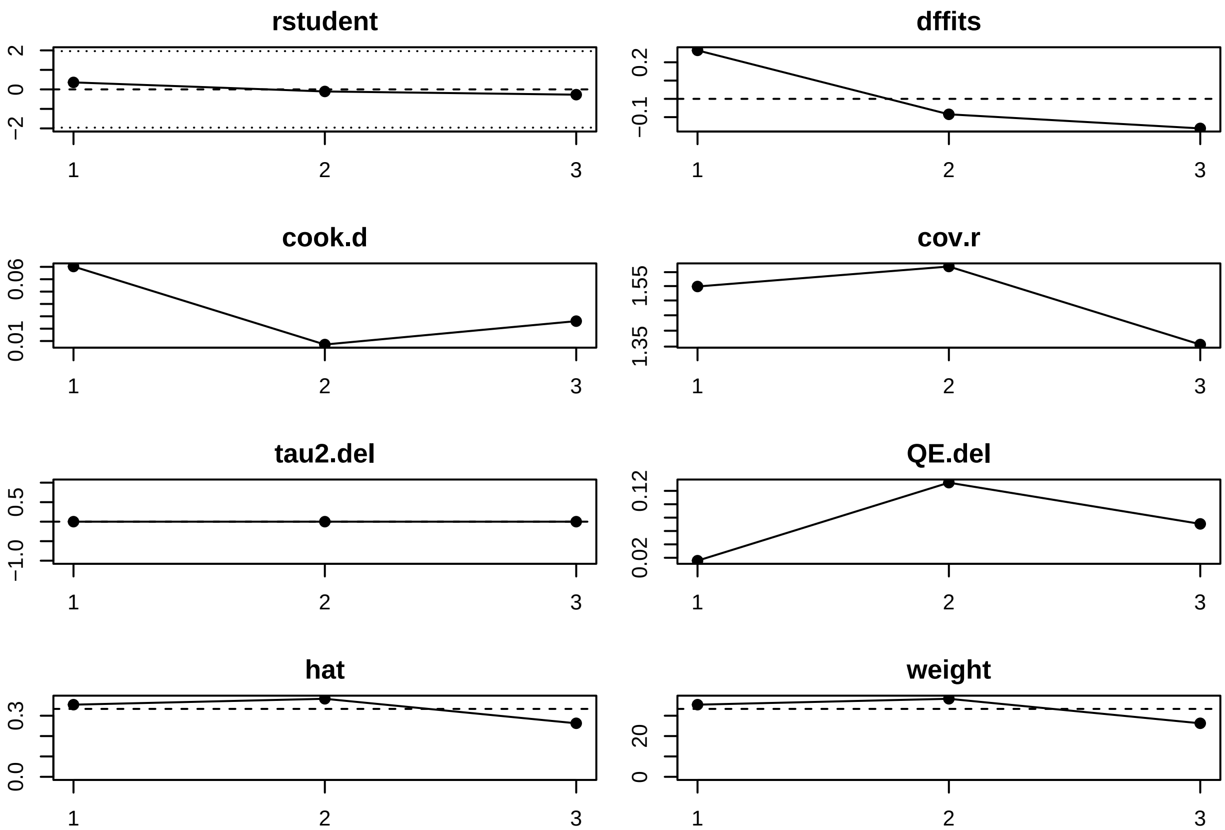
```
plot(influence(rma(`Effect Size`, `Effect Size Variance`,
                   data=thiv_effect_df[-3,], method="REML")))
```




```r
rma(`Effect Size`, `Effect Size Variance`,
    data=thiv_effect_df[-c(2,3),], method="REML")
```

```
##
## Random-Effects Model (k = 3; tau^2 estimator: REML)
##
## tau^2 (estimated amount of total heterogeneity): 0 (SE = 0.0498)
## tau (square root of estimated tau^2 value):      0
## I^2 (total heterogeneity / total variability):   0.00%
## H^2 (total variability / sampling variability):  1.00
##
## Test for Heterogeneity:
## Q(df = 2) = 0.1438, p-val = 0.9306
##
## Model Results:
##
## estimate      se    zval    pval   ci.lb   ci.ub
##   0.5178  0.1286  4.0284  <.0001  0.2659  0.7698  ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

```r
plot(influence(rma(`Effect Size`, `Effect Size Variance`,
                   data=thiv_effect_df[-c(2,3),], method="REML")))
```



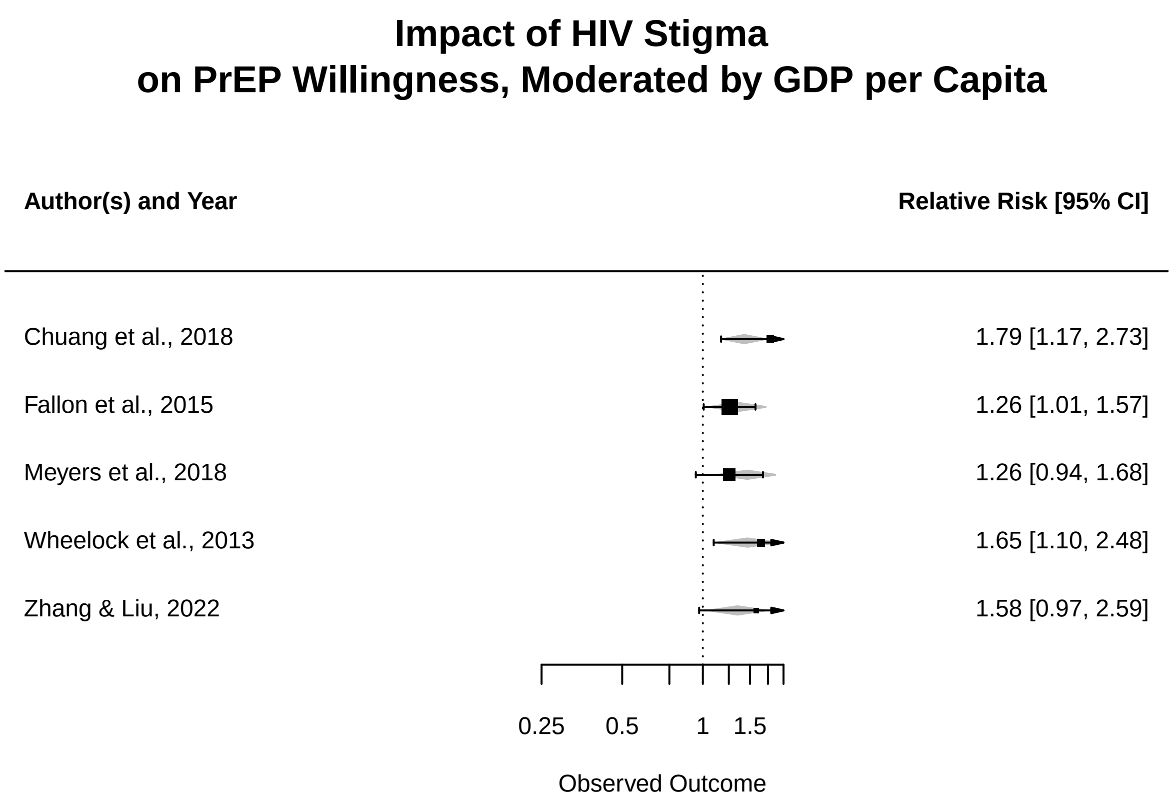
2.3.3 Mixed Effects Models

```r
reg_hiv_gdp <- rma(yi = `Effect Size`,
               vi = `Effect Size Variance`,
               data = thiv_effect_df,
               mods = ~ `Standardized GDP per Capita`,
               method = "REML")

reg_hiv_gdp
```

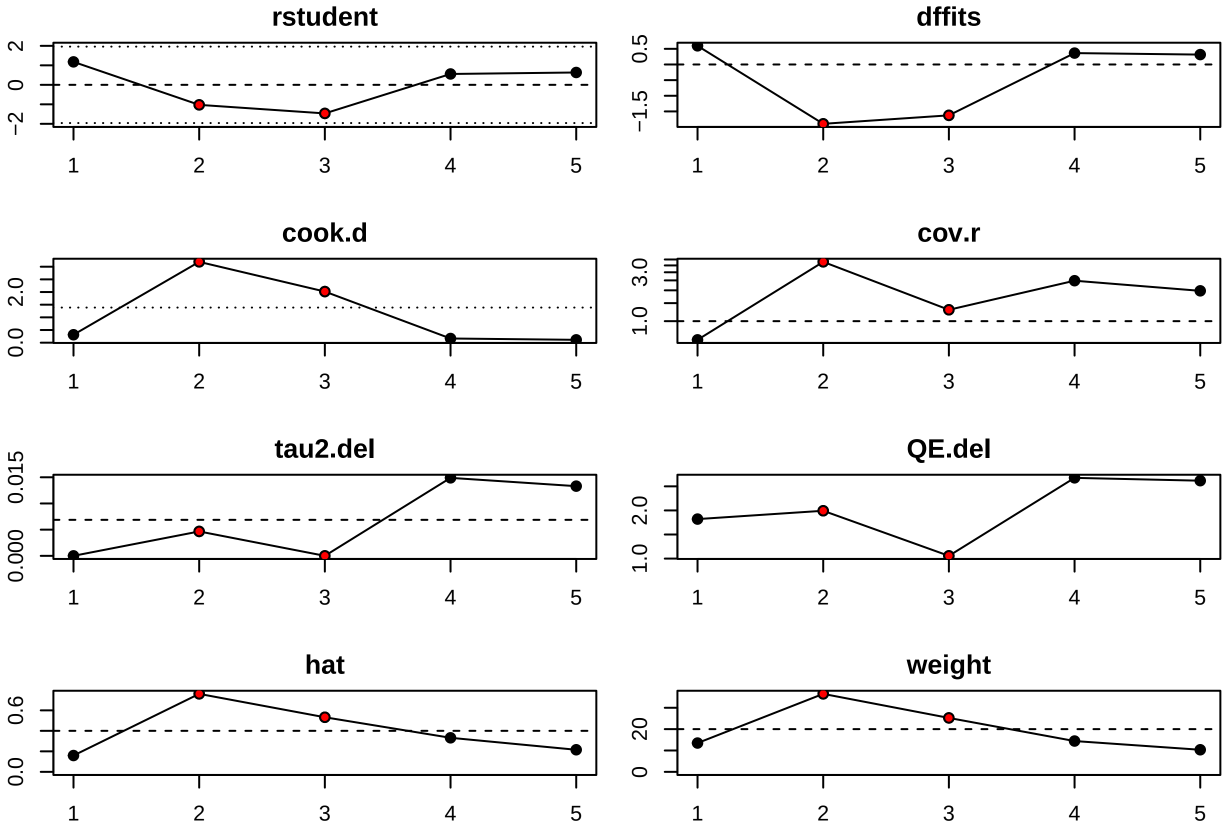
```
##
## Mixed-Effects Model (k = 5; tau^2 estimator: REML)
##
## tau^2 (estimated amount of residual heterogeneity):     0.0069 (SE = 0.0352)
## tau (square root of estimated tau^2 value):             0.0829
## I^2 (residual heterogeneity / unaccounted variability): 15.83%
## H^2 (unaccounted variability / sampling variability):   1.19
## R^2 (amount of heterogeneity accounted for):            0.00%
##
## Test for Residual Heterogeneity:
## QE(df = 3) = 3.2078, p-val = 0.3607
##
## Test of Moderators (coefficient 2):
## QM(df = 1) = 0.2158, p-val = 0.6423
##
## Model Results:
##
```

```
##                                    estimate      se     zval    pval    ci.lb
## intrcpt                             0.3436  0.0854   4.0224  <.0001   0.1762
## `Standardized GDP per Capita`      -0.0428  0.0921  -0.4645  0.6423  -0.2233
##                                     ci.ub
## intrcpt                            0.5111  ***
## `Standardized GDP per Capita`      0.1377
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
```

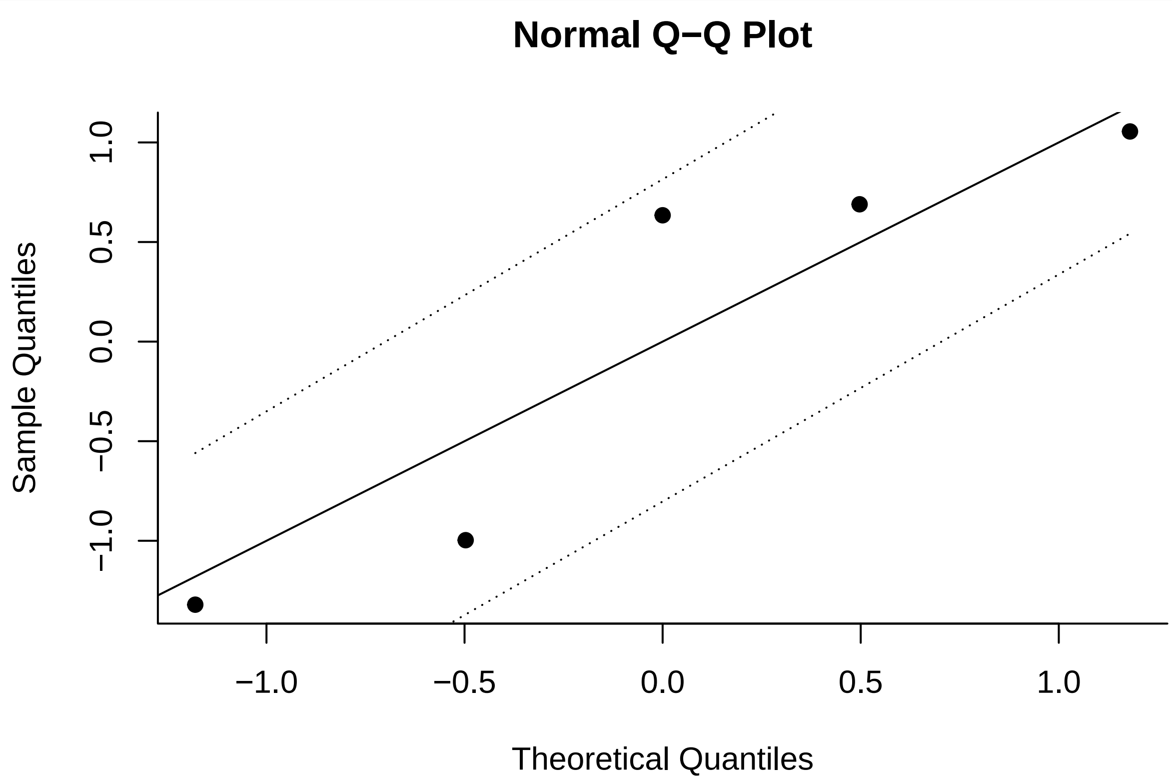
```
forest(reg_hiv_gdp, slab = paste(thiv_effect_df$Authors,
                                 thiv_effect_df$`Year`, sep = ", "),
       main = "Impact of HIV Stigma \n on PrEP Willingness, Moderated by GDP per Capita",
                 xlim = c(-6, 4),
       at = log(c(0.25, 0.5, 0.75, 1, 1.25, 1.5, 1.75, 2)), atransf = exp,
                 cex = 0.75)
op <- par(cex = 0.75, font = 2)
text(-6, 7, "Author(s) and Year", pos = 4)
text(4, 7, "Relative Risk [95% CI]", pos = 2)
```




```
par(op)

reg_hiv_gdp_inf.ME <- influence(reg_hiv_gdp)
plot(reg_hiv_gdp_inf.ME)
```




```
qqnorm(reg_hiv_gdp)
```



```r
reg_hiv_mod.RE.ML <- rma(yi=`Effect Size`,
                        vi=`Effect Size Variance`,
                        data=thiv_effect_df,
                        method="ML")
reg_hiv_gdp_mod.ME.ML <- rma(yi = `Effect Size`,
              vi = `Effect Size Variance`,
              data = thiv_effect_df,
              mods = ~ `Standardized GDP per Capita`,
              method = "ML")
reg_hiv_year_mod.ME.ML <- rma(yi = `Effect Size`,
              vi = `Effect Size Variance`,
              data = thiv_effect_df,
              mods = ~ `Median Study Year`,
              method = "ML")
reg_hiv_hci_mod.ME.ML <- rma(yi = `Effect Size`,
              vi = `Effect Size Variance`,
              data = thiv_effect_df,
              mods = ~ `Homophobic Climate Index (HCI)`,
              method = "ML")
reg_hiv_year_gdp_mod.ME.ML <- rma(yi = `Effect Size`,
              vi = `Effect Size Variance`,
              data = thiv_effect_df,
              mods = ~ `Median Study Year` + `Standardized GDP per Capita`,
              method = "ML")

knitr::kable(cbind(fitstats(reg_hiv_mod.RE.ML),
                   fitstats(reg_hiv_gdp_mod.ME.ML),
                   fitstats(reg_hiv_year_mod.ME.ML),
                   fitstats(reg_hiv_hci_mod.ME.ML),
                   fitstats(reg_hiv_year_gdp_mod.ME.ML)),
             digits = 3, col.names=c("Random Effects",
                                     "Mixed Effects (GDP)",
                                     "Mixed Effects (Year)",
                                     "Mixed Effects (HCI)",
                                     "Mixed Effects (Year + GDP)"))
```

	Random Effects	Mixed Effects (GDP)	Mixed Effects (Year)	Mixed Effects (HCI)	Mixed Effects (Year + GDP)
logLik:	2.219	2.380	2.221	2.255	2.479
deviance:	3.529	3.208	3.525	3.456	3.010
AIC:	-0.438	1.241	1.557	1.489	3.043
BIC:	-1.219	0.069	0.386	0.317	1.481
AICc:	5.562	25.241	25.557	25.489	43.043