

Phaco meta analysis

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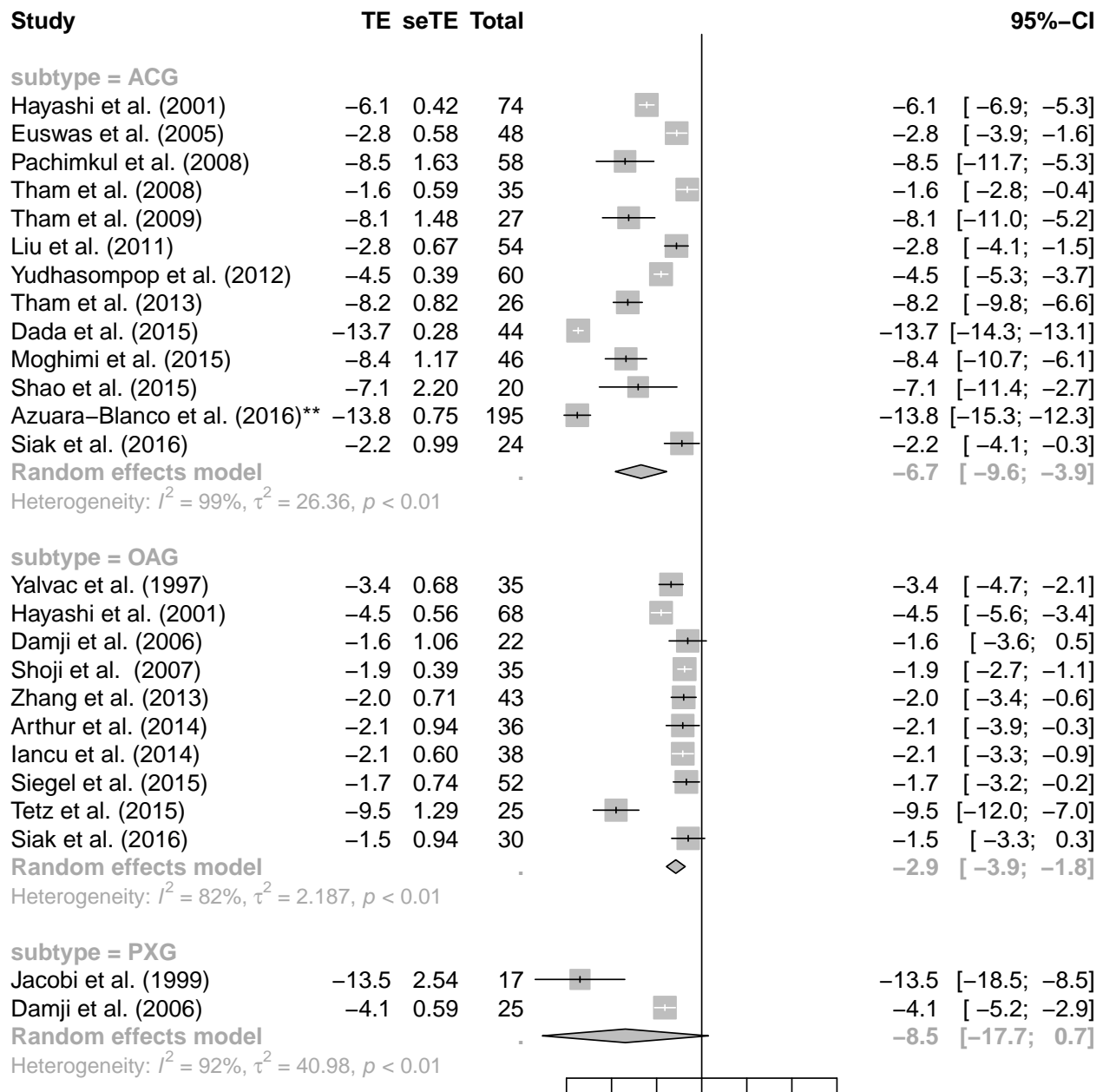
TODO

- Find a better way to deal with wash out - in some cases, the readings may refer to pre-meds or post-meds and some studies have pre- or post-op washout and it's all very annoying.

Analysis of full dataset

6 month follow-up

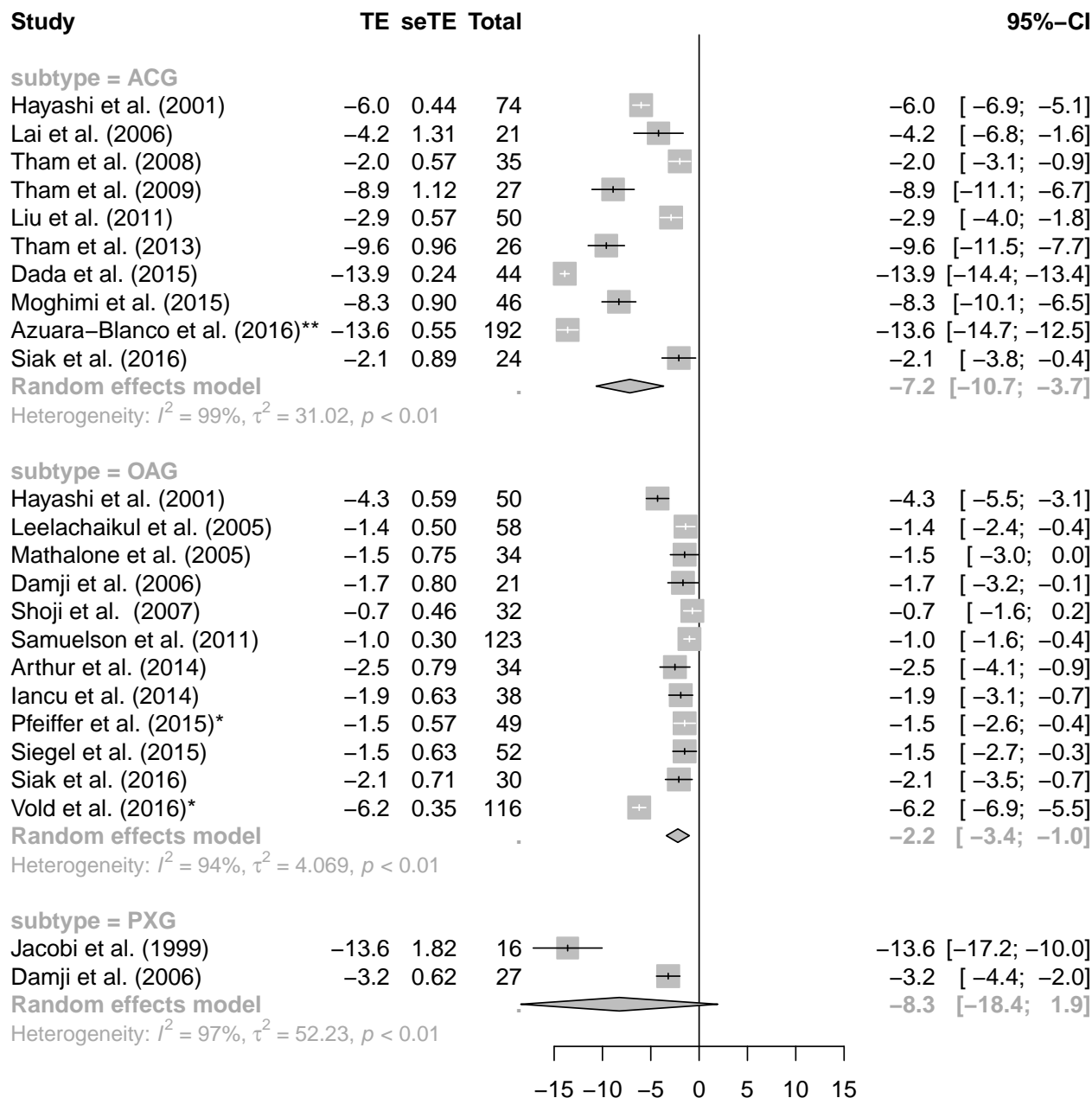
```
df_ <- df %>%
  filter(!is.na(SixMoAbsIOPChangeMean), subtype != "acute") %>%
  mutate(subtype=factor(subtype))
m <- metagen(SixMoAbsIOPChangeMean,
             SixMoAbsIOPChangeStdDev / sqrt(SixMoEyes),
             study.name,
             data=df_,
             byvar=subtype,
             n.e=SixMoEyes)
forest(m,
       comb.fixed=FALSE,
       digits=1,
       digits.se = 2,
       overall=FALSE,
       leftcols=c("studlab", "TE", "seTE", "n.e"))
```



12-month follow up

```
df_ <- df %>%
  filter(!is.na(OneYAbsIOPChangeMean), subtype != "acute", MIGsYorN == 'N') %>%
  mutate(subtype=factor(subtype))
m <- metagen(OneYAbsIOPChangeMean,
             OneYAbsIOPChangeStdDev / sqrt(OneYEyes),
             study.name,
             data=df_,
             byvar=subtype,
             n.e=OneYEyes)
forest(m,
```

```
comb.fixed=FALSE,
digits=1,
digits.se = 2,
overall=FALSE,
leftcols=c("studlab", "TE", "seTE", "n.e"))
```



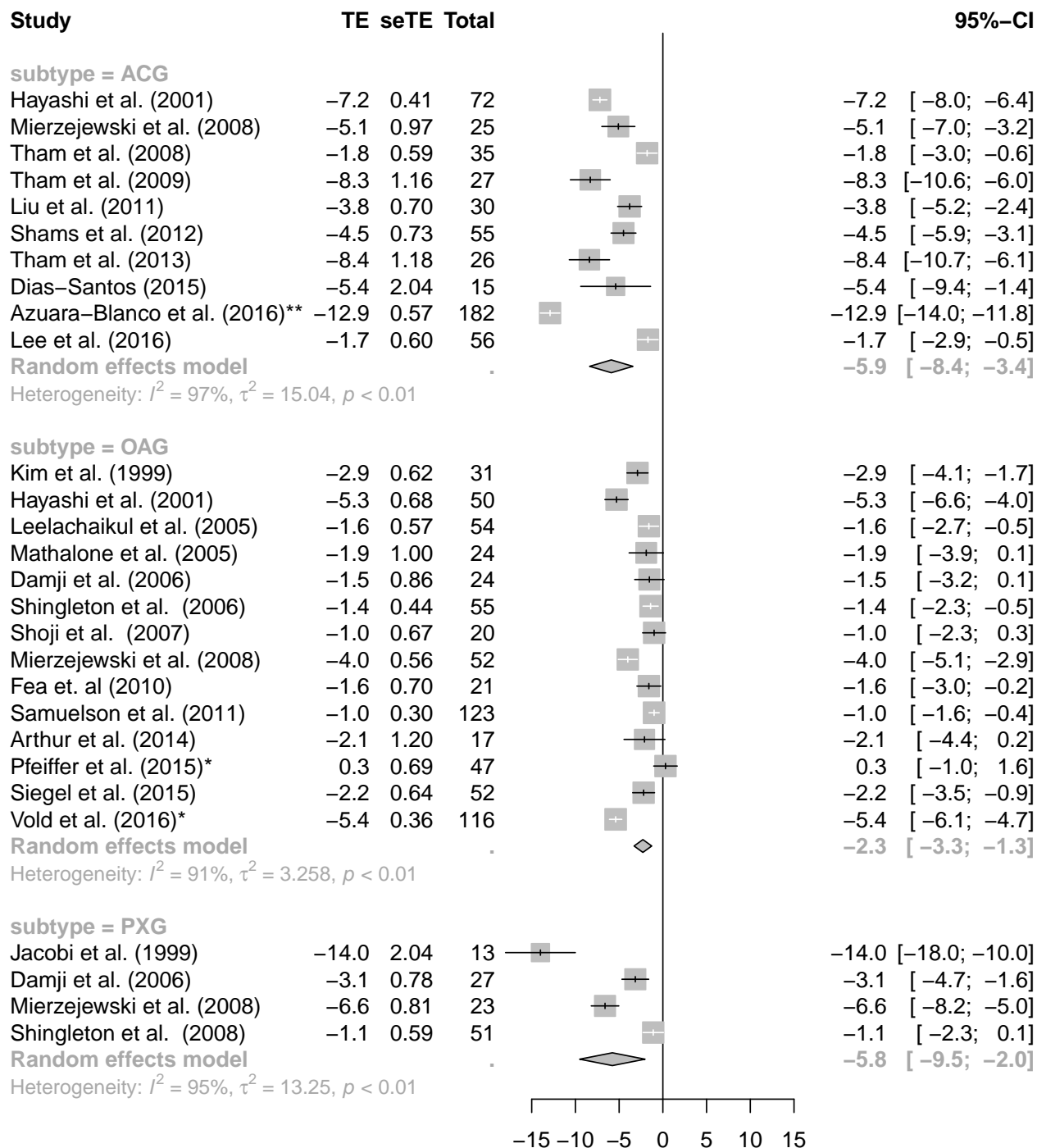
Last period

```
df_ <- df %>%
  filter(!is.na>LastPeriodAbsIOPChangeMean), subtype != "acute", MIGsYorN == 'N') %>%
  mutate(subtype=factor(subtype))
m <- metagen>LastPeriodAbsIOPChangeMean,
```

```

        LastPeriodAbsIOPChangeStdDev / sqrt(LastPeriodEyes),
        study.name,
        data=df_,
        byvar=subtype,
        n.e=LastPeriodEyes)
forest(m,
       comb.fixed=FALSE,
       digits=1,
       digits.se = 2,
       overall=FALSE,
       leftcols=c("studlab", "TE", "seTE", "n.e"))

```



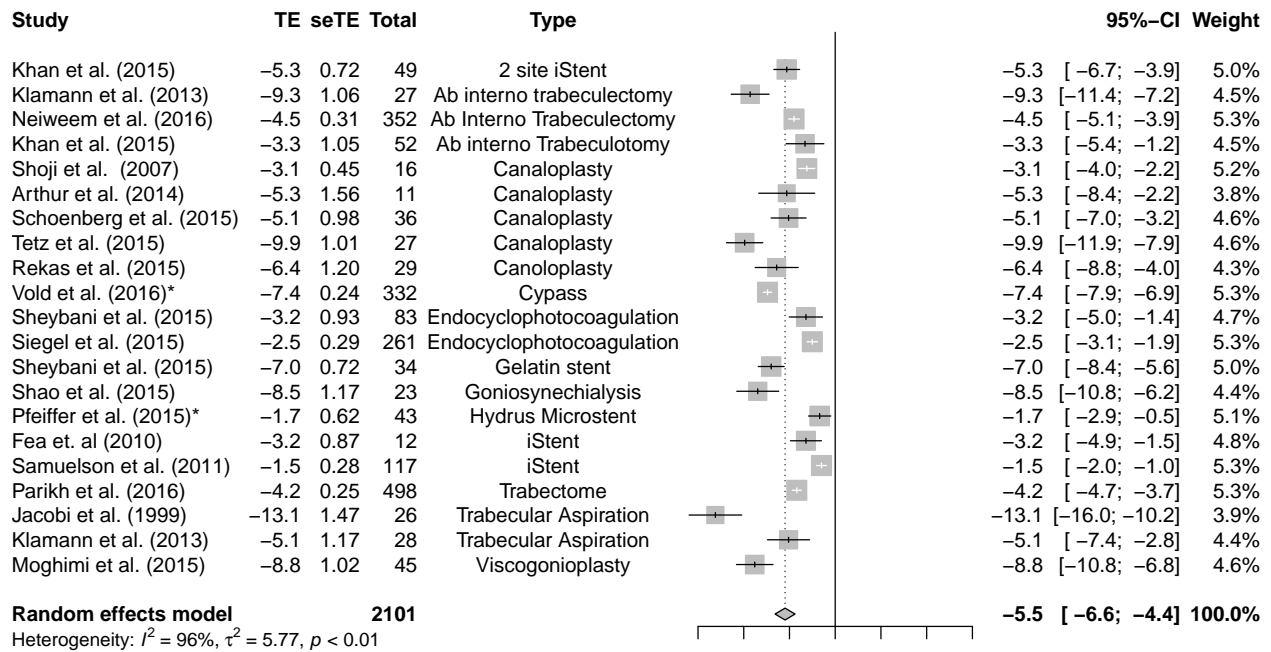
MIGS

```
df_ <- df %>%
  filter(!is.na>LastPeriodAbsIOPChangeMean), subtype != "acute", MIGsYorN == 'Y') %>%
  mutate(subtype=factor(subtype)) %>% dplyr::arrange(TypesofMIGSifany, Year)
m <- metagen>LastPeriodAbsIOPChangeMean,
  LastPeriodAbsIOPChangeStdDev / sqrt>LastPeriodEyes),
  study.name,
```

```

data=df_,
n.e=LastPeriodEyes)
forest(m,
  comb.fixed=FALSE,
  digits=1,
  digits.se = 2,
  overall=TRUE,
  leftcols=c("studlab", "TE", "seTE", "n.e", "TypesofMIGSifany"),
  leftlabs=c("Study", "TE", "seTE", "Total", "Type"))

```



Acute

```

cat("=====\n")
cat("Six months: \n")
cat("=====\n")
df_ <- df %>%
  filter(!is.na(SixMoAbsIOPChangeMean), subtype == "acute", MIGsYorN == 'N') %>%
  mutate(subtype=factor(subtype)) %>% dplyr::arrange(Year)
m <- metagen(SixMoAbsIOPChangeMean,
  SixMoAbsIOPChangeStdDev / sqrt(SixMoEyes),
  study.name,
  data=df_,
  n.e=SixMoEyes, comb.fixed = FALSE)
print(m)

cat("=====\n")
cat("One year: \n")
cat("=====\n")
df_ <- df %>%
  filter(!is.na(OneYAbsIOPChangeMean), subtype == "acute", MIGsYorN == 'N') %>%
  mutate(subtype=factor(subtype)) %>% dplyr::arrange(Year)

```

```

m <- metagen(OneYAbsIOPChangeMean,
             OneYAbsIOPChangeStdDev / sqrt(OneYEyes),
             study.name,
             data=df_,
             n.e=OneYEyes, comb.fixed = FALSE)
print(m)

cat("=====\n")
cat("Last period: \n")
cat("=====\n")
df_ <- df %>%
  filter(!is.na(LastPeriodAbsIOPChangeMean), subtype == "acute", MIGsYorN == 'N') %>%
  mutate(subtype=factor(subtype)) %>% dplyr::arrange(Year)
m <- metagen(LastPeriodAbsIOPChangeMean,
             LastPeriodAbsIOPChangeStdDev / sqrt(LastPeriodEyes),
             study.name,
             data=df_,
             n.e=LastPeriodEyes, comb.fixed = FALSE)
print(m)

```

```

## =====
## Six months:
## =====
##                               95%-CI %W(random)
## Lam et al. (2008) -47.0000 [-51.0521; -42.9479]      50.2
## Hou et al. (2015) -38.2000 [-42.4159; -33.9841]      49.8
##
## Number of studies combined: k = 2
##
##                               95%-CI      z  p-value
## Random effects model -42.62 [-51.2438; -33.9963] -9.69 < 0.0001
##
## Quantifying heterogeneity:
## tau^2 = 34.2694; H = 2.95; I^2 = 88.5%;
## Rb = 88.5%
##
## Test of heterogeneity:
##      Q d.f.  p-value
## 8.70    1    0.0032
##
## Details on meta-analytical method:
## - Inverse variance method
## - DerSimonian-Laird estimator for tau^2
## =====
## One year:
## =====
##                               95%-CI %W(random)
## Lam et al. (2008) -47.6000 [-50.4731; -44.7269]      50.1
## Hou et al. (2015) -35.9600 [-38.9540; -32.9660]      49.9
##
## Number of studies combined: k = 2
##
##                               95%-CI      z  p-value
## Random effects model -41.7879 [-53.1949; -30.3809] -7.18 < 0.0001

```

```
##
## Quantifying heterogeneity:
## tau^2 = 65.5036; H = 5.50; I^2 = 96.7%;
## Rb = 96.7%
##
## Test of heterogeneity:
##      Q d.f.  p-value
## 30.23    1 < 0.0001
##
## Details on meta-analytical method:
## - Inverse variance method
## - DerSimonian-Laird estimator for tau^2
## =====
## Last period:
## =====
##                                     95%-CI %W(random)
## Jacobi et al. (2002) -22.7000 [-23.6565; -21.7435]      25.6
## Lam et al. (2008)    -47.1000 [-50.0449; -44.1551]      25.3
## Lee et al. (2010)    -35.8000 [-39.5586; -32.0414]      25.1
## Husain et al. (2012) -44.5000 [-51.8668; -37.1332]      24.0
##
## Number of studies combined: k = 4
##
##                                     95%-CI      z  p-value
## Random effects model -37.3974 [-51.7129; -23.0820] -5.12 < 0.0001
##
## Quantifying heterogeneity:
## tau^2 = 208.4467; H = 9.89 [8.06; 12.13]; I^2 = 99.0% [98.5%; 99.3%];
## Rb = 97.7% [93.1%; 100.0%]
##
## Test of heterogeneity:
##      Q d.f.  p-value
## 293.22    3 < 0.0001
##
## Details on meta-analytical method:
## - Inverse variance method
## - DerSimonian-Laird estimator for tau^2
```

Meds

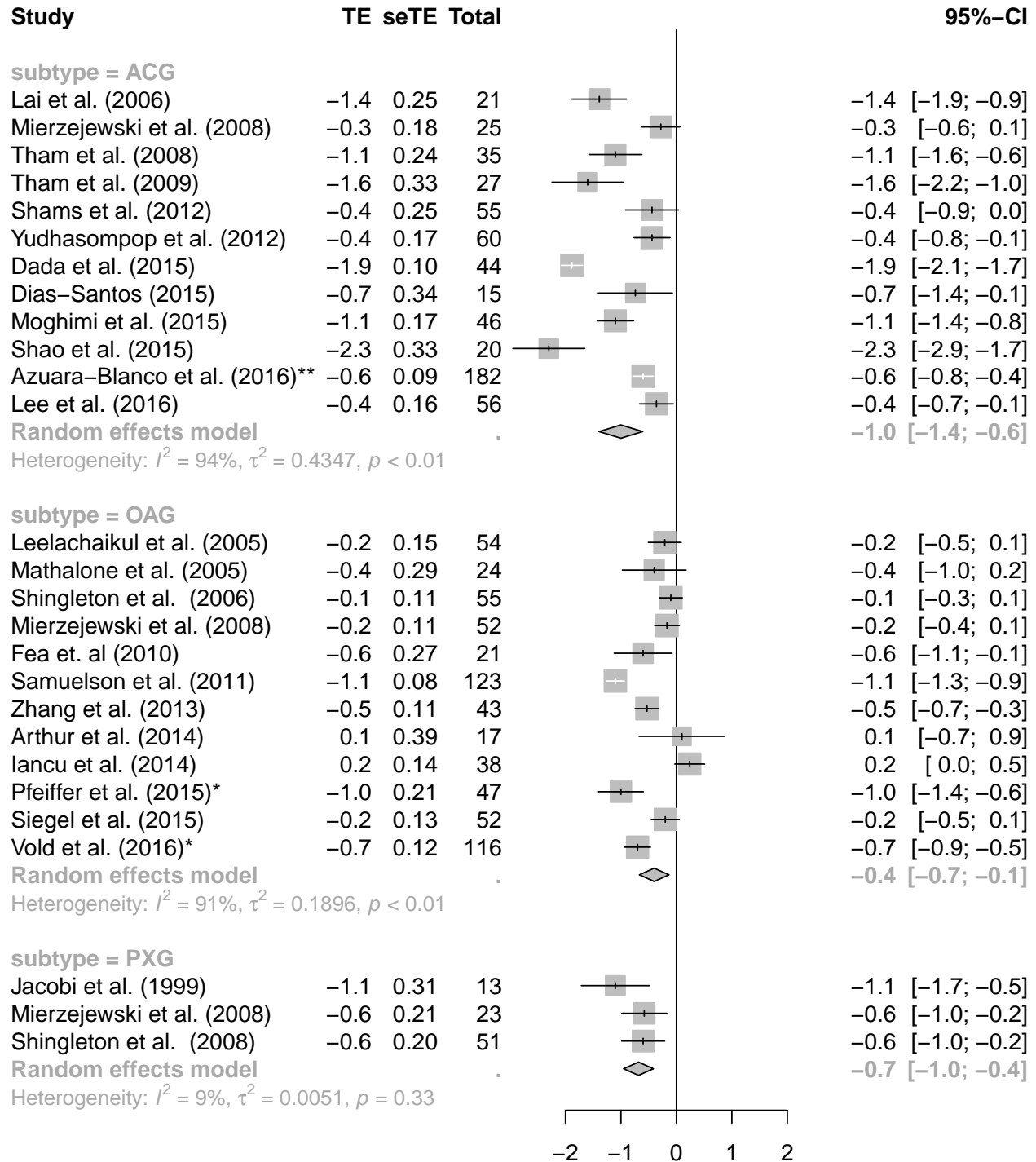
```
df_ <- df %>%
  filter(!is.na(RxChangeMean), !is.na(RxChangeStdDev),
         df$subtype != "acute", MIGsYorN == 'N') %>%
  mutate(subtype=factor(subtype))
m <- metagen(RxChangeMean,
             sqrt(RxPostOpStdDev** 2 + RxPreOpStdDev ** 2) / sqrt>LastPeriodEyes),
             study.name,
             data=df_,
             byvar=subtype,
             n.e>LastPeriodEyes)
forest(m,
       comb.fixed=FALSE,
```



```

digits=1,
digits.se = 2,
overall=FALSE,
leftcols=c("studlab", "TE", "seTE", "n.e"))

```



Correlation between meds and drop in IOP

How is IOP drop related to change in meds? Two hypotheses:

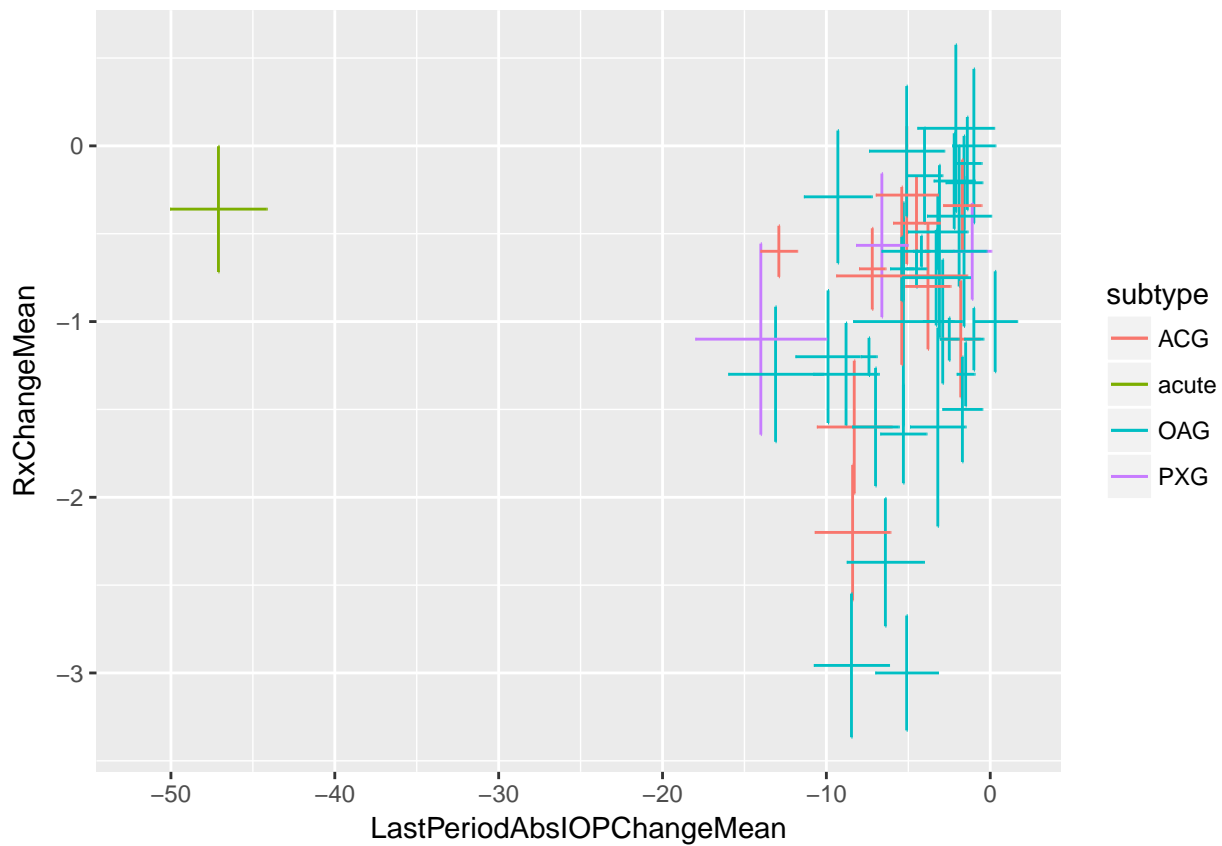
- Those studies that see the largest IOP drops also have drop in meds, as doctors see that can use the newfound *slack* to decrease the number of meds people take
- The studies that see the largest IOP drops are those that don't change meds, because dropping meds would also increase IOP

So which is it?

```
df_ <- df %>% mutate(RxChangeMean = RxPostOpMean - RxPreOpMean,  
                     RxChangeSEM = sqrt(1 / ifelse(is.na(LastPeriodEyes), OneYEyes, LastPeriodEyes)),  
                     LastPeriodAbsIOPChangeSEM = LastPeriodAbsIOPChangeStdDev / sqrt(LastPeriodEyes))  
  
ggplot(df_, aes(x =LastPeriodAbsIOPChangeMean,  
                xmin=LastPeriodAbsIOPChangeMean - 1.96*LastPeriodAbsIOPChangeSEM,  
                xmax=LastPeriodAbsIOPChangeMean + 1.96*LastPeriodAbsIOPChangeSEM,  
                y =RxChangeMean,  
                ymin=RxChangeMean - 1.96*RxChangeSEM,  
                ymax=RxChangeMean + 1.96*RxChangeSEM,  
                color=subtype  
                )) + geom_errorbar() + geom_errorbarh()
```

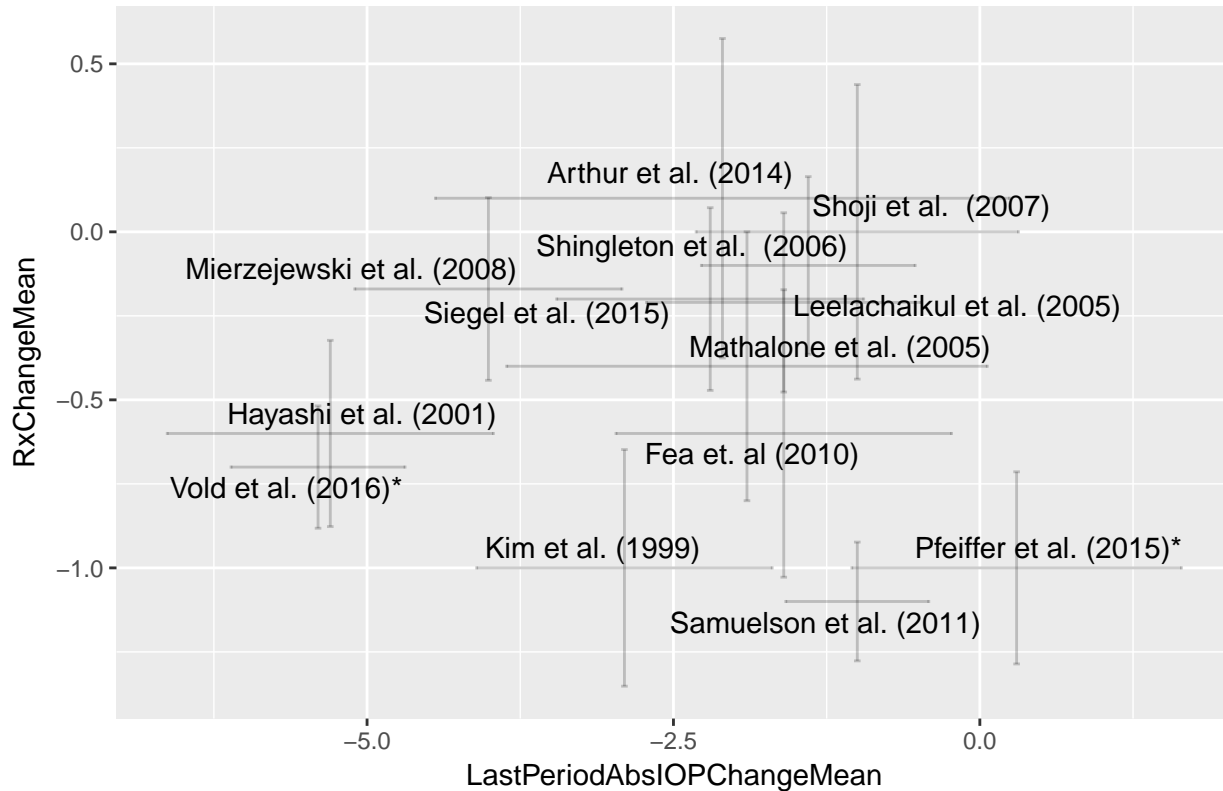
```
## Warning: Removed 18 rows containing missing values (geom_errorbar).
```

```
## Warning: Removed 18 rows containing missing values (geom_errorbarh).
```



```
ggplot(df_ %>% filter(subtype=='OAG' & MIGsYorN == 'N'),
  aes(x =LastPeriodAbsIOPChangeMean,
    xmin=LastPeriodAbsIOPChangeMean - 1.96*LastPeriodAbsIOPChangeSEM,
    xmax=LastPeriodAbsIOPChangeMean + 1.96*LastPeriodAbsIOPChangeSEM,
    y =RxChangeMean,
    ymin=RxChangeMean - 1.96*RxChangeSEM,
    ymax=RxChangeMean + 1.96*RxChangeSEM,
    label=study.name
  )) + geom_errorbar(alpha=.2) + geom_errorbarh(alpha=.2) + ggtitle('OAG only') + geom_text_repel
```

OAG only



There is an apparent positive correlation between the two effect sizes: studies with larger drops in IOP also tend to see larger drops in Rx. This is clearer when we reject the studies with washout.

```
draw.corr <- function(x.mean, x.sem, y.mean, y.sem) {
  d_ <- data.frame(x = rnorm(n = length(x.mean), mean=x.mean, sd = x.sem),
    y = rnorm(n = length(x.mean), mean=y.mean, sd = y.sem))
  with(d_ %>% filter(!is.na(x) & !is.na(y)), cor(x, y))
}

cat("Mean +- SE correlation, all studies\n")

## Mean +- SE correlation, all studies

df_ <- df %>% filter(subtype=='OAG', MIGsYorN == 'N')
drawn.corr <- with(df_, replicate(n = 100,
  draw.corr(LastPeriodAbsIOPChangeMean,
    LastPeriodAbsIOPChangeStdDev / sqrt(LastPeriodEyes),
    RxPostOpMean - RxPreOpMean,
```

```

1 / sqrt(LastPeriodEyes)))
mean(drawn.corr)

## [1] -0.001909355
sd(drawn.corr)

## [1] 0.1418261
cat("Mean +- SE correlation, no washout\n")

## Mean +- SE correlation, no washout
df_ <- filter.data(df, 'nowashout') %>% filter(subtype=='OAG', MIGsYorN == 'N')
drawn.corr <- with(df_, replicate(n = 100,
                                draw.corr(LastPeriodAbsIOPChangeMean,
                                           LastPeriodAbsIOPChangeStdDev / sqrt(LastPeriodEyes),
                                           RxPostOpMean - RxPreOpMean,
                                           1 / sqrt(LastPeriodEyes))))
mean(drawn.corr)

## [1] 0.07823413
sd(drawn.corr)

## [1] 0.1724061

```

Correlation among time points

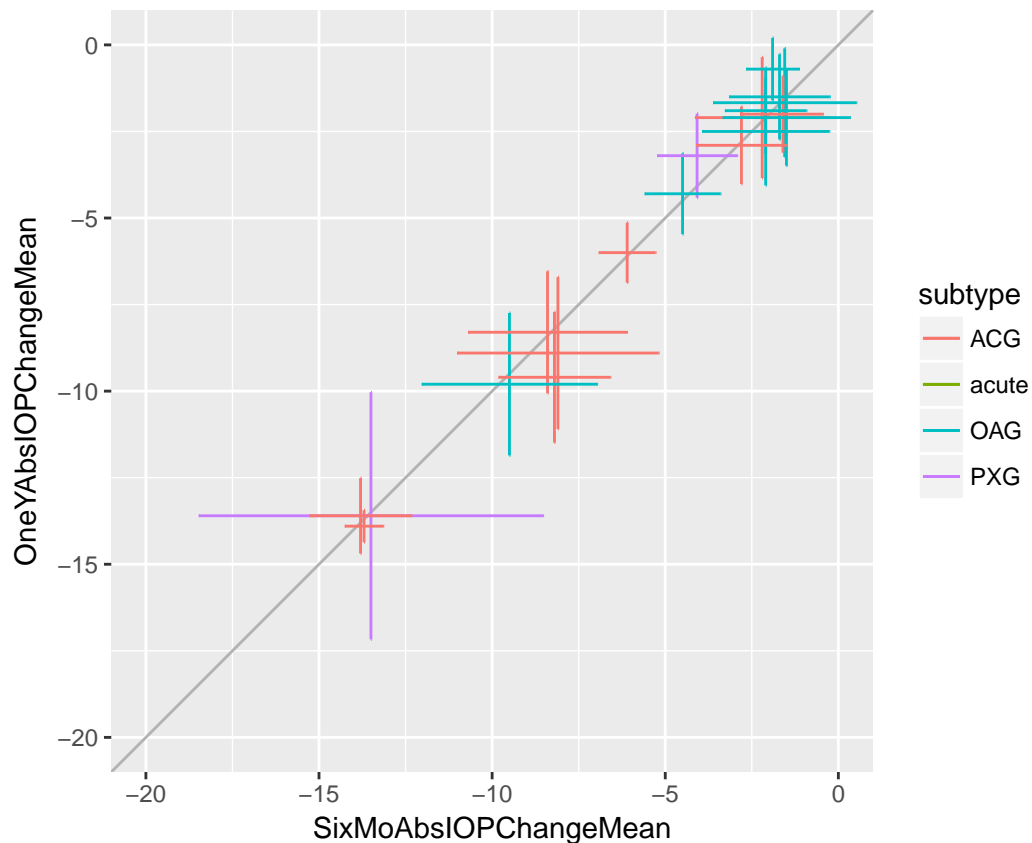
Measure the correlation between different outcomes (IOP at 6 months vs. 12 months).

```

ggplot(df, aes(x =SixMoAbsIOPChangeMean,
               xmin=SixMoAbsIOPChangeMean - 1.96*SixMoAbsIOPChangeStdDev / sqrt(SixMoEyes),
               xmax=SixMoAbsIOPChangeMean + 1.96*SixMoAbsIOPChangeStdDev / sqrt(SixMoEyes),
               y = OneYAbsIOPChangeMean,
               ymin= OneYAbsIOPChangeMean - 1.96*OneYAbsIOPChangeStdDev / sqrt(OneYEyes),
               ymax= OneYAbsIOPChangeMean + 1.96*OneYAbsIOPChangeStdDev / sqrt(OneYEyes),
               label=study.name,
               color=subtype
               )) +
  geom_abline(slope = 1, color="gray70") +
  geom_errorbar() + geom_errorbarh() +
  coord_fixed(xlim=c(-20, 0), ylim=c(-20,0))

## Warning: Removed 45 rows containing missing values (geom_errorbar).
## Warning: Removed 45 rows containing missing values (geom_errorbarh).

```



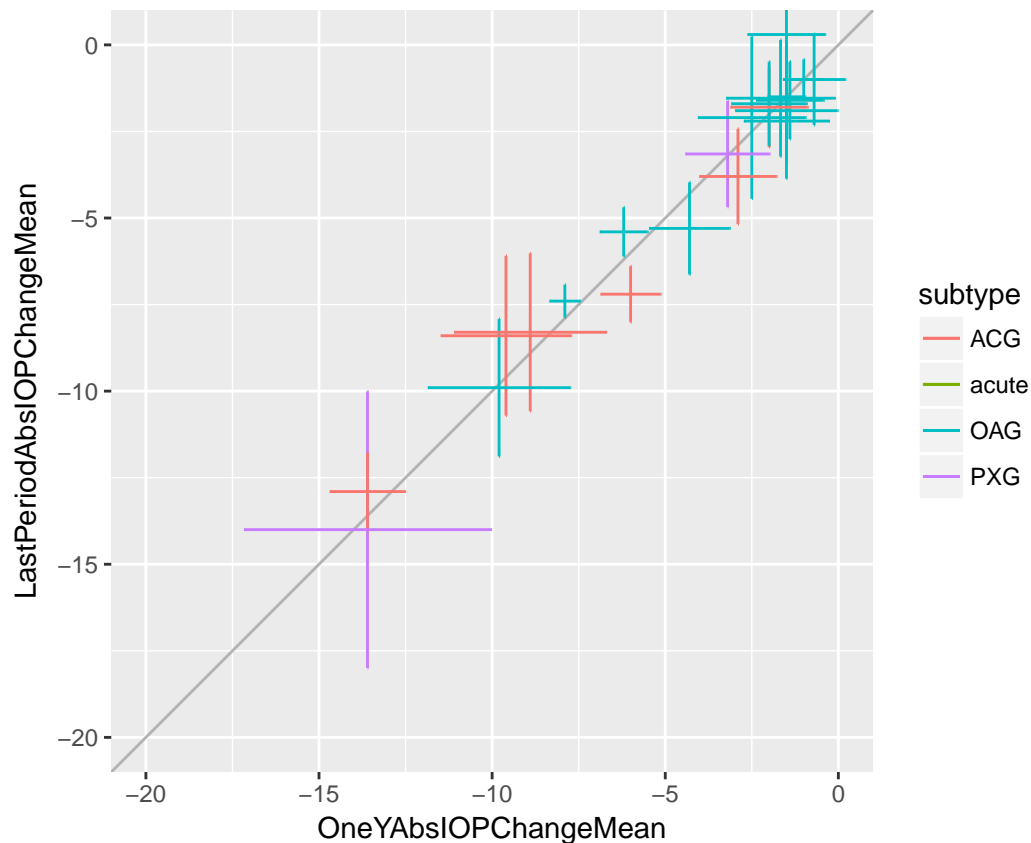
It's very clear that six months and 12 months IOP are highly correlated.

Similarly for one-year vs. last period:

```
ggplot(df, aes(y = LastPeriodAbsIOPChangeMean,
  ymin=LastPeriodAbsIOPChangeMean - 1.96*LastPeriodAbsIOPChangeStdDev / sqrt(LastPeriodEyes),
  ymax=LastPeriodAbsIOPChangeMean + 1.96*LastPeriodAbsIOPChangeStdDev / sqrt(LastPeriodEyes),
  x = OneYAbsIOPChangeMean,
  xmin= OneYAbsIOPChangeMean - 1.96*OneYAbsIOPChangeStdDev / sqrt(OneYEyes),
  xmax= OneYAbsIOPChangeMean + 1.96*OneYAbsIOPChangeStdDev / sqrt(OneYEyes),
  label=study.name,
  color=subtype
)) +
  geom_abline(slope = 1, color="gray70") +
  geom_errorbar() + geom_errorbarh() +
  coord_fixed(xlim=c(-20, 0), ylim=c(-20,0))
```

```
## Warning: Removed 43 rows containing missing values (geom_errorbar).
```

```
## Warning: Removed 43 rows containing missing values (geom_errorbarh).
```



Again, correlations are very high. Present this in another way.

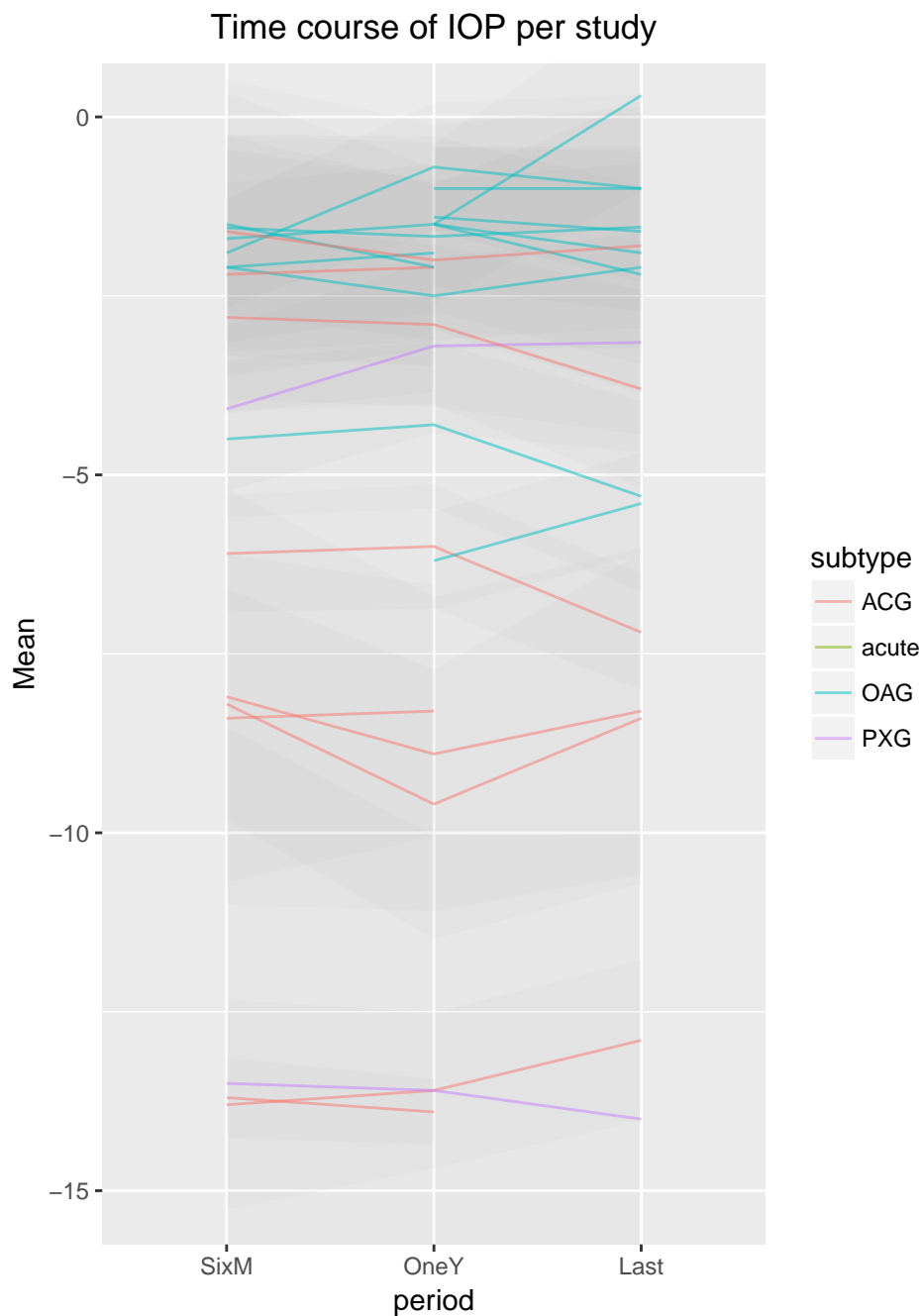
```
library(reshape2)
```

```
##
## Attaching package: 'reshape2'

## The following object is masked from 'package:tidyr':
##
## smiths

nd <- melt(df %>%
  filter(MIGsYorN == 'N',
    1*is.na(SixMoAbsIOPChangeMean) +
    1*is.na(OneYAbsIOPChangeMean) +
    1*is.na>LastPeriodAbsIOPChangeMean) < 2) %>%
  mutate(SixMoChangeSEM = SixMoAbsIOPChangeStdDev / sqrt(SixMoEyes),
    OneYChangeSEM = OneYAbsIOPChangeStdDev / sqrt(OneYEyes),
    LastPeriodChangeSEM = LastPeriodAbsIOPChangeStdDev / sqrt>LastPeriodEyes)) %>%
  select(study.name, subtype,
    SixMoAbsIOPChangeMean,
    OneYAbsIOPChangeMean,
    LastPeriodAbsIOPChangeMean,
    SixMoChangeSEM,
    OneYChangeSEM,
    LastPeriodChangeSEM), id.vars=c("study.name", "subtype"))
nd$metric <- substr(nd$variable, nchar(as.character(nd$variable)) - 3, nchar(as.character(nd$variable)))
nd$period <- substr(nd$variable, 0, 4)
df_ <- dcast(nd, formula = study.name + subtype + period ~ metric)
```

```
df_ <- df_ %>% mutate(period = factor(period, c('SixM', 'OneY', 'Last')),
                      g = paste(study.name, as.character(subtype))) %>% filter(!is.na(Mean))
ggplot(df_, aes(y = Mean,
                ymin=Mean - 1.96*eSEM,
                ymax=Mean + 1.96*eSEM,
                x = period,
                label=study.name,
                group=g)) +
  geom_ribbon(alpha=.02) +
  geom_line(alpha=.5, aes(color=subtype)) +
  coord_cartesian(y=c(-15, 0)) + ggtitle('Time course of IOP per study') + theme(plot.title = element_t
```



It's remarkable how consistent measurements are between time periods. At most, we find a change of ± 2.5 mm Hg between the first and last period.

```
df_ <- df %>% filter(subtype=='OAG')
drawn.corr <- with(df_, replicate(n = 100,
                                draw.corr(SixMoAbsIOPChangeMean,
                                           SixMoAbsIOPChangeStdDev / sqrt(SixMoEyes),
                                           OneYAbsIOPChangeMean,
                                           OneYAbsIOPChangeStdDev / sqrt(OneYEyes))))
cat("Mean +- SE correlation, OAG only\n")
```

```
## Mean +- SE correlation, OAG only
```

```
print(mean(drawn.corr))
```

```
## [1] 0.923427
```

```
print(sd(drawn.corr))
```

```
## [1] 0.04206775
```

```
df_ <- df
drawn.corr <- with(df_, replicate(n = 100,
                                draw.corr(SixMoAbsIOPChangeMean,
                                           SixMoAbsIOPChangeStdDev / sqrt(SixMoEyes),
                                           OneYAbsIOPChangeMean,
                                           OneYAbsIOPChangeStdDev / sqrt(OneYEyes))))
cat("Mean +- SE correlation, All subtypes\n")
```

```
## Mean +- SE correlation, All subtypes
```

```
print(mean(drawn.corr))
```

```
## [1] 0.9915564
```

```
print(sd(drawn.corr))
```

```
## [1] 0.003696022
```

This is also reflected in the correlations - even accounting for noise, the correlations are $> .9$ between month 6 and month 12.

Multivariate inference

Let's use `mvmeta` to infer the effect size for all periods together.

```
library(mvmeta)
```

```
## This is mvmeta 0.4.7. For an overview type: help('mvmeta-package').
```

```
fill.na <- function(x, y, z) {
  return(ifelse(!is.na(x),
                x,
                ifelse(is.na(y),
                      z,
                      ifelse(is.na(z),
                            y,
                            sqrt((y**2 + z**2) / 2 )))))
}
```



```

}

get.correlation.matrices.tri <- function(x, y, z, assumed.rho) {
  S <- list()
  for(i in 1:length(x)) {
    xx <- fill.na(x[i], y[i], z[i])
    yy <- fill.na(y[i], x[i], z[i])
    zz <- fill.na(z[i], x[i], y[i])
    S[[i]] <- matrix(c(xx ** 2, xx * yy * assumed.rho, xx * zz * assumed.rho ** 2,
                      xx * yy * assumed.rho, yy ** 2, zz * yy * assumed.rho,
                      xx * zz * assumed.rho ** 2, zz * yy * assumed.rho, zz * zz), ncol=3)
  }
  S
}

df_ <- df %>% filter(!is.na>LastPeriodAbsIOPChangeStdDev) |
  !is.na(SixMoAbsIOPChangeStdDev) |
  !is.na(OneYAbsIOPChangeStdDev), subtype %in% c('OAG', 'ACG'), MIGsYorN == 'N')

thefit <- mvmeta(cbind(SixMoAbsIOPChangeMean, OneYAbsIOPChangeMean, LastPeriodAbsIOPChangeMean) ~ subtype,
  S=get.correlation.matrices.tri(df_$SixMoAbsIOPChangeStdDev / sqrt(df_$SixMoEyes),
    df_$OneYAbsIOPChangeStdDev / sqrt(df_$OneYEyes),
    df_$LastPeriodAbsIOPChangeStdDev / sqrt(df_$LastPeriodEyes), .7),
  data=df_,
  method="reml")

summary(thefit)

## Call: mvmeta(formula = cbind(SixMoAbsIOPChangeMean, OneYAbsIOPChangeMean,
## LastPeriodAbsIOPChangeMean) ~ subtype, S = get.correlation.matrices.tri(df_$SixMoAbsIOPChangeStdDev /
## sqrt(df_$SixMoEyes), df_$OneYAbsIOPChangeStdDev / sqrt(df_$OneYEyes), df_$LastPeriodAbsIOPChangeStdDev / sqrt(df_$LastPeriodEyes), .7), data = df_, method = "reml")
##
## Multivariate random-effects meta-regression
## Dimension: 3
## Estimation method: REML
##
## Fixed-effects coefficients
## SixMoAbsIOPChangeMean :
##      Estimate Std. Error      z Pr(>|z|) 95%ci.lb 95%ci.ub
## (Intercept)  -5.9217    0.7061 -8.3865  0.0000  -7.3057  -4.5378
## subtypeOAG    3.3355    0.9870  3.3795  0.0007   1.4011   5.2699
##
## (Intercept) ***
## subtypeOAG ***
## OneYAbsIOPChangeMean :
##      Estimate Std. Error      z Pr(>|z|) 95%ci.lb 95%ci.ub
## (Intercept)  -6.1285    0.7102 -8.6292  0.0000  -7.5205  -4.7365
## subtypeOAG    3.8138    0.9841  3.8754  0.0001   1.8850   5.7425
##
## (Intercept) ***
## subtypeOAG ***
## LastPeriodAbsIOPChangeMean :
##      Estimate Std. Error      z Pr(>|z|) 95%ci.lb 95%ci.ub

```

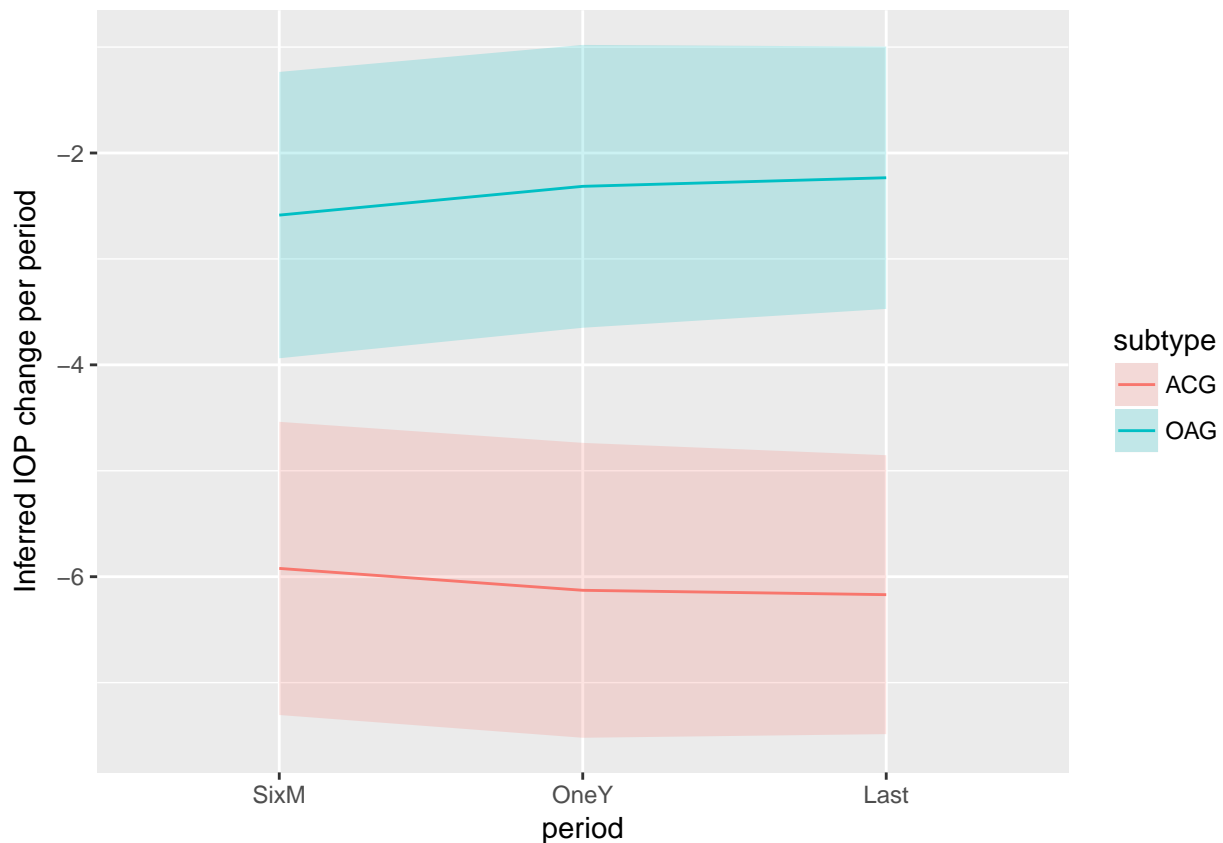
```
## (Intercept)    -6.1695      0.6717   -9.1853      0.0000    -7.4860    -4.8531
## subtypeOAG      3.9360      0.9221    4.2683      0.0000     2.1286     5.7433
##
## (Intercept)    ***
## subtypeOAG      ***
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1
##
## Between-study random-effects (co)variance components
## Structure: General positive-definite
##
##              Std. Dev              Corr
## SixMoAbsIOPChangeMean      2.7657 SixMoAbsIOPChangeMean
## OneYAbsIOPChangeMean      2.7806      0.9963
## LastPeriodAbsIOPChangeMean 2.5526      0.9813
##
## SixMoAbsIOPChangeMean      OneYAbsIOPChangeMean
## OneYAbsIOPChangeMean
## LastPeriodAbsIOPChangeMean      0.9677
##
## Multivariate Cochran Q-test for residual heterogeneity:
## Q = 1537.5043 (df = 62), p-value = 0.0000
## I-square statistic = 96.0%
##
## 36 studies, 68 observations, 6 fixed and 6 random-effects parameters
##      logLik      AIC      BIC
## -118.6183   261.2367   286.7623
```

```
newdata <- data.frame(subtype=c('OAG', 'ACG'))
pred <- predict(thefit, newdata, se=TRUE)
newdata$SixMoAbsIOPChangeMean <- pred$fit[,1]
newdata$OneYAbsIOPChangeMean <- pred$fit[,2]
newdata$LastPeriodAbsIOPChangeMean <- pred$fit[,3]
newdata$SixMoAbsIOPChangeSEM <- pred$se[,1]
newdata$OneYAbsIOPChangeSEM <- pred$se[,2]
newdata$LastPeriodAbsIOPChangeSEM <- pred$se[,3]
```

```
library(reshape2)
nd <- melt(newdata)
```

```
## Using subtype as id variables
```

```
nd$period <- substr(nd$variable, 0, 4)
nd$metric <- substr(nd$variable, nchar(as.character(nd$variable)) - 3, nchar(as.character(nd$variable)))
df_ <- dcast(nd, formula = subtype + period ~ metric)
df_$period <- factor(df_$period, c('SixM', 'OneY', 'Last'))
ggplot(df_, aes(x=period,
                y=Mean,
                ymin=Mean - 1.96*eSEM,
                ymax=Mean + 1.96*eSEM,
                group=subtype,
                fill=subtype)) + geom_ribbon(alpha=.2) + geom_line(aes(color=subtype)) + ylab("Inferred")
```



Meta-regression

Consider relationships between different covariates and outcomes. Focus on the IOP drop at one year and its correlation with different factors.

```
df_ <- df %>% filter(!is.na(OneYAbsIOPChangeMean), subtype != "acute", MIGsYorN == 'N') %>%
  mutate(subtype=relevel(factor(subtype), ref="OAG"))
m <- metagen(OneYAbsIOPChangeMean,
             OneYAbsIOPChangeStdDev / sqrt(OneYEyes),
             study.name,
             data=df_,
             byvar=subtype,
             n.e=OneYEyes)

print(metareg(~ OneYEyes, x=m))
```

```
##
## Mixed-Effects Model (k = 24; tau^2 estimator: DL)
##
## tau^2 (estimated amount of residual heterogeneity):      30.8712 (SE = 12.8681)
## tau (square root of estimated tau^2 value):             5.5562
## I^2 (residual heterogeneity / unaccounted variability): 99.02%
## H^2 (unaccounted variability / sampling variability):    102.25
## R^2 (amount of heterogeneity accounted for):             0.00%
##
## Test for Residual Heterogeneity:
```

```

## QE(df = 22) = 2249.5296, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.9026, p-val = 0.3421
##
## Model Results:
##
##           estimate      se      zval      pval      ci.lb      ci.ub
## intrcpt      -3.3325   1.8721  -1.7801   0.0751   -7.0019   0.3368 .
## OneYEyes     -0.0275   0.0290  -0.9500   0.3421   -0.0843   0.0293
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

print(metareg(~ OneYEyes * subtype, x=m))

##
## Mixed-Effects Model (k = 24; tau^2 estimator: DL)
##
## tau^2 (estimated amount of residual heterogeneity):      17.0380 (SE = 7.3921)
## tau (square root of estimated tau^2 value):              4.1277
## I^2 (residual heterogeneity / unaccounted variability):  98.16%
## H^2 (unaccounted variability / sampling variability):     54.33
## R^2 (amount of heterogeneity accounted for):              39.83%
##
## Test for Residual Heterogeneity:
## QE(df = 18) = 977.8565, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6):
## QM(df = 5) = 14.6923, p-val = 0.0118
##
## Model Results:
##
##           estimate      se      zval      pval      ci.lb      ci.ub
## intrcpt          -1.1839   2.3639  -0.5008   0.6165   -5.8170   3.4491
## OneYEyes          -0.0189   0.0381  -0.4956   0.6202   -0.0936   0.0558
## subtypeACG        -3.5831   3.0929  -1.1585   0.2467   -9.6452   2.4789
## subtypePXG       -27.5433  12.8476  -2.1438   0.0320  -52.7243  -2.3624
## OneYEyes:subtypeACG -0.0253   0.0469  -0.5397   0.5894   -0.1172   0.0666
## OneYEyes:subtypePXG  0.9644   0.5600   1.7220   0.0851   -0.1333   2.0620
##
## intrcpt
## OneYEyes
## subtypeACG
## subtypePXG      *
## OneYEyes:subtypeACG
## OneYEyes:subtypePXG .
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

print(metareg(~ Year, x=m))

##
## Mixed-Effects Model (k = 24; tau^2 estimator: DL)

```

```

##
## tau^2 (estimated amount of residual heterogeneity):      25.2200 (SE = 10.5747)
## tau (square root of estimated tau^2 value):             5.0219
## I^2 (residual heterogeneity / unaccounted variability): 98.82%
## H^2 (unaccounted variability / sampling variability):    84.52
## R^2 (amount of heterogeneity accounted for):             10.94%
##
## Test for Residual Heterogeneity:
## QE(df = 22) = 1859.3429, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 0.0302, p-val = 0.8621
##
## Model Results:
##
##           estimate      se      zval      pval      ci.lb      ci.ub
## intrcpt    63.5684   393.3358   0.1616   0.8716  -707.3556   834.4924
## Year       -0.0340    0.1957  -0.1736   0.8621   -0.4175    0.3496
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

print(metareg(~ Year * subtype, x=m))

##
## Mixed-Effects Model (k = 24; tau^2 estimator: DL)
##
## tau^2 (estimated amount of residual heterogeneity):      11.2606 (SE = 4.8038)
## tau (square root of estimated tau^2 value):             3.3557
## I^2 (residual heterogeneity / unaccounted variability): 97.24%
## H^2 (unaccounted variability / sampling variability):    36.21
## R^2 (amount of heterogeneity accounted for):             60.23%
##
## Test for Residual Heterogeneity:
## QE(df = 18) = 651.7540, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6):
## QM(df = 5) = 19.9554, p-val = 0.0013
##
## Model Results:
##
##           estimate      se      zval      pval      ci.lb
## intrcpt    68.7364   390.2739   0.1761   0.8602  -696.1864
## Year       -0.0353    0.1941  -0.1817   0.8558   -0.4158
## subtypeACG  668.7765  603.7615   1.1077   0.2680  -514.5744
## subtypePXG -3052.2792 1516.1880  -2.0131   0.0441 -6023.9531
## Year:subtypeACG -0.3350   0.3003  -1.1158   0.2645   -0.9235
## Year:subtypePXG  1.5210   0.7568   2.0097   0.0445    0.0377
##           ci.ub
## intrcpt    833.6592
## Year         0.3452
## subtypeACG 1852.1273
## subtypePXG -80.6053 *
## Year:subtypeACG  0.2535
## Year:subtypePXG  3.0043 *

```

```
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

print(metareg(~ PreOpIOPMean, x=m))

##
## Mixed-Effects Model (k = 24; tau^2 estimator: DL)
##
## tau^2 (estimated amount of residual heterogeneity):      4.4783 (SE = 1.8384)
## tau (square root of estimated tau^2 value):             2.1162
## I^2 (residual heterogeneity / unaccounted variability): 93.40%
## H^2 (unaccounted variability / sampling variability):    15.14
## R^2 (amount of heterogeneity accounted for):             84.19%
##
## Test for Residual Heterogeneity:
## QE(df = 22) = 333.0958, p-val < .0001
##
## Test of Moderators (coefficient(s) 2):
## QM(df = 1) = 65.1891, p-val < .0001
##
## Model Results:
##
##              estimate      se      zval      pval      ci.lb      ci.ub
## intrcpt          13.0744  2.2388   5.8399 <.0001   8.6864  17.4624 ***
## PreOpIOPMean    -0.8673  0.1074  -8.0740 <.0001  -1.0779  -0.6568 ***
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

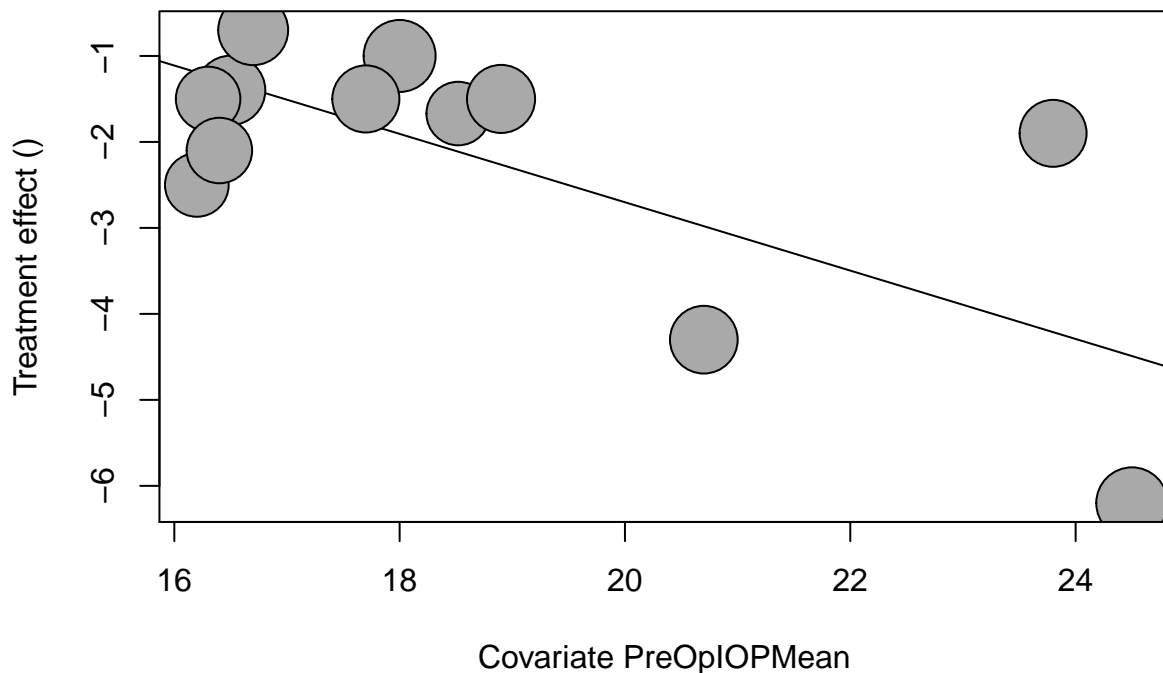
print(metareg(~ PreOpIOPMean * subtype, x=m))

##
## Mixed-Effects Model (k = 24; tau^2 estimator: DL)
##
## tau^2 (estimated amount of residual heterogeneity):      1.2655 (SE = 0.6125)
## tau (square root of estimated tau^2 value):             1.1249
## I^2 (residual heterogeneity / unaccounted variability): 79.37%
## H^2 (unaccounted variability / sampling variability):    4.85
## R^2 (amount of heterogeneity accounted for):             95.53%
##
## Test for Residual Heterogeneity:
## QE(df = 18) = 87.2305, p-val < .0001
##
## Test of Moderators (coefficient(s) 2,3,4,5,6):
## QM(df = 5) = 218.5070, p-val < .0001
##
## Model Results:
##
##              estimate      se      zval      pval      ci.lb
## intrcpt          5.2227  2.4821   2.1041  0.0354   0.3578
## PreOpIOPMean    -0.3961  0.1307  -3.0318  0.0024  -0.6522
## subtypeACG       8.2042  3.2360   2.5353  0.0112   1.8617
## subtypePXG       8.4784  5.4425   1.5578  0.1193  -2.1888
## PreOpIOPMean:subtypeACG -0.5532  0.1601  -3.4547  0.0006  -0.8671
```

```
## PreOpIOPMean:subtypePXG    -0.4570  0.2429  -1.8817  0.0599  -0.9330
##                               ci.lb  ci.ub
## intrcpt                    10.0876    *
## PreOpIOPMean                -0.1400    **
## subtypeACG                   14.5467    *
## subtypePXG                   19.1455
## PreOpIOPMean:subtypeACG     -0.2394    ***
## PreOpIOPMean:subtypePXG      0.0190    .
##
## ---
## Signif. codes:  0 '***' 0.001 '**' 0.01 '*' 0.05 '.' 0.1 ' ' 1

# Same, restricted to OAG only
df_ <- df %>% filter(!is.na(OneYAbsIOPChangeMean), subtype == "OAG", MIGsYorN == 'N') %>%
  mutate(subtype=relevel(factor(subtype), ref="OAG"))
m <- metagen(OneYAbsIOPChangeMean,
             OneYAbsIOPChangeStdDev / sqrt(OneYEyes),
             study.name,
             data=df_,
             byvar=subtype,
             n.e=OneYEyes)

bubble(metareg(~ PreOpIOPMean, x=m))
```



Small study bias

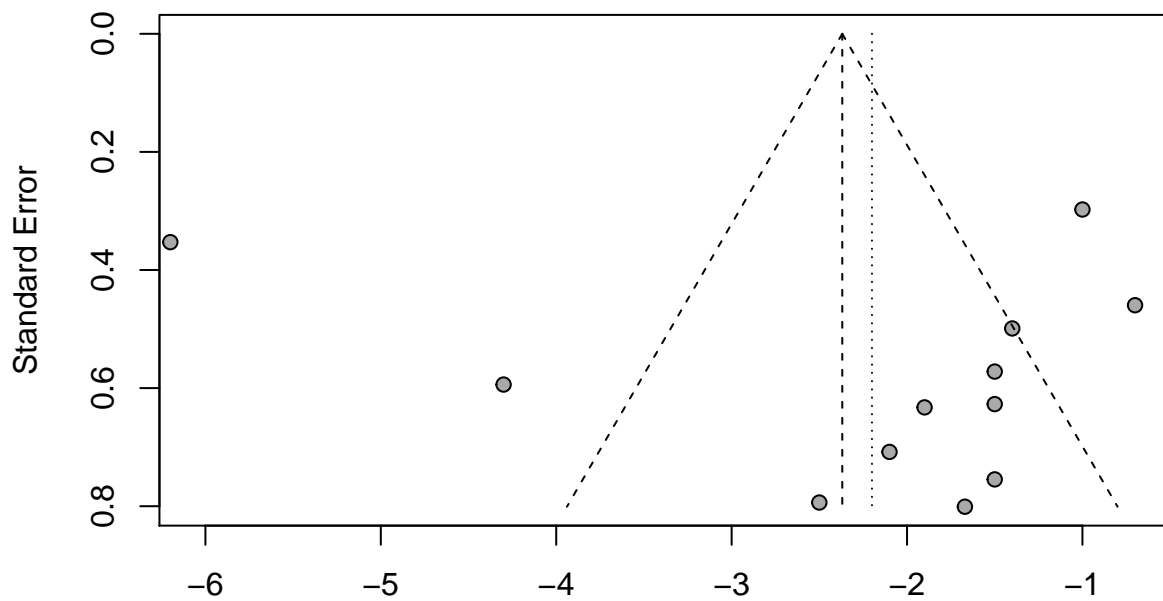
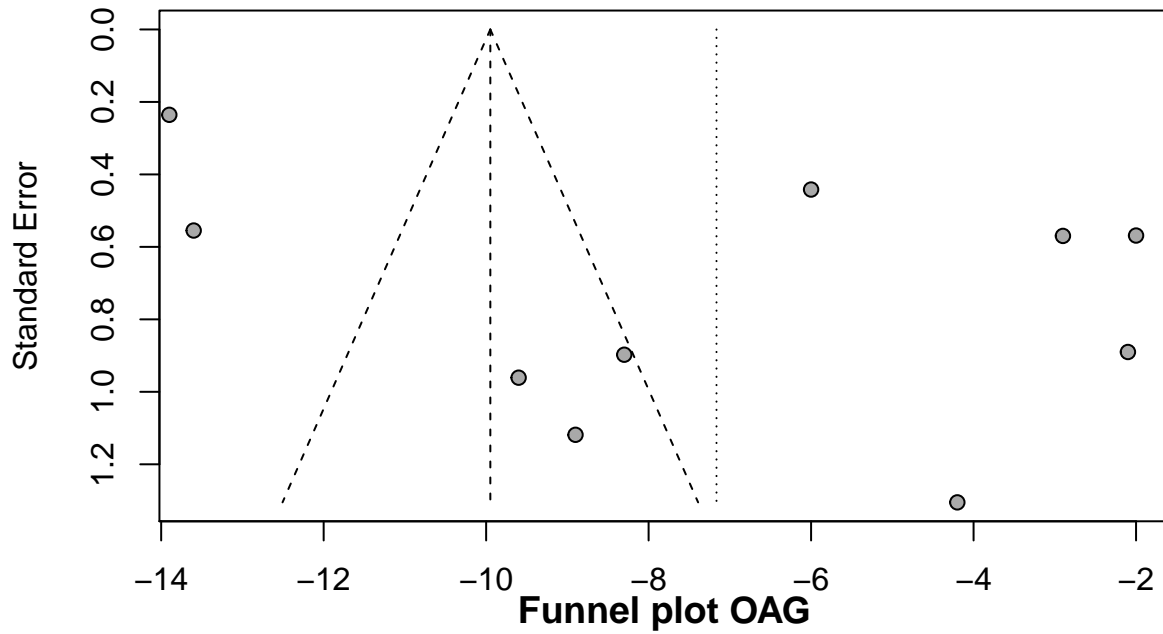
```
df_ <- df %>% filter(!is.na(df$OneYAbsIOPChangeMean),
                    df$subtype != "acute",
                    MIGsYorN == 'N') %>% mutate(subtype=factor(subtype))
for(l in levels(df_$subtype)) {
  m <- metagen(OneYAbsIOPChangeMean,
```

```

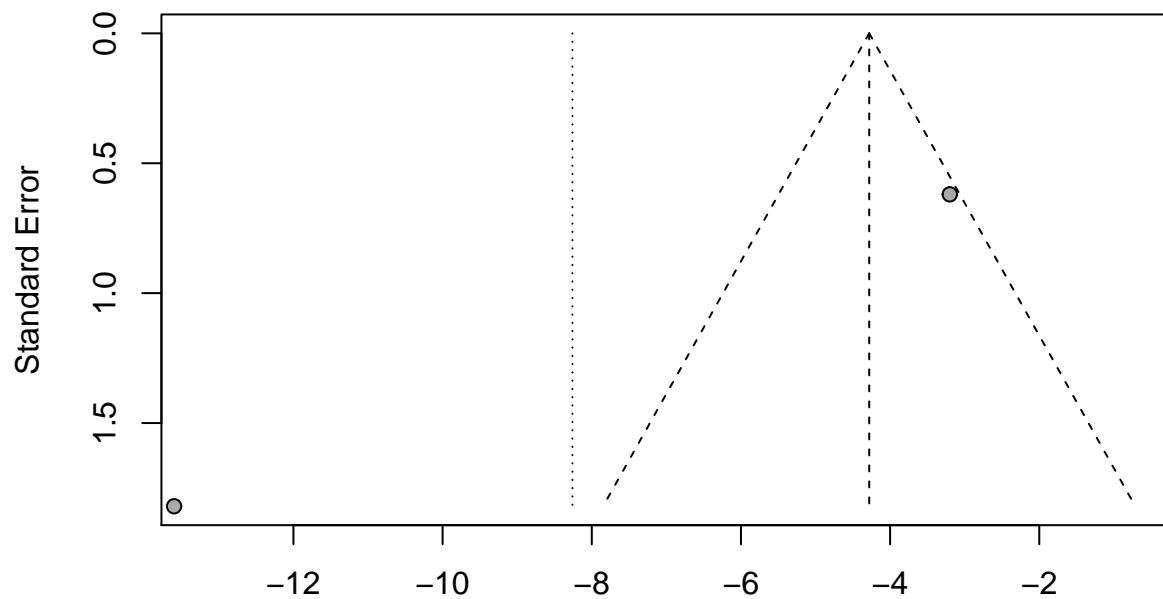
OneYAbsIOPChangeStdDev / sqrt(OneYEyes),
study.name,
data=df_ %>% filter(subtype == 1),
n.e=OneYEyes)
funnel(m)
title(paste('Funnel plot', 1))
}

```

Funnel plot ACG



Funnel plot PXG

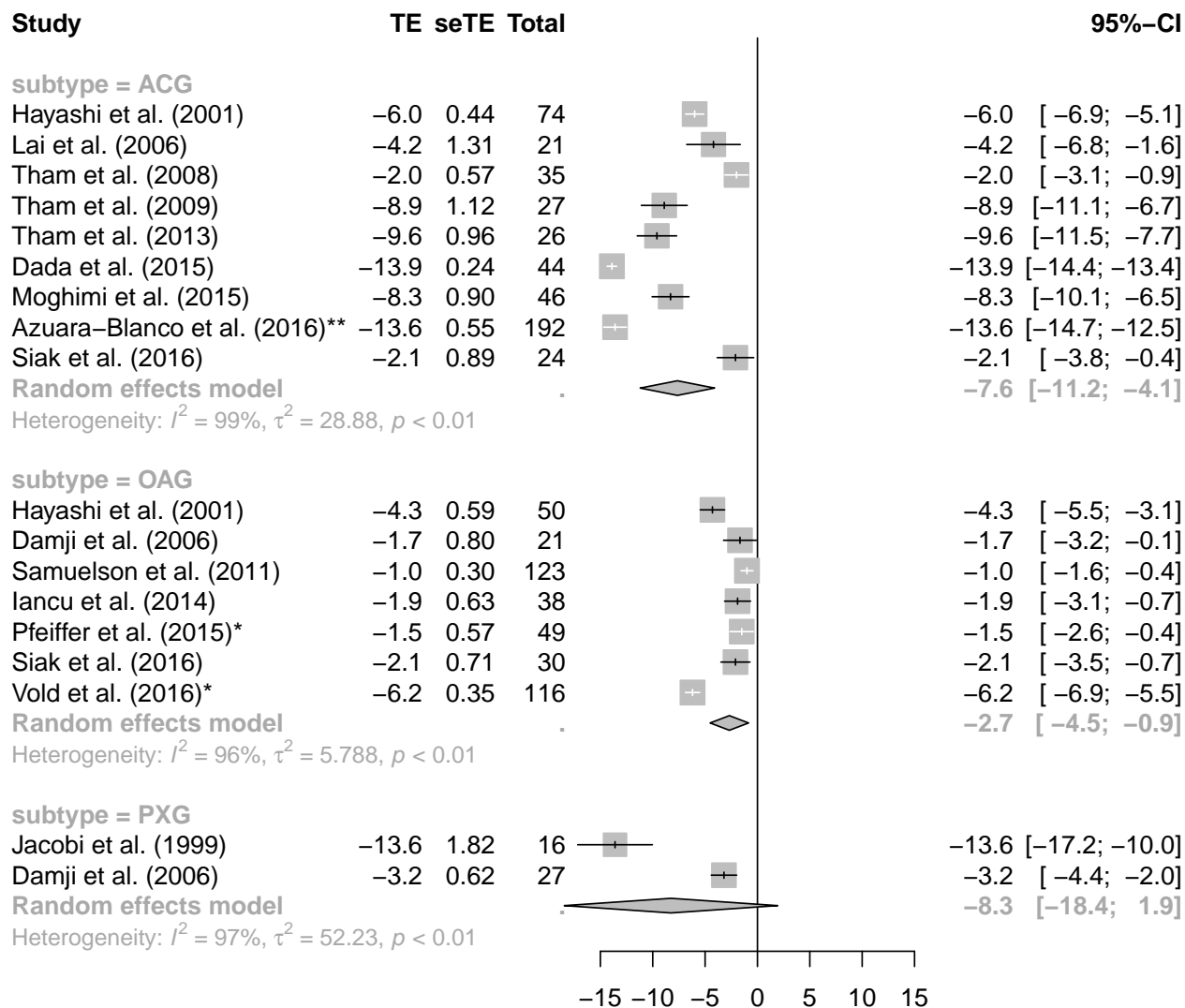


Alternative filterings of the data

Prospective studies only

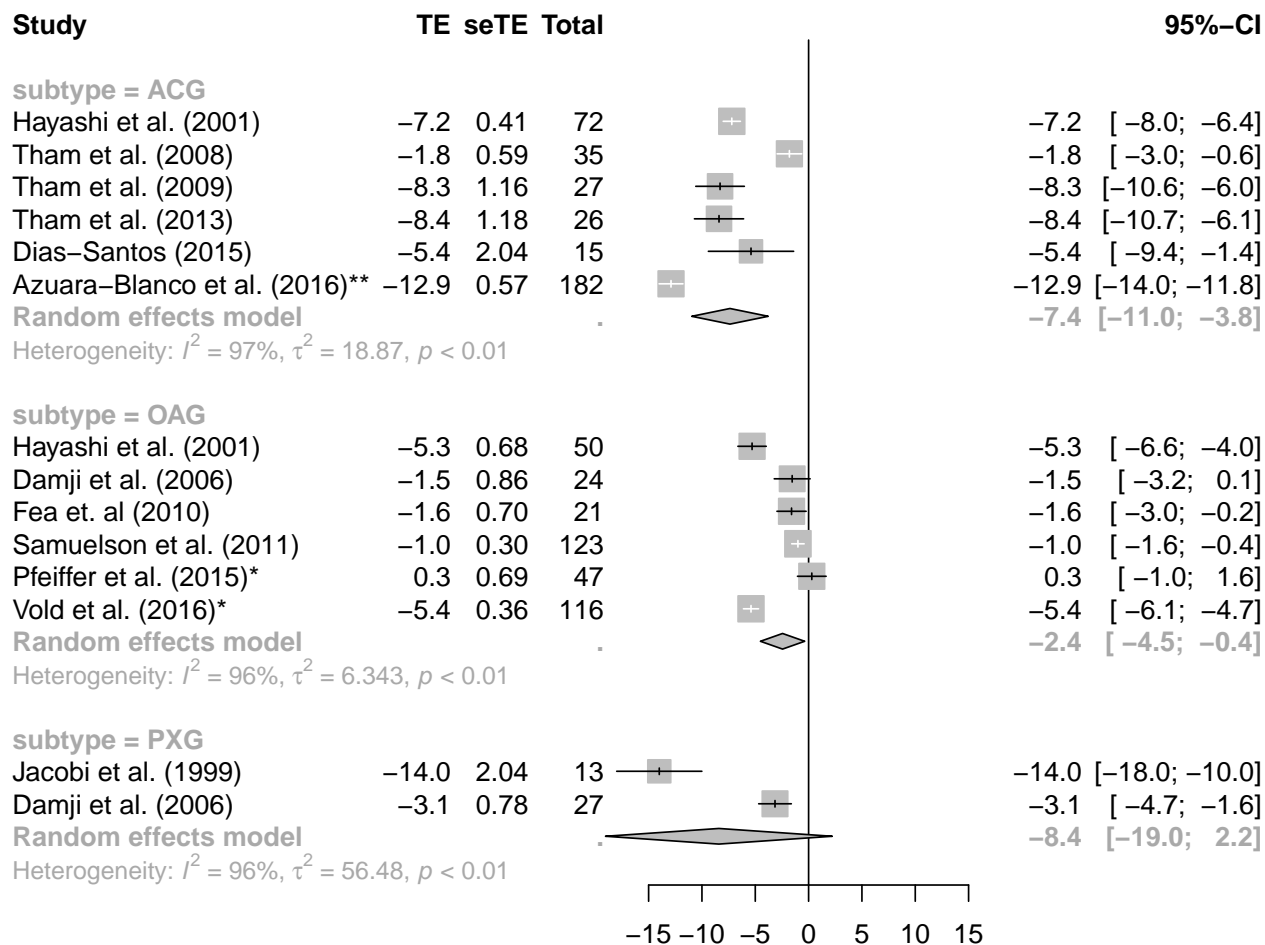
One year

```
df_ <- df %>%
  filter(!is.na(OneYAbsIOPChangeMean), subtype != "acute", MIGsYorN == 'N') %>%
  mutate(subtype=factor(subtype))
m <- metagen(OneYAbsIOPChangeMean,
             OneYAbsIOPChangeStdDev / sqrt(OneYEyes),
             study.name,
             data=df_,
             byvar=subtype,
             n.e=OneYEyes)
forest(m,
       comb.fixed=FALSE,
       digits=1,
       digits.se = 2,
       overall=FALSE,
       leftcols=c("studlab", "TE", "seTE", "n.e"))
```



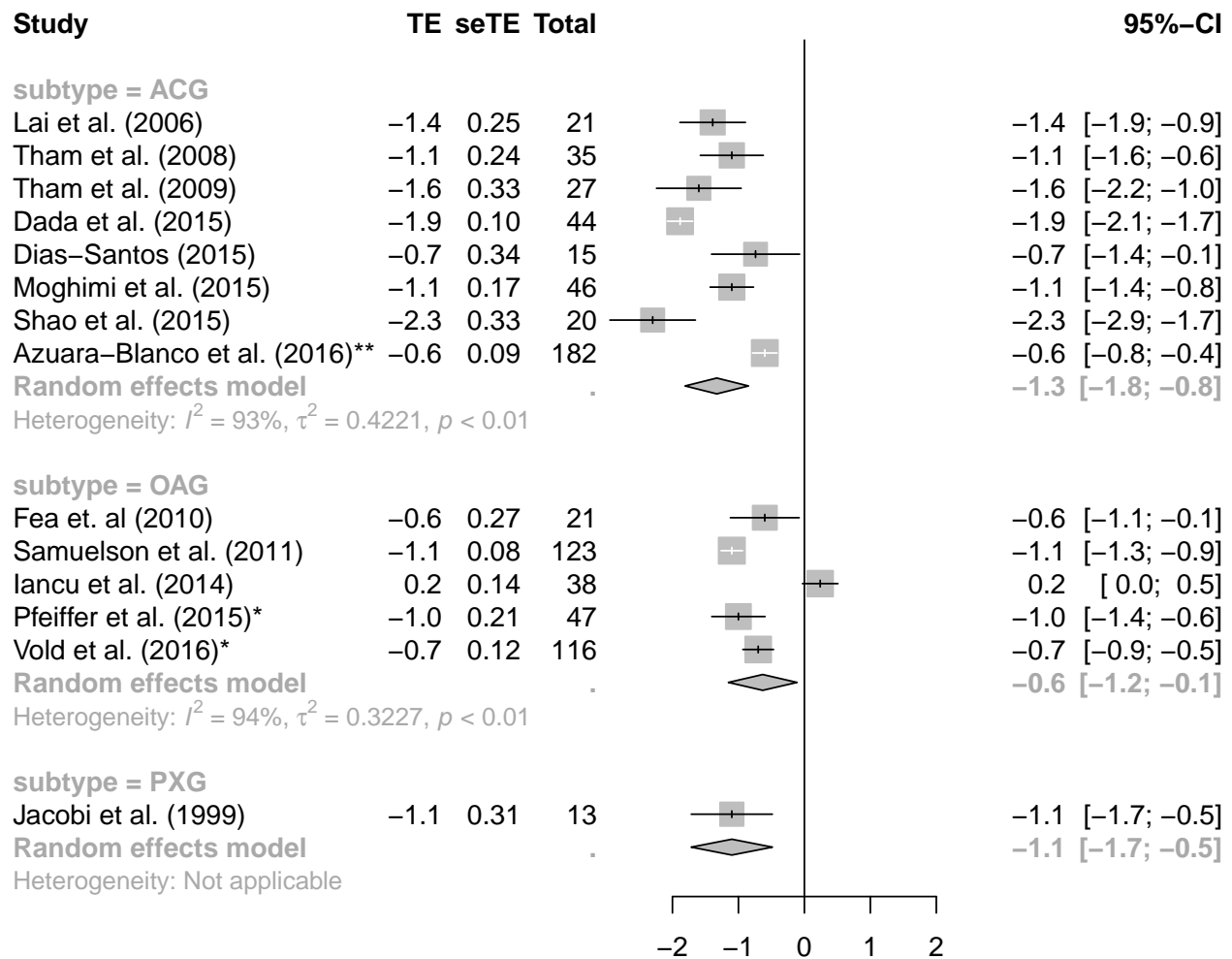
Last period

```
df_ <- df %>%
  filter(!is.na>LastPeriodAbsIOPChangeMean), subtype != "acute", MIGsYorN == 'N') %>%
  mutate(subtype=factor(subtype))
m <- metagen>LastPeriodAbsIOPChangeMean,
  LastPeriodAbsIOPChangeStdDev / sqrt>LastPeriodEyes),
  study.name,
  data=df_,
  byvar=subtype,
  n.e>LastPeriodEyes)
forest(m,
  comb.fixed=FALSE,
  digits=1,
  digits.se = 2,
  overall=FALSE,
  leftcols=c("studlab", "TE", "seTE", "n.e"))
```



Meds

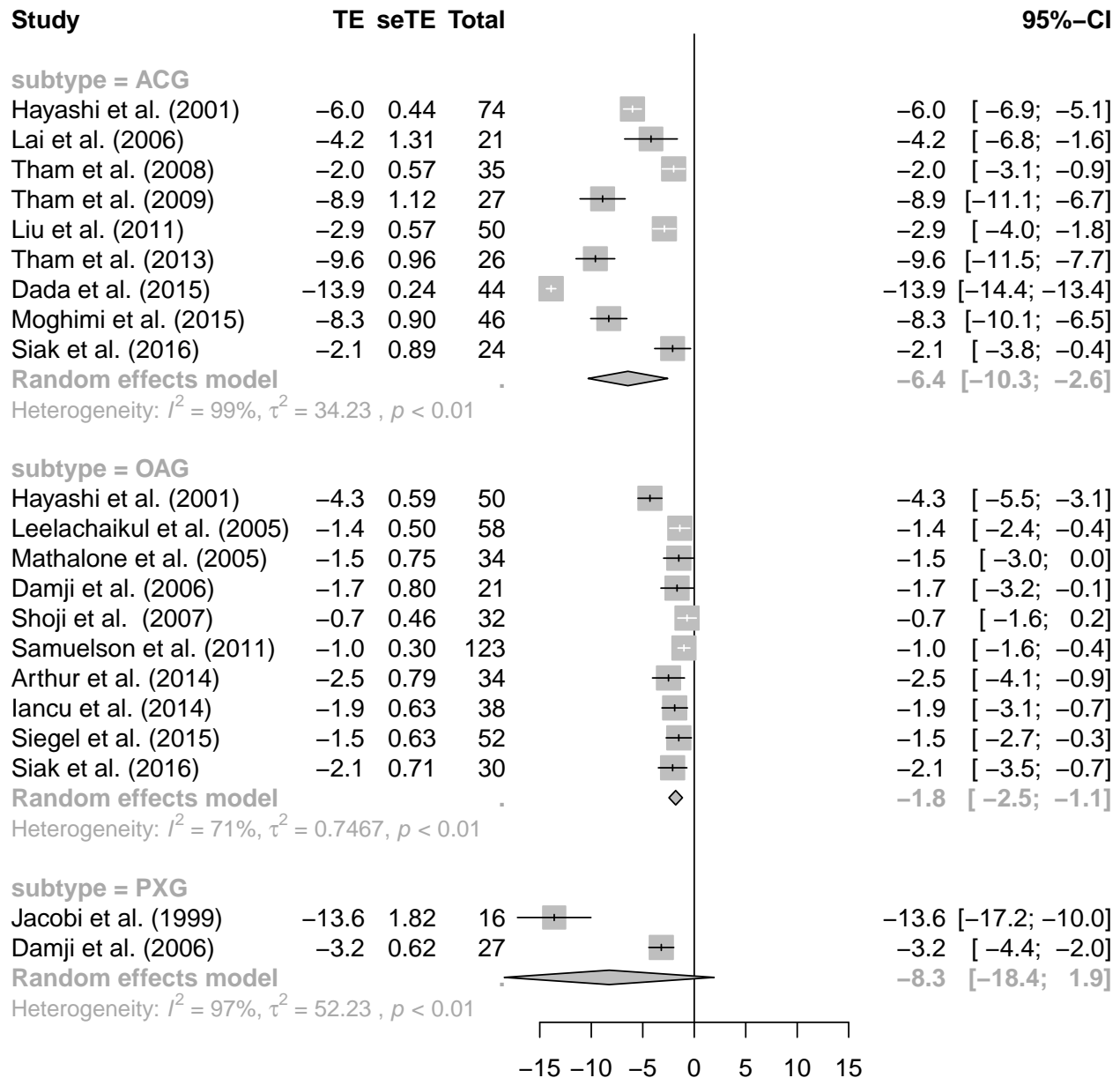
```
df_ <- df %>%
  filter(!is.na(RxChangeMean), !is.na(RxChangeStdDev),
         df$subtype != "acute", MIGsYorN == 'N') %>%
  mutate(subtype=factor(subtype))
m <- metagen(RxChangeMean,
             sqrt(RxPostOpStdDev** 2 + RxPreOpStdDev ** 2) / sqrt>LastPeriodEyes),
         study.name,
         data=df_,
         byvar=subtype,
         n.e=LastPeriodEyes)
forest(m,
       comb.fixed=FALSE,
       digits=1,
       digits.se = 2,
       overall=FALSE,
       leftcols=c("studlab", "TE", "seTE", "n.e"))
```



Excluding washout studies

One year

```
df_ <- df %>%
  filter(!is.na(OneYAbsIOPChangeMean), subtype != "acute", MIGsYorN == 'N') %>%
  mutate(subtype=factor(subtype))
m <- metagen(OneYAbsIOPChangeMean,
             OneYAbsIOPChangeStdDev / sqrt(OneYEyes),
             study.name,
             data=df_,
             byvar=subtype,
             n.e=OneYEyes)
forest(m,
       comb.fixed=FALSE,
       digits=1,
       digits.se = 2,
       overall=FALSE,
       leftcols=c("studlab", "TE", "seTE", "n.e"))
```



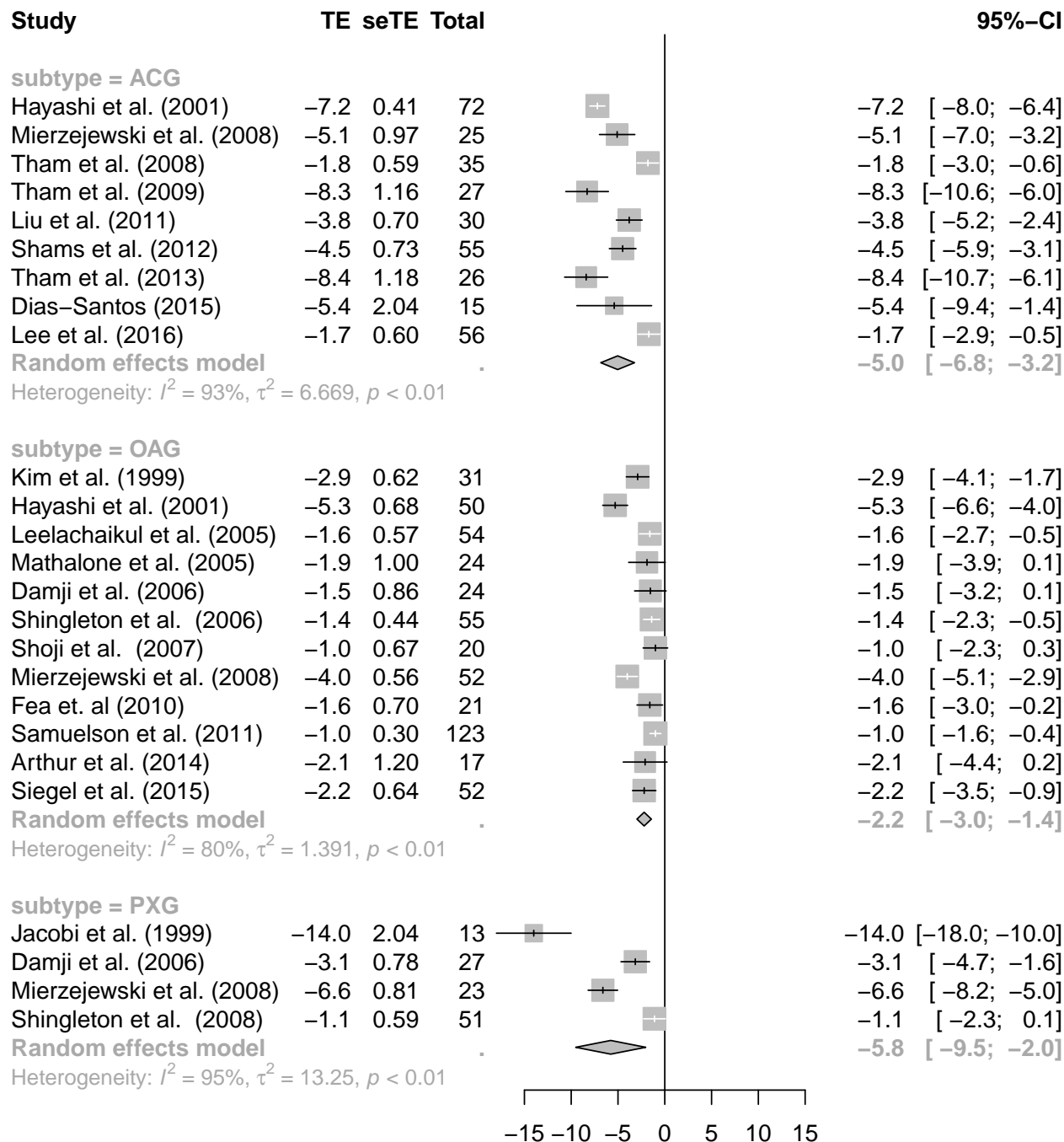
Last period

```
df_ <- df %>%
  filter(!is.na>LastPeriodAbsIOPChangeMean), subtype != "acute", MIGsYorN == 'N') %>%
  mutate(subtype=factor(subtype))
m <- metagen>LastPeriodAbsIOPChangeMean,
  LastPeriodAbsIOPChangeStdDev / sqrt>LastPeriodEyes),
  study.name,
  data=df_,
  byvar=subtype,
  n.e>LastPeriodEyes)
forest(m,
  comb.fixed=FALSE,
```

```

digits=1,
digits.se = 2,
overall=FALSE,
leftcols=c("studlab", "TE", "seTE", "n.e"))

```



Meds

```

df_ <- df %>%
  filter(!is.na(RxChangeMean), !is.na(RxChangeStdDev),

```

```

      df$subtype != "acute", MIGsYorN == 'N') %>%
  mutate(subtype=factor(subtype))
m <- metagen(RxChangeMean,
             sqrt(RxPostOpStdDev** 2 + RxPreOpStdDev ** 2) / sqrt>LastPeriodEyes),
             study.name,
             data=df_,
             byvar=subtype,
             n.e>LastPeriodEyes)
forest(m,
       comb.fixed=FALSE,
       digits=1,
       digits.se = 2,
       overall=FALSE,
       leftcols=c("studlab", "TE", "seTE", "n.e"))

```

