

# Assignment 5 - Meta-analysis of pitch in schizophrenia

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## Building on the shoulders of giants: meta-analysis

### Questions to be answered

#### 1. What is the current evidence for distinctive patterns of pitch mean and pitch sd in schizophrenia?

**Report how many papers report quantitative estimates, your method to analyze them, the estimated effect size of the difference (mean effect size and standard error for pitch mean, same for pitch sd) and forest plots representing it.**

Report how many papers report quantitative estimates: 5 studies report an estimate of the mean of f0, fundamental frequency. 192 participants with schizophrenia and 121 control participants.

The overall estimated difference, cohen's d in mean between the schizophrenia group and the control group was 0.24 [-0.12, 0.59]. We cannot be certain that the effect is different from zero, as the confidence intervals crosses zero.

14 studies report an estimate of the range in pitch. 605 participants with schizophrenia and 469 control participants.

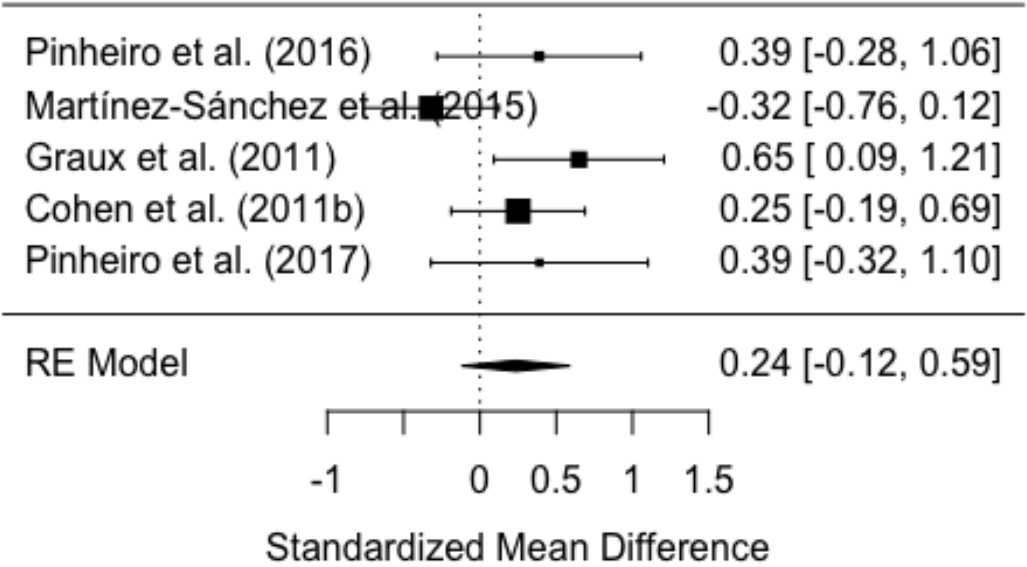
The overall estimated difference, cohen's d in range between the schizophrenia group and the control group was -0.23 [-0.84, 0.39].

Again, we cannot be sure whether there is an effect different from zero, as the confidence intervals cross zero.

When looking at study Cohen et al. (2014), we can see that the effect size is much different from the effect sizes observed in the other studies. We will return to this matter, when looking at influential studies.

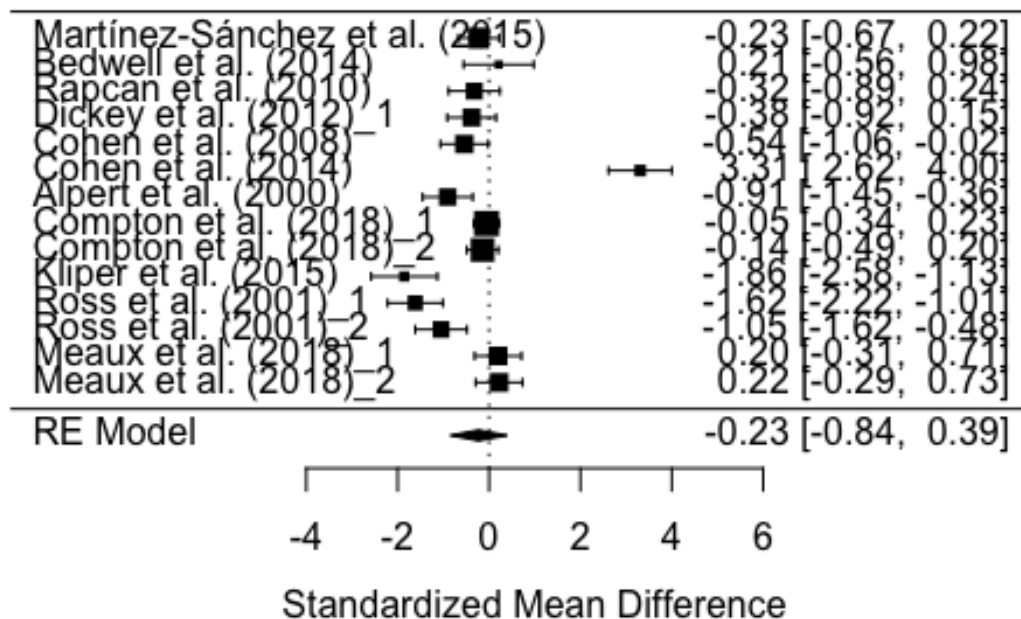
Here are forest plots presenting the findings: #Pitch mean

`forest(mean_rma)`



**Pitch range**

`forest(range_rma)`



2. Do the results match your own analysis from Assignment 3? If you add your results to the meta-analysis, do the estimated effect sizes change? Report the new estimates and the new forest plots.

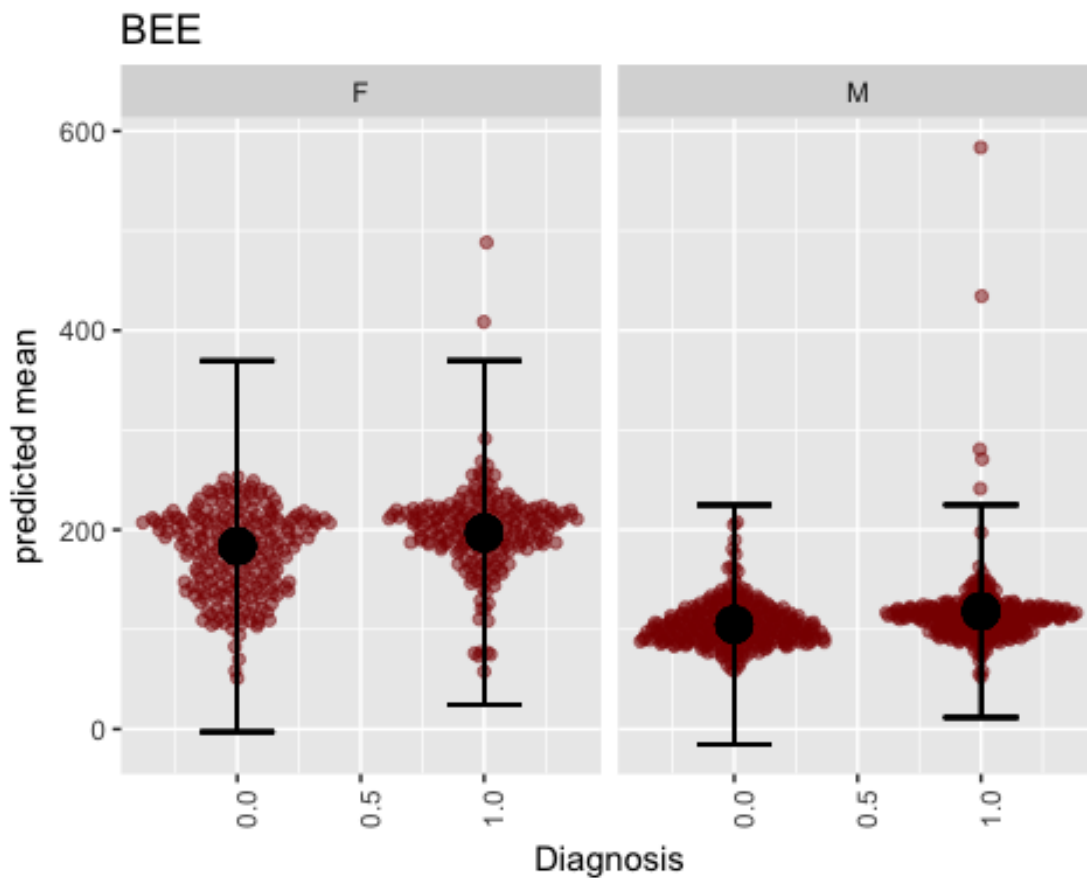
### Plotting predictions

```
plot <- ggplot(na.omit(all_pitch), aes(x = Diagnosis.x, y = mean_f0)) +
  geom_quasirandom(alpha = 0.5, colour = "dark red") +
  labs(x = "Diagnosis", y = "predicted mean", title = "BEE") +

  #geom_boxplot(alpha = 0.5) +p
  geom_point(aes(y = pred_mean), data = na.omit(model_pred), size = 5) +
  geom_errorbar(aes(y = NULL, ymin = pred_mean-2*pred_range, ymax =
pred_mean+2*pred_range), data = model_pred, width = .3) +
  facet_wrap(~Gender) +
  theme(axis.text.x = element_text(angle = 90, hjust = 1))

## Warning: Ignoring unknown aesthetics: y
```

plot



Comparing the effect sizes from our own study from Assignment 3 with the following effect sizes: mean: 0.33 [0.03, 0.63] and range: -0.39 [-0.81, 0.33]. These both fall within the confidence intervals from the analysis above. From this we can still infer that the studies are trying to measure the same effect.

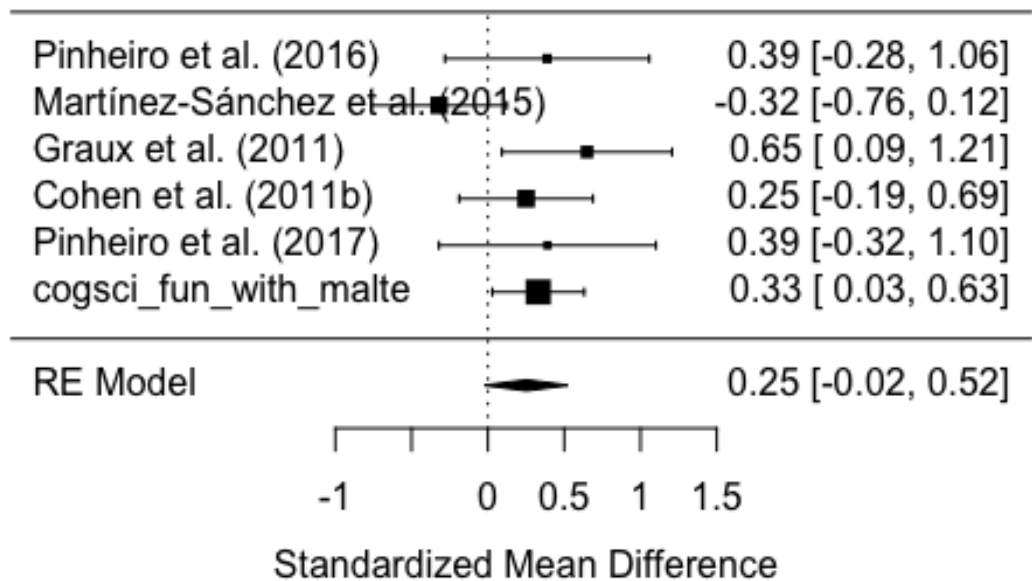
When including our study, we obtained these new effect sizes in the meta analysis: mean: 0.25 [-0.02, 0.52] range: -0.24 [-0.81, 0.33]

The estimates of the effect sizes has not changed radically. Both effect sizes' confidence intervals cross zero as before. Thus, our study does not change the overall conclusion from the previous analysis.

Below are the updated forest plots:

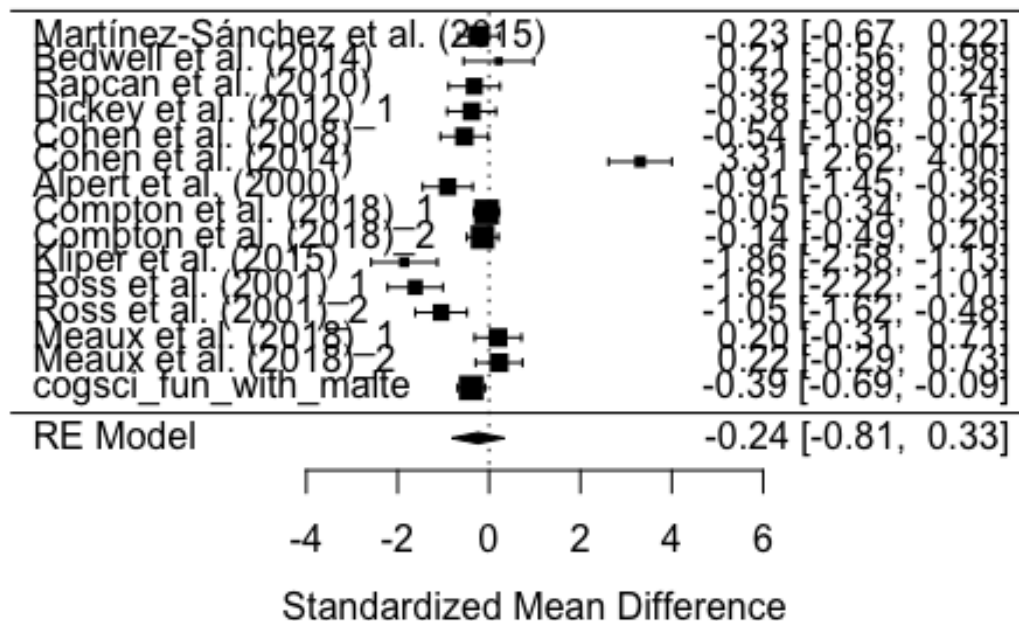
## Pith mean

```
forest(new_mean_rma)
```



## Pitch range

`forest(new_range_rma)`



### 3. Assess the quality of the literature: report and comment on heterogeneity of the studies (tau, I<sup>2</sup>), on publication bias (funnel plot), and on influential studies.

#### Tau squared and I squared:

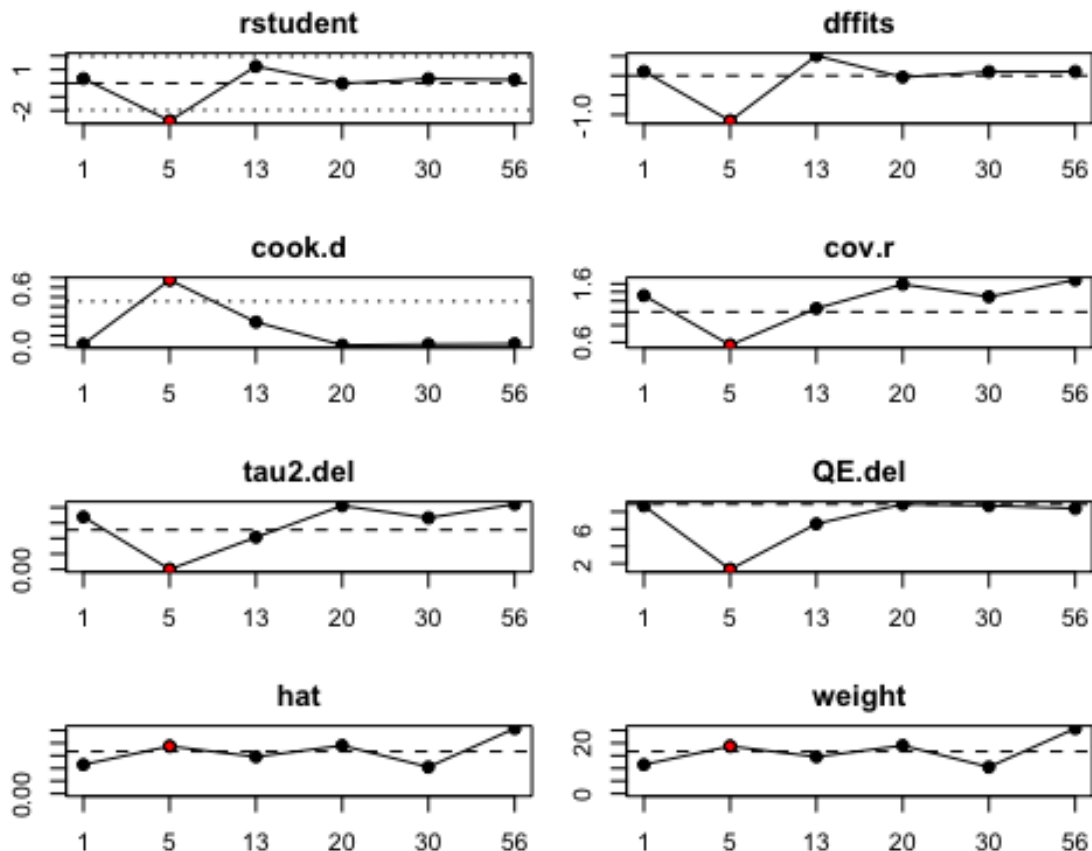
For the mean of f0 the overall variance ( $\tau^2$ ) of 0.0510 (SE = 0.0716). Some of the variance (I<sup>2</sup>: 46.30%) could not be reduced to random sample variability between studies (Q-stats = 8.8688, p-val = 0.1144). With an insignificant p-value we cannot reject the null hypothesis, that the studies show heterogeneity, and we can believe, they all come from the same underlying distribution and measure the same effect.

For the pitch range the overall variance ( $\tau^2$ ) of 1.1934 (SE = 0.4797). Most of the variance (I<sup>2</sup>: 95.39%) could not be reduced to random sample variability between studies (Q-stats = 165.3459, p-val < .0001). With a significant p-value we can reject the null hypothesis, that the studies show heterogeneity, and we can believe, they all do not come from the same underlying distribution and measure the same effect. Much of the variance from between studies should come from the

one outlying study Cohen et al. (2014), which show a much higher effect size (3.31) than the overall mean (-0.24). We will take a closer look at this now.

## Influential studies mean

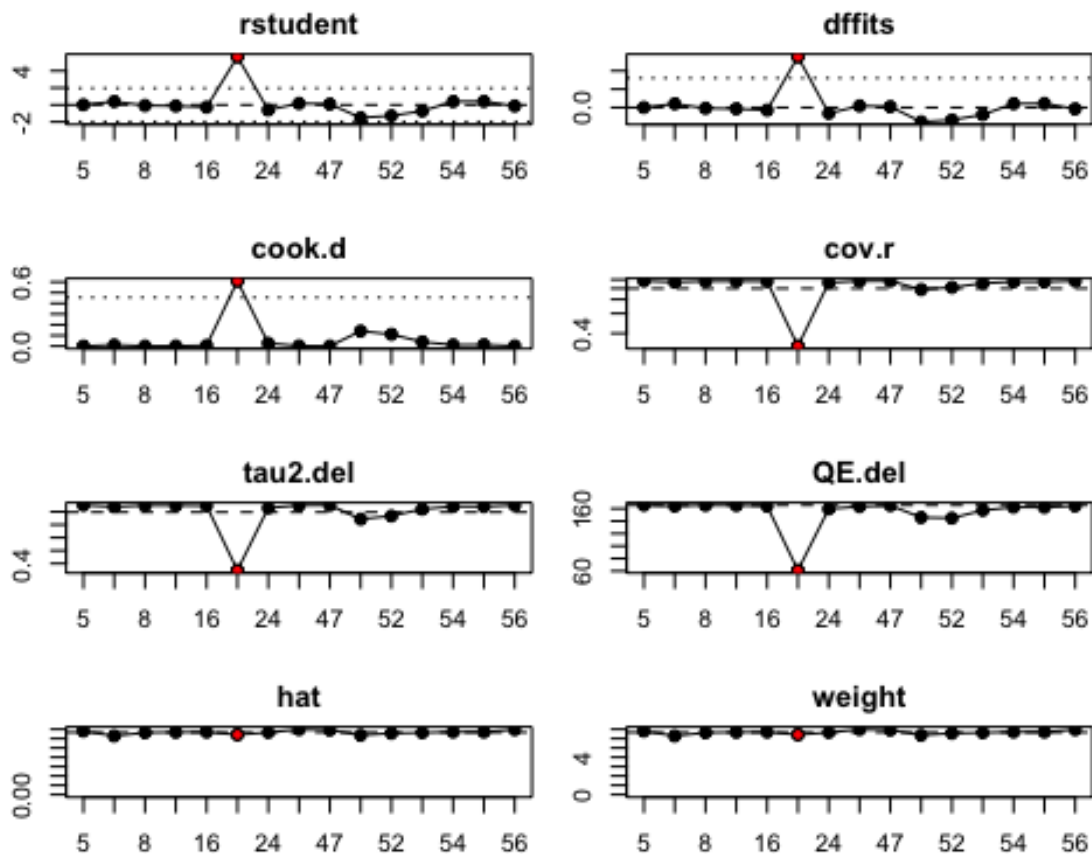
```
#influential studies
inf <- influence(new_mean_rma)
#print(inf)
plot(inf)
```



Here is shown the most influential study for the mean of  $f_0$ , given different measures. We see that study #5 always show up as the most influential study, but as we do not find heterogeneity in the Q-test, we do not find it necessary to remove potential outliers.

## Influential studies range

```
inf <- influence(new_range_rma)
#print(inf)
plot(inf)
```



Here we show the most influential studies from the analysis of pitch range. We see that one study in particular (#17) always show up as very influential. This gives us a clue, that this study probably is not drawn from the same distribution as the other studies. After looking at the description of the study, we do not find any cause for this strong effect. But because we will try to do the meta analysis without this study, and see how this changes our estimated overall effect size.

## Publication bias (funnel plots)

With funnel plots we plot the effect sizes of the studies against their standard error. By doing this we can assess if the unsure studies are the ones with the good results. If this happens to be the case there might be a publication bias in this field of studies, meaning that only the significant findings are published and thereby biasing the literature on the effect that is studied.

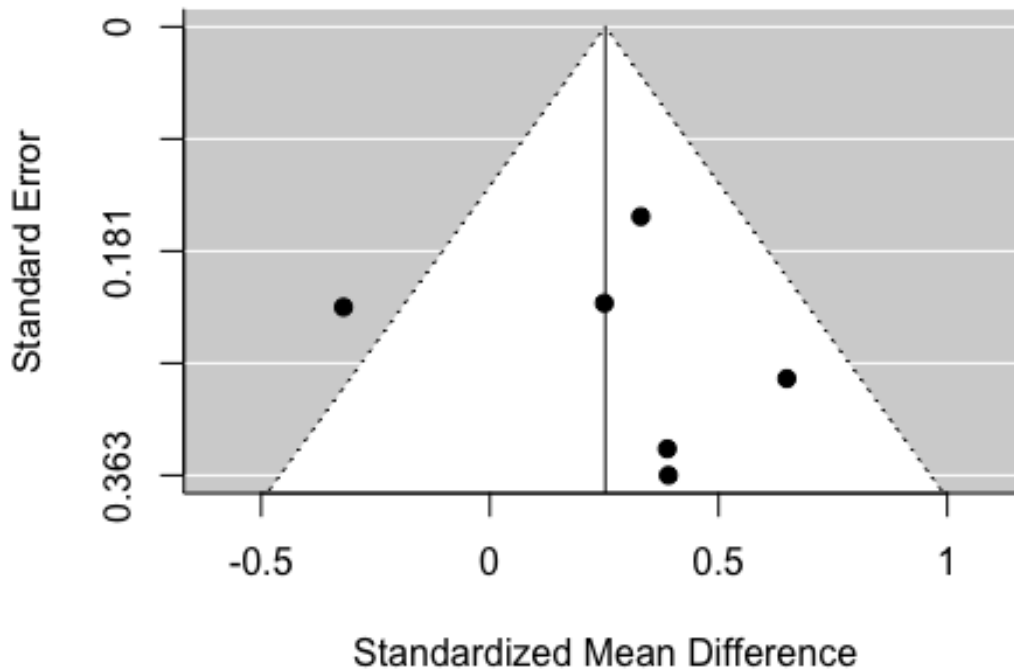
### Mean

```
#mean
```

```
funnel(new_mean_rma, main = "Random-Effects Model: Mean", xlab = "Standardized  
Mean Difference")
```



## Random-Effects Model: Mean



```
regtest(new_mean_rma)

##
## Regression Test for Funnel Plot Asymmetry
##
## model:      mixed-effects meta-regression model
## predictor: standard error
##
## test for funnel plot asymmetry: z = 0.5542, p = 0.5794

ranktest(new_mean_rma)

##
## Rank Correlation Test for Funnel Plot Asymmetry
##
## Kendall's tau = -0.0667, p = 1.0000
```

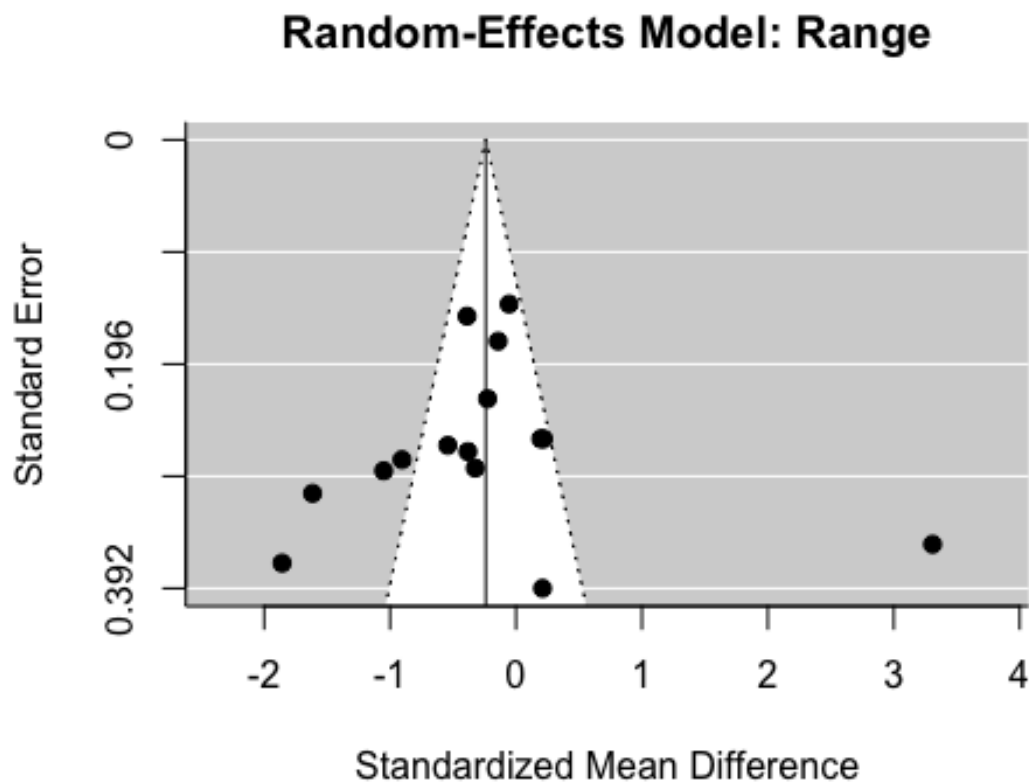
Visually inspecting the funnel plot for mean is first of all a bit problematic, due to the very few datapoints. This makes it difficult to conclude on general tendencies. I.e. it would be possible to both the accept and reject symmetry. However, we can inspect it numerically via the ranktest.

This is non-significant, and thus points to the fact that there is no obvious publication bias (Kendall's tau = -0.0667, p = 1.0).

## Range

*#range*

```
funnel(new_range_rma, main = "Random-Effects Model: Range", xlab = "Standardized  
Mean Difference")
```



```
regtest(new_range_rma)
```

```
##
```

```
## Regression Test for Funnel Plot Asymmetry
```

```
##
```

```
## model:      mixed-effects meta-regression model
```

```
## predictor: standard error
```

```
##
```

```
## test for funnel plot asymmetry: z = 0.2608, p = 0.7943
```

```
ranktest(new_range_rma)
```

```
##
```

```
## Rank Correlation Test for Funnel Plot Asymmetry
```

```
##  
## Kendall's tau = -0.2381, p = 0.2395
```

Inspecting the funnel plot with range it does not look like there is an obvious correlation between the datapoints (effect size and SE). However, the influential study: Cohen, 2014, might disturb the interpretation of the plot, as it would change radically without this study. The ranktest is still non-significant (Kendall's tau = -0.2381, p = 0.24).

Looking at the range data for Cohen 2014, we find that the standard deviations associated with the range is unlikely small. The data is logtransformed. range\_mean\_schizo = 3.35, range\_sd\_schizo = 0.193 and for control range\_mean\_control = 2.87, range\_sd\_control = 0.05. By having so small standard deviations relatively to the mean estimates, the study gets an incredibly high effect size on 3.31. An effect size in that magnitude is highly unlikely. It could suggest an artifact in the data collection.

However, apart from the pitch being log-transformed in the Cohen 2014 study, there are no acceptable reasons to exclude the study, as the methods and analyses are congruent with the rest of the studies' we compare it to in the meta-analysis.

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### Tips on the process to follow:

- Download the data on all published articles analyzing pitch in schizophrenia (on gitlab)
- Look through the dataset to find out which columns to use, and if there is any additional information written as comments (real world data is always messy!).
  - Hint: Make sure you read the comments in the columns: pitch\_f0\_variability, frequency, Title, ACOUST\_ANA\_DESCR, DESCRIPTION, and COMMENTS
- Following the procedure in the slides calculate effect size and standard error of the effect size per each study. N.B. we focus on pitch mean and pitch standard deviation. . first try using lmer (to connect to what you know of mixed effects models) . then use rma() (to get some juicy additional statistics)
- Build a forest plot of the results (forest(model))
- Go back to Assignment 3, add your own study to the data table, and re-run meta-analysis. Do the results change?
- Now look at the output of rma() and check tau and I<sup>2</sup>