

Assignment 2: Meta-analysis

Question 1:

Simulate data to setup the analysis and gain insight on the structure of the problem.

Simulate:

- *One data set of 100 studies with a mean effect size of 0.4, average deviation by study of 0.4 and measurement error of 0.8.*
- *N of participants should follow a normal distribution with mean of 20, SD of 10, but no fewer than 10 participants).*

The data should consist of:

a) one row per study, with an effect size mean and standard error.

Then:

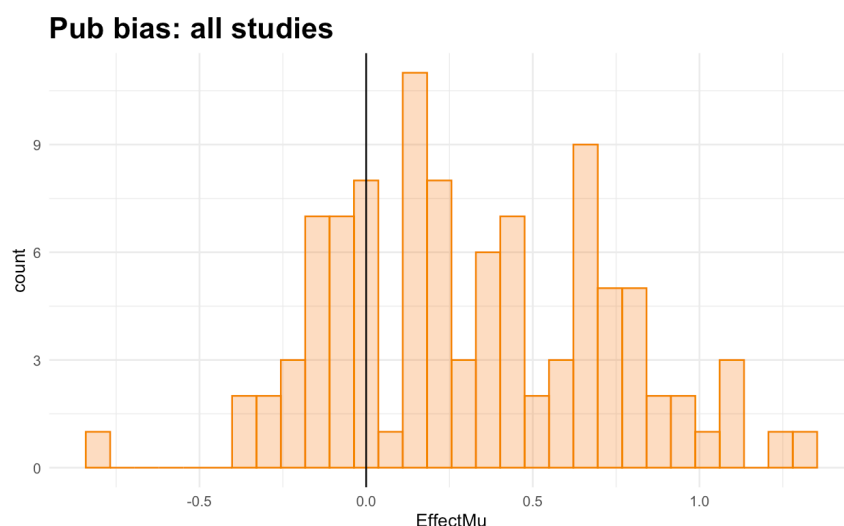
b) Build a proper Bayesian model to analyze the simulated data.

c) Then simulate publication bias (only some of the studies you simulate are likely to be published, which?), the effect of publication bias on your estimates (re-run the model on published studies, assess the difference),

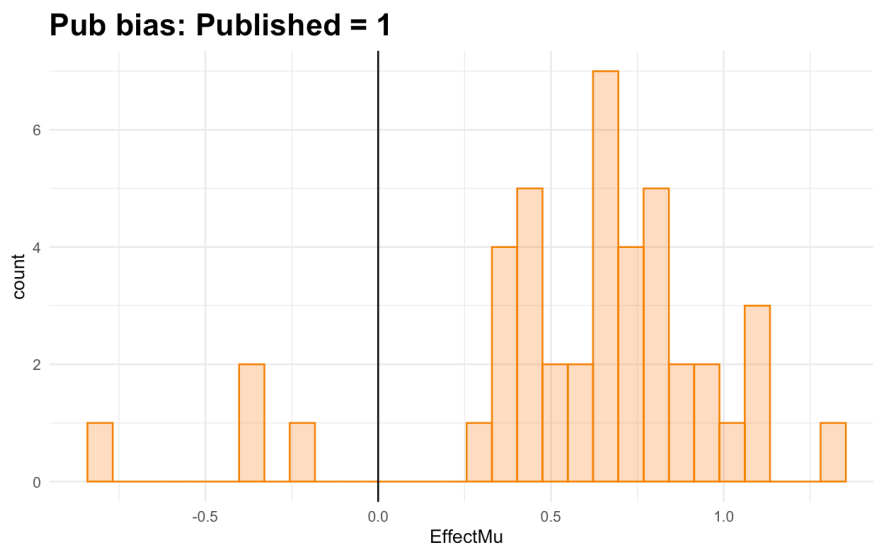
d) Discuss what this implies for your model.

e) Use at least one plot to visualize your results.

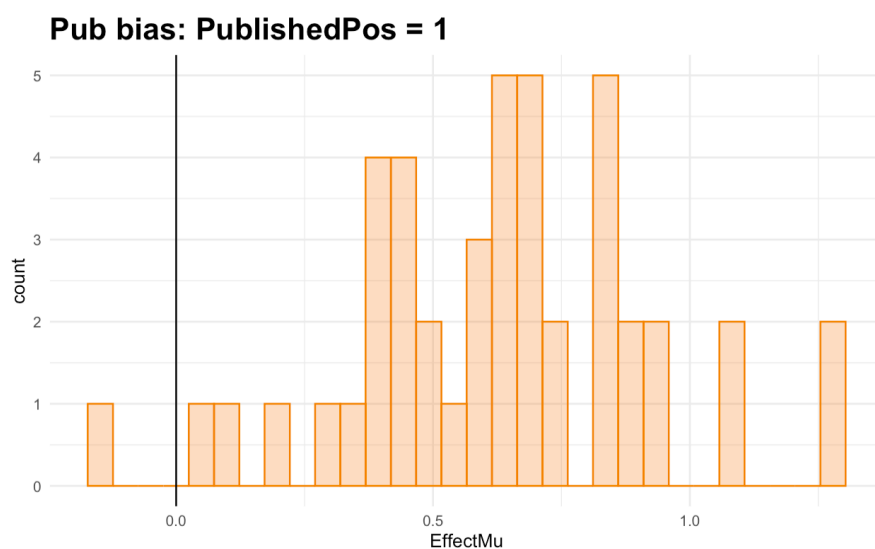
The data was simulated according to the requirements. In order to visualize the results, I have plotted data according to the publication bias (the output that was generated running the code for the first time):



Plot of simulated data: all studies. Includes effect size mean of 0, more studies have positive effect size rather than negative.



Plot of simulated data: consist of studies that end up being published when the results are significant.



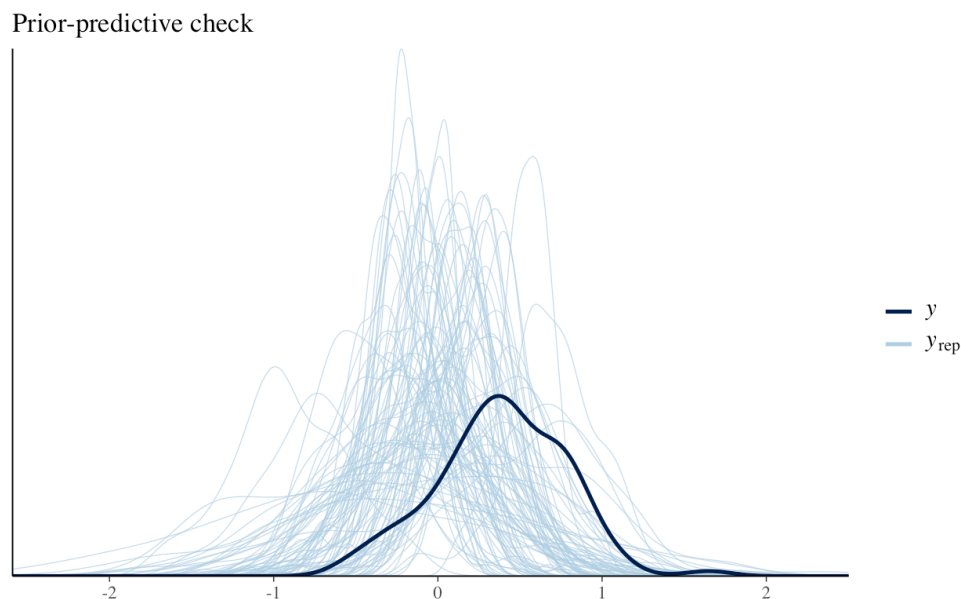
Plot of simulated data: consist of studies that end up being published when the results are significant and outcome is the one as expected.

In order to perform a meta-analytic multilevel modeling, for the Bayesian model this formula has been used:

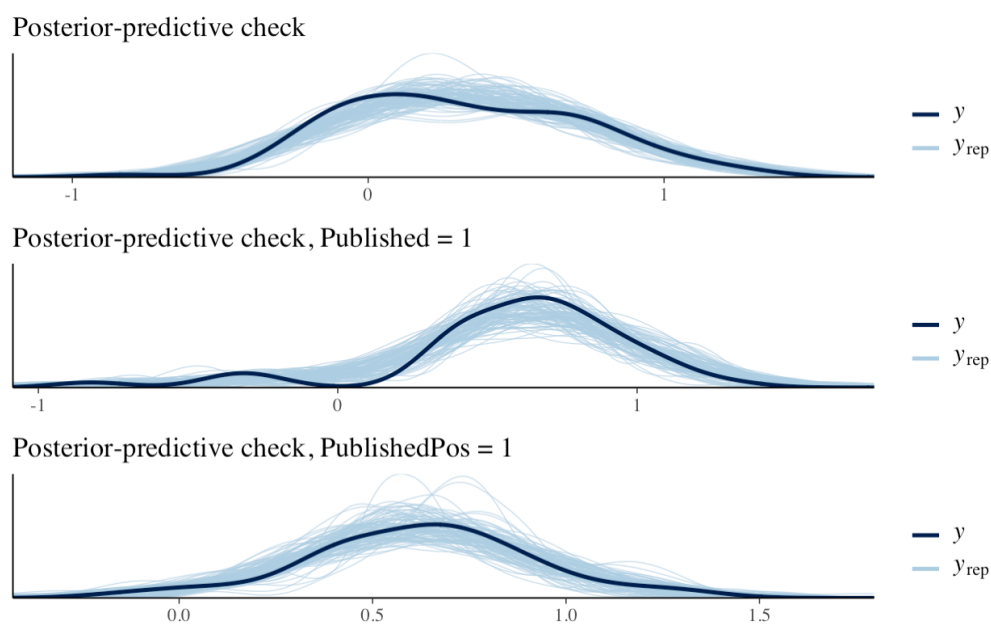
$$(\text{EffectMu} \mid \text{se}(\text{EffectSigma}) \sim 1 + (1 \mid \text{Study})),$$

which means that effect size mean and standard error varies by study, indicating that the outcome is not just one point, but the distribution.

Later, the priors were chosen in the way that they would not be restricting too much. Prior-predictive check model looks like this:



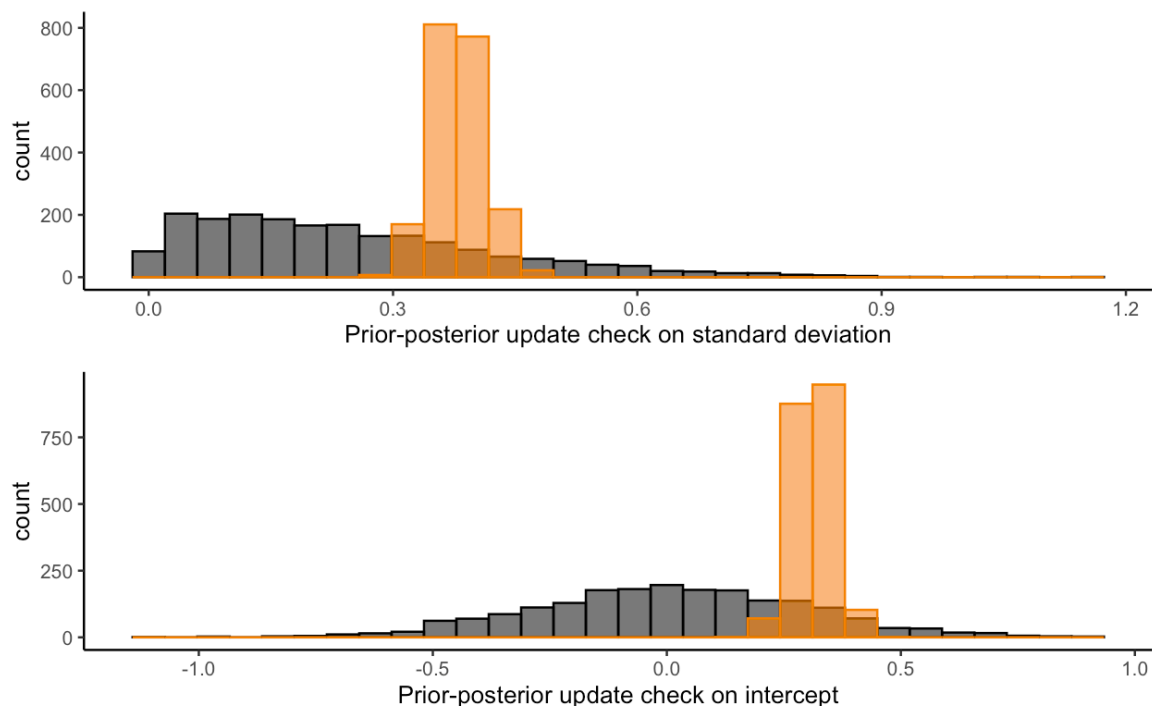
The range of possible outcome values seems to be quite possible (within the order of magnitude), therefore I have not adjusted any priors that I have defined in the first place. After that, the model was built for the actual data:



It seems like the model is capturing the data pretty well (1st plot – “Posterior-predictive check”).

The second and the third plot takes publication bias into account. The plot in the middle indicates that symmetric publication bias is being analyzed, by excluding studies that do not get published (no significant outcome). The last plot indicates the analysis of the asymmetric publication bias, meaning that studies, that have a significant and expected outcome, get published.

The publication bias is not coded-in to the model itself, therefore, the model is trying to “smooth-out” the outcome of 0 (the middle plot). In all three plots, the draws (blue lines) are close to the real data (black line).



The prior-posterior update check on simulated data is plotted above. It includes all of the studies, regardless of publication bias. The posterior seems like it learned from the priors, and shows the confidence.

Question 2:

2. What is the current evidence for distinctive vocal patterns in schizophrenia?

2.1) Describe the data available (studies, participants).

2.2) Using the model from question 1 analyze the data, visualize and report the findings: **population level effect size; how well studies reflect it; influential studies, publication bias.**

The data from Parola et al (2020) consists of 50 studies, which are published between years 1977 and 2018. On average (median), each study consisted of 17 male and 7 female participants of schizophrenia, 13 male and 11 female participants of people in control group. Average (mean) age of participants of schizophrenia is 35.95, with standard deviation of 8.6. Average age of participants in control group is 35.34, with standard deviation of 9.

As the focus variable is pitch variability, the fundamental frequency of pitch (F0) in the control group on average varies by 21.6 SD, while F0 in participants of schizophrenia varies more – 26.8 SD.

To analyze the data, the model from the first part of the assignment was used (with adjusted variable names).

As each paper might use different scales for variables of interest, the outcomes were converted to Cohen's D.

Therefore, the mean and standard deviation values of pitch F0 for schizophrenic and control group were adjusted.

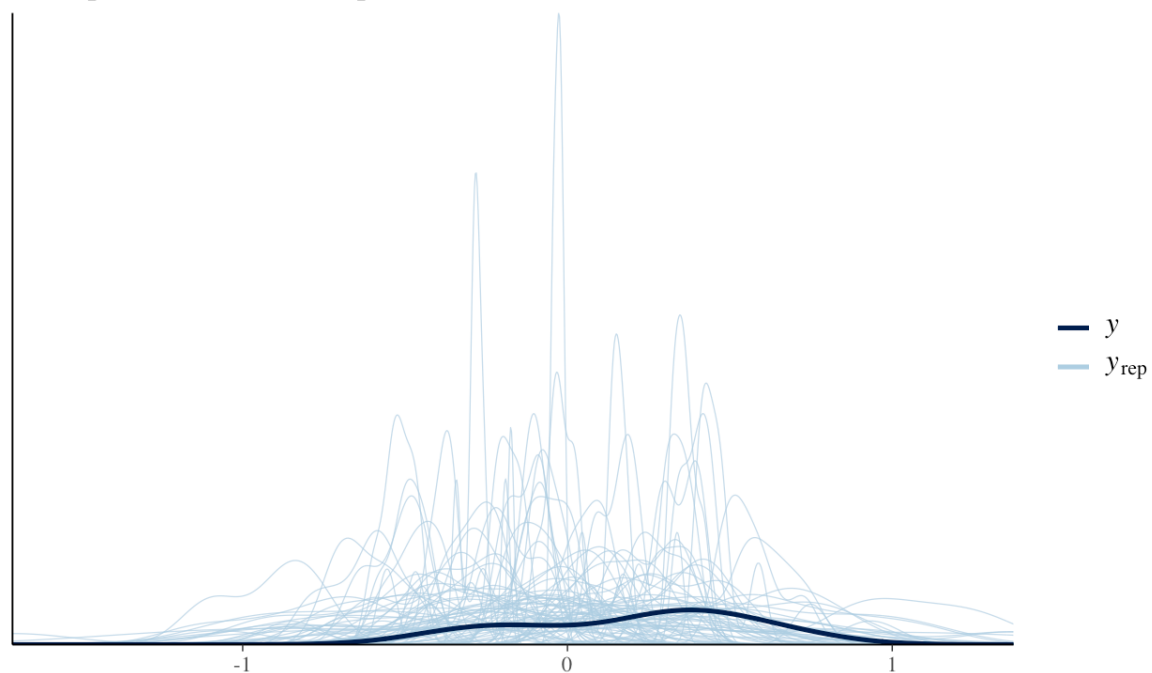
Formula, used in the model to analyze the pitch is:

$$y_i | se(v_i) \sim 1 + (1 | \text{StudyID}),$$

where “ y_i ” is the effect size and the “ v_i ” is standard error of each study, converted to the Cohen's D scale.

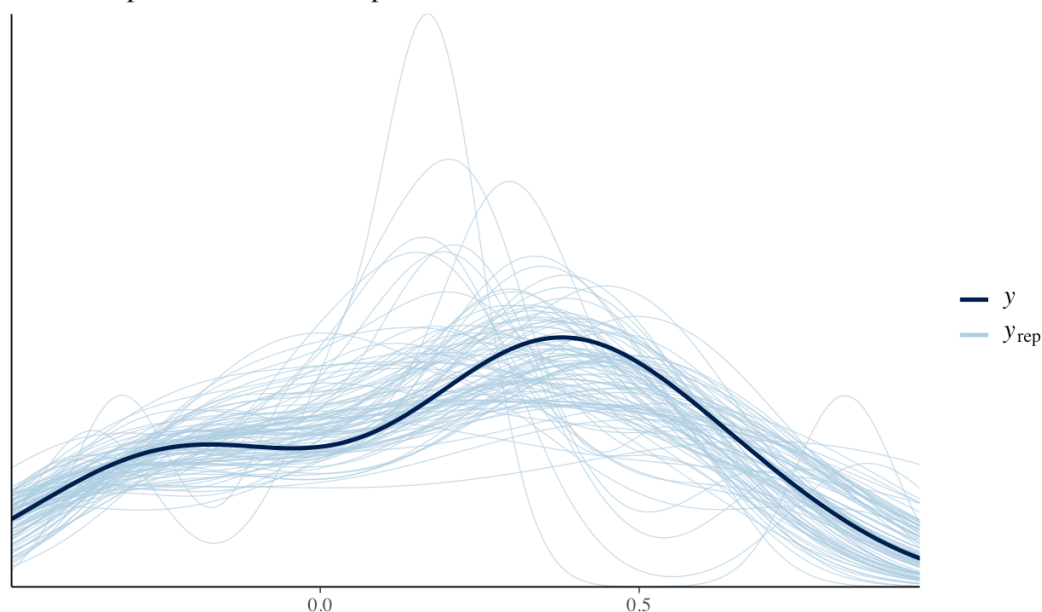
The same priors were used as in the model from the part 1. Again, prior and posterior predictive checks were performed on real data:

Prior-predictive check, empirical data

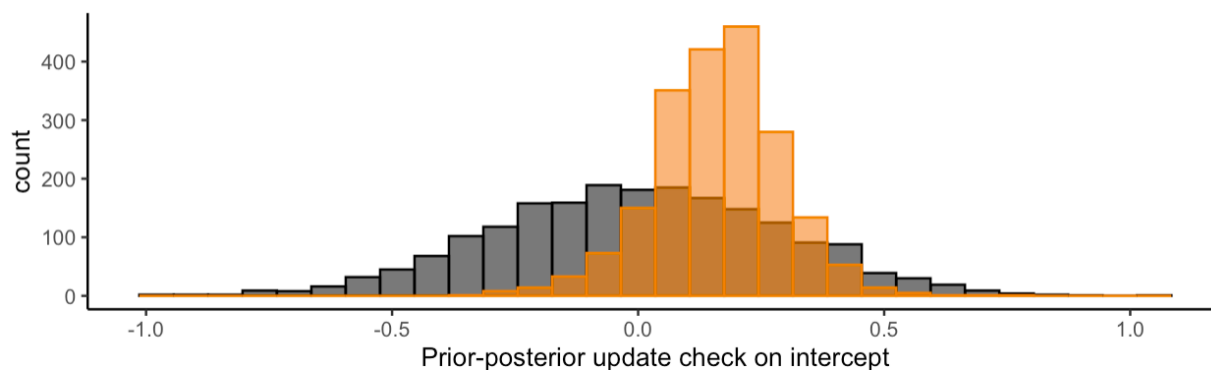
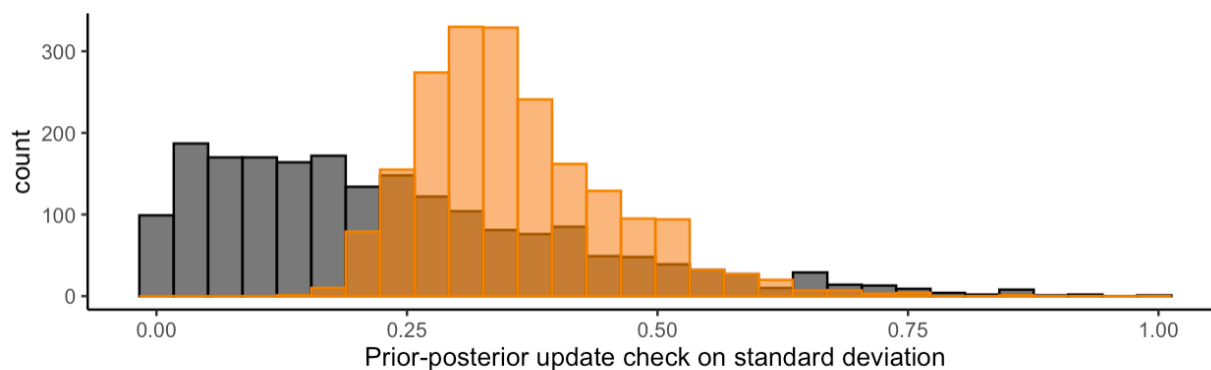


Values of the priors seem to be in the right order of magnitude.

Posterior-predictive check, empirical data



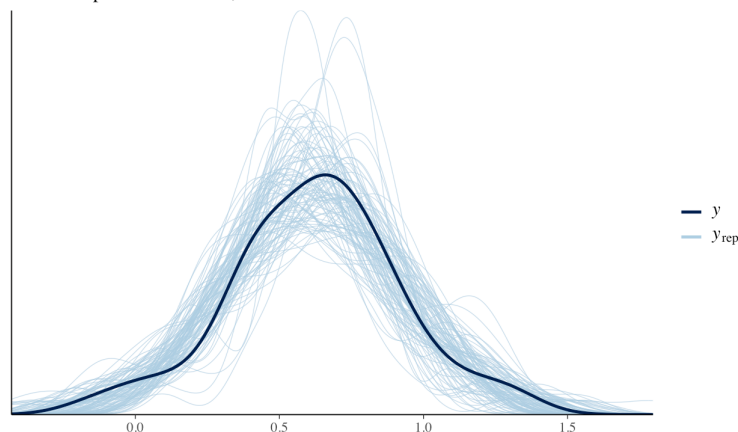
It seems like the model roughly captures the overall distribution of the variable of interest, although there is uncertainty in the predictions of the model. Prior-posterior update check might help to see how well the model updates from the priors after being exposed to the real data.



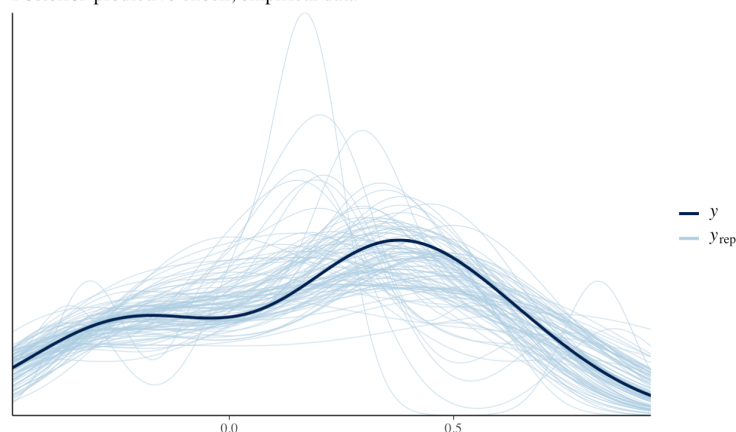
The plots indicate that both posterior distributions become much more confident and learns from the prior. It is not being pushed at the tails of the prior distribution, meaning that the chosen priors might not be adjusted.

When comparing the distribution of effect sizes across the studies, the distribution from the model with the real data looks kind of similar to the distribution of the simulated data with asymmetric publication bias:

Posterior-predictive check, PublishedPos = 1



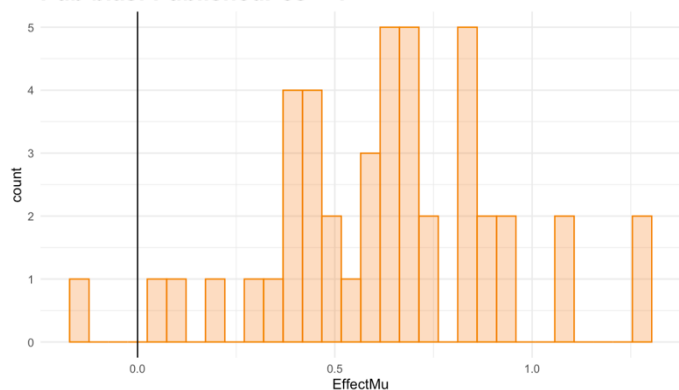
Posterior-predictive check, empirical data



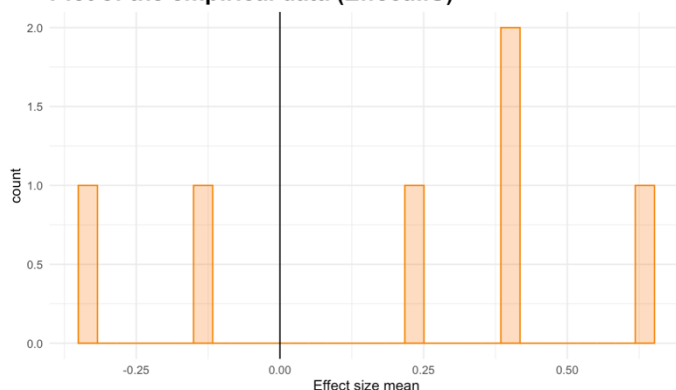
Although the magnitude of possible values is greater in the model with simulated data compared to empirical, it might be possible to make an assumption, that the empirical data also consists of asymmetric publication bias.

If the real data actually has publication bias, and there are multiple studies that do not get to be published, it might be that published studies are positively biased, and we should be careful when looking at their results. In this specific case, the expected results in regards to pitch are published.

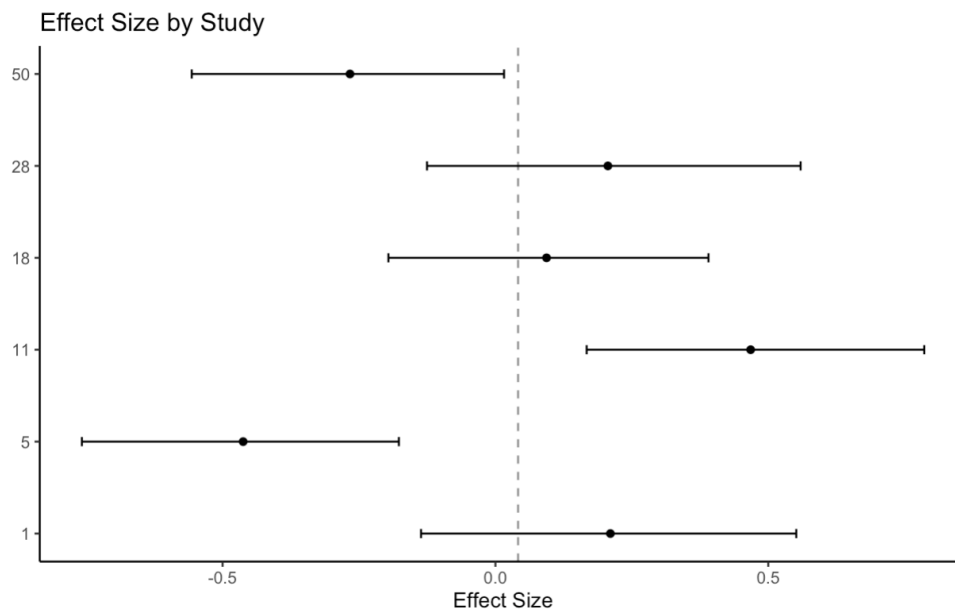
Pub bias: PublishedPos = 1



Plot of the empirical data (EffectMU)

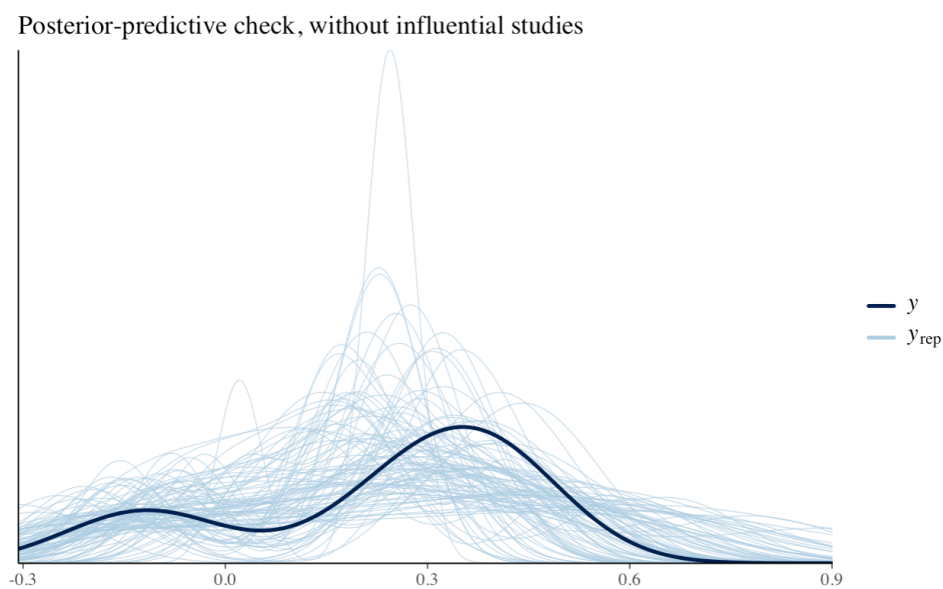


The first histogram above indicates the distribution of effect sizes in the simulated data, where only the studies with significant and expected results are published. The second histogram indicates effect sizes of the studies in the empirical data set. Here, only 6 mean effect sizes are computed, as data set consists of multiple NAs. Nevertheless, the distribution of the empirical data looks closest to the simulated studies on the left, which might again indicate this type of publication bias (of course, keeping in mind that the data on the left is pure simulation).



The plot above visualizes the estimated effects from the model (of empirical data). The mean effect size is indicated by the dashed line, each estimated study effect is represented by the mean and upper/lower quantiles. It seems like the 5th, 11th, and the 50th studies do not capture the overall mean. The 5th and 11th study is the furthest from the rest.

After running the model on the data without influential studies, the posterior predictive check is:



Now, the output looks more like the simulation of published studies only, regardless whether the results are as expected or not.