

# hypothesis testing normal mean with known variance

Dr. Merlise Clyde



## Bayes factor: known $\sigma^2$

- ▶ data  $Y_1, \dots, Y_n$  random sample  $N(\mu, \sigma^2)$

## Bayes factor: known $\sigma^2$

- ▶ data  $Y_1, \dots, Y_n$  random sample  $N(\mu, \sigma^2)$
- ▶ hypothesis  $H_1 : \mu = m_0$

## Bayes factor: known $\sigma^2$

- ▶ data  $Y_1, \dots, Y_n$  random sample  $N(\mu, \sigma^2)$

- ▶ hypothesis
  - $H_1 : \mu = m_0$
  - $H_2 : \mu \neq m_0$

## Bayes factor: known $\sigma^2$

- ▶ data  $Y_1, \dots, Y_n$  random sample  $N(\mu, \sigma^2)$
- ▶ hypothesis 
$$\begin{aligned} H_1 &: \mu = m_0 \\ H_2 &: \mu \neq m_0 \end{aligned}$$
- ▶ priors  $H_1 : \mu = m_0$  with probability 1

## Bayes factor: known $\sigma^2$

- ▶ data  $Y_1, \dots, Y_n$  random sample  $N(\mu, \sigma^2)$
- ▶ hypothesis 
$$\begin{aligned} H_1 &: \mu = m_0 \\ H_2 &: \mu \neq m_0 \end{aligned}$$
- ▶ priors 
$$\begin{aligned} H_1 &: \mu = m_0 \text{ with probability 1} \\ H_2 &: \mu \sim N(m_0, \sigma^2/n_0) \end{aligned}$$

# Bayes factor: known $\sigma^2$

- ▶ data  $Y_1, \dots, Y_n$  random sample  $N(\mu, \sigma^2)$

- ▶ hypothesis

$$H_1 : \mu = m_0$$

$$H_2 : \mu \neq m_0$$

- ▶ priors

$$H_1 : \mu = m_0 \text{ with probability 1}$$

$$H_2 : \mu \sim N(m_0, \sigma^2 / n_0)$$

- ▶ Bayes factor

$$BF[H_1 : H_2] = \frac{p(\text{data} \mid \mu = m_0, \sigma^2)}{\int p(\text{data} \mid \mu, \sigma^2) p(\mu \mid m_0, n_0, \sigma^2) d\mu}$$

# Bayes factor: known $\sigma^2$

- ▶ data  $Y_1, \dots, Y_n$  random sample  $N(\mu, \sigma^2)$

- ▶ hypothesis

$$H_1 : \mu = m_0$$

$$H_2 : \mu \neq m_0$$

- ▶ priors

$$H_1 : \mu = m_0 \text{ with probability 1}$$

$$H_2 : \mu \sim N(m_0, \sigma^2 / \textcolor{orange}{n}_0)$$

- ▶ Bayes factor

$$BF[H_1 : H_2] = \frac{p(\text{data} \mid \mu = m_0, \sigma^2)}{\int p(\text{data} \mid \mu, \sigma^2) p(\mu \mid m_0, \textcolor{orange}{n}_0, \sigma^2) d\mu}$$

$$BF[H_1 : H_2] = \left( \frac{n + \textcolor{orange}{n}_0}{\textcolor{orange}{n}_0} \right)^{1/2} \exp \left\{ -\frac{1}{2} \frac{n}{n + \textcolor{orange}{n}_0} Z^2 \right\}$$

# Bayes factor: known $\sigma^2$

- ▶ data  $Y_1, \dots, Y_n$  random sample  $N(\mu, \sigma^2)$

- ▶ hypothesis

$$H_1 : \mu = m_0$$

$$H_2 : \mu \neq m_0$$

- ▶ priors

$$H_1 : \mu = m_0 \text{ with probability 1}$$

$$H_2 : \mu \sim N(m_0, \sigma^2 / \textcolor{orange}{n}_0)$$

- ▶ Bayes factor

$$BF[H_1 : H_2] = \frac{p(\text{data} \mid \mu = m_0, \sigma^2)}{\int p(\text{data} \mid \mu, \sigma^2) p(\mu \mid m_0, \textcolor{orange}{n}_0, \sigma^2) d\mu}$$

$$BF[H_1 : H_2] = \left( \frac{n + \textcolor{orange}{n}_0}{\textcolor{orange}{n}_0} \right)^{1/2} \exp \left\{ -\frac{1}{2} \frac{n}{n + \textcolor{orange}{n}_0} Z^2 \right\}$$

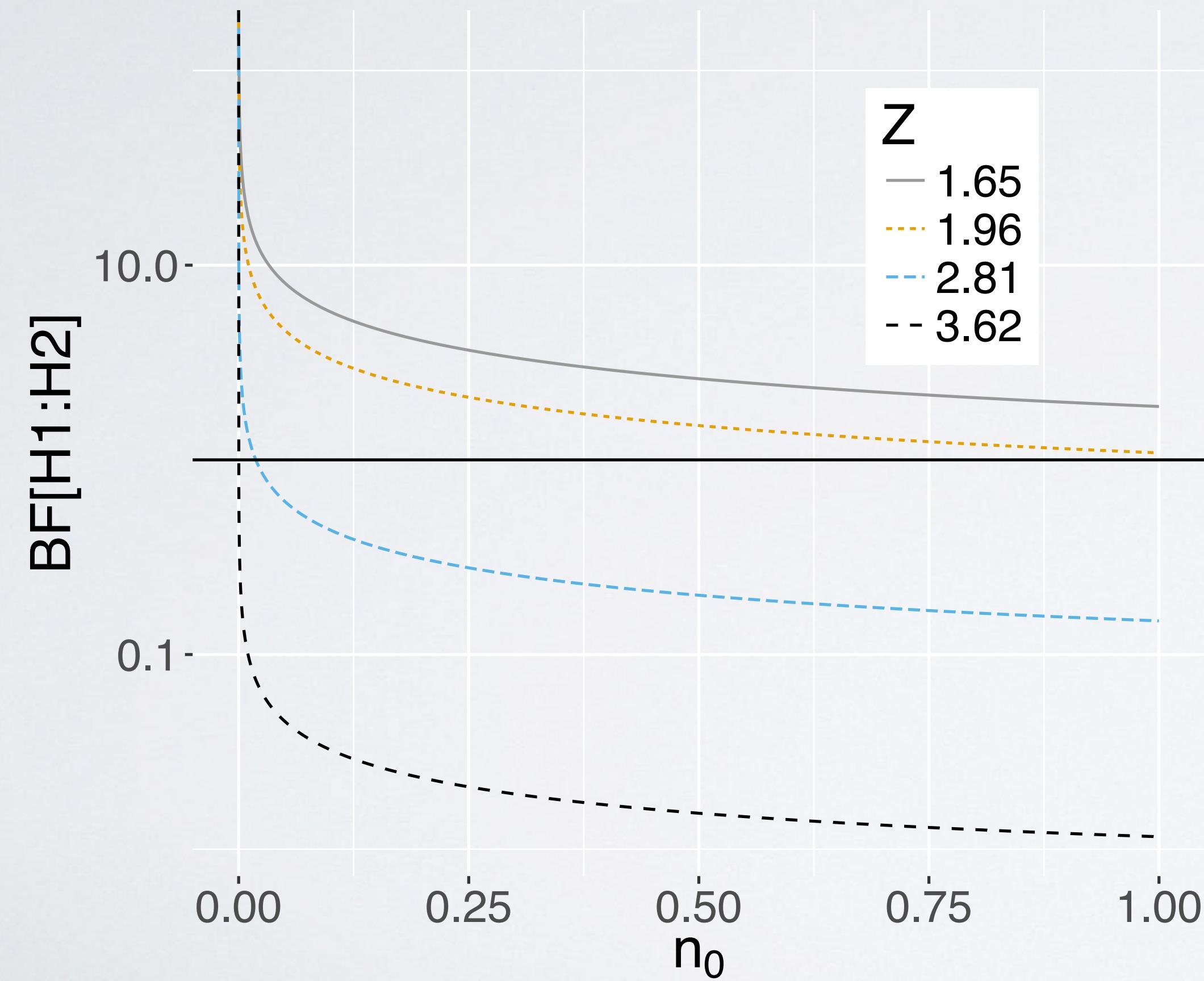
$$Z = \frac{(\bar{Y} - m_0)}{\sigma / \sqrt{n}}$$

vague prior for  $\mu : n = 100$

$$BF[H_1 : H_2] = \left( \frac{n + \textcolor{orange}{n}_0}{\textcolor{orange}{n}_0} \right)^{1/2} \exp \left\{ -\frac{1}{2} \frac{n}{n + \textcolor{orange}{n}_0} Z^2 \right\}$$

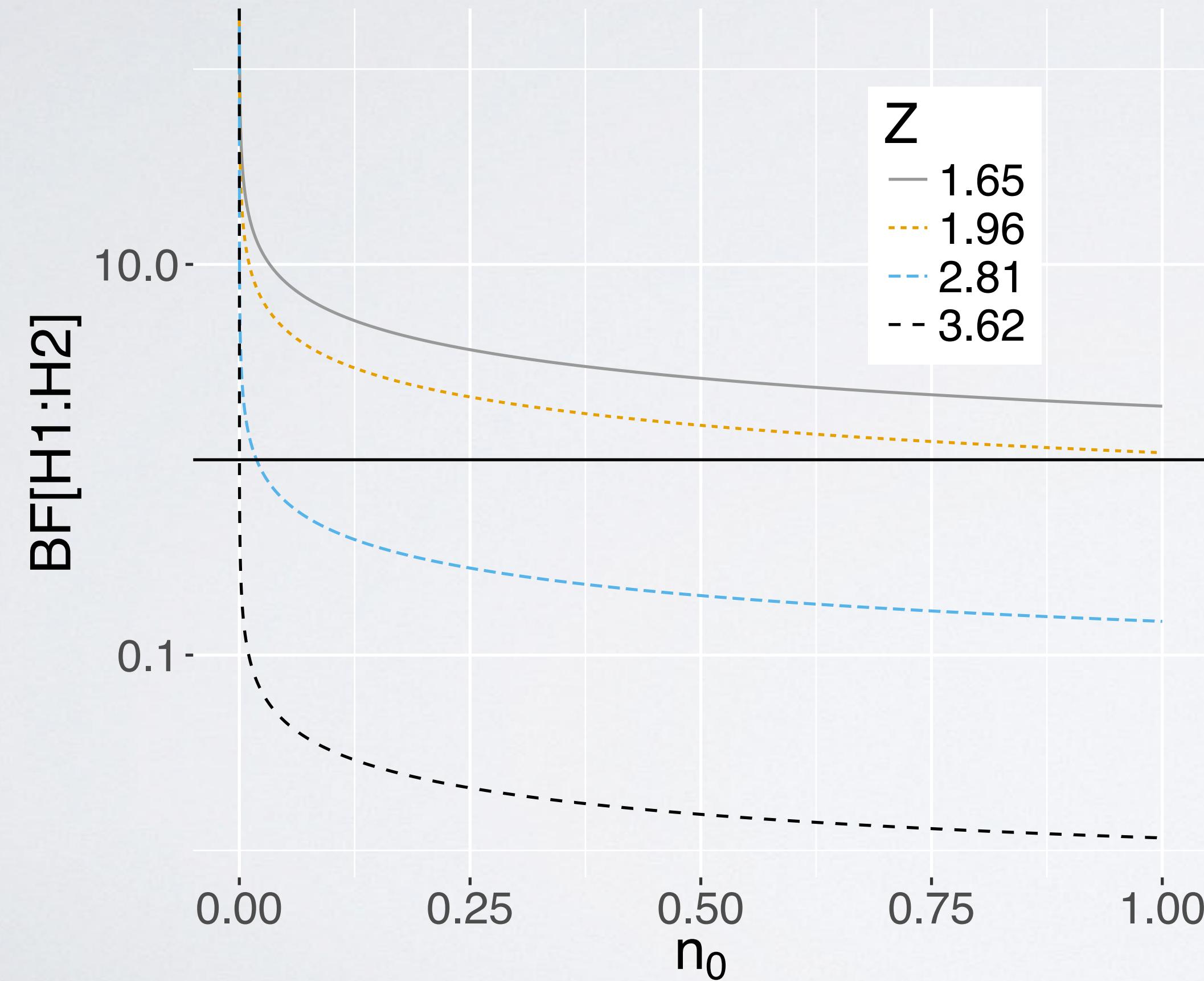
vague prior for  $\mu : n = 100$

$$BF[H_1 : H_2] = \left( \frac{n+n_0}{n_0} \right)^{1/2} \exp \left\{ -\frac{1}{2} \frac{n}{n+n_0} Z^2 \right\}$$



vague prior for  $\mu : n = 100$

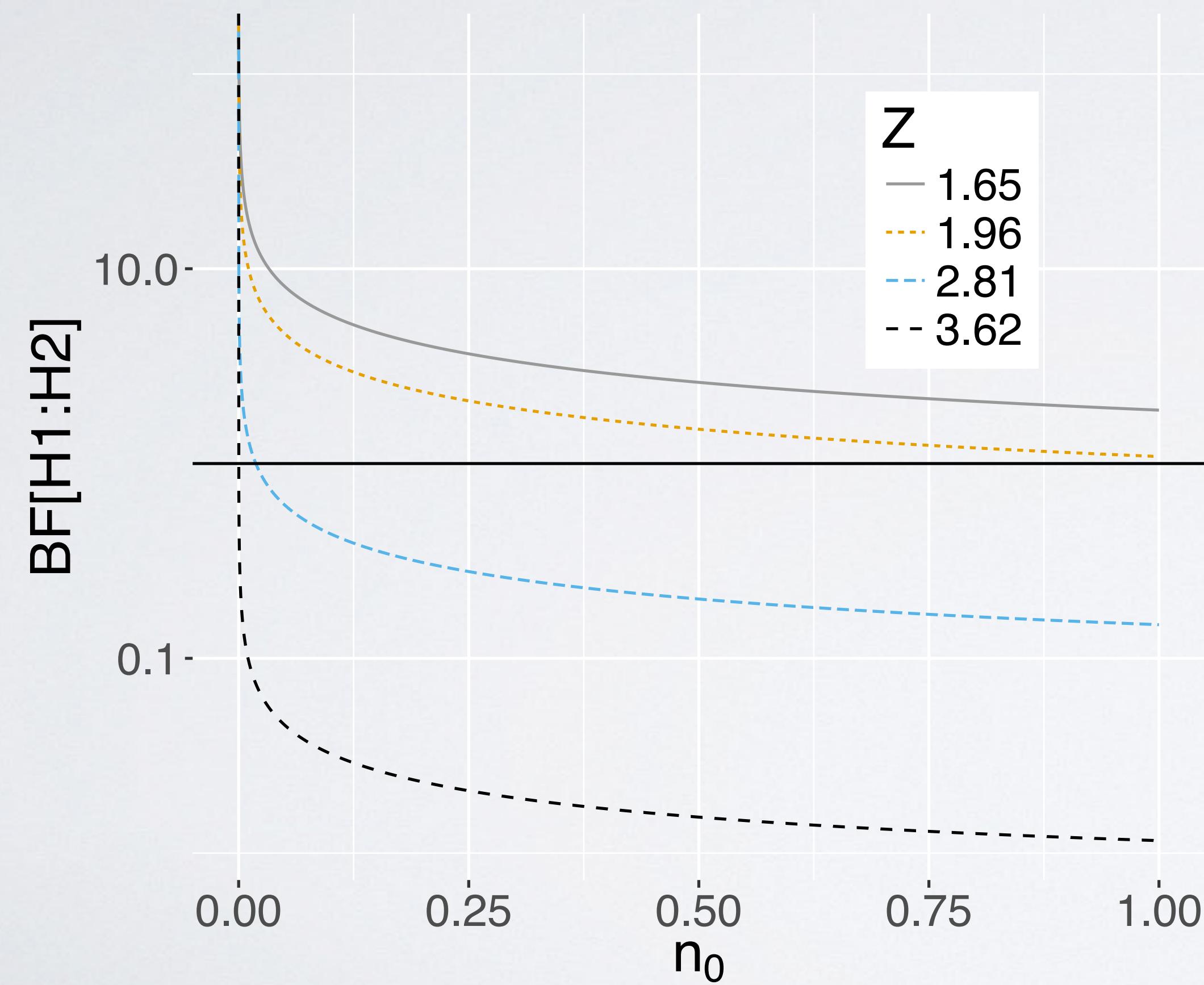
$$BF[H_1 : H_2] = \left( \frac{n+n_0}{n_0} \right)^{1/2} \exp \left\{ -\frac{1}{2} \frac{n}{n+n_0} Z^2 \right\} \quad \blacktriangleright n_0 \text{ goes to zero}$$



# vague prior for $\mu : n = 100$

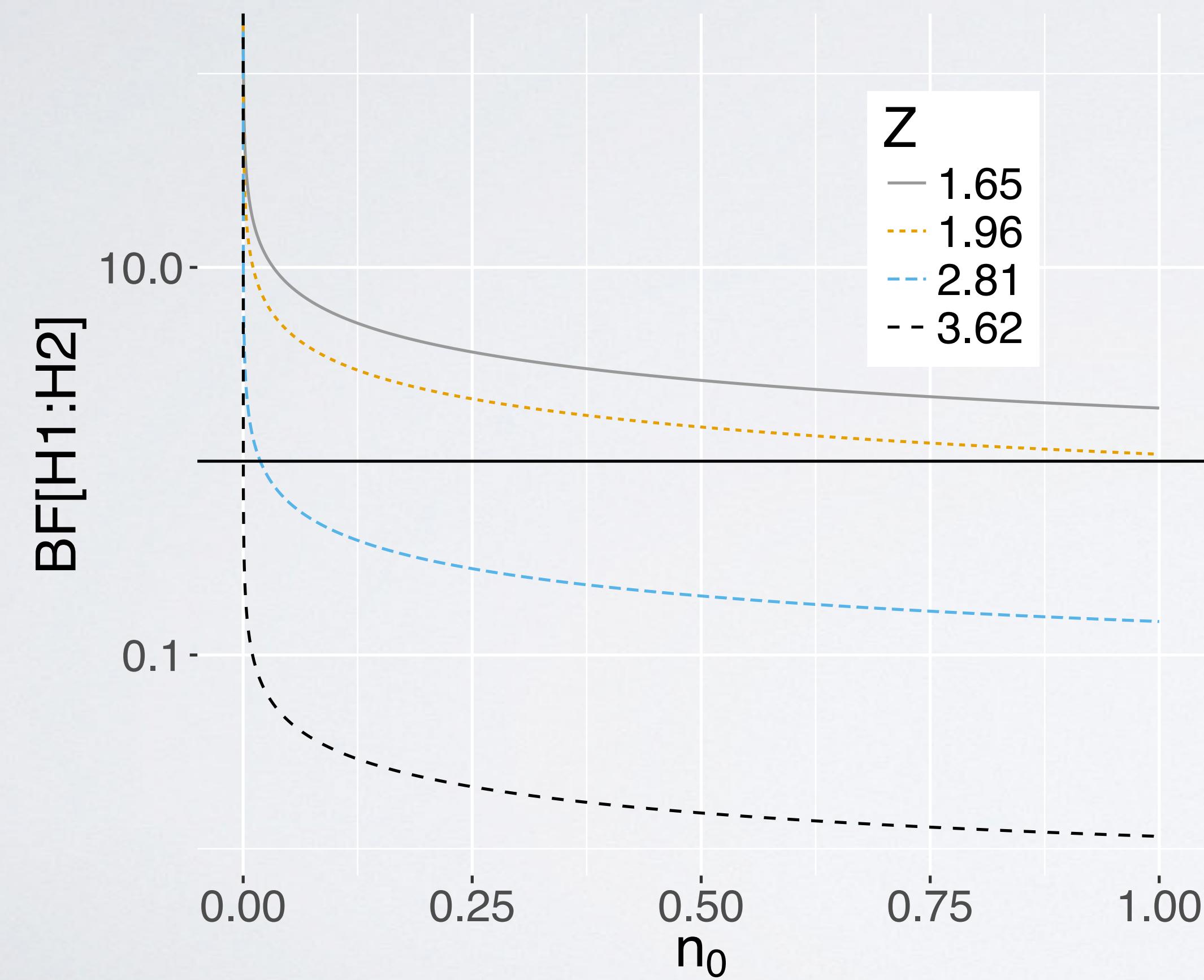
$$BF[H_1 : H_2] = \left( \frac{n+n_0}{n_0} \right)^{1/2} \exp \left\{ -\frac{1}{2} \frac{n}{n+n_0} Z^2 \right\}$$

- ▶  $n_0$  goes to zero
- ▶  $BF[H_1 : H_2]$  goes to infinity



# vague prior for $\mu : n = 100$

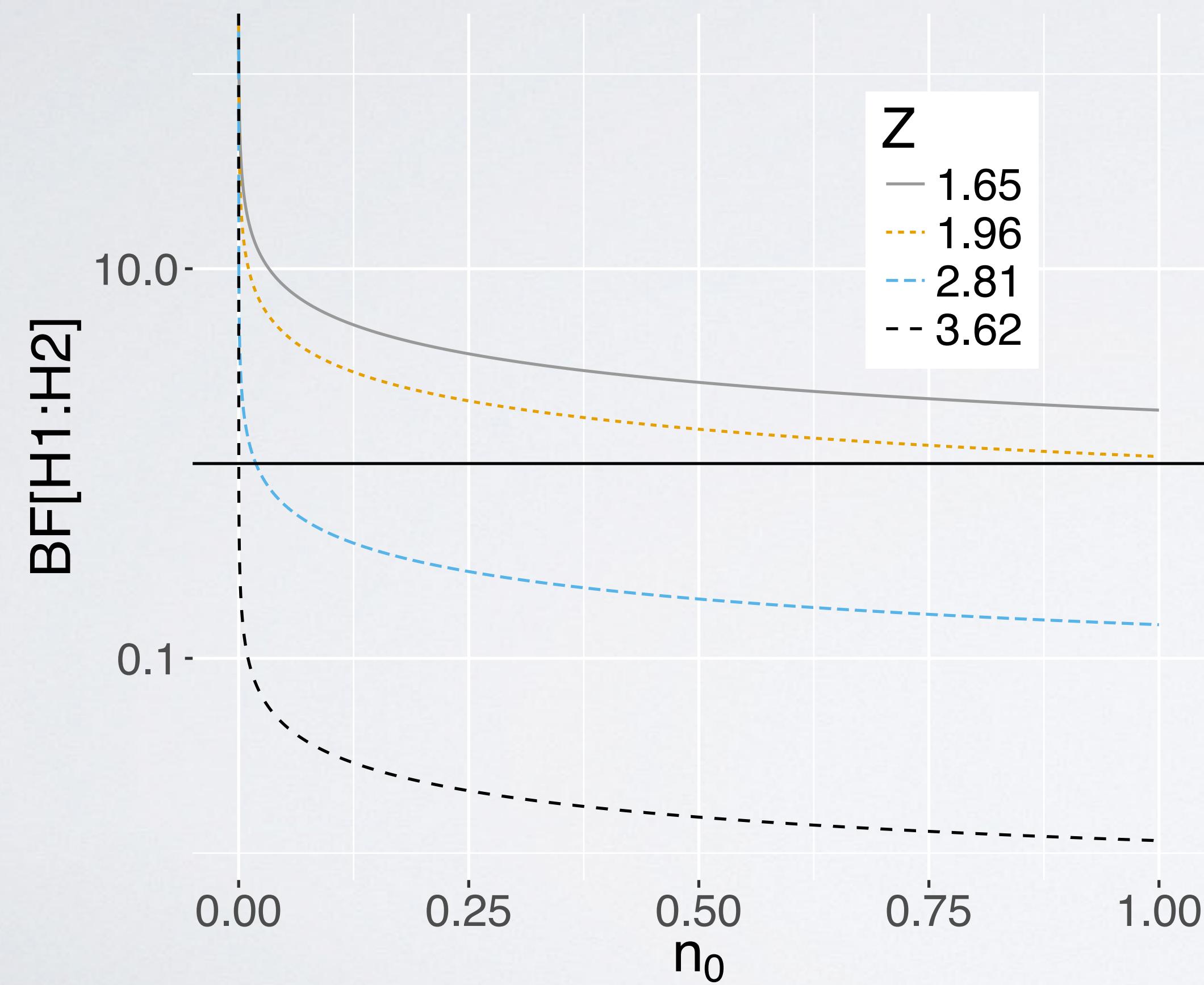
$$BF[H_1 : H_2] = \left( \frac{n+n_0}{n_0} \right)^{1/2} \exp \left\{ -\frac{1}{2} \frac{n}{n+n_0} Z^2 \right\}$$



- ▶  $n_0$  goes to zero
- ▶  $BF[H_1 : H_2]$  goes to infinity
- ▶ no improper priors for  $\mu$

# vague prior for $\mu : n = 100$

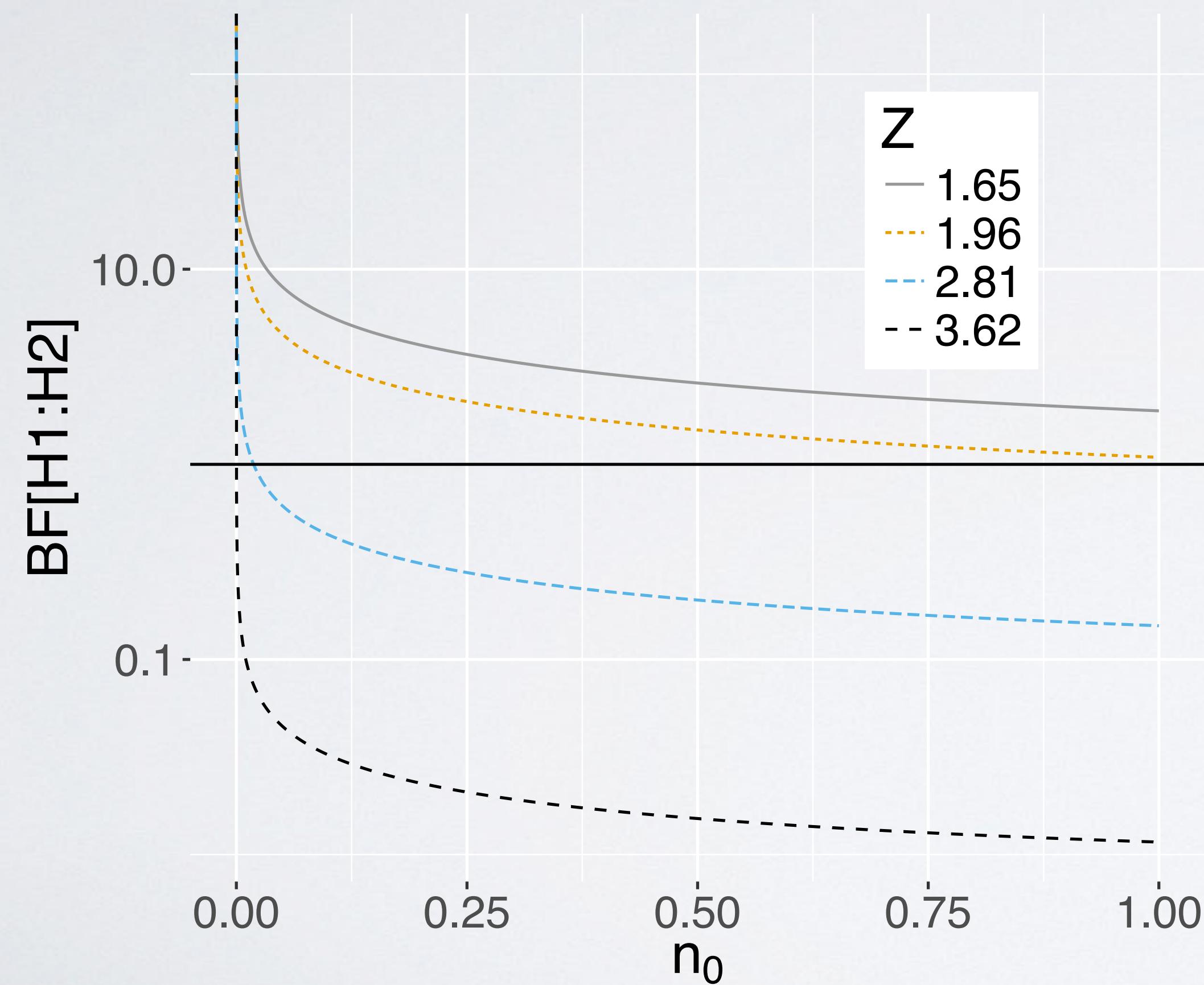
$$BF[H_1 : H_2] = \left( \frac{n+n_0}{n_0} \right)^{1/2} \exp \left\{ -\frac{1}{2} \frac{n}{n+n_0} Z^2 \right\}$$



- ▶  $n_0$  goes to zero
- ▶  $BF[H_1 : H_2]$  goes to infinity
- ▶ no improper priors for  $\mu$
- ▶ problems with vague priors

# vague prior for $\mu : n = 100$

$$BF[H_1 : H_2] = \left( \frac{n+n_0}{n_0} \right)^{1/2} \exp \left\{ -\frac{1}{2} \frac{n}{n+n_0} Z^2 \right\}$$



- ▶  $n_0$  goes to zero
- ▶  $BF[H_1 : H_2]$  goes to infinity
- ▶ no improper priors for  $\mu$
- ▶ problems with vague priors
- ▶ Bartlett's paradox or  
Jeffreys-Lindley's paradox

## prior on standardized effect size

- ▶ standardized effect size:  $\delta = \frac{\mu - m_0}{\sigma}$

## prior on standardized effect size

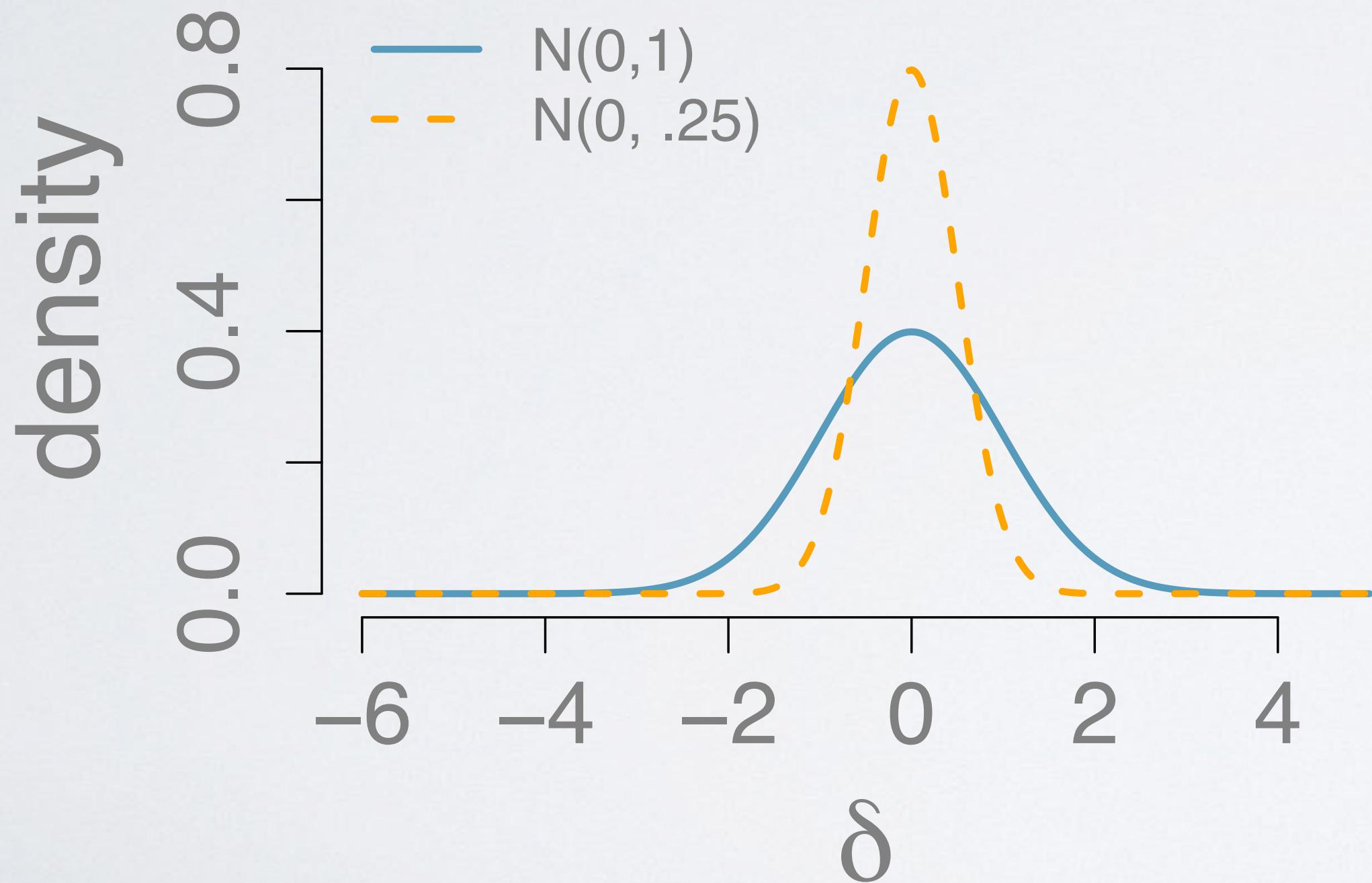
- ▶ standardized effect size:  $\delta = \frac{\mu - m_0}{\sigma}$
- ▶ priors:  $\delta | H_2 \sim N(0, \frac{1}{n_0})$

## prior on standardized effect size

- ▶ standardized effect size:  $\delta = \frac{\mu - m_0}{\sigma}$
- ▶ priors:  $\delta | H_2 \sim N(0, \frac{1}{n_0})$
- ▶ default  $n_0 = 1$  unit information

# prior on standardized effect size

- ▶ standardized effect size:  $\delta = \frac{\mu - m_0}{\sigma}$
- ▶ priors:  $\delta | H_2 \sim N(0, \frac{1}{n_0})$
- ▶ default  $n_0 = 1$  unit information



# extra sensory perception



# extra sensory perception



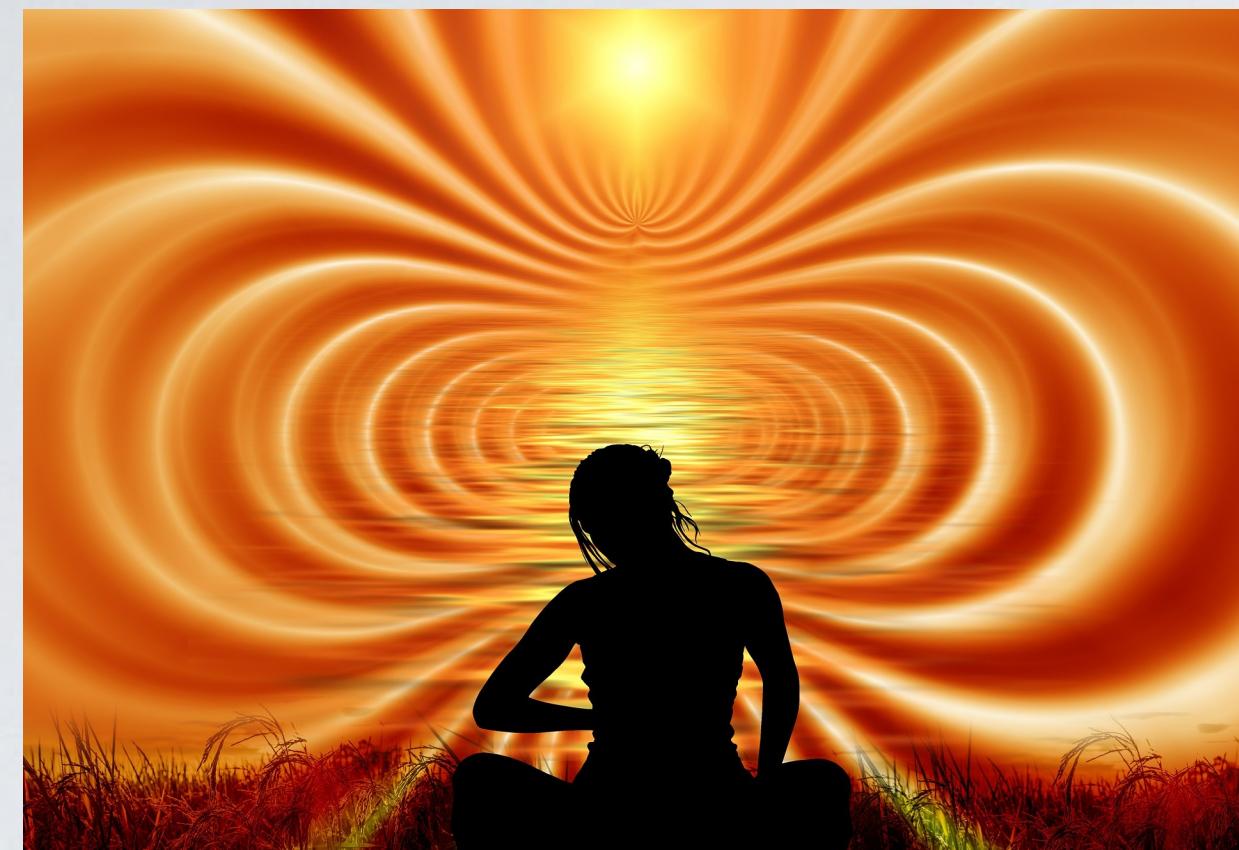
- ▶  $H_1 : \mu = .5$  versus  $H_2 : \mu \neq .5$

# extra sensory perception



- ▶  $H_1 : \mu = .5$  versus  $H_2 : \mu \neq .5$
- ▶ 95% chance std effect is  $(-0.03/\sigma, 0.03/\sigma)$

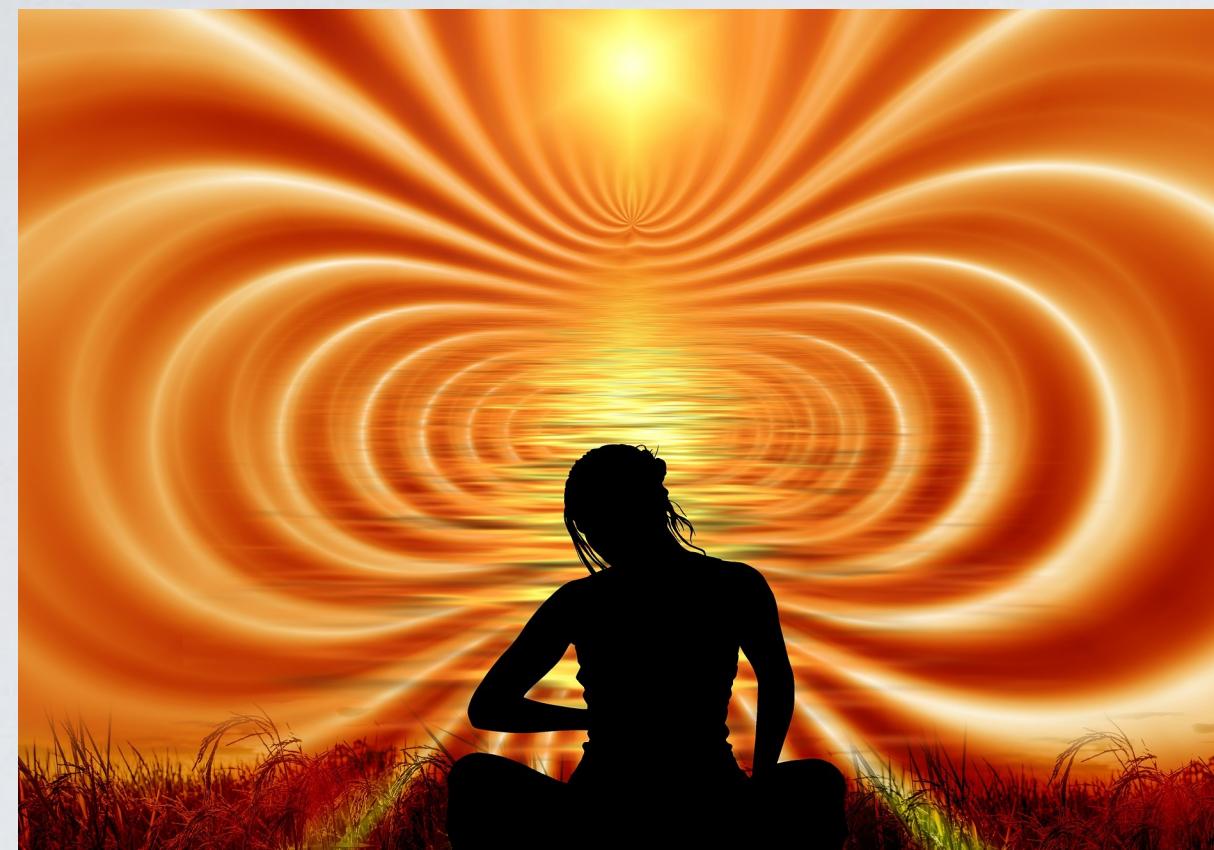
# extra sensory perception



- ▶  $H_1 : \mu = .5$  versus  $H_2 : \mu \neq .5$
- ▶ 95% chance std effect is  $(-0.03/\sigma, 0.03/\sigma)$

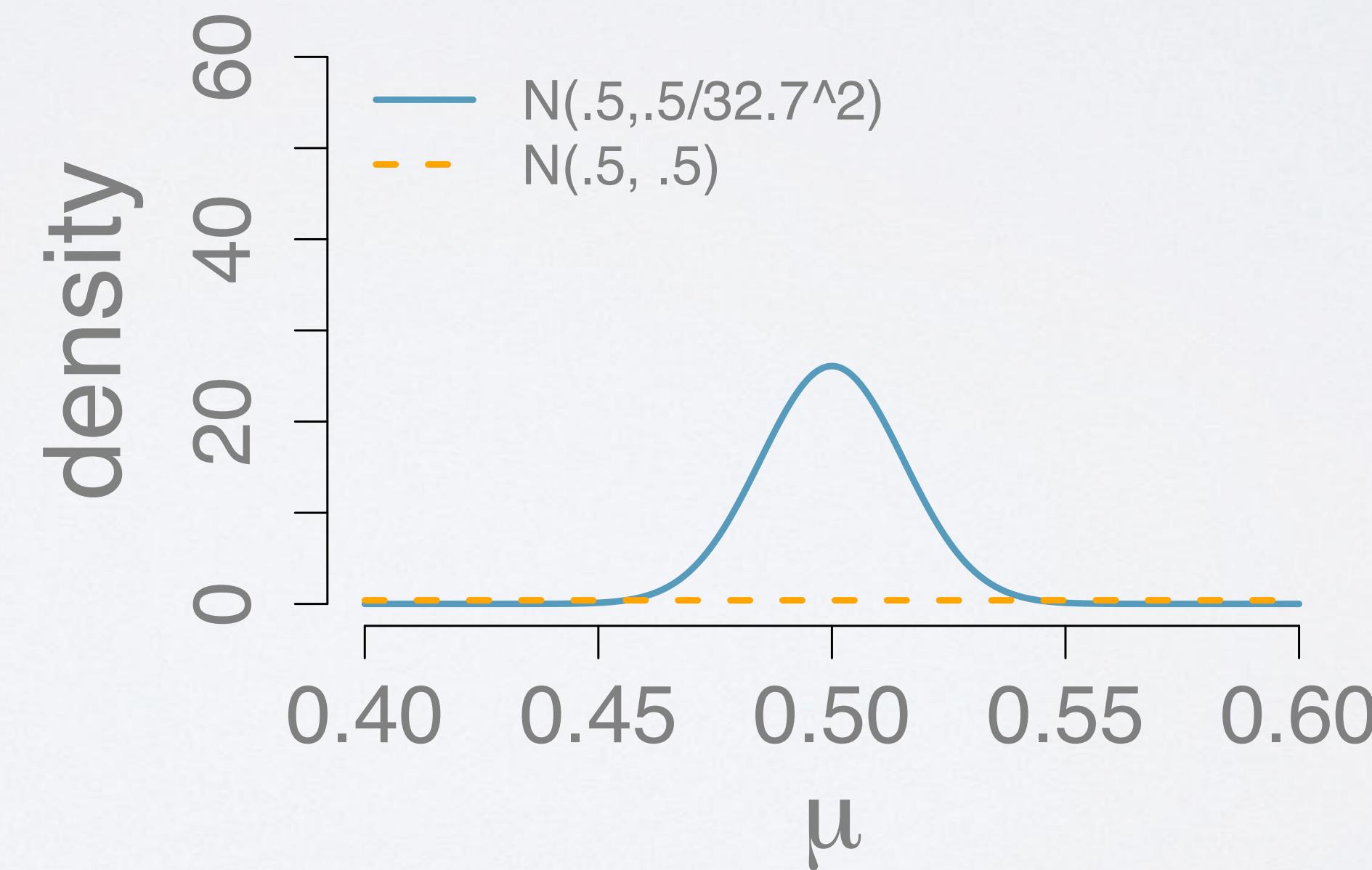
$$n_0 = (1.96 \sigma / 0.03)^2 = 32.7^2$$

# extra sensory perception

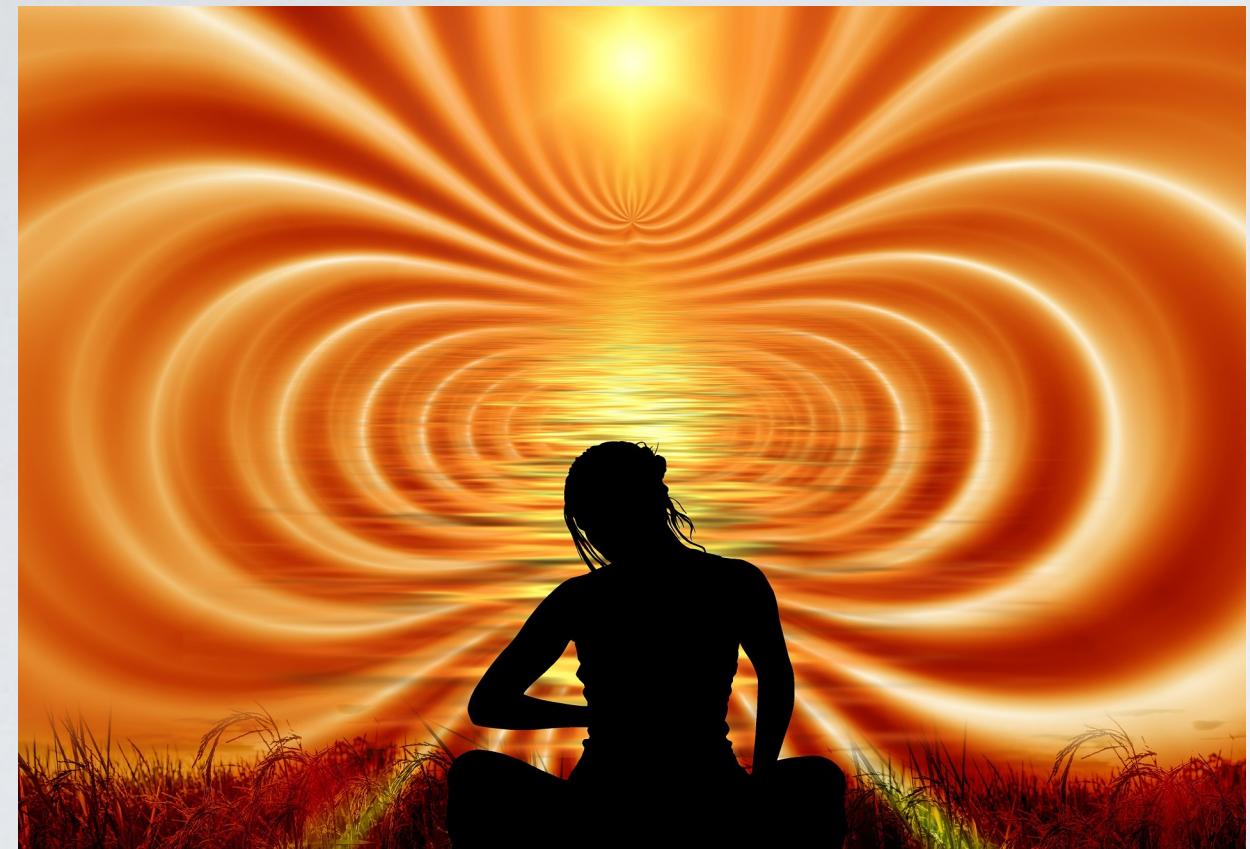


- ▶  $H_1 : \mu = .5$  versus  $H_2 : \mu \neq .5$
- ▶ 95% chance std effect is  $(-0.03/\sigma, 0.03/\sigma)$

$$n_0 = (1.96 \sigma / 0.03)^2 = 32.7^2$$



# Bayes factors



►  $n = 1.0449 \times 10^8$

# Bayes factors



- ▶  $n = 1.0449 \times 10^8$
- ▶  $\bar{y} = 0.500177$

# Bayes factors



- ▶  $n = 1.0449 \times 10^8$
- ▶  $\bar{y} = 0.500177, \sigma = 0.5$

# Bayes factors



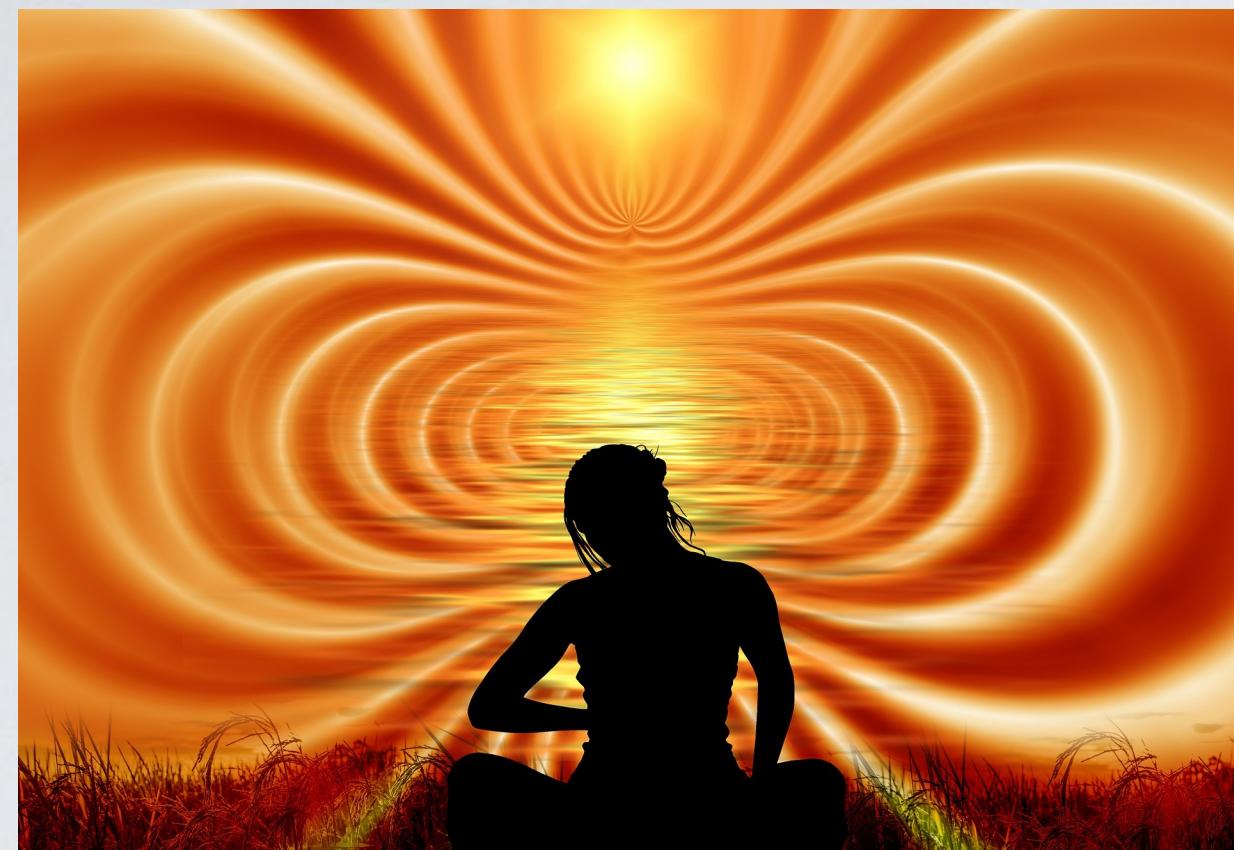
- ▶  $n = 1.0449 \times 10^8$
- ▶  $\bar{y} = 0.500177, \sigma = 0.5$
- ▶  $Z = 3.61$

# Bayes factors



- ▶  $n = 1.0449 \times 10^8$
- ▶  $\bar{y} = 0.500177, \sigma = 0.5$
- ▶  $Z = 3.61$
- ▶ informative  $BF[H1 : H2] = 0.46$

# Bayes factors



- ▶  $n = 1.0449 \times 10^8$
- ▶  $\bar{y} = 0.500177, \sigma = 0.5$
- ▶  $Z = 3.61$
- ▶ informative  $BF[H1 : H2] = 0.46$
- ▶  $BF[H2 : H1] = 1/BF[H1 : H2] = 2.19$

# summary

- ▶ Bayes factors with known  $\sigma$

## summary

- ▶ Bayes factors with known  $\sigma$
- ▶ cannot use vague or improper priors for  $\mu$

## summary

- ▶ Bayes factors with known  $\sigma$
- ▶ cannot use vague or improper priors for  $\mu$
- ▶ Bayes factors with normal priors sensitive to choice of  $n_0$

# summary

- ▶ Bayes factors with known  $\sigma$
- ▶ cannot use vague or improper priors for  $\mu$
- ▶ Bayes factors with normal priors sensitive to choice of  $n_0$
- ▶ subjective information for standardized effect size

# summary

- ▶ Bayes factors with known  $\sigma$
- ▶ cannot use vague or improper priors for  $\mu$
- ▶ Bayes factors with normal priors sensitive to choice of  $n_0$
- ▶ subjective information for standardized effect size
- ▶ ESP versus bias in random number generators

# summary

- ▶ Bayes factors with known  $\sigma$
- ▶ cannot use vague or improper priors for  $\mu$
- ▶ Bayes factors with normal priors sensitive to choice of  $n_0$
- ▶ subjective information for standardized effect size
- ▶ ESP versus bias in random number generators

next: testing with unknown variance