

# From $\Lambda$ CDM to EDE

## Lecture 2: Observation

# Overview

**Lecture 1:** Theory from  $\Lambda$ CDM to EDE (1:30h)

**Hands-on session 1:** From theory to predictions (1h)

**Lecture 2:** Observation – Can EDE solve the Hubble tension? (1h)

**Hands-on session 2:** Let's analyse EDE with the cosmic microwave background and supernovae (1:30h)

# Outline: Can EDE solve the Hubble tension?

1. Overview over statistical tools
2. Recap EDE
3. Can EDE resolve the  $H_0$  tension? – Review of constraints from the literature
4. Conclusions

# **Statistical tools**

**Overview Bayesian & frequentist statistics**

# Statistical tools

- I will only give a very short overview here about:
  - ▶ Point estimates
  - ▶ Bayesian and frequentist parameter intervals
- Matteo Martinelli will go into details about Bayesian statistics and MCMC, so stay tuned for the afternoon lecture!

# The likelihood

- The central quantity in both Bayesian & frequentist statistics is the likelihood:

$$\mathcal{L}(x | \mu(\theta)) \equiv \mathcal{L}_x(\theta)$$

- “Probability of the data  $x$  given the model  $\mu$  with parameter(s)  $\theta$ ”
- The data  $x$ , model  $\mu$ , parameter(s)  $\theta$  can be a single number or a vector

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- The likelihood is typically computed for a fixed (measured or simulated) data set, hence  $x$  is often written as a subscript or dropped
- The larger  $\mathcal{L}_x(\theta)$  the better the agreement of the model with the data

# Gaussian likelihood

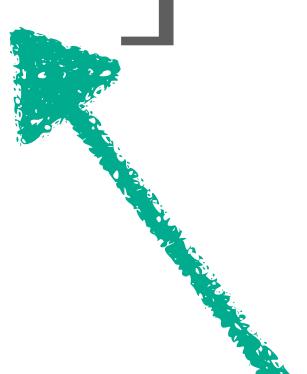
- One very common likelihood is the Gaussian likelihood

$$\mathcal{L}_x(\mu(\theta)) = \frac{1}{\sqrt{(2\pi)^n |C|}} \exp \left[ -\frac{1}{2} \sum_{i,j} [x^i - \mu^i(\theta)]^T C_{ij}^{-1} [x^j - \mu^j(\theta)] \right]$$


- The covariance matrix  $C_{ij}$  gives the correlation between different data points; it typically needs to be estimated from simulations or analytically

# Gaussian likelihood

- In one dimension, the likelihood simplifies:

$$\mathcal{L}_x(\mu(\theta)) = \frac{1}{\sqrt{2\pi\sigma^2}} \exp \left[ -\frac{[x - \mu(\theta)]^2}{2\sigma^2} \right]$$


variance

- The Gaussian likelihood is commonly encountered in cosmological data analysis and many other areas

# Point Estimates

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1. Maximum likelihood estimator (MLE)  $\hat{\theta}$ :

$$\left. \frac{\partial \ln(\mathcal{L})}{\partial \theta_i} \right|_{\theta=\hat{\theta}} = 0$$

- I.e.  $\hat{\theta}$  is the parameter (set), which maximizes the likelihood
- Since  $\mathcal{L}$  typically has one extremum, the above condition is enough
- This is also called the “bestfit”

# Point Estimates

## 2. Least squares estimator:

$$\frac{\partial \chi^2}{\partial \theta_i} \Bigg|_{\theta=\hat{\theta}} = 0 \text{ with}$$

$$\chi^2(\theta) = \sum_{i,j} [x^i - \mu^i(\theta)]^T C_{ij}^{-1} [x^j - \mu^j(\theta)]$$

“data - model”

covariance matrix

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- This is also called the “minimum chi<sup>2</sup>”
- The least-squares estimator coincides with the MLE for a Gaussian likelihood  
 $\chi^2 = -2 \log \mathcal{L}$

$$\mathcal{L}_x(\mu(\theta)) \sim \exp \left[ -\frac{1}{2} \sum_{i,j} [x^i - \mu^i(\theta)]^T C_{ij}^{-1} [x^j - \mu^j(\theta)] \right]$$

# Bayes theorem

$$P(\theta | x) = \frac{\mathcal{L}(x | \theta) \cdot \pi(\theta)}{P(x)}$$

The diagram illustrates the components of Bayes' theorem. The equation is  $P(\theta | x) = \frac{\mathcal{L}(x | \theta) \cdot \pi(\theta)}{P(x)}$ . Three green arrows point to the terms: one arrow points to  $\mathcal{L}(x | \theta)$  with the label "evidence", another points to  $\pi(\theta)$  with the label "prior", and a third points to the entire fraction with the label "posterior".

- The posterior gives the “probability of the model parameters  $\theta$  given the data  $x$ ”
- Since the evidence depends only on the data, it contributes only a constant factor and is not important

# Parameter intervals

- Apart from finding the “bestfit” parameter, it is important to give an **errorbar** or **interval of a parameter**, e.g.  $H_0 = 70.0 \pm 1.0 \text{ km/s/Mpc}$
- There are two main philosophies of statistics:
  - Bayesian statistics
  - Frequentist statistics
- Both construct parameter intervals in different ways

# Bayesian credible intervals

- ▶ Uses Bayes theorem: based on posterior (data & prior):

$$P(\theta | x) \sim \mathcal{L}(x | \theta) \cdot \pi(\theta)$$

- ▶ Credible interval  $[\theta^-, \theta^+]$  of C.L.  $\alpha$ :

$$\int_{\theta^-}^{\theta^+} P(\theta | x) d\theta = \alpha$$

- ▶ Method: Obtain posterior from Markov-Chain Monte-Carlo (MCMC)

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- ▶ Method: Obtain posterior from Markov-Chain Monte-Carlo (MCMC)
- ▶ Interpretation: “Given the data and the priors, I believe that the true value  $\theta_0$  is within  $[\theta^-, \theta^+]$  with probability  $\alpha$ ” – degree of belief

# Bayesian credible intervals

- ▶ How to choose the prior?



$$P(\theta | x) \sim \mathcal{L}(x | \theta) \cdot \pi(\theta)$$

- ▶ The prior can encode prior information and beliefs
- ▶ It can be flat, log, Gaussian,...

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- ▶ If the data is not very constraining, i.e. the likelihood  $\mathcal{L}$  is very flat, then the parameter constraints can have a strong dependence on the prior  $\pi$
- ▶ Hence, it is important to check the sensitivity of the results on the choice of  $\pi$

# Frequentist confidence intervals

- ▶ Based on the goodness of fit to the data, i.e. on the likelihood (only data):

$$\mathcal{L}(x | \theta)$$

- ▶ No posterior, no prior
- ▶ Interpretation: “The true value  $\theta_0$  is contained in  $[\theta^-, \theta^+]$  a fraction  $\alpha$  of the experiments” — statement about the repetition of the experiment
- ▶ Method: Profile likelihood & Neyman construction
  - ▶ in the limit of a large data set (the likelihood ratio follows a  $\chi^2$ -distribution)

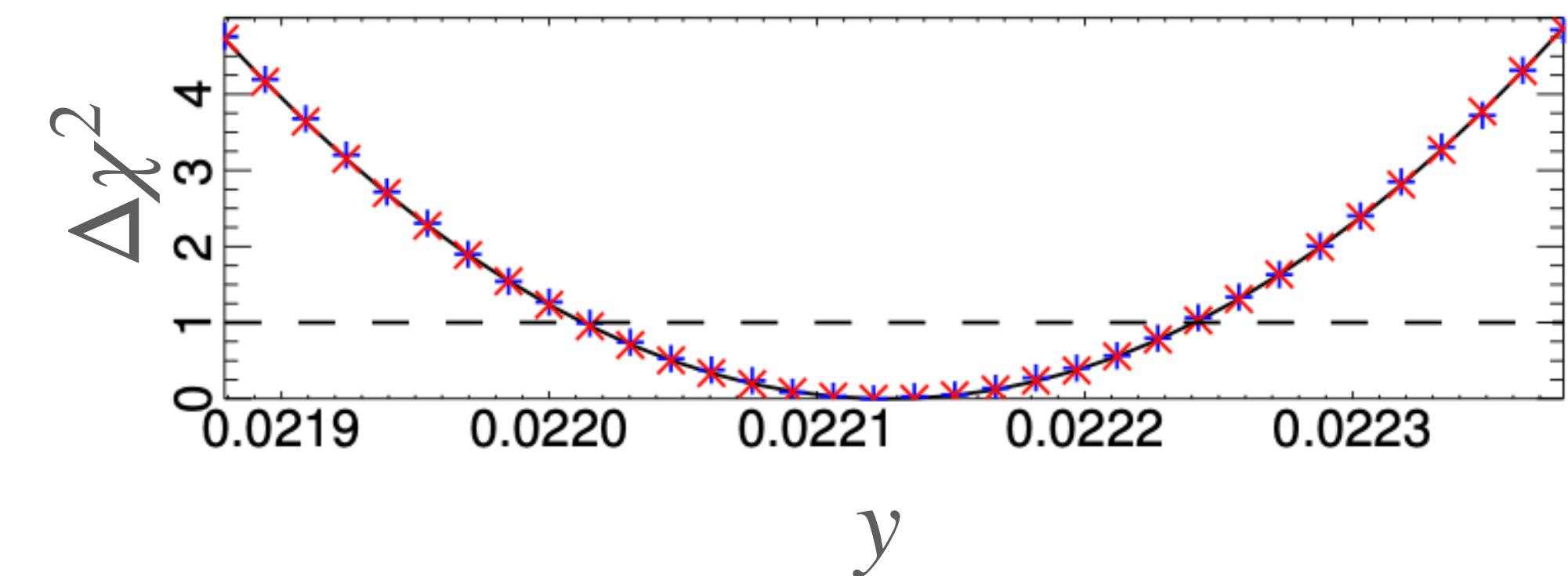
# Frequentist confidence intervals

**Profile likelihood:** Fix parameter  $y$  of interest to different values, minimize  $\chi^2 = -2 \log(\mathcal{L})$  w.r.t. all other parameters

**Confidence interval (graphical method):**

*In the asymptotic limit (Wilks theorem):*

- ▶ Read off  $1\sigma$  at the intersection with  $\Delta\chi^2 = 1$
- ▶ Read off  $2\sigma$  at the intersection with  $\Delta\chi^2 = 4$
- ▶ etc.



*Example: Planck col. XVI, 2013*

# Bayesian and frequentist intervals

## **Bayesian intervals (MCMC):**

- Includes prior knowledge as priors:  
$$P(M | D) \sim \mathcal{L}(D | M) \cdot P(M).$$
- Identifies bulk volumes that fit data well.
- Problem: If data is not constraining enough, can be subject to prior effects.  
Solution: Use more/better data, less free parameters.

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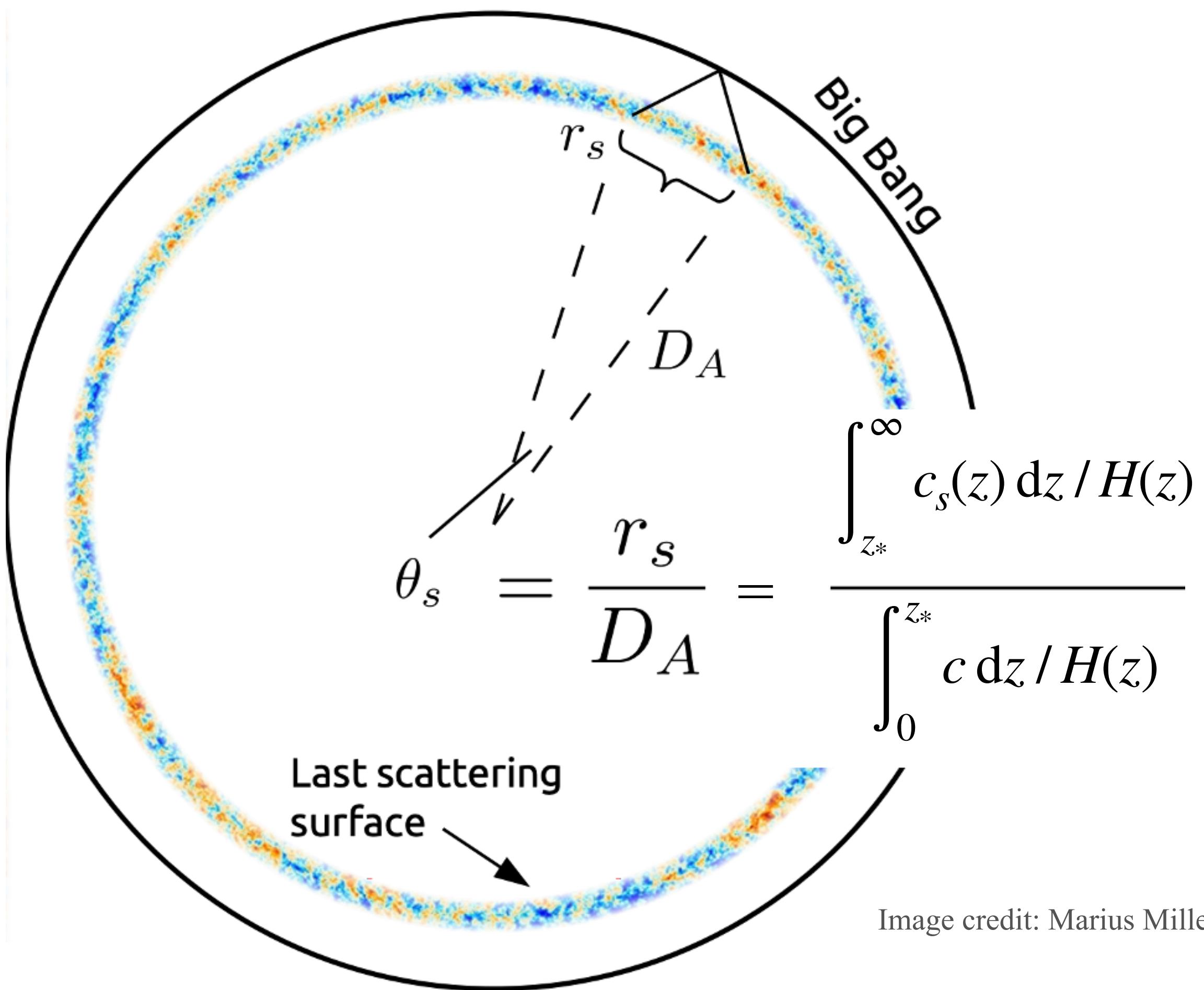
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Both statistical approaches should agree in the limit of a large

# Recap EDE

# Early Dark Energy (EDE)

Kamionkowski et al. 2014, Karwal & Kamionkowski 2016, Caldwell & Devulder 2018, Poulin et al. 2019



Idea of EDE:

Angular scale of sound horizon  $\theta_s$  measured with 0.03% precision by *Planck*.



Introducing an additional component before recombination reduces the sound horizon  $r_s$ .



Angular diameter distance  $D_A$  decreases.



$H_0$  increases.

$$H(z) = H_0 \sqrt{\Omega_m(z) + \Omega_r(z) + \Omega_\Lambda}$$

# Early Dark Energy (EDE)

Kamionkowski et al. 2014, Karwal & Kamionkowski 2016, Caldwell & Devulder 2018, Poulin et al. 2019

Axion-like EDE model: scalar field  $\phi$  with potential

$$V(\phi) = V_0 [1 - \cos(\phi/f)]^n$$

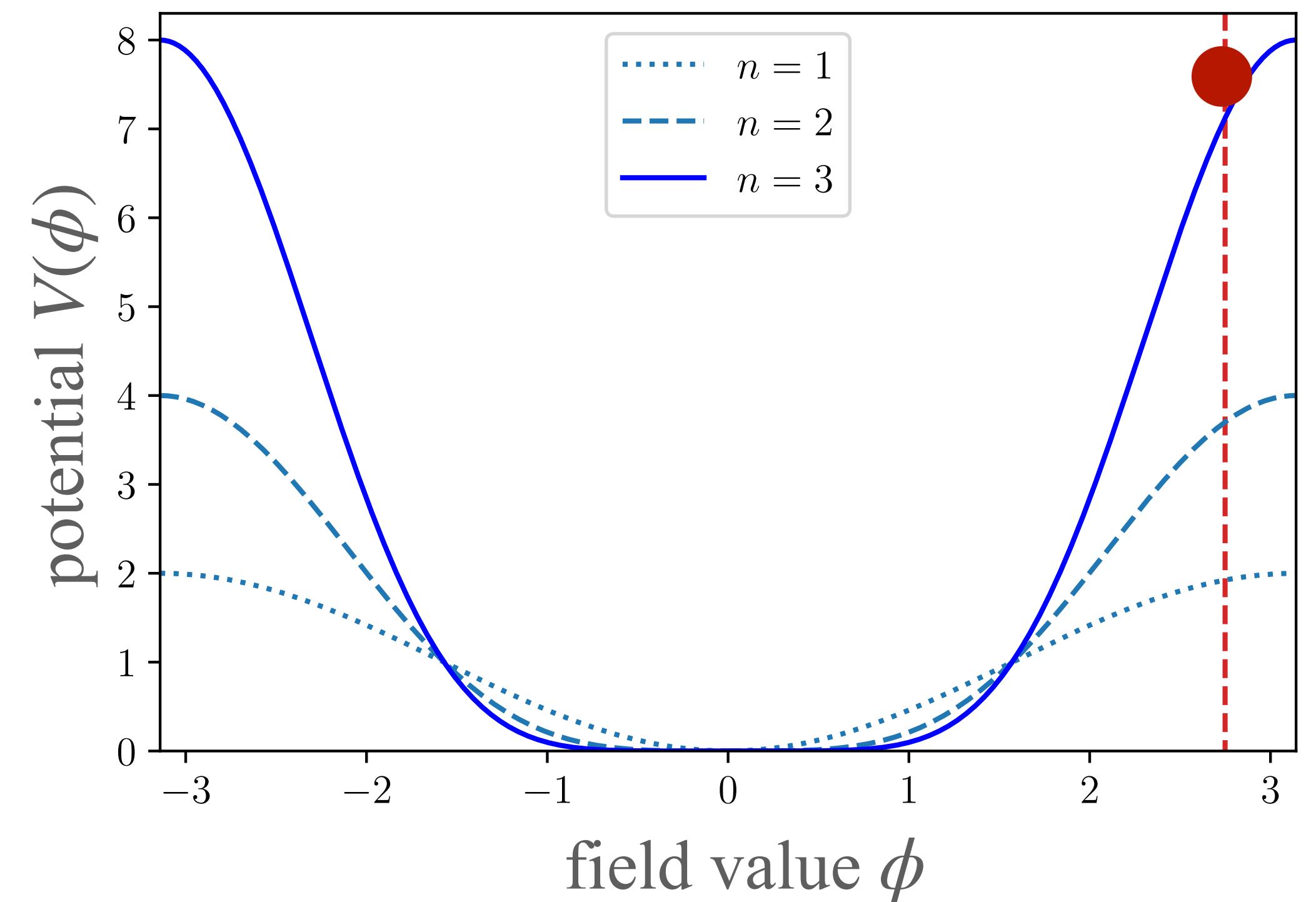
Free parameters:

$m$ : ‘mass’ of  $\phi$   $\rightarrow V_0 = m^2 f^2$ ,

$f$ : decay constant,

$\theta_i \equiv \phi_i/f$ : initial value of the field,

$n = 3$ : EDE decays quickly enough.



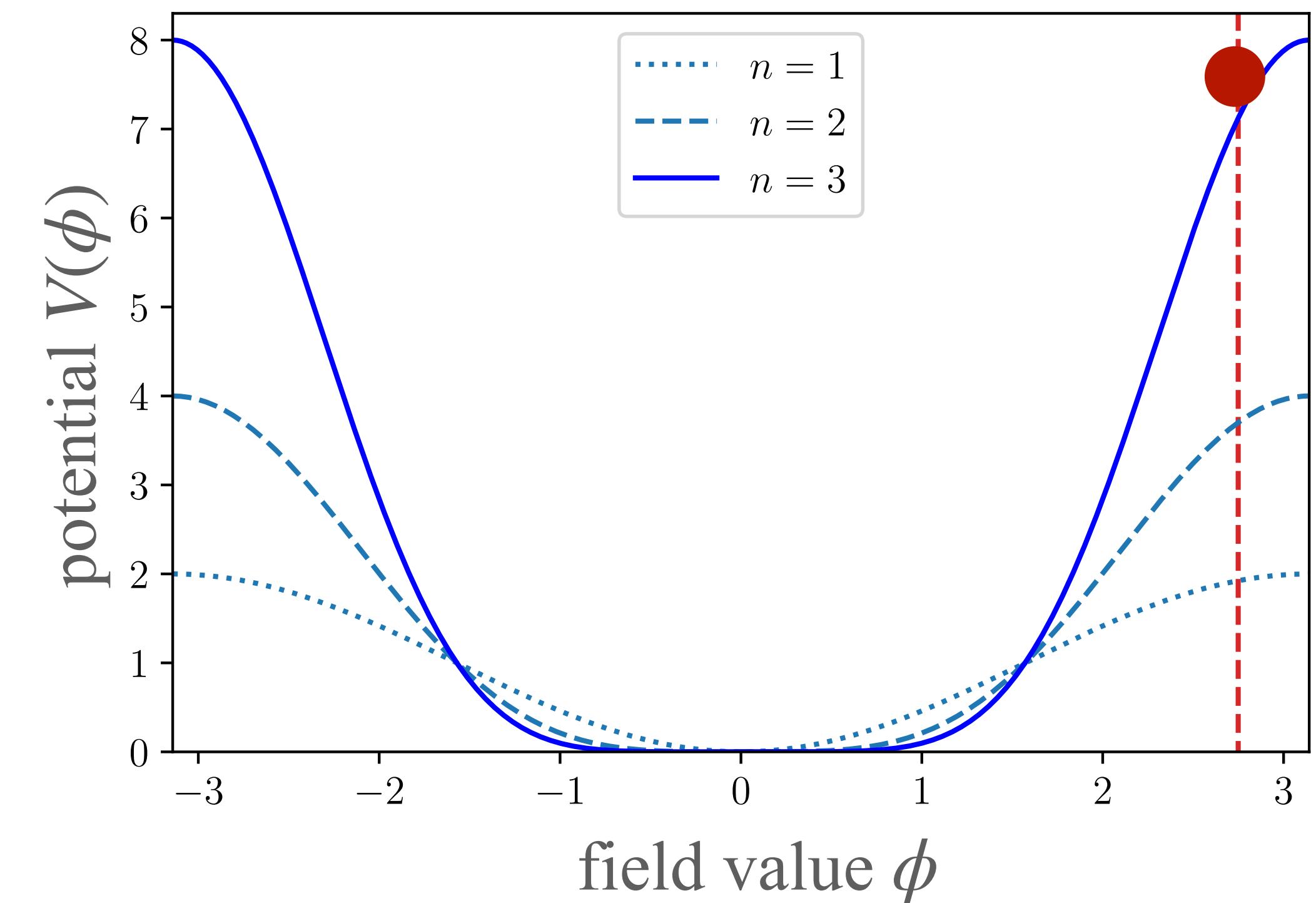
→ Field inspired by axion ( $n = 1$ ) with extremely small mass  $\sim 10^{-27}$  eV

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Dynamics:  $\ddot{\phi} + 3H\dot{\phi} + \frac{dV(\phi)}{d\phi} = 0$

- Initially: Hubble friction dominates:  $\phi$  frozen  
—> behaves as DE
- At  $z_c$ : Hubble friction < potential term:  $\phi$  starts oscillating and decays faster than matter



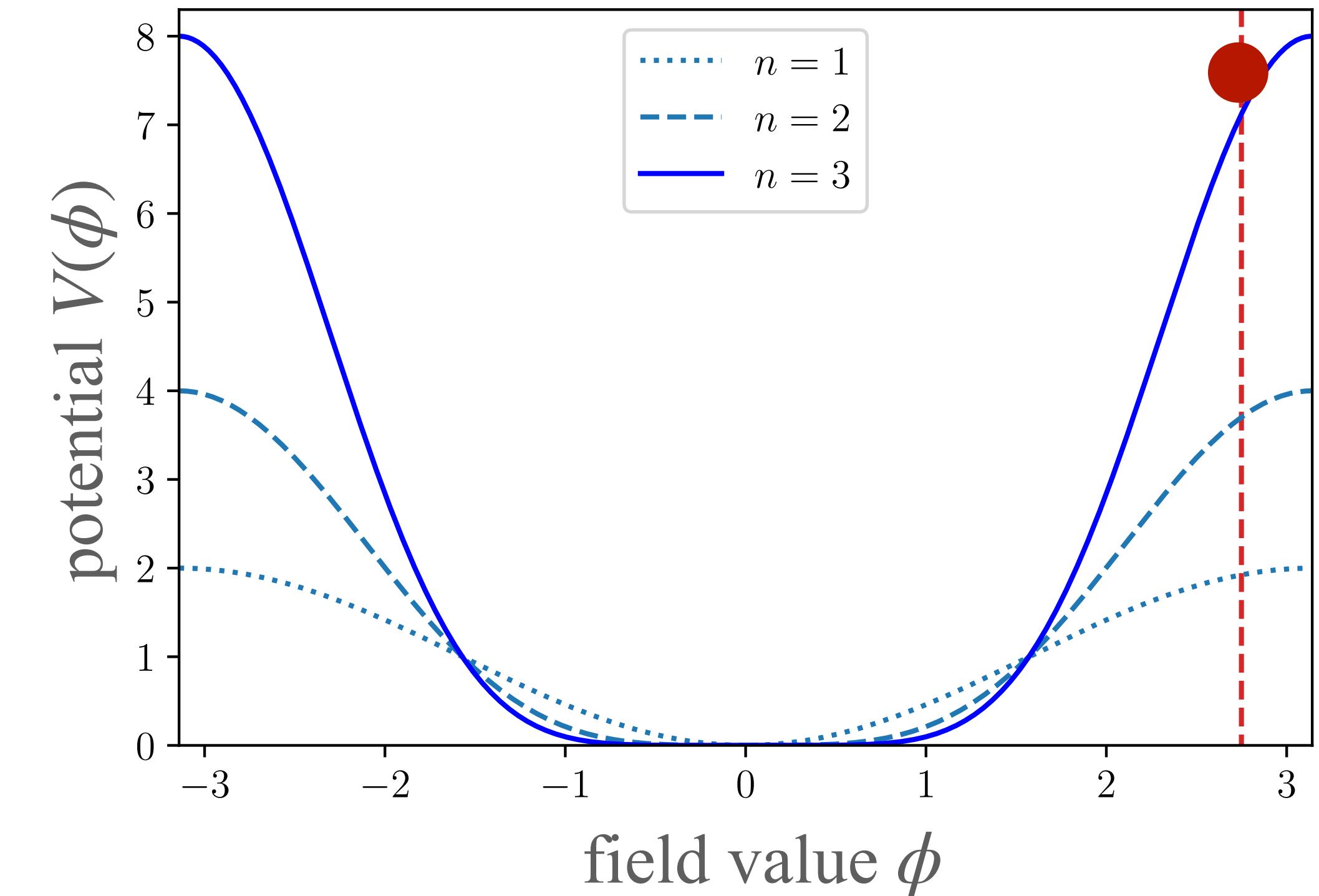
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Eq. of state:  $\left\{ \begin{array}{l} w = -1 \text{ for } z > z_c \\ \langle w \rangle = \frac{n-1}{n+1} = \frac{1}{2} \text{ for } z < z_c \end{array} \right.$



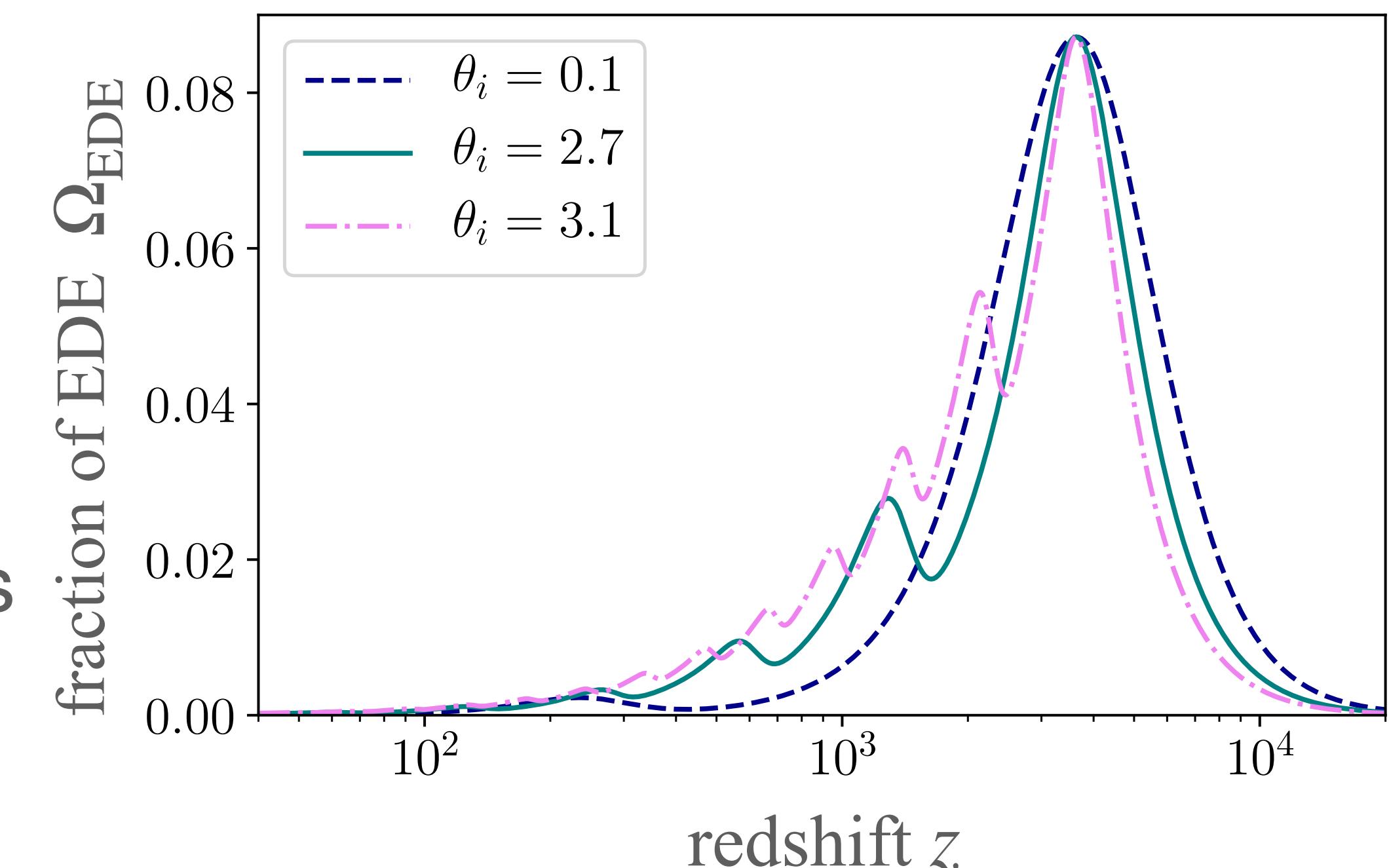
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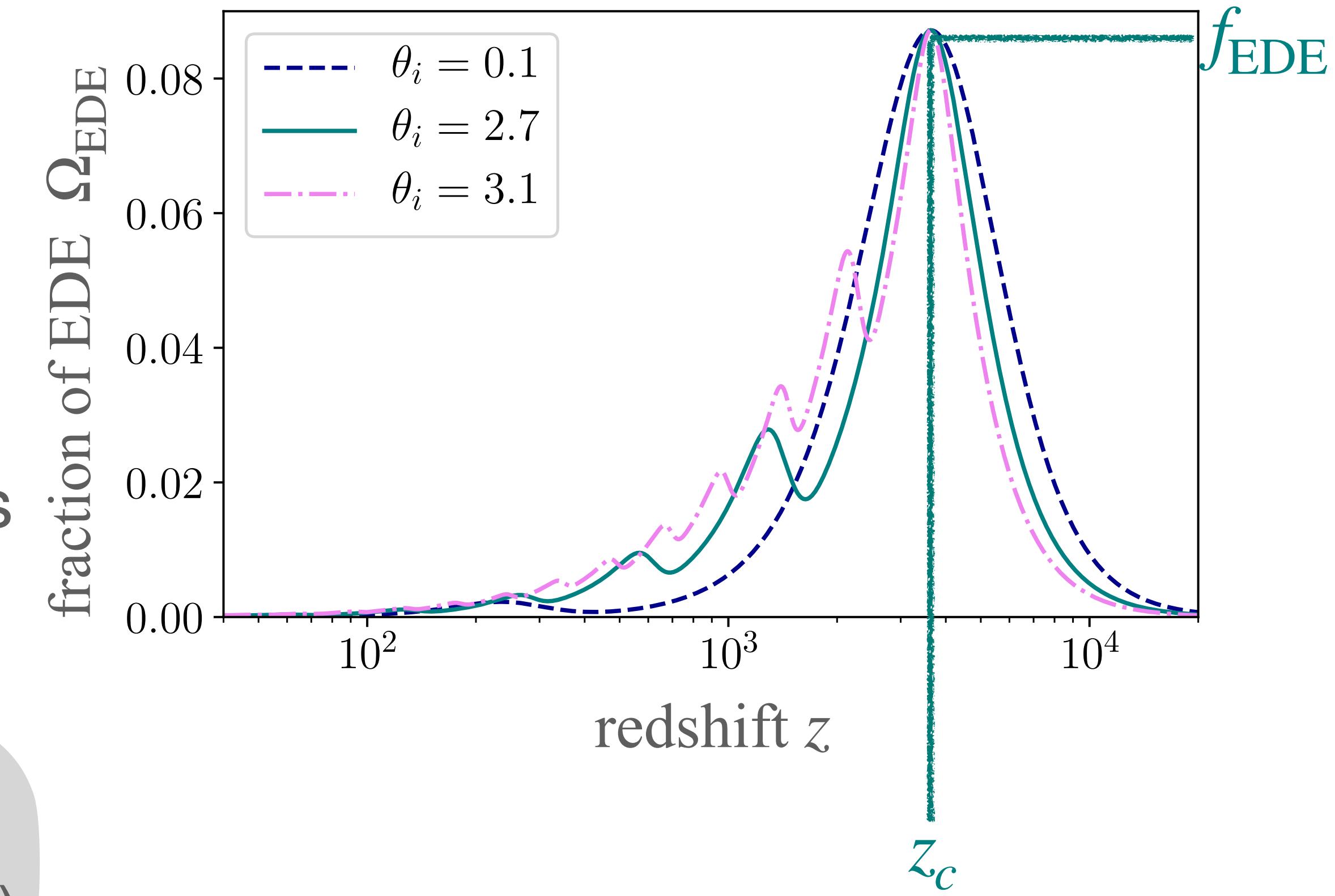
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From  $m, f, \theta_i$  one can calculate:  
 $f_{\text{EDE}}, z_c, \theta_i$  (3 additional parameters to  $\Lambda\text{CDM}$ )



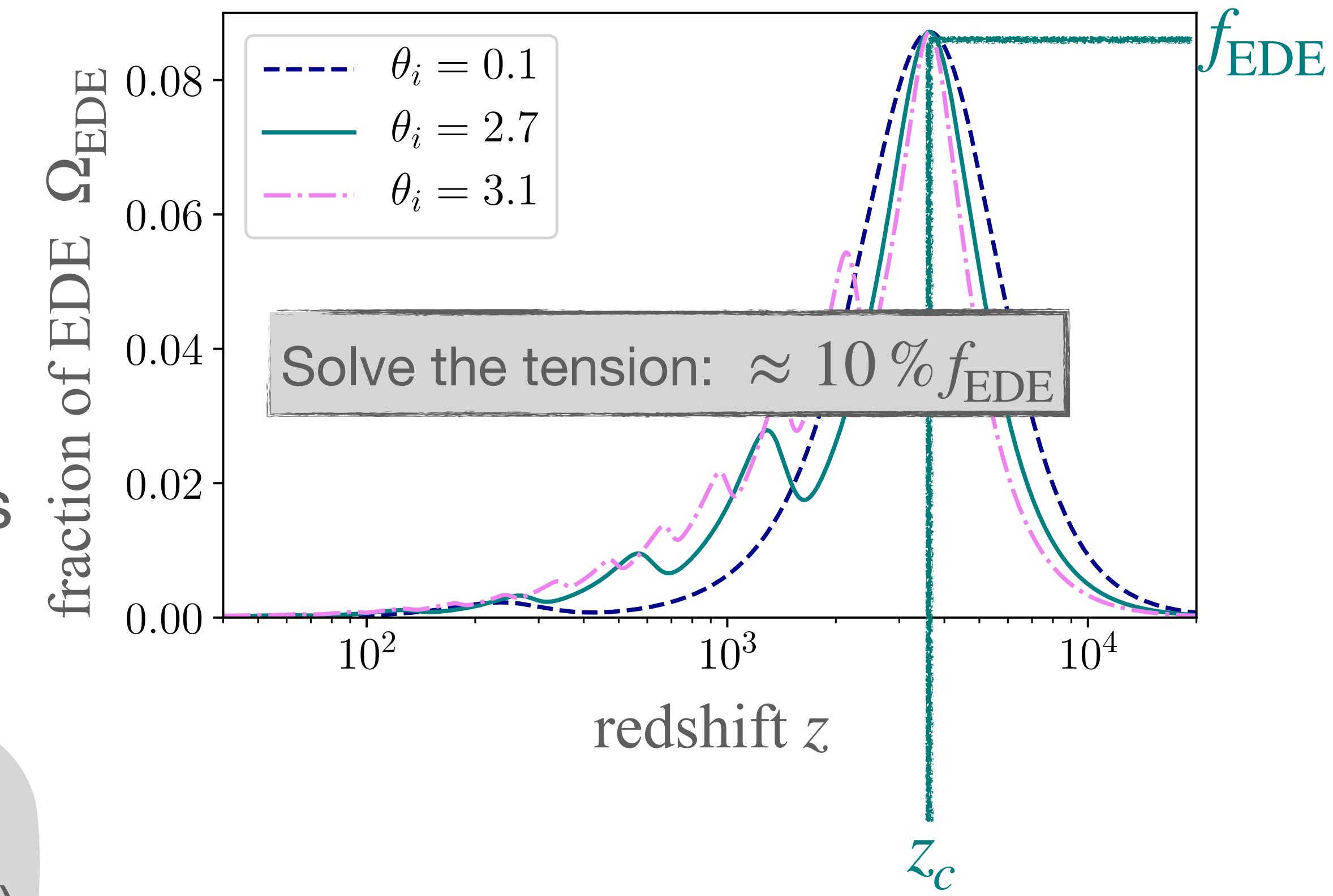
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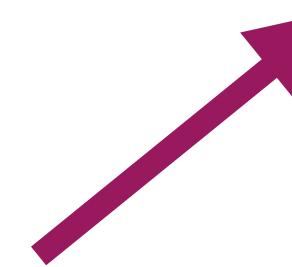


Can EDE resolve the  $H_0$  tension  
... and fit all available data sets?

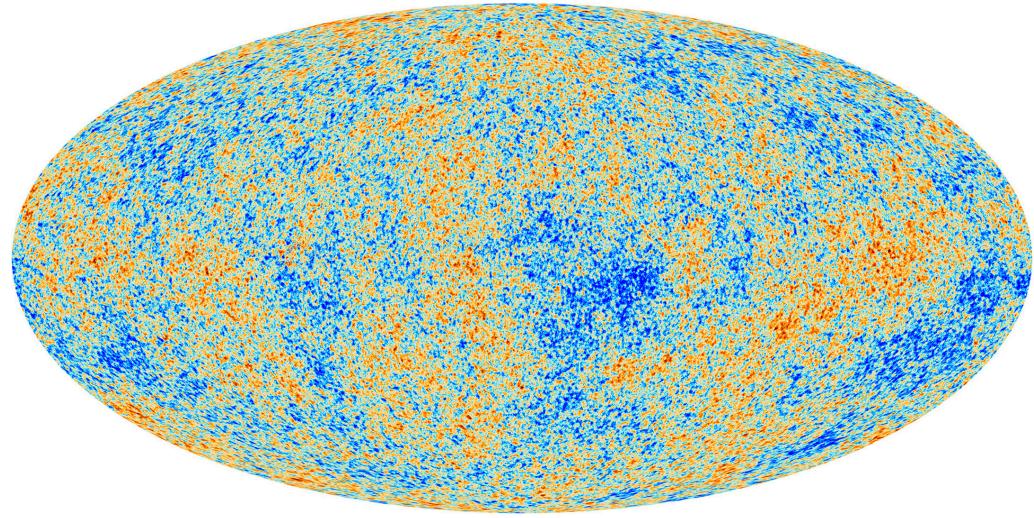
Disclaimer: this review about constraints on EDE is **not** complete

# Can EDE solve the $H_0$ tension and fit these data sets?

*Data sets: Planck + 6dFGS + BOSS DR12 BAO/  
RSD + Pantheon + SH0ES 2016*



CMB (TT, TE, EE, lensing)

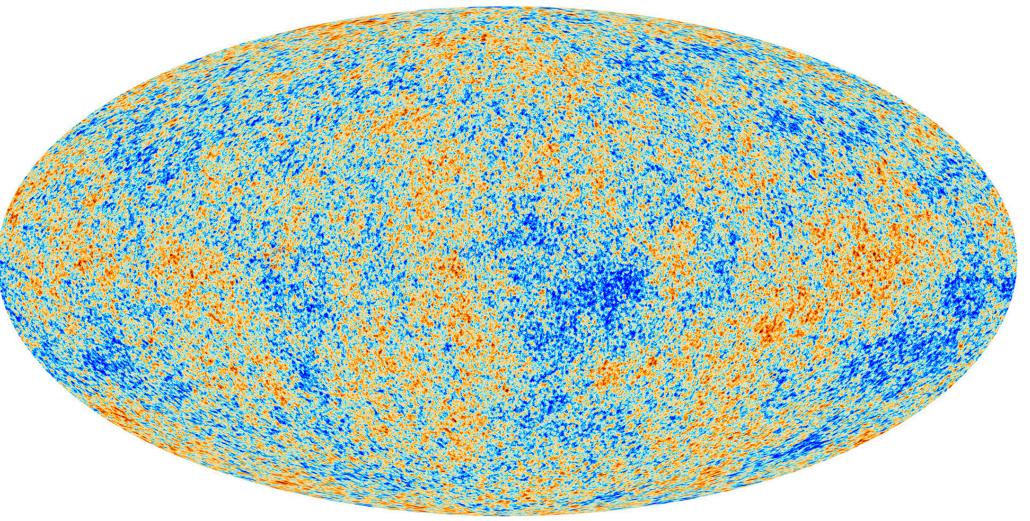


ESA

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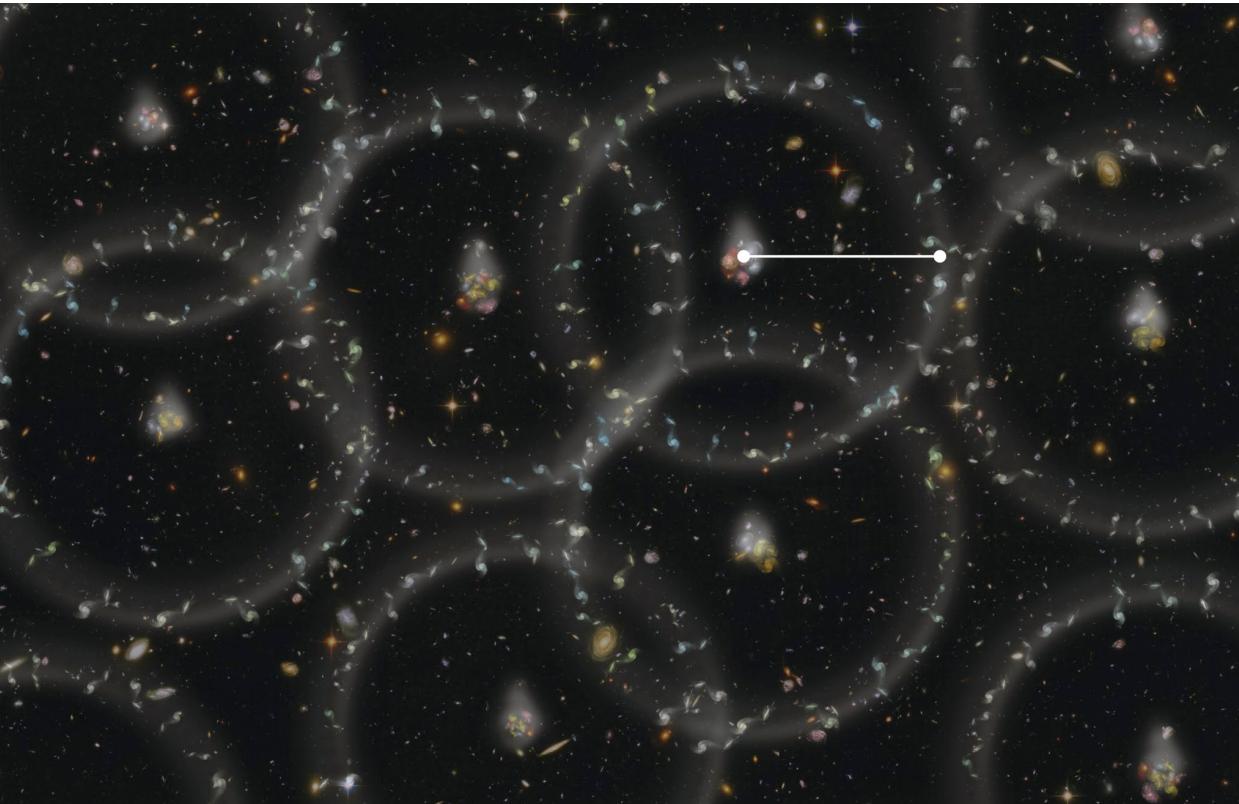
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CMB ( $\text{TT}$ ,  $\text{TE}$ ,  $\text{EE}$ , lensing)



ESA

Baryon acoustic oscillations



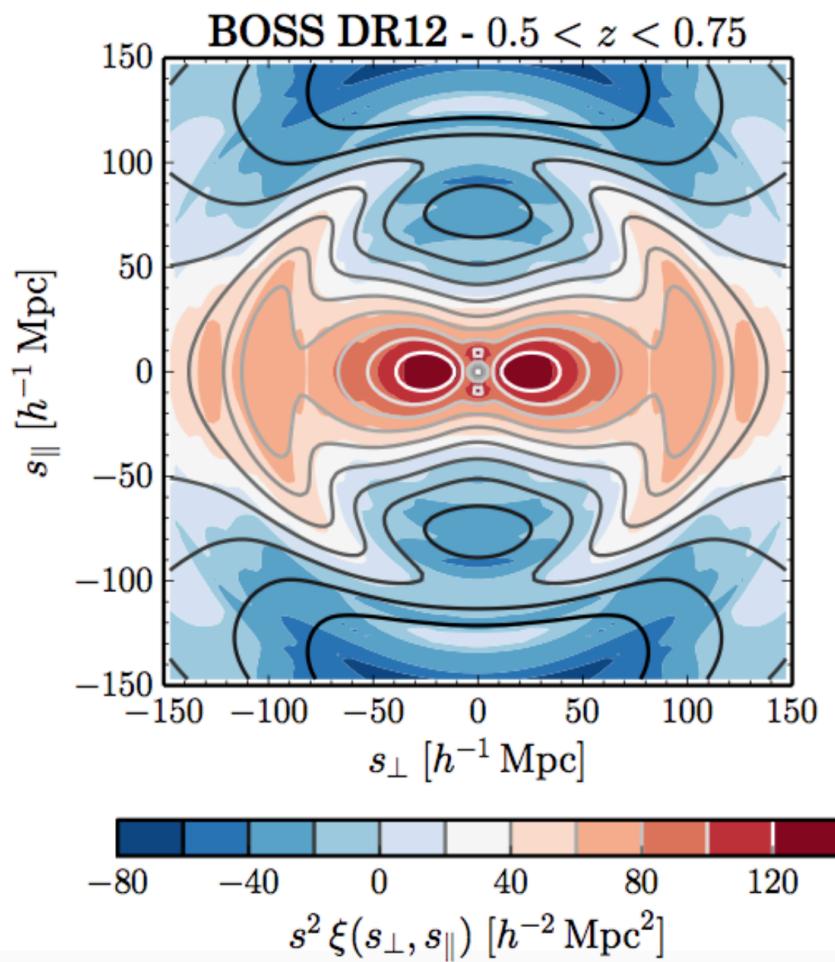
BOSS collaboration

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## Redshift space distortions

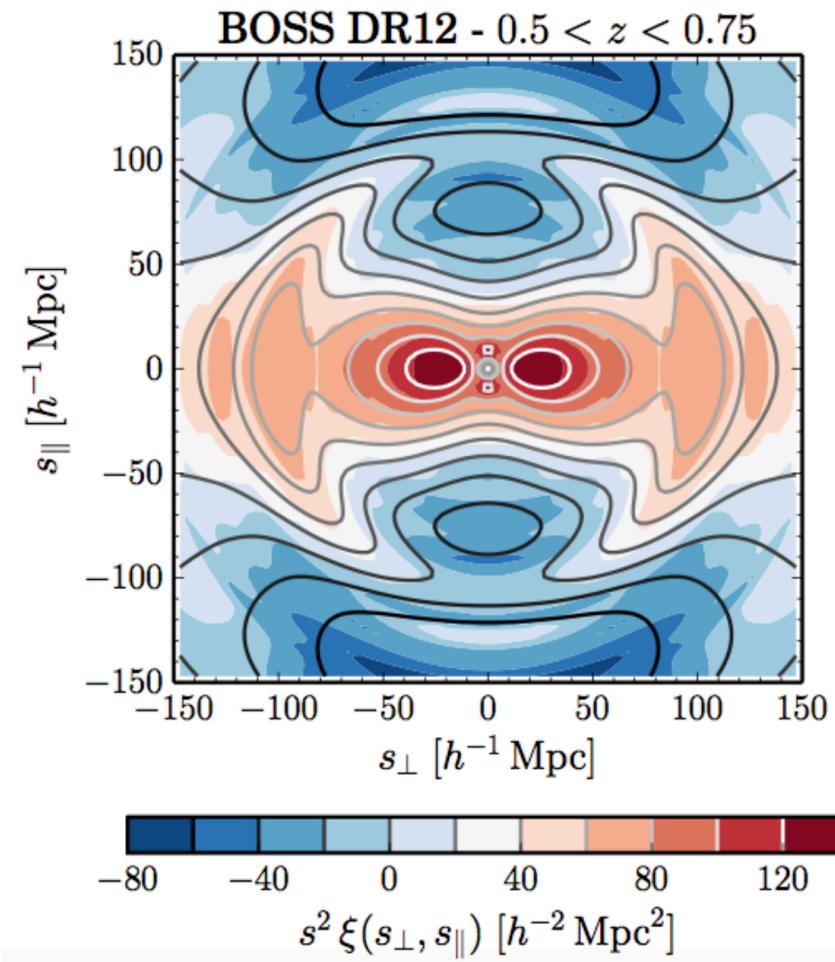


BOSS collaboration (Sanchez++ 2016)

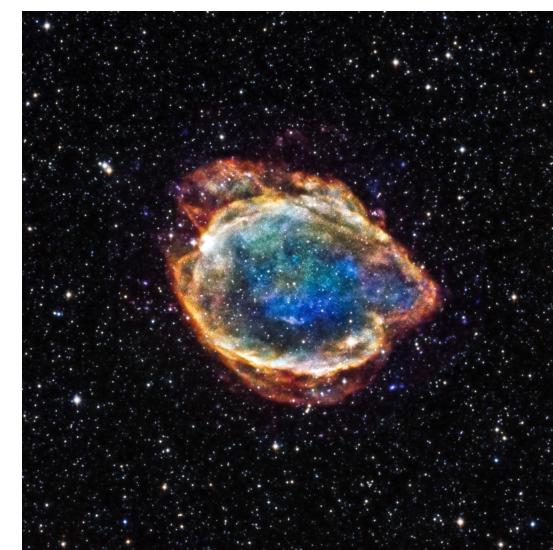
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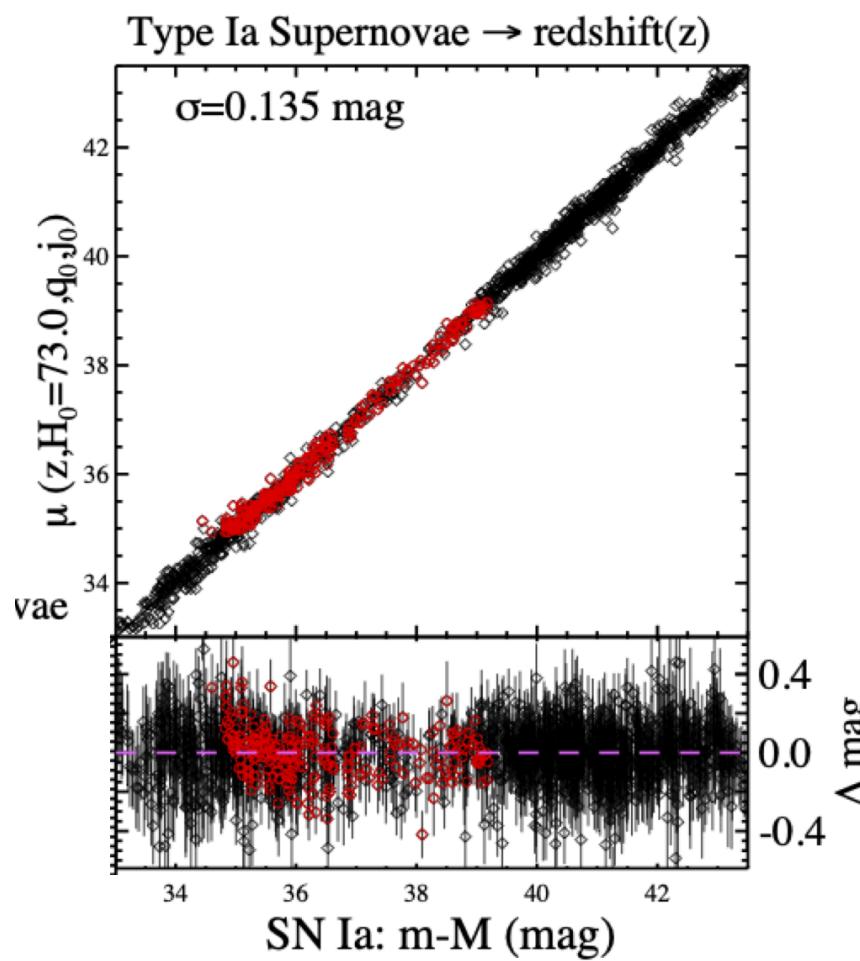
Redshift space distortions



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NASA



SH0ES col.

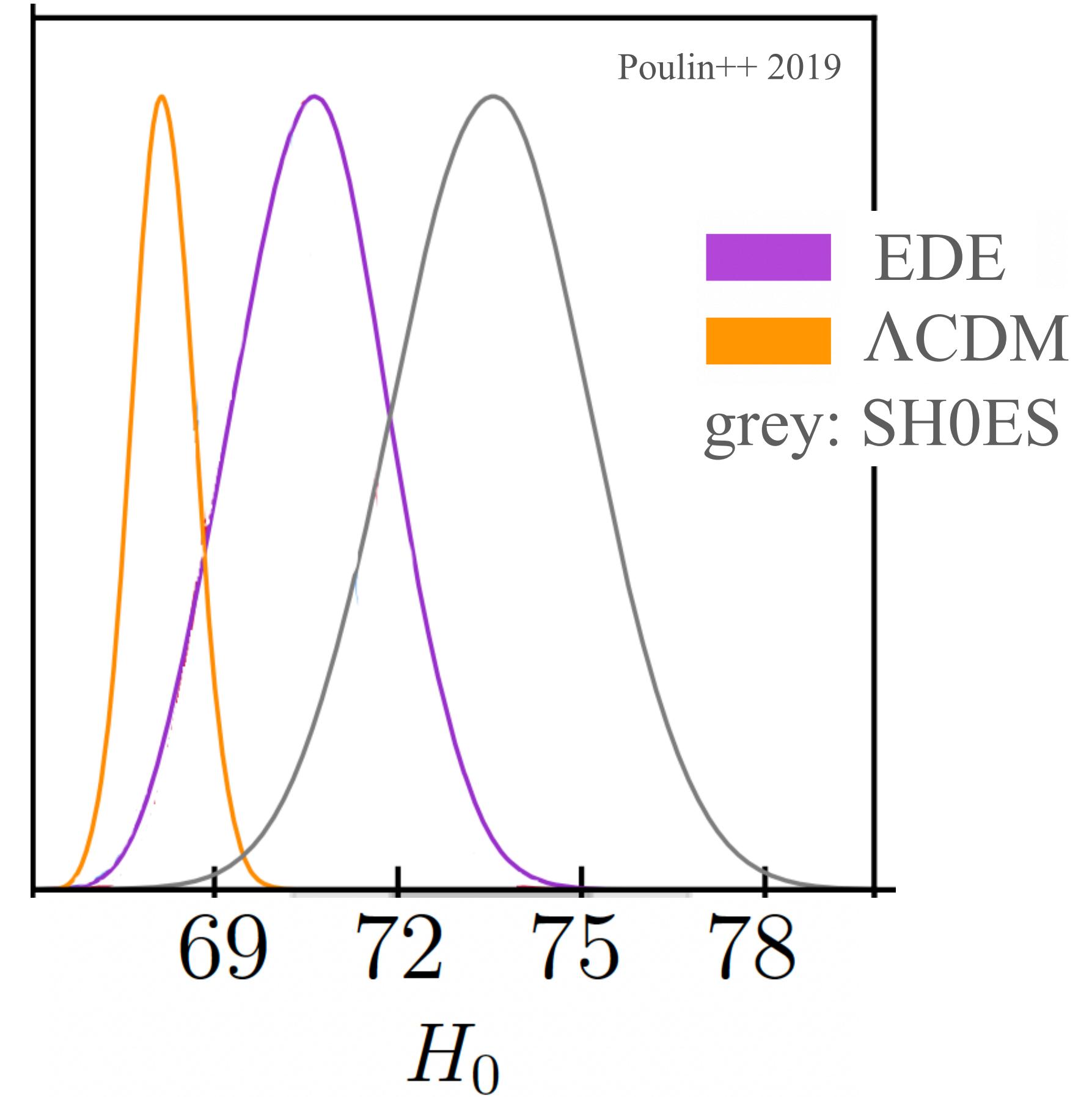
# 2019: EDE can solve the $H_0$ tension!

Poulin, Smith, Karwal, Kamionkowski, 2019

**Data sets:** Planck + 6dFGS + BOSS DR12 BAO/  
RSD + Pantheon + SH0ES 2016

- $f_{\text{EDE}} = 0.107^{+0.035}_{-0.030}$  (mean  $\pm 1\sigma$ )
- $H_0 = 71.49 \pm 1.20$  km/s/Mpc

Markov Chain Monte Carlo (MCMC)

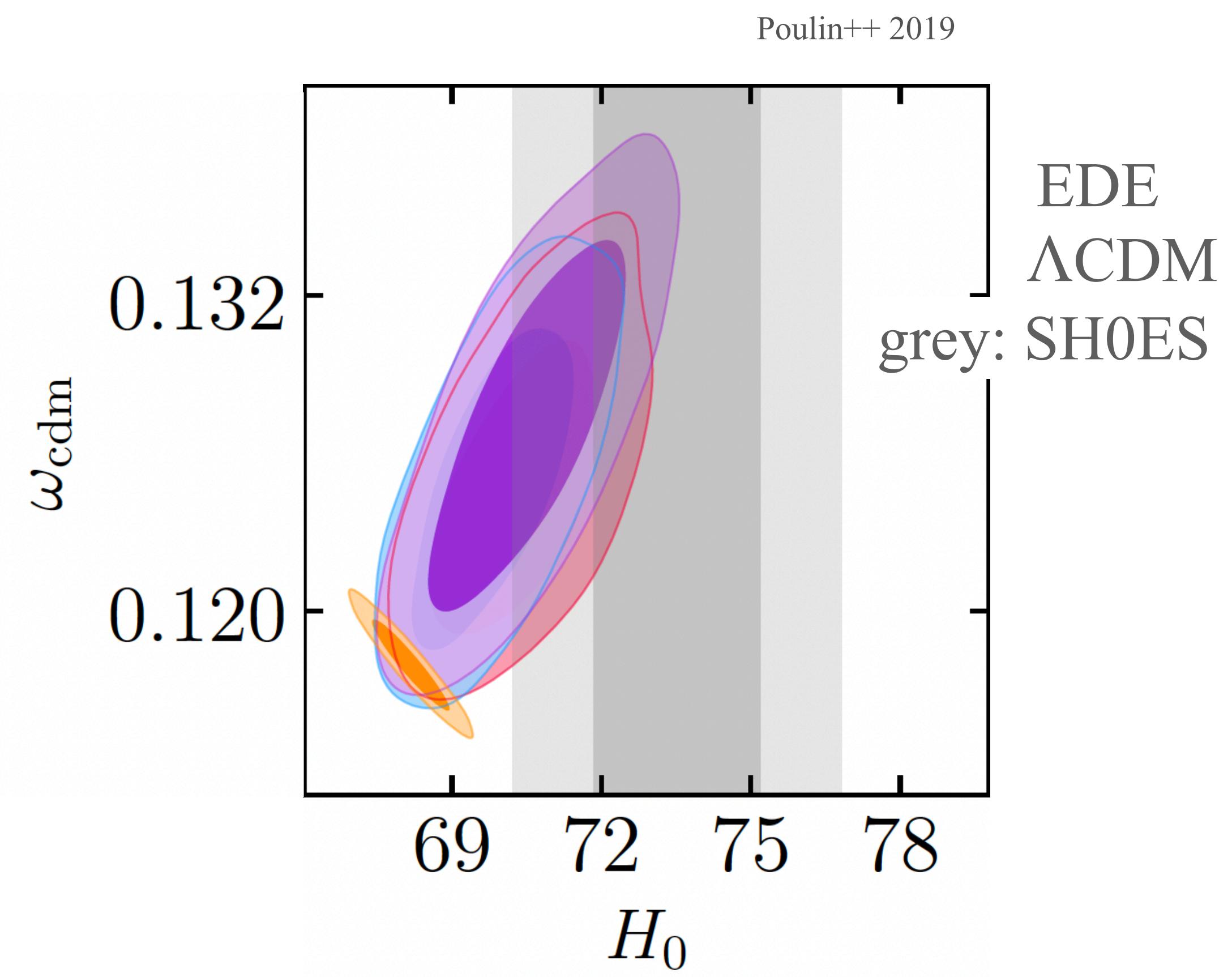


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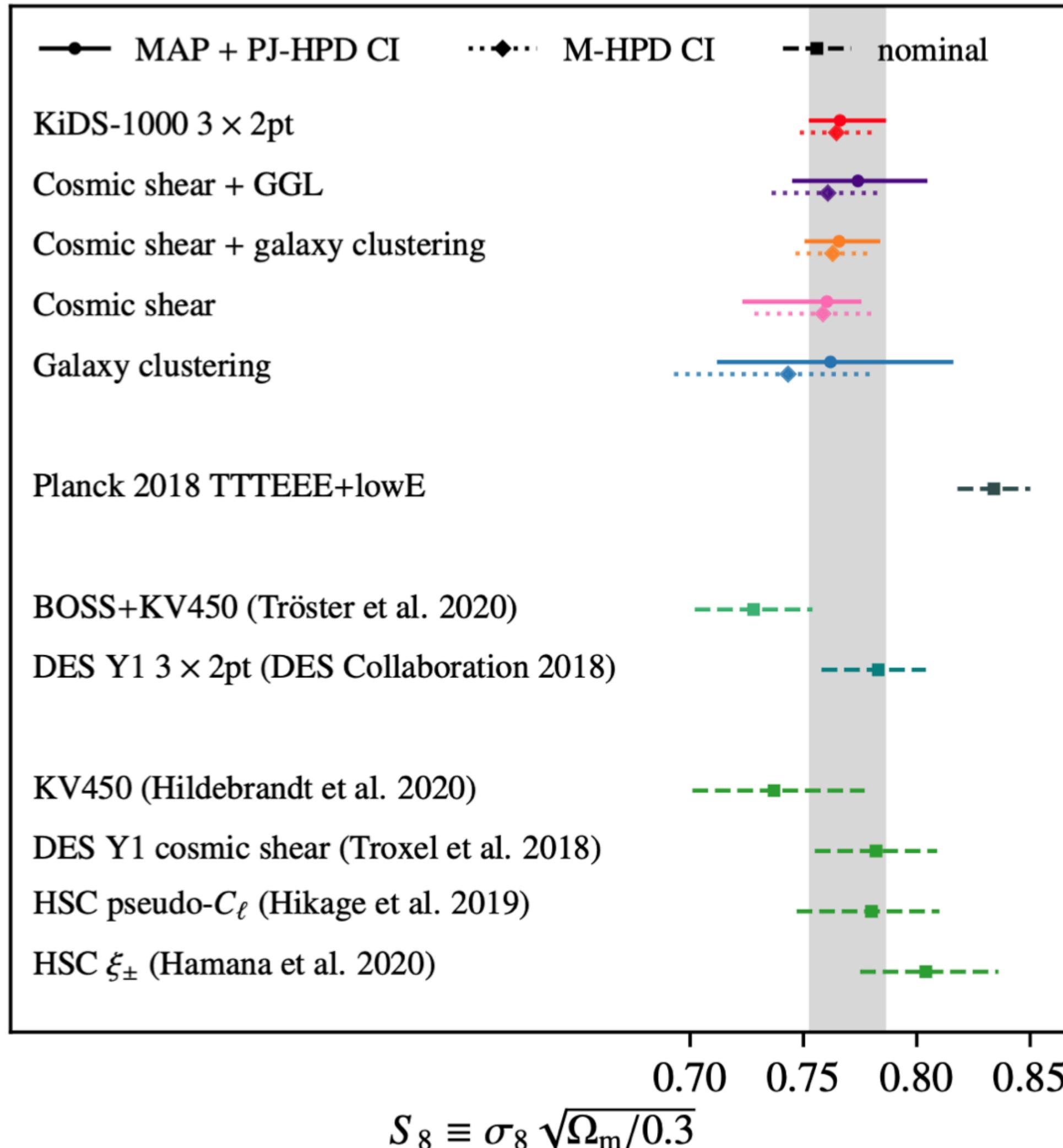
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- $H_0 = 71.49 \pm 1.20$  km/s/Mpc
- **Also other parameters shift:**  
EDE suppresses growth of perturbations at early times
  - $\omega_{\text{CDM}}$  and  $n_s$  increase
  - $\sigma_8$  increases, worsening the so-called  $\sigma_8$  discrepancy



# Aside: $\sigma_8$ discrepancy

Cosmology Intertwined 2021



$$\sigma_8^2 = \int dk^3 |W(k)|^2 P_{\text{lin}}(k),$$

Fourier transform of top-hat filter  
with radius 8 Mpc/h

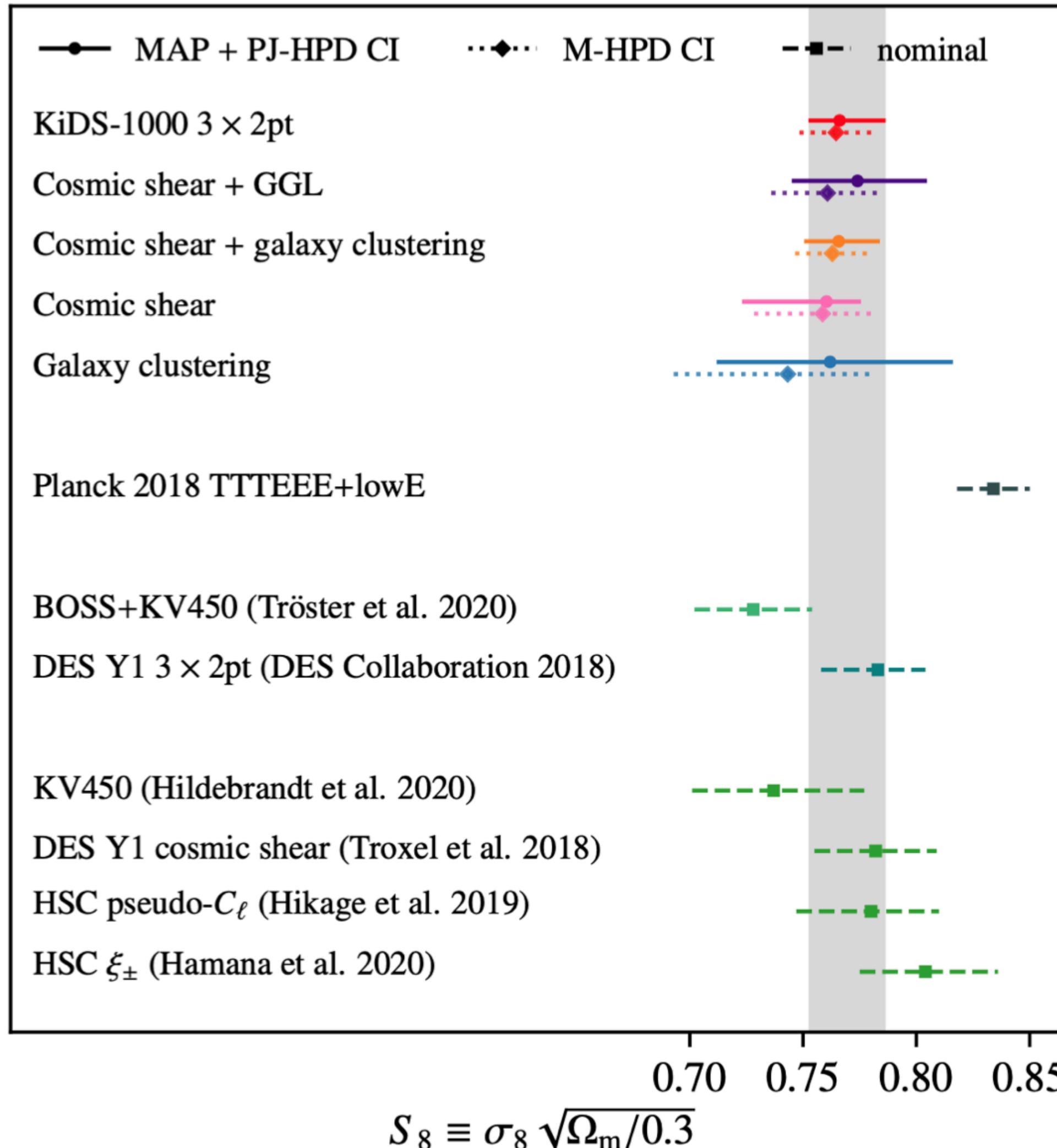
$$S_8 = \sigma_8 \sqrt{\Omega_m / 0.3}$$

linear matter power spectrum

*Planck prefers 2-3  $\sigma$  higher  $S_8$  than weak lensing experiments (DES, KiDS, HSC)*

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Cosmology Intertwined 2021



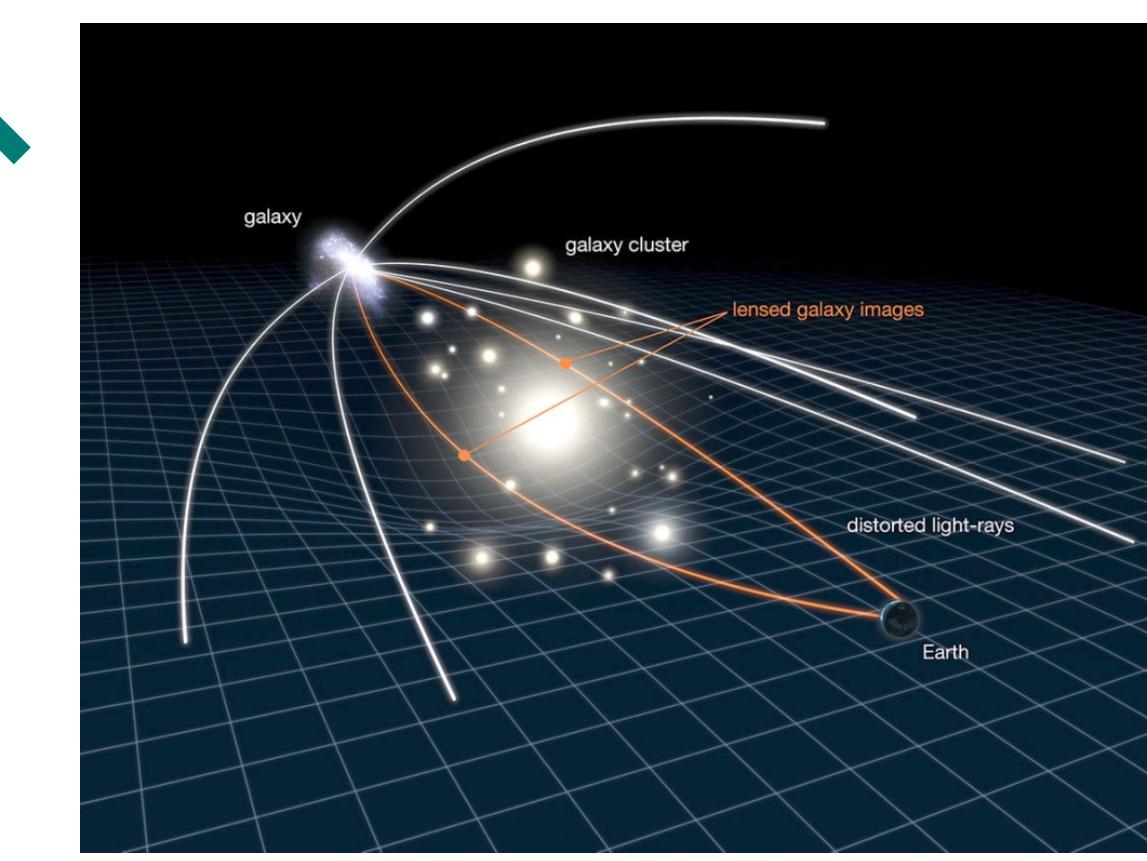
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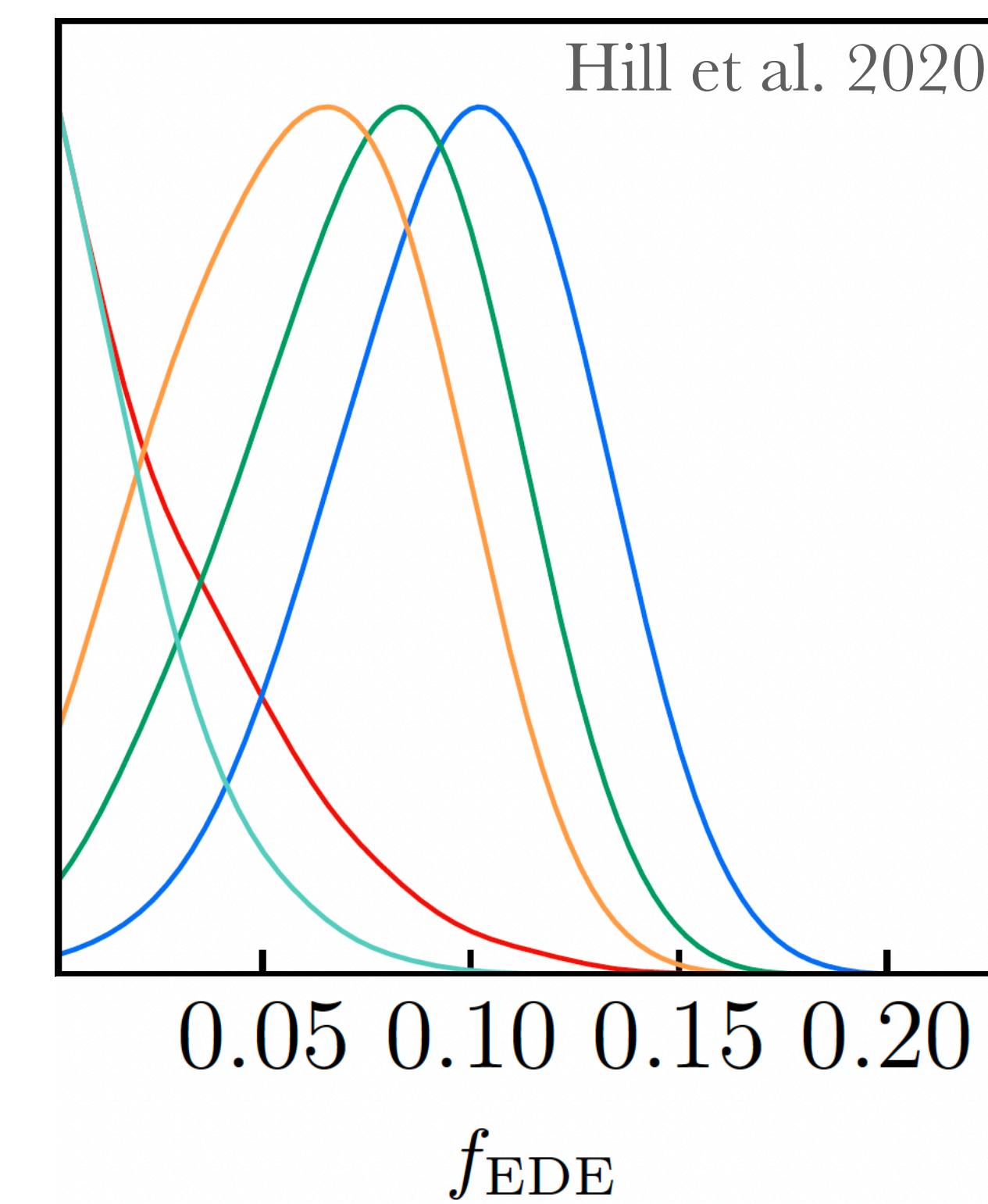
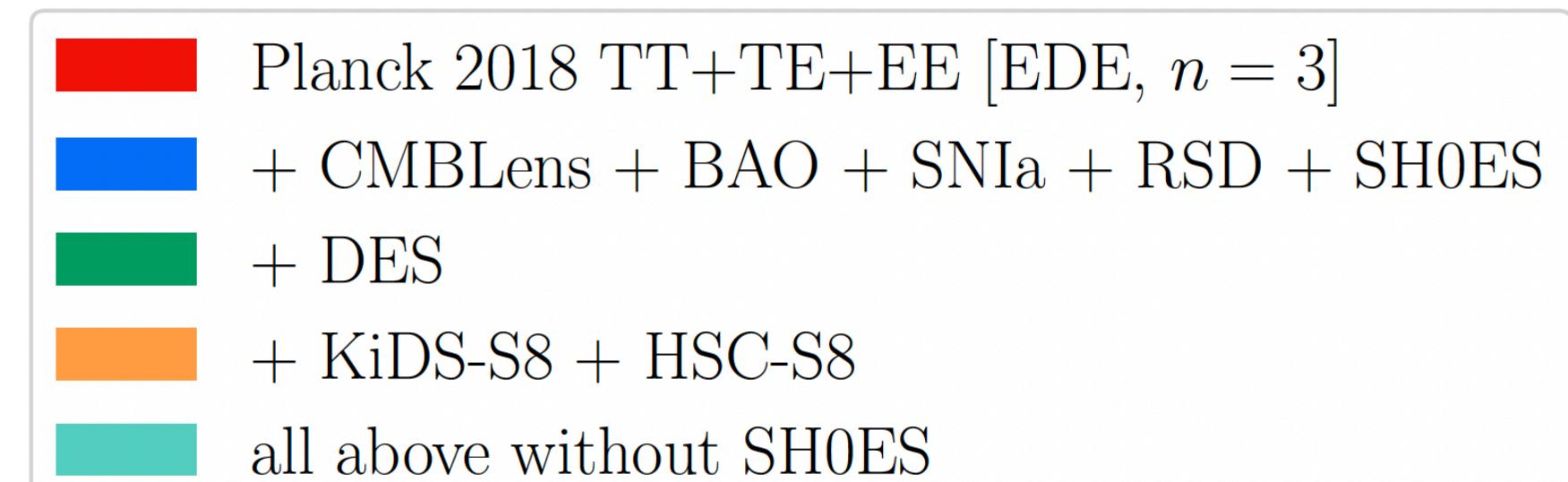
NASA

# Adding LSS data: EDE is ruled out?

Hill et al. 2020; Murgia et al. 2021

*Data sets:* Planck + 6dFGS + BOSS DR12  
BAO/RSD + Pantheon + ~~SH0ES 2016~~ +  
DES + KiDS + HSC

- $f_{\text{EDE}} < 0.06$  (95% C.L.)
- $H_0 = 68.92^{+0.57}_{-0.59}$  km/s/Mpc
- No SH0ES → no preference for EDE

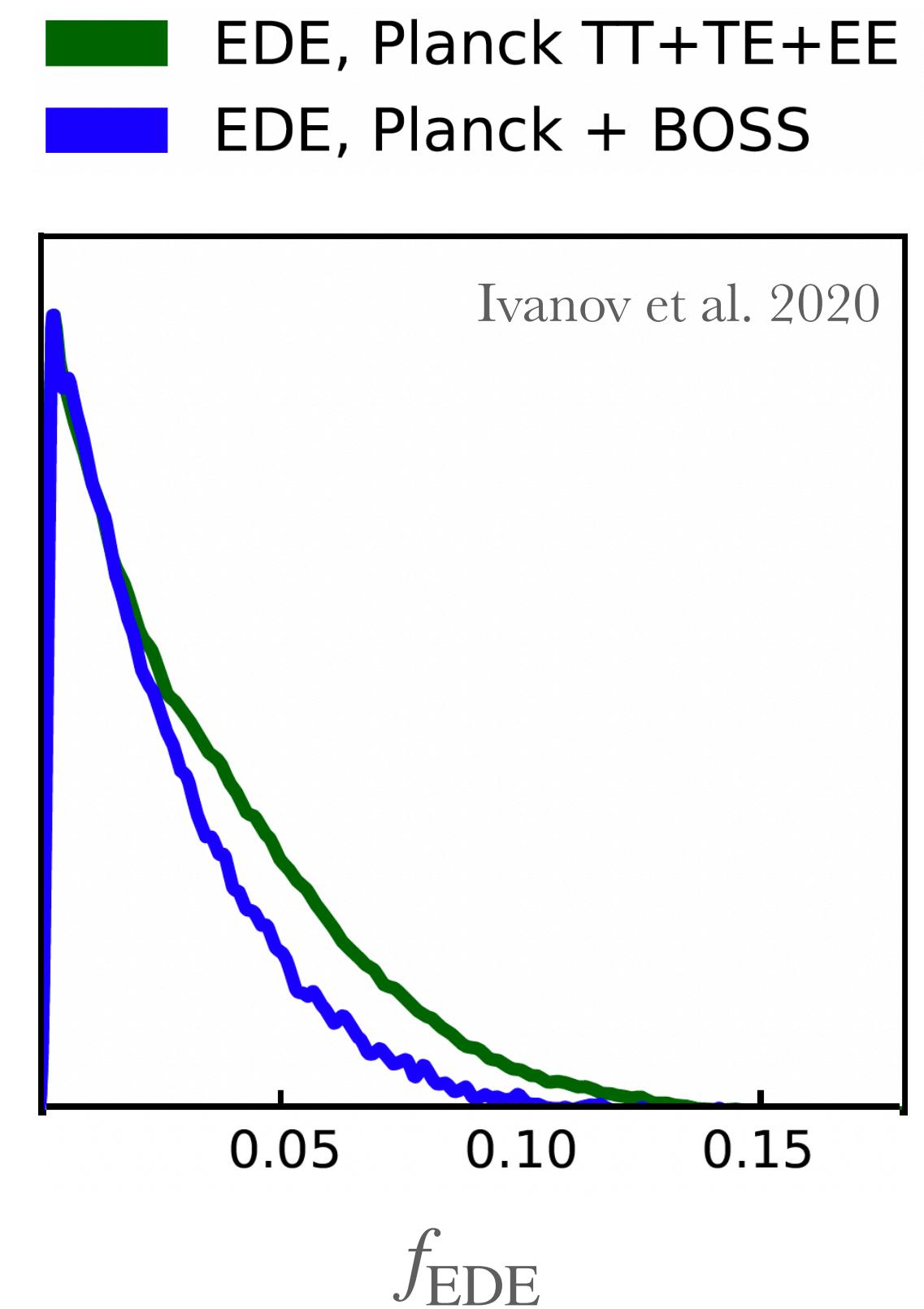


# Adding LSS data: EDE is ruled out?

Ivanov et al. 2020; D'Amico et al. 2020

*Data sets: Planck + BOSS DR12 BAO  
+ full-shape analysis based on EFT of LSS*

- $f_{\text{EDE}} < 0.072$  (95% CL)
  - $H_0 = 68.54^{+0.52}_{-0.95}$  km/s/Mpc
- EDE cannot restore cosmological concordance

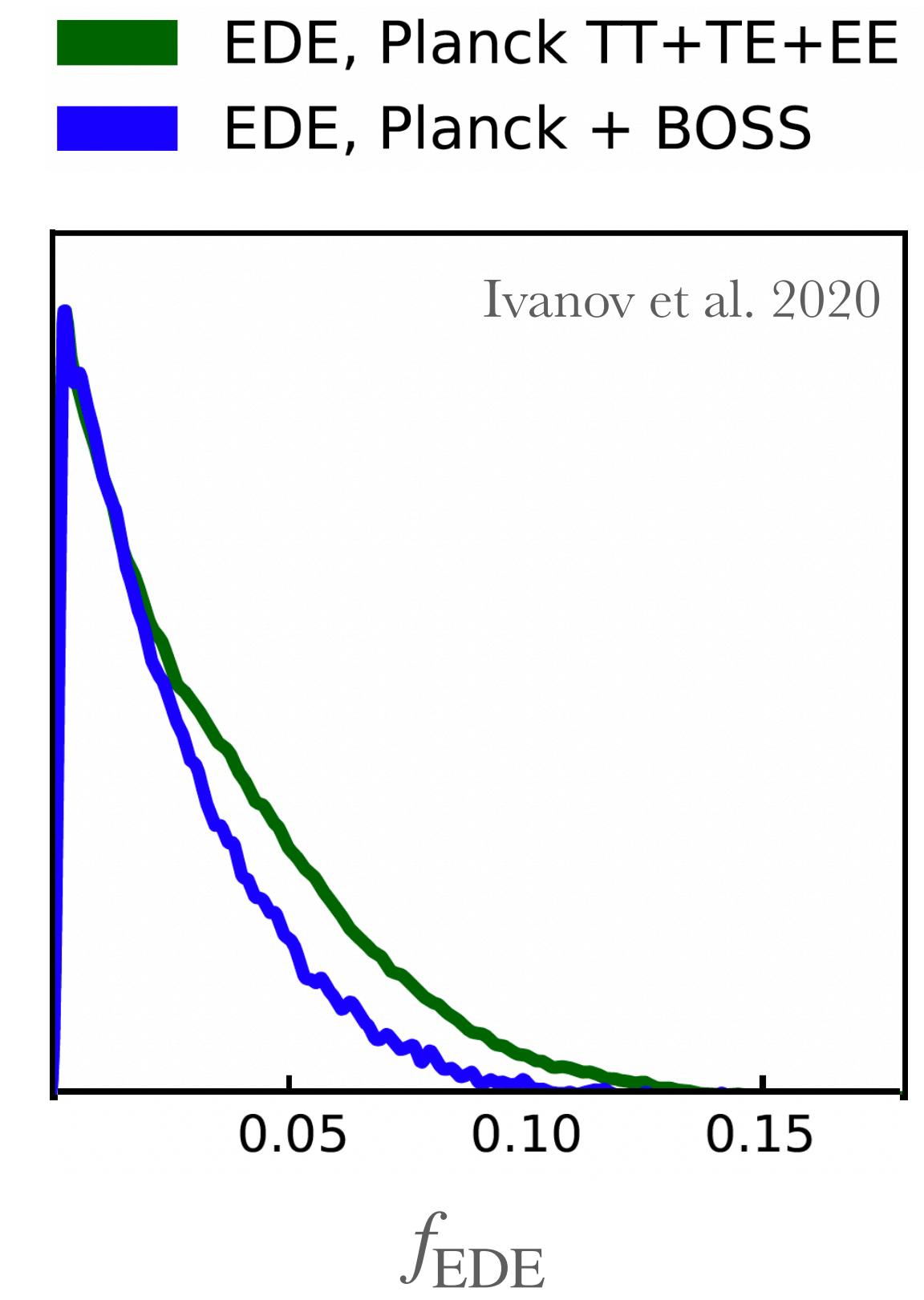


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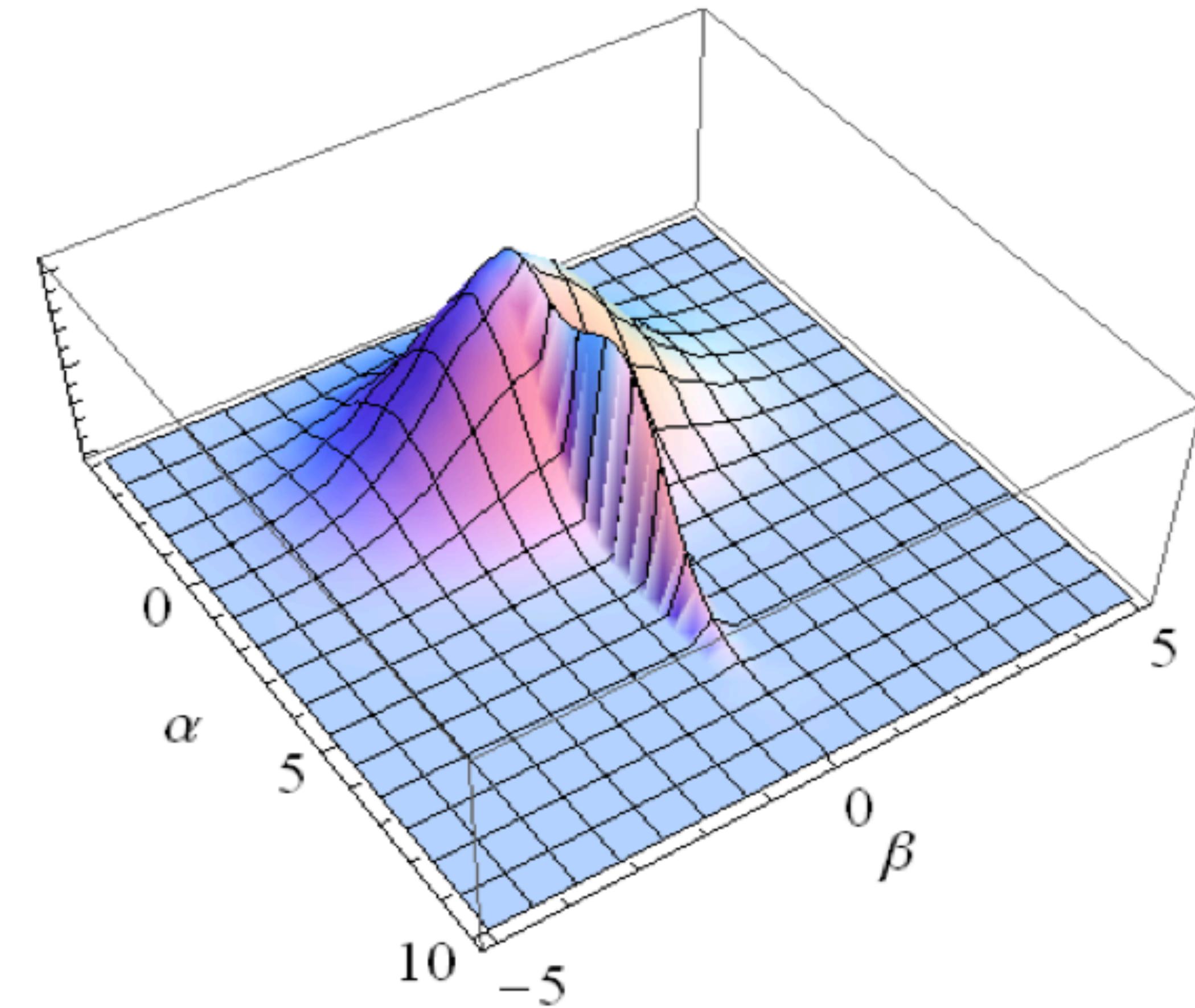
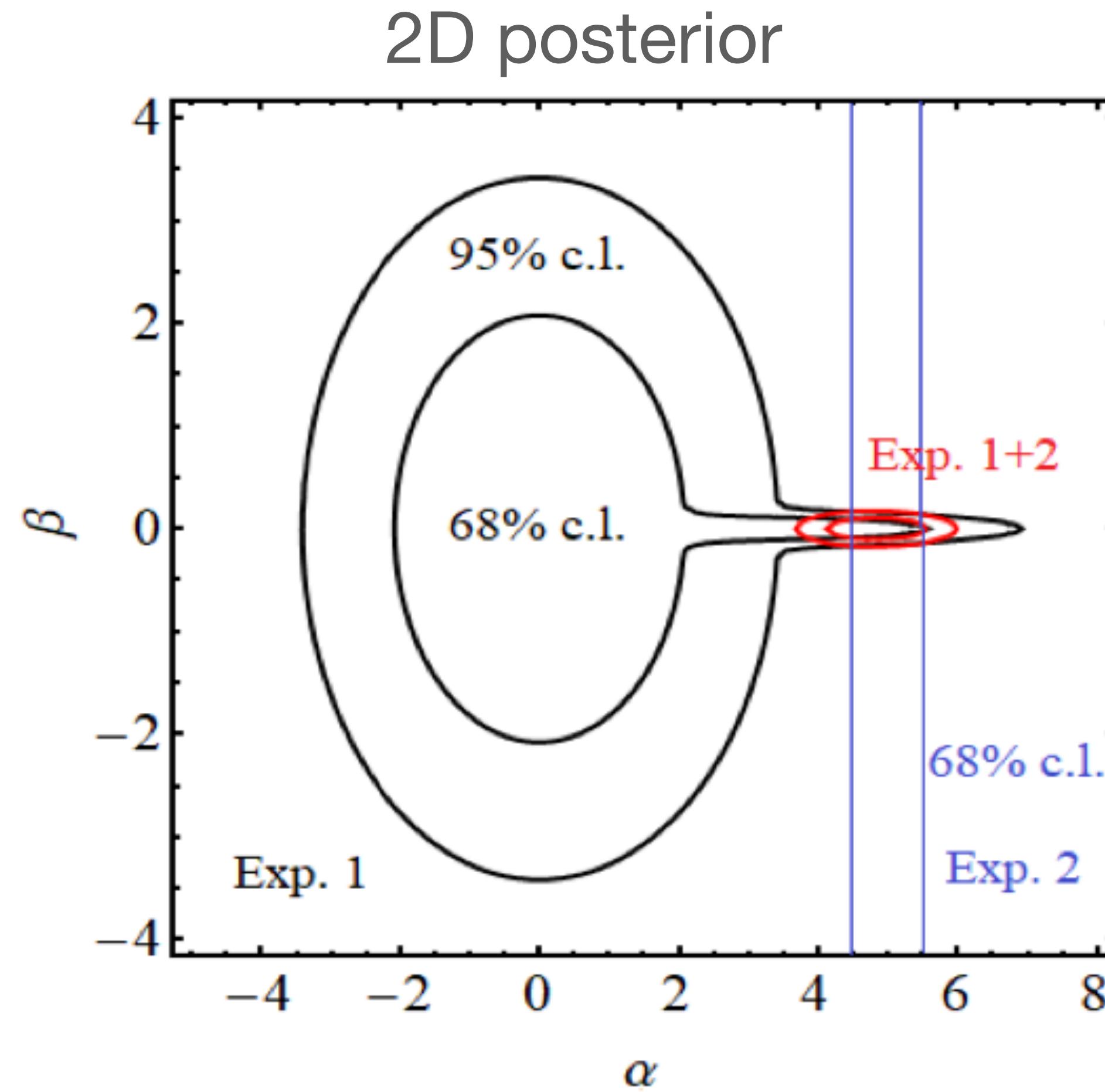


Could **volume effects** affect the results?

Smith++ 2020, Niedermann++ 2020, Smith++ 2021

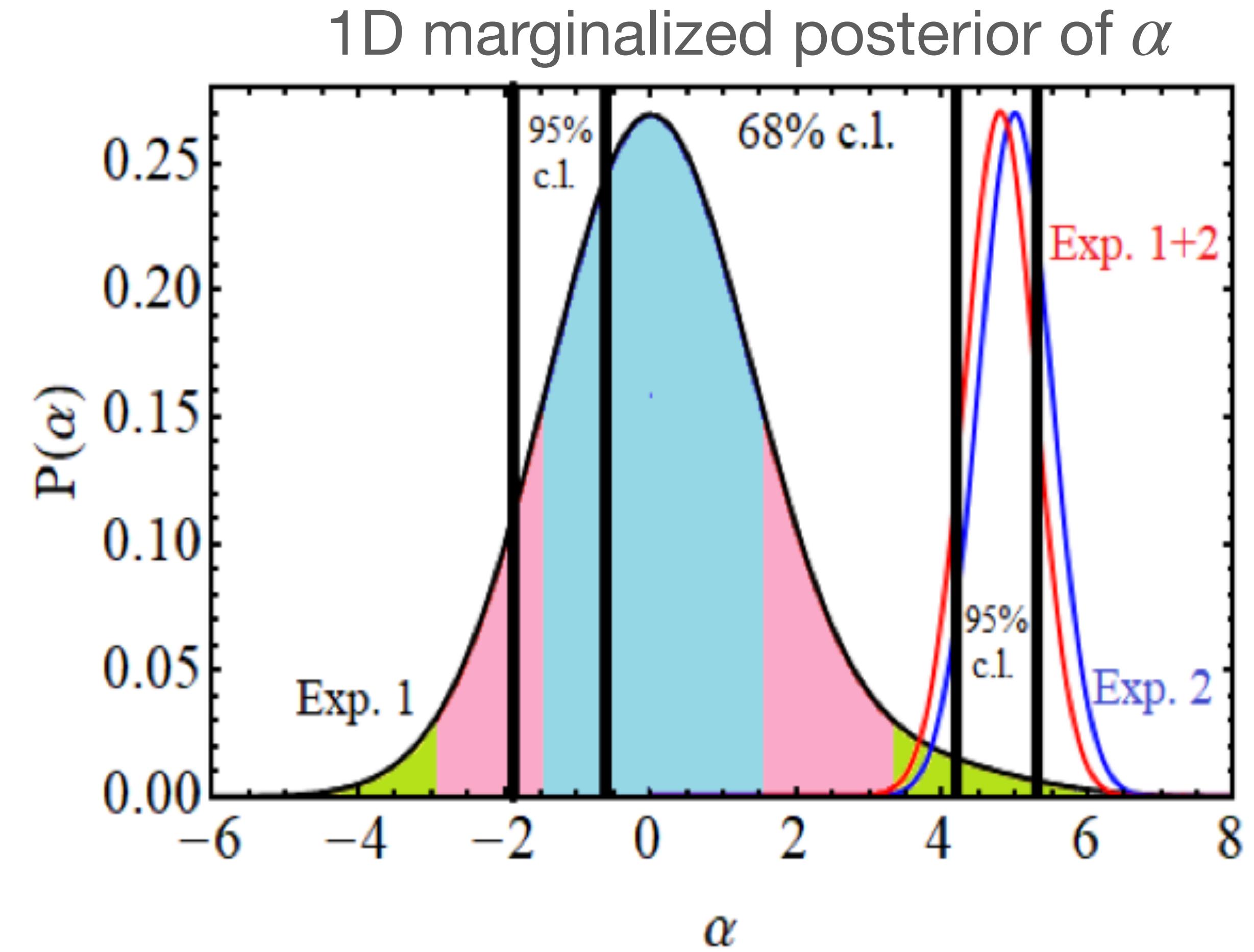
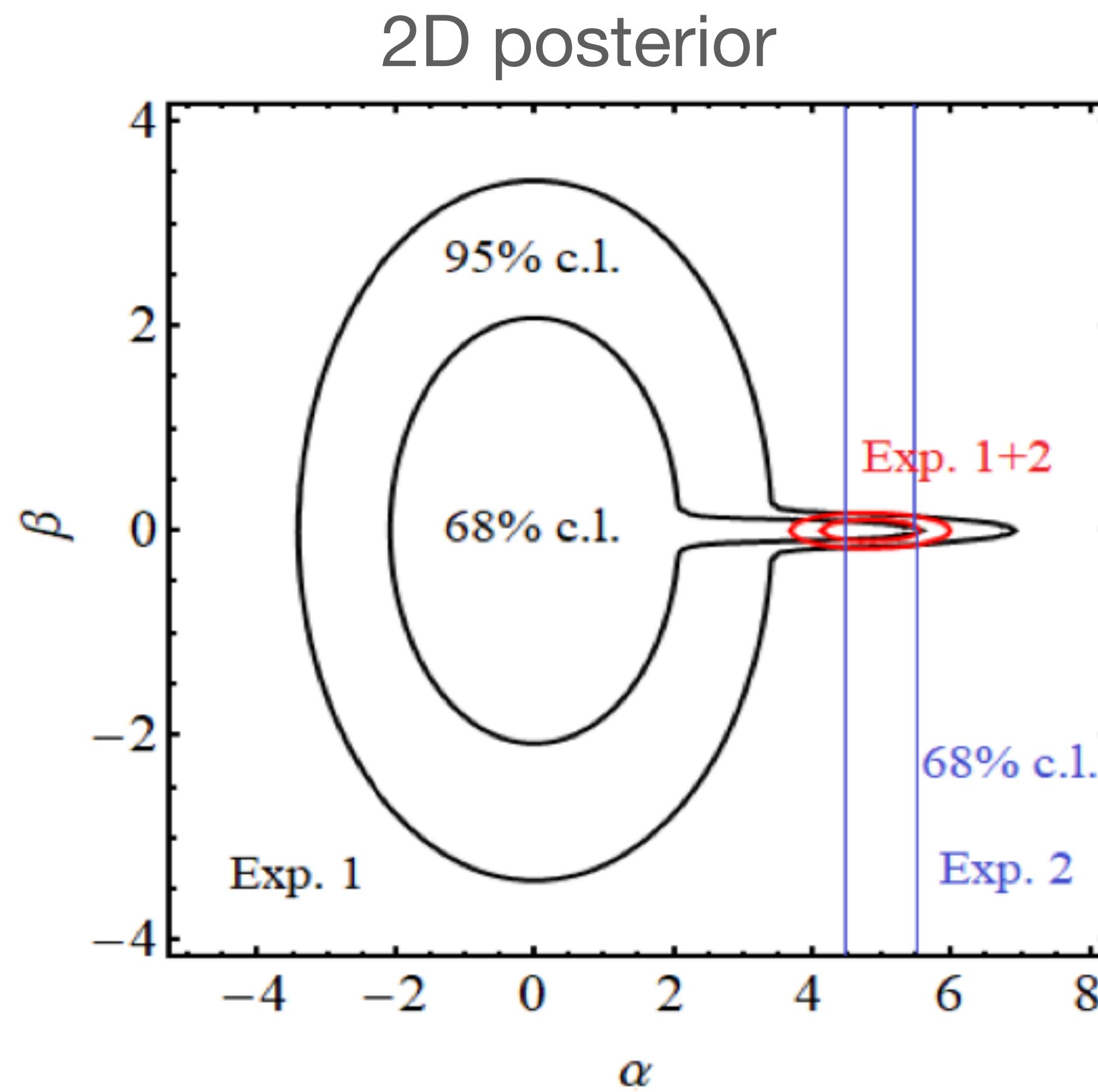
# Toy example: Prior volume / projection effect

Gomez-Valent 2022



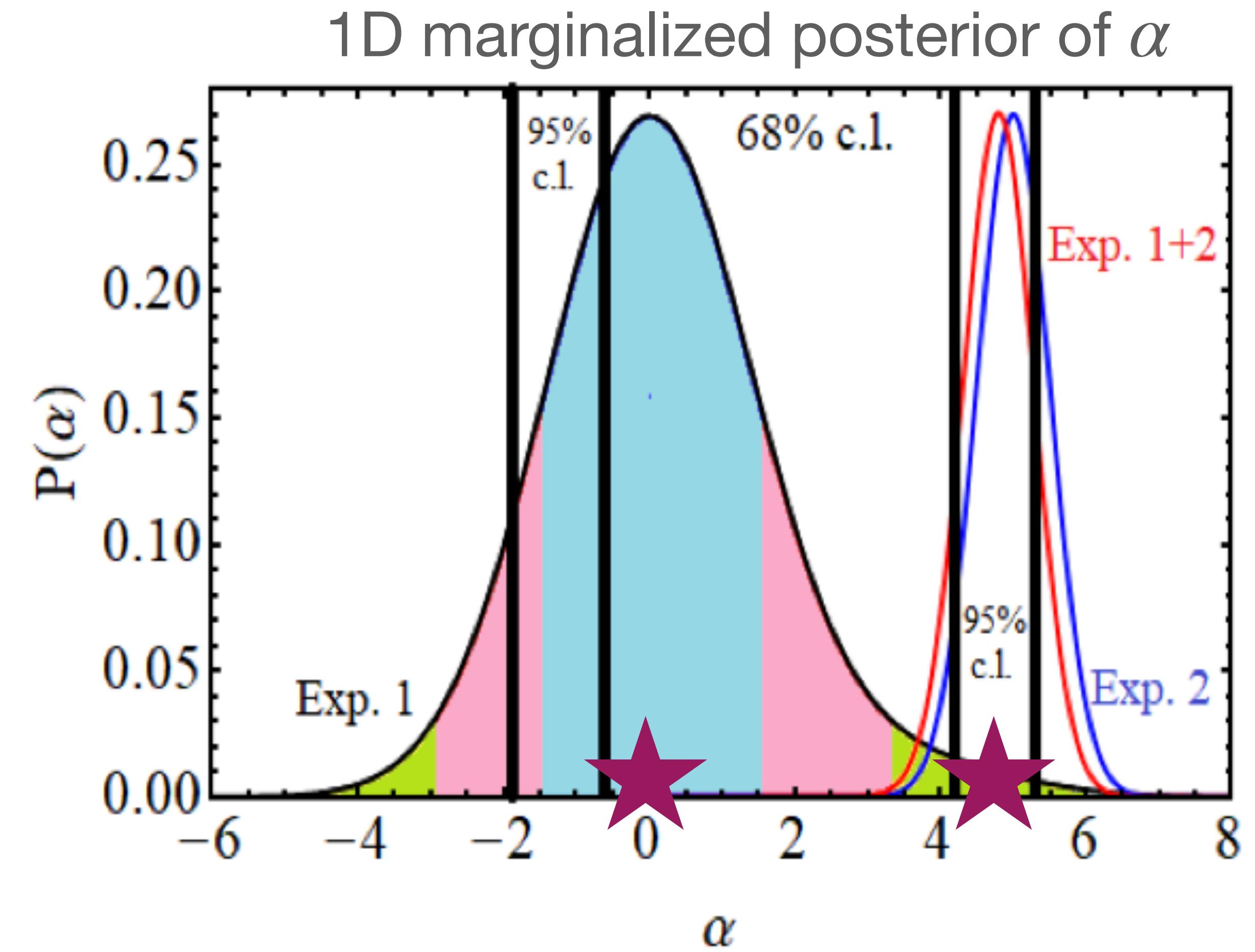
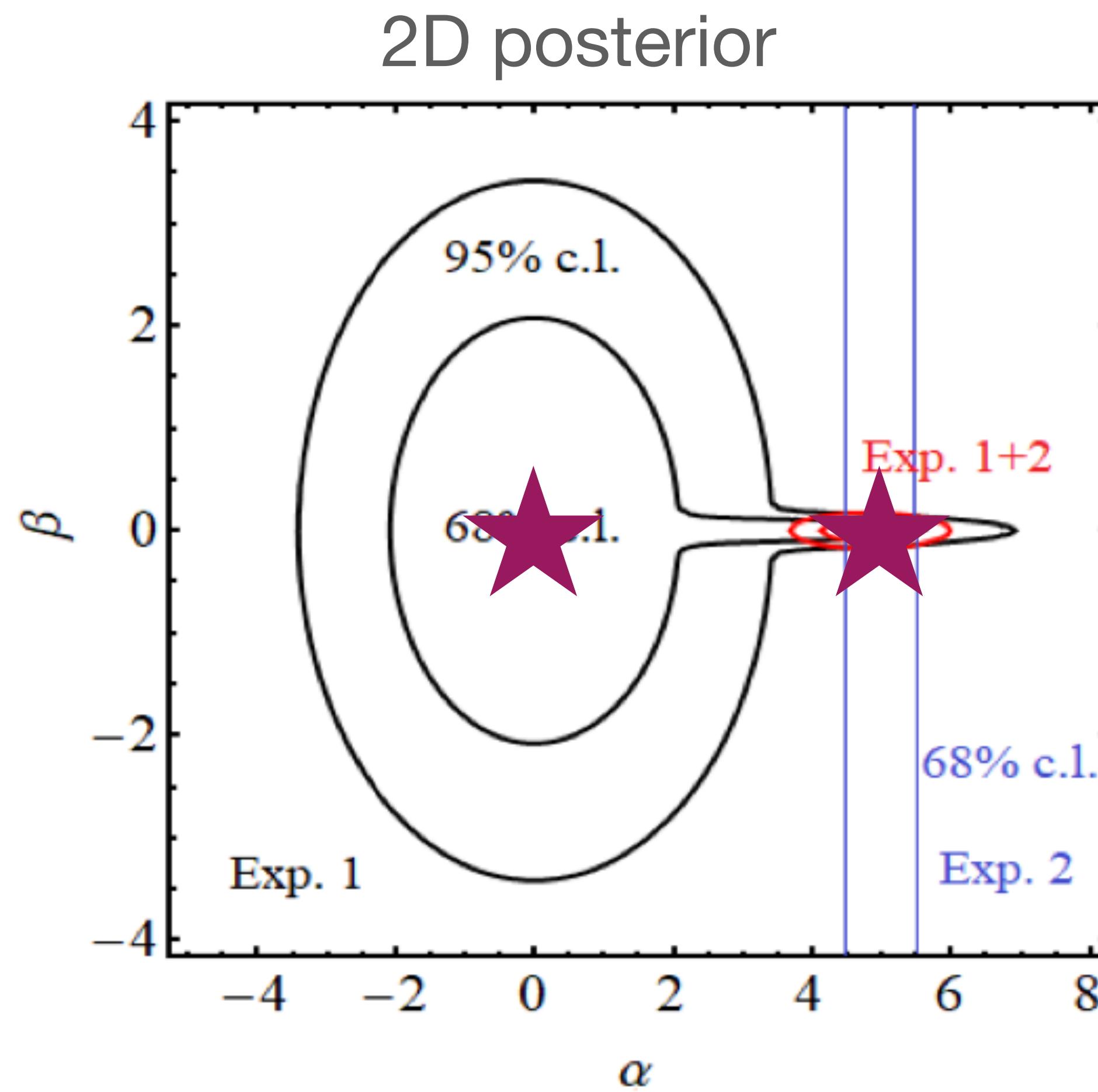
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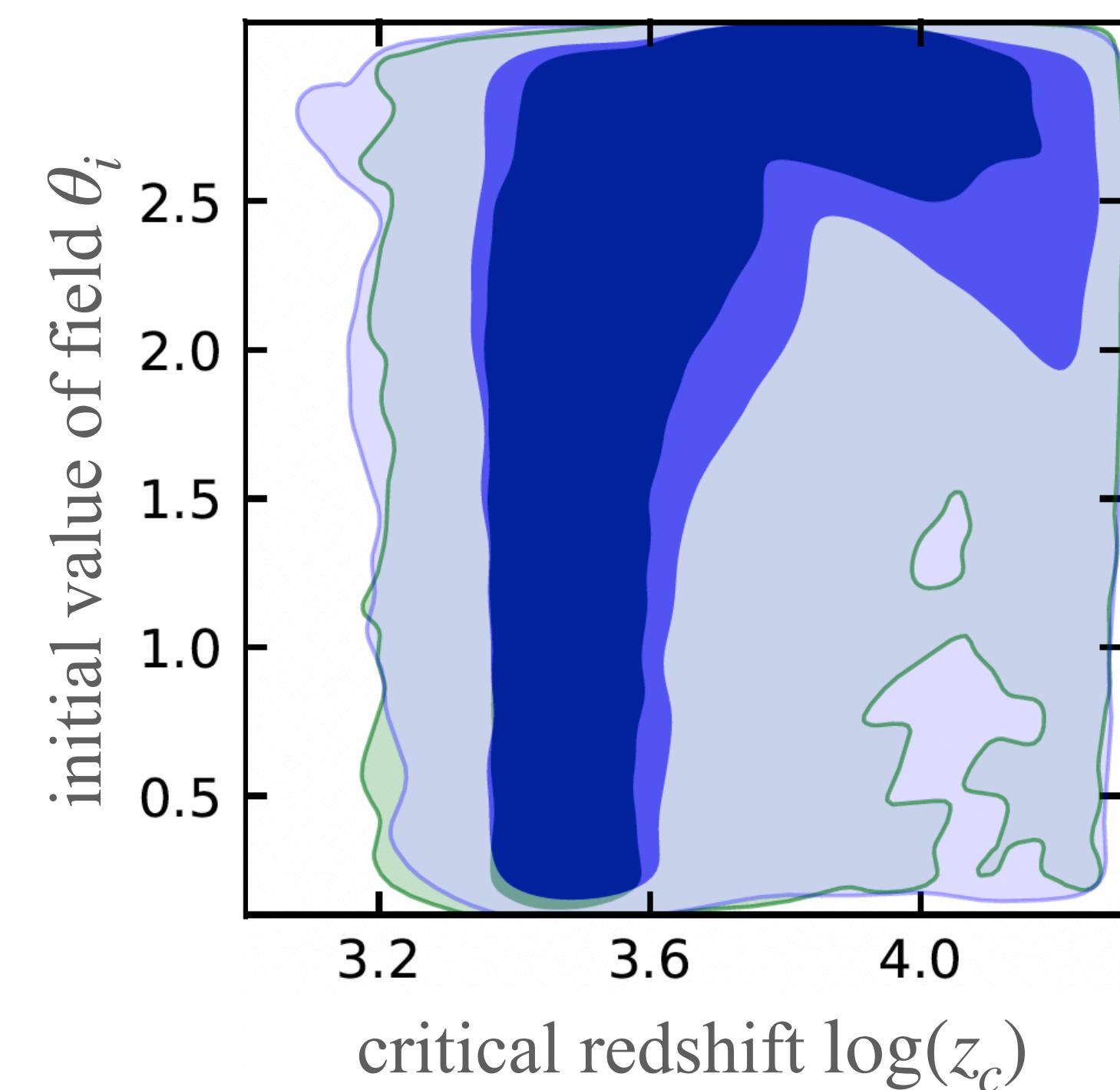
# Prior volume / projection / marginalisation effects

Ivanov et al. 2020

...appear if the posterior is influenced by the prior volume.

Reasons:

- Model has too many parameters / data is not constraining.
- Posterior is very non-Gaussian.
- Parameter structure of the model generates large volume differences.

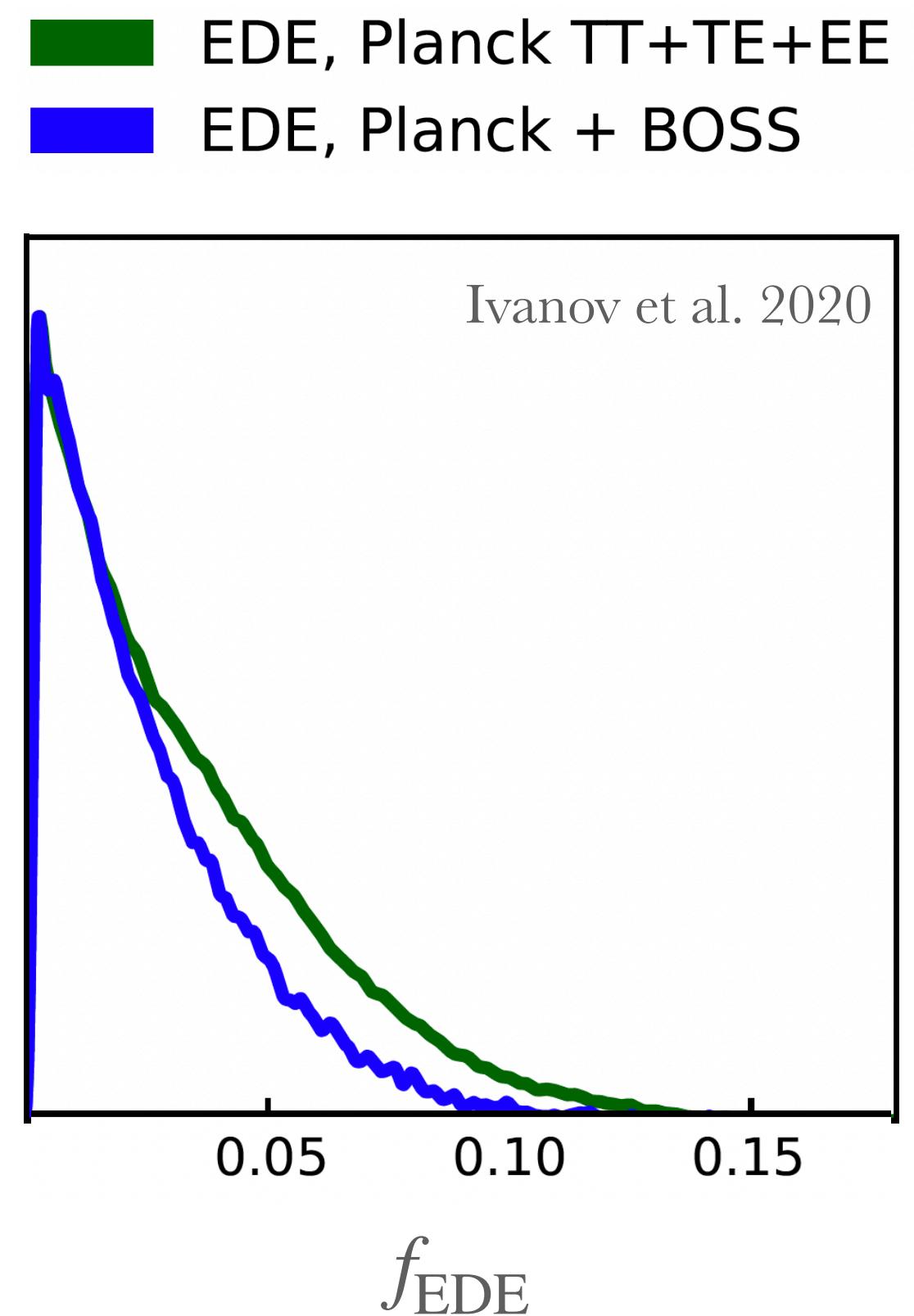


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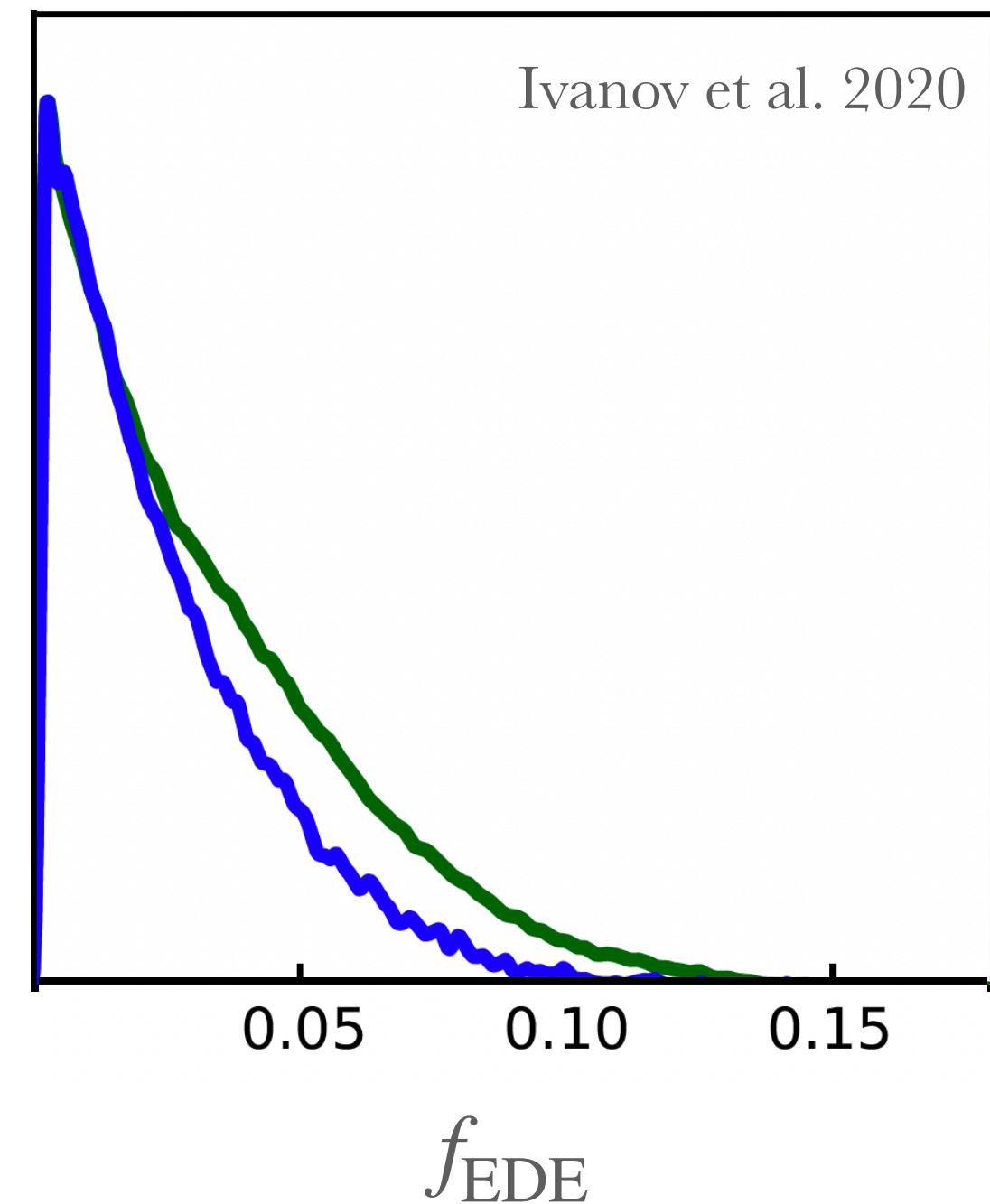
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Reasons:

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→ Bias in the marginalised posterior.

- EDE, Planck TT+TE+EE
- EDE, Planck + BOSS



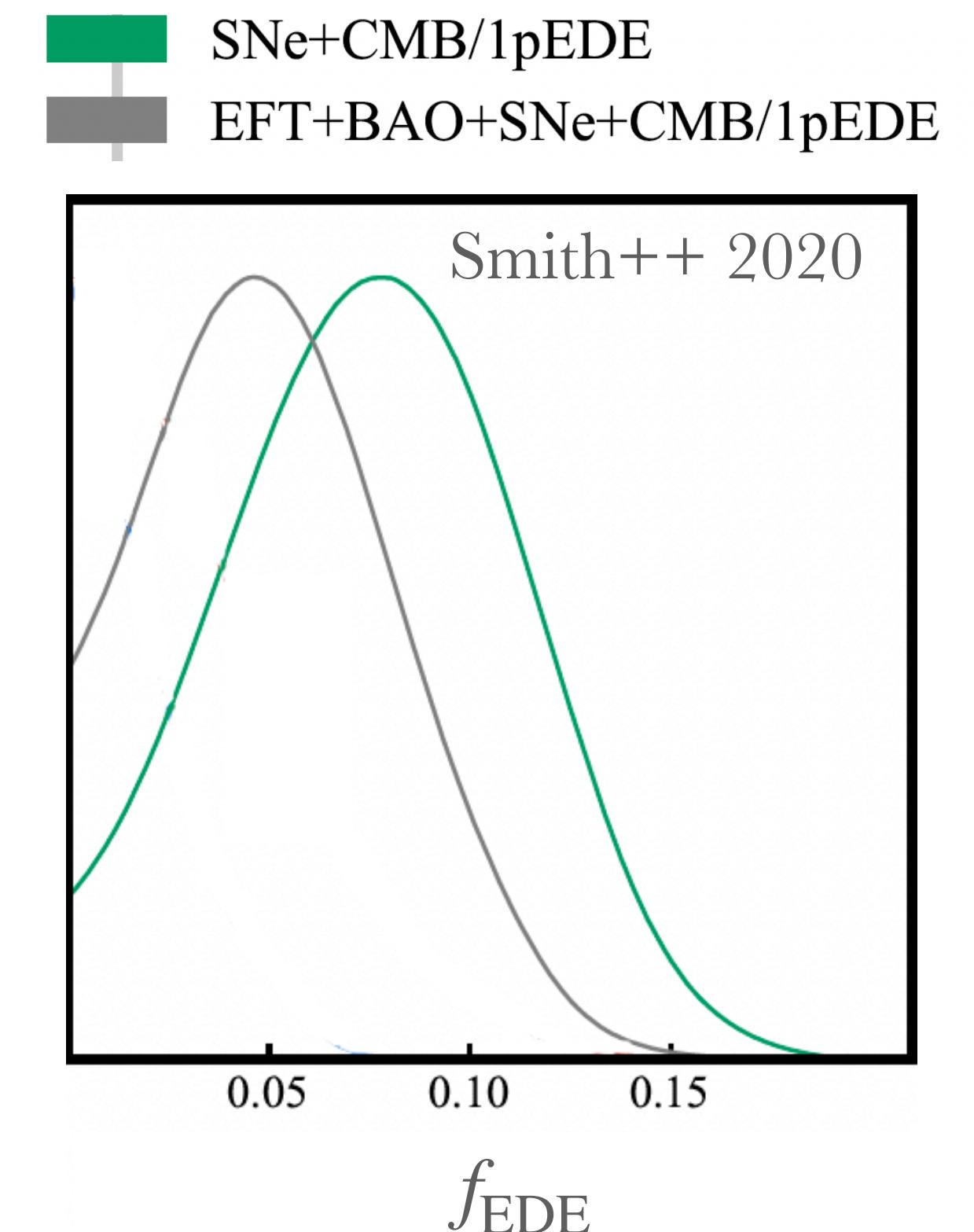
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# EDE is not ruled out by LSS?

*Smith, Poulin, Bernal, Boddy, Kamionkowski, Murgia, 2020; Niedermann, Sloth, 2019 (for NEDE)*

**Data sets:** Planck + BOSS DR12 BAO + full-shape analysis +  
Pantheon

- fixing  $z_c$ ,  $\theta_i$  to bestfit to *Planck* – “1-parameter model”
- $f_{\text{EDE}} = 0.072 \pm 0.034$  (mean  $\pm 1\sigma$ )
- Same data set, but different conclusion than Ivanov et al.,  
D’Amico et al., **suspect volume effects**

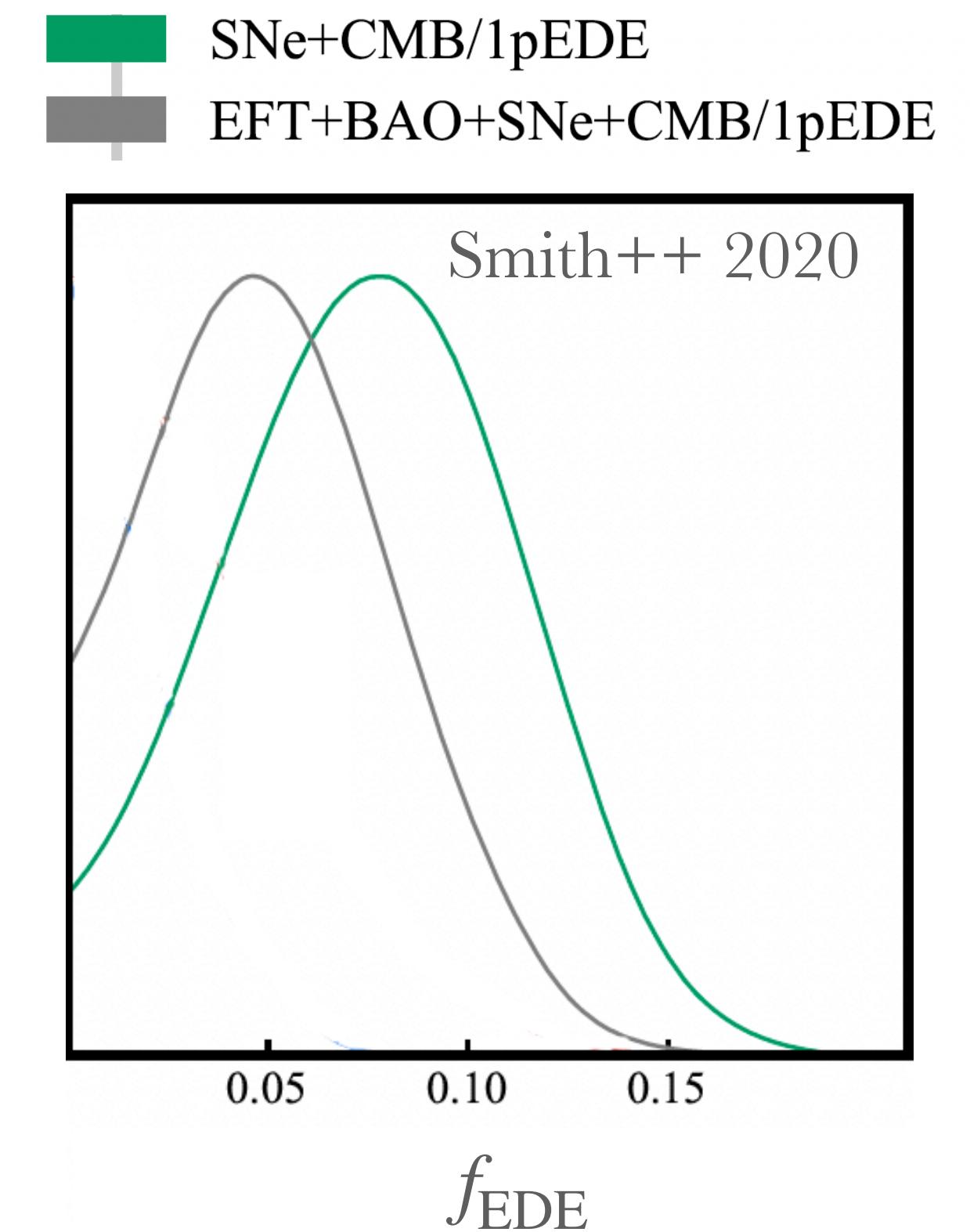


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However: Not a full Bayesian analysis

# Planck + BOSS (baseline data set)

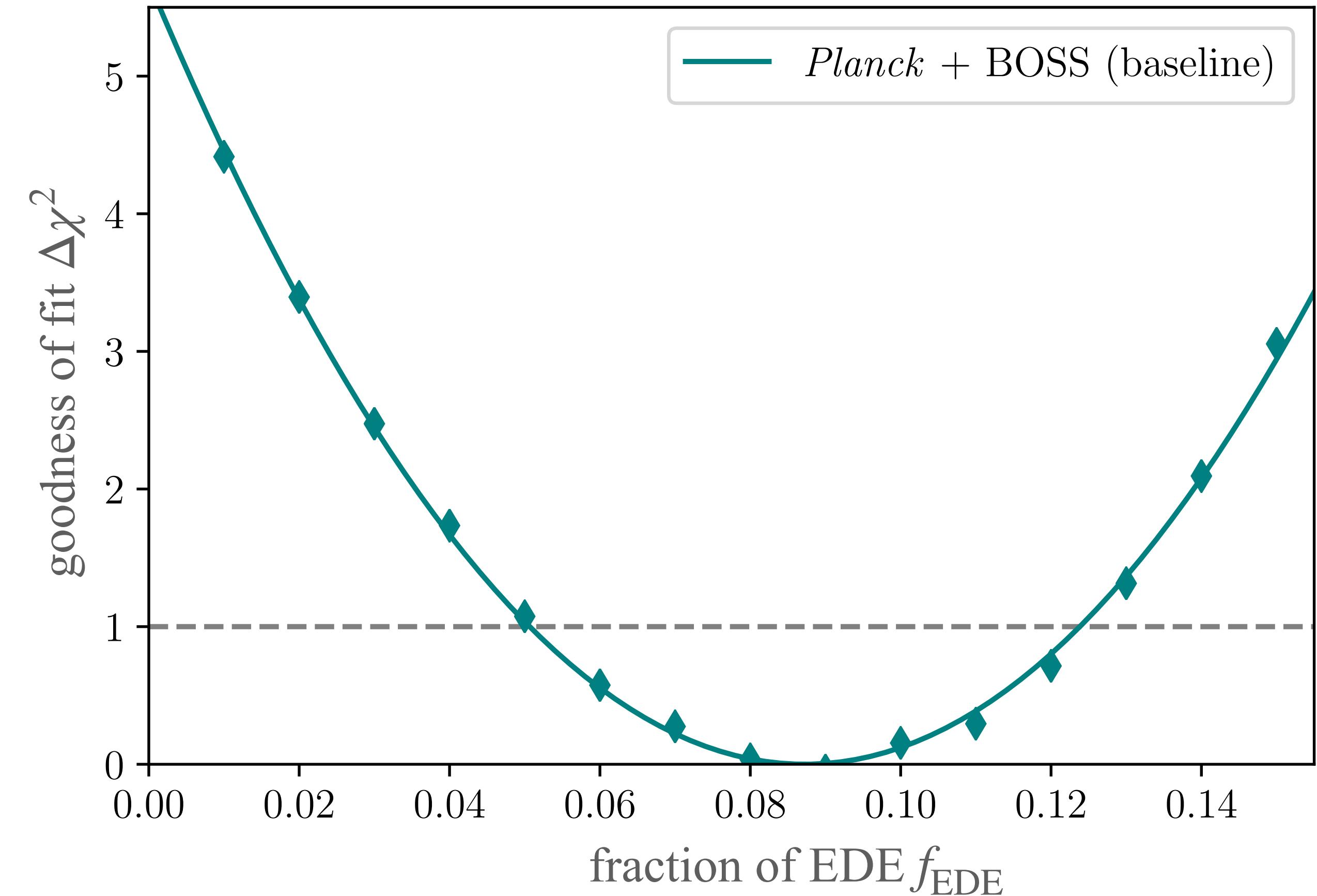
LH++ 2021; LH, Ferreira 2022

## MCMC results:

- $f_{\text{EDE}} < 0.072$  (95% C.L.),  
 $H_0 = 68.55^{+0.62}_{-1.06}$  km/s/Mpc
- $z_c$  and  $\theta_i$  not well constrained

## Profile likelihood results:

- $f_{\text{EDE}} = 0.087 \pm 0.037$ ,



# Planck + BOSS

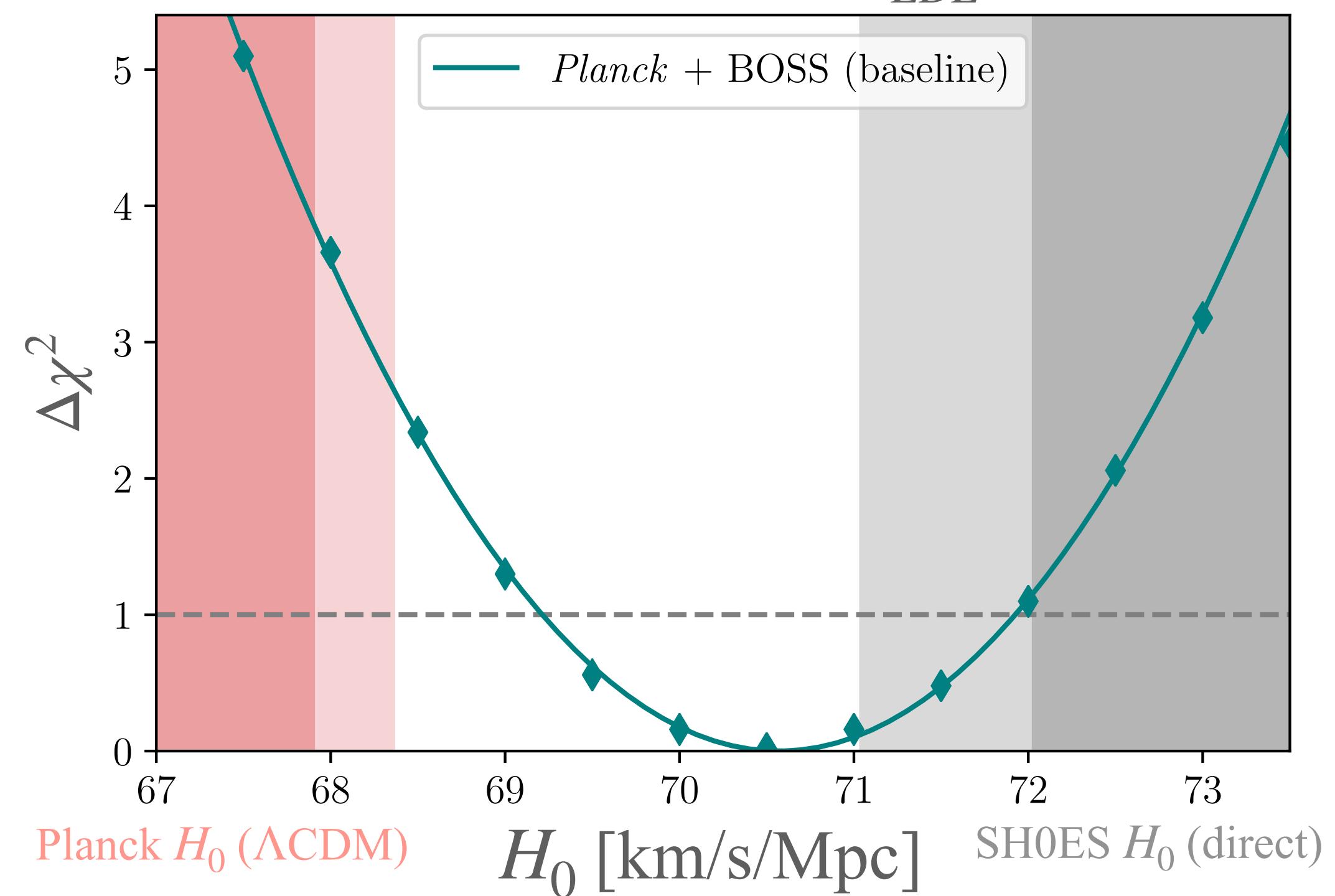
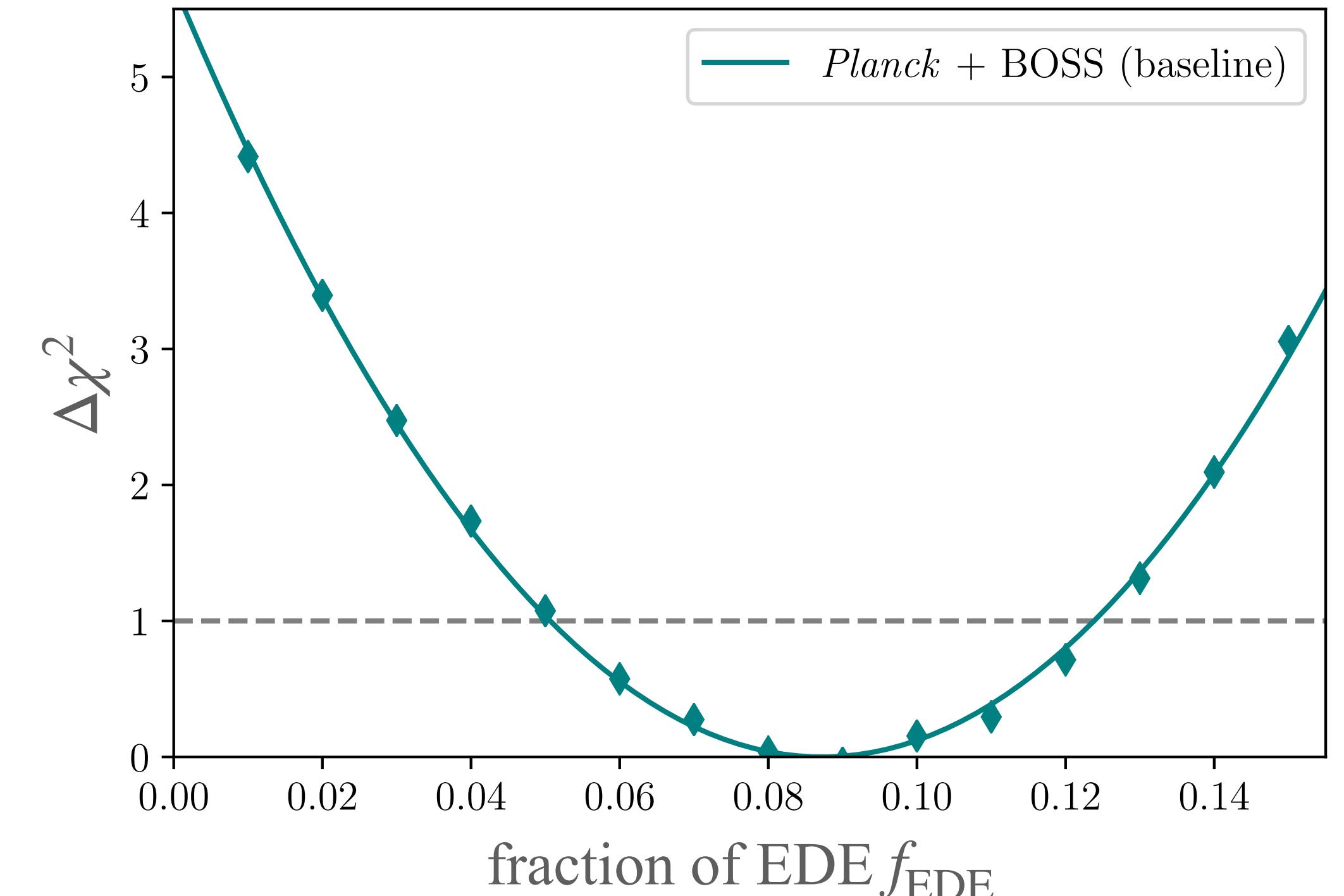
LH, Ferreira 2022

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## Profile likelihood results:

- $f_{\text{EDE}} = 0.087 \pm 0.037$ ,  
 $H_0 = 70.57 \pm 1.36$  km/s/Mpc
- Consistency with SH0ES at  $1.4\sigma$
- However:  $S_8$  tension worsens slightly  
( $\Lambda\text{CDM}$ : 0.828, EDE: 0.840, DES: 0.776)

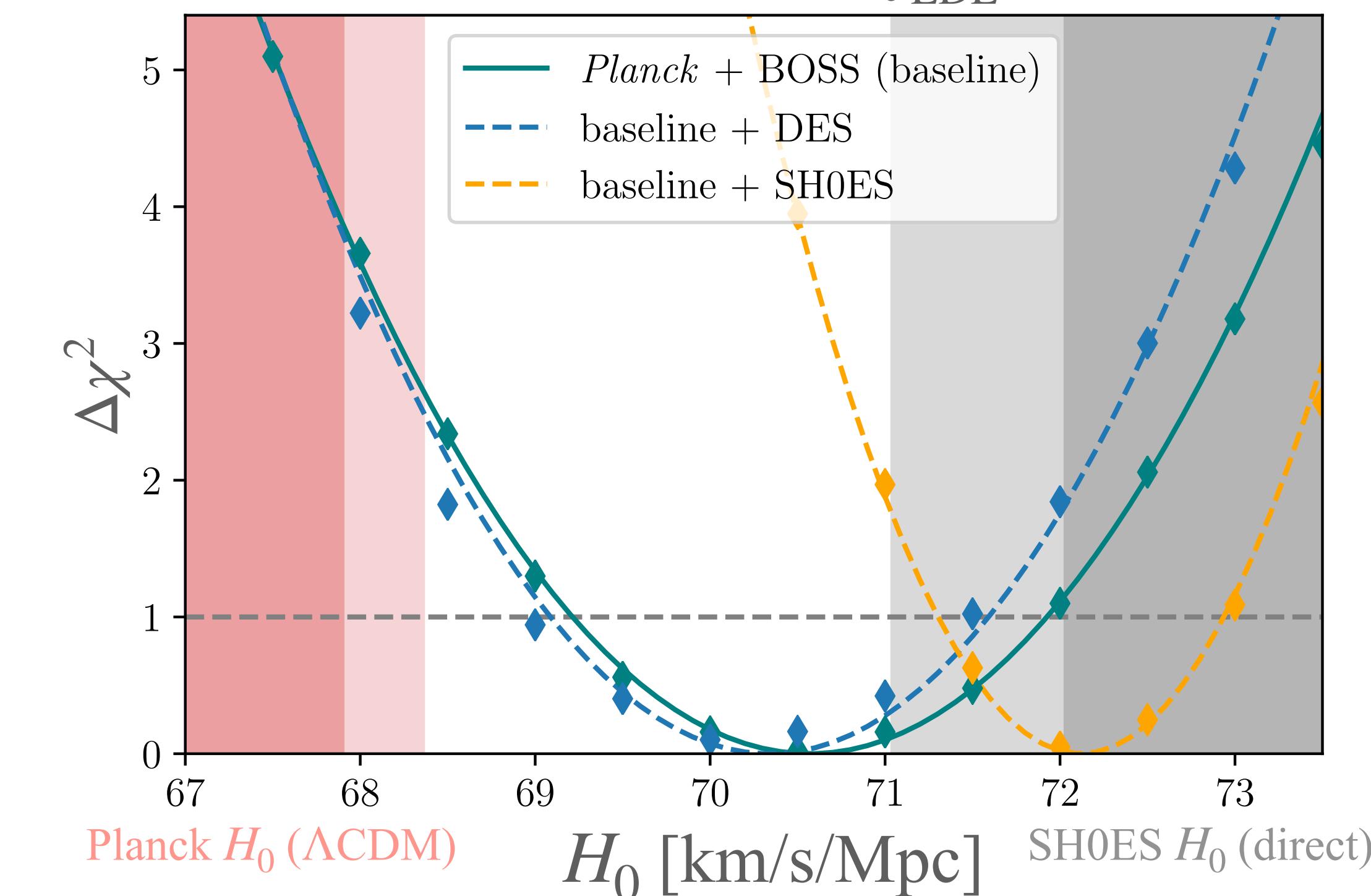
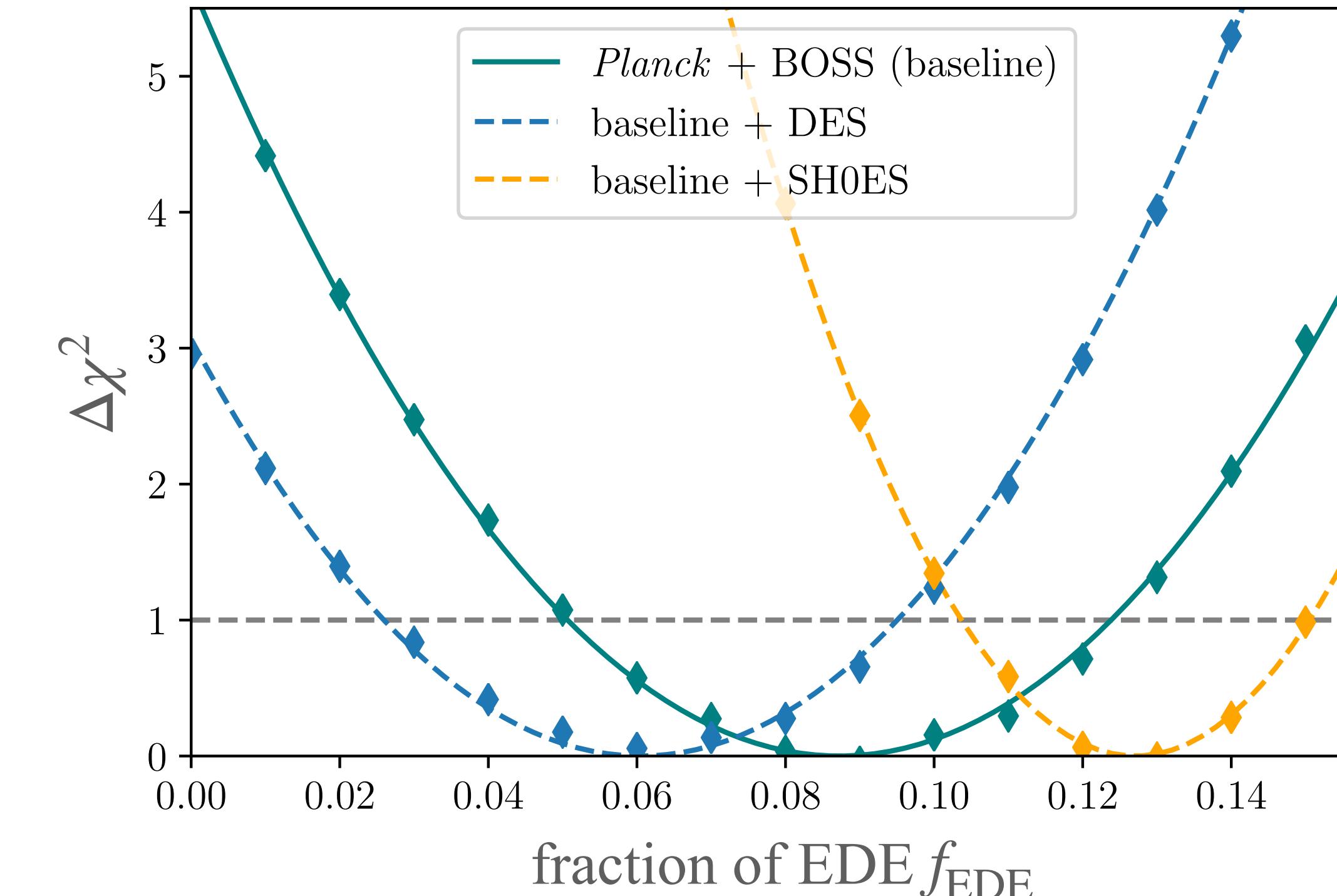


# Baseline + DES

LH, Ferreira 2022

Baseline+DES ( $S_8 = 0.776 \pm 0.017$ ):

- $f_{\text{EDE}} = 0.061^{+0.035}_{-0.034}$ ,  
 $H_0 = 70.28 \pm 1.33 \text{ km/s/Mpc}$
- Consistency with SH0ES at  $1.6\sigma$
- Including weak lensing reduces  $f_{\text{EDE}}$  and  $H_0$  slightly but does not rule out EDE
- Prior volume effect seems to be the dominating effect (compared to clustering enhancement)

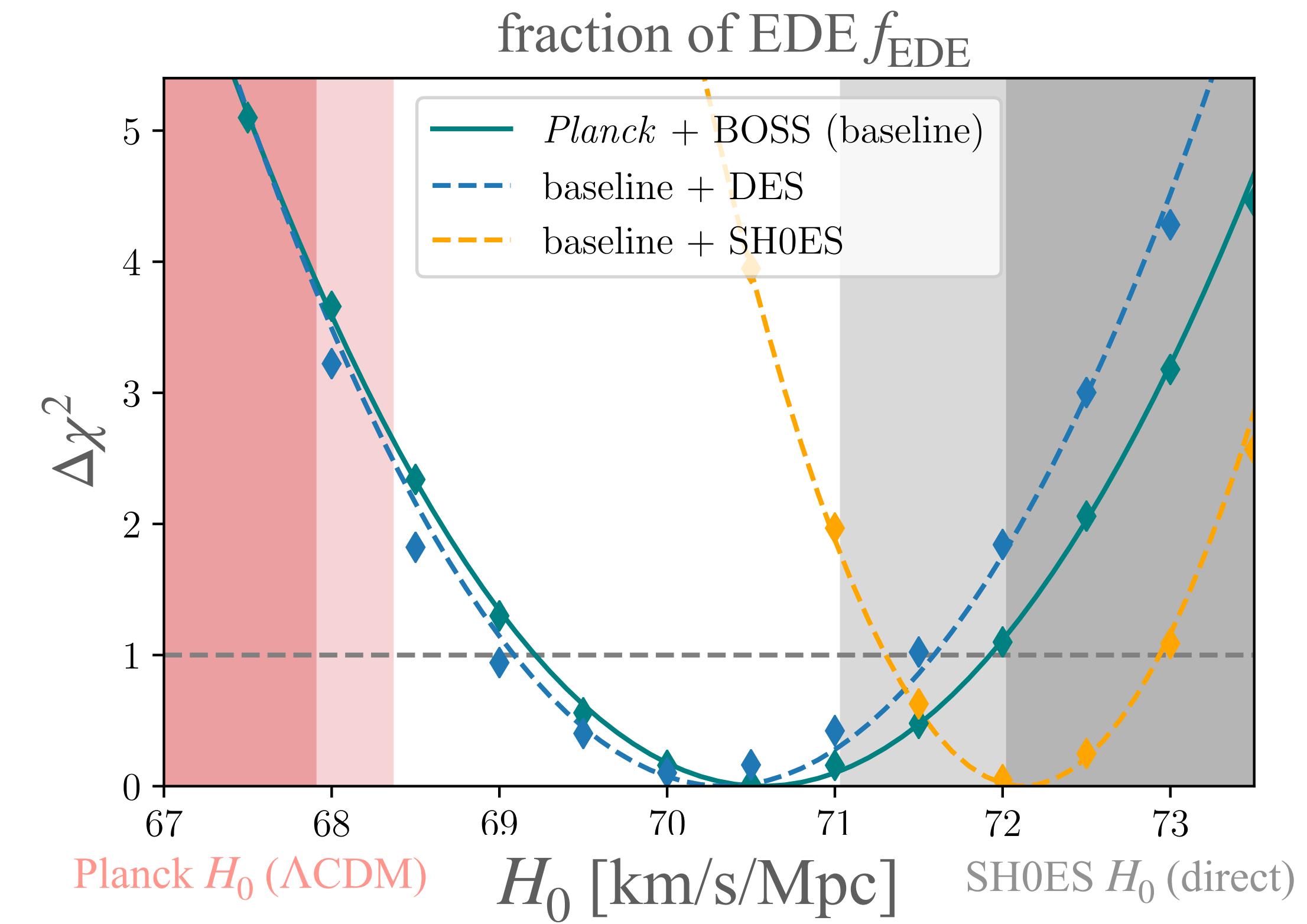
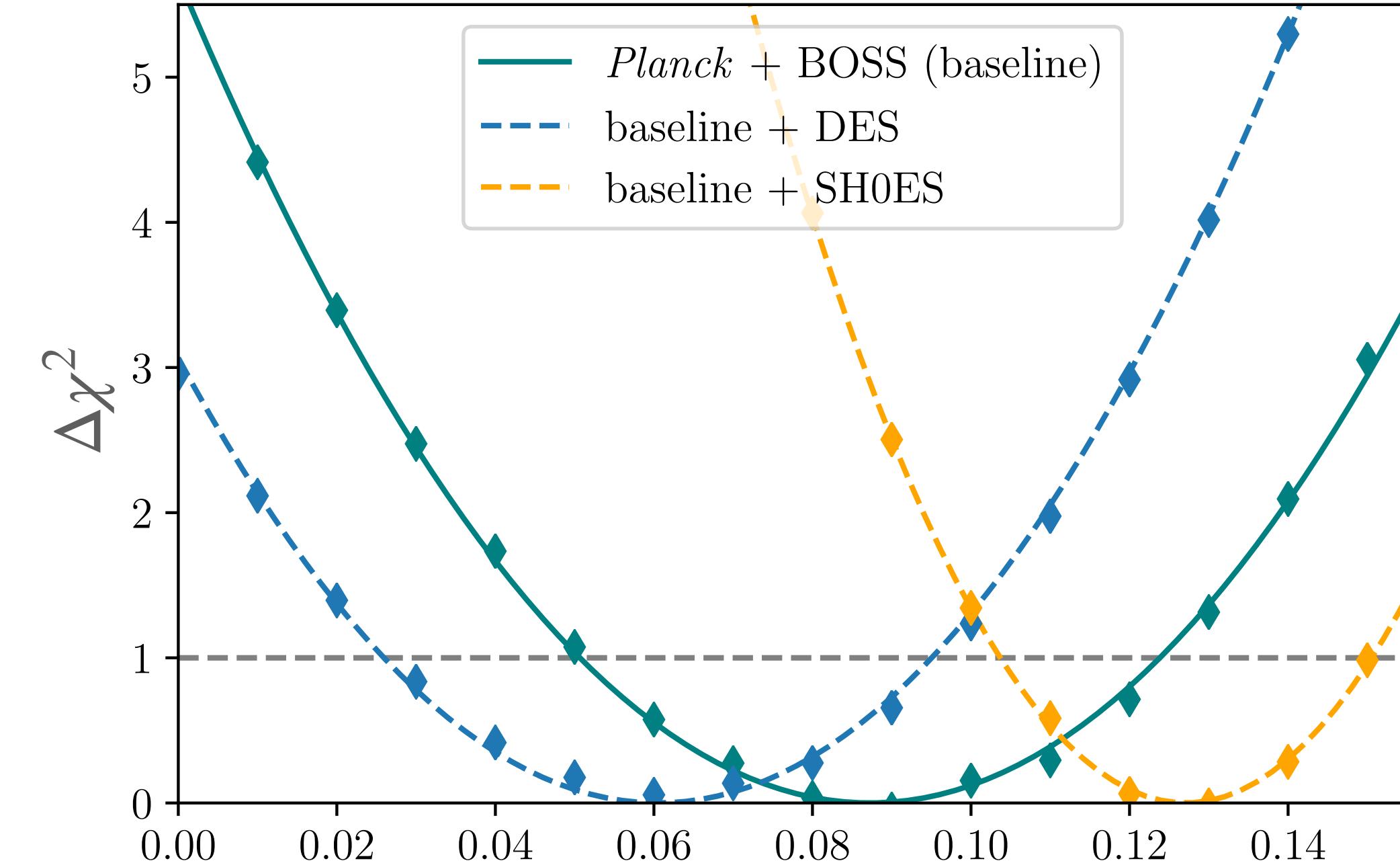


# Baseline + SH0ES

LH, Ferreira 2022

Baseline+SH0ES  
 $(H_0 = 73.04 \pm 1.04 \text{ km/s/Mpc})$ :

- Since we find that  $H_0$  for the baseline data set is in agreement with SH0ES, we can combine both data sets
- $f_{\text{EDE}} = 0.127 \pm 0.023$ ,  
 $H_0 = 72.12 \pm 0.82 \text{ km/s/Mpc}$
- Consistency with SH0ES at  $0.69 \sigma$

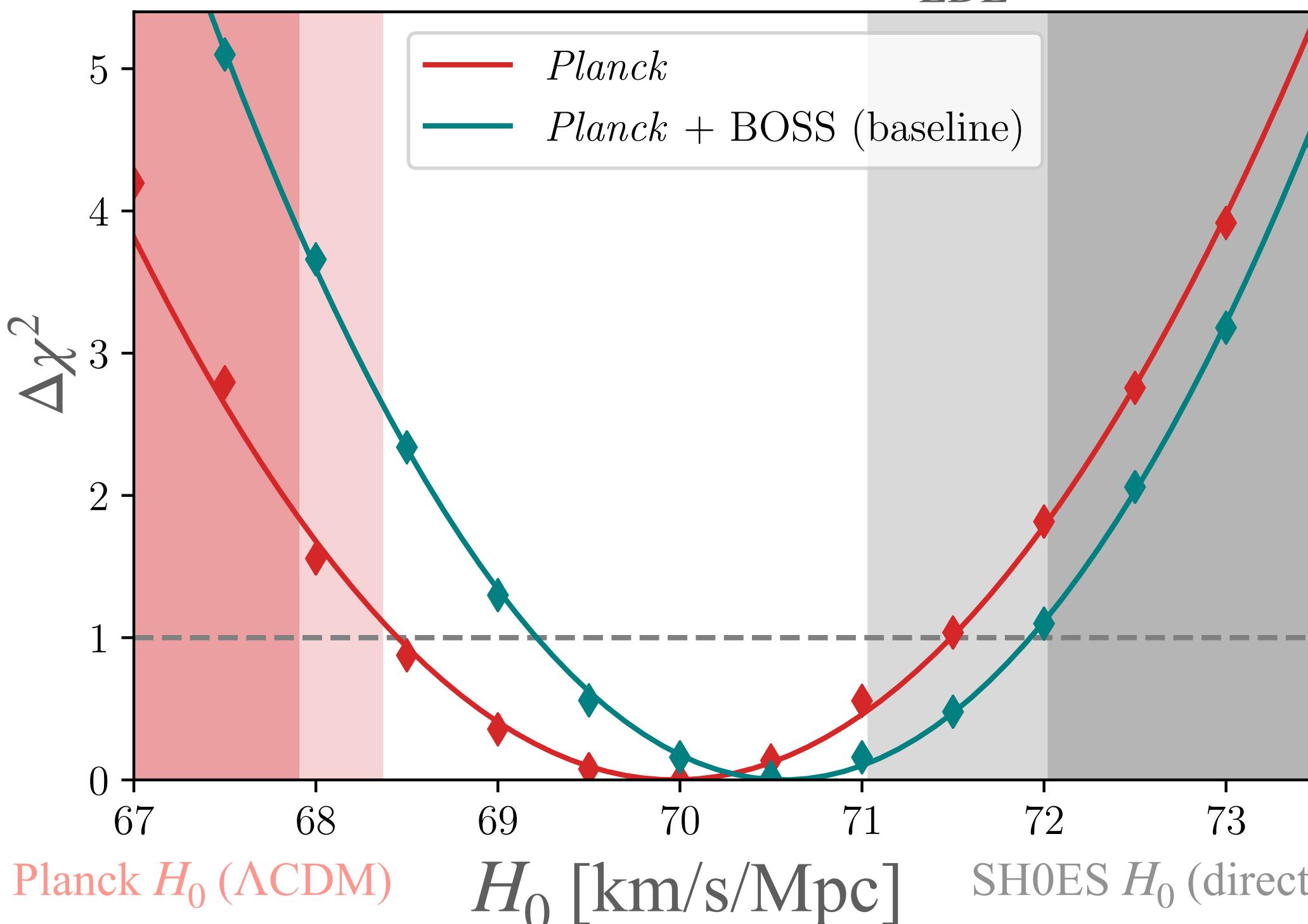
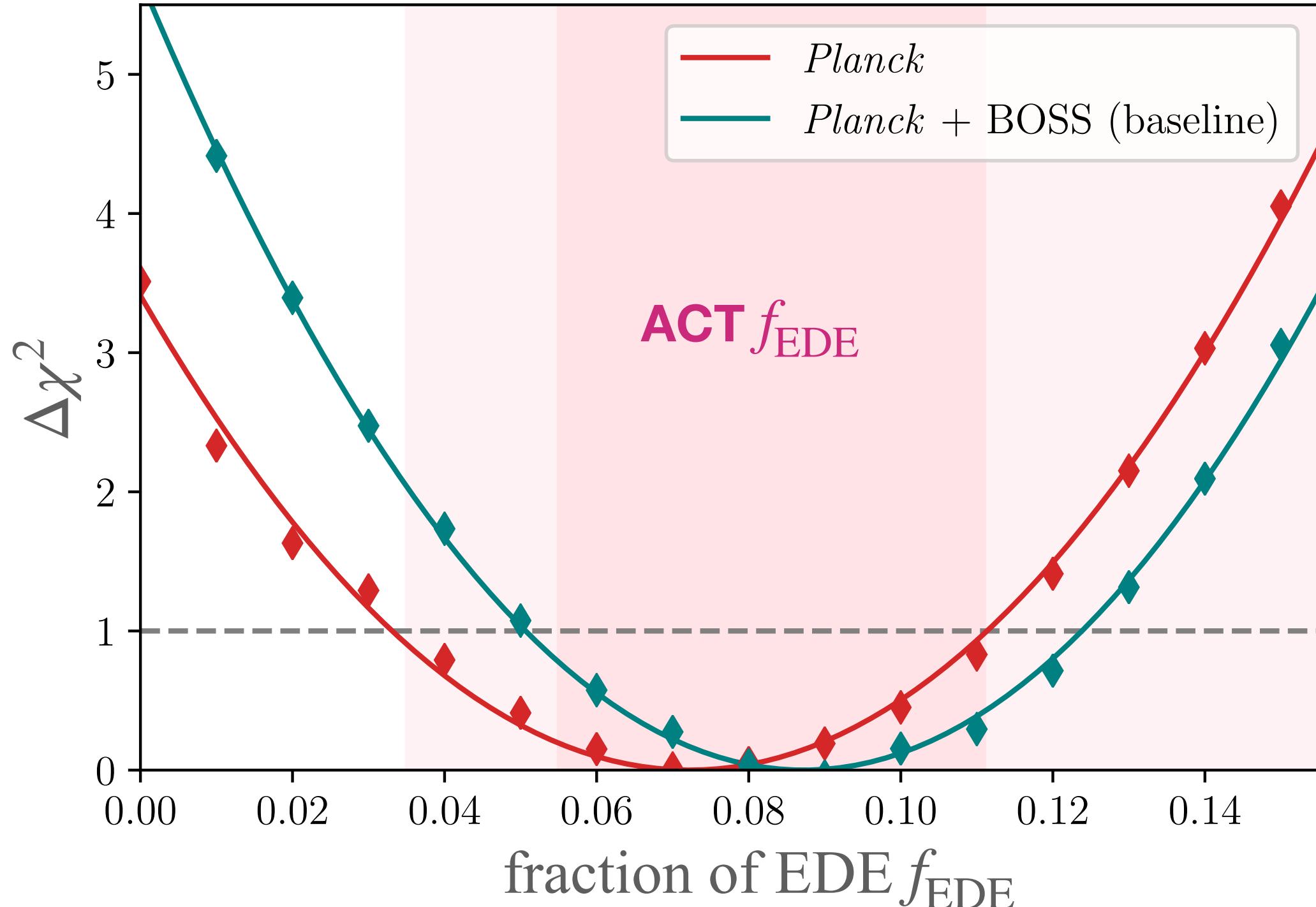


# Planck only

LH, Ferreira 2022

*Planck only:*

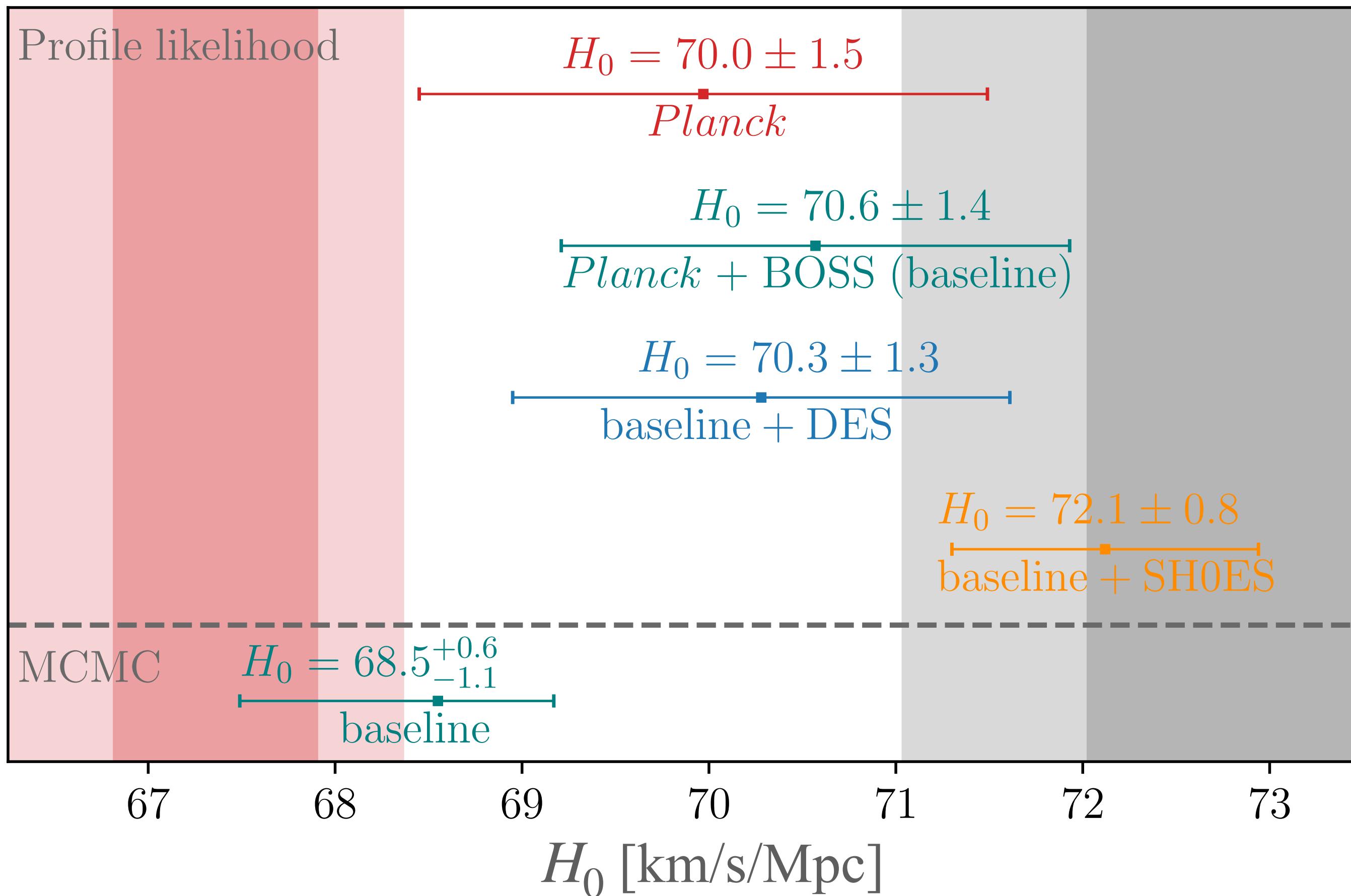
- $f_{\text{EDE}} = 0.072 \pm 0.039$ ,  
 $H_0 = 69.97 \pm 1.52 \text{ km/s/Mpc}$
- Agreement with SH0ES at  $1.7 \sigma$
- Agrees with recent MCMC results from the Atacama cosmology telescope (ACT):  
 $f_{\text{EDE}} = 0.091^{+0.020}_{-0.036}$  (Hill++ 2022)



# Profile likelihood – results

LH, Ferreira 2022

Planck  $H_0$  ( $\Lambda$ CDM)



## Results:

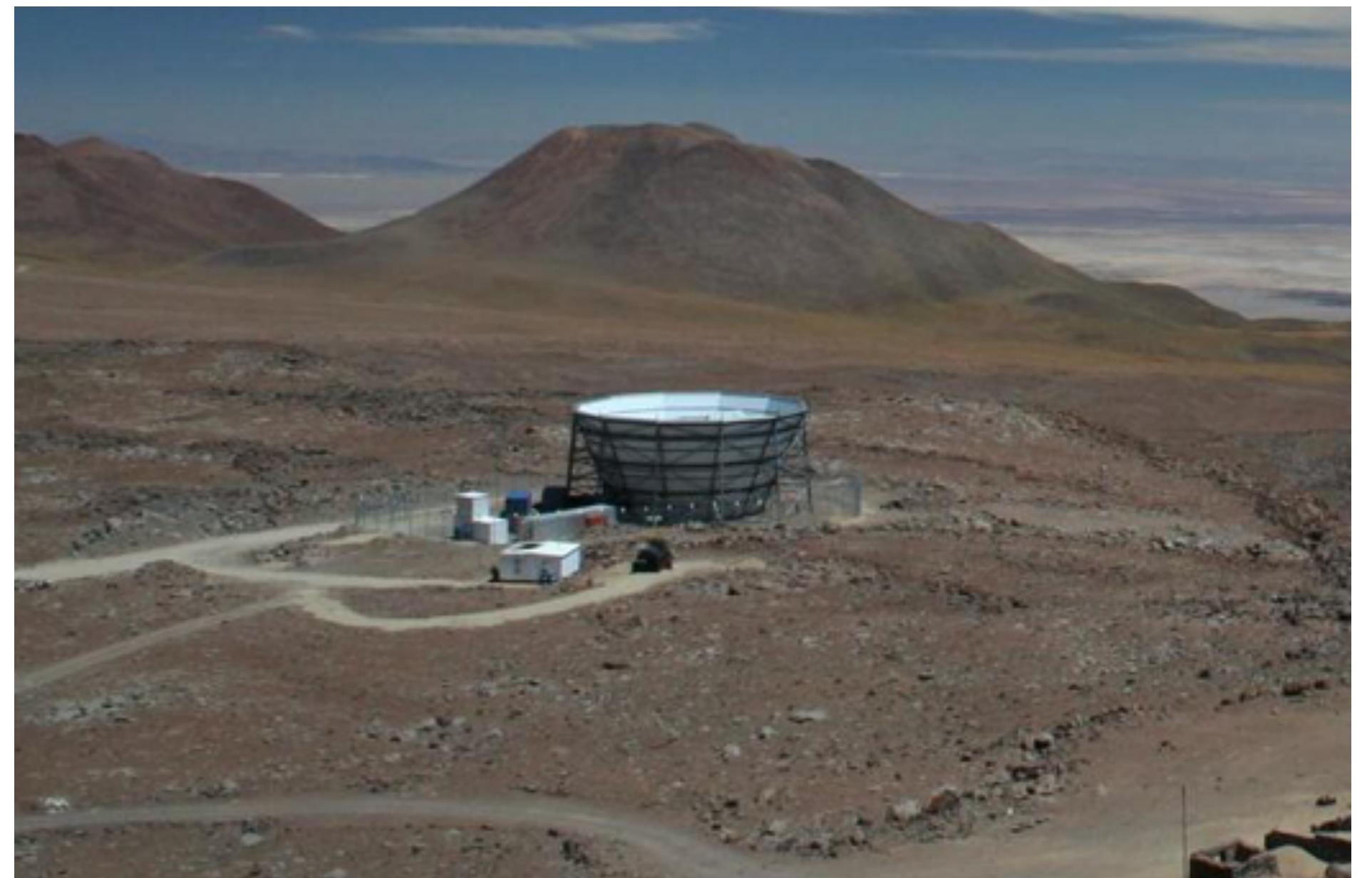
- Evidence for prior volume effects.
- $H_0$  in EDE model within  $1.7\sigma$  of SH0ES measurement for all data sets (incl. galaxy clustering, weak lensing).
- EDE viable solution to Hubble tension.

# Results from ACT

*Hill et al. 2021, Poulin et al. 2021*

*Data sets:* ACT DR4 + large-scale Planck TT+lensing + BOSS BAO (yellow line)

- prefers the EDE model over  $\Lambda$ CDM by 2-3  $\sigma$
- $H_0 = 70.9_{-2.0}^{+1.0}$  km/s/Mpc,  
 $f_{\text{EDE}} = 0.091_{-0.036}^{+0.020}$
- Driven by ACT  $TE+EE$  power spectra



ACT collaboration

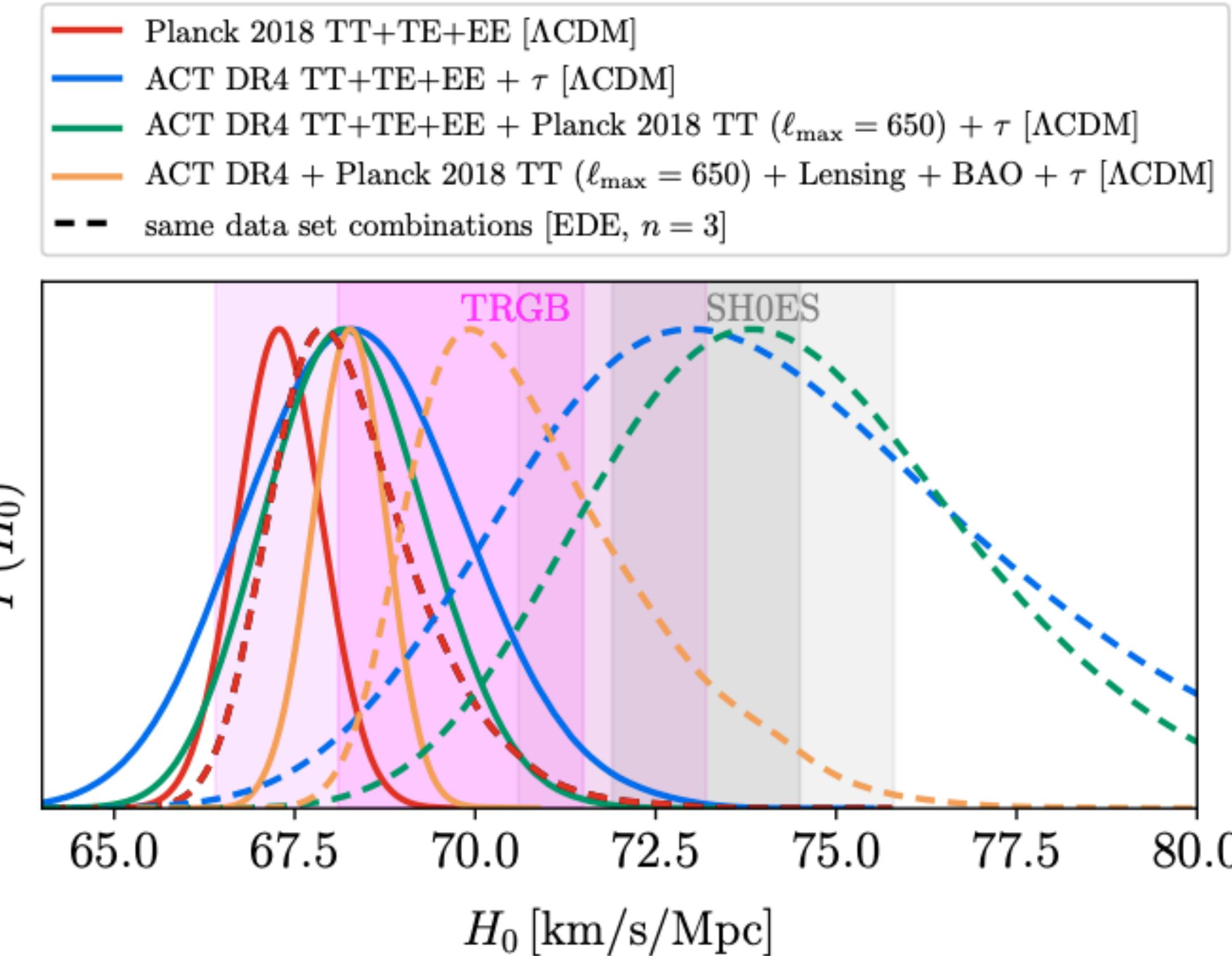
# Results from ACT

Hill et al. 2021, Poulin et al. 2021, Smith et al. 2022

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# EDE constraints from South Pole Telescope

*La Posta++ 2021, Smith++ 2022*



Credit Luong-Van

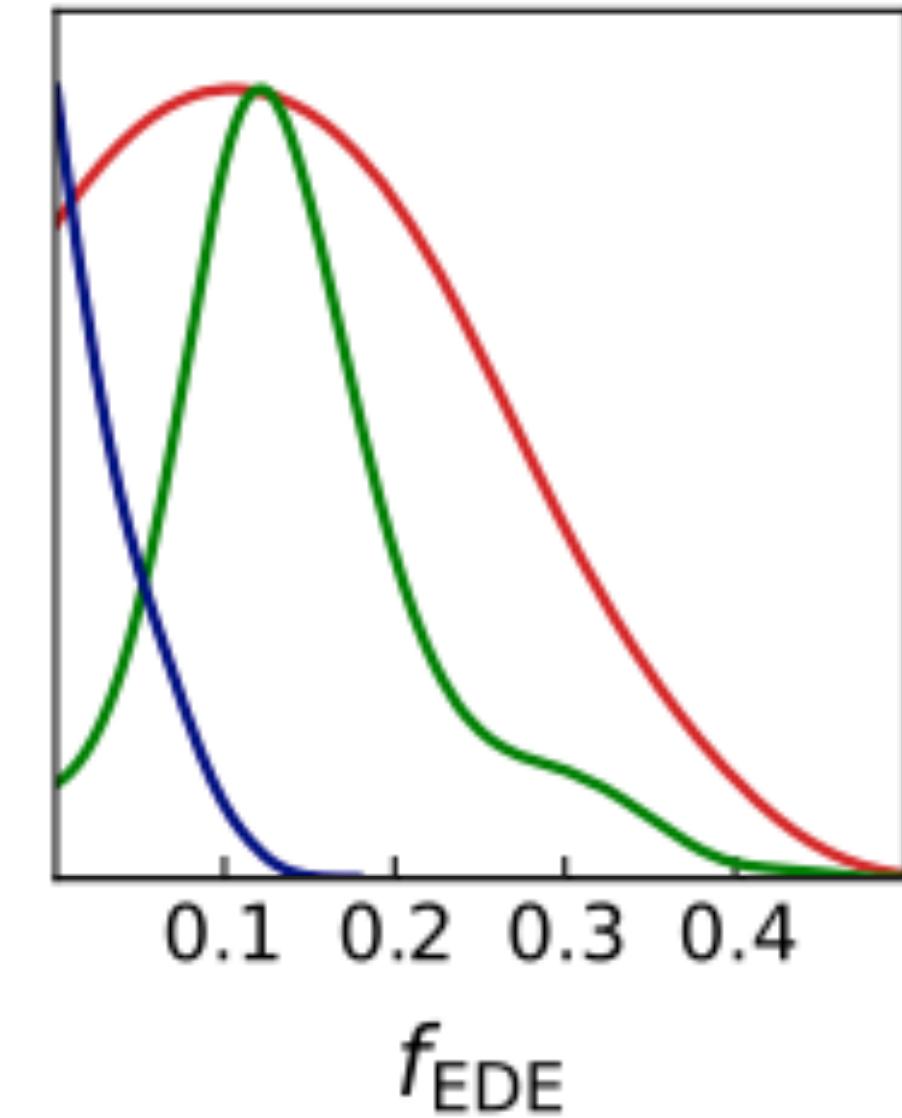
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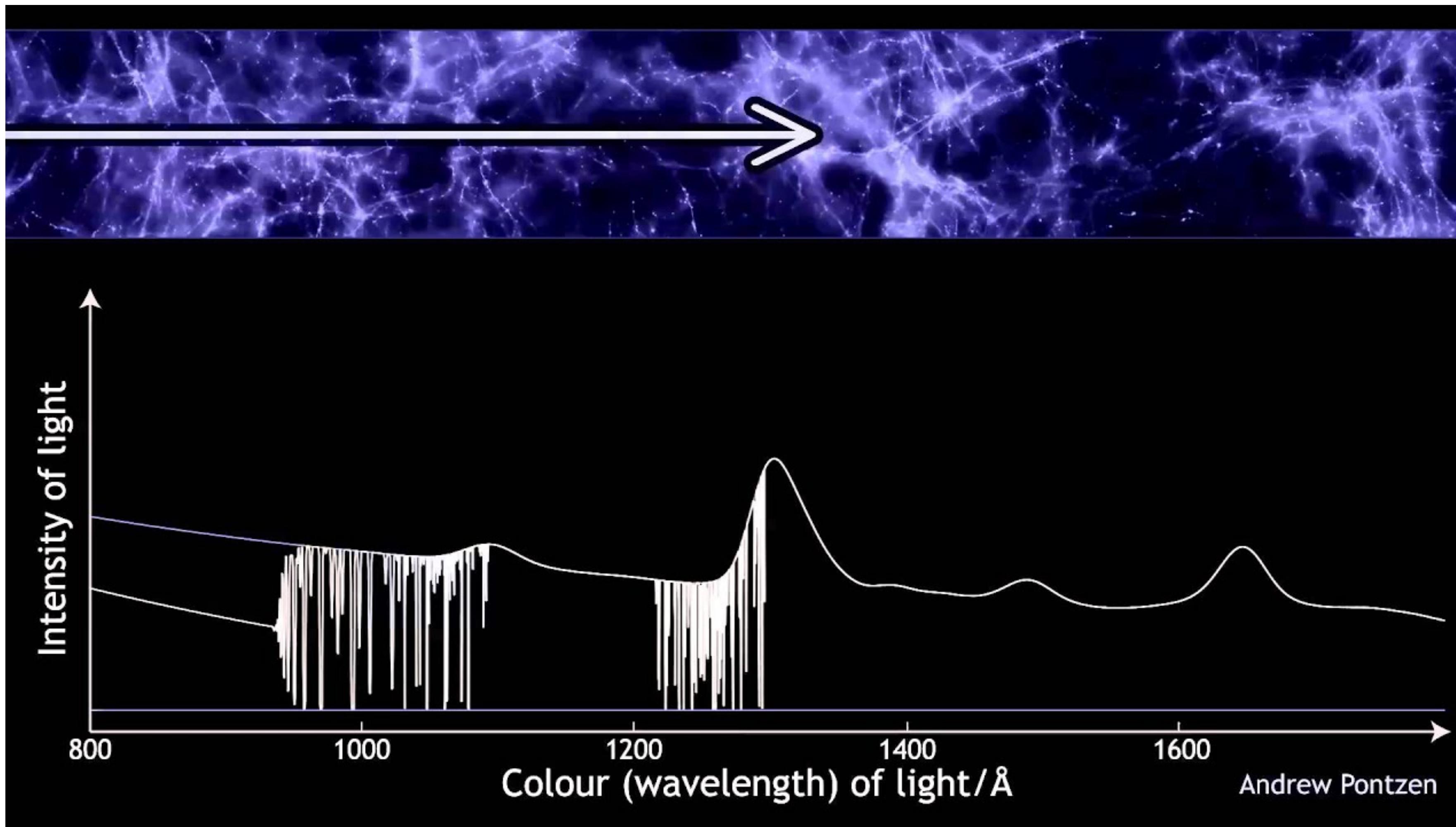
La Posta++ 2021



- SPT is consistent with ACT but with larger errorbar
- It is also consistent with  $f_{\text{EDE}} = 0$

- Planck +  $\tau$ -prior [EDE,  $n = 3$ ]
- ACT DR4 +  $\tau$ -prior [EDE,  $n = 3$ ]
- SPT-3G +  $\tau$ -prior [EDE,  $n = 3$ ]

# EDE constraints from Ly $\alpha$ forest

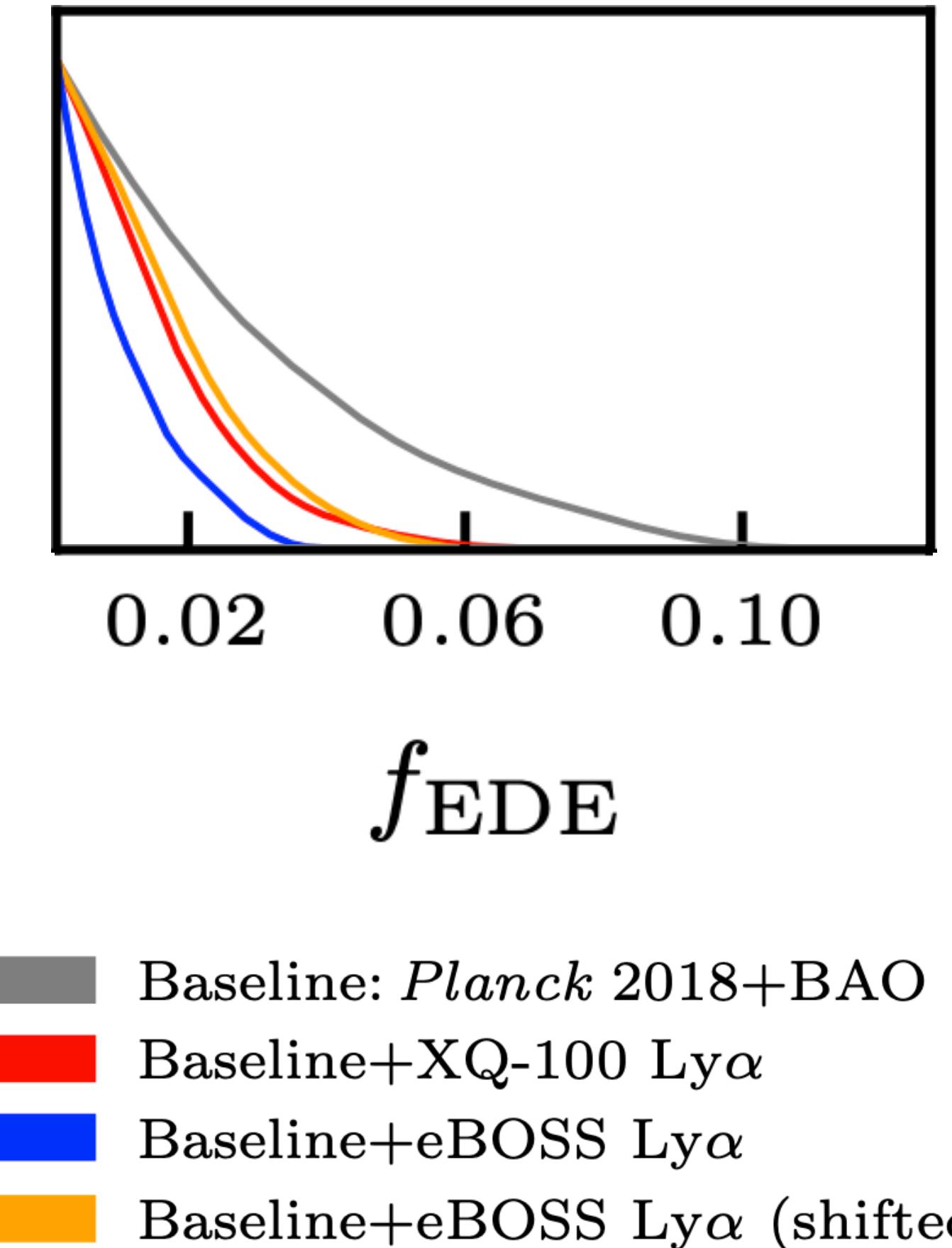


# EDE constraints from Ly- $\alpha$ forest

Goldstein et al. 2023

- Lyman- $\alpha$  forest constraints the matter power spectrum at small scales
- Combined with Planck data, it gives very tight upper limits on  $f_{\text{EDE}}$
- However, there seem to be some internal discrepancies in Ly- $\alpha$  data, so EDE-constraints need to be taken with a grain of salt

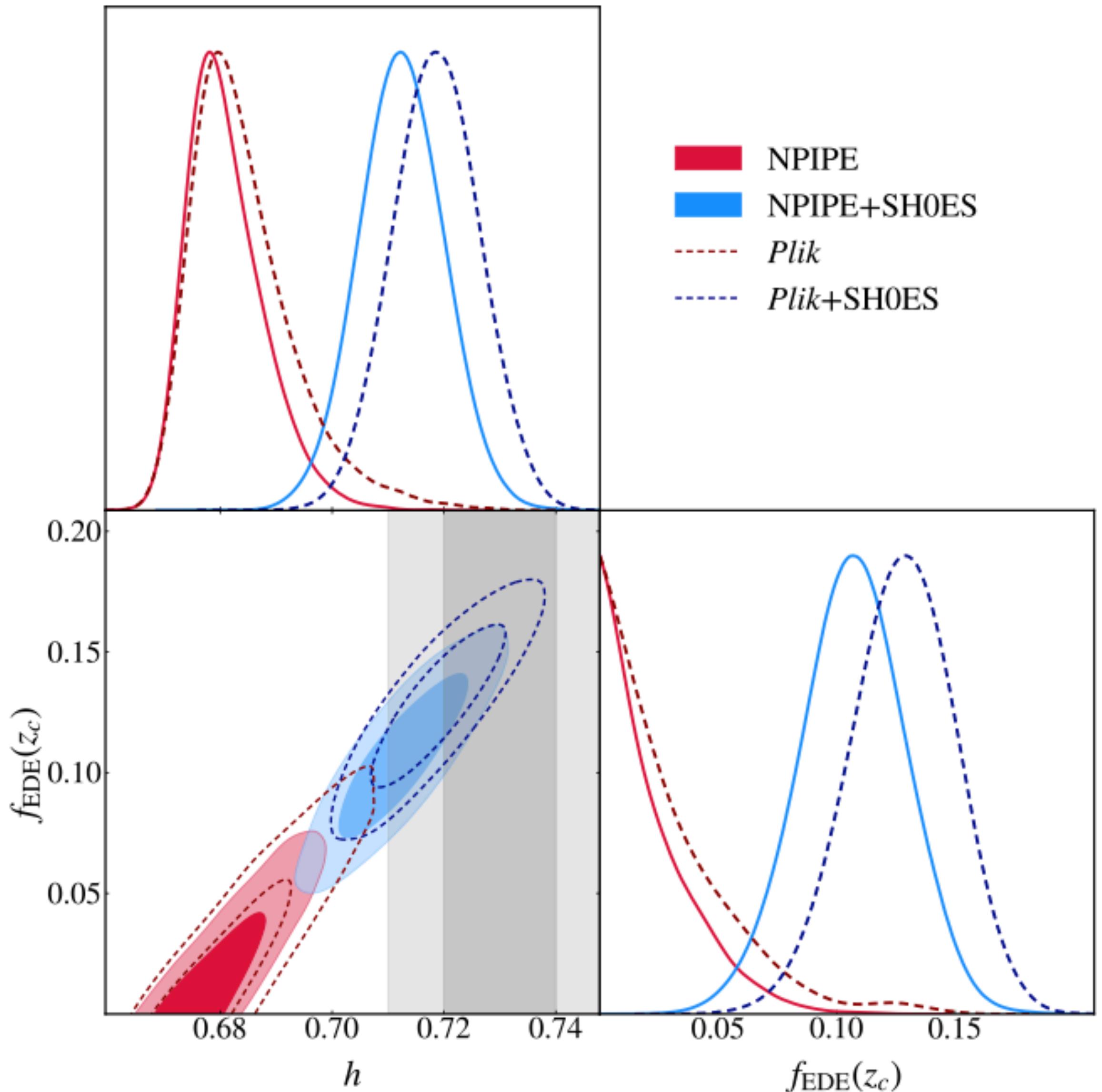
Goldstein++ 2023



# Alternative NPIPE Planck pipeline

*Efstathiou et al. 2023*

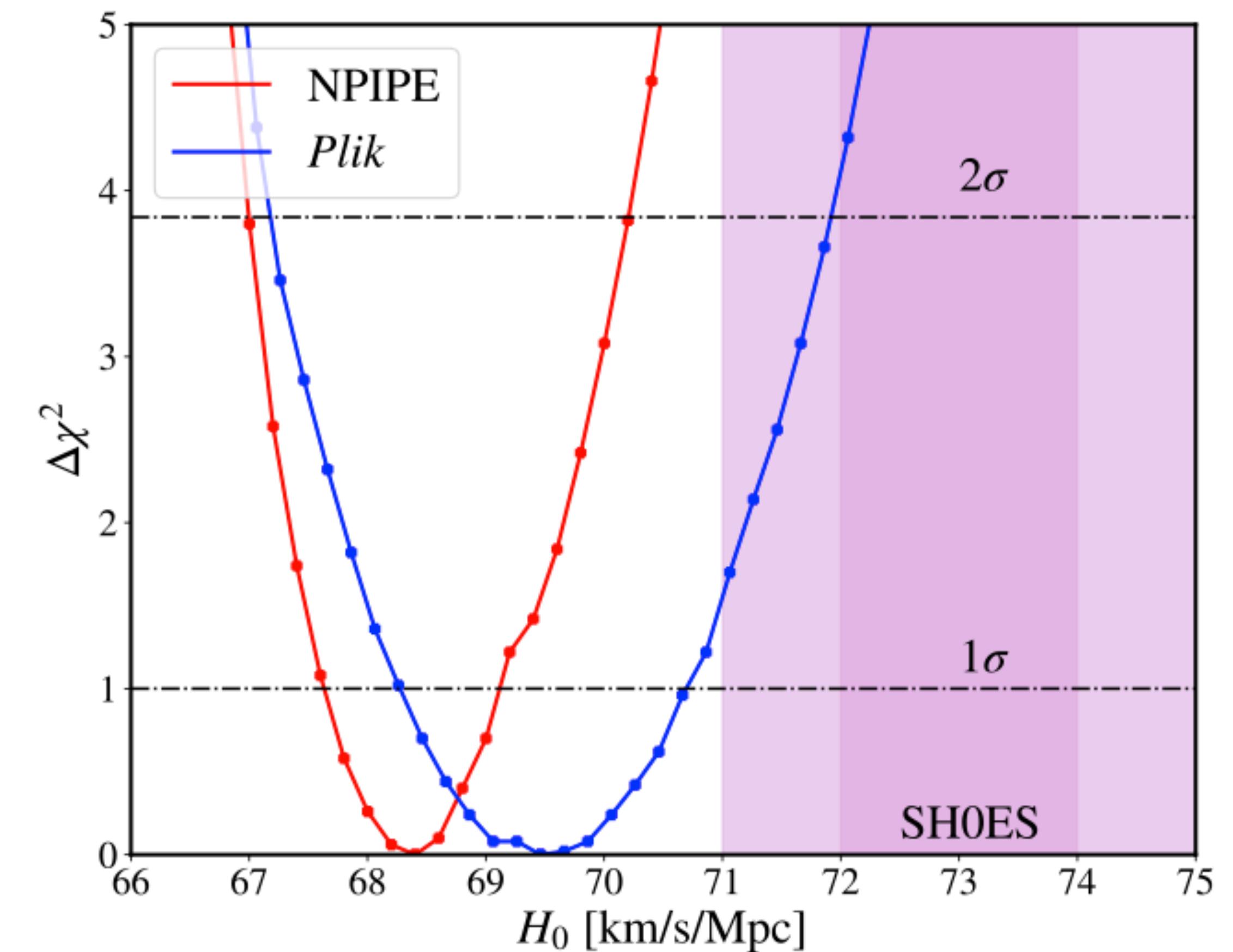
- An alternative Planck pipeline NPIPE
  - using more sky area at high frequencies
  - reducing the  $\Lambda$ CDM residuals
- NPIPE gives tighter constraints on  $f_{\text{EDE}}$  in a Bayesian MCMC...



# Alternative NPIPE Planck pipeline

*Efstathiou et al. 2023*

- An alternative Planck pipeline NPIPE
  - using more sky area at high frequencies
  - reducing the  $\Lambda$ CDM residuals
- NPIPE gives tighter constraints on  $f_{\text{EDE}}$  in a Bayesian MCMC and frequentist profile likelihood



# Recap Lecture 2

# The Hubble Tension and Early Dark Energy

- The reason behind the Hubble tension is still unknown
- EDE is a promising solution to the Hubble tension
- EDE has a complicated parameter structure ( $f_{\text{EDE}}$ ,  $z_c$ ,  $\theta_i$ ) and one needs to take care in the analysis
- However, there seem to be more indications that the simple canonical axion-like EDE model is disfavoured
- EDE-type solutions are still the “least unlikely” ones — Need to be more clever in constructing the models?

# Two statistical philosophies

- Bayesian and frequentist approaches gave different parameter intervals for EDE due to its complicated parameter structure
- In Bayesian approaches it is important to test the sensitivity on the choice of prior
- In Frequentist approaches it is important to consider fine-tuning effects
- If both approaches differ: more data is necessary to give a final answer

# Thanks to:

**Elisa Ferreira, Eiichiro Komatsu and, Graeme Addison**, who inspired lectures & notebooks!

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**Thanks to you for listening!**