

From Λ CDM to EDE

Lecture 2: Observation

Overview

Lecture 1: Theory from Λ 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 μ with parameter(s) θ ”
- The data x , model μ , parameter(s) θ can be a single number or a vector

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 μ with parameter(s) θ ”
- The data x , model μ , parameter(s) θ can be a single number or a vector
- The likelihood is typically computed for a fixed (measured or simulated) data set, hence x is often written as a subscript or dropped

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 μ with parameter(s) θ ”
- The data x , model μ , parameter(s) θ can be a single number or a vector
- 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

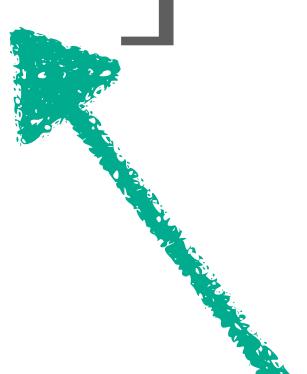
- One very common likelihood is the Gaussian likelihood

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


- 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

- One central question of data analysis is to find the most likely value of a model parameter θ

Point Estimates

- One central question of data analysis is to find the most likely value of a model parameter θ

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

- This is also called the “minimum chi²”

Point Estimates

2. Least squares estimator:

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

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

“data - model”

covariance matrix

- This is also called the “minimum chi²”
- 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 θ 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. α :

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

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

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. α :

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

- ▶ Method: Obtain posterior from Markov-Chain Monte-Carlo (MCMC)
- ▶ Interpretation: “Given the data and the priors, I believe that the true value θ_0 is within $[\theta^-, \theta^+]$ with probability α ” – 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,...

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,...
- ▶ 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 π

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,...
- ▶ 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 π
- ▶ Hence, it is important to check the sensitivity of the results on the choice of π

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 θ_0 is contained in $[\theta^-, \theta^+]$ a fraction α 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 χ^2 -distribution)

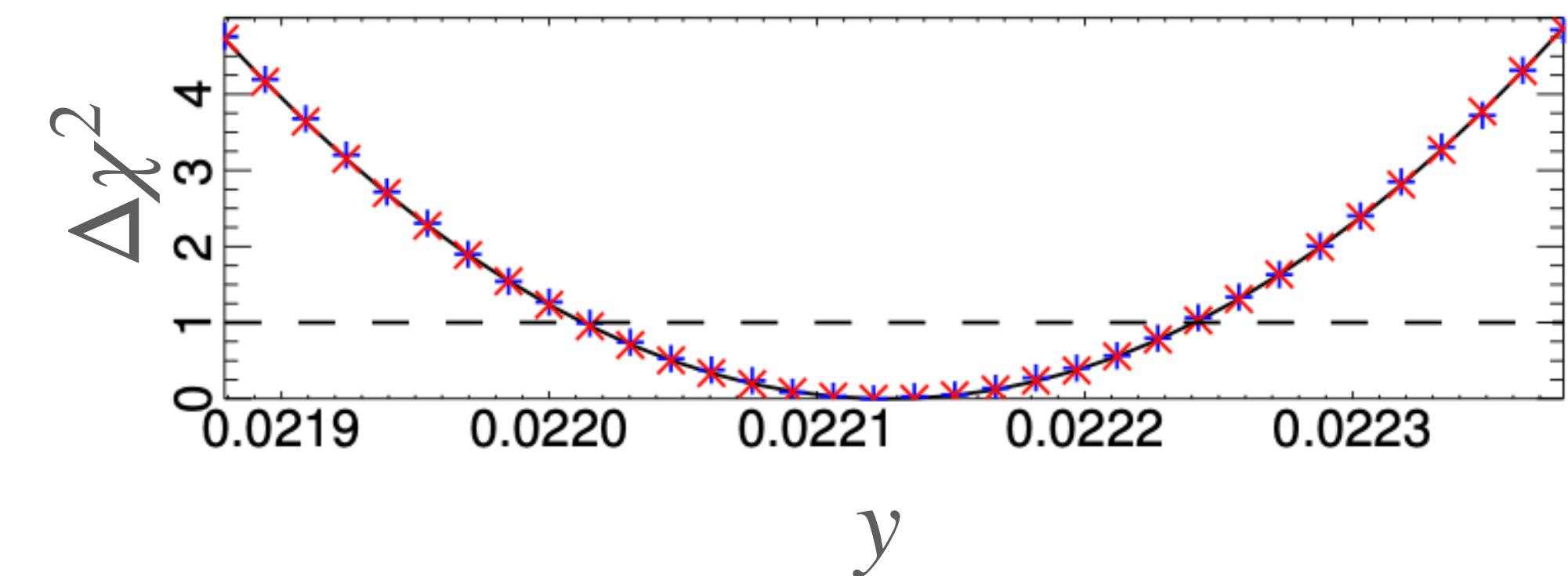
Frequentist confidence intervals

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

Frequentist intervals (Profile likelihood):

- Only based on the likelihood $\mathcal{L}(D | M)$ or on $\chi^2 = -2 \log(\mathcal{L})$.
- No posterior, no prior dependence.
- Problem: Can prefer cosmology with very small parameter volume — “fine tuning”.
Solution: Construct physically motivated model.

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.

Frequentist intervals (Profile likelihood):

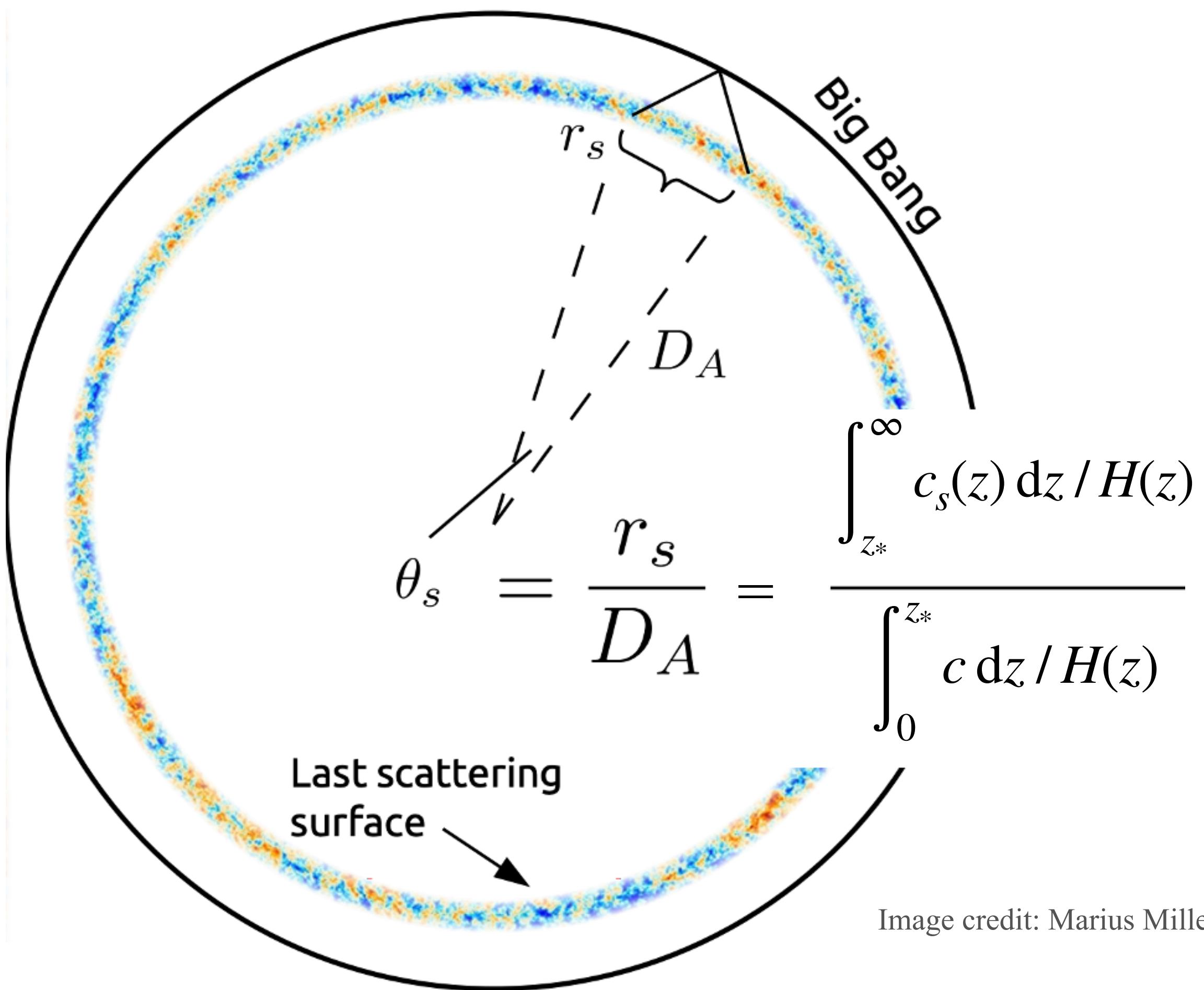
- Only based on the likelihood $\mathcal{L}(D | M)$ or on $\chi^2 = -2 \log(\mathcal{L})$.
- No posterior, no prior dependence.
- Problem: Can prefer cosmology with very small parameter volume — “fine tuning”.
Solution: Construct physically motivated model.

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 θ_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 ϕ with potential

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

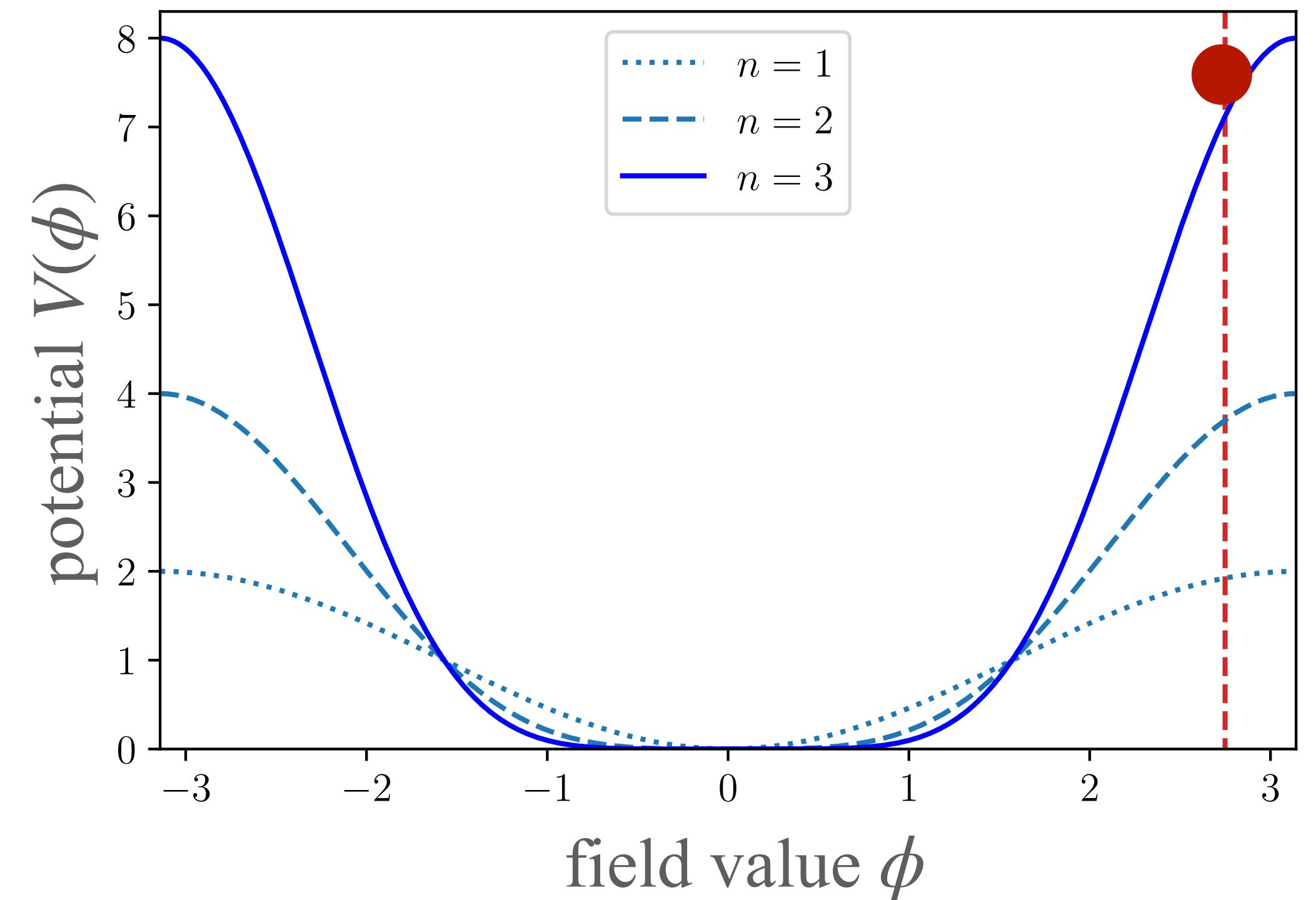
Free parameters:

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

f : decay constant,

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

$n = 3$: EDE decays quickly enough.



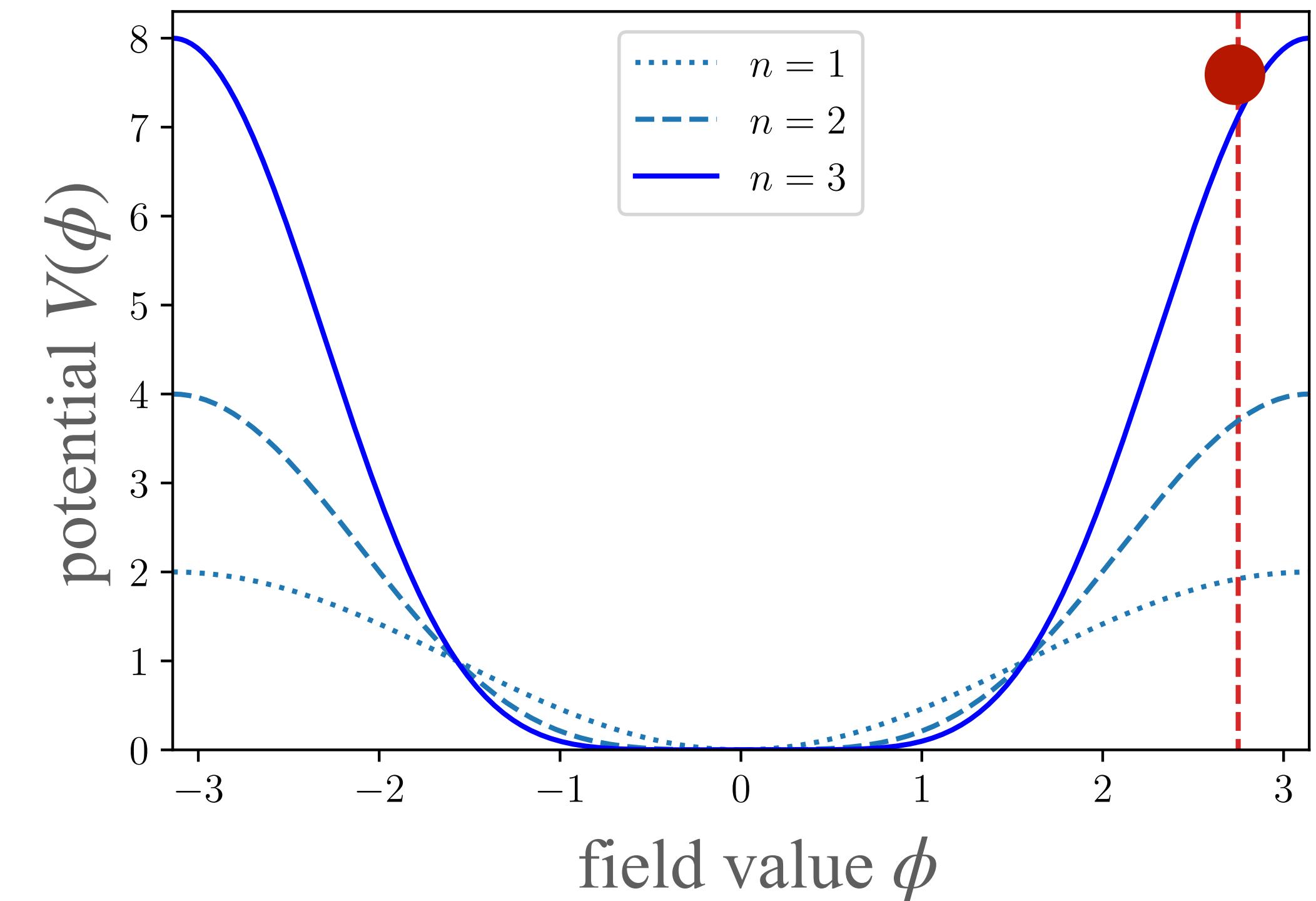
→ Field inspired by axion ($n = 1$) with extremely small mass $\sim 10^{-27}$ eV

Early Dark Energy (EDE)

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

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

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



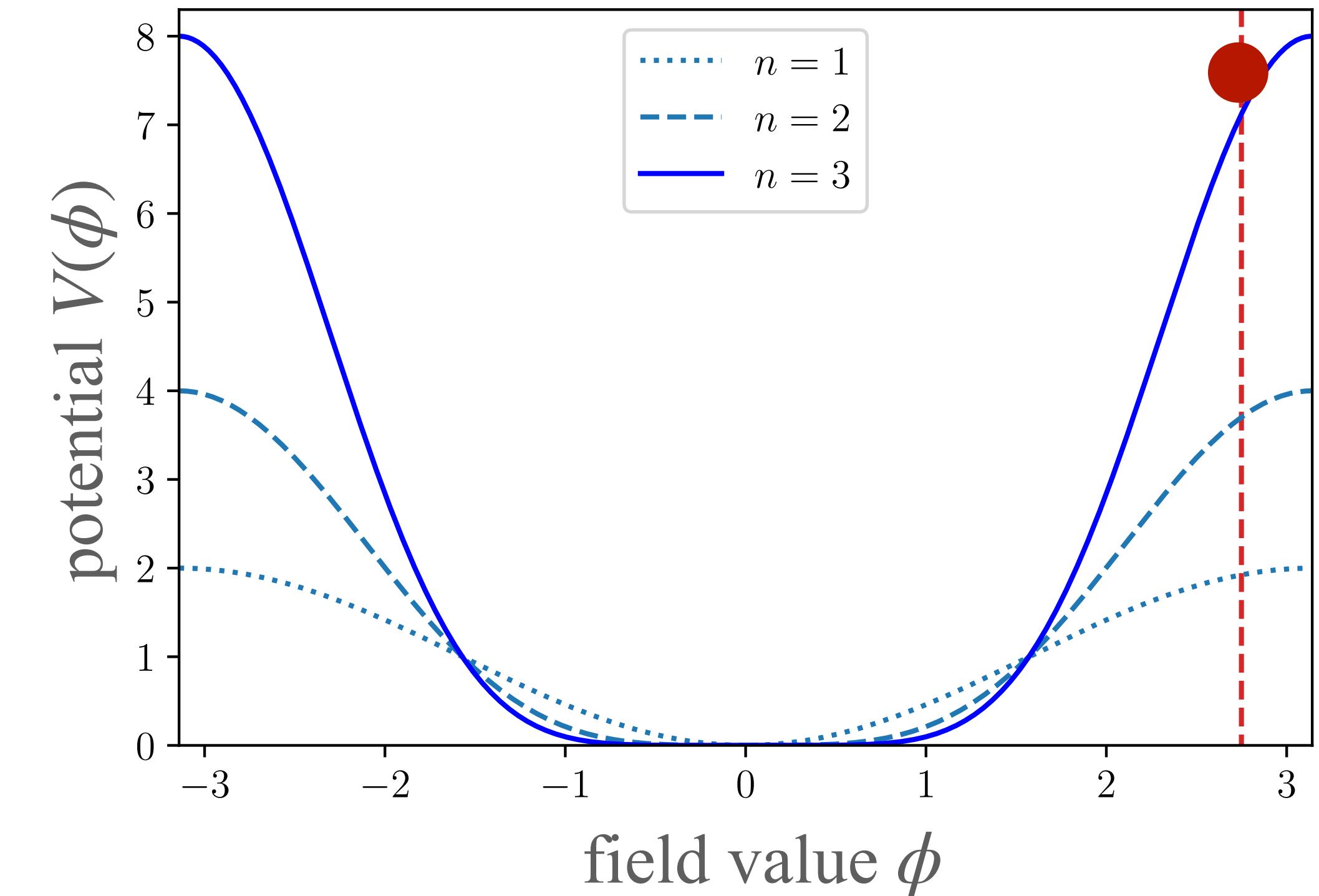
Early Dark Energy (EDE)

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

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

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

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



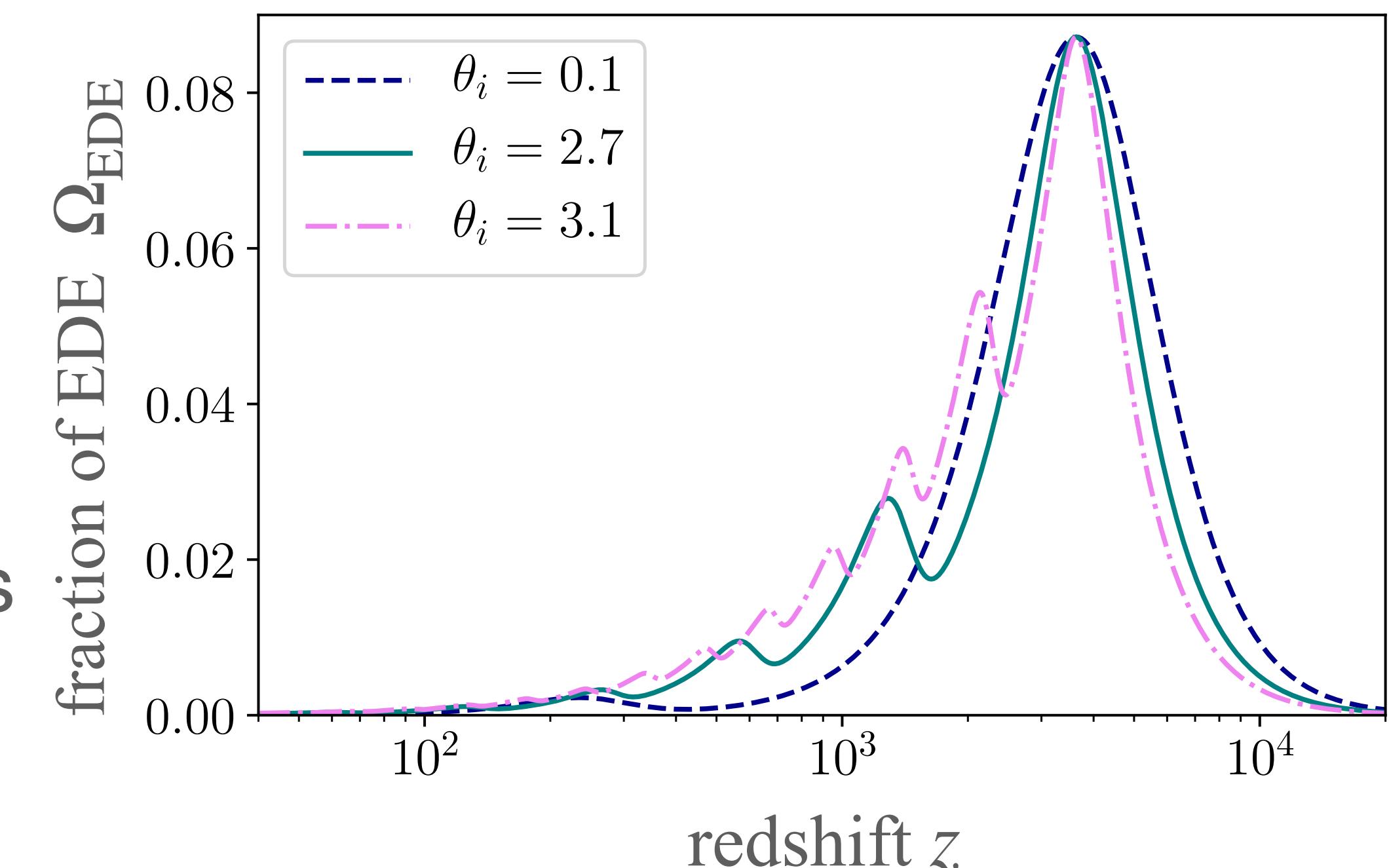
Early Dark Energy (EDE)

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

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

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

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



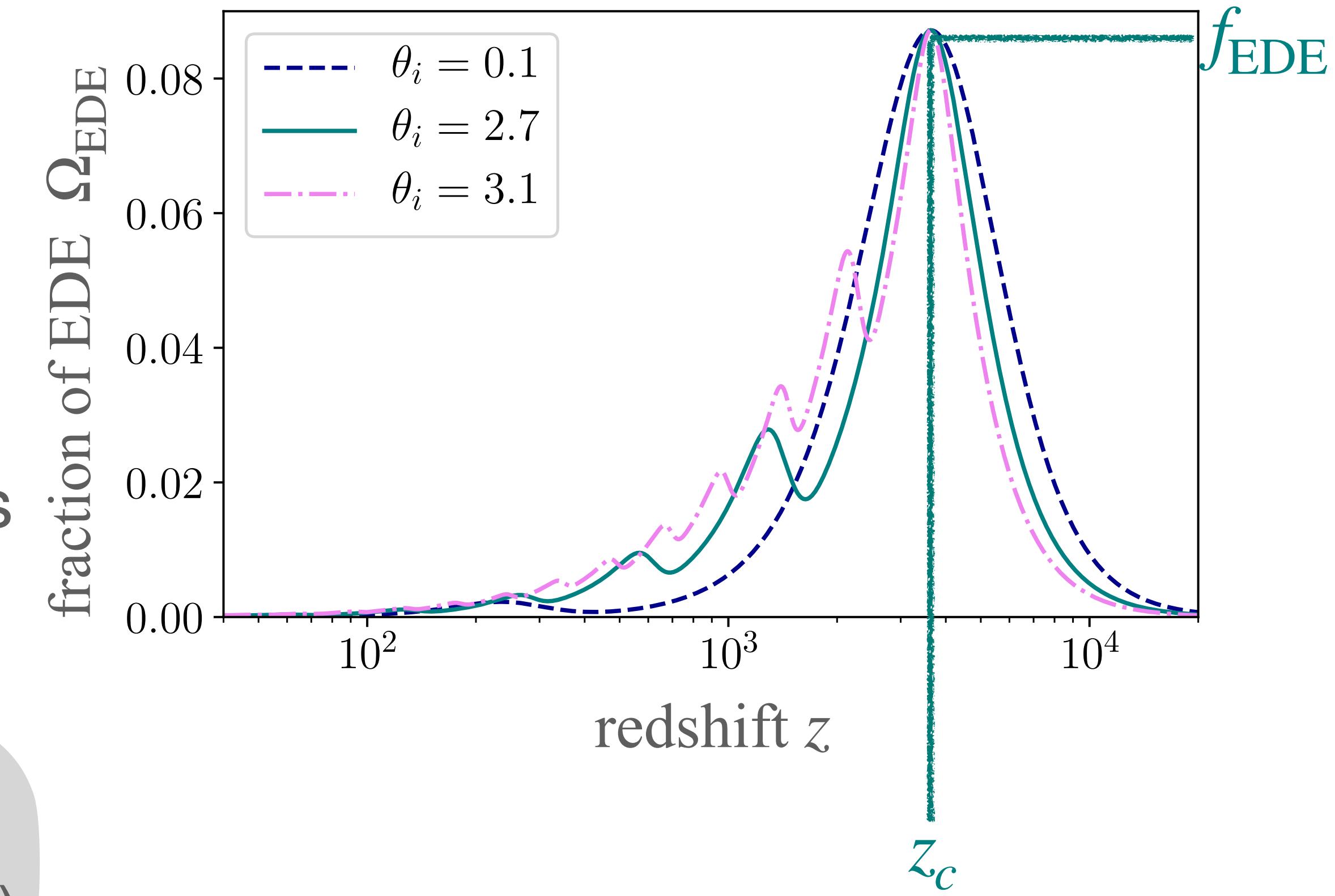
Early Dark Energy (EDE)

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

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

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

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



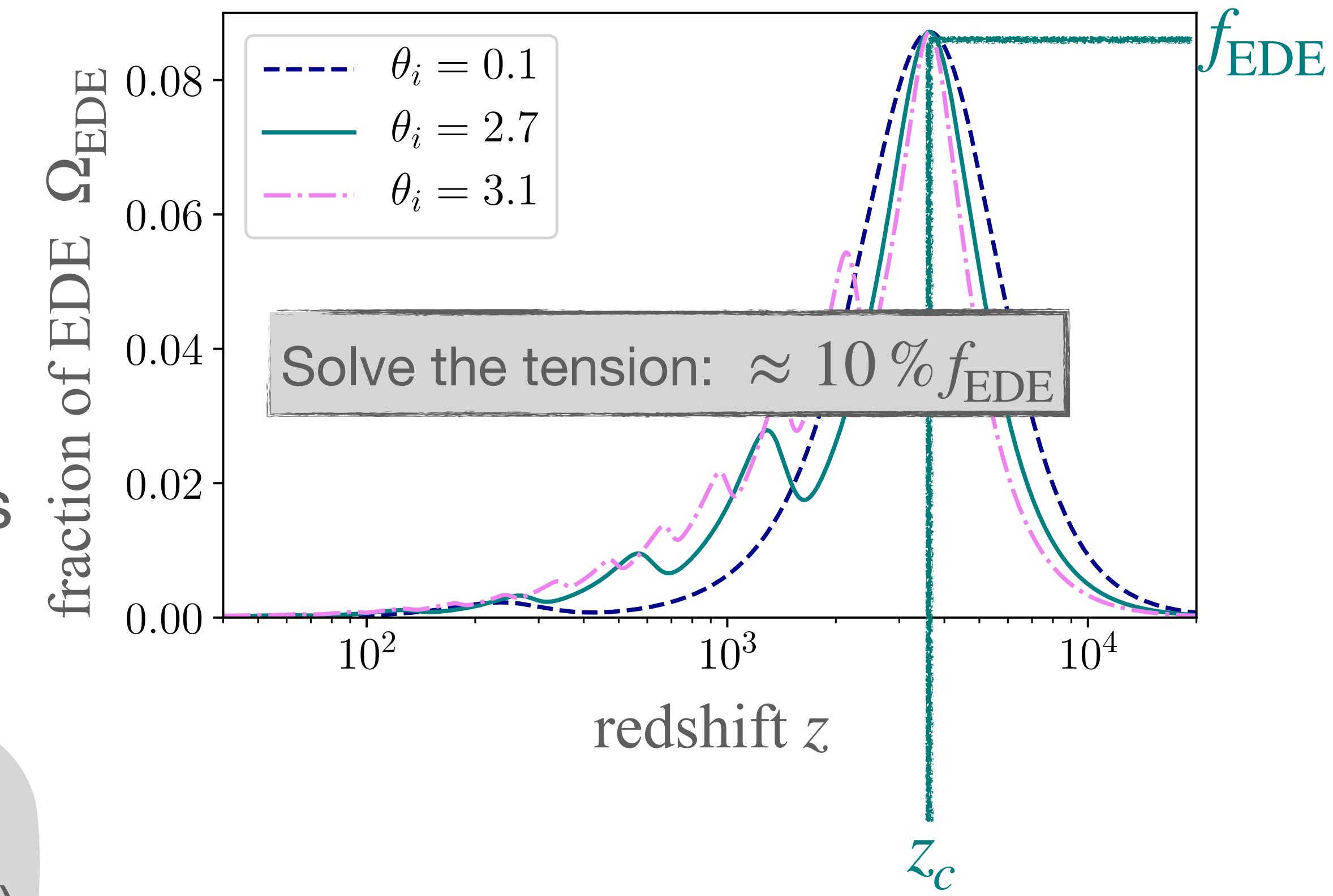
Early Dark Energy (EDE)

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

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

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

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

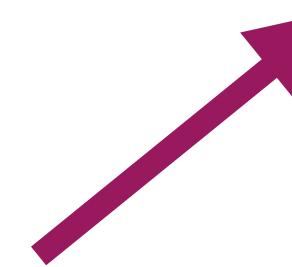


Can EDE resolve the H_0 tension
... and fit all available data sets?

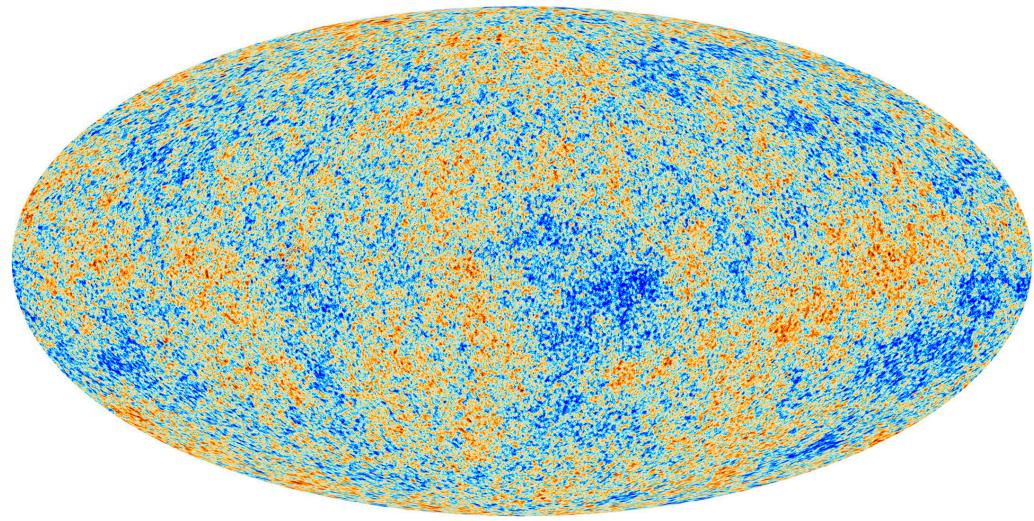
Disclaimer: this review about constraints on EDE is **not** complete

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)

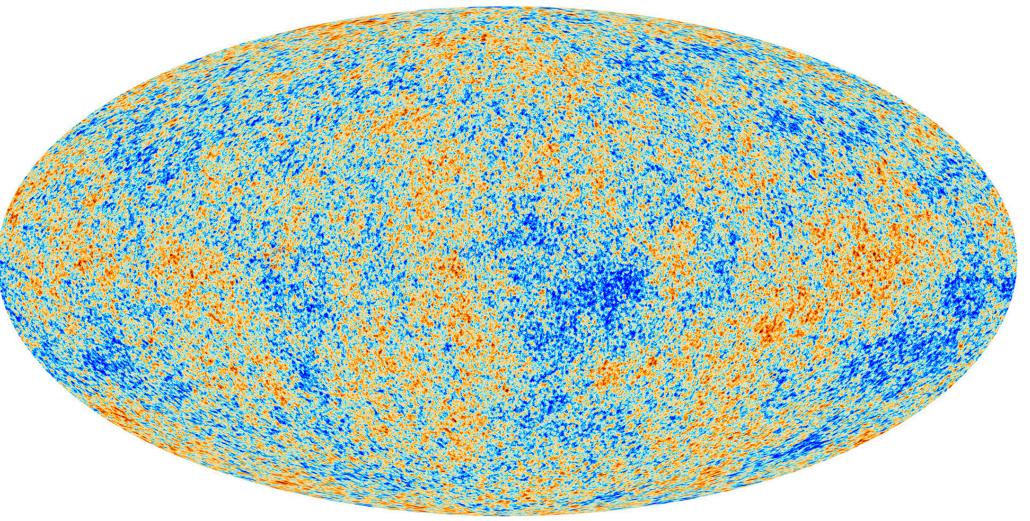


ESA

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

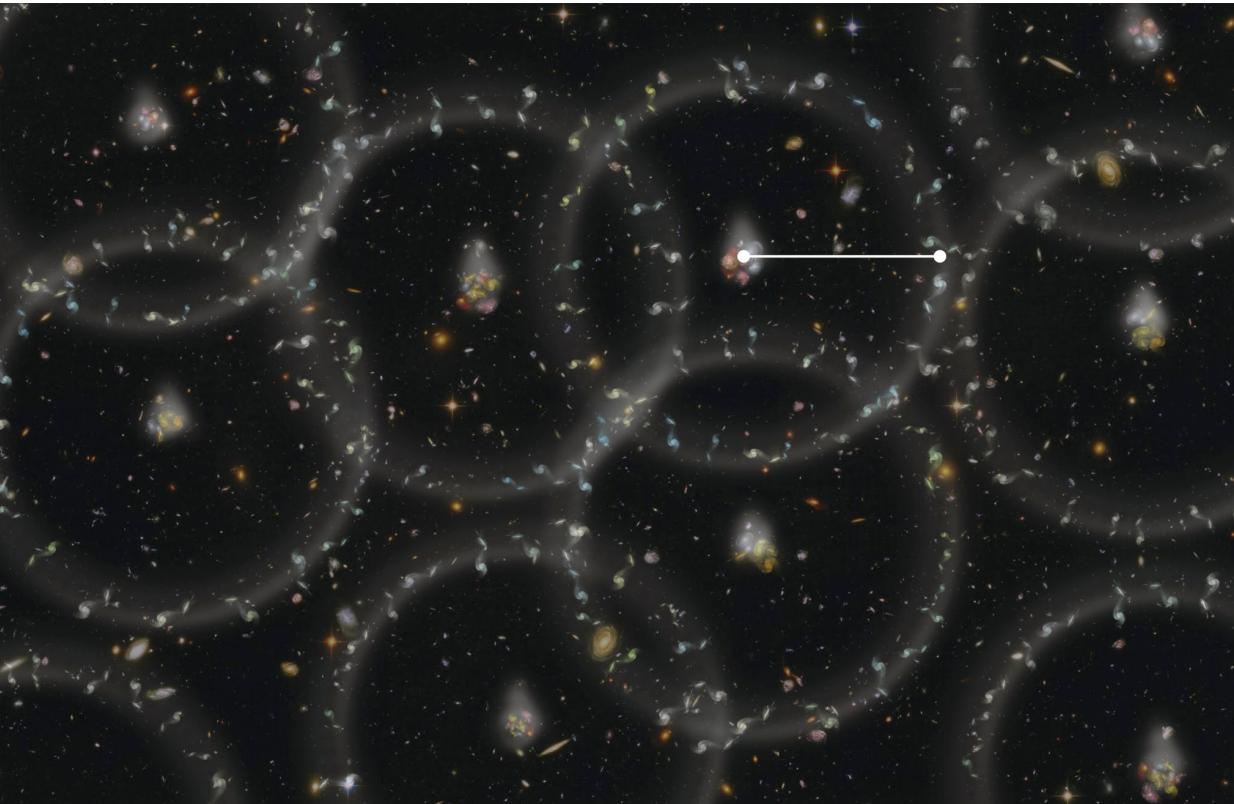
*Data sets: Planck + 6dFGS + BOSS DR12 BAO/
RSD + Pantheon + SH0ES 2016*

CMB (TT , TE , EE , lensing)



ESA

Baryon acoustic oscillations



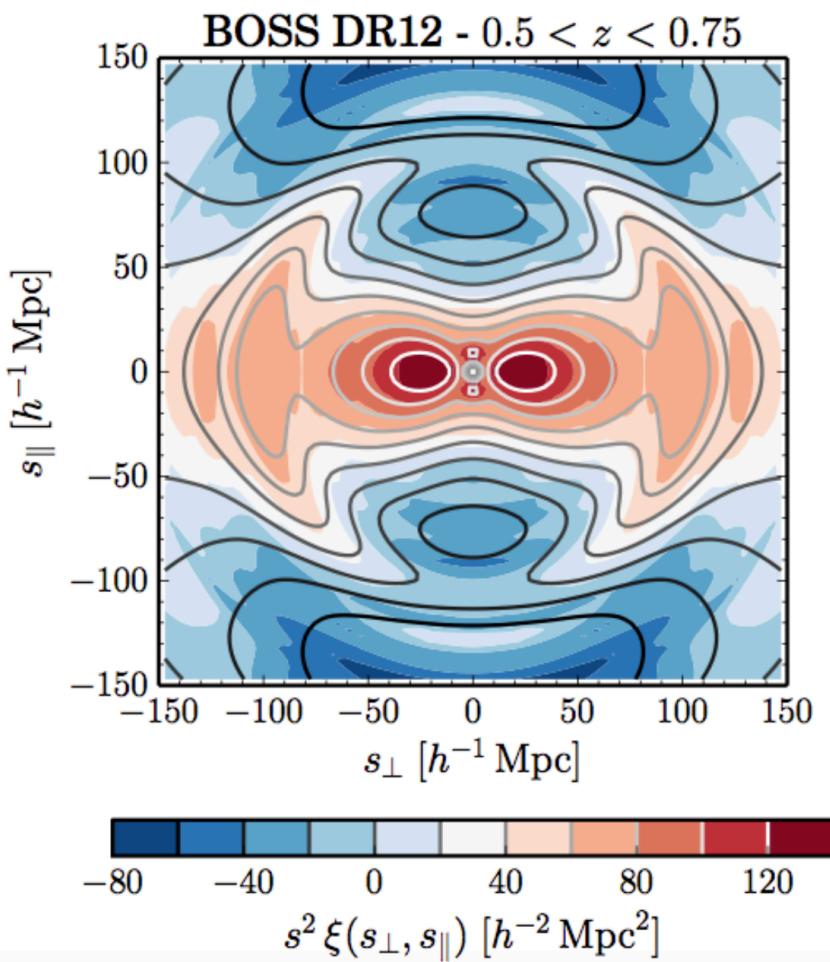
BOSS collaboration

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

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



Redshift space distortions

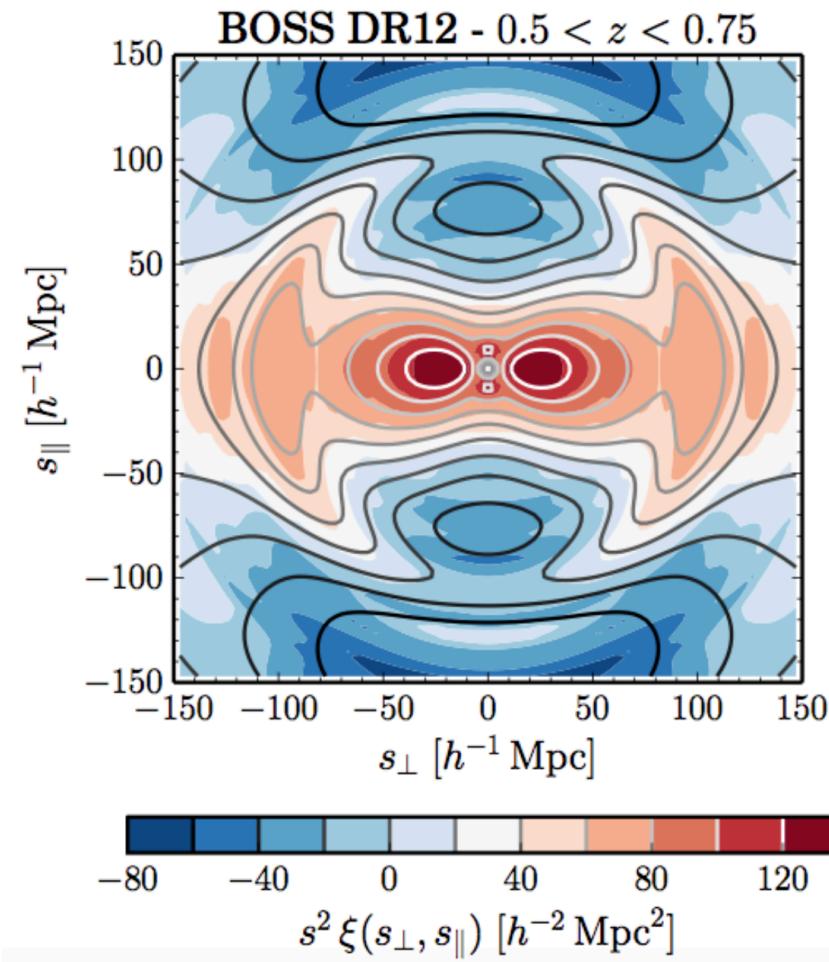


BOSS collaboration (Sanchez++ 2016)

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

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

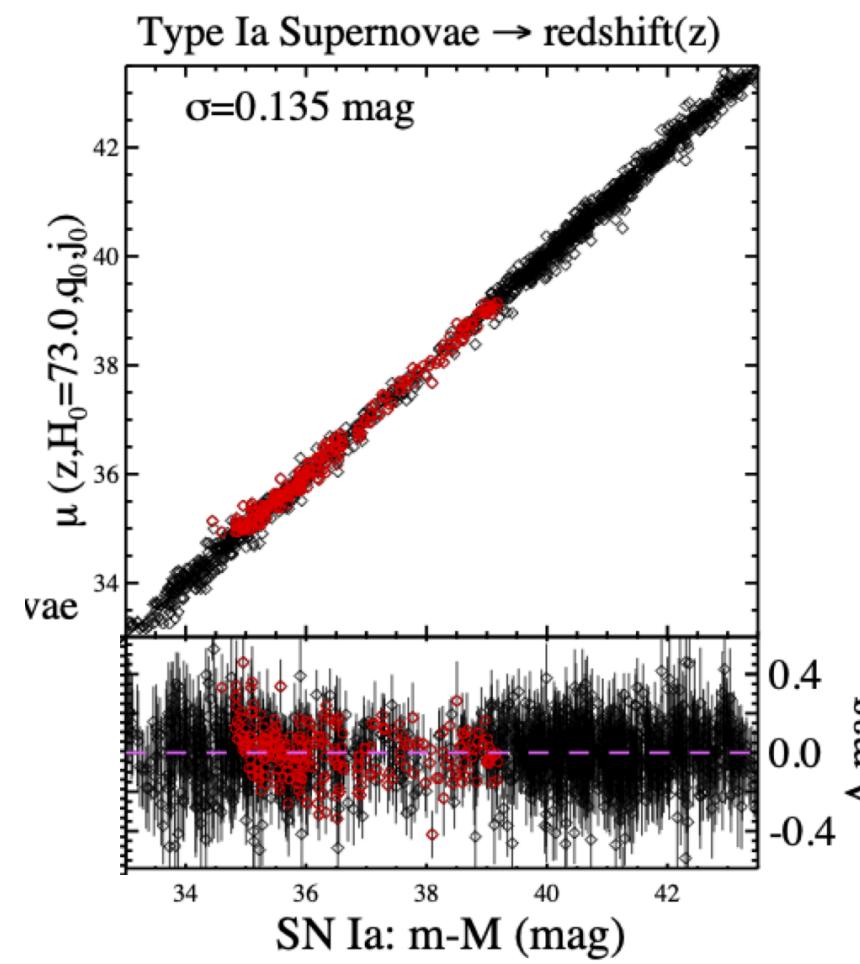
Redshift space distortions



BOSS collaboration (Sanchez++ 2016)



NASA



SH0ES col.

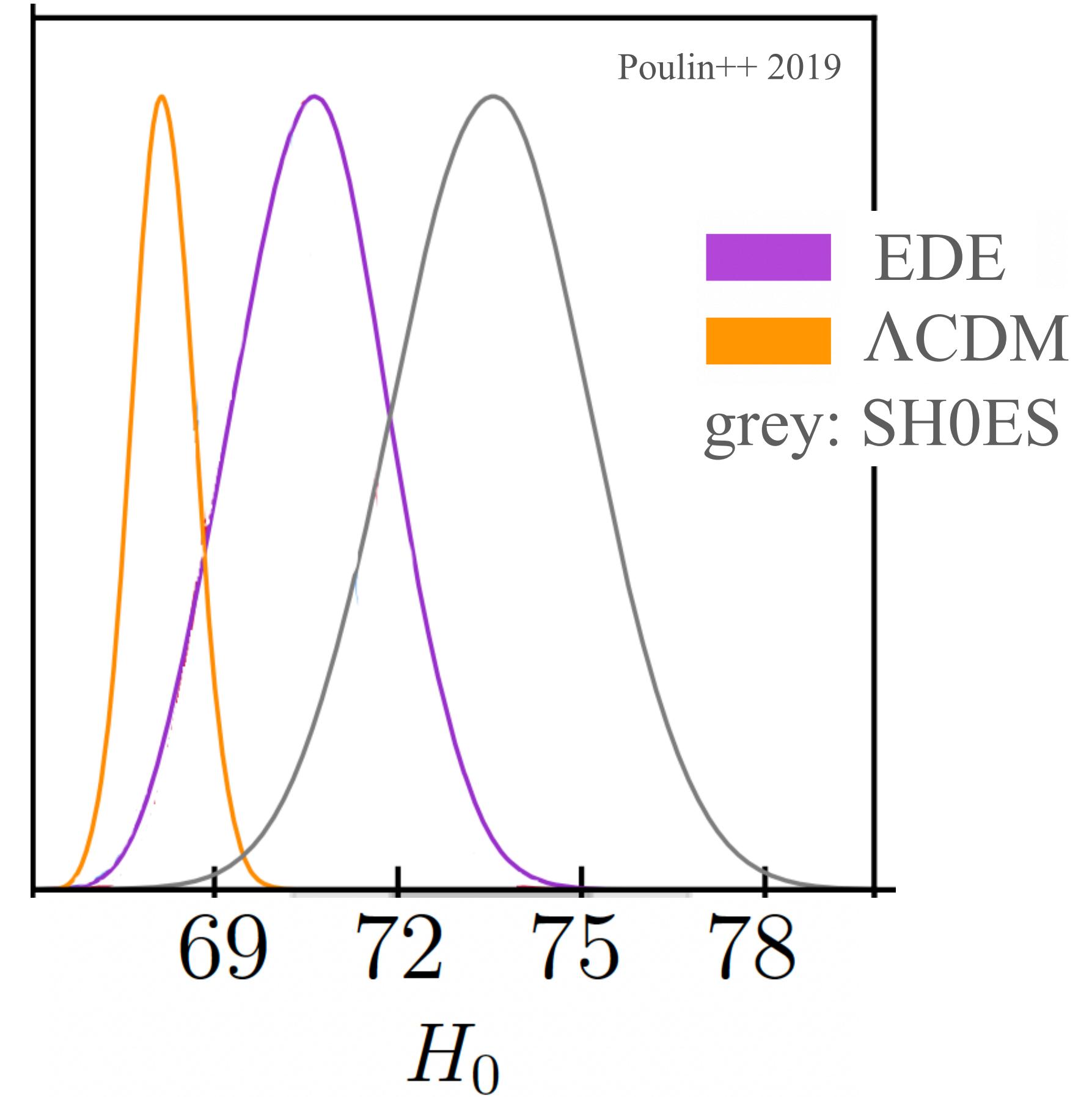
2019: EDE can solve the H_0 tension!

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)

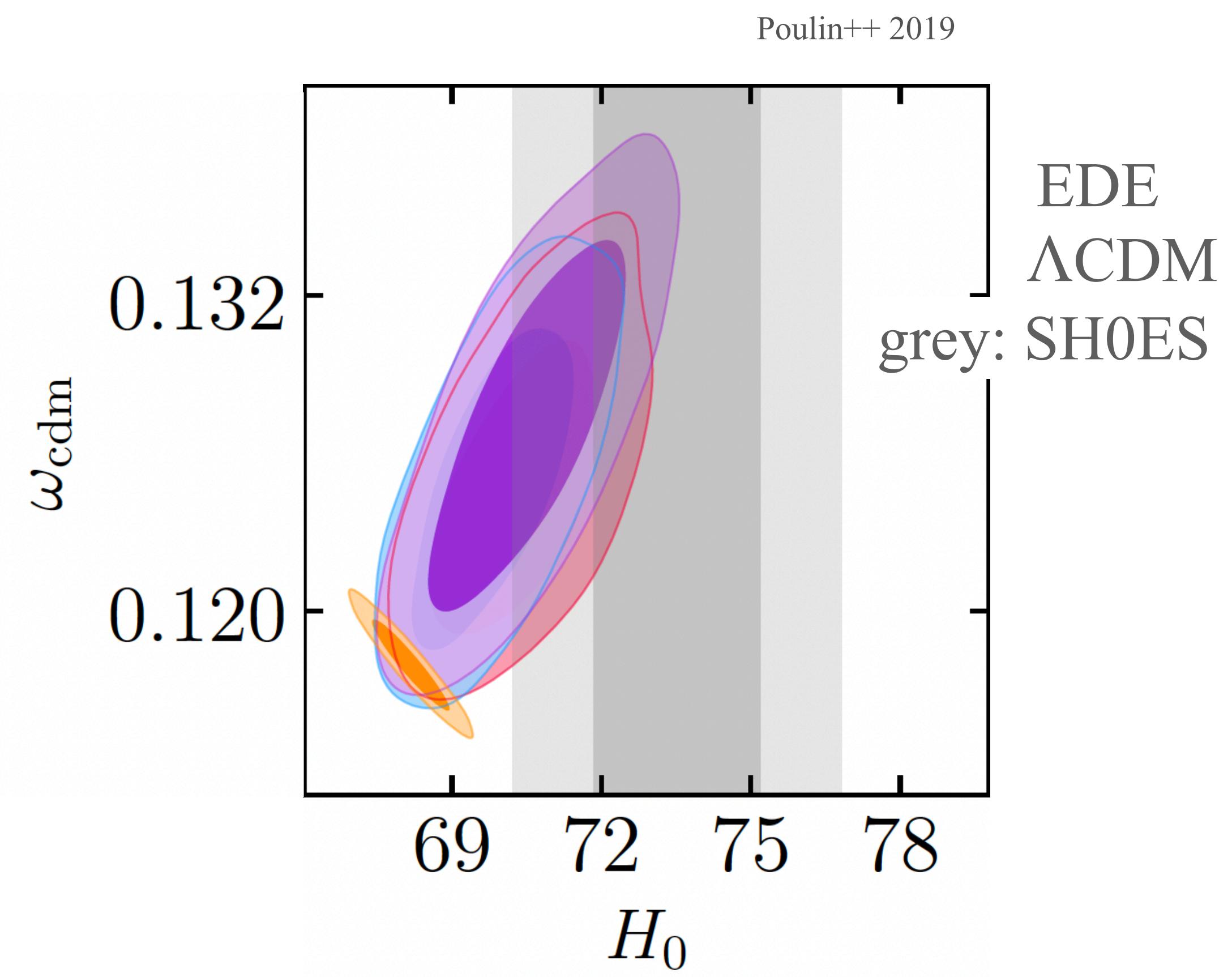


2019: EDE can solve the H_0 tension!

Poulin, Smith, Karwal, Kamionkowski, 2019

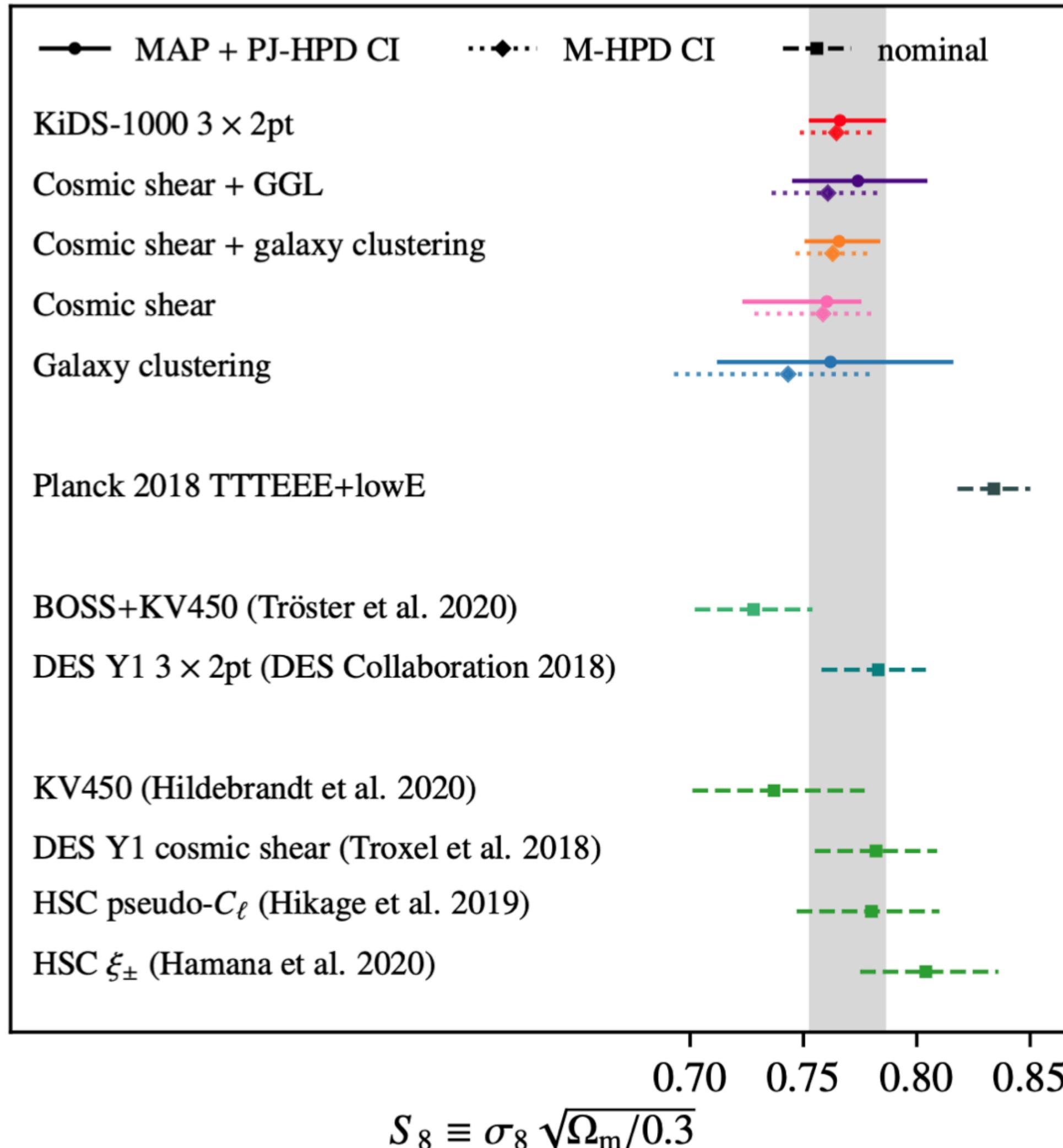
Data sets: Planck + 6dFGS + BOSS DR12 BAO/
RSD + Pantheon + SH0ES 2016

- $f_{\text{EDE}} = 0.107^{+0.035}_{-0.030}$ (mean $\pm 1\sigma$)
- $H_0 = 71.49 \pm 1.20$ km/s/Mpc
- **Also other parameters shift:**
EDE suppresses growth of perturbations at early times
 - ω_{CDM} and n_s increase
 - σ_8 increases, worsening the so-called σ_8 discrepancy



Aside: σ_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

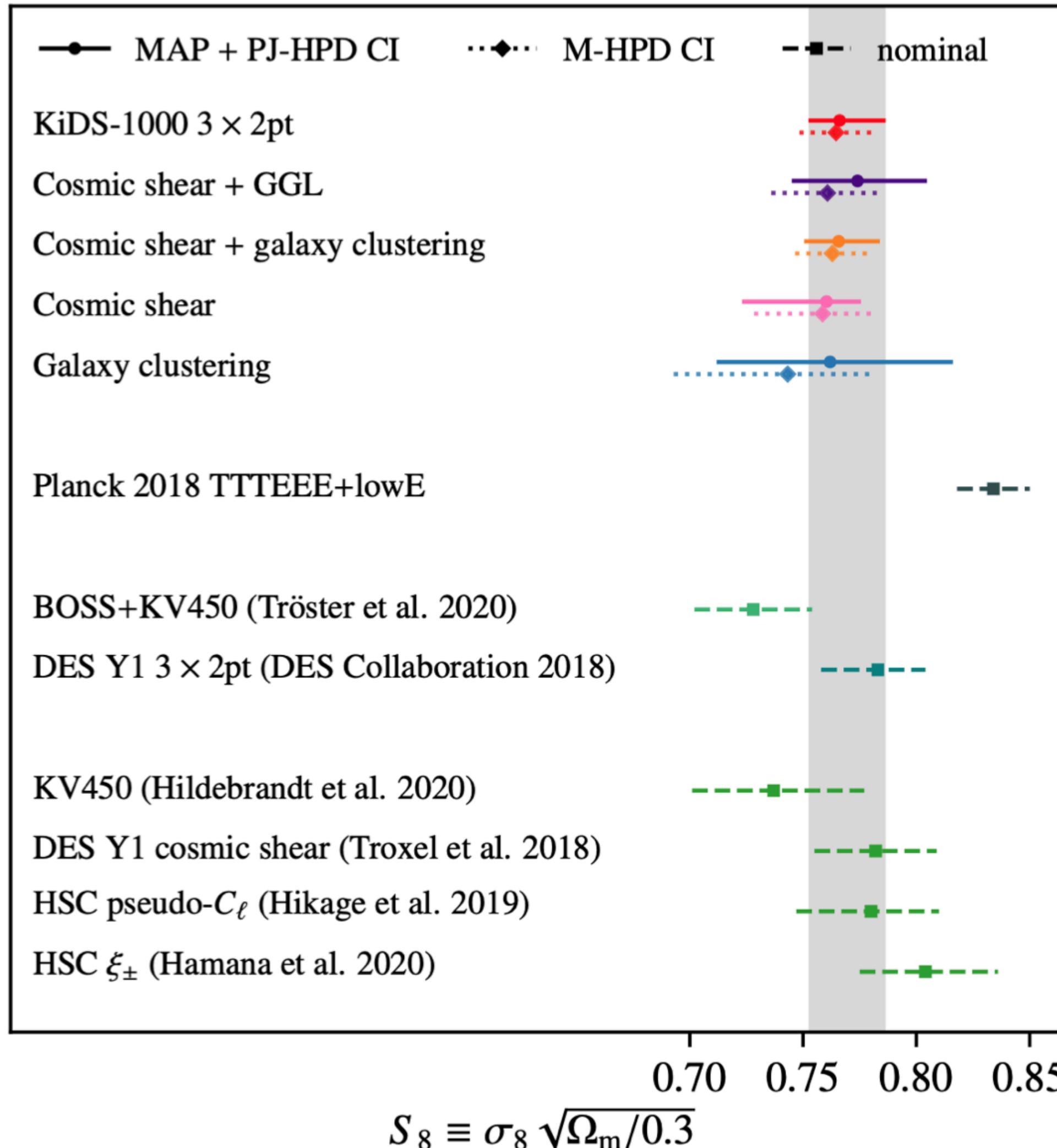
$$S_8 = \sigma_8 \sqrt{\Omega_m / 0.3}$$

linear matter power spectrum

Planck prefers 2-3 σ higher S_8 than weak lensing experiments (DES, KiDS, HSC)

Aside: σ_8 discrepancy

Cosmology Intertwined 2021



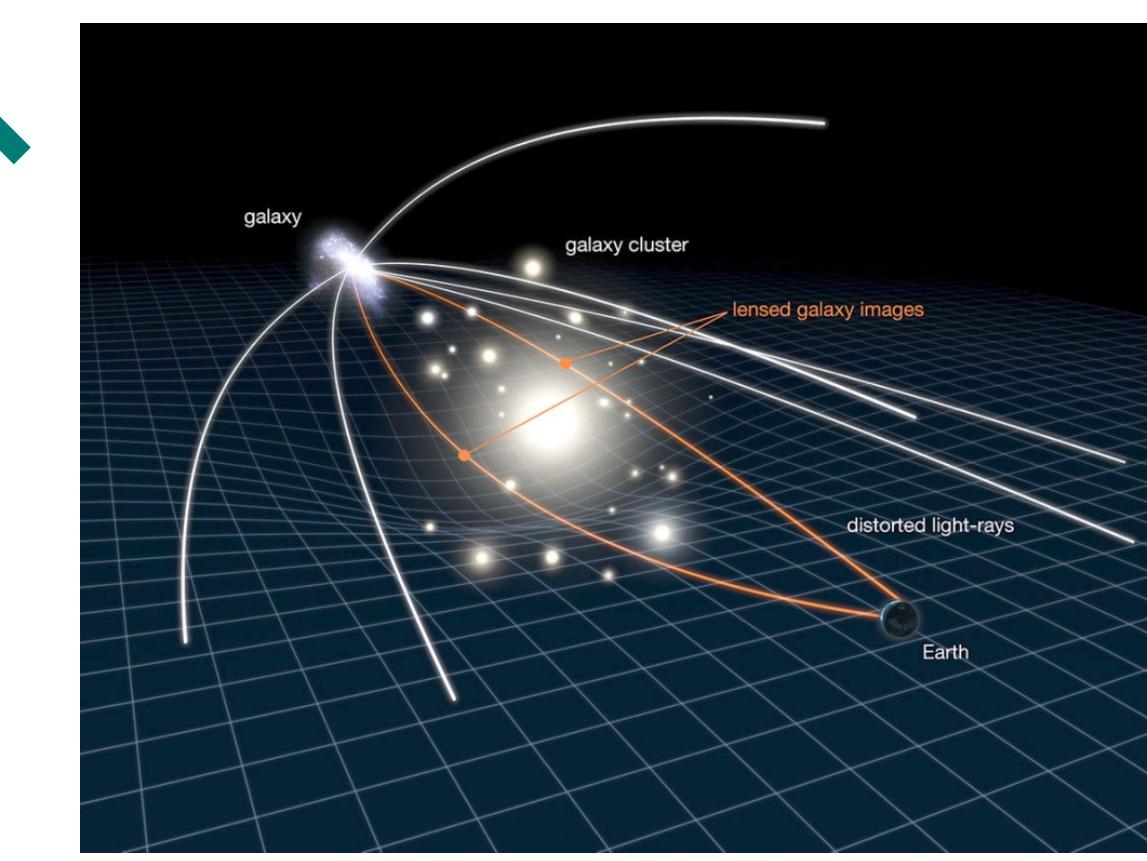
$$\sigma_8^2 = \int dk^3 |W(k)|^2 P_{\text{lin}}(k),$$

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 σ higher S_8 than
weak lensing experiments (DES, KiDS, HSC)



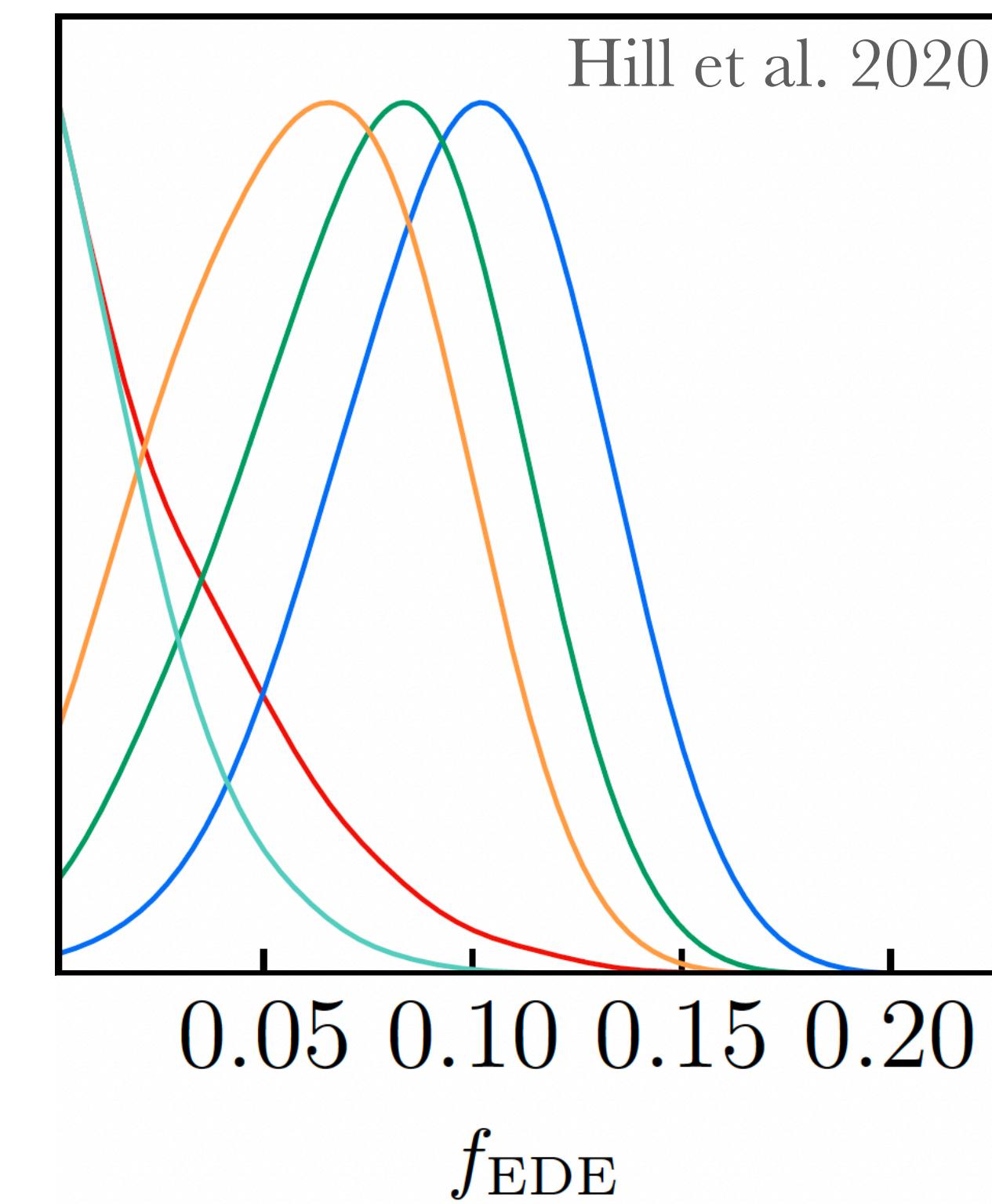
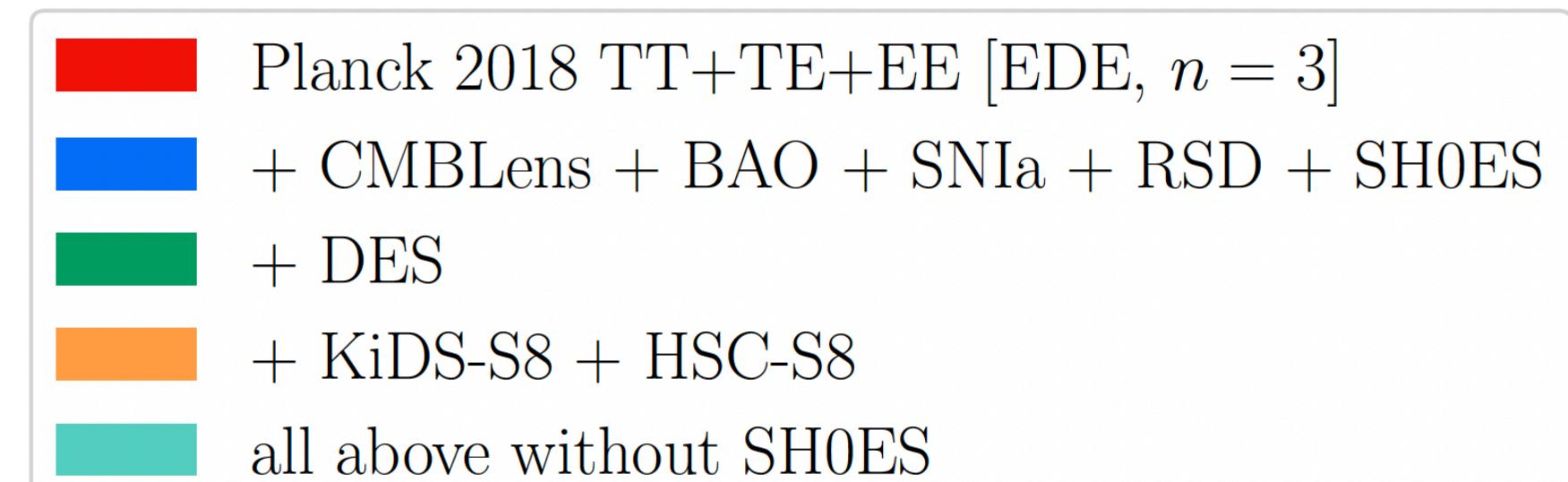
NASA

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

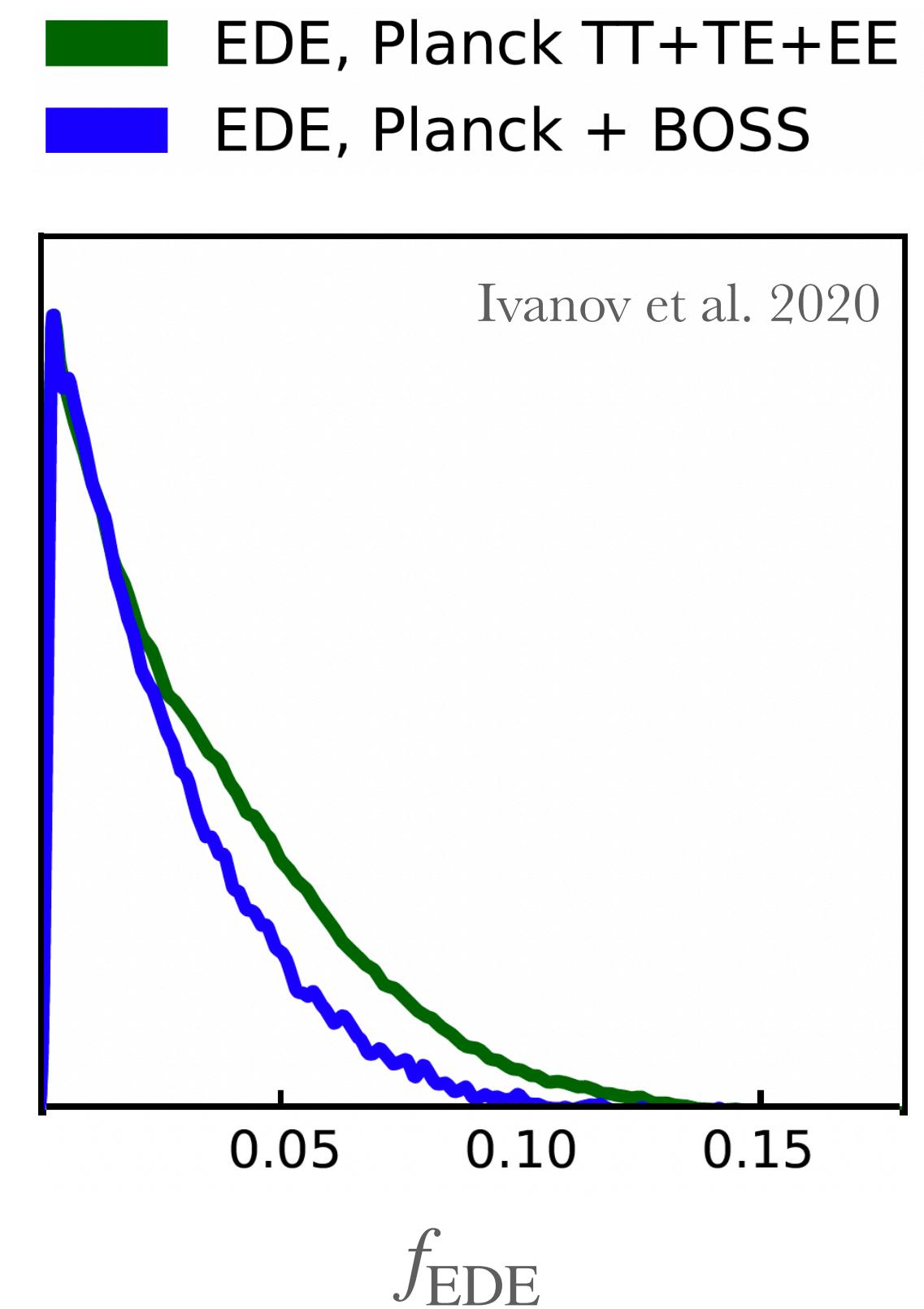


Adding LSS data: EDE is ruled out?

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

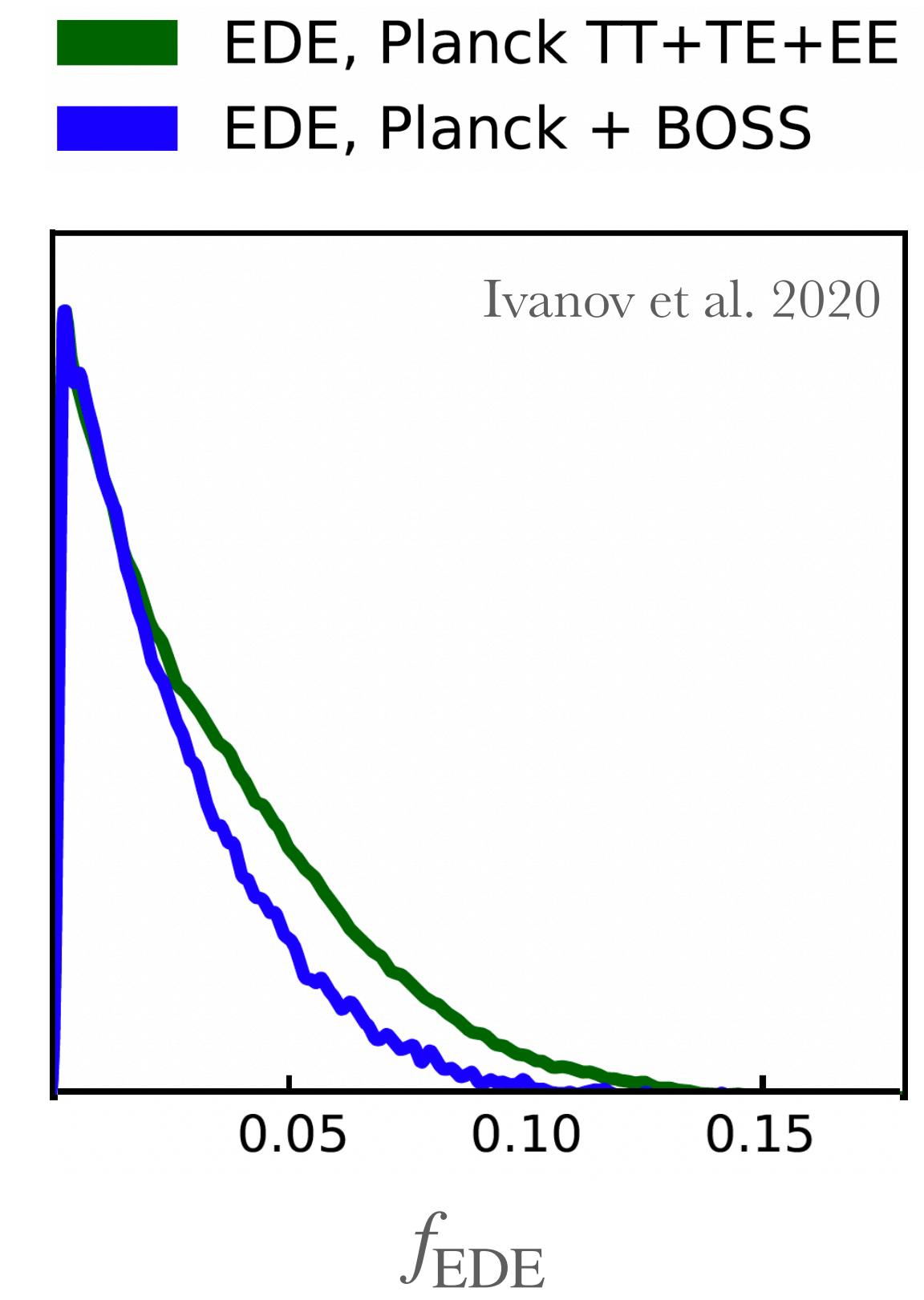


Adding LSS data: EDE is ruled out?

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

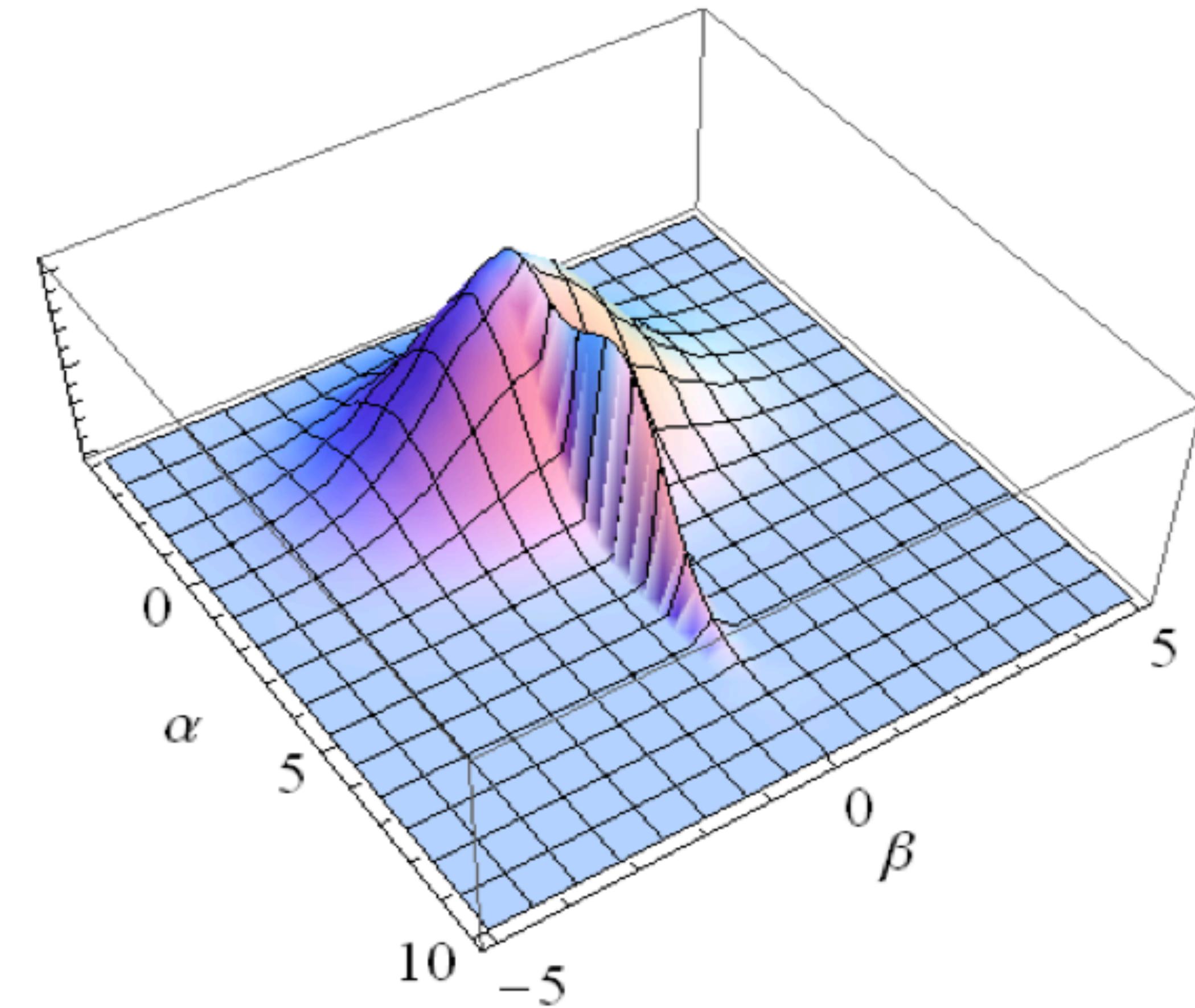
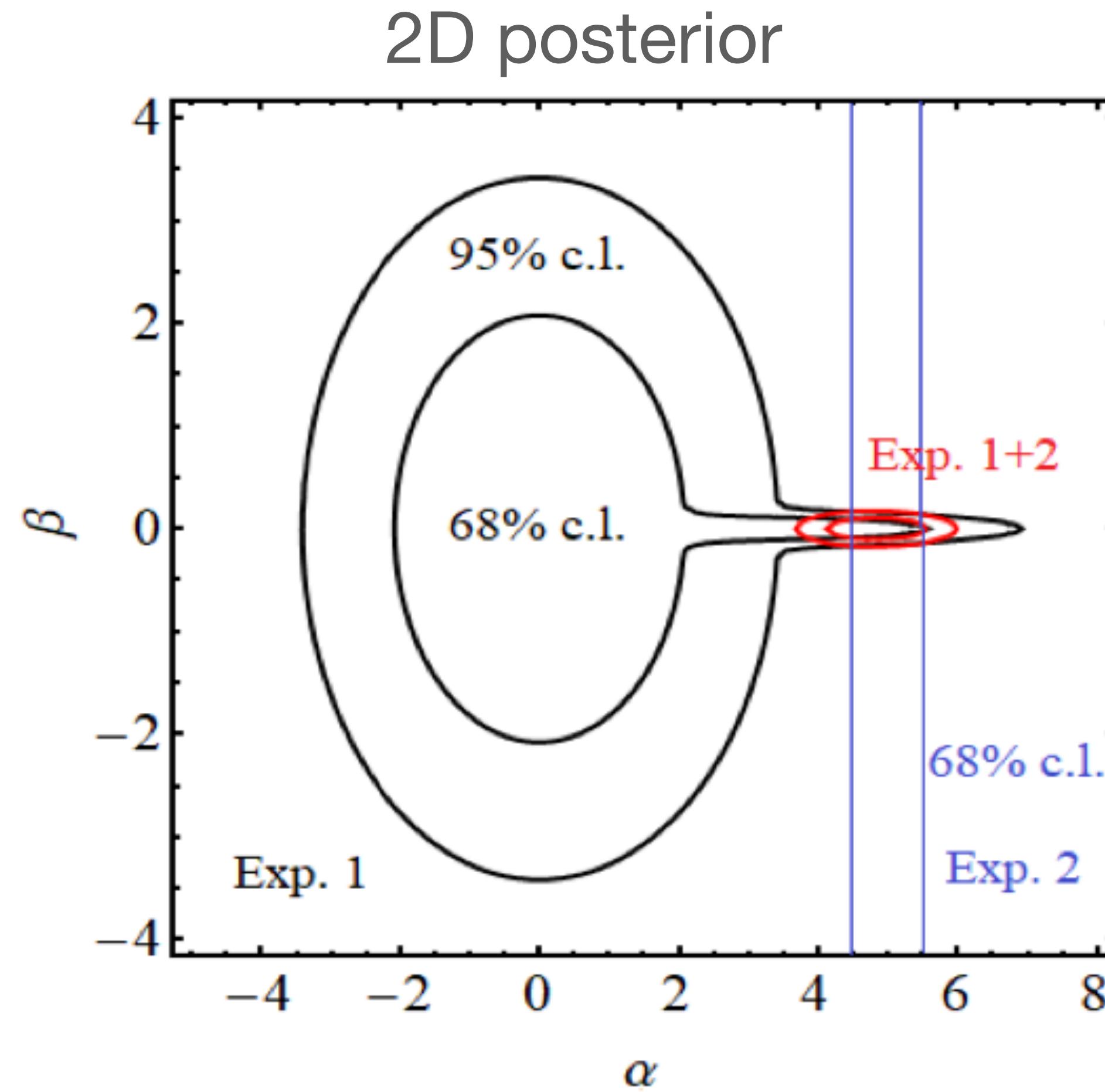


Could **volume effects** affect the results?

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

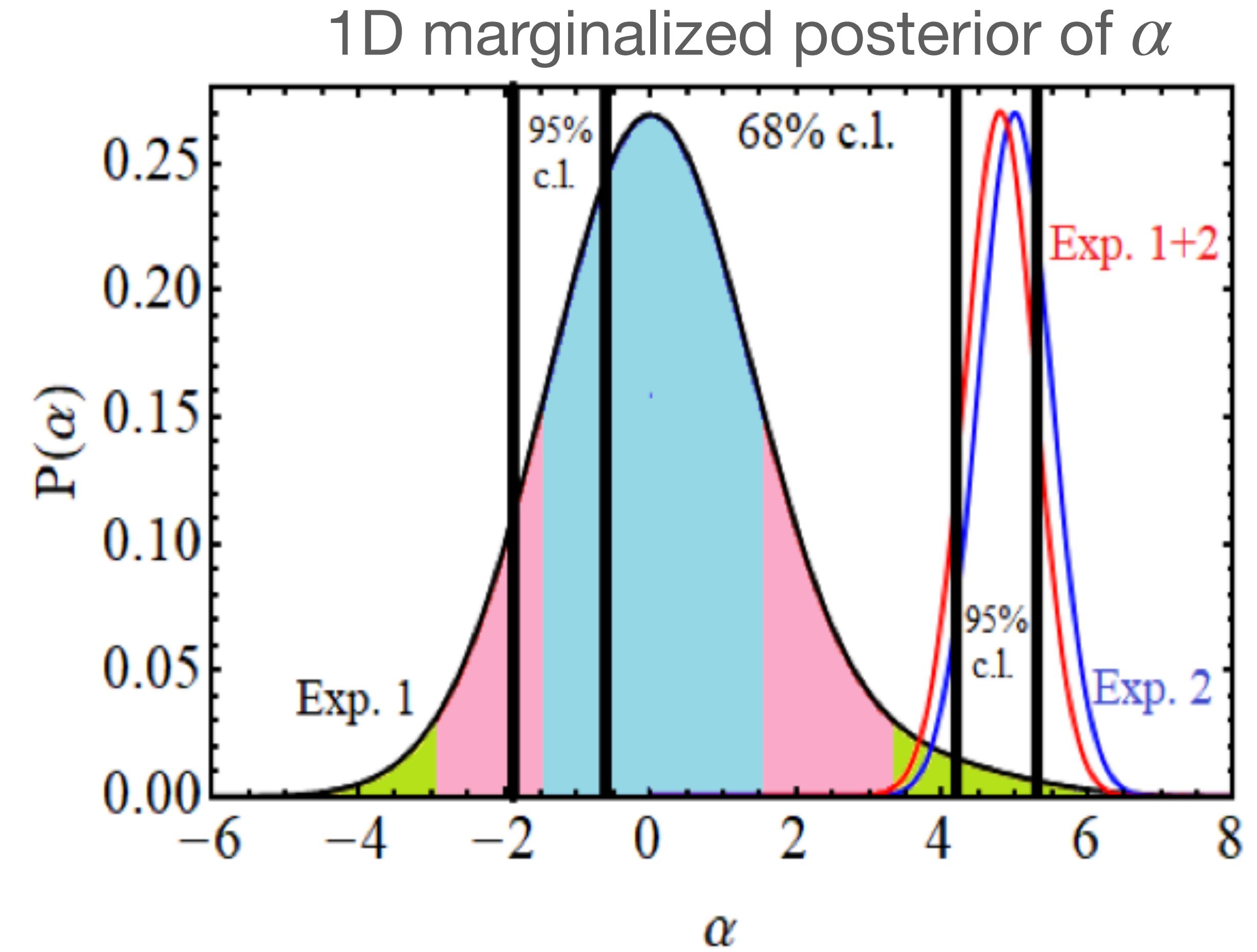
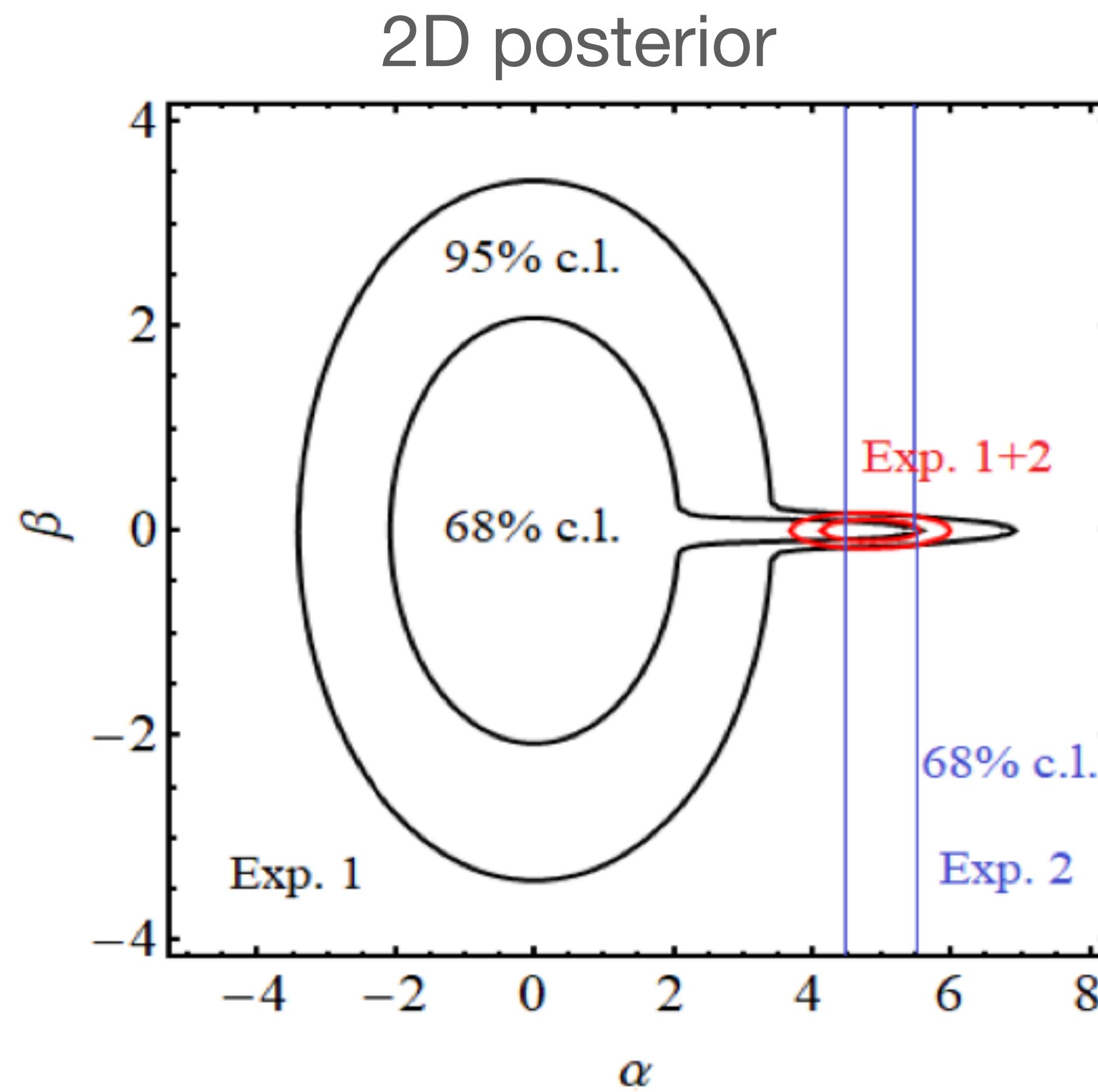
Toy example: Prior volume / projection effect

Gomez-Valent 2022



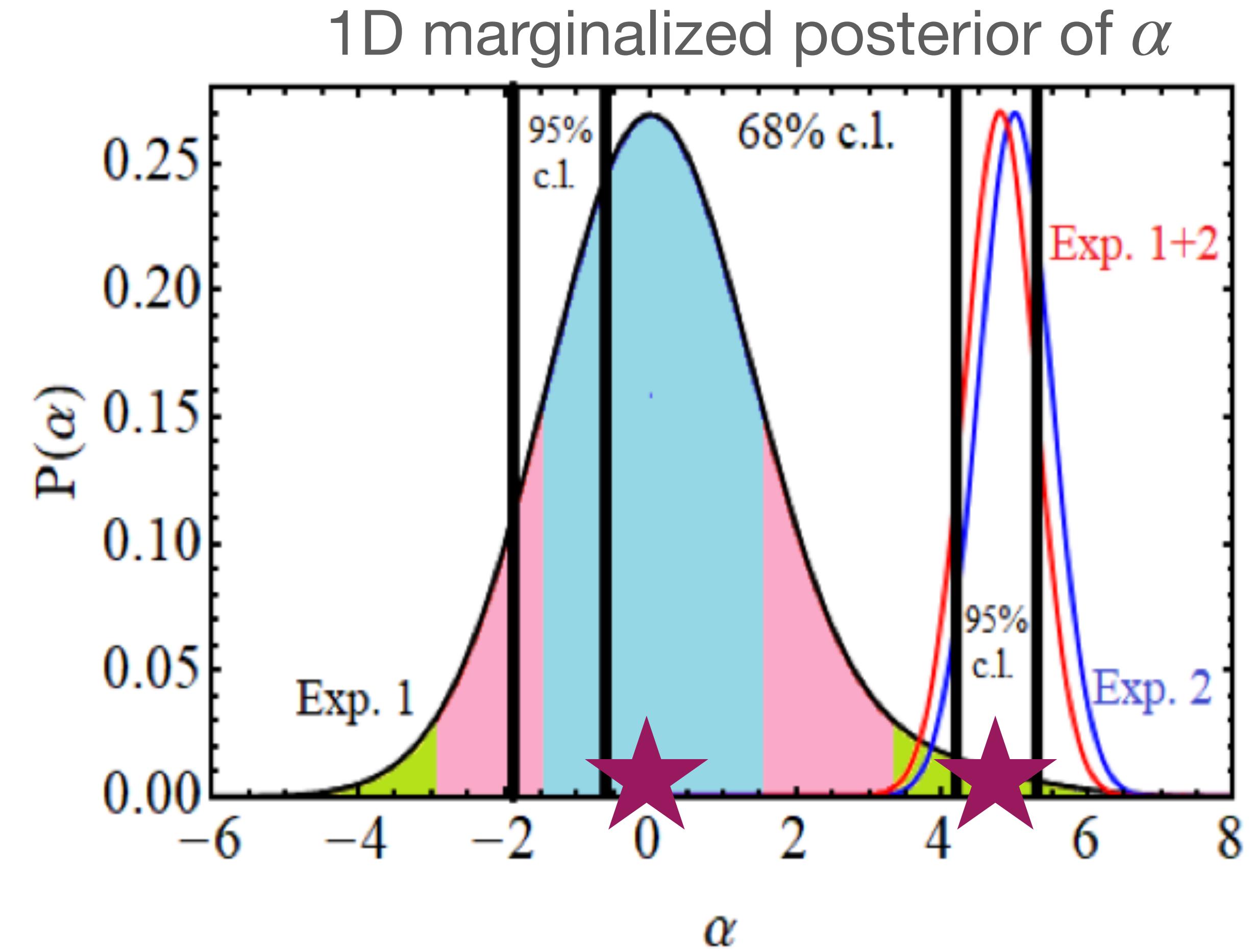
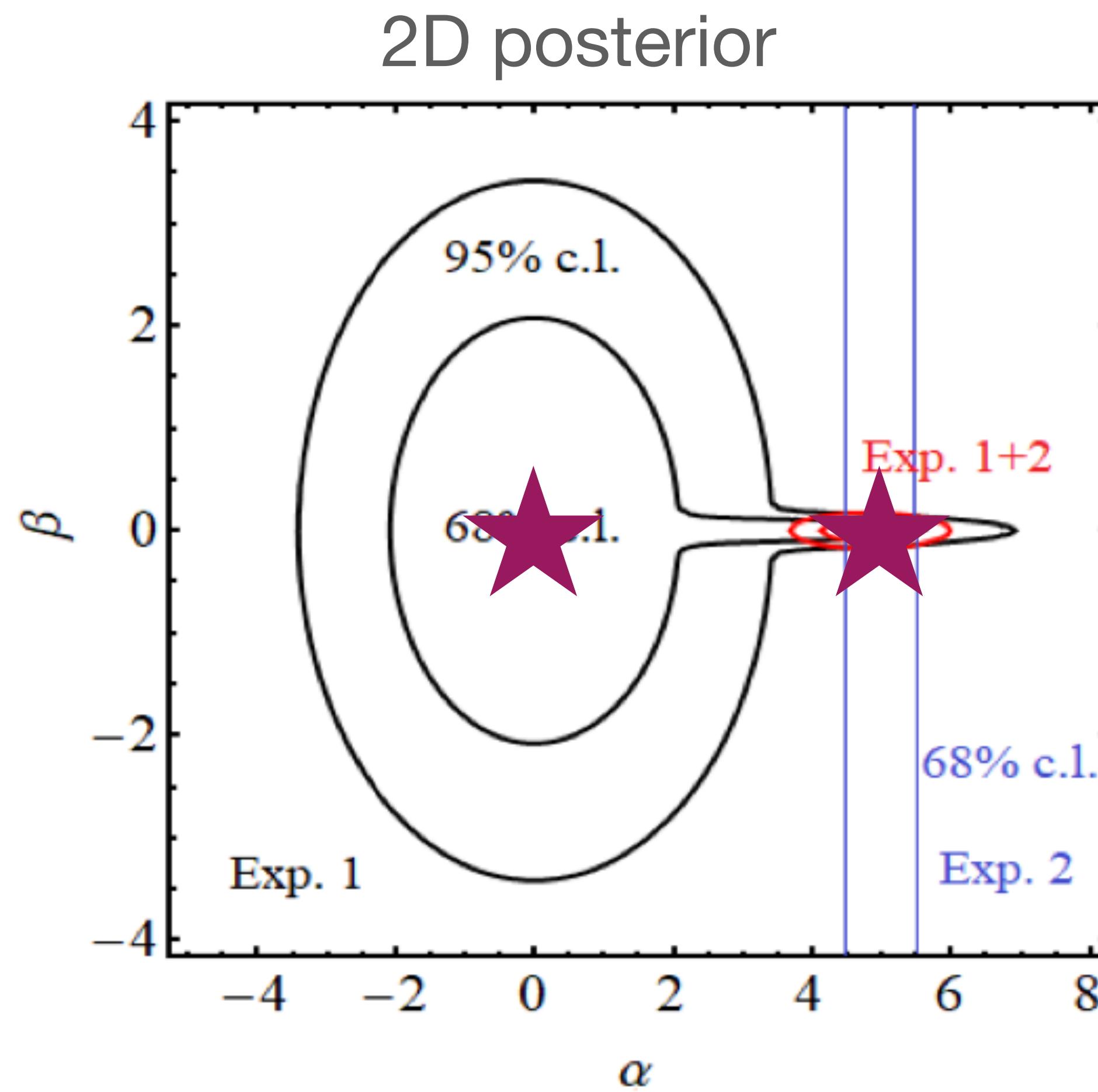
Toy example: Prior volume / projection effect

Gomez-Valent 2022



Toy example: Prior volume / projection effect

Gomez-Valent 2022



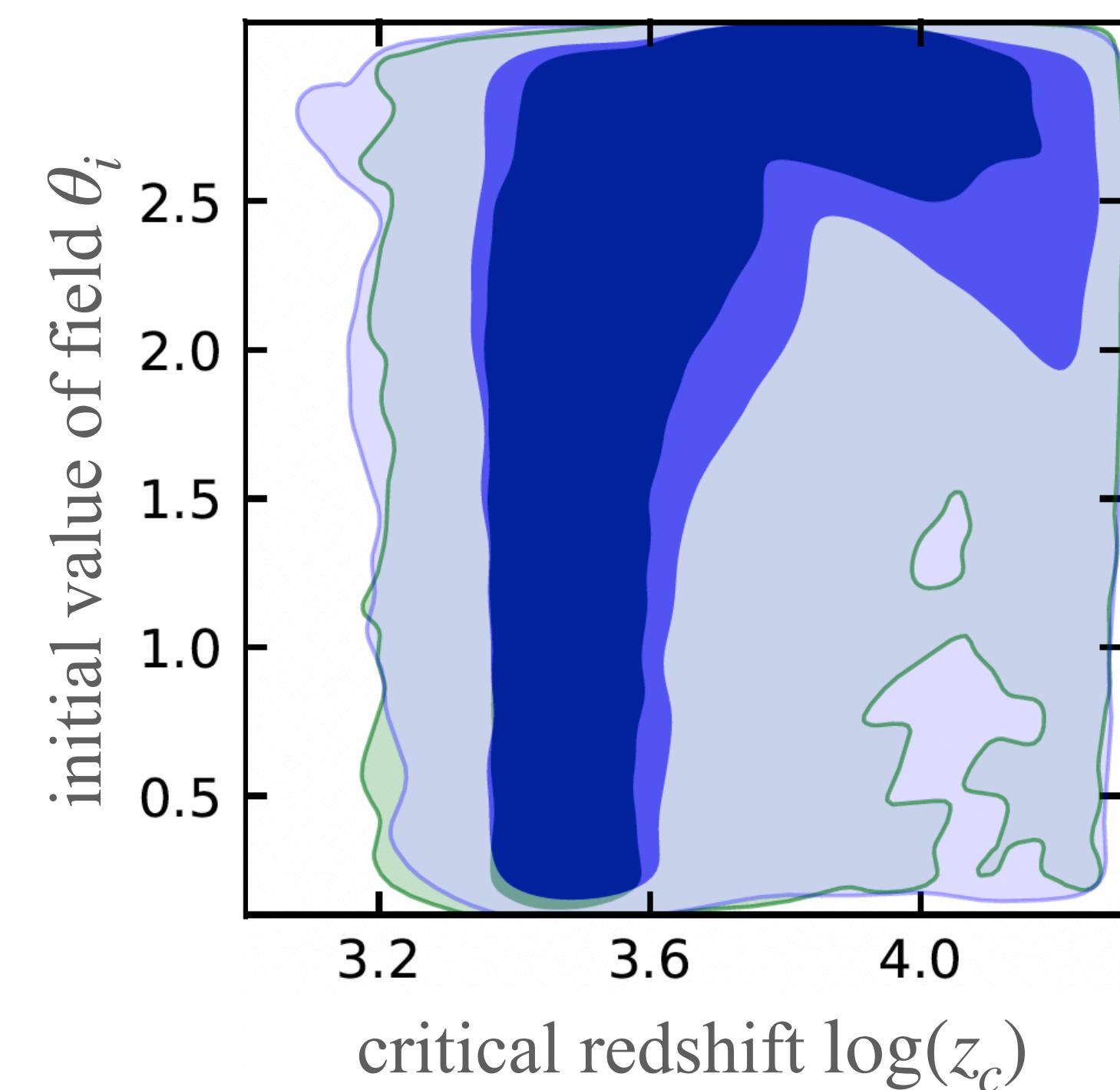
Prior volume / projection / marginalisation effects

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.



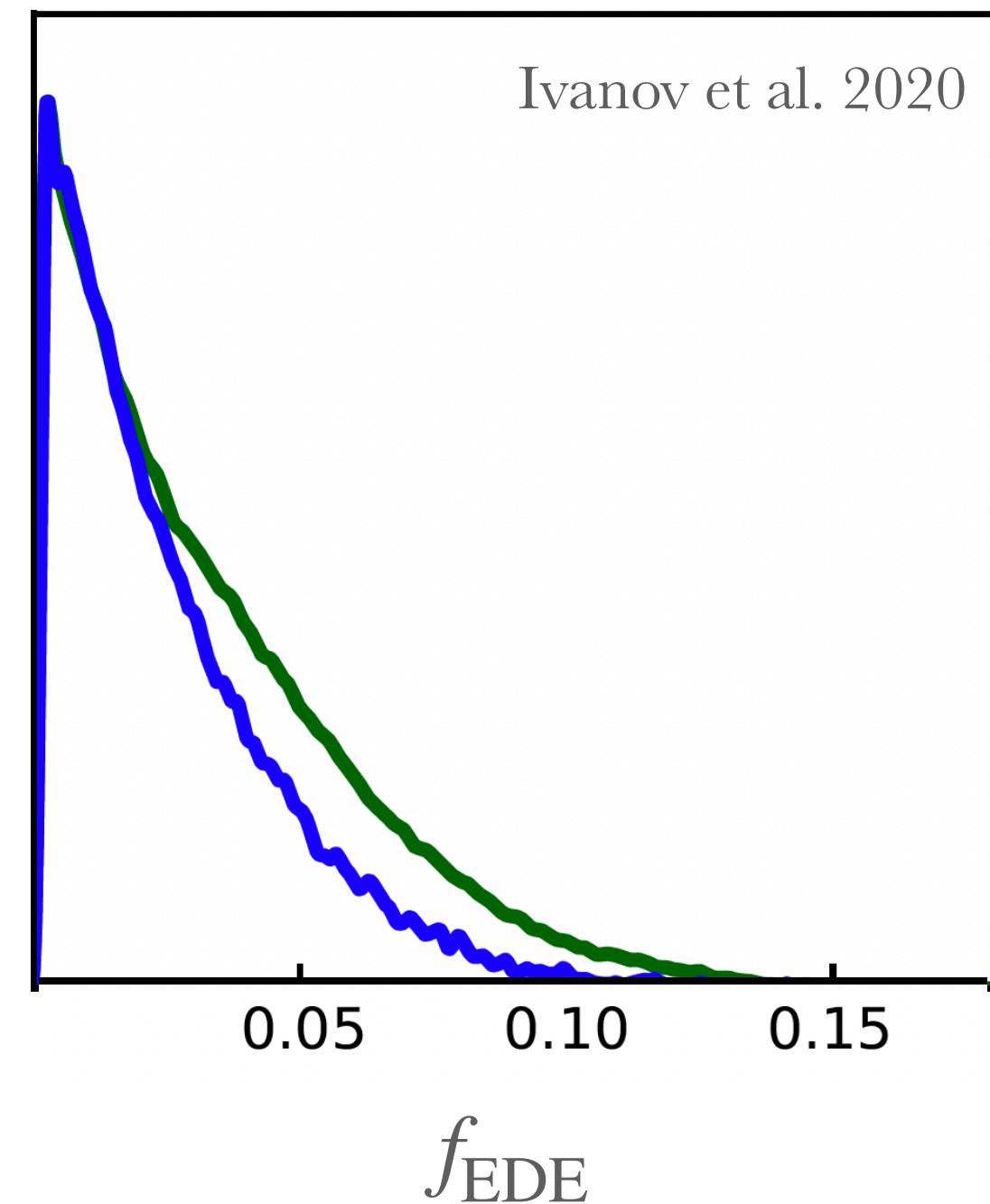
Prior volume / projection / marginalisation effects

...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.

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



$f_{\text{EDE}} \approx 0$: all values of z_c, θ_i unconstrained (ΛCDM limit)

Prior volume / projection / marginalisation effects

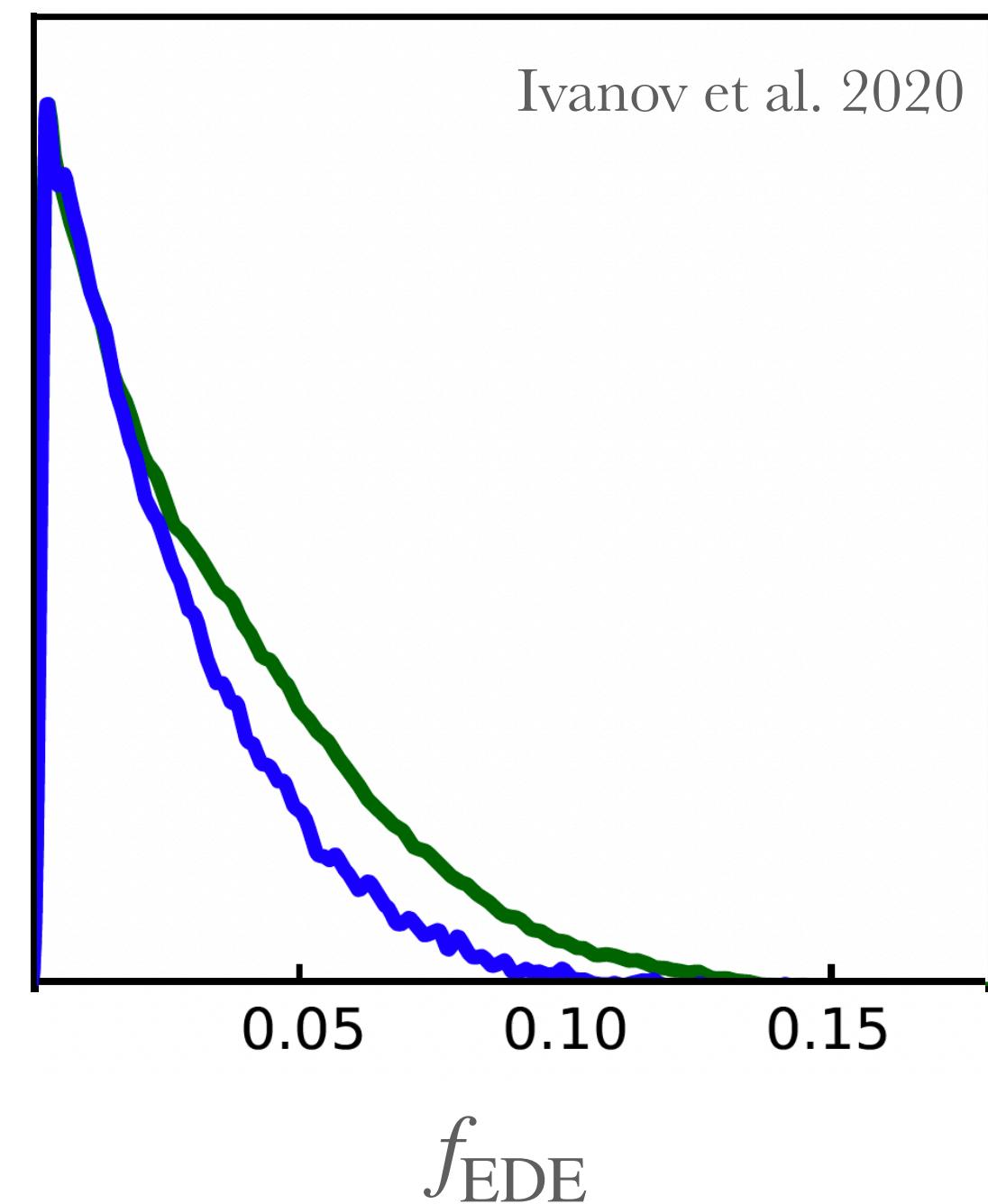
...appear if the posterior is influenced by the prior volume.

Reasons:

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

→ Bias in the marginalised posterior.

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



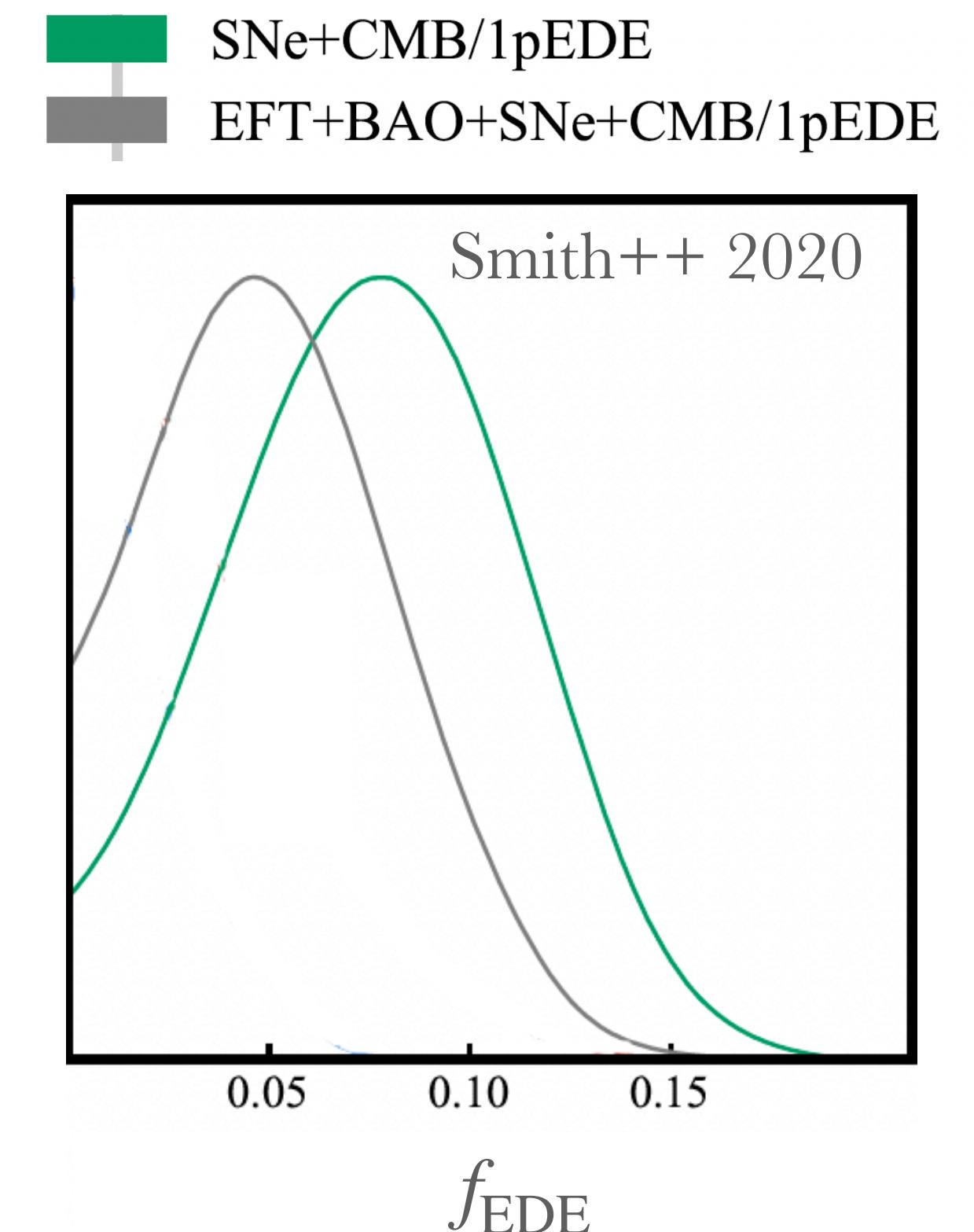
$f_{\text{EDE}} \approx 0$: all values of z_c, θ_i unconstrained (ΛCDM limit)

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 , θ_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**

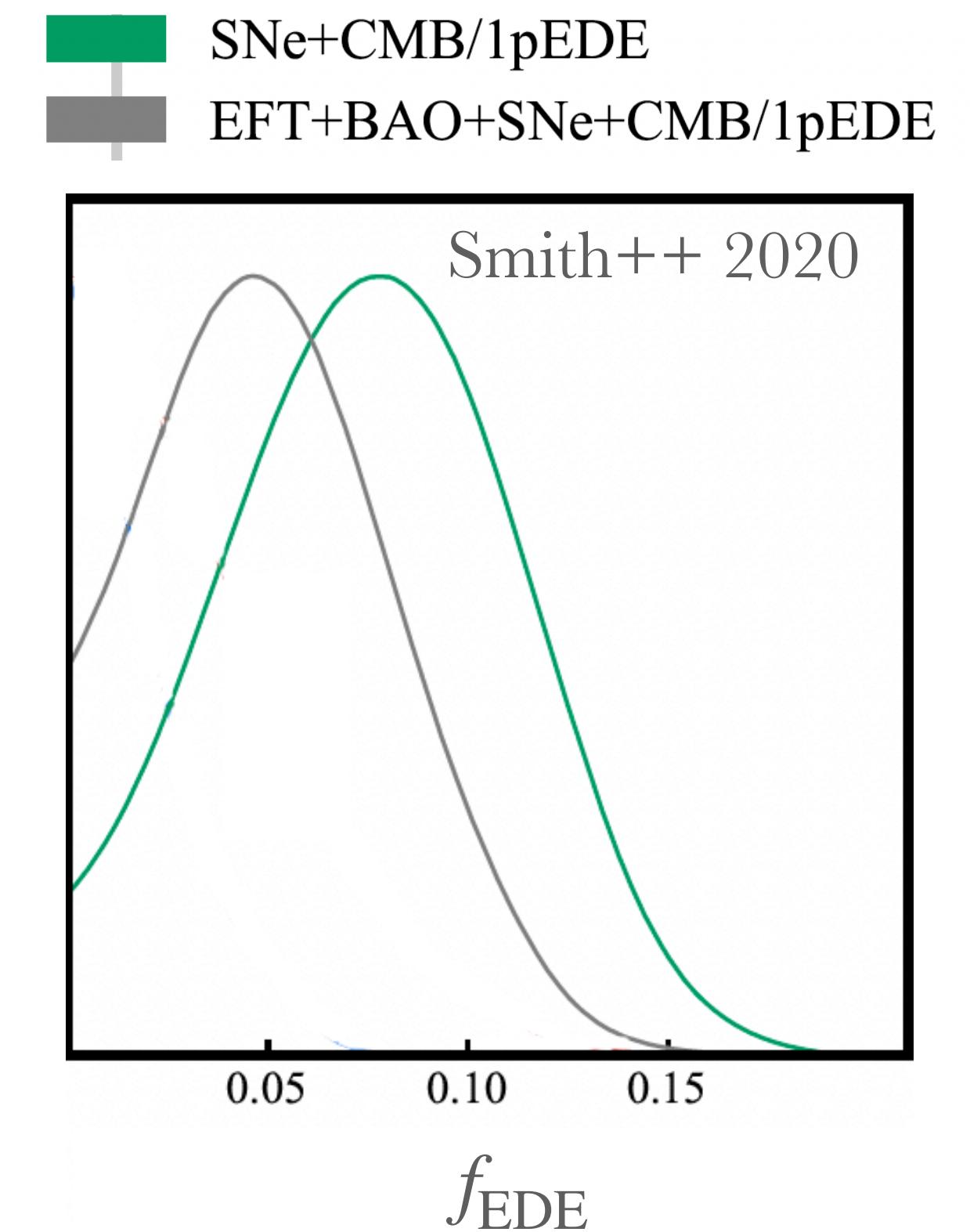


EDE is not ruled out by LSS?

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, θ_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**



However: Not a full Bayesian analysis

Planck + BOSS (baseline data set)

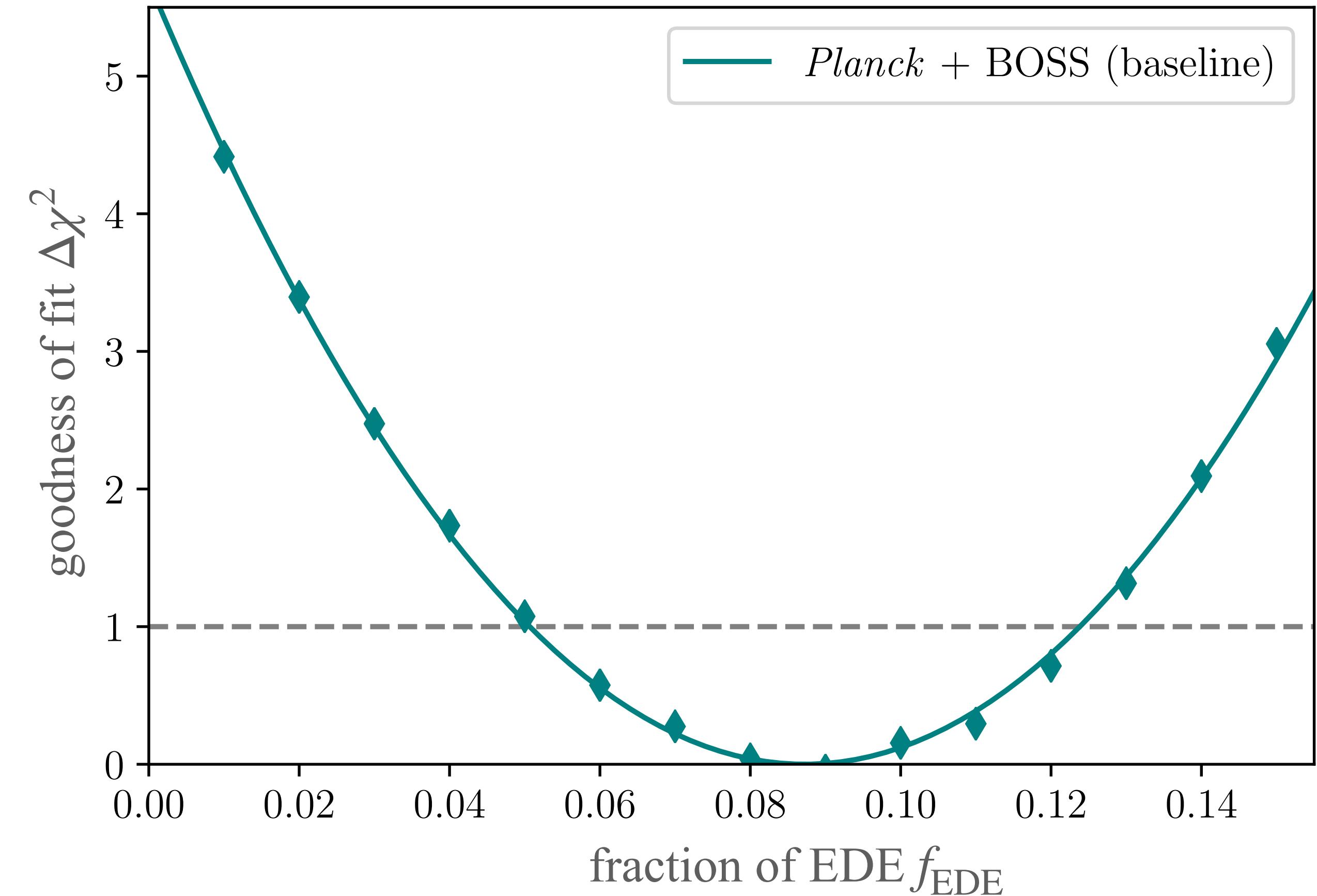
LH++ 2021; LH, Ferreira 2022

MCMC results:

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

Profile likelihood results:

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



Planck + BOSS

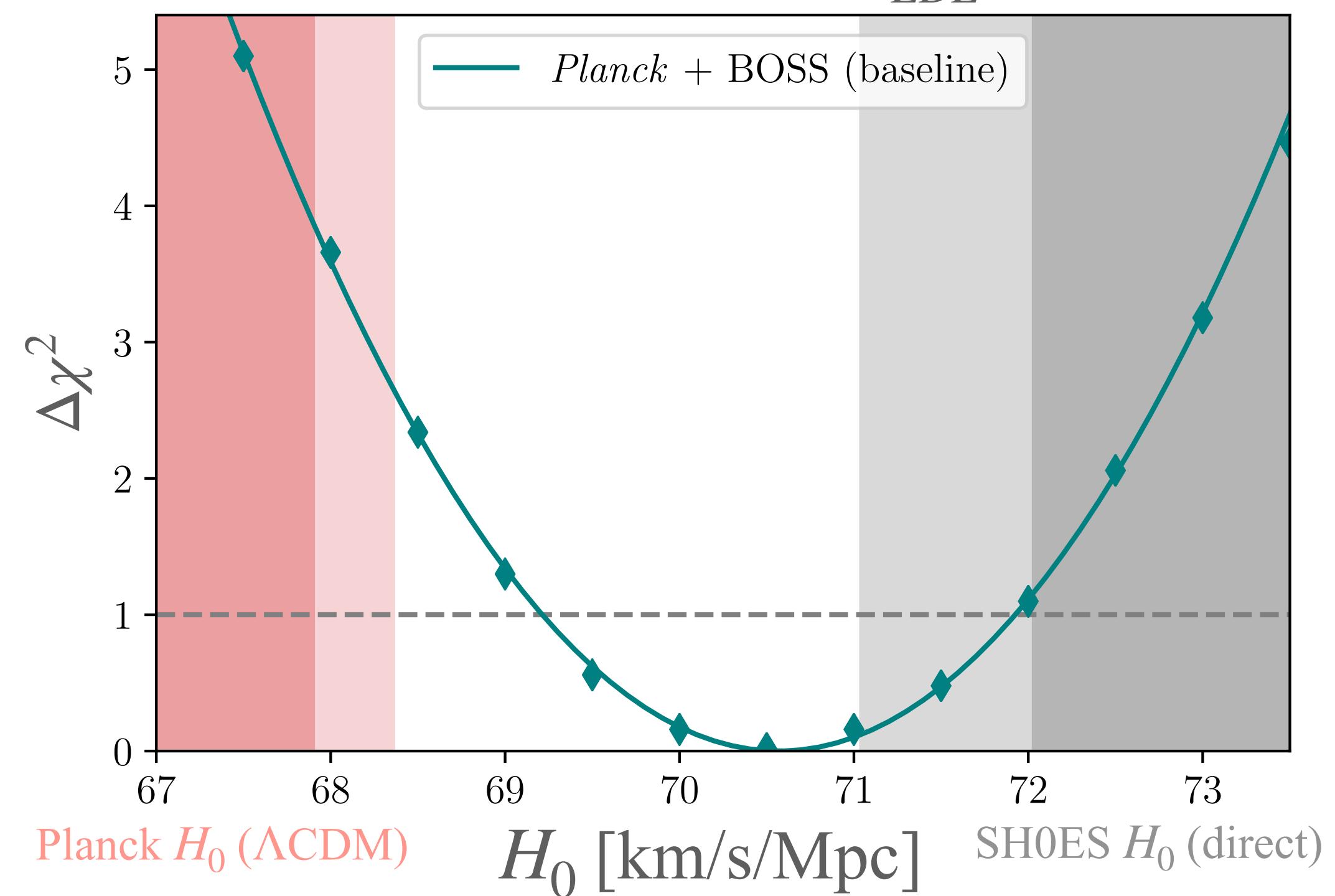
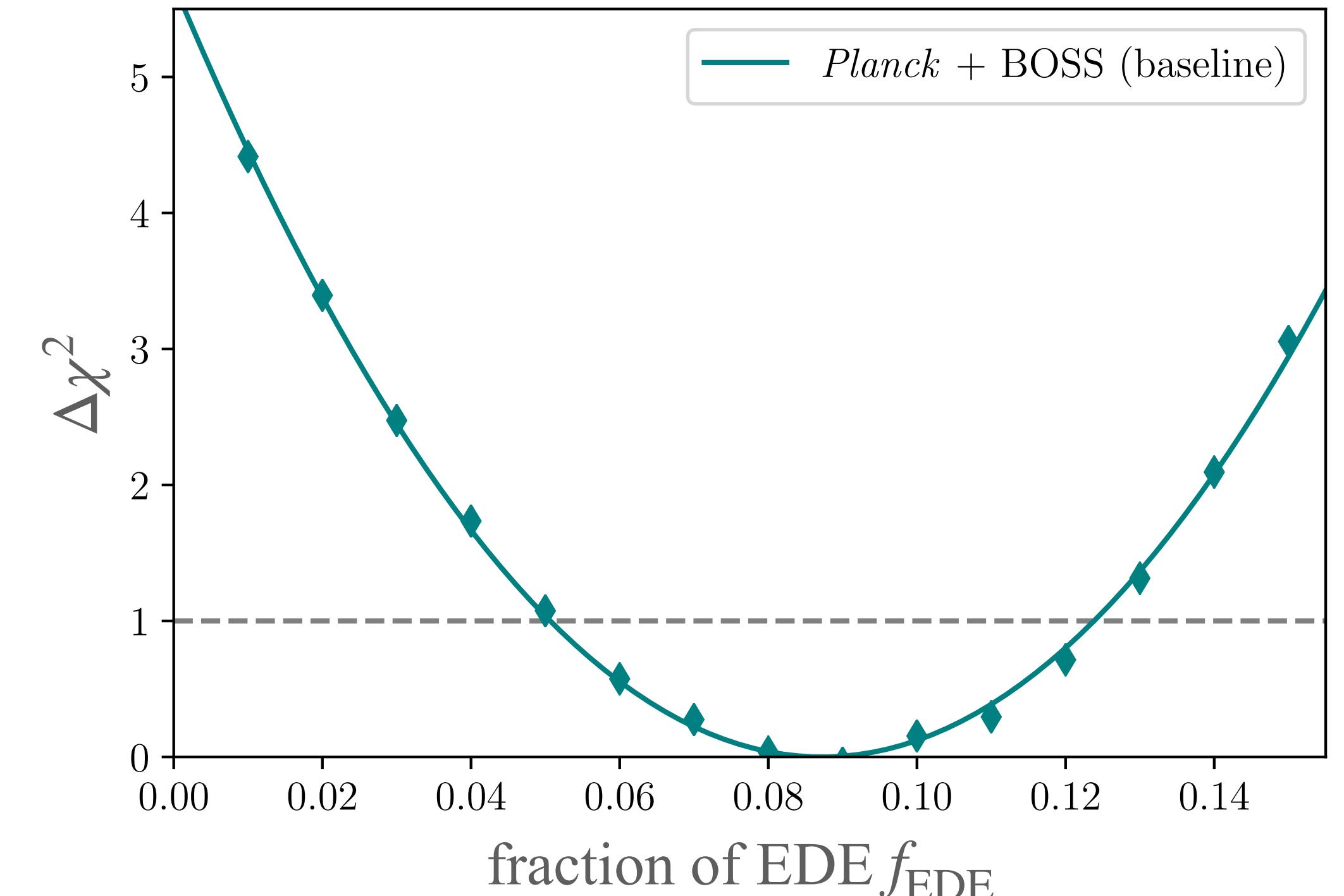
LH, Ferreira 2022

MCMC results:

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

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 1.4σ
- However: S_8 tension worsens slightly
(ΛCDM : 0.828, EDE: 0.840, DES: 0.776)

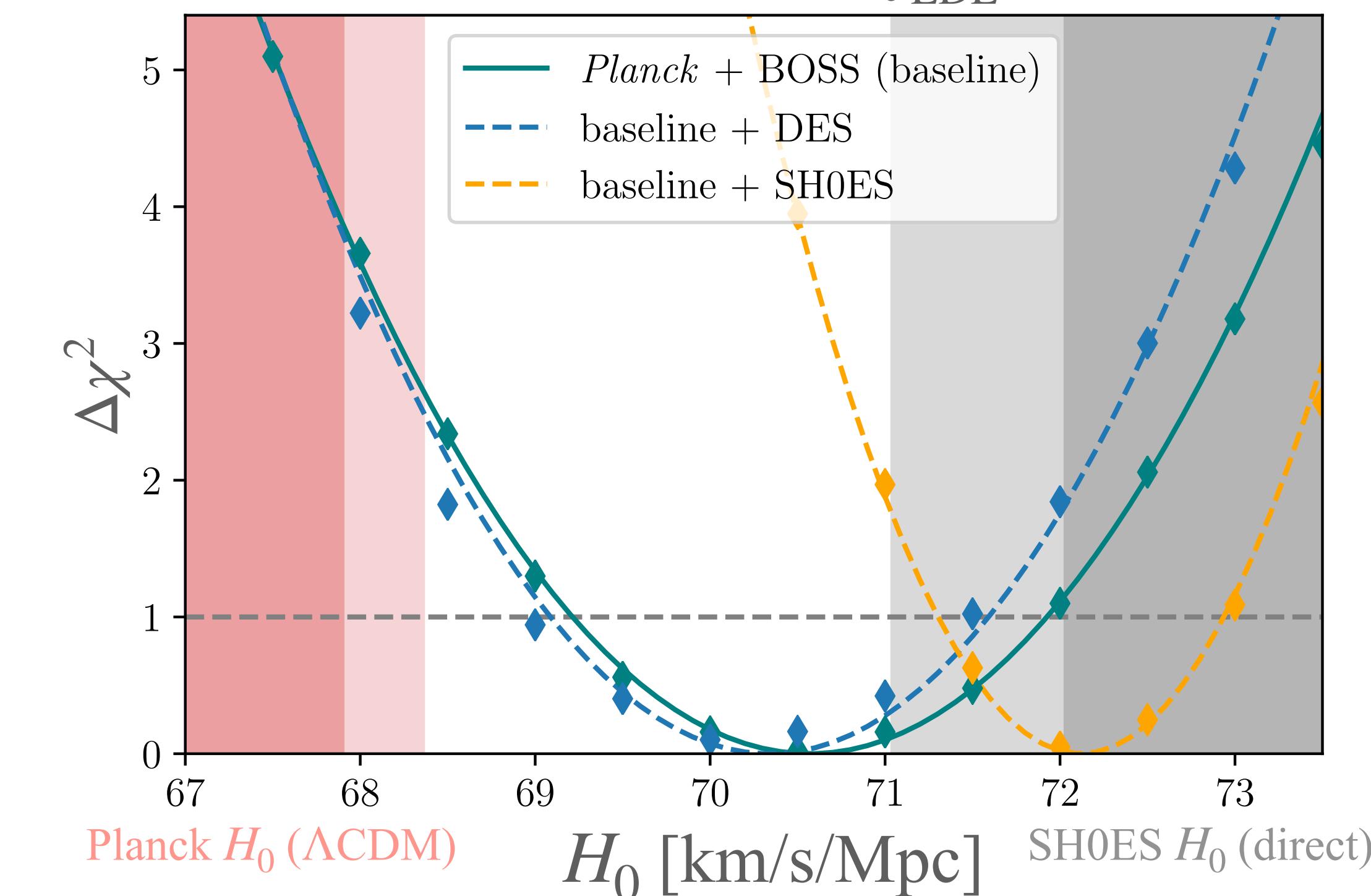
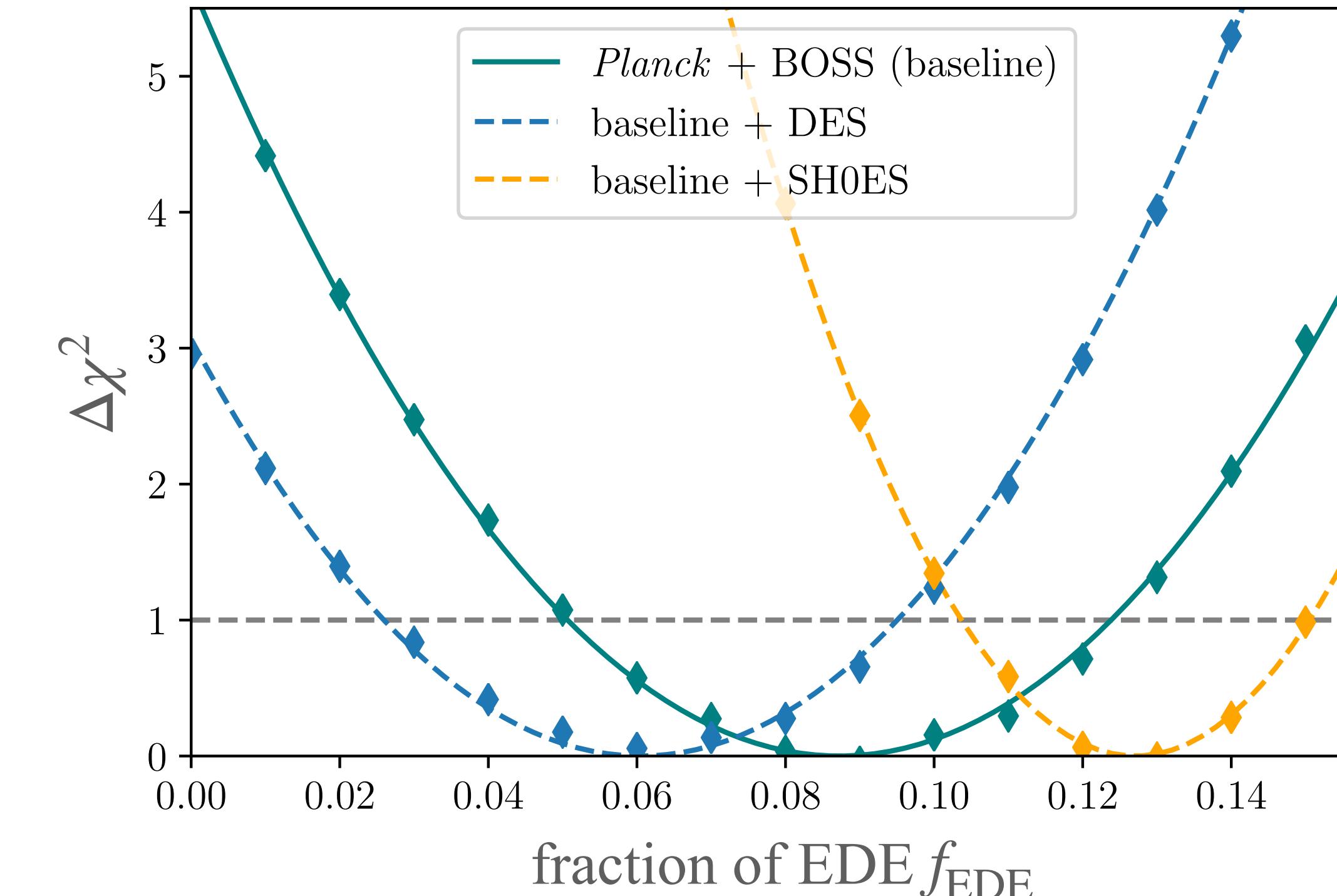


Baseline + DES

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 1.6σ
- Including weak lensing reduces f_{EDE} and H_0 slightly but does not rule out EDE
- Prior volume effect seems to be the dominating effect (compared to clustering enhancement)

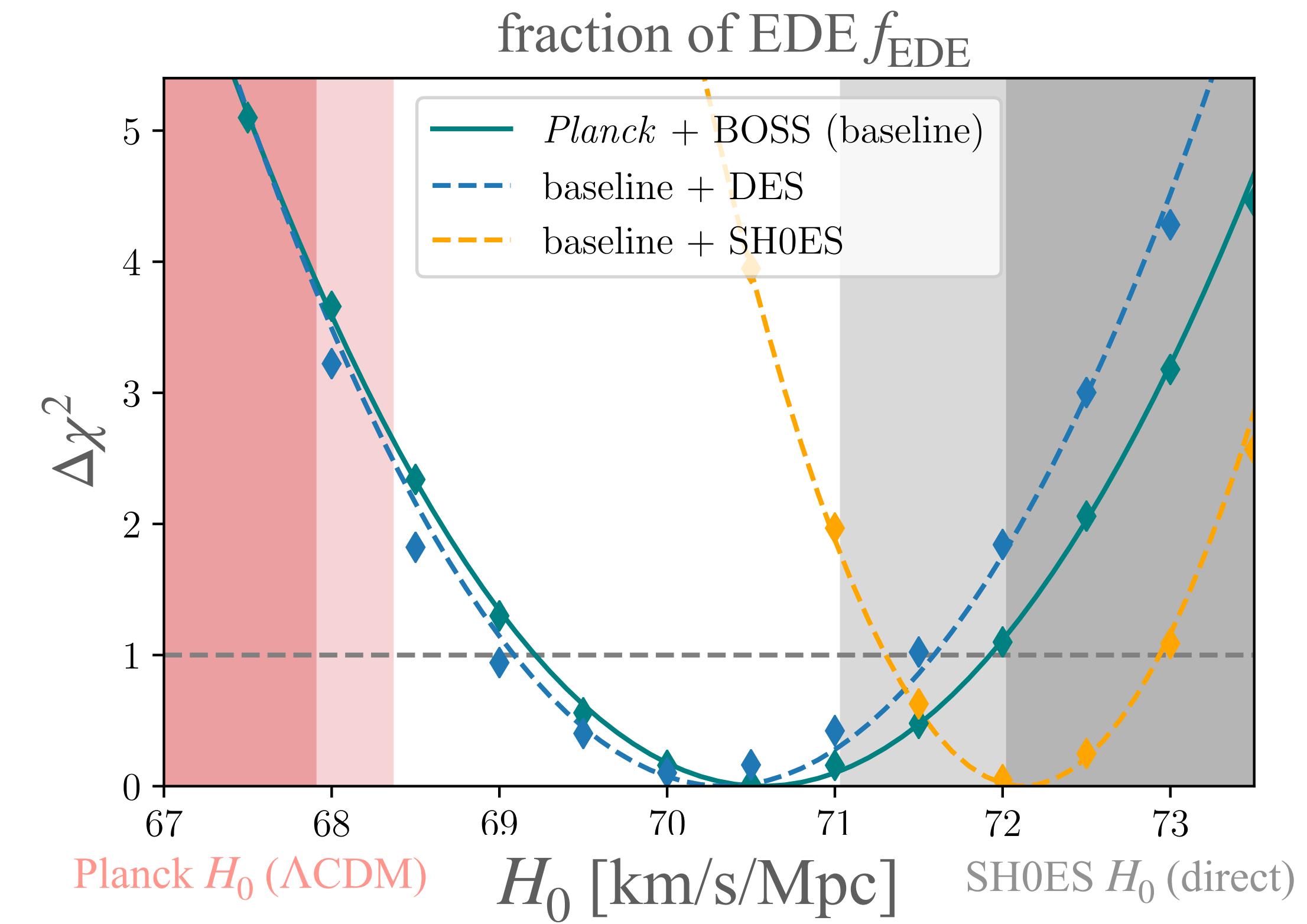
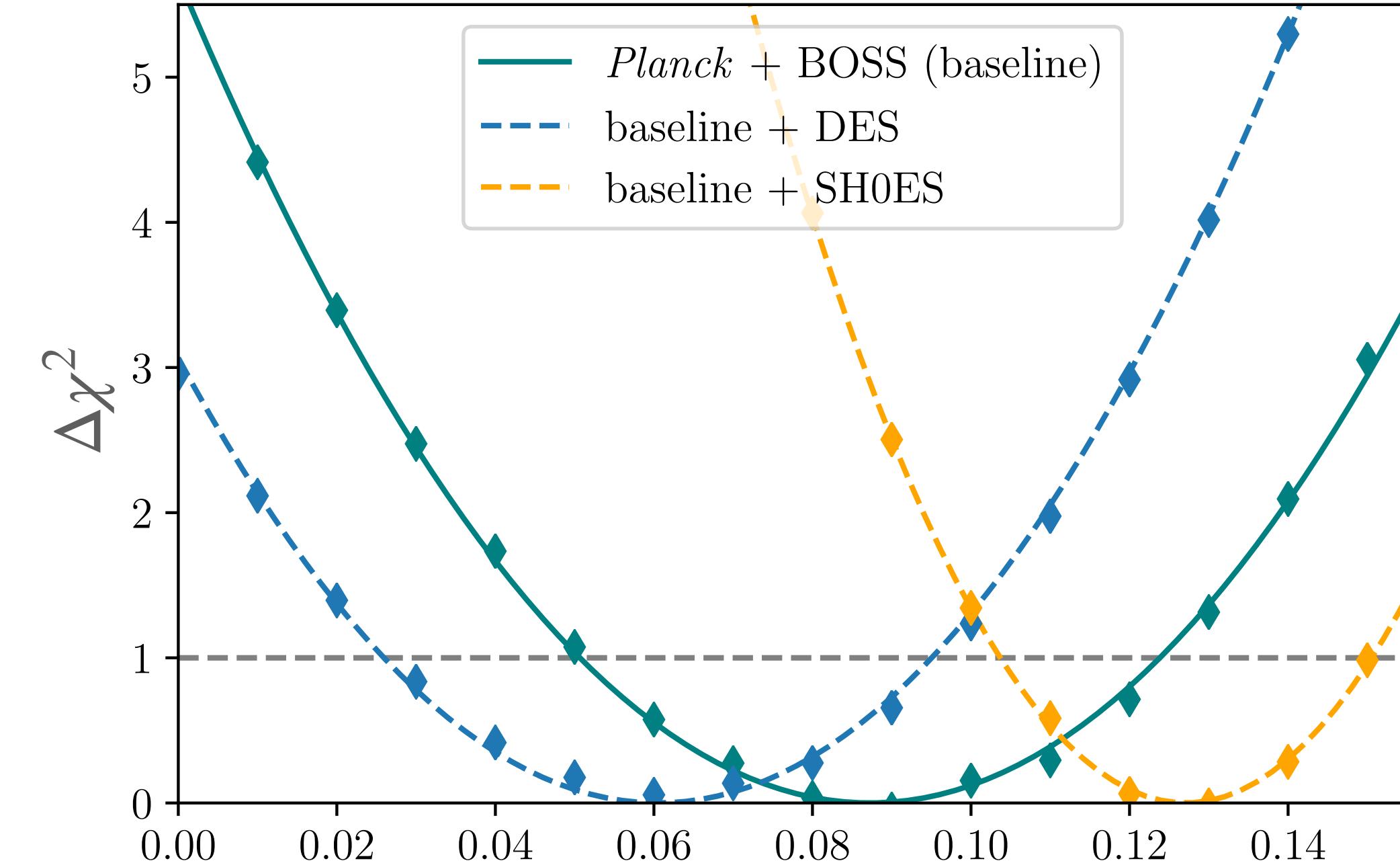


Baseline + SH0ES

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 0.69σ

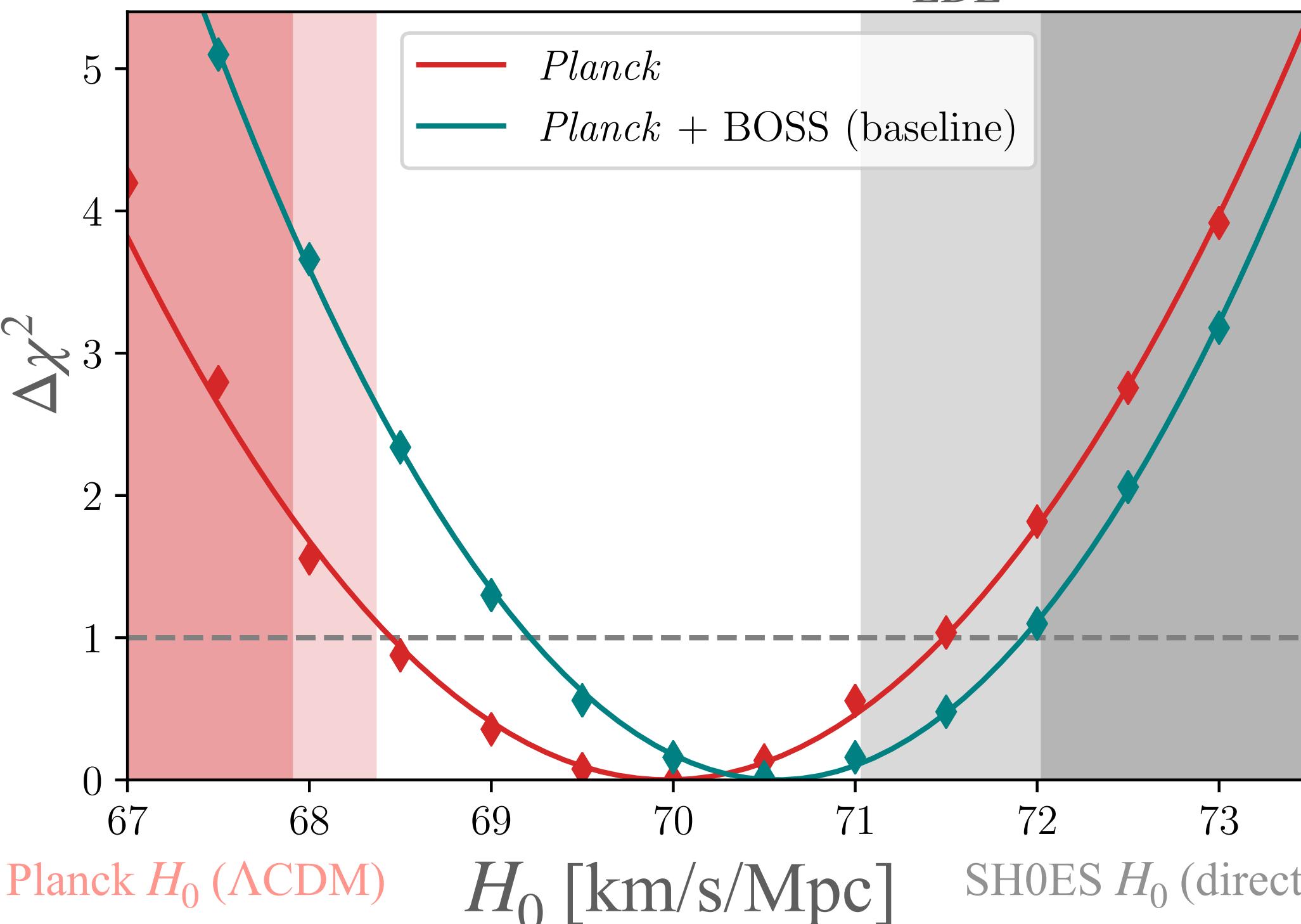
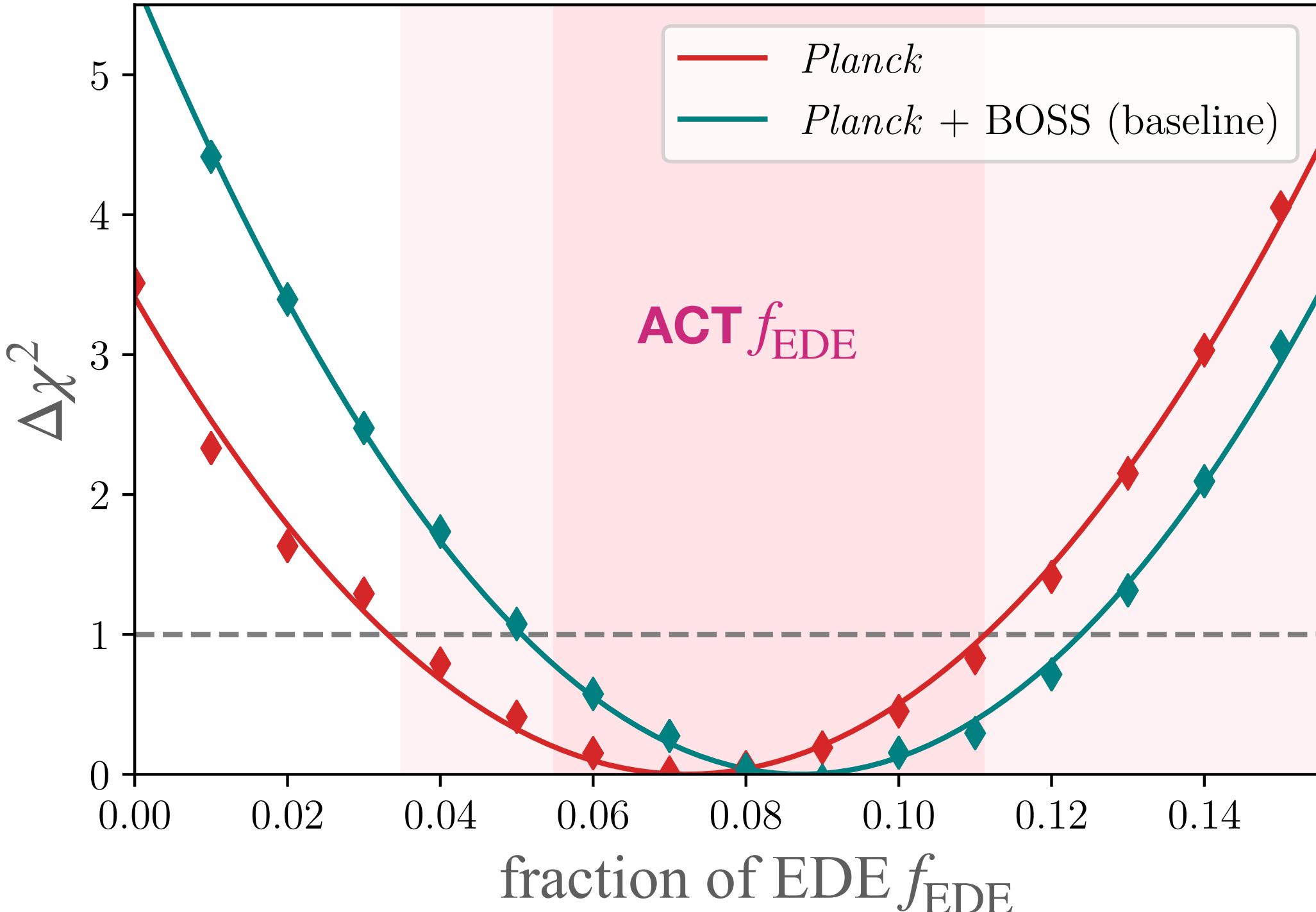


Planck only

LH, Ferreira 2022

Planck only:

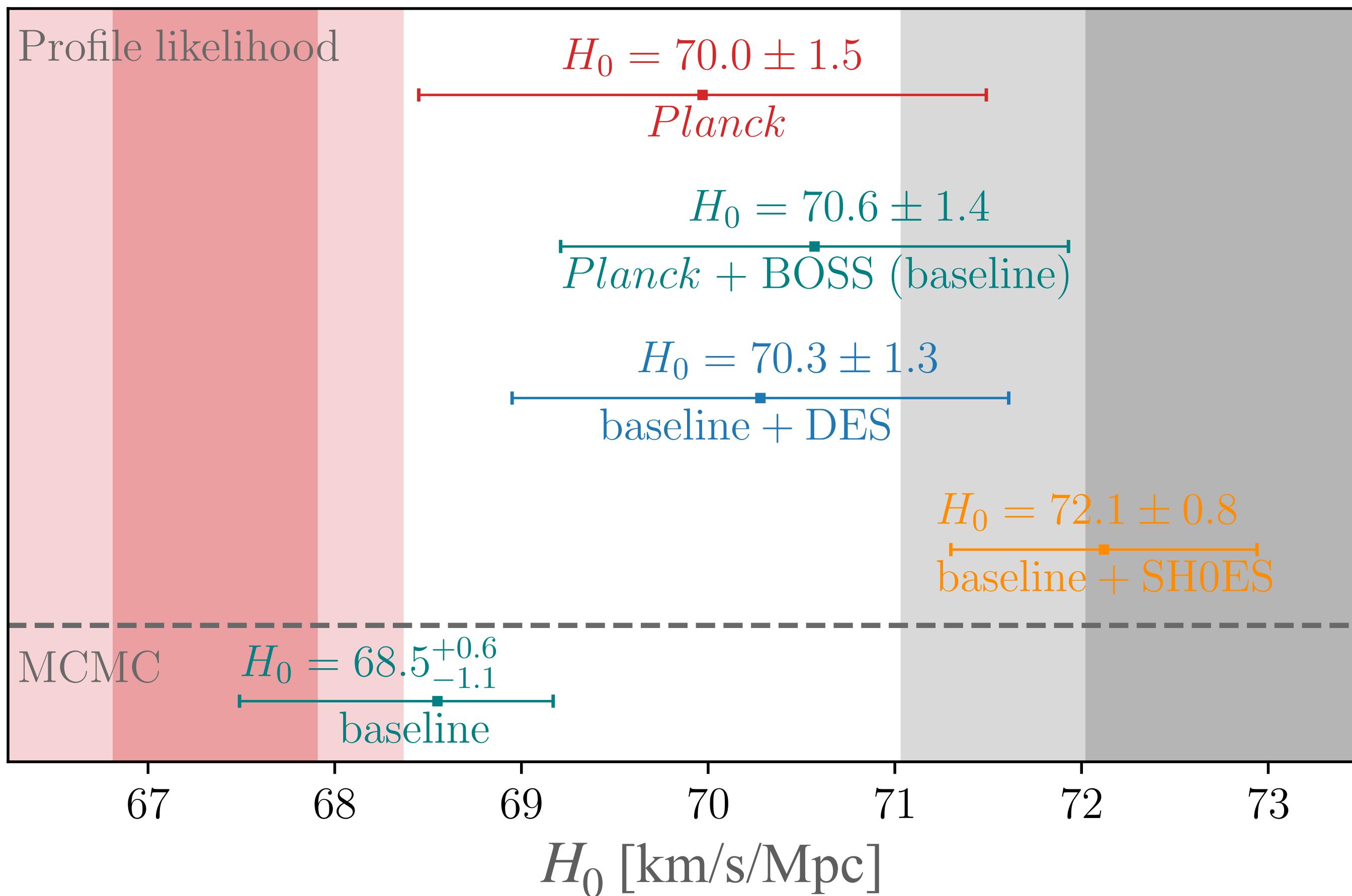
- $f_{\text{EDE}} = 0.072 \pm 0.039$,
 $H_0 = 69.97 \pm 1.52 \text{ km/s/Mpc}$
- Agreement with SH0ES at 1.7σ
- Agrees with recent MCMC results from the Atacama cosmology telescope (ACT):
 $f_{\text{EDE}} = 0.091^{+0.020}_{-0.036}$ (Hill++ 2022)



Profile likelihood – results

LH, Ferreira 2022

Planck H_0 (Λ CDM)



Results:

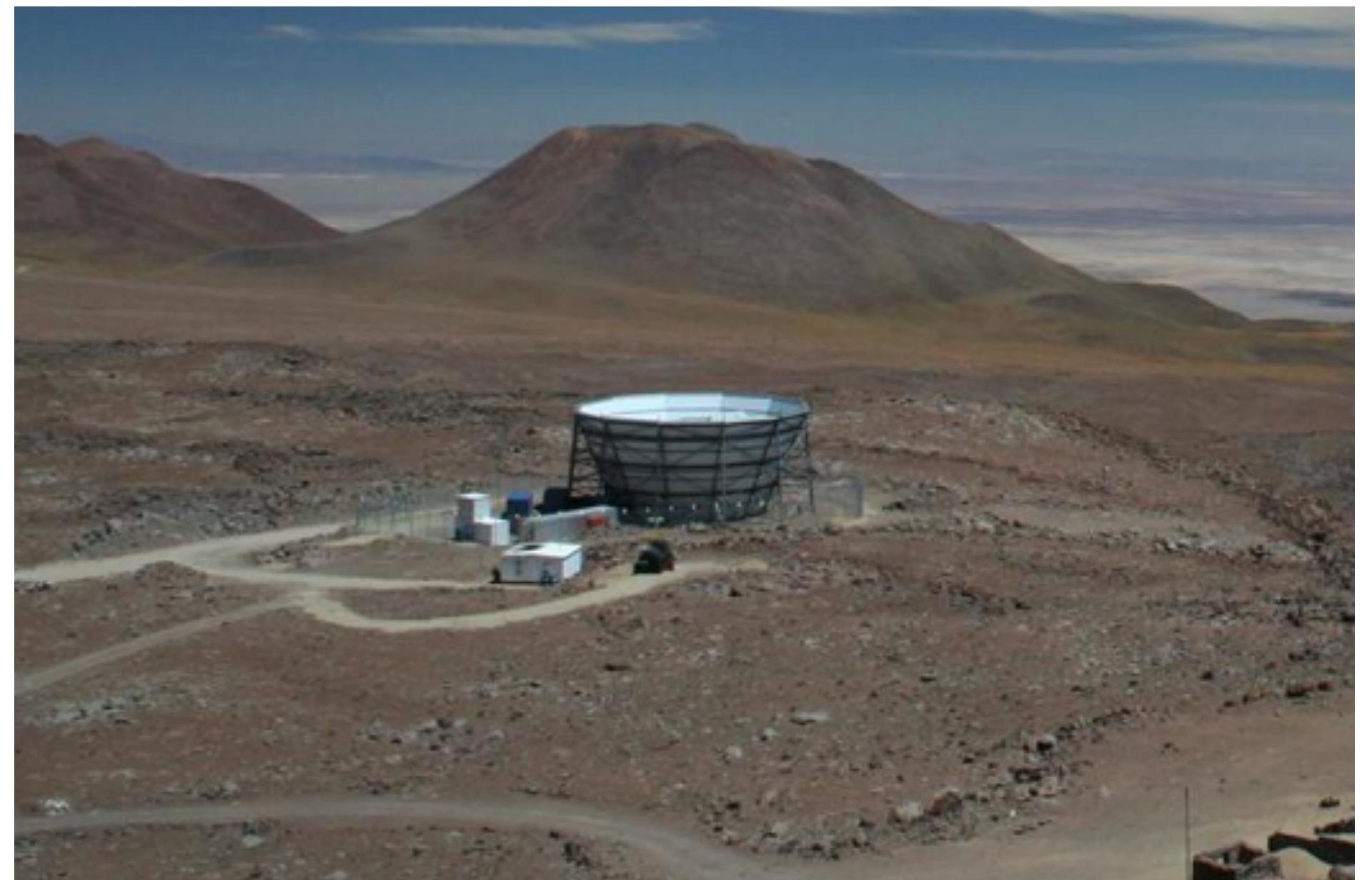
- Evidence for prior volume effects.
- H_0 in EDE model within 1.7σ of SH0ES measurement for all data sets (incl. galaxy clustering, weak lensing).
- EDE viable solution to Hubble tension.

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



ACT collaboration

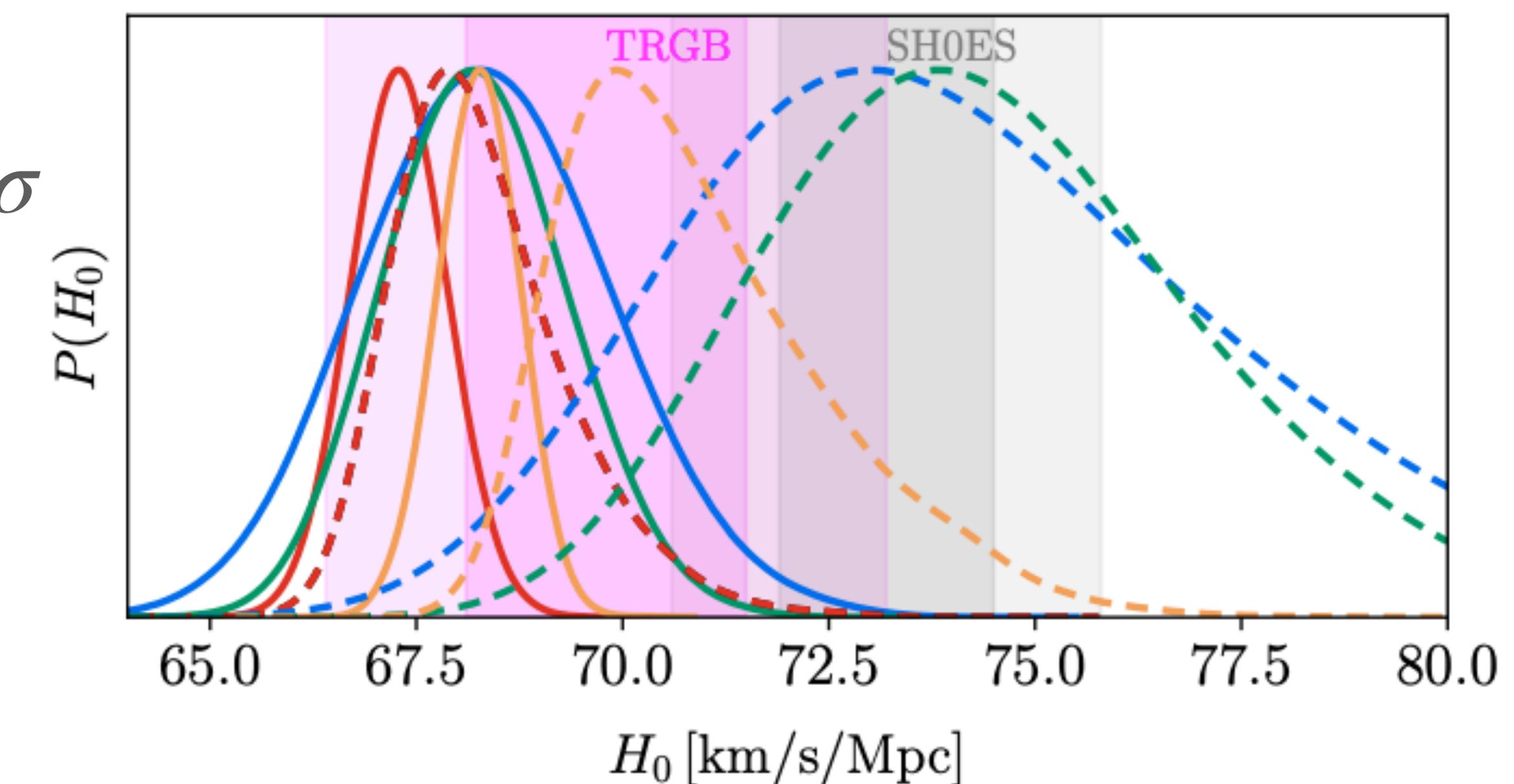
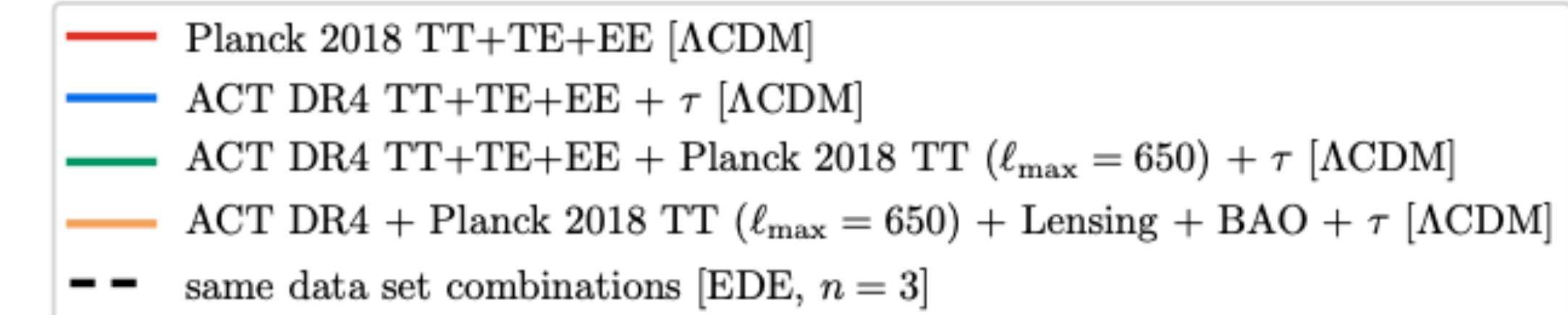
Results from ACT

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

Hill et al. 2021

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

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



EDE constraints from South Pole Telescope

La Posta++ 2021, Smith++ 2022



Credit Luong-Van

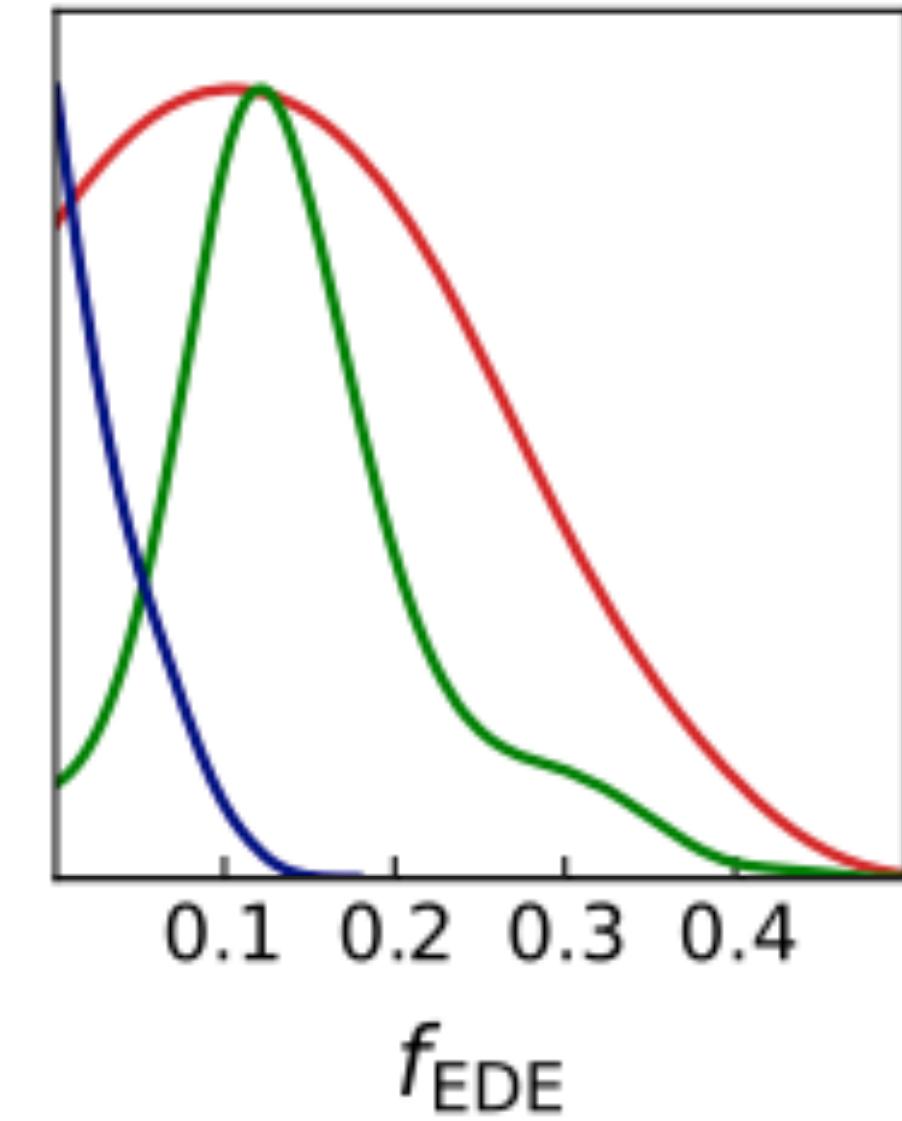
EDE constraints from South Pole Telescope

La Posta++ 2021, Smith++ 2022



Credit Luong-Van

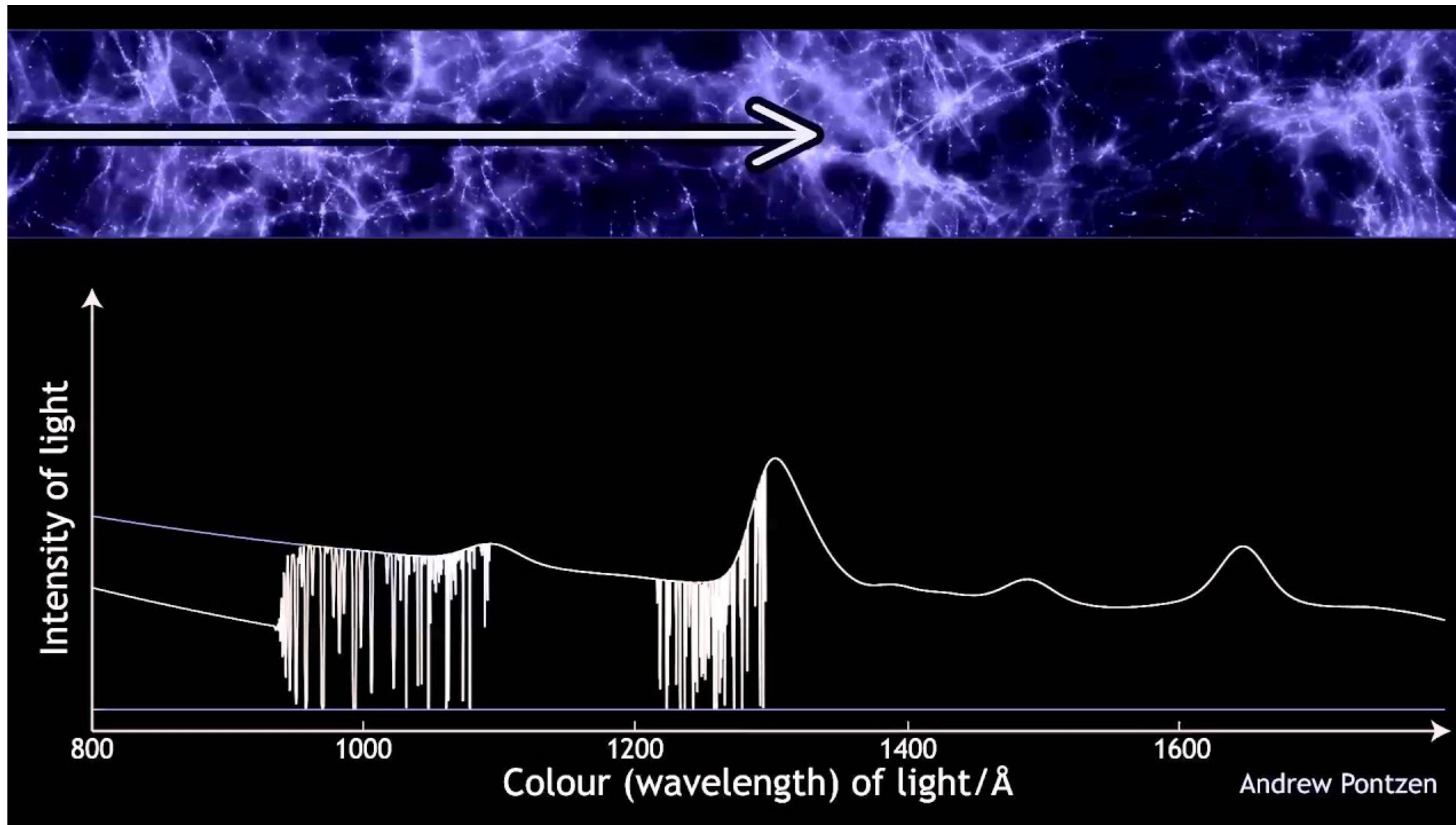
La Posta++ 2021



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

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

EDE constraints from Ly α forest

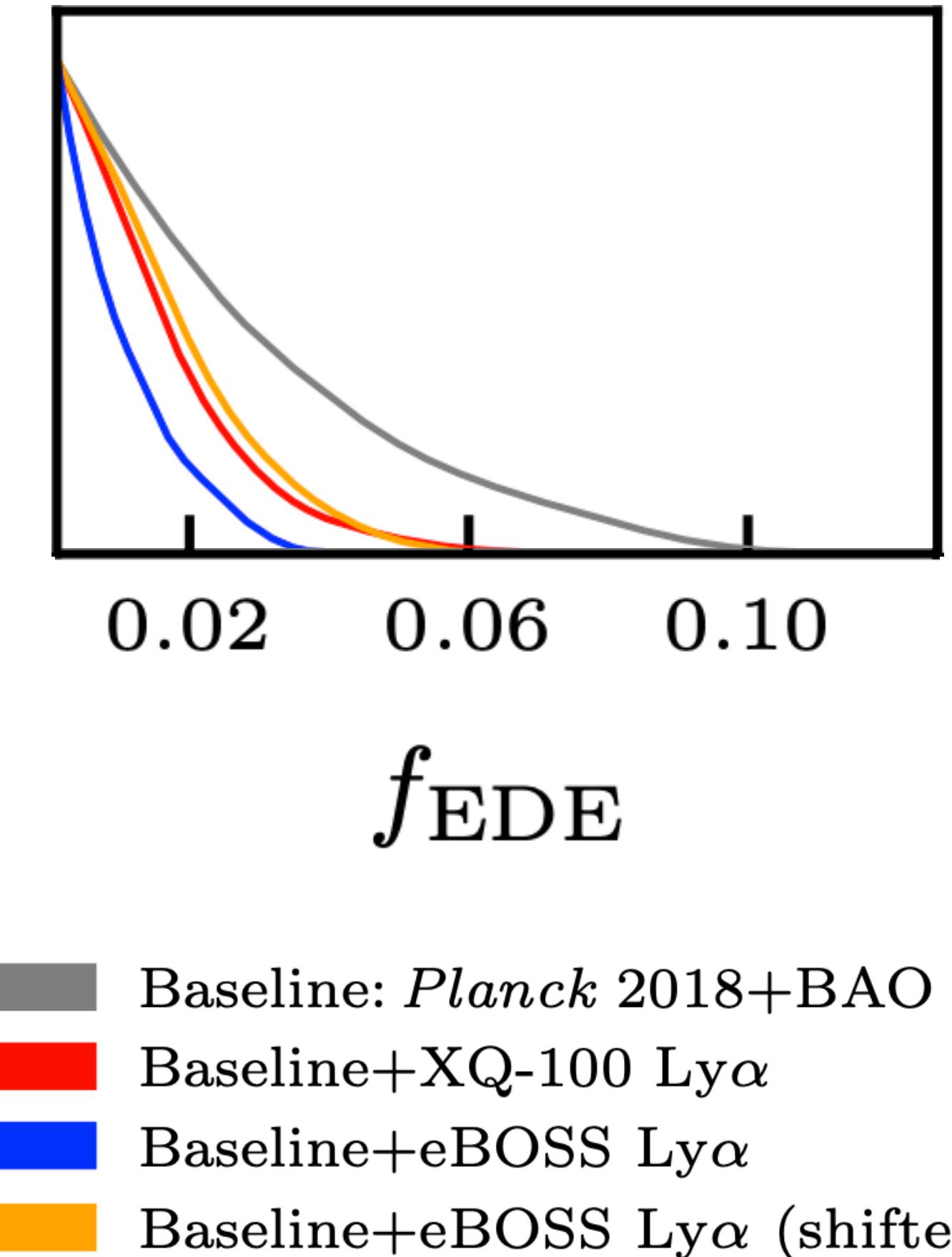


EDE constraints from Ly- α forest

Goldstein et al. 2023

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

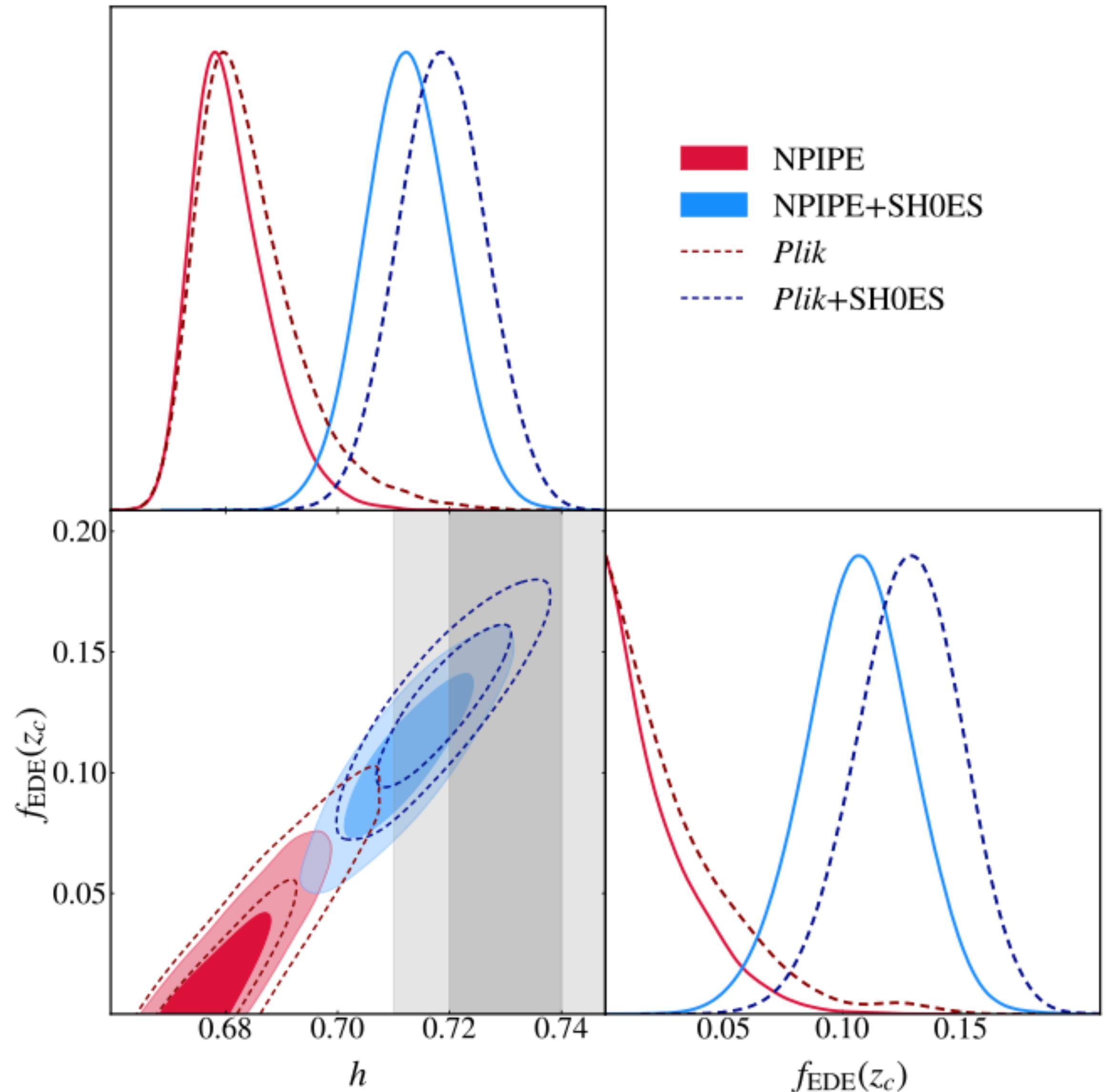
Goldstein++ 2023



Alternative NPIPE Planck pipeline

Efstathiou et al. 2023

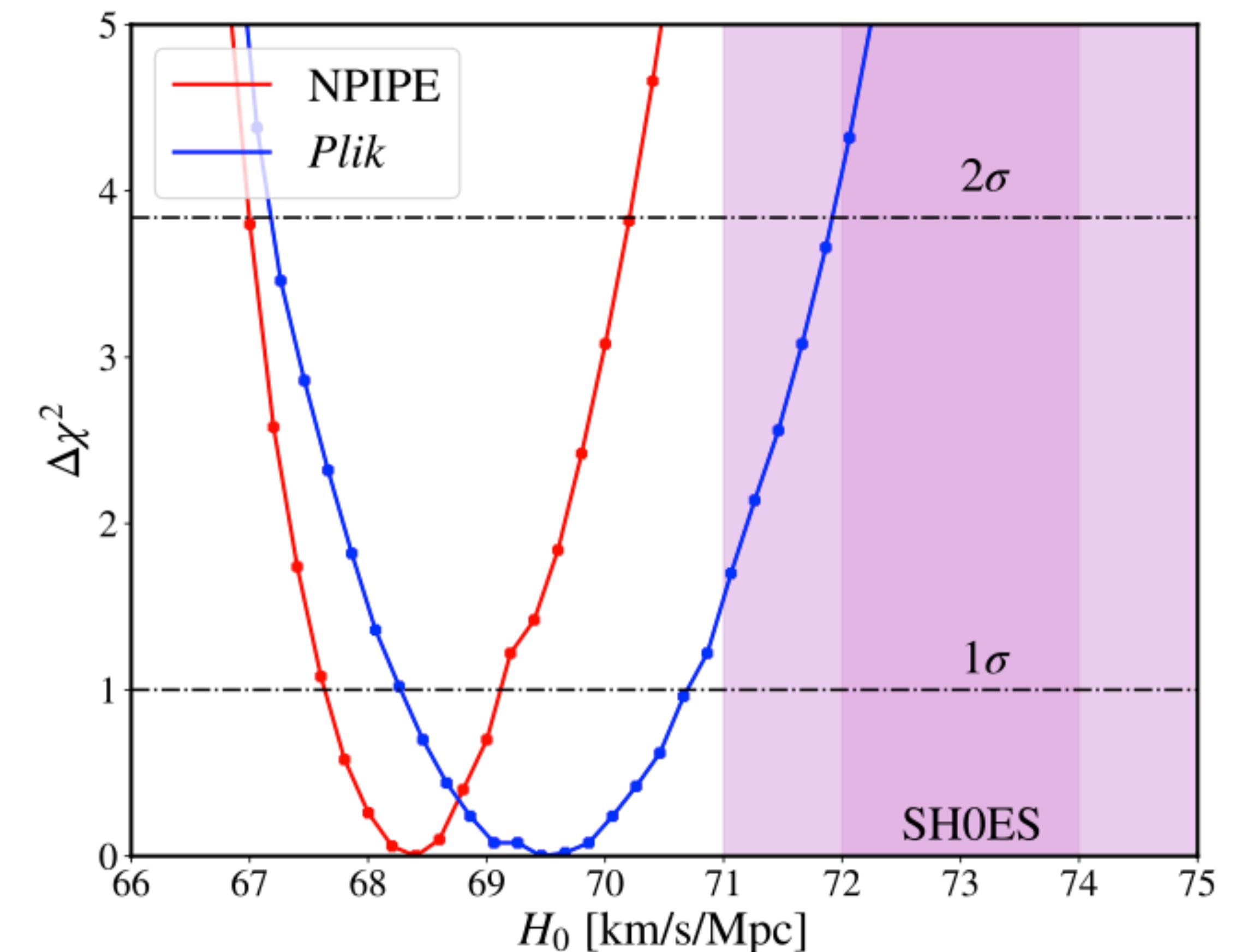
- An alternative Planck pipeline NPIPE
 - using more sky area at high frequencies
 - reducing the Λ CDM residuals
- NPIPE gives tighter constraints on f_{EDE} in a Bayesian MCMC...



Alternative NPIPE Planck pipeline

Efstathiou et al. 2023

- An alternative Planck pipeline NPIPE
 - using more sky area at high frequencies
 - reducing the Λ CDM residuals
- NPIPE gives tighter constraints on f_{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_{EDE} , z_c , θ_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