

How much information can be extracted from galaxy clustering at the field level?

Beatriz Tucci

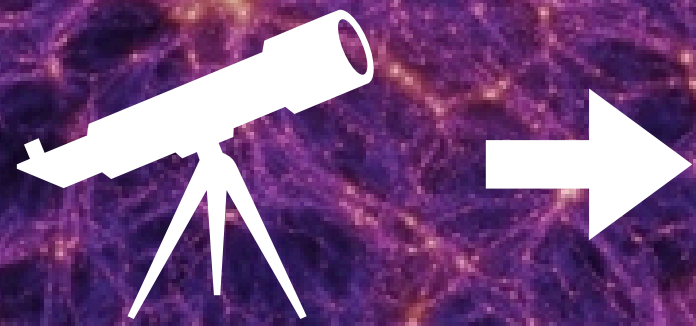
with Nhat-Minh Nguyen, Fabian Schmidt,
Andrija Kostić, Martin Reinecke

Based on [arXiv:2403.03220](https://arxiv.org/abs/2403.03220)



A visualization of the cosmic web, showing a complex network of dark matter filaments and clusters. The filaments are thin, purple lines that form a dense, interconnected web. At the intersections and along the filaments, there are numerous bright, yellowish-orange points representing galaxies and galaxy clusters. The background is a deep purple color.
$$\mathcal{P}(\theta | \text{telescope})$$

fundamental physics!

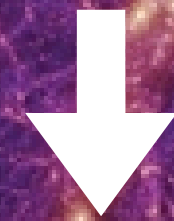


Summary
Statistics

A visualization of the cosmic web, showing a complex network of filaments and nodes of galaxies. The filaments are thin, purple lines, and the nodes are bright, yellowish-orange clusters of galaxies. The background is dark purple.

Summary
Statistics

*How much reliable
information can we gain?*



Field level

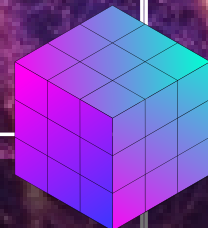
The background is a visualization of the cosmic web, showing a complex network of filaments and nodes of galaxies in shades of purple and blue. Several stylized white icons of galaxies with spiral arms and central bulges are scattered across the field. A white grid is overlaid on the entire image.

Field level

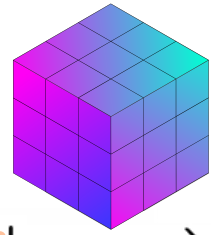
Galaxy density field

$$\delta_g(x) = \frac{n_g(x)}{\bar{n}_g} - 1$$

$\mathcal{P}(\theta | \delta_g^{\text{obs}})$



How to get the field level posterior?



$$\mathcal{P} \left(\boldsymbol{\theta}, \{\mathit{b}_O\}, \{\sigma_\varepsilon\} \mid \delta_g^{\text{obs}} \right)$$

Bias and stochastic
“nuisance” parameters

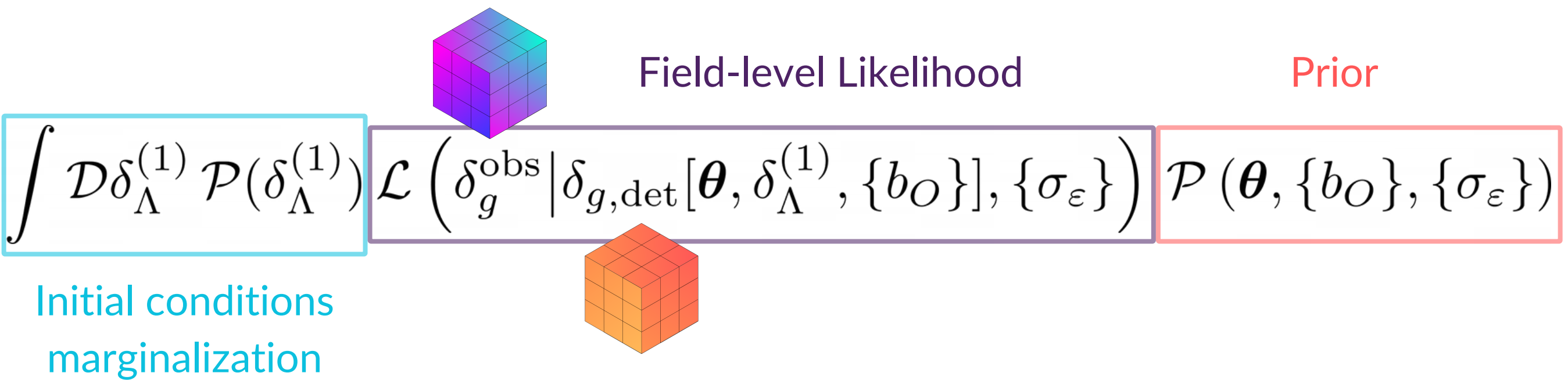
How to get the field level posterior?

$$\mathcal{P}(\boldsymbol{\theta}, \{b_O\}, \{\sigma_\varepsilon\} | \delta_g^{\text{obs}}) \propto \int \mathcal{D}\delta_\Lambda^{(1)} \mathcal{P}(\delta_\Lambda^{(1)}) \mathcal{L}(\delta_g^{\text{obs}} | \delta_{g, \det}[\boldsymbol{\theta}, \delta_\Lambda^{(1)}, \{b_O\}], \{\sigma_\varepsilon\}) \mathcal{P}(\boldsymbol{\theta}, \{b_O\}, \{\sigma_\varepsilon\})$$

Initial conditions marginalization

Field-level Likelihood

Prior



How to get the field level posterior?

$$\mathcal{P}(\boldsymbol{\theta}, \{b_O\}, \{\sigma_\varepsilon\} | \delta_g^{\text{obs}}) \propto \int \mathcal{D}\delta_\Lambda^{(1)} \mathcal{P}(\delta_\Lambda^{(1)}) \mathcal{L}(\delta_g^{\text{obs}} | \delta_{g, \det}[\boldsymbol{\theta}, \delta_\Lambda^{(1)}, \{b_O\}], \{\sigma_\varepsilon\}) \mathcal{P}(\boldsymbol{\theta}, \{b_O\}, \{\sigma_\varepsilon\})$$

Initial conditions marginalization

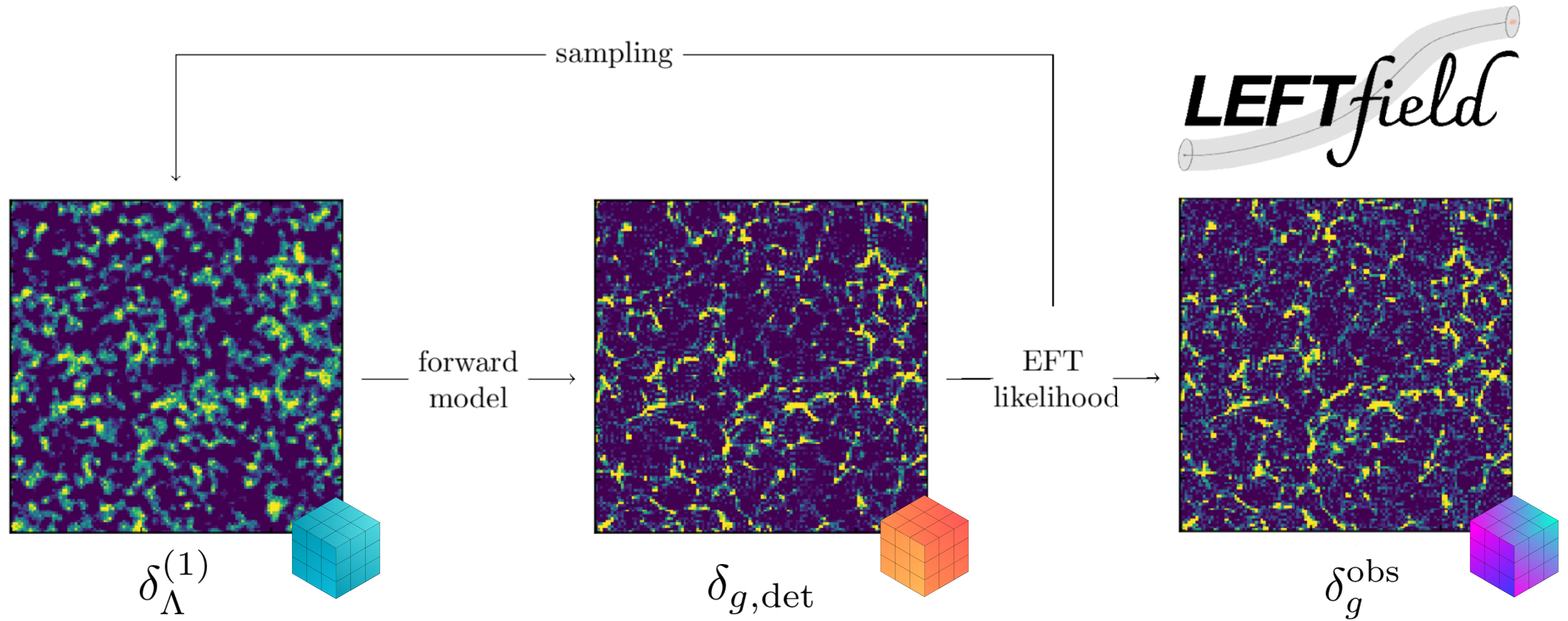
Field-level Likelihood

Prior

$\left\{ \delta_{\Lambda, i}^{(1)} \right\}_{i=1}^{N_g^\Lambda}$

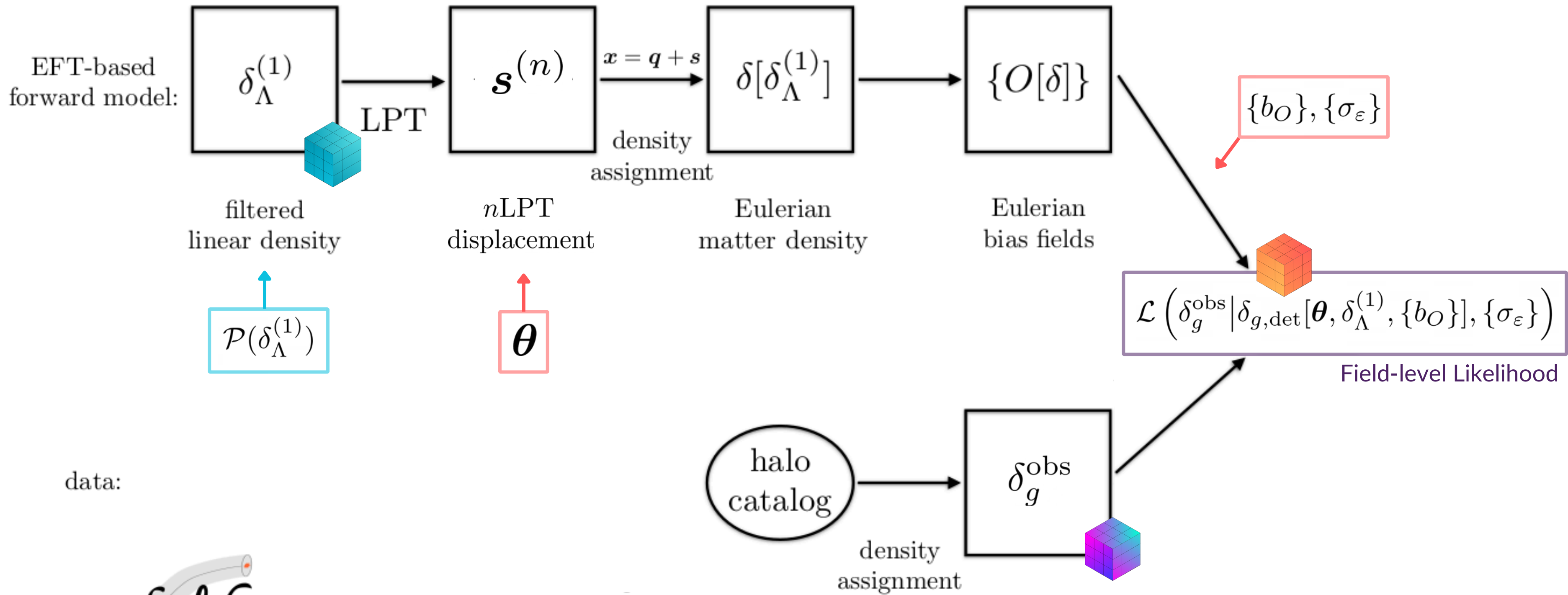
Field-level inference

Schmidt et al (2018, 2020)
Cabass & Schmidt (2019, 2020)
Babic, Schmidt, Tucci (2022)
Kostic et al (2020)
Stadler et al (2023)



Credits: Julia Stadler

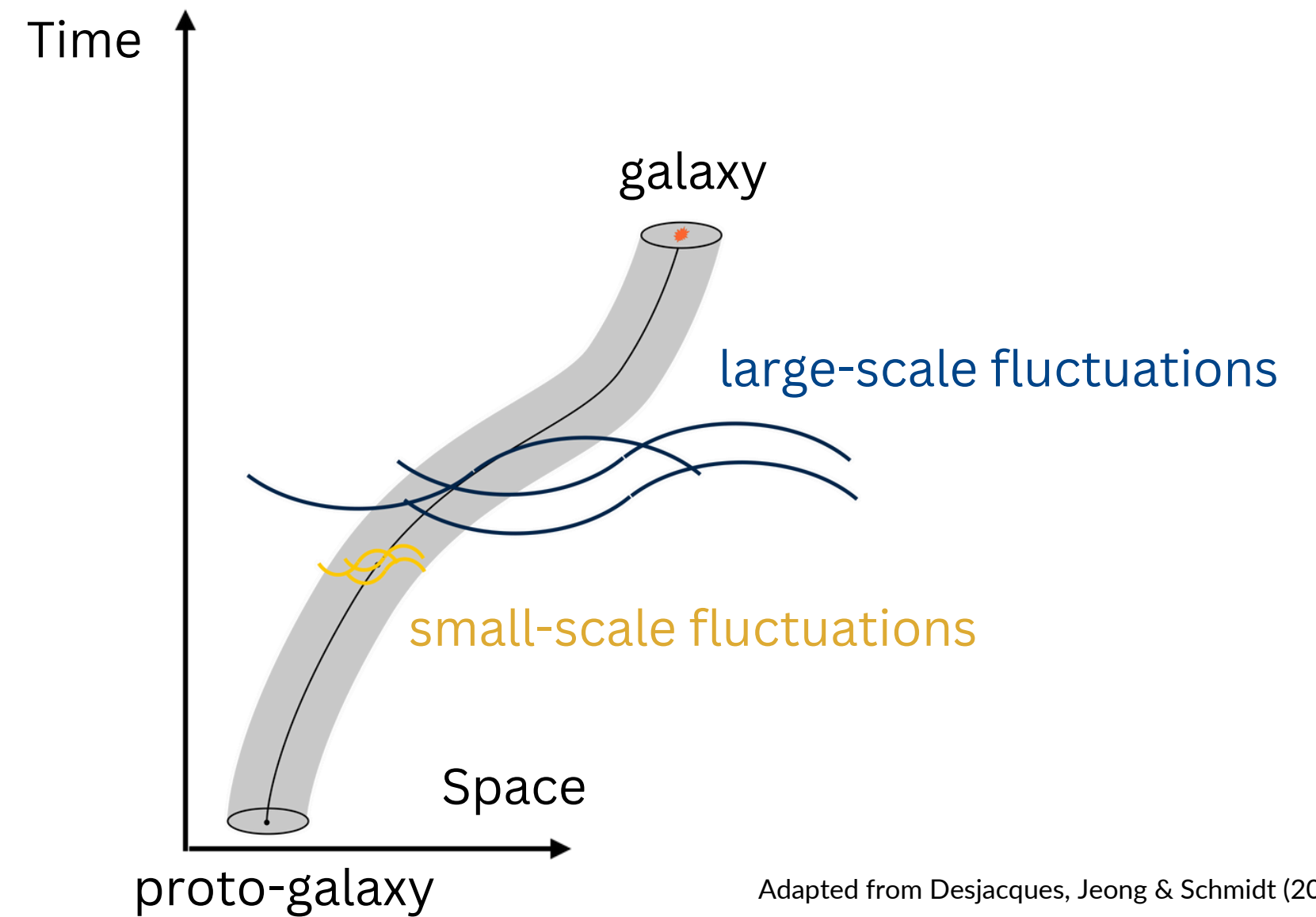
Forward model



Bias expansion

c.f. Pierre's talk

$$\delta_g(\mathbf{k}, z) = \delta_{g,\text{det}}(\mathbf{k}, z) + \delta_{g,\text{stoch}}(\mathbf{k}, z)$$



Bias expansion

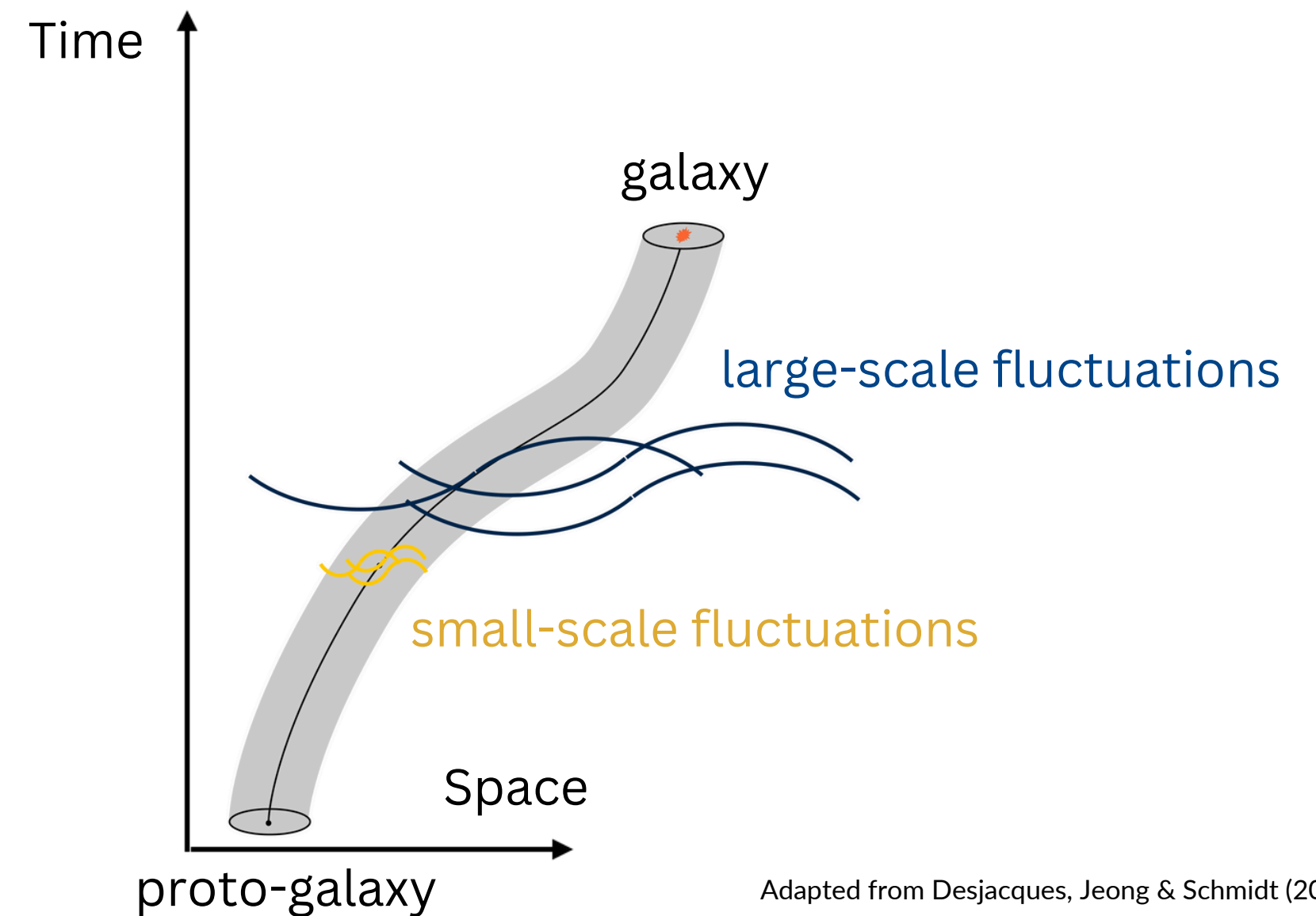
$$\begin{aligned}\delta_g(\mathbf{k}, z) &= \delta_{g,\text{det}}(\mathbf{k}, z) + \delta_{g,\text{stoch}}(\mathbf{k}, z) \\ &= \sum_O b_O(z) O(\mathbf{k}, z) + \varepsilon(\mathbf{k}, z)\end{aligned}$$

$\{b_O\}$ Free bias parameters

$$O \in [\delta, \delta^2, K^2, \delta^3, K^3, \delta K^2, O_{\text{td}}, \nabla^2 \delta]$$

3rd order Eulerian bias

Desjacques, Jeong & Schmidt (2016)
Mirbabayi, Schmidt, Zaldarriaga (2015)



Adapted from Desjacques, Jeong & Schmidt (2016)

Bias expansion

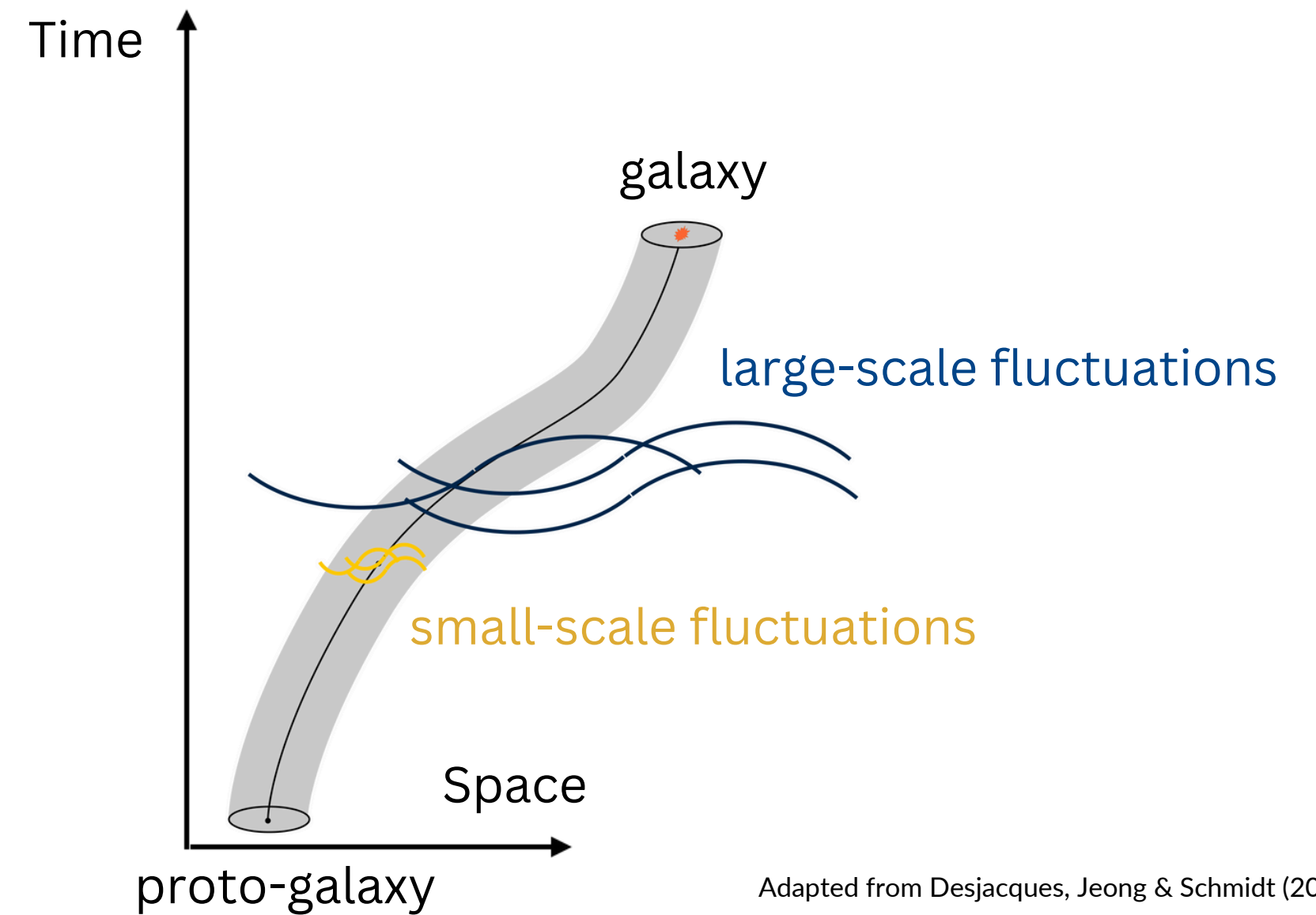
$$\begin{aligned}\delta_g(\mathbf{k}, z) &= \delta_{g,\text{det}}(\mathbf{k}, z) + \delta_{g,\text{stoch}}(\mathbf{k}, z) \\ &= \sum_O b_O(z) O(\mathbf{k}, z) + \varepsilon(\mathbf{k}, z)\end{aligned}$$

$$\langle \varepsilon(\mathbf{k}, z) \varepsilon(\mathbf{k}', z) \rangle' \propto \sigma_\varepsilon^2(k)$$

$$\sigma_\varepsilon(k) = \sigma_{\varepsilon,0} [1 + \sigma_{\varepsilon,k^2} k^2]$$

Free stochastic
parameters

$$\{\sigma_\varepsilon\}$$



Adapted from Desjacques, Jeong & Schmidt (2016)

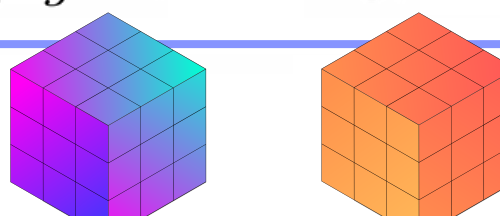
Field level Likelihood

$$k_{\max} \leq \Lambda$$

$$\ln \mathcal{L} \left(\delta_g^{\text{obs}} \mid \delta_{g,\text{det}}[\boldsymbol{\theta}, \delta_{\Lambda}^{(1)}, \{b_O\}], \{\sigma_{\varepsilon}\} \right) = -\frac{1}{2} \sum_{k < k_{\max}} \left[\frac{1}{\sigma_{\varepsilon}^2(k)} \left| \delta_g^{\text{obs}}(\mathbf{k}) - \delta_{g,\text{det}}[\boldsymbol{\theta}, \delta_{\Lambda}^{(1)}, \{b_O\}](\mathbf{k}) \right|^2 + \ln[2\pi\sigma_{\varepsilon}^2(k)] \right]$$

Field level Likelihood

**Mode by mode
data and theory
comparison!**

$$\ln \mathcal{L} \left(\delta_g^{\text{obs}} \mid \delta_{g,\text{det}}[\boldsymbol{\theta}, \delta_{\Lambda}^{(1)}, \{b_O\}], \{\sigma_{\varepsilon}\} \right) = -\frac{1}{2} \sum_{k < k_{\text{max}}} \left[\frac{1}{\sigma_{\varepsilon}^2(k)} \left| \delta_g^{\text{obs}}(\mathbf{k}) - \delta_{g,\text{det}}[\boldsymbol{\theta}, \delta_{\Lambda}^{(1)}, \{b_O\}](\mathbf{k}) \right|^2 + \ln[2\pi\sigma_{\varepsilon}^2(k)] \right]$$


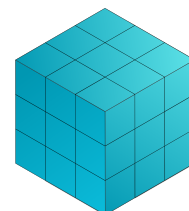
Field level Likelihood

$$\ln \mathcal{L} \left(\delta_g^{\text{obs}} \mid \delta_{g,\text{det}}[\boldsymbol{\theta}, \delta_{\Lambda}^{(1)}, \{b_O\}], \{\sigma_{\varepsilon}\} \right) = -\frac{1}{2} \sum_{k < k_{\text{max}}} \left[\frac{1}{\sigma_{\varepsilon}^2(k)} \left| \delta_g^{\text{obs}}(\mathbf{k}) - \delta_{g,\text{det}}[\boldsymbol{\theta}, \delta_{\Lambda}^{(1)}, \{b_O\}](\mathbf{k}) \right|^2 + \ln[2\pi\sigma_{\varepsilon}^2(k)] \right]$$

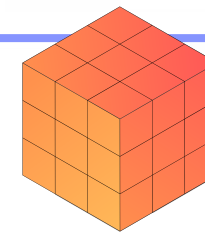
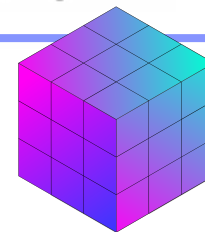
↓ HMC

$$\mathcal{P} \left(\boldsymbol{\theta}, \delta_{\Lambda}^{(1)}, \{b_O\}, \{\sigma_{\varepsilon}\} \mid \delta_g^{\text{obs}} \right)$$

Full posterior
including initial
conditions!



$$\left\{ \delta_{\Lambda,i}^{(1)} \right\}_{i=1}^{N_g^{\Lambda}}$$



Inference setup

Using Nbody halos as observed data, can we break the degeneracy between σ_8 and bias parameters with field level inference?

$$\alpha \equiv \sigma_8 / \sigma_8^{\text{true}}$$

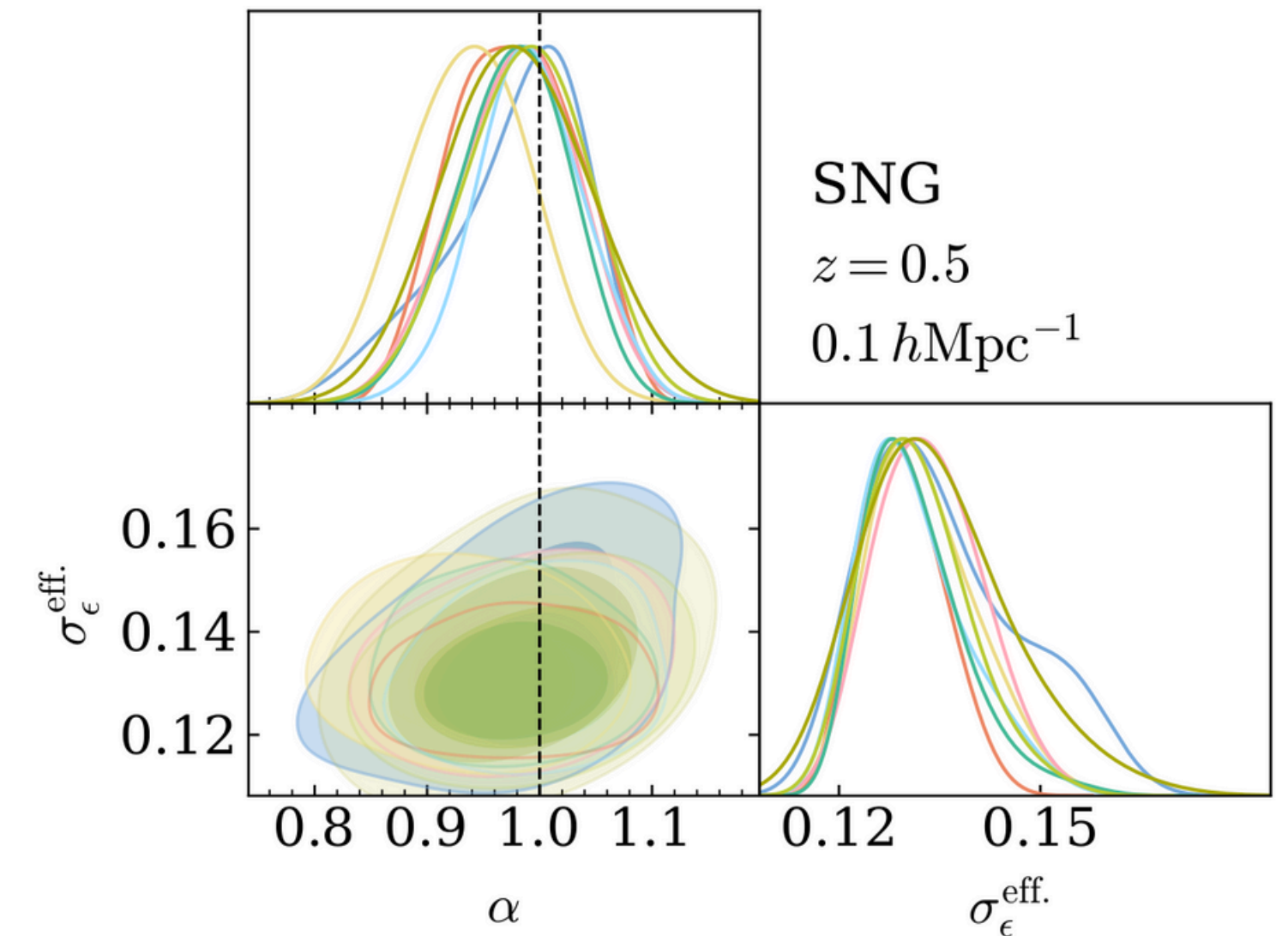
$$\theta = \{\alpha\}$$

Inference setup: halo samples

	SNG	Uchuu
Redshift	$z = 0.50$	$z = 1.03$
$V [h^{-3}\text{Mpc}^3]$	2000^3	2000^3
$\bar{n}_g [h^3\text{Mpc}^{-3}]$	1.3×10^{-3}	3.6×10^{-3}

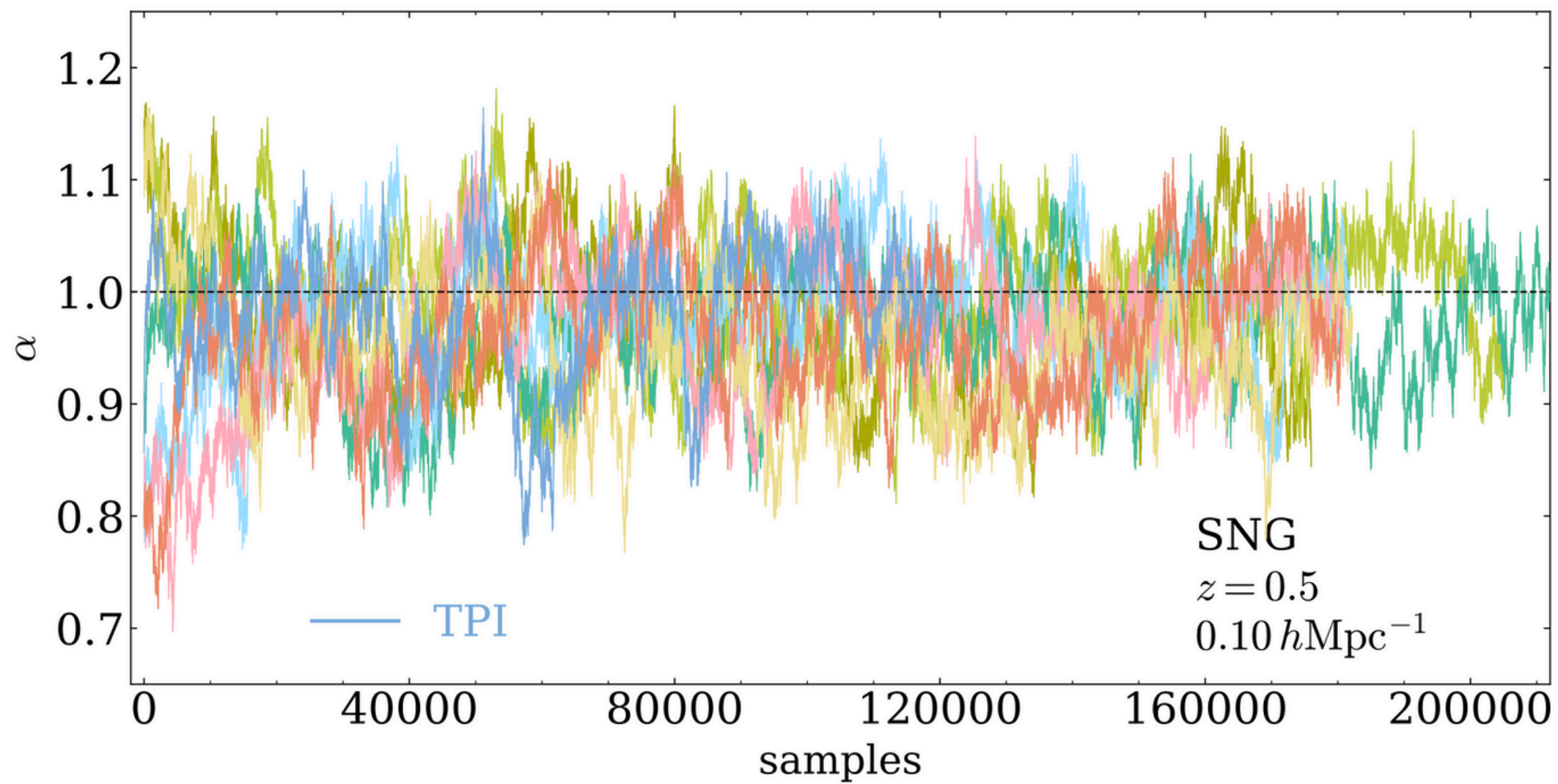
Field level inference results

	SNG	Uchuu
$k_{\max} = 0.10 h\text{Mpc}^{-1}$	$\alpha = 0.976 \pm 0.056$	$\alpha = 0.941 \pm 0.090$
$k_{\max} = 0.12 h\text{Mpc}^{-1}$	$\alpha = 1.013 \pm 0.033$	$\alpha = 0.993 \pm 0.053$

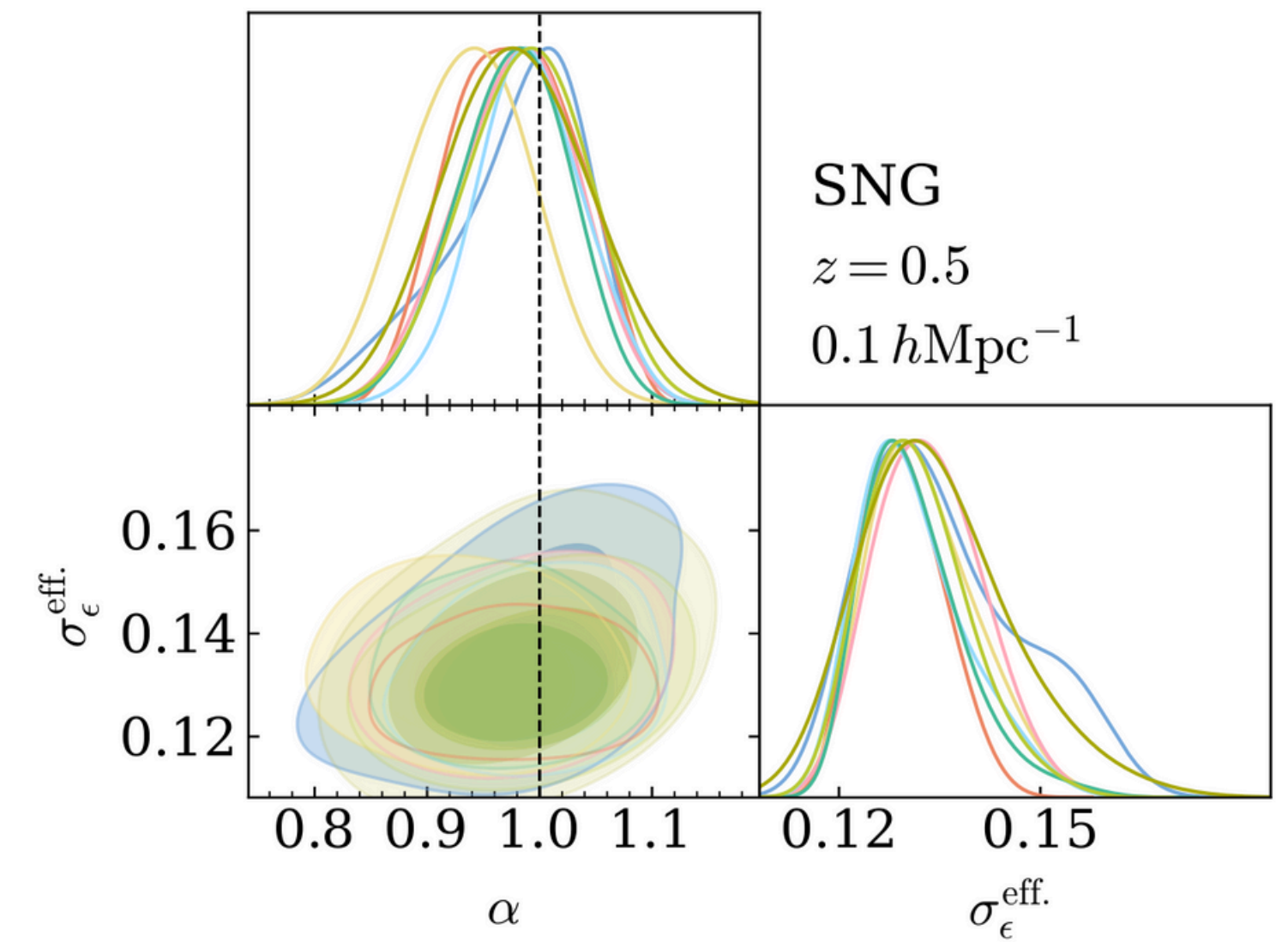


Field level inference results

Trace plot for independent HMC chains



Posterior for independent HMC chains



Information content?

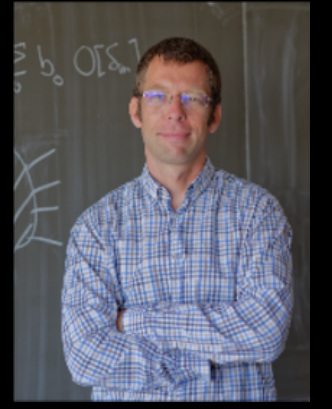
How can we quantify the cosmological information extracted from field-level inference?

How much information can be extracted from galaxy clustering at the field level?

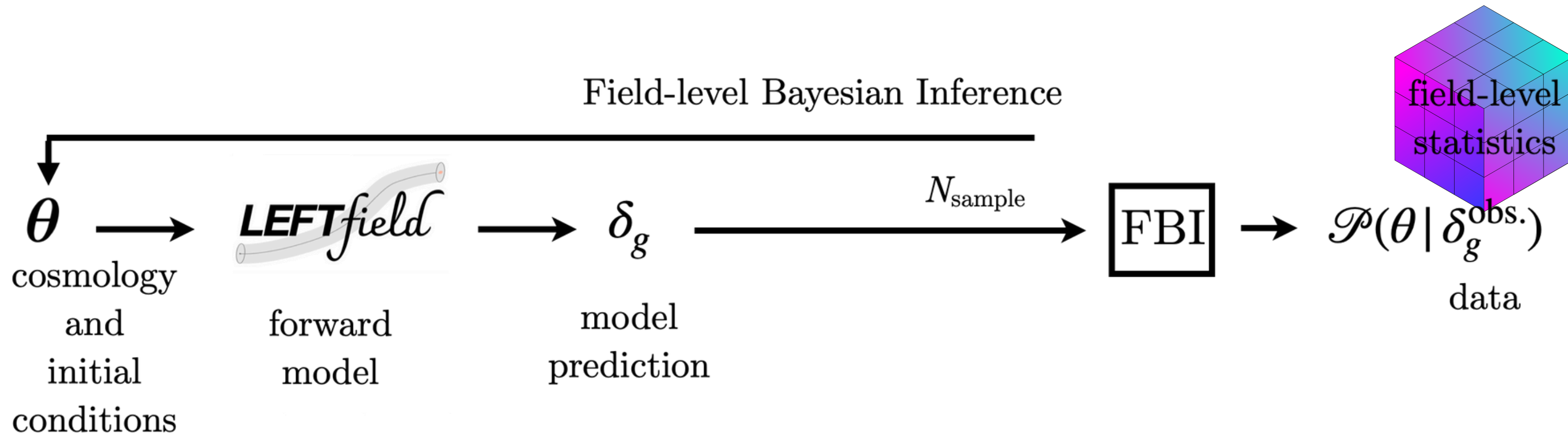
[arXiv:2403.03220](https://arxiv.org/abs/2403.03220)



Nhat-Minh Nguyen
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Fabian Schmidt
(MPA)

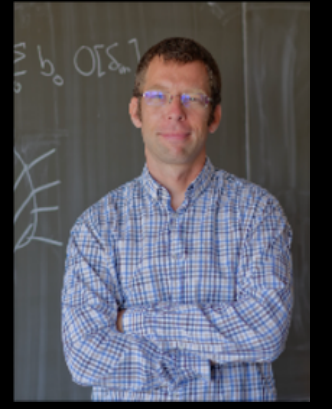


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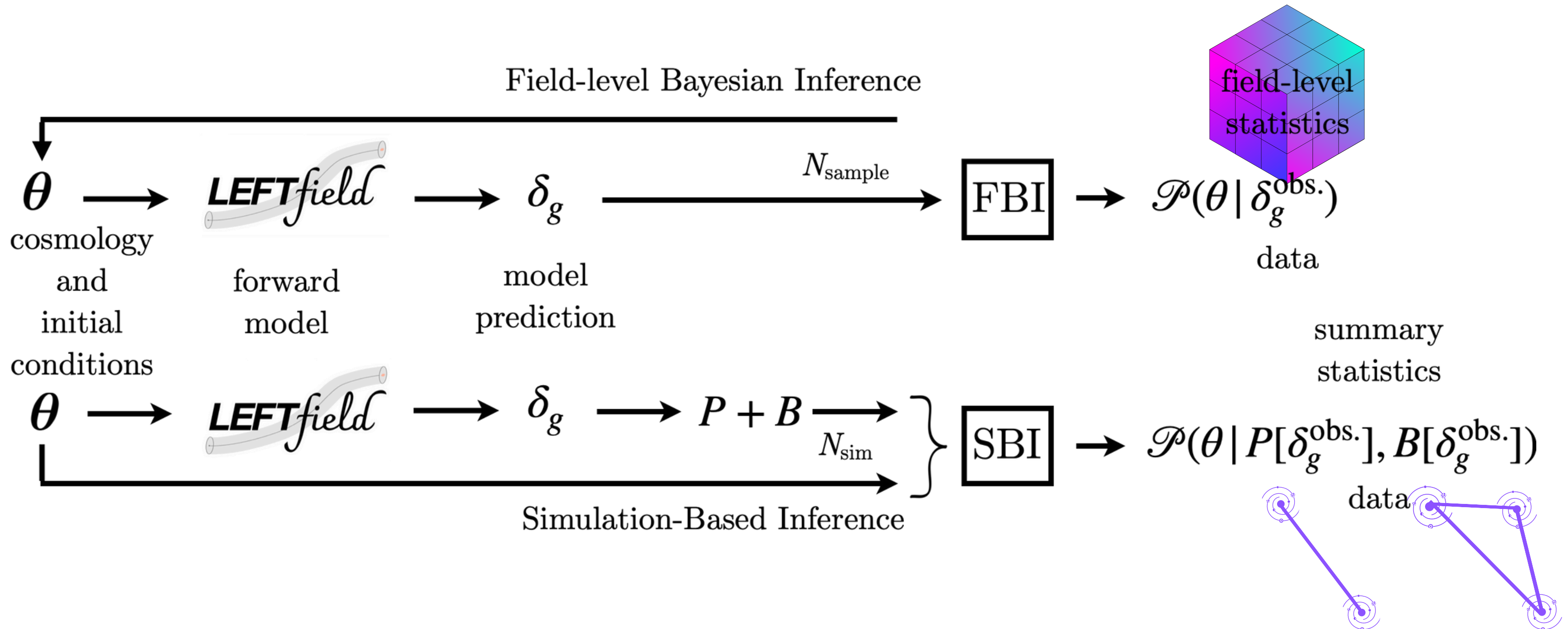
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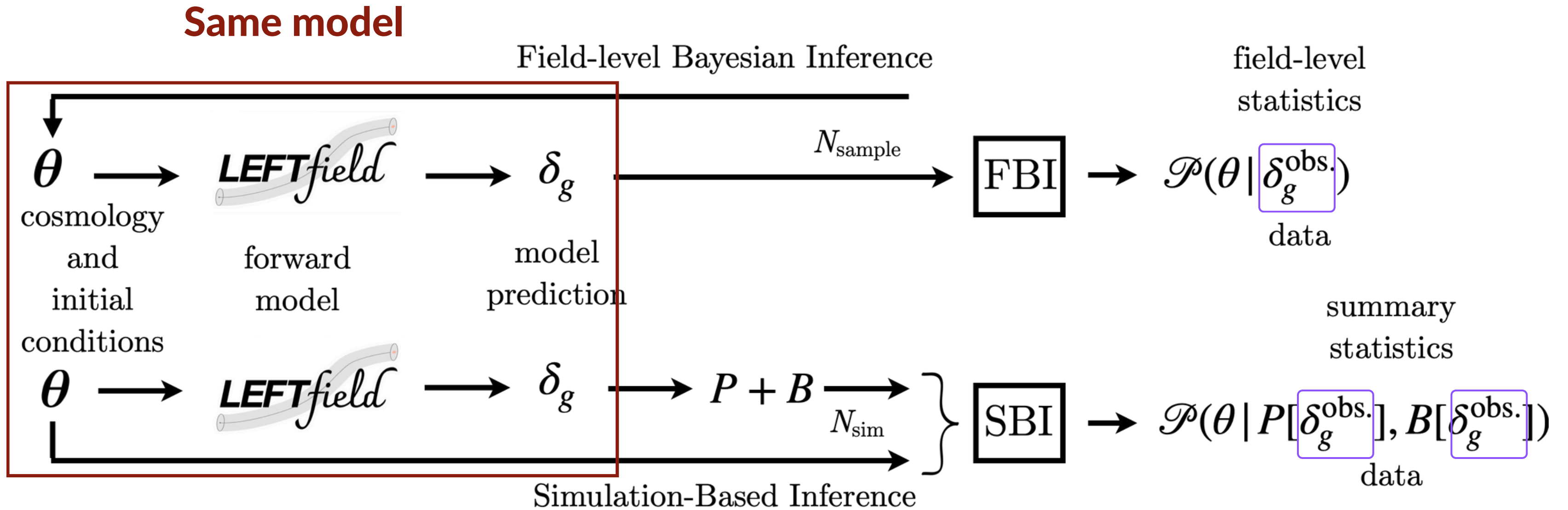
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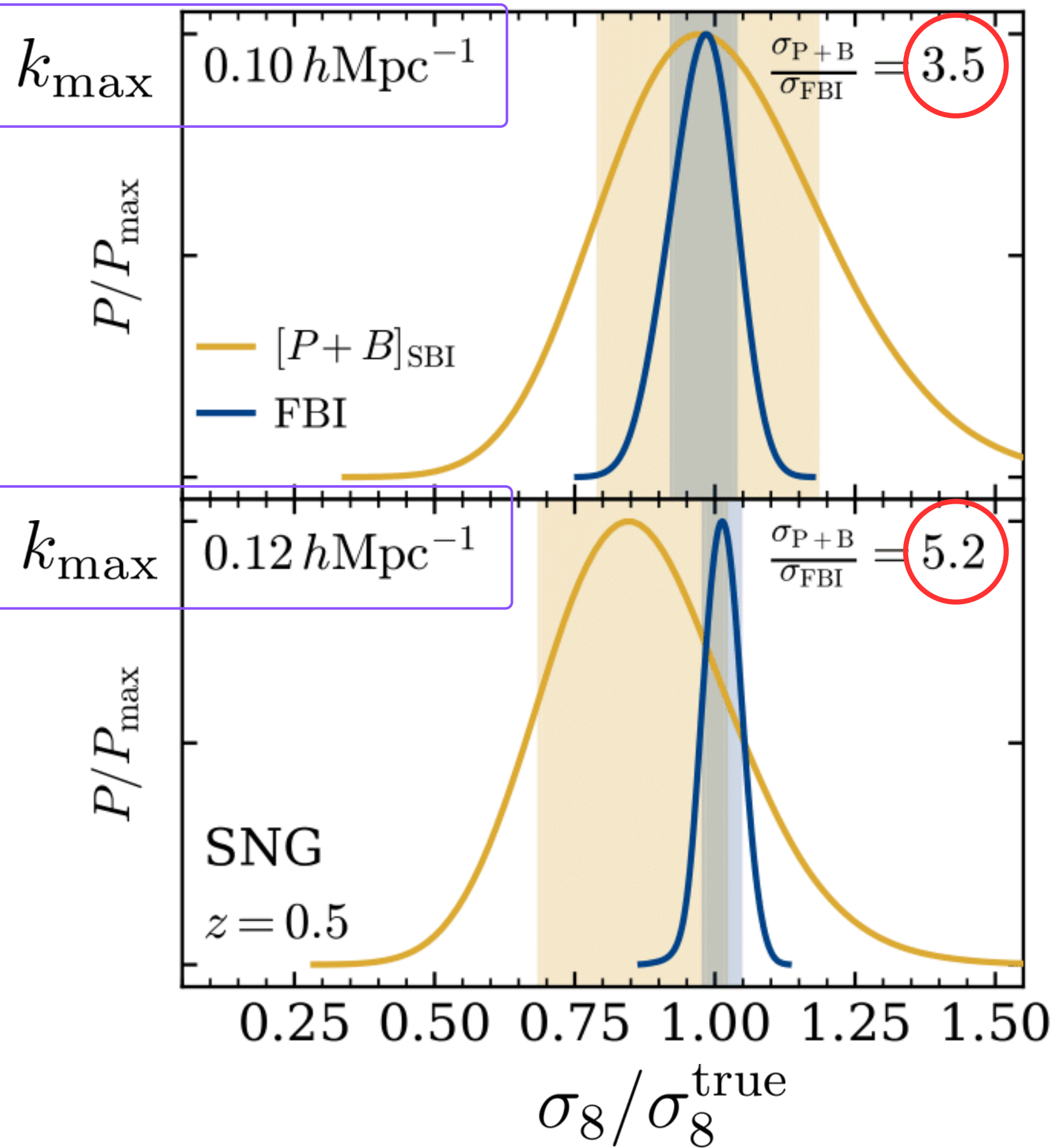


Apples-to-apples comparison

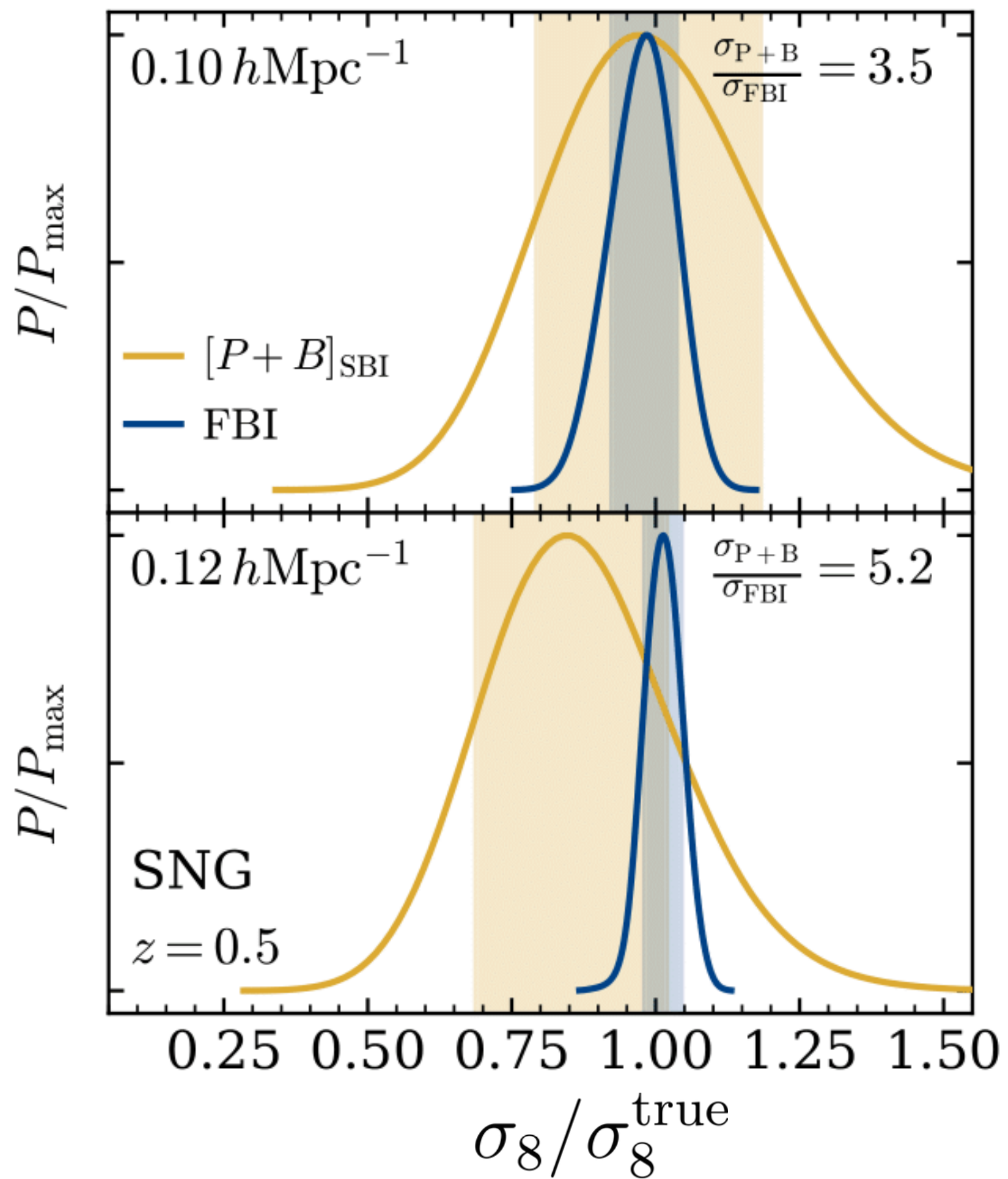


Same halos
Same scale cuts

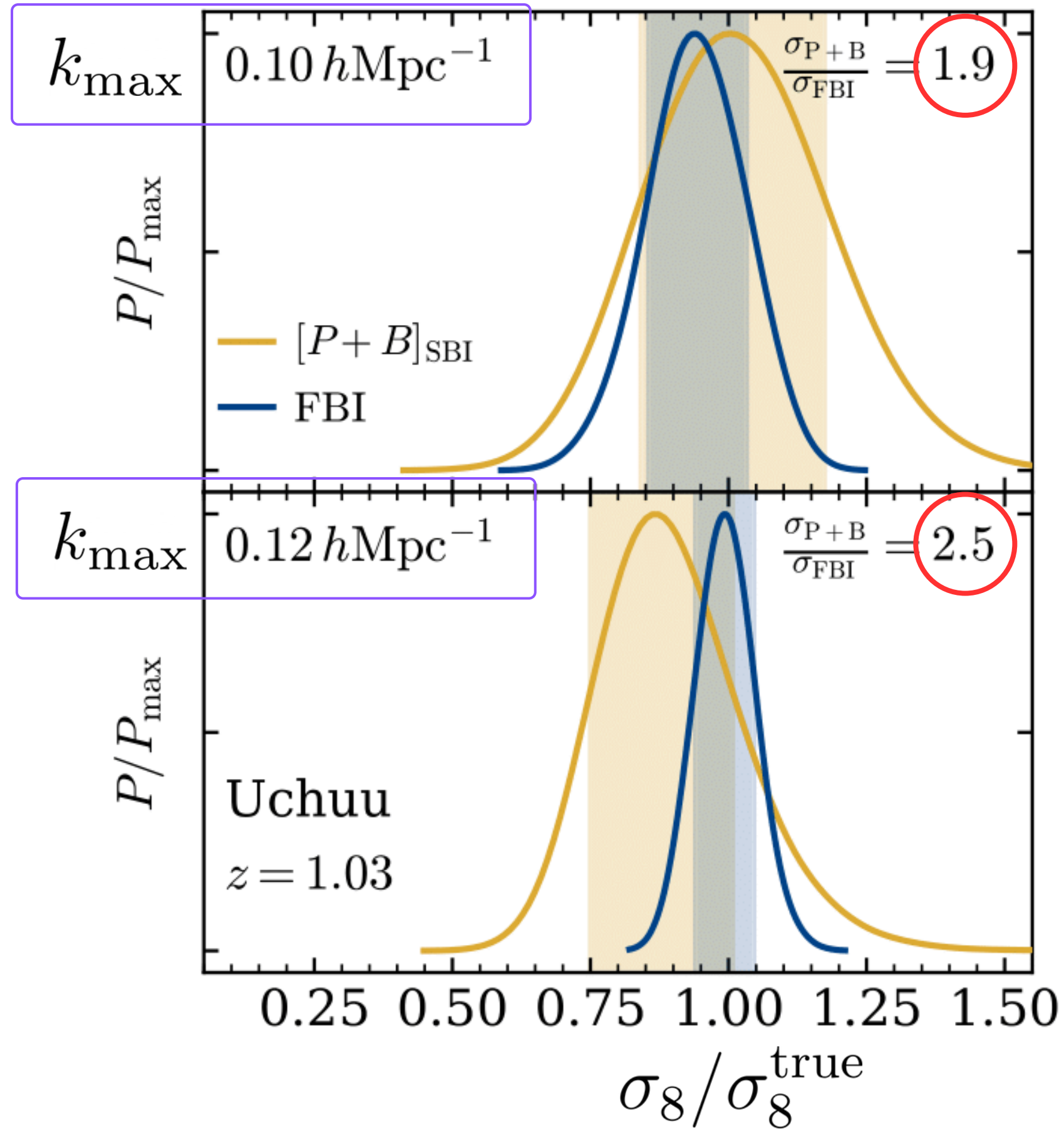
SNG



SNG



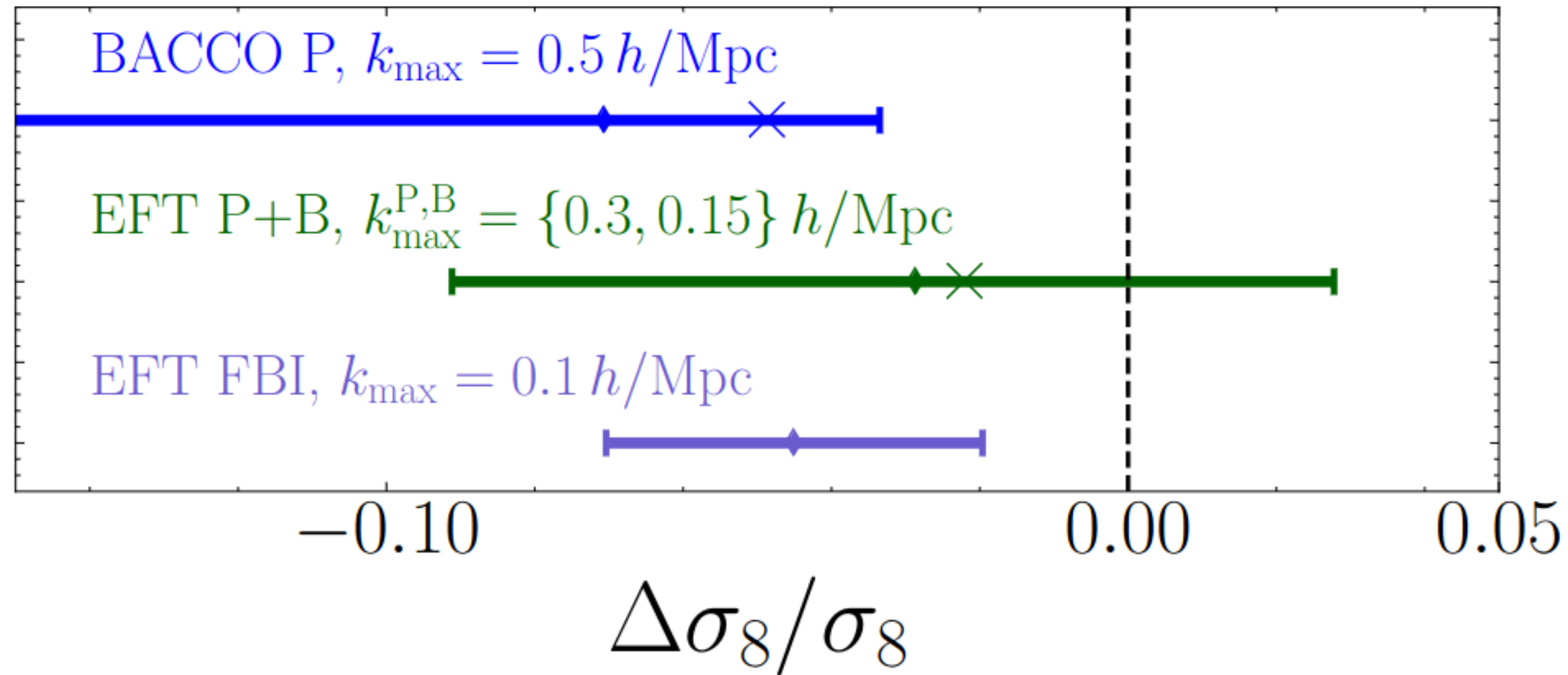
Uchuu



Beyond 2-point mock data challenge

Krause, ..., Nguyen, Schmidt+ (2024)
arXiv:2405.02252

real-space snapshots (mean of 10 realizations), fixed $\omega_m, \omega_b, n_s, h$



Conclusion & Next Steps

- **Field-level inference** is a very **challenging** task, but very **promising!**
- We demonstrated to have **unbiased** and **accurate** results from halo catalogs.
- **Apple-to-apple comparison** of FBI and SBI P+B shows that there is a lot of **reliable** information beyond 2+3-point functions in the 3D maps of galaxies.
- See **Ivana Babić** talk on Friday on full **field-level BAO scale inference** with LEFTfield!

Next step to connect with observations

- Include more observational effects
- Expand the cosmological parameter space
- More efficient sampling
- Explore summaries in SBI

