

Sep 29, 2025 – Oct 03, 2025

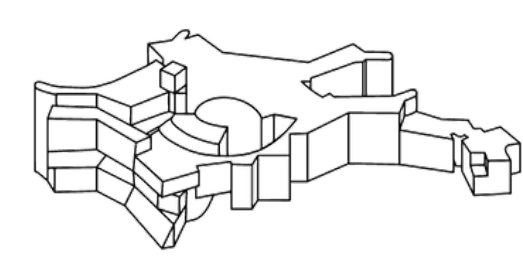
New Physics from Galaxy Clustering

GGI

Ivana Nikolac

Fabian Schmidt

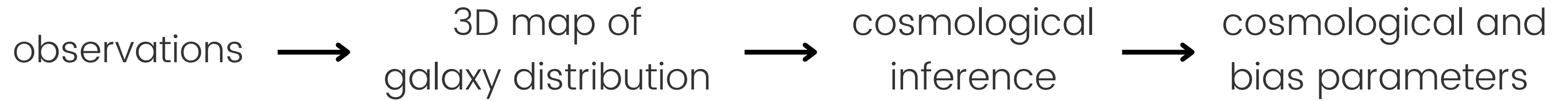
Beatriz Tucci



MAX PLANCK INSTITUTE
FOR ASTROPHYSICS

Connecting Field- level and Summary Statistics from Galaxy Clustering

Seeing the Universe Voxel by Voxel: The Field-Level Approach



**“STANDARD”
COSMOLOGICAL
INFERENCE**

Seeing the Universe Voxel by Voxel: The Field-Level Approach

observations → 3D map of galaxy distribution → cosmological inference → cosmological and bias parameters

**“STANDARD”
COSMOLOGICAL
INFERENCE**



**SUMMARY
STATISTICS**

2- and 3- point
correlation functions

Seeing the Universe Voxel by Voxel: The Field-Level Approach

“STANDARD”
COSMOLOGICAL
INFERENCE



SUMMARY
STATISTICS

2- and 3- point
correlation functions



FIELD
LEVEL

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

Seeing the Universe Voxel by Voxel: The Field-Level Approach

How much reliable
cosmological information
can be extracted?

“STANDARD”
COSMOLOGICAL
INFERENCE



SUMMARY
STATISTICS

2- and 3- point
correlation functions



FIELD
LEVEL

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

HOW MUCH INFORMATION CAN BE EXTRACTED FROM GALAXY CLUSTERING AT THE FIELD LEVEL?

Nguyen, Schmidt, Tucci et al. (2024)



Nhat-Minh Nguyen
IPMU, University of Tokyo

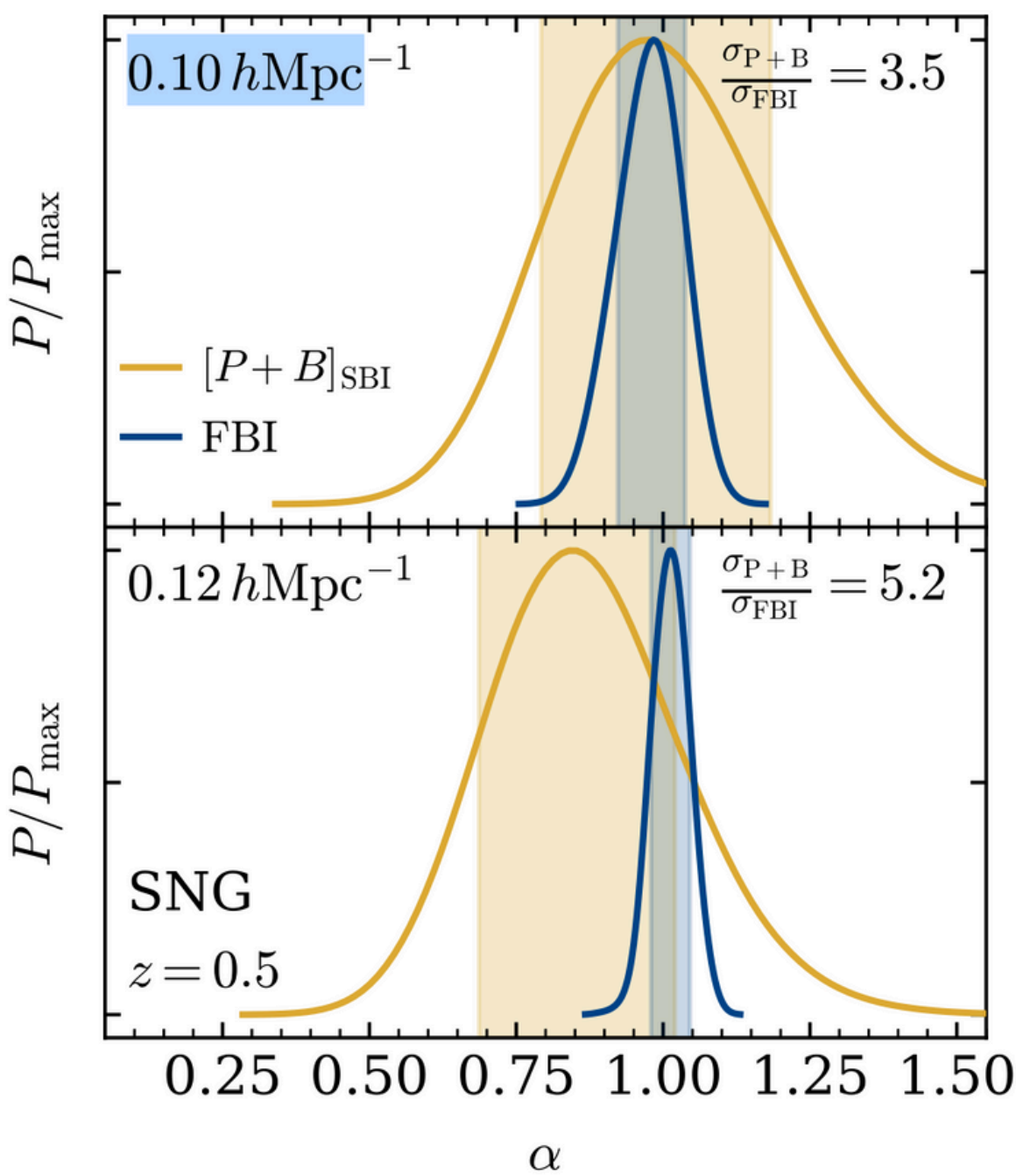
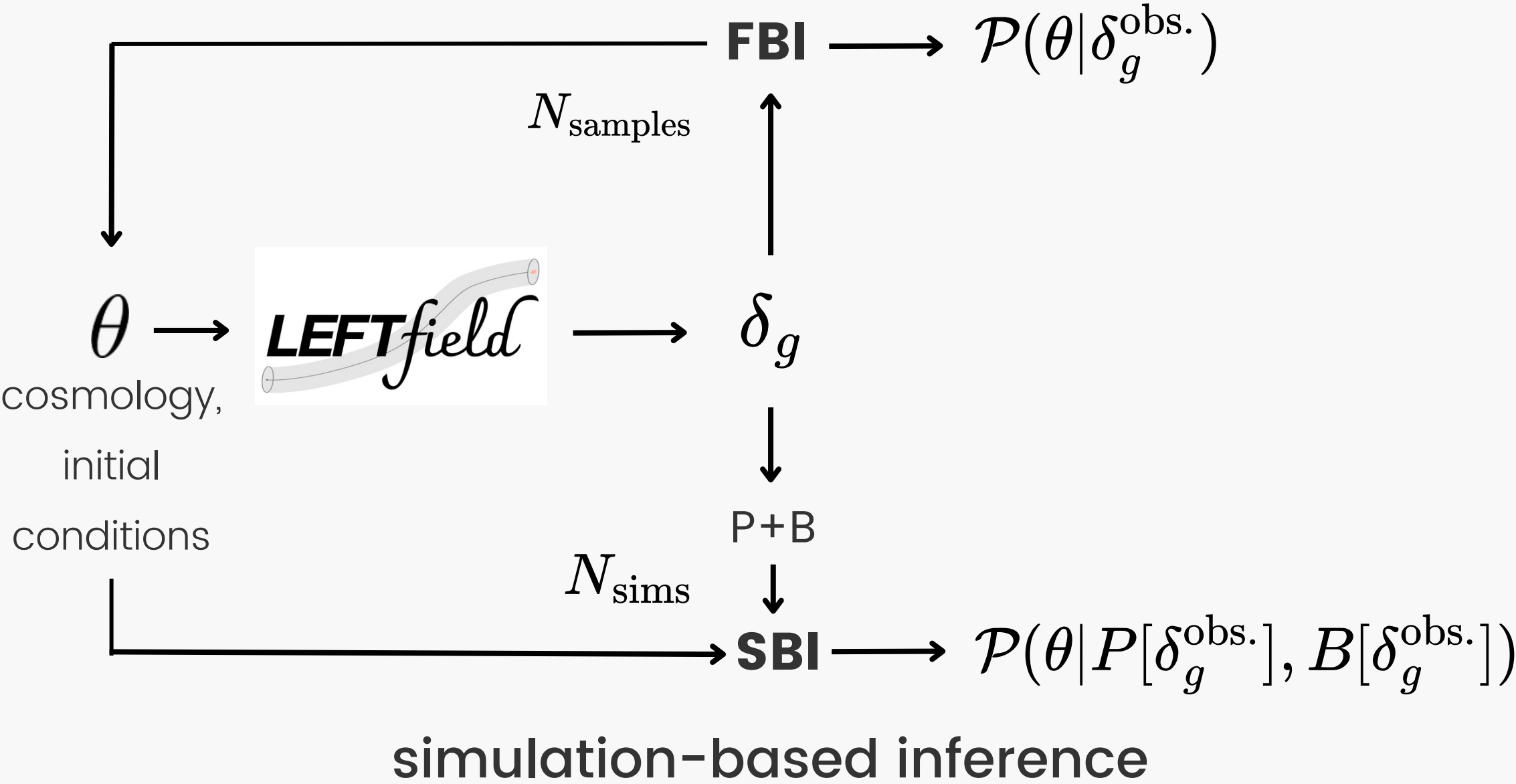


Fabian Schmidt
MPA



Beatriz Tucci
MPA-Stanford

field-level Bayesian inference



A TOY SCENARIO

as discussed in [Cabass et al.\(2023\)](#)
and [Schmidt \(2025\)](#).

$$\delta_{g,\text{det}}(\boldsymbol{x}) = b_{\delta}\delta^{(1)}(\boldsymbol{x}) + b_{\delta^2}[\delta^{(1)}(\boldsymbol{x}) - \langle\delta^{(1)}\rangle]^2 + \varepsilon(\boldsymbol{x})$$

A TOY SCENARIO

$$\delta_{g,\text{det}}(\boldsymbol{x}) = b_{\delta}\delta^{(1)}(\boldsymbol{x}) + b_{\delta^2}[\delta^{(1)}(\boldsymbol{x}) - \langle\delta^{(1)}\rangle]^2 + \varepsilon(\boldsymbol{x})$$

A TOY SCENARIO

$$\delta_{g,\text{det}}(\boldsymbol{x}) = b_{\delta}\delta^{(1)}(\boldsymbol{x}) + b_{\delta^2}[\delta^{(1)}(\boldsymbol{x}) - \langle\delta^{(1)}\rangle]^2 + \varepsilon(\boldsymbol{x})$$

assumptions: $k_{\text{max}} = \Lambda$

$$P_{\varepsilon} \rightarrow 0$$

A TOY SCENARIO

$$\delta_{g,\text{det}}(\boldsymbol{x}) = b_\delta \delta^{(1)}(\boldsymbol{x}) + b_{\delta^2} [\delta^{(1)}(\boldsymbol{x}) - \langle \delta^{(1)} \rangle]^2 + \varepsilon(\boldsymbol{x})$$

assumptions: $k_{\text{max}} = \Lambda$

$$P_\varepsilon \rightarrow 0$$

MAP expression for b_{δ^2} : $b_{\delta^2} = \frac{N[\delta_g]}{D[\delta_g]}$ with
(at field level)

$$N[\delta_g] = \frac{1}{b_\delta^2} \int_{\boldsymbol{k}}^{\Lambda} \frac{1}{P_L(k)} (\delta_g^2)(-\boldsymbol{k}) \delta_g(\boldsymbol{k}) - 2 \int_{\boldsymbol{x}} \delta_g(\boldsymbol{x})$$

$$D[\delta_g] = \frac{1}{b_\delta^4} \int_{\boldsymbol{k}}^{\Lambda} \frac{1}{P_L(k)} (\delta_g^2)(-\boldsymbol{k}) (\delta_g^2)(\boldsymbol{k}) - \frac{8}{b_\delta^2} \int_{\boldsymbol{x}} \delta_g^2(\boldsymbol{x})$$

A TOY SCENARIO

$$\delta_{g,\text{det}}(\boldsymbol{x}) = b_\delta \delta^{(1)}(\boldsymbol{x}) + b_{\delta^2} [\delta^{(1)}(\boldsymbol{x}) - \langle \delta^{(1)} \rangle]^2 + \varepsilon(\boldsymbol{x})$$

assumptions: $k_{\text{max}} = \Lambda$

$$P_\varepsilon \rightarrow 0$$

MAP expression for b_{δ^2} : $b_{\delta^2} = \frac{N[\delta_g]}{D[\delta_g]}$ with
(at field level)

$$N[\delta_g] = \frac{1}{b_\delta^2} \int_k^\Lambda \frac{1}{P_L(k)} (\delta_g^2)(-\boldsymbol{k}) \delta_g(\boldsymbol{k}) - 2 \int_x \delta_g(\boldsymbol{x})$$

$$D[\delta_g] = \frac{1}{b_\delta^4} \int_k^\Lambda \frac{1}{P_L(k)} (\delta_g^2)(-\boldsymbol{k}) (\delta_g^2)(\boldsymbol{k}) - \frac{8}{b_\delta^2} \int_x \delta_g^2(\boldsymbol{x})$$

OPERATOR CORRELATORS (OC)

MAP expression for b_{δ^2} : $b_{\delta^2} = \frac{N[\delta_g]}{D[\delta_g]}$ with

$$N[\delta_g] = \frac{1}{b_\delta^2} \int_{\mathbf{k}}^\Lambda \frac{1}{P_L(k)} (\delta_g^2)(-\mathbf{k}) \delta_g(\mathbf{k}) - 2 \int_{\mathbf{x}} \delta_g(\mathbf{x})$$

$$D[\delta_g] = \frac{1}{b_\delta^4} \int_{\mathbf{k}}^\Lambda \frac{1}{P_L(k)} (\delta_g^2)(-\mathbf{k}) (\delta_g^2)(\mathbf{k}) - \frac{8}{b_\delta^2} \int_{\mathbf{x}} \delta_g^2(\mathbf{x})$$

new summaries: $\{\langle O^{(n)}[\delta_g] | O^{(m)}[\delta_g] \rangle\}$

OPERATOR CORRELATORS (OC)

MAP expression for b_{δ^2} : $b_{\delta^2} = \frac{N[\delta_g]}{D[\delta_g]}$ with

$$N[\delta_g] = \frac{1}{b_\delta^2} \int_{\mathbf{k}}^\Lambda \frac{1}{P_L(k)} (\delta_g^2)(-\mathbf{k}) \delta_g(\mathbf{k}) - 2 \int_{\mathbf{x}} \delta_g(\mathbf{x})$$

$$D[\delta_g] = \frac{1}{b_\delta^4} \int_{\mathbf{k}}^\Lambda \frac{1}{P_L(k)} (\delta_g^2)(-\mathbf{k}) (\delta_g^2)(\mathbf{k}) - \frac{8}{b_\delta^2} \int_{\mathbf{x}} \delta_g^2(\mathbf{x})$$

new summaries: $\{\langle O^{(n)}[\delta_g] | O^{(m)}[\delta_g] \rangle\}$

→ correlators of powers of δ_g :

OC 2nd, LO: $\{\langle \delta_g \delta_g \rangle, \langle \delta_g \delta_g^2 \rangle\}$

OC 2nd, full: $\{\langle \delta_g \delta_g \rangle, \langle \delta_g \delta_g^2 \rangle, \langle \delta_g^2 \delta_g^2 \rangle\}$

OPERATOR CORRELATORS (OC)

MAP expression for b_{δ^2} : $b_{\delta^2} = \frac{N[\delta_g]}{D[\delta_g]}$ with

$$N[\delta_g] = \frac{1}{b_\delta^2} \int_{\mathbf{k}}^\Lambda \frac{1}{P_L(k)} (\delta_g^2)(-\mathbf{k}) \delta_g(\mathbf{k}) - 2 \int_{\mathbf{x}} \delta_g(\mathbf{x})$$

$$D[\delta_g] = \frac{1}{b_\delta^4} \int_{\mathbf{k}}^\Lambda \frac{1}{P_L(k)} (\delta_g^2)(-\mathbf{k}) (\delta_g^2)(\mathbf{k}) - \frac{8}{b_\delta^2} \int_{\mathbf{x}} \delta_g^2(\mathbf{x})$$

new summaries: $\{\langle O^{(n)}[\delta_g] | O^{(m)}[\delta_g] \rangle\}$

→ correlators of powers of δ_g :

OC 2nd, LO: $\{\langle \delta_g \delta_g \rangle, \langle \delta_g \delta_g^2 \rangle\}$

OC 2nd, full: $\{\langle \delta_g \delta_g \rangle, \langle \delta_g \delta_g^2 \rangle, \langle \delta_g^2 \delta_g^2 \rangle\}$

P + tree-level bispectrum

add part of LO trispectrum

OPERATOR CORRELATORS (OC)

MAP expression for b_{δ^2} : $b_{\delta^2} = \frac{N[\delta_g]}{D[\delta_g]}$ with

$$N[\delta_g] = \frac{1}{b_\delta^2} \int_{\mathbf{k}}^{\Lambda} \frac{1}{P_L(k)} (\delta_g^2)(-\mathbf{k}) \delta_g(\mathbf{k}) - 2 \int_{\mathbf{x}} \delta_g(\mathbf{x})$$

$$D[\delta_g] = \frac{1}{b_\delta^4} \int_{\mathbf{k}}^{\Lambda} \frac{1}{P_L(k)} (\delta_g^2)(-\mathbf{k}) (\delta_g^2)(\mathbf{k}) - \frac{8}{b_\delta^2} \int_{\mathbf{x}} \delta_g^2(\mathbf{x})$$

new summaries: $\{\langle O^{(n)}[\delta_g] | O^{(m)}[\delta_g] \rangle\}$

→ correlators of powers of δ_g :

OC 2nd, LO: $\{\langle \delta_g \delta_g \rangle, \langle \delta_g \delta_g^2 \rangle\}$

OC 2nd, full: $\{\langle \delta_g \delta_g \rangle, \langle \delta_g \delta_g^2 \rangle, \langle \delta_g^2 \delta_g^2 \rangle\}$

OC 3rd, LO: $\{\langle \delta_g \delta_g \rangle, \langle \delta_g \delta_g^2 \rangle, \langle \delta_g^2 \delta_g^2 \rangle, \langle \delta_g \delta_g^3 \rangle\}$

OC 3rd, full: $\{\langle \delta_g \delta_g \rangle, \langle \delta_g \delta_g^2 \rangle, \langle \delta_g^2 \delta_g^2 \rangle, \langle \delta_g \delta_g^3 \rangle, \langle \delta_g^2 \delta_g^3 \rangle, \langle \delta_g^3 \delta_g^3 \rangle\}$

P + tree-level bispectrum

add part of LO trispectrum

P + tree-level B + tree-level T

add part of 5- and 6-point functions

FIELD-LEVEL POSTERIOR

$$\mathcal{P}(\boldsymbol{\theta}, \delta_{\text{in}}, \{b_O\}, \{\sigma_\varepsilon\} | \delta_g^{\text{obs.}}) \quad \longrightarrow \quad \mathcal{P}(\{b_O\}, \sigma_\varepsilon | \delta_g^{\text{obs.}})$$

FIELD-LEVEL POSTERIOR

$$\mathcal{P}(\boldsymbol{\theta}, \delta_{\text{in}}, \{b_O\}, \{\sigma_\varepsilon\} | \delta_g^{\text{obs.}}) \quad \longrightarrow \quad \mathcal{P}(\{b_O\}, \sigma_\varepsilon | \delta_g^{\text{obs.}})$$

EFT likelihood

$$\ln \mathcal{L}_{\text{EFT}}(\delta_g^{\text{obs.}} | \boldsymbol{\theta}, \delta_{\text{in}}, \{b_O\}, \{\sigma_\varepsilon\}) =$$

$$-\frac{1}{2} \sum_{|\mathbf{k}| < k_{\text{max}}} \left(\ln 2\pi \sigma_\varepsilon^2(k) + \frac{1}{\sigma_\varepsilon^2(k)} \left| \delta_g^{\text{obs.}}(\mathbf{k}) - \sum_O b_O O[\boldsymbol{\theta}, \delta_{\text{in}}](\mathbf{k}) \right|^2 \right)$$

FIELD-LEVEL POSTERIOR

$$\mathcal{P}(\boldsymbol{\theta}, \delta_{\text{in}}, \{b_O\}, \{\sigma_\varepsilon\} | \delta_g^{\text{obs.}}) \quad \longrightarrow \quad \mathcal{P}(\{b_O\}, \sigma_\varepsilon | \delta_g^{\text{obs.}})$$

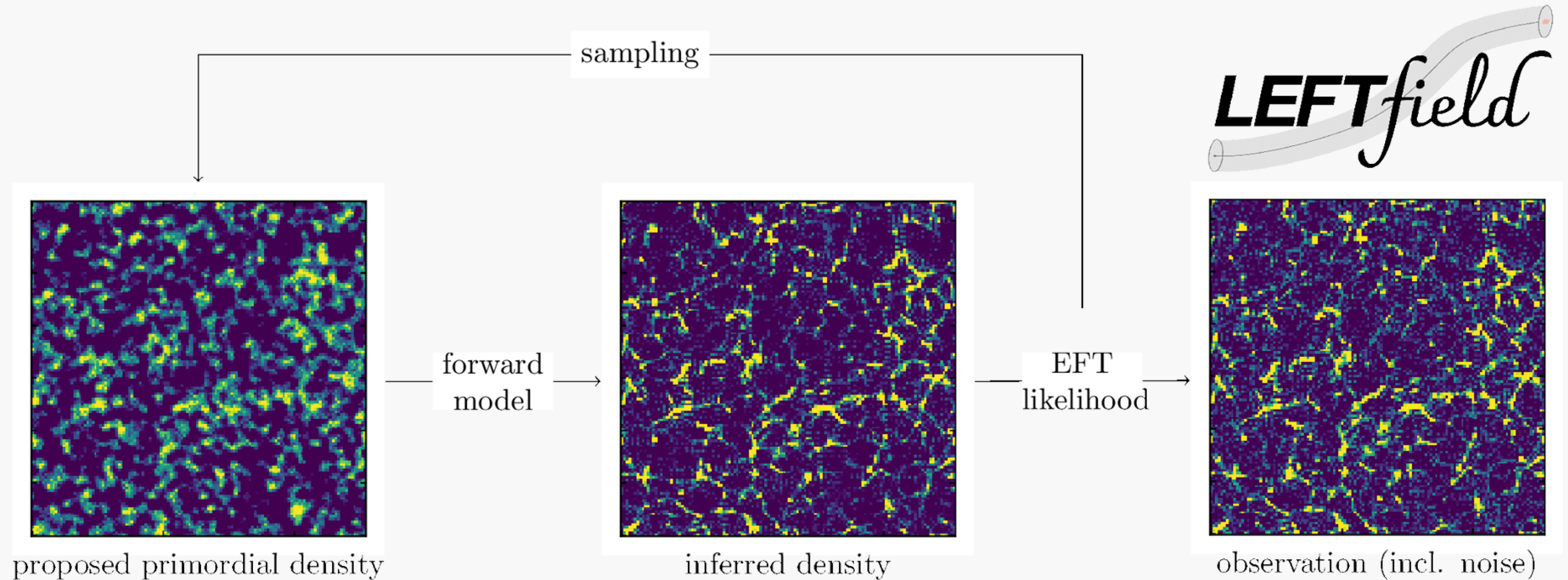
EFT likelihood

$$\ln \mathcal{L}_{\text{EFT}}(\delta_g^{\text{obs.}} | \boldsymbol{\theta}, \delta_{\text{in}}, \{b_O\}, \{\sigma_\varepsilon\}) =$$

$$-\frac{1}{2} \sum_{|\mathbf{k}| < k_{\text{max}}} \left(\ln 2\pi \sigma_\varepsilon^2(k) + \frac{1}{\sigma_\varepsilon^2(k)} \left| \underset{\text{data}}{\delta_g^{\text{obs.}}}(\mathbf{k}) - \sum_O \underset{\text{model}}{b_O O[\boldsymbol{\theta}, \delta_{\text{in}}]}(\mathbf{k}) \right|^2 \right)$$

FORWARD MODEL

FIELD-LEVEL BAYESIAN INFERENCE (FBI)



Schmidt (2021)

Credits: Julia Stadler

SIMULATION-BASED INFERENCE (SBI)

parameters
drawn from
prior

$\theta \rightarrow$



samples
 $\rightarrow \delta_g$

summary
statistics

\mathbf{X}

density
estimator

\mathbf{x}^{obs}

posterior

$\mathcal{P}(\theta, \{b_O\}, \{\sigma_\varepsilon\} | \mathbf{x}^{\text{obs}})$

OC convergence test

$$k_{\max} = 0.14h \text{ Mpc}^{-1}$$

$$L_{\text{box}} = 2000h^{-1} \text{ Mpc}$$

$$\Delta k \approx 2k_f$$

size of data vector:

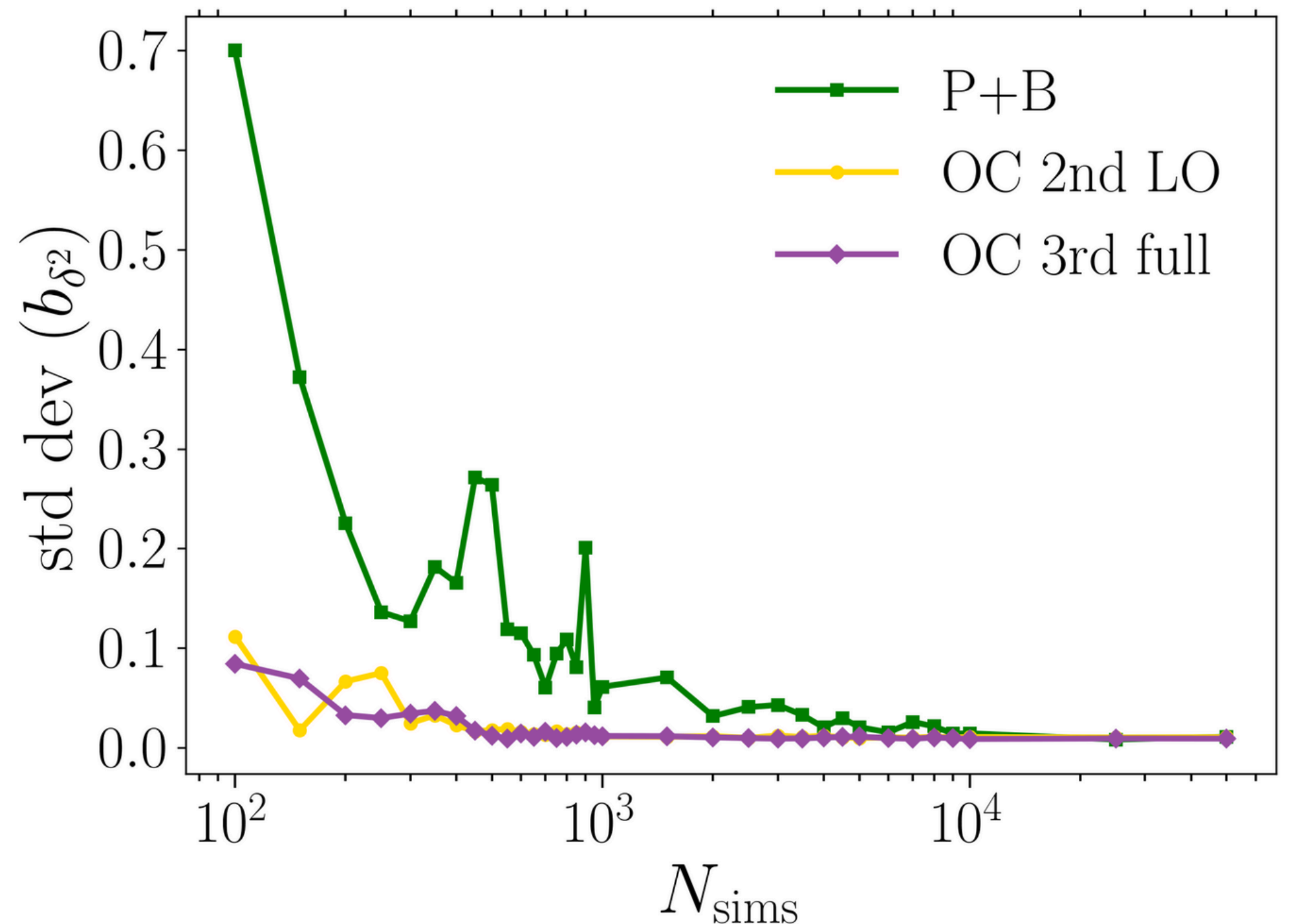
PB: 945 (PBT: ~ 15 000)

OC 2nd, LO: 40

OC 2nd, full: 60

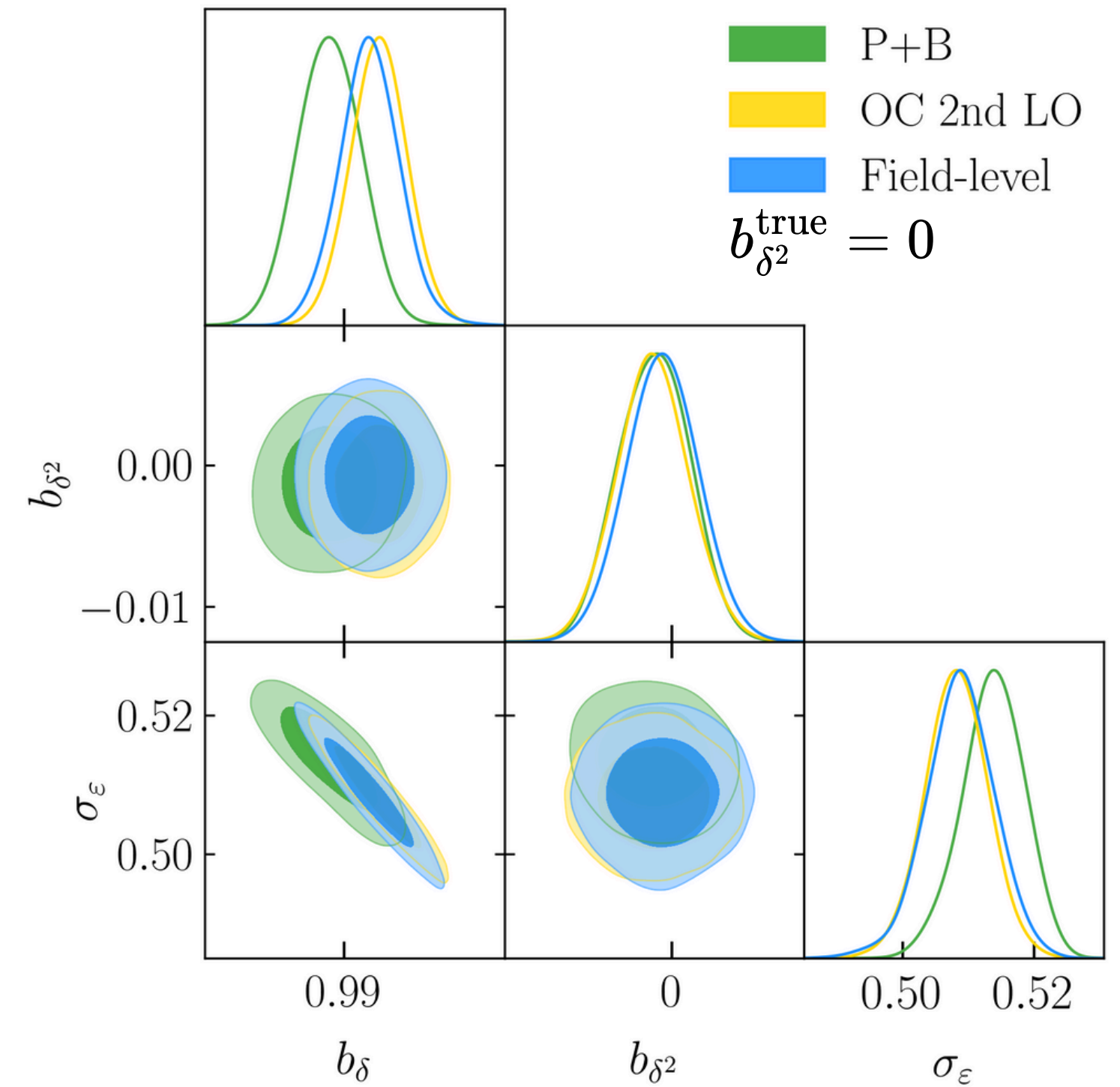
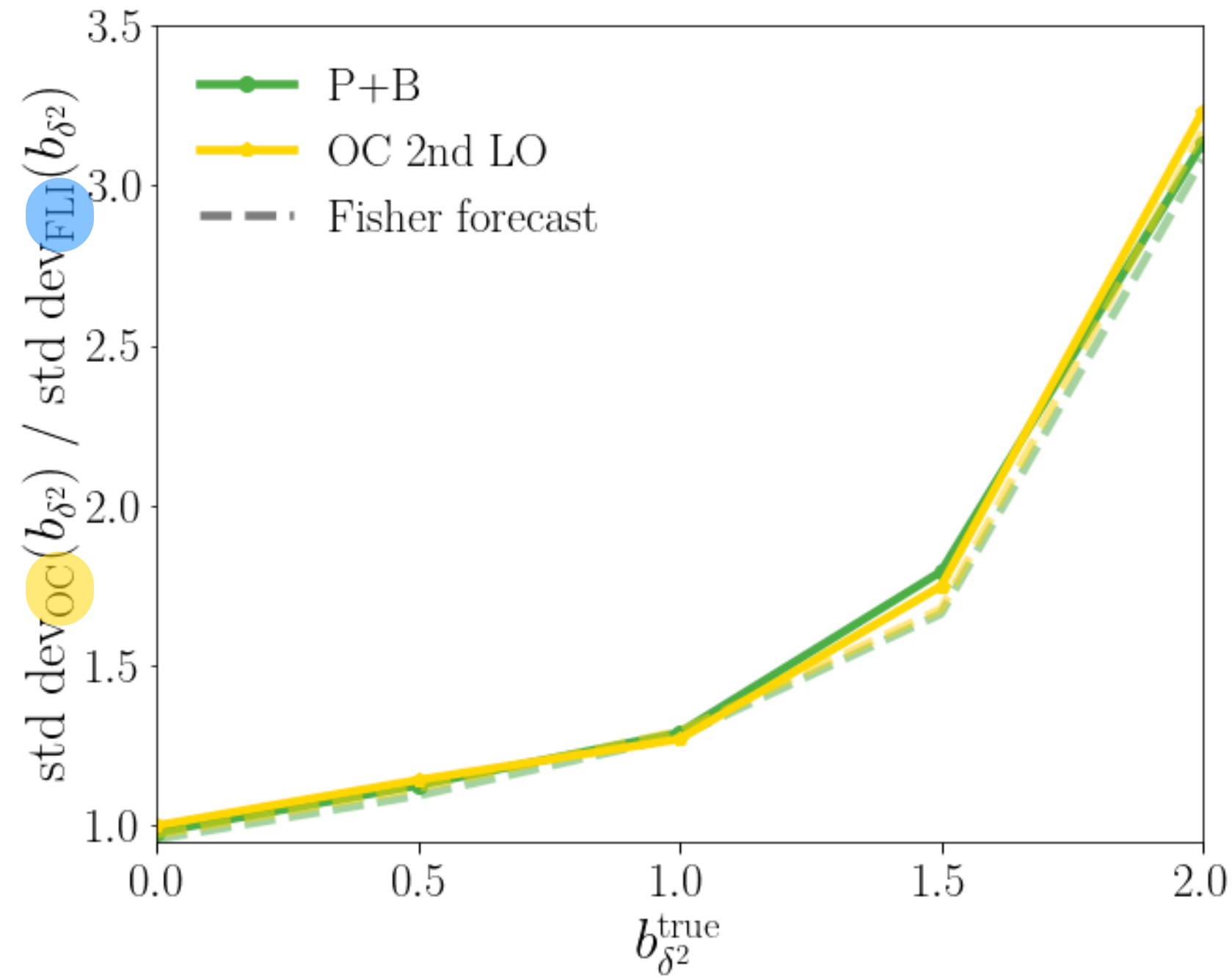
OC 3rd, LO: 80

OC 3rd, full: 120



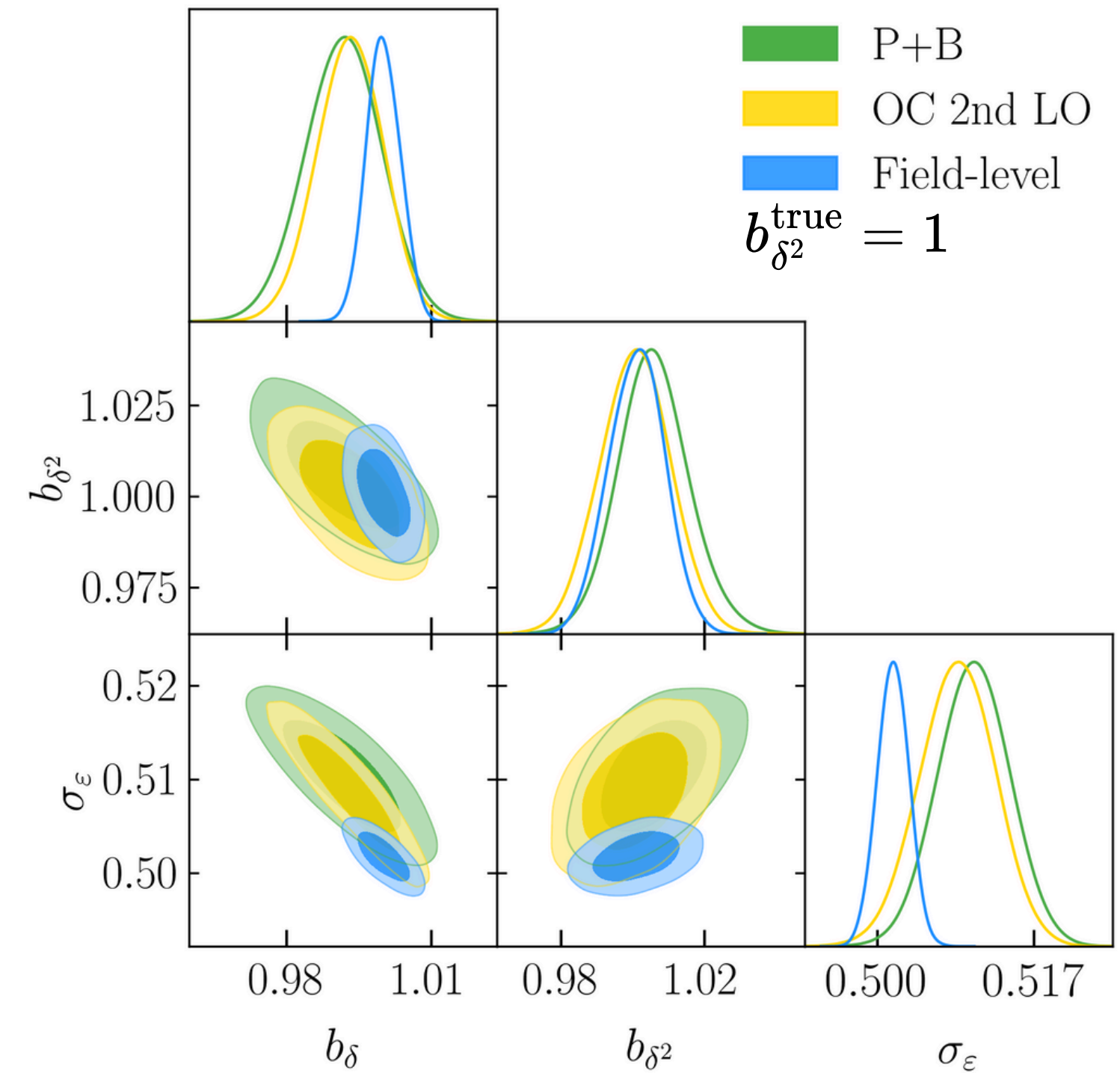
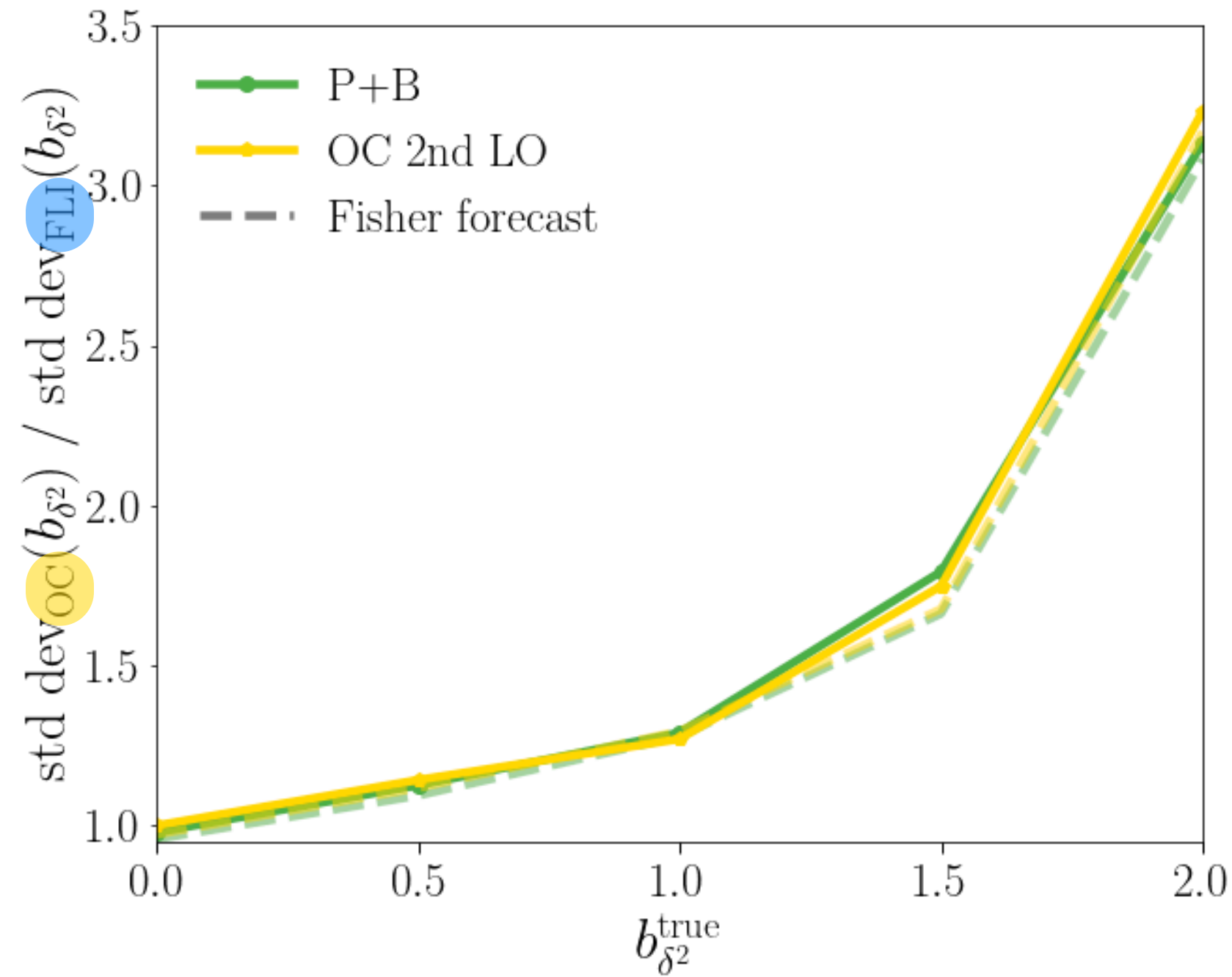
convergence below 10^3 sims

FBI to SBI comparison - OC2ndLO (vs P+B)



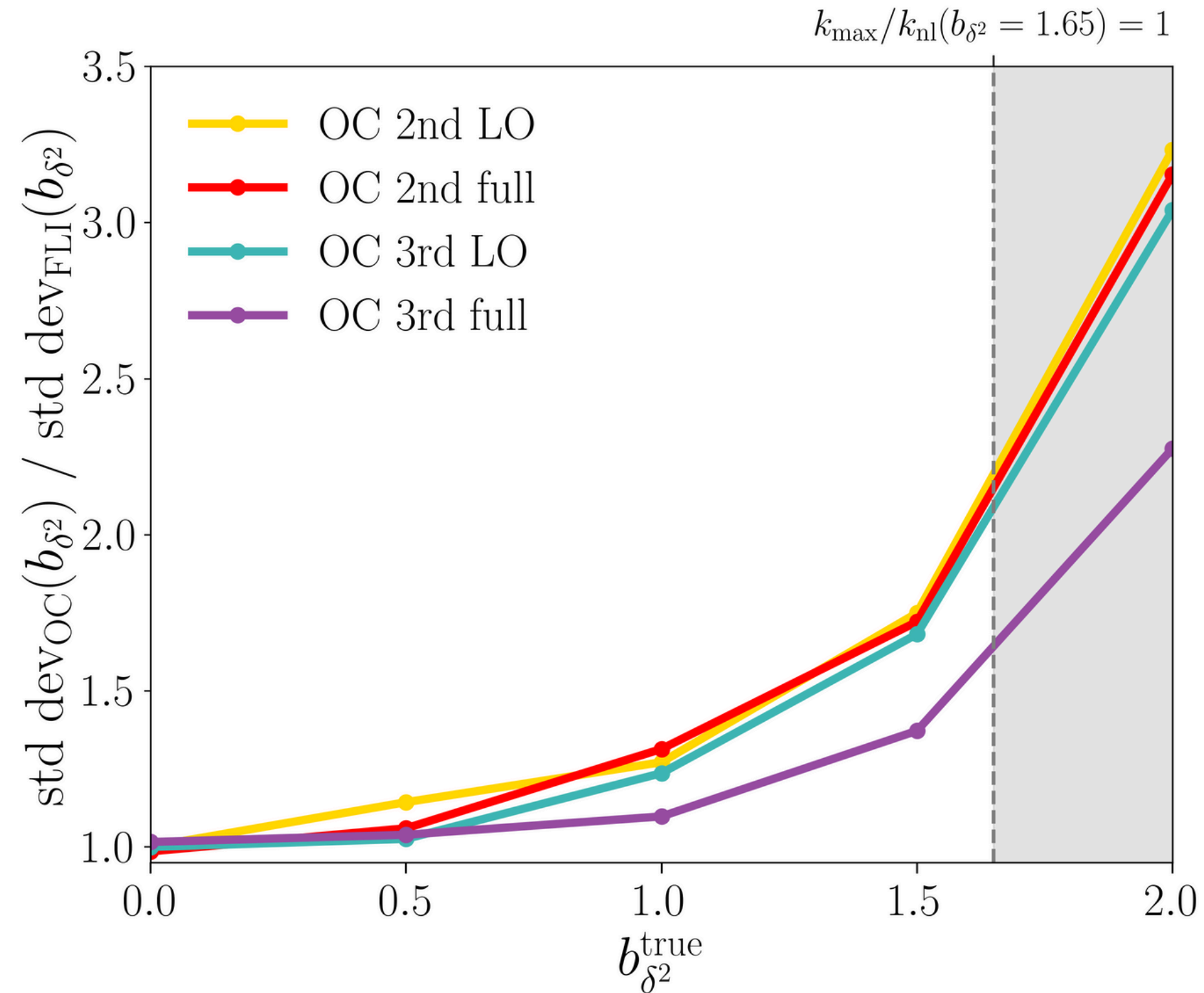
IN, Schmidt, Tucci, in prep.

FBI to SBI comparison - OC2ndLO (vs P+B)



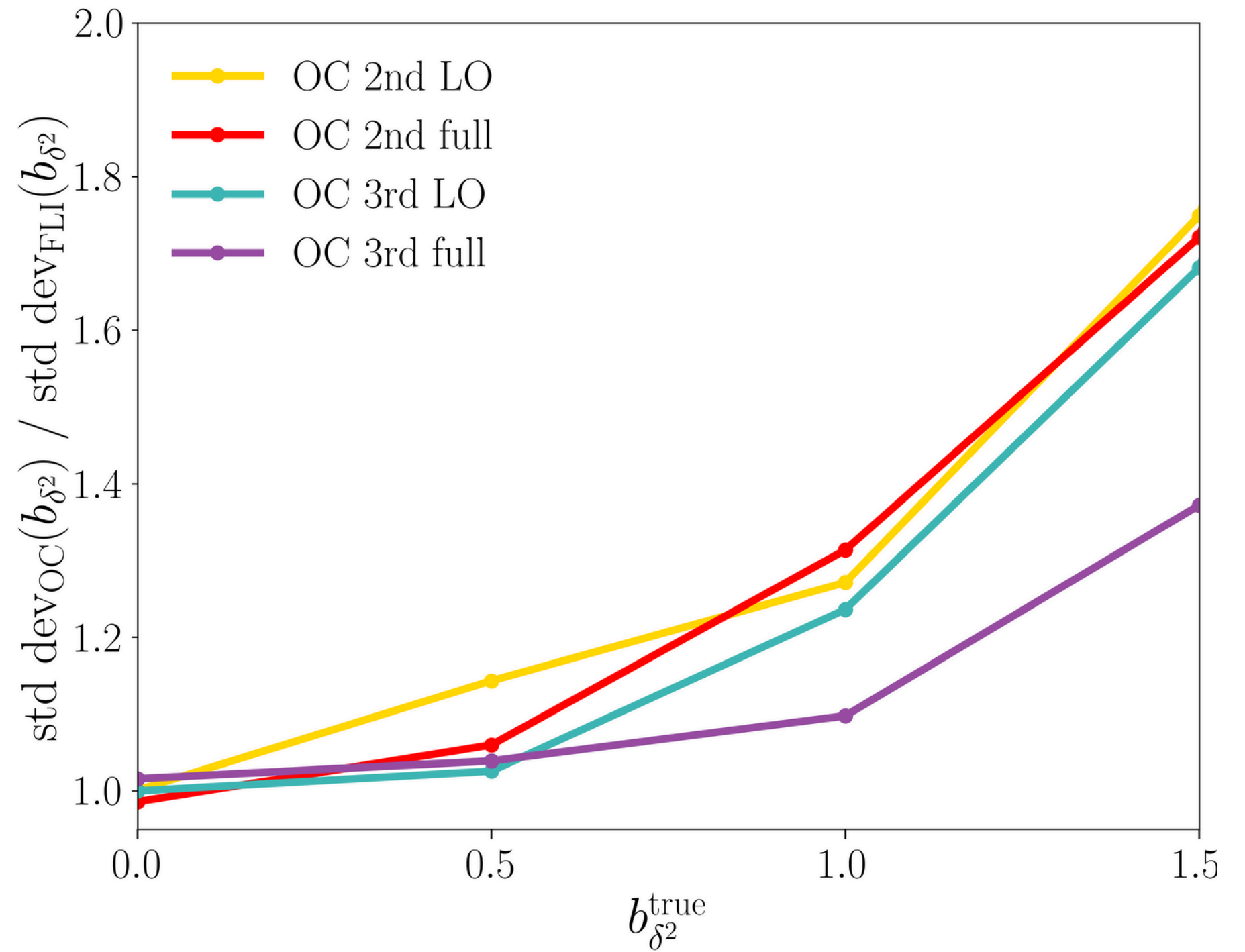
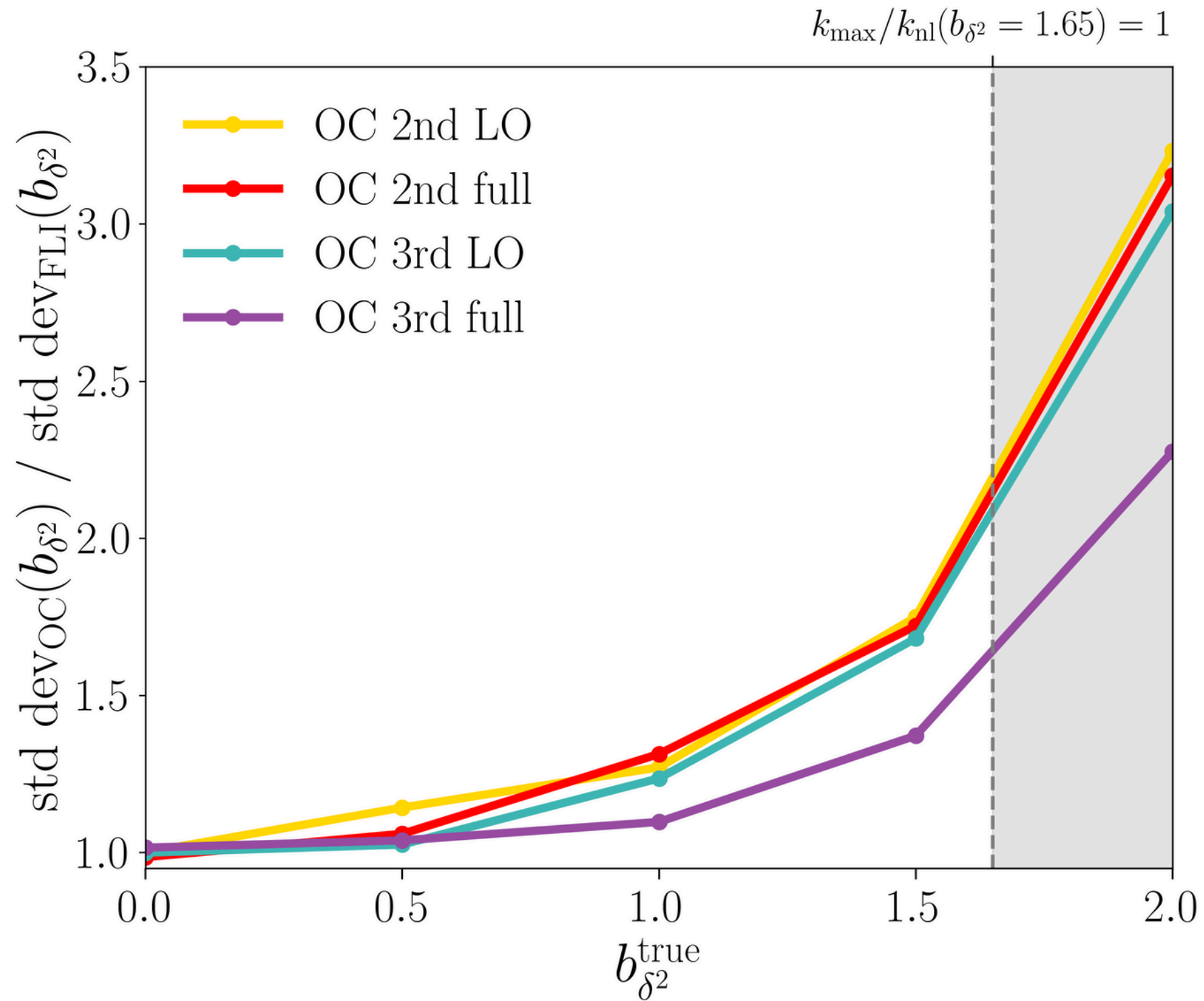
IN, Schmidt, Tucci, in prep.

FBI to SBI comparison – OC cases



IN, Schmidt, Tucci, in prep.

FBI to SBI comparison – OC cases



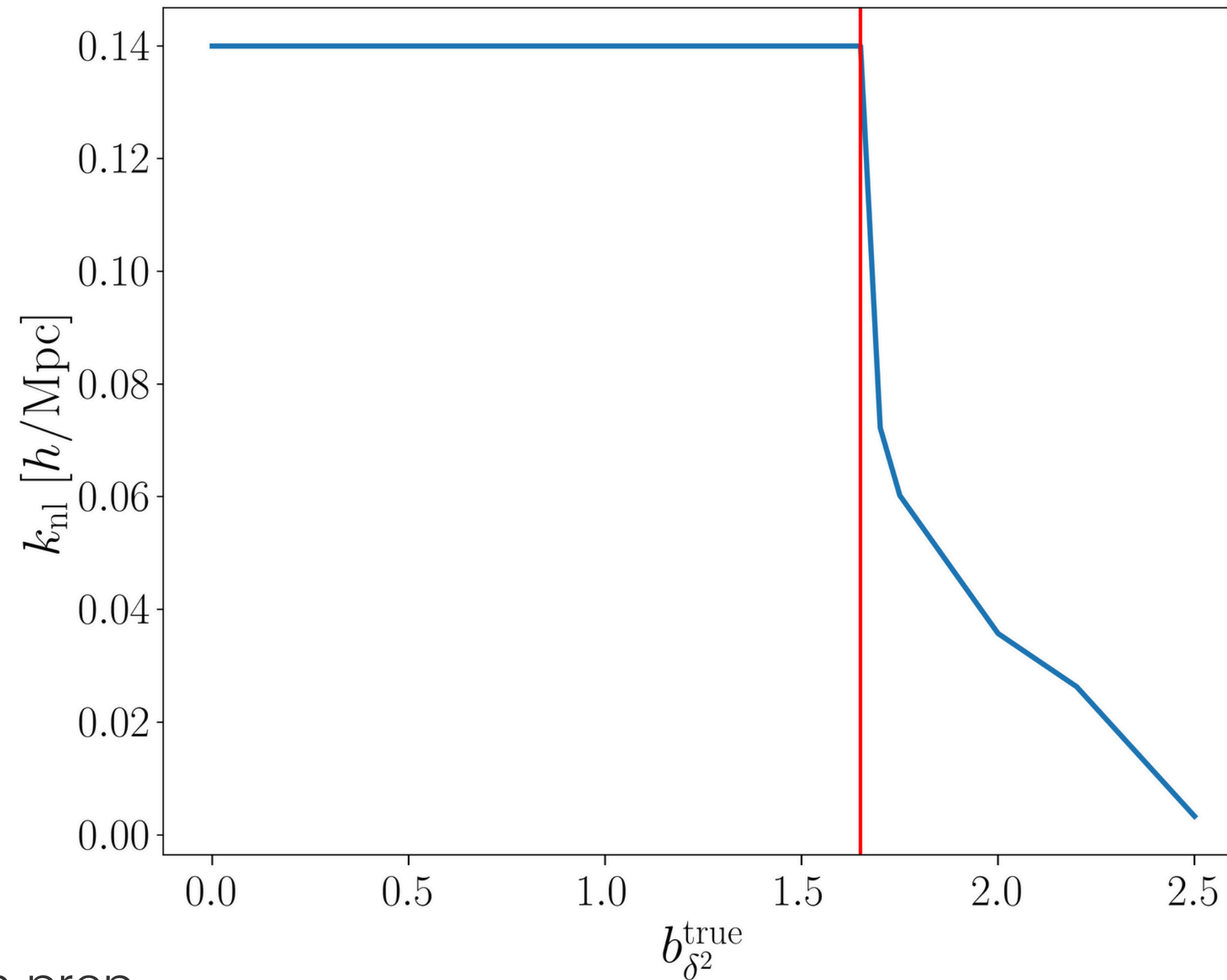
IN, Schmidt, Tucci, in prep.

KEY TAKEAWAYS

- Field-level inference with LEFTfield is a powerful tool for galaxy clustering analysis
- Apples-to-apples comparison of FBI and SBI summaries shows that there is a lot of reliable information beyond 2+3-point functions
- Operator correlators (OC) offer an efficient way of including higher order n -point functions in our analysis
- Going higher order in OCs extracts more information in the perturbative regime

DETERMINING k_{nl}

(backup slides)

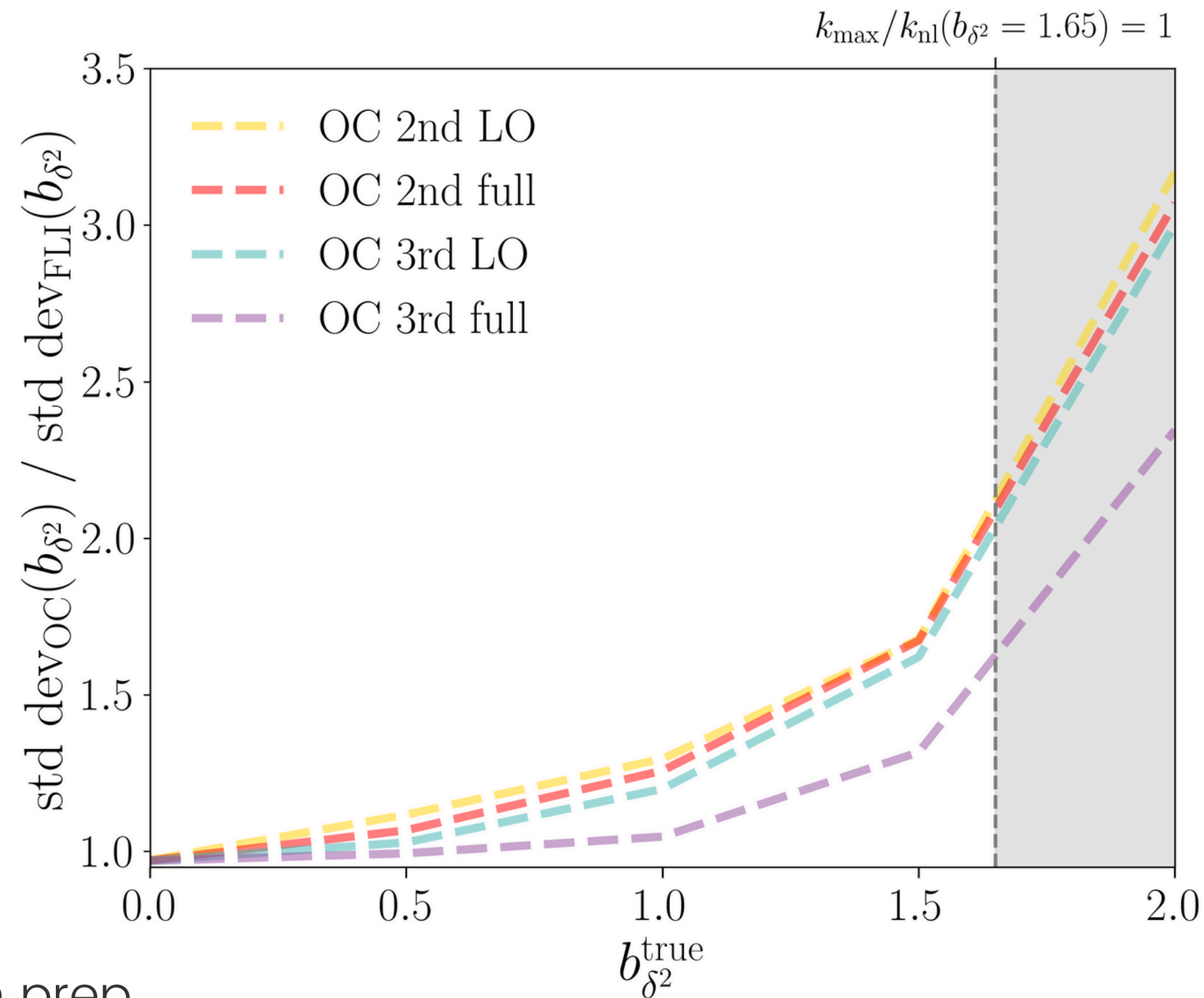


$$\max_{k \leq k_{\text{nl}}} \frac{P_{\text{1-loop}}(k)}{P_{\text{tree}}(k)} = 1$$

IN, Schmidt, Tucci, in prep.

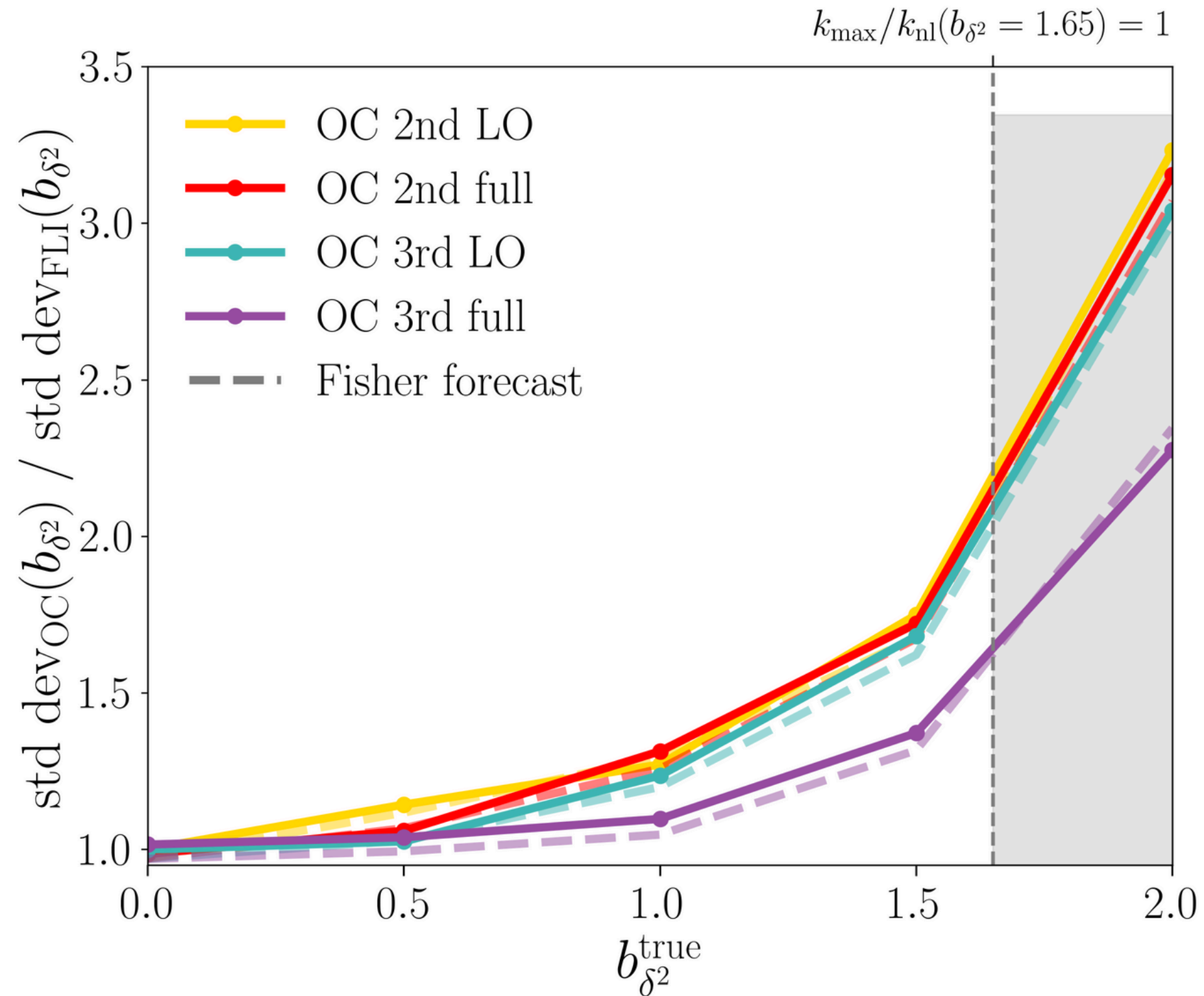
FBI to SBI comparison – OC Fisher forecast

(backup slides)



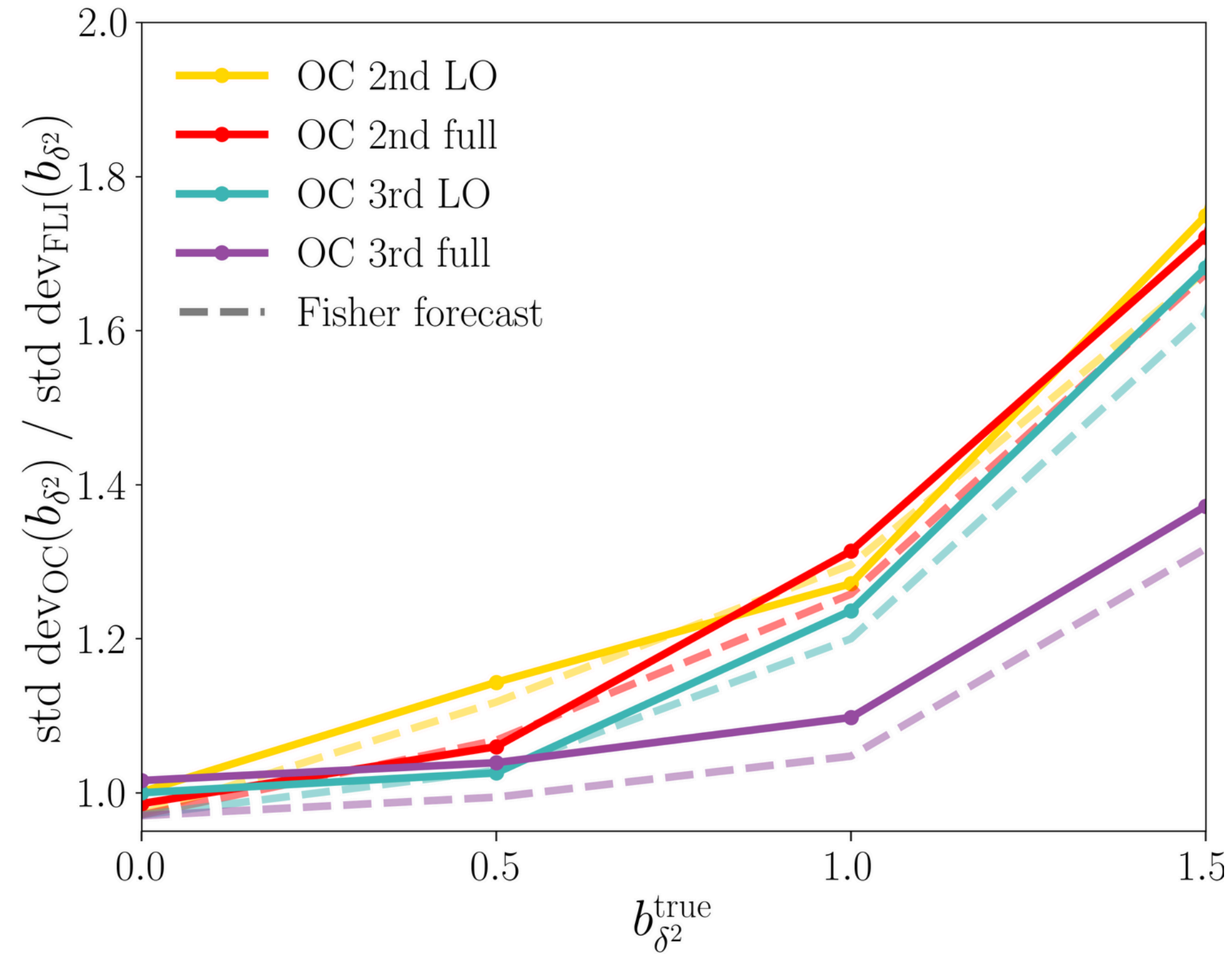
IN, Schmidt, Tucci, in prep.

FBI to SBI comparison – OC cases with Fisher (backup slides)



IN, Schmidt, Tucci, in prep.

FBI to SBI comparison – OC cases with Fisher (backup slides)



IN, Schmidt, Tucci, in prep.