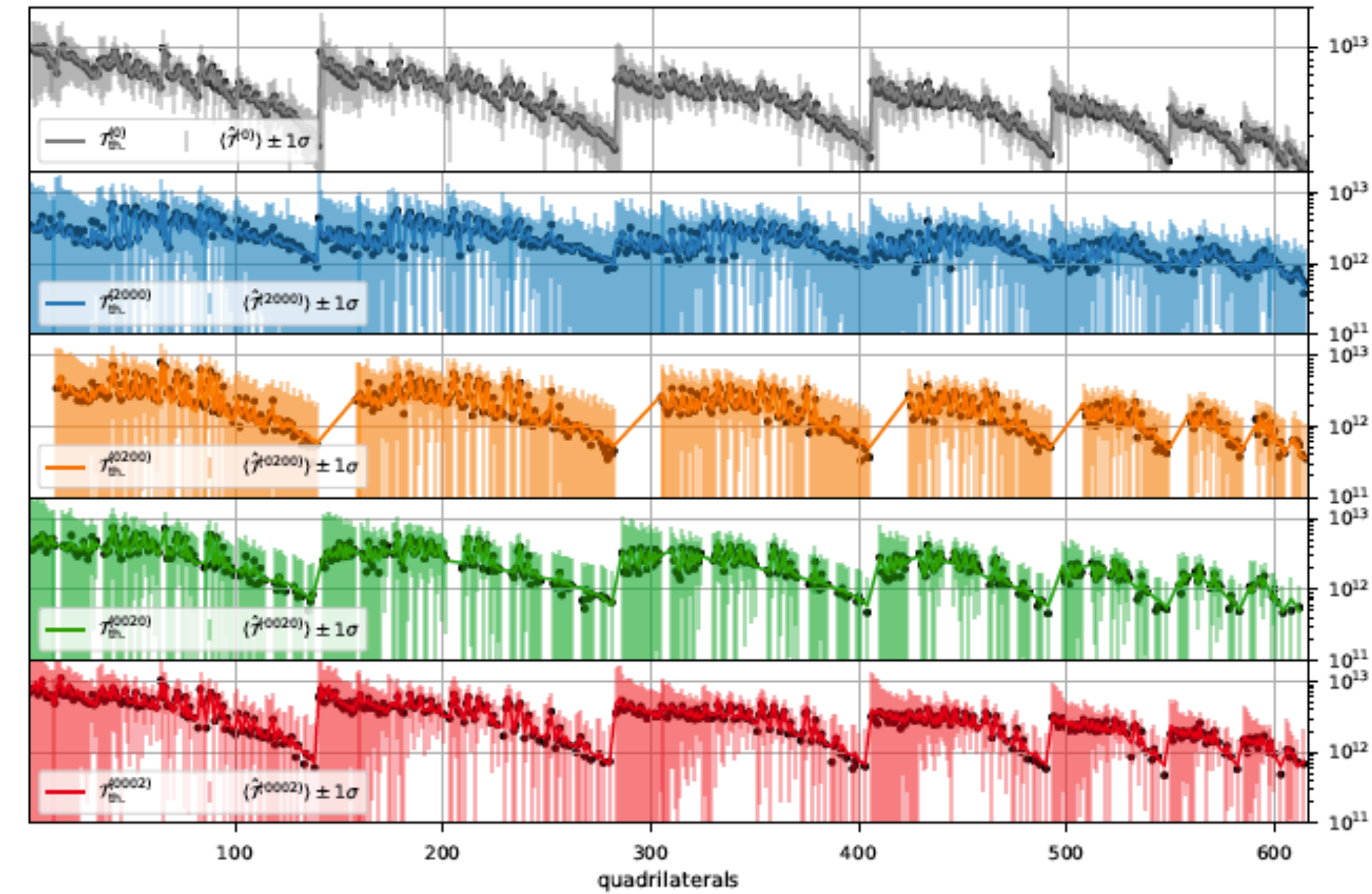


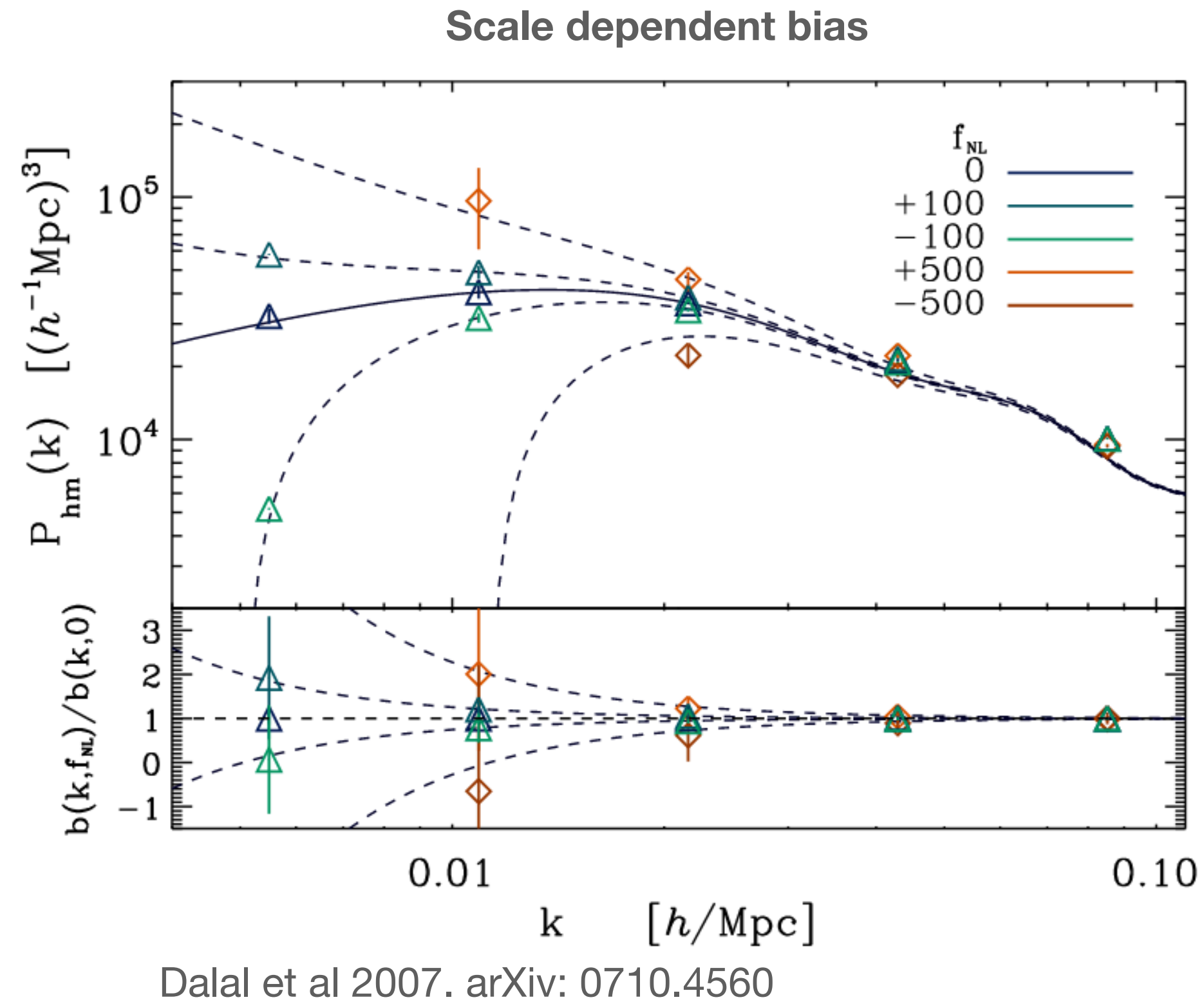
# The role of the galaxy bispectrum and trispectrum for PNG detections in LSS

*Héctor Gil-Marín, in collaboration with Davide Gualdi & Licia Verde  
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*A window to fundamental physics, PNG and beyond. Madrid Sept. 2022*

# Motivation



- Measuring  $f_{\text{NL}}$ ,  $g_{\text{NL}}$  signal would be a direct probe of inflation.
- Current and on-going LSS data open a new window for this potential detection
- Main technique relies on the scale-dependent bias detection (see Eva's talk on eBOSS data).
- But it has drawbacks, we need to know very well galaxy formation and evolution (see Alex talk)
- **An alternative is a measurement of  $f_{\text{NL}}$  from the actual shape of the matter bispectrum and trispectrum**

# Joint analysis of anisotropic power spectrum, bispectrum and trispectrum: application to N-body simulations

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**JCAP Vol 2021, Issue 07, id.008**

**arXiv: 2104.03976**



Fast mcmc

Bispectrum estimator

Trispectrum estimator

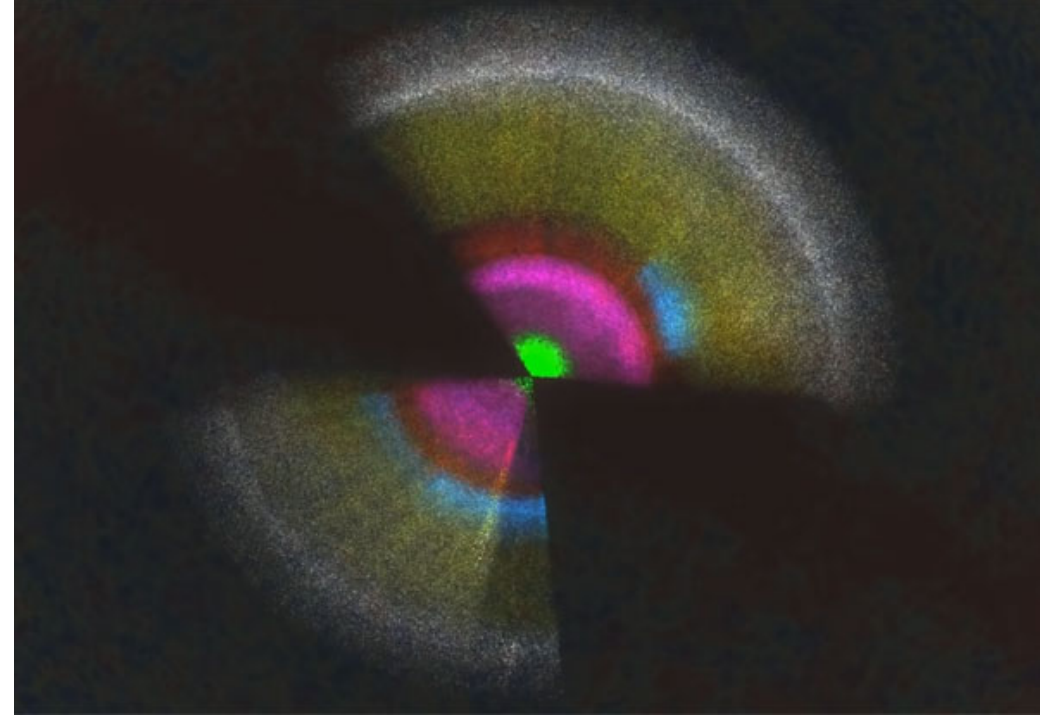
Effective kernels

$f_{nl}$  trispectrum signal

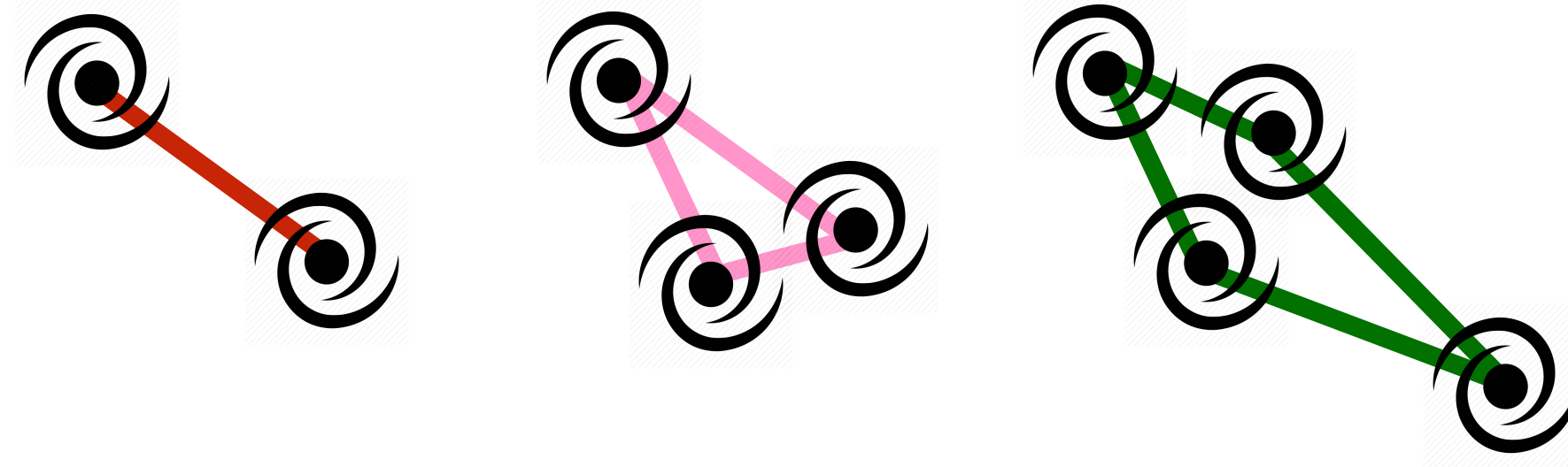
Full covariance

Trispectrum detection on BOSS data

# Summary Statistics



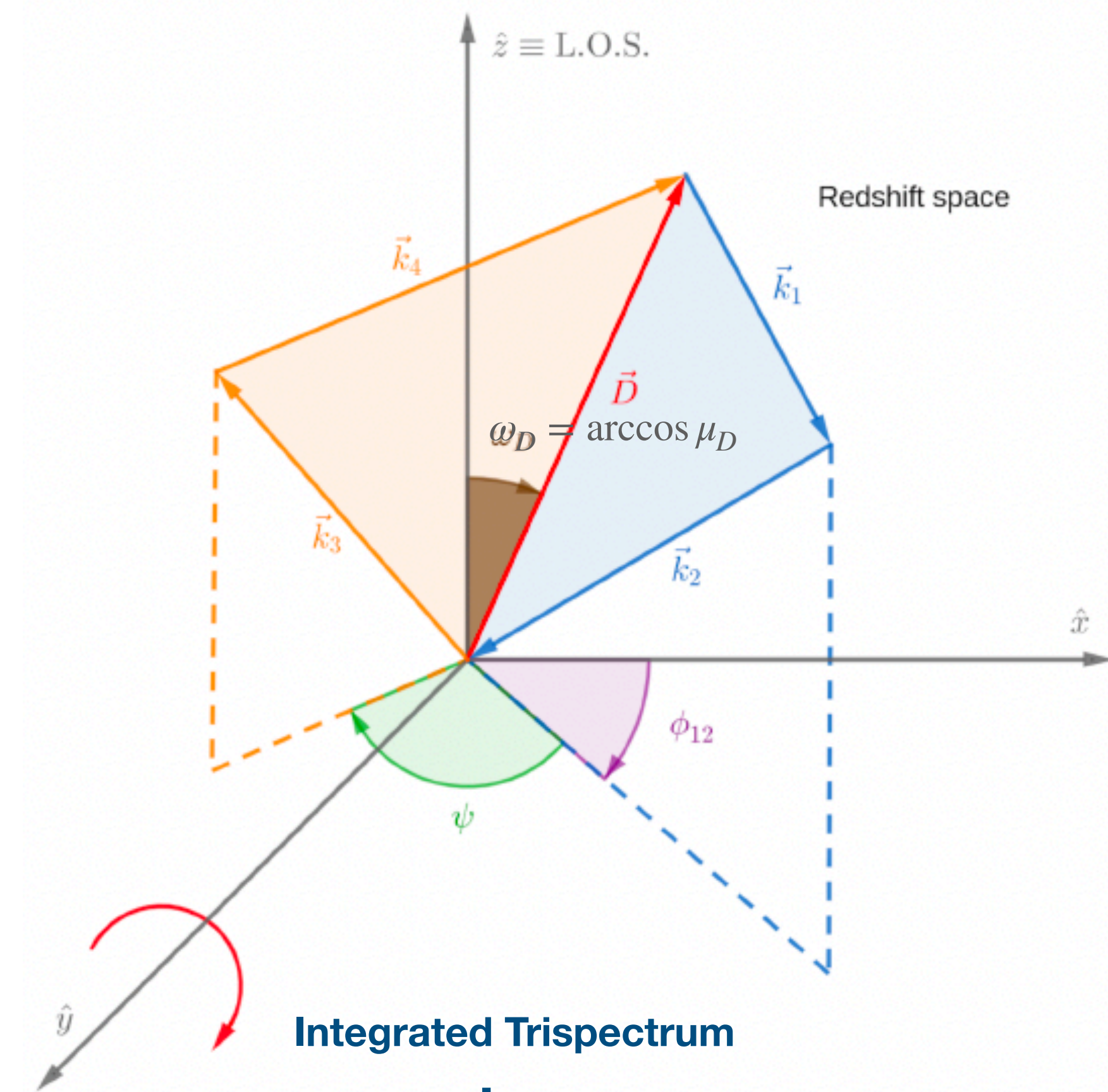
$$P(\mathbf{k}) \oplus B(\mathbf{k}_1, \mathbf{k}_2) \oplus T(\mathbf{k}_1, \mathbf{k}_2, \dots)$$



$$\langle \delta_{\mathbf{k}} \delta'_{\mathbf{k}'} \rangle = P(\mathbf{k}) \delta^D(\mathbf{k} + \mathbf{k}')$$

$$\langle \delta_{\mathbf{k}_1} \delta_{\mathbf{k}_2} \delta_{\mathbf{k}_3} \rangle = B(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3) \delta^D(\mathbf{k}_1 + \mathbf{k}_2 + \mathbf{k}_3)$$

$$\langle \delta_{\mathbf{k}_1} \delta_{\mathbf{k}_2} \delta_{\mathbf{k}_3} \delta_{\mathbf{k}_4} \rangle = T(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3, \mathbf{k}_4) \delta^D(\mathbf{k}_1 + \mathbf{k}_2 + \mathbf{k}_3 + \mathbf{k}_4)$$



Integrated Trispectrum

## Line-of-sight expansion

$$P^{(\ell)}(k) = \frac{(2\ell + 1)}{2\alpha_{\parallel} \alpha_{\perp}^2} \int_{-1}^{+1} d\mu \mathcal{L}_{\ell}(\mu) P(p, \eta)$$

$$B^{(\ell_i)}(k_1, k_2, k_3) = \frac{(2\ell + 1)}{8\pi \alpha_{\parallel}^2 \alpha_{\perp}^4} \int_{-1}^{+1} d\mu_1 \int_0^{2\pi} d\phi \mathcal{L}_{\ell}(\mu_i) B(p_1, p_2, p_3, \eta_1, \eta_2),$$

$$B^{(\ell_1)} = B^{(\ell, 0, 0)}; \quad B^{(\ell_2)} = B^{(0, \ell, 0)}; \quad B^{(\ell_3)} = B^{(0, 0, \ell)}$$

$$B^{(0, 2)} \equiv B^{(0)} \oplus B^{(2_1)} \oplus B^{(2_2)} \oplus B^{(2_3)}$$

$$\begin{aligned} \mathcal{T}^{(\ell_i)}(k_1, k_2, k_3, k_4) &= \frac{1}{3} \sum_{\substack{k_1, k_2, k_3, k_4 \\ k_1, k_3, k_2, k_4 \\ k_1, k_2, k_4, k_3}} \frac{2\ell + 1}{16\pi^2 \Delta D \alpha_{\parallel}^3 \alpha_{\perp}^6} \int_{D_{\min}}^{D_{\max}} dD \int_{-1}^{+1} d\mu_D \int_0^{2\pi} d\phi_{12} \int_0^{2\pi} d\psi \\ &\times \mathcal{L}_{\ell}(\mu_i) T^{\text{S}}(p_1, p_2, p_3, p_4, D, \eta_D, \phi_{12}, \psi). \end{aligned}$$

$$T^{(\ell_1)} = T^{(\ell, 0, 0, 0)}; \quad T^{(\ell_2)} = T^{(0, \ell, 0, 0)}; \quad \dots$$

$$T^{(0, 2)} \equiv T^{(0)} \oplus T^{(2_1)} \oplus T^{(2_2)} \oplus T^{(2_3)} \oplus T^{(2_4)}$$

# Summary Statistics

- We aim to use the **full P+B+T multipoles** to jointly constrain  $\{\alpha_{\text{para}}, \alpha_{\text{perp}}, f, \sigma_8, f_{\text{nl}}\}$

**BAO dilation scales**

$$\alpha_{\parallel} \equiv \frac{D_H/r_s}{[D_H/r_s]^{\text{fid}}}$$
$$\alpha_{\perp} \equiv \frac{D_M/r_s}{[D_M/r_s]^{\text{fid}}}$$

**RSD parameter**

$$f(z) = \Omega_m(z)^\gamma$$

**Primordial features**

$$\sigma_8^2 = \int dk P_{\text{lin}}(k, z=0) W_{TH}(k \cdot R_8)$$
$$f_{\text{nl}}$$

- We use **Quijote** N-body sim 1 [Gpc/h]<sup>3</sup> boxes to get the **data-vector** and its **covariance**
- We will run both Fisher-like and a Monte Carlo Markov Chain like analyses.
- The aim is to extract  $f_{\text{nl}}$  from the shape of the summary statistics.
- We will not employ the scale-dependent bias feature to measure  $f_{\text{nl}}$

# Summary Statistics

## Theoretical modelling: Gravitational evolution

We take the SPT functional form for the tree-level expressions for both B and T

$$B_{\text{FPT}}(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3) = 2Z_{\text{FPT}}^{(1)}[\mathbf{k}_1] Z_{\text{FPT}}^{(1)}[\mathbf{k}_2] Z_{\text{FPT}}^{(2)}[\mathbf{k}_1, \mathbf{k}_2] P(k_1) P(k_2) + 2 \text{ permutations,}$$

$$T_{\text{FPT}}(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3, \mathbf{k}_4) = 4P(k_1)P(k_2)Z_{\text{SPT}}^{(1)}[\mathbf{k}_1] Z_{\text{SPT}}^{(1)}[\mathbf{k}_2] \times \left\{ Z_{\text{FPT}}^{(2)}[\mathbf{k}_1, -\mathbf{k}_{13}] Z_{\text{FPT}}^{(2)}[\mathbf{k}_2, \mathbf{k}_{13}] P(k_{13}) + Z_{\text{FPT}}^{(2)}[\mathbf{k}_1, -\mathbf{k}_{14}] Z_{\text{FPT}}^{(2)}[\mathbf{k}_2, \mathbf{k}_{14}] P(k_{14}) \right\} + 5 \text{ p.} + 6 Z_{\text{SPT}}^{(1)}[\mathbf{k}_1] Z_{\text{SPT}}^{(1)}[\mathbf{k}_2] Z_{\text{SPT}}^{(1)}[\mathbf{k}_3] Z_{\text{FPT}}^{(3)}[\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3] P(k_1)P(k_2)P(k_3) + 3 \text{ p.,}$$

Promote the SPT kernels to an effective kernels (FPT) where we fit for  $f_1, f_2, f_3, g_1, g_2, g_3$  (Scoccimarro 2001, Gil-Marín 2011, 2014)

$$F_{\text{FPT}}^{(2)}[\mathbf{k}_a, \mathbf{k}_b] = f_1 \frac{5}{7} + f_2 \frac{1}{2} \frac{\mathbf{k}_a \cdot \mathbf{k}_b}{k_a k_b} \left( \frac{k_a}{k_b} + \frac{k_b}{k_a} \right) + f_3 \frac{2}{7} \frac{(\mathbf{k}_a \cdot \mathbf{k}_b)^2}{k_a^2 k_b^2}$$

$$G_{\text{FPT}}^{(2)}[\mathbf{k}_a, \mathbf{k}_b] = g_1 \frac{3}{7} + g_2 \frac{1}{2} \frac{\mathbf{k}_a \cdot \mathbf{k}_b}{k_a k_b} \left( \frac{k_a}{k_b} + \frac{k_b}{k_a} \right) + g_3 \frac{4}{7} \frac{(\mathbf{k}_a \cdot \mathbf{k}_b)^2}{k_a^2 k_b^2}.$$

- Extend the k-range of validity of SPT
- Same  $f_i, g_i$  for different redshifts and cosmologies

# Summary Statistics

## Theoretical modelling: PNG ( $f_{\text{nl}}$ )

$$\begin{aligned}
 B^{\text{PNG}}(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3) &= Z^{(1)}(k_1)Z^{(1)}(k_2)Z^{(1)}(k_3) \frac{\mathcal{M}(k_1)}{\mathcal{M}(k_2)\mathcal{M}(k_3)} \frac{2f_{\text{nl}}}{c^2} P(k_2)P(k_3) + \text{cyc.} \\
 T^{\text{PNG}}(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3, \mathbf{k}_4) &= \frac{f_{\text{nl}}}{c^2} Z^{(1)}(k_1)Z^{(1)}(k_2)Z^{(1)}(k_3) \\
 &\times \left\{ \left[ 4 \frac{\mathcal{M}(k_1)}{\mathcal{M}(k_2)} P(k_2)P(k_3) \frac{P(|\mathbf{k}_3 + \mathbf{k}_4|)}{\mathcal{M}(|\mathbf{k}_3 + \mathbf{k}_4|)} Z_{\text{FPT}}^{(2)}[-\mathbf{k}_3, \mathbf{k}_3 + \mathbf{k}_4] + 5 \text{p.} \right] \right. \\
 &+ \left. \left[ 2 \frac{\mathcal{M}(|\mathbf{k}_3 + \mathbf{k}_4|)}{\mathcal{M}(k_1)\mathcal{M}(k_2)} P(k_1)P(k_2)P(k_3) Z_{\text{FPT}}^{(2)}[\mathbf{k}_3 + \mathbf{k}_4, -\mathbf{k}_3] + 2 \text{p.} \right] \right\} \\
 &+ 3 \text{p.}
 \end{aligned}$$

$$\mathcal{M}_k \equiv \frac{3}{5} k^2 \mathbb{T}_k D_+ / (\Omega_m H_0^2)$$

$\mathbb{T}_k$  Power Spectrum transfer function

# Summary Statistics

## Theoretical modelling: PNG ( $f_{\text{nl}}$ )

$$\begin{aligned}
 B^{\text{PNG}}(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3) &= Z^{(1)}(k_1)Z^{(1)}(k_2)Z^{(1)}(k_3) \frac{\mathcal{M}(k_1)}{\mathcal{M}(k_2)\mathcal{M}(k_3)} \frac{2f_{\text{nl}}}{c^2} P(k_2)P(k_3) + \text{cyc.} \\
 T^{\text{PNG}}(\mathbf{k}_1, \mathbf{k}_2, \mathbf{k}_3, \mathbf{k}_4) &= \frac{f_{\text{nl}}}{c^2} Z^{(1)}(k_1)Z^{(1)}(k_2)Z^{(1)}(k_3) \\
 &\times \left\{ \left[ 4 \frac{\mathcal{M}(k_1)}{\mathcal{M}(k_2)} P(k_2)P(k_3) \frac{P(|\mathbf{k}_3 + \mathbf{k}_4|)}{\mathcal{M}(|\mathbf{k}_3 + \mathbf{k}_4|)} Z_{\text{FPT}}^{(2)}[-\mathbf{k}_3, \mathbf{k}_3 + \mathbf{k}_4] + 5 \text{p.} \right] \right. \\
 &+ \left. \left[ 2 \frac{\mathcal{M}(|\mathbf{k}_3 + \mathbf{k}_4|)}{\mathcal{M}(k_1)\mathcal{M}(k_2)} P(k_1)P(k_2)P(k_3) Z_{\text{FPT}}^{(2)}[\mathbf{k}_3 + \mathbf{k}_4, -\mathbf{k}_3] + 2 \text{p.} \right] \right\} \\
 &+ 3 \text{p.}
 \end{aligned}$$

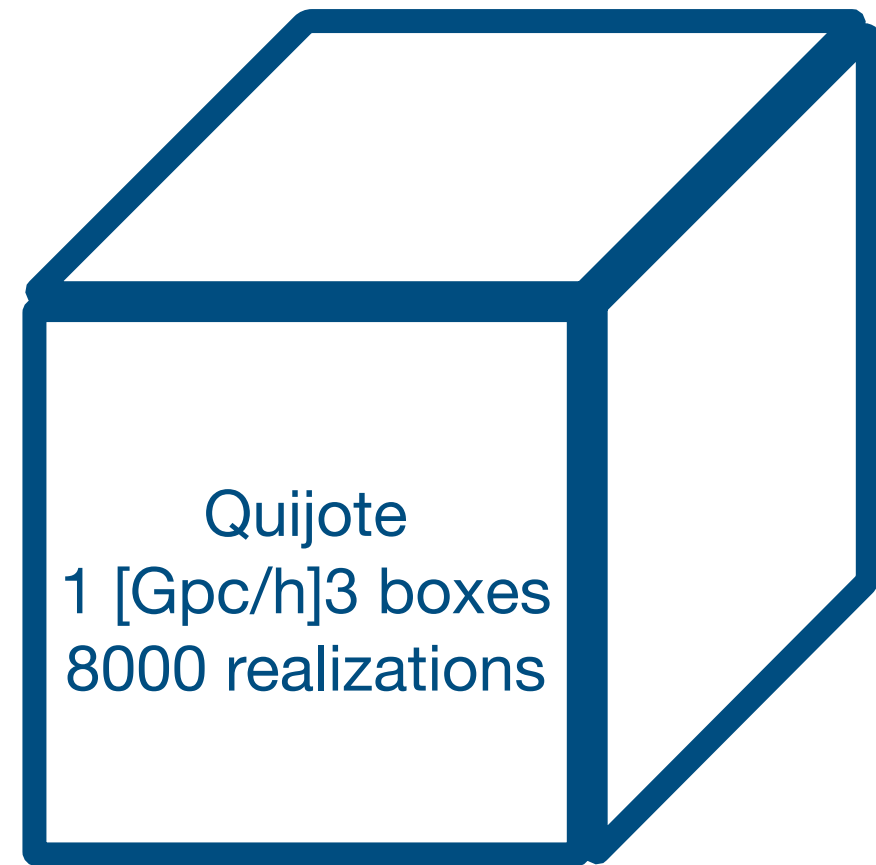
In the bispectrum  $f_{\text{nl}}$  signal is purely primordial, in the trispectrum it couples with  $Z^{(2)}$  kernel (gravity)

$$\mathcal{M}_k \equiv \frac{3}{5} k^2 \mathbb{T}_k D_+ / (\Omega_m H_0^2)$$

$\mathbb{T}_k$  Power Spectrum transfer function

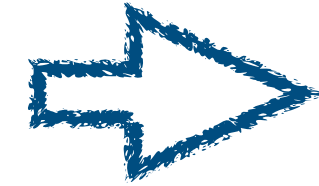


# Methodology

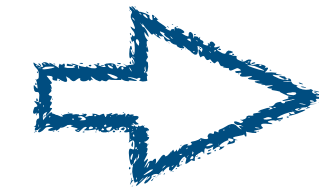
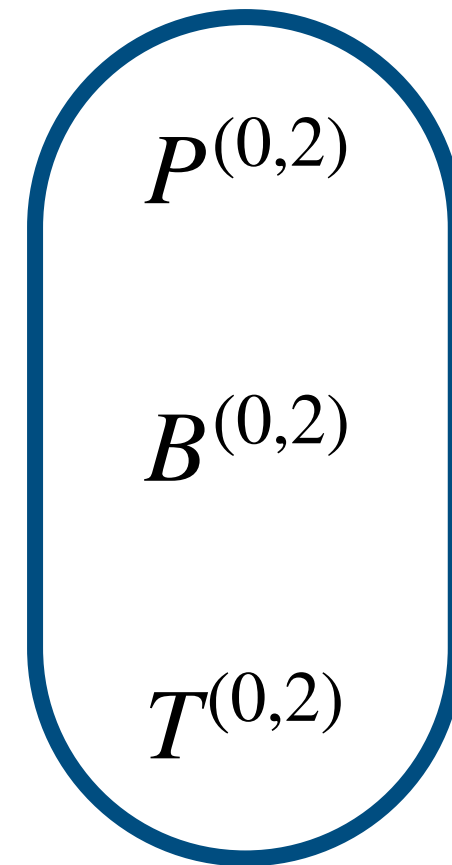


Dark Matter particles  
Main density  
downsample to match  
galaxy density

$$\bar{n} = 5 \cdot 10^{-4} [\text{Mpc}/h]^{-3}$$

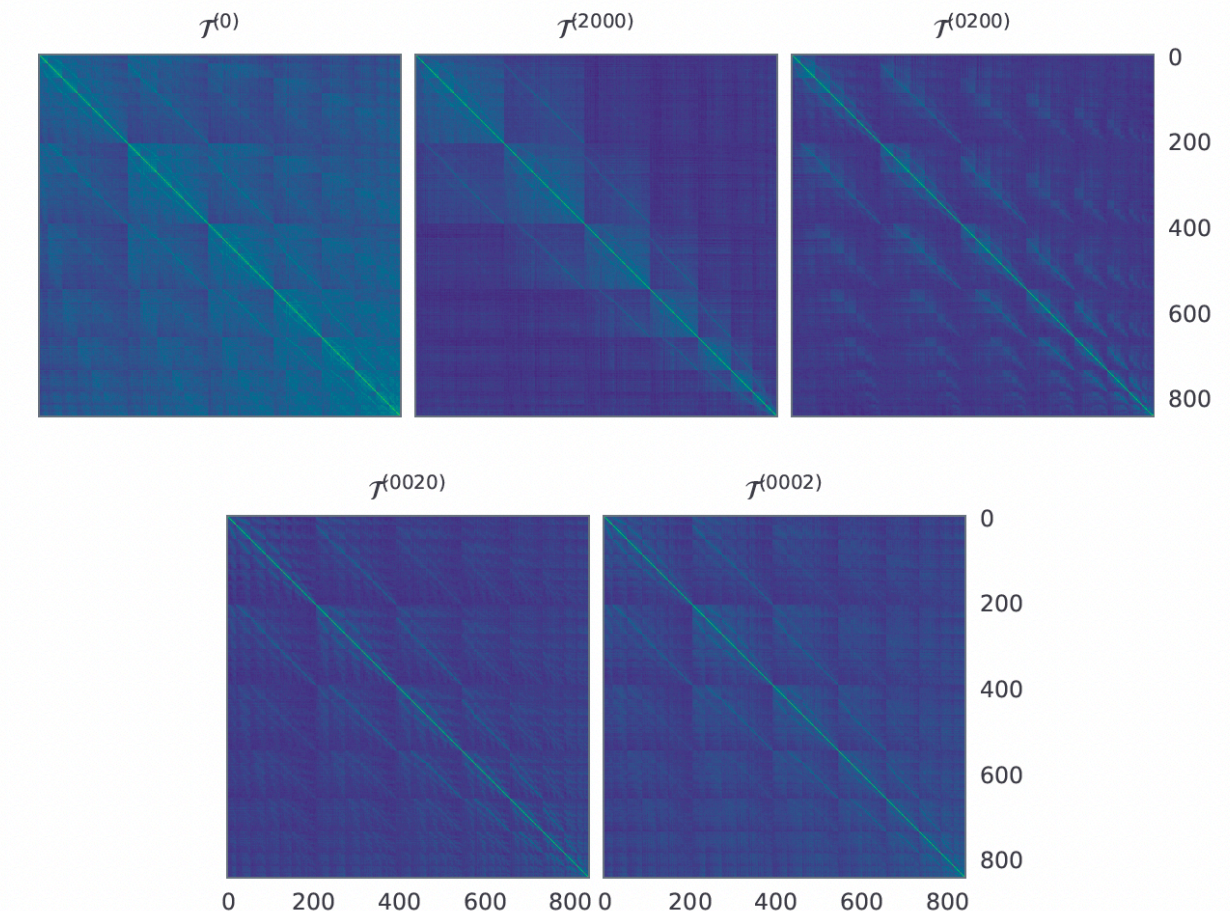


3615 elements



$0.04 < k < 0.13$   $P^{(0)}$   
 $0.06 < k < 0.13$   $P^{(2)}$   
 $0.04 < k < 0.12$   $B^{(0,2)}; T^{(0,2)}$

Full PBT covariance matrix  
(trispectrum-only covariance shown)



$C_{ij}$

Scaled to a volume of  $25 [\text{Gpc}/h]^3$   
+ Sellentin & Heavens correction

DESI/LSST/  
EUCLID like  
surveys

Estimate the errors: 1) à la Fisher; 2) à la MCMC

$$\{\alpha_{\parallel}, \alpha_{\perp}, f, \sigma_8, f_{\text{nl}}, | b_1, b_2, b_3, A_{\text{noise}}, \sigma_P, \sigma_B, \sigma_T \} + b_{3\text{nl}}, b_{s2}$$

5 physical variables

7 Nuisance / galaxy variables

2 non-local biases fixed to  
local Lagrangian

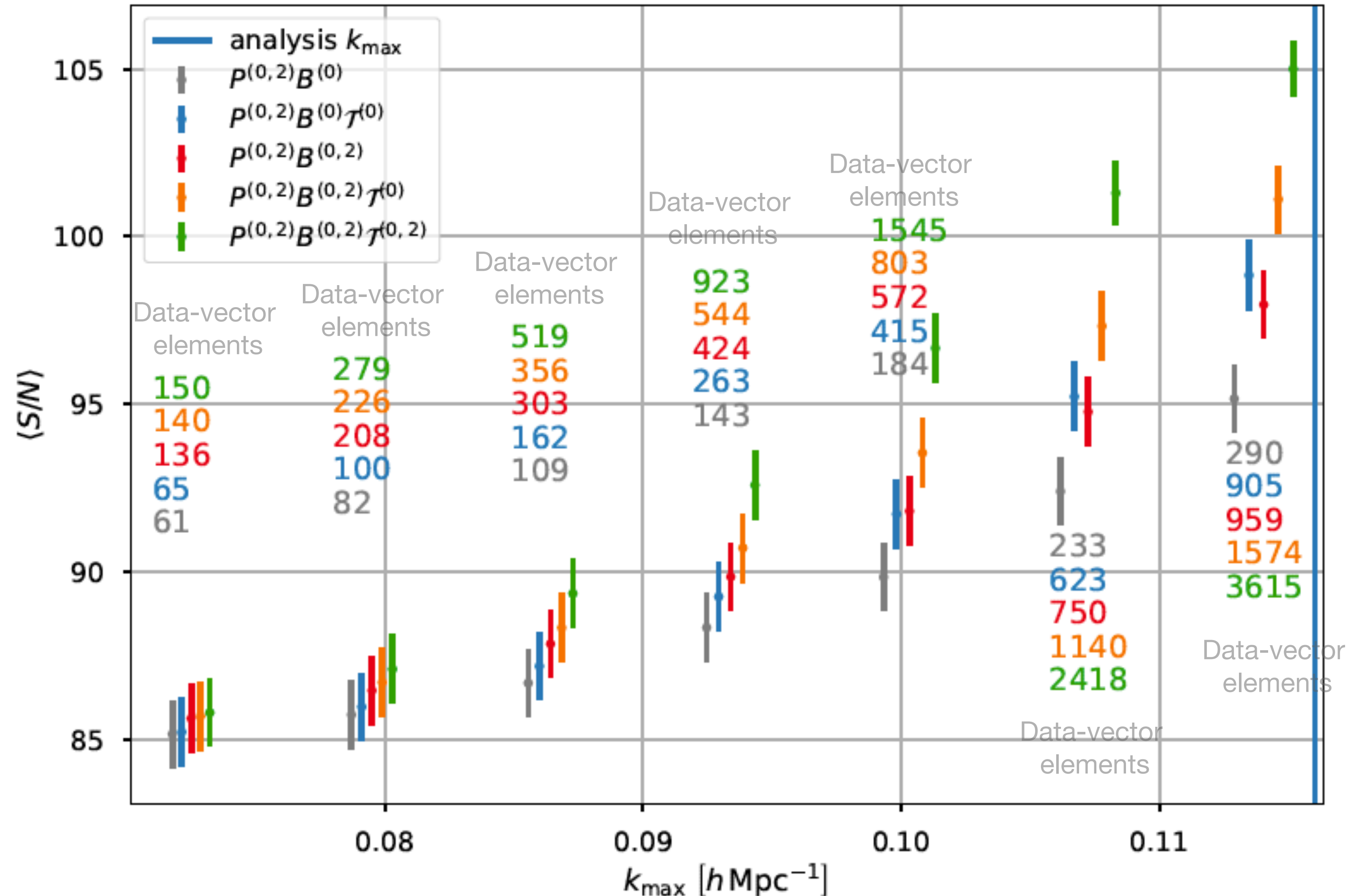
Simultaneously vary all of them, as if we were fitting an actual galaxy field

# Results I. Signal-to-Noise

How much do we gain as we go to larger k-values?

$$\langle S/N \rangle = \frac{1}{N_{\text{sim}}} \sum_{i=1}^{N_{\text{sim}}} \sqrt{\hat{\mathbf{d}}_i^T \text{Cov}_d^{-1} \hat{\mathbf{d}}_i},$$

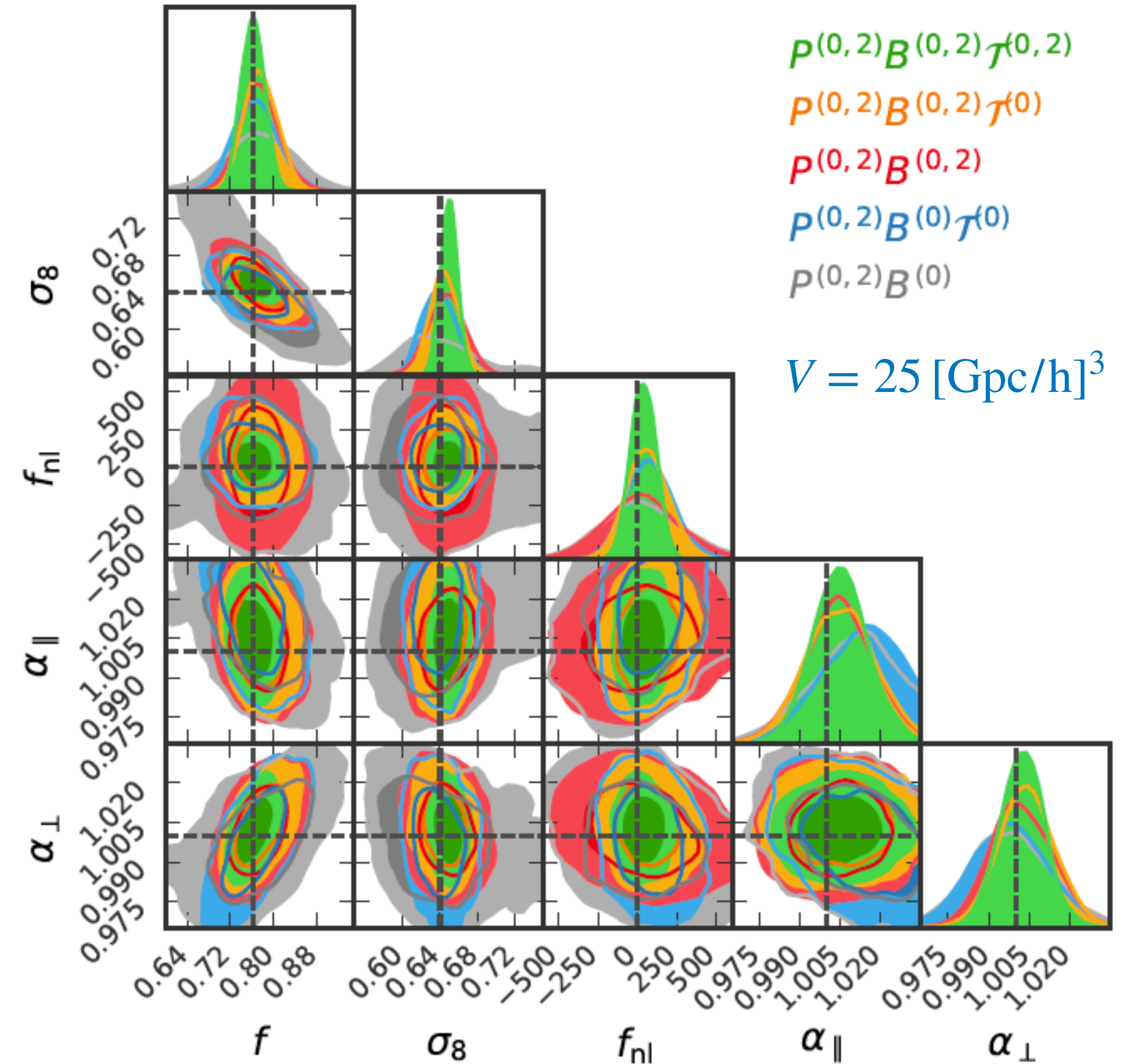
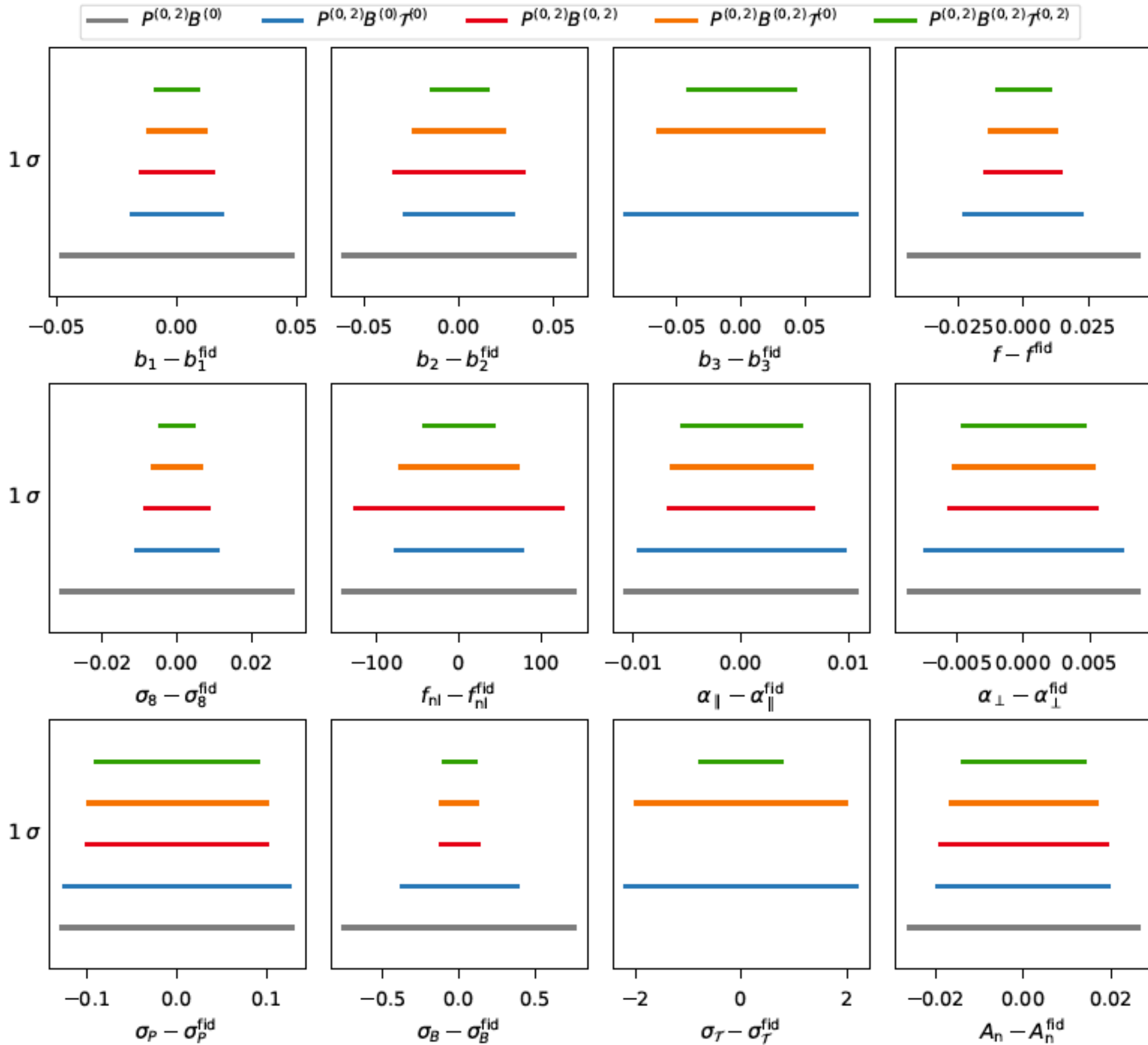
- Above  $k > 0.1$  adding higher order multipoles boosts SN.
- Adding bispectrum quadrupole is very complementary to trispectrum monopole



# Results II. Fisher & MCMC

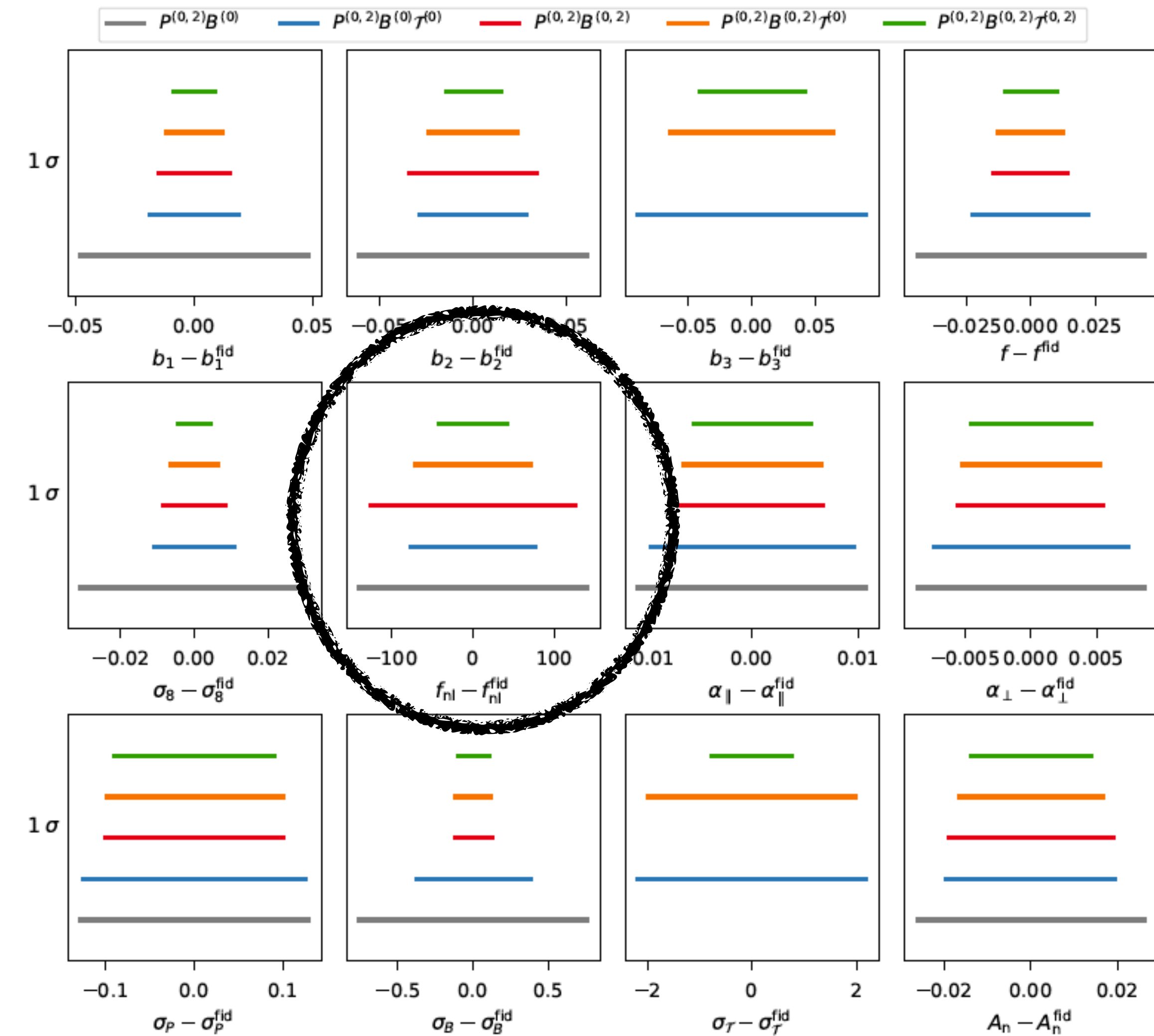
## Fisher

## Monte Carlo Markov Chains

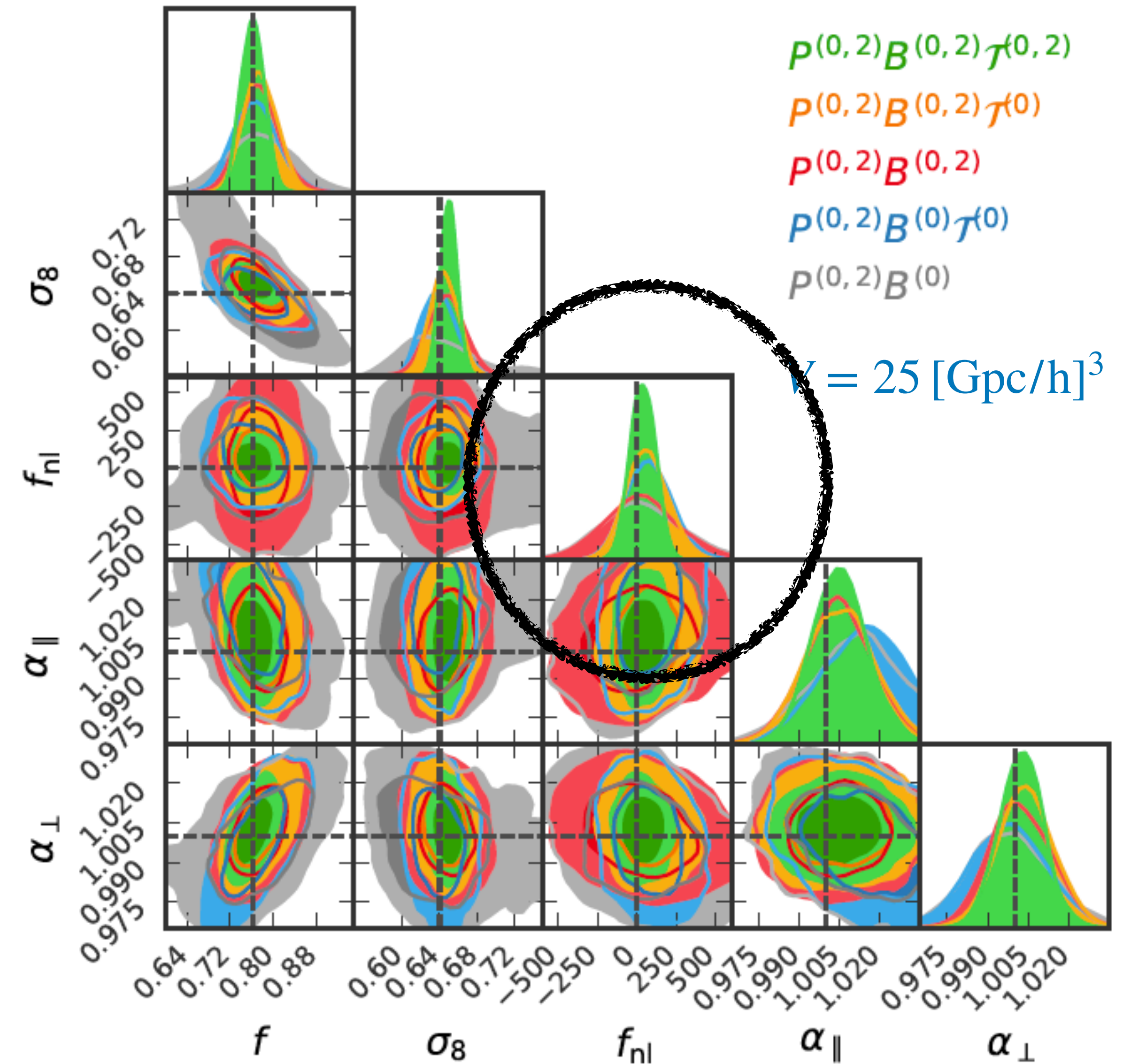


# Results II. Fisher & MCMC

## Fisher



## Monte Carlo Markov Chains



# Results II. Fisher & MCMC

Parameter error  
For  $P^{(0,2)} B^{(0)}$

		MCMC (Fisher Forecasts)				$V = 25 [\text{Gpc}/h]^3$			
$\Delta\theta$		$1 - (\Delta\theta/\Delta\theta_{P^{(0,2)} B^{(0)}}) [\%]$							
$P^{(0,2)} B^{(0)}$		$P^{(0,2)} B^{(0)} \mathcal{T}^{(0)}$	$P^{(0,2)} B^{(0,2)}$	$P^{(0,2)} B^{(0,2)} \mathcal{T}^{(0)}$	$P^{(0,2)} B^{(0,2)} \mathcal{T}^{(0,2)}$				
$f$	<b>0.140</b> (0.090)	42.8 (48.8)	46.4 (66.8)	57.7 (70.4)	71.9 (76.5)				
$\sigma_8$	<b>0.078</b> (0.062)	52.3 (64.1)	40.6 (71.5)	62.3 (77.8)	78.2 (85.1)				
$f_{\text{nl}}$	<b>536</b> (282)	49.1 (44.4)	9.5 (9.5)	55.1 (48.6)	71.7 (68.7)				
$\alpha_{\parallel}$	<b>0.036</b> (0.022)	13.9 (10.6)	30.6 (37.2)	34.2 (39)	46.8 (47.7)				
$\alpha_{\perp}$	<b>0.032</b> (0.018)	14.3 (14.5)	29.1 (35.8)	33 (39.2)	46.3 (46.3)				
average improvement		31.3 (36.5)	32.1 (44.2)	44.6 (55)	61 (64.9)				

$f_{\text{nl}} = \pm 150$

# Results II. Fisher & MCMC

Parameter error  
For  $P^{(0,2)} B^{(0)}$

		MCMC (Fisher Forecasts)				$V = 25 [\text{Gpc}/h]^3$			
$\Delta\theta$		$1 - (\Delta\theta/\Delta\theta_{P^{(0,2)} B^{(0)}}) [\%]$							
$P^{(0,2)} B^{(0)}$		$P^{(0,2)} B^{(0)} \mathcal{T}^{(0)}$	$P^{(0,2)} B^{(0,2)}$	$P^{(0,2)} B^{(0,2)} \mathcal{T}^{(0)}$	$P^{(0,2)} B^{(0,2)} \mathcal{T}^{(0,2)}$				
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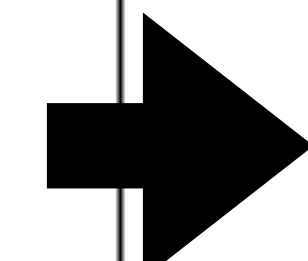
$$f = \pm 0.040$$

$$\sigma_8 = \pm 0.017$$

$$f_{\text{nl}} = \pm 150$$

$$\alpha_{\parallel} = \pm 0.019$$

$$\alpha_{\perp} = \pm 0.017$$



# Conclusions

- Covariance corresponds to  $25 \text{ [Gpc/h]}^3$  of order of what DESI/EUCLID/VR will map
- Number density of objects is similar to what you expect from LRGs  $5 \times 10^{-4}$
- k-range for B & T is realistic to the current modelling techniques  $0.04 < k < 0.12$
- We have marginalised over the rest of relevant cosmological variables, and bias parameters
- The covariance have been inferred from actual Nbody simulations
- **This approach is a complementary approach to the scale-dependent bias and does not rely on  $b_\phi$  or p calibration issue. Complementarity => Robustness!**

$$f = \pm 0.040$$

$$\sigma_8 = \pm 0.017$$

$$f_{\text{nl}} = \pm 150$$

$$\alpha_{\parallel} = \pm 0.019$$

$$\alpha_{\perp} = \pm 0.017$$

# Results III. Trispectrum detection in BOSS

## Detection of iT in BOSS DR12 LRG sample

## Integrated trispectrum detection from BOSS DR12 NGC CMASS

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<sup>a</sup>Institut de Ciències del Cosmos, University of Barcelona, ICCUB, Barcelona 08028, Spain

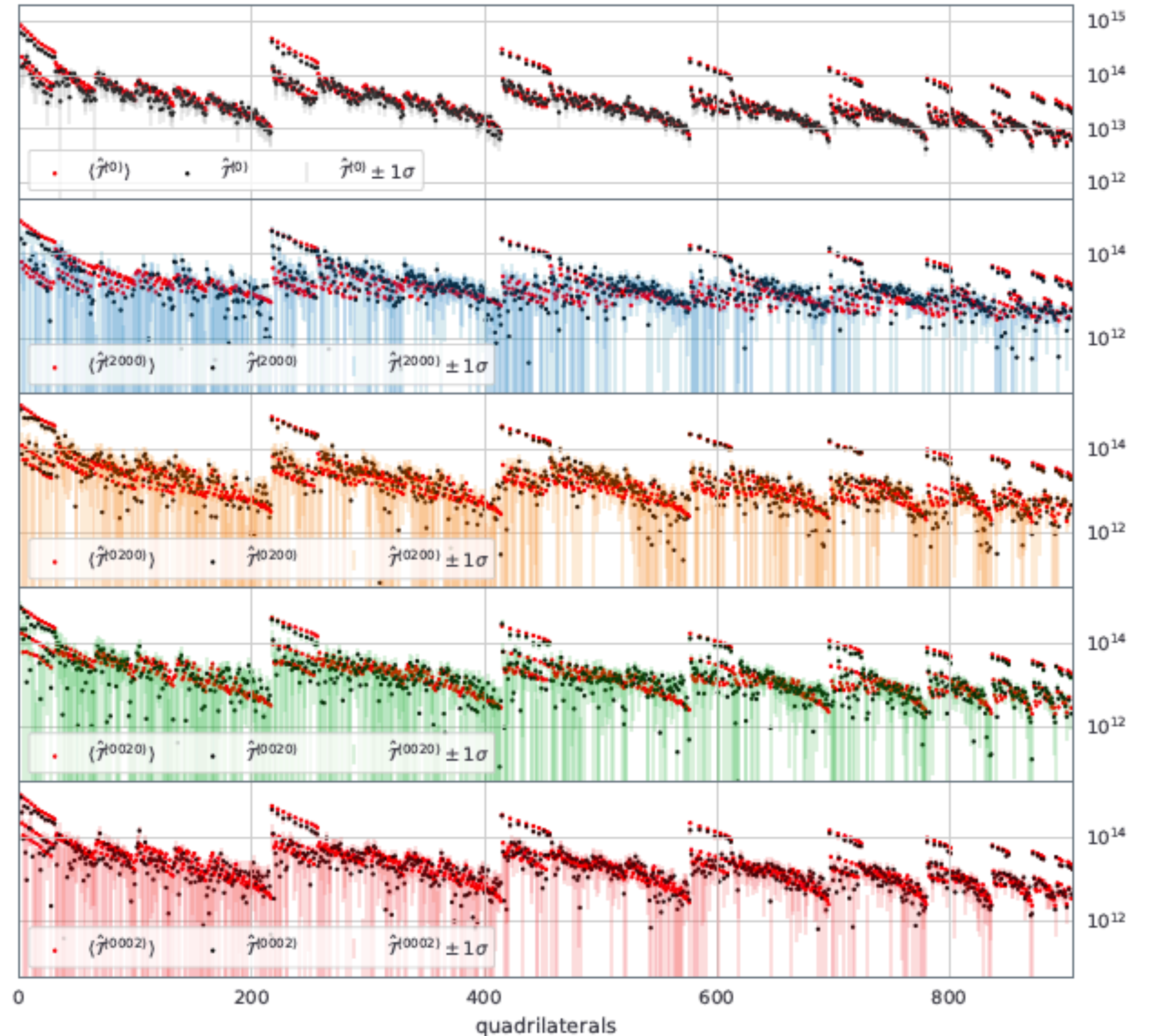
<sup>b</sup>Institute of Space Studies of Catalonia (IEEC), E-08034 Barcelona, Spain

<sup>c</sup>Institució Catalana de Recerca i Estudis Avançats, Passeig Lluís Companys 23, Barcelona 08010, Spain

E-mail: [dgualdi@icc.ub.edu](mailto:dgualdi@icc.ub.edu), [liciaverde@icc.ub.edu](mailto:liciaverde@icc.ub.edu)

[2022arXiv220106932](https://arxiv.org/abs/2022arXiv220106932)

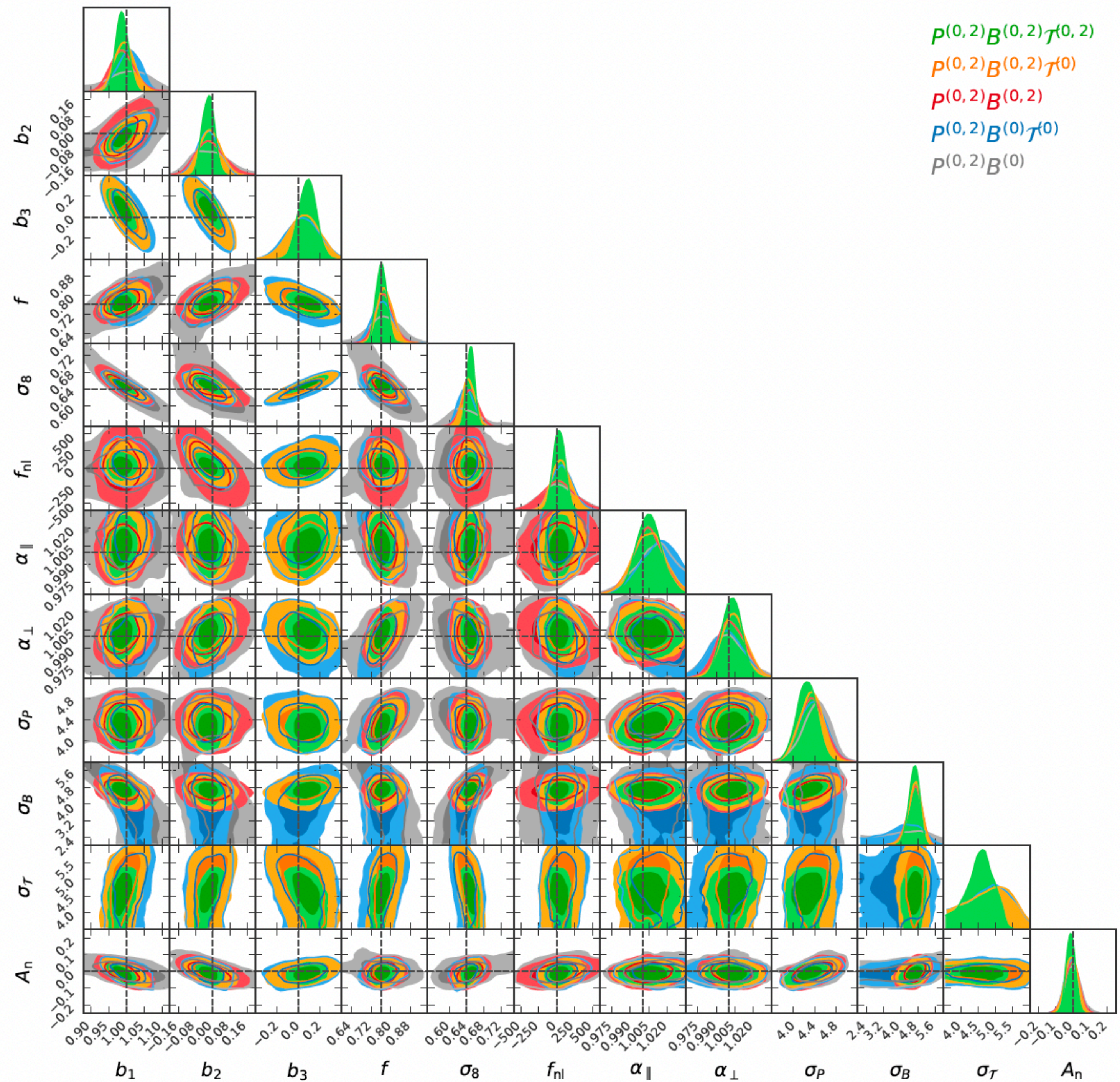
- **Detection of iTrispectrum,**
- $\mathcal{T}(0,0,0,0)$  at  $10.4\sigma$
- $\mathcal{T}(2,0,0,0)$  at  $5.2\sigma$
- $\mathcal{T}(0,2,0,0)$  at  $8.3\sigma$
- $\mathcal{T}(0,0,2,0)$  at  $1.1\sigma$
- $\mathcal{T}(0,0,0,2)$  at  $3.1\sigma$





# Bonus Slides

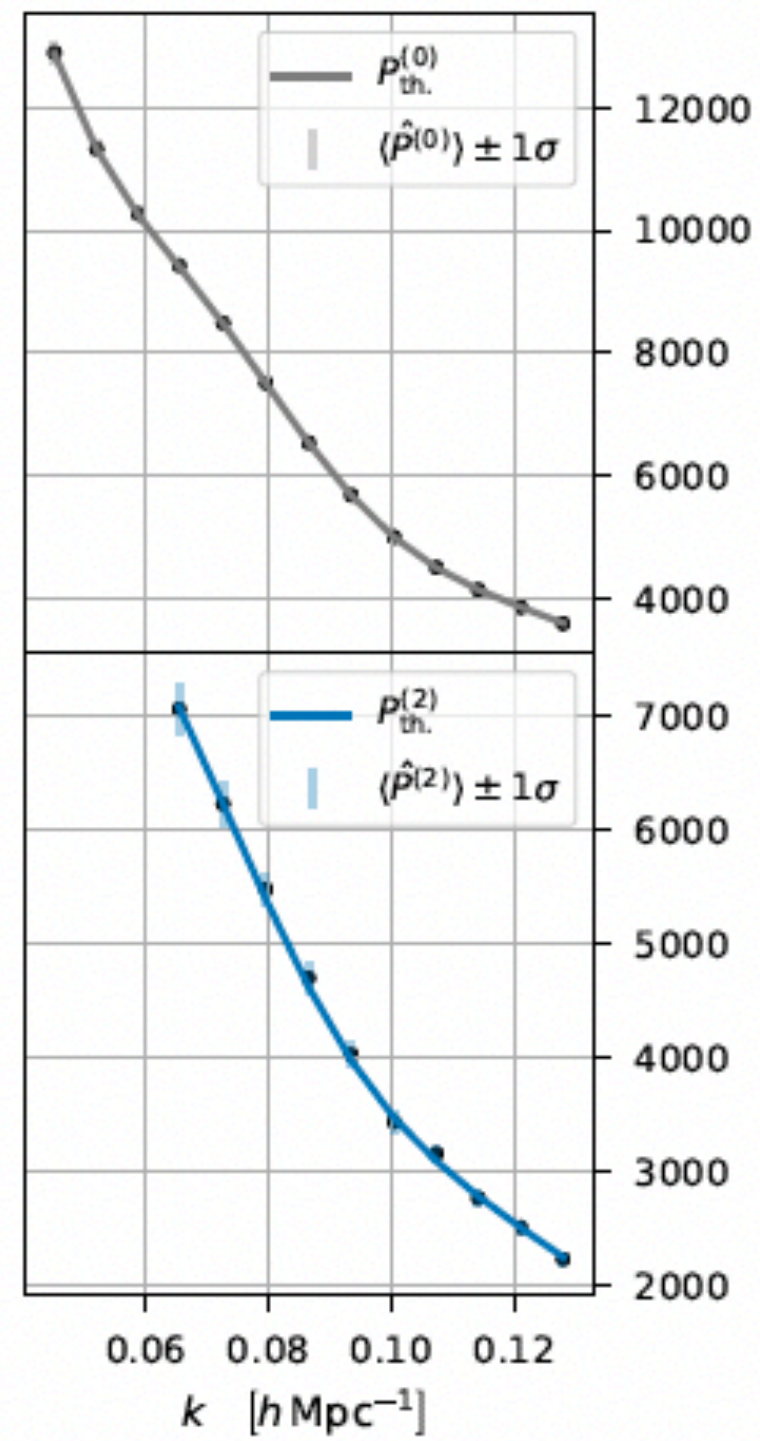
Full data-vector



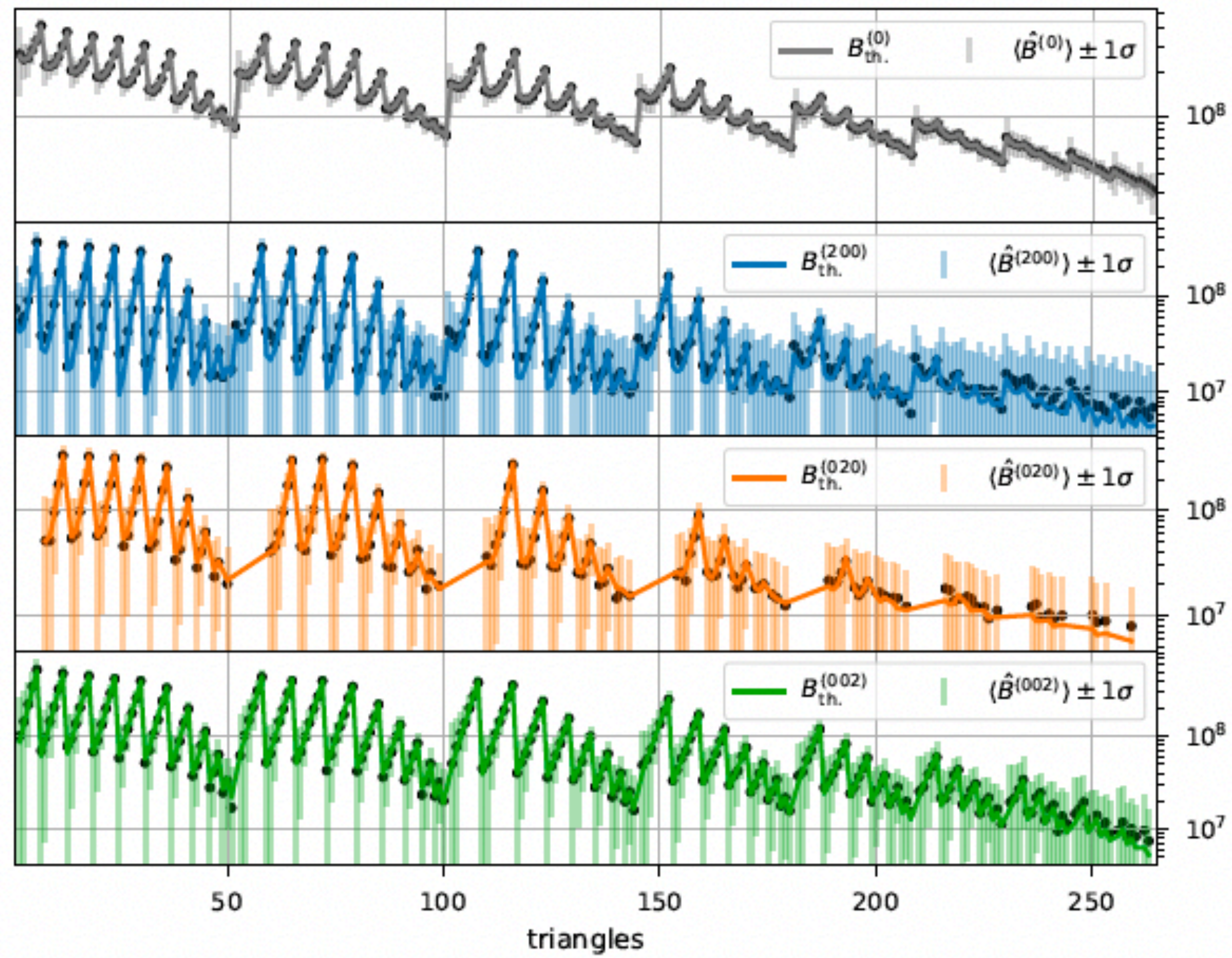
# Bonus Slides

## Full model data-vector

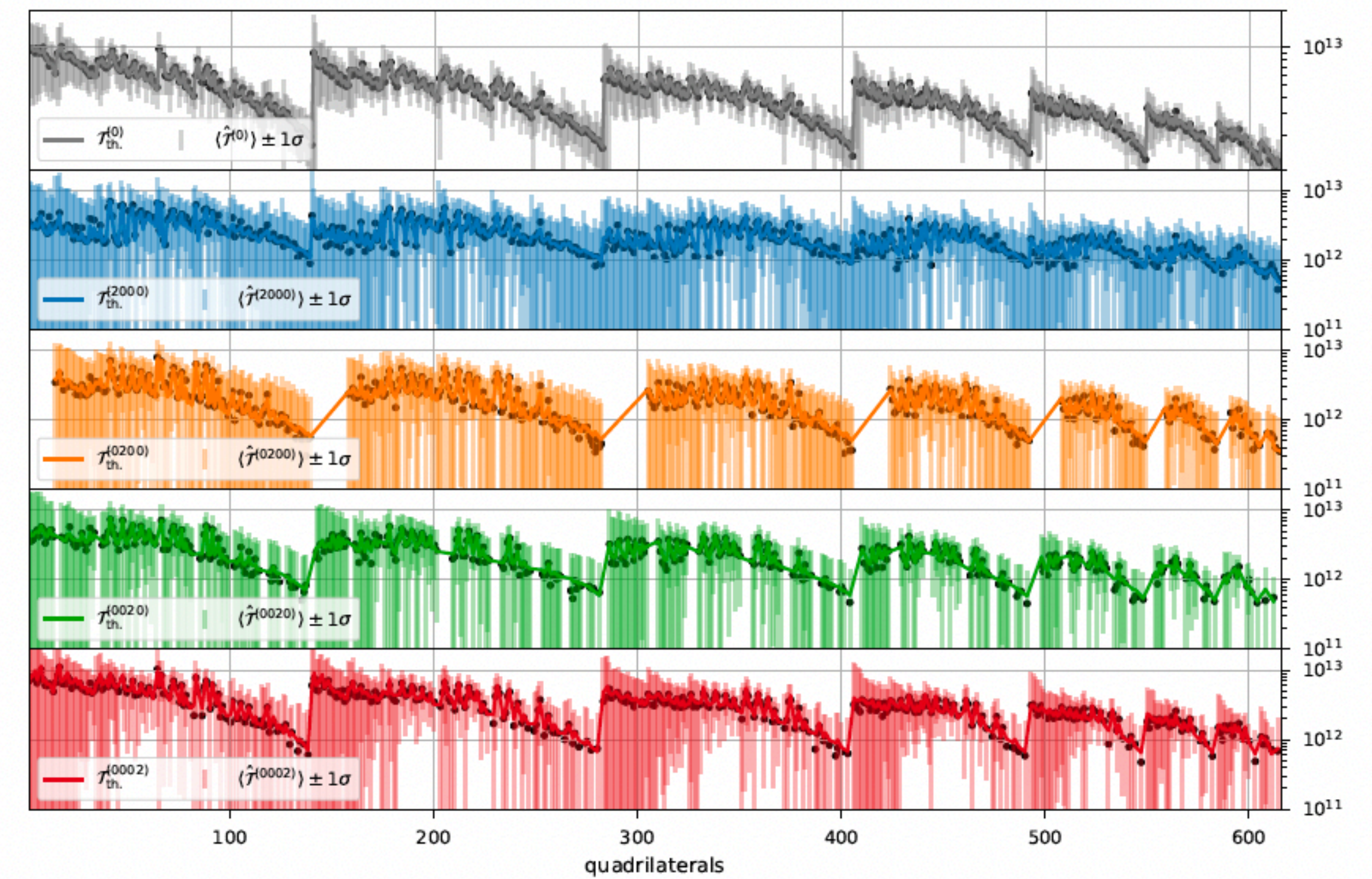
### Power Spectrum



### Bispectrum



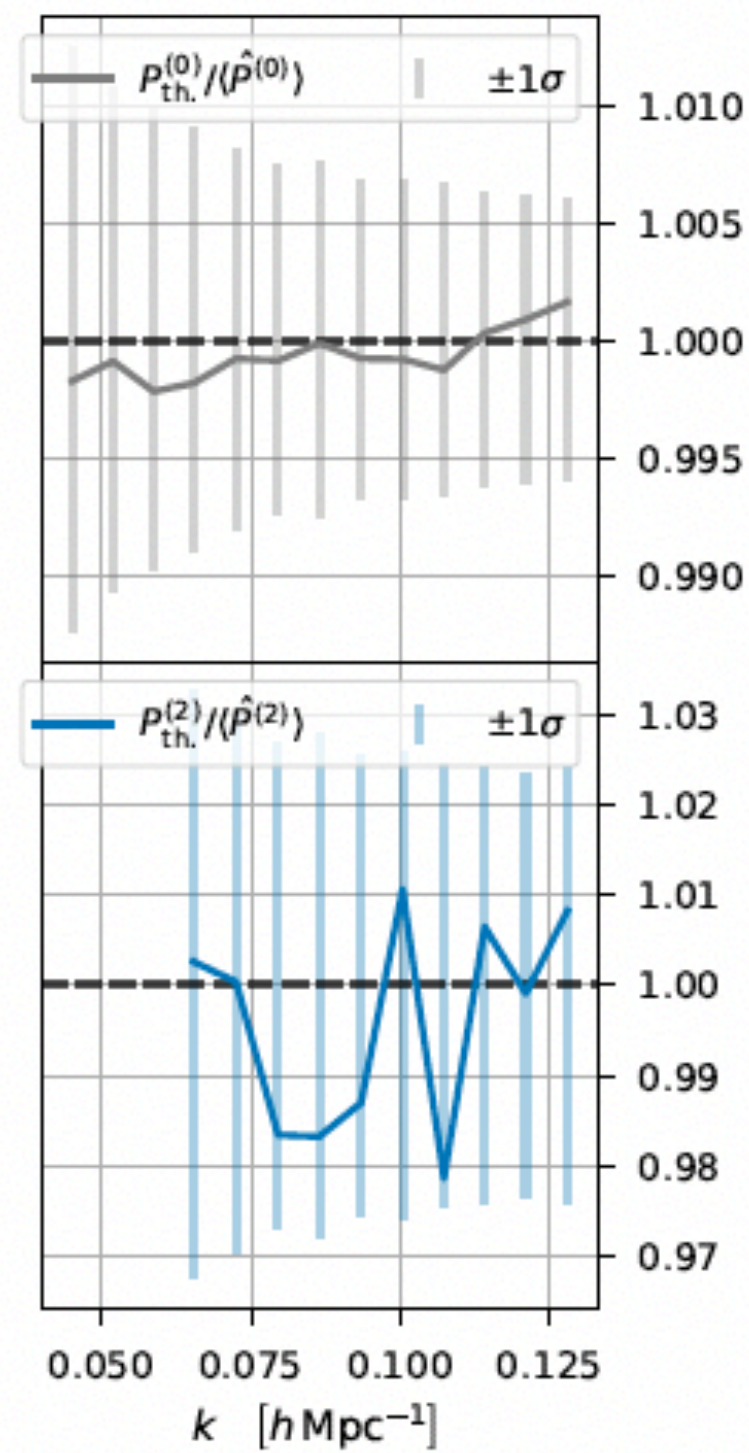
### Trispectrum



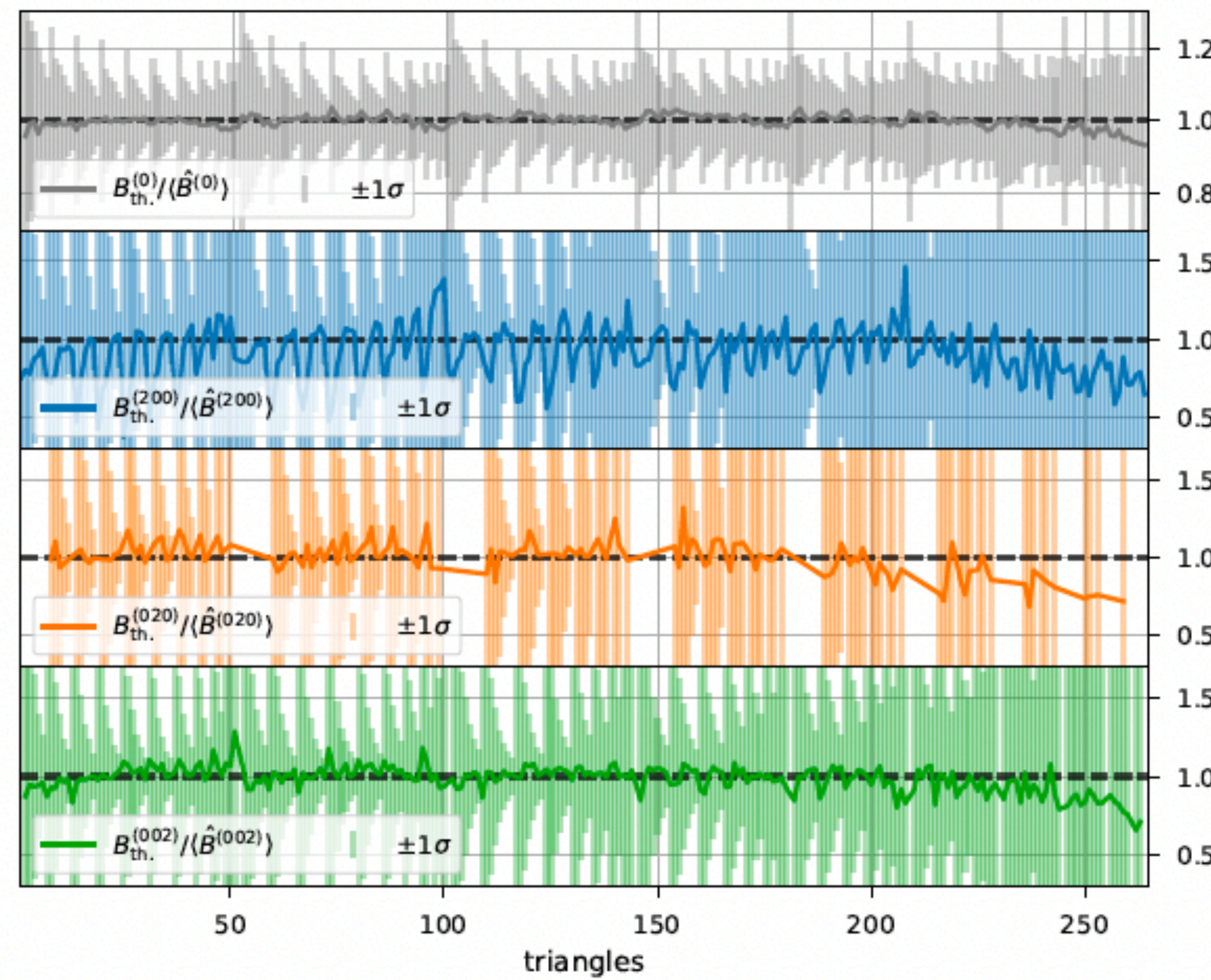
# Bonus Slides

## Full model data-vector: Ratios

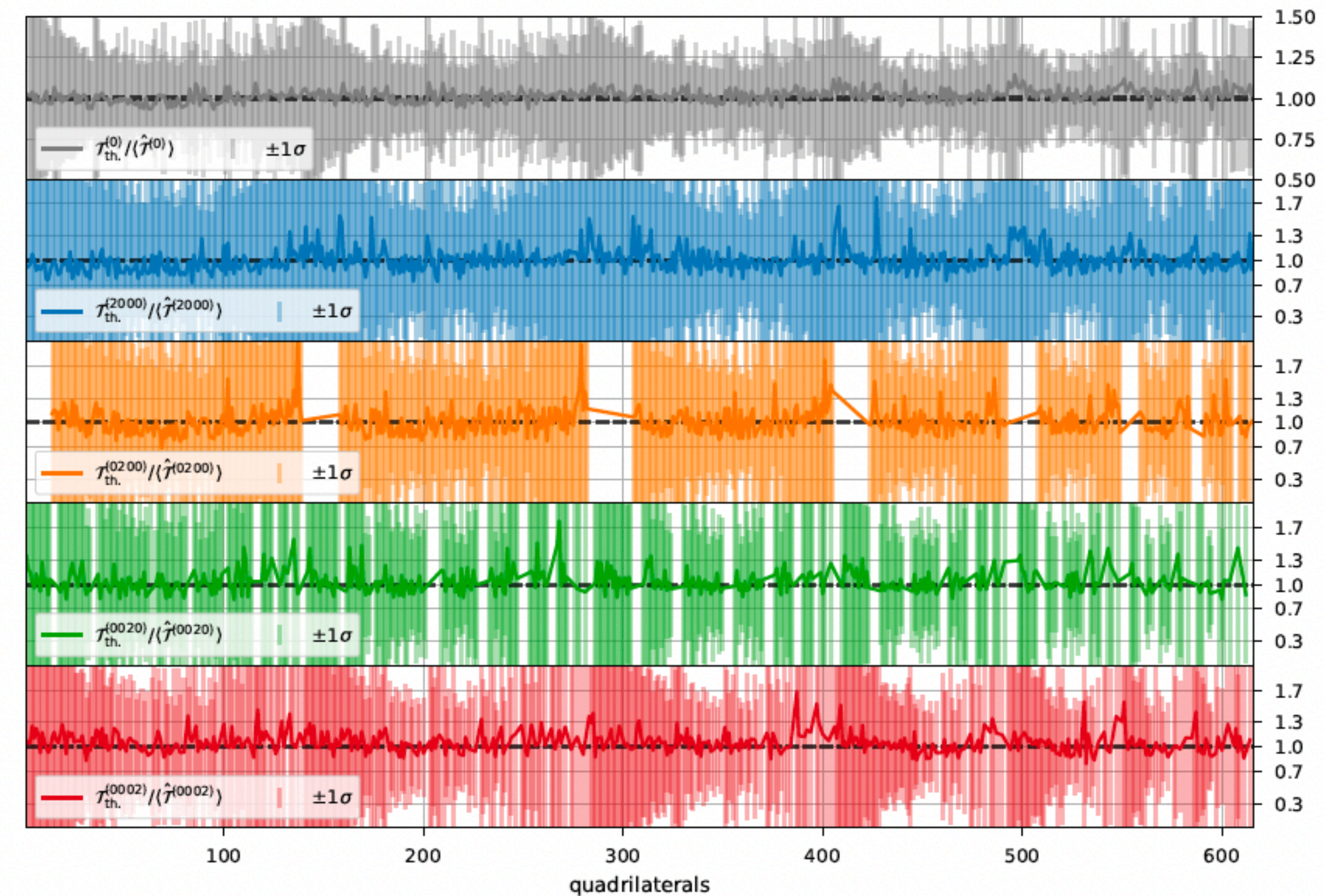
### Power Spectrum



### Bispectrum

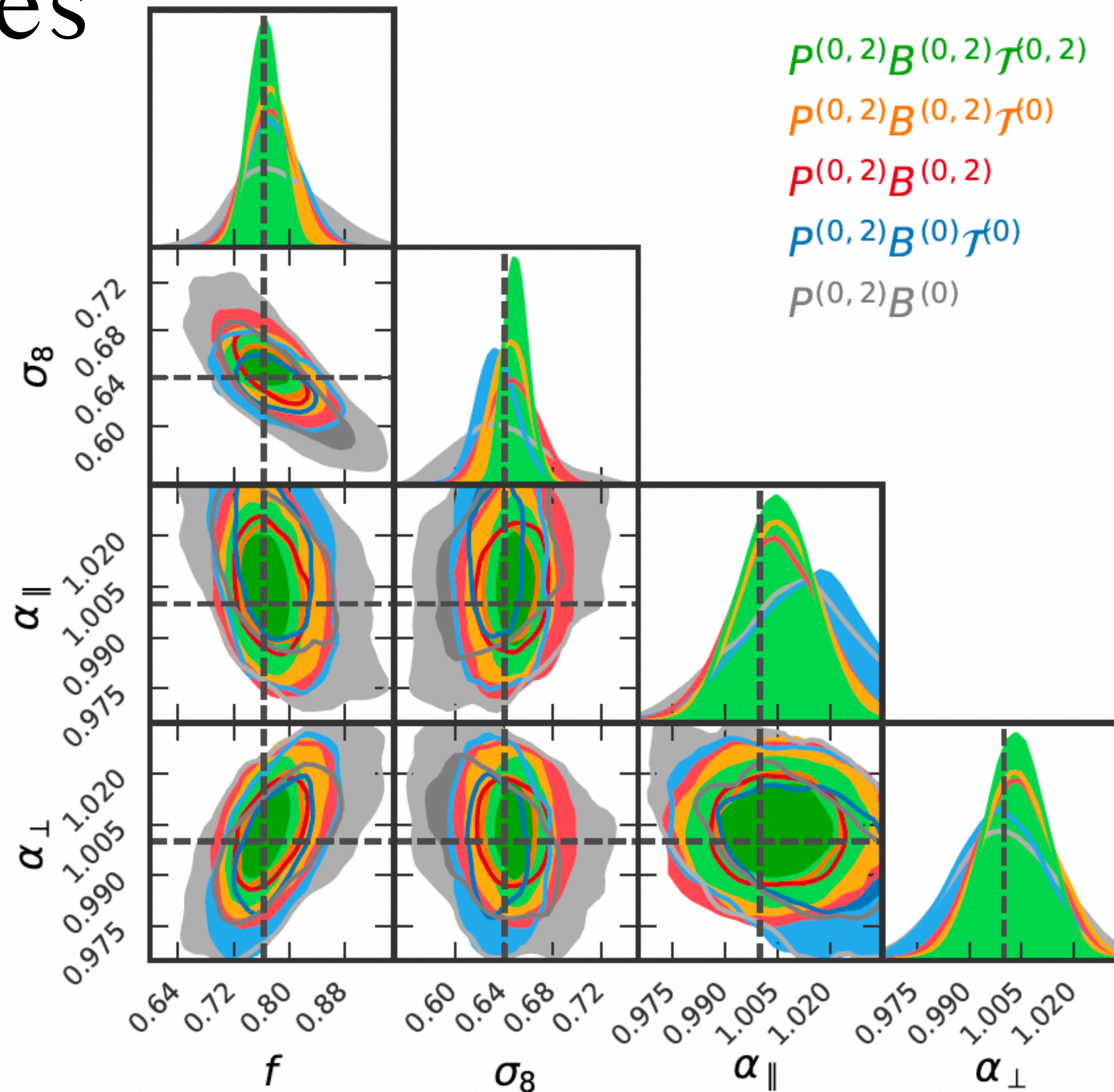


### Trispectrum



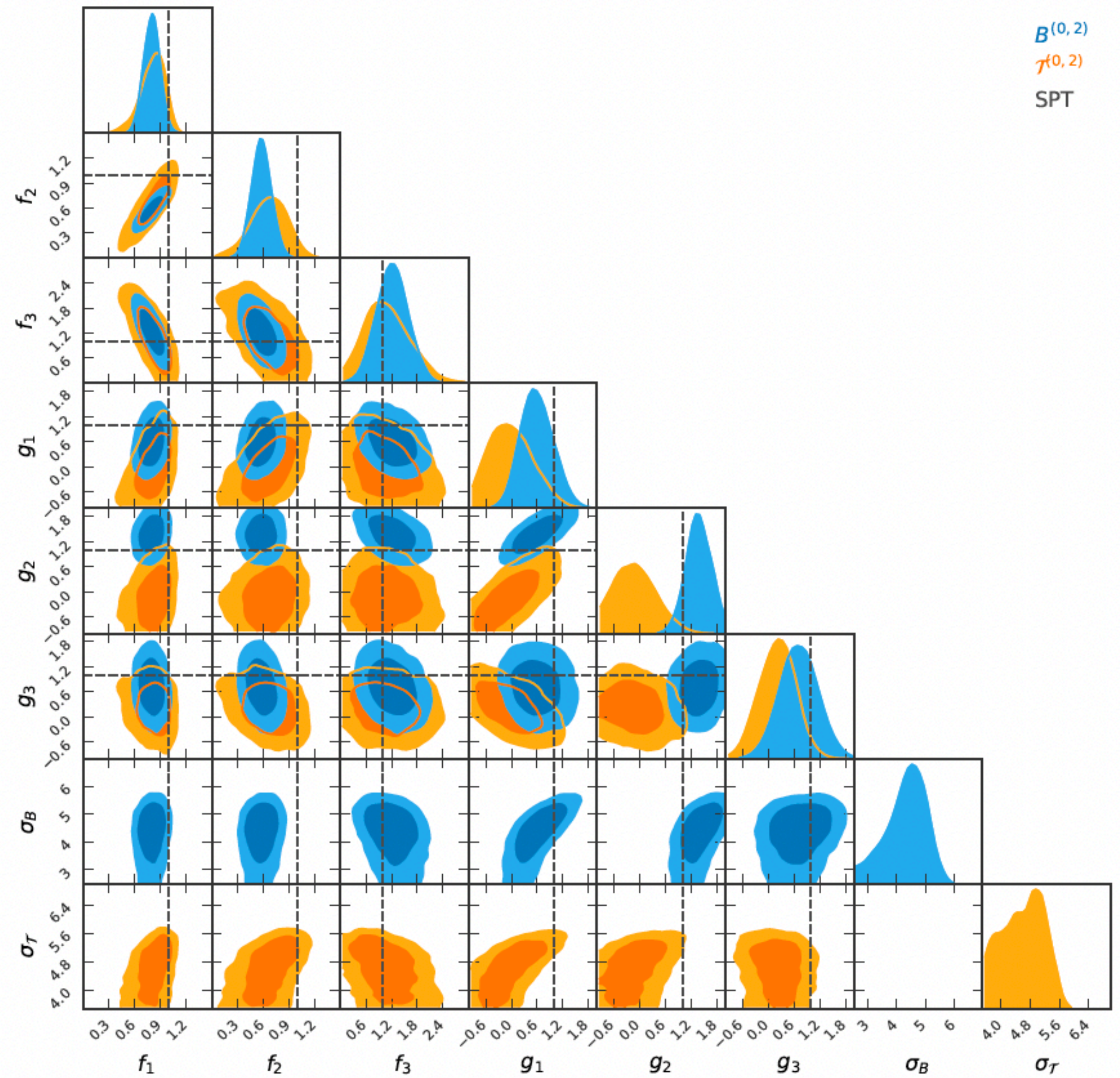
# Bonus Slides

$f_{nl}=0$  results



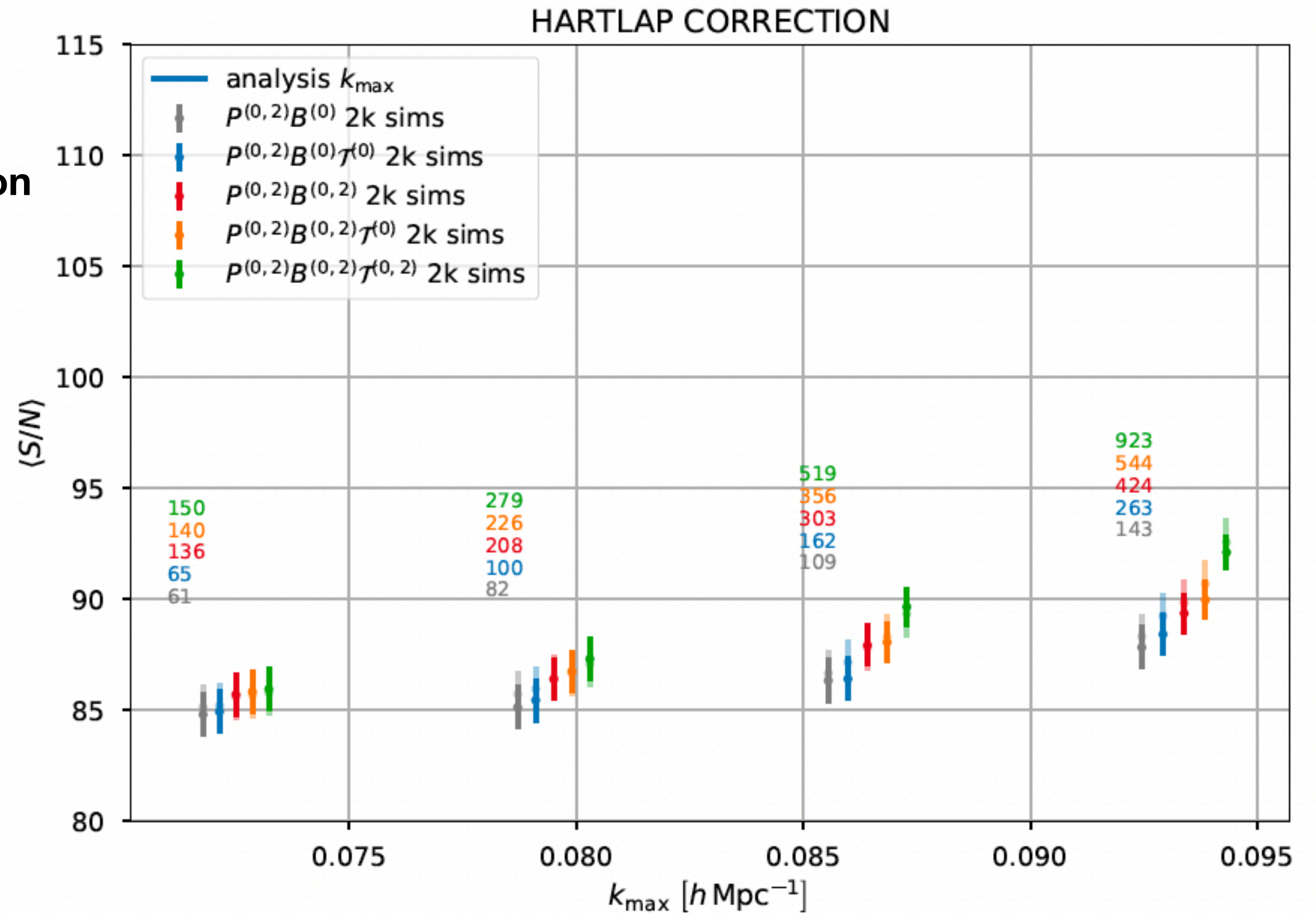
# Bonus Slides

## FPT model parameters



# Bonus Slides

## Covariance Hartlap Correction precision



**Figure 11.** Comparison between the  $\langle S/N \rangle$  computed using 2000 (opaque colours) and 8000 (transparent colours) simulations to estimate the covariance matrices for the different data-vectors combinations, respectively. Applying in both cases the appropriate Hartlap correction the  $\langle S/N \rangle$  remains approximately constant with respect to the number of simulations used.