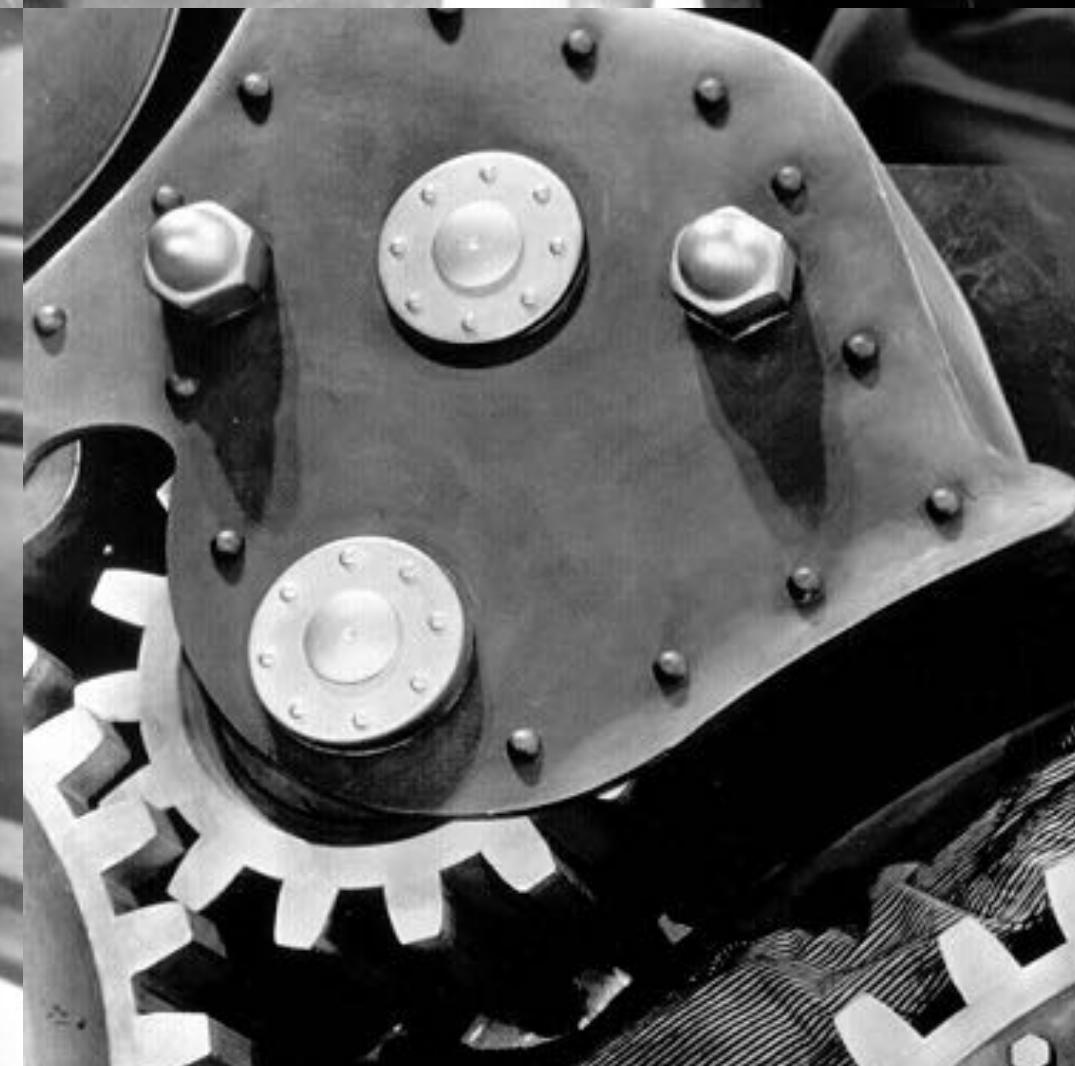


IA Modelling

Simulation Based

Francisco Maion, PhD Candidate, 23/09/24, Princeton & IAS



Universidad
del País Vasco

Euskal Herriko
Unibertsitatea

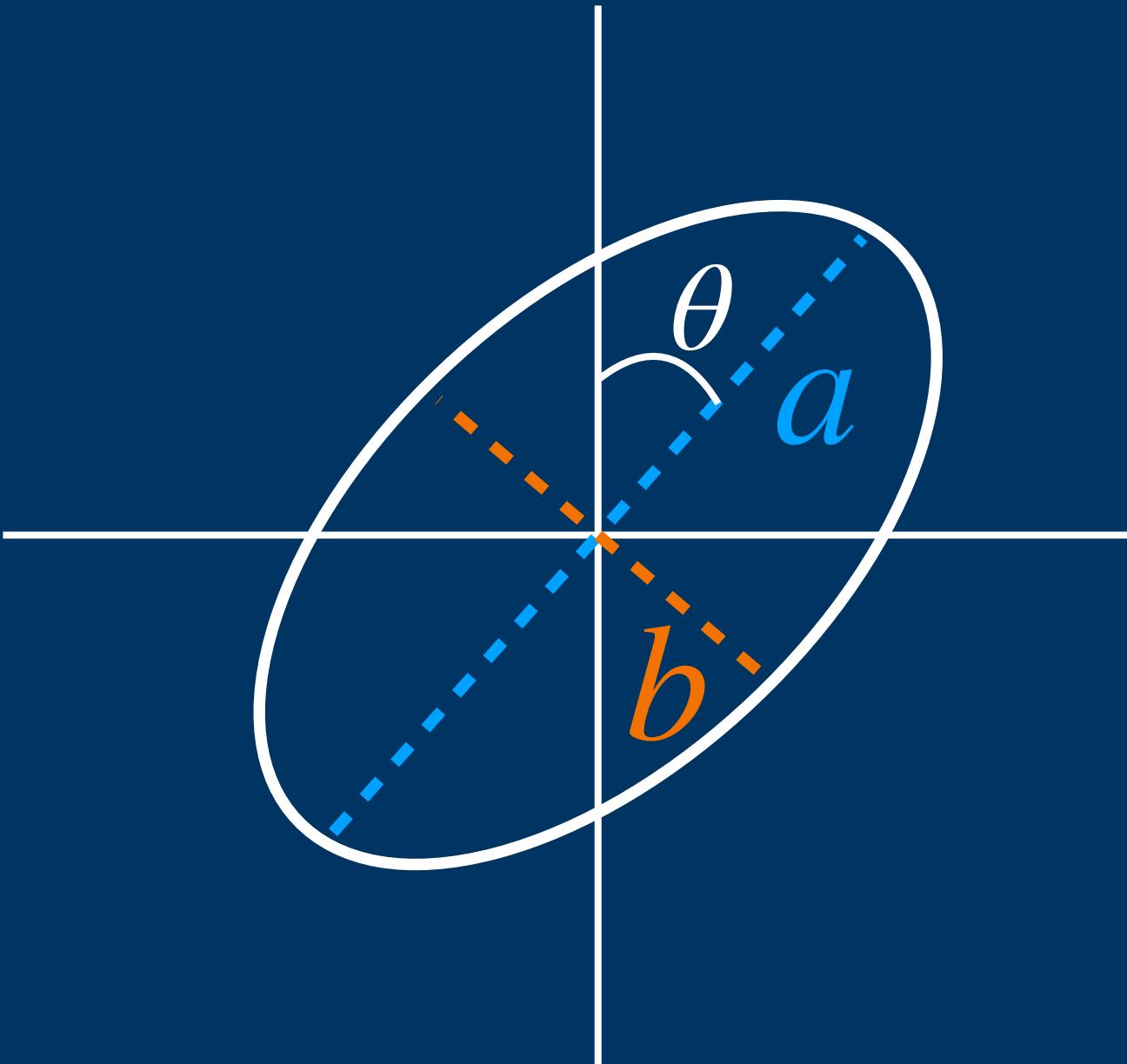


MINISTERIO
DE CIENCIA, INNOVACIÓN
Y UNIVERSIDADES

Introduction

Cosmic-Shear

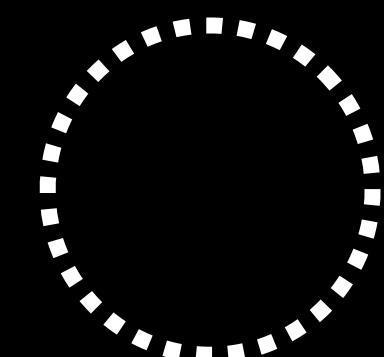
- Light travelling through the LSS gets gravitationally distorted
- Galaxy shapes will get distorted as well, or “sheared”



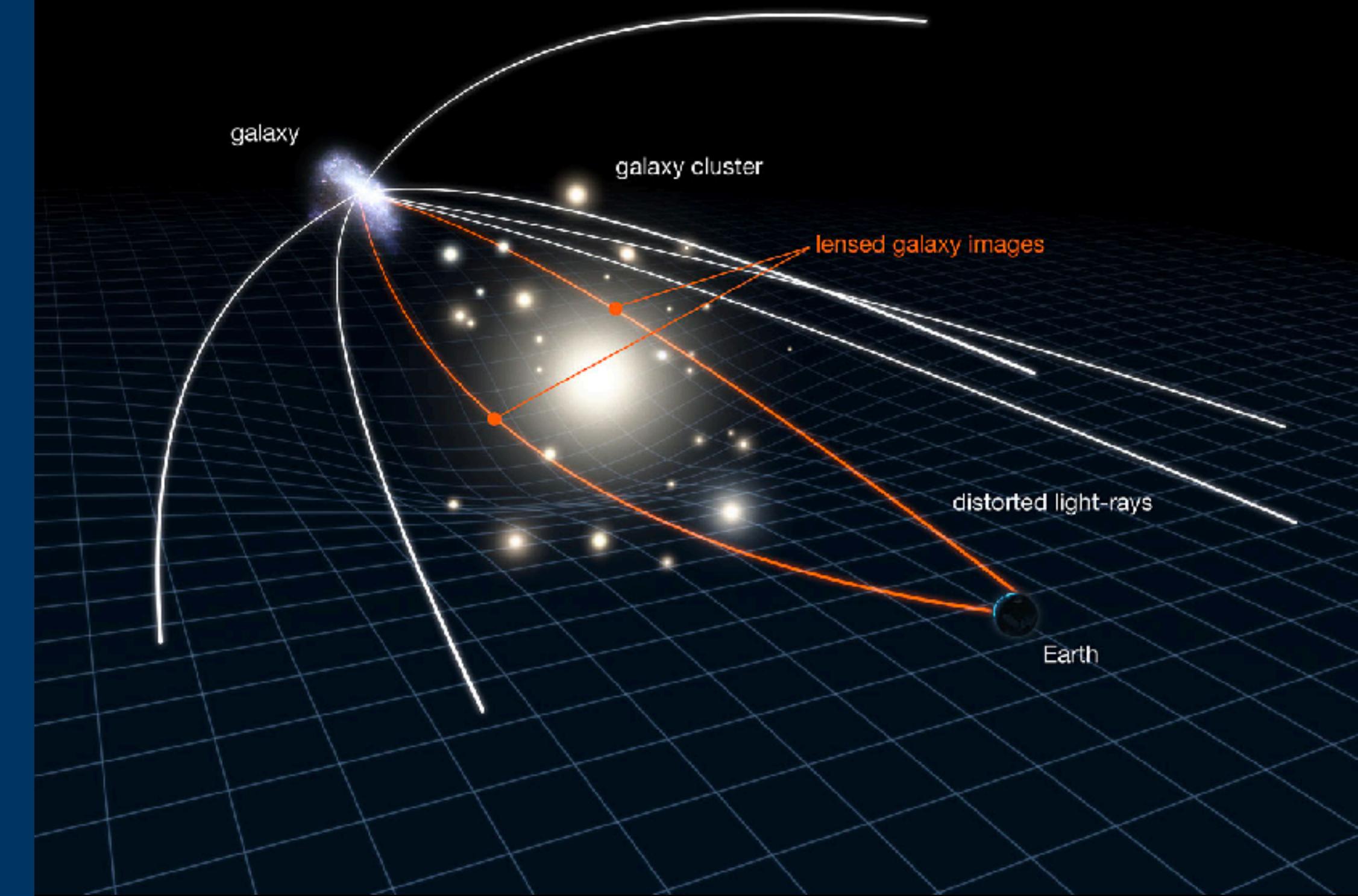
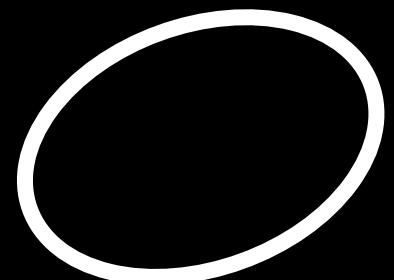
$$\varepsilon = \frac{a - b}{a + b} e^{2i\theta}$$

$$\varepsilon = \frac{\varepsilon^{(s)} + g}{1 + g * \varepsilon^{(s)}} \approx \varepsilon^{(s)} + g$$

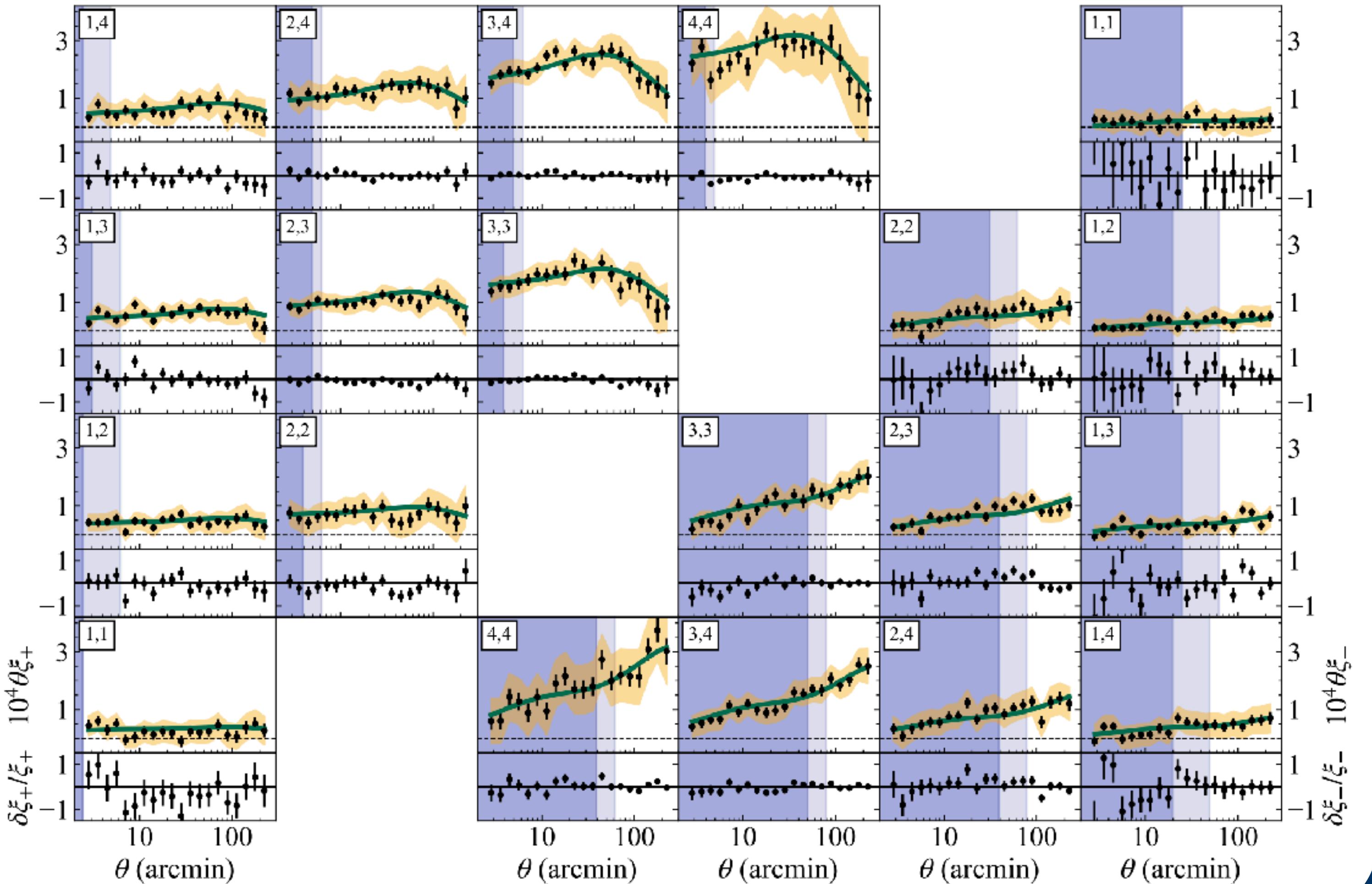
Original



Sheared



Cosmic-Shear



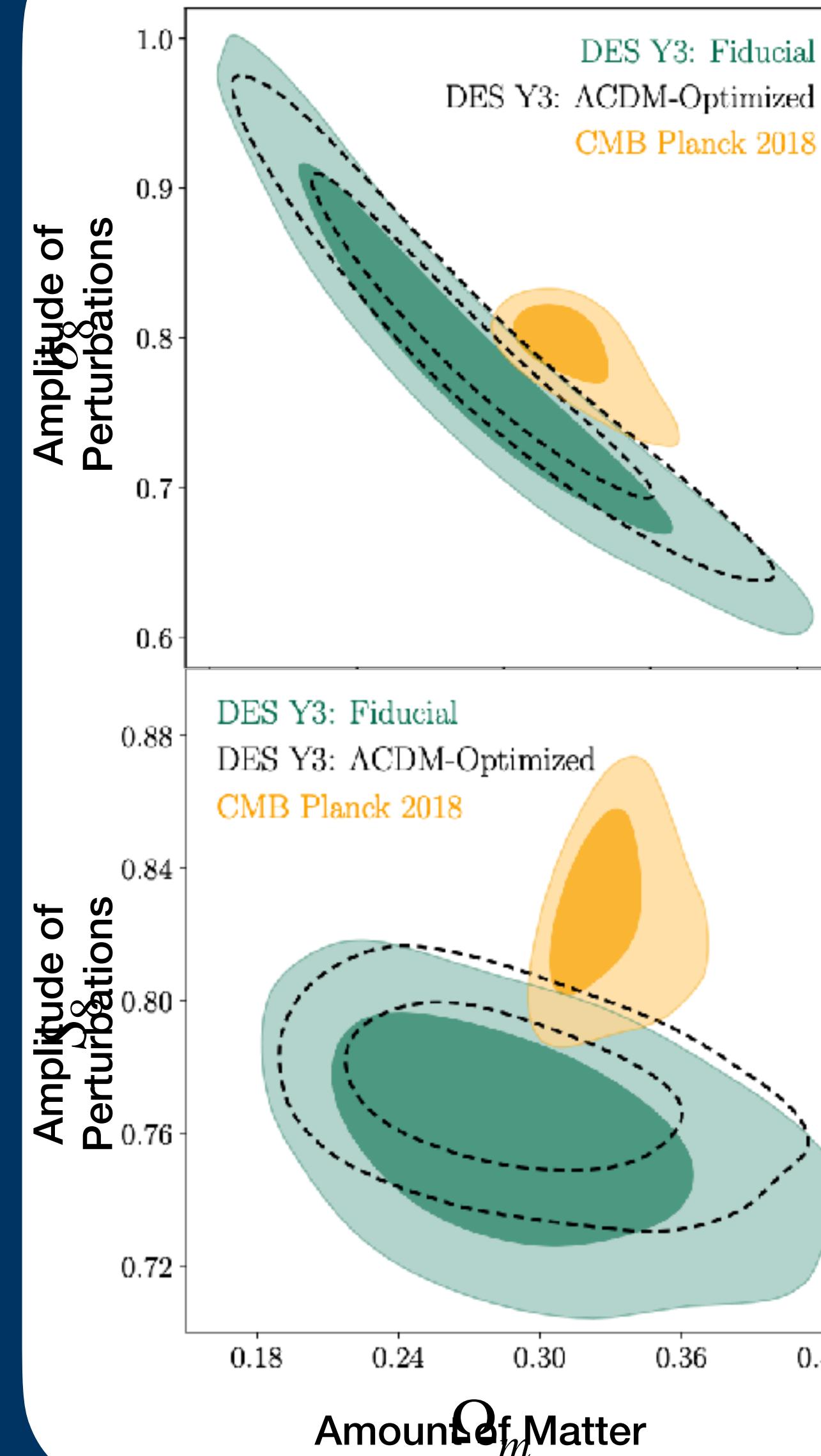
$$\xi_+^{ij} = \int_0^\infty \frac{d\ell}{2\pi} \ell J_0(\ell\theta) P_{ij}(\ell)$$

$$\xi_-^{ij} = \int_0^\infty \frac{d\ell}{2\pi} \ell J_4(\ell\theta) P_{ij}(\ell)$$

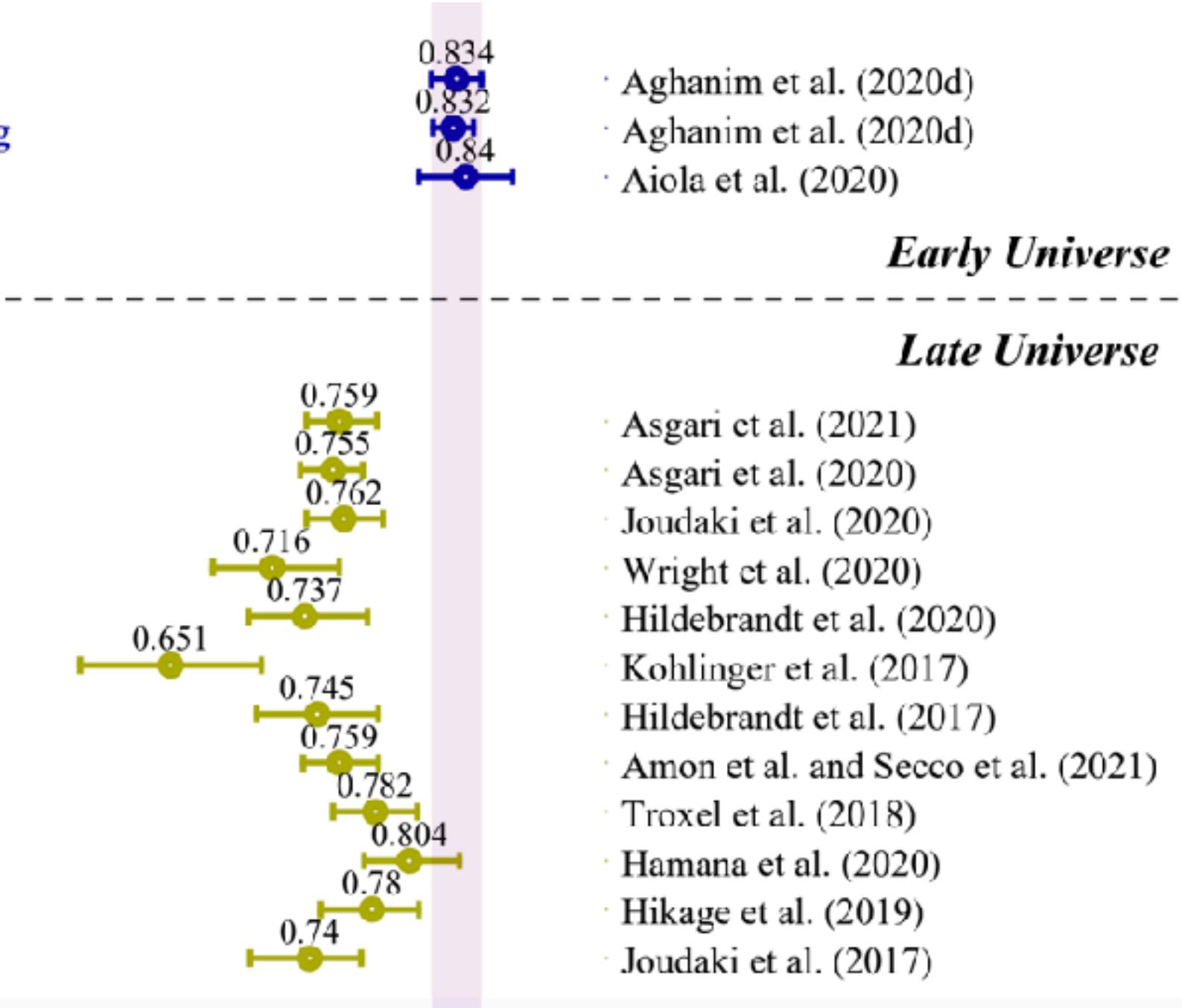
$$P_{ij}(\ell) = \int dw \frac{q_i(w)q_j(w)}{f_K^2(w)} P_\delta \left(\frac{\ell}{f_K(w)}, w \right)$$

DES-Y3

Adapted from
Amon et al (2021)
Secco & Samuroff (2021)



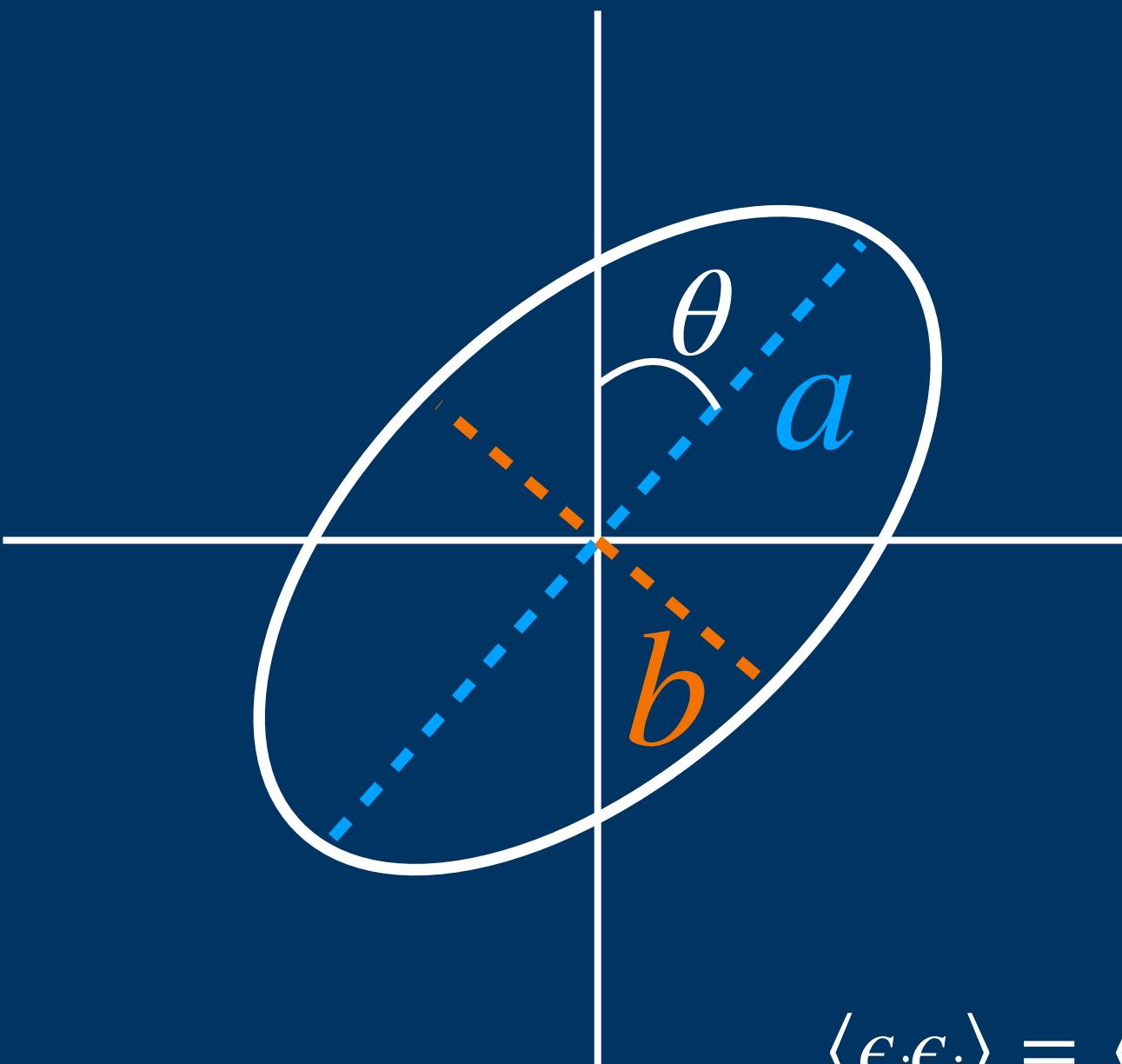
- CMB Planck TT,TE,EE+lowE
- CMB Planck TT,TE,EE+lowE+lensing
- CMB ACT+WMAP
- WL KiDS-1000
- WL KiDS+VIKING+DES-Y1
- WL KiDS+VIKING+DES-Y1
- WL KiDS+VIKING-450
- WL KiDS+VIKING-450
- WL KiDS-450
- WL KiDS-450
- WL DES-Y3
- WL DES-Y1
- WL HSC-TPCF
- WL HSC-pseudo- C_l
- WL CFHTLenS



Adapted from “Cosmology Intertwined: A Review of the Particle Physics, Astrophysics, and Cosmology Associated with the Cosmological Tensions and Anomalies”

Cosmic-Shear

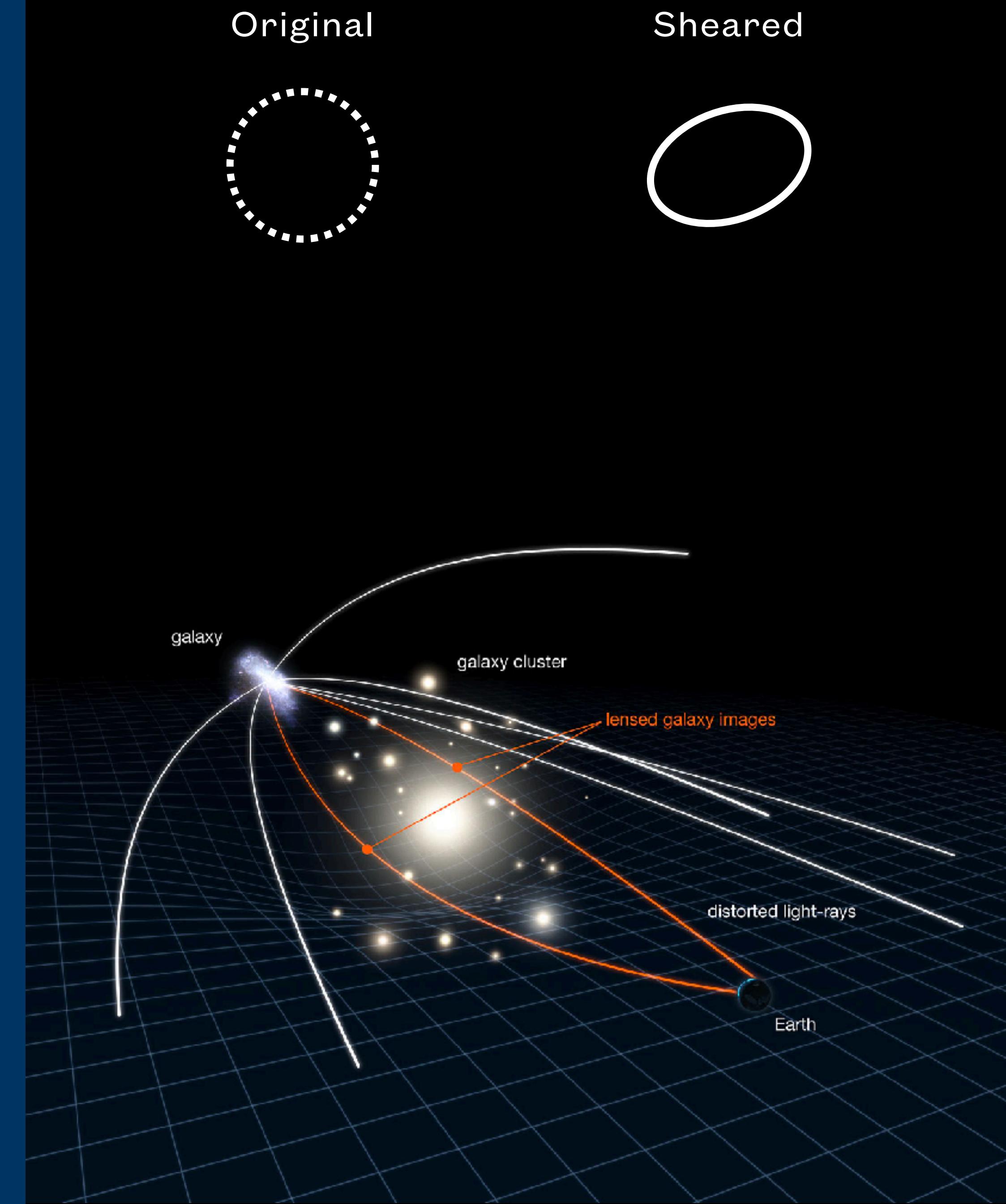
- Light travelling through the LSS gets gravitationally distorted
- Galaxy shapes will get distorted as well, or “sheared”



$$\varepsilon = \frac{a - b}{a + b} e^{2i\theta}$$

$$\varepsilon = \frac{\varepsilon^{(s)} + g}{1 + g^* \varepsilon^{(s)}} \approx \varepsilon^{(s)} + g$$

$$\langle \epsilon_i \epsilon_j \rangle = \underbrace{\langle g_i g_j \rangle}_{GG} + \underbrace{\langle \epsilon_i^{(s)} \epsilon_j^{(s)} \rangle}_{II} + \underbrace{\langle \epsilon_i^{(s)} g_j \rangle}_{IG} + \underbrace{\langle g_i \epsilon_j^{(s)} \rangle}_{GI}.$$



Intrinsic-Alignments

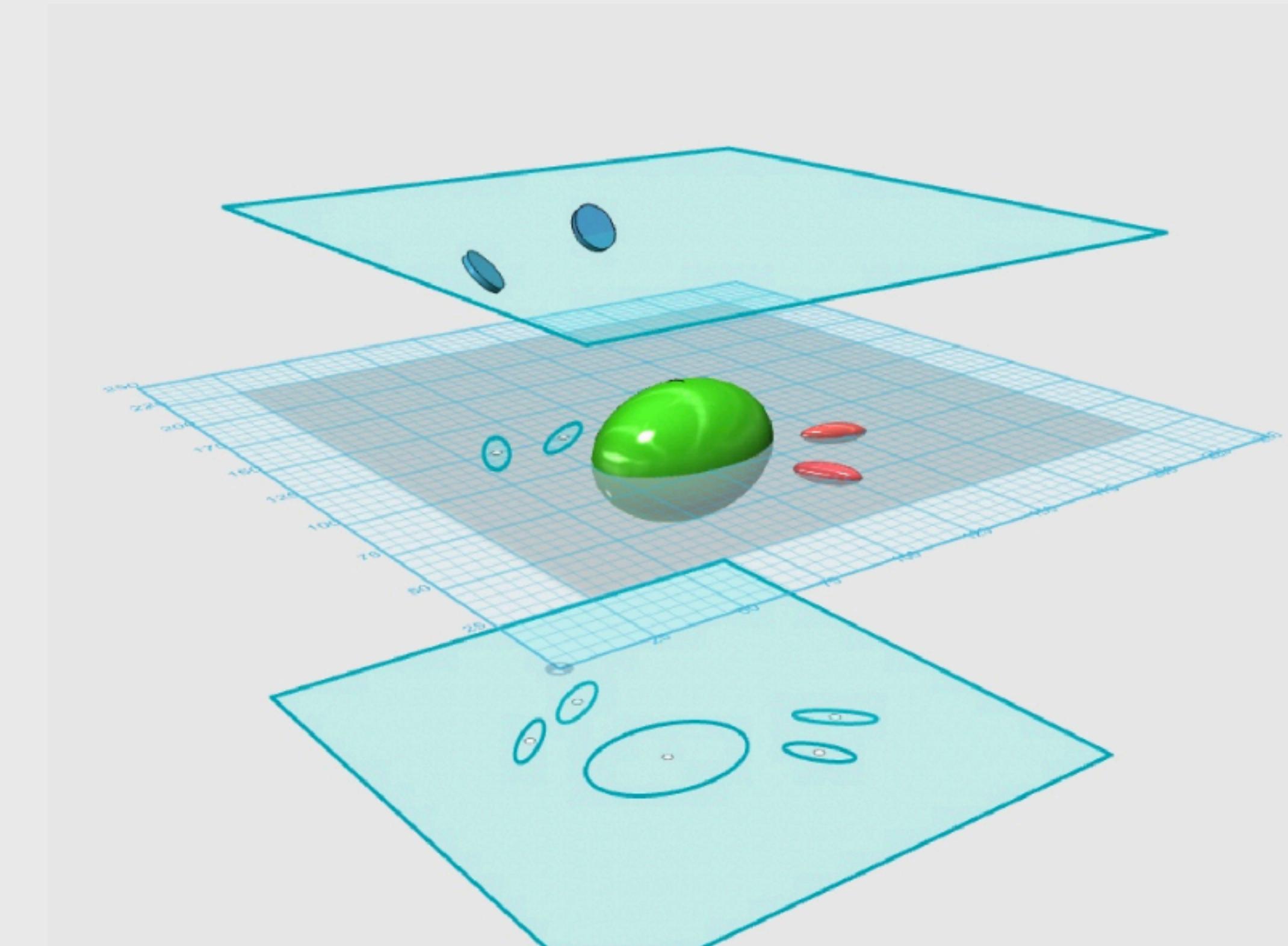
$$\langle \epsilon_i \epsilon_j \rangle = \underbrace{\langle g_i g_j \rangle}_{GG} + \underbrace{\langle \epsilon_i^{(s)} \epsilon_j^{(s)} \rangle}_{II} + \underbrace{\langle \epsilon_i^{(s)} g_j \rangle}_{IG} + \underbrace{\langle g_i \epsilon_j^{(s)} \rangle}_{GI}$$

II term: Correlations between physically close galaxies

- Positive correlation

GI term: Correlations between one foreground galaxy and one background galaxy

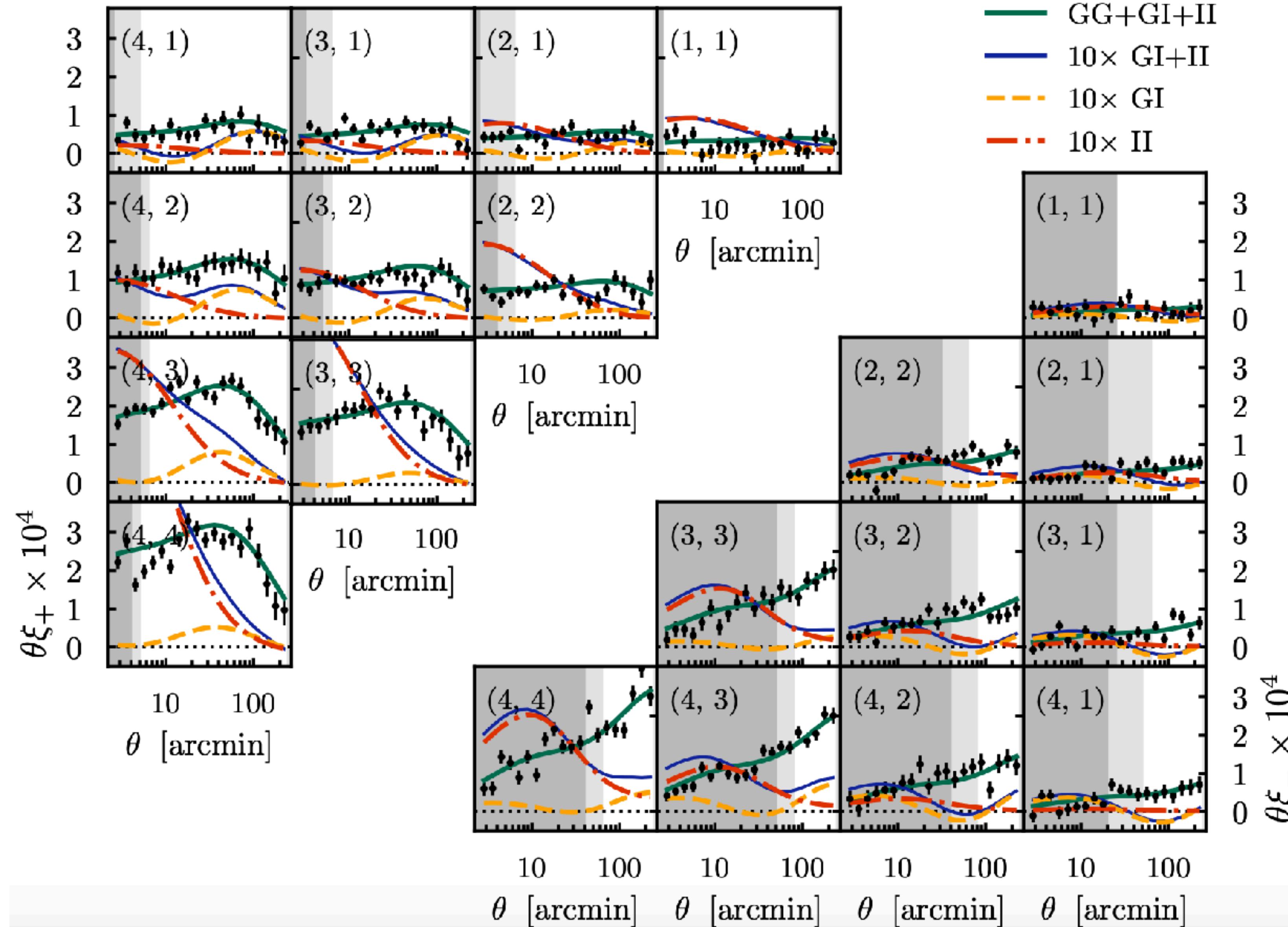
- Negative correlation



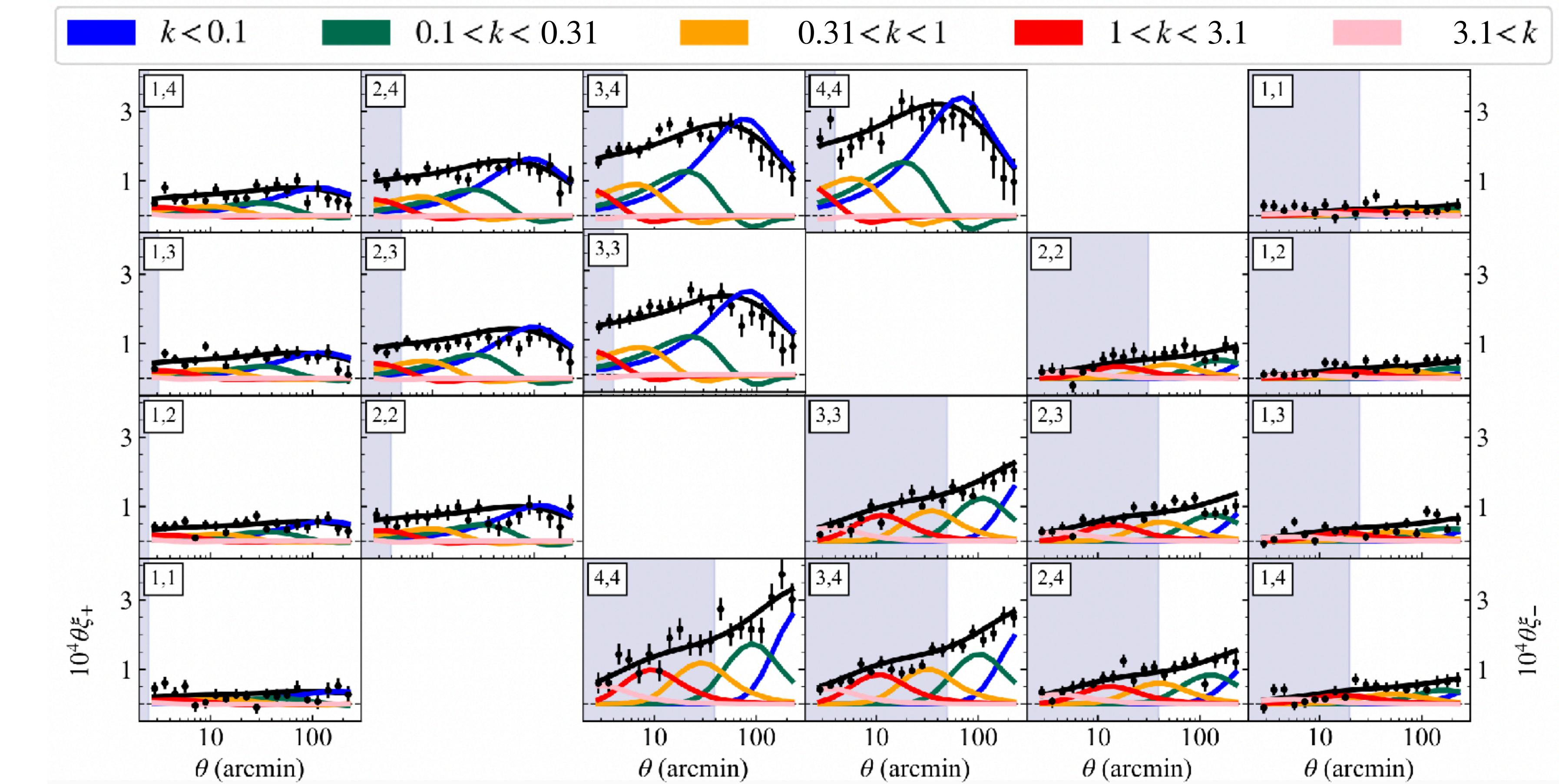
Adapted from
Joachimi et al (2015)

Intrinsic-Alignments

Adapted from
Secco & Samuroff (2021)



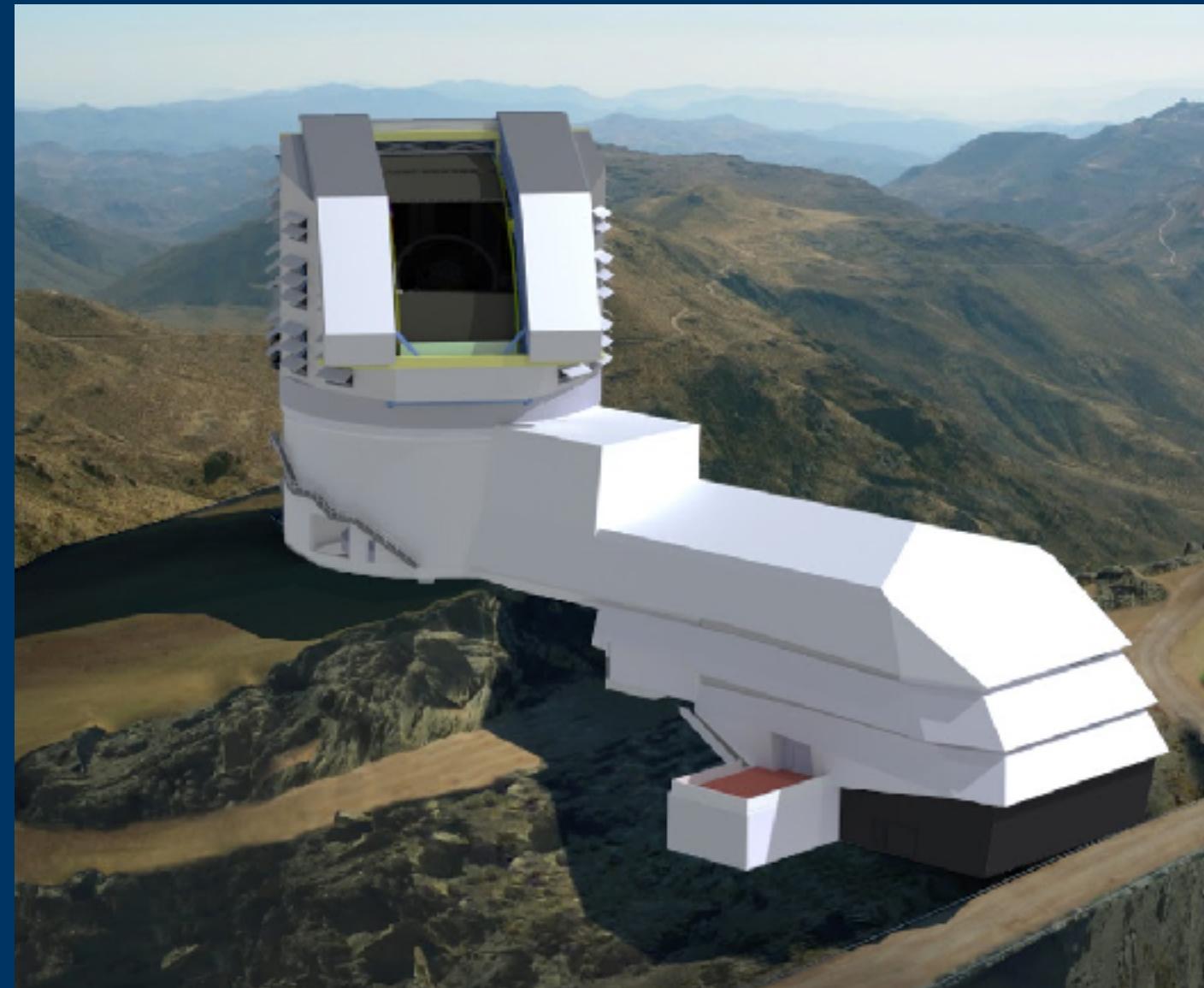
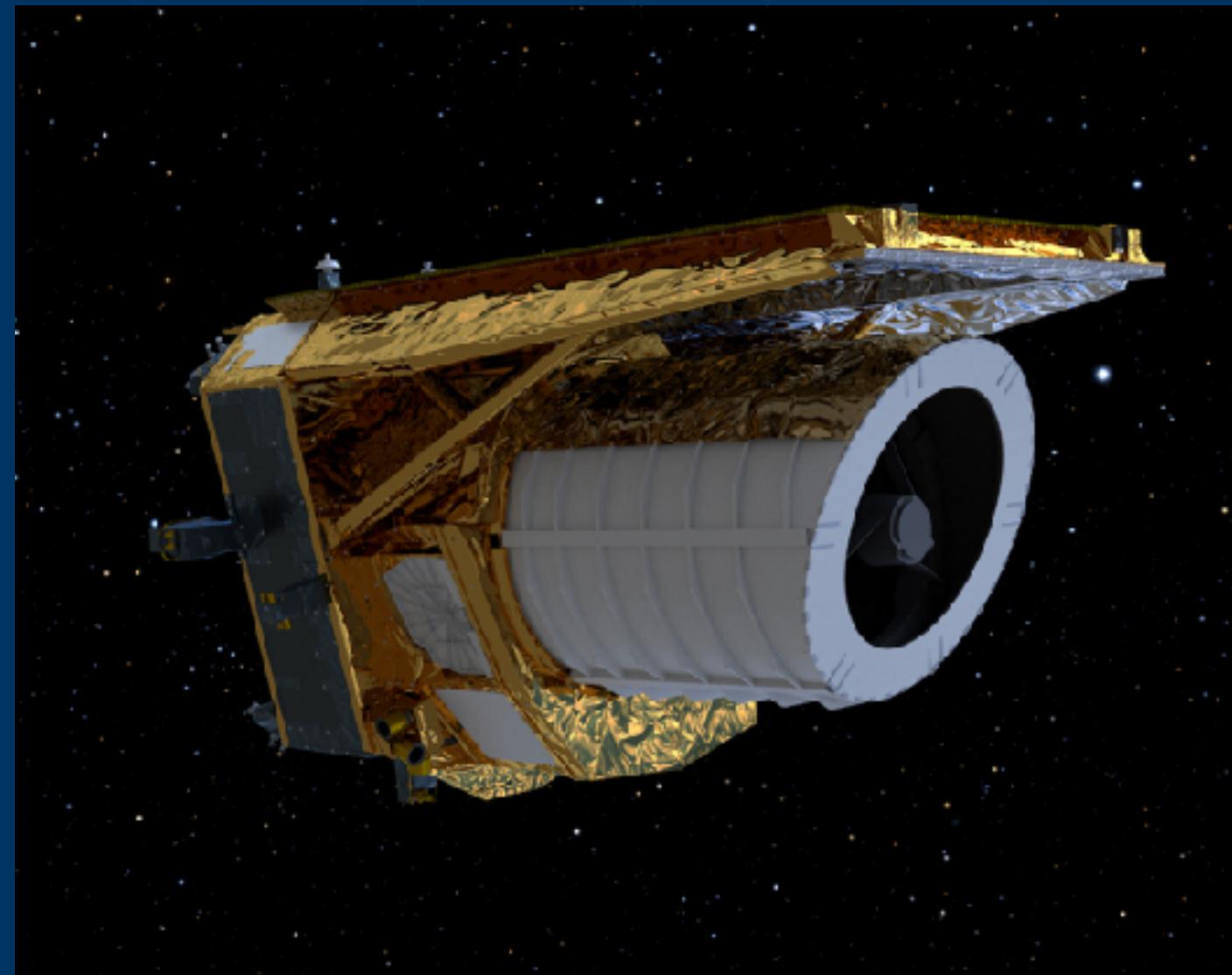
Non-Linearity



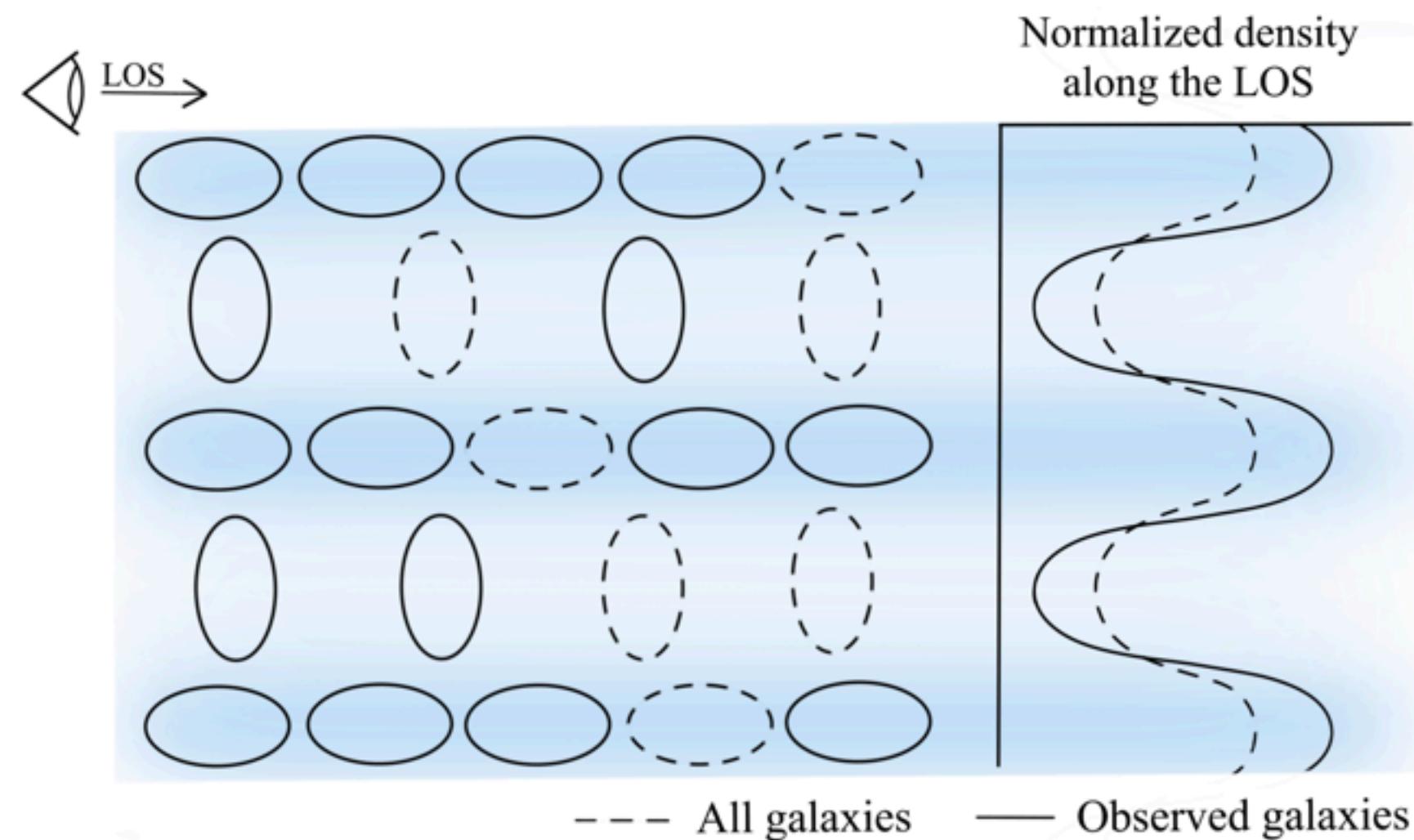
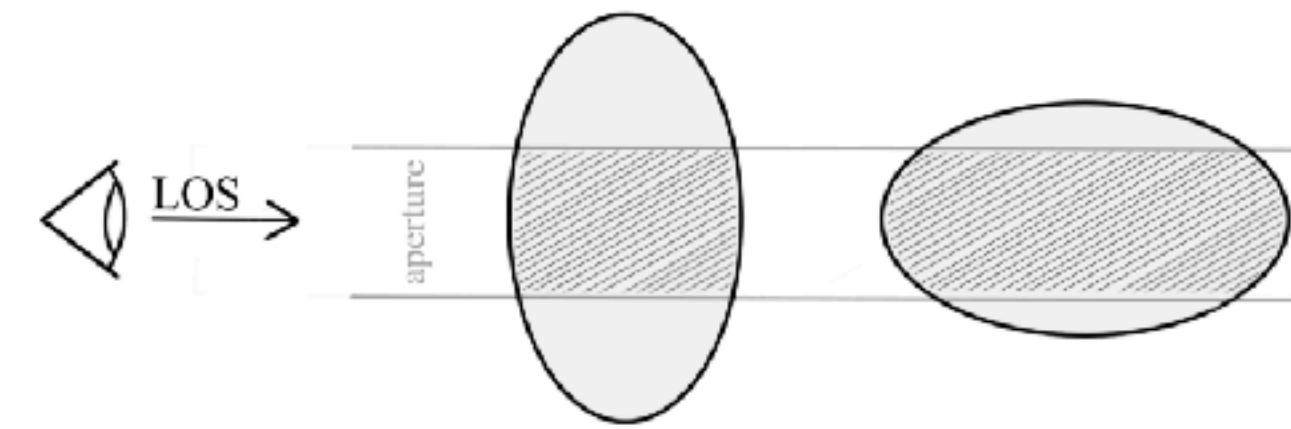
Adapted from
Preston et. al (2023)

Why Should You Care?

Adapted from
Lamman et al (2022)



Galaxy light that falls within aperture





Alignments probe cosmology

Physics	Proposed	Verified in sims	Constrained from LOWZ
Growth rate	Taruya & Okumura (2020)	X	Okumura & Taruya (2023)
Primordial (anisotropic) non-Gaussianity	Schmidt, Chisari, Dvorkin (2015)	Akitsu+ (2021)	Kurita & Takada (2023)
Primordial magnetic fields	Schmidt, Chisari, Dvorkin (2015) Saga+ (2023)	through PNG only	X
Isotropy	Shiraishi, Okumura, Akitsu (2023)	X	X
BAO	Chisari & Dvorkin (2013)	Okumura, Taruya & Nishimichi (2019)	Xu+ (2023)
Primordial gravitational waves	Schmidt, Pajer, Zaldarriaga (2014) Chisari, Dvorkin, Schmidt (2014)	Akitsu, Li & Okumura (2023)	X
Parity breaking	Biagetti & Orlando (2020)	X	X



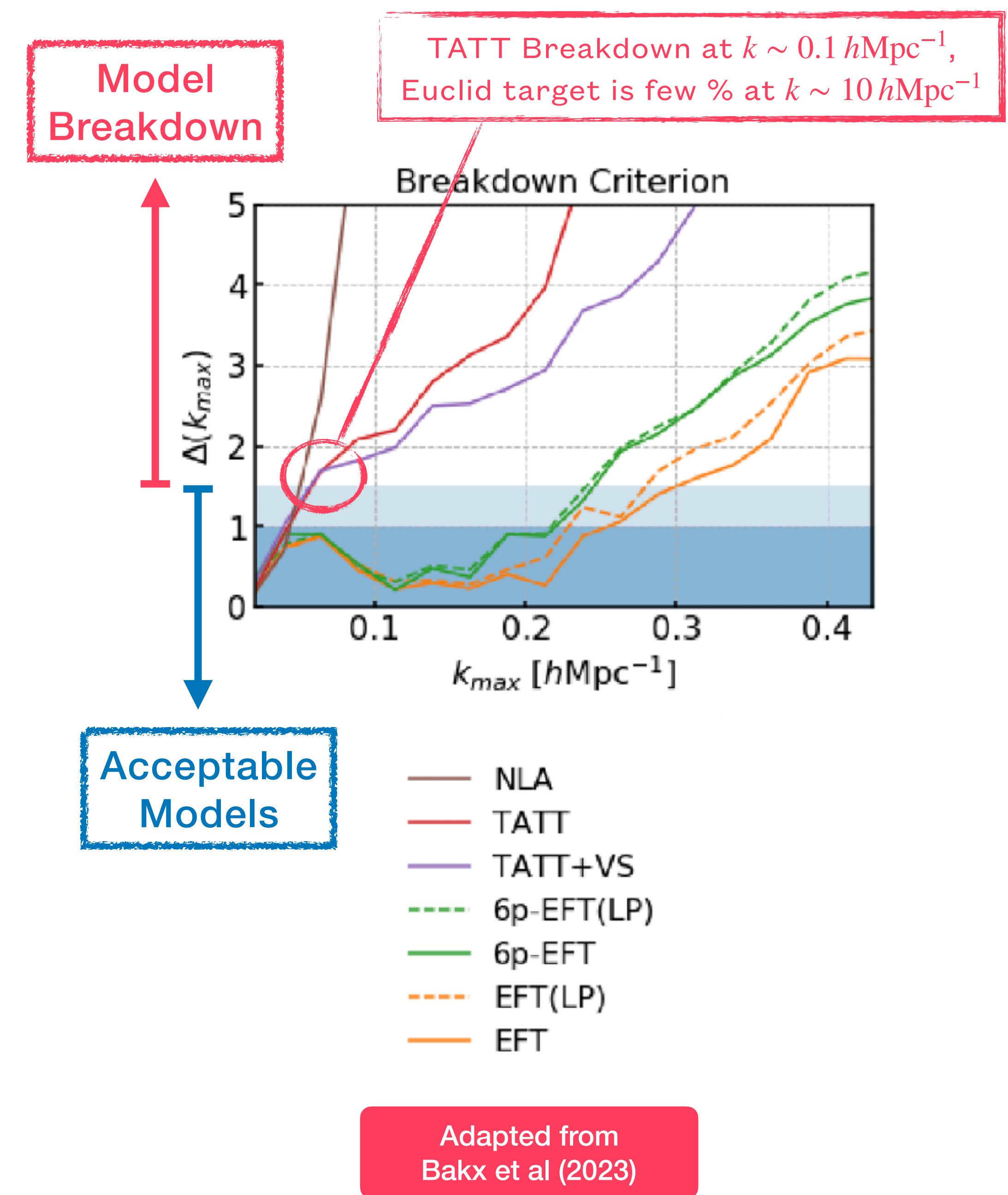
Non-Linearity

To lowest order, the intrinsic shear of the galaxy shapes will be linearly related to the matter tidal field

$$\gamma^I = c_s s_{ij} = c_s \left(\partial_x^2 - \partial_y^2, 2\partial_x\partial_y \right) \nabla^{-2} \delta$$

Breaks down quickly at small scales.

EFTofIA can reach $k_{max} = 0.28 h/\text{Mpc}$ at the expense of adding many free parameters



Simulation-Based Modelling

Variance-Reduced Initial Conditions

(Maion et. al 2022)
(Giri, Schneider, Maion, Angulo,
2023)

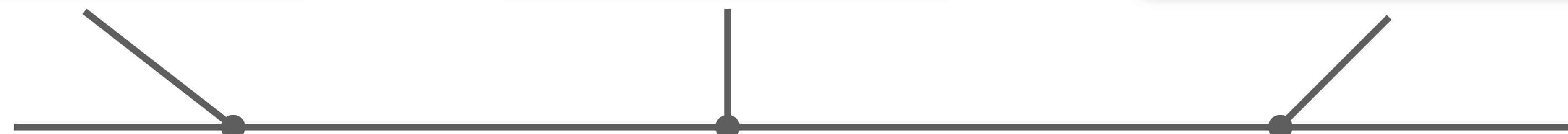
Simulation-Based Models for IA and GC

(Maion et. al 2024)
(Pellejero-Ibáñez, ... , Maion
2023)

Priors on Bias Parameters

(Zennaro, ..., Maion, 2022)

N-Body
Simulations



Cosmological
Inference

Hydrodynamical
Simulations

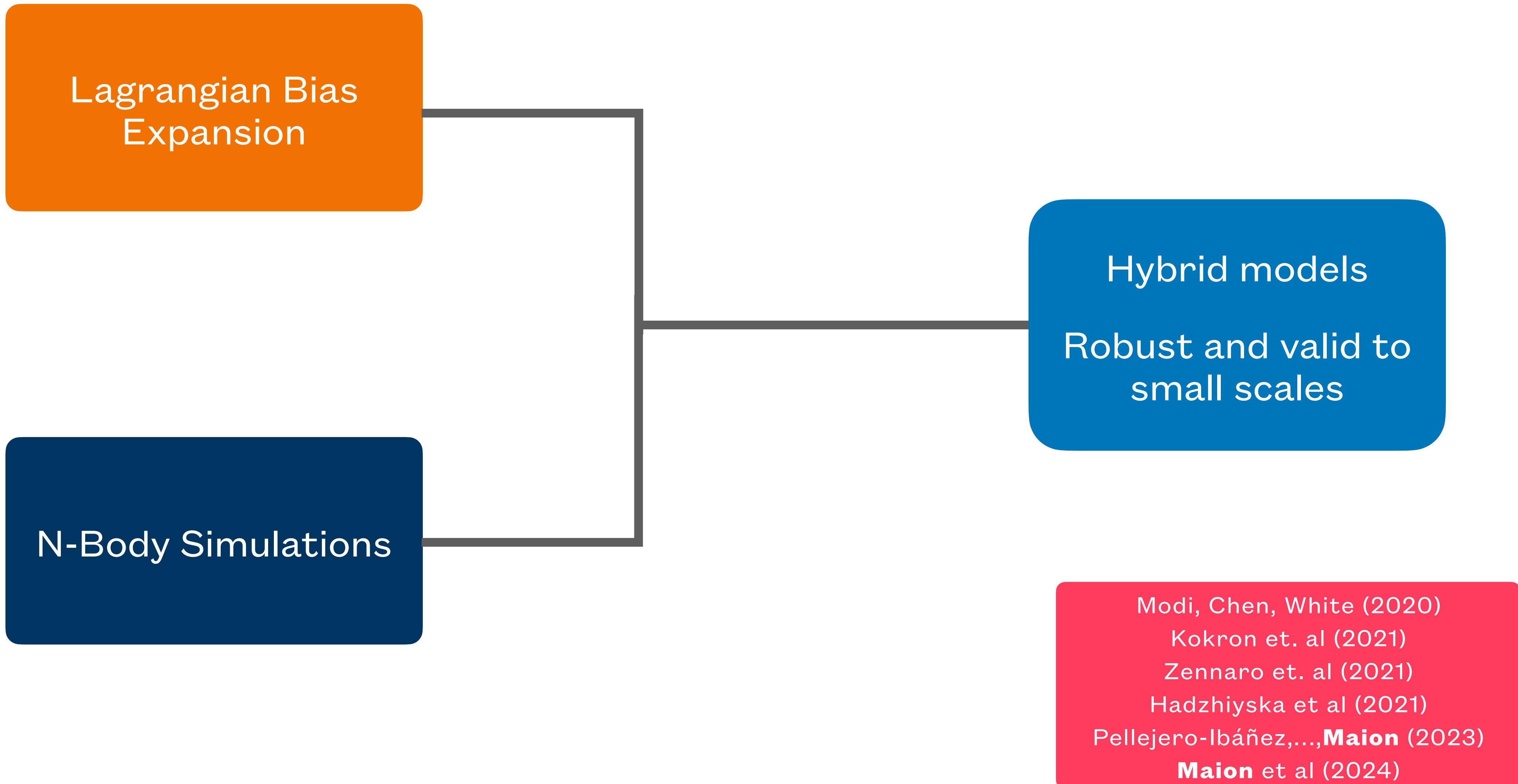
Fast and Flexible Bias Estimators

(Maion et. al 2024)
(Stucker, Pellejero-Ibáñez, Angulo,
Maion, Voivodic, 2024)

Physical Origins
of IA

Hybrid Lagrangian Models

Hybrid Lagrangian Models

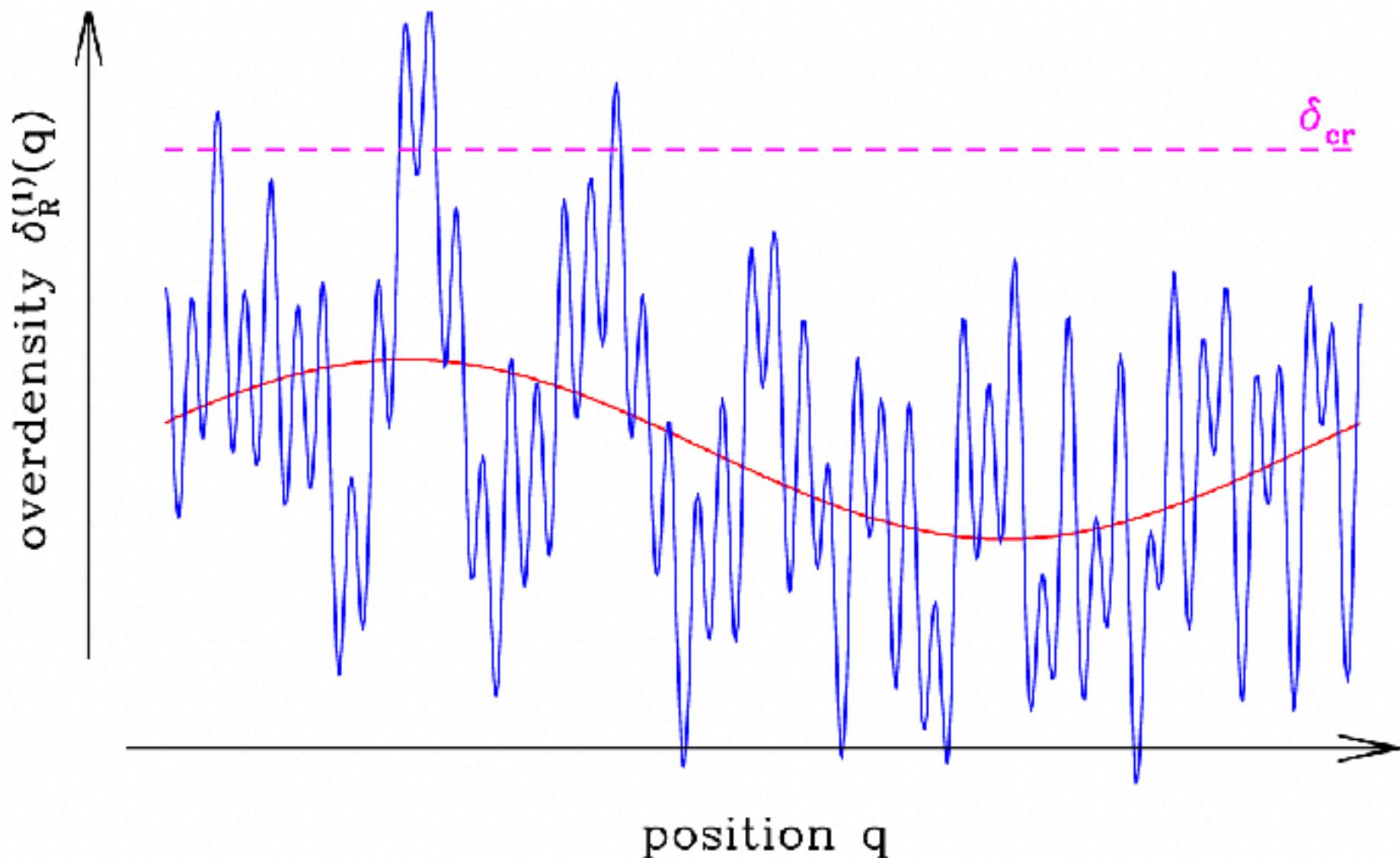


Bias Expansion

Symmetries and Physical Principles:

- Equivalence Principle (only $\partial^{2n}\Phi$ contributions allowed)
- Statistical Homogeneity
- Statistical Isotropy
- Scalar under rotations

Adapted from
Desjacques et. al (2016)



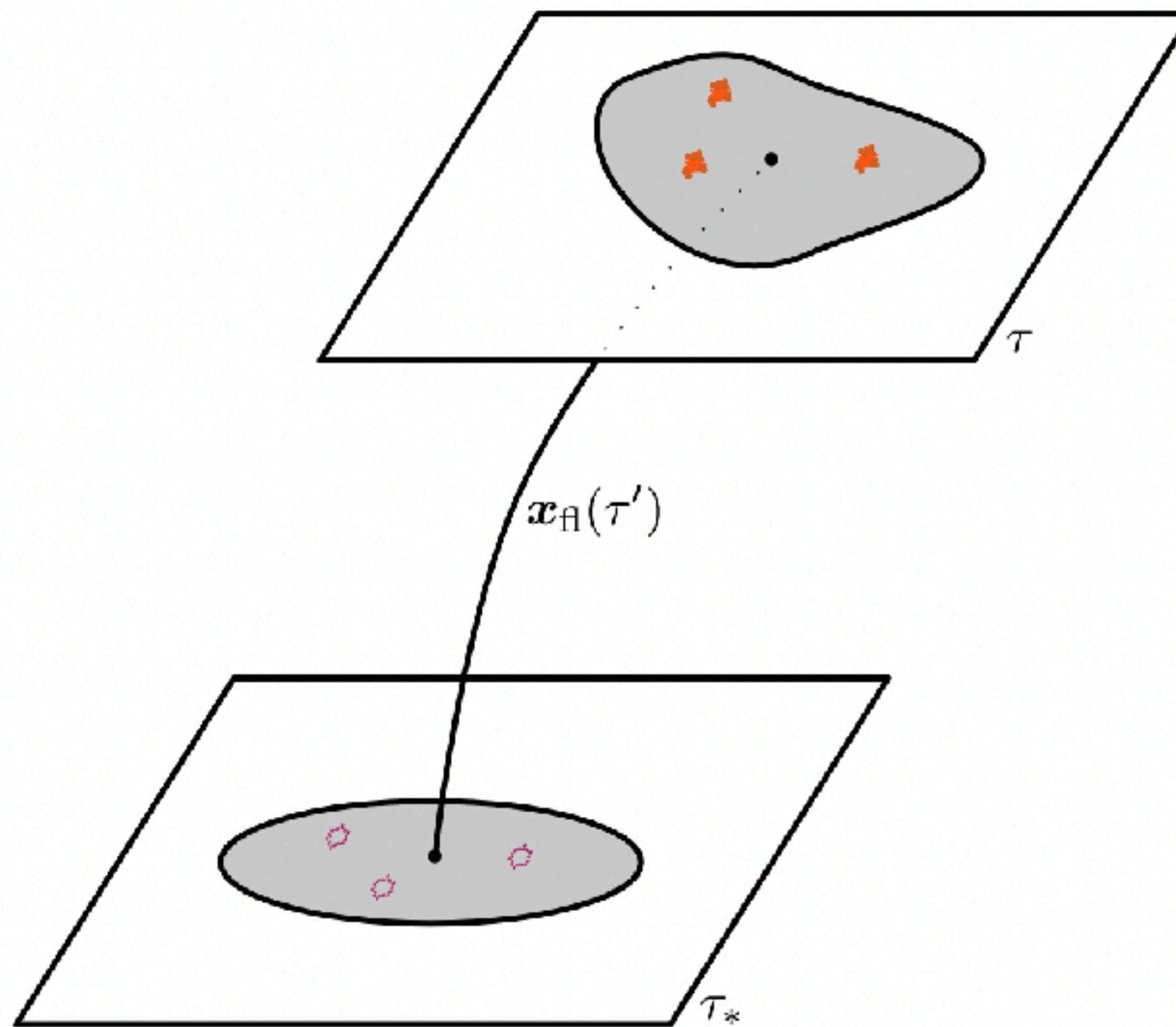
Density:
$$\begin{cases} \text{1st order} & : \delta \\ \text{2nd order} & : \delta^2, s^2 \\ \text{Non-local} & : \nabla^2 \delta \\ \text{Stochastic} & : \varepsilon \end{cases}$$

$$\delta_g = b_1 \delta + b_2 \delta^2 + b_s s^2 + b_{\nabla^2} \nabla^2 \delta + \varepsilon$$

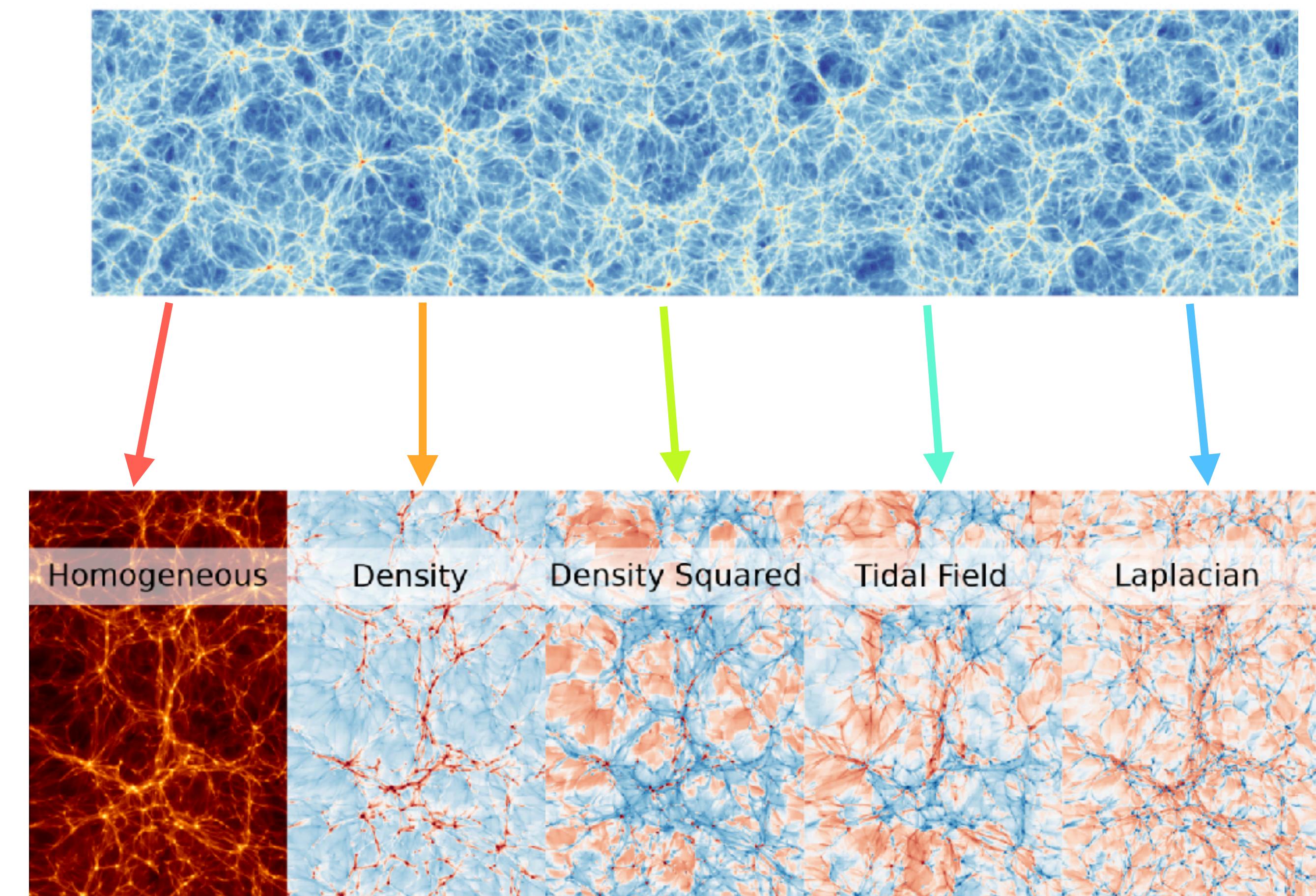
Correlations are setup very early in the universe

Advection

The modelled galaxy field must be advected from Lagrangian to Eulerian space



$$1 + \delta_g = 1 + b_1 \delta + b_2 \delta^2 + b_{s^2} s^2 + b_{\nabla^2} \nabla^2 \delta + \varepsilon$$



Shape Bias-Expansion

Symmetries and Physical Principles:

- Equivalence Principle (only $\partial^{2n}\Phi$ contributions allowed)
- Statistical Homogeneity
- Statistical Isotropy
- Rank-2 tensor under rotations

$$g_{ij} = c_s s_{ij} + c_{s\delta} \delta s_{ij} + c_{s\otimes s} (s \otimes s)_{ij} + c_t t_{ij} + c_{\nabla^2} \nabla^2 s_{ij} + \varepsilon_{ij}$$

Shapes:

$$\begin{cases} \text{1st order} & : s_{ij} \\ \text{2nd order} & : (s \otimes s)_{ij}, \delta s_{ij}, t_{ij} \\ \text{Non-local} & : \nabla^2 s_{ij} \\ \text{Stochastic} & : \varepsilon_{ij} \end{cases}$$

$$(s \otimes s)_{ij} = \left(s_{il} s_{lj} - \delta_{ij}^K \frac{s^2}{3} \right)$$

$$t_{ij} = \left(\frac{\partial_i \partial_j}{\nabla^2} - \frac{1}{3} \delta_{ij}^K \right) (\theta(\mathbf{x}) - \delta(\mathbf{x}))$$

HYMALAIA

Monthly Notices
of the
ROYAL ASTRONOMICAL SOCIETY

MNRAS 531, 2684–2700 (2024)
Advance Access publication 2024 May 23



<https://doi.org/10.1093/mnras/stae1331>

HYMALAIA: a hybrid lagrangian model for intrinsic alignments

Francisco Maion   ^{1,2}★ Raul E. Angulo  ^{1,3} Thomas Bakx ⁴ Nora Elisa Chisari  ⁴ Toshiki Kurita  ⁵ and Marcos Pellejero-Ibáñez 

¹*Donostia International Physics Center, Manuel Lardizabal Ibilbidea, 4, E-20018 Donostia-San Sebastián, Gipuzkoa, Spain*

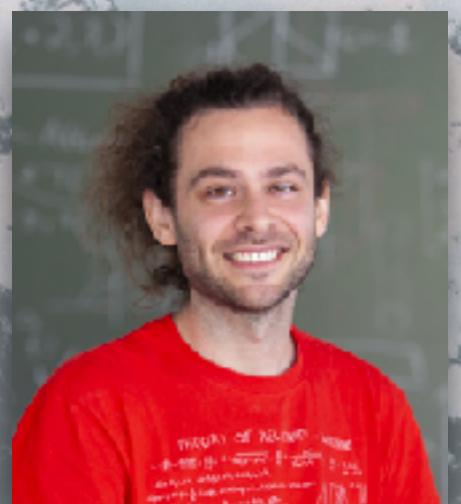
²*Euskal Herriko Unibertsitatea, Edificio Ignacio María Barriola, Plaza Elhuyar, 1, E- 20018 Donostia-San Sebastián, Gipuzkoa, Spain*

³*IKERBASQUE, Basque Foundation for Science, E-48013 Bilbao, Bizkaya, Spain*

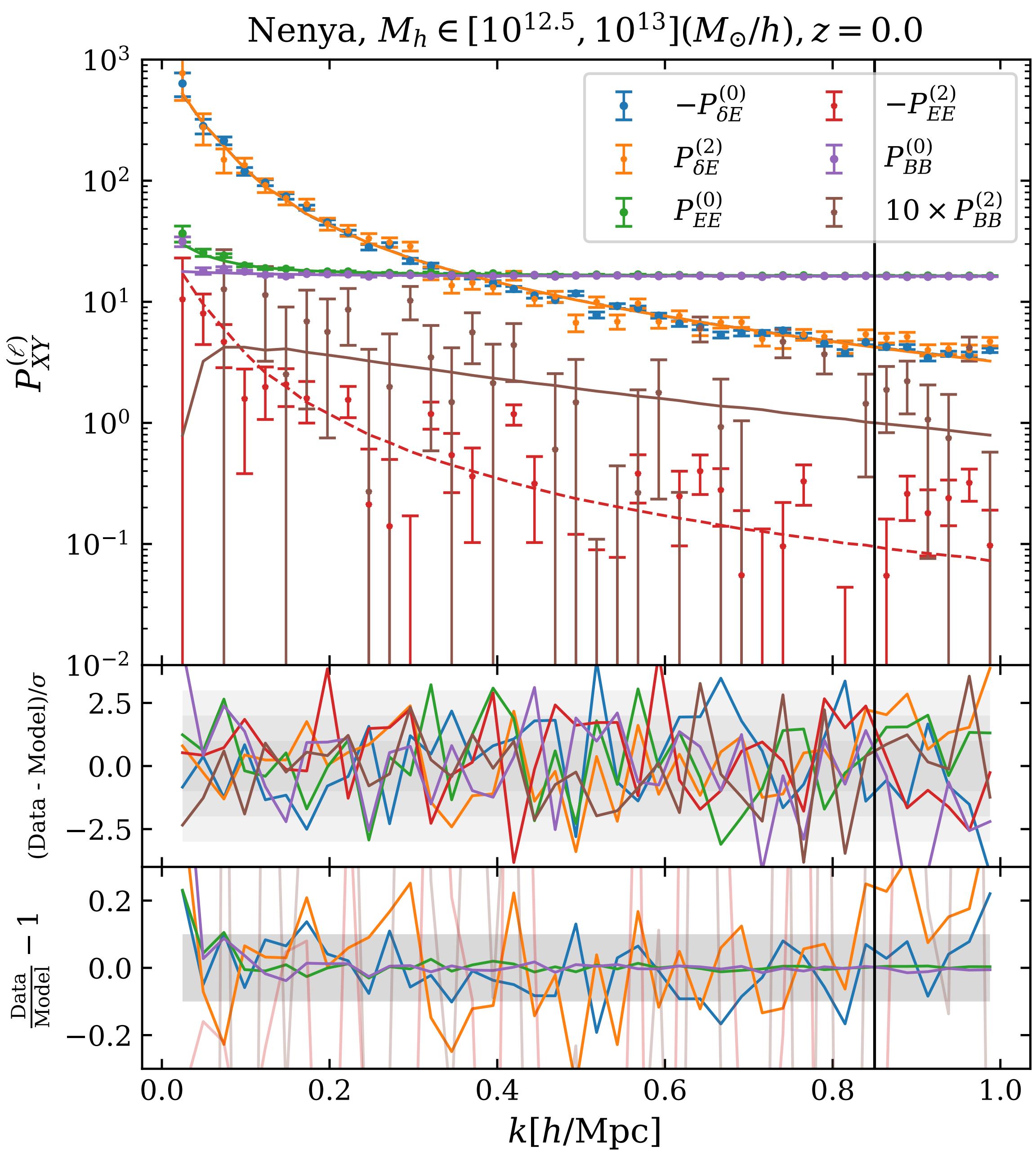
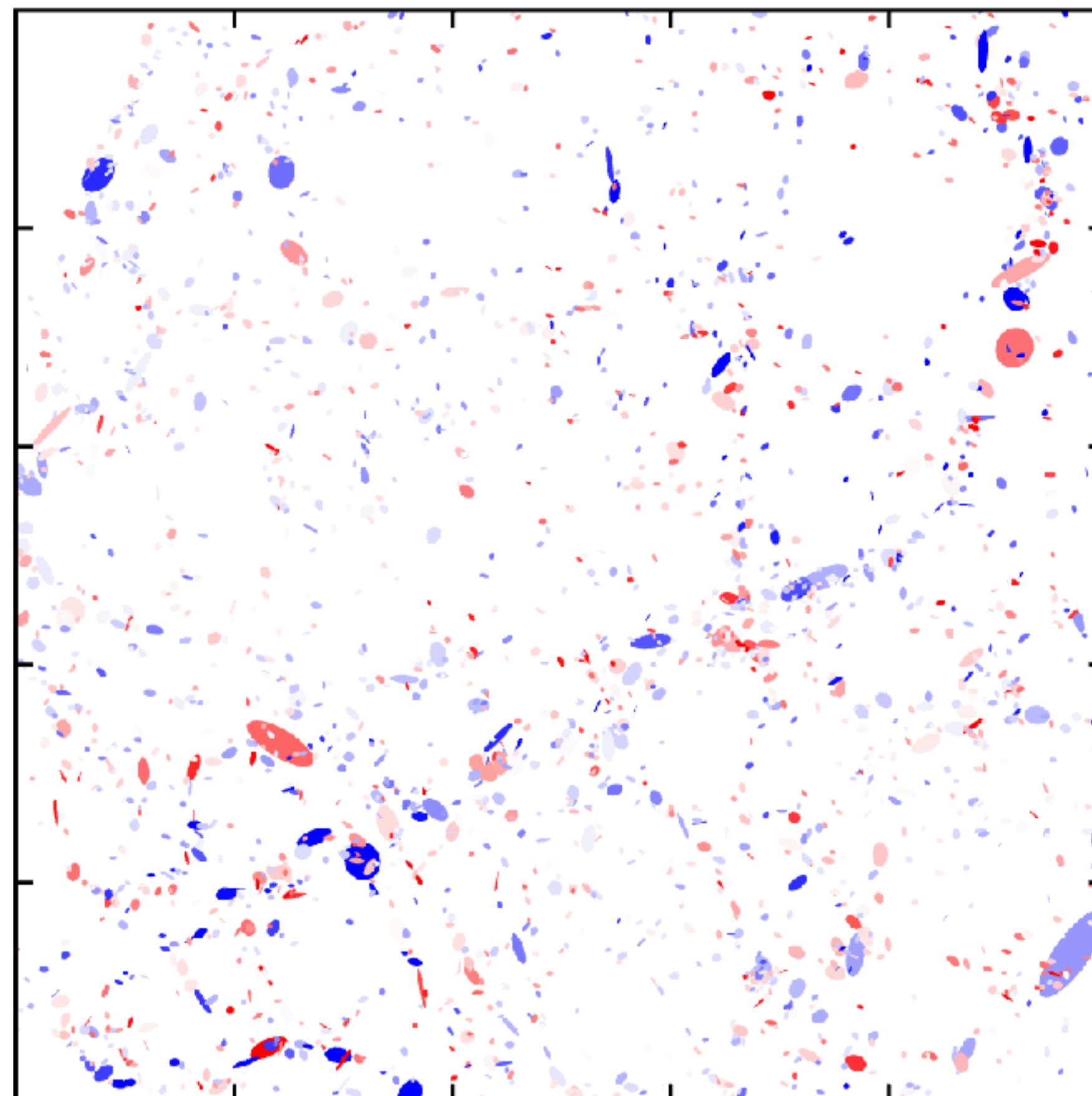
⁴*Institute for Theoretical Physics, Utrecht University, Princetonplein 5, NL-3584 CC Utrecht, the Netherlands*

⁵*Kavli Institute for the Physics and Mathematics of the Universe (WPI), The University of Tokyo Institutes for Advanced Study (UTIAS), The University of Tokyo, Chiba 277-8583, Japan*

Accepted 2024 May 21. Received 2024 May 21; in original form 2023 August 1



HYMALAIA



Model Validation

To evaluate the performance of the model we will use the reduced chi-squared,

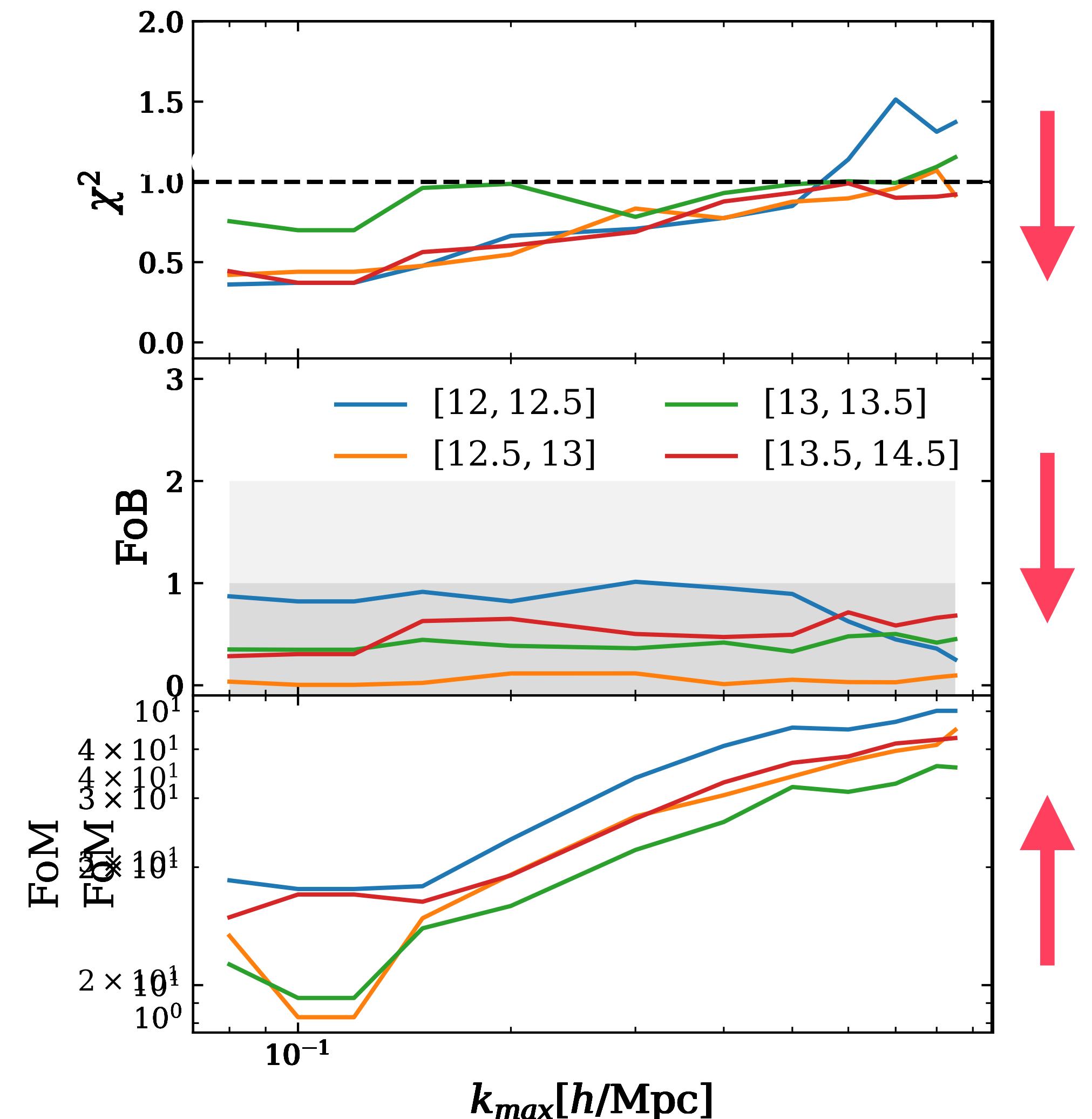
$$\chi^2_{\text{red}} = \frac{1}{N_{\text{dof}}} \sum_{\ell, \ell'=0,2} \sum_{\alpha, \beta} \sum_{i,j} \left(P_{\alpha}^{(\ell)}(k_i, \Theta) - \widehat{P}_{\alpha}^{(\ell)}(k_i) \right) \left[C_{\alpha, \beta}^{\ell, \ell'} \right]_{ij}^{-1} \left(P_{\beta}^{(\ell')}(k_j, \Theta) - \widehat{P}_{\beta}^{(\ell')}(k_j) \right)$$

the Figure of Bias, defined as

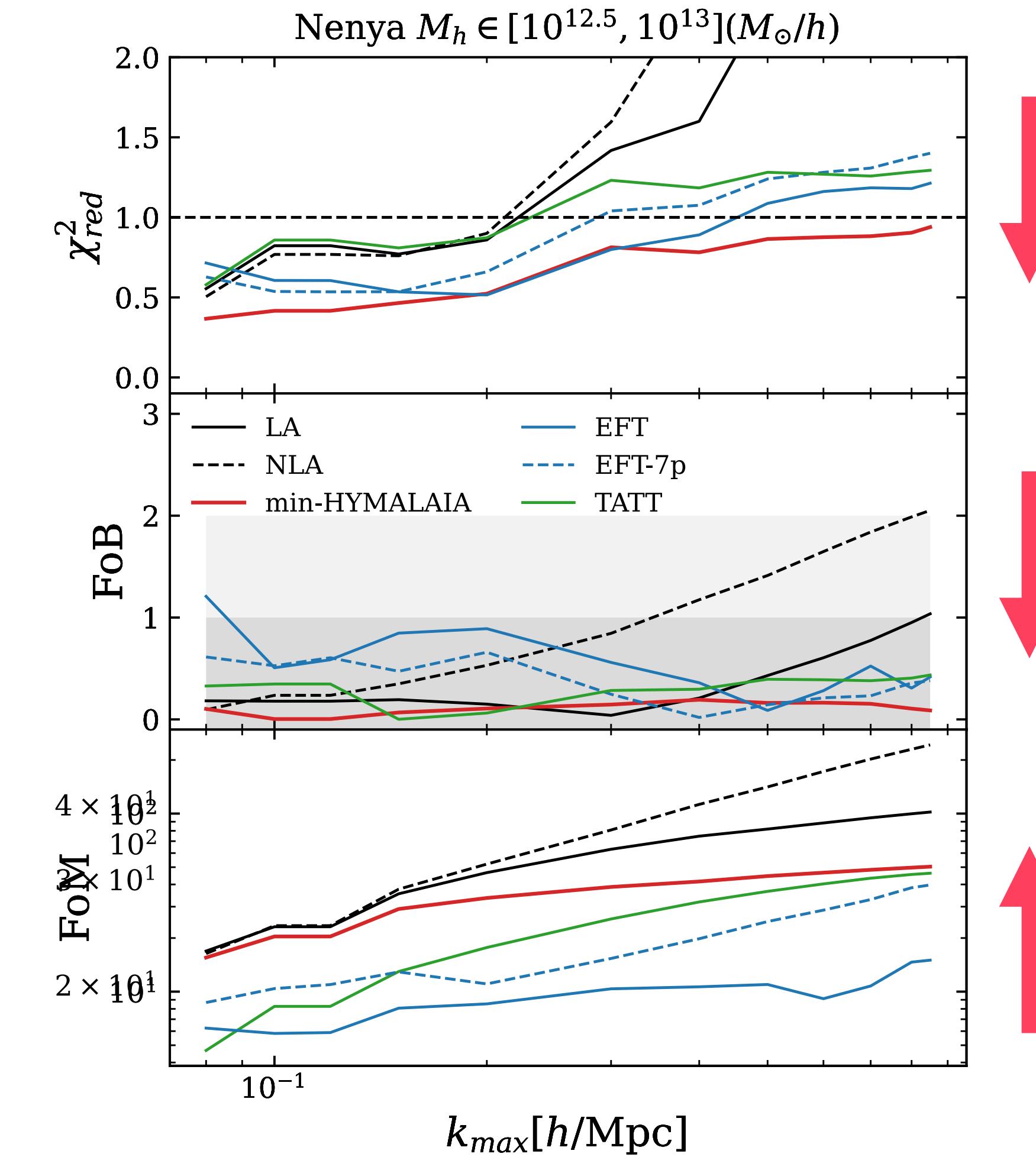
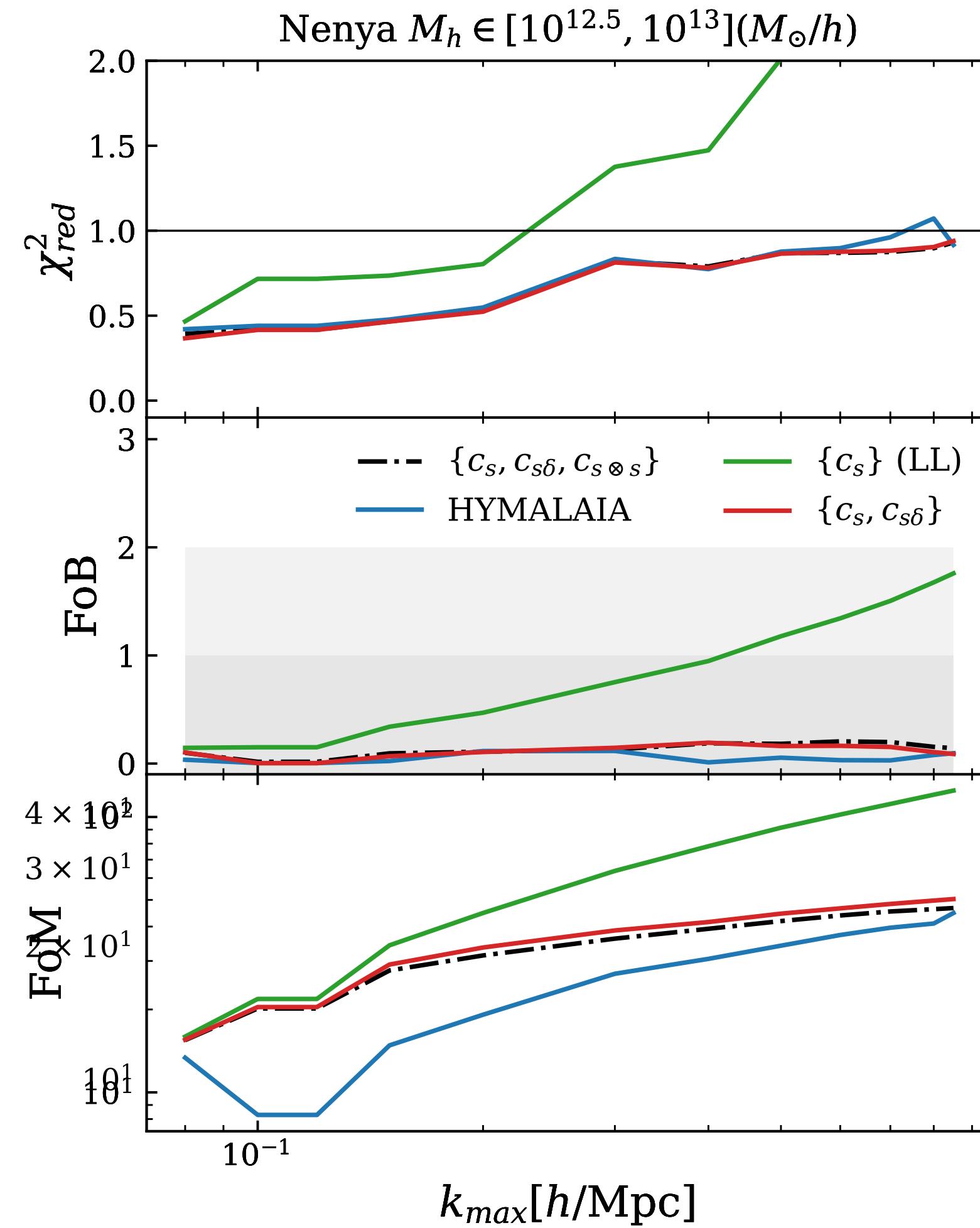
$$\text{FoB}(k_{\max}) = \frac{|c_s^{\text{fid}} - c_s(k_{\max})|}{\sqrt{\sigma_{\text{fid}}^2 + \sigma_{c_s}^2(k_{\max})}}$$

and the Figure of Merit, given by

$$\text{FoM} = \sqrt{\det \left[\frac{\Theta_{\alpha\beta}}{\theta_{\alpha}^{\text{fid}} \theta_{\beta}^{\text{fid}}} \right]^{-1}}$$

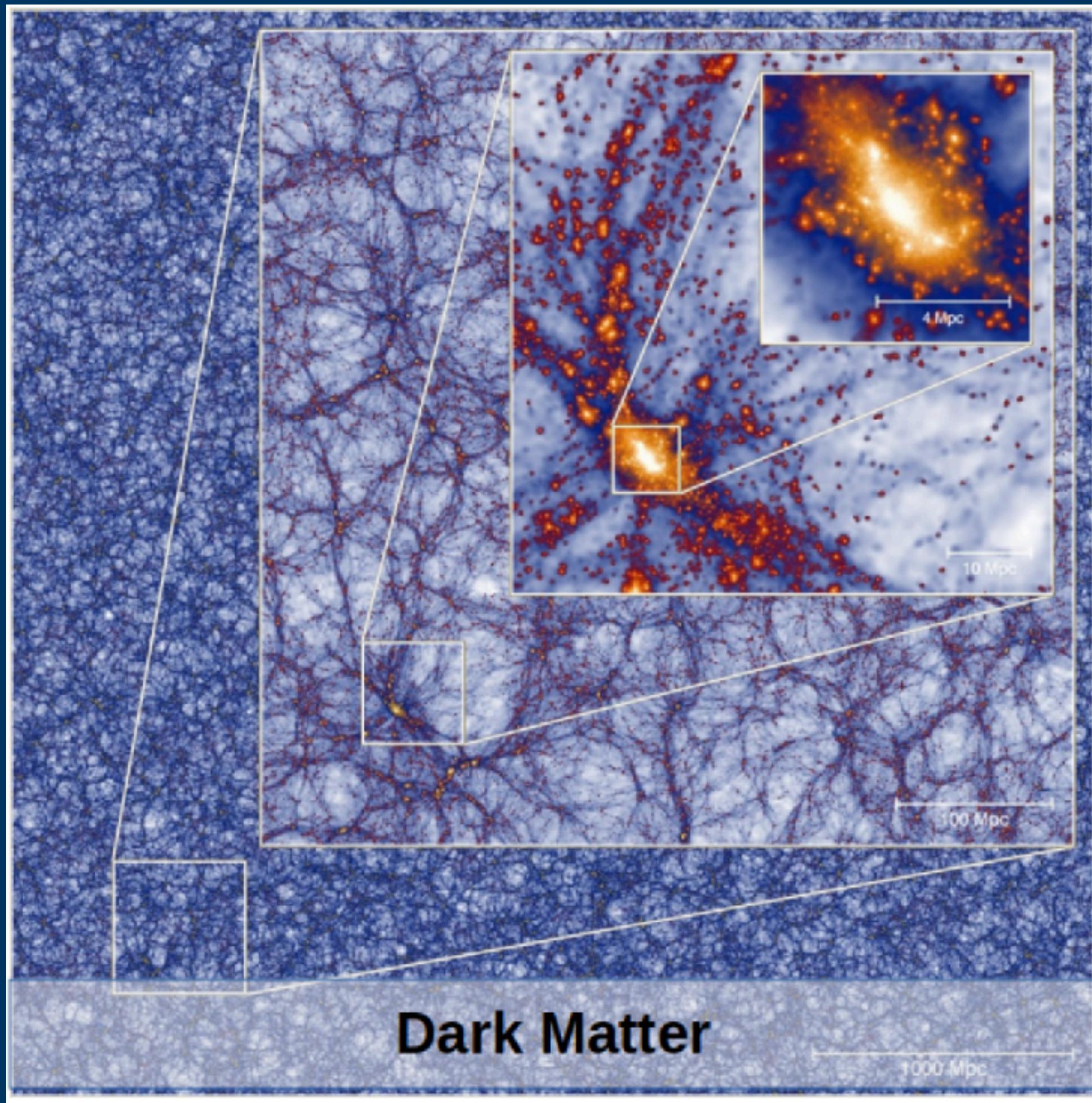


Model Validation

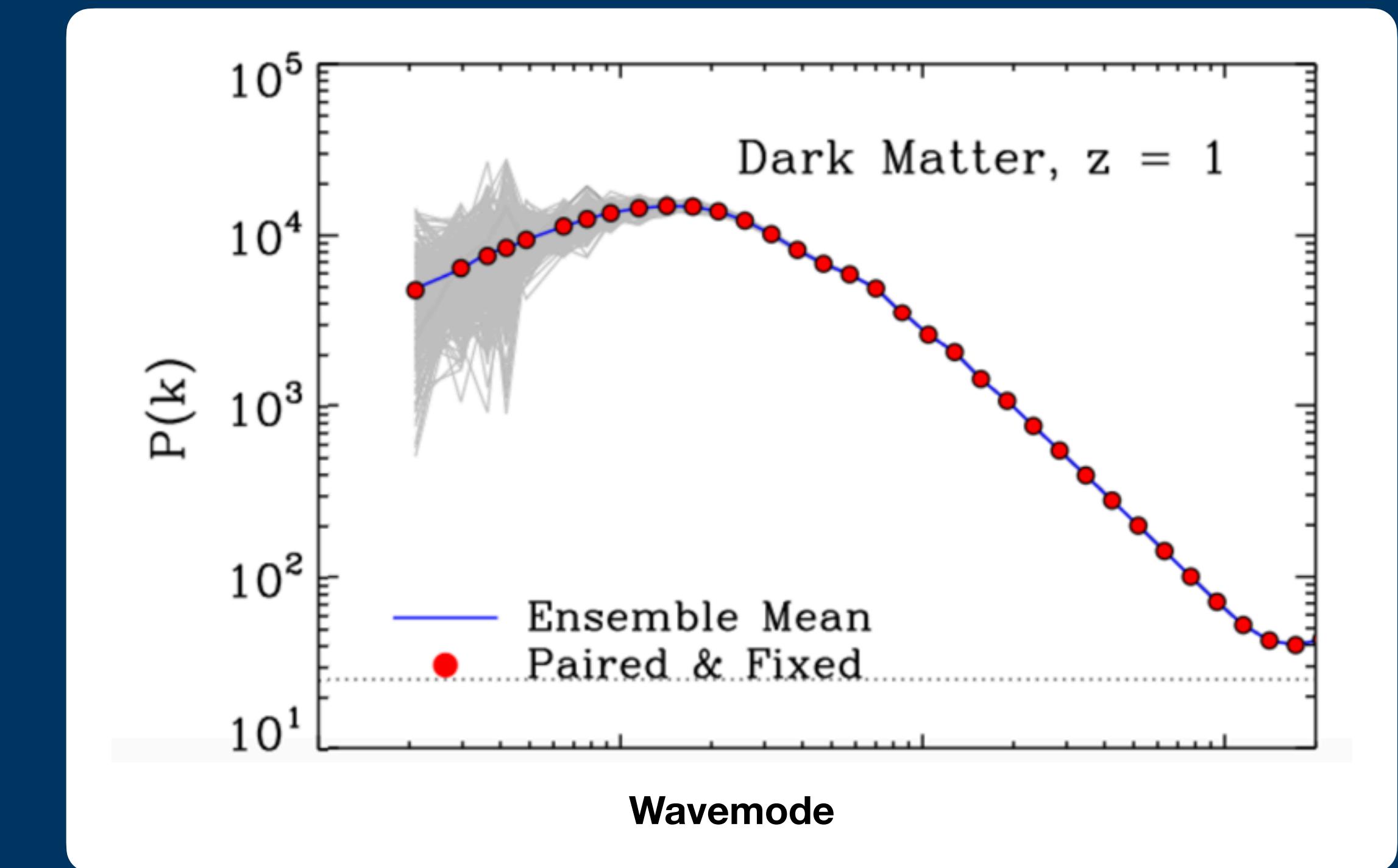


Variance Reduction

Variance Reduction



MXXL Simulation (Angulo et al 2013)



Angulo & Pontoon (2016)

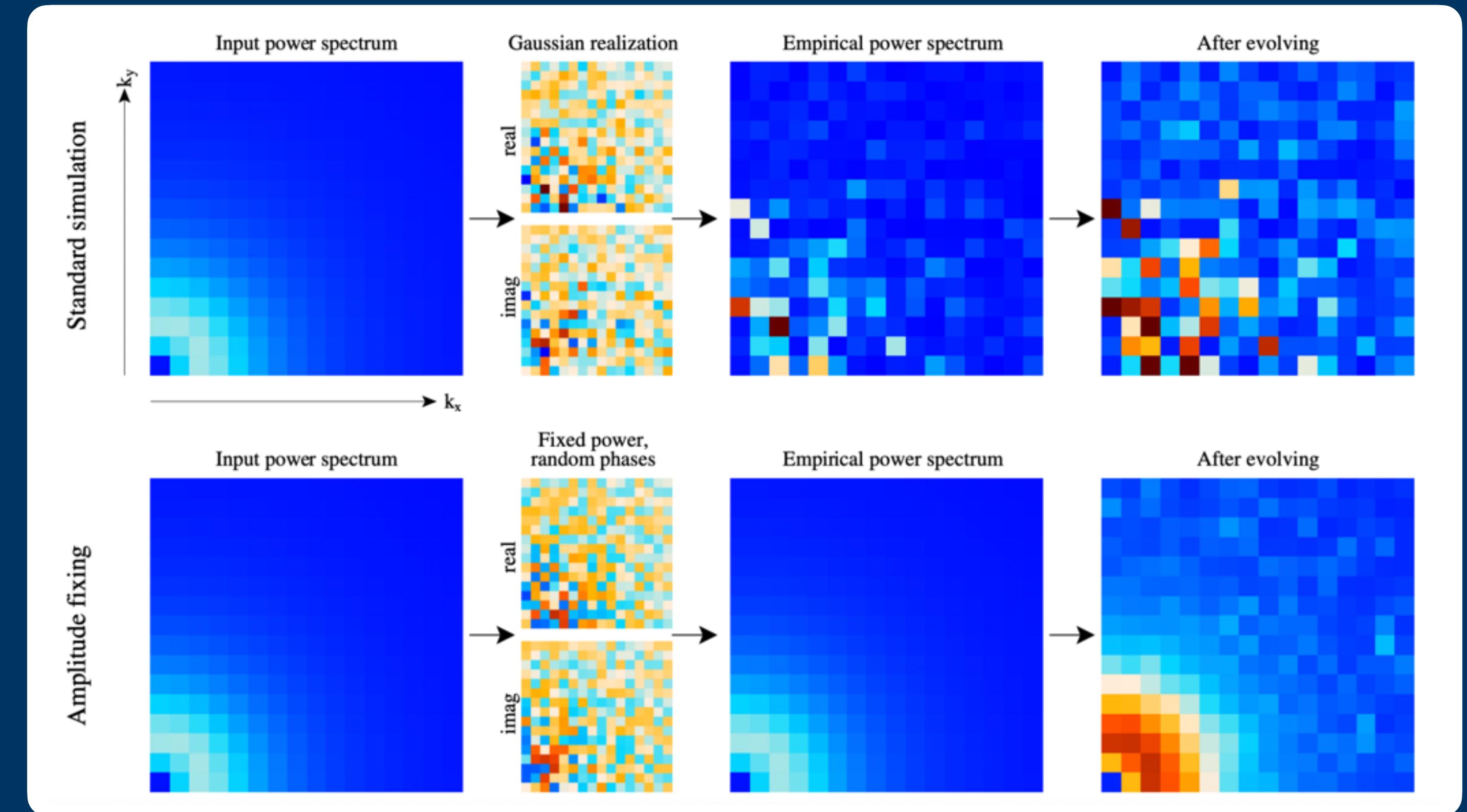
Fixing

$$\mathcal{P}(|\delta(\mathbf{k})|, \theta_{\mathbf{k}}) = \frac{|\delta|}{L^3 P} e^{-|\delta|^2 / L^3 P}$$

Fix amplitudes of the initial modes to:

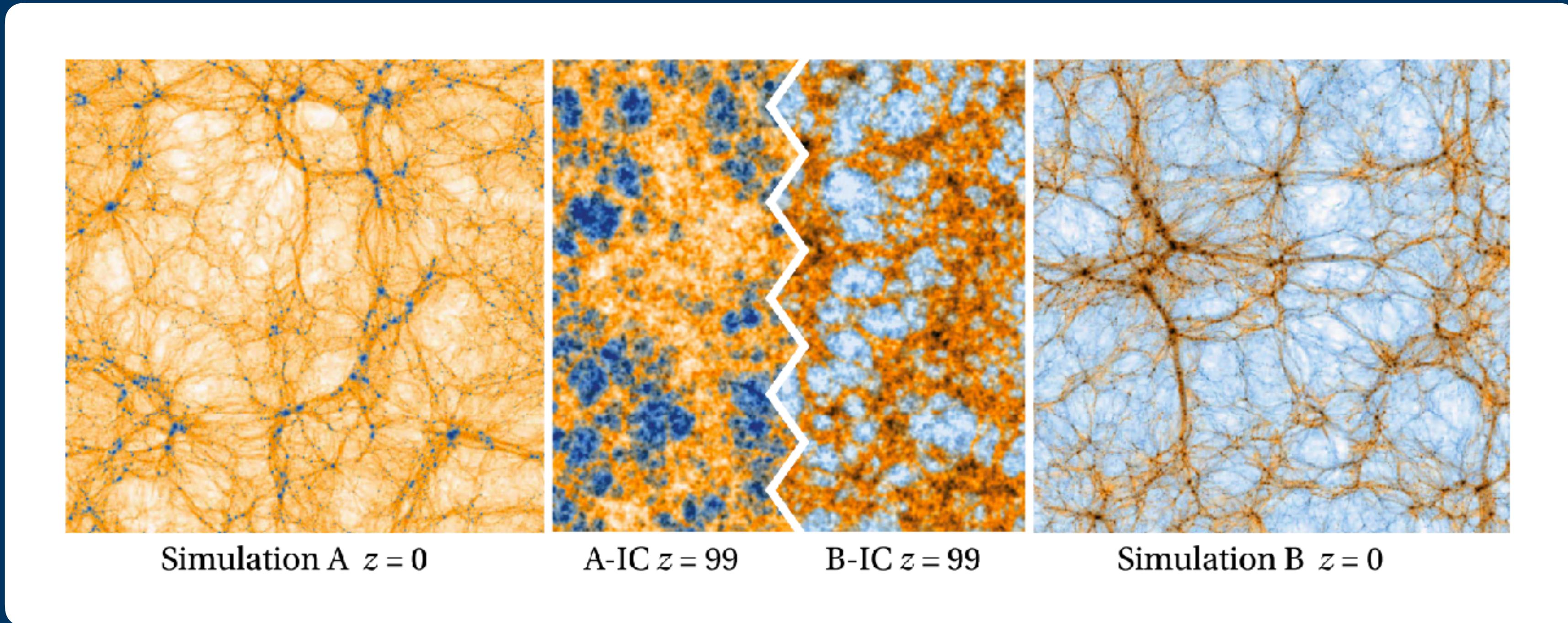
$$|\delta_L(\mathbf{k})| = \sqrt{P(k)} \quad \theta(\mathbf{k}) \in [0, 2\pi]$$

$$\delta(\mathbf{k})\delta(-\mathbf{k}) = \sqrt{P(k)}e^{i\theta(\mathbf{k})}\sqrt{P(k)}e^{-i\theta(\mathbf{k})} = P(k)$$



Villaescusa-Navarro (2018)

Pairing



$$\delta_A(\mathbf{k}) = \sqrt{P(k)} e^{i\theta(\mathbf{k})}$$

$$\delta_B(\mathbf{k}) = \sqrt{P(k)} e^{i(\theta(\mathbf{k}) + \pi)} = -\delta_A(\mathbf{k})$$

Statistics of biased tracers in variance-suppressed simulations

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^bDepartamento de Física Matemática, Instituto de Física, Universidade de São Paulo,
Rua do Matão 1371, São Paulo CEP 05508-090, Brazil

^cIKERBASQUE, Basque Foundation for Science,
Bilbao 48013, Spain

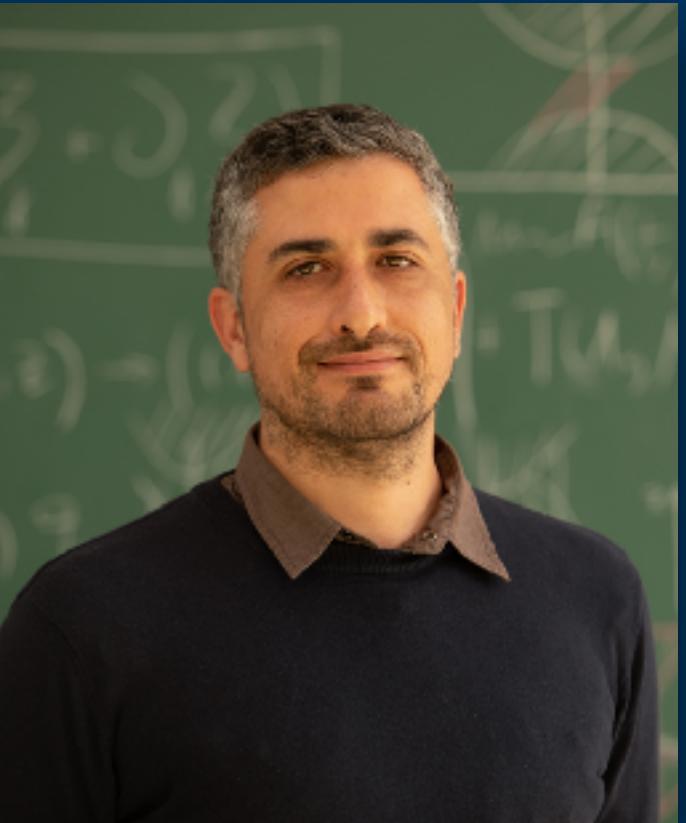
E-mail: francisco.maion@dipc.org, reangulo@dipc.org,
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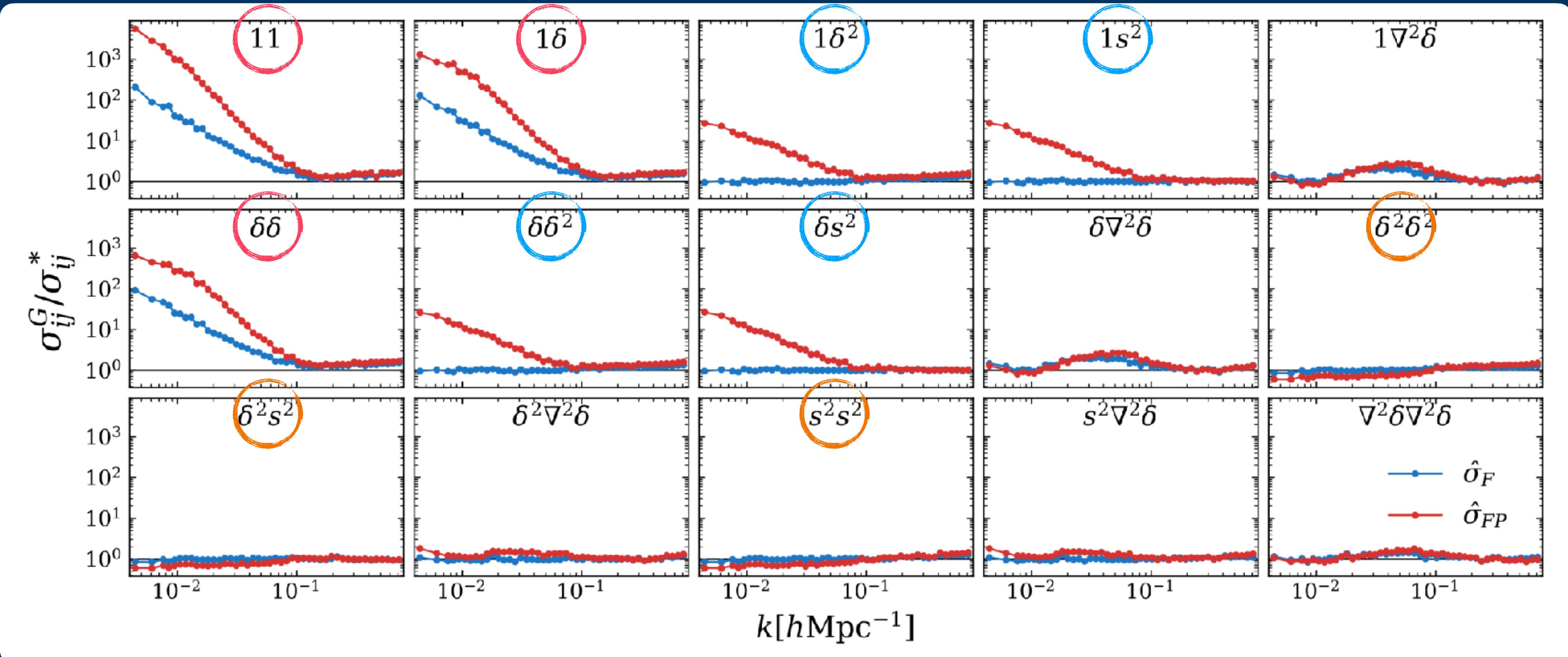


Raul Angulo



Matteo Zennaro

COLA Simulations



- Both Methods

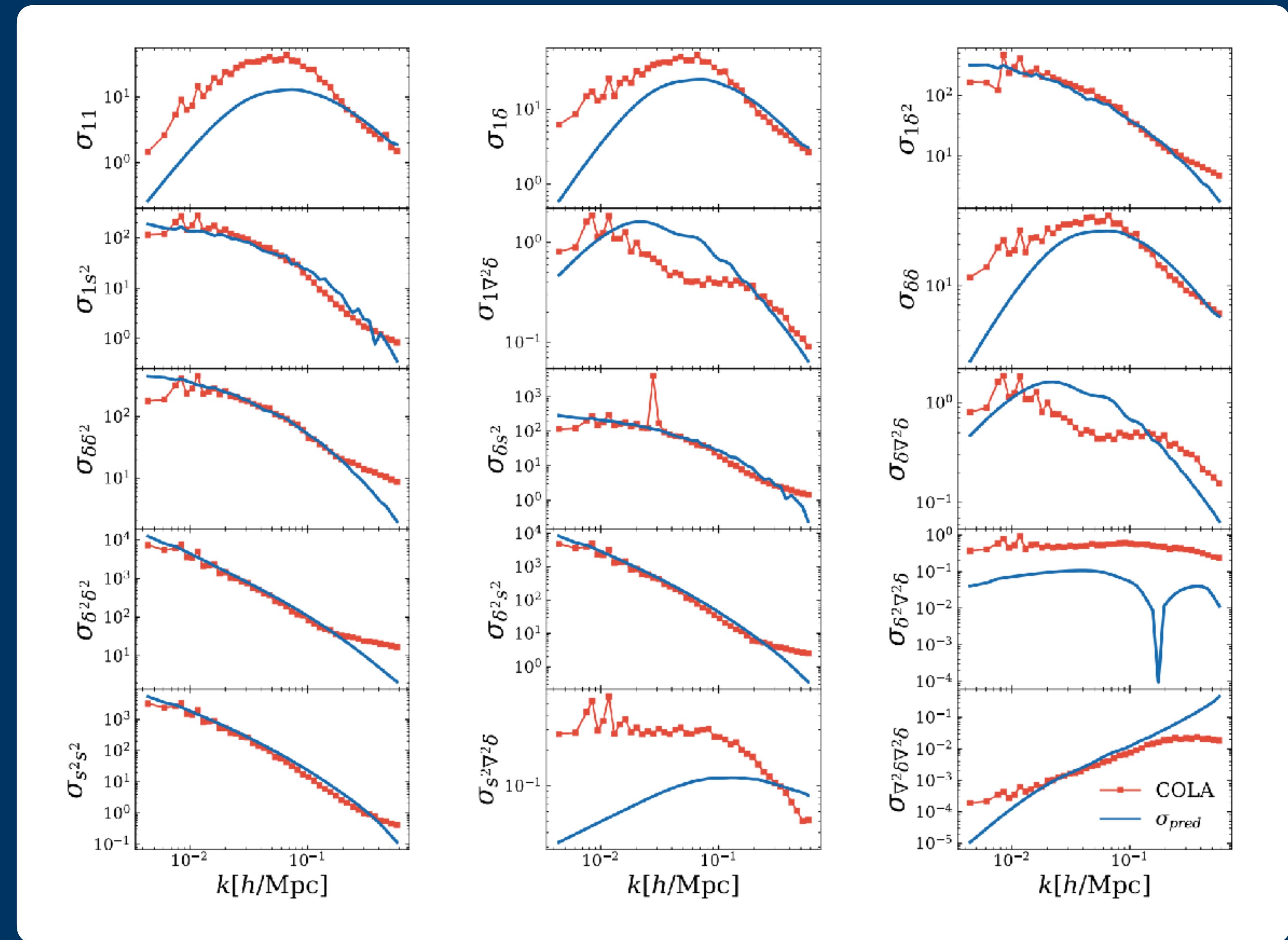


- Just Pairing

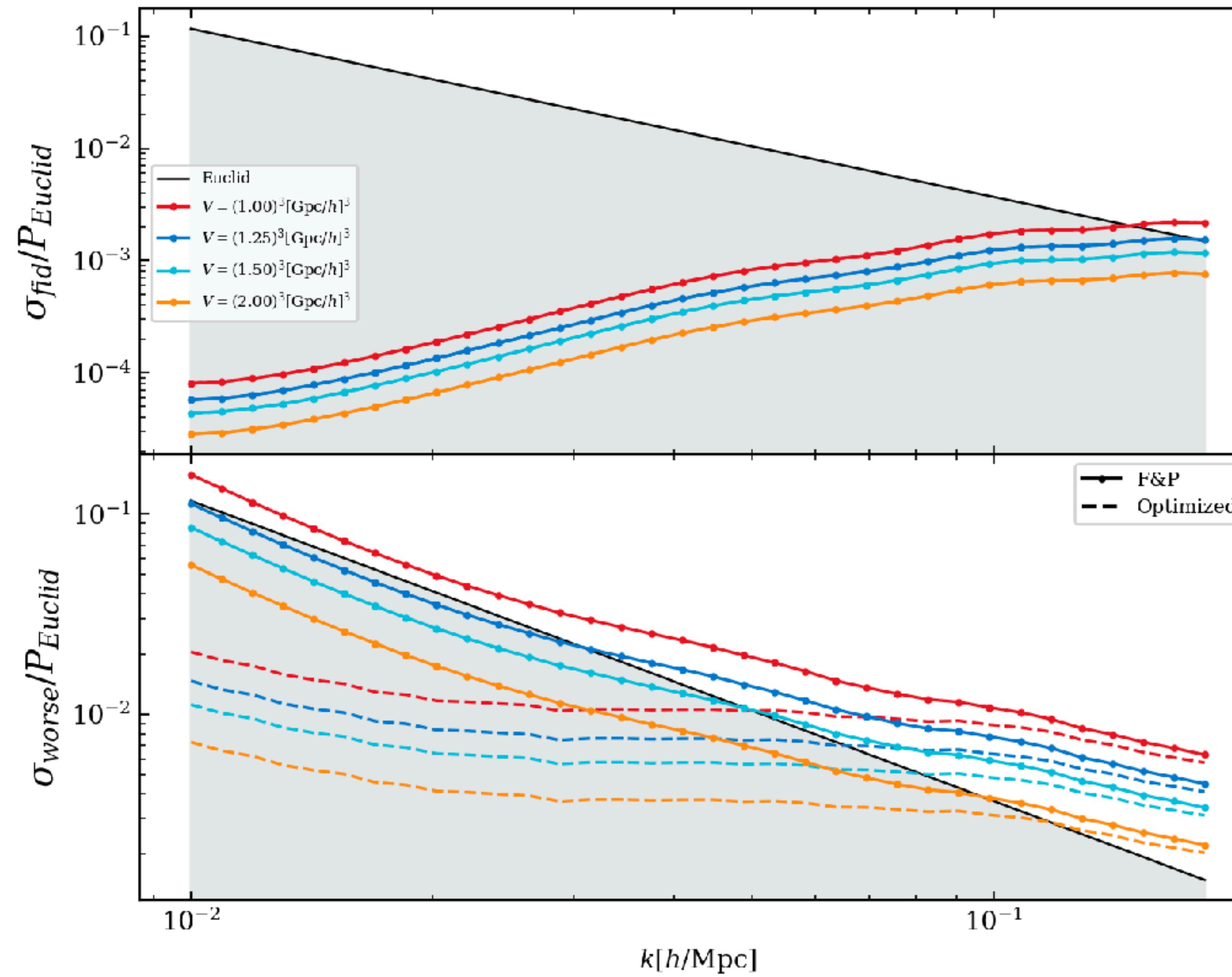


- None

Variance Predictions

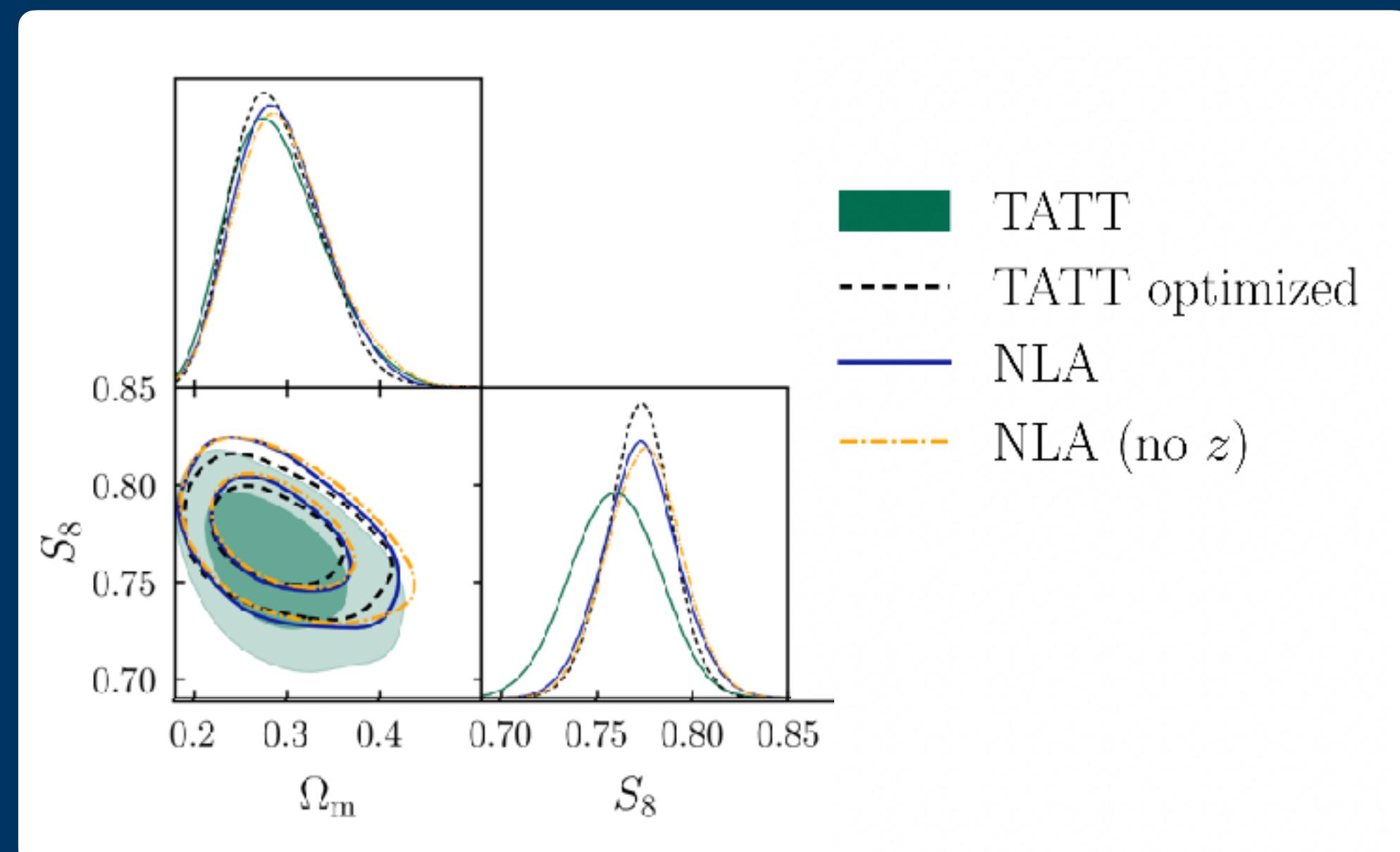


Model Precision

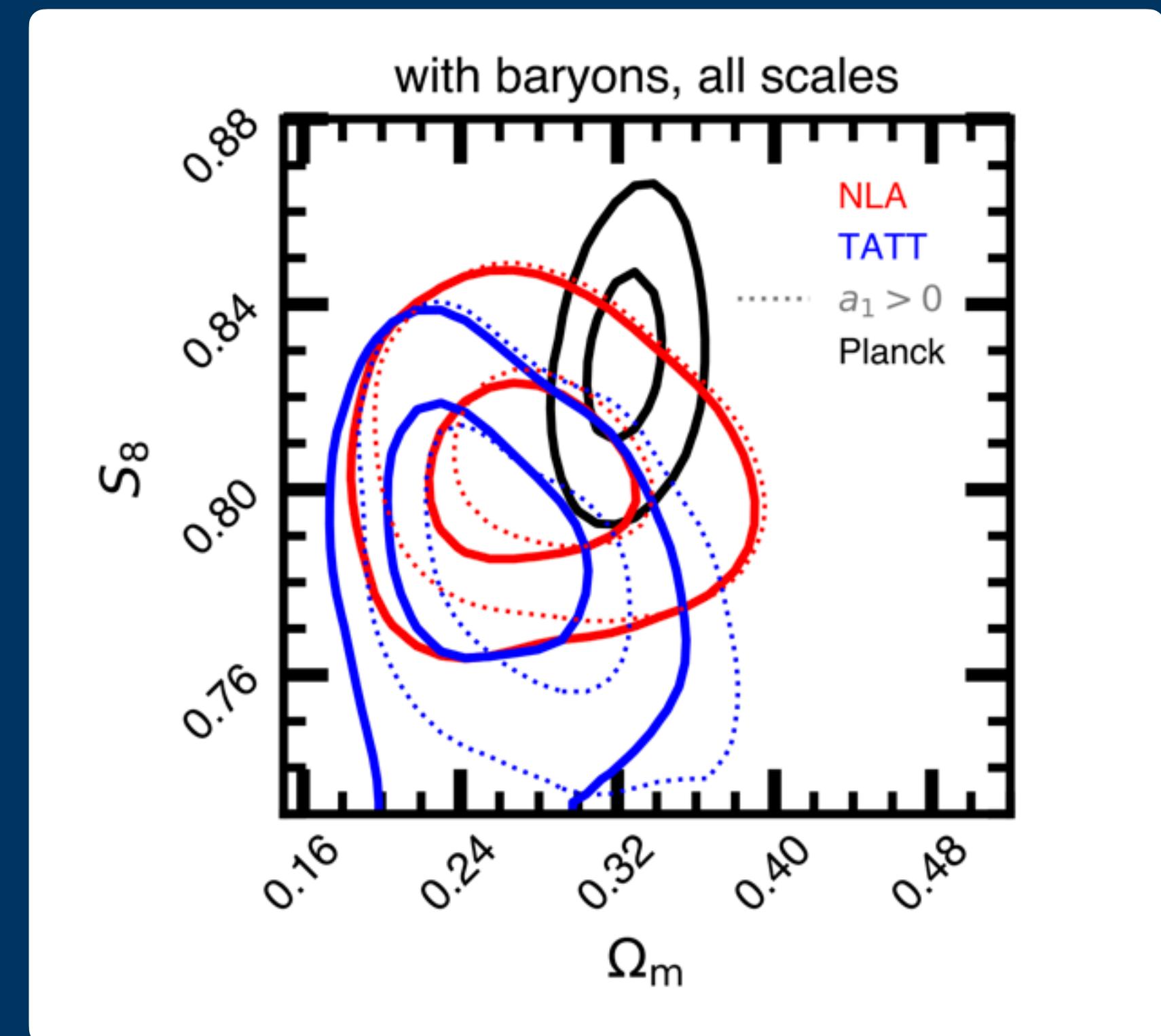


A simulation with mere 20% of the volume of one Euclid survey redshift slice is sufficient

Priors on Bias



Secco & Samuroff (2021)



Aricò et al (2021)

Bias Measurements

Probabilistic Shape Bias

Astronomy & Astrophysics manuscript no. output
September 23, 2024

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Probabilistic Estimators of Lagrangian Shape Biases: Universal Relations and Physical Insights

F. Maion^{1,2}, J. Stüber^{1,3}, and R. E. Angulo^{1,4}

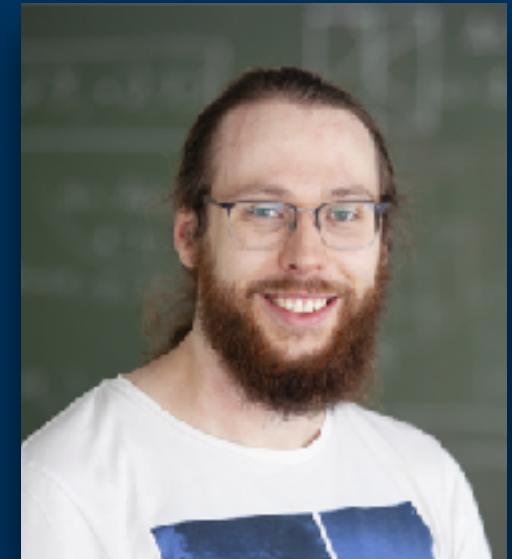
¹ Donostia International Physics Center, Manuel Lardizabal Ibilbidea, 4, 20018 Donostia, Gipuzkoa, Spain

² Euskal Herriko Unibertsitatea, Edificio Ignacio Maria Barriola, Plaza Elhuyar, 1, 20018 Donostia-San Sebastián, Spain

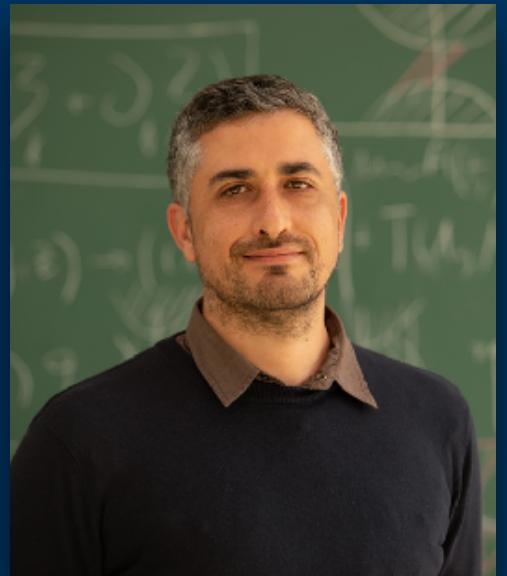
³ Department of Astrophysics, University of Vienna, Türkenschanzstraße 17, 1180 Vienna, Austria

⁴ IKERBASQUE, Basque Foundation for Science, 48013, Bilbao, Spain

September 23, 2024

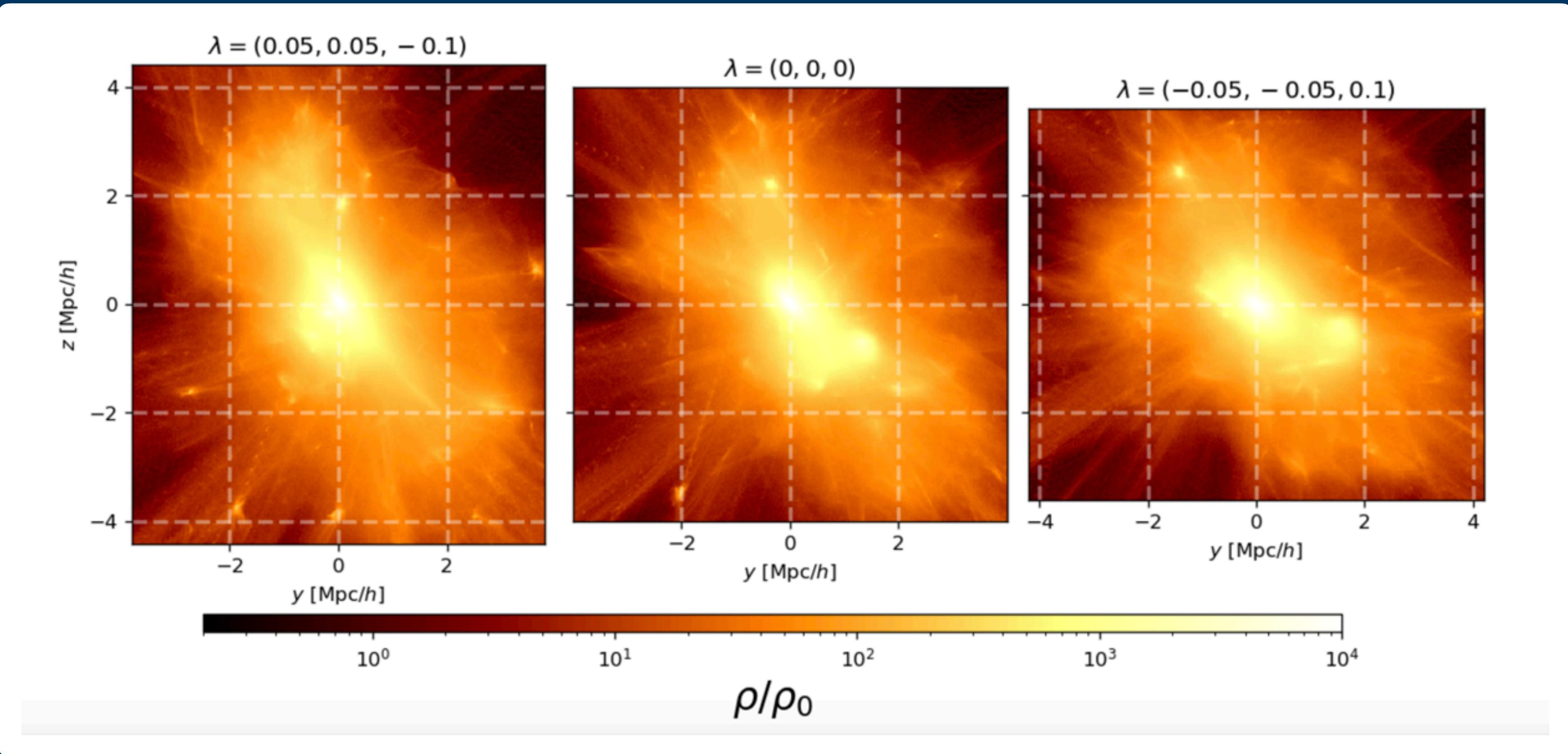


Jens Stüber



Raul Angulo

Probabilistic Shape Bias

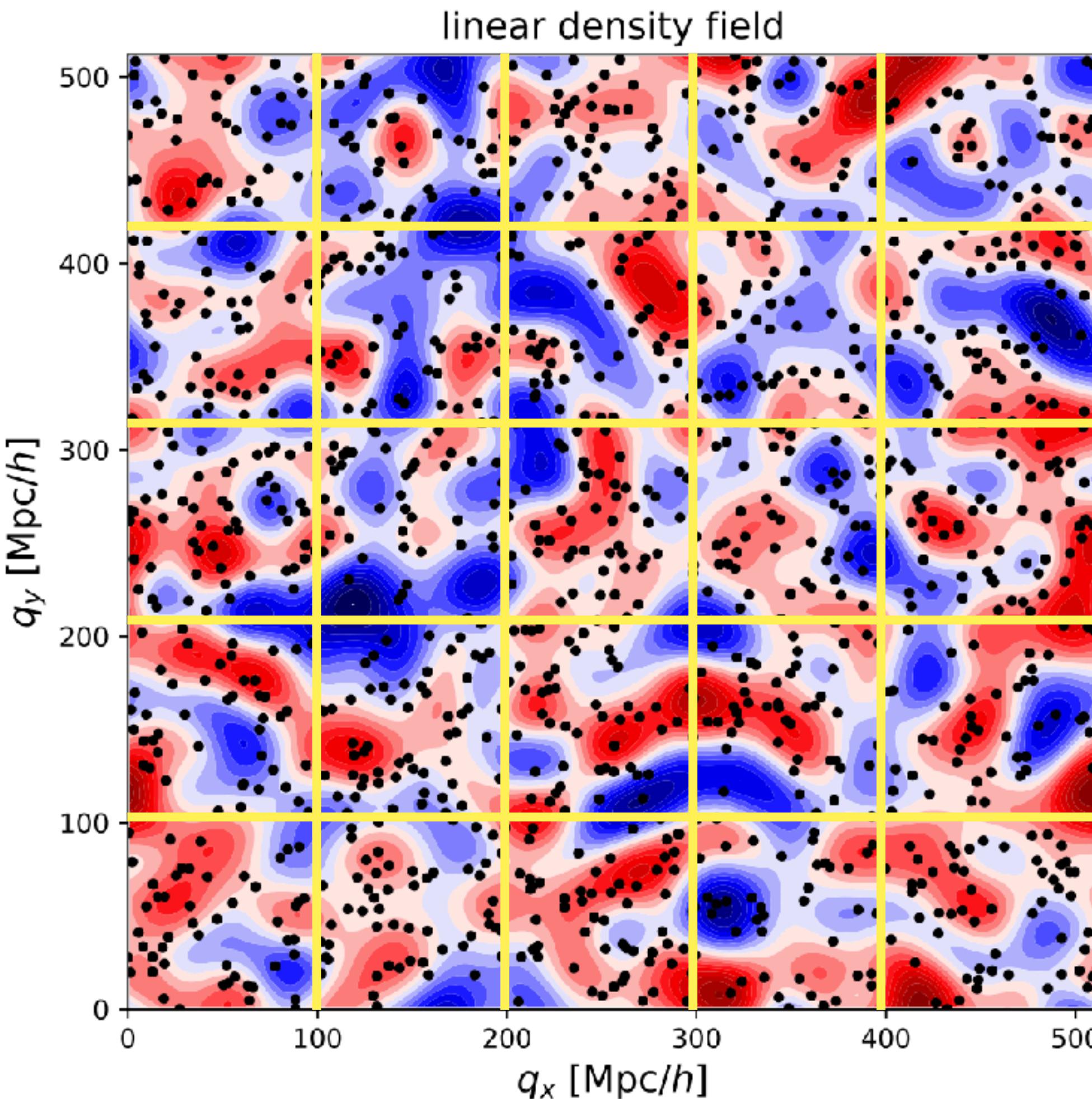


Let I be the shape-tensor
of halos/galaxies

$$\langle I | T_0 \rangle$$

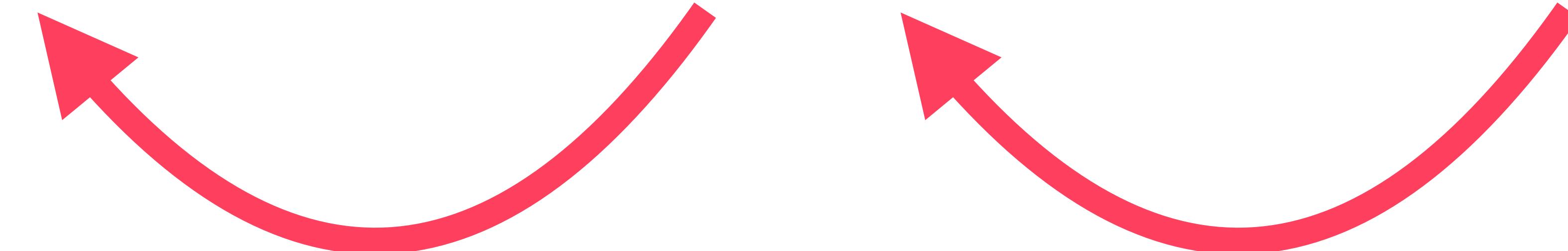
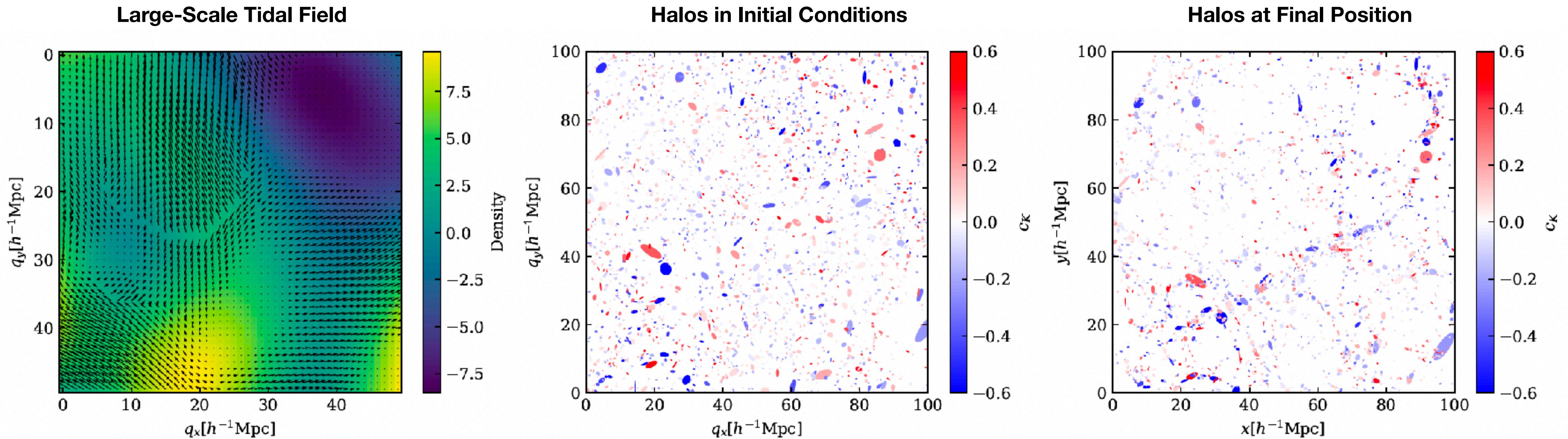
$$C_{K,n} = \frac{\partial^n \langle I | T_0 \rangle}{\partial T_0^n} \Big|_{T_0=0}$$

Probabilistic Shape Bias



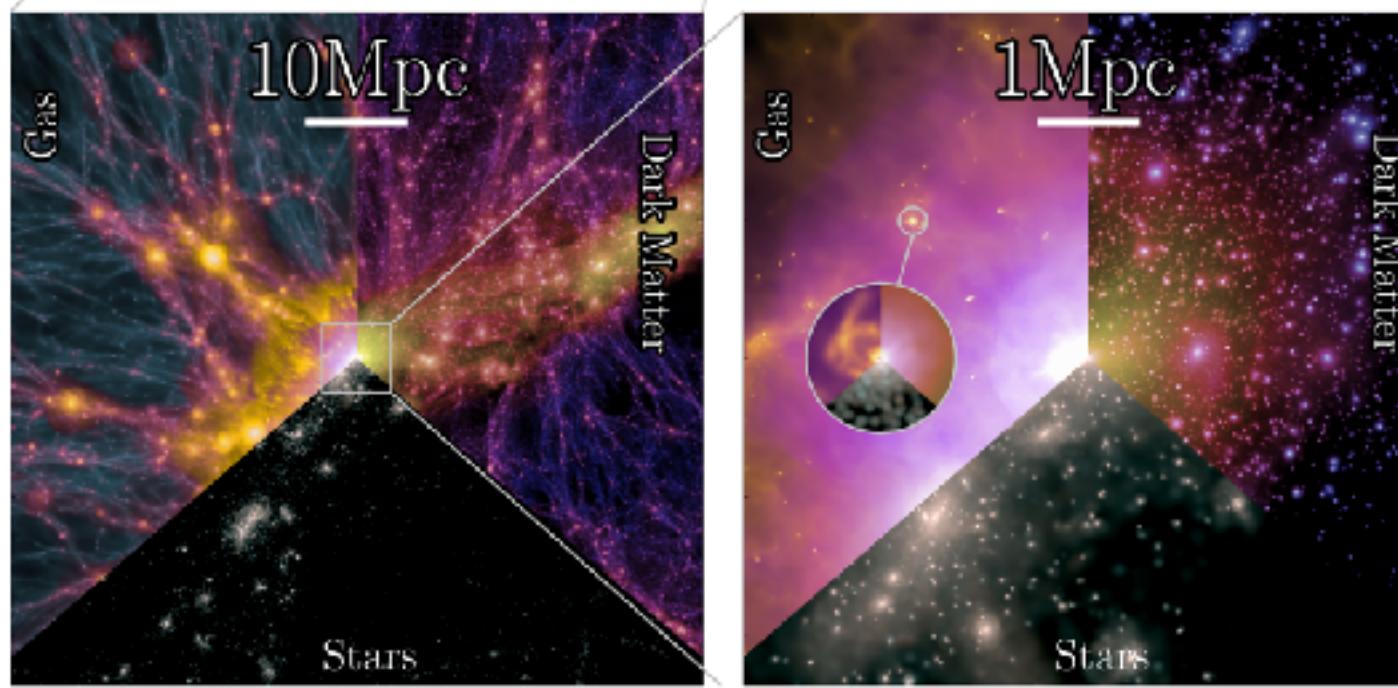
$$\langle \mathbf{I} | \mathbf{T}_0 \rangle_g = \frac{1}{F(\mathbf{T}_0)} \left\langle \mathbf{I} \frac{p(\mathbf{T} | \mathbf{T}_0)}{p(\mathbf{T})} \right\rangle_g$$

Probabilistic Bias for IA



Probabilistic Bias for IA

MillenniumTNG
Pakmor et. al (2022)

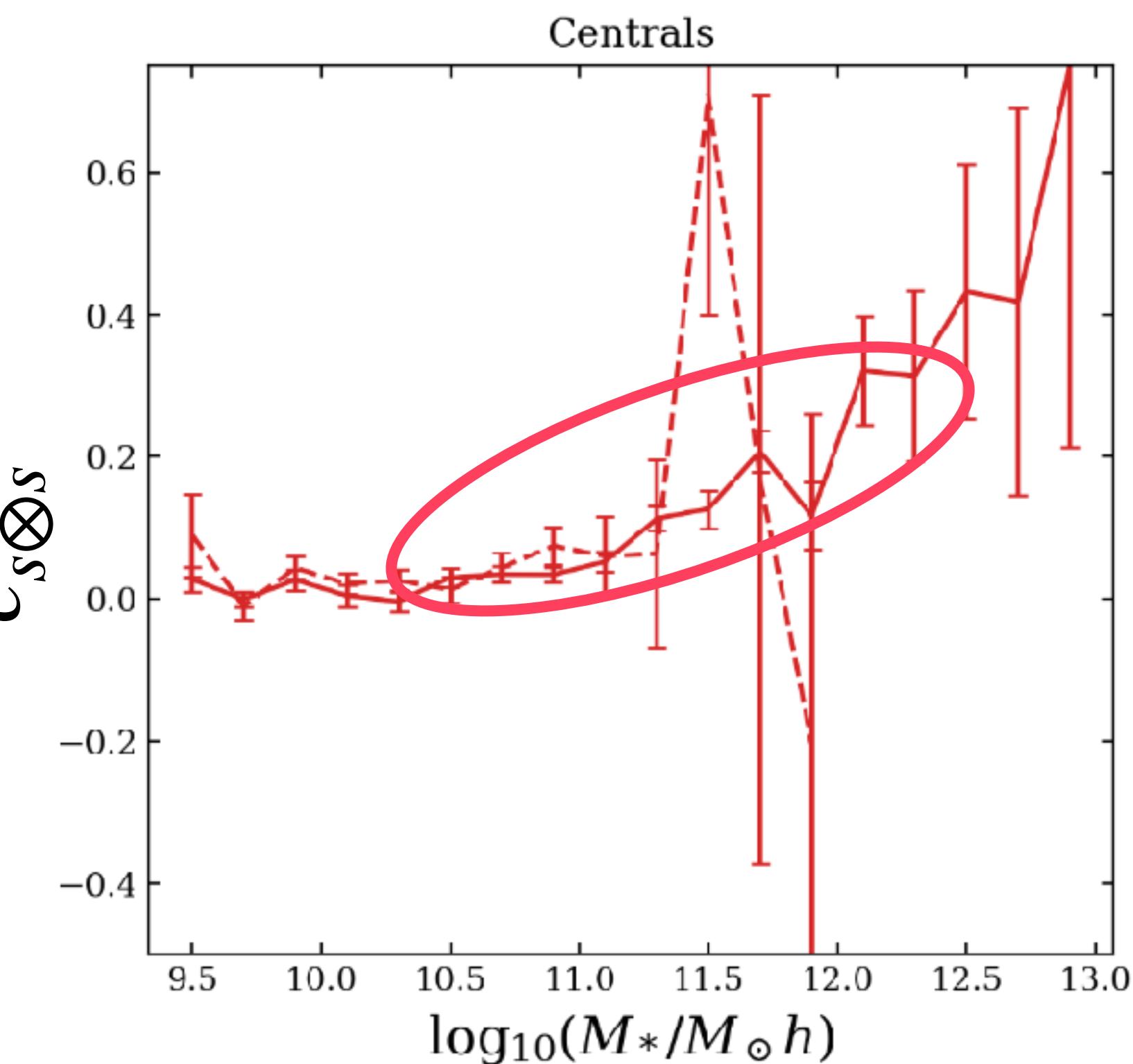
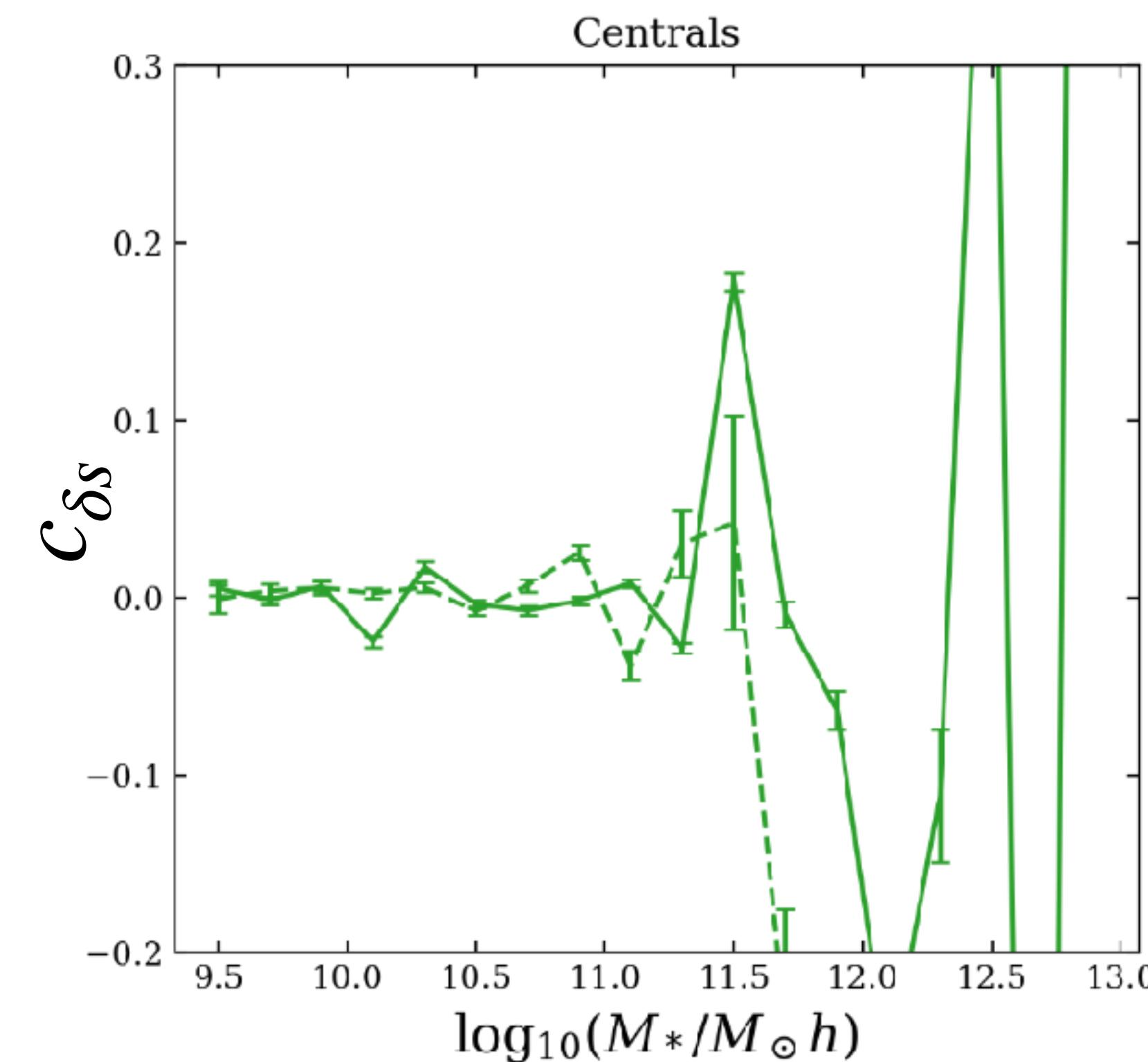
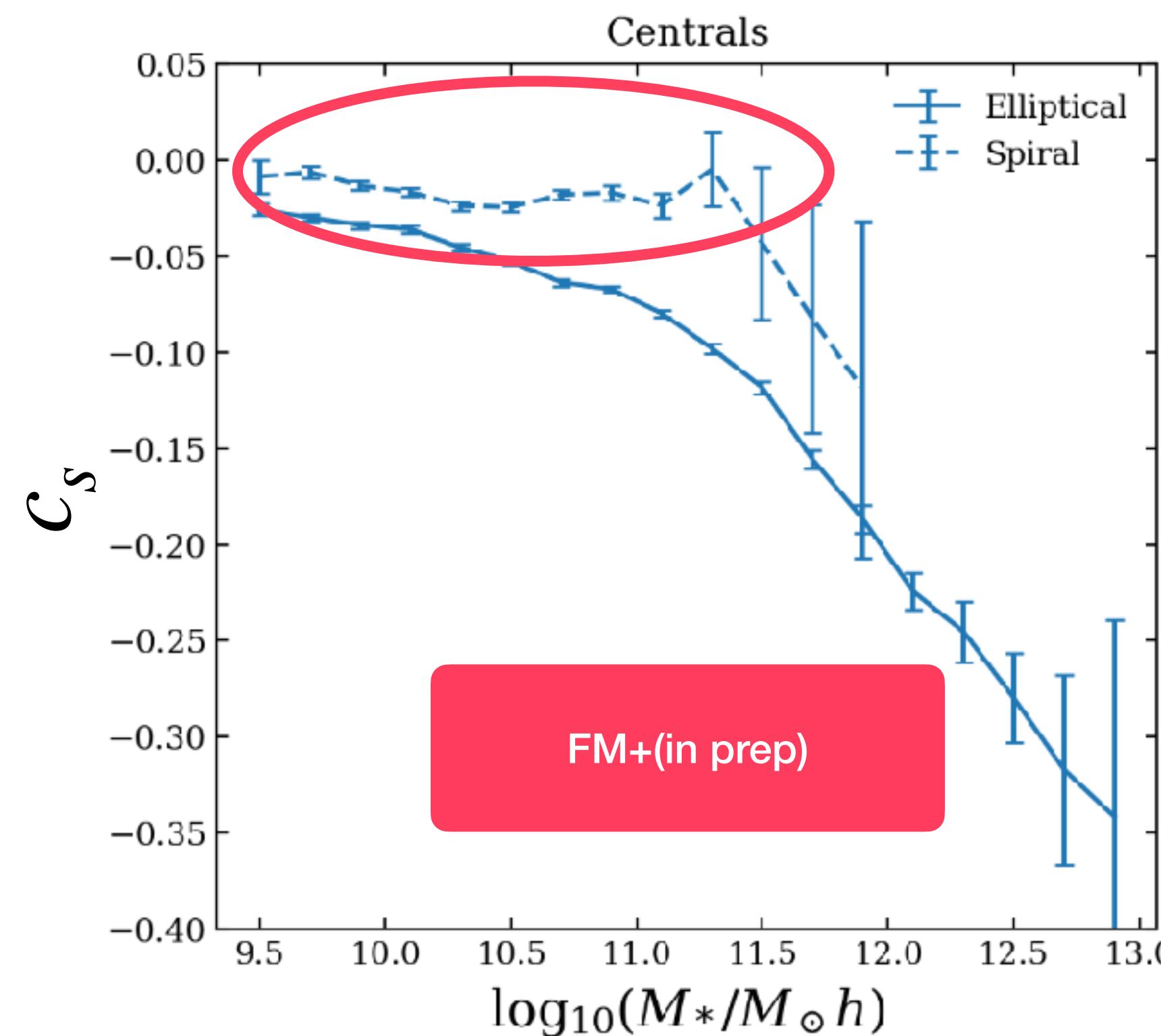


Jens Stucker



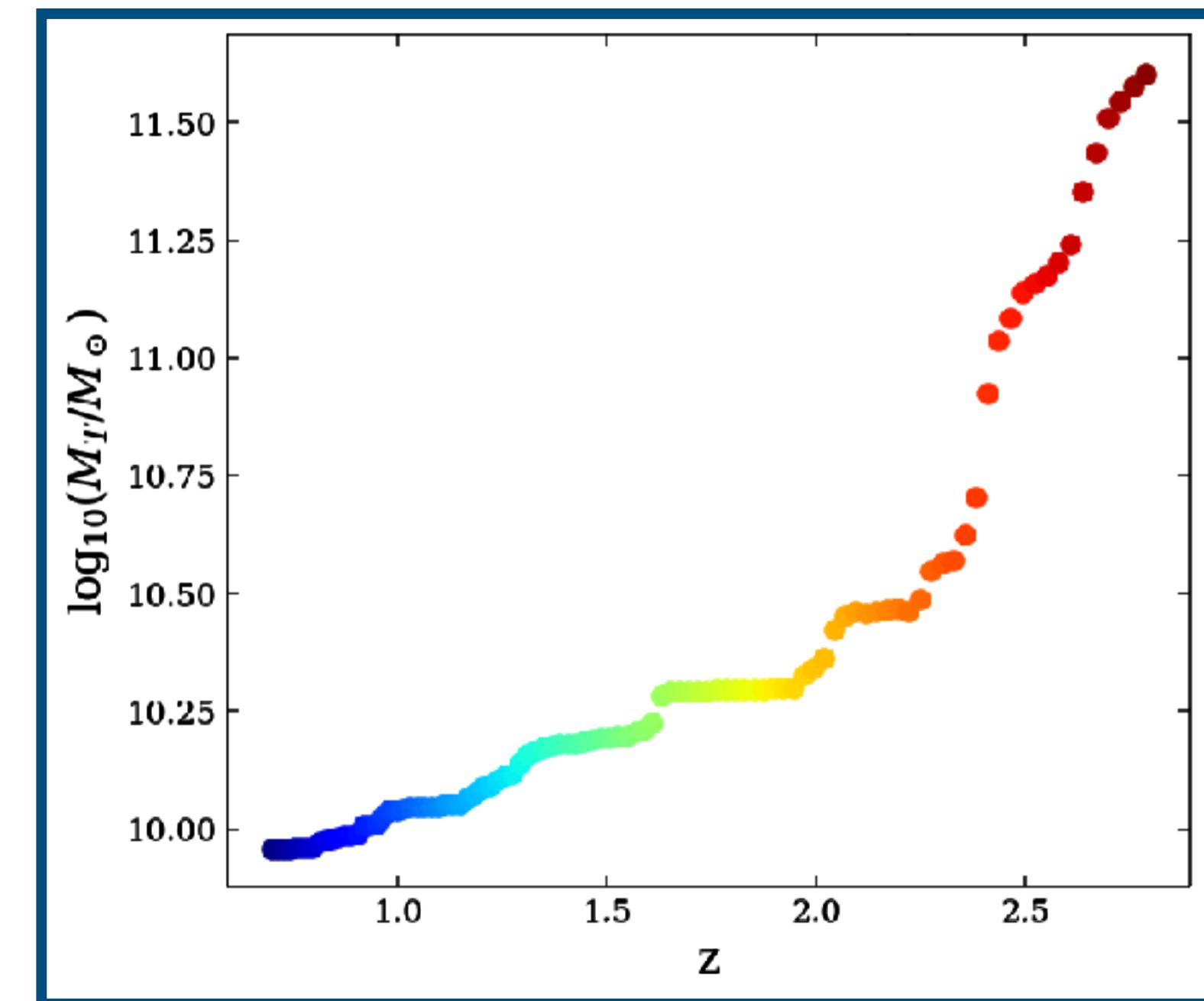
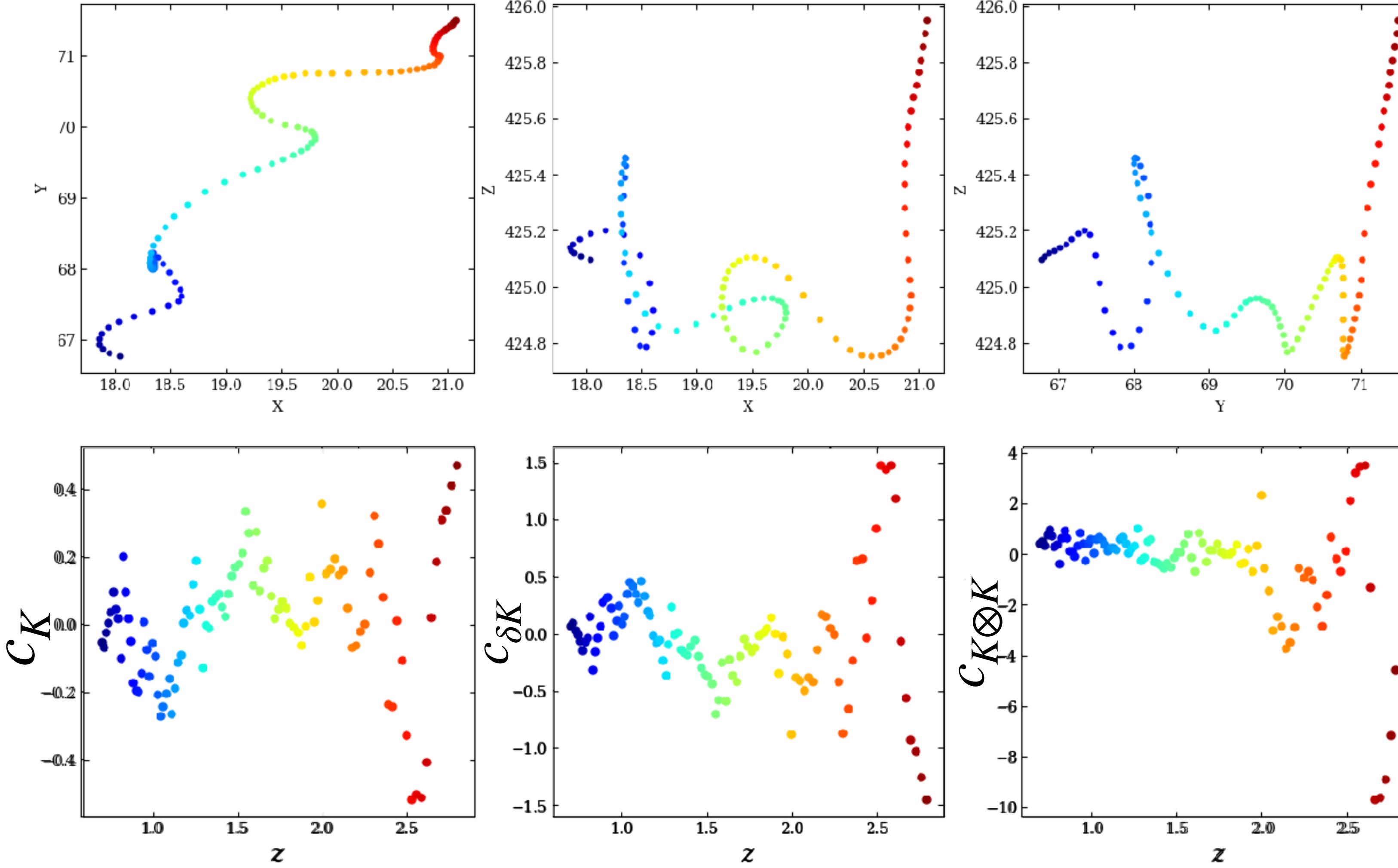
Raul Angulo

+
MTNG
Collaboration
+
many others



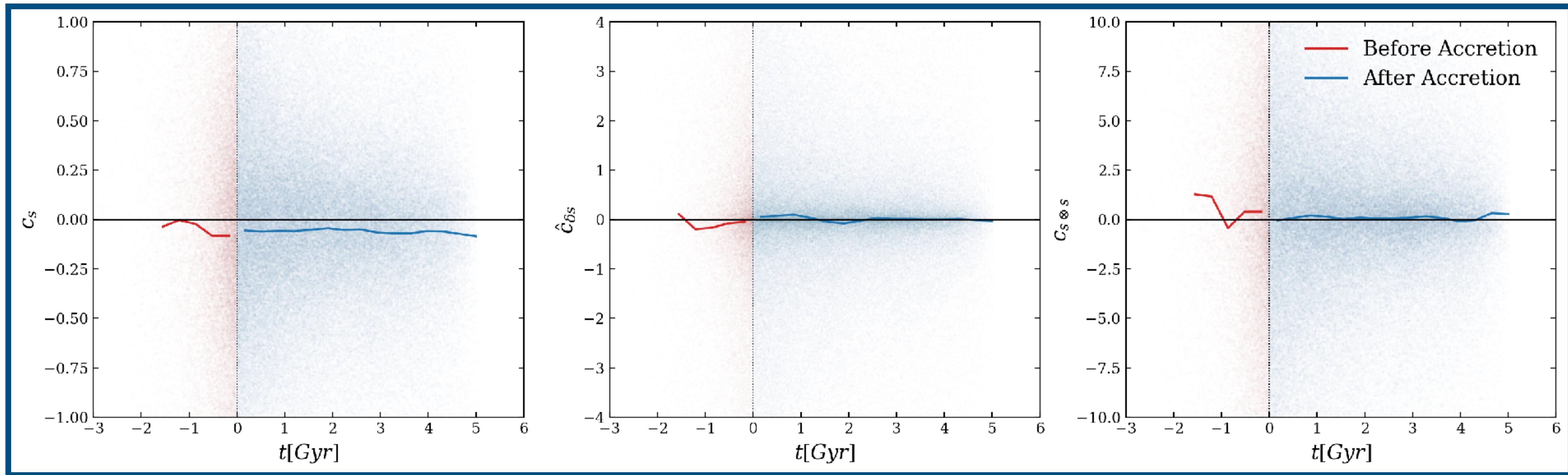
Probabilistic Bias for IA

Tracing galaxies, their biases and mass throughout merger-trees



FM+(in prep)

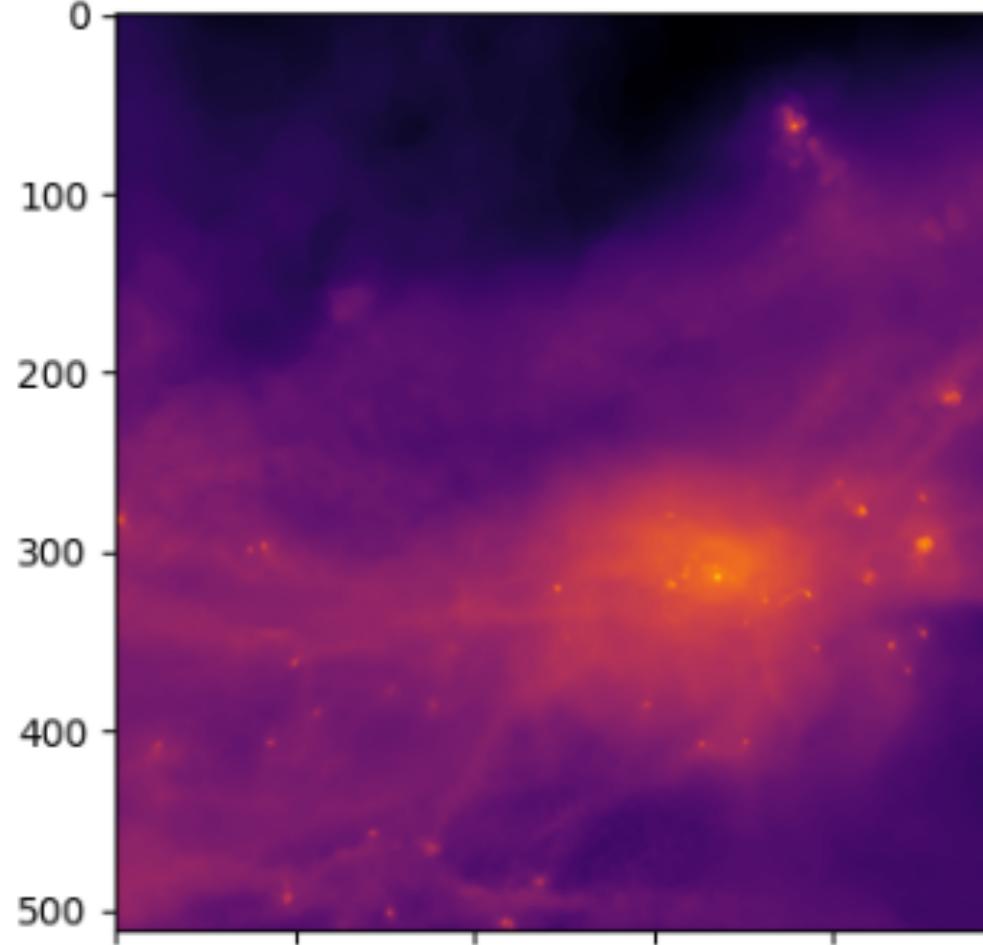
Probabilistic Bias for IA



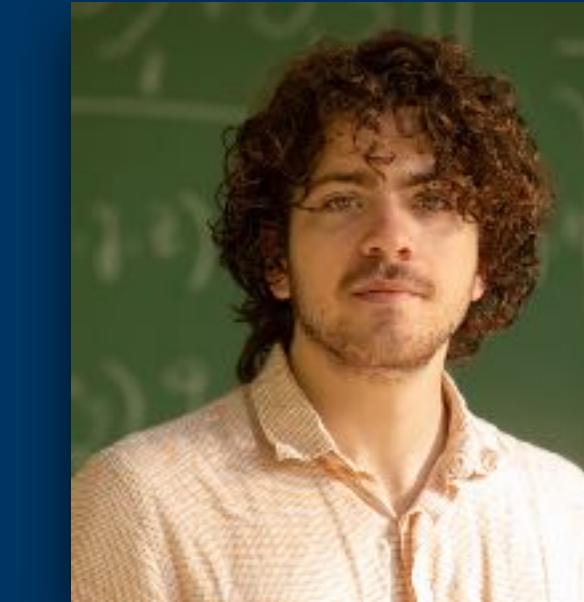
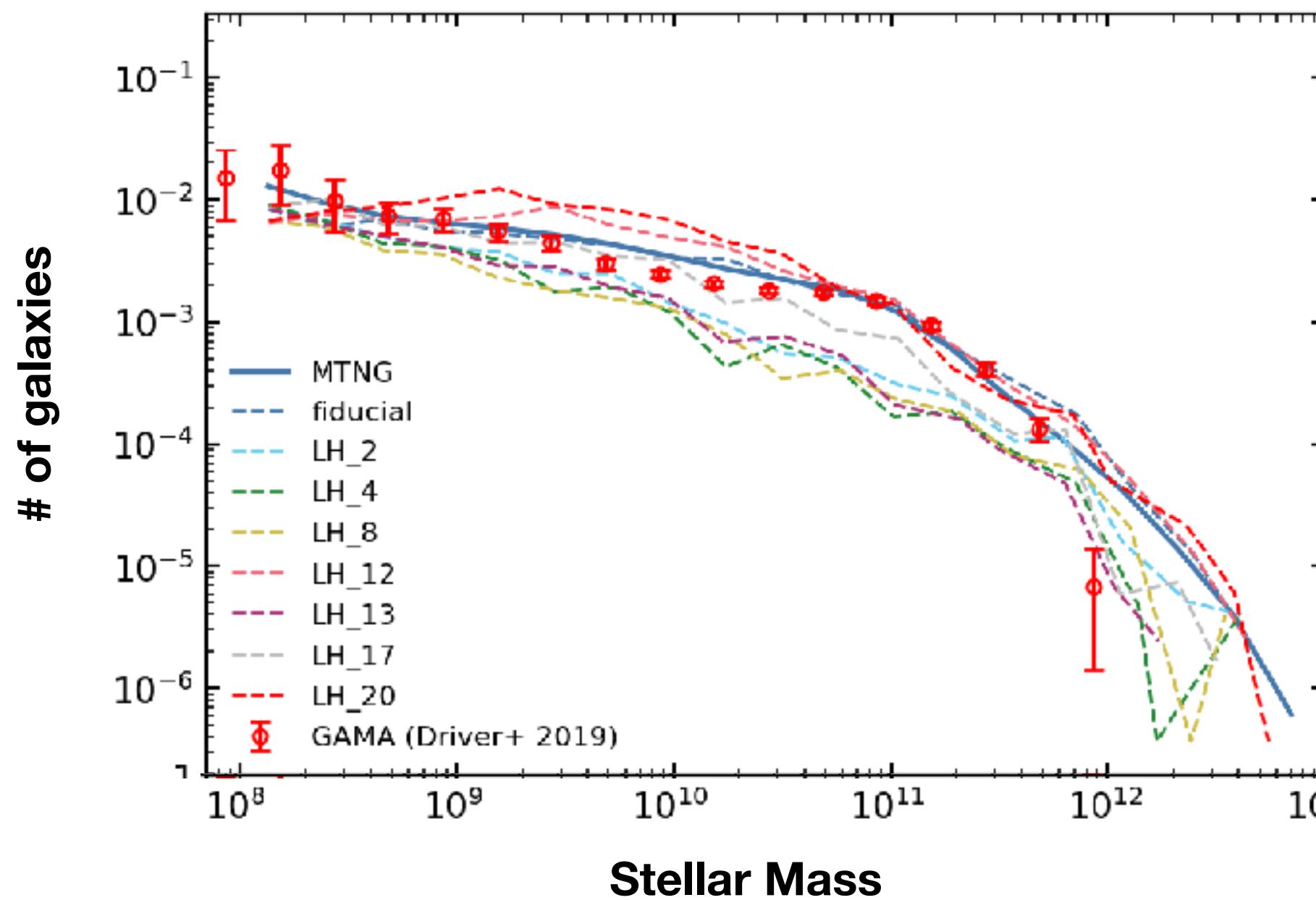
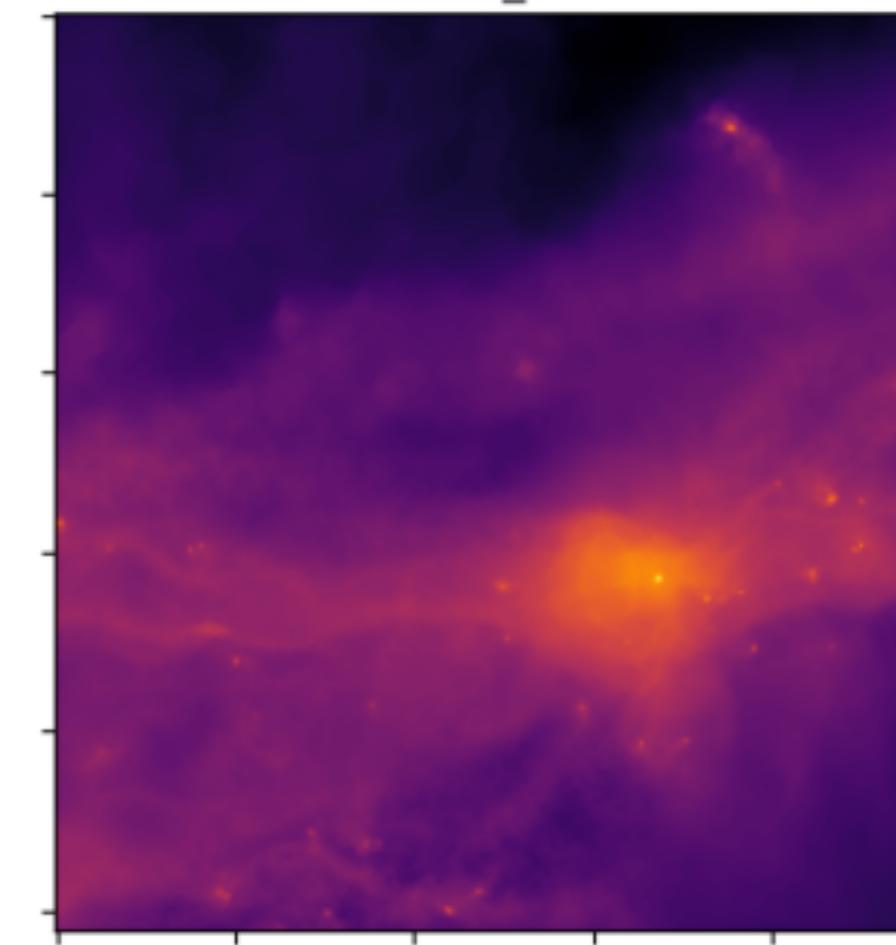
FM+(in prep)

MillenniumTNG

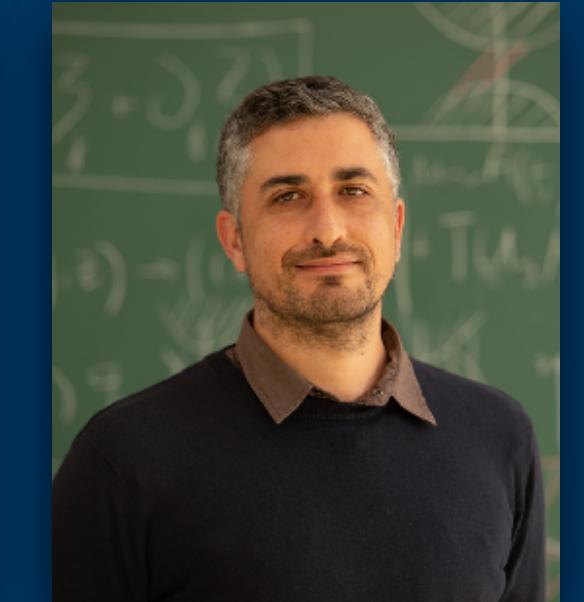
MTNG



More Stellar Winds



Francisco Maion
(Co-PI)



Raul Angulo
(Co-PI)



Volker Springel

+
MTNG Collaboration
+
many others

- ❖ Carefully selected set of 500 DM-halos
- ❖ Varying 7 parameters of the IllustrisTNG GFM
 - ❖ Stellar Winds
 - ❖ BH Feedback
 - ❖ Star-Formation Efficiency
- ❖ 30 points distributed in a wide Latin-Hypercube design
- ❖ 100k CPU-hours per resimulation

Conclusions

- IA modelling is crucial
 - ❖ Extracting info. from Euclid, LSST
 - ❖ Relevant from linear to non-linear regime
 - ❖ HYMALAIA goes well beyond linear regime
 - ❖ Precise with variance reduction
- Learning from simulations
 - ❖ Developed new estimators of shape bias
 - ❖ Priors from hydrodynamical simulations
 - ❖ Constrain shape-formation scenarios
- IA vs Baryonic Feedback
 - ❖ Innovative multi-zoom simulations with various sub-grid parameters

Find me at:

franciscomaion.com

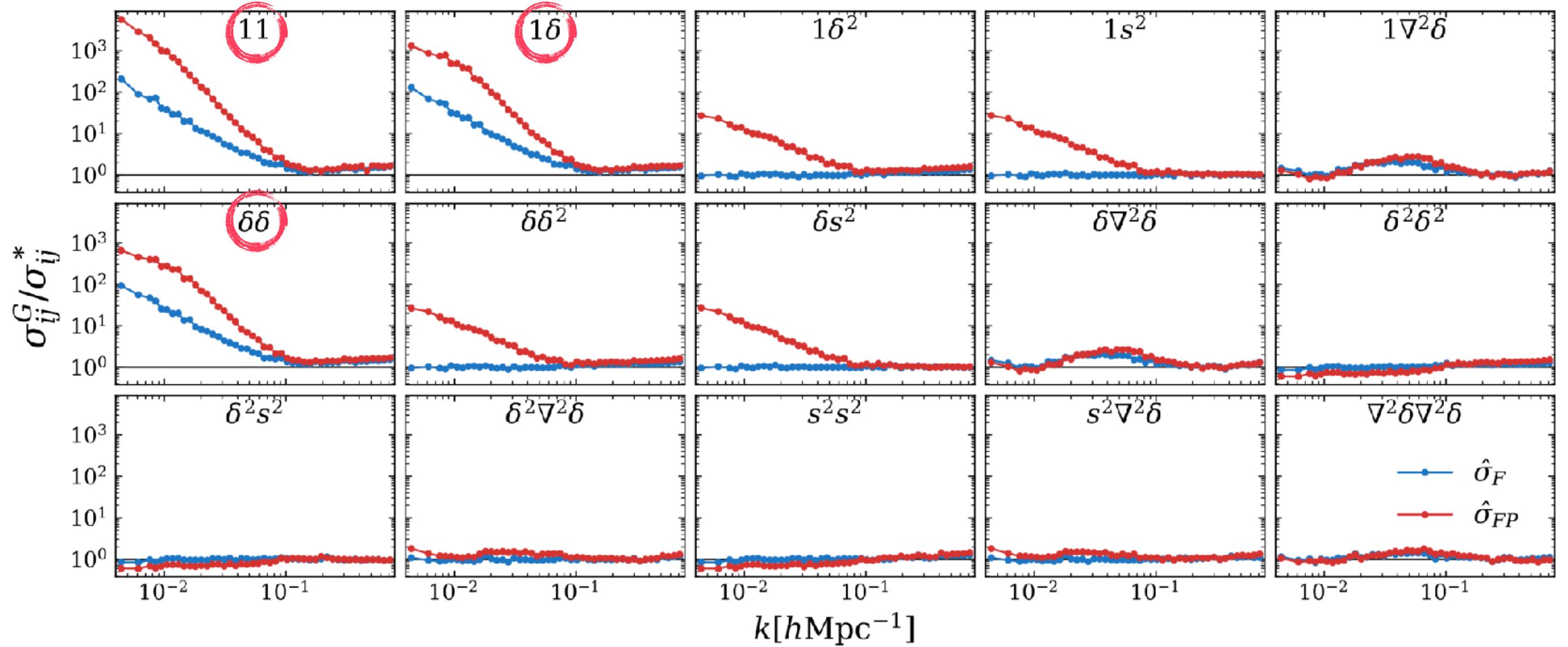
Write to me at:

francisco.maion@dipc.org



Extra Slides

Qualitative Understanding



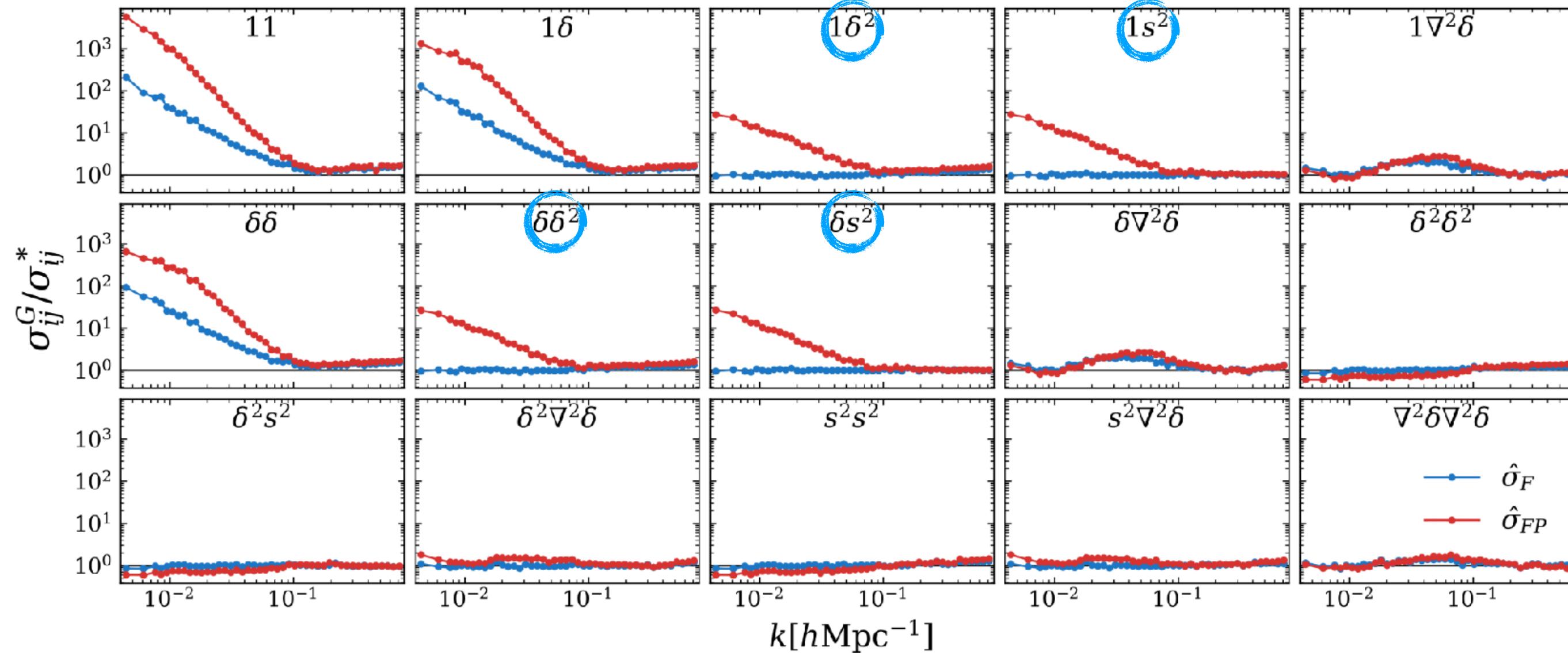
~~$$\begin{aligned}
 P_{11}^F(\mathbf{k}) &\approx P_{\mathbf{k}}^L + V^{1/2} \int_{\mathbf{q}_1} \sqrt{P_{\mathbf{k}}^L P_{\mathbf{q}_1}^L P_{\mathbf{q}_1 - \mathbf{k}}^L} \cos [\theta_{\mathbf{k}} - \theta_{\mathbf{q}_1} - \theta_{\mathbf{q}_1 - \mathbf{k}}] F_{ZA}(\mathbf{q}_1, \mathbf{k} - \mathbf{q}_1, \mathbf{k}) \\
 &+ \frac{V}{4} \int_{\mathbf{q}_1} \int_{\mathbf{q}_2} \sqrt{P_{\mathbf{q}_1}^L P_{\mathbf{k} - \mathbf{q}_1}^L P_{\mathbf{q}_2}^L P_{\mathbf{q}_2 - \mathbf{k}}^L} \cos [\theta_{\mathbf{q}_1} + \theta_{\mathbf{k} - \mathbf{q}_1} - \theta_{\mathbf{q}_2} - \theta_{\mathbf{k} - \mathbf{q}_2}] \\
 &\times F_{ZA}(\mathbf{q}_1, \mathbf{k} - \mathbf{q}_1, \mathbf{k}) F_{ZA}(\mathbf{q}_2, \mathbf{k} - \mathbf{q}_2, \mathbf{k}).
 \end{aligned}$$~~

$$P_{11}, P_{1\delta}, P_{\delta\delta} \supset P^L$$

$$\begin{aligned}
 (\delta\delta\delta)_\pi &\sim \int_{\mathbf{q}_1} \underbrace{\sqrt{\dots} \cos [\theta_{\mathbf{k}} - \theta_{\mathbf{q}_1} - \theta_{\mathbf{q}_1 - \mathbf{k}} - \pi]}_{-\cos [\theta_{\mathbf{k}} - \theta_{\mathbf{q}_1} - \theta_{\mathbf{q}_1 - \mathbf{k}}]} F_{ZA}(\mathbf{q}_1, \mathbf{k} - \mathbf{q}_1, \mathbf{k}) \\
 &= -(\delta\delta\delta).
 \end{aligned}$$

$$P_{11}, P_{1\delta}, P_{\delta\delta} \supset (\delta\delta\delta)$$

Qualitative Understanding

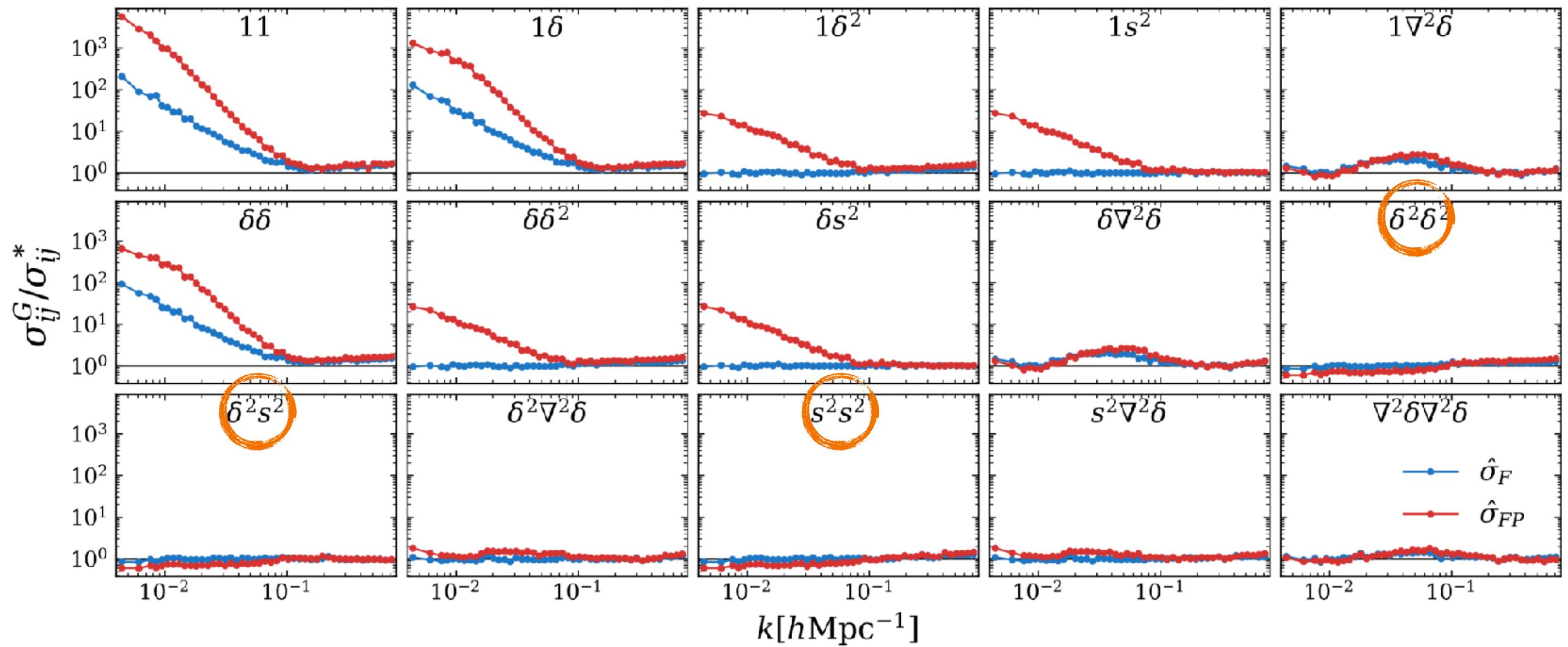


$$\begin{aligned}
 (\delta\delta\delta)_\pi &\sim \int_{\mathbf{q}_1} \underbrace{\sqrt{\dots} \cos [\theta_{\mathbf{k}} - \theta_{\mathbf{q}_1} - \theta_{\mathbf{q}_1 - \mathbf{k}} - \pi]}_{-\cos [\theta_{\mathbf{k}} - \theta_{\mathbf{q}_1} - \theta_{\mathbf{q}_1 - \mathbf{k}}]} F_{ZA}(\mathbf{q}_1, \mathbf{k} - \mathbf{q}_1, \mathbf{k}) \\
 &= -(\delta\delta\delta).
 \end{aligned}$$

$$P_{11}, P_{1\delta}, P_{\delta\delta} \supset (\delta\delta\delta)$$

$$\begin{aligned}
 P_{1\delta^2}^F(\mathbf{k}) &\approx V^{1/2} \int_{\mathbf{q}_1} \sqrt{P_{\mathbf{k}}^L P_{\mathbf{q}_1}^L P_{\mathbf{q}_1 - \mathbf{k}}^L} \cos [\theta_{\mathbf{k}} - \theta_{\mathbf{q}_1} - \theta_{\mathbf{k} - \mathbf{q}_1}] \\
 &\quad + V \int_{\mathbf{q}_1} \int_{\mathbf{q}_2} \frac{\mathbf{k} \cdot (\mathbf{k} - \mathbf{q}_{12})}{|\mathbf{k} - \mathbf{q}_{12}|^2} \sqrt{P_{\mathbf{k}}^L P_{\mathbf{q}_1}^L P_{\mathbf{q}_2}^L P_{\mathbf{k} - \mathbf{q}_{12}}^L} \cos [\theta_{\mathbf{k}} - \theta_{\mathbf{q}_1} - \theta_{\mathbf{q}_2} - \theta_{\mathbf{k} - \mathbf{q}_{12}}] \\
 &\quad + \frac{V}{2} \int_{\mathbf{q}_1} \int_{\mathbf{q}_2} \mathcal{K}_1(\mathbf{q}_1, \mathbf{k} - \mathbf{q}_1) \sqrt{P_{\mathbf{q}_1}^L P_{\mathbf{k} - \mathbf{q}_1}^L P_{\mathbf{q}_2}^L P_{\mathbf{k} - \mathbf{q}_2}^L} \cos [\theta_{\mathbf{q}_1} + \theta_{\mathbf{k} - \mathbf{q}_1} - \theta_{\mathbf{q}_2} - \theta_{\mathbf{k} - \mathbf{q}_2}]
 \end{aligned}$$

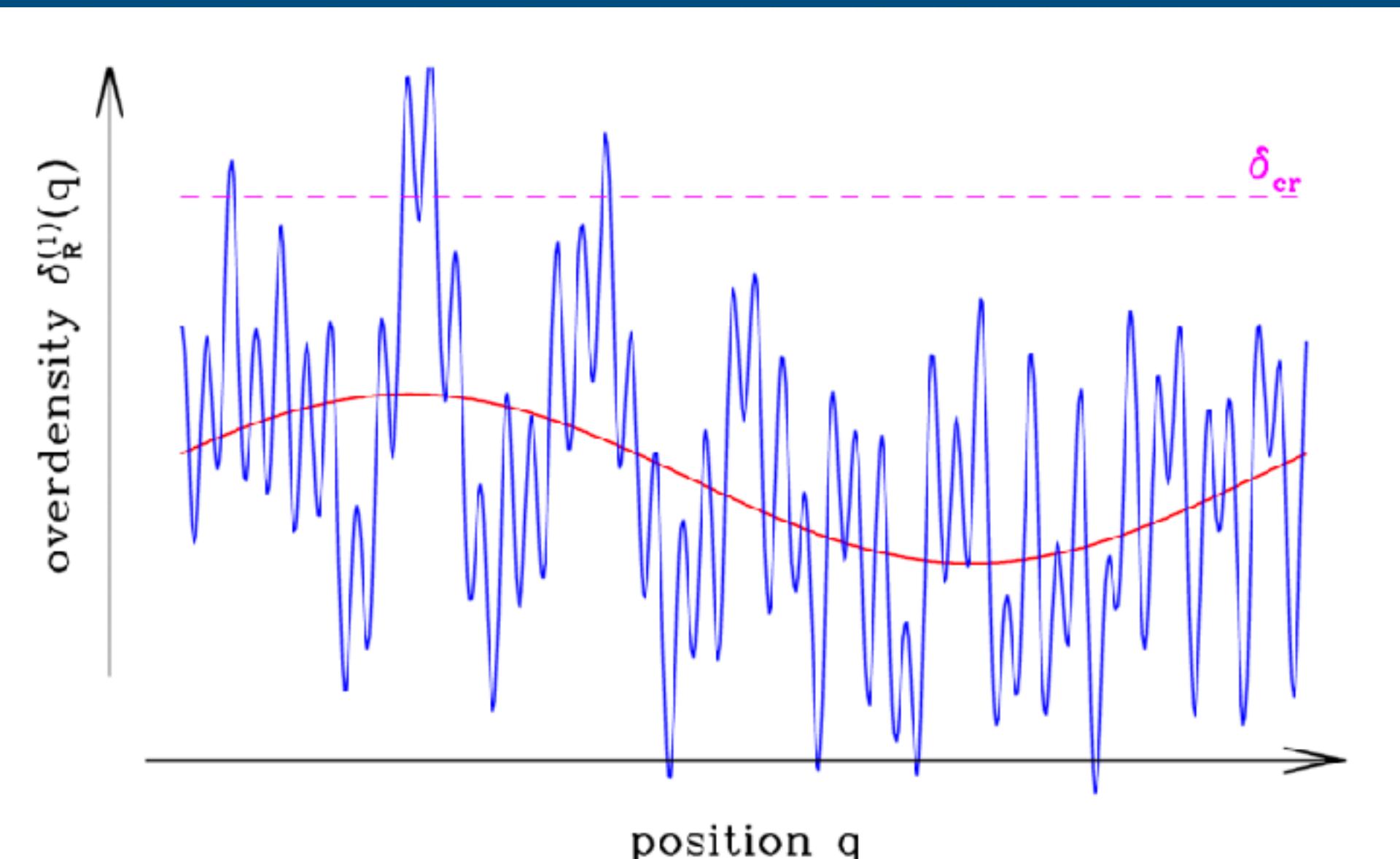
Qualitative Understanding



$$P_{\delta^2\delta^2}^{F\&P} \approx \frac{1}{V_f} \int_{\mathbf{q}_1} \int_{\mathbf{q}_2} \sqrt{P_{\mathbf{q}_1}^L P_{\mathbf{k}-\mathbf{q}_1}^L P_{\mathbf{q}_2}^L P_{\mathbf{k}-\mathbf{q}_2}^L} \cos [\theta_{\mathbf{q}_1} + \theta_{\mathbf{k}-\mathbf{q}_1} - \theta_{\mathbf{q}_2} - \theta_{\mathbf{k}-\mathbf{q}_2}]$$

Probabilistic Bias for IA

PBS Formalism



Desjacques+2016

Let f be the local density bias function

$$f(\mathbf{T}) = \frac{p(g \mid \mathbf{T})}{p(g)}$$

and

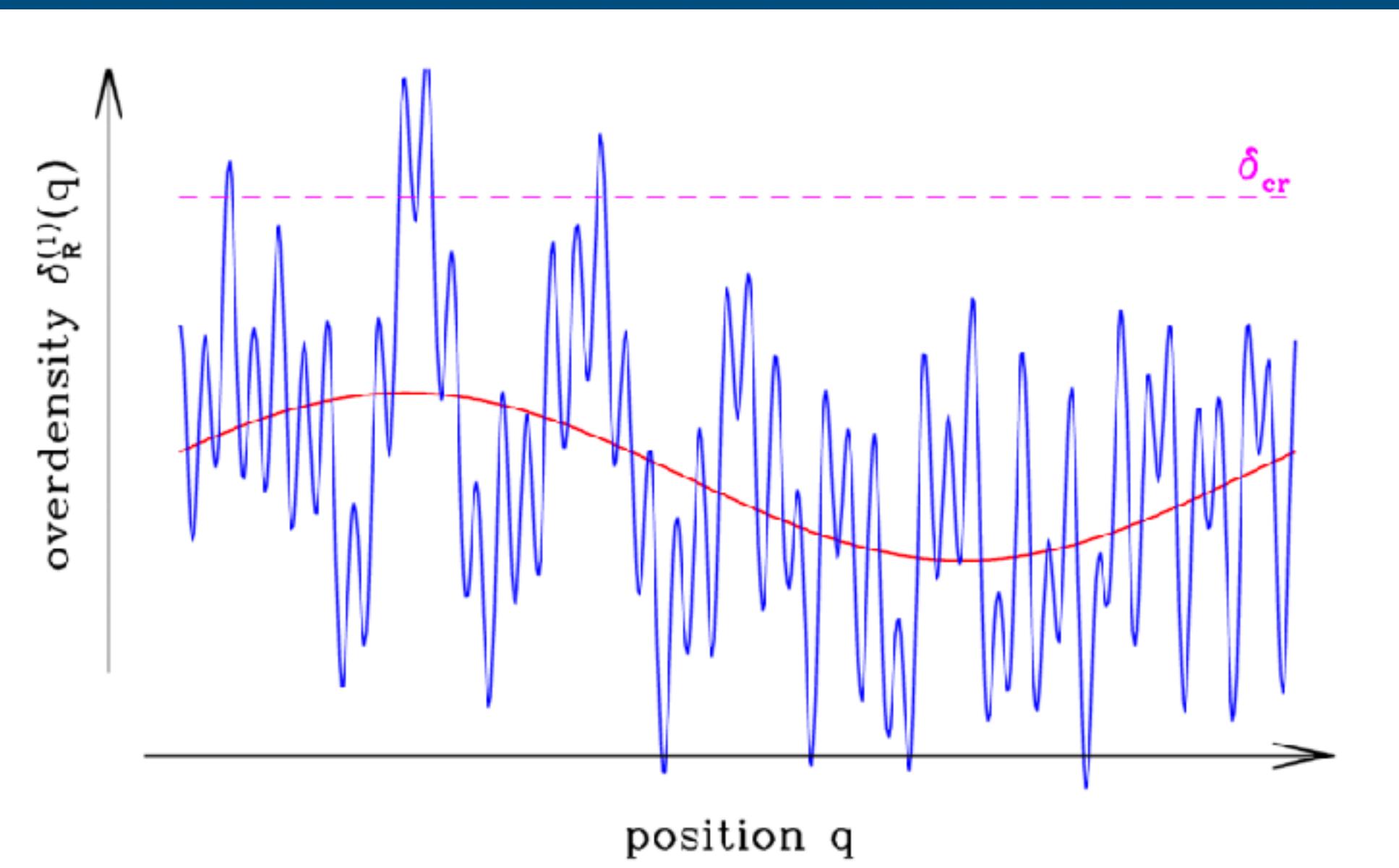
$$\langle h \mid x \rangle = \frac{\int \langle h \mid x, y \rangle p(y \mid x) dy}{\int p(y \mid x) dy}$$

then

$$\langle \mathbf{I} \mid \mathbf{T}_0 \rangle = \frac{1}{f(\mathbf{T}_0)} \int \langle \mathbf{I} \mid \mathbf{T}_S \rangle_g f(\mathbf{T}_S) p(\mathbf{T}_S \mid \mathbf{T}_0) d\mathbf{T}_S$$

Probabilistic Bias for IA

PBS Formalism



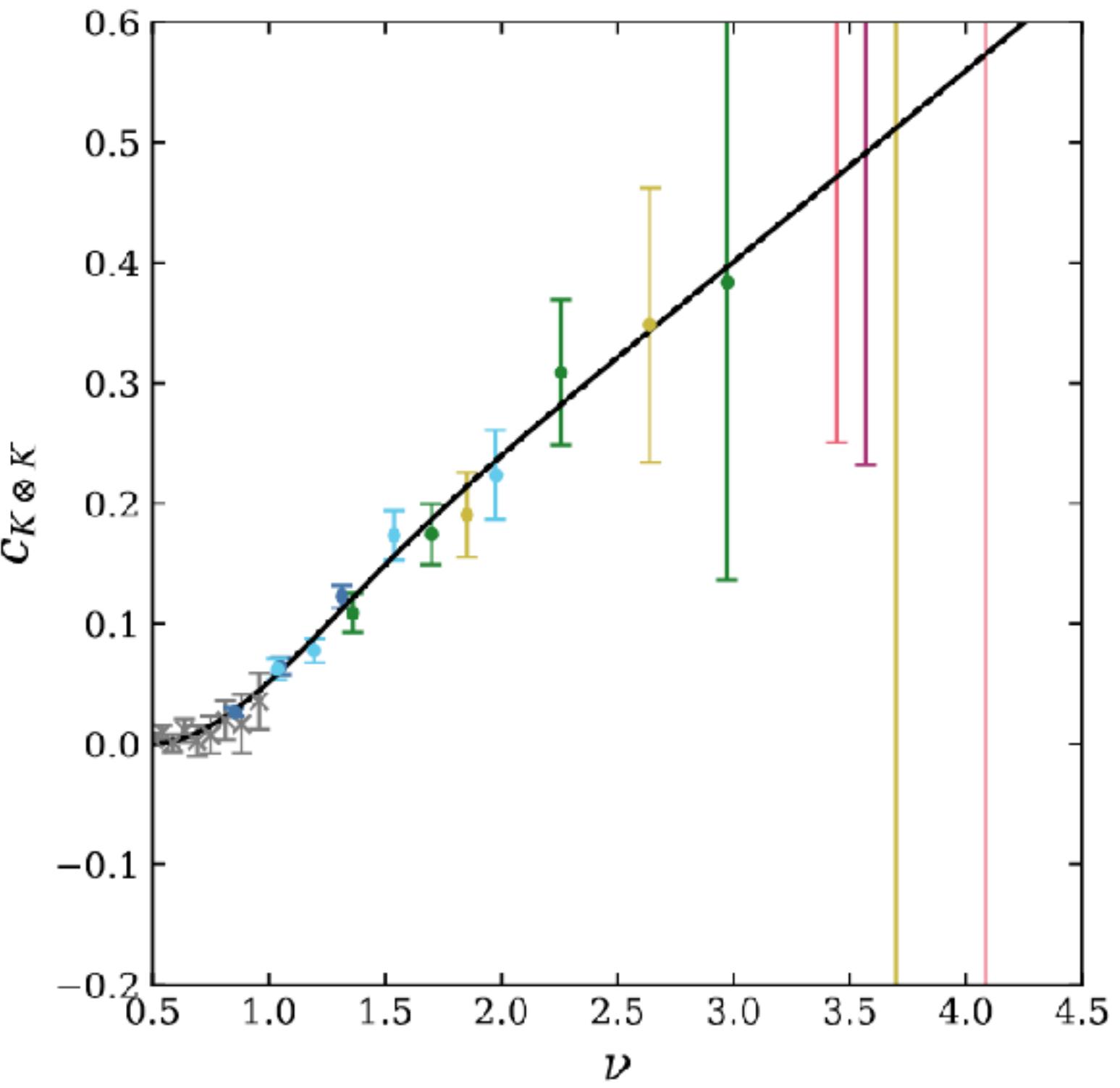
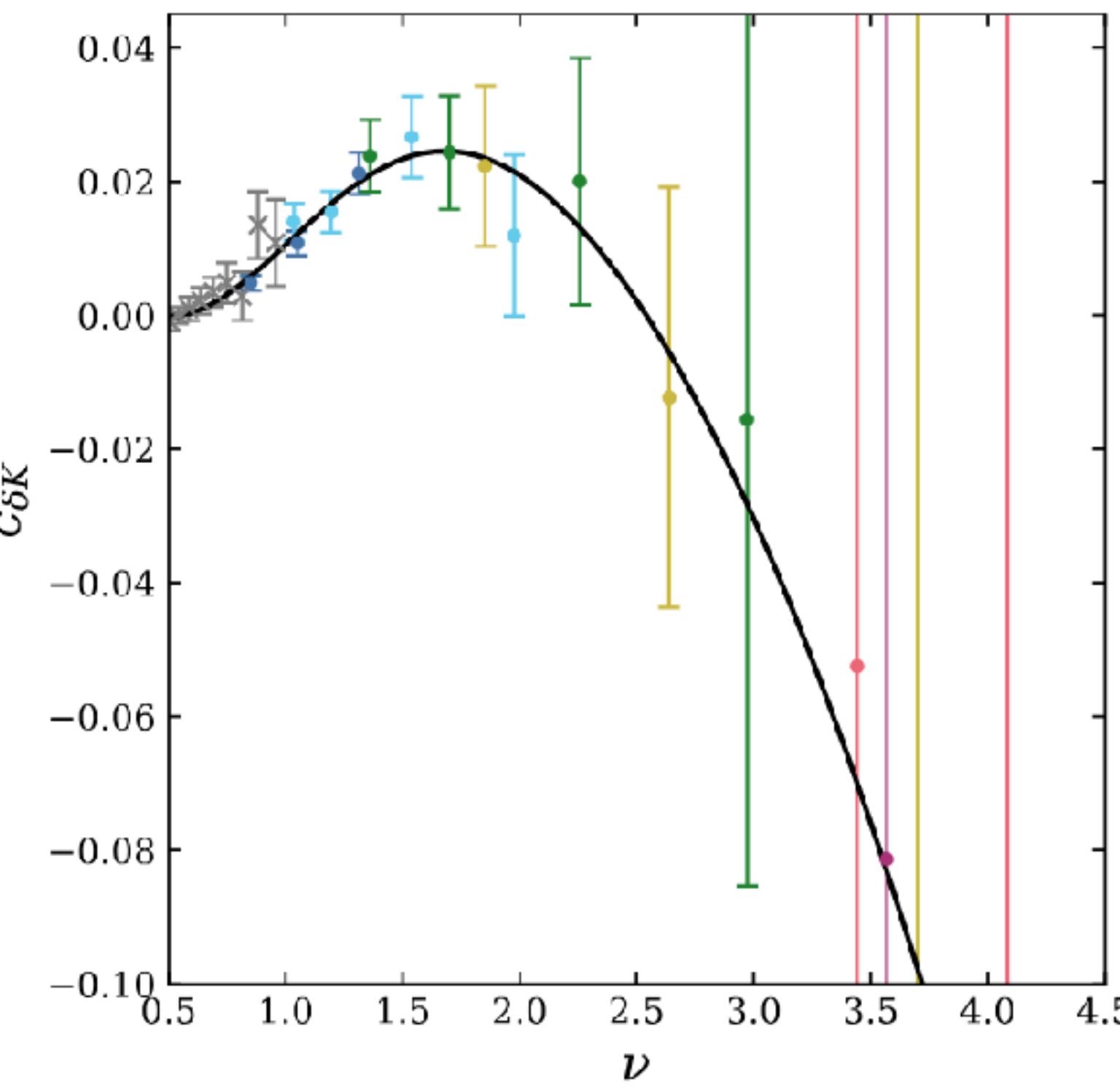
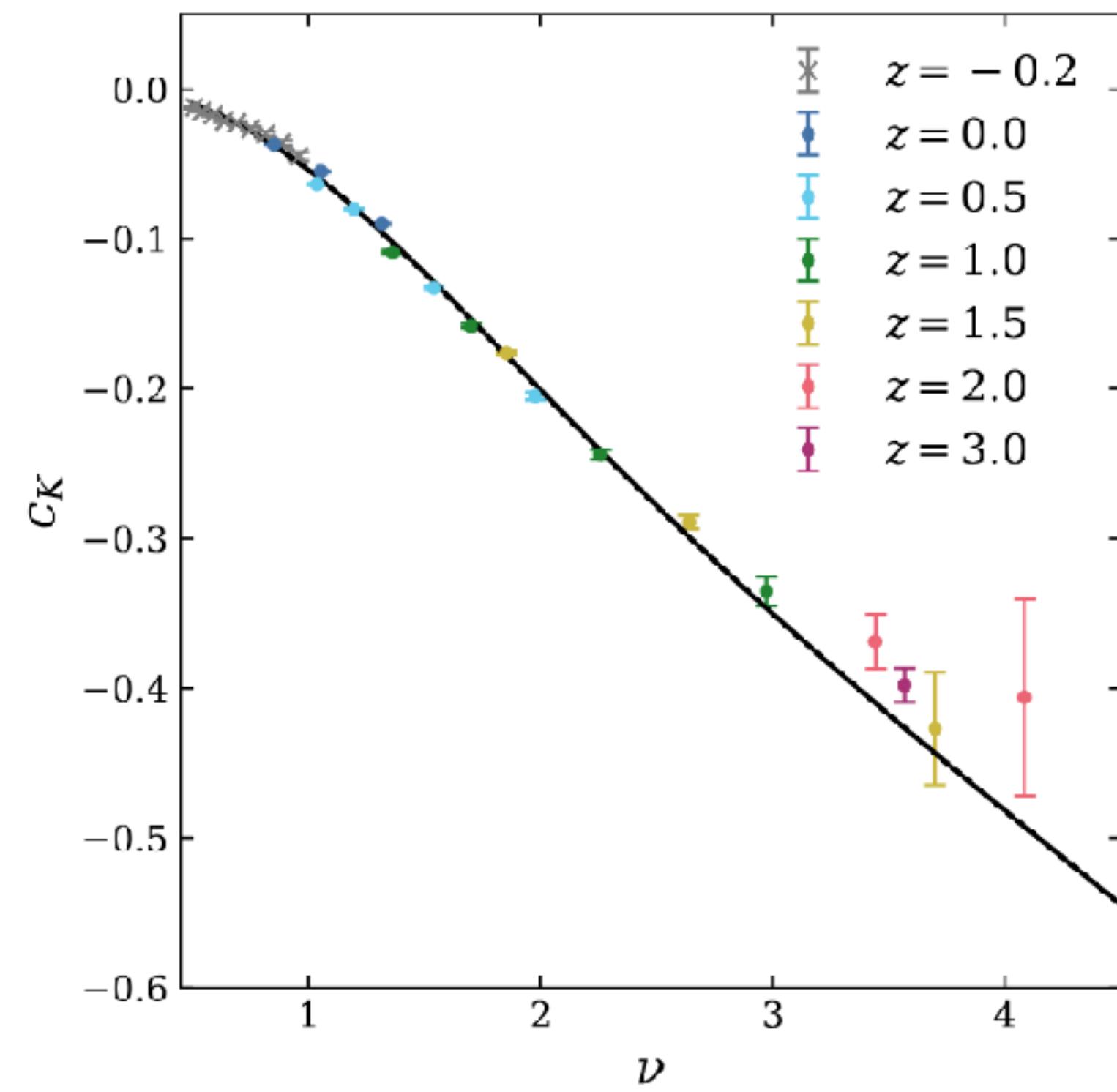
Desjacques+2016

Per-object Bias Estimators

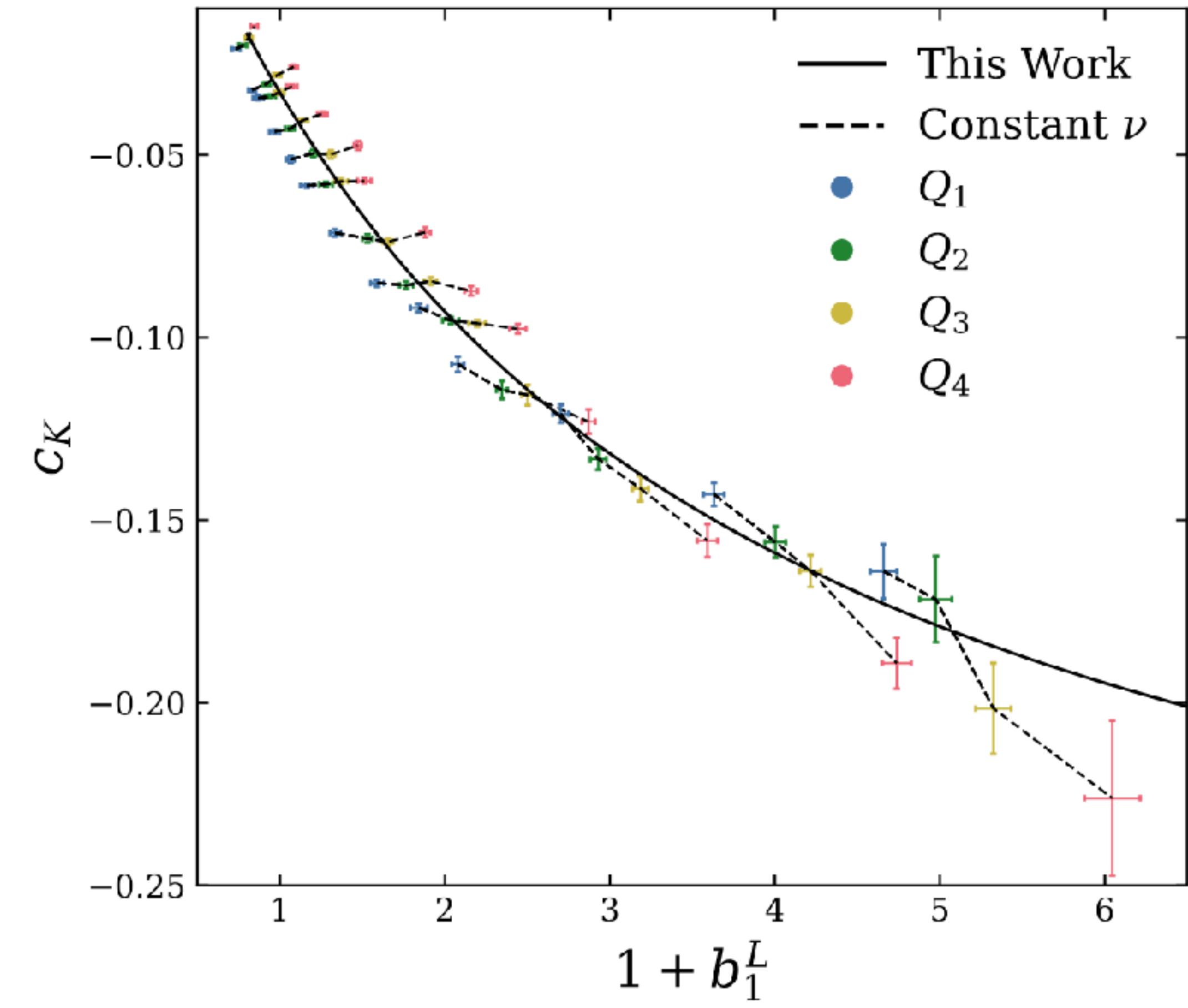
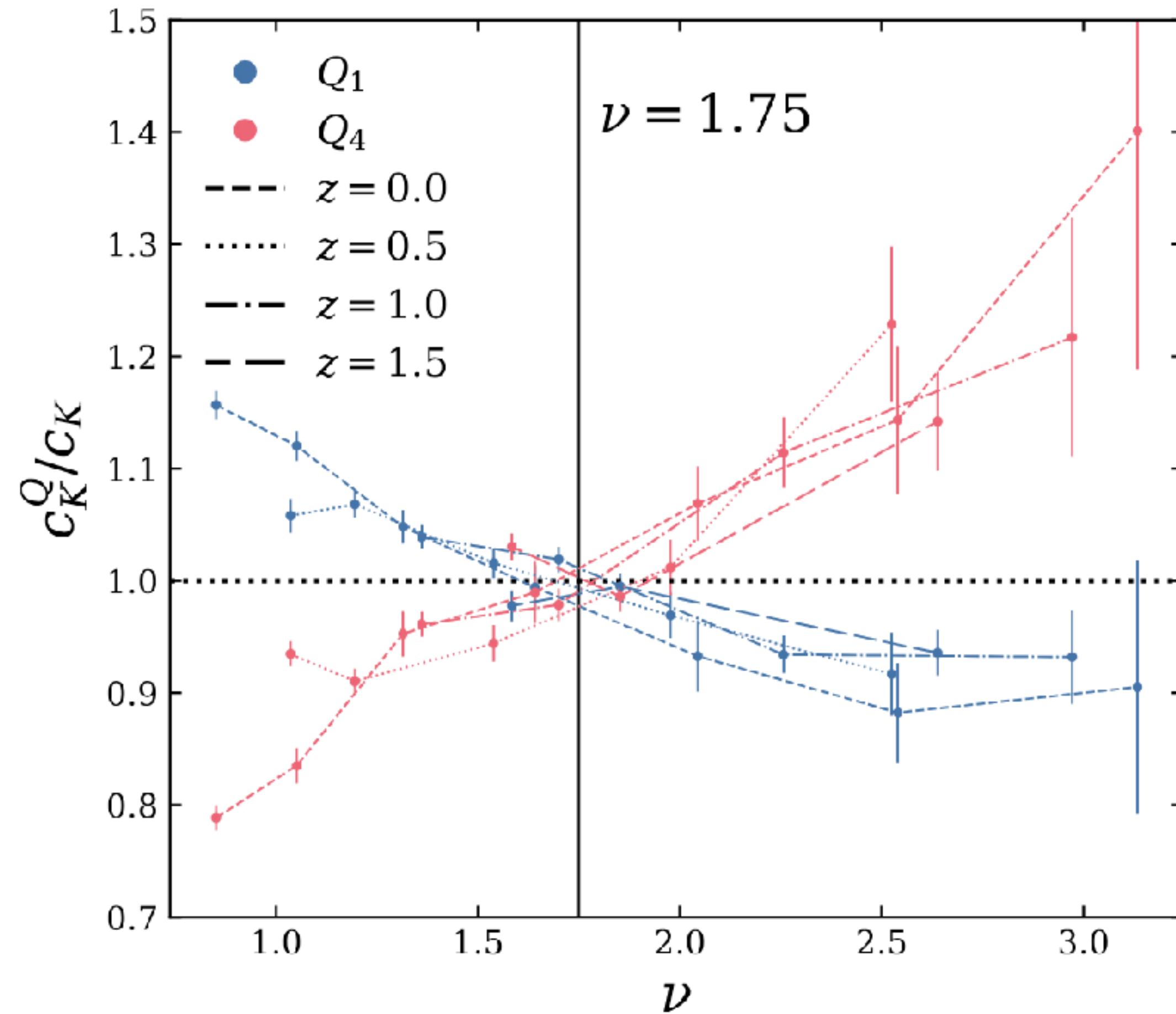
$$C_{K,n} = \frac{\partial^n \langle \mathbf{I} | \mathbf{T}_0 \rangle}{\partial \mathbf{T}_0^n} \Big|_{\mathbf{T}_0=0}$$

$$c_K = -\frac{3}{2} \text{tr}(\mathbf{K}\mathbf{I})$$

Universal Relation



Secondary Dependence



Linear Lagrangian Bias

